NBER WORKING PAPER SERIES

HETEROGENEITY IN TARGET-DATE FUNDS:
OPTIMAL RISK TAKING OR RISK MATCHING?

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Working Paper 17886
http://www.nber.org/papers/w17886

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2012

The authors thank Ryan Alfred and Brooks Herman of BrightScope for providing them with retirement plan-level data, and Lauren Beaudette and Bianca Werner for excellent research assistance. The authors also thank Jeffrey Brown, Bjarne Astrup Jensen (discussant), Mark Warshawsky (discus- sant), and seminar participants at the 13th Annual Retirement Research Consortium Conference, Boston College, and the 2012 European Finance Association meetings. Corresponding author: Jonathan Reuter, Carroll School of Management, Boston College, 140 Commonwealth Avenue, Chestnut Hill, Massachusetts, 02467; Tel: (617) 552-2863; Fax: (617) 552-0431; email: reuterj@bc.edu. The research was supported by a grant from the U.S. Social Security Administration (SSA) as part of the Retirement Research Consortium (RRC). The findings and conclusions expressed are solely those of the authors and do not represent the views of SSA, any agency of the federal government, Boston College, or the National Bureau of Economic Research. An earlier version of this paper was titled "Heterogeneity in Target-Date Funds and the Pension Protection Act of 2006."

Heterogeneity in Target-Date Funds: Optimal Risk Taking or Risk Matching?
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NBER Working Paper No. 17886
March 2012, Revised June 2013
JEL No. G11,G18,G23

ABSTRACT

The recent growth in the market for target-date funds (TDFs) allows us to study how mutual fund families structure new investment products. Given the widespread, legislation-induced use of TDFs as default investments in defined contribution retirement plans, this market holds special policy significance. We document pronounced heterogeneity in TDF returns between 1994 and 2009. We find strong evidence that return heterogeneity reflects optimal risk taking by families new to the market, with few assets to lose. We find little evidence that 401(k) plan sponsors match the risk profile of the TDFs in their plans to the risks of their companies.

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1 Introduction

A common implication of normative optimal portfolio models is that, as investors age, it is optimal for them to shift their financial wealth away from stocks and toward bonds.[1] This normative implication has found its way into the design of investment products: target-date mutual funds (TDFs). Wells Fargo introduced the first TDFs in 1994. According to Seth Harris, Deputy Secretary of the Department of Labor (DOL), TDFs "were designed to be simple, long-term investment vehicles for individuals with a specific retirement date in mind."[2] For example, investors who plan to retire in 2030 are encouraged to invest all of their 401(k) assets in the Wells Fargo LifePath 2030 fund. The innovation, relative to traditional balanced mutual funds, is that TDFs relieve investors of the need to make asset allocation decisions: when the target date is far away, the TDF invests primarily in risky assets, such as domestic and foreign equity and, as the number of years to the target date declines, the TDF automatically reduces its exposure to risk.[3] The promise of a simple, long-term retirement investment prompted the DOL, through the Pension Protection Act of 2006 (PPA), to encourage firms to use TDFs as default investment vehicles in employer-sponsored defined contribution (DC) retirement plans.

More recently, however, policy makers have begun to worry about risk taking by TDFs. In 2009, Herb Kohl, chairman of the Senate Special Committee on Aging, wrote: "While well-constructed target date funds have great potential for improving retirement income security, it is currently unclear whether investment firms are prudently designing these funds in the best interest

[1] Merton (1971) shows that when an investor faces time-series variation in the first and second conditional moments of asset returns, her optimal portfolio is composed of both a myopic component and an intertemporal component, the "hedging" demand. Balduzzi and Lynch (1999) and Lynch (2001) argue that mean reversion in equity prices causes the hedging demand for equity to *decrease* as the investment horizon decreases. Jagannathan and Kocherlachota (1996) and Cocco et al. (2005) argue that older workers should allocate more of their financial wealth to bonds, because they can expect to receive shorter streams of bond-like income from their human capital. Bodie et al. (1992) come to the same conclusion by arguing that older workers have fewer opportunities to adjust their labor supply in response to realized returns on their assets.

[2] DOL and SEC Joint Public Hearing on TDFs and Other Similar Investment Options: June 18, 2009.

[3] The formula used to determine how a TDF's asset allocation changes as the number of years to the target date declines is known as the "glide path." TDFs are also referred to as lifecycle funds.

of the plan sponsors and their participants. In fact, an Aging Committee investigation conducted in early 2009 found significant differences in the asset allocations and equity holdings within these funds, raising questions about whether plan sponsors and participants understand the underlying assumptions and risk associated with these products" (Special Committee on Aging (2009)).

In summary, there are at least two reasons why it is important to study the market for TDFs. First, this is a relatively new market whose size was suddenly—and exogenously—increased by the PPA of 2006. Hence, the TDF market is a "laboratory" in which we can study how mutual fund families structure new investment products. Second, TDFs are quickly becoming the investment option of choice in DC retirement plans. Hence, given the increasing role of defined contribution plans in the funding of retirement, the investment behavior of TDFs has special policy significance.

In this paper, we study the evolution of the market for TDFs between 1994 and 2009. Our first objective is to measure heterogeneity in the performance and investment decisions of TDFs. Since DC retirement plans typically offer the TDFs of a single mutual fund family, we are interested in determining whether TDFs with the same target date are more like S&P 500 index funds, which offer the same risk exposure across mutual fund families, or more like traditional balanced funds, which differ in terms of asset allocation, market timing, and security selection. We find that TDFs are more like balanced funds. The cross-sectional dispersion in TDF returns is substantial—especially when we focus on the years immediately after the PPA is passed. For example, in 2009, there are 75 TDFs with target dates of 2015 or 2020. The average annual return is 25.1%, the cross-sectional standard deviation is 4.4%, and the range (the difference between the maximum and minimum return) is 23.5%. Importantly, a similar pattern holds for the *idiosyncratic* component of returns, "alpha." In 2009, the cross-sectional standard deviation of the 2015–2020 TDF alphas is 3.3% and the range is 16.2%. The remaining dispersion arises from differences in systematic risk. For example, within the sample of 2015–2020 TDFs in 2009, the average allocation to equity is 63.5%, with a standard deviation of 13.5%, and a range of 69.8%. In summary, the substantial heterogeneity in TDF returns reflects heterogeneity in both idiosyncratic and systematic risk. If regulators had assumed that TDFs with the same target date would provide investors with the same exposure to risk, they were mistaken.

The second objective of our study is to investigate the economic determinants of heterogeneity in TDF returns. Our main hypothesis is that this heterogeneity reflects optimal risk-taking behavior by TDFs. For a mutual fund family entering the TDF market, the risk-taking incentives seem obvious: underperforming relative to existing funds costs little (other than reputation), since the TDF has few assets to lose, whereas outperforming is likely to attract flows. Hence, pronounced heterogeneity in TDF returns is exactly what we would expect in this relatively new segment of the mutual fund industry. To test this "risk-taking" hypothesis, we study the effect of the Pension Protection Act of 2006 on the market for TDFs. By creating an incentive for firms to use TDFs as default investments, the PPA increased demand for TDFs, thereby increasing the incentive for mutual fund families to introduce TDFs. Between 2006 and 2009, assets under management in TDFs more than doubled, increasing from \$110.5 billion to \$245.4 billion, and the number of mutual fund families offering TDFs jumped from 27 to 44. In other words, the passage of the PPA provides us with a "natural experiment" that can be used to test whether heterogeneity in TDF returns reflects the risk-taking incentives of entrants.

We find robust evidence that the increased volatility in TDF returns following the passage of the PPA reflects risk taking by entrants. When we relate the cross-sectional dispersion of monthly returns to fund characteristics, we find that mutual fund families that enter the market for TDFs after 2006 offer funds whose returns differ markedly from their peers. The monthly returns on these new funds differ from the average monthly return of other funds with the same target date by 77 to 79 basis points—approximately, 9% annually. Interestingly, alphas for these new TDFs differ from the average alpha by roughly the same amount, between 74 and 79 basis points. Hence, the higher heterogeneity of the returns offered by new entrants is mainly due to heterogeneity in idiosyncratic returns.[4]

Next, we show that the decision of new entrants in the TDF market to load on idiosyncratic risk is consistent with the way that performance is rewarded in this segment of the market. Namely, we show that flows into TDFs respond significantly to idiosyncratic returns, rather than to total returns. We also use the estimated flow-performance relation to calibrate a model of risk taking by mutual fund managers whose utility is defined over the first two moments of flows, and who control the volatility of idiosyncratic fund returns. Since a fund cannot lose more than the existing funds under management, new funds, with no assets to lose, face a stronger incentive than established funds to take on idiosyncratic risk. Indeed, for a realistic choice of parameters, we find that it is only optimal for new and small funds to load on idiosyncratic risk.[5]

Finally, we test the "risk-matching" hypothesis that TDFs offer different levels of risk to cater to the heterogeneous preferences of different investor clienteles. We exploit newly-available data from BrightScope on the investment menus of several thousand DC retirement plans in 2010. Note that this snapshot of the DC retirement plan universe takes place after the PPA of 2006 and, hence, at a time when plan sponsors have the largest set of TDFs from which to choose. For firms with publicly-traded equity, we regress the systematic (idiosyncratic) risk of the 2020 TDF offered in each plan on the systematic (idiosyncratic) risk of the firm's equity. To expand our sample, we also regress the risk of the 2020 TDF offered in each plan on the median risk of firms within the same industry. Regardless of whether we focus on systematic or idiosyncratic risk, we find little evidence of risk matching. Riskier firms are no more or less likely to choose riskier TDFs than safer

[4]New funds are also more aggressive in their asset allocation choices, although these effects are quantitatively modest. They allocate 5.2% more of their portfolio to equity, and their estimated CAPM betas are 0.034 higher.

[5]The risk-taking incentives faced by a new TDF are akin to the incentives faced by new funds being "incubated" by mutual fund families; see Evans (2010).

firms.

In summary, we document pronounced heterogeneity in investor exposure to both systematic and idiosyncratic risk across TDFs with the same target date. This heterogeneity increases with the passage of the PPA in 2006, which draws new families into the TDF market. We show that the decision of these families to load on idiosyncratic risk is consistent with optimal risk-taking behavior. On the other hand, we find no evidence that the heterogeneity in systematic or idiosyncratic risk taking is driven by matching between TDF and sponsoring firm's risk characteristics. Our findings are important for two main reasons: First, from a normative standpoint, more transparency regarding TDF glide paths and systematic risk is not enough, since entrants have differentiated their products mainly in terms of idiosyncratic returns.[6] Second, from a positive standpoint, we provide an explanation for an apparently puzzling degree of heterogeneity in TDF returns.

The remainder of the paper is organized as follows: Section 2 provides institutional background on the market for TDFs and a brief review of the related literature. Section 3 describes the mutual fund data used in the study. Section 4 documents cross-sectional differences in annual total and idiosyncratic returns, CAPM betas, and asset allocation. Section 5 explores whether the heterogeneity reflects optimal risk taking. Section 6 describes the retirement plan-level data and explores empirically the alternative explanation of risk matching. Section 7 concludes.

2 Institutional background and review of the literature

Although target-date funds (TDFs) were virtually nonexistent 10 years ago, the Pension Protection Act of 2006 (PPA) created an incentive for firms to make TDFs the default investment option within

[6] Our findings are also relevant to the issue of *obfuscation* in retail financial markets as discussed by Carlin (2009) and Carlin and Manso (2011). To the extent that investors assume that TDFs with the same target date are close substitutes, we can view the deviation of a TDF's return from the average return of TDFs with the same target date as a measure of obfuscation of the properties of a TDF as a financial product. Under this interpretation, we show that increased competition leads to more obfuscation overall, and, in particular, on the part of the entrants.

401(k) retirement plans. The regulatory goal was to direct investors who might otherwise have been defaulted (and stayed) into money market funds into age-appropriate, long-term investment vehicles.[7] To accomplish this goal, the PPA relieves plan sponsors of liability for market losses when they default employees into a Qualified Default Investment Alternative (QDIA). The set of QDIAs is limited to TDFs, balanced funds, and managed accounts. While TDFs were perceived to be an important innovation in the market for retirement products, commentators have recently expressed concerns about the lack of transparency regarding risk.[8]

The Investment Company Institute reports that the share of 401(k) plans offering target date funds increased from 57% in 2006 to 77% in 2009. Similarly, the share of 401(k) plan participants offered target date funds increased from 62% to 71%. At year-end 2009, 33% of 401(k) participants held at least some plan assets in TDFs, up from 19% at year-end 2006. More importantly, while TDFs account for 4% of total retirement assets in 2009, the Financial Research Corporation forecasts that they will account for more than 10% of the market by 2015, and that their market share will continue to rise.[9] It is conceivable that employees just entering the labor force will finance their retirement through a combination of TDF returns and Social Security benefits. Because the PPA effectively directs investors toward TDFs, we believe it is important to study the impact of this legislation on these emerging investment vehicles.

Interestingly, the two current leaders in the market for TDFs take very different approaches to the design of their products. Vanguard's approach is to allocate investments across five low cost index funds. Fidelity's approach, on the other hand, is to allocate investments across as many as 27 actively managed mutual funds. Whether one approach is better for investors than the other

[7]The tendency of investors to stick to their default investment allocation (i.e., inertia), has been discussed by Benartzi and Thaler (2001), Madrian and Shea (2001) and Agnew et al. (2003), among others.

[8]The Appendix, Sections A.1 and A.2, includes a detailed description of the PPA and a selection of quotes on the pros and cons of TDFs.

[9]This forecast comes from the Financial Research Corporation's study "Rethinking Lifecycle Funds," released on May 20, 2010. According to our sample of investment menus from BrightScope, 9.7% of all 401(k) and 403(b) retirement plan assets in 2010 were invested in TDFs.

is an open question, but the two approaches highlight a significant source of heterogeneity in how TDFs are constructed.

This is the first paper to focus on the heterogeneity of TDFs and to study the impact of the Pension Protection Act of 2006 on the characteristics of TDFs. The existing literature mainly compares TDFs to other investment vehicles and studies the factors driving individual demand for TDFs.[10] The paper most closely related to our own is Sandhya (2011), who compares TDFs to balanced funds offered within the same mutual fund family.[11] While Sandhya (2011) focuses on average differences in fund expenses and returns, our paper focuses on variation in TDF investment performance and decisions, with particular interest in variation arising from the PPA. In addition, as we discuss below, we take a different approach to estimating flow-performance sensitivity. Finally, our sample includes all TDFs, not just those belonging to families that also offer balanced funds.

3 Data

We obtain data on mutual fund names, characteristics, fees, and monthly returns from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. CRSP does not distinguish TDFs from other types of mutual funds, but they are easily identified by the target retirement year in the fund name (e.g., AllianceBernstein 2030 Retirement Strategy). Through much of the paper, our unit of observation is family i's mutual fund with target date j in month t. For example, T. Rowe Price offers ten distinct TDFs in December 2009, with target dates of 2005, 2010, ..., 2045, and 2050. As with

[10] Yamaguchi et al. (2007), Park and VanDerhei (2008), Park (2009), and Mitchell et al. (2009) study investor demand for the particular TDFs introduced into their samples of DC retirement plans. Shiller (2008), Gomes et al. (2008), and Viceira (2009) use simulations and calibrated lifecycle models to compare the properties of representative TDFs to those of other investment vehicles. Pagliaro and Utkus (2010) and Mitchell and Utkus (2012) study the role of a 401(k) plan's architecture on TDF demand. Ameriks et al. (2011), Morrin et al. (2012), and Agnew et al. (2012) use survey data to identify the factors behind TDF investment.

[11] Also relevant to our study is Pang and Warshawsky (2009), who study the effect of heterogeneity in glide paths on the distribution of terminal wealth. Note, though, that their simulation analysis assumes that different TDFs invest in the same three assets. Hence, their study abstracts from other sources of heterogeneity in TDF returns, such as heterogeneity in betas and idiosyncratic risk.

other types of mutual funds, many TDFs offer multiple share classes. To calculate a fund's size, we sum the assets under management at the beginning of month t across all of its share classes. To calculate a fund's expense ratio, we weight each share class's expense ratio by its assets under management at the beginning of the month. To calculate a fund's age, we use the number of months since its oldest share class was introduced. To identify families that enter the market after December 31, 2006, we use the year when each mutual fund family offered its first TDF. Because the expense data that CRSP reports for TDFs do not reflect the expenses charged by the underlying mutual fund investments, they offer an incomplete measure of total investor expenses. Since we expect plan sponsors to consider these fees when evaluating TDFs, for the 2004–2009 period, we hand collected data on the asset-weighted expense ratios charged by the mutual funds that are held by each TDF.[12] Because CRSP lacks expense ratio data for some TDFs, we also hand collected data on the management fees charged by TDFs.

Table 1 presents summary statistics on the evolution of the TDF market over the 1994–2009 period. Wells Fargo introduced the first TDFs in 1994. Between 1994 and 2009, the number of TDFs grew from 5 to 298 and the number of mutual fund families offering TDFs grew from one to 44, with total assets under management going from \$278 million to \$245 billion, almost a one-thousand-fold increase. In particular, 17 families entered the market in 2007, 2008, and 2009, allowing us to study differences between older and newer TDFs, and between fund families that are older and newer to the TDF market. While Wells Fargo was the market leader until 1997, Fidelity took the lead in 1998. Fidelity's dominant position has been eroded, though, dropping from a maximum market share of 88.1% in 2002, to 39.6% in 2009. In 2009, the number of families offering funds with a particular target date ranges from two families, for the 2000 target date, to 38 families each, for the 2020, 2030, and 2040 target dates.

[12] On July 31, 2006, the SEC began requiring fund-of-funds to explicitly state "Acquired Fund Fees and Expenses" in the table describing fund fees. We are missing data on the fees charged by the underlying funds for 13.5% of the fund-year observations between 2004-2006, but only for 1.1% of the fund-year observations between 2007-2009.

We also use the CRSP mutual fund database to construct a sample of traditional (non-TDF) balanced funds and a sample of S&P 500 index funds. To obtain our sample of traditional balanced funds, we dropped all of the funds that we identify as being TDFs, and then restrict the sample to funds where the Lipper objective (as reported in CRSP) is "Balanced Fund." To obtain our sample of S&P 500 index funds, we first require that the fund name include "S&P" or "500." Then, we manually drop funds that are not traditional S&P 500 index funds (e.g., the Direxion Funds S&P 500 Bear 2.5x Fund).

4 Empirical analysis

4.1 Characterizing the cross-sectional heterogeneity in TDFs

We start by characterizing the cross-sectional heterogeneity in TDFs. Namely, for each year and target date, we compute the cross-sectional dispersion in total and idiosyncratic annual returns, reported allocations to equity, and CAPM betas.

4.1.1 Cross-sectional dispersion of TDF returns

Table 2 documents the substantial cross-sectional dispersion in realized annual returns of TDFs during our sample period.[13] In order to increase the size of the cross-section for each year, we combine TDFs with adjacent target dates (e.g., 2015 and 2020). The table reveals an upward trend in the cross-sectional dispersion of returns. For example, for the 2015–2020 funds, the cross-sectional standard deviation increases from 0.5% in 2000 to 4.4% in 2009. The increase was especially marked between 2007 and 2008, jumping from 2.0% to 5.2%. The range experienced a similar pattern. It increased from 1.1% to 23.5% between 2000 and 2009, and from 7.2% to 27.3% between 2007 and

[13] To facilitate comparisons between Tables 2, 3, and 4, we calculate statistics for a constant sample of funds. Specifically, to appear in Table 2, 3, or 4, we must observe the TDFs annual return, its allocation to equity, and the 12 lagged monthly returns required to estimate its CAPM beta.

2008. As mentioned in the Introduction, this is the main stylized fact of our study: the cross-sectional variation in returns of TDFs with the same target date is substantial, and it increases in the years immediately after the passage of the PPA.

Note that the large cross-sectional dispersion of returns does not simply reflect large (in absolute value) average TDF returns.[14] Consider 2003, when 2015–2020 funds delivered an average return of 21.7%, the third largest (in absolute value) average return of the 2000–2009 sample; the cross-sectional standard deviation was only 2.8%, and the range was 5.2%. Similarly, 2025–2030 funds delivered an average return of 25.2%, but the cross-sectional standard deviation and range were only 2.8% and 5.0%, respectively.

4.1.2 Cross-sectional dispersion of TDF alphas

Table 3 documents the cross-sectional dispersion in the idiosyncratic component of annual TDF returns. The fund's alpha is the sum of the intercept and residual from a regression of a TDF's excess return on the excess returns on various indices: we estimate the index model with data up to month t and then we construct the alpha going one month out of sample.[15]

Overall, the cross-sectional dispersion in alphas is of the same order of magnitude as that in total returns. For some of the funds, as in the case of total returns, there is an upward trend in the cross-sectional dispersion of alphas. For example, for the 2035–2040 funds, the cross-sectional standard deviation increases from 0.3% in 2000 to 2.7% in 2009. The range experienced a similar pattern, increasing from 0.4% to 11.7% between 2000 and 2009. In other words, a significant fraction of the dispersion in total returns appears to be driven by dispersion in idiosyncratic risk

[14] A direct relation between average returns and the cross-sectional dispersion of returns would arise if what differentiates TDFs with the same target date is simply the asset allocation decision.

[15] We consider two specifications of the index model: In the first specification, the indices are the MSCI World Index and the Barclays Global Aggregate Bond Index. In the second specification, the indices are the S&P 500 Index and the Barclays Aggregate Bond Index. Both specification are estimated using monthly returns over the prior 12 months. Returns are in excess of the one-month T-bill rate posted on Ken French's website. The results reported in Table 3 are for alphas calculated according to the second specification—results for alphas calculated according to the first specification are similar and available from the authors upon request.

rather than systematic risk.

4.1.3 Cross-sectional dispersion in the allocation to equity

Table 4 reports summary statistics for the cross-sectional distribution of the reported fraction of the portfolio allocated to equity. Three patterns are worth noting. First, although we are following cross-sections of TDFs that are getting closer to their target date, there is only a slight downward trend in the average allocation to equity. For example, for the 2015–2020 target date, the average allocation to equity goes from 67.2% in 2000, to 63.5% in 2009, with upward and downward fluctuations over the sample period. Second, the cross-sectional dispersion in equity allocations is substantial. In 2009, for example, the cross-sectional standard deviation was 12.1%, 13.5%, and 12.4%, for the 2005–2010, 2015–2020, and 2025–2030 target dates, respectively. Third, there is no obvious trend in the cross-sectional standard deviation of equity allocations. This suggests that the increasing cross-sectional dispersion of returns documented in Table 2 is driven by increasingly diverse targeted asset allocation choices (e.g., value versus growth, and large- versus small-cap equities) and individual security selections, rather than by increasing differences in the broad asset allocation choice—the stock versus cash and bond decision. Hence, consistent with the evidence above that a significant portion of the heterogeneity in returns is due to idiosyncratic risk, the broad stock versus bond allocation of a TDF does not appear to be a sufficient statistic for the risk of the investment.

4.1.4 Cross-sectional dispersion of CAPM betas

We also measure differences in investment behavior using the CAPM beta, which is a measure of a TDF's exposure to equity market risk. We estimate the one-factor beta in December of each year using monthly fund-level returns (in excess of the one-month T-bill rate from Ken French's website) and the monthly value-weighted return on all NYSE, AMEX, and NASDAQ stocks (in excess of the one-month T-bill rate).

Table 5 presents the results of the analysis. Two patterns are noteworthy. First, for all five target dates, there is an upward trend in the average market beta. For the 2005–2010 target date TDFs, the average beta goes from 0.46 in 2000 to 0.56 in 2009; for the 2015–2020 target date TDFs, the average beta goes from 0.62 in 2000 to 0.69 in 2009; for the 2025–2030 TDFs, the average beta goes from 0.73 to 0.83; for the 2035–2040 TDFs, the average beta goes from 0.81 to 0.91; and for the 2045–2050 target date TDFs, the average beta goes from 0.92 in 2006 (the first year for which we can estimate beta) to 0.96 in 2009. These increases are noteworthy because, over time, established TDFs should be decreasing their exposure to equity. Hence, the overall upward trend is likely to reflect the entry of new funds that offer higher exposure to equities.

Second, we observe some evidence of an increase in the cross-sectional dispersion of betas. For the 2035–2040 target date, for example, the cross-sectional standard deviation of betas goes from 0 in 2000 to 0.08 in 2009. More significantly, the range of estimated betas goes from 0 to 0.38. The patterns in Table 5 suggest that entry by TDFs is both driving up the average beta, and increasing the dispersion of betas among funds with the same target date in the same year.

4.2 Decomposition: total dispersion, market dispersion, and fund dispersion

In order to quantify the incidence of the cross-sectional dispersion on the overall dispersion of returns, for each target date we compute two measures. First, we compute the "Total Dispersion," the total standard deviation of returns for TDFs with target date j:

$$\hat{\sigma}_{Tj} = \sqrt{\frac{1}{\sum_{t=1}^{T_j} N_{jt}} \sum_{t=1}^{T_j} \sum_{i=1}^{N_{jt}} (r_{ijt} - \bar{\bar{r}}_j)^2}, \tag{1}$$

where r_{ijt} is a TDF's yearly return and $\overline{\overline{r}}_j$ is the average return across all TDFs with target date j and all years. This is the variability of TDF returns around the overall average return for that target date, and measures the total risk faced by investors who invest in TDFs with target date j: in a balanced panel, this variability can be thought of as the risk faced by an investor who is assigned randomly to a TDF at the beginning of the sample, and who stays in that TDF for the remainder of the sample. Second, we compute the "Market Dispersion," the standard deviation over time of the return on an equally-weighted portfolio of TDFs with target date j:

$$\hat{\sigma}_{Mj} = \sqrt{\frac{1}{\sum_{t=1}^{T_j} N_{jt}} \sum_{t=1}^{T_j} N_{jt}(\overline{r}_{jt} - \overline{\overline{r}}_{jt})^2}, \tag{2}$$

where $\overline{r}_{jt}$ is the year-t return on an equally-weighted portfolio of TDFs with target date j. Third, we compute the "Fund Dispersion," the standard deviation *within* target date j:

$$\sqrt{\hat{\sigma}^2_{Tj} - \hat{\sigma}^2_{Mj}} = \sqrt{\frac{1}{\sum_{t=1}^{T_j} N_{jt}} \sum_{t=1}^{T_j} \sum_{i=1}^{N_{jt}} (r_{ijt} - \overline{r}_j)^2}. \tag{3}$$

In a balanced panel, this is the extra risk that an investor bears because of having chosen the i-th TDF with target date j, as opposed to an equally-weighted portfolio of TDFs with target date j. This general approach can also used to decompose the dispersion of equity allocations and CAPM betas. Results are presented in Table 6.

We first focus on the variability of TDF returns. Looking across the five samples of TDFs, we see that much of the risk associated with investing in TDFs comes from Market Dispersion: Total Dispersion ranges between 16.6% and 29.7%, and Market Dispersion ranges between 16.1% and 29.5%. However, there remains significant Fund Dispersion. Fund Dispersion ranges from 2.7% for 2035–2040 funds to 4.0% for 2005–2010 funds, showing the surprising fact that there is more Fund Dispersion in TDF returns when target dates are near than when they are far. By way of comparison, we perform a similar variance decomposition on the annual returns of traditional balanced funds and S&P 500 index funds. For balanced funds, which arguably have more discretion over asset allocation, market timing, and security selection, Total Dispersion is 14.7% and Fund Dispersion is 5.1%. In contrast, for S&P 500 index funds, Total Dispersion is 21.5% and Fund Dispersion is 0.4%. Hence, TDFs in all five samples expose investors to greater Total Dispersion than traditional balanced funds. Perhaps more surprisingly, TDFs in three out five samples expose investors to greater Total Dispersion than S&P 500 index funds, which invest close to 100% in U.S. equity. It is worth noting that the Fund Dispersion in TDFs falls between that of differentiated products (traditional balanced funds) and commodities (S&P 500 index funds). When we switch our focus from total returns to idiosyncratic returns (measured using the annualized 2-factor alphas from Table 3), we find that Market and Fund dispersion are roughly equal and that both Total Dispersion and Fund Dispersion fall between those of Balanced Funds and S&P 500 Index funds. It is worth noting that Fund Dispersion in alphas is similar to Fund Dispersion in total returns, especially for the TDFs with the most distant target dates.

Next, we turn to the equity allocation. Unlike returns, the variance decomposition in Table 6 suggests that most of the variation in the fraction allocated to equity is driven by across-fund differences in asset allocation. In this case, Total Dispersion ranges between 8.1% and 14.5%, and Fund Dispersion ranges between 8.4% and 13.9%. Market Dispersion, on the other hand, only ranges between 1.7% and 4.2%. Hence, the breakdown of the overall dispersion in TDF equity allocations is comparable to that for Balanced Funds: 11.6%, 1.5%, and 11.5%, for Total Dispersion, Market Dispersion, and Fund Dispersion, respectively.

Finally, we turn to the CAPM betas. As with equity allocations, most of the dispersion in the equity exposure is driven by across-fund differences in asset allocations: Total Dispersion ranges between 0.078 and 0.137, and Fund Dispersion ranges between 0.079 and 0.124. Market Dispersion ranges between 0.025 and 0.059, and is always lower than Fund Dispersion. Again, this breakdown of the overall dispersion in CAPM betas is quite comparable to that for Balanced Funds: 0.172, 0.043, and 0.166, for Total Dispersion, Market Dispersion, and Fund Dispersion, respectively. In summary, this analysis confirms the impression given by Tables 2–5 that the heterogeneity in TDF returns has little to do, on average, with the heterogeneity in broad asset allocation choices.

4.3 Regression analysis

In this section, we study the determinants of the cross-sectional dispersion in returns, the level and cross-sectional dispersion of alphas, the level of equity allocations, and the level of fund betas.

4.3.1 Explaining the cross-sectional dispersion in monthly fund-level returns

We regress a measure of the heterogeneity of individual TDF returns on aggregate time-varying factors, time-varying factors that are specific to a given target date, and time-varying factors that are specific to a given TDF. We estimate the regression model:

$$(r_{ijt} - \overline{r}_{jt})^2 = a_j + b^\top X_t + c^\top Y_{jt} + d^\top Z_{ijt} + \epsilon_{ijt}, \tag{4}$$

where r_{ijt} is the TDF's monthly return and $\overline{r}_{jt}$ is the cross-sectional average of the rates of return of TDFs with target date j in month t.

In this and in the three regression models that follow, the X_t vector includes a linear time trend and a post-2006 dummy variable. The Y_{jt} vector includes the natural logarithm of the total number of funds with target date j in month t. The Z_{ijt} vector includes three variables that allow us to test for differences between the TDFs of new and established market participants: a dummy equal to one if the fund was introduced after 2006; a dummy equal to one if the fund was introduced after 2006 *and* the fund family entered the TDF market after 2006; and the fund's age in month t.

Because funds with higher expense ratios and more assets under management have been shown to earn lower returns (e.g., Carhart, 1997, and Chen et al., 2004), the Z_{ijt} vector also includes: the fund-level expense ratio measured in month $t-1$; and the natural logarithm of fund-level assets under management in month $t-1$. Here and in the three regression models that follow, we control for target-date fixed effects (i.e., the intercept in (4) is target-date specific), and standard errors are clustered by mutual fund family and month.

Table 7 presents the results from several regression specifications.[16] In the first column, we control for the linear time trend, post-2006 dummy variable, and target-date fixed effects. We find that return dispersion jumped during the last three years of our sample. In the second column, we add the natural logarithm of the number of funds within each target-date-by-month cell (to measure the degree of competition) and a dummy variable that indicates whether TDF_{ijt} was introduced in 2007, 2008, or 2009. We find that the post-2006 effect is being driven both by an increase in the number of competitors, and by the introduction of new TDFs. In the third column, we distinguish between new TDFs being offered by existing market participants and new TDFs being offered by those families that offer their first TDF after 2006. We continue to find that dispersion increases with an increase in the number of competitors. Furthermore, we find that the new TDF effect in the second column is being driven entirely by new TDFs being offered by families that are new to the TDF market. This is the main finding of Table 7. Notably, it survives the addition of fund-level controls in the fourth column. In terms of economic significance, funds introduced by a family that entered the TDF market after 2006 have returns that are significantly different from the cross-sectional average: these funds have returns that deviate between 77 and 79 basis points—between 9.3% and 9.5% on an annual basis—from the target-date average more than other new funds.[17] The implication is that families entering the market pursue more volatile investment

[16]When we re-estimate the specifications in Table 7 as censored-regression models (with two-way clustering), to allow for the fact that the dependent variable cannot be negative, we obtain quantitatively similar results.

[17]Because the dependent variable is the squared deviation, we estimate these effects by taking the square root of

strategies than incumbent families introducing new TDFs.

4.3.2 Explaining differences in monthly fund-level alphas

The cross-sectional dispersion in TDF returns can be attributed to idiosyncratic and systematic factors, i.e., to "alphas" and "betas." We start by investigating patterns in alphas. We estimate the models

$$\alpha_{ijt} = a_j + b^\top X_t + d^\top Z_{ijt} + \epsilon_{ijt}, \tag{5}$$

and

$$(\alpha_{ijt} - \overline{\alpha}_{jt})^2 = a_j + b^\top X_t + d^\top Z_{ijt} + \epsilon_{ijt}, \tag{6}$$

where α_{ijt} is the sum of the intercept and residual from a regression of a TDF's excess return on the excess returns on various indices (see earlier explanation).

Results of the analysis are presented in Table 8. The main result from the table is that funds introduced by a fund family that entered the TDF market after 2006 have alphas that are significantly lower than other new funds: between 16 and 19 basis points per month, or about 2% per year. Moreover, these funds have alphas that deviate from the cross-sectional average more than the other new funds: between 74 and 79 basis points per month, or between 8.8% and 9.5% per year. The fact that entrants are exposing TDF investors to more idiosyncratic risk than existing firms motivates us, below, to study the risk-taking incentives of TDFs.

the estimated coefficients.

4.3.3 Explaining the allocation to equity

The second main driver of the cross-sectional dispersion in TDF returns is heterogeneity in betas and, hence, heterogeneity in equity allocations. We estimate the model

$$w_{ijt} = a_j + b^\top X_t + d^\top Z_{ijt} + \epsilon_{ijt}, \tag{7}$$

where w_{ijt} is the fraction of a TDF's portfolio that is allocated to equity in the month of December of each year, as reported in CRSP.[18]

Results of the analysis are presented in Table 9, which has the same structure as Table 7. The main result from the table is that, while funds introduced after 2006 have lower allocations to equities—between 2.2% and 8.8%, depending on the specification—new funds introduced by a fund family new to the TDF market have *higher* allocations to equities—between 4.5% and 5.2%. This suggests that entrants are exposing TDF investors to both more idiosyncratic risk and more systematic risk than existing fund families.[19]

4.3.4 Explaining the level of CAPM beta

We now investigate how the patterns in equity allocations documented in the previous section translate into patterns in equity exposure. We estimate the model

$$\hat{\beta}_{ijt} = a_j + b^\top X_t + c^\top Y_{jt} + d^\top Z_{ijt} + \epsilon_{ijt}, \tag{8}$$

where $\hat{\beta}_{ijt}$ is the December beta estimate, obtained by regressing monthly TDF excess returns on the excess returns on the CRSP value-weighted index over the prior 12 months.

[18] Note that the covariates measured in month $t-1$ are measured in November.

[19] Christoffersen and Simutin (2012) investigate the risk-taking incentives of mutual funds with different investor clienteles. They observe a monotonically increasing relation between market beta and the fraction of retirement money in the fund, and conclude that managers load on systematic risk because retirement money is relatively sticky.

Results are presented in Table 10. The main result from this table mirrors the main result from the previous table: while funds introduced after 2006 have slightly lower equity betas than other new funds—between 0.01 and 0.07 lower, depending on the specification—new funds introduced by a *new* fund family have slightly *higher* equity betas—0.03 higher. This reinforces our earlier finding that new entrants tilt their portfolio toward equity.

4.4 Summary of heterogeneity results

The following patterns emerge from our characterization of heterogeneity in TDFs:

> Cross-sectional dispersion in TDF returns and alphas is substantial and has increased over time.
>
> Cross-sectional dispersion in equity allocations and CAPM betas is also substantial, with some evidence of an upward trend.
>
> Departures of TDF returns and alphas from the target-date average are larger when the TDF is offered by a family that is new to the market.
>
> New entrants also tend to offer funds that have higher allocations to equities and slightly higher CAPM betas.

In summary, we document substantial and increasing heterogeneity in both systematic and idiosyncratic risk. Part of this increasing heterogeneity can be attributed to entrants in the TDF market after 2006 deviating from existing competitors. In the remainder of the paper, we explore whether the behavior of the new entries post-2006 reflects optimal risk taking on the part of mutual fund families, or optimal matching of heterogeneous TDFs to heterogeneous firms.

5 Does TDF heterogeneity reflect optimal risk taking?

We investigate the risk-taking hypothesis in two steps. First, because entrants in the TDF market post-2006 differentiate themselves from existing competitors mainly in term of alpha, we investigate whether TDF flows respond more to risk-adjusted returns than to total returns. Second, we formulate a simple optimization model for a risk-averse fund manager and we check whether, for realistic parameter values, the model delivers heterogeneity in risk-adjusted returns on the part of new entrants.

5.1 Flows and performance

We investigate the sensitivity of long-run (three–year) percentage net flows to long-run (three–year) past performance. We focus on *long-run* flows and performance because TDFs attract funds from DC retirement plans. While DC investors rarely rebalance their allocations, DC plan sponsors monitor the performance of plan options and periodically adjust investment options available to participants.[20] As a result, the flow-performance link is likely to manifest itself at lower frequencies than in the case of other types of mutual funds that cater mainly to non-DC investors.

In Table 11, we estimate the model

$$\text{flow}_{ijt} = a_j + b_t + c^\top Y_{jt} + d^\top Z_{ijt} + \epsilon_{ijt}, \tag{9}$$

where flow_{ijt} is the three-year net flow as a percentage of assets under management at the beginning of the three-year period. In this model, the Y_{jt} vector includes the natural logarithm of the total number of funds with target date j in month t. The Z_{ijt} vector includes: the compounded total TDF return between years $t-2$ and t; the compounded TDF alpha between years $t-2$ and t; a

[20]For a study of how investment options are added or deleted from 401(k) plans see, for example, Pool et al. (2013).

dummy equal to one if the fund was introduced after 2006; the fund-level expense ratio measured in year t; the fund-level management fee measured in year t; the average expense ratio of the underlying funds in year t; the natural logarithm of the fund assets at the beginning of year $t-2$; and the fund age measured in year t. The first three columns differ in whether and how we control for TDF fees.[21] In the last column, we regress the net flow in year t on three-year returns measured through year $t-1$. All specifications include both calendar-year fixed effects and target-date fixed effects. Standard errors are clustered on mutual fund family.

Our main finding is that TDF flows chase alphas.[22] In the first three columns, we find that a 1% increase in alpha between years $t-2$ and t is associated with a contemporaneous increase in percentage flows of between 6.1% and 7.8% (p-values range from 0.000 to 0.044). In contrast, the estimated coefficients on total returns are smaller and statistically indistinguishable from zero. When we estimate the impact of returns earned between years $t-3$ and $t-1$ on percentage flows in year t, we again find that flows respond to idiosyncratic returns. In this specification, a 1% increase in lagged alpha is associated with a one-year increase in percentage flows of 5.1%.

The results above complement existing results on the performance sensitivity of DC versus non-DC investors. Sandhya (2011) documents that quarterly TDF flows—likely dominated by the behavior of DC investors—are insensitive to past quarterly performance, whereas balanced-fund flows—likely dominated by the behavior of non-DC investors—are sensitive to past quarterly performance. The fact that TDF flows are sensitive to performance measured over longer horizons supports the notion that the appropriate horizon to evaluate the flow-performance relation may be different for funds catering to DC and non-DC investors. Sialm et al. (2012) find that yearly

[21] Note that while the sample sizes in the middle regressions are similar, they focus on slightly different sets of TDFs. This is because there are 47 TDFs for which CRSP reports an expense ratio but we lack a management fee, and there are 44 TDFs for which we possess a management fee but CRSP lacks an expense ratio.

[22] Del Guercio and Reuter (2012) document that flows chase risk-adjusted returns, rather than total returns, within the segment of mutual funds marketed directly to retail investors. Our result complements theirs, by showing that DC investors also focus on risk-adjusted performance.

flows of DC assets into mutual funds are more volatile and react more strongly to past yearly returns than non-DC asset flows. Their findings are consistent with DC plan sponsors actively adjusting investment menus in response to funds' past returns. Our findings are consistent with plan sponsors focusing on idiosyncratic returns rather than total returns when choosing or switching between TDFs.

5.2 A simple model

We develop a simple partial-equilibrium model, in which the fund manager maximizes a utility function that rewards expected dollar flows and penalizes the variance of dollar flows, and in which dollar flows respond positively and linearly to idiosyncratic performance, i.e., alpha. The manager has no skill—the expected alpha is zero—but she can control the idiosyncratic risk of the fund.

While the model is highly stylized, it generates useful insights: Since a fund cannot lose more than the existing funds under management, the flow-performance relation is *convex* and expected fund flows increase with idiosyncratic risk. The level of idiosyncratic risk at which the convexity kicks in, though, is higher for larger funds, as they have more assets to lose if they underperform. In addition, as idiosyncratic risk increases, the effect of risk on expected flows tends to be overcome by the effect on the variance of flows. As a result, in our model, large funds are less likely than small funds to take on *any* idiosyncratic risk.

When we calibrate this simple model using realistic parameter values, we find that new and small funds, with few or no assets to lose in case of bad performance, deviate from the benchmark and generate a volatile alpha. In contrast, we find that all other funds choose to track the benchmark and keep idiosyncratic risk at zero. Details of our model and calibration exercise are in the Appendix, Section A.3.

6 Does TDF heterogeneity reflect risk matching?

In the previous section, we used TDF-level data to show that demand for TDFs responds to risk-adjusted performance. This flow-performance relation provides entrants, who have few assets to lose, with a strong incentive to generate volatile alphas. However, demand for TDFs may also respond to the shape of the glide path. In particular, when choosing the default investment option for its 401(k) retirement plan, a "risky firm" may want the allocation to equity to fall more quickly as retirement approaches than a "safe firm." Alternatively, if the risk aversion of the representative employee varies across firms (Berk et al., 2010), and if different firms appeal to employees with different levels of risk aversion, firm risk and the risk of the default investment option may be positively correlated. To the extent that entrants benefit from offering glide paths that differ from those of existing TDFs, the incentive to offer different glide paths would help to rationalize the heterogeneity in glide paths that we document above.

To test the risk-matching hypothesis, we obtain retirement plan-level data for 2010 from BrightScope.[23] These data cover 16,766 distinct 401(k) and 403(b) plans, offered by 15,403 distinct firms (e.g., United Airlines offers separate retirement plans for its pilots and ground employees). Firm-level data include the firm's name, primary address, and 6-digit North American Industry Classification System (NAICS) code. We are able to locate a ticker and estimate a CAPM beta for 1,680 of the firms in the BrightScope database.[24] Plan-level data include assets under management, number of participants, whether it offers company stock, and whether the plan has auto enrollment. Investment-level data include the name and type (mutual fund, collective trust, separate account, company stock, etc.) of each investment option offered by each plan, as well as the total dollars

[23]Because BrightScope must hand collect data on investment menus, our sample is skewed toward firms with larger 401(k) or 403(b) retirement plans. A comparison of our sample to Form 5500 filings of plans with at least $1 million in assets suggests that BrightScope covers 78.4% of all defined contribution retirement plan participants in 2010 and 89.3% of all defined contribution retirement plan assets.

[24]We use the 36 monthly returns between December 2006 and November 2009 to estimate the CAPM beta as of December 2009. Our proxy for the market portfolio is the CRSP value-weighted index.

invested in each option. For mutual funds, BrightScope also provides data on fees. Summary statistics for the BrightScope data set are presented in Table 12.

When we count TDFs with different target retirement dates as a single investment option, TDFs represent 2.6% of the investment options and 9.8% ($244 billion) of the $2,497 billion in assets under management in 2010.[25] The fact that TDFs manage almost 10% of defined contribution retirement plan assets highlights the important role that TDFs now play in retirement wealth accumulation. The advantage of using plan data from 2010 to test for risk matching is that plan sponsors are able to choose from the full range of TDFs introduced following the PPA.

To test for a correlation between the riskiness of a firm and the riskiness of the TDF that the firm offers to its employees, we estimate the model

$$\text{TDF risk}_{ijk} = a + b \text{ firm risk}_j + c^\top Y_i + \epsilon_{ijk}, \tag{10}$$

where TDF risk_{ijk} measures of the risk of the TDF offered in plan i sponsored by firm j, and firm risk_j measures the risk of the plan sponsor. If there is risk matching between firms and TDFs of the type described above, the estimated coefficient on firm risk_j will be negative. If there is any type of matching, the estimated coefficient will be non-zero. The Y_i vector includes several plan-level controls: the natural logarithm of plan assets in 2010; the natural logarithm of the number of plan participants in 2010; a dummy equal to one if the plan features auto enrollment; a dummy equal to one if the plan offers company stock; and the average risk of the non-TDF mutual fund options. In some specifications, we include a separate fixed effect for each industry (defined using the first 3 digits of the NAICS code). Standard errors are clustered on industry.

We report the regression results in Table 13. Because we find above that heterogeneity in

[25]TDFs account for 3.0% of the investment options and 14.0% ($159 billion) of the $1,133 billion in assets under management by mutual funds.

equity exposure is larger for TDFs whose target retirement year is closer, our main measure of TDF risk is the CAPM beta of the TDF with a target retirement date of 2020. Our main measure of firm risk is the CAPM beta on the firm's equity, which limits our sample to 872 plans offered by publicly-traded firms. Within this sample, the estimated coefficients on firm risk are negative, but they are neither statistically nor economically distinguishable from zero. Moreover, the limited explanatory power of the industry fixed effects suggest little matching at the industry level. Among our control variables, our most robust finding is that TDF risk decreases slightly with plan assets. When we exclude industry fixed effects, we find weak evidence that CAPM betas of TDFs are positively correlated with the average CAPM betas of the other mutual funds in the investment menu.

When we instead measure firm risk as the median CAPM beta of firms in the same industry, we are able to increase the sample to 7,320 plans.[26] Within this larger sample, the estimated coefficient on firm risk is positive and statistically significant (p-value of 0.011), suggesting that riskier firms choose riskier TDFs. However, the effect is quite small. A one-standard deviation increase in the median industry beta (0.459) is predicted to increase the CAPM beta of the TDF by only 0.006. In other words, we find little evidence that demand for TDF glide paths is correlated with firm-level or industry-level risk.

In the remaining regressions, we shift our focus from systematic risk to idiosyncratic risk. Specifically, we use each firm's and TDF's estimated CAPM beta to decompose its monthly returns into systematic and idiosyncratic components. We then calculate the standard deviation of the idiosyncratic returns over the prior 36 months.[27] Our findings are qualitatively similar to those based on measures of systematic risk, providing little evidence of risk matching at either the firm

[26]When we regress a firm's CAPM beta on a separate fixed effect for each 3-digit NAICS code, the adjusted R^2 is 20.7%. By way of comparison, when we regress a firm's CAPM beta on a separate fixed effect for each state in which a plan is located, the adjusted R^2 is 3.5%.

[27]Because the mean of the dependent variable is only 0.007, for ease of comparison, we multiply the estimated coefficients by 100.

or the industry level.

7 Conclusions

The market for TDFs is important for at least two reasons: First, because TDFs are a relatively new financial product, this market allows us to study how mutual fund families structure new investment products. Second, given the widespread, legislation-induced use of TDFs as default investments in DC retirement plans, this is a market with special policy significance.

We document pronounced heterogeneity in the TDF universe: TDFs with the same target date have delivered very different returns to investors. The heterogeneity of returns has increased over time, especially after the passage of the PPA of 2006. Indeed, we can attribute some of this increased heterogeneity to the entry of new mutual fund families into the TDF market during the 2007–2009 period. Because we show that flows into TDFs respond to alpha rather than total returns, these patterns are consistent with new entrants responding to their incentives to attract retirement plan sponsors by generating higher idiosyncratic returns. On the other hand, we find little evidence that the heterogeneity in risk that we document is driven by TDFs catering to different risk clienteles.

Our findings suggest that the widespread adoption of TDFs will not necessarily equalize the returns earned by investors enrolled in different 401(k) plans. Indeed, the cross-sectional dispersion in returns of funds with 2015–2020 target dates was so large in 2008 and 2009, that it came to the attention of regulators. On November 29, 2010, regulation was proposed to increase investor understanding of how TDFs operate. Specifically, TDFs would be required to provide: i) a description and graphical illustration of the asset allocation, how it will change over time, and the point when it will be the most conservative; ii) a clarification of the relevance of the date (if the name includes a target date) and the target age group for which the investment is designed; and iii) a statement that a participant is not immune from risk of loss, even near or after retirement, and that no guarantee of sufficient returns to sustain an adequate retirement income can be given.[28]

The pronounced heterogeneity in TDF returns that we document means that a well-informed 410(k) investor, who is limited to the TDFs of a single mutual fund family, may face returns that depart significantly from the industry average. Importantly, these differences in returns are largely driven by differences in alphas and cannot be anticipated based on disclosed differences in glide path. In any case, even if we assume that differences in disclosed asset allocations perfectly capture differences in risk, it is still true that those investors who are the most likely to be defaulted into TDFs—and to stay in TDFs—may be the least able to make an informed choice between TDFs and other investment vehicles.[29]

[28]DOL: EBSA Federal Register: 29 CFR Part 2550, RIN 1210-AB38, October 20, 2010. On May 24, 2012, additional disclosure requirements were proposed, based "on evidence that plan participants and beneficiaries would benefit from additional information concerning these investments" (DOL: EBSA Federal Register: 29 CFR Part 2550, RIN 1210-AB38, May 24, 2012). Both rules are still pending, but the DOL expects to issue them in November 2013.

[29]Morrin et al. (2012) show that the decision to invest in a TDF is negatively related to an investor's financial knowledge. Agnew et al. (2012) show that lower financial literacy increases the probability that an investor holds all of her 401(k) assets in a single TDF, i.e., that she is a "pure" TDF investor. Pagliaro and Utkus (2010) show that pure TDF investors tend to be younger and poorer than other investors.

Appendix

A.1 The Pension Protection Act of 2006

A.1.1 Overview

The PPA of 2006 amends Title I of the Employee Retirement Income Security Act (ERISA) of 1974. Of particular interest to our study, it relieves sponsors of DC retirement plans of liability for investment losses when they default plan participants into "qualified default investment alternatives" (QDIAs). As specified by the Department of Labor's (DOL) Employee Benefits Security Administration (EBSA), QDIAs must be diversified to decrease probability of large losses; be managed by an investment manager/company registered under the Investment Company Act of 1940; not penalize or prevent a participant from transferring their assets from a QDIA to another investment alternative available under the plan; and not invest participant contributions directly in employer securities.[30] Potential QDIAs include TDFs, balanced funds, and professionally managed accounts. Note that plan sponsors and fiduciaries are not relieved of liability for the prudent selection and monitoring of a QDIA.

A.1.2 Timeline

In January of 2005, a proposal regarding the funding of pensions was created, indicating new minimum funding requirements for pension plans with the hope of strengthening the overall pension system. Later that year, major pension reform bills were proposed in the House (The Pension Protection Act) and the Senate (The Pension Security and Transparency Act). The PPA of 2006 resulted from negotiations between the House and the Senate conducted in March of 2006.[31] The final ruling was passed by the House on July 28, 2006, passed by the Senate on August 3, 2006, and

[30] DOL: EBSA Federal Register: 29 CFR Part 2550, October 24, 2007.
[31] Congressional Research Service Report for Congress, October 23, 2006.

signed into law on August 17, 2006. On September 27, 2006, the DOL proposed rules regarding "Default Investment Alternatives Under Participant Directed Individual Account Plans," to define which investment vehicles are appropriate default investments. These rules went into effect on December 24, 2007.

A.2 Public Statements Summarizing Advantages and Disadvantages of TDFs

Source for all quotes: DOL and SEC Joint Public Hearing on TDFs and Other Similar Investment Options: June 18, 2009.

Advantages:

- "Target date funds were expected to make investing easier for the typical American and avoid the need for investors to constantly monitor market movements and realign their personal investment allocations." SEC Chairman Mary Shapiro
- "Target Date Funds are one of the most important recent innovations in retirement savings. They provide a convenient way for an investor to purchase a mix of asset classes within a single fund that will rebalance the asset allocation and become more conservative as the investor ages." Karrie McMillan, general counsel of the Investment Company Institute
- "Target Date Fund investors avoid extreme asset allocations that we often observe in retirement savings." Karrie McMillan, general counsel of the Investment Company Institute
- "Target date funds were designed to be easy to use and require little maintenance." Richard Whitney, Director of Asset Allocation of T. Rowe Price
- "...the fundamental purpose of Target Date Funds is to provide investors a diversified, prudently-managed, appropriate exposure to investment risks." John Ameriks, economist and principal at the Vanguard Group

- "When evaluating the performance of Target date funds, it's important to acknowledge the extreme severity of the financial meltdown we have just experienced ... in our view they performed as designed. In particular, in the vast majority of cases, older investors were exposed to far less risks than younger investors and consequently suffered less dramatic losses." John Ameriks, economist and principal at the Vanguard Group

- "... it is important for investors to stay committed to a retirement savings plan. Target Date Funds are designed to help participants maintain this discipline." Derrick Young, Chief Investment Officer of the Fidelity Global Asset Allocation Group

Disadvantages:

- "While Target Date Mutual Funds currently do a good job of describing their objectives, risks and glide paths, we do see gaps in the public understanding of Target date funds." Karrie McMillan, general counsel of the Investment Company Institute

- "Target date funds are not designed to be riskless or to provide a guaranteed amount of retirement income ..." John Ameriks, economist and a principal at the Vanguard Group

- "Retirees do a lot of different things with the money in these plans at the point of retirement, and so there is some debate around exactly how the money is going to be used ... it's very difficult to come up with a sort of specific answer that solves the problem for everybody." John Ameriks, economist and a principal at the Vanguard Group

- "We have serious concerns that these funds are fundamentally misleading to investors because they're allowed to be managed in ways that are inconsistent with reasonable expectations that are created by the titles and the use of the names." Marilyn Capelli-Dimitroff, Chair of the Certified Financial Planner Board of Standards

- "Appropriate disclosures are required and must be provided, but in reality, disclosures are seldom read or understood fully despite our ongoing education of clients." Marilyn Capelli-Dimitroff, Chair of the Certified Financial Planner Board of Standards

- "When plan sponsors and participants started adopting TDFs in big meaningful numbers starting in 2002, the race was on for performance numbers, and this is where the train went off the track . . . There is some theoretical rationale for employing a glide path through the accumulation phase. No credible rationale has ever been proffered for using a glide path in the distribution phase. This is what caused the unacceptably large losses in 2010 funds in 2008." Joe Nagengast, Target Date Analytics

- ". . . part of the concern here is when you have a fund of funds, it may become a lot easier to, for example, hide under-performing funds in Target Date Funds, [or] hide higher fee funds in a Target Date Fund that may not be completely appropriate." Dave Certner, Legislative Counselor and Legislative Policy Director at AARP

A.3 Size and risk incentives: a simple model

A.3.1 Convexity in the flow-performance relation

Let A_t denote assets under management. Assume that dollar flows obey the *convex* relation

$$\Delta A_1(\alpha_1) = \max\{a + b\alpha_1 + cA_0, -A_0\}, \tag{A.1}$$

where α_1 is the risk-adjusted fund return and, realistically, a, b, and c are all positive.

We assume that $\alpha_1 = \pm\sigma$, with equal probability, where the fund manager controls σ. In other words, the fund manager has no skill ($E_0(\alpha_1) = 0$), but she controls the amount of idiosyncratic risk.

By setting

$$a - b\bar{\sigma} + cA_0 = -A_0, \tag{A.2}$$

we obtain the level of volatility $\bar{\sigma}$ where the convexity in percentage flows kicks in, and expected flows increase with σ:

$$\bar{\sigma} \equiv \frac{a + (1+c)A_0}{b}. \tag{A.3}$$

Hence, $\bar{\sigma}$ increases with A_0: the incentive to load on volatility, because of the convexity in the flow-performance relation, kicks in at a higher level of volatility for larger funds.

A.3.2 The manager's problem

Assume that the manager maximizes a utility function defined over the first two moments of dollar flows:

$$U_0 = 2[E_0(\Delta A_1)] - 2\gamma \mathrm{Var}_0(\Delta A_1), \tag{A.4}$$

and dollar flows obey (A.1).

For $\sigma < \bar{\sigma}$, the convexity in the flow-performance relation does not matter, and we have

$$U_0 = 2(a + cA_0) - 2\gamma(b\sigma)^2, \tag{A.5}$$

which is monotonically decreasing in σ: increasing the volatility of risk-adjusted returns does not improve expected flows, while it generates a penalty through its effect on the volatility of flows. Hence, the optimal policy is to set $\sigma = 0$.

For $\sigma \geq \bar{\sigma}$, we have[32]

$$U_0 = -A_0 + (a + b\sigma + cA_0) - 2\gamma \left[\frac{1}{2}A_0 + \frac{1}{2}(a + b\sigma + cA_0)\right]^2. \tag{A.6}$$

In this case, expected flows increase with σ and it is possible that the manager finds it optimal to set $\sigma > 0$. Indeed, we have

$$\frac{dU_0}{d\sigma} = b - 4\gamma \left[\frac{1}{2}A_0 + \frac{1}{2}(a + b\sigma + cA_0)\right] \frac{1}{2}b = b - \gamma[A_0 + (a + b\sigma + cA_0)]b. \tag{A.7}$$

Setting the first derivative above equal to zero, we have

$$\sigma^\star = \frac{1 - \gamma[a + (1 + c)A_0]}{\gamma b}. \tag{A.8}$$

Provided that $\sigma^\star > \bar{\sigma}$ and $U_0(\sigma^\star) > U_0(0)$, the fund manager optimally chooses $\sigma = \sigma^\star > 0$.

Note that $\sigma^\star$ decreases in A_0. The reason for this result is that, as A_0 increases, $dE_0(\Delta A_1)/d\sigma$ is unaffected, whereas $d\text{Var}_0(\Delta A_1)/d\sigma$ increases; see the first and second term in the r.h.s. of equation (A.7), respectively.[33] Hence, for large funds it is optimal to generate less volatile risk-adjusted returns than for small funds.

A.3.3 Parameter values

We set

$$a = 800 \tag{A.9}$$

[32]Note that

$$\text{Var}_0(\Delta A_1) = \left\{\frac{1}{2}[\Delta A_1(\sigma) - \Delta A_1(-\sigma)]\right\}^2.$$

[33]Note that this effects holds even if $c = 0$.

$$b = 10000 \tag{A.10}$$

$$c = 0.5. \tag{A.11}$$

The values above are chosen based on estimates of the three-year dollar flow-performance relation for our sample. γ is chosen so that, for a *new* fund ($A_0 = 0$), the optimal volatility of three-year risk-adjusted returns equals the roughly realistic value of $\sigma^\star = 0.3$.

A.3.4 Solutions

Figure (1) plots $U_0(\sigma)$ for a new fund ($A_0 = 0$). In this case, utility decreases with σ up until $\bar{\sigma} = 0.08$. Beyond this threshold, expected flows start increasing with σ, and utility peaks at $\sigma^\star = 0.3$. Since $U_0(\sigma^\star) > U_0(0)$, we have that the overall maximizer of the optimization problem, $\sigma^{\mathrm{M}ax}$, equals $\sigma^\star$.

Figure (2) plots $U_0(\sigma)$ for a large fund ($A_0 = 1600000000$, roughly, twice the average size of a TDF in 2009). In this case, the threshold $\bar{\sigma}$ exceeds $\sigma^\star$, and the manager finds it optimal to eliminate all idiosyncratic volatility and sets $\sigma^{\mathrm{M}ax} = 0.0$.

Figure (3) plots $\sigma^{\mathrm{M}ax}$, together with $\bar{\sigma}$ and $\sigma^\star$, as a function of A_0. As discussed earlier, the threshold $\bar{\sigma}$ increases with A_0. On the other hand, the interior maximizer, $\sigma^\star$, decreases with A_0. The overall maximizer, $\sigma^{\mathrm{M}ax}$, equals $\sigma^\star > 0$, for new and very small funds, and equals zero, for the other funds.[34]

[34] Note that for $A_0 > 100$, $\sigma^{\mathrm{Max}} = 0.0$, even though $\sigma^\star > \bar{\sigma}$. This is because $U_0(0) > U_0(\sigma^\star)$.

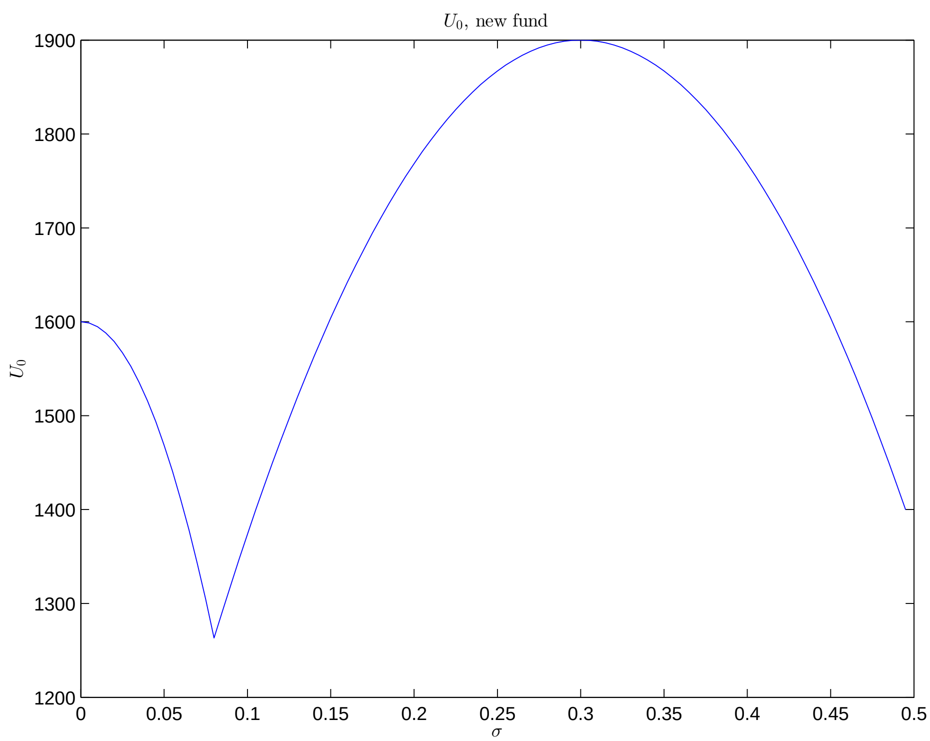

Figure 1: This figure plots U_0 as a function of σ, for a new fund.

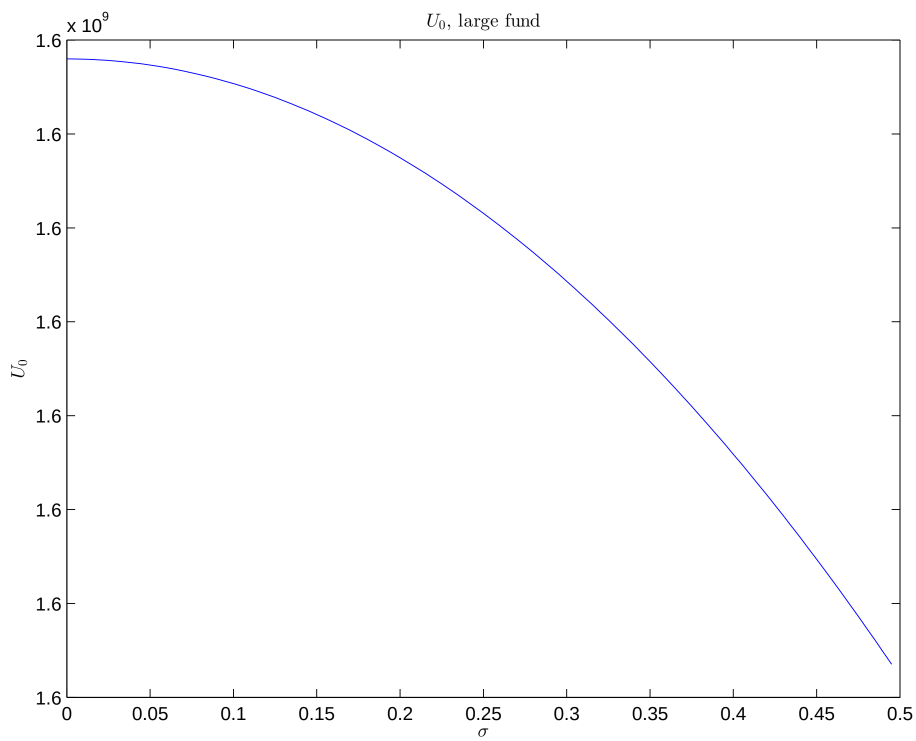

Figure 2: This figure plots U_0 as a function of σ, for a large fund.

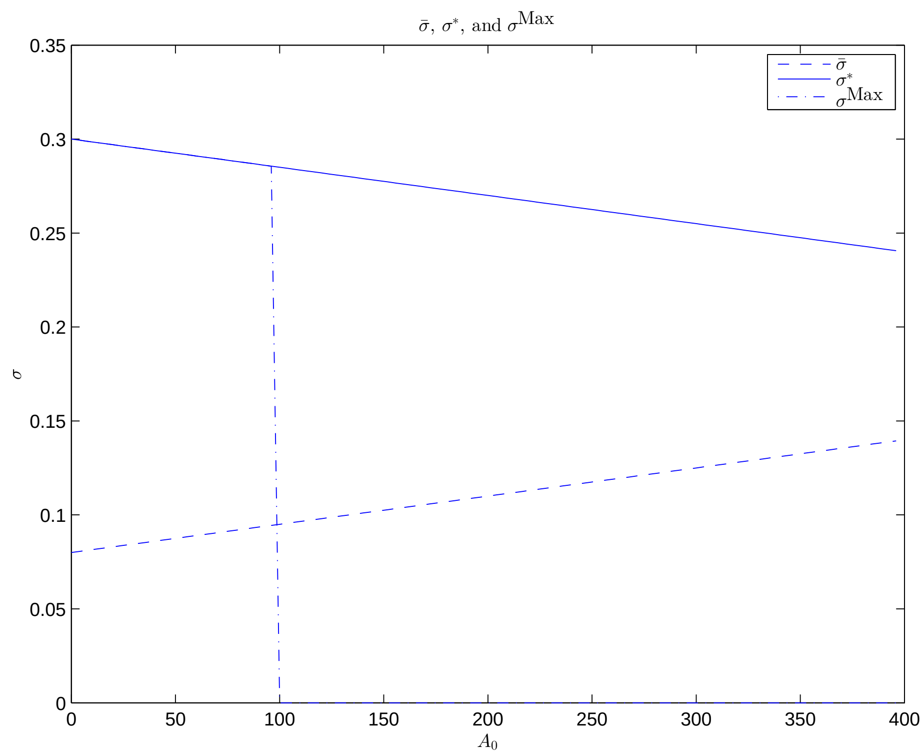

Figure 3: This figure plots $\bar{\sigma}$, $\sigma^{\star}$, and σ^{Max} as functions of A_0.

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Table 1: Summary statistics

This table provides annual snapshots of the market for TDFs. All of the data used to calculate the numbers in this table comes from the CRSP Survivorship-bias-free US Mutual Fund Database. The first eleven columns indicate the number of mutual fund families that offer a TDF with a target date of 2000, 2005, 2010, …, 2040, 2045, and 2050 at the end of each year. The next column indicates the number of distinct mutual fund families that offer at least one TDF. AUM measures total assets under management in TDFs at the end of the year, summed across all mutual fund families. The last two columns indicate the name of the mutual fund family with the largest market share (based on AUM) at the end of the year. Through 2000, the only market participants were American Independence Financial Services, Barclays Global Fund Advisors, Fidelity Management and Research, and Wells Fargo.

	# Firms offering TDF with each target retirement date in each year											# Firms offering TDFs	AUM ($ mil.)	Firm with Largest Market Share	
	2000	2005	2010	2015	2020	2025	2030	2035	2040	2045	2050				
1994	1		1		1		1		1			1	278.4	Wells Fargo	100.0%
1995	1		1		1		1		1			1	590.1	Wells Fargo	100.0%
1996	3		3		3		3		2			3	893.5	Wells Fargo	64.0%
1997	2		3		3		3		2			3	1469.9	Wells Fargo	43.6%
1998	2		3		3		3		2			3	3977.9	Fidelity	64.3%
1999	2		4		4		4		3			4	6167.3	Fidelity	76.3%
2000	1		4		4		4		4			4	7666.7	Fidelity	80.3%
2001	1		5		5		5		5		1	5	10849.8	Fidelity	84.8%
2002	1		6		6		6		6		1	6	13272.0	Fidelity	88.1%
2003	1	2	7	2	7	2	7	2	7	1	1	8	23608.3	Fidelity	85.4%
2004	1	3	10	6	10	6	10	6	10	3	1	12	40363.2	Fidelity	72.1%
2005	2	4	16	11	16	11	16	10	15	6	2	21	65822.2	Fidelity	62.3%
2006	2	5	21	18	21	16	21	16	20	11	4	27	110499.1	Fidelity	55.4%
2007	2	6	29	25	29	22	29	22	28	17	14	37	168556.3	Fidelity	50.8%
2008	2	6	34	35	41	32	40	30	40	25	28	48	153392.3	Fidelity	43.4%
2009	2	6	31	33	38	30	38	29	38	25	28	44	245353.5	Fidelity	39.6%
N	26	32	178	130	192	119	191	115	184	88	80				

Table 2: Cross-sectional dispersion of TDF returns

This table summarizes the annual returns earned by target date funds with different target dates in different calendar years. Each calendar year, the sample is limited to TDFs for which we observe 12 monthly returns, and for which CRSP reports the fraction of portfolio assets allocated to debt, equity, and cash. Within each target date-year cell, we report the number of TDFs, the average annual after-fee return, standard deviation of annual after-fee returns, and the range between the minimum and maximum annual after-fee returns.

	2005 & 2010				2015 & 2020				2025 & 2030			
	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range
2000	2	0.7%	0.0%	0.0%	3	-3.6%	0.5%	1.1%	3	-5.6%	0.5%	1.0%
2001	3	-2.1%	2.0%	3.6%	3	-7.3%	1.5%	2.6%	2	-11.0%	1.0%	1.5%
2002	3	-8.2%	1.2%	2.4%	3	-13.4%	0.8%	1.4%	3	-16.7%	0.8%	1.6%
2003	3	16.1%	0.9%	1.6%	3	21.7%	2.8%	5.2%	3	25.2%	2.8%	5.0%
2004	8	7.5%	1.5%	5.1%	9	9.0%	1.6%	5.6%	9	10.3%	1.6%	5.5%
2005	12	4.7%	1.0%	3.2%	14	6.1%	1.1%	3.6%	13	7.1%	1.2%	4.0%
2006	20	9.5%	2.2%	7.3%	26	11.7%	2.3%	9.5%	26	13.6%	2.2%	8.5%
2007	26	6.0%	1.5%	5.4%	38	6.0%	2%	7.2%	37	6.6%	2.3%	8.3%
2008	37	-23.9%	6.1%	32.3%	58	-29.3%	5.2%	27.3%	54	-34.5%	3.7%	19.6%
2009	41	22.4%	4.6%	24.1%	75	25.1%	4.4%	23.5%	72	28.4%	4.1%	19.2%

	2035 & 2040				2045 & 2050			
	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range
2000	2	-9.9%	0.3%	0.4%				
2001	1	-13.9%	0.0%	0.0%				
2002	3	-19.5%	0.7%	1.3%				
2003	3	28.6%	2.2%	4.2%				
2004	9	11.3%	1.4%	4.7%	1	12.9%	0.0%	0.0%
2005	14	7.7%	1.0%	3.5%	3	8.1%	1.1%	2.3%
2006	23	14.6%	1.7%	6.6%	6	15.9%	1.1%	3.0%
2007	36	6.9%	2.4%	8.8%	16	7.1%	2.7%	9.4%
2008	52	-37%	2.5%	10.8%	35	-38%	2.4%	8.9%
2009	70	30.3%	3.9%	19.0%	55	31.5%	3.8%	22%

Table 3: Cross-sectional dispersion of TDF alphas

This table summarizes the annualized 2-factor alphas earned by TDFs with different target dates in different calendar years. We estimate the 2-factor alpha for fund i in month t using the excess return on the S&P 500 Index and the excess return on the Barclays Aggregate Bond Index over the prior 12 months. The sample is smaller than in Table 2 because it restricted to TDFs for which we are able to estimate alphas in January through December. Within each target date-year cell, we report the number of TDFs, the average annualized after-fee alpha, standard deviation of the annualized after-fee alpha, and the range between the minimum and maximum annualized after-fee alpha.

	2005 & 2010				2015 & 2020				2025 & 2030			
	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range
2000	2	1.8%	3.4%	4.7%	3	0.8%	3.6%	6.6%	3	1.3%	3.3%	5.9%
2001	3	-1.5%	0.2%	0.4%	3	-2.6%	0.3%	0.6%	2	-3.8%	1.1%	1.6%
2002	3	-2.8%	1.9%	3.6%	3	-2.1%	1.3%	2.7%	3	-1.9%	0.9%	1.7%
2003	3	-1.6%	1.5%	2.8%	3	-1.9%	1.8%	3.5%	3	-2.4%	2.2%	3.9%
2004	5	-0.9%	1.1%	2.7%	5	-1%	1.3%	3.2%	5	-1%	1.3%	3.2%
2005	11	-0.3%	0.8%	2.6%	12	0.3%	0.9%	2.7%	11	0.5%	1.1%	3.4%
2006	14	-1%	1%	3.6%	18	-1%	1.2%	3.7%	18	-0.9%	1.6%	5.6%
2007	20	-1.4%	1.5%	4.5%	27	-1.5%	2.3%	8.7%	27	-1.2%	2.4%	8.6%
2008	32	-3.4%	2.7%	13.1%	49	-2.5%	3.1%	16.9%	45	-1.8%	2.5%	11%
2009	35	1.8%	3.6%	18.1%	54	1%	3.3%	16.2%	51	0.3%	2.9%	11.8%
	2035 & 2040				2045 & 2050							
	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range				
2000	2	-1.4%	0.3%	0.4%								
2001	1	-5.2%	0%	0%								
2002	3	-1.2%	0.7%	1.2%								
2003	3	-2.5%	1.9%	3.6%								
2004	5	-1.1%	1.3%	3.2%								
2005	12	0.7%	1.1%	3.4%	2	1.0%	1.4%	2.0%				
2006	17	-0.9%	1.8%	6.2%	3	-0.3%	1.0%	2.0%				
2007	26	-1%	2.6%	8.3%	8	-1.8%	2.9%	8.6%				
2008	42	-1.3%	2.6%	10.9%	22	-1.8%	2.5%	10.2%				
2009	49	-0.1%	2.7%	11.7%	35	0.1%	2.8%	11.8%				

Table 4: Cross-sectional dispersion in allocation to equity

This table summarizes the asset allocation of target date funds with different target dates in different calendar years. Each calendar year, the sample is limited to TDFs for which we observe 12 monthly returns, and for which CRSP reports the fraction of portfolio assets allocated to debt, equity, and cash. It is further limited to TDFs for which we are able to estimate two-factor alphas in January through December. Within each target date-year cell, we report the number of TDFs, the average fraction allocated to equity (which is equivalent to one minus the fraction allocated to debt plus cash), the standard deviation of the fraction allocated to equity, and the range between the minimum and maximum fractions allocated to equity.

	2005 & 2010				2015 & 2020				2025 & 2030			
	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range
2000	2	49.0%	15.3%	21.6%	3	67.2%	5.8%	11.7%	3	78.4%	3.0%	5.5%
2001	3	47.4%	9.3%	18.4%	3	67.9%	5.3%	9.2%	2	84.5%	2.1%	2.9%
2002	3	54.1%	5.9%	10.7%	3	68.7%	7.8%	15.1%	3	83.3%	1.5%	3.0%
2003	3	48.0%	1.1%	2.0%	3	65.9%	3.6%	6.8%	3	77.9%	3.7%	7.3%
2004	8	50.7%	19.4%	64.1%	9	66.2%	14.3%	50.9%	9	78.6%	10.6%	40.3%
2005	12	48.9%	18.4%	69.7%	14	62.8%	14.4%	61.3%	13	77.3%	10.9%	43.0%
2006	20	44.9%	10.7%	43.0%	26	62.4%	11.1%	48.1%	26	79.3%	9.1%	34.0%
2007	26	52.1%	18.6%	78.0%	38	67.4%	13.8%	60.4%	37	83.4%	9.4%	33.9%
2008	37	49.3%	11.8%	45.1%	58	63.7%	11.4%	53.0%	54	79.1%	9.9%	57.7%
2009	41	49.6%	12.1%	75.2%	75	63.5%	13.5%	69.8%	72	77.2%	12.4%	62.0%

	2035 & 2040				2045 & 2050			
	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range
2000	2	91.3%	0.5%	0.7%				
2001	1	96.0%	0.0%	0.0%				
2002	3	92.9%	2.4%	4.3%				
2003	3	84.2%	8.5%	15.0%				
2004	9	85.2%	5.6%	15.8%	1	87.7%	0.0%	0.0%
2005	14	85.4%	10.8%	44.8%	3	94.2%	6.3%	12.4%
2006	23	87.4%	6.7%	26.7%	6	90.9%	4.1%	11.0%
2007	36	89.7%	6.0%	21.2%	16	91.1%	4.6%	14.9%
2008	52	87.1%	8.2%	57.1%	35	89.5%	8.8%	51.5%
2009	70	85.8%	10.5%	55.8%	55	89.3%	9.0%	52.1%

Table 5: Cross-sectional dispersion of CAPM betas

This table summarizes the CAPM betas of target date funds with different target dates in different years. We estimate the CAPM beta in December of each year using monthly fund-level returns (in excess of the one-month T-bill rate) and the monthly value-weighted return on all NYSE, AMEX, and NASDAQ stocks (in excess of the one-month T-bill rate). Each calendar year, the sample is limited to TDFs for which we observe 12 monthly returns, and for which CRSP reports the fraction of portfolio assets allocated to debt, equity, and cash. Within each target date-year cell, we report the number of TDFs, the average beta, the standard deviation of beta, and the range between the minimum and maximum estimated beta.

	2005 & 2010				2015 & 2020				2025 & 2030			
	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range
2000	2	0.46	0.17	0.24	3	0.62	0.14	0.24	3	0.73	0.11	0.2
2001	3	0.38	0.08	0.13	3	0.62	0.07	0.13	2	0.77	0.07	0.1
2002	3	0.48	0.06	0.11	3	0.68	0.00	0.00	3	0.81	0.01	0.01
2003	3	0.46	0.04	0.07	3	0.65	0.02	0.03	3	0.76	0.03	0.05
2004	8	0.52	0.10	0.34	9	0.70	0.09	0.33	9	0.84	0.10	0.36
2005	12	0.44	0.10	0.37	14	0.62	0.09	0.35	13	0.77	0.09	0.36
2006	20	0.53	0.14	0.56	26	0.72	0.17	0.75	26	0.9	0.18	0.71
2007	26	0.47	0.16	0.65	38	0.66	0.12	0.57	37	0.83	0.1	0.41
2008	37	0.60	0.13	0.70	58	0.74	0.12	0.63	54	0.87	0.09	0.49
2009	41	0.56	0.11	0.43	75	0.69	0.10	0.55	72	0.83	0.09	0.49
	2035 & 2040				2045 & 2050							
	# Funds	Mean	Std. Dev.	Range	# Funds	Mean	Std. Dev.	Range				
2000	2	0.81	0.00	0.00								
2001	1	0.89	0.00	0.00								
2002	3	0.93	0.01	0.02								
2003	3	0.87	0.02	0.03								
2004	9	0.94	0.06	0.18	1	0.92	0.00	0.00				
2005	14	0.86	0.06	0.25	3	0.88	0.06	0.11				
2006	23	0.99	0.14	0.55	6	1.06	0.14	0.36				
2007	36	0.91	0.07	0.28	16	0.94	0.07	0.22				
2008	52	0.93	0.07	0.31	35	0.96	0.06	0.21				
2009	70	0.91	0.08	0.38	55	0.96	0.08	0.30				

Table 6: Decomposition: total dispersion, market dispersion, and fund dispersion

In this table, we measure dispersion in annual returns, annualized 2-factor alphas, allocations to equity, and CAPM betas. Let x_{ijt} be the value for TDF i with target date j in year t, $\overline{x}_{jt}$ be the equal-weighted average of all funds with target date j in year t, and $\overline{\overline{x}}_j$ be the equal-weighted average of all (TDF i, year t) pairs within target date j. "Total dispersion" measures the variation of x_{ijt} around $\overline{\overline{x}}_j$. "Market dispersion" measures the time-series variation of $\overline{x}_{jt}$ around $\overline{\overline{x}}_j$. For example, when x_{ijt} is the annual after-fee return of TDF i with target date j in year t, "Market dispersion" measures time-series variation in the annual after-fee returns of an equal-weighted portfolio of TDFs with target date j. This is the variability that investors are exposed to when they invest in the average TDF. "Fund dispersion" measures that additional variability that investors are exposed to when they are randomly assigned to a single TDF rather than to the average TDF. When "Total dispersion", "Market dispersion", and "Fund dispersion" are measured as variances, "Fund dispersion" equals "Total dispersion" minus "Market dispersion". However, in the table, we report the corresponding standard deviations. For comparison, we perform a similar decomposition for the universe of traditional balanced funds, and for S&P 500 index funds.

	Annual Return			Annualized Alpha			Allocation to Equity			CAPM Beta		
	Total	Market	Fund	Total	Market	Fund	Total	Market	Fund	Total	Market	Fund
Target Date Funds												
2005 & 2010 TDFs	16.6%	16.1%	4.0%	3.8%	2.8%	2.5%	14.5%	4.2%	13.9%	0.137	0.059	0.124
2015 & 2020 TDFs	20.6%	20.3%	3.6%	3.8%	2.7%	2.7%	12.7%	3.8%	12.1%	0.121	0.046	0.112
2025 & 2030 TDFs	23.6%	23.4%	3.1%	3.5%	2.5%	2.4%	10.6%	3.7%	10.0%	0.111	0.048	0.100
2035 & 2040 TDFs	25.3%	25.2%	2.7%	3.4%	2.4%	2.3%	8.7%	2.3%	8.4%	0.087	0.035	0.079
2045 & 2050 TDFs	29.7%	29.5%	3.0%	3.8%	2.8%	2.6%	8.1%	1.7%	7.9%	0.078	0.025	0.073
Balanced Funds	14.7%	13.8%	5.1%	5.5%	1.9%	5.1%	11.6%	1.5%	11.5%	0.172	0.043	0.166
S&P 500 Index Funds	21.5%	21.5%	0.4%	0.4%	0.2%	0.4%	2.7%	0.9%	2.6%	0.069	0.053	0.045

Table 7: Explaining the cross-sectional dispersion in monthly fund-level returns

The unit of observation is the TDF offered by family i with target date j in month t. The dependent variable is $(r_{ijt} - \overline{r}_j t)^2$. To calculate the dependent variable we require that there be at least two TDFs with target date j in month t. The full set of independent variables includes: a linear time trend; a post-2006 dummy variable; the natural logarithm of the total number of funds with target date j in month t; a dummy equal to one if the fund was introduced after 2006; a dummy equal to one if the fund was introduced after 2006 *and* the fund family entered the TDF market after 2006; the fund-level expense ratio measured in month $t-1$; the natural logarithm of fund-level assets under management in month $t-1$; and the fund's age in month t. We also control for target-date fixed effects (i.e., 2005, . . . , 2045, and 2050). The sample includes all TDFs with target dates between 2005 and 2050 for which we observe the dependent and independent variables. Estimation is via OLS. Standard errors are simultaneously clustered on mutual fund family and month. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	$(ret_{ijt} - \bar{ret}_{jt})^2$			
Linear time trend	0.004	−0.009	−0.010	−0.005
	(0.004)	(0.007)	(0.007)	(0.009)
2007, 2008, or 2009?	0.338*	0.117	0.089	0.172
	(0.193)	(0.170)	(0.171)	(0.167)
Ln Total Number of Funds with TD j in month t		0.506*	0.543*	0.381
		(0.281)	(0.281)	(0.316)
Fund introduced after 2006?		0.507**	0.008	−0.146
		(0.207)	(0.108)	(0.141)
Fund introduced by family introducing TDFs after 2006?			0.628***	0.596***
			(0.236)	(0.214)
Lagged expense ratio				0.254
				(0.291)
Ln fund size measured in month $t-1$				−0.053
				(0.037)
Fund age measured in month t				0.000
				(0.021)
Target date fixed effects?	Yes	Yes	Yes	Yes
Standard error clustering:	Family & Month	Family & Month	Family & Month	Family & Month
N	13956	13956	13956	11552
R^2	1.85%	3.06%	3.57%	3.98%

Table 8: Explaining differences in monthly fund-level alphas

The unit of observation is the TDF offered by family i with target date j in month t. The dependent variable is either the estimated monthly α_{ijt}, or the squared deviation of α_{ijt} from the equal-weighted α of TDFs with target date j in month t. We estimate α using two different factor models. In model (1), the factors are the MSCI World Index and the Barclays Global Aggregate Bond Index. In model (2), the factors are the S&P 500 Index and the Barclays Aggregate Bond Index. We estimate both models using monthly returns over the prior 12 months. The full set of independent variables includes: a linear time trend; a post-2006 dummy variable; the natural logarithm of the total number of funds with target date j in month t; a dummy equal to one if the fund was introduced after 2006; a dummy equal to one if the fund was introduced after 2006 *and* the fund family entered the TDF market after 2006; the fund-level expense ratio measured in month $t-1$; the natural logarithm of fund-level assets under management in month $t-1$; and the fund's age in month t. We also control for target-date fixed effects (i.e., 2005, ..., 2045, and 2050). The sample includes all TDFs with target dates between 2005 and 2050 for which we observe the dependent and independent variables. Estimation is via OLS. Standard errors are simultaneously clustered on mutual fund family and month. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	α_{ijt}		$(\alpha_{ijt}-\bar{\alpha}_{jt})^2$	
Factors:	Global	US	Global	US
Model:	(1)	(2)	(1)	(2)
Linear time trend	-0.003	-0.005	-0.012^{**}	-0.015^{**}
	(0.010)	(0.012)	(0.006)	(0.007)
2007, 2008, or 2009?	0.129	-0.054	0.128	0.167
	(0.227)	(0.250)	(0.105)	(0.117)
Ln Total Number of Funds	0.047	0.253	0.471^{***}	0.576^{**}
with TD j in month t	(0.357)	(0.491)	(0.180)	(0.234)
Fund introduced after 2006?	0.214^{**}	0.085	-0.141	-0.149
	(0.109)	(0.113)	(0.091)	(0.108)
Fund introduced by family	-0.164^{***}	-0.192^{***}	0.543^{***}	0.630^{***}
introducing TDFs after 2006?	(0.051)	(0.044)	(0.148)	(0.182)
Lagged expense ratio	-0.104^{**}	-0.164^{**}	-0.028	-0.051
	(0.065)	(0.065)	(0.141)	(0.157)
Ln fund size measured	-0.027^{***}	-0.034^{**}	-0.060^{**}	-0.065^{**}
in month $t-1$	(0.005)	(0.015)	(0.026)	(0.029)
Fund age measured in month t	0.018^{**}	0.013^{**}	0.013	0.012
	(0.008)	(0.006)	(0.012)	(0.013)
Target date fixed effects?	Yes	Yes	Yes	Yes
Standard error clustering:	Family & Month	Family & Month	Family & Month	Family & Month
N	9735	9735	9735	9735
R^2	0.68%	0.68%	4.57%	5.31%

Table 9: Explaining the allocation to equity

The unit of observation is the TDF offered by family i with target date j in month t, but the sample is restricted to December 2000, December 2001, etc. The dependent variable is the fraction of the TDF's portfolio that is allocated to equity, as reported in CRSP. The full set of independent variables includes: a linear time trend; a post-2006 dummy variable; the natural logarithm of the total number of funds with target date j in month t; a dummy equal to one if the fund was introduced after 2006; a dummy equal to one if the fund was introduced after 2006 *and* the fund family entered the TDF market after 2006; the fund-level expense ratio measured in month $t-1$; the natural logarithm of fund-level assets under management in month $t-1$; and the fund's age in month t. We also control for target-date fixed effects (i.e., 2005, ..., 2045, and 2050). The sample includes all TDFs with target dates between 2005 and 2050 for which we observe the dependent and independent variables. Estimation is via OLS. Standard errors are simultaneously clustered on mutual fund family and month. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	Equity$_{ijt}$			
Linear time trend	-0.101	-0.153^{*}	-0.148^{*}	-0.060
	(0.068)	(0.085)	(0.081)	(0.047)
2007, 2008, or 2009?	3.498	3.863	3.637	7.072^{***}
	(3.765)	(3.078)	(2.895)	(2.038)
Ln Total Number of Funds		2.844	2.808	-1.837^{***}
with TD j in month t		(3.350)	(3.264)	(0.608)
Fund introduced after 2006?		-2.246	-5.661^{***}	-8.769^{***}
		(2.347)	(1.434)	(1.447)
Fund introduced by family			4.469^{*}	5.225^{***}
introducing TDFs after 2006?			(2.658)	(1.845)
Lagged expense ratio				2.191
				(3.957)
Ln fund size measured				0.184
in month $t-1$				(0.467)
Fund age measured in month t				-0.933^{**}
				(0.406)
Target date fixed effects?	Yes	Yes	Yes	Yes
Standard error clustering:	Family & Year	Family & Year	Family & Year	Family & Year
N	1227	1227	1227	896
R^2	58.47%	58.80%	59.23%	60.65%

Table 10: Explaining the level of CAPM Beta

The unit of observation is the TDF offered by family i with target date j in month t, but the sample is restricted to December 2000, December 2001, etc. The dependent variable is estimated using the CRSP value-weighted index and monthly returns over the prior 12 months. The full set of independent variables includes: a linear time trend; a post-2006 dummy variable; the natural logarithm of the total number of funds with target date j in month t; a dummy equal to one if the fund was introduced after 2006; a dummy equal to one if the fund was introduced after 2006 *and* the fund family entered the TDF market after 2006; the fund-level expense ratio measured in month $t-1$; the natural logarithm of fund-level assets under management in month $t-1$; and the fund's age in month t. We also control for target-date fixed effects (i.e., 2005, ..., 2045, and 2050). The sample includes all TDFs with target dates between 2005 and 2050 for which we observe the dependent and independent variables. Estimation is via OLS. Standard errors are simultaneously clustered on mutual fund family and month. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	CAPM Beta$_{ijt}$			
Linear time trend	0.002***	0.001	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)
2007, 2008, or 2009?	−0.034	−0.038	−0.039	−0.033
	(0.039)	(0.034)	(0.034)	(0.036)
Ln Total Number of Funds		0.045	0.044	0.050
with TD j in month t		(0.035)	(0.034)	(0.033)
Fund introduced after 2006?		−0.012	−0.039***	−0.068***
		(0.020)	(0.013)	(0.019)
Fund introduced by family			0.034	0.034*
introducing TDFs after 2006?			(0.021)	(0.018)
Fund age measured in month t				−0.012***
				(0.004)
Lagged expense ratio				0.066
				(0.045)
Ln fund size measured				0.009
in month $t-1$				(0.005)
Target date fixed effects?	Yes	Yes	Yes	Yes
Standard error clustering:	Family & Month	Family & Month	Family & Month	Family & Month
N	1058	1058	1058	919
R^2	67.39%	67.60%	67.75%	68.07%

Table 11: Flow-performance sensitivity

The unit of observation is the TDF offered by family i with target date j in month t, but the sample is restricted to December 2000, December 2001, etc. The dependent variable is estimated percentage net flow, measured over the three years or one year ending in December of year t. The full set of independent variables includes: the natural logarithm of the total number of funds with target date j in December of year t; the compounded total TDF return, measured over a three year period ending in December of year t or December of year $t-1$; the compounded TDF alpha, measured over the same three year period; a dummy equal to one if the fund was introduced after 2006; the fund-level expense ratio measured in year t (reported by CRSP); the fund-level management fee measured in year t (hand collected from prospectuses); the average expense ratio of the underlying funds in year t (hand collected from prospectuses); the natural logarithm of the fund assets in December of year $t-3$ or December of year $t-1$; and the fund age measured in December of year t. We control for both year fixed effects and target-date fixed effects. The sample includes all TDFs with target dates between 2005 and 2050 for which we observe the dependent and independent variables. Estimation is via OLS. Standard errors are clustered on mutual fund family. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	Net Flow into TDF_{ij}, Years $t-2$ to t			Net Flow into TDF_{ij}, Year t
Ln Total Number of Funds with TD j in year t	1.206	1.862	0.324	0.213
	(1.194)	(1.086)	(1.305)	(0.189)
Cumulative 3-year total return, $t-2$ to t	2.136	2.743	0.554	
	(1.789)	(1.944)	(1.779)	
Cumulative 3-year alpha, $t-2$ to t	7.761***	6.075**	6.270***	
	(1.813)	(2.833)	(2.122)	
Cumulative 3-year total return, $t-3$ to $t-1$				−0.327
				(0.307)
Cumulative 3-year alpha, $t-3$ to $t-1$				5.106***
				(1.458)
Fund introduced after 2006?	−1.334***	−1.166***	−1.191**	0.015
	(0.344)	(0.359)	(0.421)	(0.211)
Expense ratio in year t		−0.403		
		(0.286)		
Management fee in year t			−1.360*	−0.116
			(0.671)	(0.277)
Expense ratio of underlying funds in year t			−1.621	−0.213
			(0.992)	(0.328)
Ln fund size measured in year $t-3$	−0.085	−0.100*	−0.160***	
	(0.050)	(0.057)	(0.053)	
Ln fund size measured in year $t-1$				−0.006
				(0.031)
Fund age measured in month t	−0.102***	−0.076**	−0.095**	0.004
	(0.027)	(0.034)	(0.035)	(0.013)
Calendar year fixed effects?	Yes	Yes	Yes	Yes
Target date fixed effects?	Yes	Yes	Yes	Yes
Standard error clustering:	Family	Family	Family	Family
N	293	249	246	165
R^2	45.42%	45.21%	48.86%	46.70%

Table 12: BrightScope Sample

We obtained data on 16,766 investment menus from BrightScope, Inc. The unit of observation is retirement plan i offered by firm j in industry k in 2010. The sample is limited to single-employer 401(k) and 403(b) retirement plans. Plan-level characteristics include assets under management (across all investment options), the number of participants with positive account balances, the age of the plan in years, and dummy variables indicating whether the plan is less than 4 years old, whether the plan is a 401(k) plan, whether the plan offers auto enrollment, whether the plan is classified as participant directed, whether the plan offers company stock as an investment option, whether the plan offers any mutual funds as investment options, whether the plan offers mutual funds, separate accounts, or collective trusts that behave like TDFs, and whether the plan offers mutual fund TDFs. We report several measures of firm risk. For those firms with publicly-traded equity, we estimate a CAPM beta. In addition, we report the standard deviation of actual monthly returns (over the past 36 months), the standard deviation of predicted monthly returns (based on the CAPM beta and return on the market portfolio), and the standard deviation of the residual monthly returns. To determine the industry-level CAPM beta, we assign each firm the median CAPM beta of the sample of publicly-traded firms that share the same first 3 digits of the North American Industrial Classification System (NAICS). To measure mutual fund risk, we use the CAPM beta. We report estimated betas separately for TDFs with target retirement dates of 2010, 2020, 2030, 2040, and 2050, for the full sample of TDFs, and for the sample of non-TDFs. The number of observations varies both because not all plans offer TDFs and because not all investment options could be matched to the CRSP mutual fund database.

Dependent variable:	N	Mean	Std. Dev.	Min	Max
Plan characteristics					
Assets (in millions)	16,766	134.62	708.67	0.01	36,741.60
Number of participants (in thousands)	16,766	2.00	8.08	0.00	306.61
Plan age in years	16,766	22.94	13.45	0.00	95.00
Plan age $\leq$ 3 years?	16,766	0.03	0.18	0.00	1.00
401(k) plan?	16,766	0.91	0.29	0.00	1.00
Auto enrollment?	16,766	0.23	0.42	0.00	1.00
Participant directed?	16,766	0.68	0.47	0.00	1.00
Offer company stock?	16,766	0.13	0.33	0.00	1.00
Offer any mutual funds?	16,766	0.85	0.36	0.00	1.00
Offer any TDFs?	16,766	0.66	0.47	0.00	1.00
Offer mutual fund TDFs?	16,766	0.50	0.50	0.00	1.00
Measures of firm risk					
CAPM beta (firm-level)	1,680	1.27	0.81	-1.00	7.41
Standard deviation of total returns	1,680	0.15	0.08	0.04	1.04
Standard deviation of predicted returns	1,680	0.08	0.05	0.00	0.45
Standard deviation of residual returns	1,680	0.12	0.07	0.03	0.93
CAPM beta (industry-level)	16,301	1.11	0.43	0.19	2.28
Measures of mutual fund risk					
CAPM beta of 2010 TDF	7,240	0.63	0.07	0.40	0.89
CAPM beta of 2020 TDF	7,924	0.78	0.06	0.63	1.00
CAPM beta of 2030 TDF	7,718	0.91	0.04	0.76	1.03
CAPM beta of 2040 TDF	7,852	0.96	0.04	0.85	1.04
CAPM beta of 2050 TDF	6,658	0.98	0.04	0.87	1.04
Average CAPM beta of mutual fund TDFs	8,278	0.79	0.06	0.32	1.02
Average CAPM beta of other mutual funds	14,079	0.84	0.14	-1.69	1.51

Table 13: Explaining TDF risk with retirement plan and firm characteristics

The unit of observation is the single-employer defined contribution retirement plan i offered by firm j in industry k in 2010. The dependent variable measures the risk of the 2020 TDF in plan i. It is either the TDF's CAPM beta estimated using monthly returns through December 2009, or the standard deviation of the TDF's idiosyncratic monthly returns. The independent variables of interest are measures of firm or industry risk that are measured in the same way as the dependent variable. Other independent variables include: the natural logarithm of retirement plan i assets at the end of 2010; the natural logarithm of the number of plan i participants at the end of 2010; a dummy equal to one if plan i has auto enrollment; a dummy equal to one if plan i offers company stock; and the average CAPM beta of non-TDF mutual funds in plan i. In some specifications, we include a separate fixed effect for each of the 70 industries (defined by the first three digits of the NAICS). Estimation is via OLS. Standard errors are clustered on industry. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	Risk of 2020 TDF in plan i					
Measure of risk:	CAPM Beta			Std. dev. of idiosyncratic returns		
Firm risk	−0.002	−0.001		−0.048	−0.011	
	(0.003)	(0.004)		(0.046)	(0.054)	
Median firm risk within industry			0.014**			0.037
			(0.005)			(0.047)
Ln plan assets	−0.010***	−0.011***	−0.012***	−0.023***	−0.023***	−0.015***
	(0.003)	(0.003)	(0.001)	(0.007)	(0.008)	(0.003)
Ln number of participants	0.008**	0.009**	0.006***	0.012*	0.012	0.009***
	(0.003)	(0.003)	(0.001)	(0.006)	(0.009)	(0.002)
Auto enrollment?	−0.004	−0.004	−0.001	0.003	0.002	0.006**
	(0.004)	(0.004)	(0.002)	(0.007)	(0.007)	(0.003)
Offer company stock?	−0.001	−0.004	0.006*	0.007	0.008	−0.006
	(0.005)	(0.005)	(0.003)	(0.007)	(0.007)	(0.004)
Average risk of non-TDFs	0.038*	0.032	0.013	−0.018	−0.311	1.55***
	(0.022)	(0.023)	(0.021)	(0.62)	(0.707)	(0.381)
Constant	0.895***	0.901***	0.926***	1.010***	1.017***	0.786***
	(0.040)	(0.046)	(0.020)	(0.094)	(0.101)	(0.055)
Industry fixed effects?	No	Yes	No	No	Yes	No
Standard error clustering?	Industry	Industry	Industry	Industry	Industry	Industry
N	872	872	7,320	872	872	7,320
Adj. R^2	2.16%	5.10%	4.43%	3.91%	8.00%	3.76%