Heterogeneity in Target-Date Funds and the Pension Protection Act of 2006*

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Abstract

This paper studies the evolution of the market for target-date funds (TDFs) during the 1994-2009 period. 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 vs. 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 to the entry of new fund families in the TDF market during the 2007-2009 period. 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.

JEL: G23
Keywords: Target-date fund, default investment, retirement savings, product differentiation, entry, regulation

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* The authors thank Lauren Beaudette and Bianca Werner for excellent research assistance. The authors also thank Jeffrey Brown, Mark Warshawsky, and participants at the 13th Annual Retirement Research Consortium Conference for useful comments. Corresponding author: Jonathan Reuter, Boston College, Carroll School of Management, Finance Department, 140 Commonwealth Avenue, Chestnut Hill, MA, 02467; e-mail: reuterj@bc.edu. This research was supported by the U.S. Social Security Administration through grant #5RRC08098400-03-00 to the National Bureau of Economic Research as part of the SSA Retirement Research Consortium. The findings and conclusions expressed are solely those of the author(s) and do not represent the views of SSA, any agency of the Federal Government, Boston College, or the NBER.

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 inter-temporal 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, Gomes, and Maenhout (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

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

[2] Bodie, Merton, and Samuelson (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) consider a setting where labor income and dividends are co-integrated. In this case, 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.

with a specific retirement date in mind."[4] For example, investors who planned to retire in 2030 were 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 Department of Labor, 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. Consider the 68 TDFs with target dates of 2015 or 2020 in 2009. The average annual return was 25.1%, the cross-sectional standard deviation was 4.4%, 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 TDF with the same target date, only earned 12.0%. We find a similarly substantial

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

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. Turning to asset allocations, the average allocation to bonds and cash was 35.3%, with a standard deviation of 16.2%, and a range of 104.4%. 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 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 76 to 77 basis points (approximately 9 percent annually). Our inference is similar when we focus on the absolute deviation of fund returns from those of the median fund, and when we focus on dispersion measured at the target-date level.

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.

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 test for changes in 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.[6] 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.

[6] 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.

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.[7]

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.[8] 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 eight low cost index funds and ETFs. Fidelity's approach, on the other hand, is to allocate investments across as many as 27 of its actively managed mutual funds. Whether one approach is better for investors than the other is an open question, but the two approaches highlight one 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 pri-

[7] The Appendix presents a detailed description of the PPA together with a selection of quotes on the pros and cons of TDFs.
[8] The forecast comes from Financial Research Corporation's study "Rethinking Lifecycle Funds," which was released on May 20, 2010.

marily compares TDFs to other investment vehicles.[9] 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 she focuses on average differences in fund expenses and returns, we focus 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.[10]

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

[9] Yamaguchi, Mitchell, Mottola, and Utkus (2007), Park and VanDerhei (2008), Park (2009), and Mitchell, Mottola, Utkus, and Yamaguchi (2009) study investor demand for the particular TDFs introduced into their samples of defined contribution retirement plans. Shiller (2008), Gomes, Kotlikoff, and Viceira (2008), and Viceira (2009) use simulations and calibrated lifecycle models to compare the properties of representative TDFs to those of other investment vehicles.

[10] Also relevant to our study is Pang and Warshawsky (2009), who use simulations to study the effect of heterogeneity in glide paths on the distribution of terminal wealth. They assume that different TDFs invest in the same three benchmarks: the S&P 500 index, the 5-year Government Bond Index, and 90-day Treasury bills. Hence, their study abstracts from other sources of heterogeneity in TDF returns, such as heterogeneity in systematic risk, under- or over-performance relative to the benchmark, and idiosyncratic risk.

by its assets under management at the beginning of the month.[11] 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.

We measure asset allocation in two ways. First, we estimate a fund's "CAPM" beta in month t using its monthly returns in months t-1 to t-24. When estimating exposure to market risk, we use the monthly value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month U.S. Treasury bill rate.[12] The need for 24 months of historical returns limits the number of funds introduced post-PPA for which we can measure beta. Second, we use the asset allocation variables in CRSP to calculate the fraction of each TDFs portfolio that is allocated to cash and bonds. (This is one minus the fraction of the portfolio allocated to common and preferred stock.)

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, 27 families entered the market between 2006 and 2009, allowing us to we 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

[11] 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 investors' expenses.
[12] We thank Kenneth French for making these data available on his website.

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

First, we study the cross-sectional properties of annual returns on the TDFs in the sample. Next, we study the cross-sectional properties of stock market exposures (CAPM betas), and allocations to cash and bonds. Finally, we study the determinants of the cross-sectional dispersion in returns at the individual fund and at the target-date levels.

4.1 Cross-sectional dispersion in annual returns

Table 2 documents the cross-sectional dispersion in realized annual returns for the TDFs in our sample. 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 5.3%. The range experienced a similar pattern. It increased from 1.1% to 23.5% between 2000 and 2009, and from 7.7% 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 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 returns across funds.[13] Consider 2003, when 2015-2020 funds delivered a return of 21.3%, on average, the third largest (in absolute value) average return of the 2000-2009 sample; the cross-sectional standard deviation was only 2.5%, and the range was 5.6%. Similarly, 2025-2030 funds delivered a return of 23.5%, on average, but the cross-sectional standard deviation and range were only 0.6% and 1.2%, respectively.

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" standard deviation for TDFs with target date *j*. 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*.[14] Second, we compute the "Across Funds" standard deviation within target date *j*. This is the variability of TDF returns around the returns of an equally-weighted portfolio of TDFs and measures the risk that investors face when choosing among different TDFs with the same target date, i.e., *fund risk*. The difference between Total and Across Funds standard deviations reflects the time-series variability of the rate of return on an equally-weighted portfolio of TDFs, i.e., *market risk*.

Looking across the four samples, we see that much of the risk associated with investing in TDFs comes from market risk. However, there remains significant fund risk. The Across

[13] 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.

[14] Total risk measures 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.

Fund standard deviations range from 2.8% for 2035-2040 funds to 3.8% for 2015-2020 funds, showing the surprising fact that there is more fund risk in TDF returns when target dates are near than when they are far.

By way of comparison, we performed a similar variance decomposition on the annual returns of balanced funds and S&P 500 index funds. For balanced funds, which arguably have more discretion over asset allocation, market timing, and security selection, the Total standard deviation is 14.6% and the Across Funds standard deviation is 5.0%. In contrast, for S&P 500 index funds, the Total standard deviation is 21.5% and the Across Funds standard deviation is 0.6%. Hence, TDFs expose investors to greater total risk than traditional balanced funds and about the same total risk as S&P 500 index funds. At the same time, the fund risk in TDFs is between that of differentiated products (traditional balanced funds) and commodities (S&P 500 index funds).

4.2 Cross-sectional dispersion in equity market exposures (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. To estimate beta, we regress the TDF's monthly excess return on the monthly excess return of the U.S. stock market. Specifically, for fund *i* in month *t*, we use monthly returns between month *t*-1 and *t*-24 to estimate the regression model:

$$r_{ijt} - r_{ft} = \alpha_{ij} + \beta_{ij}(r_{mt} - r_{ft}) + e_{ijt}, \qquad (1)$$

where r_{ft} is the rate on one-month U.S. Treasury bills in month *t*, and r_{mt} is the monthly value-weighted return on all NYSE, AMEX, and NASDAQ stocks.

Table 3 presents the results of the analysis. The reduction in sample size relative to Table

2 reflects the fact that we lack 24 monthly observations for TDFs introduced in 2008 and 2009. Two patterns in the table are noteworthy. First, for all four target dates, there is an upward trend in the average market beta. 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 0.88; for the 2035-2040 TDFs, the average beta goes from 0.83 to 0.94; 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 0.98 in 2009. These increases are noteworthy because, over time, established TDFs should *de-crease* 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 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 0.01 in 2000 to 0.07 in 2009. More significantly, the range of estimated betas goes from 0.02 to 0.30. The patterns in Table 3 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. The variance decomposition at the bottom of Table 3 suggests that most of the variation in betas is driven by across-fund variation.

4.3 Cross-sectional dispersion in cash and bond allocations

Table 4 reports summary statistics for the cross-sectional distribution of the fraction of the portfolio allocated to cash and bonds. Three patterns are worth noting: First, although we are following cross-sections of TDFs that are getting closer to their target date, there is no obvious upward trend in the average allocation to cash and bonds. For example, for the 2015-2020 target date, the average allocation to cash and bonds goes from 42.5% in 2000, to 35.3% in 2009, with upward and downward fluctuations over the sample period. Second, the cross-sectional dispersion in bond allocations is substantial. In 2009, for example, the cross-sectional standard deviation was 16.2%, 11.5%, and 8.3%, for the 2015-2020, 2025-2030, and 2035-2040 target dates, respectively. Indeed, as we found with betas, the variance decomposition at the bottom of Table 4 suggests that most of the variation in the fraction allocated to cash and bonds is driven by across-fund differences in asset allocation. Third, there is no obvious trend in the cross-sectional standard deviation of cash and bond 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 vs. growth, and large- vs. small-cap equities) and individual security selections, rather than by increasing differences in the broad asset allocation choice. Hence, the stock vs. bond allocation of a TDF is not a summary statistic for the risk of the investment.

4.4 Testing for changes in the cross-sectional dispersion of monthly returns

We now turn to investigating the individual and aggregate determinants of the cross-sectional dispersion in returns. We start by regressing measures of heterogeneity of the individual TDFs 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 two regression models:

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

and

$$\left| r_{ijt} - r_{jt}^m \right| = a_j + b' X_t + c' Y_{jt} + d' Z_{ijt} + \varepsilon_{ijt} \,, \tag{3}$$

where r_{jt}^m denotes the cross-sectional median. The X_t vector includes a time trend, and a post-2006 dummy. The Y_{jt} vector includes the log of the total number of funds with target date j in month t. The Z_{ijt} vector includes 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's age in month t, the log of the fund size in month t-1, the fund's expense ratio in month t-1, the square of the deviation of the fund's allocation to cash and bonds from the average for that target date in month t, and the absolute value of the deviation of the fund's allocation to cash and bonds from the median for that target date in month t. We control for target-date fixed effects (the intercepts in (2) and (3) are target-date specific), and standard errors are clustered either by month and fund, or by month and fund family.

Table 5 presents the regression results.[15] In the specifications that only include the linear time trend and the post-PPA dummy variable, we find that dispersion in monthly returns is significantly higher post-PPA. This is the same pattern that we found in Table 2. When we add a dummy variable indicating whether fund i was introduced after 2006, we find evidence that new funds have more volatile returns than existing funds. But, when we add a dummy variable indicating whether fund i was introduced after 2006 by a mutual fund family that only began introducing TDFs after 2006, we find that the increased volatility is driven entirely by new funds from families that are new to the market for TDFs. For example, focusing on estimates from equation (2), we find that this subset of new entrants has monthly returns that deviate between 76 and 77 basis points from the target-date average. (Because the dependent variable is the squared deviation, we estimate these effects by taking the square root of the estimated coefficients.) The implication is that families entering the market pursue more volatile investment strategies than incumbent families introducing new TDFs.

Throughout the table, we also find that deviations from the mean and median are increas-

[15] When we re-estimate equations (2) and (3) 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.

ing in the total number of mutual fund families that offer a TDF with target date j in month t. This suggests a more general impact of competition on dispersion. Again focusing on estimates from equation (2), a one-standard deviation increase in the log of the number of families offering TDFs with target date j in month t is associated with deviations of 56 to 61 basis points.[16] Not surprisingly, the fit of the various specifications is rather poor—we are essentially modeling monthly returns in deviation from the cross-sectional average or median—ranging between 0.0179 and 0.1003.

We also estimate the following two regression models at the target date-month level:

$$Std(r_{jt}) = a_j + b'X_t + c'Y_{jt} + \varepsilon_{jt} \tag{4}$$

and

$$IQR(r_{jt}) = a_j + b'X_t + c'Y_{jt} + \varepsilon_{jt}, \tag{5}$$

where $Std(r_{jt})$ and $IQR(r_{jt})$ denote the cross-sectional standard deviation and the cross-sectional inter-quartile range, respectively. X_t again includes a time trend and a post-2006 dummy. Y_{jt} includes either the fraction of funds with target date j in month t from fund families that have been offering TDFs after 2006, or the log of the number of funds with target date j in month t from fund families that have been offering TDFs after 2006. Y_{jt} also includes the log of the total number of funds with target date j in month t. We control for target-date fixed effects, and standard errors are clustered by month.

We report the estimated coefficients from both regressions in Table 6.[17] All of the estimated coefficients on the fraction of funds from families new to the market are positive and sta-

[16] The standard deviation of the log number of families offering TDFs with target date j in month t is 0.697. To estimate the impact of a one-standard deviation increase in the long number of families offering TDFs with target date j in month t, we multiply the estimated coefficient by 0.697 and then, because the dependent variable is the squared deviation, take the square root.

[17] When we re-estimate equations (4) and (5) as censored-regression models (with two-way clustering), to allow for the fact that the dependent variable cannot be negative, we again obtain quantitatively similar results.

tistically significant at the 1% level, indicating that it is entry by new mutual fund families that drives up the cross-sectional dispersion in returns. In terms of economic significance, when we focus on estimates for equation (4), a one-standard deviation in the fraction of new funds from families entering the market after 2006 increases the standard deviation of monthly returns by 0.20%. This is approximately one-third of the average across-fund standard deviation of monthly returns between 2000 and 2009, which is 0.59%. We find similar effects when we focus on the number of funds from new families between 2007 and 2009. A one-standard deviation increase in this variable is associated with a 0.27% increase in the standard deviation of monthly returns. This is slightly more than one-third of 0.72%, the average across-fund standard deviation of monthly returns between 2007 and 2009. In other words, the increased cross-sectional dispersion in TDF returns in 2007, 2008, and 2009 is due to entry by mutual fund families seeking to differentiate their funds from established TDFs.

5. Conclusion

To the extent that TDFs have exposure to equities and automatically reduce the equity exposure as investors age, they are an improvement as default investments in retirement plans relative to money market funds and traditional balanced funds. That is the good news. The bad news is that 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 introduce TDFs with different risk profiles. 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: 1) 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; 2) 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 3) 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.[18] Our finding that the cross-sectional dispersion of returns has been increasing over time, without a corresponding increase in the dispersion of stated asset allocation choices, suggests that increased disclosure may not reduce the incentive for mutual fund families to pursue different risk profiles.

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.

[18] Department of Labor: 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).[19] 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)."[20] 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.[21] 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 pension system. Later that year, major pension reform bills were proposed in the House (The

[19] Department of Labor: EBSA Federal Register: 29 CFR Part 2550, October 24, 2007.
[20] Congressional Research Service Report for Congress, October 23, 2006.
[21] Congressional Research Service Report for Congress, October 23, 2006.

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.[22] 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.

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

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."[23] 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[24]:

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.

[23] Department of Labor: EBSA Newsroom, September 26, 2006.
[10] Department of Labor: EBSA Federal Register: 29 CFR Part 2550, October 24, 2007.

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 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 re-balance 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 a 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 a 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. Proliferation of Target Date Retirement Funds, 1994-2009

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 Survivor-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 year *t*. 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 year *t*, 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 year *t*. Until 2001, the only market participants were American Independence Financial Services, Barclays Global Fund Advisors, Fidelity Management and Research, and Wells Fargo.

	# Families offering TDF with 20## target retirement date											Families offering TDFs	AUM (*$million*)	Family 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	1,469.9	Wells Fargo	43.6%
1998	2		3		3		3		2			3	3,977.9	Fidelity	64.3%
1999	2		4		4		4		3			4	6,167.3	Fidelity	76.3%
2000	1		4		4		4		4			4	7,666.7	Fidelity	80.3%
2001	1		5		5		5		5		1	5	10,849.8	Fidelity	84.8%
2002	1		6		6		6		6		1	6	13,272.0	Fidelity	88.1%
2003	1	2	6	2	6	2	7	2	6	1	1	8	23,608.3	Fidelity	85.4%
2004	1	3	9	6	9	6	10	6	9	3	1	12	40,363.2	Fidelity	72.1%
2005	2	4	15	11	15	11	16	10	14	6	2	21	65,822.2	Fidelity	62.3%
2006	2	5	20	18	20	16	21	16	19	11	4	27	110,499.1	Fidelity	55.4%
2007	2	6	28	25	28	22	29	22	27	17	14	37	168,556.3	Fidelity	50.8%
2008	2	6	33	35	41	32	40	30	39	25	28	48	153,392.3	Fidelity	43.4%
2009	2	6	31	33	38	30	38	29	38	25	28	44	245,353.5	Fidelity	39.6%
Obs	26	32	172	130	187	119	191	115	178	88	80				

Table 2. Documenting Cross-Sectional Dispersion in Annual Returns, 2000-2009

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. Wthin each target date-year cell, we report the number of TDFs, the average annual return, standard deviation of annual returns, and range between the minimum and maximum annual returns. For the purposes of this table, we combine 2015 and 2020 funds, 2025 and 2030 funds, 2035 and 2040 funds, and 2045 and 2050 funds. "Total" is the standard deviation of annual returns for the full sample of TDFs with target date *j*. "Across Funds" measures the variability of the annual returns around the average return earned by all TDFs with target date *j* in year *t* .

	2015 & 2020				**2025 & 2030**				**2035 & 2040**				**2045 & 2050**			
	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range
2000	4	-3.7%	0.5%	1.1%	4	-5.7%	0.5%	1.0%	3	-9.9%	0.2%	0.4%				
2001	4	-7.2%	1.2%	2.6%	4	-10.6%	0.8%	1.8%	4	-13.7%	0.3%	0.5%				
2002	5	-12.0%	2.8%	6.9%	5	-15.2%	2.9%	7.1%	5	-18.0%	3.0%	7.3%				
2003	4	21.3%	2.5%	5.6%	4	23.5%	0.6%	1.2%	4	27.9%	3.0%	7.0%				
2004	8	9.4%	2.0%	5.6%	9	10.6%	1.7%	5.5%	7	11.5%	1.7%	4.7%	1	12.9%	0.0%	0.0%
2005	15	5.6%	1.1%	3.3%	16	6.7%	1.2%	3.4%	15	7.3%	1.2%	3.9%	4	8.1%	0.9%	2.3%
2006	27	11.7%	2.4%	9.5%	27	13.6%	2.2%	8.5%	24	14.6%	1.7%	6.6%	8	15.9%	0.9%	3.0%
2007	35	6.1%	2.0%	7.7%	34	6.6%	2.4%	8.3%	31	7.1%	2.5%	9.2%	14	7.1%	3.0%	9.8%
2008	54	-29.3%	5.3%	27.3%	51	-34.4%	3.8%	19.6%	46	-36.9%	2.5%	10.8%	31	-37.8%	2.4%	8.9%
2009	68	25.1%	4.4%	23.5%	61	28.4%	4.2%	17.5%	63	30.2%	4.1%	19.0%	49	31.6%	4.0%	22.0%
Total			21.0%				23.6%				25.8%				29.9%	
Across Funds			3.8%				3.1%				2.8%				3.1%	

Table 3. Documenting Cross-Sectional Dispersion in CAPM Beta, 2000-2009

This table summarizes the CAPM betas of target date funds with different target dates in different calendar years. We estimate the one-factor beta in December of each year using monthly fund-level returns over the prior 24 months (minus the one-month T-bill rate) and the monthly value-weighted return on all NYSE, AMEX, and NASDAQ stocks (minus the one-month T-bill rate). Because we require 24 months of return data, the sample is smaller than in Table 2. Wthin 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. For the purposes of this table, we combine 2015 and 2020 funds, 2025 and 2030 funds, 2035 and 2040 funds, and 2045 and 2050 funds. "Total" is the standard deviation of beta for the full sample of TDFs with target date j. "Across Funds" measures the variability of the betas around the average beta for all TDFs with target date *j* in year *t*.

	2015 & 2020				2025 & 2030				2035 & 2040				2045 & 2050			
	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range
2000	4	0.61	0.10	0.20	4	0.73	0.07	0.15	2	0.83	0.01	0.02				
2001	4	0.60	0.09	0.18	4	0.73	0.08	0.15	3	0.85	0.00	0.00				
2002	4	0.64	0.04	0.07	4	0.77	0.03	0.07	4	0.91	0.00	0.01				
2003	3	0.60	0.13	0.23	4	0.73	0.11	0.23	3	0.83	0.15	0.26				
2004	3	0.60	0.05	0.09	5	0.78	0.11	0.29	4	0.88	0.10	0.21				
2005	8	0.65	0.10	0.34	10	0.79	0.10	0.36	9	0.89	0.07	0.24				
2006	19	0.61	0.10	0.41	18	0.78	0.08	0.32	17	0.88	0.06	0.22	4	0.92	0.06	0.15
2007	24	0.66	0.13	0.54	25	0.84	0.11	0.45	22	0.92	0.08	0.29	8	0.97	0.10	0.22
2008	39	0.75	0.13	0.62	37	0.88	0.10	0.47	32	0.95	0.07	0.27	16	0.98	0.06	0.19
2009	49	0.75	0.11	0.49	42	0.88	0.09	0.42	41	0.94	0.07	0.30	30	0.98	0.06	0.23
Total			0.129				0.107				0.077				0.070	
Across Funds			0.111				0.088				0.067				0.065	

Table 4. Documenting Cross-Sectional Dispersion in Fraction of Portfolio Allocated to Cash and Bonds, 2000-2009

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. Wthin each target date-year cell, we report the number of TDFs, the average fraction allocated to debt plus cash (which is equivalent to one minus the fraction allocated to common stock plus preferred stock), the standard deviation of the fraction allocated to debt plus cash, and the range between the minimum and maximum fractions allocated to debt plus cash. For the purposes of this table, we combine 2015 and 2020 funds, 2025 and 2030 funds, 2035 and 2040 funds, and 2045 and 2050 funds. "Total" is the standard deviation of the fraction allocated to cash and bonds for the full sample of TDFs with target date *j*. "Across Funds" measures the variability of the cash and bond allocation around the average cash and bond allocation for all TDFs with target date *j* in year *t*.

	2015 & 2020				**2025 & 2030**				**2035 & 2040**				**2045 & 2050**			
	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range	#	Mean	Std Dev	Range
2000	3	42.5%	22.1%	41.0%	3	27.5%	12.3%	23.3%	2	11.9%	4.1%	5.8%				
2001	3	51.0%	20.0%	39.0%	2	22.0%	7.1%	10.0%	2	8.4%	1.8%	2.5%				
2002	3	31.3%	7.8%	15.1%	3	16.7%	1.5%	3.0%	3	7.1%	2.4%	4.3%				
2003	2	33.4%	4.8%	6.8%	2	24.0%	2.3%	3.2%	2	23.0%	16.7%	23.6%				
2004	6	33.4%	17.8%	50.9%	7	21.8%	12.1%	40.3%	6	17.6%	9.5%	25.0%				
2005	11	37.6%	16.2%	61.3%	11	21.1%	10.8%	43.0%	11	11.6%	6.9%	24.8%	3	0.8%	0.3%	12.4%
2006	23	38.0%	11.9%	48.1%	24	20.4%	9.5%	34.0%	20	12.4%	7.1%	26.7%	6	9.1%	0.1%	11.0%
2007	33	29.1%	18.5%	60.9%	33	16.7%	10.3%	41.9%	30	10.1%	6.9%	27.9%	13	0.3%	0.8%	21.0%
2008	54	34.7%	15.6%	68.7%	51	20.8%	11.1%	61.4%	46	12.2%	8.9%	56.5%	31	0.6%	0.5%	49.5%
2009	68	35.3%	16.2%	104.4%	61	20.0%	11.5%	62.0%	63	12.2%	8.3%	55.8%	49	0.4%	1.0%	52.1%
Total			16.0%				10.7%				8.4%				8.0%	
Across Funds			15.3%				10.0%				7.9%				7.7%	

Table 5. Testing for Changes in the Cross-sectional Volatility of Fund-level Monthly Returns, January 2000-December 2009

The unit of observation is the TDF offered by family *i* with target date *j* in month *t*. The dependent variable is either the squared difference between return_{ijt} and mean return_{jt}, or the absolute value of the difference between return_{ijt} and median return_{jt}. To calculate the dependent variable we require that there be at least two TDFs with target date *j* in month *t*. All regressions include a linear time trend, dummy variable indicating whether month *t* occurs in 2007, 2008, or 2009, and a fixed effect for each target retirement date (i.e., 2000, 2005, …, 2045, and 2050). Other independent variables include: a dummy variable indicating whether family *i* introduced target date *j* after 2006; a dummy variable indicating whether the TDF was introduced by a mutual fund family that introduced its first TDF after 2006; the natural logarithm of the total number of funds with target date *j* in month *t*; the fund's age measured in years; the natural logarithm of lagged fund-level assets under management in month t-1; the fund-level expense ratio measured in month *t*-1; and a measure of the difference between the fund's allocation to bonds plus cash and the mean or median fund with target date *j* in month *t*. Estimation is via OLS. Standard errors are simultaneously clustered on mutual fund (or mutual fund family) and month. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent Variable:	$(Return_{ijt}$ - Mean $Return_{jt})^2$				$\mid Return_{ijt}$ - Median $Return_{jt} \mid$			
Linear time trend	0.004	-0.008	-0.008	-0.004	0.002	-0.003	-0.003	-0.002
	(0.004)	(0.006)	(0.006)	(0.009)	(0.002)	(0.003)	(0.003)	(0.005)
2007, 2008, or 2009?	0.322 *	0.063	0.037	0.057	0.165 **	0.058	0.048	0.041
	(0.168)	(0.143)	(0.183)	(0.184)	(0.071)	(0.065)	(0.088)	(0.091)
Ln total number of funds with TD j in month t		0.502 ***	0.537 **	0.457 *		0.238 ***	0.252 ***	0.226 **
		(0.193)	(0.223)	(0.274)		(0.079)	(0.091)	(0.112)
Fund introduced after 2006?		0.466 ***	-0.017	-0.185		0.160 ***	-0.022	-0.088
		(0.139)	(0.118)	(0.141)		(0.040)	(0.055)	(0.067)
Fund introduced by family introducing TDFs after 2006?			0.598 **	0.572 ***			0.226 ***	0.221 ***
			(0.242)	(0.212)			(0.073)	(0.066)
Fund age measured in month t				0.007				0.002
				(0.022)				(0.009)
Ln fund size measured in month t-1				-0.046				-0.019
				(0.042)				(0.015)
Expense ratio measured in month t-1				0.321				0.053
				(0.298)				(0.114)
Squared deviation of % bonds and cash from mean allocation				0.000				
				(0.000)				
Absolute deviation of % bonds and cash from median allocation								0.009 ***
								(0.003)
Target date fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering:	Month & Fund	Month & Fund	Month & Family	Month & Family	Month & Fund	Month & Fund	Month & Family	Month & Family
Sample Size	12,731	12,731	12,731	9,779	12,731	12,731	12,731	9,779
R2	0.0179	0.0289	0.0334	0.0472	0.0469	0.0632	0.0702	0.1003

Table 6. Testing for Changes in the Cross-sectional Volatility of Target-date-level Monthly Returns, January 2000-December 2009

The unit of observation is target date *j* in month *t*. The dependent variable is either the standard deviation of monthly returns for target date *j* in month *t*, or the interquartile range of monthly returns for target date *j* in month *t*. To calculate the dependent variable we require that there be at least two TDFs with target date *j* in month *t*. All regressions include a linear time trend, dummy variable indicating whether month *t* occurs in 2007, 2008, or 2009, and a fixed effect for each target retirement date (i.e., 2000, 2005, …, 2045, and 2050). Other independent variables include: the fraction of funds with target date *j* in month *t* that were introduced by families that introduced their first TDF after 2006, the natural logarithm of the number of funds with target date *j* in month *t* introduced by families that introduced their first TDF after 2006, and the natural logarithm of the total number of funds with target date *j* in month *t*. In the last specification for each dependent variable, we restrict the sample to the period after the PPA of 2006 has been signed into law. Estimation is via OLS. Standard errors are clustered on month. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent Variable:	Standard Deviation of Returns within TD j in Month t								Interquartile Range of Returns within TD j in Month t							
Sample Period:	2000-2009						2007-2009		2000-2009						2007-2009	
Linear time trend	0.000		-0.002		-0.004	**	-0.005		0.002		0.000		0.000		-0.013	
	(0.001)		(0.001)		(0.002)		(0.007)		(0.001)		(0.001)		(0.002)		(0.008)	
2007, 2008, or 2009?	0.265	***	-0.049		-0.058				0.269	***	-0.074		-0.073			
	(0.088)		(0.096)		(0.099)				(0.094)		(0.109)		(0.108)			
Fraction of funds with TD j in month t from families adding TDFs after 2006			1.286	***	1.141	***					1.406	***	1.412	***		
			(0.269)		(0.292)						(0.312)		(0.337)			
Ln number of Funds with TD j in month t from families adding TDFs after 2006							0.311	***							0.508	***
							(0.100)								(0.142)	
Ln total number of funds with TD j in month t					0.119	**	0.190						-0.005		0.082	
					(0.054)		(0.187)						(0.067)		(0.227)	
Constant	0.464	***	0.687	***	0.703	***	0.230		0.306	*	0.550	***	0.549	***	1.576	
	(0.148)		(0.143)		(0.142)		(0.918)		(0.158)		(0.146)		(0.150)		(1.104)	
Target date fixed effects?	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Standard Error Clustering:	Month		Month		Month		Month		Month		Month		Month		Month	
Sample Size	935		935		935		357		935		935		935		357	
R2	0.1192		0.1663		0.1722		0.2104		0.1821		0.2205		0.2206		0.2092	