On the demand for high-beta stocks: Evidence from mutual funds

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ABSTRACT:

Prior studies have documented that pension plan sponsors rigorously monitor a fund's performance relative to a benchmark. We use a first-difference approach to causally show that in an effort to beat benchmarks, fund managers controlling large pension assets reduce fees and increase their exposure to high-beta stocks. Managers increase beta without affecting tracking error because they strategically substitute low-beta stocks for high-beta stocks with low idiosyncratic volatility. The findings support theoretical conjectures that benchmarking pressures increase demand for high-beta stocks and help to explain their low returns. Managerial risk-taking responses to benchmarking pressures complicate financial planning for investors.

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The movement from defined benefit to defined contribution plans over the past 20 years has opened the retirement market to mutual funds. Since 1995, retirement assets controlled by mutual funds have increased from $914 billion to $4.7 trillion, more than double the pace of total retirement savings growth and serving as a large source of growth for the mutual fund industry. Competition to enter and stay on pension platforms is fierce and the selection criteria set by pension sponsors are well-known to market participants.[1] Several studies find strong evidence that a fund's past performance and expenses are strong predictors of a fund's inclusion as an offering to employees in a sponsor's pension plan (see Goyal and Wahal, 2008; Sialm, Starks, and Zhang, 2013; and Pool, Sialm, and Stefanescu, 2013). In addition, plan sponsors rely on benchmarking as a defensible mechanism to decide which funds to remove from and keep on the plan:

> *Once an investment management firm has been hired, its performance is generally monitored on a quarterly basis. If performance relative to a benchmark deteriorates over consecutive evaluation horizons, the firm may be put on a "watch list." If performance improves, the firm is removed from the watch list. Continued deterioration in performance may result in the firm's contract being terminated.* (Goyal and Wahal, 2008)

If mutual fund managers are aware of the criteria needed to stay on the plan, the question we consider is whether they alter their behavior in response to the external benchmarking pressures from the sponsor. Our main premise is that managers with a larger proportion of sponsor-controlled assets in their funds are most sensitive to the benchmarking criteria and therefore more apt to change their behavior to beat benchmarks.

How might managers alter their behavior? To beat a benchmark, two strategies are possible. The first might be to reduce fees since they simply create a drag on performance. The second tactic would be to increase exposure to high-beta stocks. To illustrate the mechanism

[1] Under the standards set by the Employee Retirement Income Security Act, sponsors of pension plans are by law asked to adhere to strict responsibilities that ensure fiduciaries of the plan act in the best interest of plan participants, act prudently in their duties, diversify plan assets, and pay reasonable expenses. Their actions and decisions must be defensible to plan participants under the law.

linking benchmarking with the demand for high-beta stocks, consider a long-only fund that is benchmarked to the market portfolio with expected return of 10%. The fund has a choice between a stock with a beta of 1.25 and alpha of –2% and another stock with a beta of 0.75 and alpha of 2%. With a requirement to beat the benchmark market return, the fund manager has a preference for the high-beta stock (despite its negative alpha) because it will yield in expectation a return above the benchmark while the low-beta stock will not.

Using a sample of funds that report their retirement holdings with Pensions & Investments from 2005 to 2011, we first establish that funds with a larger portion of defined contribution (DC) assets have lower subsequent expenses and hold higher-beta stocks. We observe that high-DC funds increase their holdings of high-beta stocks while at the same time decreasing their exposure to low-beta stocks consistent with a manager attempting to beat a benchmark and as discussed below, to minimize the effects on tracking error. Sorting funds into quintiles on the proportion of DC assets reveals that future annual expenses decrease by over 20bp and fund beta rises by over 8% as a fund increases its DC holdings from 3% (bottom quintile) to 57% (top quintile).

We rule out the possibility that this relation is simply an artifact of the plan sponsor selecting funds with low fees and high betas using a first-difference approach. We document that an *increase* in DC assets causes a subsequent *decrease* in future fees and *increase* in future fund betas. In contrast, we do not observe a reverse relation between *changes* in fees or betas and future *changes* in DC assets. This evidence is strengthened by looking at how managers choose the weights on stocks in their portfolios. Instead of focusing only on changes in fund beta, we also take a weighted average of the betas of individual stocks in the portfolio to create a "holdings-level" beta. As with the fund beta, the holdings-level beta also *increases* in response to *increases* in DC assets of the fund. The observed changes in fund beta therefore arise from managers shifting their portfolio to high-beta stocks. Overall, the first-difference approach identifies causality as going from the accumulation of pension assets to the future reduction in fees and to the subsequent increase in the fund beta.

By tilting the portfolio to high-beta stocks, the fund manager increases the chance to "beat" the benchmark but runs the risk of increasing tracking error. To the extent that managers have an incentive to reduce this risk, the question is whether managers strategically increase beta while trying to minimize the impact on tracking error. One possible strategy to increase fund beta without driving up tracking error is to replace low-beta stocks with high-beta stocks. For instance, substituting a stock with beta of 0.9 with a stock whose beta is 1.1 will not impact tracking error but will increase fund beta. When looking at portfolio holdings of funds with a large portion of DC assets, we see strong evidence of such substitution. We observe that such funds shift almost 3% of the portfolio from the low-beta to the high-beta tercile of stocks. A refinement of this strategy would be to search for stocks that have both high beta and low idiosyncratic volatility. We confirm that funds also engage in this behavior.

We test how the strategic shifting of portfolio holdings to high-beta low-idiosyncratic volatility stocks in response to DC flows affects funds' tracking errors. We also examine the effects on another measure of co-movement of fund returns and benchmark returns, the R-squared proxy for managerial passiveness proposed by Amihud and Goyenko (2013). We find that higher levels of DC assets predict *lower* tracking errors and *higher* R-squared measures. Using our first-difference approach to isolate causality, we observe that an *increase* in DC assets results in an *increase* in subsequent R-squared measures of passiveness and does not significantly change the future tracking error. On all accounts, it appears that managers are strategically increasing beta exposure while managing and even reducing the volatility of returns around the benchmark.

The demand for stocks with high beta and low idiosyncratic volatility can have important implications for pricing of these securities. In classifying all stocks by beta tercile and by the median level of idiosyncratic risk, we find that only 9% of all stocks are characterized as having both high beta and low idiosyncratic volatility. Therefore, the demand for these types of stocks can drive the prices of these stocks up and future returns down. Consistent with demand pressures, we find a significant negative relation between beta and future returns only in the subgroup of stocks with low idiosyncratic volatility.

Given extensive empirical evidence that high-beta stocks persistently underperform low-beta stocks,[2] Baker, Bradley, and Wurgler (2011) posit benchmarking as a possible theoretical reason for the persistence of the anomaly but indicate that "conducting a direct test of [the] proposed mechanism is difficult". One of our contributions is to provide the first direct test of the impact of benchmarking on institutional portfolios and show that increased attentiveness to benchmarks coincides with greater demand for high-beta exposure and avoidance of low-beta, high-return stocks. Funds that are more susceptible to benchmarking pressures from pension sponsors increase their demand for high-beta stocks but do so in a way to minimize the impact on tracking error by simultaneously reducing their exposure to low-beta stocks and increasing their allocations to low-idiosyncratic volatility stocks.

Our paper offers two new contributions to the literature. First, it documents the effects that pension plan sponsors have on mutual fund managers. Prior research has focused on the criteria used by pension plan sponsors in adding funds to and eliminating funds from their menus,

[2] See Black (1972), Black, Jensen, and Scholes (1972), Hong and Sraer (2012), and Frazzini and Pedersen (2013).

whereas this study shows how these criteria influence managers' behavior while they are on the plan platform and under stringent sponsor oversight. Second, the results provide direct evidence that benchmarking encourages investment in high-beta stocks and limits the appetite for low-beta stocks. With over $14 trillion in assets, limits to arbitrage among mutual funds could therefore have a significant impact on capital markets and explain why the high-beta, low-return anomaly might persist.

We find no evidence that benchmarking pressures corresponds to better outcomes for investors. Consistent with Sialm and Starks (2012), returns are no better among funds with more DC assets despite the lowering of fees. Similarly, future risk-adjusted returns and Treynor ratios are unrelated to sponsor involvement. From a policy perspective, absence of a requirement to disclose the composition of retirement and non-retirement money leaves investors unaware of potential agency conflicts and can complicate individual financial planning. Moreover, the documented low returns on high-beta investments would suggest that this is not an optimal investment strategy for investors. Interestingly the literature has focused on the cost of short-term investors on long-term ones (Johnson, 2004), but in this case long-term investors come with their own costs which are unfortunately borne by everyone in the fund.

The remainder of the paper is divided as follows. Section I provides a brief overview of the relevant literature and Section II summarizes the data. Section III and IV present the hypotheses and the key empirical findings. Sections V and VI discuss how managerial risk-taking incentives affect fund returns and impact investors. Section VII concludes.

I. Related Literature

This paper bridges three lines of the literature. The first strand of literature relates to the growing interest in retirement investment through defined contribution plans and in the role of a plan sponsor. The second contribution of the paper lies in examining the high-beta/low-return anomaly first documented by Black (1972) and Black, Jensen, and Scholes (1972), and in testing whether benchmarking serves as a limit to arbitrage that may enable the anomaly to persist. Lastly, the paper adds to the literature discussing risk-taking incentives of mutual fund managers.

A. Retirement savings

Our study relates to a growing literature on retirement savings. Much of this literature discusses asset allocation and trading decisions of retirement plan participants. For example, Madrian and Shea (2001) show that most 401(k) investors do not modify their allocations over time, choosing instead to keep the default savings rate and investment funds suggested by the employer. Agnew, Balduzzi, and Sunden (2003) and Mitchell, Mottola, Utkus, and Yamaguchi (2006) provide strong evidence of inertia in trading decisions of plan participants.[3]

The emphasis in this literature has been on how investors respond to changes in characteristics of their retirement plans rather than to the performance of their fund. More recently, Goyal and Wahal (2008) examine the selection and termination of funds by plan sponsors. A study by Sialm, Starks, and Zhang (2013) uses data similar to ours and shows that flows of funds with larger amounts of retirement money have higher sensitivity to extreme fund performance. Their finding suggests a strong role of the pension plan sponsor in deciding

[3] See also Mitchell, Utkus, and Yang (2005), Choi, Laibson, Madrian, and Metrick (2004, 2006), and Mitchell, Mottola, Utkus, and Yamaguchi (2006). Benartzi and Thaler (2007) provide an excellent review of biases in investment decisions of retirement plan participants.

whether to include or remove managers from sponsor plans and implies that the actions of the plan sponsor seem to overcome investor passiveness. Expenses and performance appear to be important criteria used by sponsors in selecting funds to the platform. Hand-collected data from Pool, Sialm, and Stefanescu (2013) on funds selected to menus supports this evidence and also indicates that funds affiliated with the trustee of the fund tend to stay longer after poor performance but also have lower fees. Our study builds on this new body of research by considering the effects of sponsor oversight on subsequent managerial behavior.

B. High-beta/low-return puzzle

Several empirical studies have identified that investing in low-beta stocks yields significantly higher returns than investing in high-beta stocks. The anomaly is puzzling as it contrasts with the underpinnings of the CAPM (e.g., Sharpe, 1964). It is difficult to rationally explain why the phenomenon does not disappear if institutions can simply take advantage of it by investing in low-beta stocks. To explain the persistence, Baker, Bradley, and Wurgler (2011) posit that benchmarking may serve as a limit to arbitrage which dissuades low-beta investment. Central to their argument is the fact that over long evaluation horizons, benchmark returns are expected to be positive. For example, if benchmark returns are iid normal with annual mean of 10% and standard deviation of 15%, then the probability of the benchmark being positive in a year is 75% (see Christoffersen and Diebold, 2006). If we instead evaluated the manager over two years, the probability of a positive benchmark return over that period would increase to 83% and then to 88% over a three year horizon.[4]

[4] If returns are distributed as $R = \mu t + \sigma\sqrt{t}z$ with $z \sim N(0,1)$, then the probability of positive returns is $\Phi(\mu\sqrt{t}/\sigma)$, where $\Phi(\cdot)$ is the N(0,1) cumulative density function. Substituting $\mu=0.1$, $\sigma=0.15$, and $t \in \{1,2,3\}$ gives the shown probabilities.

Given the high likelihood of observing a positive benchmark return over the evaluation horizon of a fund manager, the manager who is evaluated relative to a benchmark index has an incentive to hold high-beta stocks since these stocks will in expectation beat the benchmark when its returns are positive. The example in the introduction shows the perverse outcome that managers targeting a benchmark with positive expected returns of 10% would prefer a negative-alpha, high-beta stock (-2%, 1.25) over a positive-alpha, low-beta stock (+2%, 0.75). Interestingly, the movement to evaluate managers over longer horizons of three or five years only increases the incentives of managers to buy high-beta stocks since the likelihood of a positive benchmark return increases with horizon.

Despite a strong theoretical basis for benchmarking to increase the demand for high-beta stocks, the empirical evidence is only suggestive and relies on aggregate return patterns. For example, Brennan and Li (2008) document a negative payoff to the idiosyncratic component of the S&P 500 which is consistent with efforts to minimize tracking error but does not directly tie an institution's benchmarking to its demand for high-beta stocks. Frazzini and Pedersen (2013) document the profitability and liquidity risks involved with a betting-against-beta portfolio but do not discuss how benchmarking by asset managers may contribute to the persistence of this pricing distortion. Hong and Sraer (2012) investigate the demand for high-beta stocks driven by disagreement in macroeconomic conditions. In their model, high-beta stocks are bets on the market and subject to speculative investing so in the presence of short-sale constraints and high degree of disagreement, these stocks are held by optimists whose demand for the stocks is reflected in high prices and low returns. Finally, Buffa, Vayanos, and Woolley (2013) develop theoretical framework where benchmarking amplifies the high-beta/low-return anomaly. In their model, managers wanting to reduce deviations from a benchmark have an incentive to buy more volatile (high-beta) stocks because these stocks explain a large portion of the overall market volatility. In contrast, managers avoid holding stocks in large supply with low volatility (even if they have high returns) because these stocks explain only a small component of the variance around the benchmark.

C. Risk-taking

Our study also contributes to the literature on risk-taking by fund managers. Brown, Harlow, and Starks (1996) study how fund performance in the first half of the year impacts risk taken on by managers in the second half. They find evidence of tournaments in mutual funds, showing that funds with relatively good (poor) performance in the earlier part of the year decrease (increase) their risk in the latter part.[5] More recently, Huang, Sialm, and Zhang (2011) show that changes in risk of a fund's portfolio relate negatively to future fund performance, which, they hypothesize, may be due to inferior abilities of managers changing risk or to agency issues. Balduzzi and Reuter (2011) study characteristics of target-date funds and document substantial heterogeneity in risk taken on by funds with the same target date. In contrast with the previous literature, we explore a new facet of managerial incentives to modify the risk of a fund: the benchmarking pressures arising from managing sponsor-controlled retirement assets.

II. Data

Our sample includes funds which report their defined contribution plan holdings with Pensions & Investments (P&I). P&I conducts annual surveys that query fund managers on their positions in DC assets as of the end of the preceding year. Our analysis is based on surveys

[5] Other studies analyzing changes in risk within a calendar year include Chevalier and Ellison (1997), Busse (2001), Kempf and Ruenzi (2008), and Schwartz (2012).

administered to domestic equity funds for the years 2004 through 2010. Similar data has been used in Christoffersen, Geczy, Musto, and Reed (2005), Sialm and Starks (2012), and Sialm, Starks, and Zhang (2013) and readers are directed to these papers for more details of the surveys.

We match P&I data to the Morningstar database, from which we collect information on funds' investment objectives, size, flows, expenses, turnover, tracking errors, and returns. For analysis based on fund holdings, we also obtain data from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free Mutual Fund Database. We restrict the sample to funds with Morningstar broad category group of 'Equity', excluding 32 funds with 'Allocation', 'Commodities', 'Tax Preferred', 'Fixed Income', and 'Alternative' categories. We also eliminate 50 fund-year instances where reported DC assets exceed fund size. The final sample contains 3,102 fund-year observations representing 856 distinct funds.

We obtain most of our variables directly from Morningstar or CRSP, and calculate the remaining variables as follows. *Beta* is the slope coefficient from market model regressions of a fund's excess returns on the excess return of the CRSP value-weighted market index. P&I data are updated annually, and we estimate betas from regressions using one year of monthly data.[6] *Idiosyncratic volatility* is the standard deviation of the monthly error terms from the same regression used to estimate beta. *Holdings-level beta* provides an alternative measure of a fund's market risk by value-weighting betas of stocks held by each fund. It is only affected by the choice of a manager to tilt the portfolio to high- or low-beta stocks, and unlike fund-level beta it is not influenced by changes in cash or leverage, or by trading costs. To calculate holdings-level beta for fund i in year t, we use daily data from year t to calculate market model beta β_{jit} for each

[6] Our results are robust to computing risk proxies using daily fund returns from CRSP.

stock j held by fund i at the end of year t-1.[7] The market return used is the daily value-weighted index from CRSP. The holdings-level beta for fund i is then calculated as the value-weighted average across all stocks, using the fraction w_{jit} of the equity portfolio allocated to each stock as weights, $\Sigma_j w_{jit}\, \beta_{jit}$. The last variable that we calculate in our analysis is the *R-squared* measure of Amihud and Goyenko (2013) which we calculate for year t as the coefficient of determination from a regression of a fund's monthly excess returns in that year on the Carhart (1996) four factors.

A. Descriptive statistics

Table 1 summarizes fund size and defined contribution plan holdings, highlighting considerable cross-sectional differences in the proportions of assets in retirement money. Whereas the average fund in the sample has approximately a quarter of its assets in DC plans, a tenth of the funds holds less than 2% and another tenth carries more than half of assets in retirement money. The size of the average fund, measured in millions of dollars ($5,220 at the end of 2010), is considerably larger than that of an average equity fund ($1,236 according to the Investment Company Institute). Despite including a small number of funds, our sample accounts for more than half of all defined contribution plan assets invested in domestic equity mutual funds ($621 out of $1,132 billion at the end of 2010). Table 1 also illustrates that the data are reported for a similar number of funds each year. This stability is important given that the data are based on a survey. We thus have consistent surveys through time from the same fund families which allow us to identify changes in behavior after the accumulation of defined contribution assets.

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[7] If a fund's last portfolio holdings disclosure occurs before the end of December of year t-1, we infer the fund's year-end positions by assuming that it did not trade since the last disclosure date. For example, if a fund revealed a position of D_j^{Nov} dollars in stock j as of the end of November, we calculate the year-end value of this position as $D_j^{Dec} = D_j^{Nov}(1 + r_j^{Dec})$, where r_j^{Dec} is the return on stock j in December.

In Table 2, we explore correlations between the fraction of DC assets in a fund, *DC fraction*, and the main variables in our sample. We report statistics for *Lagged relative return*, the fund return relative to other funds with the same Morningstar investment objective, measured in decimals and calculated over the preceding year. Average *Lagged relative return* for our sample is 42bp per year which is not statistically different from zero. In addition, we include *Expenses* and *Turnover* measured in percent of fund assets and *Fund size* expressed in millions of dollars. We calculate three different proxies of risk: *Beta*, *Idiosyncratic volatility,* and *Tracking error*. The first two measures are computed based on monthly market model regressions and are reported as decimals. *Tracking error* comes directly from Morningstar and is expressed in percent per year. It measures the standard deviation of the difference between a fund's daily return compared to its Morningstar-defined benchmark. All three proxies of risk and expenses are defined over year *t+1* while fund size, turnover, fraction, and lagged relative return are defined over year *t*. *R-squared*, our measure of managerial passiveness is computed using a fund's returns in year t+1. Higher values of R-squared indicate a higher level of passive investing.

The correlation matrix reported in Table 2 provides interesting early evidence on the relation between the fraction of a fund's assets in retirement money and fund characteristics. Funds with high retirement fractions are larger, consistent with the selection criteria used by sponsors to choose large funds as found in prior research. New to this study, we document that funds with a higher incentive to beat their benchmark, proxied by the fraction of assets in retirement money, increase their exposure to high-beta stocks and lower fees. Initial evidence shows a positive correlation between DC assets and beta and the opposite for fees. Also, the fraction of DC assets correlates negatively with tracking errors and positively with R-squared levels, suggesting that managers are altering their portfolios in a way to increase beta exposure while at the same to minimizing the impact on volatility around the benchmark. All these observations are consistent with managers responding to benchmarking pressures from sponsors. We now turn to explore more thoroughly how sponsors affect managerial decisions and to analyze the direction of causation between these variables.

III. Hypotheses and Preliminary Analysis

Our main objective is to determine whether more oversight from plan sponsors causes managers to change their investment behavior so as to beat benchmarks set as evaluation criteria. Unlike prior studies which focus on the criteria used to select funds to a pension platform, we test whether those already managing a larger portion of sponsor-controlled assets tend to alter their *subsequent* behavior to beat benchmarks. Drawing from our discussion in Section II, we test two tactics that a manager may employ to beat the benchmark: (1) lowering expenses and (2) increasing exposure to high-beta stocks. Our main hypotheses are therefore:

H1. Funds with higher fractions of sponsor-controlled pension assets charge lower future expenses.

H2. Funds with higher fractions of sponsor-controlled pension assets take on more market risk by investing in high-beta stocks.

H3. Funds with <u>increased</u> sponsor-controlled pension assets <u>decrease</u> their future expenses.

H4. Funds with <u>increased</u> sponsor-controlled pension assets <u>increase</u> their portfolio weights on high-beta stocks.

In hypotheses H1 and H3, we test in both levels and changes whether managers actively reduce fees to improve their returns relative to a benchmark in response to accumulating more DC assets. The predictions of H2 and H4 are based on theoretical models. As pointed out in Baker, Bradley, and Wurgler (2011), managers aiming to beat the benchmark have an incentive to load more heavily on it since the expected benchmark return is positive. Subsequent work by Buffa, Vayanos, and Woolley (2013) argues that benchmarking encourages investment in high-volatility stocks because these stocks make up a larger portion of the market variance so actually help the portfolio manager better mimic overall market volatility and reduce tracking error around the benchmark. Both theoretical models lead to the same prediction that benchmarking will associate with investment in high-beta stocks.

One potential downside to ramping up beta in a portfolio is that it may increase deviations around the benchmark. This creates a constraint on how managers concerned with meeting benchmarks might adjust their portfolio. Two strategies that a manager could use to reduce the impact of a high-beta strategy on tracking error would be to: (1) focus on increasing the demand for high-beta stocks with low idiosyncratic volatility and (2) substitute the holdings of low-beta stocks with high-beta stocks. In our next set of tests, we study whether managers strategically choose high-beta stocks so as to minimize the impact on tracking errors. The two additional hypotheses we test are:

H5. Managers of funds with high portions of sponsor-controlled assets increase their demand for high-beta stocks with low idiosyncratic volatility to reduce the impact on tracking errors.

H6. Managers of funds with high portions of sponsor-controlled assets increase their demand for high-beta stocks while at the same time reducing their holdings of low-beta rather than mid-beta stocks.

Finding positive evidence of all hypotheses provides very strong evidence of managers responding to sponsor oversight by employing tactics to optimize fund returns around benchmarks. The next section empirically tests our predictions.

A. Analyzing retirement asset quintiles

The correlations in Table 2 identify relations between variables but make it difficult to evaluate causality and the economic significance of these relations. Table 3 therefore divides the sample into quintiles on the basis of the fraction of sponsor-controlled retirement money in each fund. For each quintile, we provide averages of several variables of interest, and show the differences between the highest and lowest quintiles in the last column. Tracking error, betas, idiosyncratic volatility, R-squared, expenses, and gross returns are measured in year $t+1$, while fraction of retirement assets, cash holdings, equity holdings, and fund size are measured at the end of year t. Several patterns emerge, providing an early indication that as the fraction of sponsor-controlled assets increase, managers respond by altering their investment portfolio to maximize the possibilities of beating the benchmark while at the same time minimizing volatility around benchmark returns.

As retirement assets increase, future expenses decline from 1.16% to 0.94% when moving from the lowest quintile to the highest quintile. This result aligns with the idea that managers with more sponsor-controlled assets reduce expenses to avoid their drag on fund performance relative to the benchmarks. Note that unlike prior studies, we are analyzing the relation of the proportion of DC assets on *future* expenses, not past or contemporaneous expenses, but the fact that expenses are highly persistent makes it difficult to identify the direction of causality. Later analysis will be able to determine causality more precisely by using a first-difference approach of measuring how *changes* in DC assets affect *future changes* in expenses.

We also observe that a fund's market beta monotonically increases with the fraction of retirement money, from 1.02 for the lowest quintile to 1.11 for the highest quintile. This increase in exposure to market risk does not come about because the manager allocates a larger fraction of assets away from cash and into equity: Rows labeled "Cash" and "Equity" show that funds with more retirement money do not appear to hold less cash, and that they increase their equity allocations in an economically insignificant way. Rather, higher betas of funds with more sponsor-controlled assets appear to be driven by managers' investments in stocks with high betas, consistent with the argument that leverage-constrained asset managers reach for high-beta stocks (see Black, 1972).

To further analyze the role of leverage in fund betas, Table 4 estimates fund beta as a function of the holdings-level beta and the proportion of assets allocated to equities, and repeats the estimation for changes in these three variables. The results clearly suggest that changes in the holdings-beta explain almost one-to-one the changes in the fund-level beta.[8] In contrast, change in leverage, as proxied by the portfolio allocation to equity, has an economically marginal and statistically insignificant effect. Not surprisingly, holdings-level beta increases significantly with DC assets in Table 3 as found with fund-level beta.

Idiosyncratic risk is unrelated to the level of DC assets in the fund. Given that high-beta stocks typically associate with high idiosyncratic volatility, with a correlation close to 0.3, the lack of increase in idiosyncratic volatility across DC fraction quintiles is at least suggestive that managers are choosing high-beta stocks so as to minimize the impact on tracking error. Analyzing this more directly, we find that future tracking errors decline significantly from 5.08% in the lowest fraction quintile to 4.68% in the highest quintile. Similarly, R-squared measures of passiveness increase from 0.91 to 0.94 for the same changes in DC assets. Thus, managers respond to more sponsor-controlled assets by forming portfolios in a way that more closely tracks their benchmarks despite at the same time weighting high-beta stocks more heavily.

[8] The coefficients on both levels and changes in holding-level beta are insignificantly different from one in both regressions.

Panels B and C of Table 3 provide some insight on how managers choose higher betas while maintaining levels of idiosyncratic risk and lowering tracking error. The panels summarize the fraction of dollars (Panel B) and the fraction of stocks (Panel C) invested in low-, medium-, and high-beta bins. Using the entire universe of stocks for each year, firms are grouped into terciles and identified as having low-, medium-, and high-betas. For each DC fraction quintile, a break-down of the portfolio across the three beta bins is provided. For instance, in Panel B, an average fund with the lowest level of DC assets has a portfolio with 33.2%, 43.8%, and 23.1% invested in low-, medium, and high-beta stocks, respectively. Portfolio allocations shift significantly and monotonically from the low-beta stocks to the high-beta bin as the DC fraction increases, with the medium-beta group left unaffected. As a result, an average fund in the high-DC quintile allocates 30.7%, 43.1%, and 26.2% to low-, medium-, and high-beta stocks, respectively. This provides some initial evidence of high-DC managers strategically choosing high-beta stocks so as to minimize the impact on tracking error outlined in hypothesis H6. The combined patterns in tracking error, R-squared, expenses, betas, and idiosyncratic risk are all consistent with managers responding to increases in sponsor influence by engaging in strategies aimed at maximizing the probability to beat benchmarks while minimizing the variation around the benchmark returns.

B. Market betas vs. benchmark betas

Throughout the descriptive analysis, we analyze how changes in benchmarking pressures relate to *market* betas and do not use betas with respect to the benchmarks. In unreported analysis, we redo all the estimation in the descriptive statistics and also in the upcoming analysis with benchmark betas. To calculate benchmark betas, we estimate benchmark returns using the average returns for funds in the same Morningstar-defined category and calculate betas with respect to these benchmarks. The correlation between market betas and benchmark betas exceeds 0.75, and our results are robust when using either market or benchmark betas. In the interest of brevity and to keep the analysis consistent across funds, we present only the results with market betas since the market index is likely to serve as a relevant benchmark for many funds. However, the results with category benchmark betas are available to the reader upon request.

IV. Empirical Results

A. Beating benchmark returns

Our main objective is to test whether fund managers change their investment strategy to beat the benchmark in response to pension sponsor oversight. To study this, we test how the fraction of defined contribution plan assets overseen by sponsors affects a manager's *future* decision to adhere to benchmarks.

In Table 5, we test H1 and H2:

$$\begin{aligned} BM_{i,t+1} &= \alpha_0 + \alpha_1 Fraction_{i,t} + \alpha_2 Log\ \ fund\ size_{i,t} + \alpha_3 Lagged\ relative\ return_{i,t} \\ &\quad + \alpha_4 Turnover_{i,t} + \alpha_5 BM_{i,t} + \varepsilon_{i,t+1}, \end{aligned}$$

where for fund *i* in year *t*, *BM* represents either *Expenses* or *Betas*: the two different strategies to "beat" the benchmark. We cluster standard errors by fund and, following the suggestion of Gormley and Masta (2014), include fixed effects for each year and Morningstar style category. Lagged values of the benchmarking proxies are included in the regression to serve as instruments and to control for possible endogeneity. The estimation of α_1 with lags therefore isolates the influence of *Fraction* on future benchmarking strategies while controlling for past decisions affecting beta and expenses. In unreported results, we find that all our results are robust to including average category values for each *BM* in place of style dummies.

Consistent with H1, the coefficient on the portion of DC assets is negative and significant when predicting future fees in the first two regressions of Table 5. The remaining columns of Table 5 show results of testing H2 using both fund beta and holdings-level beta. In all cases, larger proportions of DC assets predict higher future levels of both fund beta and holdings-level beta. The effect is prominent. Economically, the coefficients suggest that acquiring half of assets in retirement money will lead the fund to increase its beta by approximately 8%.

Table 6 provides definitive evidence of the direction of causality between greater sponsor oversight and managerial decisions to optimize their returns with respect to a benchmark. To test H3 and H4, we estimate a first-difference regression where *changes* in DC are included as regressors to predict *future changes* in fees and betas.

$$\Delta BM_{i,t+1} = \alpha_0 + \alpha_1 \Delta DC\ assets_{i,t} + \alpha_2 Log\ \ fund\ size_{i,t} + \alpha_3 Lagged\ relative\ return_{i,t} \\ + \alpha_4 Turnover_{i,t} + \alpha_5 BM_{i,t} + \varepsilon_{i,t+1},$$

By analyzing the relation between first-difference changes, we remove any possibility of endogeneity that might be present in levels. It is clear that the presence of more sponsor oversight has a significant and causal impact on managerial behavior, as measured through the future changes in their expenses and fund- and holdings-level beta. In all three cases, we observe that managers respond to benchmarking pressures in a way consistent with our hypotheses.

B. Fund flows and feedback

Given that we observe changes in beta and expenses that are consistent with a manager acting to beat a benchmark, it is interesting to consider whether there are additional direct effects of changing either beta and expenses which might reinforce or undermine this behavior. In this section, we therefore analyse two follow-up questions concerning how plan sponsors decide on which funds to include on their platform. First, how important is the relative return to the sponsor's decision to adopt a fund to its platform? And second, do the choices of beta and expenses have any *direct* effects on flows that may reinforce or offset the *indirect* pressure to affect relative performance? In answering the first question, it is clear from flow estimations of Sialm, Starks, and Zhang (2013) and from the selection criteria analyzed in Goyal and Wahal (2008) that a fund's relative performance and its expense ratio are of first order concern in selecting funds to the sponsor plans. Our focus is therefore on the latter question.

The model of fund flows that we use to address this question draws from prior research and includes fund size, expenses, and relative past performance as important factors to sponsors for fund selection. We also include lagged betas and lagged changes in betas and lagged changes in expenses to test whether they have any direct feedback effects on future flows. If so, we want to evaluate their economic significance compared to the indirect effect of influencing relative returns.

We also include a measure of risk-adjusted return, *Alpha*, which is the intercept from the same market model regression used to estimate *Beta*. Our purpose for including alpha in the regression is to compare its importance with lagged relative returns. If fund sponsors use alpha as a decision variable for the selection of funds then this should undermine the incentive to simply choose high-beta stocks. However, if alpha is an unimportant criterion for selection then managers may have more incentive to focus solely on increasing beta to boost relative returns, even at the cost of low alpha. Our fund flow model is therefore:

$$\begin{aligned} DC\ flows_{i,t+1} &= \alpha_0 + \alpha_1 Lagged\ relative\ return_{i,t} + \alpha_2 Log\ \ fund\ size + \alpha_3 Turnover_{i,t} + \alpha_4 Beta_{i,t} \\ &+ \alpha_5 Expenses_{i,t} + \alpha_6 \Delta Beta_{i,t} + \alpha_7 \Delta Expenses_{i,t} + \alpha_8 Alpha_{i,t} + \varepsilon_{i,t+1}, \end{aligned}$$

where $DC\ flows_{i,t+1}$ is the change in DC assets managed by fund manager i from year t to $t+1$ divided by the total DC assets in the fund as defined in Sialm, Starks, and Zhang (2013).

$$DC\ flows_{i,t+1} = \frac{DC\ assets_{i,t+1} - DC\ assets_{i,t}\left(1 + Return_{i,t+1}\right)}{DC\ assets_{i,t}}.$$

As found in other studies, lagged relative performance is of first order economic importance to sponsor flows. The coefficient of 1.88 suggests that outperforming the benchmark by 10% will increase flows by 18.8%. Given this economically large effect, it is not surprising that managers take actions to improve their relative returns. In Table 7, we are particularly interested in whether lagged *Beta* or *Expenses* and the changes in these variables enter significantly in the estimation as direct effects on flows. Neither Δ*Beta* nor Δ*Expenses* enter significantly. The lack of significance in these changes reinforces the direction of causality. We clearly observe in Table 6 that changes in DC assets predict future changes in beta and expenses but have no evidence of the reverse causality in Table 7.

In levels, *Expenses* enters significantly and negatively as found in Sialm, Starks, and Zhang (2013). Low expenses are therefore an important criterion, in addition to high relative performance, for bringing a fund onto a platform. This suggests that managers have two incentives to lower fees subsequent to attracting DC assets. One is this direct effect and the other is the indirect effect of influencing relative returns which in turn attract flows.

In contrast, DC flows do not respond directly to the level of beta so fund beta does not appear to be an important factor in whether a fund is placed on a pension platform. The coefficient on lagged beta is economically small and statistically insignificant. DC sponsors therefore appear not to avoid funds with higher market exposures so there is no direct effect on flows which would prevent managers from pursuing high-beta strategies to improve relative returns.

One last point can be drawn from our estimation of flows. The coefficient on $Alpha_t$ is insignificant once $Lagged\ relative\ return_t$ is included in the regression, suggesting that DC assets are allocated based on historical relative returns rather than risk-adjusted returns. This is important when considering the subsequent decisions of the manager to attempt to beat benchmark returns by investing in high-beta stocks. Managers are not penalized by sponsors for choosing stocks with high betas and low alphas since $Alpha_t$ is not an important selection criterion used by plan sponsors. This lack of constraint of having to attain high alpha only exacerbates incentives to increase the loading on high-beta stocks.

C. Reducing return volatility around the benchmark

We next explore whether managers strategically satisfy an increased demand for beta by investing in high-beta stocks without increasing the volatility of returns around the benchmark. To address this, we first study whether changes in sponsor involvement correlate with return volatility around the benchmark. We use the regression framework from Tables 5 and 6 but instead estimate if *Tracking error* and *R-squared* vary with the fraction of DC assets. In levels we observe tracking error decreasing and R-squared increasing with the proportion of retirement money in the fund. In differences, changes in DC assets predict positive changes in R-squared and negative changes in tracking error, but only the changes in R-squared are significant. These results, summarized in Table 8, paint a consistent picture that the changes in managers' demand for high-beta stocks do not come at the cost of increased volatility around the benchmark. If anything, we observe funds appearing more passive as they increase DC assets.

We consider two hypotheses about how managers could keep tracking errors low while increasing beta. First in H5, we explore whether managers limit their search for high-beta stocks to those with low-idiosyncratic volatility. The alternative strategy outlined in H6 is to simply replace low-beta stocks with high-beta stocks.

To identify a stock by its beta and idiosyncratic volatility, each year we assign all common stocks listed on the NYSE, NASDAQ, and AMEX into 6 groups determined by the intersection of two idiosyncratic volatility bins and three beta bins. The table below summarizes the fraction of stocks in each group and highlights a distinct positive correlation between idiosyncratic volatility and beta (estimated at 0.3). High-beta and low-idiosyncratic volatility bin is the least populated, suggesting that increased demand for stocks in that group can more easily impact their prices than prices of securities in other bins.

	Low Beta	Medium Beta	High Beta
Low idiosyncratic volatility	19.65%	20.61%	9.73%
High idiosyncratic volatility	13.36%	13.39%	23.26%

In Table 9, we show the average portfolio weights that funds with different DC fractions allocate to the six idiosyncratic volatility and beta bins. Each row adds to 1, so the value of 0.221 in the upper left corner of Panel A implies that 22.1% of a low-DC portfolio is invested into stocks with low idiosyncratic volatility and low beta. The identification of stocks is based on the full sample of all stocks determined above. In Panel B, we show average proportion of the number of stocks that funds allocate to each bin. Therefore, the value of 0.194 in the upper left corner of Panel B suggests that 19.4% of all stocks in portfolios of low-DC funds have both low idiosyncratic volatility and low beta.

Several patterns emerge when looking at fund holdings in Table 9. First, in support of H5, we observe that the increase in holdings of high-beta stocks is concentrated almost entirely among stocks with low idiosyncratic volatility. Second, in support of H6, we observe that all of the increase in holdings of high-beta stocks comes at the cost of a decrease in holdings of low-beta stocks. So, funds respond to benchmarking pressures by replacing their holdings of low-beta stocks with positions in high-beta low-volatility equities. Managers of DC assets are thus taking strategic measures to increase beta while minimizing tracking errors. Evidence of both hypothesized effects provides a more refined test that benchmarking incentives influence managerial decisions on multiple dimensions.

V. Implications for Returns

Baker, Bradley, and Wurgler (2011) conjecture that benchmarking creates demand for high-beta stocks, which could explain the persistent and puzzling low returns on high-beta stocks. Current work by Buffa, Vayanos, and Woolley (2013) provides an equilibrium framework showing that benchmarking incentives create demand for volatile (high-beta) stocks because their price movements closely track those of the benchmark index. What is particularly interesting about their model is that the feedback between benchmarking pressures and asset returns is expected to have the greatest effect when the asset in demand is in short supply. Table 9 shows that demand for low-idiosyncratic volatility stocks is high, with nearly 70% of portfolios concentrated in these securities. Within low-idiosyncratic volatility stocks, the supply of high-beta equities is particularly short. As we note above, only 9% of stocks are characterized as having both low idiosyncratic volatility and high beta. Yet, these are precisely the stocks that are in greatest demand by asset managers facing benchmarking pressures. We would therefore expect price pressures on high-beta stocks to be particularly pronounced among the low-idiosyncratic volatility stocks where supply is short and demand is high.

Table 10 summarizes the returns for 25 portfolios created by sorting stocks into idiosyncratic volatility quintiles and beta quintiles. Consistent with prior literature, we observe a negative relation between idiosyncratic volatility and future returns. Explaining this pattern is outside the discussion of this paper and readers are directed to the literature pioneered by Ang, Hodrick, Xing, and Zhang (2006). Our focus is instead on the low-idiosyncratic volatility portfolios, where the benchmarking-induced demand for high-beta stocks is the strongest and hence where the high-beta/low-return anomaly can be expected to deliver the highest profits. Table 10 shows precisely this pattern. We observe the high-beta/low-return link only among stocks with the lowest levels of idiosyncratic volatility. This result is consistent with the idea that high demand for assets in short supply affects their returns.

VI. Implication for Investors

What do our results imply for investors? We first ask whether any of the added risk or outcomes of benchmarking strategies lead to better performance which may benefit investors. Table 11 estimates net returns, Carhart (1997) four-factor alphas, and Treynor ratios as a function of the fraction of DC assets in a fund. Consistent with findings in Sialm and Starks (2012), we observe no evidence that the additional sponsor oversight provides any benefit to the investors in terms of better fund performance.

Do managers of funds with large amounts of retirement money benefit their investors through means other than better fund performance? Our results provide compelling evidence that in response to benchmarking pressures that come with more sponsor-controlled assets, these managers resort to more passive investment strategies while at the same time trying to take on higher market risk to increase the possibility of beating benchmark returns. Passivity certainly provides no benefit to investors who pay the managers to follow active investment strategies.

Added risk is particularly troublesome and raises important policy questions as well as questions about the fiduciary responsibility of managers. Funds do not reveal the composition of retirement and non-retirement money they have under management. Investors therefore are unaware *ex-ante* that the manager may change a fund's investment strategy or risk and are unable to avoid or undo this change. Risk-shifting thus complicates financial planning. Investors would have optimally allocated less to a fund had they only known that the manager would increase the risk.

Does the increased risk affect short- and long-term investors differently? Greater exposure to the market almost certainly provides no benefits to short-term investors who can face higher volatility as a consequence. In this sense, the presence of long-term retirement investors imposes a cost on short-term investors, a twist on the usual assumption of short-term investors extracting rents from those around for the long-run (Johnson, 2004).

For long-term investors, the consequences of more risk are less clear and deserve some discussion as they depend on views of long-run volatility. Pastor and Stambaugh (2011) show that long-run volatility is actually higher than short-run volatility despite the large body of evidence of long-run mean-reversion in benchmark returns (Barberis, 2000, and Siegel, 2008). They argue that mean-reversion is more than offset by uncertainties about expected returns. In fact, using reasonable assumptions, they find that at a 25-year horizon, long-run expected volatility is 30% higher than over one year and that it is 80% higher than over one year when measured over a 50-year horizon. With these estimates of long-run volatility, funds of retirement money seem to be adding anywhere from 12% to 18% more volatility to the retirement portfolio. Thus even long-horizon investors may suffer from the additional risk that managers take after acquiring more retirement assets.

VII. Conclusion

In this paper we examine the effects that the presence of plan sponsor-controlled retirement assets and the accompanying stringent oversight have on managerial decisions. Prior literature shows that sponsors evaluate fund performance relative to a benchmark index. We therefore posit that managers with a higher fraction of fund assets in retirement money face greater pressure to beat their benchmarks and change their behavior accordingly. We use a first-difference approach to causally show that in an effort to beat benchmarks, fund managers controlling large pension assets reduce fees and increase their exposure to high-beta stocks. The evidence that managers tilt their portfolio to high-beta stocks in response to benchmarking pressures is of particular significance as it provides the first direct empirical evidence that benchmarking contributes to the persistence of the high-beta/low-return puzzle as theoretically conjectured in Baker, Bradley, Wurgler (2011) and Buffa, Vayanos, and Woolley (2013).

We check whether plan sponsors select funds based on high alphas or low betas, which might potentially dissuade a high-beta, low-alpha strategy. We find no evidence of either. DC asset flows seem to depend only on relative lagged performance, not alpha, so a strategy that selects high-beta stocks is not penalized by DC plan sponsors. Additionally, we observe no evidence that DC sponsors avoid funds with high betas.

We show that managers increase beta while at the same time managing and even reducing the volatility of returns around the benchmark. They achieve the two goals by strategically substituting low-beta stocks for high-beta stocks with low idiosyncratic volatility. As a result, the tracking error declines and the r-squared measure of managerial passiveness increase with DC assets. High benchmarking-induced demand for high-beta low-idiosyncratic volatility stocks and the relative scarcity of these stocks in the sample of all equities have important implications for asset returns. In particular, we hypothesize and find that the high-beta/low-return phenomenon is observed only among the stocks with low levels of idiosyncratic volatility.

Neither the increased exposure to market risk nor the more passive investment approach brings any performance benefit for investors. Higher risk, however, can lead to negative outcomes. In particular, unlike in life-cycle or target-date funds, retirement investors in mixed funds have different horizons, so even if increasing market exposure is beneficial for long-run investors in general, the effects and benefits will differ across the subsets of retirement investors who have a full range of investment horizons. This mixing of investors makes it almost impossible for an investment adviser to optimally invest for all members of the fund.

Greater risk-taking of funds with more retirement money raises important policy questions especially in the wake of large retirement losses during the recent crisis. Absence of a requirement to disclose the composition of retirement and non-retirement assets implies that investors are ex-ante unaware of potential agency conflicts and are unable to avoid them, complicating financial planning.

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Table 1
Fund size and assets held in defined contribution plans

This table summarizes size and retirement assets for funds that report their holdings with Pensions & Investments. The first column indicates the year as of the end of which the data on defined contribution plan assets are collected by Pensions & Investments.

	Fund size, \$ million		DC assets, \$ million		DC assets as a fraction of fund size						
Year	Mean	Median	Mean	Median	Mean	Median	Min	P10	P90	Max	Funds
2004	4,998	1,232	1,448	204	0.25	0.18	0.00	0.03	0.60	1.00	414
2005	4,960	1,265	1,358	201	0.23	0.18	0.00	0.02	0.50	1.00	464
2006	5,612	1,461	1,552	241	0.24	0.19	0.00	0.03	0.50	1.00	438
2007	6,159	1,699	1,604	254	0.23	0.18	0.00	0.03	0.50	0.97	444
2008	3,496	971	872	159	0.24	0.18	0.00	0.02	0.52	0.97	439
2009	4,464	1,294	1,157	176	0.24	0.19	0.00	0.02	0.51	0.99	454
2010	5,220	1,587	1,383	232	0.25	0.19	0.00	0.02	0.52	0.98	449
2004-2010	4,987	1,349	1,338	208	0.24	0.18	0.00	0.02	0.51	1.00	3,102

Table 2
Summary statistics

This table presents summary statistics for funds that report their retirement holdings with Pensions & Investments as of the end of year t. Shown are means, medians, standard deviations, 10th and 90th percentiles, and a correlation matrix. DC fraction is the ratio of defined contribution assets to fund size as of the end of year t. Fund size, in millions of dollars, is measured as of the end of year t. Lagged relative return is the 12-month fund return relative to other funds in the same Morningstar category during year t, shown in decimals. Turnover is in percent. R-squared are from four-factor model regressions. Expenses during year $t + 1$ include fee waivers and are shown in percent. Beta and idiosyncratic volatility are from market model regressions on monthly data in year $t + 1$. Tracking error is in percent per year.

				Percentiles		Correlations							
Variable	Mean	Median	St. dev	10th	90th	DC fraction	Fund size	Lagged rel. ret	Turn-over	R^2	Exp.	Market beta	Idios. vol
DC fraction$_t$	0.238	0.183	0.208	0.024	0.512								
Fund size$_t$	4,987	1,349	13,131	126	9,786	0.055							
Lagged rel. ret$_t$	0.004	0.002	0.057	-0.057	0.065	0.007	0.006						
Turnover$_t$	63.41	52.00	50.73	11.00	130.0	-0.022	-0.177	-0.027					
R-squared$_{t+1}$	0.924	0.957	0.105	0.833	0.991	0.105	0.073	0.026	-0.017				
Expenses$_{t+1}$	1.052	1.050	0.429	0.530	1.510	-0.174	-0.302	-0.023	0.250	-0.176			
Market beta$_{t+1}$	1.068	1.020	0.266	0.798	1.395	0.085	-0.117	0.020	0.116	0.086	0.185		
Idiosyc. vol$_{t+1}$	0.014	0.012	0.008	0.005	0.023	-0.024	-0.166	0.029	0.148	-0.325	0.331	0.349	
Tracking error$_{t+1}$	4.899	4.365	2.944	1.928	8.499	-0.066	-0.107	0.073	0.111	-0.137	0.326	0.131	0.564

Table 3
Characteristics of funds with different fractions of assets in DC plans

This table reports in Panel A average characteristics of funds assigned into groups on the basis of the fraction of a fund's assets in defined contribution plans at the end of year t (DC fraction). R-squared from four-factor model regressions, expenses, betas, idiosyncratic volatility, tracking errors, and gross excess returns are calculated using data in year $t+1$. Betas and idiosyncratic volatility are from market model regressions. Tracking error is in percent per year. Cash and equity are in percent of portfolio. Fund size is in millions of dollars. Turnover is in percent. Panel B shows the equity portfolio weights that funds allocate to stocks with different market betas. Panel C shows the fraction of low-, medium-, and high-beta stocks that funds hold in their portfolios. Both of these Panels summarize results for portfolios formed by sorting funds into quintiles on the fraction of assets in DC plans as of the end of year t. Betas are computed using monthly data in year $t+1$. Assignment into market beta terciles is determined by the distribution of year $t+1$ market betas of all common stocks listed on NYSE, AMEX, and Nasdaq. The last two columns show the differences between average characteristics of the high and low DC fraction quintiles and the corresponding t-statistics.

Variable	Low DC	Quintile 2	Quintile 3	Quintile 4	High DC	High-Low	
A. Average characteristics of funds							
DC fraction	0.025	0.094	0.186	0.311	0.573	0.547	[84.77]
R-squared	0.911	0.919	0.925	0.928	0.939	0.028	[4.56]
Expenses	1.160	1.082	1.063	1.016	0.939	-0.222	[-9.40]
Fund beta	1.023	1.053	1.075	1.082	1.106	0.083	[5.52]
Beta of fund holdings	1.061	1.065	1.099	1.092	1.111	0.049	[4.40]
Idiosyncratic volatility	0.013	0.014	0.014	0.014	0.013	0.000	[0.07]
Tracking error	5.083	4.933	4.901	4.898	4.681	-0.402	[-2.32]
Gross return	0.170	0.205	0.226	0.261	0.305	0.135	[1.53]
Cash	3.685	2.682	2.725	3.128	3.157	-0.528	[-1.68]
Equity	95.19	96.81	96.40	96.39	96.63	1.442	[3.52]
Fund size	2,997	4,428	4,961	6,113	6,414	3,417	[4.75]
Turnover	61.10	62.39	65.98	65.16	62.39	1.287	[0.42]
B. Fraction of dollars allocated to different beta groups							
Low market beta	0.332	0.328	0.316	0.326	0.307	-0.025	[-2.67]
Medium market beta	0.438	0.437	0.441	0.429	0.431	-0.007	[-0.79]
High market beta	0.231	0.235	0.243	0.245	0.262	0.032	[6.30]
C. Fraction of stocks held in different beta groups							
Low market beta	0.302	0.301	0.305	0.294	0.280	-0.023	[-2.51]
Medium market beta	0.425	0.433	0.429	0.431	0.416	-0.009	[-1.54]
High market beta	0.273	0.266	0.267	0.276	0.304	0.031	[5.53]

Table 4
Explaining the level of and the change in fund beta with holdings beta

This table reports coefficients, t-statistics, and adjusted R^2 values from two regressions. In the first regression, fund-level market betas estimated in year t are regressed on holdings-level betas calculated over the same period and on the percentages of funds' portfolios allocated to equity at the beginning of year t. In the second regression, changes in fund-level betas between years t and $t+1$ are regressed on changes in holdings-level betas over the same period and on changes in the percentages of funds' portfolios allocated to equity between beginnings of years t and $t+1$. T-statistics shown in square brackets are based on standard errors clustered by fund. All regressions include year and Morningstar style category fixed effects.

	Dependent variable is	
	Fund-level beta	Change in fund-level beta
Variable	(1)	(2)
Holdings-level beta	1.013	
	[18.04]	
Proportion of assets in equity	0.010	
	[5.85]	
Change in holdings-level beta		1.061
		[5.76]
Change in proportion of assets in equity		0.001
		[0.44]
Year and style fixed effects	Yes	Yes
Cluster by fund	Yes	Yes
R^2	0.689	0.455

Table 5
Effect of DC assets on funds' future betas and expenses

This table reports coefficients, t-statistics, and adjusted R^2 values from regressions of fund expenses (regressions 1-2), fund-level betas (regressions 3-4), and holdings-level betas (regressions 5-6) in year $t+1$ on fund characteristics measured at the end of year t. Fund-level beta is computed from the market model regressions on monthly fund returns in year $t+1$. To compute a holdings-level beta for a fund, market beta of each stock it holds at the end of year t is calculated in year $t+1$ using daily data. Value-weighting stock betas gives the holdings-level beta. T-statistics shown in square brackets are based on standard errors clustered by fund. All regressions include year and Morningstar style category fixed effects.

	Dependent variable is					
	Fund expenses		Fund-level beta		Holdings-level beta	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DC fraction	-0.314	-0.094	0.060	0.052	0.046	0.039
	[-5.92]	[-2.15]	[2.43]	[2.91]	[2.90]	[3.31]
Log fund size	-0.087	-0.016	0.003	0.002	0.001	0.001
	[-9.38]	[-1.94]	[1.00]	[1.10]	[0.62]	[0.79]
Lagged relative return	-0.149	-0.152	0.144	0.170	0.159	0.140
	[-1.30]	[-2.27]	[2.03]	[2.71]	[3.25]	[3.20]
Turnover	0.094	0.035	0.017	0.006	0.021	0.020
	[3.42]	[2.77]	[0.92]	[0.50]	[2.55]	[3.41]
Expenses			0.020	0.011	0.016	0.010
			[1.38]	[1.01]	[1.72]	[1.38]
Lagged fund expenses		0.725				
		[8.23]				
Lagged fund-level beta				0.345		
				[11.99]		
Lagged holdings-level beta						0.261
						[12.82]
Style and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by fund	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.342	0.755	0.391	0.472	0.431	0.521

Table 6
Determinants of changes in funds' betas and expenses

This table reports coefficients, t-statistics, and adjusted R^2 values from regressions of changes in fund expenses (regression 1), fund-level betas (regression 2), and holdings-level betas (regression 3) between years t and $t+1$ on variables measured at the end of year t. Fund-level betas are from market model regressions on monthly data. To compute a year $t+1$ holdings-level beta for a fund, market beta of each stock it holds at the end of year t is calculated in year $t+1$ using daily data. Value-weighting stock betas gives the holdings-level beta. T-statistics shown in square brackets are based on standard errors clustered by fund. All regressions include year and Morningstar style category fixed effects.

	Dependent variable is change in		
	expenses	fund-level beta	holdings-level beta
Variable	(1)	(2)	(3)
Change in DC fraction	-0.004	0.011	0.017
	[-2.04]	[2.72]	[2.42]
DC fraction	0.003	0.020	0.019
	[0.22]	[1.25]	[1.37]
Lagged relative return	-0.099	0.150	-0.003
	[-2.03]	[1.84]	[-0.04]
Log fund size	0.000	0.003	0.002
	[-0.15]	[1.53]	[0.90]
Turnover	0.011	-0.008	0.005
	[1.60]	[-1.08]	[0.55]
Fund-level beta	0.008		
	[0.82]		
Expenses		0.005	0.001
		[0.43]	[0.13]
Style and year fixed effects	Yes	Yes	Yes
Cluster by fund	Yes	Yes	Yes
R^2	0.036	0.128	0.199

Table 7
Determinants of changes in defined contribution plan assets

This table reports coefficients, t-statistics, and adjusted R^2 values from regressions of changes defined contribution plan assets between years t and $t+1$ on variables measured at the end of year t. Changes in DC assets are scaled by their value at the end of t. Betas are from market model regressions on monthly data. T-statistics shown in square brackets are based on standard errors clustered by fund. All regressions include year and Morningstar style category fixed effects.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Lagged relative return	1.882	1.853	1.850	1.689		1.749
	[5.51]	[5.46]	[5.41]	[5.54]		[4.65]
Log fund size	-0.066	-0.077	-0.077	-0.072	-0.072	-0.072
	[-4.31]	[-4.65]	[-4.64]	[-4.40]	[-4.36]	[-4.40]
Turnover	-0.050	-0.036	-0.034	-0.030	-0.029	-0.031
	[-1.15]	[-0.81]	[-0.79]	[-0.70]	[-0.65]	[-0.72]
Idiosyncratic volatility	-3.667	-2.641	-2.320	-1.873	-1.034	-1.707
	[-1.26]	[-0.95]	[-0.79]	[-0.64]	[-0.35]	[-0.58]
Expenses		-0.133	-0.134	-0.159	-0.167	-0.159
		[-2.79]	[-2.78]	[-3.25]	[-3.39]	[-3.25]
Beta	-0.030		-0.036	-0.057	-0.057	-0.063
	[-0.26]		[-0.31]	[-0.51]	[-0.52]	[-0.57]
Change in expenses				0.008	0.009	0.007
				[0.17]	[0.21]	[0.16]
Change in beta				-0.039	-0.078	-0.029
				[-0.54]	[-1.05]	[-0.36]
Alpha					6.643	-1.258
					[2.49]	[-0.38]
Style and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by fund	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.049	0.052	0.052	0.053	0.042	0.053

Table 8
Effects of level and change in DC assets on funds' future tracking error and R^2

This table reports coefficients, t-statistics, and adjusted R^2 values from regressions of funds' tracking errors in year $t+1$ (regressions 1-2), changes in tracking errors between years t and $t+1$ (regression 3), R-squared in year $t+1$ (regressions 4-5) and change in R-squared between years t and $t+1$ (regression 6) on fund characteristics measured at the end of year t. Fund-level beta is computed from the market model regressions on monthly fund returns in year t. R-squared are from four-factor model regressions. T-statistics shown in square brackets are based on standard errors clustered by fund. All regressions include year and Morningstar style category fixed effects.

	Dependent variable is					
	Tracking error		Change in tracking error	R-squared		Change in R-squared
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DC fraction	-0.038	-0.017	-0.014	0.021	0.013	0.002
	[-2.10]	[-2.18]	[-0.62]	[2.63]	[2.29]	[0.19]
Change in DC fraction			-0.002			0.009
			[-0.43]			[2.07]
Log fund size	0.010	0.004	0.006	-0.001	-0.001	0.000
	[3.42]	[3.02]	[1.63]	[-1.42]	[-1.37]	[0.15]
Lagged relative return	0.227	0.104	0.323	-0.026	-0.005	0.014
	[3.52]	[2.02]	[2.56]	[-1.06]	[-0.24]	[0.27]
Turnover	0.013	0.006	0.015	-0.003	-0.003	-0.005
	[1.49]	[1.49]	[1.26]	[-0.73]	[-0.80]	[-0.82]
Expenses	0.102	0.026	0.007	-0.027	-0.018	0.011
	[6.49]	[5.10]	[0.53]	[-5.81]	[-5.03]	[1.96]
Beta	0.022	-0.018		0.024	0.002	0.055
	[1.06]	[-1.82]		[1.93]	[0.18]	[3.19]
Lagged R-squared					0.333	
					[12.20]	
Lagged tracking error		0.712				
		[39.81]				
Style and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by fund	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.475	0.723	0.725	0.518	0.582	0.260

Table 9
DC assets and propensity to invest in stocks with different betas and idiosyncratic volatility

This table reports in Panel A the equity portfolio weights that funds allocate to stocks with different market betas and idiosyncratic volatility (IV). Panel B shows the fraction of low-, medium-, and high-beta stocks with low or high IV that funds hold in their portfolios. Both Panels summarize results for portfolios formed by sorting funds into quintiles on the fraction of assets in DC plans as of the end of year t. Betas and IV are computed using monthly data in year $t + 1$. Assignment into market beta and IV groups is determined by the distribution of year $t + 1$ of the betas and IVs of all common stocks listed on NYSE, AMEX, and Nasdaq. The last two rows of each Panel show the differences between average characteristics of the high and low DC fraction quintiles and the corresponding t-statistics.

	Low Beta			Med Beta			High Beta		
DC assets	Low IV	High IV	Lo-Hi	Low IV	High IV	Lo-Hi	Low IV	High IV	Lo-Hi
A. Fraction of dollars allocated to different beta/idiosyncratic volatility groups									
Low	0.221	0.110	0.111	0.292	0.146	0.146	0.184	0.046	0.138
2	0.217	0.111	0.105	0.288	0.149	0.139	0.195	0.040	0.154
3	0.204	0.112	0.092	0.289	0.152	0.137	0.198	0.044	0.154
4	0.216	0.110	0.106	0.277	0.152	0.125	0.197	0.047	0.150
High	0.192	0.115	0.076	0.270	0.161	0.109	0.211	0.051	0.160
High-Low	-0.030	0.005	-0.035	-0.022	0.015	-0.037	0.027	0.005	0.023
t-statistic	[-3.54]	[2.86]	[-4.43]	[-2.51]	[3.89]	[-3.67]	[7.37]	[2.36]	[7.45]
B. Fraction of stocks held in different beta/idiosyncratic volatility groups									
Low	0.194	0.121	0.073	0.269	0.162	0.107	0.192	0.062	0.130
2	0.193	0.122	0.071	0.262	0.165	0.097	0.204	0.054	0.150
3	0.179	0.124	0.055	0.263	0.171	0.092	0.203	0.059	0.145
4	0.186	0.124	0.062	0.252	0.169	0.083	0.205	0.064	0.141
High	0.161	0.129	0.032	0.236	0.181	0.055	0.219	0.073	0.145
High-Low	-0.033	0.008	-0.041	-0.032	0.020	-0.052	0.027	0.012	0.015
t-statistic	[-4.35]	[2.48]	[-4.75]	[-4.91]	[7.37]	[-6.84]	[7.51]	[5.68]	[5.76]

Table 10
Idiosyncratic volatility and the low-risk anomaly

This table reports alphas, in percent per year, for portfolios sorted by market beta and idiosyncratic volatility (IV). At the end of each month t, common stocks listed on NYSE, Amex, and Nasdaq are independently assigned into quintiles on the basis of betas and IVs, both estimated from market model regressions on monthly data from the previous five years ($t - 59$ to t). A minimum of 24 valid observations are required for regressions. Value-weighted returns in month $t + 1$ are next calculated for each portfolio. For each of the 25 time series, unconditional alphas are computed as intercepts from regressing excess returns of the portfolio on market excess returns. The bottom two rows show the differences in alphas of low- and high-beta portfolios and the corresponding t-statistics. The sample period is 1968-2012.

	Idiosyncratic volatility				
Beta	Low	2	3	4	High
Low	2.74	2.30	2.01	0.92	-7.02
2	2.28	3.45	1.95	-3.09	-4.75
3	0.09	1.12	1.14	0.68	-5.65
4	-2.97	-0.81	1.52	-3.51	-8.30
High	-3.79	-2.96	-1.04	-2.72	-9.75
Low-High	6.53	5.26	3.05	3.64	2.73
t-statistic	[2.01]	[1.90]	[1.05]	[1.12]	[0.86]

Table 11
Defined contribution plan assets and future fund performance

This table reports the results of monthly Fama-MacBeth (1973) regressions of funds' net-of-expenses excess returns, four-factor alphas, and Treynor ratios in year $t + 1$ on fund characteristics measured at the end of year t. The Newey-West (1987) t-statistics are shown in square brackets.

	Net Return		Four-Factor Alpha		Treynor Ratio	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DC fraction	0.0007	0.0011	0.0003	0.0004	-0.0001	0.0003
	[0.90]	[1.05]	[0.66]	[0.75]	[-0.08]	[0.38]
Log fund size		-0.0002		-0.0002		-0.0001
		[-1.36]		[-1.80]		[-0.77]
Expenses		0.0003		-0.0004		0.0003
		[0.36]		[-1.15]		[0.45]
Lagged relative return		0.0024		0.0059		0.0020
		[0.32]		[1.02]		[0.36]
Turnover		-0.0001		0.000		0.0001
		[-0.15]		[0.11]		[0.12]