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ABSTRACT

This paper studies the evolution of the market for target-date funds (TDFs) between 1994 and 2009. We document pronounced heterogeneity in the TDF universe: TDFs with the same target date have delivered very different returns because of differences in systematic risk in the stock allocations, and because of differences in the stock versus bond allocations. This heterogeneity has increased over time, especially after the passage of the Pension Protection Plan of 2006. Indeed, we can attribute the increased heterogeneity in TDFs to the entry of new fund families in the TDF market between 2007 and 2009. These developments in the TDF market are consistent with new entries in the market adopting a product-differentiation strategy. Our findings suggest that the widespread adoption of TDFs will not result in returns that are similar across investors enrolled in different 401(k) plans, and that the current proposals for further disclosure in TDF offerings may have little impact on the incentive for fund families to offer similar risk profiles.

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1 Introduction

In his seminal article, 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 (the "tangency" portfolio) and an intertemporal component (the "hedging" demand). As Balduzzi and Lynch (1999), Lynch (2001), and others demonstrate, the time-series properties of U.S. stock returns are such that a long-term investor should allocate a larger fraction of her wealth to stocks than a short-term investor. In this case, the hedging demand for equities is positive and decreases as the investor ages.[1] In addition, as Jagannathan and Kocherlachota (1996) and Cocco et al. (2005) argue, young investors can expect to receive a long stream of bond-like labor income. As they age, this stream shortens, and the value of their human capital falls. Optimally, investors should respond to the declining value of their human capital by shifting their financial wealth away from stocks and toward bonds.[2]

In summary, there are good reasons for investors to reduce their equity exposure as they age. This basic implication from optimal portfolio theory has found its way into the design of investment products: target-date mutual funds (TDFs).[3] Wells Fargo introduced the first target-date mutual funds 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."[4] For example, investors who planned to retire in 2030 were

[1]The same implication holds in the static portfolio setting of Barberis (2000), where parameter uncertainty is also accounted for.

[2]Bodie et al. (1992) note that individuals may have some ability to change their supply of labor in response to realized returns on their assets. For most individuals, the degree of labor flexibility is likely to diminish over the life cycle, and this would also lead to more conservative investment behavior as retirement nears.

[3]Note, though, that some authors have qualified this implication. Benzoni et al. (2007) note that when labor income and dividends are co-integrated, the pattern of equity holdings over the life-cycle should be hump-shaped, rather than monotonically decreasing. Pastor and Stambaugh (2011) argue that in the presence of parameter uncertainty and imperfect predictability, the equity allocation of an optimal TDF should depend not only on the remaining time until retirement, but also on the initial length of the investor's horizon.

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

encouraged to invest all of their 401(k) assets in the Wells Fargo LifePath 2030 fund. The innovation, relative to traditional balanced mutual funds, was that target-date funds relieved investors of the need to make asset allocation decisions: when the target date is far away, the TDF invests primarily in risky assets, like domestic and foreign equity and, as the number of years to the target date declines, the TDF automatically reduces its exposure to risk.[5] 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 retirement plans.

In this paper, we study the evolution of the market for TDFs between 1994 and 2009. The first objective is to measure heterogeneity in the performance and investment decisions of TDFs. Since defined contribution retirement plans are likely to 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 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 were 74 TDFs with target dates of 2015 or 2020. The average annual return was 25.2%, the cross-sectional standard deviation was 4.3%, and the range (the difference between the maximum and minimum return) was 23.5%. Some investors earned an annual return of 35.4% while other investors, investing in a different TDF with the same target date, only earned 12.0%. Turning to asset allocations, the average allocation to equity was 63.7%, with a standard deviation of 13.6%, and a range

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

of 69.8%. We find a similarly substantial dispersion in equity market exposures: the average "CAPM" beta was 0.75, the cross-sectional standard deviation was 0.11, and the range was 0.49. Our findings demonstrate that TDFs with similar target dates can follow significantly different investment strategies. If regulators assumed that TDFs with the same target date would provide investors with similar exposure to risk, the assumption is questionable.

The second objective of the study is to quantify the impact 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. Consequently, the PPA created an 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 funds offering TDFs jumped from 27 to 44.

We ask whether the increased volatility in TDF returns following the passage of the PPA reflects the incentive for new entrants to differentiate their TDFs from established TDFs. We find robust evidence that the answer is yes. 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 75 to 78 basis points (approximately 9% annually).

The patterns that we document are consistent with Carpenter and Nakamoto's (1989) discussion of effective marketing strategies in the presence of first-movers or "pioneers." They argue that "me-too" strategies, strategies close to those of the pioneers, are unlikely to succeed if the ideal attribute combination—in our setting, the asset allocation and security selection of a TDF—is ambiguous. Instead, new entrants should segment the market by offering differentiated products.

Consistent with their prediction, we find strong evidence that competition for TDF investors drives heterogeneity in TDF investment behavior and performance. Importantly, this heterogeneity undermines the assumption that investors only need to know their target retirement date to pick an appropriate long-term retirement investment vehicle—an assumption underlying the use of target-date funds as default investment vehicles.[6]

The remainder of the paper is organized as follows: Section 2 provides some institutional background on the market for TDFs and a brief review of the related literature. Section 3 describes the data used in the study. Section 4 documents cross-sectional differences in annual returns, CAPM betas, and asset allocation. It also describes the regressions used to further investigate the sources of the cross-sectional dispersion of returns. Section 5 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 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

[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, our findings show that increased competition leads to more obfuscation overall, and, in particular, on the part of the new entrants in the market.

[7] The tendency of investors to stick to their default investment allocation (i.e., inertia), has been documented by Agnew, Balduzzi, and Sundén (2003), among others.

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 is an open question, but the two approaches highlight a significant source of heterogeneity in how TDFs are constructed. At a minimum, Fidelity's approach may make it harder for investors to infer the TDFs broad allocations to domestic equity, international equity, and debt.

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

[8] The Appendix presents a detailed description of the PPA together with a selection of quotes on the pros and cons of TDFs.

[9] The forecast comes from the Financial Research Corporation's study "Rethinking Lifecycle Funds," released on May 20, 2010.

primarily compares TDFs to other investment vehicles.[10] The paper most closely related to our own is Sandhya (2010), who compares TDFs to balanced funds offered within the same mutual fund family. While Sandhya (2010) 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, our sample includes all TDFs, not just those belonging to families that also offer balanced funds.[11]

3 Data

We obtain data on mutual fund names, characteristics, fees, and monthly returns from the CRSP Survivor-Bias-Free US 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 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.[12] To calculate a fund's age, we use the number of

[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 defined contribution 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.

[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 the presence of alphas and idiosyncratic risk.

[12] Note that because expense ratios for TDFs do not reflect the expense ratios of underlying mutual fund investments, they offer an incomplete measure of total investor expenses.

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.

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 between 2006 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.

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 returns, reported allocations to equity, and CAPM betas.

4.1.1 Cross-sectional dispersion of TDF returns

Table 2 documents the 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 sample, 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 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

[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.

[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.

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 in the allocation to equity

Table 3 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-cap 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, the broad stock versus bond allocation of a TDF does not appear to be a sufficient statistic for the risk of the investment.

4.1.3 Cross-sectional dispersion of CAPM betas

We first 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 4 presents the results of the analysis. Two patterns in the table 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 0.61 in 2000 to 0.75 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 4 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:

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

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:

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

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 5.

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 16.7% and 30.0%, and Market Dispersion ranges between 16.3% and 29.9%. However, there remains significant Fund Dispersion. Fund Dispersion ranges from 2.7% for 2035–2040 funds to 3.8% 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 14.6% and Fund Dispersion is 5.0%. In contrast, for S&P 500 index funds, Total Dispersion is 21.9% and Fund Dispersion is 0.3%. 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. Finally, 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).

Next, we turn to the equity allocation. Unlike returns, the variance decomposition in Table 5 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 8.2% and 14.1%, and Fund Dispersion ranges between 8.1% and 13.6%. Market Dispersion, on the other hand, only ranges between 1.6% and 3.7%. Hence, the breakdown of the overall dispersion in TDF equity allocations is quite comparable to that for Balanced Funds: 12.1%, 2.1%, and 11.9%, 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 0.08 and 0.13, and Fund Dispersion ranges between 0.07 and 0.12. Market Dispersion ranges between 0.03 and 0.06, 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: 0.17, 0.04, and 0.17, for Total Dispersion, Market Dispersion, and Fund Dispersion, respectively. In summary, this analysis confirms the impression given by Tables 2–4 that the heterogeneity in TDF returns has little to do, on average, with the heterogeneity in broad asset allocation choices.

4.3 Explaining realized returns using glide paths

It is natural to ask how much of the cross-sectional variation in returns can be explained by heterogeneity in equity allocations, i.e., heterogeneity in glide paths. We construct benchmark returns for each TDF based on that TDF's equity allocation and based on the returns on broad equity and bond indices and a cash index. We consider two choices of benchmarks: the MSCI World Index, the Barclays Global Aggregate Bond Index, and the J.P. Morgan US Cash Index; and the S&P 500 Index, the Barclays Aggregate Bond Index, and the J.P. Morgan US Cash Index. For each year and each target date, we run a *pooled* regression of the monthly TDF return r_{ijt} on a constant and the return on the benchmark corresponding to that TDF, where both the TDF and the benchmark returns are in deviations from the cross-sectional average for that month.[15] R-squareds of the regressions are reported in Table 6. To the extent that TDFs are investing in these indices, R-squareds should be close to one.

We find pronounced heterogeneity in the cross-sectional R-squareds, although, across target dates, we also see an overall upward trend. Consider the first choice of benchmarks. The cross-sectional R-squared is as low as 0.05% for 2035–2040 funds in 2000; and as high as 53.69% for

[15] This is equivalent to running a *panel* regression with a separate month fixed effect for each target date.

2035–2040 funds in 2009. When we average across all target dates and years, we have an average cross-sectional R-squared of 41.66%. Results are somewhat different, but comparable, overall, for the second choice of benchmarks. In this case, the cross-sectional R-squared is as low as 0.07% for 2035-2040 funds in 2000; and as high as 67.51% for 2005–2010 funds in 2006. The average cross-sectional R-squared is 35.54% for this second choice of indices.

4.4 Regression analysis

In this section, we perform a series of regression exercises to 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.

4.4.1 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 other regression models, 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 four 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 other regression models, we control for target date fixed effects (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

[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.

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 75 and 77 basis points—between 9.00% and 9.27% 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 strategies than incumbent families introducing new TDFs. Not surprisingly, the fit of the various specifications is rather poor—we are essentially modeling monthly returns in deviation from the cross-sectional average—ranging between 1.79% and 3.96%.

4.4.2 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: we estimate the index model with data up to month t and then we construct the alpha going one month out of sample.[18]

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

[18] 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

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: about 16 basis points per month, or about 1.9% per year. Moreover, these funds have alphas that deviate from the cross-sectional average more than the other new funds: between 74 and 77 basis points per month, or between 8.86% and 9.27% per year. As with the model of the previous section, the fit of the various specifications is rather poor, ranging between 0.72% and 5.50%.

4.4.3 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.[19]

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 2.18% and 8.80%, depending on the specification—new funds introduced by a fund family new to the TDF market have *higher* allocations to equities—between 4.59% and 5.42%. This suggests that new entrants are exposing TDF investors to more market risk than existing firms, perhaps with the goal of attracting investors who focus on raw rather than risk-

and the Barclays Aggregate Bond Index. Both specification are estimated using monthly returns over the prior 12 months. Again, returns are in excess of the one-month T-bill rate posted on Ken French's website.

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

adjusted performance.

4.4.4 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.

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.

5 Conclusions

We document pronounced heterogeneity in the TDF universe: TDFs with the same target date have delivered very different returns to investors. This heterogeneity has increased over time, especially after the passage of the PPA of 2006. Indeed, we can attribute the increased heterogeneity to the entry of new mutual fund families in the TDF market during the 2007–2009 period. These patterns are consistent with new entrants adopting a product-differentiation strategy. Instead of offering TDFs with the same risk profile as the TDFs offered by incumbents (and, therefore, being forced to compete on fees), the late entrants introduced TDFs with different risk profiles. Moreover, if we view the deviation of a TDF's return from the average TDF return as a measure of obfuscation, our findings show that increased competition leads to more obfuscation overall, and, in particular, on the part of the new entrants in the market. 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 30, 2010, regulation was proposed to increase investor understanding of how TDFs operate. Specifically, TDFs are 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; i) 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.[20]

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 a suboptimal set of retirement savings options. 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.

[20] DOL: EBSA Federal Register: 29 CFR Part 2550, October 20, 2010.

Appendix: Overview of the Pension Protection Act of 2006

The PPA of 2006 amends Title I of the Employee Retirement Income Security Act of 1974, providing reform for deferred compensation plans for highly compensated employees, for defined benefit (DB) retirement plans regarding contribution and funding requirements, and for defined contribution (DC) retirement plans regarding catch up limits, contribution limits, and automatic enrollment plans. With respect to the automatic enrollment feature of DC retirement plans, the PPA of 2006 relieves fiduciaries of liability for investment losses when they default plan participants into QDIAs, given that they adhere to conditions specified by the DOL's Employee Benefits Security Administration (EBSA).[21] However, plan sponsors and fiduciaries will not be relieved of liability for the prudent selection and monitoring of a QDIA.

The PPA of 2006 was "prompted by the default in recent years of several large defined benefit pension plans and the increasing deficit of Pension Benefit Guaranty Corporation (PBGC)."[22] The PBGC, founded in 1975, was created to insure companies with DB pension plans, providing guarantees to employees of those companies that their pensions would be safe. Since its creation, the PBGC faced several pension claims. However, of the ten largest pension claims against the PBGC, nine occurred between 2001 and 2005.[23] Examples of defaulting firms include: Bethlehem Steel in 2002, for which PBGC insured approximately 95,000 pensions; National Steel in 2003, for which PBGC insured approximately 35,000 pensions; and United Airlines in 2005, for which PBGC assumed responsibility for approximately 134,000 pensions.

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

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

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.[24] The final ruling was passed by the House on July 28, 2006, passed by the Senate on August 3, 2006, and signed into law on August 17, 2006.

A.1 Time line of the Pension Protection Act of 2006

1. 7/28/2006 Introduced in House.
2. 7/28/2006 Passed/agreed to in House.
3. 8/3/2006 Passed in Senate without amendment by Yea-Nay Vote.
4. 8/3/2006 Cleared for White House.
5. 8/14/2006 Presented to President.
6. 8/17/2006 PPA signed by President and became public law No. 109-280.
7. 9/27/2006 DOL proposed rules regarding "Default Investment Alternatives Under Participant Directed Individual Account Plans" to define which investment vehicles are appropriate default investments.
8. 10/24/2007 DOL made final ruling on regulations for the proposed rules.
9. 12/24/2007 Final rule was effective.

[24] Congressional Research Service Report for Congress, October 23, 2006.

A.2 DC Plans and automatic enrollment: QDIAs

According to U.S. Secretary of Labor, Elaine L. Chao, the PPA of 2006 "would boost retirement savings by establishing default investments for these workers that are appropriate for long-term savings."[25] QDIAs are those investment vehicles into which firms can default participants (who do not actively choose their own investment vehicles) without being liable for investment losses. QDIAs must:[26]

1. Be diversified to decrease probability of large losses.
2. Be managed by an investment manager/company registered under the Investment Company Act of 1940.
3. Not penalize or prevent a participant from transferring their assets from a QDIA to another investment alternative available under the plan.
4. Not invest participant contributions directly in employer securities. Potential QDIAs include TDFs, balanced funds, and professionally managed accounts.

A.3 Quotes 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

[25] DOL: EBSA Newsroom, September 26, 2006.
[26] DOL: EBSA Federal Register: 29 CFR Part 2550, October 24, 2007.

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

- “Challenges ... exist in getting disengaged participants to read and fully digest any information provided to them.” 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

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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 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. 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 4: 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 5: Decomposition: total dispersion, market dispersion, and fund dispersion

In this table, we measure dispersion in annual returns, 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. 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. For comparison, we perform a similar decomposition for the universe of traditional balanced funds, and for S&P 500 index funds.

	Annual Return			Allocation to Equity			CAPM Beta		
	Total	Market	Fund	Total	Market	Fund	Total	Market	Fund
Target Date Funds									
2005 & 2010 TDFs	16.7%	16.3%	3.8%	14.1%	3.7%	13.6%	0.13	0.06	0.12
2015 & 2020 TDFs	20.8%	20.5%	3.6%	12.7%	3.8%	12.1%	0.12	0.05	0.11
2025 & 2030 TDFs	23.7%	23.5%	3.0%	10.5%	3.6%	9.9%	0.11	0.05	0.10
2035 & 2040 TDFs	25.6%	25.4%	2.7%	8.6%	2.2%	8.4%	0.09	0.04	0.08
2045 & 2050 TDFs	30.0%	29.9%	3.1%	8.2%	1.6%	8.1%	0.08	0.03	0.07
Balanced Funds	14.6%	13.7%	5.0%	12.1%	2.1%	11.9%	0.17	0.04	0.17
S&P 500 Index Funds	21.9%	21.8%	0.3%	2.7%	0.0%	2.7%	0.07	0.05	0.04

Table 6: Explaining realized returns using glide paths

In this table, we report R^2-s from pooled regressions of realized monthly returns on predicted monthly returns, where both realized and predicted returns are in deviations from the cross-sectional average for that month. The unit of observation is TDF i with target date j in month t. The predicted monthly return for fund i in month t is calculated using the fund's allocations to equity, debt, and cash (as most recently reported in CRSP), and monthly benchmark returns for each asset class. (The only TDFs that we exclude from this analysis are those for which we do not observe the allocation to equity, debt, and cash.) In Panel A, our benchmarks for equity and debt are the MSCI World Index and the Barclays Global Aggregate Bond Index, respectively. In Panel B, we switch to the S&P 500 Index and the Barclays Aggregate Bond Index. In both panels, our benchmark for cash is the J.P. Morgan US Cash Index. In most regressions, our sample is restricted to the subset of TDFs in a single calendar year (e.g., TDFs with target dates of 2015 or 2020 that are in operation during any part of 2004).

Panel A. Predicting monthly TDF returns using international benchmarks

	2005 & 2010	2015 & 2020	2025 & 2030	2035 & 2040	2045 & 2050	ALL
2000	13.08%	27.90%	35.40%	0.05%		22.66%
2001	5.30%	11.22%	16.60%	0.18%		8.46%
2002	10.21%	10.13%	9.78%	12.45%		10.25%
2003	2.14%	6.23%	21.36%	25.42%		8.89%
2004	12.58%	14.06%	30.56%	33.17%		18.05%
2005	11.09%	11.67%	15.48%	14.03%	7.56%	12.65%
2006	38.50%	45.50%	50.62%	48.52%	39.59%	44.91%
2007	39.80%	37.22%	37.30%	36.81%	42.32%	38.12%
2008	44.48%	49.07%	49.59%	45.70%	39.86%	46.22%
2009	40.29%	49.54%	52.78%	53.69%	53.28%	49.86%
ALL	35.00%	42.97%	44.95%	43.35%	43.32%	41.66%

Panel B. Predicting monthly TDF returns using domestic benchmarks

	2005 & 2010	2015 & 2020	2025 & 2030	2035 & 2040	2045 & 2050	ALL
2000	39.59%	41.70%	37.31%	0.07%		35.71%
2001	35.71%	37.40%	29.57%	0.51%		32.21%
2002	60.08%	39.72%	25.72%	23.49%		35.11%
2003	28.20%	45.40%	44.87%	39.39%		39.09%
2004	64.55%	37.19%	29.98%	18.90%		31.73%
2005	58.97%	38.69%	33.95%	24.95%	9.99%	33.05%
2006	67.51%	54.61%	40.49%	33.80%	24.21%	44.86%
2007	64.93%	51.86%	38.57%	33.21%	34.31%	42.45%
2008	54.66%	45.12%	33.89%	25.43%	20.84%	34.88%
2009	65.60%	58.29%	44.48%	36.93%	34.81%	45.50%
ALL	52.44%	44.79%	34.42%	27.57%	24.25%	35.54%

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., 2000, 2005, . . . , 2045, and 2050). The sample includes all TDFs 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	−0.006
	(0.004)	(0.007)	(0.007)	(0.009)
2007, 2008, or 2009?	0.332*	0.114	0.087	0.169
	(0.189)	(0.171)	(0.171)	(0.168)
Ln Total Number of Funds		0.513*	0.548**	0.411
with TD j in month t		(0.266)	(0.268)	(0.298)
Fund introduced after 2006?		0.488**	0.016	−0.128
		(0.201)	(0.109)	(0.144)
Fund introduced by family			0.598**	0.563***
introducing TDFs after 2006?			(0.234)	(0.212)
Fund age measured in month t				0.010
				(0.020)
Lagged expense ratio				0.196
				(0.270)
Ln fund size measured				−0.061
in month $t-1$				(0.038)
TD fixed effects?	Yes	Yes	Yes	Yes
Standard error clustering:	Family & Month	Family & Month	Family & Month	Family & Month
N	13956	13956	13956	11534
R^2	1.79%	3.03%	3.52%	3.96%

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., 2000, 2005, ..., 2045, and 2050). The sample includes all TDFs 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	-0.004	0.000	-0.012^{**}	-0.013^{**}
	(0.009)	(0.007)	(0.006)	(0.006)
2007, 2008, or 2009?	0.121	-0.130	0.120	0.132
	(0.227)	(0.124)	(0.104)	(0.095)
Ln Total Number of Funds	0.072	0.093	0.473^{***}	0.522^{**}
with TD j in month t	(0.342)	(0.255)	(0.172)	(0.213)
Fund introduced after 2006?	0.212^{*}	0.087	-0.145	-0.168^{*}
	(0.109)	(0.057)	(0.090)	(0.098)
Fund introduced by family	-0.154^{***}	-0.168^{***}	0.545^{***}	0.597^{***}
introducing TDFs after 2006?	(0.051)	(0.039)	(0.148)	(0.161)
Fund age measured in month t	0.017^{**}	0.011^{**}	0.014	0.015
	(0.007)	(0.005)	(0.012)	(0.012)
Lagged expense ratio	-0.106^{***}	-0.164^{***}	-0.037	-0.060
	(0.024)	(0.024)	(0.138)	(0.132)
Ln fund size measured	-0.027^{***}	-0.027^{***}	-0.060^{**}	-0.069^{**}
in month $t-1$	(0.004)	(0.009)	(0.027)	(0.028)
TD fixed effects?	Yes	Yes	Yes	Yes
Standard error clustering:	Family & Month	Family & Month	Family & Month	Family & Month
N	9732	9732	9732	9732
R^2	0.72%	1.11%	4.63%	5.50%

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., 2000, 2005, ..., 2045, and 2050). The sample includes all TDFs 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	-0.105	-0.143^{*}	-0.138^{*}	-0.050
	(0.069)	(0.080)	(0.077)	(0.048)
2007, 2008, or 2009?	3.881	4.327	4.098	7.883^{***}
	(3.893)	(3.273)	(3.094)	(2.423)
Ln Total Number of Funds		2.156	2.136	-2.743^{***}
with TD j in month t		(3.235)	(3.170)	(0.678)
Fund introduced after 2006?		-2.184	-5.667^{***}	-8.798^{***}
		(2.405)	(1.446)	(1.368)
Fund introduced by family			4.591^{*}	5.424^{***}
introducing TDFs after 2006?			(2.712)	(1.977)
Fund age measured in month t				-1.023^{**}
				(0.400)
Lagged expense ratio				2.611
				(3.919)
Ln fund size measured				0.212
in month $t-1$				(0.451)
TD fixed effects?	Yes	Yes	Yes	Yes
Standard error clustering:	Family & Year	Family & Year	Family & Year	Family & Year
N	1224	1224	1224	900
R^2	58.55%	58.83%	59.28%	60.92%

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., 2000, 2005, ..., 2045, and 2050). The sample includes all TDFs 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)
TD 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%