Heterogeneity in Target Date Funds: Strategic Risk-Taking or Risk Matching?

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ABSTRACT

Following the Pension Protection Act of 2006, there was a sharp increase in the use of target date funds (TDFs) as default options in 401(k) plans. We document large differences in realized returns and ex-ante risk, even for TDFs with the same target retirement date. Analyzing fund-level data, we find robust evidence that this heterogeneity reflects strategic risk-taking by families with low market share, especially those entering the TDF market after 2006. Analyzing plan-level data, we find little evidence that 401(k) plan sponsors consider the risk profiles of their firms to any economically meaningful degree when choosing among TDFs.

JEL codes: G11, G18, G23, G28
Keywords: Default investments, retirement savings, asset allocation, flow-performance, regulation

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1 Introduction

A common implication of normative optimal portfolio models is that, as investors age, it is optimal for them to shift their financial wealth away from stocks and toward bonds.[1] This normative implication found its way into the design of target date mutual funds (TDFs). Wells Fargo introduced the first TDFs in 1994. According to Seth Harris, Deputy Secretary of the Department of Labor (DOL), TDFs "were designed to be simple, long-term investment vehicles for individuals with a specific retirement date in mind."[2] Investors who plan to retire in 2030, for example, could invest all of their 401(k) assets in the Wells Fargo LifePath 2030 fund. The innovation, relative to traditional balanced funds (BFs), is that TDFs relieve investors of the need to make asset allocation decisions or rebalance their portfolio. When the target date is far away, the TDF invests primarily in domestic and foreign equity, but as the number of years to the target date declines, the TDF automatically reduces its exposure to risky assets.[3]

The promise of a simple, long-term retirement investment prompted the DOL, through the Pension Protection Act of 2006 (PPA), to allow firms to adopt TDFs as default investment vehicles in employer-sponsored defined contribution (DC) retirement plans.[4] Shortly thereafter, however, policy makers began to worry about the return characteristics of TDFs. In 2009, Herb Kohl, chairman of the Senate Special Committee on Aging, wrote: "While well-constructed target date funds have great potential for improving retirement income security, it is currently unclear whether investment firms are prudently designing these funds in the best interest of the plan sponsors and their participants" (Special Committee on Aging 2009). Our goals in this paper are to document

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

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

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

[4] Indeed, TDFs have been viewed as instruments that could limit risk, moving defined contribution retirement plans closer to the defined benefit retirement plans that they replaced. See, for example, the Turner Investments position paper http://www.turnerinvestments.com/index.cfm/fuseaction/documents.detail/CID/3190. In light of this observation, the heterogeneity in realized returns and risk profiles documented in this study is even more surprising.

changes in the return characteristics of TDFs between 2000 and 2012, and to relate these changes to the incentives of plan sponsors, mutual fund families, or both.

We begin by establishing two stylized facts. The first is that it is common for TDFs with the same target date to earn significantly different realized returns and exhibit significantly different levels of ex-ante risk. For example, consider the 67 TDFs in 2009 with target dates of 2015 or 2020. The average annual realized return within this sample is 25.1%, the cross-sectional standard deviation is 4.4%, and the range between the maximum and minimum annual returns is 23.5%. A similar pattern holds for the idiosyncratic component of realized returns, "alpha."[5] The cross-sectional standard deviation of five-factor alphas is 3.1%, and the range is 12.9%. These differences reflect economically meaningful differences in realized returns.

To measure differences in ex-ante risk, we focus on the time-series standard deviation of monthly five-factor alphas, as well as five-factor model R^2s and betas.[6] Consistent with our prior that these measures capture portfolio characteristics that are under the control of TDF managers, we find that these measures are highly persistent. For the same 67 TDFs in 2009, the average standard deviation of alphas is 2.4%, the minimum is 0.9%, and the maximum is 5.6%, indicating large differences in the level of idiosyncratic risk. The R^2s, a measure of systematic risk, were similarly diverse, with an average of 97.3%, but a minimum of 84.8%. Finally, the standard deviation of the beta on US equity is 0.12, and the range is 0.64.

The second stylized fact is that dispersion in TDF risk profiles increases following the PPA. When we compare the distribution of risk profiles in 2000–2006 ("Pre-PPA") to those in 2007–2012 ("Post-PPA"), we find that idiosyncratic volatility and cross-sectional dispersion in monthly net returns, monthly five-factor alphas, and US equity betas all increase in the Post-PPA period. When we switch to difference-in-differences specifications that compare TDFs to BFs, we find even stronger evidence of increased risk-taking by TDFs during the Post-PPA period. Importantly, none of these findings are being driven by the financial crisis. Although the financial crisis was associated with increased return dispersion among TDFs and (especially) BFs, we obtain similar results when

[5]Note that our definition of alpha includes both the intercept and the residual from a five-factor model.

[6]We estimate a separate five-factor model for each TDF each calendar year using daily data on excess returns. While we recognize that dispersion in betas may reflect new families seeking to differentiate their TDFs by offering glide paths that differ from those of incumbents, increases in idiosyncratic volatility and decreases in R^2 correspond to unambiguous increases in ex-ante risk.

we exclude 2008 and 2009. In fact, difference-in-differences specifications that exclude the financial crisis yield the strongest evidence of increased dispersion in the risk profiles of TDFs with the same target date.

We hypothesize two reasons why dispersion in risk profiles may have increased following the PPA. First, there is a large literature on risk-taking by mutual fund families to attract investor flows (e.g., Brown, Harlow, and Starks 1996, Chevalier and Ellison 1997, Sirri and Tufano 1998, and Evans 2010). Under the "strategic risk-taking" hypothesis, families increased their TDF risk exposures to achieve greater expected performance and thereby potentially increase their market share. Second, beginning with Davis and Willen (2000a), academic studies have emphasized the role of labor-income heterogeneity in the construction of optimal portfolios. Under the "risk-matching" hypothesis, families may offer TDFs with increasingly different risk profiles so that plan sponsors can choose TDFs that better offset the risk from being employed in a given firm or industry ("human-capital risk matching"), or better match the overall risk preferences of the employees covered by their DC plans ("risk-preference matching"). Understanding the economic determinants of the heterogeneity in returns and risk exposures is important. If it is driven by families strategically responding to risk-taking incentives, then it could prove harmful to TDF investors, especially those who are limited to the TDFs from a single family.[7] Alternatively, if the heterogeneity in TDF return properties is driven by risk-matching considerations, it could prove beneficial to TDF investors.

We base our risk-taking predictions on four observations. First, by increasing the expected market share of TDFs inside retirement plans, the PPA increased the incentive for families to enter this market. Indeed, between 2006 and 2012, assets under management in TDFs more than quadrupled, increasing from \$116.0 billion to \$480.2 billion, and, at the same time, the number of mutual fund families offering TDFs jumped from 27 to 44, before falling back down to 37. Second, because TDF flows are likely driven by the choices of plan sponsors (Sialm, Starks, and Zhang 2015), we expect—and provide supporting evidence—that TDF flows respond primarily to risk-adjusted returns. Competing on idiosyncratic returns can encourage TDFs to load up on idiosyncratic risk. Third, the fact that new entrants—and incumbents with low market share—have few assets under

[7] Among the 8,406 plans in our BrightScope sample that offer TDF mutual funds, 8,057 (95.9%) offer TDFs from a single mutual fund family. These plans collectively cover 91.8% of plan participants.

management to lose adds convexity to the flow-performance relation and, thereby, an additional incentive to engage in risk-taking. Fourth, families that enter the market after the PPA are likely to be less constrained in terms of investment behavior than families that chose their glide paths and underlying set of funds before the PPA. Collectively, these observations lead us to predict that increased risk-taking during the Post-PPA period is being driven by families with low market share, especially those families entering the TDF market after 2006.

Our findings are broadly consistent with this prediction of strategic risk-taking. After confirming that flows into TDFs respond primarily to the idiosyncratic component of returns, we estimate a series of regressions that relate TDF return characteristics to family-level market share and date of entry. To control for time-series variation in both market returns and market structure, each regression includes a full set of target date-by-time period fixed effects. While we find consistent evidence of increased risk-taking by TDFs from Pre-PPA families with low market share, we find the strongest evidence of increased risk-taking—both economically and statistically—when we focus on TDFs from Post-PPA families with low market share. For example, even within the sample of TDFs with low market share, the net returns (five-factor alphas) of TDFs from Post-PPA families differ from those of TDFs from Pre-PPA families by approximately 6% (3%) annually. We also find large differences in idiosyncratic volatility and R^2, and in the sensitivities of TDF returns to indices for global bonds, stocks, and commodities. Our general finding of increased risk-taking by TDFs from Post-PPA families with low market share is robust to controlling for the return characteristics of BFs in the same family, limiting our tests to the Post-PPA sample period, and excluding the financial crisis.

To investigate the risk-matching hypothesis, we exploit data from BrightScope on the investment menus of thousands of DC retirement plans in 2010, when plan sponsors have a large set of TDFs from which to choose. For firms with publicly traded equity, we regress the systematic (idiosyncratic) risk of the TDFs offered in each plan on the systematic (idiosyncratic) risk of the firm's equity. To expand our sample to include private firms, we also regress the risk of the TDFs offered in each plan on the median risk of firms within the same industry. Regardless of whether we focus on systematic or idiosyncratic risk, we find little evidence of economically meaningful risk matching. This remains true when we focus on the subset of plans with automatic enrollment.[8] Moreover, the R^2s of our regressions remain low when we include industry fixed effects to control for differences in the volatility of employment and other time-invariant differences across industries. Instead, within the sample of TDFs included in investment menus in 2010, the variables with the most explanatory power are those that measure the market share of the plan's record keeper and that indicate whether the TDF is from a family with low TDF market share. Because we find that risky firms are no more or less likely to choose risky TDFs than safe firms, we conclude that the increased heterogeneity in TDF return characteristics is unlikely to reflect growing demand from plan sponsors for new TDF risk profiles.

Finally, we perform a simulation exercise to assess the possible welfare costs of heterogeneity in the properties of TDF returns, under the assumption that this heterogeneity does not reflect underlying heterogeneity in investors' endowments or preferences. We compare investors who are assigned to a known benchmark TDF ("benchmark assignment") to otherwise identical investors who are randomly assigned to the TDF of a single family ("random assignment"). We simulate the distribution of random-assignment terminal wealth scaled by benchmark-assignment terminal wealth over 25- and 45-year investment horizons. We find that the dispersion of the relative-wealth ratio can be quite large. Over 45 years, the interquartile range is as high as 39%, and the probability of random assignment resulting in underperformance of 15% or more is as high as 24%. Importantly, both the dispersion of the relative-wealth ratio and the utility costs associated with random assignment are substantially larger when we calibrate the simulation to Post-PPA data. For example, the utility cost associated with random assignment can be as high as 62% of initial portfolio wealth. Therefore, in the absence of risk matching, our simulations suggest that Post-PPA changes in the TDF return characteristics had the potential to adversely effect investor welfare.

[8]It is also true when we regress the absolute value of (demeaned) TDF risk on the absolute value of (demeaned) firm risk, a specification that should detect risk matching when some firms' choice of TDFs are motivated by human-capital risk matching and others are motivated by risk-preference matching.

2 Institutional background and review of TDF literature

Although only four fund families offered target date funds (TDFs) in 2000, the Pension Protection Act of 2006 (PPA) allowed firms to offer TDFs as default investment options within 401(k) retirement plans. The regulatory goal was to redirect investors from money market funds—the dominant default investment option—to age-appropriate, long-term investment vehicles. 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, BFs, and managed accounts. While TDFs were perceived to be an important innovation in the market for retirement products, some commentators began expressing concerns about the lack of transparency regarding risk.[9]

The Investment Company Institute (ICI) reports that the share of 401(k) plans offering TDFs increased from 57% in 2006 to 74% in 2014.[10] Similarly, the share of 401(k) plan participants offered TDFs increased from 62% to 73%. At year-end 2014, 48% of 401(k) participants held at least some plan assets in TDFs, up from 19% at year-end 2006. The fraction of mutual assets in DC plans that are invested in TDFs rose from 4% to 13% between 2006 and 2014; according to both ICI and our sample of investment menus from BrightScope, it was 10% in 2010. However, ICI reports that 401(k) plan participants in their twenties collectively allocated 42.4% of their retirement assets to TDFs in 2014. Therefore, employees just entering the labor force appear likely to finance their retirement through a combination of TDF returns and Social Security benefits.[11]

Interestingly, the two current leaders in the market for TDFs take very different approaches to the design of their products. Vanguard allocates investments across five low cost index funds. Fidelity, on the other hand, started out with active TDFs and only later (in 2009) added index

[9] Section A.3 of the Internet Appendix includes a selection of quotes on the pros and cons of TDFs.

[10] All of the numbers in this paragraph except for our calculation using BrightScope data are taken from Figures 7.12, 7.14, and 7.26 of the *2016 Investment Company Institute Fact Book.*

[11] As documented by Benartzi and Thaler (2001), Madrian and Shea (2001), and Agnew et al. (2003), 401(k) investors exhibit inertia in their asset allocations. Hence, young investors defaulted into a TDF are likely to remain invested in that TDF. Inertia is likely to be even more pronounced for TDFs, which are designed to automatically adjust their allocations as investors age. In addition, Mitchell and Utkus (2012) show that, independently of default effects, new plan entrants adopted TDF voluntarily at an average 31% rate, during the 2003–2010 period. The appeal of TDFs as a long-run investment choice may derive from the fact that the funds' glide paths effectively amount to implicit investment advice; see Chalmers and Reuter (2015) and Mitchell and Utkus (2012). For these reasons, outflows from TDFs are likely to reflect investment menu changes by plan sponsors; see Sialm et al. (2015).

TDFs. Fidelity's active TDFs allocate investments across as many as 27 actively managed 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.

This is the first paper to focus on the heterogeneity of TDFs realized returns and risk profiles and to study changes in the population of TDFs around the introduction of the PPA. The existing literature mainly compares TDFs to other investment vehicles and studies the factors driving individual demand for TDFs.[12] The paper most closely related to our own is Sandhya (2011), who compares TDFs to BFs offered within the same mutual fund family. While Sandhya (2011) focuses on average differences in fund expenses and returns, our paper links heterogeneity in idiosyncratic risk to risk-taking incentives arising from the PPA. Also related is Elton et al. (2014), who use data on underlying mutual fund holdings to study both the level of TDF fees and how deviations from TDF glide paths affect fund-level returns. Their findings that TDFs have become increasing likely to invest in emerging markets, real estate, and commodities complements our findings related to heterogeneity in TDF betas. However, they do not ask whether risk-taking by entrants helps to explain the movement into new asset classes. Moreover, none of the existing papers explores the extent to which plan sponsors consider measures of ex-ante TDF risk when constructing their investment menus.[13] Our unique plan-level data allow us to test for risk matching between firms and TDFs.

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

[12] Yamaguchi et al. (2007), Park and VanDerhei (2008), Park (2009), and Mitchell et al. (2009) study investor demand for the particular TDFs introduced into their samples of DC retirement plans. Pagliaro and Utkus (2010) and Mitchell and Utkus (2012) study the role of a 401(k) plan's architecture on TDF demand. Chalmers and Reuter (2015) argue that TDFs are cost-effective substitutes for financial advisors. Ameriks et al. (2011), Morrin et al. (2012), and Agnew et al. (2012) use survey data to identify the factors behind TDF investment.

[13] Shiller (2005), 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. Pang and Warshawsky (2009) study the effect of heterogeneity in glide paths on the distribution of terminal wealth.

is family i's mutual fund with target date j in month t. For example, T. Rowe Price offers twelve distinct TDFs in December 2012, with target dates of 2005, 2010, . . . , 2045, 2055, plus an income fund. As with other types of mutual funds, TDFs typically offer multiple share classes. To calculate a fund's size, we sum the assets under management at the beginning of month t across all of its share classes. To calculate a fund's expense ratio, we weight each share class's expense ratio by its assets under management at the beginning of the month. To calculate a fund's age, we use the number of months since its oldest share class was introduced. To identify families that enter the market after December 31, 2006, we use the year when each mutual fund family offered its first TDF. Because we find that CRSP data on the holdings of equity, debt, and cash are unreliable for TDFs, we infer investment strategies from the betas estimated in factor models.[14]

Table 1 presents summary statistics on the evolution of the TDF market over the 1994–2012 period. Wells Fargo introduced the first TDFs in 1994. Between 1994 and 2012, the number of TDFs grew from five to 368 and the number of mutual fund families offering TDFs grew from one to 37, with total assets under management going from \$278 million to \$480 billion, a seventeen-hundred-fold increase.[15] In particular, 20 families entered the market after 2006, allowing us to study differences between the TDFs of new entrants and more established mutual fund families. 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 32.7% in 2012. Similarly, although the market for TDFs remains quite concentrated, the market share of the top three firms has fallen gradually from 97.8% in 2002, to 75.1% in 2012. Firms that entered the market after 2006 (and remained in the market through 2012) have a combined market share of 4.4%. It is worth noting that seven of the ten families that exit the TDF market between 2009 and 2012 also entered the market after 2006. These include Goldman Sachs and Oppenheimer.

We also use CRSP to construct samples of traditional (non-TDF) BFs and S&P 500 index funds. To obtain our sample of traditional BFs, we drop all of the funds that we identify as TDFs,

[14] We document inconsistencies in CRSP equity holdings data in Section F of the Internet Appendix.

[15] The number of distinct TDFs cannot be directly calculated from Table 1 because some families offer multiple TDFs within a given range of target dates (e.g., Fidelity offers TDFs with target dates of 2015 and 2020) and some offer multiple TDFs with a given target date (e.g., Fidelity now offers active and passive versions of each TDF).

and then restrict the sample to funds where the Lipper objective (as reported in CRSP) is "Balanced Fund." It includes four Lipper classifications: Flexible Portfolio Funds (FX), Mixed-Asset Target Allocation Conservative Funds (MTAC), Mixed-Asset Target Allocation Moderate Funds (MTAG), or Mixed-Asset Target Allocation Growth Funds (MTAM). 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 Characterizing cross-sectional heterogeneity in TDFs

We begin by summarizing the return properties of TDFs with different target dates in each calendar year of our sample. Doing so reveals two stylized facts. First, TDFs with the same target date exhibit significant cross-sectional dispersion in realized returns and ex-ante risk profiles. Second, this dispersion increases following the PPA. We then show in formal tests that the increased dispersion following the PPA is not driven by the financial crisis and, by comparing TDFs to BFs, that it is unique to TDFs.

4.1 Summary statistics

For each year and target date, we compute statistics summarizing the heterogeneity in *realized* returns and alphas. We then turn to statistics meant to capture differences in *ex-ante* TDF risk profiles: the time-series volatility of alphas, and the R^2s and US equity betas from factor models.[16] Given the high market concentration documented in Table 1, we compute both equal-weighted and value-weighted cross-sectional standard deviations of the different measures. We also report descriptive statistics for the sample of BFs offered by families that offer TDFs during our sample period (but we defer formal comparisons between TDFs and BFs to the next section).

Table 2 documents the substantial cross-sectional dispersion in realized annual returns of

[16] Specifically, assume that, within the year, the daily excess returns on the i-th TDF, r_{it}, are drawn from a stationary distribution with mean $E(r_{it}) = a_i + \beta_i^\top \mu_t$ and volatility $\text{Var}(r_{it}) = \beta_i^\top \Sigma_{ff} \beta_i + \sigma_{\epsilon_i}^2$, where a_i is the constant component of the excess return, β_i is a vector of factor return sensitivities, μ_f is a vector of mean factor returns, Σ_{ff} is the covariance matrix of factor returns, and σ_{ϵ_i} is the idiosyncratic volatility. Let a "hat" denote OLS estimates. The sample standard deviation of $\hat{\alpha}_{it} \equiv r_{it} - \hat{\beta}_i^\top f_t$ is a consistent estimate of the ex-ante idiosyncratic volatility σ_{ϵ_i}.

TDFs during our sample period.[17] For example, for the 2015–2020 TDFs, the equal-weighted cross-sectional standard deviation increases from 0.5% in 2000 to 1.8% in 2012. The increase was especially marked between 2007 and 2008, jumping from 2.0% to 5.1%. Similarly, the value-weighted standard deviation increases from 0.4% in 2000 to 1.8% in 2012, and jumps from 1.2% to 3.5% between 2007 and 2008. The range increases from 1.1% to 8.5% between 2000 and 2012, and from 7.3% to 27.2% between 2007 and 2008. The patterns are similar for the other four pairs of target dates. In every case, we find that the standard deviation of annual returns is higher in the years after the PPA (2007–2012) than in the years before (2000–2006). Across all five target dates, the equal-weighted standard deviations increase by between 0.9% and 1.8%, and the value-weighted standard deviations increase by between 0.4% and 1.3%.[18] The fact that we find the greatest Post-PPA return dispersion among TDFs with the earliest target dates suggests that those investors closest to retirement face the greatest uncertainty about TDF returns. The fact that BFs exhibit more cross-sectional dispersion, on average, than TDFs is consistent with there being a wider range of investment strategies among BFs (which span four Lipper classifications) than within TDFs with similar target dates. However, for BFs, the equal-weighted standard deviation increases by 0.2% following the PPA and the value-weighted standard deviation *decreases* by 0.4%.

In Table 3, we focus on the idiosyncratic component of realized annual TDF returns. To control for the effect of systematic factors on TDF returns, we estimate alpha using a five-factor model and daily excess returns.[19] We find that there is significant cross-sectional dispersion in the alphas, and that the dispersion is higher in the years after the PPA. Across all five target dates, the equal-weighted standard deviations increase by between 0.5% and 1.2%, and the value-weighted standard deviations increase by between 0.4% and 0.8%. Because these differences are of the same order of magnitude as the differences in Table 2, it appears that a significant fraction of

[17] To increase the size of each cross-section, we combine TDFs with adjacent target dates (e.g., 2015 and 2020).

[18] The fact that the changes in dispersion are qualitatively similar using the equal-weighted and value-weighted measures indicates that the heterogeneity that we document is not being driven by a small number of funds with few assets under management. At the same time, the fact that the value-weighted measures are consistently lower than the equal-weighted measures is consistent with our hypothesis that families with low market share face a greater incentive to generate idiosyncratic returns than market leaders.

[19] The five factors are the daily excess returns of the value-weighted CRSP US market, MSCI World Index excluding the US, Barclays US Aggregate Bond Index, Barclays Global Aggregate excluding the US, and GSCI Commodity Index. To calculate fund i's five-factor alpha in month t, we estimate the index model in month $t-1$ using daily returns from months $t-12$ to $t-1$. To calculate fund i's five-factor alpha in year t, we compound the alphas obtained from the rolling twelve-month regressions.

the dispersion in total returns is being driven by dispersion in idiosyncratic returns.

The analysis above documents significant heterogeneity in realized, or *ex-post*, TDF returns. Differences in realized returns and alphas must reflect underlying *ex-ante* differences in asset allocation, security selection, or both. Nevertheless, it is possible that, despite these ex-post differences, the ex-ante distributions of returns for different TDFs were not that different. To address this potential concern, we also consider ex-ante measures of risk. Table 4 reports statistics for idiosyncratic volatilities, estimated as the annualized—scaled by $\sqrt{12}$—within-TDF standard deviation of monthly five-factor alphas during each calendar year. We then compute yearly summary statistics of the idiosyncratic volatilities across TDFs with similar target dates. The patterns are qualitatively similar to those documented in Table 3. Idiosyncratic volatility approximately doubles across all five target dates during the post-PPA period. In unreported fund-level regressions, we find that the serial correlation in idiosyncratic volatilities is 0.480, which is both economically and statistically significant (p-value of 0.000).[20] The persistence in realized idiosyncratic volatility increases our confidence that it captures ex-ante differences in risk-taking.

Table 5 reports statistics for another estimate of ex-ante risk-taking: the R^2s of the five-factor model. In unreported fund-level regressions, we estimate the serial correlation in the R^2s of TDFs to be near 0.900.[21] Despite this high level of persistence within TDF, we document a decrease in average R^2s and an increase in the dispersion of R^2s across all five pairs of target dates, suggesting that entrants have lower average R^2s than incumbents. For example, for the 2005–2010 funds, the average R^2 decreases from 96.3% in 2001 to 94.7% in 2012, whereas the equal-weighted (value-weighted) standard deviation increases from 1.2% (0.8%) to 6.2% (4.1%). Amihud and Goyenko (2013) interpret lower R^2s as evidence of greater manager selectivity. In our setting, on the other hand, it appears that growth in the TDF market is associated with more idiosyncratic volatility and (as we document below) lower average alphas. Interestingly, this increase in cross-sectional dispersion seems to be mainly driven by some funds producing returns with especially low R^2s. For the 2005–2010 TDFs, the lowest R^2 is 95.3% in 2001, but only 64.8% in 2012. More

[20]The estimated coefficient is 0.478 (t-statistic of 5.78) in a univariate regression and 0.480 (t-statistic of 5.74) when we include target-date-by-year fixed effects. Standard errors are two-way clustered on family and year.

[21]The estimated coefficient is 0.925 (t-statistic of 8.56) in a univariate regression and 0.897 (t-statistic of 6.60) when we include target-date-by-year fixed effects. Standard errors are two-way clustered on family and year.

generally, the drop in the minimum R^2s is especially pronounced during the last three years of our sample, after the financial crisis.

Finally, to capture dispersion in glide paths, we focus on dispersion in US equity betas. The US equity beta is estimated year-by-year, using daily excess returns, in the same five-factor model that we use to estimate alphas. We report the summary statistics in Table 6. Across all five target dates, we find that average US equity betas are significantly lower in 2012 than in 2001. For example, for 2015-2020 TDFs, they fall from 0.58 to 0.46. This decline is precisely what we expect to observe across TDFs as the target date approaches. However, we also find evidence of increased dispersion in betas in the years after the PPA, with the equal-weighted standard deviations increasing between 0.02 and 0.06, and the value-weighted standard deviations increasing by similar magnitudes. One interpretation is that entrants are offering TDFs with distinct new glide paths, with the goal of appealing to 401(k) plan sponsors in particular industries. Another interpretation is that entrants simply differentiated their glide paths from those of incumbents. Regardless, the patterns across Tables 2–6 suggest that cross-sectional dispersion in realized returns, idiosyncratic volatility, and factor loadings all increased in the Post-PPA period.[22]

4.2 Formal tests

In Table 7, we test for differences in the return characteristics of TDFs before and after the PPA of 2006. We also estimate difference-in-differences between TDFs and BFs. The five measures are related to those summarized in Tables 2–6. We report tests based on two Post-PPA periods: "2007–2012" and "2007–2012 (excl. crisis)," which drops observations from 2008 and 2009. We measure cross-sectional dispersion in monthly net returns, monthly five-factor alphas, and annual US equity betas of TDFs as the squared deviations relative to average TDFs with the same target date. Similarly, we measure cross-sectional dispersion in monthly net returns, monthly five-factor

[22]We perform an additional exercise to characterize and benchmark the heterogeneity in TDFs in Section B.1 of the Internet Appendix. We decompose the total dispersion in the various TDF measures into what is driven by time variation of the average measure for a TDF with a given target date, and what is driven by cross-sectional variation around the average. We focus on the full sample period, Pre-PPA period, and Post-PPA period. We then perform the same exercise on BFs and S&P 500 index funds. Regardless of the measure, we find that fund dispersion is highest for BFs and lowest for index funds, with TDFs of all target dates falling in between. Hence, perhaps not surprisingly, TDFs are characterized by more heterogeneity than commodity-like index funds, but less heterogeneity than BFs, which may be more varied in their investment goals. However, we also find that for TDFs, fund dispersion increases systematically between the Pre-PPA and Post-PPA periods.

alphas, and annual US equity betas of BFs as the squared deviations relative to average BFs with the same Lipper classification. As in the earlier tables, we compare the full sample of TDFs to the subsample of BFs offered by families that ever offer TDFs during our sample period.[23]

When we focus on TDFs, we find significant increases in idiosyncratic volatilities and in the cross-sectional dispersions of monthly net returns, monthly five-factor alphas, and US equity betas between the Pre-PPA and Post-PPA periods. These increases are not due to the financial crisis. When we exclude 2008 and 2009, the increases tend to be smaller in magnitude, but statistical inferences are similar. The evidence for changes in the return characteristics of TDFs is at least as strong when we switch from difference tests within the sample of TDFs to difference-in-difference tests that compare TDFs to BFs. We detect statistically and economically significant differences (in differences) for three of the five measures when we focus on the full Post-PPA period and for all five measures when we exclude 2008 and 2009. While the financial crisis was associated with increased dispersion of TDF return characteristics, it was associated with even an greater increase in dispersion among BFs. When we exclude the financial crisis period, we find that the dispersion of TDFs (within target date) has increased while the dispersion of BFs (within Lipper classification) has decreased.[24] In the remainder of the paper, we seek to explain the increased dispersion in the realized returns and ex-ante risk profiles of TDFs following the PPA of 2006.

5 Does TDF heterogeneity reflect strategic risk-taking?

5.1 The role of risk-taking incentives

We base our strategic risk-taking predictions on four observations related to the incentives of mutual fund families. First, by increasing demand for TDFs as default investment options, the PPA significantly increased the future share of retirement plan assets that will be invested in TDFs. As a result, the PPA increased the incentive for mutual fund families to place their TDFs on DC investment menus. Because we cannot observe the counterfactual market structure, we

[23] Inferences are similar when the comparison group is the full sample of BFs. See Internet Appendix Table B.3.

[24] In Internet Appendix Table B.4, we compare the TDFs and BFs of families that entered the TDF market before and after December 31, 2006. We find that the Post-PPA TDFs of Post-PPA families have significantly higher levels of cross-sectional dispersion in monthly five-factor alphas and idiosyncratic volatility than the Post-PPA TDFs of Pre-PPA families. This is true regardless of whether we exclude 2008 and 2009.

cannot quantify the strength of this incentive. TDFs were, after all, gaining market share before the PPA. Nevertheless, the passage of the PPA likely helps to explain why, in Table 1, we observe 17 families entering the TDF market in 2007 and 2008, increasing the total from 27 to 44. The large number of entrants is likely to have intensified competition for market share.

Second, because flows into TDFs are likely to be driven by plan sponsor decisions about the TDFs to include in their investment menus, and because plan sponsors are likely to be more sophisticated than the typical individual investor (e.g., Pool, Sialm, and Stefanescu 2016; Sialm, Starks, and Zhang 2015), we expect (and provide supporting evidence) that flows into TDFs load on the idiosyncratic component of TDF returns. Third, there is a well-established literature showing that mutual funds facing more convex payoffs are more likely to engage in risk-taking (e.g., Brown, Harlow, and Starks 1996; Evans 2010). In our setting, convexity arises from the fact that entrants and incumbents with low market share have fewer assets—and therefore fewer management fees—to lose if they underperform their peers. Fourth, we expect families entering the TDF market after the PPA to be less constrained with respect to their choice of glide path and set of underlying funds than incumbents, who made these choices before the PPA and disclosed them to existing investors.

The first three observations lead us to predict that the increased dispersion in TDF return characteristics in Tables 2–7 reflects increased risk-taking by families with low market share in the TDF market. The last observation leads us to predict that the link between low market share and risk-taking will be strongest among families that enter the market after 2006. Note that this second prediction is consistent with two different types of behavior. Following the PPA, entrants may be more likely to assign funds pursuing more idiosyncratic strategies to their TDFs. Alternatively, families pursuing more idiosyncratic strategies may have been more likely to enter the TDF market after the PPA. While this is not a crucial distinction from the investor's perspective, we are able to shed light on the origin of any change in risk-taking by comparing specifications that do and do not control for the investment behavior of a family's BFs.

A separate issue is that families face a choice about when to enter the market and pursue an idiosyncratic investment strategy. To the extent that pursuing the volatility option this year prevents families from pursuing it next year, the incentives of entrants and other families with low market share to pursue idiosyncratic strategies may be weaker than we claim. Our conjecture is that mutual fund families not yet in the TDF market viewed the passage of the PPA as a unique opportunity to gain market share and quickly designed new products to pursue this opportunity. One piece of suggestive evidence is that we observe 17 entrants between 2007 and 2008, and only 3 entrants between 2009 and 2012. Another piece of suggestive evidence is that many of the families that exit the TDF market during the end of our sample period entered the market after 2006. However, the extent to which entrants are responsible for the increased level of risk-taking is one of the empirical questions that we seek to answer in this section.

5.2 Flows and performance

The existing literature finds that DB and DC plan sponsors are more sophisticated than the typical individual mutual fund investor (e.g., Del Guercio and Tkac 2002; Sialm, Starks, and Zhang 2015). These findings lead us to predict that TDF flows respond primarily to the idiosyncratic component of returns. In Table 8, we estimate the following flow-performance model:

$$\text{flow}_{ijt} = a_j + b_t + c^\top X_{jt} + d^\top Z_{ijt} + \epsilon_{ijt}, \tag{1}$$

where flow_{ijt} is the one-year net flow, measured as a percentage of assets under management at the beginning of the period. The specification is motivated by the flow-performance regression in Del Guercio and Reuter (2014), who run a horse race between raw and risk-adjusted returns. However, following Barber, Odean, and Huang (2016), we decompose net returns into alphas and predicted (or systematic) returns, which are the product of betas and factor realizations. We also extend the specification to capture features of the TDF market. The X_{jt} vector includes the natural logarithm of the total number of funds with target date j in year t, which is a measure of the degree of competition for flows. The Z_{ijt} vector includes: the one-year predicted fund return in year $t-1$; the one-year alpha in year $t-1$; the volatility of monthly predicted fund returns in year $t-1$; the volatility of monthly alphas in year $t-1$; the net flow into fund i in year $t-1$; a dummy equal to one if the fund was introduced after December 2006; a dummy equal to one if the fund was introduced by a family that entered the TDF market after December 2006; the fund-level expense ratio measured in year t; the natural logarithm of fund assets under management in year $t-1$; and the natural logarithm of family assets under management in year $t-1$. To capture potential convexities in the flow-performance relation (Sirri and Tufano 1998), one specification includes dummy variables that indicate whether fund i's one-year alpha was in the first, second, third, or fourth quartile of alphas earned by TDFs with the same target date in year $t-1$. Specifications with TDF flows as the dependent variable include calendar-year fixed effects and target date fixed effects. For comparison, we also estimate comparable flow-performance specifications for BFs. These specifications include calendar-year fixed effects and Lipper classification fixed effects. In all regressions, standard errors are simultaneously clustered on mutual fund family and year.

We find that flows into TDFs respond primarily to alphas, whereas flows into BFs respond to both systematic returns and alphas. For BFs, a one-standard deviation increase in systematic return increases flows by 4.0% versus 5.8% for a one-standard deviation increase in alpha. Both effects are statistically significant at the 1% level. In the comparable specification for TDFs (in the third column), the corresponding estimates are a statistically insignificant 2.0% for systematic returns (p-value of 0.622) and a statistically significant 7.7% for alpha (p-value of 0.000). A possible explanation for this difference in results is that the beta of a BF might be perceived as being more discretionary, so investors are rewarding the BF both for choosing betas and for picking securities. In the TDF context, if investors perceive the beta as being non-discretionary, there is no basis for rewarding managers based on beta timing.[25] In the fourth column, the difference in flows between the top quartile and bottom quartile of TDFs is an economically and statistically significant 17.1%.

JR: When we simultaneously include the volatility of systematic returns and the volatility of alphas, the coefficient on the volatility of systematic returns is large and negative and statistically significant at the 5% level and below. A one-standard deviation increase in the volatility of systematic returns is associated with a 21.7% decrease in flows. The coefficients on the volatility of alpha, on the other hand, are positive but statistically indistinguishable from zero. (In column three, which includes the largest set of control variables, we can reject the hypothesis that the coefficients on systematic volatility and idiosyncratic volatility are equal.) In other words, flows into TDFs

[25] We thank an anonymous referee for suggesting this interpretation.

are lower when those TDFs have larger factor loadings and more volatile factor returns, but not when they have more volatile alphas. These patterns are consistent with plan sponsors believing that managers with lower R^2s are more skilled (Amihud and Goyenko 2013). In summary, the patterns in Table 8 confirm that TDFs are primarily rewarded for generating higher idiosyncratic returns.

5.3 Explaining cross-sectional dispersion in TDF returns and alphas and levels of idiosyncratic risk, alphas, and information ratios

This section contains our first tests for strategic risk-taking. We begin with the regression model:

$$(r_{ijt} - \overline{r}_{jt})^2 = a_{jt} + b^\top X_{ijt} + \epsilon_{ijt}, \tag{2}$$

where r_{ijt} is the monthly return of TDF i and $\overline{r}_{jt}$ is the cross-sectional average return of TDFs with target date j in month t; a_{jt} is a target date-specific fixed effect for month t; and X_{ijt} is a vector of covariates intended to capture family-level incentives and investment strategies.[26] This vector includes: a dummy variable equal to one if the market share of family j's TDFs was $\leq 1\%$ ("Low Market Share") interacted with dummy variables equal to one if family k entered the TDF market before or after December 31, 2006 ("Pre-PPA Family" versus "Post-PPA Family"); a dummy variable equal to one if the market share of family j's TDFs was $> 1\%$ and $\leq 5\%$ ("Medium Market Share") in month $t-1$; and a dummy variable equal to one if TDF i invests in index funds. In the second specification, we also include the average cross-sectional return dispersion for BFs in TDF i's family in month t, where the cross-sectional return dispersion for each BF is measured within the full cross-section of BFs with the same Lipper classification, squared, and then averaged across all of the family's BFs.

These regression specifications allow us to test the prediction that TDFs from families with Low Market Share contribute more to cross-sectional dispersion than TDFs from families with Medium Market Share or High Market Share (the omitted category), and the prediction that increased cross-sectional dispersion following the PPA is being driven by the investment strategies

[26]The specifications differ from those in Table 8 because our focus has shifted from investor and plan-level decisions about how to allocate retirement assets to family-level decisions about risk-taking as a function of TDF market share.

of the Post-PPA families with Low Market Share.[27] We expect TDFs investing in index funds to exhibit less cross-sectional return dispersion than TDFs based on actively managed funds. To the extent that some families pursue more volatile investment strategies across their full range of funds, we also expect the average cross-sectional return dispersion of a family's BFs to be positively correlated with the cross-sectional return dispersion of its TDFs. By including a separate fixed effect for each target date-month pair, we are comparing the return dispersion of different TDFs with the same target date in the same month. Therefore, while the patterns in Tables 2–7 may partially reflect time-series variation in the properties of market returns and in the number of TDFs offered with a particular target date, the coefficients in equation (2) are being identified entirely by cross-sectional variation within target date and month. Standard errors are two-way clustered on family and month.

We find support for both risk-taking predictions in Table 9. In the first two columns, we find that TDFs from Low Market Share families exhibit greater cross-sectional dispersion in monthly net returns than TDFs from other families. Both estimated coefficients are positive and statistically significant from zero at the 10% level (and below), and we can reject the hypothesis that they are both equal to zero at the 5% level. Consistent with our second prediction, we also find that the estimated coefficient for Post-PPA families with Low Market Share is consistently larger than that for Pre-PPA families with Low Market Share. We can reject the hypothesis that these coefficients are equal at the 10% level. In terms of economic significance, TDFs from Post-PPA families with Low Market Share exhibit annualized cross-sectional dispersion in net returns that are 6.90% higher than TDFs from High Marker Share families and 4.36% higher than TDFs from Pre-PPA families with Low Market Share.[28] Controlling for the cross-sectional dispersion of a family's BFs significantly increases the R^2 (from 11.23% to 17.35%), but does not otherwise

[27]As a practical matter, there is little distinction between the sample of Post-PPA families and the sample of Post-PPA families with Low Market Share. The only Post-PPA family to rise from Low Market Share to Medium Market Share is American Funds, which has one of the largest market shares in the broader mutual fund market throughout our sample period. See Internet Appendix Table B.2 for the number of families and TDF-month observations each year based on TDF market share level (Low, Medium, or High) and date of entry (Pre-PPA or Post-PPA).

[28]To calculate these differences (and comparable differences for monthly five-factor alphas), we first calculate the average predicted value over our sample period for TDFs from (a) Post-PPA families with Low Market Share, (b) Pre-PPA families with Low Market Share, and (c) families with High Market Share. Next, we calculate the square root of each average predicted value and multiplied by 12, to convert from monthly to annual. Finally, we compare the annualized values for Post-PPA families with Low Market Share to those for Post-PPA families with Low Market Share and for families with High Market Share.

change our inference that TDFs from families with Low Market Share exhibit greater cross-sectional dispersion in monthly net returns. This implies that these TDFs have more diverse betas, higher levels of idiosyncratic risk, or both.

Our findings are quite similar when we study cross-sectional dispersion in monthly five-factor alphas. In this case, TDFs from Post-PPA families with Low Market Share exhibit annualized cross-sectional dispersion in alphas that are 4.16% higher than TDFs from High Marker Share families and 2.20% higher than TDFs from Pre-PPA families with Low Market Share. In other words, we find that more than half of the increased cross-sectional dispersion in the net returns of TDFs from Post-PPA families with Low Market Share reflects increased cross-sectional dispersion in the idiosyncratic component of returns.[29]

We estimate analogous fund-level specifications for the annualized idiosyncratic volatility of TDF i in year t, our first measure of ex-ante risk-taking. Because the unit of observation switches from month to year, we focus on market shares calculated in month $t-12$. We find strong evidence that TDFs from Low Market Share families have higher levels of idiosyncratic risk than their peers. The estimated coefficients on both Low Market Share dummy variables are positive and statistically significant at the 5% level, and we can reject the hypothesis that both coefficients are equal to zero at the 1% level. Furthermore, because the estimated coefficients for TDFs from Post-PPA families with Low Market Share are approximately double those for TDFs from Pre-PPA families with Low Market Share, we can reject the hypothesis that these coefficients are equal at the 10% level. This remains true even when we control for the average (Lipper classification adjusted) idiosyncratic volatility of the family's BFs, which has a strong positive correlation with the dependent variable. In other words, while the PPA may have drawn families with more idiosyncratic investment strategies into the TDF market (as reflected by the reduction in the coefficient on the Low Market Share, Post-PPA family dummy variable between columns five and six), when we control for this family-level trait, we continue to find significantly higher levels of idiosyncratic risk among TDFs from Post-PPA families with Low Market Share. We also find that TDFs based on index funds exhibit much lower levels of idiosyncratic risk than TDFs based on actively managed funds.

[29] We obtain similar findings when we limit our sample to the Post-PPA period or the Post-PPA period excluding 2008 and 2009, and when we instead focus on absolute deviations. See Internet Appendix Table B.5.

In the remaining columns of Table 9, we estimate specifications that focus on the average monthly five-factor alpha during calendar year t, and the information ratio, defined as the average monthly five-factor alpha over the prior 12 months divided by idiosyncratic volatility in calendar year t. Our goal is to determine whether investors being exposed to higher levels of idiosyncratic risk are being compensated for this risk with higher risk-adjusted returns. Our estimates imply that they are not. TDFs from Post-PPA families with Low Market Share, which have the highest levels of idiosyncratic risk, earn alphas that are 6.7 basis points per month lower than TDFs from families with High Market Share. When we control for the average (Lipper classification adjusted) monthly five-factor alpha of the family's BFs, the coefficients on all three market share dummy variables shrink towards zero, implying that some of the underperformance can be thought of as a family-level trait. Nevertheless, we continue to find the largest underperformance among TDFs from Post-PPA families with Low Market Share: 3.6 basis points per month (p-value of 0.086).[30]

Finally, we find that TDFs from Post-PPA families with Low Market Share and TDFs from families with Medium Market Share both have lower information ratios than TDFs from families with High Market Share (because TDFs from families with Medium Market Share have less negative alphas but also much lower levels of idiosyncratic risk). However, when we control for the average (Lipper classification adjusted) information ratios of the family's BFs, we can reject the hypothesis that TDFs from Post-PPA families with Low Market Share have the same information ratios as TDFs from Pre-PPA families with Low market Share at the 10% level.

5.4 Explaining differences in levels of factor-model R^2s

As an alternative measure of ex-ante risk, we turn to factor-model R^2s. We consider a single-factor model, with the US equity excess return as the only factor ("CAPM"), and the five-factor model used through the paper ("five-factor model"). The dependent variable is the R^2 of TDF i in year t, and the regression specifications mirror those introduced in the previous section.

Since lower R^2s are associated with more idiosyncratic returns, our predictions for the coefficients on the Low Market Share dummy variables are the opposite of those for idiosyncratic

[30] From the standpoint of an investor, what matters is the total magnitude of the underperformance, not its origin, making −6.7 basis points the relevant figure.

risk. Consistent with the prediction that TDFs from Low Market Share exhibit lower R^2s than other TDFs, the estimated coefficients on both Low Market Share dummy variables are negative and statistically significant across all four specifications in Table 10. We can reject the hypothesis that TDFs from Low Market Share families have the same R^2s as TDFs from High Market Share families at the 5% level and below, whether or not we control for the average (Lipper classification adjusted) R^2s of the family's BFs.

However, we also find strong evidence that the lower R^2s of TDFs from Low Market Share families are driven by the investment behavior of those TDFs offered by Post-PPA families. The R^2s of TDFs from Post-PPA families with Low Market Share are between 6.6% and 7.2% lower than those of TDFs from families with High Market Share when we focus on the one-factor model, and 3.5% lower when we focus on the five-factor model. All of these differences are statistically significant from zero at the 1% level, and we can reject the hypothesis that TDFs from Post-PPA families with Low Market Share have the same R^2s as TDFs from Pre-PPA families with Low Market Share at the 10% level and below. In terms of economic significance, the differences in five-factor R^2 are uniformly larger than all of the equal-weighted cross-sectional standard deviations that we report in Table 5 for 2007–2009, and between 56% and 97% of those for 2010–2012.

5.5 Explaining differences in levels and the dispersion of five-factor-model betas

In this section, we test for differences in factor-model betas, another measure of ex-ante risk. Because we have seen that plan sponsors focus on the idiosyncratic component of returns, we do not necessarily expect TDFs from entrants to offer systematically higher equity betas than TDFs from other families. Nor do we expect TDFs from incumbents with Low Market Share, which have already publicized their glide paths, to increase their equity betas. Rather, because entrants may find it difficult to market their TDFs to plan sponsors if they have the same glide paths as incumbents, we expect entrants to differentiate themselves from incumbents through the weights placed on different asset classes along the glide path.

The regressions in Table 11 mirror those in Tables 9 and 10. The dependent variable in Panel A is the deviation of the beta of TDF i in year t from the equal-weighted average of all TDFs with the same target date in year t. In this panel, positive coefficients imply positive tilts in beta. The dependent variable in Panel B is the squared deviation for TDF i in year t, so that positive coefficients imply greater cross-sectional dispersion in beta.

We find evidence in Panel A that TDFs from Post-PPA families with Low Market Share have higher loadings on US debt, global debt, and commodities than other TDFs. We also find that the beta tilts of TDFs are strongly positively correlated with the beta tilts of a family's BFs. The effect is especially large for the exposure to the commodity factor, where a 0.10 increase in the commodity betas of a family's BFs is associated with a 0.07 increase in the commodity betas of its TDFs. Of course, the typical investor is unlikely to know or care whether her TDF is offered by a family that has above-average allocations to global equity or commodities. The main finding in Panel B is that TDFs from Post-PPA families with Low Market Share exhibit more diverse betas with respect to US equity, global equity, global debt, and commodities. Overall, Table 11 suggests that the movement into riskier asset classes documented in Elton et al. (2014) is being driven by families entering the TDF market following the PPA.

5.6 Robustness

We find that TDFs from Post-PPA families with Low Market Share engage in more risk-taking than TDFs from Pre-PPA families with Low Market Share which, in turn, engage in more risk-taking than other TDFs. This general pattern holds in alternative specifications and sample periods. For example, we find similar evidence of strategic risk-taking by TDFs from Post-PPA families with Low Market Share when, in Internet Appendix Table B.6, we re-estimate our main specifications using family-level data.

One potential concern is that, because our regression specifications do not allow the coefficient on the Pre-PPA family with Low Market Share dummy variable to change following the PPA, we are overstating the difference in risk-taking by TDFs from Post-PPA versus Pre-PPA families with Low Market Share. This is not the case. Estimated magnitudes and statistical inferences with respect to differences in realized returns and ex-ante risk are similar when, in Tables B.7–B.9, we re-estimate the specifications in Tables 9–11 using only data from 2007–2012. The estimated coefficients on the Medium Market Share dummy are also similar.

Many of our findings of strategic risk-taking also continue to hold, in Internet Appendix Tables B.10–B.12, when we further limit the sample period by excluding 2008 and 2009. Namely, we continue to find that Post-PPA families with Low Market Share exhibit the highest levels of cross-sectional dispersion in five-factor alphas and idiosyncratic risk and the lowest R^2s. However, fewer of the estimated coefficients on the Low Market Share dummy variables are statistically significant in the regressions that focus on factor loadings, and we can no longer reject the hypothesis that the cross-sectional dispersion in net returns is greater for TDFs from Post-PPA families with Low Market Share than for comparable TDFs from Pre-PPA families with Low Market Share.

Although our tests focus on a family's share of the TDF market, the expected costs and benefits of increasing idiosyncratic risk may also depend on the family's share of the overall mutual fund market or 401(k) market. Specifically, families with the lowest overall market shares may have the least to gain from pursuing an idiosyncratic return strategy, because consultants may still be reluctant to add them to retirement plan menus. Families with the highest overall market shares, on the other hand, may have the most to lose if abnormally low TDF returns damage their existing reputation with plan sponsors. We test these predictions in Internet Appendix Table B.13. One set of specifications includes dummy variables indicating low or medium market share in the overall mutual fund market (based on total assets under management in CRSP), rather than in the TDF market. Another set of specifications interact the dummy variables indicating low, medium, and high market share in the TDF market with dummy variables indicating low, medium, and high market shares in the overall mutual fund market. While we find the strongest evidence of risk-taking by families with Low Market Share in the TDF market and Medium Market Share in the overall market, we also continue to find significantly higher levels of cross-sectional dispersion in net returns and five-factor alphas and higher levels of idiosyncratic risk among Post-PPA families. In our final set of robustness tests, reported in Internet Appendix Table B.14, we focus only on each family's year of entry, ignoring measures of market share. We find that TDFs from Post-PPA families have higher levels of cross-sectional dispersion in net returns and five-factor alphas and higher levels of idiosyncratic risk than families that entered before 2003. We conclude that a significant fraction of the increased dispersion in realized returns and the increased levels of idiosyncratic risk following the PPA reflects strategic risk-taking.

6 Does TDF heterogeneity reflect risk matching?

6.1 The role of risk matching incentives

Authors have shown that the properties of human capital returns have important implications for optimal portfolio choice and that ignoring them can lead to substantial utility costs (e.g., Davis and Willen 2000a; Davis and Willen 2000b; Davis and Willen 2002; Maurer et al. 2010; Fugazza et al. 2011; Guidolin and Hyde 2012; Bagliano et al. 2013).[31] Of special interest is the heterogeneity in the properties of human capital returns across occupations and industries.[32] Therefore, another explanation for the increased heterogeneity in TDF investment behavior is that it reflects an intentional differentiation of ex-ante risk profiles to better match the heterogeneity in investor human capital and risk aversion across firms.

As dispersion in glide paths is readily observable to plan sponsors and their consultants, one hypothesis is that firms whose employees have riskier human-capital endowments will pick safer TDFs for their 401(k) plans. For example, since firms in more competitive industries expose their employees to higher human-capital risk, they may choose to avoid TDFs with larger-than-average allocations to equity. This effect may be especially true when the plans feature automatic enrollment, since the TDFs in these plans are likely to be the default investment options. This form of risk matching, which we denote "human-capital risk matching," implies a negative correlation between TDF risk and firm risk.

Viceira (2009) highlights the potential benefits of human-capital risk matching: "Employees with volatile labor earnings or labor earnings that are highly correlated with equity returns should

[31] See also our own calculations in Section D.2.4 of the Internet Appendix. For example, a household whose labor income is originated in the mining sector, and is assigned a portfolio optimized for the median exposure of labor income growth to the stock market, suffers an annual certainty-equivalent return loss of 1.8%. For a household in the government sector, the loss is 0.31%. In addition, human capital can substantially affect capital market equilibrium; see, for example, Eiling (2013).

[32] Because the broader literature on the implications of human capital for optimal portfolio choice is too vast to summarize here, we refer interested readers to the review article by Benzoni and Chyruk (2013). Mitchell and Turner (2009) review the literature on the interaction between labor market uncertainty and pension plan design.

avoid investing in the current generation of life-cycle funds, which exhibit significant equity tilts. For these investors, their human wealth is less 'bond-like' and more 'equity-like.' Therefore they already have exposure to equities through their human wealth and should avoid excessive exposure, or any exposure at all, to equities in their portfolios. Since the correlation of labor earnings with stock returns is likely to be similar for employees within the same industry or company, these considerations suggest that there is a benefit to the creation of industry-specific or company-specific life-cycle funds."[33]

On the other hand, if the risk attitudes of the representative employee vary across firms (Berk et al. 2010), and if different firms appeal to employees with different levels of risk aversion, then we should observe a positive, rather than negative correlation, between TDF risk profiles and firm risk profiles. We denote this "risk-preference matching." Indeed, Viceira (2009) suggests that: "Mutual fund companies might want to consider offering life-cycle funds that exhibit different equity tilts. That is, they might want to offer 'conservative,' 'moderate,' and 'aggressive' life-cycle funds. These funds will help capture investor heterogeneity in risk tolerance."

Interestingly, DOL (2013) emphasizes the need for plan fiduciaries to consider investor characteristics when choosing among TDF providers.[34] While this memo highlights the benefits of a marketplace in which different TDFs offer different ex ante risk profiles, it also highlights the possibility that benefits from risk matching were not yet salient to the typical plan sponsor of mutual fund family. We do not take a stand on the form of the possible risk matching (human-capital risk matching versus risk-preferences matching). In our main specifications, we simply test for non-zero correlations between firm risk and TDF risk using plan-level data and measures of systematic and idiosyncratic risk. Hence, we seek to characterize "average" patterns in risk matching, with the goal of determining whether risk-matching considerations help to explain the increased heterogeneity in TDF investment behavior in our sample following the PPA. However, as a robustness test, we also estimate specifications based on the absolute values of TDF risk and firm risk. These specifications

[33] In Section D.2.4 of the Internet Appendix, we show analytically how an increase in labor earnings volatility and in the correlation between labor earnings growth and equity returns reduces the optimal equity allocation.

[34] DOL (2013) states: "You should consider how well the TDFs' characteristics align with eligible employees ages and likely retirement dates. It also may be helpful for plan fiduciaries to discuss with their prospective TDF providers the possible significance of other characteristics of the participant population, such as participation in a traditional defined benefit pension plan offered by the employer, salary levels, turnover rates, contribution rates and withdrawal patterns."

are intended to capture situations whether some firms choose TDFs based on human-capital risk matching while others simultaneously choose TDFs based on risk-preference matching.

6.2 Testing for risk matching in plan-level data

To test the risk matching hypothesis, we analyze retirement plan-level data from BrightScope.[35] The full database covers 16,766 distinct 401(k) and 403(b) plans, offered by 15,403 distinct firms, in 2010. There are more plans than firms because some firms offer multiple plans. For example, United Airlines offers separate retirement plans for its pilots and ground employees. Firm-level data include the firm's name, primary address, and 6-digit North American Industry Classification System (NAICS) code. We are able to locate a ticker and estimate a CAPM beta for 1,740 of the firms in the BrightScope database.[36] Plan-level data include assets under management, number of participants, whether the plan offers company stock, whether the plan has auto enrollment, whether the plan has a single record keeper (SRK), and the identity of the record keeper. Investment-level data include the name and type (mutual fund, collective trust, separate account, company stock, etc.) of each investment option offered by each plan, whether the investment option is a TDF, and the total dollars invested in the option.

Summary statistics for the BrightScope data set are presented in Table 12. Approximately 66% of the plans offer some form of TDF, with 50% offering TDF mutual funds. When we count TDFs with different target retirement dates as a single investment option, TDFs represent 2.7% of the investment options and 9.7% ($242 billion) of the $2,495 billion in assets under management in our sample of plans in 2010.[37] The fact that TDFs managed almost 10% of DC assets in 2010 highlights the important role that TDFs have come to play in retirement wealth accumulation.

The advantage of using plan data from 2010 to test for risk matching is that plan sponsors were able to choose from the full range of TDFs introduced following the PPA. Table 12 reveals

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

[36] We use the 24 monthly returns between December 2007 and November 2009 to estimate the CAPM beta as of December 2009. Our proxy for the market portfolio is the excess return on the market as reported on Kenneth French's website. For comparability, we use the same time period and market portfolio to estimate the CAPM beta of each mutual fund in the BrightScope sample.

[37] When we focus only on mutual funds, TDFs account for 3.0% of the investment options and 13.9% ($157 billion) of the $1,131 billion in assets under management.

considerable dispersion in firm risk, whether measured by the CAPM beta or the standard deviation of residual returns. Consistent with our earlier analysis, it also reveals significant dispersion in the CAPM betas of the TDFs offered within the plans. For example, the estimated CAPM betas of 2020 TDFs range from 0.63 to 1.00.[38]

Within our sample, there are 7,687 retirement plans that offer TDFs and employ an SRK that is also an asset management firm. When we distinguish investment options managed by SRKs from investment options managed by other asset management firms, we find that 76% of TDFs are managed by SRKs versus 39% of non-TDF investments. The fact that plan sponsors disproportionately offer the TDFs of their record keepers is suggestive evidence against risk matching, but only if plan sponsors are not choosing record keepers based on the TDFs that they offer.[39]

To formally test for a correlation between the riskiness of a firm and the riskiness of the TDF that the firm offers to its employees, we estimate the following cross-sectional model:

$$\text{TDF risk}_{ijk} = a + b \text{ firm risk}_j + c^\top X_i + \epsilon_{ijk}, \tag{3}$$

where TDF risk_{ijk} measures of the risk of the TDF(s) offered in plan i sponsored by firm j in industry k, and firm risk_j measures the risk of the plan sponsor. For each target date, we subtract the average CAPM beta (or idiosyncratic volatility) of TDFs with the same target date and then average the target date-level tilts across all target dates. The resulting plan-level tilt is the dependent variable. If there is any form of risk matching, the estimated coefficient on firm risk_j will be non-zero. The X_i vector includes several plan-level (i.e., demand-side) controls. Because plan sponsors may focus more on TDF risk when plans feature auto enrollment, we include a dummy indicating if the plan features auto enrollment and, in some specifications, an interaction between the measure of firm risk and the dummy indicating if the plan has auto enrollment. Our measure of plan-level risk is the average risk of the non-TDF mutual fund options. We also include the natural logarithm of plan assets, the natural logarithm of plan participants, a dummy indicating if the plan

[38]It is worth noting that this range of beta estimates contrasts with what reported in Table 6, where 2015-2020 TDF betas range from 0.14 to 0.66. The reason for the discrepancy is that betas here are estimated from a single-factor model, rather than a five-factor model.

[39]We cannot directly test this alternative because we lack date on when plan sponsors hire record keepers. However, (unreported) regressions of firm-level risk on record keeper fixed effects yield adjusted R^2s between 0.91% and 1.51%.

offers company stock. The X_i vector also includes several family-level (i.e., supply-side) controls. Because we find that plans are more likely to offer the TDFs of their record keepers, we include either a dummy equal to one if plan i has an SRK, or the market share of the SRK's investment options in the BrightScope sample. The prediction, based on our earlier findings, is that TDFs offered by families with a higher share of the 401(k) market will exhibit lower levels of risk-taking.[40] We also include dummy variables indicating whether the TDF is offered by a Pre-PPA family with Low Market Share or a Post-PPA family with Low Market Share. These variables allow us to explore whether we continue to observe higher levels of risk-taking by Low Market Share families that appear on at least one investment menu. In some specifications, we include a separate fixed effect for each industry (defined using the first 3 digits of the NAICS code), to control for average differences in firm risk across industries. Standard errors are clustered on industry.

We include in the analysis plans that offer at least one TDF that BrightScope classifies as a mutual fund regardless of the target date, for a total of 7,983 retirement plans, 968 of which are offered by a publicly traded firm. We report the regression results in Table 13. Within the sample of publicly traded firms, the estimated regression coefficients on firm risk are negative, but they are neither statistically nor economically distinguishable from zero. While the adjusted R^2 in the first specification is 11.57%, most of the explanatory power is coming from the supply-side variables. When we exclude the SRK and Low Market Share dummy variables, the adjusted R^2 is only 2.18%. Moreover, the modest increase in adjusted R^2 (from 11.57% to 14.21%) when we introduce industry fixed effects, suggests limited matching of TDF risk to average industry risk. Among the demand-side variables, we find that TDF risk decreases with plan assets and increases with the number of plan participants, but neither effect is economically large.

When we instead measure firm-level risk as the median CAPM beta of firms in the same industry, we find a weak positive correlation between the CAPM beta of the TDF and the CAPM beta of the industry. The estimated coefficient of 0.005 implies that a one-standard deviation increase in industry risk (0.495) is associated with an increase of less than 0.003 in TDF equity betas. When we estimate a specification that allows the correlation between TDF risk and firm risk

[40]The correlation between the market share of an SRK's investment options and the market share of its TDF options is 0.982, further justifying our earlier focus on a family's market share in the TDF market.

to vary with automatic enrollment, we find that the negative coefficient on the interaction term is similar in magnitude to the positive coefficient on firm risk. Consequently, we find a weak positive correlation between TDF risk and firm risk in the sample of plans without automatic enrollment and no correlation in the sample of plans with auto-enrollment. To explore the possibility that riskier firms offer investment menus skewed toward riskier funds, the final specification controls for the average CAPM beta of the plan's non-TDF mutual funds (where each fund's beta is measured relative to other funds with the same investment objective). The estimated coefficient on plan risk is positive and statistically significant at the 5% level, suggesting that plans offering riskier-than-average non-TDF options are slightly more likely to offer riskier-than-average TDFs, but the estimated coefficients on the other variables are largely unchanged.

The coefficients on the supply-side variables are consistent with strategic risk-taking within this (important) sample of TDFs. We find that that TDF risk is lower in plans that offer a SRK and, within this sample of plans, is decreasing in the market share of the SRK. A one-standard-deviation increase in market share (0.090) within our sample is associated with a reduction in beta of 0.012, while an increase from the 25th to the 75th percentile (0.187) is associated with a reduction in beta of 0.026. We also find that the TDFs offered by Post-PPA with Low Market Share have CAPM betas that are 0.077–0.102 higher than other TDFs, a much larger effect. More generally, much of the explanatory power comes from the supply-side variables; adjusted R^2s are between 11.57% and 19.61% when we include them, but only between 2.18% and 5.73% when we exclude them.

In Panel B, we shift our focus from systematic risk to idiosyncratic risk. Specifically, we use each firm's and TDF's estimated CAPM beta to decompose its monthly returns into systematic and idiosyncratic components. We then calculate the standard deviation of the idiosyncratic returns over the prior 24 months. Because the mean of the dependent variable is only 0.010, for ease of comparison, we multiply the estimated coefficients by 100.

We find some evidence of human-capital risk matching, but only in the industry-level regressions, and only in plans that do not feature automatic enrollment. The effects are small. A one standard deviation in industry risk (0.031) is predicted to decrease TDF idiosyncratic risk by less than 0.00006, which is less than 0.038 standard deviations of the dependent variable. In contrast, we continue to find much larger effects for the supply-side variables. A one standard deviation in the market share of the SRK is predicted to decrease TDF risk by 0.031% (0.174 standard deviations). Furthermore, TDFs from Low Market Share families exhibit consistently higher levels of idiosyncratic risk. In the final specification, the magnitudes are 0.086% (0.569 standard deviations) for Pre-PPA families and 0.167% (1.110 standard deviations) for Post-PPA families. These patterns are consistent with Low Market Share families increasing idiosyncratic volatility to compete for flows. The differences between Panels A and B are consistent with Pre-PPA families being less constrained with respect to the level of idiosyncratic volatility than they are with respect to the level of CAPM beta.

One interpretation of the low correlations that we document between TDF risk and firm risk is that the value of risk matching was not yet salient to plan sponsors. Another interpretation is that the low correlations reflect offsetting behavior: some risky firms seek out safe TDFs (human-capital risk matching) while other risky firms seek out risky TDFs (risk-preference matching). In Internet Appendix Table B.15, we assign TDFs and firms to terciles based on their risk levels and then report the number of plans within each bin. We report numbers based on both systematic and idiosyncratic risk for the full sample of plans and for the subsample that features auto-enrollment. In only two of the four panels can we reject the hypothesis that TDF risk is independent of firm risk. In Internet Appendix Table B.16, we re-estimate the specifications in Table 13 using the absolute value of TDF risk as new dependent variables and the absolute value of (demeaned) firm risk as new independent variables. To the extent that the safest or riskiest firms are more likely to match with the safest or riskiest TDFs, the predicted coefficient on the absolute value of firm risk is positive. Across both panels, one of the fourteen estimated coefficients is positive and statistically significant, three are negative and statistically significant, and economic significance remains low.

Finally, under the risk-matching hypothesis, the Post-PPA increase in heterogeneity in TDF risk characteristics should mirror a Post-PPA increase in heterogeneity in the risk characteristics of the companies offering TDFs in their plans. We present suggestive evidence in Internet Appendix Table B.17 that this has not been the case. Specifically, we obtain data on Form 5500 from the DOL website for 2005, the year before the PPA, and 2012, the end of our sample period. We then use the NAICS6 industry classification code to calculate the fraction of plan participants working in different industries. These fractions are qualitatively similar in both cross sections. The two exceptions are a decrease in the market share of manufacturing and an increase in the market share of health care. We conclude that risk matching is unlikely to explain a significant fraction of the increased heterogeneity in TDF investment behavior following the PPA.

7 Heterogeneity in TDF returns: why should we care?

7.1 Existing studies

Our study has uncovered large differences in realized returns and ex-ante risk profiles for TDFs with the same target date. Moreover, while we have been able to relate these differences to the risk-taking incentives of families offering TDFs, we have not been able to relate them to the characteristics of the firms offering TDFs in their retirement plans. A crucial question is whether the differences that we document have a economically meaningful impact on the welfare of TDF investors. Existing studies show that utility costs associated with heterogeneity in TDF investment behavior can be substantial (e.g., Gomes et al. 2008; Bagliano et al. 2013; Pang and Warshawsky 2009). In these studies, heterogeneity in TDF returns arises solely from differences in exposure to systematic risk. However, our analysis finds that a large component of the heterogeneity in TDF returns is due to heterogeneity in idiosyncratic returns. The presence of idiosyncratic returns has the potential to generate additional utility costs unless it is compensated with higher expected returns (which we do not find to be the case given the evidence in Table 9).

There is also the issue of transparency. Existing studies have shown that utility costs can increase when the properties of TDF returns are not known with certainty. Therefore, investors and plan sponsors should know the risk levels—both systematic and idiosyncratic—that investors are exposed to when investing in a TDF. Indeed, the introduction of TDFs has been predicated on the grounds that TDF investors are less likely to be exposed to too little systematic equity risk when young, and too much systematic equity risk when old, and will be less tempted to rebalance their portfolios in response to recent market returns. In the presence of unclear risk profiles, investors may be better off choosing investments on their own. Moreover, as the reputation of TDFs is tarnished, investors may become more reluctant to invest in TDFs. In November 2010, responding to the large cross-sectional dispersion in TDF returns during the financial crisis, DOL proposed rules to increase investor understanding of how TDFs operate.[41] The rules are still pending.

The arguments above are strengthened when one considers that over 90% of 401(k) plan participants are limited to the TDFs offered by a single family. Hence, for the typical investor, the expected utility costs associated with heterogeneity in TDF risk profiles cannot easily be diversified away by investing in a portfolio of TDFs with the same target date.

7.2 The costs of TDF heterogeneity

To further investigate the costs of TDF heterogeneity, we perform a simulation exercise.[42] We simulate the terminal wealth realized by a homogeneous investor who is randomly assigned to a TDF with the characteristics—systematic risk, idiosyncratic risk, and abnormal returns—of the TDFs offered by a specific fund family, where the probability of being assigned that TDF reflects the family's market share. We compare the terminal wealth resulting from a random TDF assignment to the terminal wealth of an investor assigned to a "benchmark" TDF with known risk characteristics. We perform the analysis assuming two investment horizons, 45 and 25 years, and we calibrate the properties of TDFs separately to the universe of TDFs in existence during the Pre-PPA and Post-PPA time periods. We also compute the difference in annualized log certainty equivalent returns (CERs) associated with benchmark and random TDF assignment. Finally, we compute the utility cost associated with random assignment as the fraction of initial wealth that a constant relative risk aversion (CRRA) investor would be willing to pay to be assigned to the benchmark TDF instead of being randomly assigned.

[41] In the initial proposal, TDFs would be required to provide: i) a description and graphical illustration of the asset allocation, how it will change over time, and the point when it will be the most conservative; ii) a clarification of the relevance of the date (if the name includes a target date) and the target age group for which the investment is designed; and iii) a statement that a participant is not immune from risk of loss, even near or after retirement, and that no guarantee of sufficient returns to sustain an adequate retirement income can be given (DOL: EBSA Federal Register: 29 CFR Part 2550, RIN 1210-AB38, October 20, 2010). In May 2012, additional disclosure requirements were proposed, based "on evidence that plan participants and beneficiaries would benefit from additional information concerning these investments" (DOL: EBSA Federal Register: 29 CFR Part 2550, RIN 1210-AB38, May 24, 2012). In April 2013, "the Securities and Exchange Commission's Investor Advisory Committee recommended that the Commission develop a glide path illustration for target date funds that is based on a standardized measure of fund risk as a replacement for, or supplement to, an asset allocation glide path illustration." Between May 27, 2014 and July 3, 2014, the DOL reopened the public comment period.

[42] We describe the simulation set-up and provide a detailed set of results in Section D of the Internet Appendix.

The simulation analysis highlights the potential welfare costs of random assignment. First, the ratio between the terminal wealth resulting from random assignment and the terminal wealth resulting from assignment to the benchmark TDF varies widely: the interquartile range is as high as 39%. Second, the probability of underperforming the benchmark TDF by 15% or more can be as high as 24%. Third, the utility costs and CER differentials are always higher for the Post-PPA than for the Pre-PPA calibration. For example, in the case where Fidelity TDFs represent the known benchmark and the investor has a 45-year investment horizon, the annualized log CER differentials are 0.18% and 2.17% for the Pre- and Post-PPA calibration, respectively, resulting in utility costs of 7.75% and 62.40% of initial wealth. These differences between the Pre-PPA and Post-PPA calibration exercises are important because they highlight how the increase in heterogeneity following the passage of the PPA had the potential to significantly reduce investor welfare.

8 Conclusion

We document pronounced heterogeneity in investor exposure to both ex-post and ex-ante risk across TDFs with the same target date. This heterogeneity increases with the passage of the PPA in 2006, which draws new families into the TDF market. The decision of families with low market share—and especially those that enter the market after 2006—to load on idiosyncratic risk is consistent with strategic risk-taking behavior. On the other hand, we find little evidence that the heterogeneity in systematic or idiosyncratic risk-taking is driven by matching between TDF and sponsoring firm's risk characteristics. Hence, our findings support the notion that the TDF heterogeneity uncovered by this paper is driven by strategic risk-taking rather than risk matching motives. We also demonstrate that heterogeneity without risk matching can impose significant utility costs on investors. Our findings have normative and positive implications. From a normative standpoint, more transparency regarding TDF glide paths and systematic risk may not help investors make informed choices, both because the typical investor is limited to TDFs from a single mutual fund family and because entrants have differentiated their products partly in terms of idiosyncratic returns. From a positive standpoint, we provide an explanation for an apparently puzzling degree of heterogeneity in TDF investment behavior.

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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 seven columns indicate the number of mutual fund families that offer at least one TDF with a target retirement date of now (income fund) or 2000, 2005 or 2010, . . . , or 2055 or 2060 at the end of each year. The next three columns indicate the number of distinct mutual fund families that offer at least one TDF at the end of each year, the number of families that enter the market, and the number of families that exit the market. AUM measures total assets under management in TDFs at the end of the year (in \$ millions), summed across all mutual fund families. The last four columns indicate the name of the mutual fund family with the largest market share (based on AUM) at the end of the year, the market share of the market leader, the combined market share of the three families with the largest market shares, and the combined market share of families entering the market in 2007 and later. Through 2000, the only market participants were American Independence Financial Services, Barclays Global Fund Advisors, Fidelity Management and Research, and Wells Fargo.

	# Families offering one or more TDF within target date range							# Families					Market Share		
	Income & 2000	2005 & 2010	2015 & 2020	2025 & 2030	2035 & 2040	2045 & 2050	2055 & 2060	Total	Enter	Exit	AUM	Market Leader	Market Leader	Top 3 Families	Post-PPA Entrants
1994	1	1	1	1	1			1	1		278.4	Wells Fargo	100.0%	100.0%	
1995	1	1	1	1	1			1			590.1	Wells Fargo	100.0%	100.0%	
1996	3	3	3	3	2			3	2		894.2	Wells Fargo	63.9%	100.0%	
1997	2	3	3	3	2			3			1,499.4	Wells Fargo	42.7%	100.0%	
1998	2	3	3	3	2			3			4,159.2	Fidelity	65.9%	100.0%	
1999	4	4	4	4	3			4	1		6,525.5	Fidelity	76.6%	99.5%	
2000	4	4	4	4	4			4			8,215.1	Fidelity	80.4%	99.4%	
2001	4	5	5	5	5	1		5	1		11,828.8	Fidelity	85.1%	99.1%	
2002	6	6	6	6	6	1		6	1		14,509.5	Fidelity	88.1%	97.8%	
2003	9	9	9	9	9	2		9	3		25,632.2	Fidelity	85.1%	92.6%	
2004	12	11	12	12	12	4		13	4		43,729.2	Fidelity	71.0%	85.3%	
2005	17	17	20	20	19	7		20	7		70,211.3	Fidelity	61.5%	85.3%	
2006	20	21	27	27	25	12	1	27	7		115,958.0	Fidelity	54.9%	84.0%	
2007	24	28	35	35	32	22	2	35	8		174,647.8	Fidelity	50.5%	81.0%	1.5%
2008	31	33	44	44	43	35	3	44	9		159,717.1	Fidelity	42.8%	79.5%	2.7%
2009	28	31	40	40	40	34	3	40	1	5	254,826.0	Fidelity	39.0%	77.5%	3.7%
2010	27	27	39	39	39	36	8	39		1	339,879.4	Fidelity	36.7%	76.3%	4.2%
2011	27	26	40	40	40	38	15	40	1		375,686.1	Fidelity	34.6%	75.7%	4.5%
2012	28	22	37	37	37	35	19	37	1	4	480,162.4	Fidelity	32.7%	75.1%	4.4%

Table 2: Annual returns

This table summarizes the annual after-fee returns earned by TDFs with different target dates in different calendar years. Each calendar year, the sample includes all TDFs for which we observe 12 monthly returns. 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 (both equal-weighted and value-weighted based on the family's market share in the TDF market), and the minimum and maximum annual after-fee returns. We also report summary statistics for BFs offered by families that ever offer TDFs.

	2005 & 2010						2015 & 2020						2025 & 2030					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2000	4	0.5%	0.2%	0.2%	0.2%	0.7%	4	-3.7%	0.5%	0.4%	-4.1%	-3.0%	4	-5.7%	0.5%	0.4%	-6.1%	-5.1%
2001	4	-1.9%	1.7%	1.2%	-4.3%	-0.7%	4	-7.2%	1.2%	0.9%	-9.1%	-6.4%	4	-10.6%	0.8%	0.6%	-11.7%	-9.9%
2002	5	-7.4%	1.8%	0.7%	-9.3%	-4.6%	5	-12.0%	2.8%	0.9%	-14.0%	-7.2%	5	-15.2%	2.9%	1.0%	-17.3%	-10.3%
2003	6	17.5%	3.4%	1.1%	14.4%	23.8%	6	22.2%	3.2%	1.5%	19.3%	27.4%	6	25.4%	3.0%	1.7%	22.8%	30.0%
2004	10	7.8%	2.0%	1.1%	5.6%	11.6%	10	9.7%	1.6%	1.0%	8.2%	12.8%	10	11.1%	1.5%	0.9%	9.9%	14.1%
2005	13	4.7%	1.0%	0.7%	3.0%	6.2%	16	5.8%	1.2%	0.8%	4.1%	7.8%	16	6.8%	1.3%	0.9%	4.8%	8.8%
2006	20	9.7%	2.2%	1.4%	6.6%	13.9%	26	11.7%	2.0%	1.5%	7.9%	16.2%	26	13.4%	2.1%	1.5%	9.5%	17.6%
2007	28	6.2%	1.6%	1.0%	2.7%	9.2%	41	6.5%	2.0%	1.2%	2.2%	9.5%	38	6.8%	2.3%	1.4%	1.9%	10.2%
2008	35	-24.0%	5.9%	3.9%	-41.5%	-10.9%	53	-29.5%	5.1%	3.5%	-43.7%	-16.5%	50	-34.4%	3.8%	2.7%	-44.6%	-25.0%
2009	34	22.5%	4.2%	3.8%	12.6%	31.4%	67	25.1%	4.4%	4.3%	11.9%	35.4%	64	28.4%	4.1%	4.2%	18.6%	37.9%
2010	34	10.7%	1.3%	1.1%	7.6%	13.7%	71	12.0%	1.5%	1.2%	7.4%	14.9%	68	13.6%	1.4%	0.9%	9.5%	17.1%
2011	33	1.5%	2.0%	1.8%	-2.6%	6.7%	74	0.0%	2.3%	1.3%	-5.4%	9.6%	72	-1.8%	2.3%	1.2%	-6.7%	10.0%
2012	29	9.9%	1.9%	1.8%	4.9%	12.8%	72	11.4%	1.8%	1.8%	6.4%	14.9%	73	13.4%	1.6%	1.6%	9.1%	17.1%
Pre-PPA			1.9%	1.3%					1.8%	1.5%					1.8%	1.6%		
Post-PPA			3.3%	2.3%					3.1%	2.3%					2.7%	2.1%		
	2035 & 2040						2045 & 2050						Balanced Funds					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2000	3	-10.0%	0.2%	0.2%	-10.1%	-9.7%							53	1.6%	6.5%	6.8%	-12.0%	18.7%
2001	4	-13.7%	0.3%	0.1%	-13.9%	-13.4%							56	-4.5%	5.4%	5.4%	-17.0%	11.0%
2002	5	-18.0%	3.0%	0.9%	-20.1%	-12.8%	1	-15.8%	0.0%	0.0%	-15.8%	-15.8%	67	-10.0%	7.2%	8.7%	-35.0%	6.1%
2003	6	28.2%	2.5%	1.6%	24.2%	31.2%	1	26.3%	0.0%	0.0%	26.3%	26.3%	60	20.6%	5.7%	9.8%	9.8%	48.6%
2004	10	11.9%	1.0%	0.7%	10.9%	14.1%	2	13.0%	0.2%	0.1%	12.9%	13.1%	73	8.7%	2.4%	2.7%	3.2%	15.0%
2005	16	7.4%	1.3%	0.8%	5.2%	9.1%	4	8.1%	0.9%	1.0%	6.9%	9.2%	78	5.2%	1.8%	2.4%	0.7%	13.2%
2006	25	14.7%	1.7%	1.3%	11.2%	17.8%	8	15.9%	0.9%	0.3%	14.6%	17.5%	140	11.0%	3.4%	3.1%	2.6%	21.9%
2007	35	6.9%	2.6%	1.5%	1.6%	10.9%	14	6.5%	2.9%	0.8%	1.4%	11.2%	193	6.0%	3.1%	2.5%	-8.9%	23.3%
2008	48	-36.9%	2.4%	1.8%	-41.4%	-30.6%	33	-37.8%	2.2%	2.3%	-41.6%	-33.6%	236	-25.7%	7.8%	6.1%	-42.7%	1.2%
2009	63	30.5%	4.0%	3.9%	20.6%	39.5%	51	31.5%	4.0%	3.8%	20.5%	42.5%	351	22.9%	7.3%	5.8%	-2.1%	47.5%
2010	67	14.6%	1.7%	0.9%	9.9%	20.9%	56	14.9%	1.5%	0.9%	12.4%	20.1%	318	11.8%	2.5%	2.3%	3.5%	21.7%
2011	71	-3.3%	2.4%	1.1%	-7.7%	10.0%	62	-3.8%	2.5%	1.2%	-8.1%	10.0%	312	0.5%	3.0%	3.3%	-7.7%	10.9%
2012	73	14.8%	1.7%	1.5%	9.5%	18.1%	67	15.3%	1.6%	1.4%	9.7%	18.2%	327	11.6%	2.9%	2.6%	-7.6%	24.1%
Pre-PPA			1.6%	1.5%					0.7%	0.6%					4.7%	4.8%		
Post-PPA			2.5%	1.9%					2.5%	1.9%					4.9%	4.4%		

Table 3: Annual five-factor-model alphas

This table summarizes the annualized after-fee alphas earned by TDFs with different target dates in different calendar years. We estimate the five-factor alpha of fund i in month t using all daily returns over the prior twelve months. The five factors are the daily excess returns of the US market, MSCI World Index excluding the US, Barclays US Aggregate Bond Index, Barclays Global Aggregate excluding the US, and GSCI Commodity Index. To calculate the five-factor alpha of fund i in year t, we compound the twelve monthly alphas. The sample sizes are smaller than in Table 2 because the sample is restricted to TDFs and calendar years for which we are able to estimate the factor model in January through December. Within each target date-year cell, we report the number of TDFs, the average annualized after-fee alpha, standard deviation of the annualized after-fee alphas (both equal-weighted and value-weighted based on the family's market share in the TDF market), and the minimum and maximum annualized after-fee alphas. We also report summary statistics for BFs offered by families that ever offer TDFs.

	2005 & 2010						2015 & 2020						2025 & 2030					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2002	4	-2.4%	1.2%	0.8%	-3.7%	-0.8%	4	-1.7%	0.8%	0.4%	-2.9%	-1.3%	4	-1.6%	0.5%	0.2%	-2.4%	-1.3%
2003	5	-1.1%	3.2%	1.5%	-3.8%	3.4%	5	-1.1%	3.4%	1.7%	-4.2%	3.3%	5	-1.4%	3.1%	1.7%	-4.4%	1.9%
2004	6	-0.5%	1.7%	0.9%	-2.0%	2.5%	6	-0.7%	1.5%	0.8%	-2.3%	1.6%	6	-0.8%	1.4%	0.8%	-2.2%	1.2%
2005	10	0.1%	0.8%	0.5%	-1.6%	1.0%	10	0.7%	0.9%	0.5%	-1.1%	1.8%	10	1.0%	1.1%	0.6%	-1.0%	2.0%
2006	11	-0.9%	0.9%	0.5%	-2.3%	1.2%	12	-1.0%	1.1%	0.8%	-2.4%	1.0%	12	-1.2%	1.3%	0.9%	-3.4%	0.7%
2007	18	-1.1%	1.7%	0.8%	-3.9%	1.7%	24	-1.0%	2.1%	1.0%	-4.5%	2.0%	22	-0.5%	2.5%	1.2%	-4.9%	2.4%
2008	30	-2.8%	3.9%	2.2%	-13.6%	3.6%	43	-1.6%	3.6%	2.4%	-10.6%	6.2%	40	-0.1%	2.9%	2.4%	-6.0%	7.3%
2009	31	4.2%	3.4%	2.7%	-2.6%	11.2%	53	3.3%	3.1%	3.0%	-2.9%	10.0%	51	2.9%	2.8%	3.0%	-3.2%	8.9%
2010	31	-0.5%	1.2%	0.5%	-2.8%	1.8%	67	-0.7%	1.6%	0.7%	-3.6%	4.0%	64	-1.1%	1.5%	0.7%	-4.1%	4.0%
2011	32	-1.7%	1.1%	0.8%	-4.2%	0.7%	71	-2.3%	1.4%	0.7%	-6.5%	3.7%	68	-3.0%	1.5%	0.8%	-6.4%	3.9%
2012	28	0.8%	1.0%	0.8%	-0.9%	3.2%	67	0.6%	1.1%	0.7%	-1.6%	3.3%	66	0.1%	1.2%	0.6%	-2.6%	2.9%
Pre-PPA			1.5%	0.9%					1.5%	1.0%					1.5%	1.2%		
Post-PPA			2.4%	1.4%					2.2%	1.6%					2.0%	1.6%		

	2035 & 2040						2045 & 2050						Balanced Funds					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2002	4	-1.0%	0.8%	0.3%	-1.8%	-0.2%							62	-2.4%	3.3%	5.9%	-16.9%	3.4%
2003	5	-1.4%	2.7%	1.7%	-4.5%	2.0%	1	-0.3%	0.0%	0.0%	-0.3%	-0.3%	57	-1.1%	2.9%	4.7%	-8.3%	11.7%
2004	6	-1.0%	1.3%	0.7%	-2.0%	0.8%	1	0.3%	0.0%	0.0%	0.3%	0.3%	73	-0.9%	1.7%	1.4%	-5.5%	2.3%
2005	10	1.1%	1.0%	0.5%	-0.6%	2.1%	2	1.3%	1.1%	0.7%	0.6%	2.1%	74	-0.1%	1.5%	1.8%	-3.5%	6.9%
2006	12	-1.2%	1.4%	0.9%	-4.0%	0.5%	3	-0.8%	1.2%	0.4%	-2.2%	0.0%	89	-0.8%	1.7%	1.8%	-4.0%	4.2%
2007	21	-0.6%	2.8%	1.3%	-5.5%	3.2%	7	-1.2%	3.2%	0.9%	-5.4%	3.3%	167	-0.9%	2.7%	2.5%	-12.9%	12.4%
2008	37	0.7%	2.7%	2.4%	-3.4%	7.2%	16	0.5%	2.5%	2.3%	-3.1%	7.3%	187	-4.0%	5.1%	4.0%	-25.8%	7.7%
2009	49	2.5%	2.9%	2.9%	-3.1%	9.2%	35	2.6%	3.3%	2.9%	-3.2%	10.5%	230	4.9%	4.7%	3.5%	-8.8%	25.7%
2010	63	-1.3%	1.6%	0.7%	-4.6%	4.0%	52	-1.5%	1.6%	0.8%	-4.9%	4.0%	305	-0.4%	2.2%	1.8%	-7.2%	8.7%
2011	67	-3.7%	1.8%	0.9%	-7.8%	4.2%	57	-3.9%	1.8%	0.9%	-7.7%	4.1%	294	-1.4%	2.4%	2.6%	-7.9%	9.2%
2012	66	-0.4%	1.2%	0.6%	-3.3%	2.7%	59	-0.5%	1.2%	0.6%	-3.3%	2.8%	302	1.0%	1.8%	1.2%	-3.5%	9.0%
Pre-PPA			1.4%	1.2%					0.8%	0.7%					2.2%	2.7%		
Post-PPA			2.1%	1.7%					2.0%	1.5%					3.2%	2.7%		

Table 4: Annual standard deviation of monthly five-factor-model alphas

This table summarizes the annualized standard deviations of monthly five-factor model alphas for TDFs with different target dates in different years. We calculate the standard deviation of monthly alphas for fund i in calendar year t and then report statistics for the cross section of TDFs. The sample is the same as Table 3 because it is also limited to TDFs for which we are able to estimate five-factor alphas in January through December of year t. Within each target date-year cell, we report the number of TDFs, the average TDF-level standard deviation (both equal-weighted and value-weighted based on the family's market share in the TDF market), the standard deviation within target date j and year t of the TDF-level standard deviations, and the minimum and maximum TDF-level standard deviations. We also report summary statistics for BFs offered by families that ever offer TDFs.

	2005 & 2010						2015 & 2020						2025 & 2030					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2002	4	1.6%	0.6%	0.3%	0.7%	2.1%	4	1.4%	0.4%	0.1%	1.0%	1.9%	4	1.4%	0.2%	0.1%	1.1%	1.6%
2003	5	1.1%	0.4%	0.3%	0.5%	1.4%	5	1.3%	0.5%	0.3%	0.5%	1.6%	5	1.5%	0.7%	0.4%	0.7%	2.2%
2004	6	0.9%	0.9%	0.5%	0.4%	2.7%	6	1.0%	0.8%	0.4%	0.5%	2.6%	6	1.1%	0.6%	0.3%	0.6%	2.3%
2005	10	0.7%	0.3%	0.1%	0.5%	1.3%	10	0.8%	0.3%	0.2%	0.4%	1.2%	10	1.0%	0.3%	0.2%	0.5%	1.5%
2006	11	0.8%	0.2%	0.2%	0.3%	1.1%	12	0.9%	0.2%	0.2%	0.5%	1.2%	12	1.1%	0.3%	0.3%	0.5%	1.4%
2007	18	1.1%	0.5%	0.3%	0.4%	2.4%	24	1.2%	0.5%	0.3%	0.4%	2.6%	22	1.5%	0.5%	0.2%	0.5%	2.8%
2008	30	3.0%	1.7%	0.7%	1.2%	9.2%	43	3.0%	1.3%	0.6%	1.4%	7.9%	40	3.0%	1.0%	0.7%	1.4%	5.4%
2009	31	2.1%	0.8%	0.5%	0.9%	3.8%	53	2.4%	0.9%	0.6%	0.9%	5.6%	51	2.7%	0.9%	0.6%	1.2%	6.4%
2010	31	1.8%	0.8%	0.3%	0.8%	4.1%	67	1.8%	0.9%	0.4%	0.7%	6.6%	64	2.0%	1.0%	0.4%	0.7%	8.3%
2011	32	1.2%	0.4%	0.3%	0.5%	2.2%	71	1.5%	0.9%	0.3%	0.6%	5.0%	68	1.6%	0.8%	0.4%	0.7%	6.2%
2012	28	1.0%	0.4%	0.2%	0.5%	2.3%	67	1.3%	0.5%	0.3%	0.5%	2.7%	66	1.5%	0.5%	0.3%	0.7%	3.0%
Pre-PPA		0.9%						1.0%						1.1%				
Post-PPA		1.7%						1.9%						2.0%				

	2035 & 2040						2045 & 2050						Balanced Funds					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2002	4	1.5%	0.1%	0.0%	1.4%	1.5%							62	2.8%	1.5%	1.4%	0.4%	7.6%
2003	5	1.4%	0.5%	0.3%	0.8%	2.0%	1	1.0%	0.0%	0.0%	1.0%	1.0%	57	1.7%	1.0%	1.1%	0.2%	5.5%
2004	6	1.1%	0.4%	0.2%	0.5%	1.7%	1	1.4%	0.0%	0.0%	1.4%	1.4%	73	1.4%	0.8%	0.6%	0.3%	4.7%
2005	10	1.1%	0.3%	0.2%	0.6%	1.6%	2	0.8%	0.1%	0.1%	0.7%	0.9%	74	1.3%	0.8%	1.1%	0.1%	3.8%
2006	12	1.2%	0.4%	0.3%	0.5%	1.7%	3	1.0%	0.5%	0.3%	0.5%	1.6%	89	1.3%	0.7%	0.5%	0.2%	3.8%
2007	21	1.6%	0.5%	0.3%	0.5%	2.9%	7	1.5%	0.6%	0.4%	0.6%	2.1%	167	1.5%	0.8%	0.9%	0.3%	5.3%
2008	37	2.9%	0.8%	0.7%	1.5%	5.2%	16	3.0%	1.0%	0.9%	1.5%	5.1%	187	3.9%	2.7%	2.4%	0.5%	15.1%
2009	49	2.9%	0.9%	0.6%	1.3%	6.8%	35	3.1%	1.1%	0.7%	1.4%	7.0%	230	2.9%	1.3%	1.0%	0.5%	8.2%
2010	63	2.3%	1.3%	0.4%	0.8%	9.4%	52	2.3%	1.3%	0.4%	1.2%	10.3%	305	1.8%	0.9%	0.8%	0.3%	4.8%
2011	67	1.8%	0.9%	0.4%	0.8%	7.5%	57	1.8%	0.6%	0.4%	0.8%	5.1%	294	1.8%	1.2%	1.0%	0.3%	8.3%
2012	66	1.8%	0.5%	0.3%	0.9%	3.3%	59	1.9%	0.6%	0.3%	1.0%	3.3%	302	1.5%	0.9%	0.9%	0.3%	7.5%
Pre-PPA		1.2%						1.0%						1.6%				
Post-PPA		2.2%						2.2%						2.1%				

Table 5: Five-factor-model R^2s

This table summarizes the R^2 of TDFs with different target dates in different years with respect to a five-factor model. The five factors are the daily excess returns on the US market, MSCI World Index excluding the US, Barclays US Aggregate Bond Index, Barclays Global Aggregate excluding the US, and GSCI Commodity Index. The sample in year t is limited to TDFs for which we observe at least 200 daily returns through December of year t. Within each target date-year cell, we report the number of TDFs, the average R^2, standard deviation of R^2 (both equal-weighted and value-weighted based on the family's market share in the TDF market), and the minimum and maximum R^2. We also report summary statistics for BFs offered by families that ever offer TDFs.

	2005 & 2010						2015 & 2020						2025 & 2030					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2001	4	96.3%	1.2%	0.8%	95.3%	98.1%	4	98.2%	0.2%	0.1%	97.9%	98.4%	4	98.3%	0.1%	0.0%	98.3%	98.4%
2002	5	98.5%	0.6%	0.2%	97.8%	99.1%	5	99.0%	0.4%	0.1%	98.4%	99.3%	5	99.1%	0.3%	0.1%	98.7%	99.3%
2003	6	97.7%	1.2%	0.5%	95.8%	98.9%	6	98.2%	0.9%	0.4%	96.5%	98.9%	6	98.4%	0.4%	0.2%	97.8%	98.9%
2004	9	96.3%	2.6%	1.3%	90.2%	98.6%	9	97.2%	1.4%	0.7%	94.4%	98.4%	9	97.6%	1.0%	0.4%	95.7%	98.6%
2005	11	96.5%	1.5%	0.9%	93.3%	98.5%	12	97.3%	0.9%	0.5%	95.7%	98.6%	12	97.5%	0.8%	0.5%	96.2%	98.7%
2006	18	95.8%	2.2%	1.1%	90.1%	98.6%	22	97.0%	1.0%	0.5%	93.3%	98.5%	22	97.1%	0.9%	0.3%	95.0%	98.2%
2007	28	97.0%	1.7%	0.8%	92.3%	99.2%	40	97.8%	1.4%	0.5%	93.4%	99.4%	37	98.0%	1.3%	0.5%	93.6%	99.5%
2008	35	97.6%	1.8%	0.6%	90.4%	99.2%	53	98.3%	1.0%	0.5%	95.2%	99.4%	50	98.6%	0.7%	0.3%	96.3%	99.5%
2009	34	96.8%	3.1%	0.7%	84.9%	99.2%	67	97.3%	2.6%	0.6%	84.8%	99.5%	64	98.0%	1.4%	0.4%	89.6%	99.6%
2010	34	96.1%	5.8%	1.0%	67.9%	99.2%	71	97.3%	3.9%	0.7%	68.5%	99.4%	68	97.8%	3.8%	0.6%	69.1%	99.4%
2011	33	96.0%	6.3%	1.7%	64.1%	99.4%	74	96.7%	6.1%	1.1%	55.4%	99.5%	72	97.7%	5.6%	0.8%	55.7%	99.5%
2012	29	94.7%	6.2%	4.1%	64.8%	98.0%	72	95.0%	6.0%	2.3%	69.2%	98.4%	73	96.7%	3.9%	0.8%	70.1%	98.7%
Pre-PPA			1.8%	1.2%					1.0%	0.6%					0.8%	0.5%		
Post-PPA			4.5%	2.2%					4.3%	1.5%					3.5%	0.7%		

	2035 & 2040						2045 & 2050						Balanced Funds					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2001	4	98.5%	0.3%	0.3%	98.0%	98.7%							56	92.3%	9.9%	8.5%	31.3%	99.8%
2002	5	99.3%	0.2%	0.1%	98.9%	99.5%	1	98.9%	0.0%	0.0%	98.9%	98.9%	67	90.5%	15.6%	2.5%	35.1%	99.8%
2003	6	98.6%	0.4%	0.1%	98.1%	99.0%	1	98.7%	0.0%	0.0%	98.7%	98.7%	60	96.7%	2.3%	3.0%	86.9%	99.7%
2004	9	97.9%	0.9%	0.3%	95.9%	98.9%	2	98.8%	0.3%	0.2%	98.6%	99.0%	73	94.9%	3.9%	2.9%	81.7%	99.6%
2005	12	97.6%	0.8%	0.5%	96.4%	99.0%	3	98.0%	1.1%	0.5%	96.8%	98.8%	78	94.6%	4.4%	3.8%	77.3%	99.7%
2006	21	97.3%	0.8%	0.4%	95.3%	98.7%	7	97.6%	1.0%	0.6%	96.3%	99.0%	140	93.3%	9.4%	5.7%	4.5%	99.7%
2007	34	97.9%	1.4%	0.4%	93.7%	99.5%	13	98.3%	1.0%	0.4%	95.4%	99.5%	193	95.1%	4.6%	6.3%	74.6%	99.8%
2008	48	98.7%	0.6%	0.3%	96.5%	99.5%	33	98.7%	0.6%	0.3%	96.5%	99.5%	236	95.3%	9.4%	4.0%	9.7%	99.7%
2009	63	98.2%	1.1%	0.4%	92.0%	99.5%	51	98.1%	1.3%	0.4%	92.2%	99.6%	350	94.3%	9.9%	5.0%	10.2%	99.8%
2010	67	97.9%	3.8%	0.6%	69.3%	99.5%	56	97.9%	4.0%	0.6%	69.7%	99.5%	318	96.2%	4.7%	3.2%	45.4%	99.7%
2011	71	97.9%	5.6%	0.7%	55.3%	99.5%	62	98.1%	5.5%	0.7%	56.1%	99.5%	312	96.4%	4.3%	3.5%	71.4%	99.8%
2012	73	97.2%	3.6%	0.7%	69.5%	99.0%	67	97.2%	3.7%	0.7%	69.6%	99.1%	327	94.0%	6.8%	6.5%	47.9%	99.6%
Pre-PPA			0.7%	0.5%					0.8%	0.6%					8.8%	5.1%		
Post-PPA			3.5%	0.6%					3.6%	0.6%					7.1%	5.0%		

Table 6: Five-factor model US equity betas

This table summarizes the US equity betas of TDFs with different target dates in different years. The betas for fund i in month t are estimated in a five-factor model using the daily excess returns of the US market, MSCI World Index excluding the US, Barclays US Aggregate Bond Index, Barclays Global Aggregate excluding the US, and GSCI Commodity Index. The sample in year t is limited to TDFs for which we observe at least 200 daily returns through December of year t. Within each target date-year cell, we report the number of TDFs, the average beta (both equal-weighted and value-weighted based on the family's market share in the TDF market), the standard deviation of beta, and the minimum and maximum estimated betas. We also report summary statistics for BFs offered by families ever offer TDFs.

	2005 & 2010						2015 & 2020						2025 & 2030					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2001	4	0.36	0.05	0.04	0.34	0.44	4	0.58	0.04	0.03	0.55	0.63	4	0.70	0.01	0.01	0.69	0.72
2002	5	0.45	0.10	0.04	0.30	0.53	5	0.59	0.12	0.03	0.38	0.65	5	0.69	0.13	0.04	0.46	0.76
2003	6	0.44	0.07	0.03	0.37	0.57	6	0.57	0.07	0.03	0.46	0.67	6	0.67	0.07	0.03	0.54	0.74
2004	9	0.45	0.07	0.04	0.34	0.62	9	0.60	0.09	0.07	0.42	0.74	9	0.71	0.09	0.06	0.50	0.83
2005	11	0.44	0.08	0.06	0.32	0.59	12	0.59	0.07	0.07	0.43	0.70	12	0.71	0.07	0.06	0.52	0.80
2006	18	0.46	0.09	0.05	0.34	0.66	22	0.62	0.08	0.06	0.49	0.80	22	0.76	0.10	0.05	0.60	0.97
2007	28	0.50	0.12	0.05	0.23	0.73	40	0.67	0.10	0.07	0.50	0.92	37	0.82	0.09	0.07	0.61	0.98
2008	35	0.47	0.10	0.05	0.26	0.66	53	0.61	0.10	0.07	0.38	0.83	50	0.76	0.08	0.06	0.55	0.89
2009	34	0.47	0.10	0.06	0.27	0.66	67	0.58	0.12	0.07	0.16	0.80	64	0.74	0.10	0.06	0.39	0.90
2010	34	0.42	0.11	0.07	0.05	0.61	71	0.53	0.13	0.09	0.08	0.74	68	0.69	0.13	0.08	0.09	0.89
2011	33	0.37	0.10	0.08	0.05	0.51	74	0.48	0.12	0.10	0.07	0.70	72	0.65	0.12	0.09	0.07	0.83
2012	29	0.37	0.09	0.07	0.07	0.49	72	0.46	0.12	0.09	0.14	0.66	73	0.62	0.12	0.08	0.16	0.82
Pre-PPA			0.08	0.05					0.08	0.06					0.09	0.06		
Post-PPA			0.10	0.07					0.12	0.09					0.11	0.08		

	2035 & 2040						2045 & 2050						Balanced Funds					
	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max	# Funds	Mean	Std. Dev. EW	Std. Dev. VW	Min	Max
2001	4	0.83	0.04	0.03	0.77	0.85							56	0.52	0.15	0.19	0.19	1.01
2002	5	0.78	0.14	0.04	0.55	0.87	1	0.64	0.00	0.00	0.64	0.64	67	0.52	0.22	0.16	0.03	1.04
2003	6	0.75	0.07	0.03	0.62	0.82	1	0.69	0.00	0.00	0.69	0.69	60	0.61	0.14	0.12	0.29	1.03
2004	9	0.81	0.07	0.04	0.66	0.91	2	0.78	0.05	0.04	0.74	0.82	73	0.60	0.15	0.16	0.17	0.97
2005	12	0.80	0.05	0.03	0.69	0.87	3	0.81	0.02	0.01	0.79	0.82	78	0.57	0.17	0.16	0.07	0.99
2006	21	0.84	0.09	0.03	0.67	1.00	7	0.86	0.06	0.02	0.78	0.97	140	0.51	0.19	0.24	-0.01	0.93
2007	34	0.89	0.07	0.05	0.70	1.01	13	0.90	0.08	0.03	0.71	1.01	193	0.53	0.19	0.22	0.09	0.95
2008	48	0.84	0.07	0.04	0.63	0.95	33	0.87	0.06	0.03	0.74	1.04	236	0.51	0.19	0.17	-0.03	1.02
2009	63	0.83	0.09	0.04	0.52	0.99	51	0.87	0.09	0.04	0.60	1.05	350	0.50	0.19	0.15	-0.01	0.92
2010	67	0.80	0.13	0.08	0.09	0.95	56	0.83	0.13	0.07	0.08	0.99	318	0.52	0.17	0.18	-0.09	0.87
2011	71	0.78	0.12	0.08	0.08	0.95	62	0.82	0.13	0.07	0.07	0.96	312	0.49	0.17	0.18	0.04	0.92
2012	73	0.74	0.12	0.08	0.17	0.92	67	0.78	0.11	0.07	0.16	0.93	327	0.48	0.18	0.18	-0.54	0.91
Pre-PPA			0.08	0.03					0.05	0.02					0.18	0.21		
Post-PPA			0.11	0.07					0.11	0.07					0.18	0.17		

Table 7: Benchmarking TDFs against BFs

The dependent variable in each OLS regression is a measure of dispersion. The unit of observation is fund i offered by family k in month or year t. The comparison group is the sample of BFs offered by families that ever offer TDFs (i.e., the same sample considered in Tables 2–6). We compute cross-sectional dispersion in monthly net returns in month t as $(r_{ijt} - \overline{r}_{jt})^2$, where j is either the TDF's target date or the BF's Lipper classification (Flexible Portfolio Funds (FX), Mixed-Asset Target Allocation Conservative Funds (MTAC), Mixed-Asset Target Allocation Moderate Funds (MTAG), or Mixed-Asset Target Allocation Growth Funds (MTAM)). The cross-sectional dispersion in monthly five-factor alphas in month t is computed similarly. Idiosyncratic volatility is the non-annualized standard deviation of monthly factor alphas earned by fund i in calendar year t. R^2 from five-factor model is the R^2 estimated using daily returns in calendar year t. The cross-sectional dispersion in US equity beta is computed as $(\beta_{ijt} - \overline{\beta}_{jt})^2$, where we focus on the betas estimated using daily returns in calendar year t. We report the average value of each measure separately for BFs and TDFs, for three time periods. Pre-PPA includes 2000-2006. Post-PPA includes 2007-2012. Post-PPA (excl. crisis) includes 2007 and 2010-2012. We also report the coefficients from regressions that test for changes in each measure for TDFs or BFs ("Difference") and for TDFs relative to each sample of BFs ("Diff.-in-Diff."). Standard errors are simultaneously clustered on family and time (month or year). *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	Cross-sectional dispersion in monthly net return		Cross-sectional dispersion in monthly 5-factor alpha		Idiosyncratic volatility		R^2 from 5-factor model		Cross-sectional dispersion in U.S. equity beta	
Fund Type:	BFs	TDFs	BFs	TDFs	BFs	TDFs	BFs	TDFs	BFs	TDFs
Frequency:	Monthly	Monthly	Monthly	Monthly	Annual	Annual	Annual	Annual	Annual	Annual
Pre-PPA	1.272	0.212	0.365	0.066	1.636	0.991	0.935	0.966	0.027	0.005
Post-PPA	1.240	0.748	0.490	0.232	2.110	1.944	0.951	0.971	0.016	0.011
Post-PPA (excl. crisis)	0.558	0.464	0.269	0.145	1.635	1.615	0.954	0.968	0.012	0.012
Difference	−0.032	0.536**	0.106	0.166***	0.474	0.953***	0.016**	0.005	−0.011***	0.005**
Difference (excl. crisis)	−0.714**	0.252*	−0.105*	0.079**	−0.001	0.624***	0.019**	0.003	−0.015***	0.006**
Diff.-in-Diff.		0.567*		0.061		0.479*		−0.011		0.016***
Diff.-in-Diff. (excl. crisis)		0.966***		0.185***		0.625***		−0.016*		0.021***

Table 8: Flows and performance

The unit of observation is the TDF offered by family i with target date j. The dependent variable is estimated percentage net flow, measured over the 12 months ending in December of year t. The full set of independent variables includes: the lagged predicted return, measured over the 12 months ending in December of year $t-1$; the lagged five-factor alpha, measured over the same 12-month period; dummy variables that equal one if the lagged five-factor alpha are in the first, second, third, or fourth quartiles of the distribution for target date j in year $t-1$; the (annualized) standard deviation of monthly predicted returns in year $t-1$; the (annualized) standard deviation of monthly five-factor alphas in year $t-1$; the lagged net flow in year $t-1$; the natural logarithm of the number of funds with target date j in December of year t; a dummy equal to one if the fund was introduced after December 2006; a dummy equal to one if the fund was offered by a family that entered the TDF market after December 2006; the fund-level expense ratio measured in year t (reported by CRSP); the natural logarithm of the fund assets in December of year $t-1$; and the natural logarithm of the family assets in December of year $t-1$. The sample in the first four columns includes all TDFs with target dates between 2005 and 2050 for which we observe the dependent and independent variables. The sample in the fifth column includes all BFs offered by families that offer at least one TDF in year t. Estimation is via OLS. We include calendar year fixed effects and either target date fixed effects or BF classification fixed effects (Flexible Portfolio Funds (FX), Mixed-Asset Target Allocation Conservative Funds (MTAC), Mixed-Asset Target Allocation Moderate Funds (MTAG), or Mixed-Asset Target Allocation Growth Funds (MTAM)). Standard errors are simultaneously clustered on family and year. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	Net flow, year t				
Sample:	TDFs				BFs
Predicted return, year $t-1$	0.331	−0.006	0.122		0.366***
	(0.397)	(0.227)	(0.247)		(0.104)
5-factor alpha, year $t-1$	2.784**	2.425***	2.497***		1.483***
	(1.286)	(0.905)	(0.669)		(0.342)
5-factor alpha in fourth quartile?				0.076**	
				(0.037)	
5-factor alpha in third quartile?				0.014	
				(0.034)	
5-factor alpha in second quartile?				—	
5-factor alpha in first quartile?				−0.095***	
				(0.032)	
Volatility of monthly predicted returns, year $t-1$		−3.372**	−3.635***	−3.568***	−0.687**
		(1.318)	(0.744)	(0.790)	(0.287)
Volatility of monthly 5-factor alphas, year $t-1$		1.277	2.245	2.256	1.091*
		(2.389)	(2.717)	(3.287)	(0.603)
Net flow, year $t-1$			0.305***	0.300***	0.438***
			(0.020)	(0.020)	(0.036)
Ln number of funds with target date j in year t		−0.074	0.070	0.051	
		(0.065)	(0.074)	(0.066)	
Fund introduced after 2006?		0.352***	0.093	0.081	0.109
		(0.064)	(0.056)	(0.061)	(0.180)
Fund managed by family entering TDF market after 2006?		−0.197**	−0.058	−0.048	−0.008
		(0.086)	(0.056)	(0.063)	(0.022)
Expense ratio, year t		−0.046	−0.011	−0.005	−0.009
		(0.040)	(0.028)	(0.028)	(0.012)
Ln fund size, year $t-1$		0.003	0.006	0.002	−0.010*
		(0.019)	(0.010)	(0.010)	(0.006)
Ln family size, year $t-1$		0.022	0.008	0.010	0.002
		(0.022)	(0.012)	(0.013)	(0.009)
H_0: Predicted return = 5-factor alpha	0.009***	0.000***	0.000***		0.029**
H_0: Volatility predicted = Volatility alpha		0.144	0.049**	0.112	0.002***
Calendar year fixed effects?	Yes	Yes	Yes	Yes	Yes
Target date fixed effects?	Yes	Yes	Yes	Yes	—
BF classification fixed effects?	—	—	—	—	Yes
N	1,285	1,105	1,076	1,076	1,158
R^2	15.00%	26.50%	52.22%	52.28%	39.22%

Table 9: Cross-sectional dispersion in TDF returns and alphas and the level of idiosyncratic risk

The unit of observation is TDF i offered by family k in month t. The dependent variables in the first three sets of regressions are measures of return dispersion. When focusing on fund-level net returns, the dependent variable is $(r_{ijt} - \overline{r}_{jt})^2$. We compute a similar measure for monthly five-factor alphas, where the alpha in each month is calculated by comparing the realized net return to the predicted net return based on the five lagged factor loadings. The third dependent variable is idiosyncratic volatility, the non-annualized standard deviation of monthly alphas earned by fund i in calendar year t. The dependent variable in the fourth set of regressions is the average monthly five-factor alpha. The dependent variable in the final set of regressions is the average monthly five-factor alpha scaled by idiosyncratic volatility. Independent variables include: a dummy variable equal to one if the market share of family j's TDFs was $\leq 1\%$ (Low Market Share) and family k entered the TDF market after December 31, 2006 (Post-PPA Family); a dummy variable equal to one if the market share of family j's TDFs was $\leq 1\%$ (Low Market Share) and family k entered the TDF market before December 31, 2006 (Pre-PPA Family); a dummy variable equal to one if the market share of family j's TDFs was between 1% and 5% (Medium Market Share); a dummy variable equal to one if TDF i invests in index funds; and the average demeaned value of the dependent variable for family k's BFs (where BF return characteristics are demeaned within four Lipper classifications for BFs: Flexible Portfolio Funds (FX), Mixed-Asset Target Allocation Conservative Funds (MTAC), Mixed-Asset Target Allocation Moderate Funds (MTAG), or Mixed-Asset Target Allocation Growth Funds (MTAM)). Estimation is via OLS. We include a separate fixed effect for each target retirement date (e.g., 2020), each time period (month or year). Standard errors are simultaneously clustered on family and time (month or year). *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent Variable:	Cross-sectional dispersion in monthly net return		Cross-sectional dispersion in monthly 5-factor alpha		Idiosyncratic volatility		Average monthly 5-factor alpha		Alpha scaled by idiosyncratic volatility	
Frequency:	Monthly	Monthly	Monthly	Monthly	Annual	Annual	Annual	Annual	Annual	Annual
Low Market Share × Post-PPA Family	0.849**	0.784**	0.347***	0.275**	0.765***	0.695***	−0.067**	−0.036*	−0.043*	−0.030*
	(0.368)	(0.346)	(0.131)	(0.119)	(0.249)	(0.229)	(0.032)	(0.021)	(0.022)	(0.016)
Low Market Share × Pre-PPA Family	0.154*	0.120*	0.096**	0.077**	0.323***	0.298**	−0.014	−0.002	−0.022*	−0.006
	(0.079)	(0.070)	(0.041)	(0.036)	(0.116)	(0.138)	(0.020)	(0.016)	(0.012)	(0.011)
Medium Market Share	0.091	0.086	0.044**	0.027	0.088	0.044	−0.020	−0.009	−0.035*	−0.029*
	(0.085)	(0.075)	(0.018)	(0.027)	(0.103)	(0.136)	(0.028)	(0.018)	(0.020)	(0.015)
Index fund based TDF	−0.078	−0.089	−0.001	0.001	−0.449***	−0.321***	−0.001	0.017	−0.024	−0.014
	(0.068)	(0.060)	(0.023)	(0.022)	(0.145)	(0.112)	(0.036)	(0.030)	(0.022)	(0.018)
Average demeaned characteristic of family's BFs		0.157**		0.255***		0.360***		0.544***		0.518***
		(0.071)		(0.046)		(0.066)		(0.040)		(0.063)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.016**	0.021**	0.004***	0.013**	0.001***	0.005***	0.035**	0.067*	0.084*	0.114
H_0: Low × Post-PPA = Low × Pre-PPA	0.059*	0.058*	0.056*	0.099*	0.085*	0.084*	0.226	0.021**	0.324	0.051*
Target date-by-time fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,788	21,788	21,788	21,788	1,609	1,609	1,609	1,609	1,609	1,609
R^2	11.23%	17.35%	10.29%	21.82%	13.92%	26.76%	50.15%	63.21%	54.66%	63.17%

Table 10: Differences in the level of factor-model R^2s

The unit of observation is TDF i offered by family k in December of year t. The dependent variable is fund i's R^2 in a one-factor or five-factor model estimated during calendar year t using daily returns. The one-factor (CAPM) model is based on the excess daily returns on the CRSP value-weighted index. The five-factor model adds the excess daily return on the Barclay US Aggregate Bond Index; the excess daily return on the MSCI World Index excluding the US, Barclays Global Aggregate excluding the US, and GSCI Commodity Index. The set of independent variables matches Table 9 except that we now control for the average demeaned R^2 of the family's BFs (where R^2s are demeaned within four Lipper classifications for BFs: Flexible Portfolio Funds (FX), Mixed-Asset Target Allocation Conservative Funds (MTAC), Mixed-Asset Target Allocation Moderate Funds (MTAG), or Mixed-Asset Target Allocation Growth Funds (MTAM)). Estimation is via OLS. Standard errors are simultaneously clustered on family and year. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Factor Model:	R^2 from CAPM		R^2 from 5-factor model	
Frequency:	Annual	Annual	Annual	Annual
Low Market Share	−0.072***	−0.066***	−0.035***	−0.035***
× Post-PPA Family	(0.027)	(0.025)	(0.013)	(0.013)
Low Market Share	−0.018*	−0.016*	−0.009***	−0.008***
× Pre-PPA Family	(0.010)	(0.009)	(0.003)	(0.003)
Medium Market Share	−0.019	−0.016	−0.005*	−0.004
	(0.012)	(0.013)	(0.003)	(0.003)
Index fund based TDF	−0.008	−0.004	0.004*	0.004
	(0.015)	(0.015)	(0.002)	(0.003)
Average demeaned R^2		0.289**		0.136
of family's BFs		(0.134)		(0.135)
H_0: Low × Post-PPA				
= Low × Pre-PPA = 0	0.013**	0.010***	0.001***	0.000***
H_0: Low × Post-PPA				
= Low × Pre-PPA	0.053*	0.048**	0.055*	0.061*
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes
N	2,000	2,000	2,000	2,000
R^2	31.50%	34.12%	22.43%	23.35%

Table 11: Levels and dispersion in five-factor model betas

The unit of observation is TDF i offered by family k in December of year t. In Panel A, the dependent variable is the beta estimated for TDF i in a five-factor model using daily returns from year t. In Panel B, the dependent variable is the squared deviation of each beta for TDF i in year t. The set of independent variables matches Tables 9 and Table 10 except that we control for the average beta tilt of the family's BFs in Panel A and for the average squared deviation of the betas of the family's BFs in Panel B. Coefficients in Panel B are multiplied by 100. Estimation is via OLS. Standard errors are simultaneously clustered on family and year. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Panel A

Beta:	U.S. Equity		U.S. Debt		Global Equity		Global Debt		Commodities	
Low Market Share × Post-PPA Family	−0.046	−0.040	0.079**	0.071**	−0.003	−0.006	0.020***	0.019***	0.010	0.013**
	(0.040)	(0.038)	(0.037)	(0.028)	(0.009)	(0.008)	(0.006)	(0.006)	(0.009)	(0.006)
Low Market Share × Pre-PPA Family	0.000	0.002	0.024	0.021	0.005	0.004	0.006**	0.006**	−0.006	−0.001
	(0.029)	(0.028)	(0.022)	(0.014)	(0.005)	(0.004)	(0.003)	(0.003)	(0.007)	(0.003)
Medium Market Share	0.002	0.003	0.058**	0.056***	−0.008*	−0.006	0.015***	0.016***	−0.013	−0.008**
	(0.030)	(0.030)	(0.025)	(0.018)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.004)
Index fund based TDF	−0.019	−0.016	0.056	0.029	−0.014**	−0.012***	0.010***	0.010***	−0.004	−0.001
	(0.016)	(0.015)	(0.036)	(0.027)	(0.006)	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)
Average demeaned beta tilt of family's BFs		0.230		0.401***		0.456***		0.425***		0.733***
		(0.186)		(0.091)		(0.105)		(0.094)		(0.112)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.413	0.456	0.088*	0.031**	0.580	0.510	0.001***	0.003***	0.011**	0.022**
H_0: Low × Post-PPA = Low × Pre-PPA	0.197	0.219	0.123	0.066**	0.444	0.297	0.024**	0.017**	0.004***	0.007***
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,000	2,000	2,000	2,000	2,000	2,000	2000	2,000	2,000	2,000
R^2	76.96%	77.51%	58.40%	63.89%	49.59%	59.54%	32.20%	39.71%	26.58%	42.40%

Panel B

Dispersion in Beta:	U.S. Equity		U.S. Debt		Global Equity		Global Debt		Commodities	
Low Market Share × Post-PPA Family	1.935*	1.959**	2.165*	1.663	0.102***	0.069**	0.055***	0.054***	0.103*	0.105*
	(0.988)	(0.971)	(1.300)	(1.158)	(0.033)	(0.031)	(0.019)	(0.019)	(0.062)	(0.060)
Low Market Share × Pre-PPA Family	0.360*	0.432**	0.047	0.012	0.075**	0.054**	0.010	0.010	−0.014	−0.010
	(0.204)	(0.210)	(0.291)	(0.266)	(0.031)	(0.022)	(0.008)	(0.008)	(0.014)	(0.014)
Medium Market Share	0.030	0.053	−0.114	−0.259	0.011	0.013	0.043	0.044	−0.016	−0.013
	(0.169)	(0.151)	(0.342)	(0.328)	(0.013)	(0.009)	(0.027)	(0.027)	(0.016)	(0.016)
Index fund based TDF	−0.178	−0.198	−0.162	−0.320	−0.004	−0.016	−0.028*	−0.027	0.014	0.016
	(0.147)	(0.171)	(0.362)	(0.278)	(0.025)	(0.017)	(0.016)	(0.017)	(0.015)	(0.013)
Average dispersion in demeaned beta of family's BFs	0.000	0.160	0.000	0.193***	0.000	0.285***	0.000	0.027	0.000	0.043
		(0.105)		(0.018)		(0.039)		(0.040)		(0.111)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.023**	0.016**	0.252	0.344	0.002***	0.016**	0.006***	0.005***	0.116	0.209
H_0: Low × Post-PPA = Low × Pre-PPA	0.127	0.127	0.103	0.145	0.511	0.634	0.031**	0.036**	0.058*	0.078*
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
R^2	6.55%	7.56%	6.75%	15.22%	11.99%	39.93%	7.21%	7.33%	7.48%	7.52%

Table 12: BrightScope sample: summary statistics

We obtained data on 16,766 investment menus from BrightScope, Inc. The unit of observation is retirement plan i offered by firm j in industry k in 2010. The sample is limited to single-employer 401(k) and 403(b) retirement plans. Plan-level characteristics include assets under management (across all investment options), the number of participants with positive account balances, the age of the plan in years, and dummy variables indicating whether the plan is a 401(k) plan, offers auto enrollment, offers company stock as an investment option, offers any mutual funds as investment options, offers any mutual funds, separate accounts, or collective trusts that behave like TDFs, offers mutual fund TDFs, and employs a single record keeper (SRK). For the subset of 7,687 plans that offer TDFs and have a single record keeper that is an asset management firm, we calculate the fraction of TDFs and non-TDFs that are managed by the SRK. We report several measures of firm risk. For those firms with publicly traded equity, we estimate a CAPM beta (using the 24 monthly stock returns through December 2009). In addition, we report the standard deviation of actual monthly returns (over the same 24 months), the standard deviation of predicted monthly returns (based on the CAPM beta and return on the market portfolio), and the standard deviation of the residual monthly returns. To determine the industry-level CAPM beta, we assign each firm the median CAPM beta of the sample of publicly traded firms that share the same first 3 digits of the North American Industrial Classification System (NAICS) code. To measure mutual fund risk, we estimate a CAPM beta (using the 24 monthly fund returns through December 2009). We report estimated betas separately for TDFs with target retirement dates of 2010, 2020, 2030, 2040, and 2050, for the full sample of TDFs, and for the sample of non-TDFs. The number of observations varies both because not all plans offer TDFs and because not all mutual funds could be matched to CRSP.

	N	Mean	Std. Dev.	Min	Max
Plan characteristics in 2010					
Assets (in millions)	16,766	134.62	708.67	0.01	36,741.60
Number of participants (in thousands)	16,766	2.00	8.08	0.00	306.61
Plan age in years	16,766	22.94	13.45	0.00	95.00
401(k) plan?	16,766	0.91	0.29	0.00	1.00
Auto enrollment?	16,766	0.23	0.42	0.00	1.00
Offers company stock?	16,766	0.13	0.33	0.00	1.00
Offers any mutual funds?	16,766	0.85	0.36	0.00	1.00
Offers any TDFs?	16,766	0.66	0.47	0.00	1.00
Offers mutual fund TDFs?	16,766	0.50	0.50	0.00	1.00
Single record keeper (SRK)?	16,766	0.75	0.43	0.00	1.00
Fraction of TDFs managed by SRK?	7,687	0.76	0.42	0.00	1.00
Fraction of non-TDFs managed by SRK?	7,687	0.39	0.28	0.00	1.00
Measures of firm risk in 2009					
CAPM beta (firm-level)	1,740	1.37	0.91	-1.26	8.65
Standard deviation of total returns	1,740	0.17	0.10	0.04	1.27
Standard deviation of predicted returns	1,740	0.10	0.06	0.00	0.60
Standard deviation of residual returns	1,740	0.14	0.08	0.03	1.12
CAPM beta (3-digit industry-level)	16,301	1.21	0.48	0.14	2.57
Measures of mutual fund risk in 2009					
CAPM beta of 2010 TDF	6,677	0.63	0.07	0.40	0.90
CAPM beta of 2020 TDF	7,581	0.78	0.06	0.63	1.00
CAPM beta of 2030 TDF	7,491	0.91	0.04	0.76	1.03
CAPM beta of 2040 TDF	7,641	0.96	0.04	0.85	1.04
CAPM beta of 2050 TDF	6,504	0.98	0.04	0.87	1.04
Average CAPM beta of mutual fund TDFs	8,277	0.79	0.06	0.32	1.02
Average CAPM beta of other mutual funds	14,064	0.83	0.15	-1.69	1.58

Table 13: Testing for risk matching in plan-level data

The unit of observation is the single-employer DC retirement plan i offered by firm j in industry k in 2010. The dependent variable measures the risk of the TDFs offered by plan i. In Panel A, our measure of risk is the average target-date adjusted tilt in CAPM beta. In Panel B, it is the average target-date adjusted standard deviation of idiosyncratic monthly returns. The sample is limited to the 95.8% of plans that offer TDFs from a single family. The independent variables of interest are analogous measures of firm-level or industry-level risk. Plan-level (i.e., demand-side) independent variables include: the natural logarithm of retirement plan i assets in 2010; the natural logarithm of the number of plan i participants in 2010; a dummy equal to one if plan i has auto enrollment; a dummy equal to one if plan i offers company stock; the average risk of non-TDF mutual funds in plan i; and an interaction between the measure of firm risk and the dummy indicating if the plan has auto enrollment. Family-level (i.e., supply-side) independent variables include: a dummy equal to one if plan i has a single record keeper (SRK); the market share of the SRK's investments in BrightScope in 2010; a dummy equal to one if TDFs are offered by a Pre-PPA family with Low Market Share in 2009; and a dummy equal to one if TDFs are offered by a Post-PPA family with Low Market Share in 2009. Some specifications include a separate fixed effect for each of the 70 industries (defined by the first three digits of the NAICS code). Estimation is via OLS. Standard errors are clustered on industry. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively. Adjusted R^2 fall significantly when we exclude the supply-side variables.

Panel A

Dependent variable:	Average CAPM beta tilt of TDFs in plan i						
CAPM beta of firm j	−0.002	−0.001	−0.003				
	(0.002)	(0.003)	(0.003)				
Median CAPM beta within industry of firm j				0.005**	0.004	0.006	0.006
				(0.002)	(0.003)	(0.004)	(0.004)
Median CAPM beta × Auto enrollment?						−0.007**	−0.007**
						(0.003)	(0.003)
Single record keeper (SRK)?	−0.020***	−0.018***		−0.007***			
	(0.004)	(0.005)		(0.002)			
Market share of SRK within BrightScope			−0.138***		−0.103***	−0.104***	−0.107***
			(0.024)		(0.012)	(0.011)	(0.012)
TDF from Pre-PPA family with Low Market Share?	−0.010***	−0.009**	−0.018***	−0.008***	−0.010***	−0.009***	−0.009***
	(0.004)	(0.004)	(0.006)	(0.002)	(0.003)	(0.003)	(0.003)
TDF from Post-PPA family with Low Market Share?	0.091***	0.089***	0.077***	0.096***	0.102***	0.102***	0.101***
	(0.017)	(0.019)	(0.016)	(0.006)	(0.006)	(0.006)	(0.006)
Ln plan assets	−0.007***	−0.007***	−0.006*	−0.008***	−0.006***	−0.006***	−0.006***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Ln number of participants	0.005**	0.006**	0.005	0.004***	0.003**	0.003**	0.003**
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Auto enrollment?	0.001	0.001	−0.001	0.001	0.000	0.008**	0.008**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)
Offer company stock?	0.000	−0.002	−0.007**	0.005**	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Average risk of non-TDFs offered by plan j							0.045**
							(0.022)
H_0: Low × Pre-PPA = Low × Post-PPA	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Industry fixed effects?	—	Yes	Yes	—	—	—	—
N	968	968	758	7,983	5,504	5,504	5,504
Adj. R^2 (excl. supply-side)	2.18%	5.73%	5.73%	3.39%	3.39%	3.44%	3.45%
Adj. R^2	11.57%	14.21%	19.25%	14.86%	19.41%	19.50%	19.61%

Panel B

Dependent variable:	Standard deviation of idiosyncratic returns tilt of TDFs in plan i						
Idiosyncratic risk of firm j	−0.002	0.004	0.004				
	(0.040)	(0.047)	(0.054)				
Median idiosyncratic risk within industry of firm j				−0.069	−0.116*	−0.159**	−0.179**
				(0.050)	(0.062)	(0.073)	(0.072)
Median idiosyncratic risk × Auto enrollment?						0.164	0.168
						(0.109)	(0.108)
Single record keeper (SRK)?	−0.007	−0.006		0.016**			
	(0.012)	(0.013)		(0.006)			
Market share of SRK within BrightScope			−0.346***		−0.306***	−0.307***	−0.289***
			(0.082)		(0.071)	(0.071)	(0.070)
TDF from Pre-PPA family with Low Market Share?	0.133***	0.128***	0.087**	0.097***	0.081***	0.080***	0.086***
	(0.033)	(0.035)	(0.041)	(0.009)	(0.019)	(0.019)	(0.018)
TDF from Post-PPA family with Low Market Share?	0.176***	0.159**	0.023	0.216***	0.167***	0.167***	0.167***
	(0.060)	(0.066)	(0.031)	(0.017)	(0.025)	(0.025)	(0.026)
Ln plan assets	−0.031***	−0.032***	−0.038***	−0.035***	−0.038***	−0.038***	−0.038***
	(0.007)	(0.009)	(0.007)	(0.003)	(0.004)	(0.004)	(0.004)
Ln number of participants	0.019***	0.022**	0.028***	0.021***	0.023***	0.023***	0.022***
	(0.007)	(0.010)	(0.009)	(0.002)	(0.003)	(0.003)	(0.003)
Auto enrollment?	−0.010	−0.011	−0.014*	0.005	0.006	−0.014	−0.014
	(0.008)	(0.008)	(0.008)	(0.004)	(0.006)	(0.014)	(0.014)
Offer company stock?	−0.012	−0.002	−0.003	−0.007	−0.005	−0.005	−0.001
	(0.009)	(0.011)	(0.012)	(0.007)	(0.008)	(0.008)	(0.008)
Average risk of non-TDFs offered by plan j							1.627*
							(0.851)
H_0: Low × Pre-PPA = Low × Post-PPA	0.517	0.687	0.172	0.000***	0.000***	0.000***	0.000***
Industry fixed effects?	—	Yes	Yes	—	—	—	—
N	968	968	758	7,983	5,504	5,504	5,504
Adj. R^2 (excl. supply-side)	5.50%	8.60%	8.60%	5.84%	5.84%	5.85%	6.64%
Adj. R^2	11.58%	13.86%	20.57%	14.23%	19.54%	19.56%	20.66%

Heterogeneity in Target Date Funds:
Strategic Risk-Taking or Risk Matching?
Internet Appendix

February 18, 2017

A The Pension Protection Act of 2006

A.1 Overview

The PPA of 2006 amends Title I of the Employee Retirement Income Security Act (ERISA) of 1974. Of particular interest to our study, it relieves sponsors of DC retirement plans of liability for investment losses when they default plan participants into "qualified default investment alternatives" (QDIAs). As specified by the Department of Labor's (DOL) Employee Benefits Security Administration (EBSA), QDIAs must be diversified to decrease the probability of large losses; be managed by an investment manager/company registered under the Investment Company Act of 1940; not penalize or prevent a participant from transferring their assets from a QDIA to another investment alternative available under the plan; and not invest participant contributions directly in employer securities.[1] Potential QDIAs include TDFs, BFs, and professionally managed accounts. It is worth noting that plan sponsors and fiduciaries are not relieved of liability for the prudent selection and monitoring of a QDIA.

A.2 Timeline

In January 2005, a proposal was put forward to strengthen the pension system by putting into place new minimum funding requirements. 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 2006.[2] 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. On September 27, 2006, the DOL published rules regarding "Default Investment Alternatives Under Participant Directed Individual Account Plans," which listed TDFs among the set of QDIAs. Although the rules technically went into effect on December 24, 2007, the likely effect on the demand for TDFs was well known to market participants in 2006.

A.3 Public Statements Summarizing Advantages and Disadvantages of TDFs

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

Advantages:

- "Target date funds were expected to make investing easier for the typical American and avoid the need for investors to constantly monitor market movements and realign their personal investment allocations." SEC Chairman Mary Shapiro
- "Target Date Funds are one of the most important recent innovations in retirement savings. They provide a convenient way for an investor to purchase a mix of asset classes within a single fund that will rebalance the asset allocation and become more conservative as the investor ages." Karrie McMillan, general counsel of the Investment Company Institute
- "Target Date Fund investors avoid extreme asset allocations that we often observe in retirement savings." Karrie McMillan, general counsel of the Investment Company Institute

[1] DOL: EBSA Federal Register: 29 CFR Part 2550, October 24, 2007.

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

- "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
- "Retirees do a lot of different things with the money in these plans at the point of retirement, and so there is some debate around exactly how the money is going to be used ...it's very difficult to come up with a sort of specific answer that solves the problem for everybody." John Ameriks, economist and a principal at the Vanguard Group
- "We have serious concerns that these funds are fundamentally misleading to investors because they're allowed to be managed in ways that are inconsistent with reasonable expectations that are created by the titles and the use of the names." Marilyn Capelli-Dimitroff, Chair of the Certified Financial Planner Board of Standards
- "Appropriate disclosures are required and must be provided, but in reality, disclosures are seldom read or understood fully despite our ongoing education of clients." Marilyn Capelli-Dimitroff, Chair of the Certified Financial Planner Board of Standards
- "When plan sponsors and participants started adopting TDFs in big meaningful numbers starting in 2002, the race was on for performance numbers, and this is where the train went off the track ...There is some theoretical rationale for employing a glide path through the accumulation phase. No credible rationale has ever been proffered for using a glide path in the distribution phase. This is what caused the unacceptably large losses in 2010 funds in 2008." Joe Nagengast, Target Date Analytics
- "...part of the concern here is when you have a fund of funds, it may become a lot easier to, for example, hide under-performing funds in Target Date Funds, [or] hide higher fee funds in a Target Date Fund that may not be completely appropriate." Dave Certner, Legislative Counselor and Legislative Policy Director at AARP

B Supplemental Analysis

B.1 Decomposing TDF variation

In this section, we benchmark dispersion in the realized returns and ex-ante risk profiles of TDFs against both BFs and S&P 500 index funds. In order to quantify the contribution of the cross-sectional dispersion on the overall dispersion of returns, we compute three measures. We describe the measures for TDFs, but they can just as easily be calculated for BFs and index funds. First, we compute the "Total Dispersion," the total standard deviation of returns for TDFs with a given target date.[3] This is the variability of realized 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 equal-weighted portfolio of TDFs with a given target date.[4] Third, we compute the "Fund Dispersion," the standard deviation *within* a given target date.[5] 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 equal-weighted portfolio of TDFs with target date j. This general approach can also be used to decompose the dispersion of alphas, idiosyncratic volatilities, five-factor R^2s, and US equity betas from the five-factor model. In Table B.1 we present results for the full sample period, as well as separately for Pre-PPA and Post-PPA periods.

We first focus on the variability of realized 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 14.0% and 18.9%, and Market Dispersion ranges between 13.6% and 18.7%. However, consistent with our earlier findings, there remains significant Fund Dispersion. Fund Dispersion ranges from 2.4% for 2035–2040 and 2045–2050 funds, to 3.2% for 2005–2010 funds, confirming that there is more Fund Dispersion in realized TDF returns when target dates are near than when they are far. Moreover, we find that Fund Dispersion approximately doubles between the Pre-PPA and Post-PPA periods.

Within the full sample of BFs, some of which have more discretion over asset allocation, market timing, and security selection, Total Dispersion is 13.9% and Fund Dispersion is 5.1%. In contrast, for S&P 500 index funds, Total Dispersion is 17.9% and Fund Dispersion is only 0.5%. Hence, all five target dates expose investors to greater Total Dispersion but less Fund Dispersion

[3] For target date j the Total Dispersion is defined as:

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

where r_{ijt} is a TDF's yearly return and $\bar{\bar{r}}_j$ is the average return across all TDFs with target date j and all years.

[4] Market Dispersion is defined as:

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

where $\bar{r}_{jt}$ is the year-t return on an equal-weighted portfolio of TDFs with target date j.

[5] Fund Dispersion is defined as:

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

than traditional BFs. Perhaps more surprisingly, 2035–2045 TDFs expose investors to greater Total Dispersion than S&P 500 index funds, which invest close to 100% in US equity. The patterns are similar when we switch our focus from total returns to idiosyncratic returns (measured using the annualized five-factor alphas from Table 3). On average, Fund Dispersion in idiosyncratic returns explains approximately 70% of the Fund Dispersion in total returns.

When we turn to idiosyncratic volatility, we find that Fund Dispersion always exceeds Market Dispersion. Again, the level of Fund Dispersion approximately doubles between the Pre-PPA and Post-PPA periods. The differences between Fund Dispersion and Market Dispersion are more pronounced for five-factor model R^2s and US equity betas. For R^2s, Total Dispersion ranges between 3.5% and 4.4%, and Market Dispersion ranges between 0.5% and 1.0%. Overall, Table B.1 confirms that TDFs with the same target date expose investors to significantly different levels of idiosyncratic and systematic risk. With respect to economic significance, the dispersion within each sample of TDFs is about half as large as within the samples of BFs.

B.2 Robustness Tests and Additional Analysis

- Table B.2 lists the number of family-year and TDF-month observations separately by market share categories for Pre-PPA and Post-PPA families.
- Table B.3 re-estimates Table 7 comparing TDFs to the full sample of BFs rather than the subsample of BFs offered by families that ever offer TDFs.
- Table B.4 compares the return dispersion of BFs and TDFs from Pre-PPA and Post-PPA families that were introduced before and after December 31, 2006.
- Table B.5 extends several of the specifications in Table 9 to consider alternative measures of cross-sectional dispersion (i.e., squared deviations and absolute deviations) and alternative sample periods (i.e., 2000–2012, 2007–2012, and 2007–2012 excluding 2008 and 2009).
- Table B.6 re-estimates several of the specifications in Tables 9–11 when dispersion is measured at the level of the mutual fund family.
- Tables B.7–B.9 re-estimate all of the specifications from Tables 9–11 using data from 2007–2012.
- Tables B.10–B.12 re-estimate all of the specifications from Tables 9–11 using data from 2007–2012 excluding 2008 and 2009.
- Table B.13 extends several of the specifications in Table 9 to consider both market share within the market for TDFs and market share within the broader market for mutual funds.
- Table B.14 extends several of the specifications in Table 9 to consider the year that a family enters the market for TDFs.
- Table B.15 complements Table 13 by providing additional plan-level evidence on TDF risk versus industry risk.
- Table B.16 re-estimates Table 13 using the absolute value of average plan-level (target-date adjusted) TDF risk as new dependent variables and the absolute value of (demeaned) firm risk as new independent variables. This allows us to explore whether the safest and riskiest firms are more likely to match with safest and riskiest TDFs.
- Table B.17 uses data from IRS Form 5500 to calculate the fraction of retirement plan participants in each broad industry category in 2005 and 2012. The fractions are quite similar except that the fraction of participants in manufacturing has fallen while the fraction of participants in health care has risen.

Table B.1: Decomposition: total dispersion, market dispersion, and fund dispersion

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

	Net Return			5-Factor Alpha			Idiosyncratic Volatility			5-Factor R^2			U.S. Equity Beta		
	Total	Market	Fund	Total	Market	Fund	Total	Market	Fund	Total	Market	Fund	Total	Market	Fund
Full Sample Period															
TDFs: 2005 & 2010	14.0%	13.6%	3.2%	3.1%	2.1%	2.2%	1.1%	0.7%	0.8%	4.4%	0.9%	4.3%	0.11	0.04	0.10
TDFs: 2015 & 2020	15.6%	15.3%	2.9%	2.8%	1.8%	2.1%	1.0%	0.6%	0.8%	4.2%	1.0%	4.0%	0.13	0.07	0.11
TDFs: 2025 & 2030	17.9%	17.7%	2.6%	2.6%	1.8%	2.0%	1.0%	0.6%	0.8%	3.5%	0.5%	3.5%	0.12	0.06	0.11
TDFs: 2035 & 2040	18.9%	18.7%	2.4%	2.8%	1.9%	2.0%	1.0%	0.6%	0.9%	3.5%	0.5%	3.5%	0.11	0.04	0.10
TDFs: 2045 & 2050	17.1%	16.9%	2.4%	2.9%	2.1%	2.0%	1.1%	0.5%	0.9%	4.0%	0.5%	4.0%	0.12	0.03	0.11
Balanced Funds (All)	13.9%	13.0%	5.1%	4.4%	2.0%	3.9%	2.2%	0.9%	2.0%	12.8%	1.3%	12.7%	0.20	0.03	0.20
Balanced Funds (TDFs)	14.0%	13.3%	4.4%	3.8%	2.3%	3.0%	1.5%	0.8%	1.3%	6.5%	0.7%	6.4%	0.18	0.03	0.18
S&P 500 Index Funds	17.9%	17.9%	0.5%	1.5%	1.5%	0.5%	0.5%	0.4%	0.3%	1.3%	0.4%	1.2%	0.03	0.03	0.01
Pre-PPA (2000–2006)															
TDFs: 2005 & 2010	6.7%	6.5%	1.6%	1.6%	0.7%	1.5%	0.5%	0.3%	0.4%	2.3%	0.9%	2.1%	0.07	0.01	0.07
TDFs: 2015 & 2020	9.1%	8.9%	1.6%	1.7%	0.8%	1.5%	0.4%	0.2%	0.4%	1.3%	0.7%	1.2%	0.07	0.01	0.06
TDFs: 2025 & 2030	10.8%	10.7%	1.5%	1.8%	1.0%	1.5%	0.4%	0.2%	0.4%	1.0%	0.6%	0.8%	0.07	0.03	0.06
TDFs: 2035 & 2040	12.3%	12.2%	1.5%	1.7%	1.0%	1.4%	0.4%	0.1%	0.4%	1.0%	0.6%	0.8%	0.07	0.03	0.06
TDFs: 2045 & 2050	6.2%	6.2%	0.7%	1.3%	1.0%	0.8%	0.4%	0.2%	0.3%	0.8%	0.0%	0.8%	0.06	0.06	0.03
Balanced Funds (All)	11.5%	10.4%	4.9%	3.7%	1.1%	3.6%	1.9%	0.6%	1.8%	13.8%	0.7%	13.8%	0.19	0.00	0.19
Balanced Funds (TDFs)	10.3%	9.4%	4.2%	2.4%	0.7%	2.2%	1.1%	0.5%	0.9%	7.8%	0.8%	7.7%	0.17	0.00	0.17
S&P 500 Index Funds	17.5%	17.5%	0.4%	1.4%	1.3%	0.4%	0.4%	0.3%	0.1%	0.5%	0.4%	0.2%	0.04	0.04	0.01
Post-PPA (2007–2012)															
TDFs: 2005 & 2010	15.1%	14.7%	3.4%	3.3%	2.3%	2.4%	1.1%	0.7%	0.9%	4.7%	0.9%	4.6%	0.11	0.04	0.10
TDFs: 2015 & 2020	16.2%	15.9%	3.0%	2.9%	1.9%	2.2%	1.1%	0.6%	0.9%	4.4%	1.0%	4.2%	0.13	0.07	0.11
TDFs: 2025 & 2030	18.6%	18.4%	2.7%	2.7%	1.9%	2.0%	1.0%	0.6%	0.8%	3.7%	0.5%	3.7%	0.13	0.06	0.11
TDFs: 2035 & 2040	19.5%	19.3%	2.5%	2.9%	2.0%	2.1%	1.0%	0.5%	0.9%	3.7%	0.5%	3.7%	0.11	0.04	0.11
TDFs: 2045 & 2050	17.3%	17.1%	2.4%	2.9%	2.1%	2.0%	1.0%	0.5%	0.9%	4.0%	0.5%	4.0%	0.12	0.03	0.11
Balanced Funds (All)	14.8%	13.9%	5.2%	4.6%	2.2%	4.1%	2.3%	1.0%	2.1%	12.3%	0.9%	12.3%	0.20	0.01	0.20
Balanced Funds (TDFs)	14.7%	14.0%	4.5%	4.1%	2.6%	3.2%	1.6%	0.8%	1.4%	6.1%	0.6%	6.1%	0.18	0.01	0.18
S&P 500 Index Funds	18.3%	18.3%	0.5%	1.5%	1.4%	0.5%	0.5%	0.3%	0.4%	1.7%	0.3%	1.6%	0.03	0.03	0.01

Table B.2: Number of mutual fund families and TDFs based on market share and whether they entered post PPA

The top panel reports the number of mutual fund families that offer TDFs each year, based on their share in the TDF market (low, medium, or high), and on whether they entered the TDF market before or after December 31, 2006 (Pre-PPA versus Post-PPA). The bottom panel reports the corresponding number of TDF-month observations. Note that the total number of TDF-month observations exceeds those included in the regressions in Tables 9–11 because we do not require that we possess sufficient historical return data to estimate five-factor alphas.

	Number of Families						
	Pre-PPA Family			Post-PPA Family			All
	Low	Medium	High	Low	Medium	High	
2000	1	0	3	0	0	0	4
2001	2	0	3	0	0	0	5
2002	2	2	2	0	0	0	6
2003	4	4	1	0	0	0	9
2004	5	5	3	0	0	0	13
2005	12	4	4	0	0	0	20
2006	16	5	4	0	0	0	25
2007	16	5	4	8	0	0	33
2008	17	5	4	17	1	0	44
2009	15	5	4	15	1	0	40
2010	14	6	4	14	1	0	39
2011	13	8	3	15	1	0	40
2012	11	8	3	14	1	0	37

	Number of TDF-months						
	Pre-PPA Family			Post-PPA Family			All
	Low	Medium	High	Low	Medium	High	
2000	60	0	185	0	0	0	245
2001	115	0	192	0	0	0	307
2002	133	64	152	0	0	0	349
2003	165	207	99	0	0	0	471
2004	190	384	192	0	0	0	766
2005	575	394	315	0	0	0	1284
2006	1114	251	421	0	0	0	1786
2007	1335	418	468	436	0	0	2657
2008	1560	488	547	969	99	0	3663
2009	1471	704	588	1433	108	0	4304
2010	1411	926	701	1154	119	0	4311
2011	1229	1376	612	1154	120	0	4491
2012	1247	1555	611	1304	120	0	4837

Table B.3: Benchmarking TDFs against full sample of BFs

The dependent variable in each OLS regression is a measure of dispersion. The unit of observation is fund i offered by family k in month or year t. Unlike Table 7 where the comparison group is the subsample of BFs offered by families that offer TDFs, the comparison group is the full sample of BFs. We compute cross-sectional dispersion in monthly net returns in month t as $(r_{ijt} - \overline{r}_{jt})^2$, where j is either the TDF's target date or the BF's Lipper classification (Flexible Portfolio Funds (FX), Mixed-Asset Target Allocation Conservative Funds (MTAC), Mixed-Asset Target Allocation Moderate Funds (MTAG), or Mixed-Asset Target Allocation Growth Funds (MTAM)). The cross-sectional dispersion in monthly five-factor alphas in month t is computed similarly. Idiosyncratic volatility is the non-annualized standard deviation of monthly factor alphas earned by fund i in calendar year t. R^2 from five-factor model is the R^2 estimated using daily returns in calendar year t. The cross-sectional dispersion in US equity beta is computed as $(\beta_{ijt} - \overline{\beta}_{jt})^2$, where we focus on the betas estimated using daily returns in calendar year t. We report the average value of each measure separately for BFs and TDFs, for three time periods. Pre-PPA includes 2000-2006. Post-PPA includes 2007-2012. Post-PPA (excl. crisis) includes 2007 and 2010-2012. We also report the coefficients from regressions that test for changes in each measure for TDFs or BFs ("Difference") and for TDFs relative to each sample of BFs ("Diff.-in-Diff."). Standard errors are simultaneously clustered on family and time (month or year). *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent variable:	Cross-sectional dispersion in monthly net return		Cross-sectional dispersion in monthly 5-factor alpha		Idiosyncratic volatility		R^2 from 5-factor model		Cross-sectional dispersion in U.S. equity beta	
Fund Type:	BFs	TDFs	BFs	TDFs	BFs	TDFs	BFs	TDFs	BFs	TDFs
Frequency:	Monthly	Monthly	Monthly	Monthly	Annual	Annual	Annual	Annual	Annual	Annual
Pre-PPA	2.156	0.212	0.903	0.066	2.340	0.991	0.899	0.966	0.035	0.005
Post-PPA	1.721	0.748	0.942	0.232	2.576	1.944	0.923	0.971	0.026	0.011
Post-PPA (excl. crisis)	1.074	0.464	0.611	0.145	2.009	1.615	0.923	0.968	0.025	0.012
Difference	−0.435	0.536**	0.039	0.166***	0.235	0.953***	0.024***	0.005	−0.010***	0.005**
Difference (excl. crisis)	−1.082***	0.252*	−0.292*	0.079**	−0.331	0.624***	0.024**	0.003	−0.010***	0.006**
Diff.-in-Diff.		0.971**		0.128		0.718**		−0.019**		0.015***
Diff.-in-Diff. (excl. crisis)		1.334***		0.371***		0.956***		−0.021**		0.017***

Table B.4: Return characteristics of Pre-PPA and Post-PPA funds from Pre-PPA and Post-PPA families

This table compares three return characteristics for four samples of BF and TDFs. The return characteristic in Panel A is the squared deviation of monthly returns (i.e., the first dependent variable in Table 9), the return characteristic in Panel B is the squared deviation of monthly alphas (i.e., the second dependent variable in Table 9), and the return characteristic in Panel C is idiosyncratic volatility (i.e., the third dependent variable in Table 9). In Panels A and B, the unit of observation is fund i in month t; in Panel C, the unit of observation is fund i in December of year t. The four samples are defined based on whether funds were introduced before or after December 31, 2006 (Pre-PPA versus Post-PPA) and whether the family offering fund i entered the TDF market before or after December 31, 2006 (Pre-PPA Family versus Post-PPA Family). In column (5), we report the coefficient from regressions that test for differences between Post-PPA BFs from Pre-PPA families (column (2)) and Pre-PPA BFs from Pre-PPA Families (column (1)). In column (6), we tests for differences between Post-PPA BFs from Post-PPA families (column (4)) and Post-PPA BFs from Pre-PPA families (column (2)). In column (10), we test for differences between Post-PPA TDFs from Pre-PPA families (column (8)) and Pre-PPA BFs from Pre-PPA Families (column (7)). In column (12), we test for differences between Post-PPA TDFs from Post-PPA families (column (10)) and Post-PPA TDFs from Pre-PPA families (column (8)). The standard errors in these regressions are simultaneously clustered on family and time (month or year), and are reported below the estimated coefficients. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Fund Type:	BFs							TDFs					
Family Type:	Pre-PPA	Pre-PPA	Post-PPA	Post-PPA				Pre-PPA	Pre-PPA	Post-PPA	Post-PPA		
Fund Age:	Pre-PPA	Post-PPA	Pre-PPA	Post-PPA	(2) - (1)	(4) - (2)	(4) - (3)	Pre-PPA	Post-PPA	Pre-PPA	Post-PPA	(9) - (8)	(11) - (9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A. Cross-sectional dispersion in monthly net return													
Pre-PPA	1.281	—	1.238	—				0.212	—	—	—		
Post-PPA	1.292	1.129	1.229	1.128	−0.163	−0.001	−0.102	0.413	0.460	—	1.606	0.047	1.146*
					(0.554)	(0.514)	(0.26)					(0.188)	(0.64)
Post-PPA (excl. crisis)	0.471	0.701	0.639	0.627	0.230	−0.074	−0.012	0.256	0.444	—	0.881	0.188	0.437
					(0.227)	(0.261)	(0.167)					(0.258)	(0.432)
Panel B. Cross-sectional dispersion in monthly 5-factor alpha													
Pre-PPA	0.346	—	0.462	—				0.066	—	—	—		
Post-PPA	0.415	0.337	0.665	0.511	−0.078	0.175	−0.154	0.196	0.119	—	0.406	−0.077	0.287***
					(0.092)	(0.264)	(0.245)					(0.043)	(0.110)
Post-PPA (excl. crisis)	0.222	0.296	0.325	0.340	0.074	0.044	0.016	0.097	0.083	—	0.300	−0.014	0.217**
					(0.092)	(0.172)	(0.128)					(0.018)	(0.101)
Panel C. Idiosyncratic volatility													
Pre-PPA	1.635	—	2.198	—				1.035	—	—	—		
Post-PPA	2.064	1.964	2.509	2.210	−0.100	0.246	−0.299	1.936	1.680	—	2.421	−0.256	0.742**
					(0.154)	(0.692)	(0.571)					(0.165)	(0.297)
Post-PPA (excl. crisis)	1.658	1.841	1.929	1.808	0.183	−0.033	−0.121	1.557	1.537	—	2.229	−0.020	0.692***
					(0.147)	(0.485)	(0.168)					(0.107)	(0.259)

Table B.5: Robustness: Two measures of cross-sectional dispersion and three sample periods

Extension of Table 9 that considers two measures of cross-sectional dispersion and three sample periods. The unit of observation is TDF i offered by family k in month t. We measure cross-sectional dispersion in monthly net returns and monthly five-factor alphas as both squared deviations from the cross-sectional mean for funds with the same target date (as in Table 9) and as absolute deviations from this cross-sectional mean. The three sample periods are "Full" (2000–2012), "Post-PPA" (2007–2012), and "Excl. Crisis" (2007–2012 excluding 2008 and 2009). Columns (1) and (7) report the specifications from Table 9, which focus on squared deviations and are estimated using data for our full sample period, 2000–2012. Columns (4) and (10) report comparable specifications where the dependent variable is now absolute deviations. The other columns differ only in the sample periods being considered. For each specification, we report the annualized difference in dispersion between low market share families that enter Post-PPA to low market share families that enter Pre-PPA. For measures of squared deviation, we compare the square root of the average predicted value for low market share families that enter Post-PPA to the square root of the average predicted value for low market share families that enter Pre-PPA. For measures of absolute deviation, we compare the average predicted value for low market share families that enter Post-PPA to the average predicted value for low market share families that enter Pre-PPA. The standard errors in these regressions are simultaneously clustered on family and month, and are reported below the estimated coefficients. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent Variable:	Cross-sectional dispersion in monthly net returns						Cross-sectional dispersion in monthly 5-factor alphas					
	Squared Deviation			Absolute Deviation			Squared Deviation			Absolute Deviation		
Time Period:	Full (1)	Post-PPA (2)	Excl. Crisis (3)	Full (4)	Post-PPA (5)	Excl. Crisis (6)	Full (7)	Post-PPA (8)	Excl. Crisis (9)	Full (10)	Post-PPA (11)	Excl. Crisis (12)
Low Market Share × Post-PPA Family	0.849**	0.863**	0.827*	0.269**	0.274***	0.266**	0.347***	0.351***	0.276**	0.190***	0.190***	0.177***
	(0.368)	(0.365)	(0.485)	(0.107)	(0.106)	(0.126)	(0.131)	(0.130)	(0.124)	(0.056)	(0.056)	(0.054)
Low Market Share × Pre-PPA Family	0.154*	0.170**	0.048	0.073	0.078	0.042	0.096**	0.102**	0.050***	0.059***	0.060***	0.054**
	(0.079)	(0.084)	(0.070)	(0.051)	(0.052)	(0.051)	(0.041)	(0.045)	(0.017)	(0.022)	(0.023)	(0.021)
Medium Market Share	0.091	0.115	0.060	0.031	0.044	0.034	0.044**	0.049**	0.029***	0.034***	0.033**	0.031**
	(0.085)	(0.098)	(0.060)	(0.047)	(0.052)	(0.041)	(0.018)	(0.021)	(0.009)	(0.011)	(0.014)	(0.015)
Index fund based TDF	−0.078	−0.089	−0.135*	−0.075*	−0.088*	−0.118**	−0.001	0.001	−0.019*	−0.026**	−0.025*	−0.036***
	(0.068)	(0.074)	(0.069)	(0.043)	(0.045)	(0.048)	(0.023)	(0.026)	(0.011)	(0.013)	(0.014)	(0.011)
H_0: Low × Post-PPA = Low × Pre-PPA	0.059*	0.058*	0.112	0.064*	0.062*	0.075*	0.056*	0.056*	0.070*	0.026**	0.026**	0.034**
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.016**	0.012***	0.185	0.031**	0.024**	0.098*	0.004***	0.005***	0.002***	0.000***	0.000***	0.000***
Annualized difference: Low × Post-PPA minus Low × Pre-PPA	4.36%	4.26%	6.37%	2.02%	1.95%	2.76%	2.20%	2.13%	3.09%	1.25%	1.20%	1.59%
Target date-by-time fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,788	19,501	13,397	21,788	19,501	13,397	21,788	19,501	13,397	21,788	19,501	13,397
R^2	11.23%	10.90%	7.61%	24.65%	23.67%	21.10%	10.29%	9.99%	4.80%	22.64%	21.10%	13.32%

Table B.6: Robustness: Family-level measures of cross-sectional dispersion in realized returns and ex-ante risk-taking

Extension of Tables 9–11 in which the unit of observation switches from the TDF to the mutual fund family. The dependent variable is the equal-weighted average of the TDF-level measures for family k in month t or year t. The sample period is 2000–2012. The first two dependent variables are cross-sectional dispersion in monthly net returns and monthly five-factor alphas, both measured as squared deviations from the cross-sectional mean for funds with the same target date and month, and then averaged across all of the TDFs offered by family k in month t. The third dependent is idiosyncratic volatility, which is demeaned within target date and year and then averaged across all of the TDFs offered by family k in year t. The fourth dependent is the R^2 from the five-factor model, which is demeaned within target date and year and then averaged across all of the TDFs offered by family k in year t. The fifth dependent variable is cross-sectional dispersion in domestic equity betas estimated in the five-factor model, which is measured as the squared deviation from the cross-sectional mean for funds with the same target date and year, and then averaged across all of the TDFs offered by family k in year t. The standard errors in these regressions are simultaneously clustered on family and month, and are reported below the estimated coefficients. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent Variable:	Cross-sectional dispersion in monthly net return		Cross-sectional dispersion in monthly 5-factor alpha		Idiosyncratic volatility		R^2 from 5-factor model		Cross-sectional dispersion in 5-Factor Domestic Equity Beta	
Frequency:	Monthly	Monthly	Monthly	Monthly	Annual	Annual	Annual	Annual	Annual	Annual
Low Market Share × Post-PPA Family	0.925**	0.811**	0.407***	0.316**	0.821***	0.723***	−0.038**	−0.038**	2.049*	2.304**
	(0.405)	(0.368)	(0.148)	(0.141)	(0.270)	(0.275)	(0.016)	(0.016)	(1.061)	(1.125)
Low Market Share × Pre-PPA Family	0.081	0.041	0.079**	0.066*	0.242**	0.233	−0.015	−0.013	0.537***	0.650**
	(0.100)	(0.092)	(0.036)	(0.036)	(0.103)	(0.144)	(0.009)	(0.009)	(0.192)	(0.263)
Medium Market Share	0.156	0.125	0.042**	0.016	0.073	0.033	−0.006***	−0.004*	0.045	0.179
	(0.138)	(0.143)	(0.021)	(0.037)	(0.104)	(0.144)	(0.002)	(0.002)	(0.142)	(0.167)
Index fund based TDF	−0.183	−0.254	−0.003	0.001	−0.467***	−0.312**	0.004	0.003***	−0.279	−0.239
	(0.171)	(0.196)	(0.030)	(0.029)	(0.134)	(0.139)	(0.002)	(0.001)	(0.226)	(0.243)
Average demeaned characteristic of family's BFs		0.177**		0.239***		0.325***		0.163		0.176
		(0.080)		(0.057)		(0.074)		(0.170)		(0.112)
H_0: Low × Post-PPA = Low × Pre-PPA	0.036**	0.040**	0.024**	0.070*	0.042**	0.066*	0.146	0.160	0.178	0.155
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.067*	0.083*	0.006***	0.030**	0.001***	0.025**	0.046*	0.044*	0.001***	0.006***
Date fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,707	2,707	2,707	2,707	207	207	246	246	264	246
R^2	13.04%	20.61%	11.12%	24.93%	17.21%	30.41%	9.62%	10.99%	8.06%	10.17%

Table B.7: Cross-sectional dispersion in TDF returns and alphas and the level of idiosyncratic risk, 2007–2012

Extension of Table 9 that limits the sample period to 2007–2012. The unit of observation is TDF i offered by family k in month t. Estimation is via OLS. We include a separate fixed effect for each target retirement date (e.g., 2020), each time period (month or year). Standard errors are simultaneously clustered on family and time (month or year). *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent Variable:	Cross-sectional dispersion in monthly net return		Cross-sectional dispersion in monthly 5-factor alpha		Idiosyncratic volatility		Average monthly 5-factor alpha		Alpha scaled by idiosyncratic volatility	
Frequency:	Monthly	Monthly	Monthly	Monthly	Annual	Annual	Annual	Annual	Annual	Annual
Low Market Share × Post-PPA Family	0.863**	0.779**	0.351***	0.266**	0.743***	0.662***	−0.062**	−0.033*	−0.038*	−0.025
	(0.365)	(0.342)	(0.130)	(0.119)	(0.253)	(0.232)	(0.032)	(0.019)	(0.022)	(0.015)
Low Market Share × Pre-PPA Family	0.170**	0.117*	0.102**	0.071*	0.304**	0.275*	−0.009	0.004	−0.016	0.001
	(0.084)	(0.070)	(0.045)	(0.037)	(0.129)	(0.148)	(0.020)	(0.015)	(0.012)	(0.010)
Medium Market Share	0.115	0.085	0.049**	0.013	0.057	−0.006	−0.015	−0.011	−0.029	−0.027*
	(0.098)	(0.088)	(0.021)	(0.029)	(0.121)	(0.143)	(0.029)	(0.019)	(0.019)	(0.015)
Index fund based TDF	−0.089	−0.111*	0.001	−0.004	−0.482***	−0.350***	0.000	0.024	−0.022	−0.007
	(0.074)	(0.059)	(0.026)	(0.023)	(0.181)	(0.134)	(0.042)	(0.034)	(0.025)	(0.022)
Average demeaned characteristic of family's BFs		0.158**		0.258***		0.377***		0.555***		0.537***
		(0.071)		(0.044)		(0.070)		(0.043)		(0.081)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.012**	0.020**	0.005***	0.021**	0.004***	0.012**	0.046**	0.042**	0.161	0.110
H_0: Low × Post-PPA = Low × Pre-PPA	0.058*	0.057*	0.056*	0.101	0.090*	0.094*	0.233	0.012**	0.316	0.036**
Target date-by-time fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,501	19,501	19,501	19,501	1,454	1,454	1,454	1,454	1,454	1,454
R^2	10.90%	17.08%	9.99%	21.71%	14.12%	27.78%	50.86%	64.20%	57.16%	66.11%

Table B.8: Differences in the level of factor-model R^2s, 2007–2012

Extension of Table 10 that limits the sample period to 2007–2012. The unit of observation is TDF i offered by family k in December of year t. The dependent variable is fund i's R^2 in a one-factor or five-factor model estimated during calendar year t using daily returns. The one-factor (CAPM) model is based on the excess daily returns on the CRSP value-weighted index. The five-factor model adds the excess daily return on the Barclay US Aggregate Bond Index; the excess daily return on the MSCI World Index excluding the US, Barclays Global Aggregate excluding the US, and GSCI Commodity Index. The set of independent variables matches Table 9 except that we now control for the average R^2 of the family's BFs. Estimation is via OLS. Standard errors are simultaneously clustered on family and year. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Factor Model:	R^2 from CAPM		R^2 from 5-factor model	
Frequency:	Annual	Annual	Annual	Annual
Low Market Share	−0.064**	−0.059**	−0.033**	−0.033**
× Post-PPA Family	(0.027)	(0.024)	(0.013)	(0.013)
Low Market Share	−0.008	−0.007	−0.006**	−0.006**
× Pre-PPA Family	(0.008)	(0.005)	(0.003)	(0.002)
Medium Market Share	−0.015	−0.012	−0.003	−0.002
	(0.014)	(0.014)	(0.003)	(0.004)
Index fund based TDF	0.007	0.010	0.005**	0.005**
	(0.009)	(0.009)	(0.002)	(0.002)
Average demeaned R^2		0.298**		0.134
of family's BFs		(0.144)		(0.155)
H_0: Low × Post-PPA				
= Low × Pre-PPA = 0	0.044**	0.022**	0.002***	0.000***
H_0: Low × Post-PPA				
= Low × Pre-PPA	0.043**	0.039**	0.051*	0.058*
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes
N	1,748	1,748	1,748	1,748
R^2	26.03%	29.17%	20.86%	21.74%

Table B.9: Levels and dispersion in five-factor model betas, 2007–2012

Extension of Table 11 that limits the sample period to 2007–2012. The unit of observation is TDF i offered by family k in December of year t . In Panel A, the dependent variable is the beta estimated for TDF i in a five-factor model. In Panel B, the dependent variable is the squared deviation of each beta for TDF i in year t. The set of independent variables matches Tables 9 and Table 10 except that we control for the average beta tilt of the family's BFs in Panel A and we control for average squared deviation of the family's BFs in Panel B. Coefficients in Panel B are multiplied by 100. Estimation is via OLS. Standard errors are simultaneously clustered on family and year. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Panel A

Beta:	U.S. Equity		U.S. Debt		Global Equity		Global Debt		Commodities	
Low Market Share × Post-PPA Family	−0.036	−0.032	0.079*	0.061**	−0.004	−0.007	0.021***	0.020***	0.008	0.012*
	(0.042)	(0.039)	(0.037)	(0.027)	(0.009)	(0.009)	(0.006)	(0.006)	(0.009)	(0.007)
Low Market Share × Pre-PPA Family	0.000	0.011	0.024	0.012	0.003	0.003	0.007**	0.007**	−0.008	−0.002
	(0.031)	(0.029)	(0.022)	(0.011)	(0.005)	(0.004)	(0.003)	(0.003)	(0.008)	(0.003)
Medium Market Share	0.008	0.008	0.058**	0.049***	−0.009**	−0.006	0.015***	0.016***	−0.016*	−0.010*
	(0.032)	(0.031)	(0.025)	(0.017)	(0.005)	(0.005)	(0.006)	(0.006)	(0.009)	(0.005)
Index fund based TDF	−0.003	−0.002	0.056	0.008	−0.013**	−0.011***	0.011***	0.011***	−0.005	−0.002
	(0.018)	(0.018)	(0.036)	(0.013)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
Average demeaned beta tilt of family's BFs		0.231		0.425***		0.515***		0.428***		0.762***
		(0.203)		(0.079)		(0.109)		(0.100)		(0.123)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.391	0.433	0.195	0.061*	0.767	0.580	0.000***	0.001***	0.011*	0.020**
H_0: Low × Post-PPA = Low × Pre-PPA	0.172	0.197	0.122	0.066*	0.506	0.317	0.030**	0.022**	0.004**	0.009***
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,748	1,748	1,748	1,748	1,748	1,748	1,748	1,748	1,748	1,748
R^2	75.67%	76.26%	57.54%	63.87%	43.26%	57.35%	25.55%	33.75%	21.44%	38.44%

Panel B

Dispersion in Beta:	U.S. Equity		U.S. Debt		Global Equity		Global Debt		Commodities	
Low Market Share × Post-PPA Family	1.843*	1.789*	2.190*	1.671	0.098***	0.059*	0.059***	0.058***	0.101	0.103*
	(0.973)	(0.957)	(1.282)	(1.153)	(0.033)	(0.031)	(0.018)	(0.019)	(0.062)	(0.060)
Low Market Share × Pre-PPA Family	0.230	0.209	0.089	0.035	0.069**	0.043**	0.013	0.013	−0.017	−0.013
	(0.192)	(0.159)	(0.235)	(0.223)	(0.034)	(0.021)	(0.009)	(0.009)	(0.017)	(0.017)
Medium Market Share	−0.019	−0.082	0.010	−0.102	0.010	0.007	0.051*	0.052*	−0.020	−0.016
	(0.167)	(0.102)	(0.295)	(0.292)	(0.014)	(0.010)	(0.031)	(0.031)	(0.020)	(0.020)
Index fund based TDF	−0.299**	−0.357**	−0.430**	−0.589***	−0.010	−0.022	−0.029	−0.029	0.016	0.017
	(0.124)	(0.144)	(0.204)	(0.176)	(0.025)	(0.017)	(0.019)	(0.019)	(0.016)	(0.013)
Average dispersion in demeaned beta of family's BFs		0.188*		0.202***		0.314***		0.028		0.047
		(0.109)		(0.022)		(0.030)		(0.043)		(0.138)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.044**	0.048**	0.221	0.350	0.006***	0.053*	0.001***	0.001***	0.123	0.215
H_0: Low × Post-PPA = Low × Pre-PPA?	0.120	0.114	0.108	0.151	0.485	0.612	0.033**	0.040**	0.057*	0.080*
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,748	1,748	1,748	1,748	1,748	1,748	1,748	1,748	1,748	1,748
R^2	6.15%	7.44%	6.51%	15.64%	11.19%	45.33%	6.05%	6.17%	7.01%	7.05%

Table B.10: Cross-sectional dispersion in TDF returns and alphas and the level of idiosyncratic risk, 2007 & 2010–2012

Extension of Table 9 that limits the sample period to 2007 and 2010–2012. The unit of observation is TDF i offered by family k in month t. Estimation is via OLS. We include a separate fixed effect for each target retirement date (e.g., 2020), each time period (month or year). Standard errors are simultaneously clustered on family and time (month or year). *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Dependent Variable:	Cross-sectional dispersion in monthly net return		Cross-sectional dispersion in monthly 5-factor alpha		Idiosyncratic volatility		Average monthly 5-factor alpha		Alpha scaled by idiosyncratic volatility	
Frequency:	Monthly	Monthly	Monthly	Monthly	Annual	Annual	Annual	Annual	Annual	Annual
Low Market Share × Post-PPA Family	0.827*	0.782*	0.276**	0.262**	0.719***	0.689***	−0.046	−0.038	−0.034	−0.024
	(0.485)	(0.464)	(0.124)	(0.122)	(0.238)	(0.217)	(0.032)	(0.033)	(0.025)	(0.024)
Low Market Share × Pre-PPA Family	0.048	0.086	0.050***	0.050***	0.273**	0.251*	−0.045**	−0.021	−0.028**	0.000
	(0.070)	(0.070)	(0.017)	(0.015)	(0.134)	(0.138)	(0.022)	(0.025)	(0.014)	(0.021)
Medium Market Share	0.060	0.100*	0.029***	0.026***	0.058	−0.020	−0.033	−0.032	−0.039	−0.040*
	(0.060)	(0.054)	(0.009)	(0.007)	(0.133)	(0.146)	(0.027)	(0.021)	(0.024)	(0.022)
Index fund based TDF	−0.135*	−0.101*	−0.019*	−0.015	−0.312***	−0.256***	−0.003	0.017	−0.031	−0.014
	(0.069)	(0.059)	(0.011)	(0.012)	(0.096)	(0.096)	(0.039)	(0.042)	(0.020)	(0.022)
Average demeaned characteristic of family's BFs		0.366**		0.089**		0.346***		0.473***		0.558***
		(0.177)		(0.039)		(0.121)		(0.101)		(0.133)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.185	0.116	0.002***	0.001***	0.006***	0.006***	0.089**	0.517	0.136	0.457
H_0: Low × Post-PPA = Low × Pre-PPA	0.112	0.138	0.070*	0.085*	0.064*	0.047**	0.975	0.536	0.773	0.244
Target date-by-time fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,397	13,397	13,397	13,397	1,031	1,031	1,031	1,031	1,031	1,031
R^2	7.61%	9.65%	4.80%	5.13%	15.36%	20.45%	45.18%	55.10%	50.47%	61.27%

Table B.11: Differences in the level of factor-model R^2s, 2007 & 2010–2012

Extension of Table 10 that limits the sample period to 2007 and 2010–2012. The unit of observation is TDF i offered by family k in December of year t. The dependent variable is fund i's R^2 in a one-factor or five-factor model estimated during calendar year t using daily returns. The one-factor (CAPM) model is based on the excess daily returns on the CRSP value-weighted index. The five-factor model adds the excess daily return on the Barclay US Aggregate Bond Index; the excess daily return on the MSCI World Index excluding the US, Barclays Global Aggregate excluding the US, and GSCI Commodity Index. The set of independent variables matches Table 9 except that we now control for the average R^2 of the family's BFs. Estimation is via OLS. Standard errors are simultaneously clustered on family and year. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Factor Model:	R^2 from CAPM		R^2 from 5-factor model	
Frequency:	Annual	Annual	Annual	Annual
Low Market Share	−0.076**	−0.070**	−0.039**	−0.040**
× Post-PPA Family	(0.035)	(0.032)	(0.016)	(0.017)
Low Market Share	−0.004	−0.009**	−0.006**	−0.005**
× Pre-PPA Family	(0.010)	(0.004)	(0.003)	(0.003)
Medium Market Share	−0.014	−0.013	−0.003	0.000
	(0.014)	(0.012)	(0.003)	(0.004)
Index fund based TDF	0.007	0.007	0.004*	0.003
	(0.009)	(0.008)	(0.002)	(0.002)
Average demeaned R^2		0.433***		0.287
of family's BFs		(0.104)		(0.239)
H_0: Low × Post-PPA				
= Low × Pre-PPA = 0	0.095*	0.005***	0.005***	0.000***
H_0: Low × Post-PPA				
= Low × Pre-PPA	0.043**	0.055*	0.050**	0.060*
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes
N	1,205	1,205	1,205	1,205
R^2	24.17%	29.30%	19.74%	22.07%

Table B.12: Levels and dispersion in five-factor model betas, 2007 & 2010–2012

Extension of Table 11 that limits the sample period to 2007 and 2010–2012. The unit of observation is TDF i offered by family k in December of year t . In Panel A, the dependent variable is the beta estimated for TDF i in a five-factor model. In Panel B, the dependent variable is the squared deviation of each beta for TDF i in year t. The set of independent variables matches Tables 9 and Table 10 except that we control for the average beta tilt of the family's BFs in Panel A and we control for average squared deviation of the family's BFs in Panel B. Coefficients in Panel B are multiplied by 100. Estimation is via OLS. Standard errors are simultaneously clustered on family and year. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Panel A

Beta:	U.S. Equity		U.S. Debt		Global Equity		Global Debt		Commodities	
Low Market Share × Post-PPA Family	−0.044	−0.037	0.079	0.071**	−0.012	−0.014	0.024***	0.024***	0.006	0.010
	(0.049)	(0.044)	(0.037)	(0.034)	(0.010)	(0.010)	(0.007)	(0.006)	(0.012)	(0.010)
Low Market Share × Pre-PPA Family	0.000	0.017	0.024	0.021*	0.004	0.003	0.005	0.005*	−0.009	−0.002
	(0.035)	(0.032)	(0.022)	(0.011)	(0.007)	(0.006)	(0.003)	(0.003)	(0.010)	(0.005)
Medium Market Share	0.018	0.018	0.058**	0.045***	−0.010**	−0.008	0.012**	0.015***	−0.021**	−0.014***
	(0.035)	(0.032)	(0.025)	(0.013)	(0.005)	(0.005)	(0.006)	(0.005)	(0.010)	(0.005)
Index fund based TDF	−0.005	−0.006	0.056	0.003	−0.013**	−0.013***	0.013***	0.013***	−0.004	−0.001
	(0.021)	(0.020)	(0.036)	(0.010)	(0.005)	(0.003)	(0.004)	(0.004)	(0.006)	(0.003)
Average demeaned beta tilt of family's BFs		0.378**		0.492***		0.494***		0.404***		0.761***
		(0.176)		(0.080)		(0.136)		(0.118)		(0.160)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.224	0.336	0.269*	0.047**	0.421	0.308	0.006***	0.001***	0.110	0.182
H_0: Low × Post-PPA = Low × Pre-PPA	0.092*	0.148	0.160	0.138**	0.193	0.133	0.005***	0.001***	0.053*	0.101
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,205	1,205	1,205	1,205	1,205	1,205	1,205	1,205	1,205	1,205
R^2	74.02%	75.45%	53.14%	59.93%	42.81%	55.70%	25.01%	31.69%	22.20%	37.09%

Panel B

Dispersion in Beta:	U.S. Equity		U.S. Debt		Global Equity		Global Debt		Commodities	
Low Market Share × Post-PPA Family	2.348*	2.286*	2.823*	2.370	0.121***	0.075*	0.059**	0.059**	0.117	0.115
	(1.288)	(1.280)	(1.615)	(1.503)	(0.041)	(0.042)	(0.024)	(0.024)	(0.093)	(0.088)
Low Market Share × Pre-PPA Family	0.093	0.180	0.084	0.205	0.087**	0.055*	0.010	0.011	−0.028	−0.032
	(0.242)	(0.219)	(0.270)	(0.248)	(0.042)	(0.032)	(0.013)	(0.017)	(0.024)	(0.027)
Medium Market Share	−0.074	−0.002	0.043	0.038	0.008	0.005	0.058*	0.059*	−0.030	−0.033
	(0.164)	(0.129)	(0.308)	(0.336)	(0.010)	(0.013)	(0.033)	(0.033)	(0.025)	(0.026)
Index fund based TDF	−0.266*	−0.188	−0.364**	−0.385***	−0.010	−0.020	−0.037*	−0.037*	0.020	0.019
	(0.146)	(0.140)	(0.168)	(0.138)	(0.024)	(0.016)	(0.020)	(0.020)	(0.018)	(0.015)
Average dispersion in demeaned beta of family's BFs		0.291***		0.298***		0.311***		0.018		−0.028
		(0.096)		(0.050)		(0.046)		(0.081)		(0.152)
H_0: Low × Post-PPA = Low × Pre-PPA = 0	0.171	0.107	0.203	0.199	0.004***	0.102	0.032**	0.030**	0.150	0.274
H_0: Low × Post-PPA = Low × Pre-PPA?	0.092	0.117	0.100*	0.158	0.527	0.655	0.088*	0.136	0.112	0.132
Target date-by-year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,205	1,205	1,205	1,205	1,205	1,205	1,205	1,205	1,205	1,205
R^2	6.89%	8.80%	6.88%	14.21%	12.04%	44.15%	5.76%	5.79%	6.73%	6.74%

Table B.13: Explaining dispersion in monthly net returns and alphas (alternative version)

Extension of Table 9 that asks how TDF-level dispersion varies with a family's market share in the TDF market and in the overall mutual fund market (based on total AUM in CRSP). For each interaction between TDF market share dummy and Total market share dummy, we report the total number of fund-month observations (All), as well as the number of fund-month observations associated with families entering the TDF market before (Pre) or after (Post) the PPA.

Dependent variable:	All	Pre	Post	Cross-sectional dispersion in monthly net return		Cross-sectional dispersion in monthly 5-factor alpha		Idiosyncratic volatility	
Frequency				Monthly	Monthly	Monthly	Monthly	Annual	Annual
TOTAL LOW?	11494	8764	2730	0.170		0.094*		0.402**	
				(0.144)		(0.055)		(0.163)	
TOTAL MEDIUM?	6980	5440	1540	0.504**		0.206**		0.637***	
				(0.241)		(0.093)		(0.224)	
TDF LOW? × TOTAL LOW?	7872	5142	2730		−0.002		0.052		0.388***
					(0.134)		(0.032)		(0.148)
TDF LOW? × TOTAL MED?	3548	2008	1540		0.593**		0.262***		0.869***
					(0.289)		(0.095)		(0.224)
TDF LOW? × TOTAL HIGH?	0	0	0						
TDF MED? × TOTAL LOW?	3112	3112	0		0.126		0.056**		0.217**
					(0.101)		(0.026)		(0.095)
TDF MED? × TOTAL MED?	2215	2215	0		0.147***		0.066**		0.417***
					(0.055)		(0.031)		(0.154)
TDF MED? × TOTAL HIGH?	684	110	574		−0.460		−0.163		−0.232
					(0.283)		(0.100)		(0.385)
TDF HIGH? × TOTAL LOW?	510	510	0		0.044		0.079**		0.780***
					(0.082)		(0.031)		(0.160)
TDF HIGH? × TOTAL MED?	1217	1217	0		0.119***		0.056***		0.173**
					(0.043)		(0.007)		(0.075)
TDF HIGH? × TOTAL HIGH?	2630	2630	0						
Post-PPA Family?				0.608**	0.586**	0.190*	0.170*	0.422**	0.330*
				(0.292)	(0.284)	(0.102)	(0.099)	(0.198)	(0.196)
Index fund based TDF?				0.052	−0.059	0.051	0.019	−0.155	−0.182*
				(0.106)	(0.071)	(0.043)	(0.015)	(0.097)	(0.100)
Average demeaned return dispersion of family's BFs				0.157**	0.156**	0.255***	0.254***	0.368***	0.367***
				(0.070)	(0.070)	(0.047)	(0.047)	(0.063)	(0.064)
Target date-by-time period fixed effects?				Yes	Yes	Yes	Yes	Yes	Yes
N				21,788	21,788	21,788	21,788	1,609	1,609
R^2				17.64%	18.14%	21.94%	22.29%	27.73%	31.94%

Table B.14: Explaining dispersion in monthly net returns and alphas (alternative version)

Extension of Table 9 that asks how TDF-level dispersion varies with the time-period during which the family first enters the TDF market. We report the number of fund-month observations (All) for families entering during three distinct time periods: [1994, 2002], [2003, 2006], and [2007, 2012]. We report the p-value from the hypothesis test that families entering between 2003 and 2006 have the same average cross-sectional dispersion as families entering after 2006. We also report the p-value from the hypothesis test that families entering between 2003 and 2006 and the families entering after 2006 have the same average cross-sectional dispersion as families entering before 2003 (the omitted category). Because there are so few entrants after 2008, it is not possible to subdivide the Post-PPA sample.

Dependent variable:	All	Cross-sectional dispersion in monthly net return		Cross-sectional dispersion in monthly 5-factor alpha		Idiosyncratic volatility	
Frequency:		Monthly	Monthly	Monthly	Monthly	Annual	Annual
Family entered market before 2003	6188						
Family entered market [2003, 2006]	10826	0.089	0.070	0.057*	0.036	0.160*	0.130
		(0.076)	(0.058)	(0.030)	(0.030)	(0.082)	(0.095)
Family entered market [2007, 2012]	4844	0.687**	0.638**	0.281**	0.206*	0.579**	0.482*
		(0.341)	(0.319)	(0.118)	(0.110)	(0.254)	(0.249)
Index fund based TDF?		−0.170***	−0.162***	−0.055	−0.044*	−0.644***	−0.509***
		(0.065)	(0.056)	(0.034)	(0.025)	(0.186)	(0.099)
Average demeaned return dispersion of family's BFs			0.158**		0.256***		0.352***
			(0.071)		(0.046)		(0.069)
$H_0 : [03, 06] = [07, 12]$		0.079*	0.076*	0.062*	0.126	0.101	0.143
$H_0 : [03, 06] = [07, 12] = 0$		0.083*	0.078*	0.014**	0.102	0.023**	0.112
Target date-by-time period fixed effects?		Yes	Yes	Yes	Yes	Yes	Yes
N		21,788	21,788	21,788	21,788	1,609	1,609
R^2		10.82%	17.01%	10.02%	21.56%	10.97%	23.17%

Table B.15: Additional plan-level evidence on TDF risk versus industry risk

In this table, we relate risk measures for the TDF held by each retirement plan to risk measures for the industry to which the firm sponsoring the plan belongs. The risk measures mirror those used in Table 13. Panels A and B focus on differences in CAPM beta and Panels C and D focus on differences in idiosyncratic risk. Panels A and C report results for the full sample of retirement plans, while Panels C and D report results for the subsample of plans that feature auto-enrollment. We use family-level measures of TDF risk to place TDFs into three risk terciles, and we use the median risk levels of the publicly traded firms within each industry to place firms into three risk terciles. Then, we plot the number of retirement plans that fall into each of the nine cells. Finally, we calculate the fraction of retirement plans within each industry risk tercile that offer TDFs from the bottom, middle, and top tercile of TDF risk. The fact that there are more observations in the lowest tercile of industry beta implies that retirement plans in the BrightScope sample come disproportionately from firms in the bottom tercile of industry betas. The fact that there are more observations in the middle tercile of TDF beta implies that retirement plans in the BrightScope sample match disproportionately with TDFs with betas that fall in the middle tercile of TDF risk. In Panels A and D, we can reject the hypothesis that industry risk is independent of TDF risk (p-values in χ^2 tests are 0.000 and 0.018). In Panels B and C, we cannot (p-values are 0.273 and 0.412).

Panel A.		Industry Beta – Full Sample						
		Tercile 1		Tercile 2		Tercile 3		Total
TDF	Tercile 1	1,294	29.9%	531	26.8%	479	28.6%	2,304
Beta	Tercile 2	2,146	49.6%	966	48.8%	749	44.7%	3,861
	Tercile 3	887	20.5%	482	24.4%	449	26.8%	1,818
	Total	4,327		1,979		1,677		7,983
Panel B.		**Industry Beta – Auto-Enrollment Sample**						
		Tercile 1		Tercile 2		Tercile 3		Total
TDF	Tercile 1	355	33.6%	181	29.1%	134	31.2%	670
Beta	Tercile 2	426	40.3%	267	43.0%	184	42.9%	877
	Tercile 3	275	26.0%	173	27.9%	111	25.9%	559
	Total	1056		621		429		2,106
Panel C.		**Industry Idiosyncratic Risk – Full Sample**						
		Tercile 1		Tercile 2		Tercile 3		Total
TDF	Tercile 1	619	26.8%	962	28.7%	629	27.1%	2,210
Idio.	Tercile 2	1,553	67.3%	2,210	65.9%	1,546	66.5%	5,309
Risk	Tercile 3	135	5.9%	180	5.4%	149	6.4%	464
	Total	2,307		3,352		2,324		7,983
Panel D.		**Industry Idiosyncratic Risk – Auto-Enrollment Sample**						
		Tercile 1		Tercile 2		Tercile 3		Total
TDF	Tercile 1	214	31.0%	202	24.3%	164	28.1%	580
Idio.	Tercile 2	432	62.6%	566	68.0%	366	62.7%	1,364
Risk	Tercile 3	44	6.4%	64	7.7%	54	9.2%	162
	Total	690		832		584		2,106

Table B.16: Testing for risk matching in plan-level data (alternative version)

Extension of Table 13. The unit of observation is the single-employer DC retirement plan i offered by firm j in industry k in 2010. The dependent variable measures the risk of the TDFs offered by plan i. In Panel A, our measure of risk is the *absolute value* of the average target-date adjusted tilt in CAPM beta. In Panel B, it is the *absolute value* of the average target-date adjusted standard deviation of idiosyncratic monthly returns. The sample is limited to the 95.8% of plans that offer TDFs from a single family. Before calculating the absolute values of our measures of firm risk, we subtract the average measure of firm risk within the sample of plans. The other plan-level and family-level control variables are the same as in Table 13, except that we also take the absolute value of the average category-adjusted measure of risk for the other investment options offered by plan i. Coefficients in Panel B are multiplied by 100. Estimation is via OLS. Standard errors are simultaneously clustered on family and year. *, **, and *** denote statistical significance at the 10% level, 5% level, and 1% level, respectively.

Panel A

Dependent variable:	Abs (Average CAPM beta tilt of TDFs in plan i)						
Abs (CAPM beta tilt of firm j)	0.002**	0.002	0.001				
	(0.001)	(0.001)	(0.001)				
Abs (Median CAPM beta tilt within industry of firm j)				−0.003	−0.007*	−0.007*	−0.008*
				(0.003)	(0.004)	(0.004)	(0.004)
Abs (Median CAPM beta) × Auto enrollment?						0.003	0.003
						(0.003)	(0.003)
Single record keeper (SRK)?	−0.012***	−0.012***		−0.008***			
	(0.002)	(0.002)		(0.001)			
Market share of SRK within BrightScope			−0.133***		−0.119***	−0.119***	−0.120***
			(0.009)		(0.010)	(0.009)	(0.009)
TDF from Pre-PPA family with Low Market Share?	−0.019***	−0.018***	−0.032***	−0.013***	−0.029***	−0.029***	−0.029***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
TDF from Post-PPA family with Low Market Share?	0.060***	0.061***	0.032***	0.065***	0.059***	0.059***	0.059***
	(0.013)	(0.013)	(0.012)	(0.005)	(0.005)	(0.005)	(0.006)
Ln plan assets	0.000	0.000	0.003***	0.000	0.003***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln number of participants	0.000	0.001	−0.002	0.000	−0.001	−0.001	−0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Auto enrollment?	0.004***	0.003**	0.004***	0.004***	0.004***	0.003**	0.003**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Offer company stock?	0.004***	0.002	0.000	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Abs (Average beta tilt of non-TDFs offered by plan j)							−0.050***
							(0.015)
H_0: Low × Pre-PPA = Low × Post-PPA?	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Industry fixed effects?	—	Yes	Yes	—	—	—	—
N	968	968	758	7,983	5,504	5,504	5,504
Adj. R^2 (excl. supply-side)	1.43%	2.23%	2.23%	0.53%	0.53%	0.71%	0.69%
Adj. R^2	17.81%	18.34%	36.41%	18.50%	35.74%	35.75%	35.94%

Panel B

Dependent variable:	Abs (Standard deviation of idiosyncratic returns tilt of TDFs in plan i)						
Abs (Idiosyncratic risk of firm j)	−0.049	−0.052	−0.070				
	(0.051)	(0.056)	(0.059)				
Abs (Median idiosyncratic risk within				0.083	0.084	0.118	0.114
industry of firm j)				(0.067)	(0.064)	(0.074)	(0.069)
Abs (Median idiosyncratic risk)						−0.140	−0.124
× Auto enrollment?						(0.117)	(0.111)
Single record keeper (SRK)?	0.005	0.005		−0.009			
	(0.010)	(0.010)		(0.006)			
Market share of SRK			0.156**		0.130**	0.130**	0.127**
within BrightScope			(0.068)		(0.055)	(0.055)	(0.054)
TDF from Pre-PPA family	0.002	0.006	0.027	−0.025***	−0.001	−0.001	0.001
with low market share?	(0.024)	(0.023)	(0.028)	(0.007)	(0.012)	(0.012)	(0.012)
TDF from Post-PPA family	0.048	0.070	0.052***	0.035**	0.057***	0.057***	0.058***
with low market share?	(0.045)	(0.051)	(0.012)	(0.015)	(0.021)	(0.021)	(0.022)
Ln plan assets	0.024***	0.026***	0.036***	0.028***	0.033***	0.033***	0.032***
	(0.005)	(0.006)	(0.006)	(0.003)	(0.004)	(0.004)	(0.003)
Ln number of participants	−0.017***	−0.019**	−0.029***	−0.018***	−0.020***	−0.021***	−0.020***
	(0.006)	(0.008)	(0.007)	(0.002)	(0.003)	(0.003)	(0.003)
Auto enrollment?	0.012*	0.011	0.014*	−0.002	−0.001	0.002	0.002
	(0.007)	(0.008)	(0.008)	(0.004)	(0.005)	(0.006)	(0.006)
Offer company stock?	0.006	−0.005	0.002	0.005	0.003	0.003	0.004
	(0.007)	(0.009)	(0.009)	(0.006)	(0.007)	(0.007)	(0.007)
Abs (Average risk of non-TDFs							−0.529***
offered by plan j)							(0.084)
H_0: Low × Pre-PPA							
= Low × Post-PPA?	0.386	0.260	0.378	0.001***	0.002***	0.002***	0.004***
Industry fixed effects?	—	Yes	Yes	—	—	—	—
N	968	968	758	7,983	5,504	5,504	5,504
Adj. R^2 (excl. supply-side)	2.99%	7.56%	7.56%	3.87%	3.87%	3.86%	4.63%
Adj. R^2	3.06%	7.96%	13.44%	4.34%	8.58%	8.58%	9.77%

Table B.17: Distribution of Retirement Plan Participants Across Industries in 2005 and 2012

In this table, we use data from Form 5500 to calculate the fraction of retirement plan participants that work in broad industry categories in 2005 and 2012. The sample is limited to filings that report both an NAICS industry classification and a positive number of plan participants. We use the first two digits of the six-digit NAICS to assign firms to broad industry groups.

		Fraction of Retirement Plan Participants Within Each Broad Industry	
Code	Industry	2005	2012
11	Agriculture	0.65%	0.53%
21	Mining	0.70%	0.86%
22	Utilities	1.75%	1.50%
23	Construction	4.67%	5.00%
31-33	Manufacturing	29.01%	24.59%
42	Wholesale Trade	3.08%	2.84%
44-45	Retail Trade	9.15%	10.93%
48	Transportation	4.62%	4.90%
49	Warehousing	0.62%	0.16%
51	IT	5.49%	4.59%
52	Finance & Insurance	10.60%	9.50%
53	Real Estate	1.18%	0.88%
54	Professional & Scientific	7.33%	6.69%
55	Management	3.49%	3.19%
56	Waste Management	2.17%	2.22%
61	Education	0.57%	2.53%
62	Health Care	9.29%	13.02%
71	Arts & Entertainment	0.81%	0.88%
72	Hotel & Food Services	2.85%	2.80%
81	Other Services	1.96%	2.34%
92	Public Administration	0.02%	0.04%

C Heterogeneity in human capital and optimal portfolio choice

C.1 Normative studies

Davis and Willen (2000a) focus on heterogeneity due to occupation. They regress occupation-level earnings innovations on size-sorted and industry-level equity portfolio returns, finding significant effects. For example, plumbers' earnings are negatively correlated with the small-minus-big portfolio return, whereas electricians' earnings are positively correlated with returns in the construction sector. As a result of this heterogeneity in human capital returns, there is considerable variation in optimal portfolio allocations over the life cycle, and large departures from the two-fund separation principle (see also Davis and Willen 2002). Davis and Willen (2000b), on the other hand, emphasize differences based on educational attainment. The correlation between aggregate equity returns and labor income shocks ranges from -0.25 over most of the life-cycle for the least educated men, to 0.25 or more for college-educated women. Indeed, the authors estimate that for college-educated (non-college-educated) men, labor income risk is equivalent to a \$50,000 long (\$25,000 short) position in the S&P 500 index. They also show that introducing new financial assets, such as an equity portfolio that matches the industry composition of the people in the cohort, leads to substantial welfare gains: assuming an annual discount rate of 2.5% and a coefficient of relative risk aversion of 3, the equilibrium welfare gains for college-educated men amount to nearly \$27,000 per person in 1998 dollars.

More recently, Maurer et al. (2010) argue that heterogeneity in labor income volatility can influence life-cycle household portfolios. Higher labor-income uncertainty boosts demand for stable income in retirement, but also when young. A declining equity glide path with age is appropriate for the worker with low income uncertainty; whereas for the high-income-risk worker, equity exposure rises until retirement.[6] Fugazza et al. (2011) focus on the benefits of international portfolio investment for the purpose of diversifying away industry-related labor income risk. They find substantial dispersion in portfolio weights for workers belonging to different industries within a country. For instance, portfolio shares in UK equity range, depending on the industry, from 0.15 to 0.16 for US workers, from 0.04 to 0.29 for Canadians, and from 0.19 to 0.30 for Italians. They conclude that the optimal portfolios in DC plans should vary depending on the industry in which the member works.[7] Finally, Bagliano et al. (2013) compute the utility costs of ignoring heterogeneity in labor income variance in constructing TDFs. (See Section D below for further discussion.)

C.2 Positive studies

Eiling (2013) derives the equilibrium implications of optimal portfolio choice in the presence of industry-specific, non-tradeable human capital. She shows that, in equilibrium, asset risk premia depend both on the exposure to the market factor and on the exposure to industry-specific human capital returns, proxied by the growth rates of earnings. When estimating the model for monthly returns on 25 size and book-to-market sorted portfolios, three out of five human capital industries have statistically significant coefficients, and the model explains 61% of the cross-sectional variation in average returns. In Section D.2.4, we use Eiling's (2013) set-up to offer our own calculations of the costs of ignoring the heterogeneity of human capital returns in the construction of an optimal portfolio. We show that these costs can be substantial.

[6] Horneff et al. (2010), on the other hand, argue that workers with higher labor income risk should purchase more annuities and earlier.

[7] Guidolin and Hyde (2012) stress the importance of accounting for the time-varying nature of the correlation between sector-specific earnings/wages dynamics and stock returns for the strategies of occupational DC funds.

D Investor's utility costs

D.1 Existing literature

Gomes et al. (2008) consider the optimal TDF for investors with constant relative risk aversion (CRRA), who begin investing at age 21 and retire at age 65, and whose life-time expected wage profile and wage volatility is realistically calibrated. They constrain an investor with a CRRA coefficient of eight to follow the average optimal asset allocation path of an investor with a CRRA coefficient of five and estimate the cost to be 234% of the investor's first-year labor income. Bagliano et al. (2013) consider the appropriateness of a typical TDF for a similar CRRA investor, who may have either normal or high labor income variance. Whereas the typical TDF is nearly optimal for the investor with normal labor income variance, it generates a cost as high as 31% of the constant consumption level for an investor with high labor income variance and a CRRA coefficient of eight. Pang and Warshawsky (2009) do not compute utility costs, but characterize the heterogeneity in outcomes from investing in TDFs with a representative set of glide paths. Their simulations show that the standard deviation of terminal wealth for an investor who starts investing at age 25 and retires at 65 can differ by as much as 20%, depending on the glide path chosen.

D.2 Our own calculations

In this section, we analyze the utility costs that a TDF investor is exposed to when: (i) the TDF equity allocation differs from the optimal allocation; (ii) the TDF equity allocation differs from the optimal allocation and there is uncertainty surrounding the equity premium; and (iii) the TDF manager generates idiosyncratic risk, and this idiosyncratic risk is not accounted for in the TDF's asset allocation choice. The analysis is cast in a simple constant relative risk aversion (CRRA) setting with investment in the equity index and a risk-free asset. This setting allows us to derive simple analytical closed-form expressions for the utility costs associated with sub-optimal policies. Obviously, the quantitative implications of our analysis only have illustrative value, as our model abstracts from the inter-temporal and human capital considerations that are the very motivation for the glide paths offered by TDFs.

D.2.1 The basic setting

Assume individual investors have CRRA preferences defined over terminal wealth:

$$U_0 = \frac{1}{1-\gamma} E_0(W_T^{1-\gamma}), \tag{1}$$

where W_T is terminal wealth ($W_0 = 1$). We define the log certainty equivalent return (CER) as:

$$\frac{1}{1-\gamma} \exp(T \times \mathrm{CER})^{1-\gamma} = U_0. \tag{2}$$

Hence, maximizing the CER is equivalent to maximizing expected utility.

Assuming log-normal returns and approximating $\Delta \ln(W_t)$ as $\Delta W_t/W_{t-1} - \frac{1}{2}\mathrm{var}_{t-1}(\Delta W_t/W_{t-1})$, we have:[8]

$$\begin{aligned} E_0(W_T^{1-\gamma}) &= \exp[T(1-\gamma)(\mu_W - \sigma_W^2/2) + (1-\gamma)^2 (T/2)\sigma_W^2] \\ &= T(1-\gamma)\left(\mu_W - \frac{\gamma}{2} + \sigma_W^2\right); \end{aligned} \tag{3}$$

[8] This approximation is used, for example, by Campbell and Viceira (1999) and becomes exact in continuous time.

and:

$$\text{CER} = \mu_W - \frac{\gamma}{2}\sigma_W^2, \tag{4}$$

where μ_W and σ_W are the mean and the volatility of $\Delta W_t/W_{t-1}$, respectively.

Assume the investor can invest in equities and the risk-free asset. We have:

$$\text{CER} = r_f + w\mu - \frac{\gamma}{2}w^2\sigma^2, \tag{5}$$

where r_f is the risk-free rate, w is the equity allocation, μ is the equity risk premium, and σ is equity volatility. The optimal equity allocation is:

$$w^\star = \frac{\mu}{\gamma\sigma^2}. \tag{6}$$

Let $x \equiv w - w^*$ denote the difference between the actual equity allocation and the optimal allocation. We consider two measures of utility costs associated with sub-optimal choices. First, we compute the difference in log CERs between the optimal and actual allocations:

$$\Delta\text{CER} \equiv \text{CER}^\star - \text{CER}. \tag{7}$$

This is the sure return that an investor facing the sub-optimal allocation would be willing to forgo, to be able to implement the optimal allocation instead of the sub-optimal allocation. Second, we compute the fraction of initial wealth that the sub-optimal investor would give up to implement the optimal allocation; i.e., the wealth-equivalent utility cost:[9]

$$\text{UC} \equiv 1 - \exp[-T(\text{CER}^\star - \text{CER})]. \tag{8}$$

We have:

$$\begin{aligned} \Delta\text{CER} &= (w^\star - w)\mu - \frac{\gamma}{2}[(w^\star)^2 - w^2]\sigma^2 \\ &\equiv x\mu + \frac{\gamma}{2}(x^2 - 2xw^\star)\sigma^2 \\ &= \frac{\gamma}{2}\sigma^2x^2 + (\mu - w^\star\gamma\sigma^2)x \\ &= \frac{\gamma}{2}\sigma^2x^2. \end{aligned} \tag{9}$$

For a given departure from optimality x, the utility cost increases with γ and σ. While the Envelope Theorem tells us that departures from optimality do not matter in a neighborhood of $x = 0$, as the departures increase in (absolute) magnitude, so do the utility costs, which are increasing in both the risk aversion of the investor and the volatility of equity returns.

The point above is illustrated in Figure 1, where we plot the utility costs of departures from optimality, as a function of the absolute size of the deviation, for three different values of γ, assuming $\sigma = 0.205$—the same value chosen by Gomes et al. (2008). The costs are reported in *percentage points*. To get a sense of the magnitudes involved, for a relatively minor departure from optimality of 10%, the utility cost for an investor with $\gamma = 8$ is 16.81 basis points per year, which translates into a wealth-equivalent utility loss of 7.29% for an investor with a 45-year horizon.

[9] This is the measure of utility costs used, for example, in Balduzzi and Lynch (1999).

D.2.2 The effect of parameter uncertainty

We now assume that the equity premium μ is not known and that the posterior density of the equity premium has volatility σ_μ (for simplicity, we assume that the volatility of equity returns σ is known). A Bayesian investor chooses:

$$w^\star = \frac{\mu}{\gamma(\sigma^2 + \sigma_\mu^2)}, \tag{10}$$

where $\sigma^2 + \sigma_\mu^2$ is the variance of the *predictive* density of returns.[10] So, the uncertainty surrounding the mean estimate *reduces* the optimal allocation to the risky asset.

When we compute the utility cost of a sub-optimal allocation, we have:

$$\Delta\text{CER} = \frac{\gamma}{2}(\sigma^2 + \sigma_\mu^2)x^2. \tag{11}$$

Comparing equations (9) and (11), we can see that uncertainty surrounding the equity premium *increases* the utility cost associated with a given departure from optimality.

D.2.3 The role of idiosyncratic risk

Assume that the TDF, by performing security selection, may outperform or underperform the equity index, but adds idiosyncratic risk to the portfolio. There are now *two* possible sources of utility costs. First, assume that idiosyncratic risk is ignored by the fund manager. Given her preferences, the investor would want the equity allocation:

$$w_\alpha^\star = \frac{\mu + \alpha}{\gamma(\sigma^2 + \sigma_\epsilon^2)}, \tag{12}$$

where α denotes the expected idiosyncratic return and σ_ϵ is the volatility of the idiosyncratic return. Instead, the fund manager ignores α and σ_ϵ and selects:

$$w = \frac{\mu}{\gamma\sigma^2}. \tag{13}$$

The utility cost of ignoring the idiosyncratic component of returns is (see equation (9)):

$$\text{CER}_\alpha^\star - \text{CER} = \frac{\gamma}{2}(\sigma^2 + \sigma_\epsilon^2)(w - w_\alpha^\star)^2. \tag{14}$$

As in equation (9), the utility cost is increasing in γ and in the total volatility of the returns on the equity allocation.

The second utility costs arises even if the manager optimally accounts for the mean and volatility of idiosyncratic returns. Without idiosyncratic risk, the maximized CER is:

$$\text{CER}^\star = r_f + w^\star\mu - \frac{\gamma}{2}(w^\star)^2\sigma^2 = r_f + \frac{\mu^2}{\gamma\sigma^2} - \frac{\gamma}{2}\frac{\mu^2}{\gamma^2\sigma^4}\sigma^2 = r_f + \frac{1}{2}\frac{\mu^2}{\gamma\sigma^2}, \tag{15}$$

[10] This follows from the fact that $\text{Var}(r|\mathbf{X}, \sigma, m) = \text{Var}(r|\mu) + \text{Var}(\mu|\mathbf{X}, \sigma, m)$, where r denotes the equity return, $\mathbf{X}$ denotes a vector of data realizations, and m denotes the mean of the prior density.

where r_f denotes the risk-free rate. With idiosyncratic risk, the maximized CER is:

$$\text{CER}^{\star}_{\alpha} = r_f + \frac{1}{2}\frac{(\mu+\alpha)^2}{\gamma(\sigma^2+\sigma_e^2)}. \tag{16}$$

Hence, the utility cost from investing in a TDF that allocates optimally, but has idiosyncratic risk, as opposed to investing in a TDF that allocates optimally, and has no idiosyncratic risk, is:

$$\text{CER}^{\star} - \text{CER}^{\star}_{\alpha} = \frac{1}{2\gamma}\left[\frac{\mu^2}{\sigma^2} - \frac{(\mu+\alpha)^2}{\sigma^2+\sigma_e^2}\right]. \tag{17}$$

This cost decreases with γ, as a higher γ reduces the maximized CER, regardless of whether there is idiosyncratic risk. This cost increases with σ_ϵ, as higher idiosyncratic risk reduces the maximized CER in the presence of idiosyncratic risk.

If we sum up the two utility costs:

$$\text{CER}^{\star}_{\alpha} - \text{CER} + \text{CER}^{\star} - \text{CER}^{\star}_{\alpha} = \Delta\text{CER}, \tag{18}$$

we obtain the total utility cost of being invested in a TDF that generates idiosyncratic risk in its equity allocation, but allocates funds ignoring the idiosyncratic risk, relative to a fund that does not generate idiosyncratic risk.

The point above is illustrated in Figure 2, where we use the same assumptions as in Figure 1, and we set $\alpha = -0.007$ and $\sigma_\epsilon = 0.01$.[11] In this case, a 10% deviation from optimality leads to a yearly utility cost of 24.49 basis points and a wealth-equivalent utility loss of 10.43%, for an investor with $\gamma = 8$ and $T = 45$.

D.2.4 Labor income

We now extend the analysis to allow for the fact that a portion of the investor's next period's wealth depends on her labor income. In this case, we have:

$$\frac{\Delta W_t}{W_{t-1}} = r_{pt} + r_{yt}, \tag{19}$$

where r_{pt} is the portfolio return and $r_{yt} = y_t/W_{t-1}$ is the re-invested labor income as a fraction of initial wealth.

Consider the case of an investor with a horizon of $T = 1$ (where, for convenience of notation, we drop the time subscripts on the variables dated $t = 1$):

$$U_0 = \frac{1}{1-\gamma}\exp(\text{CER})^{1-\gamma}. \tag{20}$$

Assuming log-normality:

$$\text{CER} = \text{constant} + w\mu - \frac{\gamma}{2}(w^2 + 2w\beta_y)\sigma^2, \tag{21}$$

where β_y measures the sensitivity of r_y to the equity return.

The set-up described above corresponds to the one used by Eiling (2013) to derive the asset

[11] These values are based on the pooled average annual alpha and average annual idiosyncratic volatility in our sample of TDFs.

pricing implications of industry-specific human capital. We specialize her setting to the case of a single risky asset and a single source of labor income. The optimal allocation to equities is given by:

$$w^{\star} = \frac{\mu}{\gamma\sigma^2} - \beta_y. \tag{22}$$

Hence, relative to the setting without human capital, the investor *reduces* her optimal allocation to equities by an amount proportional to the sensitivity of labor earnings to the equity return. By writing the labor income beta as:

$$\beta_y = \rho_{ry}\frac{\sigma_y}{\sigma}, \tag{23}$$

where $\sigma_y^2 = \text{var}(r_y)$, it is immediate that, for given volatility of equity returns, a higher correlation between equity returns and labor income growth and a higher volatility of labor income reduces the optimal equity allocation.

Let us now consider the case where the actual equity allocation is based on the "wrong" sensitivity of labor income to equity returns, $\tilde{\beta}_y$:

$$w = \frac{\mu}{\gamma\sigma^2} - \tilde{\beta}_y; \tag{24}$$

and:

$$w - w^{\star} = \tilde{\beta}_y - \beta_y \equiv x. \tag{25}$$

As in equation (9), the difference in CER between the optimal and the actual allocation is given by:

$$\Delta\text{CER} = \frac{\gamma}{2}\sigma^2 x^2. \tag{26}$$

Assume again $\sigma = 0.205$ and $\gamma = 8$. Also, from Eiling (2013), Table 2, the beta of the growth rate of industry-specific labor income with respect to an equally-weighted portfolio of 8 industry portfolios ranges between -0.203 (government) and 0.417 (mining), with a median of -0.0224. In 2011, the US Census Bureau reports a median household income of \$50,502 and median net wealth of \$68,828.[12] Now, consider a household with median 2011 income and net wealth, whose labor income is originated in the mining sector. Assume that the household is assigned a portfolio reflecting the median exposure of labor income growth to the stock market of -0.0224, leading to:[13]

$$\Delta\beta_y = \frac{50,502}{68,828} \times (-0.0224 - 0.417) = -0.328. \tag{27}$$

This departure from optimality translates into an ΔCER of 1.81%. Applying the same calculations to a household whose labor income is originated in the government sector, we obtain a ΔCER of 0.31%.

[12] https://www.census.gov/prod/2012pubs/acsbr11-02.pdf and http://www.census.gov/people/wealth/.

[13] Note that we can write: $\beta_{yt-1} = (y_{t-1}/W_{t-1})(y_t/y_{t-1})$.

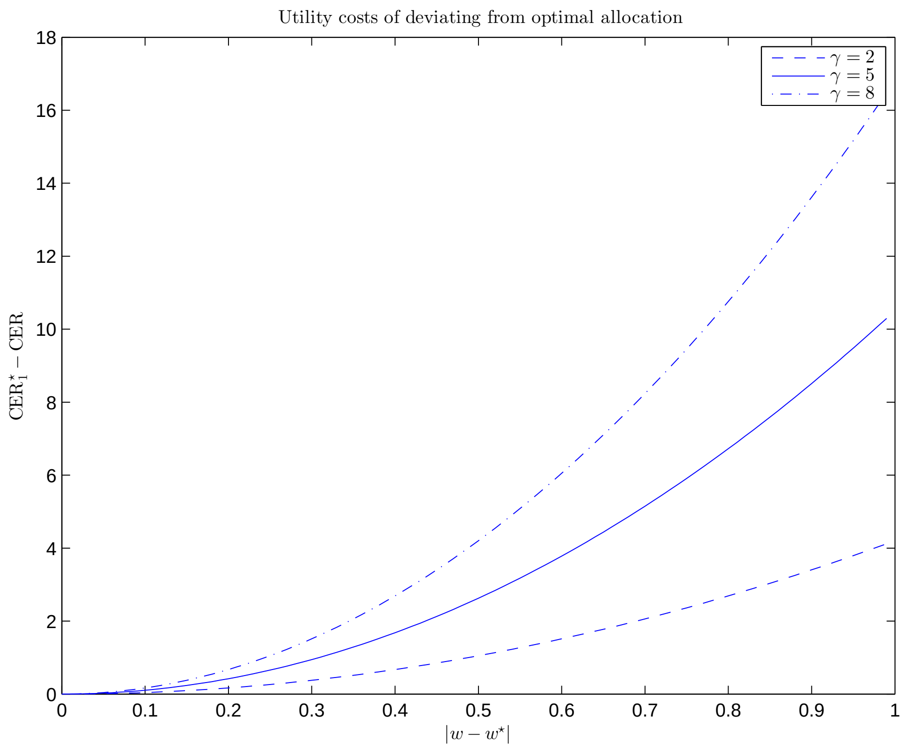

Figure 1: This figure plots $\mathrm{CER}^\star - \mathrm{CER}$ as a function of $|w^\star - w|$.

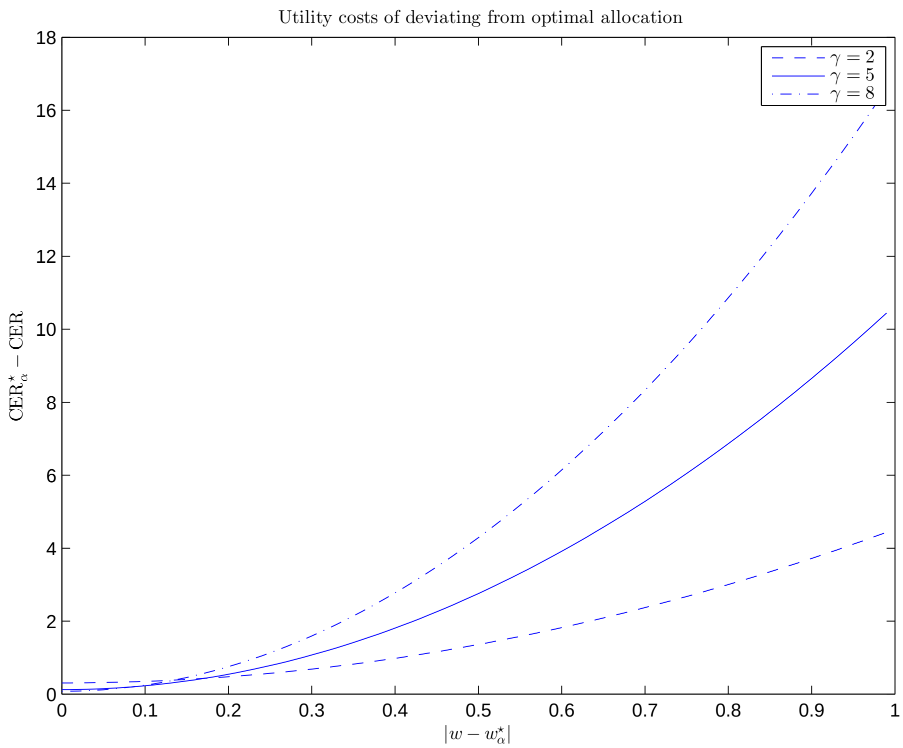

Figure 2: This figure plots $\mathrm{CER}^{\star}_{\alpha} - \mathrm{CER}$ as a function of $|w^{\star}_{\alpha} - w|$.

E The "costs" of TDF heterogeneity

Let $\bar{R}_t$ denote the gross return on a "benchmark" TDF with target date T:

$$\bar{R}_t = R_{ft-1} + \bar{\alpha}_{(T-t)}\bar{\beta}_{(T-t)}^{\top} f_t + \bar{\sigma}_{(T-t)}\bar{\epsilon}_t, \tag{28}$$

where R_{ft-1} is the gross risk-free rate, $\bar{\alpha}_{(T-t)}$ is the constant component of the idiosyncratic return, $\bar{\beta}_{(T-t)}$ is the vector of factor betas, and f_t is a vector of benchmark excess returns. Similarly, for the i-th TDF, we have:

$$R_{it} = R_{ft-1} + \alpha_{i(T-t)} + \beta_{i(T-t)}^{\top} f_t + \sigma_{i(T-t)}\epsilon_{it}, \tag{29}$$

where ϵ_{it} is an i.i.d. residual. The risk characteristics $\bar{\alpha}_{i(T-t)}$, $\bar{\beta}_{i(T-t)}$, $\bar{\sigma}_{(T-t)}$, $\alpha_{i(T-t)}$, $\beta_{i(T-t)}$, $\bar{\beta}_{i(T-t)}$, and $\sigma_{i(T-t)}$ vary deterministically with the distance from the target date, $(T-t)$.

If the investor is assigned to TDF i, her terminal wealth relative to the wealth resulting from the assignment to the benchmark TDF is:

$$\frac{W_{iT}}{\bar{W}_T} \;=\; \exp\left[\sum_{t=1}^{T} \ln(R_{it}) - \ln(\bar{R}_t)\right]. \tag{30}$$

Assuming i.i.d. factors and using the approximations $\ln(R_{it}) \approx R_{1t} - 1 - \frac{1}{2}\mathrm{var}_{t-1}(R_{i,t})$ and $\ln(R_{it}) \approx \bar{R}_t - 1 - \frac{1}{2}\mathrm{var}_{t-1}(\bar{R}_t)$, we can write the log wealth differential of being assigned to the i-th TDF instead of the benchmark as:[14]

$$\begin{aligned}\ln(W_{iT}) - \ln(\bar{W}_T) \;&=\; \sum_{t=1}^{T} \alpha_{i(T-t)} - \bar{\alpha}_{(T-t)} + (\beta_{i(T-t)} - \bar{\beta}_{(T-t)})^{\top} f_t + \sigma_{i(T-t)}\epsilon_{it} - \bar{\sigma}_{(T-t)}\bar{\epsilon}_t \\ &\quad -\frac{1}{2}[\beta_{i(T-t)}^{\top}\Sigma_{ff}\beta_{i(T-t)} + \sigma_{i(T-t)}^2 - \bar{\beta}_{(T-t)}^{\top}\Sigma_{ff}\bar{\beta}_{(T-t)} - \bar{\sigma}_{(T-t)}^2]; \end{aligned} \tag{31}$$

where:[15]

$$\begin{aligned} E[\ln(W_{iT}) - \ln(\bar{W}_T)] \;&=\; \sum_{t=1}^{T} \alpha_{i(T-t)} - \bar{\alpha}_{(T-t)} + (\beta_{i(T-t)} - \bar{\beta}_{(T-t)})^{\top}\mu_f \\ &\quad -\frac{1}{2}[\beta_{i(T-t)}^{\top}\Sigma_{ff}\beta_{i(T-t)} + \sigma_{i(T-t)}^2 - \bar{\beta}_{(T-t)}^{\top}\Sigma_{ff}\bar{\beta}_{(T-t)} - \bar{\sigma}_{(T-t)}^2] \end{aligned} \tag{32}$$

$$\begin{aligned} \mathrm{Var}[\ln(W_{iT}) - \ln(\bar{W}_T)] \;&=\; \sum_{t=1}^{T}(\beta_{i(T-t)} - \bar{\beta}_{(T-t)})^{\top}\Sigma_{ff}(\beta_{i(T-t)} - \bar{\beta}_{(T-t)}) \\ &\quad +\bar{\sigma}_{(T-t)}^2 + \sigma_{i(T-t)}^2. \end{aligned} \tag{33}$$

Assuming log-normal returns, relative terminal wealth is distributed log-normal.

We assume that the investor is randomly assigned to a TDF at the beginning of the investment horizon. The distribution of log terminal wealth is drawn from a mixture of Gaussian distributions with means $E[\ln(W_{iT}) - \ln(\bar{W}_T)]$ and variances $\mathrm{Var}[\ln(W_{iT}) - \ln(\bar{W}_T)]$. The mixing parameters are the probabilities of being assigned to the different TDFs, proxied by the fraction of

[14] The two approximations become exact in continuous time.

[15] We assume that $\bar{\epsilon}_t$ and ϵ_{it} are uncorrelated.

total TDF assets under management by the different mutual fund families.[16] We perform 10,000,000 draws from the mixture of Gaussian distributions to compute the quartiles of the relative-wealth distribution and the probability of the relative wealth falling below 0.85.

We also compute the (log) CERs of being randomly assigned to a TDF and of being assigned to the benchmark TDF, for an investor with CRRA preferences. Specifically, we compute:

$$\begin{aligned} \bar{\text{CER}} &= \frac{1}{T}\ln\left\{\left[E\left(\bar{W}_T^{1-\gamma}\right)\right]^{1/(1-\gamma)}\right\} && (34)\\ \text{CER}_\pi &= \frac{1}{T}\ln\left\{\sum_{i=1}^{N}\pi_i\left[E\left(W_{iT}^{1-\gamma}\right)\right]^{1/(1-\gamma)}\right\}, && (35)\end{aligned}$$

where π_i denotes the probability of being assigned to TDF i. We compute the difference in CERs:

$$\Delta\text{CER} \equiv \bar{\text{CER}} - \text{CER}_\pi; \tag{36}$$

as well as the utility cost:

$$\text{UC} = 1 - \exp[-T(\bar{\text{CER}} - \text{CER}_\pi)]. \tag{37}$$

Expected utility from being randomly assigned to a TDF can be computed analytically as:

$$U_{\pi 0} = \frac{1}{1-\gamma}\sum_{i=1}^{N}\left\{\pi_i \exp\left[\sum_{t=1}^{T}(1-\gamma)\mu_{it-1} + \frac{(1-\gamma)^2}{2}\sigma_{it-1}^2\right]\right\}, \tag{38}$$

where μ_{it} and σ_{it} are the conditional mean and volatility of the (log) return on TDF i. Similarly, the expected utility from investing in the benchmark TDF is given by:

$$\bar{U}_0 = \frac{1}{1-\gamma}\exp\left[\sum_{t=1}^{T}(1-\gamma)\bar{\mu}_{t-1} + \frac{(1-\gamma)^2}{2}\bar{\sigma}_{t-1}^2\right], \tag{39}$$

where $\bar{\mu}_t$ and $\bar{\sigma}_t$ are the mean and volatility of the (log) return on the benchmark TDF.

We consider two benchmark TDFs:

1. "Value-weighted:" $\bar{\alpha}_{(T-t)} = \alpha_{VW(T-t)}$, $\bar{\sigma}_{(T-t)} = \sigma_{VW(T-t)}$, and $\bar{\beta}_{(T-t)} = \beta_{VW(T-t)}$.
2. "Fidelity:" $\bar{\alpha}_{(T-t)} = \alpha_{F(T-t)}$, $\bar{\sigma}_{(T-t)} = \sigma_{F(T-t)}$, and $\bar{\beta}_{(T-t)} = \beta_{F(T-t)}$, where F denotes the Fidelity family of TDFs.

We perform the analysis described above calibrating the TDF return characteristics separately to the pre- and Post-PPA sample. The moments of the factors are calibrated using the cross-inference approach of Stambaugh (1997) applied to the histories of excess returns on the five indices: value-weighted CRSP US market (1926:7–2015:11), MSCI World Index excluding the US (1969:12–2015:12), Barclays US Aggregate Bond Index (1976:1–2015:12), Barclays Global Aggregate excluding the US (1990:1–2015:12), and GSCI Commodity Index (1969:12–2015:12).

The risk-free rate is assumed to be constant and, thus, does not affect relative terminal wealth, nor utility costs or log CER differentials. We consider 25- and 45-year investment horizons.

[16]We consider nine families for the Pre-PPA calibration and 30 families for the Post-PPA calibration. The probabilities are the average fractions of the assets under management at the beginning and at the end of the Pre-PPA and Post-PPA samples, respectively.

The constant relative risk aversion coefficient is set at 8. Results of the analysis are presented in Tables E.1. We find that utility costs are increasing in investment horizon (Panel A versus Panel B), which is not surprising, but also systematically higher during the post-PPA period.

Table E.1: The costs of TDF heterogeneity

The table reports the quartiles of the distribution of the terminal wealth resulting from random assignment to a TDF relative to the terminal wealth resulting from assignment to the benchmark TDF. The table also reports the difference in the annual log CERs associated with assignment to the benchmark and random assignment (ΔCER) and the wealth loss associated with random assignment as opposed to assignment to the benchmark TDF (UC). The coefficient of constant relative risk aversion coefficient in the calculation of CERs is 8. The investment horizon is 45 years in Panel A and 25 years in Panel B.

Panel A

Benchmark: value-weighted TDF

	$Q_{.25}$	$Q_{.5}$	$Q_{.75}$	Cdf(0.85)	ΔCER	UC
Pre-PPA	0.87	0.93	1.02	0.20	0.50	20.20
Post-PPA	0.86	1.01	1.19	0.24	1.99	59.16

Benchmark: Fidelity

	$Q_{.25}$	$Q_{.5}$	$Q_{.75}$	Cdf(0.85)	ΔCER	UC
Pre-PPA	0.95	1.02	1.11	0.07	0.18	7.75
Post-PPA	0.99	1.16	1.38	0.09	2.17	62.40

Panel B

Benchmark: value-weighted TDF

	$Q_{.25}$	$Q_{.5}$	$Q_{.75}$	Cdf(0.85)	ΔCER	UC
Pre-PPA	0.94	0.99	1.04	0.06	0.43	10.30
Post-PPA	0.90	1.00	1.11	0.15	0.96	21.37

Benchmark: Fidelity

	$Q_{.25}$	$Q_{.5}$	$Q_{.75}$	Cdf(0.85)	ΔCER	UC
Pre-PPA	0.96	1.01	1.06	0.05	0.30	7.34
Post-PPA	0.99	1.10	1.23	0.05	0.75	17.03

F Inconsistencies in CRSP equity holdings data

In earlier versions of this paper, we used CRSP data on allocations to equity, bonds, and cash, to document dispersion in TDF glide paths. However, after downloading a version of the CRSP mutual fund database that extended our sample through 2012, we lost faith in the quality of these CRSP variables. This is why, in the current version, we test for dispersion in glide paths by testing for dispersion in factor loadings estimated using daily returns.

This section of the appendix documents significant differences in the fraction of a TDF's portfolio invested in common stock (PER_COM) between the old and new versions of the CRSP data. CRSP changed data vendors, resulting in "new" historical data for PER_COM from 1998 to the present. Table F.1 compares the availability of equity holdings data for 5,870 share class-level observations between 1994 and 2009. We observe either PER_COM_OLD or PER_COM_NEW for 93.3% of the observations. However, we possess both PER_COM_OLD and PER_COM_NEW for only 77.0% of the observations. Moreover, the correlation between PER_COM_NEW and PER_COM_OLD is only 0.5608. Because TDFs are structured as funds of funds they disclose their holdings of the underlying funds rather than their indirect holdings of equity and debt. This likely explains the large number of observations for which PER_COM_NEW or PER_COM_OLD is missing or coded as zero.

Table F.2 calculates the average difference between PER_COM_NEW and PER_COM_OLD for different samples of TDFs. The unit of observations is TDF portfolio i in calendar year t. We drop any TDF-year observation for which PER_COM_NEW or PER_COM_OLD equals zero. The average difference is close to zero, but there are significant differences across calendar years (-11.8% in 2004 to 16.9% in 2006), target date differences (6.4% for 2010 TDFs and -4.2% for 2050 TDFs), and target date-year cells (-24.9% to 32.0%).

Table F.1: Comparing equity holdings in NEW and OLD versions of CRSP Mutual Fund Data

This table compares equity holdings data from two different versions of the CRSP mutual fund database. The OLD version was downloaded from WRDS in 2010 and the NEW version was downloaded in 2013. The sample is limited to TDFs. The unit of observation is share class i in year t. We observe equity holdings (PER_COM) from both versions for 77.0% of the observations. The correlation between PER_COM_NEW and PER_COM_OLD is 0.5608.

	ALL	NEW or OLD		NEW and OLD			NEW only		OLD only		Neither	
	#	#	%	#	%	Corr.	#	%	#	%	#	%
1994	10	10	100.0%	10	100.0%	1.0000	0	0.0%	0	0.0%	0	0.0%
1995	10	10	100.0%	10	100.0%	1.0000	0	0.0%	0	0.0%	0	0.0%
1996	15	15	100.0%	15	100.0%	1.0000	0	0.0%	0	0.0%	0	0.0%
1997	18	18	100.0%	18	100.0%	1.0000	0	0.0%	0	0.0%	0	0.0%
1998	24	19	79.2%	0	0.0%		0	0.0%	19	79.2%	5	20.8%
1999	35	30	85.7%	0	0.0%		0	0.0%	30	85.7%	5	14.3%
2000	36	22	61.1%	0	0.0%		0	0.0%	22	61.1%	14	38.9%
2001	69	31	44.9%	0	0.0%		0	0.0%	31	44.9%	38	55.1%
2002	87	37	42.5%	6	6.9%	0.9969	0	0.0%	31	35.6%	50	57.5%
2003	146	57	39.0%	30	20.5%	0.9097	15	10.3%	12	8.2%	89	61.0%
2004	261	134	51.3%	35	13.4%	0.5523	30	11.5%	69	26.4%	127	48.7%
2005	460	426	92.6%	208	45.2%	0.4194	104	22.6%	114	24.8%	34	7.4%
2006	690	670	97.1%	505	73.2%	0.3880	45	6.5%	120	17.4%	20	2.9%
2007	1,069	1,063	99.4%	846	79.1%	0.3137	34	3.2%	183	17.1%	6	0.6%
2008	1,476	1,472	99.7%	1,394	94.4%	0.7862	30	2.0%	48	3.3%	4	0.3%
2009	1,464	1,461	99.8%	1,445	98.7%	0.7010	9	0.6%	7	0.5%	3	0.2%
ALL	5,870	5,475	93.3%	4,522	77.0%	0.5608	267	4.5%	686	11.7%	395	6.7%

Table F.2: Changes in equity holdings from OLD to NEW versions of CRSP Mutual Fund Data

This table reports the average difference between PER_COM_NEW and PER_COM_OLD. The unit of observation is portfolio i in year t. The sample is limited to TDFs for which we observe both PER_COM_NEW and PER_COM_OLD, and for which neither variable equals zero.

	2010	2020	2030	2040	2050	ALL
2002	-0.19%		-2.24%	-1.92%		-1.45%
2003	-5.05%	-7.18%	-6.79%	-0.83%		-4.96%
2004	-0.80%	0.40%	-24.94%	-21.91%		-11.81%
2005	7.80%	23.65%	5.50%	8.35%	1.86%	10.68%
2006	32.00%	27.26%	12.95%	3.12%	4.72%	16.91%
2007	22.69%	23.59%	11.61%	4.82%	5.77%	13.76%
2008	-4.14%	-4.40%	-5.68%	-5.59%	-6.99%	-5.39%
2009	-5.89%	-6.36%	-6.30%	-6.48%	-7.25%	-6.48%
ALL	6.39%	4.75%	-0.07%	-2.52%	-4.22%	0.80%

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