Defined Contribution Pension Plans: Sticky or Discerning Money?

By

Clemens Sialm
Department of Finance
McCombs School of Business
University of Texas
Austin, TX 78712

Laura Starks
Department of Finance
McCombs School of Business
University of Texas
Austin, TX 78712

Hanjiang Zhang
Division of Banking & Finance
College of Business
Nanyang Technological University
Singapore

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Abstract

A much-studied empirical result about defined contribution (DC) pension plans is that their participants rarely adjust their portfolio allocations, which suggests that their investment choices and consequent flows are sticky. Yet DC plan sponsors monitor the performance of plan options and actively adjust investment options available to participants. We empirically examine these countervailing influences on fund flows and find that flows of DC assets into mutual funds are more volatile and react more sensitively to performance than are non-DC asset flows. Overall fund flows in DC plans are less sticky and more discerning than fund flows into non-DC plans.

Retirement mutual fund holdings, especially in defined contribution pension plans are an important segment of the financial markets. Total retirement assets (defined contribution plans and individual retirement accounts) constituted at year end 2011, 40% of all mutual fund assets and 48% of equity mutual fund assets according to the Investment Company Institute (ICI).[1] Retirement mutual fund holdings are expected to remain important with the increasing number of Americans moving toward retirement and with the increased movement by corporations and public entities towards the use of defined contribution plans rather than defined benefit plans. Figure 1 depicts the recent growth in mutual fund assets in retirement and non-retirement environments.

Despite the importance of mutual fund holdings in employer-sponsored retirement accounts, little is known about the effects of defined contribution plan assets on mutual fund flows. The major question that arises is whether these plans constitute a source of sticky or discerning money for mutual funds. It is well-documented that defined contribution pension plan participants trade and rebalance infrequently, suggesting that the retirement money should be sticky, leading to the commonly held belief that retirement money flows should have low volatility, high autocorrelation, and low sensitivity to fund performance. However, the infrequent trading instead could be offset by the plan sponsors' actions to remove or add a mutual fund from the plan's menu of options, suggesting that defined contribution money could act as an important disciplining mechanism for fund managers with higher volatility, less autocorrelation, and higher flow-performance sensitivity.

Having a better understanding of the impact of defined contribution plans on fund flows and their sensitivity to fund performance is important for several reasons. First, fund flows can affect the resource allocation of capital markets through their effects on asset prices. They thus influence which sectors and companies obtain financial resources. Second, performance-based

[1] 2012 Investment Company Handbook, p. 124.

compensation in the mutual fund industry occurs primarily through fund flows. That is, high-performing funds garner more assets and since management fees are typically a fixed percentage of assets, such funds receive higher remuneration. The incentives derived from these flows can affect the portfolio managers' decisions (e.g., Brown, Harlow and Starks (1996); Chevalier and Ellison (1997); Sirri and Tufano (1998); Del Guercio and Tkac (2002); Huang, Wei, and Yan (2007, 2012); and Ivkovich and Weisbenner (2009)). Finally, fund flows exert externalities on the remaining fund investors in several ways. For example, fund flows can require fund managers to adjust their portfolios, incur trading costs, and change their investment strategies (e.g., Edelen (1999); Dickson, Shoven, and Sialm (2000); Alexander, Cici and Gibson (2007); Coval and Stafford, (2007); Chen, Goldstein and Jiang (2010); and Sialm and Starks (2012)).

Mutual fund flows are generated primarily in two different investor environments: from investors with direct holdings through traditional individual mutual fund accounts (either traditional taxable accounts or tax-qualified individual retirement accounts (IRAs)) or from investors with indirect holdings through employer-sponsored defined contribution pension plans (DC plans). An important distinction between these two types of environments is in the choice of funds available to the investors. Funds held in traditional accounts are typically selected directly by investors who have flexibility to choose among the universe of mutual funds. In contrast, participants in employer-sponsored DC pension plans typically have limited choices of mutual funds, which are selected through a two-stage process. In a first stage the plan sponsor (e.g., the employer) selects a menu of mutual fund investment options and adjusts these options through time by removing or adding mutual funds.[2] In a second stage, given the list of investment options, the employee allocates the DC account balances among the available options.

[2] In a 2011 Deloitte survey of defined contribution plan sponsors, the mean (median) number of investment options is 18 (16). Some plans have wider choices by offering a brokerage or mutual fund window to the plan participants. The survey indicates that 43% (87%) of plans replaced a fund due to poor performance within the previous year (previous five years).

These two types of mutual fund selection environments have different implications for the performance-sensitivity of fund flows. When investors are trading mutual funds directly, they are subject to their own individual preferences, including risk preferences, investment horizons and tax incentives. In contrast, when investors are selecting funds as participants in their employer-sponsored DC plans, they are subject not only to their own preferences but also to other factors such as constraints placed on their behavior by the plan sponsors, the preferences of the plan sponsors regarding fund choices, and regulations imposed by governmental entities such as the Labor Department (which has oversight over ERISA retirement plans, including corporate DC plans).[3] Thus, these two diverse environments suggest that decisions regarding investment options may be made differently by investors in each environment, resulting in differences in flow distributions and flow-performance sensitivities of funds being traded in these environments.[4]

There are two offsetting influences on the flow-performance relation for mutual funds held by DC versus non-DC investors. First, an important literature in economics and finance has documented significant inertia by DC plan participants. That is, retirement savers have a tendency to rebalance and trade infrequently and to follow default options (e.g., Benartzi and Thaler (2001); Madrian and Shea (2001); Choi, Laibson, Madrian, and Metrick (2002); Agnew, Balduzzi, and Sunden (2003); Duflo and Saez (2003); Huberman and Jiang (2006); and Carroll et al. (2009)). In contrast, evidence suggests that individual investors exhibit relatively high turnover in their traditional directly held brokerage accounts (e.g., Barber and Odean (2000, 2001), Grinblatt and Keloharju (2001, 2009), and Ivković and Weisbenner (2009)). If the inertia

[3] ERISA retirement plans are those that are covered by the Employee Retirement Income Security Act of 1974.

[4] Papers on the design of DC pension plans include Benartzi and Thaler (2001); Madrian and Shea (2001); Choi, Laibson, Madrian, and Metrick (2002, 2006); Agnew, Balduzzi, and Sunden (2003); Duflo and Saez (2003); Brown, Liang, and Weisbenner (2007); Davis and Kim (2007); Elton, Gruber, and Blake (2006, 2007); Huberman and Jiang (2006); Rauh (2006); Huberman, Iyengar, and Jiang (2007); Goyal and Wahal (2008); Carroll et al. (2009); Cohen and Schmidt (2009); Brown and Harlow (2011); Tang, Mitchell, Mottola, and Utkus (2010); and Christoffersen and Simutin (2012)

documented in participant choices in DC pension plans dominates in the aggregate for mutual funds, then we should find lower sensitivity of fund flows to performance in funds with substantial DC assets as compared to funds with mainly traditional mutual fund accounts.[5]

The second influence on the flow-performance sensitivity of DC funds versus non-DC funds is the actions of the plan sponsors. That is, the flow-performance sensitivity of DC accounts may be higher than that for traditional mutual fund accounts if plan sponsors are adjusting the plan investment options and replacing options that have had a period of poor performance with investment options that exhibited superior prior performance. Such a higher flow-performance relation could result because plan sponsors effectively monitor the plans and replace inferior investment options with superior options or because plan sponsors might chase prior performance without improving the future plan allocations. For example, Del Guercio and Tkac (2002) and Goyal and Wahal (2008) find that defined benefit (DB) pension plans terminate managers after poor performance. A similar performance-chasing phenomenon could also apply to DC plan sponsors.

These potential offsetting influences on the flow-performance sensitivity of mutual funds lead to the following hypotheses. The null hypothesis is that there are no systematic differences in the distribution of flows and the flow performance sensitivity across funds associated with their level of DC assets. The first alternative hypothesis is that DC money is sticky and funds with high DC assets have lower flow-performance sensitivity. The second alternative hypothesis is that funds with high DC assets are less sticky and have greater flow-performance sensitivity, which could be caused by the actions of the funds' sponsors.

To test these hypotheses, we compare the flows of DC and non-DC mutual fund investors. We find that DC asset flows tend to be less sticky than non-DC assets flows. Further,

[5] Tax considerations are an additional factor that differs between DC and non-DC investments. The tax aspects have been analyzed previously by Barclay, Pearson, and Weisbach (1998); Khorana and Servaes (1999); Bergstresser and Poterba (2002); Christoffersen, Geczy, Musto, and Reed (2006); Ivković and Weisbenner (2009); and Sialm and Starks (2012), among others.

the flows into mutual funds by DC plan participants are more volatile and exhibit a lower serial correlation than the flows into mutual funds by non-DC investors. Using a number of different approaches, we also find that DC flows react more sensitively to fund performance than do non-DC flows. The flow-performance sensitivity is particularly pronounced for DC flows for the highest (top quintile) and the lowest (bottom quintile) performers.

To investigate in more depth whether DC fund flows are more discerning than non-DC flows, we consider whether mutual fund flows from DC and non-DC investors can predict funds' long-term future return performance. Berk and Green (2004) present a model with decreasing returns to scale in fund management where fund flows rationally respond to past performance. Their model implies that fund flows do not predict future fund performance. However, the empirical literature has found that fund flows are positively related with fund returns over the short term (Gruber (1996) and Zheng (1999)) and negatively related with the returns on the funds' holdings over the longer term (Frazzini and Lamont (2009)). Further, Frazzini and Lamont (2009) use mutual fund flows as a measure of individual investor sentiment for different stocks and find that high sentiment predicts low future returns. A difference in the longer-term performance predictability of flows for DC and non-DC investors could result due to the relative sophistication of the plan sponsor and their use of consultants. Testing these hypotheses we find that DC fund flows do not have significant predictability for future performance.[6] On the other hand, non-DC flows predict future performance negatively.

Overall, our results indicate that DC money is less sticky and more discerning than non-DC money, as DC money is more volatile and more sensitive to superior and inferior performance and as DC money does not predict lower future returns.

The remainder of this paper is organized as follows. Section I describes the data sources and summarizes the key variables. Section II contrasts the flow-performance relation for DC and

[6] In contrast to Gruber (1996) and Zheng (1999) we focus on the predictability over a one-year horizon.

non-DC fund assets. Section III analyzes the flow-performance relation by comparing funds with a relatively large proportion of DC assets with funds with a relatively small proportion of DC assets. Section IV studies the performance predictability of DC and non-DC fund flows and Section V concludes.

I. Data

A. Data Sources

We employ several different databases for our analysis. The first set of data is derived from annual surveys of mutual fund management companies conducted by *Pensions & Investments* (*P&I)* over the 1997-2010 time period.[7] In these surveys the companies are asked to report the dollar amount of the mutual fund assets held in Defined Contribution (DC) retirement accounts (as of December 31st of the year prior to the survey date) for the mutual funds most used by DC plans in broad investment categories (Domestic Equity Funds, Domestic Fixed Income Funds, International Equity Funds, Balanced Funds, Money Market Funds).[8] Mutual fund families are asked in the survey to report the DC plan assets for the twelve funds in each category with the largest DC assets. Because they are the most used mutual funds in DC plans over our sample period and we can abstract from changes in asset class across the plans, we focus on the category of domestic equity funds.[9]

Our second set of data consists of mutual fund characteristics such as fund returns, total assets under management, fees, and investment objectives, which is derived from the CRSP

[7] We thank David Klein from *Pensions & Investments* for providing us with the survey data. Additional information about the survey can be obtained from the website at http://www.pionline.com. Earlier surveys from the same data source have been used previously by Christoffersen, Geczy, Musto and Reed (2006) and Sialm and Starks (2012). In a contemporaneous paper Christoffersen and Simutin (2012) investigate the risk taking incentives of mutual funds with different investor clienteles.

[8] This specifically excludes other tax qualified investment vehicles that could be held in mutual funds such as Individual Retirement Accounts (IRAs), Keoghs and SARSEPs. It also does not include other retirement assets under administration by the fund family such as sponsoring company stock.

[9] Specifically, we eliminate balanced, bond, international, and money market funds, as well as funds that, on average, hold less than 80% of common stock. Index funds are included. However, our results are not affected qualitatively if we exclude index funds.

Survivorship Bias Free Mutual Fund database. We merge this data with the survey data using the funds' ticker symbols and names.[10] We also merge the CRSP database with the Thomson Financial CDA/Spectrum holdings database and the CRSP stock price database using the MFLINKS file based on Wermers (2000) and available through the Wharton Research Data Services.

In order to understand the potential generalizability of our analysis, we compare the domestic equity funds listed in the *P&I* dataset to those included in the CRSP database. We find that the *P&I* dataset has wide coverage – the fund families in our sample control over 77% of the total value of equity funds included in CRSP. In addition, although we do not have the level of DC assets for all funds in families that have many mutual funds, the levels of assets that we do have indicate that the excluded funds tend to have relatively low assets. In particular, the funds in our database (with non-censored DC assets) account for 85% of the total equity assets of the surveyed fund families.

Our third data set derives from mutual fund management companies' required semi-annual reports to the Securities and Exchange Commission (SEC) on the monthly purchases and redemptions of shares in the fund. These filings (termed N-SAR filings) were hand-gathered from the SEC EDGAR website for each fund on the *Pensions and Investments* list that had available data. This data allows us to examine fund inflows (sales of fund shares) separately from fund outflows (redemptions of fund shares) which we do in Section III.

[10] To avoid the incubation bias described by Evans (2010), we exclude funds which in the previous month managed less than $10 million, funds with missing fund names in the CRSP database, and funds where the year for the observation is in the same year or in an earlier year than the reported fund starting year. For funds with multiple share classes, we combine the classes into one observation per fund and compute the fund-level variables by aggregating across the different share classes

B. Flow Definitions

We measure fund flows in three different ways. In the first part of the paper, we employ the *Pensions and Investments* data to calculate the fund flows from the two sources by dividing the flows into DC flows and non-DC flows as follows:

$$DC\ Flow_{f,t} = \frac{DC\ Assets_{f,t} - DC\ Assets_{f,t-1}\left(1 + R_{f,t}\right)}{DC\ Assets_{f,t-1}\left(1 + R_{f,t}\right)} \tag{1}$$

and

$$NonDC\ Flow_{f,t} = \frac{NonDC\ Assets_{f,t} - NonDC\ Assets_{f,t-1}\left(1 + R_{f,t}\right)}{NonDC\ Assets_{f,t-1}\left(1 + R_{f,t}\right)} \tag{2}$$

where $DC\ Flow_{f,t}$ denotes the defined contribution flows to fund f at year t based on the difference between the end of the year DC assets less the product of the beginning of the year DC assets and one plus the fund's return in that year. The denominator ensures that the fund flows never fall below -100%. The $NonDC\ Flow_{f,t}$ is defined analogously where $NonDC\ Assets_{f,t}$ are fund f's total assets at time t less the fund's DC assets at time t adjusted for the fund returns.

In our second way of measuring DC flows instead of separating DC and non-DC flows, we analyze the total flows of funds with different DC ratios. That is, we separate funds into three separate groups according to their DC ratios. This analysis is presented in Section III.

$$Flow_{f,t} = \frac{Assets_{f,t} - Assets_{f,t-1}\left(1 + R_{f,t}\right)}{Assets_{f,t-1}\left(1 + R_{f,t}\right)} \tag{3}$$

Finally, rather than estimating flows through the traditional method, we use the funds' N-SAR filings to obtain their actual inflows and outflows as reported to the SEC. This analysis is presented in Section III.

C. Summary Statistics

Our primary sample of merged data from the CRSP and *P&I* databases covers 1,078 distinct equity funds and 5,808 fund-year observations over the period between 1996 and 2009. Panel A of Table I shows the summary statistics. The equal-weighted mean of the proportion of assets in the mutual funds held in DC plans (DC Ratio) is 25.4%, with the first quartile being 8.5% ranging up to 35.5% for the third quartile. However, some large actively managed funds have very high DC ratios. For example, in 2010, Fidelity's Contrafund had a DC ratio of 65.9%, Vanguard's Primecap Fund had a DC ratio of 53.4% and American Fund's Growth Fund of America had a DC ratio of 42.5%. The funds in the sample have average assets under management of around \$3.9 billion, are on average 16 years old, charge an average expense ratio of 1.2%, and exhibit an average turnover rate of 78%.

To reduce the impact of outliers, we winsorize the extreme fund flows at the 2.5% level. Table I shows that the annual growth in DC assets for the average fund in our sample has been much larger than the annual growth in the NonDC assets at 32.0% compared to 6.7%. Part of this difference is due to the fact that DC assets start on average from a smaller base, as the average annual percentage flow for the funds in our sample is 5.7%.[11] Whereas the average monthly net

[11] The following stylized example illustrates how the average growth rate of total assets can be less than the average growth rates of the both asset components. Suppose Fund A has initially DC assets of \$10M and non-DC assets of \$90M. The DC and non-DC assets increase subsequently to \$20M and to \$99M. Thus, the flows (assuming a zero return) for the DC and non-DC assets are 100% and 10%, respectively. The total assets of Fund A increase by 19% from \$100M to \$119M. Fund B has initially DC assets of \$90M and non-DC assets of \$10M. The DC and non-DC assets increase subsequently to \$99M and to \$20M. Thus, the flows (assuming a zero return) for the DC and non-DC assets are 10% and 100%, respectively. The total assets of Fund B also increase by 19% from \$100M to \$119M. Overall, the average DC and non-DC flows across the two funds both equal 55% and exceed the average total flows of 19%.

total flows have a mean close to zero for our sample period, the inflows and outflows based on the N-SAR filings have mean monthly growth rates of 3.486% and 3.079%, respectively.[12] Thus, the average inflows offset a significant portion of the outflows for a typical mutual fund.

Panel B of Table I summarizes the correlations between the key variables. While the DC ratio for a fund is positively correlated with Total Net Assets, it is negatively correlated with expense ratio, fund age, and fund turnover. Thus, DC plans tend to focus on large but relatively younger mutual funds with low expense ratios and low turnovers.

D. Moments of Fund Flows

Table I shows that DC flows tend to be substantially more volatile than non-DC flows. This relation is at first glance surprising since DC contributions and withdrawals are generally very stable over time, which might translate into stable flows for the mutual funds held by DC investors. On the other hand, plan participants and plan sponsors can reallocate their DC assets across different mutual funds creating more volatile flows for funds with high DC assets.

To investigate whether DC money is more stable than non-DC money in mutual funds, we report in Table II the relation between fund characteristics and the standard deviation and the autocorrelation of the growth rate of new money. Panel A reports the regression results in which the DC and non-DC flows are computed annually based on equations (1) and (2). For each fund in our sample we compute the standard deviation of the annual flow and the autocorrelation of the flow over the time period the fund appears in our sample.[13] In the regressions we pool the DC and non-DC flows together. In the first and third columns of the table we regress the moments against an indicator variable for whether the flow is for DC assets. In the second and fourth

[12] The average total flows based on CRSP data differ slightly from the average total flows based on N-SAR data for two main reasons. First, the sample is slightly different since we cannot find N-SAR filings for all our funds. Second, the growth rates of new money computed based on equations (1) – (3) are approximations since the exact timing of the flows during a month or a year is not known.
[13] To compute these moments we require funds to have at least five years of available flow data.

columns we add control variables for fund characteristics, such as size, age, expense ratio, and turnover. We find that the standard deviation and autocorrelation of DC flows exceed the corresponding moments of non-DC flows before and after controlling for other fund characteristics. For example, the standard deviation of annual DC flows exceeds the standard deviation of non-DC flows by between 23.6% and 52.2% per year depending on whether we adjust for other fund characteristics. The difference in standard deviations is reduced after adjusting for fund characteristics primarily because the amount of DC assets in a fund tends to be smaller than the level of non-DC assets. Furthermore, the autocorrelation of DC flows is between 0.110 and 0.138 points lower than for non-DC flows. These results support the hypothesis that DC flows are not stickier than non-DC flows. In fact, counter to conventional wisdom, the DC flows are actually significantly more volatile with less autocorrelation.

An alternative approach to analyzing whether DC flows are stickier than non-DC flows is to investigate the moments of flows for funds with different proportions of DC assets. We separate mutual funds in each period into three equal-sized groups according to the proportion invested by DC investors. Low DC, Mid DC, and High DC correspond to indicator variables for these DC ratio terciles. It must be kept in mind that the majority of the fund investors are non-DC investors, as the average DC ratios equal 5.68%, 19.79%, and 50.12% for the three terciles. We regress the standard deviation and the autocorrelation of the monthly total flows over each calendar year on indicator variables for Mid DC and High DC funds and on additional fund characteristics. The regressions include time-fixed effects and the standard errors of the coefficients are adjusted for clustering at the fund level. The results are shown in Panel B of Table II. Without controlling for other fund characteristics, the results of the first regression suggest that the standard deviation of flows is lower for funds with a higher proportion of DC assets. However, this relation is driven by the fact that funds with a high proportion of DC assets tend to be significantly larger than funds with a lower proportion of DC assets, as shown in Panel

B of Table I.[14] After controlling for fund size and other fund characteristics, we find that funds with a higher proportion of DC assets tend to exhibit a higher flow volatility consistent with our results in Panel A. Finally, Panel B also shows that funds with high proportions of DC assets tend to have a significantly lower autocorrelation of flows than funds with a low proportion of DC assets, regardless of whether we control for other fund characteristics.

These regression results indicate that DC flows are actually more volatile and less autocorrelated than non-DC flows after controlling for fund characteristics, which contradicts the often held belief that DC flows into mutual funds are more sticky.

II. Flow-Performance Relation for DC and Non-DC Assets

We next test our hypotheses regarding the flow-performance sensitivity of DC versus non-DC assets. To test whether a difference exists in the flow-performance relation between DC and non-DC assets, we first examine the percentage flows by DC and non-DC assets separately. A difference in the flow performance sensitivity in the two environments could occur because of the actions of plan participants and sponsors. A lower flow-performance sensitivity for DC assets could occur if plan participants and plan sponsors are inert and do not change their portfolio allocations in their DC accounts as frequently as non-DC investors. On the other hand, if the plan participants or the plan sponsors actively adjust their plan choices based on the prior fund performance, then we should find more sensitivity to performance for DC assets. In particular, this heightened sensitivity could result because when plan sponsors adjust their investment option menus, they typically will move the participants' assets from a poorly performing fund to a replacement fund. Moreover, the replacement selection process usually restricts the replacement fund to a set of better performing funds in the investment objective group.

[14] For example, the average TNAs of funds in the DC ratio terciles equal $1,873, $4,303, and $5,669 million, respectively.

A. Methodology

In this section we compare the flow-performance relation for DC and non-DC assets. For each fund in our sample we employ the *P&I* data to separate the DC and non-DC assets and compute the annual percentage flows (growth rates) of DC and non-DC assets according to equations (1) and (2). To capture the flow-performance sensitivity, we relate these annual flows to the relative fund performance rank (*Rank*) over the prior year while controlling for other fund characteristics, such as the logarithms of the total DC and non-DC assets (*DC Size* and *NonDC Size*), the logarithm of the time period since fund initiation (*Age*), the lagged expense ratio (*Exp*), the lagged annual turnover of the fund (*Turn*), the monthly return volatility over the prior year (*Vol*), the average contemporaneous flow of funds in the same style category following Sirri and Tufano (1998) (*SFlow*), and year fixed effects:

$$\begin{aligned} Flow_{f,t} = {} & f\left(Rank_{f,t}\right) + \beta_1 DC\,Size_{f,t-1} + \beta_2 NonDC\,Size_{f,t-1} + \beta_3 Age_{f,t-1} + \\ & \beta_4 Exp_{f,t-1} + \beta_5 Turn_{f,t-1} + \beta_6 Vol_{f,t-1} + \beta_7 SFlow_{f,t-1} + \beta_t + \varepsilon_{f,t} \end{aligned} \quad (4)$$

We define the fund performance measure $Rank_{f,t}$ as the percentile performance rank a particular fund *f* obtains across all equity funds in the sample during each individual year *t*. Funds in the worst performance percentile obtain a rank of 0.01 and funds in the best performance percentile obtain a rank of 1.00.[15]

To capture non-linearities in the flow-performance relation we use three different functional forms for $f(Rank_{f,t})$. The first non-parametric functional form simply estimates separate effects for each percentile:

[15] We also present robustness tests, where the performance rank is computed within objective-code categories, within holdings-based style categories, and using the Carhart (1997) four-factor adjusted performance measure over the prior year.

$$f_1\left(Rank_{f,t}\right)=\sum_{j=1}^{100}\gamma_j I\left(100\times Rank_{f,t}=j\right) \tag{5}$$

where $I(100\times Rank = j)$ is an indicator variable that equals one if the performance rank of a specific fund falls in the j^{th} percentile and zero otherwise. The coefficient γ_j captures the average flow of funds in the j^{th} percentile if all the other covariates of equation (4) are equal to zero. In this specification we estimate 100 different performance-sensitivity coefficients γ.

A second functional form follows Sirri and Tufano (1998) and estimates a piecewise linear specification:

$$f_2\left(Rank_{f,t}\right)=\gamma_L Low_{f,t}+\gamma_M Mid_{f,t}+\gamma_H High_{f,t}, \tag{6}$$

where $Low_{f,t} = \min(Rank_{f,t}, 0.2)$; $Mid_{f,t} = \min(Rank_{f,t} - Low_{f,t}, 0.6)$; and $High_{f,t} = (Rank_{f,t} - Low_{f,t} - Mid_{f,t})$. The performance coefficients γ_L, γ_M, and γ_H capture the flow-performance sensitivities in the bottom quintile, in the three middle quintiles, and in the top quintile, respectively. For example, a fund in the 15$^{\text{th}}$ percentile would experience flows of $0.15\times\gamma_L$ if all the other covariates were equal to zero. On the other hand, a fund in the 85$^{\text{th}}$ percentile would experience flows of $0.2\times\gamma_L + 0.6\times\gamma_M + 0.05\times\gamma_H$ if all the other covariates were zero. This specification estimates a continuous piecewise linear function.

Finally, the third specification simply estimates a parametric cubic flow-performance relation.

$$f_3\left(Rank_{f,t}\right)=\gamma_1\left(Rank_{f,t}-0.5\right)+\gamma_2\left(Rank_{f,t}-0.5\right)^2+\gamma_3\left(Rank_{f,t}-0.5\right)^3 \tag{7}$$

This specification allows us to determine whether the flow-performance relation differs from a linear relation, whether the relation is convex or concave, or whether it has some more complex functional form.

B. Percentile Flows

Figure 2 depicts the flow-performance relation for the non-parametric specification using the percentile ranks. Panels A and B depict the results for DC and non-DC assets, respectively. The dots show the average flows for the 100 performance groups, where the remaining covariates are evaluated at their sample means. The solid curves show the least-squares cubic relation. Since the funds in our sample are held in both DC and non-DC environments, we obtain for each fund two different asset growth rates corresponding to DC assets and non-DC assets. Thus, the funds depicted in each percentile in Panel A are identical to the funds depicted in the same percentile in Panel B.

Whereas the flow-performance relation is close to linear for the non-DC assets, the relation is non-linear for DC assets. The flow-performance relation is particularly steep for DC assets corresponding to funds in the top and bottom performance groups. For example, funds in the bottom decile experience an average outflow of 8.21% and funds in the top decile experience an average inflow of 55.92% of DC assets. On the other hand, funds in the bottom decile experience an average outflow of 11.68% and funds in the top decile experience an average inflow of 18.39% of non-DC assets.

In addition, we observe that DC assets on average experience larger fund flows than non-DC assets due to the significant growth of tax-qualified retirement accounts over our sample period. Funds with performance ranks in the middle 10% (i.e., funds with performance ranks between the 46th and the 55th percentile) experience inflows of 25.71% for DC assets and 3.28% for non-DC assets.

C. Piecewise Linear Specification

The non-parametric flow-performance relation from Figure 2 justifies the piecewise linear specification suggested by Sirri and Tufano (1998), who estimate different flow-performance sensitivities for the top and bottom performance quintiles. The results of these alternative panel regressions are summarized in Table III. The first two columns report the coefficient estimates for DC and non-DC percentage flows. The third column summarizes the coefficient estimates for a regression in which the dependent variable equals the difference between the DC and the non-DC percentage flows. The standard errors of the coefficients are reported in parentheses and adjust for clustering at the fund level. The regressions also include time-fixed effects.

Consistent with Figure 2, Table III indicates a substantially stronger flow-performance relation for the extreme performance quintiles using the DC flows. A ten-percentile increase in the performance rank increases the DC flows by 11.77% for the bottom quintile, by 2.44% for the middle three quintiles, and by 18.37% for the top quintile. On the other hand, the flow-performance relation is more linear and slightly convex for the non-DC flows. For example, a ten-percentile increase in the performance rank increases the non-DC flows by 3.12% for the bottom quintile, by 2.93% for the middle three quintiles, and by 5.47% for the top quintile. The third column indicates that the difference in flow-performance sensitivities is significantly different between DC and non-DC flows for the top and the bottom performance quintiles. Figure 3 depicts the flow-performance relation for DC and non-DC flows evaluated at the means of the remaining covariates.[16]

[16] The results are not affected qualitatively if we estimate according to the Fama-MacBeth (1973) method, as summarized in Table A-I in the Appendix. Furthermore, the results become stronger if we estimate a piecewise linear specification where $Low_{f,t} = \min(Rank_{f,t}, 0.1)$; $Mid_{f,t} = \min(Rank_{f,t} - Low_{f,t}, 0.9)$; and $High_{f,t} = (Rank_{f,t} - Low_{f,t} - Mid_{f,t})$, as shown in Table A-II in the Appendix.

The most important remaining explanatory variables for fund flows are the sizes of the DC and non-DC assets. Whereas the fund's DC asset size has a negative effect on the DC flows, it has a positive effect on the non-DC flows. Conversely, the fund's non-DC size has a positive effect on the DC flows and a negative effect on the non-DC flows. The direct effects are negative because the growth rates of fund flows tend to decline with the size of the mutual funds (e.g., Sirri and Tufano (1998)). The positive indirect effects are more interesting and capture positive spillovers across DC and non-DC clienteles. Mutual funds with relatively large DC assets tend to attract relatively more non-DC assets and mutual funds with relatively large non-DC assets tend to attract relatively more DC assets.

The flow-performance relation for DC assets differs substantially from the relationship reported in the literature by Chevalier and Ellison (1997), Sirri and Tufano (1998), Huang, Wei, and Yan (2007), and Kim (2011), among others. These studies typically find a convex flow-performance relation for the total mutual fund assets. Our results indicate that *as a group*, DC savers and their sponsors are monitoring their mutual funds more closely than traditional mutual fund investors, resulting in a more sensitive flow-performance relation for extreme performers.

D. Linear and Cubic Specification

Table IV uses the third functional form for performance rank which assumes a parametric linear or cubic flow-performance relation, corresponding to equation (7). In the linear specification we find that DC flows are more sensitive to performance than non-DC flows. For the cubic specification, only the cubic term is statistically significant for the DC flows and only the linear term is statistically significant for the non-DC flows, which is consistent with Figure 2. Since the various functional forms of the flow-performance sensitivity shown in Figures 2 and 3 and Tables III and IV are broadly consistent, we focus our subsequent analysis on the piecewise linear specification.

E. Alternative Performance Benchmarks

Since performance can be measured in many different ways, in this section we consider the flow-performance relation for alternative performance measures. The results are summarized in Table V. The first set of columns ranks our sample of funds within the three objective codes given by the Thomson Financial fund holdings database for domestic equity mutual funds (Aggressive Growth, Growth, Growth and Income). The second set of columns uses holdings-based style measures to rank the performance of funds. Following Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2003), we group each stock listed in CRSP into respective quintiles according to its market value (using NYSE cutoff levels) and its industry-adjusted book-to-market ratio. Using the quintile information of stocks held by a mutual fund, we compute the value-weighted size and book-to-market scores for each fund in each period. Mutual funds are subsequently divided into terciles according to their average size score and their average book-to-market score. Based on the size and book-to-market terciles, we form nine style groups. Finally, each year we rank the equity funds within each of the nine size and book-to-market groups according to their raw performance. The third set of columns ranks mutual funds according to their Fama-French (1993)-Carhart (1997) alphas over the prior year using weekly returns, which reflect the funds' performance after adjustment by a market factor, a size factor, a book-to-market factor, and a momentum factor.

In all three alternative specifications we find that the sensitivity of flows to prior performance is stronger for DC assets than for non-DC assets confirming our previous results. Thus, our results are not driven by style or objective effects.

F. Different Subperiods

The relation between mutual fund flows and past performance can vary over time as shown by Kim (2011). For example, during the 2000s when markets are volatile and there is less dispersion in performance across funds, the relation is not convex. To allow for variation of the flow-performance relation over time, we run the piecewise linear specification over two continuous subperiods (1996-2002 and 2003-2009) and over two different market environments (down markets and up markets). Down (up) markets are defined as years in which the value-weighted CRSP index is below (above) its median value.

Table VI reports the results over the two continuous subperiods. Consistent with Kim (2011) for the non-DC assets we find a convex flow-performance relation between 1996 and 2002 and no convex relation between 2003 and 2009. On the other hand, for DC assets we find a strong flow-performance sensitivity for the bottom and the top performance quintiles over the period between 2003 and 2009. Interestingly, the sensitivity of flows to bottom quintile performance is relatively weak over the period 1996-2002 and strengthens significantly (and particularly for DC assets) during the period 2003-2009. Thus, fund investors in general and investors in DC pension plans became more sensitive to poor performance over the recent time period.

Table VII reports the results over the two different market environments. Consistent with our base-case results, we find that DC flows tend to be more sensitive to extreme performance over both market environments than non-DC flows, although the differences are not always statistically significant.

G. Interactions with Asset Size and Age

The flow-performance sensitivity might differ depending on the size and the age of the funds. Although we control in the previous specifications for the DC and non-DC asset sizes and for the age of the funds, we do not allow the flow-performance relation to differ by asset size and age. Since the DC and the non-DC asset sizes are related to the distribution of flows, it might be important to control for the interactions between the fund performance variables and these fund characteristics. Table VIII indicates that none of the interaction coefficients are significant at a 5% significance level. Furthermore, the estimated coefficients on the three piecewise linear performance segments remain very similar to the results reported in Table III.[17]

The percentage flows to DC and non-DC assets could be inflated for funds with relatively small DC or non-DC asset sizes. To mitigate this problem we winsorize all the flows at a 2.5% level. In addition, we control in some specifications for funds' assets under management and for interactions between the asset size and the piecewise linear performance measures. In a robustness test we replace the percentage DC and non-DC flows with the percentiles of DC and non-DC flows. Consistent with our base case specification in Table III, we find that the percentile DC flows are more sensitive to top and bottom quintile performance than the middle three performance quintiles. Furthermore, the relationship is close to linear using the percentile of non-DC flows.[18]

H. Sample Selection

One potential concern regarding our analysis is that we typically only observe the amount of DC assets for the twelve domestic equity funds within a fund family that have the largest amount of DC assets. Since some mutual fund families have more than 12 domestic equity funds, we might not observe the DC assets for smaller funds within that family or for funds with relatively small proportions of DC assets. This sample selection can be problematic since we cannot compute the DC and the non-DC flows for funds that enter and exit our sample.

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[17] For the interaction effects we use the demeaned DC size, the demeaned non-DC size, and the demeaned age, so that the coefficients on the piecewise linear performance ranks can be interpreted as the coefficients of funds with a mean DC size, mean non-DC size, and mean age.
[18] The results are available in Table A-III in the appendix.

To analyze the relevance of this sample selection issue we consider funds that listed DC assets in the prior period and have missing DC assets in the current period (exit funds) and funds that had missing DC assets in the prior period and have available DC assets in the current period (entry funds).[19]

Table IX reports the coefficient estimates of a multinomial logit regression for fund entry and exit decisions. The base group corresponds to funds that have non-missing DC assets for two consecutive time periods. We find that funds with poor prior performance are more likely to exit the sample and that funds with superior prior performance are more likely to enter the sample. Furthermore, this sample selection issue is more problematic for small funds, since large funds are more likely to consistently remain in the sample.

These results are consistent with our earlier results regarding the flow-performance sensitivity of DC assets. They indicate that DC assets are more likely to flee poorly performing funds (and thus, become missing from the data set), if the fund experiences poor prior performance. Similarly, DC assets are more likely to increase and enter the data set if the fund experiences superior prior performance. Moreover, these selection effects likely attenuate the flow-performance relation for DC assets in our base case specifications. Taking into account these selection effects would likely further increase the sensitivity of DC flows to performance.

III. Flow-Performance Relation by DC Ratio

An alternative method to study the flow-performance relation across funds with different clienteles is to analyze mutual funds with differing proportions of assets invested in DC pension plans.

[19] Since we are interested in the entry and exit decisions of individual funds we do not include the entry and exit decisions of mutual funds that are determined by the entry and exit decisions of whole families.

A. DC Ratio Tercile Results

Table X reports the flow-performance panel regression results for three subsamples of mutual funds sorted according to the proportion of assets invested in DC accounts. The DC ratio is defined as the DC assets divided by the Total Net Assets (TNA) of a fund. One problem of this specification is that the DC proportions tend to be relatively small for typical funds. For example, even for the High DC tercile only half of the assets are held in DC accounts.

Whereas the low and the mid DC terciles exhibit a monotonic and slightly convex flow-performance relation, the high DC tercile exhibits a non-monotonic flow-performance relation. Consistent with the results from Table III, we find that flows of mutual funds with a high proportion of DC assets tend to be more sensitive to extreme performance. For example, a ten-percentile increase in the performance rank increases the flows by 0.38% for the bottom quintile, by 0.22% for the middle three quintiles, and by 0.61% for the top quintile for high DC funds.

In addition, we also find that the expense ratio has a statistically significant impact on high DC funds, whereas the expense ratio has no significant impact on low and mid DC funds. Thus, the investors and the sponsors of DC plans tend to avoid funds with relatively high expense ratios. High expense funds have been shown to exhibit relatively poor performance before and after adjusting for expenses (e.g., Gil-Bazo and Ruiz-Verdu (2009)).

In a robustness test we also estimate a Fama-MacBeth (1973) specification for the three DC tercile subsamples. The results are summarized in Appendix Table A-IV. The estimated flow-performance relation is broadly consistent with the results reported in Table X. One advantage of the Fama-MacBeth specification is that it easily allows us to determine whether the subsamples have different performance sensitivities. These results indicate that High DC funds tend to have statistically significantly higher sensitivities to extreme performance than Low DC funds.

B. Separation of Fund Inflows and Outflows

The previous tests approximate the flows of funds using the changes in assets after adjusting for the fund returns, as described in Section I. However, the analysis of net flows does not allow us to determine whether the flow-performance relation is driven primarily by inflows of new funds or by outflows of existing funds. To separate inflows and outflows, we take advantage of the semi-annual N-SAR filings by mutual fund management companies with the SEC. The filings include the monthly sales (inflows) and redemptions (outflows) of the funds' investors. We hand collect the N-SAR flows for our sample of funds with available DC assets.

Table XI separates the piecewise linear flow-performance panel regressions for the DC terciles into inflows, outflows, and net flows, where net flow is simply defined as the difference between the inflows and the outflows.

The first set of columns summarizes the results based on fund inflows. Whereas fund inflows are not sensitive to increases in performance in the bottom performance quintile, the flows become significantly more sensitive in the middle and top performance quintiles. This result is broadly consistent with the well-known performance-chasing phenomenon. Mutual funds with superior past performance attract significant inflows.

On the other hand, we find a substantially different relation for the outflows of funds with different clienteles. The outflows of funds for mid and high DC tercile funds tend to decline with increasing performance for the bottom four performance quintiles. However, the outflows of low DC tercile funds sharply increase with performance for the top quintile. For example, a ten-percentile performance rank increase for low DC funds *decreases* outflows by 0.25% for the bottom quintile and by 0.22% for the three middle quintiles, whereas an increase in the performance rank of 10 percentile points *increases* outflows by 0.51% for the top quintile. This evidence is consistent with a disposition effect discussed by Kahneman and Tversky (1979), Shefrin and Statman (1985), Odean (1998), Barber and Odean (2000, 2003), Grinblatt and

Keloharju (2001), Frazzini (2006), Ivkovich and Weisbenner (2009), Jin and Scherbina (2011) and Seru, Shumway, and Stoffman (2010) among others. These fund investors have a higher propensity to liquidate their mutual funds after a very strong relative performance. It is insightful that this effect only exists for low DC funds, which are more likely directly held by taxable retail investors. A strategy of realizing winners contradicts tax-efficient fund management, which suggests realizing losing positions and deferring winning positions, as discussed by Sialm and Starks (2012).

The results using net flows are broadly consistent with the results from Table X and again indicate that the flows are more sensitive to extreme fund performance for high DC funds.

Our decomposition of net flows into inflows and outflows for high DC funds indicates that the higher flow-performance sensitivity for bottom quintile performers is primarily driven by outflows of existing funds, whereas the higher flow-performance sensitivity for top quintile performers is primarily driven by inflows of new money. Thus, both inflows and outflows depend on fund performance.

IV. Performance Predictability

The previous tests have shown that DC flows tend to chase performance. However, this result does not necessarily imply that DC money is smart, that is, that DC money can predict future fund abnormal performance. In fact, Berk and Green (2004) derive in a rational model that flows should not predict future abnormal performance. They assume that skilled managers will attract larger flows and that the resulting increase in fund size will subsequently deteriorate the average investment ability of these managers due to decreasing returns to scale. The empirical literature has shown that flows are smart in the short term (Gruber (1996) and Zheng (1999)) but dumb at longer horizons (Frazzini and Lamont (2009)).

The relative sophistication of the plan sponsors and their use of consultants would imply that DC fund flows are more discerning than non-DC flows. Thus, we test whether mutual fund flows from DC or non-DC investors can predict funds' long-term future performance. Since we only have annual measures of DC and non-DC flows, we run our performance predictability regression at an annual frequency.

$$\begin{aligned} Perf_{f,t} = {} & \beta_1 DC\,Flow_{f,t-1} + \beta_2 Non\,DC\,Flow_{f,t-1} + \beta_3 Perf_{f,t-1} + \beta_4 Size_{f,t-1} \\ & + \beta_5 Age_{f,t-1} + \beta_6 Exp_{f,t-1} + \beta_7 Turn_{f,t-1} + \beta_8 DC\,Ratio_{f,t-1} + \beta_t + \varepsilon_{f,t} \end{aligned} \tag{8}$$

To evaluate the performance differences across DC and non-DC flows, we employ a number of different measures of mutual fund return performance: raw fund return per month, objective-adjusted return (where we subtract the mean return of funds in the same objective category from the fund return), style-adjusted return (where we subtract the mean return of funds in the same style classification based on the fund holdings),[20] and alphas based on the Capital Asset Pricing Model, the Fama-French (1993) model, and the Carhart (1997) model. The remaining control variables are the return over the prior year, the logarithm of the total assets of a fund, the logarithm of fund age, the expense ratio, the turnover, and the DC ratio. The specifications also include year-fixed effects and cluster the standard errors by fund.

Table XII presents the results for the tests of flow predictability of fund performance. As the table shows, we find different effects for DC and non-DC flows. For the latter, consistent with the Frazzini and Lamont (2009) dumb money effect, we find a negative relationship between non-DC flows and next year's performance using the various performance measures. On the other hand, we do not find a significant relationship between DC flows and subsequent fund performance. Furthermore, we also report in last row the *p*-values of an *F*-test that

[20] The holdings-based styles are determined by dividing mutual funds into terciles according to the mean size and mean book-to-market ratio of their holdings. Thus, in each period we obtain nine different fund styles according to the holdings (e.g., small-cap growth, mid-cap growth, large-cap growth, small-cap blend, …, large-cap value).

investigates whether the coefficients on DC flows equal the coefficients on Non-DC flows. The results indicate that coefficients between the two flow measures differ significantly for all considered performance measures.

These insignificant performance predictability results for DC flows are broadly consistent with Berk and Green's (2004) theoretical model. The results indicate that in contrast to retail investors the performance-chasing phenomenon of DC pension plans does not harm their long-term performance prospects.

V. Conclusions

In this paper we examine the effects of defined contribution plans on the mutual funds in which they invest. Flows into DC mutual funds are partially driven by the decisions of individual plan participants and partially driven by the menu choices offered by plan sponsors. On the other hand, flows into non-DC mutual funds are primarily driven by the decisions of fund investors. Our results indicate that DC money is more volatile and exhibits more flow-performance sensitivity than non-DC money. Our results also hold when we take an alternative approach and examine the flow-performance sensitivity of funds with the highest proportion of DC assets compared to funds with the lowest proportion of DC assets. Further when we examine inflows and outflows from the funds' N-SAR filings with the SEC we find that the higher flow-performance sensitivity for the bottom quintile performers is primarily driven by outflows of existing funds, whereas the higher flow-performance sensitivity for top quintile performers is primarily driven by inflows of new money. These results show that both inflows and outflows depend on fund performance. We also examine whether the fund selections of DC plan sponsors and their participants are more discerning than the non-DC investors. We test whether mutual fund flows from DC or non-DC investors can predict funds' long-term future return performance consistent with the smart money effect of Gruber (1996) and Zheng (1999). We find that non-DC fund flows predict future performance negatively, consistent with the Frazzini and Lamont (2009) dumb money effect. However, the DC fund flows have no predictability, suggesting that these investors are neither smart nor dumb money.

Our results have several implications. First, the difference in fund flow patterns between DC and non-DC assets suggests that the role of plan sponsors can counteract the potential effects of inertia on the part of plan participants in removing poorly performing funds from their portfolios and adding well-performing funds. Second, this plan sponsor role has implications for the composition of the fund industry, particularly given the growth in defined contribution plans. Third, it appears that mutual funds can diversify their net fund flows by offering their funds to both DC and non-DC investors. However, having such a mixed clientele in terms of tax status may be difficult for portfolio manager strategies.

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Appendix

In this appendix we include some additional robustness tests not included in the main body of the paper. In addition, we explain in more detail the performance measures used in the paper.

A. Robustness Tests

Tables A-I, A-II, A-III, and A-IV provide the results of additional robustness tests of the flow-performance sensitivity of DC and non-DC flows. In Tables A-I and A-IV we show that our results are robust to the use of an alternative methodology to the panel regressions in Tables III and X in the paper. In both tables we conduct cross-sectional regressions and then aggregate the coefficients across the years using the Fama-MacBeth (1973) approach. In both tables the primary variables of interest are low, middle and high ranked return performance where the lowest is min($Rank_{f,t}$, 0.2); the middle is min($Rank_{f,t} - Low_{f,t}$, 0.6); and the highest is ($Rank_{f,t} - Low_{f,t} - Mid_{f,t}$). We also control for other characteristics of the fund. Specifically in Table A-I we use piecewise linear regressions of DC and non-DC asset flows on fund variables while in Table A-V we provide the results of the piecewise linear regressions of fund flows when the funds are divided into terciles according to the proportions of DC assets invested in the funds.

In Table A-II we show that the results of Table III are robust to different classifications of performance. We again use the panel regressions employed in the main body of the paper and run a piecewise linear panel regression of DC and non-DC asset flows on fund variables. Low, Mid and High ranked return continue to represent the funds' ranked return performance but we change the definitions so that $Low_{f,t}$ = min($Rank_{f,t}$, 0.1 or 0.3); $Mid_{f,t}$ = min($Rank_{f,t} - Low_{f,t}$, 0.8 or 0.4); and $High_{f,t}$ = ($Rank_{f,t} - Low_{f,t} - Mid_{f,t}$). The other variables are characteristics of the funds.

The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level and the regressions also include time-fixed effects.

In Table A-III we summarize the coefficients of a piecewise linear panel regression of DC and non-DC asset percentile flows on fund variables. The dependent variables are the percentiles of the DC and non-DC flows in each year and the percentile of the difference between the DC and non-DC flows. The other variables are characteristics of the fund. Consistent with our base case specification in Table III, we find that the percentile DC flows are more sensitive to top and bottom quintile performance than the middle three performance quintiles. Furthermore, the relationship is close to linear using the percentile of non-DC flows.

B. Details on Mutual Fund Performance Tests

The performance measures we employ in the paper are the raw return, objective-adjusted return, style-adjusted return, CAPM-adjusted performance, Fama-French adjusted performance and Carhart adjusted performance. The objective-adjusted return is defined as the difference between the fund return and the mean return of funds in the same objective category. The style-adjusted return is defined as the difference between the fund return and the mean return of funds in the same style classification based on the fund holdings, where the holdings-based styles are determined by dividing mutual funds into terciles according to the mean size and the mean book-to-market ratio of their holdings. Thus, in each period we obtain 9 different fund styles according to the holdings (e.g., small-cap growth, mid-cap growth, large-cap growth, small-cap blend, …, large-cap value).

Our performance measures also include several risk-adjusted measures of return including alphas from the Capital Asset Pricing Model, Fama-French (1993) model and Carhart (1997) model:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_{i,M}(R_{M,t} - R_{F,t}) + \varepsilon_{i,t} \tag{A1}$$

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_{i,M}(R_{M,t} - R_{F,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \varepsilon_{i,t} \tag{A2}$$

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_{i,M}(R_{M,t} - R_{F,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,UMD}UMD_t + \varepsilon_{i,t} \tag{A3}$$

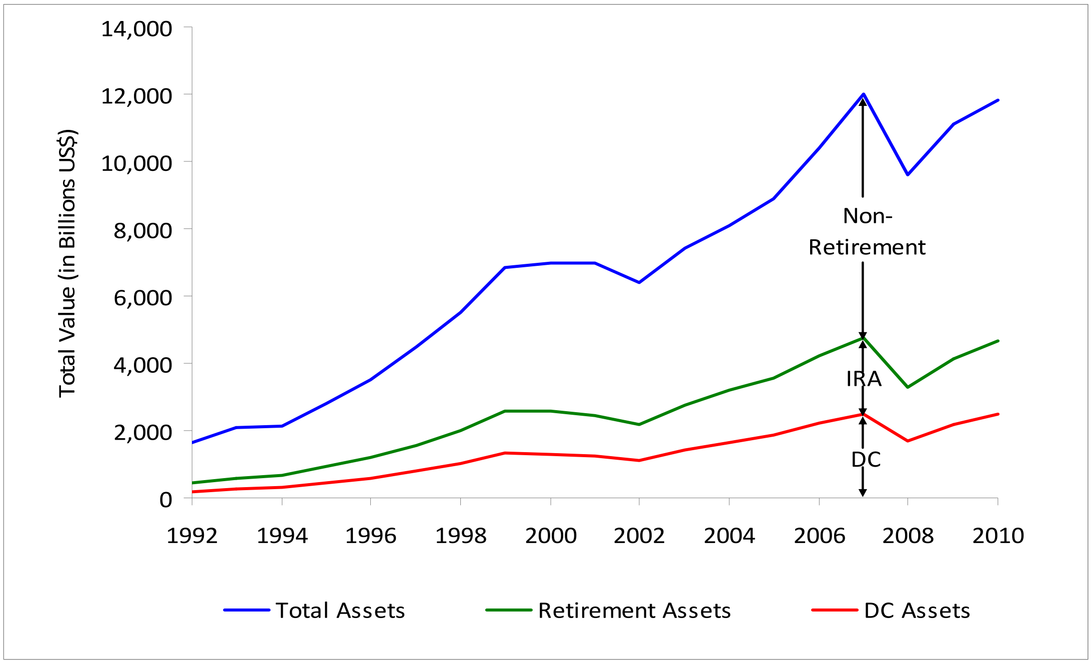
where $R_{i,t} - R_{F,t}$ and $R_{M,t} - R_{F,t}$ are the monthly excess returns on the fund portfolio and the market portfolio respectively, and SMB_t , HML_t and UMD_t are the monthly size, value and momentum factor returns.[21]

[21] The market, size, book-to-market, momentum factors and the risk-free rate are obtained from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html).

Figure 1
Growth in Total Mutual Fund Assets

These figures show the growth in total and equity mutual fund assets from 1992 through 2010, divided into those assets held in defined contribution accounts (DC), individual retirement accounts (IRA), and non-retirement accounts.

Panel A: Total Mutual Fund Assets



Panel B: Total Equity Mutual Fund Assets

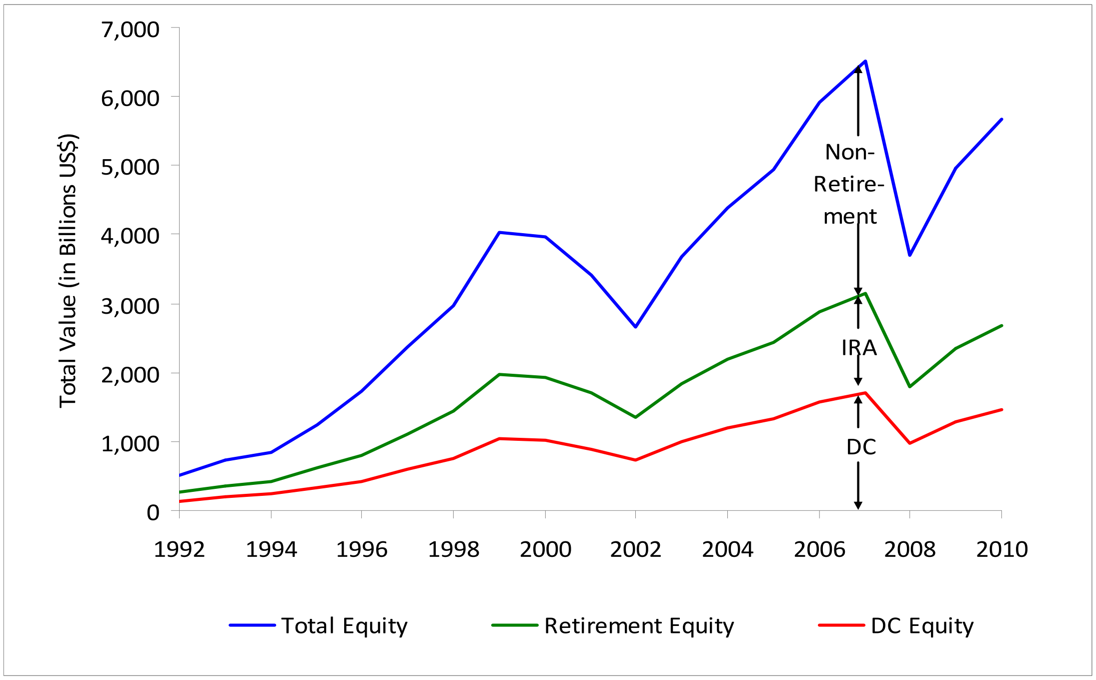
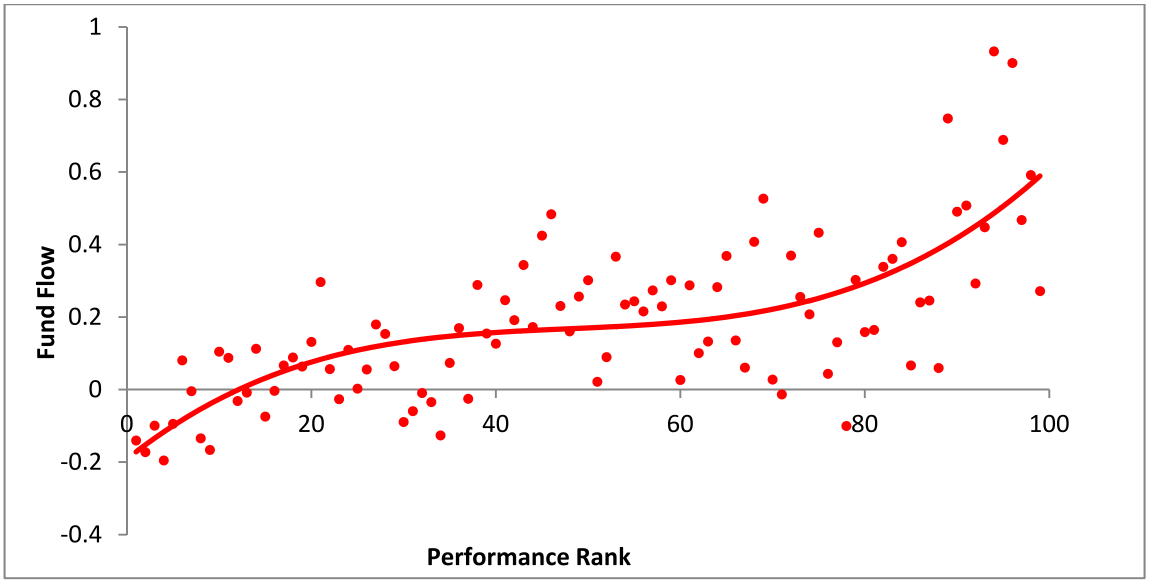


Figure 2
Flow-Performance Relation for Percentile Performance Portfolios of DC and Non-DC Assets

These figures show the flow-performance relation for DC and non-DC assets using nonparametric specifications. The dots represent the average flows for 100 performance groups, where the remaining covariates are evaluated at their sample means. The solid curves show the least-squares cubic relations.

Panel A: DC Assets



Panel B: Non-DC Assets

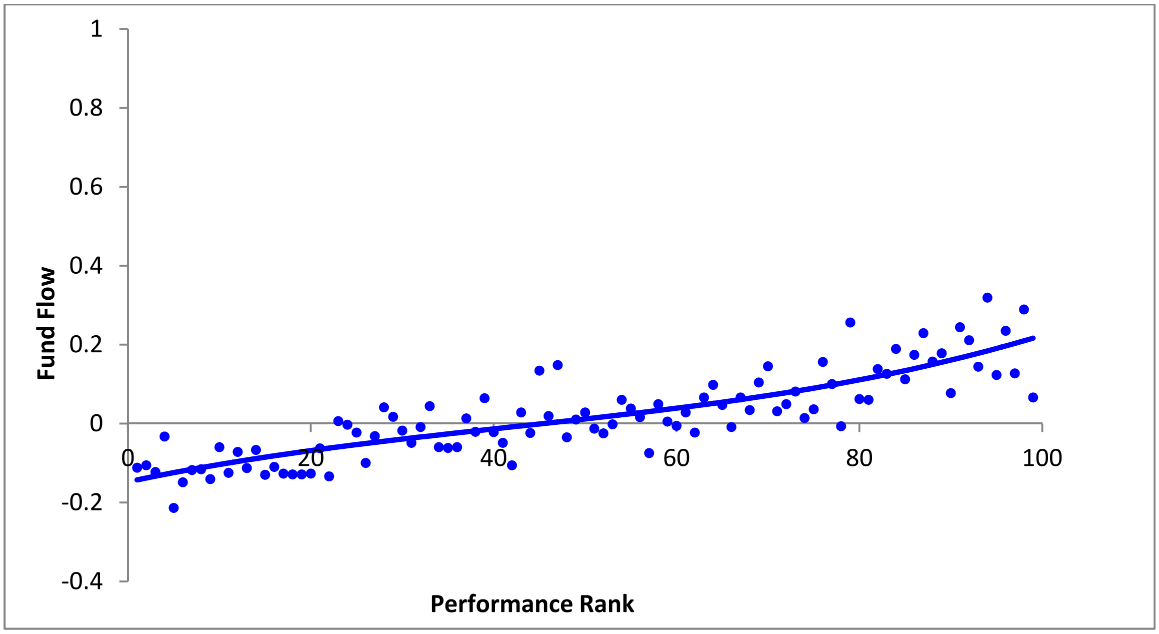


Figure 3
Piecewise Linear Flow-Performance Relation for Percentile Performance Portfolios of DC Assets and Non-DC Assets

This figure shows the flow-performance relation for DC and non-DC assets. The lines represent the piecewise linear relation following Sirri and Tufano (1998), as summarized in Table III.

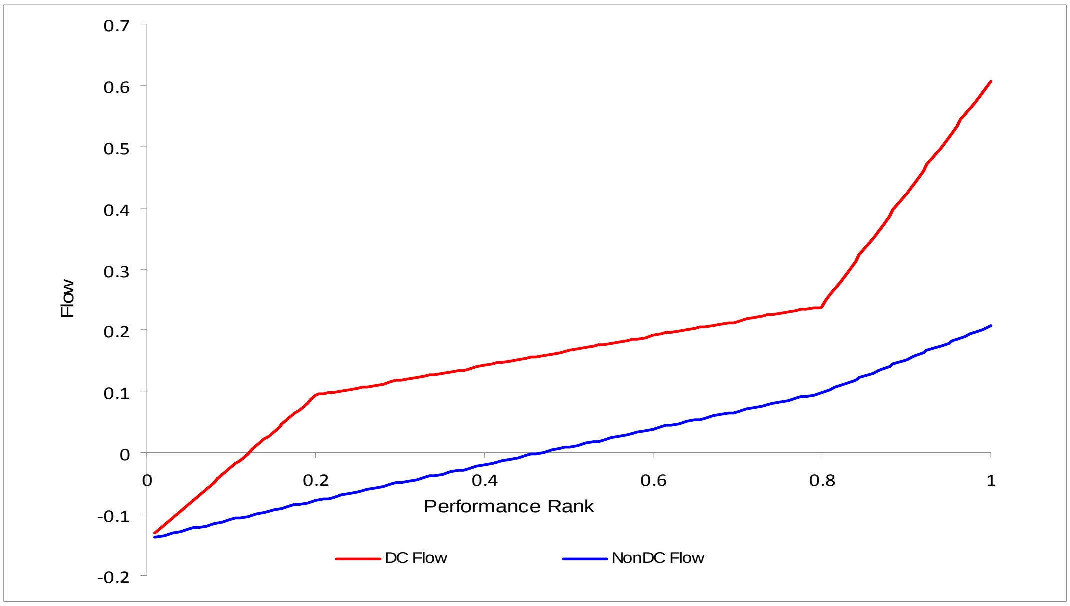


Table I
Summary Statistics

This table provides the summary statistics for the sample of mutual funds over the 1996-2009 period. The DC ratio is the percentage of the fund assets held by defined contribution accounts at the end of the year. The Total Net Assets (TNA), age, expenses, and turnover are fund characteristics based on the CRSP mutual fund database. The annual total flow is the percentage growth rate in total net assets after adjusting for asset returns based on CRSP data. The annual DC flow is the percentage flow of DC assets based on the annual surveys by *Pensions & Investments*, and the annual Non-DC flow is the percentage flow to the difference between total fund assets and DC assets. The monthly total flow is the percentage growth rate in total net assets after adjusting for asset return based on CRSP. The monthly N-SAR flows, inflows, and outflows are based on the semi-annual N-SAR filings by mutual funds. The monthly fund return is from CRSP.

Panel A: Moments

Variable	Mean	Std. Dev.	Minimum	First Quartile	Median	Third Quartile	Maximum
DC Ratio (in %)	25.383	21.999	0.000	8.504	19.854	35.522	100.000
Total Net Assets (in millions of dollars)	3931.43	10288.58	3.30	268.90	967.35	3121.60	193453.10
Age (in years)	16.325	15.460	0.000	7.000	11.000	19.000	85.000
Expense Ratio (in %)	1.157	0.448	0.010	0.902	1.159	1.423	3.503
Turnover (in % per year)	78.259	82.596	1.000	30.510	61.000	103.000	1,697.000
Annual Total Flow (in %)	5.700	37.412	-38.949	-14.373	-3.570	12.579	180.596
Annual DC Flow (in %)	32.006	119.339	-78.133	-20.776	-0.226	32.764	621.847
Annual Non-DC Flow (in %)	6.653	44.372	-56.216	-16.135	-3.956	14.063	190.573
Monthly Fund Flow (in %)	0.049	3.807	-10.465	-1.473	-0.374	0.963	27.429
Monthly N-SAR Fund Flow (in %)	0.040	3.086	-6.524	-1.434	-0.347	0.897	14.072
Monthly N-SAR Fund Inflow (in %)	3.486	4.219	0.169	1.080	2.019	3.928	23.862
Monthly N-SAR Fund Outflow (in %)	3.079	2.891	0.000	1.518	2.232	3.439	16.591
Monthly Fund Return (in %)	0.437	5.883	-41.602	-2.445	0.890	3.851	55.578
Number of Annual Fund-Year Observations	5808						

Table I (Cont.)

Panel B: Correlations

Variable	DC Ratio	TNA	Age	Exp. Ratio	Turn-over	Tot. Flow	DC Flow	Non-DC Flow	Month. Flow	N-SAR Flow	N-SAR Inflow	N-SAR Outflow
DC Ratio	1.000											
Total Net Assets	0.116	1.000										
Age	-0.107	0.292	1.000									
Expense Ratio	-0.321	-0.288	-0.133	1.000								
Turnover	-0.101	-0.079	-0.018	0.151	1.000							
Annual Total Flow	-0.029	-0.034	-0.182	0.024	0.017	1.000						
Annual DC Flow	-0.023	-0.067	-0.126	0.097	0.012	0.483	1.000					
Annual Non-DC Flow	-0.072	-0.039	-0.153	-0.003	0.026	0.814	0.228	1.000				
Monthly Fund Flow	-0.002	0.003	-0.105	-0.012	-0.010	0.613	0.313	0.510	1.000			
Monthly N-SAR Fund Flow	-0.001	0.004	-0.122	-0.020	-0.045	0.620	0.325	0.507	0.813	1.000		
Monthly N-SAR Fund Inflow	-0.012	-0.081	-0.172	0.078	0.065	0.424	0.255	0.337	0.489	0.531	1.000	
Monthly N-SAR Fund Outflow	-0.010	-0.127	-0.123	0.131	0.138	-0.080	0.006	-0.079	-0.246	-0.282	0.493	1.000
Monthly Fund Return	-0.002	0.005	-0.011	0.001	-0.008	0.064	0.028	0.056	0.121	0.115	0.059	-0.088

Table II
Relation Between Flow Variability and Fund Characteristics

This table summarizes the coefficients of a regression of moments of flows on fund characteristics. The dependent variables in Panel A are defined as the standard deviation and the autocorrelation of the annual DC and non-DC flows over the lifetime of a fund, requiring that funds have at least five annual observations. The independent variables include an indicator variable for DC or non-DC flows, and the initial DC or non-DC size, and other initial fund characteristics. The dependent variables in Panel B are defined as the standard deviation and the autocorrelation of the monthly total flows within each calendar year. The independent variables are indicator variables for the middle and the top tercile of the lagged DC ratio and lagged fund characteristics. The standard errors in Panel B adjusted for clustering at the fund level. All standard errors are reported in parentheses. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

Panel A: Moments of Annual DC- and Non-DC Flows

	Standard Deviation of Flow		Autocorrelation of Flow	
DC Indicator	0.522***	0.236***	-0.138***	-0.110***
	(0.033)	(0.028)	(0.026)	(0.034)
Log Size		-0.150***		0.014
		(0.012)		(0.010)
Log Age		0.033		-0.025
		(0.026)		(0.023)
Expense Ratio		1.154**		-0.415
		(0.468)		(0.510)
Turnover		-0.007		0.028***
		(0.015)		(0.011)
Observations	1,032	987	1,032	987
R-Squared	0.162	0.386	0.018	0.024

Panel B: Moments of Total Flows

	Standard Deviation of Flow		Autocorrelation of Flow	
Mid DC	-0.238**	0.165**	-0.017	-0.036**
	(0.001)	(0.074)	(0.015)	(0.014)
High DC	-0.191*	0.267***	-0.032**	-0.047***
	(0.104)	(0.082)	(0.015)	(0.015)
Log Size		-0.422***		0.045***
		(0.024)		(0.005)
Log Age		-0.329***		-0.029***
		(0.045)		(0.009)
Expense Ratio		-3.033***		0.939***
		(0.967)		(0.184)
Turnover		0.120**		-0.000
		(0.050)		(0.006)
Observations	5,365	5,117	5,365	5,117
R-Squared	0.003	0.217	0.001	0.034

Table III
Piecewise Linear Panel Regressions of DC and Non-DC Flows

This table summarizes the coefficients of a piecewise linear panel regression of DC and non-DC asset flows on fund variables. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t} = \min(Rank_{f,t}, 0.2)$; $Mid_{f,t} = \min(Rank_{f,t} - Low_{f,t}, 0.6)$; and $High_{f,t} = (Rank_{f,t} - Low_{f,t} - Mid_{f,t})$. The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	DC Flow	Non-DC Flow	Difference
Low Rank	1.177***	0.312**	0.866**
	(0.376)	(0.141)	(0.373)
Mid Rank	0.244***	0.293***	-0.049
	(0.087)	(0.037)	(0.090)
High Rank	1.837***	0.547***	1.289***
	(0.492)	(0.180)	(0.473)
Log DC Size	-0.125***	0.017***	-0.143***
	(0.016)	(0.006)	(0.016)
Log Non-DC Size	0.058***	-0.053***	0.111***
	(0.016)	(0.008)	(0.017)
Log Age	-0.042*	-0.002	-0.040*
	(0.024)	(0.010)	(0.022)
Expense Ratio	-0.486	-0.239	-0.248
	(0.557)	(0.224)	(0.511)
Turnover	-0.021	-0.013	-0.007
	(0.019)	(0.009)	(0.016)
Volatility	1.032	0.014	1.017
	(0.863)	(0.320)	(0.857)
Style Flow	0.491	0.413***	0.078
	(0.317)	(0.133)	(0.288)
Observations	3,851	3,851	3,851
R-squared	0.096	0.112	0.064

Table IV
Linear and Cubic Flow-Performance Relation

This table summarizes the coefficients of linear and cubic panel regressions of DC and non-DC asset flows on fund variables. Rank captures the ranked performance and the other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	Linear Specification			Cubic Specification		
	DC Flow	Non-DC Flow	Difference	DC Flow	Non-DC Flow	Difference
(Rank-0.5)	0.507***	0.323***	0.184***	0.138	0.267***	-0.129
	(0.058)	(0.023)	(0.058)	(0.126)	(0.053)	(0.129)
$(\text{Rank-0.5})^2$				0.095	0.087	0.008
				(0.240)	(0.085)	(0.233)
$(\text{Rank-0.5})^3$				2.481***	0.362	2.119**
				(0.856)	(0.333)	(0.848)
Log DC Size	-0.126***	0.017***	-0.143***	-0.126***	0.017***	-0.143***
	(0.016)	(0.006)	(0.016)	(0.016)	(0.006)	(0.015)
Log Non-DC Size	0.060***	-0.052***	0.112***	0.059***	-0.053***	0.112***
	(0.016)	(0.008)	(0.017)	(0.016)	(0.008)	(0.017)
Log Age	-0.047**	-0.003	-0.043*	-0.043*	-0.002	-0.041*
	(0.024)	(0.010)	(0.022)	(0.024)	(0.010)	(0.022)
Expense Ratio	-0.393	-0.208	-0.185	-0.428	-0.239	-0.189
	(0.550)	(0.222)	(0.499)	(0.563)	(0.225)	(0.515)
Turnover	-0.021	-0.014	-0.008	-0.021	-0.014	-0.008
	(0.020)	(0.009)	(0.017)	(0.019)	(0.009)	(0.016)
Volatility	1.102	0.086	1.017	1.182	0.031	1.151
	(0.811)	(0.318)	(0.814)	(0.865)	(0.319)	(0.863)
Style Flow	0.500	0.416***	0.084	0.496	0.414***	0.082
	(0.318)	(0.133)	(0.288)	(0.318)	(0.133)	(0.288)
Observations	3,851	3,851	3,851	3,851	3,851	3,851
R-squared	0.093	0.111	0.061	0.095	0.112	0.063

Table V

Piecewise Linear Panel Regression with Different Performance Benchmark Measures

This table summarizes the coefficients of a piecewise linear panel regression of DC and non-DC asset flows on fund variables. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t} = \min(Rank_{f,t}, 0.2)$; $Mid_{f,t} = \min(Rank_{f,t} - Low_{f,t}, 0.6)$; and $High_{f,t} = (Rank_{f,t} - Low_{f,t} - Mid_{f,t})$. The other variables are characteristics of the fund. The performance measures correspond to the objective code-adjusted performance, the style-adjusted performance, and the Carhart-adjusted performance. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

Table V (Cont.)

	Objective Code-Adjusted Performance			Style-Adjusted Performance			Carhart-Adjusted Performance		
	DC Flow	Non-DC Flow	Difference	DC Flow	Non-DC Flow	Difference	DC Flow	Non-DC Flow	Difference
Low Rank	1.208***	0.534***	0.673*	1.152***	0.170	0.982***	0.925**	0.071	0.854**
	(0.378)	(0.149)	(0.391)	(0.361)	(0.155)	(0.372)	(0.406)	(0.171)	(0.426)
Mid Rank	0.220**	0.239***	-0.019	0.197**	0.243***	-0.046	0.140	0.283***	-0.143
	(0.091)	(0.037)	(0.096)	(0.098)	(0.036)	(0.100)	(0.100)	(0.037)	(0.106)
High Rank	1.896***	0.522***	1.374***	1.448***	0.485**	0.963**	1.680***	0.340*	1.340***
	(0.448)	(0.181)	(0.434)	(0.446)	(0.189)	(0.445)	(0.508)	(0.188)	(0.475)
Log DC Size	-0.125***	0.017***	-0.141***	-0.132***	0.016**	-0.148***	-0.119***	0.021***	-0.141***
	(0.016)	(0.006)	(0.016)	(0.017)	(0.006)	(0.016)	(0.017)	(0.006)	(0.017)
Log Non-DC Size	0.057***	-0.053***	0.110***	0.056***	-0.055***	0.111***	0.048***	-0.057***	0.105***
	(0.016)	(0.008)	(0.017)	(0.017)	(0.009)	(0.018)	(0.017)	(0.009)	(0.018)
Log Age	-0.041*	-0.000	-0.041*	-0.053**	-0.012	-0.041*	-0.042	-0.007	-0.035
	(0.024)	(0.010)	(0.023)	(0.024)	(0.010)	(0.022)	(0.027)	(0.010)	(0.026)
Expense Ratio	-0.460	-0.230	-0.230	-0.423	-0.189	-0.234	-0.109	0.075	-0.185
	(0.551)	(0.224)	(0.504)	(0.566)	(0.231)	(0.512)	(0.586)	(0.232)	(0.537)
Turnover	-0.019	-0.013	-0.006	-0.023	-0.016*	-0.007	-0.025	-0.012	-0.014
	(0.019)	(0.009)	(0.016)	(0.019)	(0.008)	(0.017)	(0.021)	(0.009)	(0.018)
Volatility	-0.316	-0.494	0.178	-0.179	-0.776	0.597	-0.017**	-0.016***	-0.001
	(1.263)	(0.462)	(1.254)	(1.723)	(0.499)	(1.736)	(0.008)	(0.003)	(0.008)
Style Flow	0.596*	0.525***	0.071	0.824***	0.698***	0.126	0.572*	0.455***	0.117
	(0.322)	(0.136)	(0.289)	(0.227)	(0.090)	(0.212)	(0.324)	(0.131)	(0.293)
Observations	3,851	3,851	3,851	3,780	3,780	3,780	3,408	3,408	3,408
R-squared	0.097	0.105	0.065	0.095	0.106	0.064	0.087	0.099	0.063

Table VI

Piecewise Linear Panel Regressions of DC and Non-DC Flows for Different Subperiods

This table summarizes the coefficients of a piecewise linear panel regression of DC and non-DC asset flows on fund variables. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t}$ = min($Rank_{f,t}$, 0.2); $Mid_{f,t}$ = min($Rank_{f,t} - Low_{f,t}$, 0.6); and $High_{f,t}$ = ($Rank_{f,t} - Low_{f,t} - Mid_{f,t}$). The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	1996-2002			2003-2009		
	DC Flow	Non-DC Flow	Difference	DC Flow	Non-DC Flow	Difference
Low Rank	0.639	0.291	0.348	1.536***	0.401**	1.134**
	(0.628)	(0.222)	(0.647)	(0.474)	(0.197)	(0.462)
Mid Rank	0.430***	0.352***	0.079	0.125	0.264***	-0.139
	(0.142)	(0.052)	(0.148)	(0.111)	(0.053)	(0.113)
High Rank	2.540***	1.305***	1.235*	1.338**	0.004	1.334**
	(0.724)	(0.303)	(0.714)	(0.646)	(0.208)	(0.622)
Log DC Size	-0.154***	0.019**	-0.173***	-0.104***	0.018**	-0.122***
	(0.027)	(0.008)	(0.028)	(0.016)	(0.008)	(0.015)
Log Non-DC Size	0.065**	-0.052***	0.117***	0.051***	-0.054***	0.105***
	(0.027)	(0.012)	(0.030)	(0.014)	(0.011)	(0.016)
Log Age	0.008	-0.009	0.018	-0.080**	0.011	-0.090***
	(0.034)	(0.014)	(0.034)	(0.032)	(0.015)	(0.031)
Expense Ratio	0.416	0.193	0.224	-0.499	-0.261	-0.238
	(0.820)	(0.348)	(0.770)	(0.673)	(0.286)	(0.617)
Turnover	0.004	-0.012	0.016	-0.060***	-0.018	-0.041*
	(0.028)	(0.010)	(0.024)	(0.022)	(0.013)	(0.025)
Volatility	1.376	0.480	0.895	-1.631	-1.650**	0.020
	(1.095)	(0.361)	(1.107)	(1.807)	(0.721)	(1.763)
Style Flow	-0.039	0.161	-0.200	0.544	0.536***	0.008
	(0.591)	(0.191)	(0.608)	(0.370)	(0.171)	(0.333)
Observations	1,759	1,759	1,759	2,092	2,092	2,092
R-squared	0.126	0.180	0.079	0.085	0.086	0.058

Table VII
Piecewise Linear Panel Regressions of DC and Non-DC Flows for Different Market Conditions

This table summarizes the coefficients of a piecewise linear panel regression of DC and non-DC asset flows on fund variables. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t}$ = min($Rank_{f,t}$, 0.2); $Mid_{f,t}$ = min($Rank_{f,t}$ – $Low_{f,t}$, 0.6); and $High_{f,t}$ = ($Rank_{f,t}$ – $Low_{f,t}$ – $Mid_{f,t}$). The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	Down Markets			Up Markets		
	DC Flow	Non-DC Flow	Difference	DC Flow	Non-DC Flow	Difference
Low Rank	0.968**	0.260	0.707	1.281**	0.300	0.981*
	(0.483)	(0.191)	(0.493)	(0.560)	(0.204)	(0.544)
Mid Rank	0.193	0.170***	0.023	0.322***	0.446***	-0.123
	(0.129)	(0.051)	(0.138)	(0.113)	(0.056)	(0.117)
High Rank	1.980***	0.793***	1.187*	1.693**	0.397	1.296**
	(0.638)	(0.242)	(0.628)	(0.680)	(0.260)	(0.653)
Log DC Size	-0.102***	0.018**	-0.120***	-0.154***	0.016*	-0.170***
	(0.018)	(0.007)	(0.018)	(0.026)	(0.010)	(0.025)
Log Non-DC Size	0.025	-0.046***	0.071***	0.095***	-0.062***	0.157***
	(0.021)	(0.010)	(0.024)	(0.022)	(0.014)	(0.024)
Log Age	0.005	-0.013	0.018	-0.092***	0.009	-0.101***
	(0.039)	(0.013)	(0.038)	(0.030)	(0.014)	(0.029)
Expense Ratio	-0.294	-0.218	-0.076	-0.778	-0.272	-0.506
	(0.688)	(0.285)	(0.684)	(0.841)	(0.317)	(0.778)
Turnover	-0.001	-0.015	0.014	-0.056**	-0.011	-0.045*
	(0.026)	(0.011)	(0.021)	(0.027)	(0.013)	(0.025)
Volatility	0.832	-0.278	1.110	0.524	-1.455	1.978
	(0.843)	(0.330)	(0.854)	(2.480)	(0.936)	(2.632)
Style Flow	0.129	0.237	-0.108	0.555	0.464***	0.091
	(0.500)	(0.219)	(0.510)	(0.387)	(0.158)	(0.355)
Observations	2,046	2,046	2,046	1,805	1,805	1,805
R-squared	0.078	0.087	0.050	0.122	0.147	0.088

Table VIII
Piecewise Linear Panel Regressions of DC and Non-DC Flows with Size and Age Interaction Effects

This table summarizes the coefficients of a piecewise linear panel regression of DC and non-DC asset flows on fund variables. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t}$ = min($Rank_{f,t}$, 0.2); $Mid_{f,t}$ = min($Rank_{f,t}$ – $Low_{f,t}$, 0.6); and $High_{f,t}$ = ($Rank_{f,t}$ – $Low_{f,t}$ – $Mid_{f,t}$). The performance ranks are interacted with the DC and non-DC sizes and with the age of the funds. The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

Table VIII (Cont.)

	Size Interactions			Age Interactions		
	DC Flow	Non-DC Flow	Difference	DC Flow	Non-DC Flow	Difference
Low Rank	0.958***	0.240	0.718*	1.128***	0.268*	0.860**
	(0.370)	(0.152)	(0.371)	(0.381)	(0.141)	(0.378)
Mid Rank	0.266***	0.302***	-0.036	0.261***	0.311***	-0.050
	(0.089)	(0.038)	(0.093)	(0.093)	(0.039)	(0.095)
High Rank	1.551***	0.422***	1.129***	1.697***	0.431**	1.266***
	(0.411)	(0.159)	(0.411)	(0.483)	(0.171)	(0.473)
Low Rank *	-0.301	-0.138	-0.163			
Log DC Size	(0.216)	(0.091)	(0.222)			
Mid Rank*	-0.065	-0.002	-0.063			
Log DC Size	(0.083)	(0.035)	(0.081)			
High Rank*	-0.272	0.070	-0.343			
Log DC Size	(0.392)	(0.139)	(0.379)			
Low Rank*	0.159	0.248	-0.089			
Log Non-DC Size	(0.306)	(0.165)	(0.312)			
Mid Rank*	0.031	-0.036	0.067			
Log Non-DC Size	(0.074)	(0.048)	(0.085)			
High Rank*	0.143	-0.317	0.460			
Log Non-DC Size	(0.456)	(0.221)	(0.481)			
Low Rank*				-0.000	-0.011	0.011
Log Age				(0.444)	(0.143)	(0.458)
Mid Rank*				-0.063	-0.086*	0.023
Log Age				(0.136)	(0.046)	(0.141)
High Rank*				-0.693	-0.437	-0.256
Log Age				(0.688)	(0.283)	(0.641)
Log DC Size	-0.044	0.042***	-0.086***	-0.124***	0.018***	-0.142***
	(0.032)	(0.014)	(0.033)	(0.016)	(0.006)	(0.015)
Log Non-DC	0.016	-0.083***	0.098*	0.057***	-0.053***	0.111***
Size	(0.053)	(0.028)	(0.054)	(0.015)	(0.008)	(0.017)
Log Age	-0.040*	-0.001	-0.039*	-0.010	0.034	-0.044
	(0.023)	(0.010)	(0.022)	(0.067)	(0.021)	(0.069)
Expense Ratio	-0.502	-0.288	-0.214	-0.536	-0.273	-0.263
	(0.546)	(0.223)	(0.500)	(0.562)	(0.221)	(0.519)
Turnover	-0.018	-0.014*	-0.004	-0.021	-0.014	-0.007
	(0.019)	(0.008)	(0.016)	(0.019)	(0.008)	(0.016)
Volatility	0.900	0.045	0.856	1.057	0.053	1.004
	(0.849)	(0.324)	(0.842)	(0.867)	(0.320)	(0.865)
Style Flow	0.525	0.438***	0.087	0.482	0.411***	0.071
	(0.319)	(0.133)	(0.287)	(0.318)	(0.133)	(0.288)
Observations	3,851	3,851	3,851	3,851	3,851	3,851
R-squared	0.101	0.118	0.067	0.098	0.117	0.064

Table IX
Multinomial Logit for Entry and Exit Decisions

This table summarizes the coefficient estimates of a multinomial logit regression for fund entry and exit decisions. The exit (entry) indicator variable equals one if funds have non-missing (missing) DC assets in the past year and missing (non-missing) DC assets in the current year. The base group consists of all funds in the sample that have non-missing DC assets for two consecutive years. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	Exit	Entry
Performance Rank	-0.703***	0.756***
	(0.213)	(0.199)
Log Size	-0.232***	-0.275***
	(0.043)	(0.043)
Log Age	-0.061	-0.326***
	(0.106)	(0.099)
Expenses	3.083*	1.727
	(1.860)	(1.633)
Turnover	0.096	0.018
	(0.063)	(0.058)
Volatility	2.763	1.043
	(2.782)	(2.900)
Style Flow	-1.461	0.793
	(1.269)	(1.168)
Observations	5,006	5,006

Table X
Flow-Performance Panel Regressions for DC Ratio Terciles

This table summarizes the coefficients of a piecewise linear panel regression of terciles of funds divided by the proportion of DC assets invested in the fund. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t}$ = min($Rank_{f,t}$, 0.2); $Mid_{f,t}$ = min($Rank_{f,t}$ – $Low_{f,t}$, 0.6); and $High_{f,t}$ = ($Rank_{f,t}$ – $Low_{f,t}$ – $Mid_{f,t}$). The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	Low DC Funds	Mid DC Funds	High DC Funds
Low Rank	0.028**	0.023	0.038**
	(0.014)	(0.015)	(0.016)
Mid Rank	0.031***	0.027***	0.022***
	(0.004)	(0.003)	(0.003)
High Rank	0.039**	0.068***	0.061***
	(0.019)	(0.018)	(0.017)
Log Size	-0.002***	-0.001	-0.001**
	(0.000)	(0.000)	(0.000)
Log Age	-0.002***	-0.003***	-0.002
	(0.001)	(0.001)	(0.001)
Expense Ratio	-0.031	-0.011	-0.077***
	(0.020)	(0.019)	(0.017)
Turnover	-0.001	-0.002**	-0.000
	(0.001)	(0.001)	(0.001)
Volatility	-0.050**	-0.023	0.101***
	(0.025)	(0.032)	(0.030)
Style Flow	0.422***	0.451***	0.647***
	(0.141)	(0.138)	(0.113)
Observations	20,974	21,091	21,026
R-squared	0.095	0.083	0.069

Table XI

Flow-Performance Relation for Fund Inflows and Outflows

This table summarizes the coefficients of a piecewise linear panel regression of fund inflows, outflows, and net flows from the funds' N-SAR filings with the SEC. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t}$ = min($Rank_{f,t}$, 0.2); $Mid_{f,t}$ = min($Rank_{f,t} - Low_{f,t}$, 0.6); and $High_{f,t}$ = ($Rank_{f,t} - Low_{f,t} - Mid_{f,t}$). The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	N-SAR Inflow			N-SAR Outflow			N-SAR Net Flow		
	Low DC	Mid DC	High DC	Low DC	Mid DC	High DC	Low DC	Mid DC	High DC
Low Rank	-0.001	-0.047	-0.005	-0.025	-0.062**	-0.037	0.014	0.013	0.032**
	(0.021)	(0.030)	(0.036)	(0.021)	(0.027)	(0.030)	(0.014)	(0.020)	(0.016)
Mid Rank	0.012**	0.021***	0.008*	-0.022***	-0.009**	-0.012***	0.032***	0.026***	0.017***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
High Rank	0.078***	0.020	0.103***	0.051***	-0.001	0.019	0.017	0.025	0.085***
	(0.024)	(0.023)	(0.020)	(0.013)	(0.016)	(0.013)	(0.021)	(0.020)	(0.017)
Log Size	-0.039	0.044	0.037	0.029	0.053*	0.084***	-0.076***	-0.028	-0.073***
	(0.028)	(0.036)	(0.034)	(0.019)	(0.028)	(0.029)	(0.024)	(0.023)	(0.021)
Log Age	-0.004***	-0.003**	-0.001	-0.002**	-0.000	-0.001	-0.002**	-0.003***	-0.000
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Exp. Ratio	-0.004***	-0.003***	-0.003***	-0.000	-0.002***	-0.002***	-0.003***	-0.001***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Turnover	0.001	-0.003**	0.001	0.003*	0.000	0.002	-0.001	-0.003***	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Volatility	0.136**	0.187**	0.362***	0.185***	0.115*	0.253**	-0.061*	0.026	0.064*
	(0.068)	(0.094)	(0.117)	(0.055)	(0.068)	(0.099)	(0.036)	(0.059)	(0.034)
Style Flow	0.242	0.449	0.187	0.092	0.110	-0.294*	0.093	0.216	0.437***
	(0.230)	(0.289)	(0.185)	(0.159)	(0.210)	(0.168)	(0.192)	(0.209)	(0.160)
Observations	13,839	13,863	13,848	13,839	13,863	13,848	13,839	13,863	13,848
R-squared	0.092	0.092	0.101	0.082	0.074	0.098	0.145	0.096	0.092

Table XII
Return Predictability Regressions

This table summarizes the coefficients of a regression of mutual fund flows from DC and non-DC investors and additional control variables on funds' long-term future performance. The table uses six different performance measures. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	Raw Performance	Objective Code-Adjusted Performance	Style-Adjusted Performance	CAPM-Adjusted Performance	FF-Adjusted Performance	Carhart-Adjusted Performance
DC Flow	-0.205	-0.205	-0.098	-0.159	0.121	-0.002
	(0.161)	(0.159)	(0.134)	(0.143)	(0.127)	(0.120)
Non-DC Flow	-1.539***	-1.070**	-0.749**	-1.106***	-0.622**	-0.890***
	(0.450)	(0.435)	(0.347)	(0.398)	(0.284)	(0.274)
Return over Past Year	0.093***	0.094***	0.013	0.138***	0.191***	0.164***
	(0.021)	(0.022)	(0.023)	(0.019)	(0.019)	(0.018)
Log Size	-0.482***	-0.440***	-0.201**	-0.487***	-0.066	-0.137*
	(0.118)	(0.115)	(0.096)	(0.108)	(0.077)	(0.074)
Log Age	-0.351	-0.183	-0.064	-0.250	0.142	0.051
	(0.289)	(0.287)	(0.226)	(0.252)	(0.194)	(0.181)
Expense Ratio	0.043	-0.202	-1.029***	-0.340	-0.803***	-0.624**
	(0.425)	(0.419)	(0.321)	(0.396)	(0.252)	(0.247)
Turnover	-0.386	-0.544**	-0.623***	-0.291	-0.533***	-0.492***
	(0.236)	(0.232)	(0.208)	(0.210)	(0.163)	(0.149)
DC Ratio	1.110	0.658	0.307	0.231	-0.160	0.012
	(0.821)	(0.785)	(0.623)	(0.769)	(0.511)	(0.513)
Observations	4,116	4,075	3,999	4,009	4,009	4,009
R-squared	0.020	0.018	0.008	0.034	0.078	0.066
p-value for *F*-Test DCFlow=NonDC Flow	0.007***	0.067*	0.088*	0.033**	0.028**	0.006***

Table A-I
Fama-MacBeth Regressions of DC and non-DC Asset Flows

This table summarizes the coefficients of piecewise linear regressions of DC and non-DC asset flows on fund variables, where we aggregate across years using the Fama-MacBeth (1973) approach. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t}$ = min($Rank_{f,t}$, 0.2); $Mid_{f,t}$ = min($Rank_{f,t}$ – $Low_{f,t}$, 0.6); and $High_{f,t}$ = ($Rank_{f,t}$ – $Low_{f,t}$ – $Mid_{f,t}$). The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	DC Flow	Non-DC Flow	Difference
Low Rank	1.2352***	0.3729**	0.8623**
	(0.3130)	(0.1616)	(0.3075)
Mid Rank	0.3592***	0.3497***	0.0095
	(0.0984)	(0.0690)	(0.0817)
High Rank	1.8117***	0.7971***	1.0146**
	(0.4184)	(0.2447)	(0.3542)
Log DC Size	-0.1322***	0.0145**	-0.1467***
	(0.0175)	(0.0066)	(0.0196)
Log Non-DC Size	0.0606***	-0.0492***	0.1099***
	(0.0176)	(0.0104)	(0.0217)
Log Age	-0.0354	-0.0030	-0.0324
	(0.0333)	(0.0109)	(0.0330)
Expense Ratio	-0.2406	0.0465	-0.2871
	(0.3897)	(0.2163)	(0.4708)
Turnover	-0.0226	-0.0127	-0.0099
	(0.0284)	(0.0171)	(0.0254)
Volatility	-0.0741	-1.5678	1.4937
	(3.0547)	(0.9866)	(3.0012)
Style Flow	0.0034	0.2810	-0.2776
	(0.5630)	(0.1713)	(0.5938)
Number of Dates	12	12	12

Table A-II
Piecewise Linear Panel Regression with Different Cut-Off Levels for Performance

This table summarizes the coefficients of a piecewise linear panel regression of DC and non-DC asset flows on fund variables. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t} = \min(Rank_{f,t}, 0.1 \text{ or } 0.3)$; $Mid_{f,t} = \min(Rank_{f,t} - Low_{f,t}, 0.8 \text{ or } 0.4)$; and $High_{f,t} = (Rank_{f,t} - Low_{f,t} - Mid_{f,t})$. The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	10/80/10 Classification			30/40/30 Classification		
	DC Flow	Non-DC Flow	Difference	DC Flow	Non-DC Flow	Difference
Low Rank	2.032**	0.062	1.969**	0.773***	0.396***	0.377*
	(0.937)	(0.348)	(0.880)	(0.222)	(0.085)	(0.227)
Mid Rank	0.391***	0.326***	0.065	0.191	0.221***	-0.030
	(0.066)	(0.029)	(0.067)	(0.128)	(0.055)	(0.135)
High Rank	2.931**	0.409	2.522**	1.069***	0.515***	0.554*
	(1.228)	(0.475)	(1.173)	(0.293)	(0.106)	(0.284)
Log DC Size	-0.125***	0.017***	-0.142***	-0.126***	0.017***	-0.143***
	(0.016)	(0.006)	(0.016)	(0.016)	(0.006)	(0.016)
Log Non-DC Size	0.058***	-0.053***	0.111***	0.059***	-0.053***	0.111***
	(0.016)	(0.008)	(0.017)	(0.016)	(0.008)	(0.017)
Log Age	-0.044*	-0.003	-0.041*	-0.044*	-0.002	-0.041*
	(0.024)	(0.010)	(0.022)	(0.024)	(0.010)	(0.022)
Expense Ratio	-0.455	-0.220	-0.235	-0.443	-0.230	-0.213
	(0.552)	(0.222)	(0.505)	(0.563)	(0.225)	(0.516)
Turnover	-0.021	-0.014	-0.008	-0.022	-0.014	-0.008
	(0.020)	(0.009)	(0.017)	(0.019)	(0.009)	(0.016)
Volatility	1.106	0.028	1.078	1.037	0.050	0.987
	(0.858)	(0.325)	(0.852)	(0.856)	(0.318)	(0.853)
Style Flow	0.487	0.415***	0.072	0.498	0.415***	0.083
	(0.318)	(0.133)	(0.288)	(0.318)	(0.133)	(0.288)
Observations	3,851	3,851	3,851	3,851	3,851	3,851
R-squared	0.095	0.111	0.063	0.095	0.112	0.062

Table A-III

Piecewise Linear Panel Regressions of DC and Non-DC Flows Using Percentile Flows

This table summarizes the coefficients of a piecewise linear panel regression of DC and non-DC asset percentile flows on fund variables. The dependent variables are the percentiles of the DC and non-DC flows in each year and the percentile of the difference between the DC and non-DC flows. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t} = \min(Rank_{f,t}, 0.2)$; $Mid_{f,t} = \min(Rank_{f,t} - Low_{f,t}, 0.6)$; and $High_{f,t} = (Rank_{f,t} - Low_{f,t} - Mid_{f,t})$. The other variables are characteristics of the fund. The standard errors of the coefficients are reported in parentheses and adjusted for clustering at the fund level. The regressions also include time-fixed effects. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	Percentile of DC Flows	Percentile of Non-DC Flow	Percentile of Difference Between DC and Non-DC Flows
Low Rank	0.499***	0.307***	0.304***
	(0.123)	(0.114)	(0.117)
Mid Rank	0.173***	0.344***	-0.017
	(0.029)	(0.028)	(0.028)
High Rank	0.455***	0.229**	0.355***
	(0.126)	(0.113)	(0.124)
Log DC Size	-0.021***	0.005	-0.025***
	(0.004)	(0.004)	(0.003)
Log Non-DC Size	0.020***	-0.015***	0.030***
	(0.004)	(0.005)	(0.004)
Log Age	-0.034***	-0.009	-0.026***
	(0.007)	(0.008)	(0.007)
Expense Ratio	-0.364**	-0.665***	0.101
	(0.157)	(0.173)	(0.140)
Turnover	-0.007	-0.025***	0.010**
	(0.005)	(0.005)	(0.005)
Volatility	0.801***	-0.065	0.695***
	(0.302)	(0.256)	(0.259)
Style Flow	0.326***	0.355***	0.079
	(0.091)	(0.095)	(0.080)
Observations	3,851	3,851	3,851
R-squared	0.097	0.152	0.040

Table A-IV

Piecewise Linear Fama-MacBeth Regression by DC Ratio Terciles

This table summarizes the coefficients of a piecewise linear regression of terciles of funds divided by the proportion of DC assets invested in the fund, where we aggregate across years using the Fama-MacBeth (1973) approach. Low, Mid and High Rank represent the funds' ranked return performance where $Low_{f,t} = \min(Rank_{f,t}, 0.2)$; $Mid_{f,t} = \min(Rank_{f,t} - Low_{f,t}, 0.6)$; and $High_{f,t} = (Rank_{f,t} - Low_{f,t} - Mid_{f,t})$. The other variables are characteristics of the fund. The Newey-West standard errors of the coefficients using 12 lags are reported in parentheses. *, **, and *** denote estimates that are statistically different from zero at the 10, 5, and 1 percent significance levels.

	Low DC Funds	Mid DC Funds	High DC Funds	High – Low
Low Rank	0.0214*	0.0123	0.0516***	0.0302*
	(0.0125)	(0.015)	(0.0138)	(0.0158)
Mid Rank	0.0354***	0.0343***	0.0240***	-0.0114***
	(0.0036)	(0.005)	(0.0032)	(0.0032)
High Rank	0.0375**	0.0777***	0.0812***	0.0437**
	(0.0157)	(0.0163)	(0.0212)	(0.0215)
Log Size	-0.0021***	-0.0008**	-0.0008***	0.0013***
	(0.0004)	(0.0004)	(0.0003)	(0.0005)
Log Age	-0.0031***	-0.0026***	-0.0017**	0.0014
	(0.0007)	(0.0007)	(0.0008)	(0.0009)
Expense Ratio	-0.0221	0.0155	-0.0638***	-0.0417**
	(0.0159)	(0.0194)	(0.0137)	(0.0171)
Turnover	-0.0007	-0.0021**	0.0002	0.0009
	(0.0008)	(0.0009)	(0.0012)	(0.0012)
Volatility	-0.0951*	-0.2078***	0.0072	0.1023*
	(0.0528)	(0.0691)	(0.0645)	(0.0584)
Style Flow	0.3163**	0.3146***	0.6493***	0.3330**
	(0.1396)	(0.0928)	(0.099)	(0.1625)
Number of Dates	156	156	156	156