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On the Demand for High-beta Stocks: Evidence from Mutual Funds

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

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ABSTRACT:

Prior studies have documented that pension plan sponsors often monitor a fund's performance relative to a benchmark. We use a first-difference approach to show that in an effort to beat benchmarks, fund managers controlling large pension assets tend to increase their exposure to high-beta stocks while at the same time aiming to maintain tracking error around the benchmark. The findings support theoretical conjectures that benchmarking can lead managers to tilt their portfolio towards high-beta stocks and away from low-beta stocks, which can reinforce observed pricing anomalies.

JEL Classification: G11, G23

Keywords: Retirement saving, agency costs, risk-taking, mutual funds, beta-return relation

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The movement from defined benefit (DB) to defined contribution (DC) 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 $7.3 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 DC pension platforms is fierce and several studies find strong evidence that a fund's past relative performance and expenses are strong predictors of a fund's inclusion as an offering to employees in a sponsor's pension plan (see Sialm, Starks, and Zhang, 2015; and Pool, Sialm, and Stefanescu, 2015).

Plan sponsors rely heavily on benchmarking as a defensible mechanism in deciding which funds to keep on and remove from the plan. In fact, Section 2550.404a-1 of the Employee Retirement Income Security Act (ERISA) outlines three criteria that fiduciaries should include, but not be limited to, as part of the "appropriate consideration" for the evaluation of investment duties. Specifically, these are: "(a) the composition of the portfolio with regard to diversification; (b) the liquidity and current return of the portfolio relative to the anticipated cash flow requirements of the plan; and (c) the projected return of the portfolio relative to the funding objectives of the plan." Given the guideline to consider returns relative to funding objectives, it is no surprise that investment policy statements of corporate DC plans often provide explicit relative benchmarks for investment options in their portfolio.[1] And even though ERISA provisions do not apply directly to state and local government plans, "these requirements

[1] Samples of DC plan investment policy statements for Morgan Stanley and a consultancy group fi360 can be found at http://www.morganstanleyfa.com/public/facilityfiles/sb090312151937/bc4a9af1-fdcd-44e0-9d6e-c5e7fc7dcb03.pdf and http://www.fi360.com/fa/help/Report_Samples/IPS_401k_Plan.pdf.

indirectly influence [government] plan design and administration in areas [of] investment and fiduciary standards."[2]

Given external benchmarking pressures from the plan sponsor, the question we consider is whether fund managers alter their behavior when they know their place on the sponsor's menu depends on outperforming a benchmark. Our main premise is that managers with a larger portion of sponsor-controlled assets in their funds are more sensitive to the benchmarking criteria and therefore more apt to change their behavior to beat benchmarks. While benchmarking is prevalent in all areas of the asset management industry, the analysis of DC plans provides a unique opportunity to investigate the effects of benchmarking since DC assets are mixed with retail assets that may be less subject to explicit benchmarks. We are therefore able to use the portion of defined contribution assets in a mutual fund as a proxy of the importance to the manager of beating benchmark returns and relate this proxy to managerial portfolio decisions.

How might fund managers alter their behavior to beat a benchmark? We consider a tactic to increase exposure to high-beta stocks.[3] To illustrate the mechanism linking benchmarking with the demand for high-beta stocks, consider a long-only fund that is benchmarked to the market portfolio with a positive expected excess return. The fund has a choice between two stocks with the same alpha but one with a beta of 1.25 and the other with a beta of 0.75. With a requirement to beat the benchmark return, a leverage-constrained fund manager has a preference for the high-beta stock (holding alpha constant) because it will yield in expectation a return that is more likely to beat the benchmark. In general, managers evaluated against a benchmark with a

[2] See p. 6 of July 2001 EBRI Issue Brief, http://www.ebri.org/pdf/briefspdf/0701ib.pdf . See also the investment policy for San Bernardino County: it mirrors the same criterion used in the investment policy statements of sample corporate plans, see http://www.sbcounty.gov/hr/PDF/investment_policy.pdf.

[3] An alternative strategy to beat the benchmark, or to increase the beta exposure of a fund, would be to borrow. Frazzini and Pedersen (2014) argue that mutual funds and pension funds are examples of leverage-constrained institutions, so our focus is on determining whether there is evidence that funds tilt towards high-beta stocks as they posit. Almazan, Brown, Carlson, and Chapman (2004) document that few mutual funds use leverage.

positive expected excess return will have this incentive (see also Baker, Bradley and Wurgler, 2011; Frazzini and Pedersen, 2014; and Buffa, Vayanos, and Woolley, 2015).

Using a sample of funds that report their retirement holdings to Pensions & Investments from 2003 to 2013, we first establish that funds with a larger portion of DC assets hold higher-beta stocks. We observe that these funds increase their holdings of high-beta stocks while decreasing their exposure to low-beta stocks, consistent with a manager attempting to beat a benchmark. Sorting funds into quintiles on the proportion of DC assets reveals that the fund beta rises by over 8% if an investor chooses a high-DC fund over a low-DC fund.

Using a first-difference approach, we provide evidence against the possibility that the relation we find is simply an artifact of the plan sponsor selecting funds with high betas. We document that an *increase* in DC assets is associated with an *increase* in future fund betas. In contrast, we do not observe a reverse relation between *changes* in betas and future *changes* in DC assets. This evidence is supported when looking at how managers choose the weights on stocks in their portfolios. Instead of focusing only on changes in fund-level beta, we also compute a weighted average beta of individual stocks in the portfolio to create a "holdings-level" beta. As with the beta calculated from fund returns, the future holdings-level beta also *increases* in response to *increases* in DC assets of the fund.

We test this shift in holdings more directly by looking at the portfolio of holdings of funds in the highest quintile of DC assets (high-DC funds) and observe that these funds hold 3.8% more of their portfolio in high-beta stocks and hold 2.8% less of their portfolio in low beta stocks.

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. Given that managers have an incentive to reduce this risk, we test whether managers with a higher portion of DC assets are more *precise* in targeting beta to lie above 1 so that overall, variance around the benchmark for these managers is minimized when compared to managers with lower amounts of DC assets. The managers in the latter group are less constrained to beat the benchmark so accordingly can choose strategies with a wider variance in beta exposure. In line with this, we find that the cross-sectional distribution of fund betas is significantly narrower when comparing funds with more sponsor-controlled assets to those with less. As a result, high-DC funds have, on average, both higher betas and lower return variance around benchmarks than do low-DC funds.

To more thoroughly evaluate the effectiveness of strategies to maintain or lower variance around benchmark returns, we relate the fraction and changes of DC assets in a fund to future levels and changes in tracking errors and three other measures of managerial activeness: (1) *Active Share* developed by Cremers and Petajisto (2009); (2) the *R-squared* proxy for managerial passiveness of Amihud and Goyenko (2013); and (3) *Active Weight* proposed by Doshi, Elkamhi, and Simutin (2015). Using our first-difference approach, we observe that an *increase* in DC assets results in an *increase* in subsequent *R-squared* measures of passiveness, a *decrease* in both *Active Share* and *Active Weight*, and does not significantly change the future tracking error. On all accounts, it appears that managers are strategically increasing beta exposure while maintaining and even reducing the volatility of returns around the benchmark.

How effective is a high-beta strategy in improving relative performance and attracting flows? Frazzini and Pedersen (2014) show that the slope of the security market line is positive but flatter than the Capital Asset Pricing Model (CAPM) predicts. Based on this, we expect funds with higher betas to achieve higher returns relative to the benchmark but with lower alphas. Our empirical evidence suggests that fund managers of large pension assets appear to improve their relative performance with no adverse effects to fund alpha, consistent with an interest to maintain absolute returns while improving relative returns. If plan sponsors pay attention to relative returns more so than betas, then the effect of a high-beta strategy could be successful in attracting investors. Our analysis shows that DC flows respond positively to relative returns, but not to the estimated beta of the fund, so overall there is a positive net indirect effect on flows by following a high-beta strategy. We find that a one standard deviation increase in fund beta improves relative performance by 0.57% annually, which in turn leads to an increase in annual DC flows of between 0.90% and 1.31%.

The remainder of the paper is divided as follows. Section I provides an overview of the relevant literature and Section II summarizes the data. Section III and IV present the hypotheses and the key empirical findings. Lastly, Section V discusses how managerial risk-taking incentives impact investors and Section VI concludes.

I. Related Literature

This paper bridges several lines of the literature on retirement investing, risk-taking incentives of fund managers, and the role of index-linked investing in altering portfolio decisions. The paper also contributes to the literature on the high-beta, low-alpha anomaly.

A. Retirement investment

Much of the literature on retirement investment discusses asset allocation and trading decisions of retirement plan participants and finds that plan participants exhibit inertia in responding to different fund characteristics and performance.[4] A study by Sialm, Starks, and Zhang (2015) uses data similar to ours and finds a strong role of the DC pension plan sponsor in overcoming this investor inertia by deciding when to include or remove managers from a menu of options. They also document that expenses and performance relative to a peer group of funds are important criteria used by sponsors in selecting funds to the platform. Hand-collected data from Pool, Sialm, and Stefanescu (2015) supports this evidence on the selection criteria used by plan sponsors and also indicates a preference towards including funds affiliated with the plan trustee. Studying defined benefit plan sponsors, Goyal and Wahal (2008) find that expenses and returns relative to the benchmark are important criteria in the selection and termination of asset managers. Our study builds on this research by considering the effects of DC plan sponsor oversight on subsequent managerial behavior.

B. High-beta, low-alpha anomaly

Several empirical studies have shown that investing in low-beta stocks yields significantly higher risk-adjusted returns than investing in high-beta stocks. While the security market is positively sloped, it is flatter than one would expect theoretically (Black, Jensen, and Scholes, 1972), and the anomaly creates a puzzle 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 either altering the leverage in their portfolios or by directly investing in low-beta stocks. Frazzini and Pedersen (2014) argue that most large asset managers are restricted in their ability to lever their portfolios. The heightened demand for high-beta stocks is theoretically explained by either disagreement about macroeconomic conditions

[4] See for example, Madrian and Shea (2001), Agnew, Balduzzi, and Sunden (2003), Mitchell, Utkus, and Yang (2005), Mitchell, Mottola, Utkus, and Yamaguchi (2006), and Choi, Laibson, Madrian, and Metrick (2004, 2006). Benartzi and Thaler (2007) provide an excellent review of investment biases of retirement plan participants.

(Hong and Sraer, 2012) or by benchmarking pressures (see Baker, Bradley and Wurgler, 2011, and Buffa, Vayanos, and Woolley, 2015).

Central to the benchmarking argument is the fact that benchmark excess returns are expected to be positive. Evaluating managers over longer horizons only exacerbates the incentives of managers to buy high-beta stocks since the likelihood of a positive benchmark return increases with the investment horizon.[5]

C. Risk-taking

Our study also contributes to the literature on risk-taking by fund managers. Brown, Harlow, and Starks (1996) show that funds with relatively poor performance early in the year increase their risk in the latter part.[6] Balduzzi and Reuter (2012) study characteristics of target-date funds and document heterogeneity in risk taken by funds with the same target date. Our findings also relate to Huang, Sialm, and Zhang (2011), who explore the impact of changes in risk of a fund's portfolio on future fund performance. 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.

D. Index-linked investing

With the growth of exchange-traded and index mutual funds, an increasing number of asset purchases and sales are tied to indices, and an extensive literature studies the impact of index-linked investing on capital markets.[7] Prior literature relating benchmarks to institutional demand for stocks has focused on the impact of index-linked investing on the returns and correlations of

[5] For example, if benchmark returns are iid normal with annual mean of 10% and standard deviation of 15%, then the probabilities of the benchmark being positive over one, two, and three years are 75%, 83%, and 88%, respectively (see Christoffersen and Diebold, 2006).
[6] Other studies analyzing changes in risk within a calendar year include Chevalier and Ellison (1997), Busse (2001), Kempf and Ruenzi (2008), and Schwartz (2012).
[7] For an excellent review, readers are directed to Wurgler (2011) and the specific research papers cited therein.

stocks being added or deleted from an index.[8] In contrast to these studies, we focus on the demand effects for high-beta stocks created by managers trying to beat index returns.

II. Data

Our sample includes funds that report their defined contribution plan holdings to Pensions & Investments (P&I). P&I conducts annual surveys that query fund managers on their positions in DC assets. Our analysis is based on surveys administered to domestic equity funds for the years 2004 through 2014 which report information for the year prior to the survey so our sample runs from 2003 to 2013. Similar data has been used in Christoffersen, Geczy, Musto, and Reed (2005), Sialm and Starks (2012), and Sialm, Starks, and Zhang (2015) 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, total expenses, turnover, tracking errors, and returns. For analysis based on fund holdings, we also obtain holdings data from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free Mutual Fund Database and Thomson Reuters. We restrict the sample to funds with Morningstar broad category group of 'Equity', excluding funds with 'Allocation', 'Commodities', 'Tax Preferred', 'Fixed Income', and 'Alternative' categories. We also eliminate instances where reported DC assets exceed fund size. The final sample contains 4,603 fund-year observations representing 1,093 distinct funds.

We obtain most of our variables directly from Morningstar or CRSP, and calculate the remaining variables as described below. *Alpha* and *Beta* are the intercept and slope coefficient from market model regressions of a fund's excess returns on the CRSP value-weighted market

[8] See Harris and Gurel (1986), Shleifer (1986), Lynch and Mendenhall (1997), Kaul, Mehotra, and Morck (2002), and Petajisto (2011) for discussions on the effect of indexing on returns. Barberis, Shleifer Wurgler (2005) investigate the effect on correlations.

return in excess of the 3-month T-bill rate. *Idiosyncratic volatility* is the standard deviation of residuals from this regression. P&I data are updated annually, and we estimate alphas, betas, and idiosyncratic volatility from regressions using one year of monthly data.[9] *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 monthly data from year *t* to calculate market model beta β_{jit} for each stock *j* held by fund *i* at the end of year *t*.[10] The holdings-level beta is then calculated as the value-weighted average across all stocks, using the fraction w_{jit} of each stock in the equity portfolio as weights, $\sum_{j=1}^{N} w_{j,i,t}\beta_{j,i,t}$. We similarly calculate *Amihud illiquidity* of a fund's stockholdings in year *t* by computing the Amihud (2002) illiquidity measure for each stock held by the fund and taking the value-weighted average. Illiquidity of a stock in a given year is the average of its daily absolute returns scaled by dollar volume where higher values correspond to higher levels of illiquidity. *Relative return* is defined as the annual net fund return less the annual Morningstar category net return. *DC flows* are expressed in decimals and calculated following Sialm, Starks, and Zhang (2015) as:

$$DC\ flows_{i,t+1} = \frac{DC\ assets_{i,t+1} - DC\ assets_{i,t}(1 + R_{i,t+1})}{DC\ assets_{i,t}(1 + R_{i,t+1})},$$

where *DC assets*$_{i,t}$ is the dollar value of defined contribution assets in fund *i* at the end of year *t* and $R_{i,t+1}$ is the realized annual return earned by investors (assuming all distributions are reinvested) from the end of year *t* to the end of year *t+1*.

9 Our results are robust to using daily fund returns from CRSP.

10 If a fund's last portfolio holdings disclosure occurs before the end of December, 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.

The last set of variables that we calculate for our analysis are those measuring managerial activeness or deviation from a benchmark. *Tracking error* comes directly from Morningstar and is expressed in percent per year. It measures the standard deviation of the difference between daily returns of a fund and its Morningstar-defined benchmark.[11] The *R-squared* measure of Amihud and Goyenko (2013) is calculated 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. It is reported as a decimal ranging from 0 to 1. *Active share* of Cremers and Petajisto (2009) is one-half times the sum of absolute differences in weights of a manager's portfolio and those of the relevant benchmark. It captures the fraction of a fund's portfolio that is different from the benchmark index and is reported in decimals, ranging from 0 to 1.[12] We also consider a newer measure of managerial activeness, *Active weight* of Doshi, Elkamhi, and Simutin (2015), defined for fund *i* at time *t* as

$$\textit{Active weight}_{it} = \frac{1}{2} \Sigma_j \left| w_{jit} - w_{jit}^m \right|,$$

where w_{jit} is the weight of stock *j* in fund *i*'s equity portfolio at time *t* and w_{jit}^m is the weight that this stock would have been assigned had the manager market-cap weighted their equity portfolio. For a long-only portfolio, *Active weight* increases from 0 for a manager whose positions are value-weighted and approaches 1 for a manager who deviates from a market cap-weighted portfolio. A manager is presumed to become more active and deviate more from the benchmark if they have lower measures of *R-squared* and higher measures of *Active share*, *Active weight*, and *Tracking error*. *Total volatility* of a fund is the annualized monthly standard deviation of fund returns expressed in percent per year.

[11] We compute tracking error from one year of daily returns rather than from 12 monthly observations to reduce estimation noise. Our results are robust to using monthly data to compute tracking error.
[12] We obtain *Active share* from Martijn Cremers' website, http://activeshare.nd.edu.

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. While the average fund in the sample has approximately a quarter of its assets in DC plans, there is a large cross-sectional dispersion in the fraction of DC assets which will be helpful in differentiating benchmarking pressures across funds. The size of the average fund, measured in millions of dollars ($6,303 in 2013), is considerably larger than that of an average domestic equity fund in 2013 ($1,794 million according to the Investment Company Institute Factbook, 2015). 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 have consistent surveys through time from the same funds, which allows us to identify changes in behavior after the accumulation of defined contribution assets. We now explore how sponsors can affect managerial decisions.

III. Hypotheses and Preliminary Analysis

Our main objective is to determine whether oversight from plan sponsors may cause funds managing a large portion of sponsor-controlled assets to alter their behavior in trying to beat benchmark returns and in so doing may contribute to the high-beta, low-alpha phenomenon. Using a simple example, we can illustrate the tradeoffs of a manager incentivized to maximize risk-adjusted returns (alpha) versus one who is benchmarked against excess market returns. Let's consider a setting where excess returns are modeled using the CAPM. Suppose the expected benchmark excess return is 10% and managers are asked to choose between two stocks: Stock A has an alpha of -2% and beta of 1.25 and Stock B has an alpha of 2% and beta of 0.75. The manager who is evaluated based on risk-adjusted returns would choose Stock B because of its higher positive alpha.

In contrast, a manager trying to beat a benchmark would favor Stock A because of its better excess return performance relative to the 10% benchmark: Stock A is expected to yield a 10.5% excess return while Stock B yields only 9.5%.[13] The willingness of a benchmarked manager to trade off alpha for beta and favor Stock A increases with a higher positive expected excess market return, arising either from a higher expected market return or lower risk-free rate.[14]

One can see immediately from this framework that the benchmarked manager has a preference for holding stocks with beta greater than 1. The insights of Buffa, Vayanos, and Woolley (2015) are also particularly relevant for our analysis as they provide an equilibrium framework where tilting towards high-beta stocks is an optimal strategy for managers facing a benchmark. In our empirical set up, we use the fraction of sponsor-controlled assets to proxy for a portfolio more closely following the portfolio choices of a benchmarked manager. Our main hypotheses are therefore:

H1. Funds with higher fractions of sponsor-controlled pension assets (DC fraction) have greater exposure to market risk by investing in high-beta stocks.

H2. Funds with <u>increased</u> sponsor-controlled pension assets (DC fraction) <u>increase</u> their exposure to market risk by investing more in high-beta stocks than their current levels.

The predictions of H1 and H2 test the level and changes in a fund's market exposure which relate to the benchmarked manager's incentive to tilt the portfolio towards high-beta stocks. One

[13] For Stock A, excess return is -2% + 1.25 x 10% = 10.5%; for Stock B, it is 2% + 0.75 x 10% = 9.5%.
[14] In the perverse case of negative expected excess returns, the optimal strategy of the manager is to choose assets with negative betas. Our focus is on cases where expected excess returns are positive since asset pricing models implicitly assume a positive expected excess market return (see Campbell and Thompson, 2008). Either higher expected market returns or lower expected interest rates result in larger positive excess market returns which increase the incentive to tilt towards high beta stocks.

potential downside of increasing portfolio beta is that it may amplify deviations around the benchmark. Benchmarked managers have incentives to reduce this deviation, and we therefore expect managers in the high-DC group to act strategically so as to maintain or even lower variance around benchmark returns. One strategy that high-DC funds might pursue, on average, is to ensure that betas of their portfolios fall within a narrow range just above 1. By contrast, low-DC managers are less constrained to beat the benchmark so accordingly can choose strategies with a wider variance in beta exposure. To illustrate this, consider a group of three low-DC fund managers with portfolio betas of 0.53, 1.03, and 1.53, and a group of three high-DC fund manager with of 1.09, 1.11, and 1.13. The average betas of these two groups are 1.03 and 1.11 but the cross-sectional standard deviation of betas and average tracking errors in the first group are considerably higher. In other words, while we expect high-DC funds to have higher betas, they have an incentive to more precisely target their fund betas to lie just above 1 so as to maintain or even reduce volatility around the benchmark.

H3. Managers of funds with high portions of sponsor-controlled assets will aim to maintain or reduce volatility around the benchmark.

Our next section provides evidence in favor of these predictions. Finding support of all hypotheses suggests managers respond to sponsor oversight by employing tactics to manage fund returns relative to benchmarks.

A. Analyzing retirement asset quintiles

Table 2 summarizes averages, medians, and standard deviations for variables of interest and also divides the sample into quintiles based on the fraction of sponsor-controlled retirement money in each fund as of the end of year *t*. 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. Betas, total and idiosyncratic volatility, active share, *R*-squared, active weight, tracking error, and cross-sectional beta dispersion are measured in year *t+1*. We use other variables such as cash and equity holdings, fund size, and expenses, as controls in our analyses and measure them at the end of year *t*. Several patterns emerge, providing an early indication that managers respond to the increase in the fraction of sponsor-controlled assets by modifying their portfolio to maximize the possibility of beating the benchmark while minimizing volatility around benchmark returns.

We first observe that a fund's market beta and its holdings beta monotonically increase with the fraction of DC money, increasing from 1.033 to 1.115 in fund market beta and from 1.071 to 1.158 in fund holdings beta when comparing the lowest and highest quintiles of DC assets. This increase in market risk exposure does not arise because the manager takes on more leverage and shifts the portfolio from cash into equity: Rows labeled "Cash" and "Equity" show that funds with more retirement money do not hold significantly less cash or economically larger positions in equity. Instead, funds with more sponsor-controlled assets have higher betas because these managers invest directly in high-beta stocks rather than borrowing or altering weights in cash and equity.[15] Also, in all our analysis we use both fund and holdings beta. While holdings beta is more susceptible to some measurement issues associated with observing holdings at infrequent intervals, the holdings beta is not directly affected by changes in fund leverage and so helps to control for this potential influence on fund beta.

[15] To formally test this, we estimate changes in fund beta, $\Delta \text{FundBeta}_{t,}$ as a function of changes in the holdings-level beta, $\Delta \text{Holdings Beta}_{t,}$ and changes in the proportion of assets allocated to equities in year t. The estimation includes year and style fixed effects; we cluster standard errors by fund. Changes in holdings-level betas explain almost one-to-one changes in fund-level betas since the coefficient, 0.905, on $\Delta \text{Holdings Beta}_t$ is insignificantly different from 1. In contrast, change in leverage, as proxied by the change in portfolio allocation to equity, has an economically marginal and statistically insignificant effect on changes in fund beta.

Table 2 also shows strong evidence that higher DC funds associate with lower volatility around the benchmark. The cross-sectional standard deviation of fund beta is significantly smaller for high-DC funds. We also find that future tracking errors decline significantly from 5.53% in the lowest fraction quintile to 5.16% in the highest quintile. Consistent with incentives to minimize deviation around the benchmark, both *Active Share* and *Active Weight* measures of activeness decline while the *R*-squared measures of passiveness increase with the level of DC assets. Thus, managers respond to more sponsor-controlled assets by forming portfolios to more closely track their benchmarks while at the same time weighting high-beta stocks more heavily. Note that while volatility around the benchmark decreases with DC assets, the total volatility of fund returns increases with higher beta exposure. Therefore, total risk of the fund is increasing with DC assets although the variation in returns around the benchmark is decreasing.

Table 2 also supports evidence documented in prior studies (see Sialm, Starks, and Zhang, 2015) that DC plan sponsors use both larger fund sizes and lower expenses as selection criteria in deciding which funds to include on their menu. Note that there is both a strong positive relation between DC fraction and fund size and also a negative correlation between the size of a fund and its beta (-0.13) so fund size does not appear to be spuriously causing our results based on these descriptive correlations. Further confirming this, Tables A1 and A2 of the Appendix show that the positive relation between DC fraction and future fund beta becomes even more pronounced when controlling for differences in fund size across the quintiles.

B. Market betas vs. benchmark betas

In the interest of brevity and to keep the analysis consistent throughout the paper, we present only the results with single-factor market betas since the market index is likely the relevant benchmark for many funds. For reference, our key results are reproduced in Table A3 of the

Appendix with style-benchmark betas rather than single-factor market betas. To calculate betas with respect to benchmarks, we first pool all funds with the same Morningstar-defined objective and compute size-weighted returns of each objective (i.e., Cremers, Ferreira, Matos, and Starks, 2015). We then calculate benchmark betas as slope coefficients from regressions of a fund's excess returns on benchmark excess returns. The correlation between market betas and style-benchmark betas exceeds 0.75, and our results remain robust when using style-benchmark betas.

IV. Empirical Results

A. DC assets and benchmark strategies

We now turn our attention to the key tests of the paper which explore whether managers respond to benchmarking pressures by altering their exposure to market risk. To study this, we proxy for benchmarking pressures from a plan sponsor using the fraction of DC assets in a fund manager's portfolio and test whether the fraction of DC assets affects a manager's *future* decision to alter benchmarking strategies.

In Table 3, we test H1 using pooled regressions of fund or holdings betas on lagged DC fraction and control variables. We cluster standard errors by fund and, following the suggestion of Petersen (2009) and Gormley and Matsa (2014), include year and style fixed effects. We also include lagged betas as regressors to mitigate potential endogeneity between DC fraction and past beta levels of the fund. Consistent with H1, the coefficient on DC fraction is positive and significant when predicting either future fund- or holdings-level beta.

Table 4 tests H2 using a first-difference regression where *changes* in DC fraction are included as regressors to predict *future changes* in betas. By analyzing the relation between first differences, we try to mitigate concerns of endogeneity that might be present in levels. The results provide support for H2: managers respond to increases in benchmarking pressures arising from having more DC money by subsequently increasing fund- and holdings-level betas. We return to the question of endogeneity in Table 7 by estimating future changes in DC assets as a function of past changes in beta and show that there is no significant reverse relation.

In all our analyses we are careful to include liquidity measures to control for potential liquidity differences in portfolio holdings of high- and low-DC asset managers. In Tables 3 and 4, the coefficient on DC fraction remains significant after controlling for both the level and changes in a fund's Amihud illiquidity measure. In Table A4 of the Appendix, we test directly to see if high-DC funds hold more illiquid assets by repeating the analysis in Tables 3 and 4, but replace the dependent variable with future Amihud illiquidity measures and, for robustness, the future liquidity betas of Pastor and Stambaugh (2003). Overall, there does not appear to be any significant relation between DC fraction and the liquidity of the portfolio. Put together, liquidity differences in fund portfolios do not explain the positive relation between DC assets and fund beta since the results in Table 3 and 4 are robust when Amihud illiquidity is included as a control and there is no evidence that DC managers have a stronger preference for more liquid or illiquid assets that may spuriously affect managerial risk-taking.

As an additional robustness check, we also ensure that our results relating DC fraction with future beta are not arising simply from observations in the financial crisis. To do this, in Table A5 of the Appendix, we rerun our analysis in Tables 3 and 4 excluding years 2007, 2008 and 2009 from our sample and obtain results with similar statistical and economic significance.

B. Stock Betas and Portfolio Weights

So far we have tested the effect of DC money on benchmarking strategies by analyzing its effect on future levels of and changes in fund beta. In this section, we provide an alternative analysis of how managers may respond to benchmarking pressures by looking directly at how portfolio weights of managers change in response to different levels of DC assets.

Using the entire universe of common stocks for each year, we group firms into terciles containing low-, medium-, and high-beta stocks. For each *DC fraction* quintile, Table 5 summarizes the fraction of dollars (Panel A) and the fraction of stocks (Panel B) invested by asset managers into low-, medium-, and high-beta stocks. For instance, in Panel A, an average fund with the lowest level of DC assets has a portfolio with 33.3%, 42.9%, and 23.9% of dollars invested in low-, medium-, and high-beta stocks, respectively. For the highest level of DC, this changes to 30.5%, 41.9%, and 27.7%. There is significant shifting from low- to high-beta stocks. Panel B provides similar portfolio break-downs but where the weights are determined by the number of stocks in the portfolio rather than their dollar value. In dollars, the portfolio tilt to high beta is approximately is 3.8% of the average fund size ($4.907 billion) which represents an approximate $186 million shift in portfolio assets.

Baker, Bradley, and Wurgler (2011) and Buffa, Vayanos, and Woolley (2015) conjecture that benchmarking creates demand for high-beta stocks and this could explain the persistent and puzzling low risk-adjusted returns on high-beta stocks. Therefore, given observed shifts in holdings, Table 5 provides some evidence supporting this conjecture. Benchmarking pressures coincide with increased demand for high-beta stocks (and lower demand for low-beta stocks) which could reinforce the observed low (high) risk-adjusted returns for these stocks.

C. Beating benchmark returns

The prior tests show that fund managers with large sponsor-controlled assets appear to alter their portfolios to beat benchmarks, but do these strategies work? In this section, we evaluate first whether beta strategies are successful in positively influencing relative returns, and in the next section we test how successful a manager can expect a beta strategy to be in attracting DC flows. To test the effectiveness of a beta strategy, we estimate the annual *Relative Return* of a fund as a function of lagged beta and other lagged controls.

The results, presented in the first two columns of Table 6, show that higher betas correspond to better future performance relative to a style benchmark. The effect is relatively strong: a one-standard deviation increase in fund beta of 0.261 increases relative performance by 57bp per year. Tilting the portfolio to high-beta stocks thus appears to be an effective strategy in improving fund performance relative to a benchmark.

In columns 3 and 4 of Table 6, we repeat the analysis but instead of predicting relative returns, we predict CAPM alphas and find that higher betas correspond insignificantly to future alphas. A manager who chooses a high-beta strategy therefore is successful in improving relative returns without a significant change in alpha so the strategy appears to not hurt the manager or shareholders in terms of risk-adjusted performance.

In columns 2 and 4, we add *DC fraction* as a regressor to evaluate whether greater sponsor oversight that comes with more DC money corresponds to stronger future relative or risk-adjusted performance that is independent of its beta decision. As Sialm and Starks (2012) find, a higher fraction of DC assets in the fund is not significantly related to either measure of subsequent performance, a result which could arise for a variety of complicating reasons such as the level of fees, size, and other portfolio constraints. The question we consider in the next section is how sponsors weigh these two effects on returns and if the beta strategy has an overall positive expected effect on flows.

D. Direct and Indirect Effects on Fund Flows

What factors are important to plan sponsors when making choices of funds to include or exclude from their offerings? Sialm, Starks, and Zhang (2015) and Pool, Sialm, and Stefanescu (2015) show that expenses and relative performance are of primary importance in the selection of managers to DC plans. In implementing a high-beta strategy one also needs to know how these criteria will weigh against other fund characteristics such as its risk-adjusted performance, alpha, or its level of risk-taking, beta. Understanding this trade-off has important implications for whether a high-beta strategy is successful.

A high-beta strategy has three possible channels to affect flows: the first is a direct channel while the other two are the indirect channels. As a direct effect of a high-beta strategy, sponsors may avoid investing in funds with higher betas because of the perceived risk. As indirect effects, the high-beta strategy may either improve relative returns or negatively impact fund alpha. If sponsors care most about fund alpha, this latter effect will have a negative impact on flows, and if sponsors care more about relative benchmark returns then this should have a positive effect on flows. Because Table 6 shows that the beta strategy has little effect on fund alpha, we do not expect this indirect channel to have any consequence for flows so our focus is on the flow response to beta and relative returns. Therefore, the open question is how plan sponsors balance higher relative returns against higher beta when deciding whether to include a fund in its menu.

As noted in the introduction, anecdotal evidence from investment policy statements of DC plans suggest that a large majority of DC plans list relative returns as the main criterion for investment. The reliance on a relative return ranking is not surprising given that ERISA specifically mentions monitoring of investment duties based on “relative returns” compared to the funding objectives of the plan. Using benchmarks as a criterion for investment is much easier to legally defend. While this evidence is only anecdotal, it does provide some support to the notion that relative returns are the dominant criterion used by DC plans for investment decisions. We therefore test how relative returns affect future *DC flows* when controlling for alpha and beta of the fund.

The model of fund flows in Table 7 builds on prior research and includes relative return, log fund size, turnover, expenses, and other variables as important factors to sponsors for fund selection.[16] Lagged level and change in *Beta* are included as independent variables to test whether they have any direct effects on future flows. We also include a measure of risk-adjusted return, *Alpha*, to compare its importance with that of relative returns. If plan sponsors use either *Beta* or *Alpha* for the selection of funds then this should undermine the incentive of fund managers to simply choose high-beta stocks with low alphas.

Consistent with the findings of Sialm, Starks, and Zhang (2015), larger fund size, lower expenses and higher relative performance are of first order economic importance to determine *DC flows*. Recall from Table 6 that a one-standard deviation increase in the fund beta of 0.261 will improve relative fund performance by 57bp. The coefficients on relative return of 1.577 and 2.296 in Table 7 suggests that a 57bp improvement in relative performance will increase fund flows by 0.90% to 1.31%. DC flows are very volatile and median DC flows are slightly negative, so a positive expected influence on flows from relative returns is economically meaningful. It is no surprise that managers take actions to improve their relative returns.

In contrast, neither level nor change in *Beta* enter significantly. We should also highlight that the insignificance of beta and changes in beta for predicting future DC flows helps to reduce

[16] Prior research that has analyzed how relative returns, alpha, and beta affect flows include Del Guercio and Tkac (2002), Berk and van Binsbergen (2016), and Barber, Huang, and Odean (2016).

concerns of potential endogeneity issues in relating *DC fraction* to future *Beta*. From Table 4, we find that changes in DC assets predict future changes in beta, but we have no evidence of the reverse causality when predicting changes in DC assets in Table 7. This is suggestive of higher DC assets influencing future choices of fund beta by the manager and not the reverse.

Alpha is a significant predictor of flows when included on its own but becomes insignificant once *Relative return* is added to the regression. This could arise from the lack of precision in estimating alphas versus relative returns and also reflects the correlation between both relative returns and alphas. Regardless, relative returns are clearly an important investment factor after controlling for risk-adjusted returns along with size and expenses. Since plan sponsors do not seem to base their selection of fund managers on beta rank, the incentives to engage in a high-beta strategy is not penalized in terms of lower flows.

E. Reducing return volatility around the benchmark

While tilting the portfolio to high-beta stocks appears effective in beating the benchmark and attracting dollars to the fund, the downside of this strategy is the potential to increase tracking error. One strategy that high-DC funds might pursue to have, on average, both higher betas and lower tracking errors is to ensure that betas of their portfolios fall within a narrow range, that is, to more *precisely* target beta to lie just above one, or just above the risk-level of the index. Doing so increases the likelihood of beating the benchmark while at the same time minimizing the deviation from it. By contrast, low-DC funds face less benchmarking pressure and can choose strategies with a wider variance in beta exposure. In line with this logic and H3, the average cross-sectional volatility of beta is significantly lower in the high-DC group than low-DC group (see Table 2). As a result, high-DC funds have on average higher future beta and lower future tracking error than low-DC funds.

As a corollary to this, we next explore whether the strategy of more precisely choosing beta is successful in reducing the volatility of returns around the benchmark. To assess this, we use the regression framework in Table 4 but instead analyze if increases in DC fraction correspond to increases, decreases, or no change in future volatility around the benchmark returns. We use four measures to proxy for deviation from the benchmark: *Tracking error, R-squared, Active share,* and *Active weight*. Table 8 tests whether *changes* in the fraction of DC assets affect future *changes* in our measures of activeness.

The results in Table 8 paint a consistent picture that the increased demand for high-beta stocks does not come at the cost of increased volatility around the benchmark. An increase in the DC assets under management results in a significant increase in *R-squared*, significant decreases in *Active share* and *Active weight*, and has no effect on a fund's tracking error. If anything, we observe that the deviation of returns around the benchmark becomes smaller and funds become more passive as their DC assets increase. Managers who face stricter benchmarking pressures with sponsor oversight seem to be able to successfully increase their beta while at the same time minimizing effects on volatility around benchmark returns.

While funds with high portions of DC assets are, on average, bigger and have a larger number of stocks in their portfolio (see Sialm and Starks, 2012), in untabulated results we find that this does not explain the documented negative relation between DC assets and volatility around the benchmark. In particular, including the level or change in the number of stocks in a fund's portfolio as independent variables to the regressions of Table 8 does not alter the relation between change in *DC fraction* and changes in measures of volatility around the benchmark.[17]

[17] We find that the correlation between the number of stocks in a fund's portfolio and subsequent tracking error is -0.002 in our sample. This is perhaps not surprising because although the number of stocks in a portfolio increases

V. Implication for Investors

What do our findings imply for investors? We have already observed that high-beta strategies improve relative returns without significantly affecting alphas and that the presence of DC sponsors does not seem to add return predictability aside from any impact they have on beta strategies (see Table 6). Our results also provide evidence that managers of large amounts of DC assets tend to take on higher market risk exposure.

For long-term investors, the consequence of more market risk exposure has unclear implications and depends on one's view of long-run market volatility. A large body of evidence suggests that long-run mean reversion in benchmark returns implies lower long-run volatilities (Barberis, 2000, and Siegel, 2008). If market volatility is lower over longer horizons, then more exposure to the market may not necessarily be a bad outcome for long-term investors. However, Pastor and Stambaugh (2011) argue that mean-reversion is more than offset by parameter uncertainties about expected returns over a long horizon, and they show that long-run volatility over a 25-year (50-year) investment horizon exceeds 1-year short-run volatility by 30% (80%). If long-run market volatility is higher than short-term volatility, then beta shifting by benchmarked managers is only going to exacerbate the exposure of retirement savings to market volatility in the long-term. 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 be exposed to different benchmarking pressures which could influence a fund's strategy and risk exposure.

with DC assets (117, 132, 116, 147, and 172 for the DC fraction quintiles), it is large even for the low-DC funds resulting in well-diversified portfolios.

VI. Conclusion

Our paper offers two new contributions to the literature. First, it documents the effects that pension plan sponsors can have on managerial incentives and actions. Prior research has focused on the criteria used by plan sponsors in adding funds to and eliminating funds from their menus, whereas we show how these criteria influence managers' behavior while they are on the plan platform and under stringent sponsor oversight.

Baker, Bradley, and Wurgler (2011) and Buffa, Vayanos, and Woolley (2015) posit benchmarking as a possible theoretical reason for the persistence of the high-beta, negative-alpha anomaly. Our second contribution is to provide empirical evidence that benchmarking appears to encourage investment in high-beta stocks and may limit the appetite for low-beta stocks. Recent efforts to evaluate managers over longer horizons would only exacerbate the demand for high-beta stocks because realized benchmark returns are more likely to be positive over longer horizons and therefore more likely to reward high-beta strategies. The demand for stocks with high beta can have important implications for pricing of these securities and extensive empirical evidence shows that high-beta stocks persistently underperform low-beta stocks on a risk-adjusted basis (e.g., Frazzini and Pedersen, 2014).

We also confirm that the high-beta strategy is an effective tool in attracting investors caring about relative benchmark returns to a fund. On average, DC asset flows depend on relative lagged performance rather than alpha or beta, so a strategy that selects high-beta stocks with low or negative alphas does not appear to be penalized by DC plan sponsors.

Managers subject to strong sponsor oversight increase beta while at the same time maintaining and even reducing the volatility of returns around the benchmark. They achieve this by more precisely targeting beta to lie on average just above one than do funds without strong sponsor oversight.

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
Mutual fund size and assets held in defined contribution plans

This table summarizes size and retirement assets for our sample of domestic equity funds. The funds disclose their defined contribution (DC) plan holdings in annual surveys conducted 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
2003	3,886	1,106	1,117	128	0.21	0.16	0.00	0.01	0.49	1.00	397
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
2011	4,316	1,530	1,216	227	0.25	0.19	0.00	0.01	0.59	0.98	378
2012	4,626	1,592	1,468	307	0.28	0.23	0.00	0.02	0.65	0.97	376
2013	6,303	2,276	1,764	340	0.24	0.19	0.00	0.02	0.57	0.98	350
2003-2013	4,907	1,415	1,352	217	0.24	0.18	0.00	0.02	0.54	1.00	4,603

Table 2
Summary statistics

This table reports in the first three columns average, median, and standard deviation of fund characteristics. In the remaining columns, it summarizes 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). The subscript t or $t + 1$ denotes that year as of which the characteristics are measured. Beta and idiosyncratic volatility are from market model regressions on monthly data in year $t + 1$. Active share for year $t + 1$ is obtained from Martijn Cremers' website and represents the proportion of a fund's holdings that is different from the holdings of the fund's benchmark, as in Cremers and Petajisto (2009). R-squared values are from four-factor model regressions on year $t + 1$ data. Active weight in decimals for year $t + 1$ is fraction of a fund's portfolio holdings that differs from the value-weighted index of these holdings, computed as one-half times the sum of the absolute differences between a portfolio weight of a stock and its weight if the portfolio were value-weighted. Tracking error for year $t + 1$ is from Morningstar. Total volatility for year $t + 1$ is the annualized monthly standard deviation of fund returns. Standard deviation of beta is the intra-quantile standard deviation. Cash and equity are in percent of portfolio. Total expenses include fee waivers. The annualized relative return of the fund is computed relative to Morningstar benchmark for year t. DC flow is the annual flow of DC assets, computed as (DC assets$_{i,t}$ $-$ DC assets$_{i,t-1}(1 + R_t))/$DC assets$_{i,t-1}(1 + R_{i,t})$, where DC assets$_{i,t}$ is the dollar value of defined contribution assets in fund i at the end of year t and $R_{i,t}$ is the realized annual return earned by investors (assuming all distributions are reinvested) from the end of year $t-1$ to the end of year t. Amihud illiquidity of a stock in a given year is the average of its daily absolute returns scaled by dollar volume, and the reported illiquidity of a fund value-weights the individual stock illiquidity measures where the value weights are determined based on the market value of stocks in the fund's portfolio.

				Characteristics of funds with different fractions of assets in DC plans						
Variable	Mean	Median	Std Dev	Low DC	Quintile 2	Quintile 3	Quintile 4	High DC	High-Low	
A. Key variables										
DC fraction$_t$ (in decimals)	0.239	0.184	0.212	0.023	0.089	0.187	0.315	0.581	0.559	[106.7]
Fund beta$_{t+1}$	1.075	1.031	0.261	1.033	1.062	1.077	1.084	1.115	0.082	[6.61]
Beta of fund holdings$_{t+1}$	1.111	1.058	0.282	1.071	1.095	1.109	1.122	1.158	0.087	[6.37]
B. Measures of deviation										
Active share$_{t+1}$ (in decimals)	0.779	0.847	0.229	0.787	0.782	0.789	0.772	0.764	-0.022	[-1.84]
R-squared$_{t+1}$ (in decimals)	0.918	0.952	0.111	0.907	0.917	0.916	0.922	0.927	0.020	[3.90]
Active weight$_{t+1}$ (in decimals)	0.620	0.636	0.241	0.674	0.632	0.607	0.610	0.577	-0.097	[-8.24]
Tracking error$_{t+1}$ (in % per year)	5.273	4.626	3.129	5.530	5.287	5.202	5.189	5.159	-0.371	[-2.43]
Idiosyncratic vol$_{t+1}$ (in % per year)	4.633	4.055	2.899	4.522	4.575	4.660	4.698	4.708	0.186	[0.89]
Total volatility$_{t+1}$ (in % per year)	13.64	12.01	5.390	13.28	13.48	13.53	13.70	14.29	1.016	[2.51]
Standard deviation of fund beta$_{t+1}$	-	-	-	0.245	0.230	0.232	0.221	0.219	-0.026	[-3.09]
C. Asset composition										
Cash$_t$ (in %)	2.804	2.142	6.862	3.408	2.263	2.300	3.058	3.029	-0.379	[-1.32]
Equity$_t$ (in %)	96.17	97.49	5.43	95.26	96.38	96.24	96.28	96.67	1.416	[4.33]
D. Control variables										
Fund size$_t$ (in millions)	4,907	1,415	12,383	2,818	3,999	5,311	6,128	6,264	3,446	[6.29]
DC flows$_t$ (in decimals)	0.216	-0.038	1.513	0.285	0.218	0.190	0.182	0.224	-0.061	[-0.58]
Turnover$_t$ (in %)	63.57	51.00	54.73	62.37	62.47	65.52	64.88	62.65	0.282	[0.11]
Expenses$_t$ (in %)	1.060	1.040	0.407	1.188	1.078	1.055	1.011	0.970	-0.218	[-11.3]
Relative return$_t$ (in decimals)	0.000	0.001	0.054	-0.001	-0.002	0.002	0.000	0.000	0.002	[0.68]
Amihud illiquidity$_t$ (in decimals)	0.006	0.000	0.050	0.015	0.005	0.004	0.003	0.004	-0.011	[-3.13]

Table 3
Effect of DC assets on funds' future betas

This table reports results from regressions of fund-level betas (regressions 1-2), and holdings-level betas (regressions 3-4) 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 monthly data. The holdings-level beta for a fund is calculated as the value-weighted average beta of all stocks in the portfolio where weights are determined by the portfolio weight of the stock holding. T-statistics shown in square brackets are based on standard errors clustered by fund. Regressions include year and style fixed effects. Variable definitions are detailed in section II and Table 2.

	Dependent variable is			
	fund-level beta$_{t+1}$		holdings-level beta$_{t+1}$	
Variable	(1)	(2)	(3)	(4)
DC fraction$_t$	0.083	0.057	0.113	0.082
	[3.67]	[3.78]	[4.68]	[4.79]
Expenses$_t$	0.058	0.034	0.084	0.054
	[3.45]	[3.12]	[5.43]	[4.80]
Log fund size$_t$	-0.002	-0.001	0.002	0.001
	[-0.71]	[-0.56]	[0.59]	[0.38]
Relative return$_t$	0.300	0.242	0.295	0.205
	[3.47]	[3.18]	[3.44]	[2.42]
Turnover$_t$	0.000	0.000	0.000	0.000
	[2.01]	[1.48]	[3.51]	[2.44]
Amihud illiquidity$_t$	-0.406	-0.233	-0.082	-0.058
	[-4.75]	[-4.53]	[-1.86]	[-1.55]
Fund beta$_t$		0.419		
		[19.5]		
Beta of fund holdings$_t$				0.366
				[19.3]
R^2	0.287	0.417	0.367	0.427
Number of observations	4,094	4,094	4,087	4,087

Table 4
Determinants of changes in funds' betas

This table reports results from regressions of changes in fund-level betas (regression 1), and holdings-level betas (regression 2) 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. The holdings-level beta for a fund is calculated as the value-weighted average beta of all stocks in the portfolio where weights are determined by the portfolio weight of the stock holding. T-statistics shown in square brackets are based on standard errors clustered by fund. Regressions include year and style fixed effects. Variable definitions are detailed in section II and Table 2.

	Dependent variable is change in	
	fund beta$_{t:t+1}$	holdings-level beta$_{t:t+1}$
Variable	(1)	(2)
Change in DC fraction$_{t-1:t}$	0.084	0.079
	[4.90]	[3.26]
Change in fund beta$_{t-1:t}$	-0.336	
	[-18.5]	
Change in beta of fund holdings$_{t-1:t}$		-0.376
		[-9.15]
Change in expenses$_{t-1:t}$	0.016	0.032
	[1.88]	[1.81]
Change in turnover$_{t-1:t}$	-0.002	-0.003
	[-0.84]	[-0.78]
Change in log fund size$_{t-1:t}$	0.003	0.001
	[1.69]	[0.80]
Change in Amihud illiquidity$_{t-1:t}$	0.000	0.000
	[-6.48]	[-3.35]
DC fraction$_t$	0.017	0.031
	[1.19]	[1.60]
Relative return$_t$	0.083	0.232
	[0.92]	[1.24]
R^2	0.287	0.365
Number of observations	2,997	2,994

Table 5
Effect of DC assets on funds' allocations into stocks with different betas

Panel A reports equity portfolio weights that funds allocate to stocks with different market betas. Panel B shows the fraction of low-, medium-, and high-beta stocks 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. Market 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.

Beta tercile	Low DC	Quintile 2	Quintile 3	Quintile 4	High DC	High-Low	
A. Fraction of dollars allocated to different beta groups							
Low	0.333	0.324	0.319	0.315	0.305	-0.028	[-4.09]
Med	0.429	0.428	0.428	0.426	0.419	-0.010	[-1.72]
High	0.239	0.248	0.252	0.259	0.277	0.038	[7.42]
B. Fraction of stocks held in different beta groups							
Low	0.318	0.312	0.309	0.301	0.291	-0.027	[-4.17]
Med	0.422	0.422	0.420	0.418	0.406	-0.016	[-1.56]
High	0.260	0.267	0.271	0.281	0.303	0.043	[8.32]

Table 6
Fund performance as explained by fund beta

This table reports results from regressions of a fund's annual return (in decimals) relative to other funds in the same Morningstar category during year $t + 1$ (regression 1) or a fund's alpha in year $t + 1$ computed from market model regressions on monthly data (regression 2) on lagged variables. T-statistics shown in square brackets are based on standard errors clustered by fund. Regressions include year and style fixed effects. Variable definitions are detailed in section II and Table 2.

	Dependent variable is a fund's			
	relative return$_{t+1}$		market alpha$_{t+1}$	
Variable	(1)	(2)	(3)	(4)
Fund beta$_t$	0.022	0.022	-0.002	-0.002
	[4.66]	[4.63]	[-0.38]	[-0.36]
Log fund size$_t$	-0.002	-0.002	-0.002	-0.002
	[-2.94]	[-2.95]	[-2.98]	[-2.98]
Expenses$_t$	-0.008	-0.008	-0.006	-0.006
	[-3.20]	[-3.07]	[-2.19]	[-2.15]
Relative return$_t$	0.021	0.021	0.005	0.005
	[1.08]	[1.08]	[0.22]	[0.22]
Turnover$_t$	0.000	0.000	0.000	0.000
	[-1.21]	[-1.21]	[-0.96]	[-0.95]
Amihud illiquidity$_t$	0.010	0.010	0.041	0.041
	[0.38]	[0.39]	[3.77]	[3.74]
DC fraction$_t$		0.001		-0.001
		[0.28]		[-0.23]
R^2	0.045	0.045	0.129	0.129
Number of observations	4,094	4,094	4,094	4,094

Table 7
Determinants of defined contribution flows

This table reports results from regressions of defined contribution flows between years t and $t+1$ on variables measured at the end of year t. T-statistics shown in square brackets are based on standard errors clustered by fund. Regressions include year and style fixed effects. Variable definitions are detailed in section II and Table 2.

Variable	(1)	(2)	(3)	(4)
Relative return$_t$	2.296		1.577	1.637
	[3.88]		[2.41]	[2.70]
Log fund size$_t$	-0.076	-0.076	-0.076	-0.081
	[-3.48]	[-3.47]	[-3.48]	[-3.90]
Turnover$_t$	-0.019	-0.020	-0.019	-0.019
	[-1.27]	[-1.48]	[-1.31]	[-1.37]
Expenses$_t$	-0.136	-0.127	-0.135	-0.136
	[-2.31]	[-2.23]	[-2.29]	[-2.13]
Fund beta$_t$	-0.061	-0.039	-0.049	-0.044
	[-0.49]	[-0.58]	[-1.11]	[-1.28]
Idiosyncratic volatility$_t$	-0.016	-0.009	-0.011	-0.009
	[-1.29]	[-0.74]	[-0.89]	[-0.74]
Amihud illiquidity$_t$	0.248	0.219	0.252	0.290
	[0.82]	[1.03]	[0.92]	[1.18]
Change in beta$_{t-1:t}$	0.035	0.037	0.037	
	[1.41]	[1.52]	[1.54]	
Fund alpha$_t$		1.740	0.678	0.646
		[3.42]	[1.41]	[1.56]
R^2	0.041	0.040	0.042	0.049
Number of observations	3,024	3,024	3,024	3,029

Table 8
Effects of change in DC assets on managerial activeness

This table reports results from regressions of changes in active share, R-squared, active weight, and tracking error between years t and $t+1$ on fund characteristics measured at the end of year t. Active share for year $t+1$ is obtained from Martijn Cremers' website and represents the proportion of a fund's holdings that is different from the holdings of the fund's benchmark, as in Cremers and Petajisto (2009). R-squared values are from four-factor model regressions on year $t+1$ data. Active weight in decimals for year $t+1$ is fraction of a fund's portfolio holdings that differs from the value-weighted index of these holdings, computed as one-half times the sum of the absolute differences between a portfolio weight of a stock and its weight if the portfolio were value-weighted. Tracking error for year $t+1$ is from Morningstar. T-statistics shown in square brackets are based on standard errors clustered by fund. Regressions include year and style fixed effects. Variable definitions are detailed in section II and Table 2.

	Dependent variable is change in			
	Active share$_{t:t+1}$	R-squared$_{t:t+1}$	Active weight$_{t:t+1}$	Tracking error$_{t:t+1}$
Variable	(1)	(2)	(3)	(4)
Change in DC fraction$_{t-1:t}$	-0.007	0.037	-0.013	-0.044
	[-3.87]	[3.65]	[-3.12]	[-1.08]
Change in log fund size$_{t-1:t}$	0.000	-0.001	0.000	0.017
	[0.15]	[-2.67]	[-0.22]	[1.55]
Change in turnover$_{t-1:t}$	0.000	0.000	0.021	-0.060
	[0.24]	[0.28]	[0.91]	[-2.02]
Change in expenses$_{t-1:t}$	-0.004	0.002	-0.008	-0.117
	[-0.76]	[0.59]	[-0.82]	[-0.20]
Change in fund beta$_{t-1:t}$	-0.007	0.010	0.023	-0.311
	[-1.42]	[0.85]	[1.52]	[-1.90]
Change in Amihud illiquidity$_{t-1:t}$	0.000	0.000	0.000	0.000
	[-0.67]	[3.18]	[1.07]	[0.16]
DC fraction$_t$	-0.013	0.003	-0.015	0.092
	[-1.62]	[0.64]	[-1.47]	[0.74]
Relative return$_t$	0.050	-0.005	-0.096	1.357
	[2.18]	[-0.18]	[-1.61]	[1.38]
Change in active share$_{t-1:t}$	-0.098			
	[-2.90]			
Change in R-square$_{t-1:t}$		-0.230		
		[-7.19]		
Change in active weight$_{t-1:t}$			-0.335	
			[-7.04]	
Change in tracking error$_{t-1:t}$				-0.229
				[-9.12]
R^2	0.104	0.335	0.247	0.542
Number of observations	2,994	2,997	2,994	2,997

Appendix

In this appendix, we provide several robustness tests to confirm that our results are not arising from fund size, our choice of benchmark returns, portfolio liquidity, or the financial crisis.

A. Robustness tests of fund size

The inclusion of log of fund size and its change in the regressions predicting levels of and changes in betas (see Tables 3 and 4 of the paper) helps alleviate concerns that our results are driven by differences in assets under management. Still, Table 2 of the paper shows a strong positive relation between size and the fraction of DC assets so we now consider additional tests to rule out the possibility that fund size may be driving our results. The critical concern that we aim to dismiss with our test is that larger size rather than higher DC assets affects future betas.

With regards this concern, we find that larger funds on average invest in larger stocks and these stocks tend to have lower betas. As a result, we find that the correlation between fund size and fund beta is negative (-0.13). Based on these descriptive relations, fund size therefore appears unlikely to explain the link between DC fraction and betas since the correlation we observe is in the opposite direction, but to remain conservative we proceed with robustness tests.

As a first test for whether fund size drives our key results, we repeat the analysis summarized in Table 2 of the paper, except we first sort funds into quintiles based on fund size, and then assign them into DC quintiles within each size group. For each DC quintile, we present the average across the size quintiles in Table A1. By sorting first by size, the averages in Table A1 remove the confounding effects of size on our dependent variables. The sort-based analysis in Table A1 is therefore useful to gauge the magnitudes more directly and to reinforce the effectiveness of our size controls in Table 3.

One can immediately see that the pre-sorting into size quintiles is effective because size does not increase monotonically when moving from the lowest DC quintile to the highest DC quintile (while in contrast there is a strong positive relation observed in Table 2 with no pre-sorting by size). With size effects removed, Table A1 shows that future betas significantly increase (by 0.092) when moving from the lowest to highest DC quintile. Given the negative correlation between fund size and beta we discussed above, it is not surprising that size controls in Table A1 tend to strengthen the relation between DC fraction and future beta, but for our purpose, the important takeaway is that economic and statistical significance remain.

We also consider an additional test based on a matched size sample. For each fund and each year in our sample, we pick a closest-in-size actively managed equity fund from the universe of funds in the CRSP mutual funds database, excluding as potential matches funds that are in our sample. We then compare betas of funds in our sample with betas of the matched funds. The results are shown in Table A2. In the first row of the table, we provide the average beta for our sample in each DC quintile and in the second row of the table, we provide the average beta for the sample matched on size. Because the matched sample is simply chosen by size and not by the portion of DC assets, we do not expect and nor do we find a relation in betas. This contrasts with our sample where we are able to separate funds by their portion of DC assets and find that beta increases monotonically with the portion of DC assets. The third row shows that there is a significant difference between the two matched samples.

Overall, the results in Tables A1 and A2 along with the size controls in our regressions suggest that difference in size of funds with different DC fractions does not spuriously drive our results.

B. Robustness tests using benchmark betas

In this section, we evaluate the robustness of the relation between DC assets and managerial risk-taking by calculating betas relative to benchmark returns rather than returns of the overall value-weighted market index as we do in the paper. To calculate betas with respect to benchmarks, we first pool all funds with the same Morningstar-defined objective and compute size-weighted returns of each objective.[1] We then calculate benchmark betas as slope coefficients from regressions of a fund's excess returns on benchmark excess returns. As in the paper, we use one year of monthly returns for our regressions.

Table A3 summarizes results from regressions of the level and change in betas computed with respect to benchmarks on the level and change in lagged *DC fraction*. Mirroring the results reported in Tables 3 and 4 of the paper, the level (change) of *DC fraction* is positively related to the subsequent level (change) in betas. The economic magnitude of the coefficients in Table A3 and their statistical significance are similar to those we report in the paper when computing beta with respect to the value-weighted market index. This evidence suggests that our results are robust to calculating beta with respect to either benchmark returns or market returns.

C. Robustness tests of fund illiquidity

In all our analyses we are careful to include liquidity measures to control for potential liquidity differences in portfolio holdings of high- and low-DC asset managers. In Tables 3 and 4, the coefficient on DC fraction remains significant after controlling for both the level and changes in a fund's Amihud illiquidity measure. In Table A4 of the Appendix, we test directly to see if high-DC funds hold more illiquid assets by repeating the analysis in Tables 3 and 4, but replace the dependent variable with future Amihud illiquidity measures and, for robustness, the

[1] This approach is motivated by the methodology in Cremers, Ferreira, Matos, and Starks (2015) who pool holdings of funds with similar objectives to approximate holdings of a benchmark.

future liquidity betas of Pastor and Stambaugh (2003). We estimate the Pastor-Stambaugh betas from annual regressions of a fund's excess return on market excess return and the Pastor-Stambaugh factor available from Lubos Pastor's website. Overall, there does not appear to be any significant relation between DC fraction and future liquidity of the portfolio, and liquidity differences in fund portfolios do not explain the positive relation between DC assets and future fund beta.

D. Robustness to excluding financial crisis

To alleviate concerns that the recent financial crisis may be driving our results, in Table A5, we repeat the key tests in Table 3 and 4 after excluding the crisis period. We consider several definitions of the crisis period. We exclude year 2007, 2008, and 2009 one at a time, and also drop two-year periods 2007-2008 and 2008-2009 from the sample. In all specifications, our variables of interest remain significant at better than 1%, consistent with the crisis period not driving our results.

Table A1
Characteristics of funds with different fractions of assets in DC plans: Double-sort on fund size

This table reports 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). Funds are first sorted into quintiles on fund size and then assigned into DC quintiles within each size group. Grouping all funds that fall into a given size group gives five DC portfolios that contain funds of approximately equal size. The subscript t or $t+1$ denotes that year as of which the characteristics are measured. Beta and idiosyncratic volatility are from market model regressions on monthly data in year $t+1$. Active share for year $t+1$ is obtained from Martijn Cremers' website and represents the proportion of a fund's holdings that is different from the holdings of the fund's benchmark, as in Cremers and Petajisto (2009). R-squared values are from four-factor model regressions on year $t+1$ data. Active weight in decimals for year $t+1$ is fraction of a fund's portfolio holdings that differs from the value-weighted index of these holdings, computed as one-half times the sum of the absolute differences between a portfolio weight of a stock and its weight if the portfolio were value-weighted. Tracking error for year $t+1$ is from Morningstar. Total volatility for year $t+1$ is the annualized monthly standard deviation of fund returns. Standard deviation of beta is the intra-quantile standard deviation. Cash and equity are in percent of portfolio. Expenses include fee waivers. The annualized relative return of the fund is computed relative to Morningstar benchmark for year t. DC flow is the annual flow of DC assets, computed as (DC assets$_{i,t}$ $-$ DC assets$_{i,t-1}(1+R_t)$)/DC assets$_{i,t-1}(1+R_{i,t})$, where DC assets$_{i,t}$ is the dollar value of defined contribution assets in fund i at the end of year t and $R_{i,t}$ is the realized annual return earned by investors (assuming all distributions are reinvested) from the end of year $t-1$ to the end of year t. Amihud illiquidity of a stock in a given year is the average of its daily absolute returns scaled by dollar volume, and the reported illiquidity of a fund value-weights the individual stock illiquidity measures where the value weights are determined based on the market value of stocks in the fund's portfolio.

Variable	Low DC	Quintile 2	Quintile 3	Quintile 4	High DC	High-Low	
A. Key variables							
DC fraction$_t$ (in decimals)	0.027	0.094	0.187	0.316	0.570	0.543	[94.2]
Fund beta$_{t+1}$	1.023	1.048	1.081	1.102	1.115	0.092	[7.32]
Beta of fund holdings$_{t+1}$	1.061	1.084	1.111	1.137	1.159	0.098	[7.04]
B. Measures of deviation							
Active share$_{t+1}$ (in decimals)	0.782	0.777	0.790	0.787	0.758	-0.025	[-1.10]
R-squared$_{t+1}$ (in decimals)	0.912	0.916	0.913	0.919	0.929	0.017	[3.41]
Active weight$_{t+1}$ (in decimals)	0.683	0.625	0.608	0.610	0.576	-0.107	[-8.87]
Tracking error$_{t+1}$ (in % per year)	5.389	5.161	5.317	5.367	5.133	-0.256	[-1.69]
Idiosyncratic vol$_{t+1}$ (in % per year)	4.445	4.407	4.836	4.809	4.651	0.206	[1.55]
Total volatility$_{t+1}$ (in % per year)	13.10	13.13	13.80	14.10	14.12	1.028	[2.25]
Standard deviation of fund beta$_{t+1}$	0.240	0.231	0.230	0.222	0.218	-0.022	[-2.53]
C. Asset composition							
Cash$_t$ (in %)	3.181	2.552	2.410	2.968	2.956	-0.226	[-0.66]
Equity$_t$ (in %)	95.06	96.38	96.11	96.52	96.75	1.688	[4.73]
D. Control variables							
Fund size$_t$ (in millions)	4,286	5,051	5,480	4,382	5,308	1,022	[1.81]
DC flows$_t$ (in decimals)	0.210	0.327	0.131	0.201	0.217	0.007	[0.08]
Turnover$_t$ (in %)	58.93	61.81	66.52	66.71	63.62	4.688	[1.69]
Expenses$_t$ (in %)	1.112	1.066	1.081	1.058	0.984	-0.128	[-6.57]
Relative return$_t$ (in decimals)	0.000	-0.003	0.003	-0.002	0.001	0.000	[0.01]
Amihud illiquidity$_t$ (in decimals)	0.011	0.008	0.004	0.004	0.004	-0.008	[-2.66]

Table A2
Betas of funds with DC assets vs size-matched funds

This table reports average market betas 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 sample) and of funds matched by size (matched sample). The bottom row shows the differences between the DC and the matched samples. Betas are calculated using monthly data in year $t+1$ and market model regressions. 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	
Fund beta$_{t+1}$, DC sample	1.033	1.062	1.077	1.084	1.115	0.082	[6.61]
Fund beta$_{t+1}$, matched sample	1.041	1.041	1.036	1.035	1.040	-0.001	[-0.27]
Fund beta$_{t+1}$, DC vs matched sample	-0.006	0.024	0.049	0.056	0.079	0.085	[6.91]

Table A3
Effect of DC assets on funds' future betas with respect to benchmark returns

This table reports results from regressions of fund-level betas in year $t + 1$ (regressions 1-2) and changes in fund-level betas between years t and $t + 1$ (regression 3) on fund characteristics measured at the end of year t. Fund-level beta is computed by regressing monthly fund excess returns on benchmark excess returns in a given year. To compute benchmark returns, we first pool all funds with the same Morningstar-defined objective and then compute total net asset-weighted returns of each objective. T-statistics shown in square brackets are based on standard errors clustered by fund. Regressions include year and style fixed effects. Variable definitions are detailed in section II of the paper and in Table A1.

	Dependent variable is		
	Benchmark beta$_{t+1}$		Change in benchmark beta$_{t:t+1}$
Variable	(1)	(2)	(3)
DC fraction$_t$	**0.077**	**0.051**	0.015
	[3.39]	**[3.47]**	[1.16]
Expenses$_t$	0.053	0.029	
	[3.10]	[2.73]	
Log fund size$_t$	-0.002	-0.001	
	[-0.64]	[-0.45]	
Relative return$_t$	0.252	0.191	0.083
	[2.84]	[2.48]	[0.65]
Turnover$_t$	0.000	0.000	
	[2.04]	[1.60]	
Amihud illiquidity$_t$	-0.407	-0.227	
	[-4.37]	[-4.03]	
Fund benchmark beta$_t$		0.437	
		[21.1]	
Change in DC fraction$_{t-1:t}$			**0.071**
			[3.98]
Change in fund benchmark beta$_{t-1:t}$			-0.425
			[-22.3]
Change in expenses$_{t-1:t}$			0.017
			[1.50]
Change in turnover$_{t-1:t}$			-0.002
			[-0.85]
Change in log fund size$_{t-1:t}$			0.003
			[1.86]
Change in Amihud illiquidity$_{t-1:t}$			0.000
			[-6.80]
R^2	0.272	0.415	0.290
Number of observations	4,094	4,094	2,997

Table A4
Effect of DC assets on funds' future Amihud illiquidity and Pastor-Stambaugh betas

This table reports results from regressions of Amihud illiquidity of fund holdings and Pastor-Stambaugh (2003) fund betas in year $t+1$ (regressions 1 and 2), as well as changes in these two variables between years t and $t+1$ (regressions 3 and 4) on variables measured at the end of year t. Amihud illiquidity of a stock in a given year is the average of its daily absolute returns scaled by dollar volume, and the reported illiquidity of a fund value-weights the individual stock illiquidity measures where the value weights are determined based on the market value of stocks in the fund's portfolio. Pastor-Stambaugh betas are from regressions of a fund's monthly excess returns on market excess returns and the Pastor-Stambaugh factor. T-statistics shown in square brackets are based on standard errors clustered by fund. Regressions include year and style fixed effects. Variable definitions are detailed in section II of the paper and in Table A1.

	Dependent variable is			
	Amihud$_{t+1}$	PS beta$_{t+1}$	Change in Amihud$_{t:t+1}$	Change in PS beta$_{t:t+1}$
Variable	(1)	(2)	(3)	(4)
DC fraction$_t$	**-0.003**	**-0.021**	0.003	-0.023
	[-1.23]	**[-1.66]**	[1.32]	[-1.59]
Expenses$_t$	0.001	0.020		
	[0.93]	[2.24]		
Log fund size$_t$	-0.001	0.000		
	[-1.26]	[-0.16]		
Relative return$_t$	0.070	0.284	0.020	0.330
	[1.12]	[4.22]	[1.78]	[4.12]
Turnover$_t$	0.000	0.000		
	[0.46]	[2.41]		
Fund beta$_t$	-0.010	0.080		
	[-1.67]	[2.93]		
Amihud illiquidity$_t$	0.676			
	[4.08]			
PS beta$_t$		0.215		
		[8.11]		
Change in DC fraction$_{t-1:t}$			**0.000**	**-0.003**
			[0.62]	**[-0.45]**
Change in fund beta$_{t-1:t}$			0.000	0.049
			[-0.06]	[1.65]
Change in log fund size$_{t-1:t}$			0.000	0.002
			[-0.59]	[0.44]
Change in expenses$_{t-1:t}$			0.001	0.015
			[0.82]	[1.31]
Change in turnover$_{t-1:t}$			0.000	-0.002
			[1.28]	[-0.32]
Change in Amihud illiquidity$_{t-1:t}$			-0.001	
			[-7.74]	
Change in PS beta$_{t-1:t}$				-0.452
				[-18.4]
R^2	0.502	0.199	0.378	0.261
Number of observations	4,087	4,094	2,994	2,997

Table A5
Effect of DC assets on funds' future betas: Excluding crisis period

This table reports results from regressions of fund-level betas in year $t+1$ (regressions 1-5) and changes in fund-level betas between years t and $t+1$ (regressions 6-10) 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 a year. Regressions are run after dropping the indicated years from the full sample. T-statistics shown in square brackets are based on standard errors clustered by fund. Regressions include year and style fixed effects. Variable definitions are detailed in section II of the paper and in Table A1.

	Dependent variable is									
	Fund-level beta$_{t+1}$					Change in fund-level beta$_{t:t+1}$				
Year(s) excluded →	2007	2008	2009	2007-08	2008-09	2007	2008	2009	2007-08	2008-09
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DC fraction$_t$	**0.055**	**0.060**	**0.061**	**0.058**	**0.066**	0.019	0.022	0.026	0.026	0.034
	[3.54]	**[3.86]**	**[3.87]**	**[3.60]**	**[3.98]**	[1.25]	[1.48]	[1.69]	[1.55]	[2.09]
Expenses$_t$	0.027	0.039	0.046	0.031	0.055					
	[2.29]	[3.28]	[3.97]	[2.41]	[4.29]					
Log fund size$_t$	-0.002	-0.002	-0.000	-0.003	-0.001					
	[-1.05]	[-0.73]	[-0.17]	[-1.25]	[-0.29]					
Relative return$_t$	0.275	0.349	0.294	0.413	0.435	0.095	0.120	0.023	0.140	0.073
	[3.24]	[4.29]	[2.95]	[4.51]	[3.94]	[0.93]	[1.23]	[0.20]	[1.25]	[0.55]
Turnover$_t$	0.000	0.000	0.000	0.000	0.000					
	[1.64]	[3.02]	[0.98]	[3.31]	[2.44]					
Amihud illiquidity$_t$	-0.225	-0.274	-0.213	-0.266	-0.278					
	[-3.70]	[-4.70]	[-5.37]	[-3.70]	[-4.64]					
Fund beta$_t$	0.411	0.395	0.446	0.380	0.414					
	[18.4]	[18.5]	[19.2]	[16.7]	[18.2]					
Change in DC fraction$_{t-1:t}$						**0.084**	**0.077**	**0.083**	**0.084**	**0.080**
						[4.54]	**[4.30]**	**[4.26]**	**[4.65]**	**[4.40]**
Change in fund beta$_{t-1:t}$						-0.386	-0.343	-0.304	-0.404	-0.312
						[-15.3]	[-17.8]	[-16.7]	[-14.6]	[-16.2]
Change in expenses$_{t-1:t}$						0.016	0.018	0.017	0.017	0.022
						[1.62]	[1.35]	[1.89]	[1.11]	[1.38]
Change in turnover$_{t-1:t}$						-0.003	-0.000	-0.004	-0.001	-0.002
						[-1.05]	[-0.14]	[-1.48]	[-0.39]	[-0.63]
Change in log fund size$_{t-1:t}$						0.002	0.002	0.003	0.001	0.002
						[1.15]	[1.13]	[1.43]	[0.46]	[0.85]
Change in Amihud illiquidity$_{t-1:t}$						-0.000	-0.000	-0.000	-0.000	-0.000
						[-5.91]	[-6.68]	[-3.72]	[-5.98]	[-3.73]
R^2	0.418	0.436	0.427	0.440	0.446	0.290	0.287	0.282	0.298	0.280
Number of observations	3,672	3,679	3,658	3,257	3,243	2,651	2,664	2,686	2,318	2,353