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Why have target-date funds performed better in the COVID-19 selloff than the 2008 selloff? ☆

Mike Qinghao Mao*, Ching Hin Wong

Department of Finance, Deakin University, Australia

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ABSTRACT

We document a reduction in both the level and cross-sectional dispersion of systematic risk in the target-date fund (TDF) market after 2008, which resulted in better performance of TDFs during the COVID-19 selloff compared to the 2008 selloff and a reduction in TDF return dispersion. We find that the shift is more pronounced in close-to-retirement funds and driven by the TDF series investing more in equities in the early period, consistent with TDFs catering to the market demand for lower risk exposure after the 2008 crisis. In addition, TDF systematic risk shifters do not exhibit more idiosyncratic risk-taking.

1. Introduction

Wealth management through dynamic portfolio allocation lies at the center of many services offered by the financial industry. With the innovation of the target-date fund (TDF) and its inclusion in defined contribution pension plans as a default option, investors are offered a simple solution to the lifecycle investment problem. TDFs are often structured as funds of funds and designed to dynamically optimize portfolio weights of underlying equity and fixed-income funds to serve the needs of holders with similar ages or target retirement years. Based on a predetermined schedule, known as the equity glide path mandate, TDFs adjust the portfolios to allocate more weight toward bonds as investors age. For example, a 2050 TDF is designed for investors who expect to retire in or around 2050. Such an age-based solution has significantly eased the burden for individuals to manage retirement savings and substantially enhanced retirement wealth over the long run (Mitchell and Utkus, 2021). [1]

Though the growth of the TDF market has been remarkable over the last two decades, with the total assets under management exceeding 2 trillion USD in 2019, the design and reliability of the product have not been without controversy. The 2008 global financial crisis (GFC) put some near-retirement TDFs with an average loss of over 30% in the spotlight, unveiling previously unexpected risks associated with retirement investments.[2] The major market turmoil triggered by the COVID-19 pandemic serves as a recent experiment through which we can revisit the resilience of the TDF market during a systematic equity market drawdown. As reported by the industry and confirmed in this study, TDFs fared better during the COVID-19 selloff compared to the GFC selloff. According to a Morningstar report in 2020, investors targeting to retire in 2010 lost, on average, 67% of the US stock market's loss in the GFC selloff, while investors intending to retire in 2020 lost, on average, 55% of the US market's loss in the COVID-19 selloff. Understanding the economic forces behind this phenomenon is essential to drawing wealth implications for TDF users in the long run. This study aims to summarize the evolution of the US TDF market and shed light on why TDFs performed better during the COVID-19 selloff compared to the 2008 selloff.

A dominant performance determinant for TDFs is their exposure to equities relative to bonds, governed by the glide path man-

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* Corresponding author.
E-mail addresses: mike.mao@deakin.edu.au (M.Q. Mao), chwo@deakin.edu.au (C.H. Wong).

[1] Mitchell and Utkus (2021) document that the adoption of low-cost TDFs in 401(k) plans leads to increased equity and bond exposure of participants, which potentially increases retirement wealth by as much as 50% over a 30-year horizon.

[2] See the news coverage (e.g., https://www.cnbc.com/2018/09/13/these-retirement-funds-took-a-beating-in-2008-it-could-happen-again.html and https://www.marketwatch.com/story/questions-arise-target-date-funds-after).

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date unique to each TDF series. A TDF series typically covers a wide range of funds corresponding to various target dates. For example, in 2008, the Vanguard Target Retirement Fund series included TDFs with target years of 2005, 2010, 2015, …, 2045, and 2050. The asset allocation is meant to follow the equity glide path, which depicts a close-to-linear relation between the equity exposure and distance to the target year (retirement). TDFs that are more distant from the target year allocate more to equities relative to fixed-income securities. TDF glide paths tend to be flat (with approximately 80–90% equity share) until they are approximately 25 years before the target date, at which point they begin to decline. After reaching the target year, the glide path becomes flat for a to-series, while that for a through-series continues to decline for about 10–25 years more. While constrained by the glide path guidance, TDF portfolio managers have the flexibility to deviate from the mandate for each asset class by a considerable amount.[3]

We start with constructing empirical glide path measures for each TDF series in each year. We apply a two-step approach involving a time-series regression and then a cross-sectional regression. The former is conducted each year to estimate individual TDFs' exposures to the US and international equity, US and international bond, and commodity indices, and the latter is performed to relate those exposures to the distance to the target year using TDFs from the same series. The empirical estimation relies on the assumptions that the glide path is linear and does not change within a year, which simplify the comparisons of TDF glide paths over time and across different fund series. The assumptions are in line with the theoretical foundations for TDFs (e.g., Merton, 1969) and largely consistent with the glide paths reported by most TDF providers. We summarize the time-varying estimated empirical glide path for each TDF series using E_0 and E_{25}, indicating the aggregate equity exposures in the target year and 25 years before the target year, respectively, as well as E_{step}, measuring the speed of aggregate equity exposure reduction. Any two of the three parameters are sufficient to pin down the linear shape of the empirical glide path.

Summarizing the average empirical glide path of the TDF market over time, we find a downward shift of the path and an increase in the equity risk reduction rate along the path from the early period of 2009-2010 to the recent period of 2018-2019. The equal-weighted (value-weighted) averages of E_0 and E_{25}, capturing the equity exposures, are 7.8 and 2.3 (6.5 and 1.7) percentage points lower, respectively, in recent times than in the early period. On the other hand, the equal-weighted (value-weighted) average E_{step}, capturing the annual reduction rate of equity exposure, has increased by 0.2 (0.2) percentage points. Collectively, the evidence suggests a trend toward more conservative equity allocation strategies in the TDF market, which is more pronounced in close-to-retirement funds. The change mainly concentrates in the years immediately after the GFC. In addition, we find that the equal-weighted (value-weighted) cross-sectional standard deviation of E_0 has reduced from 0.14 (0.07) in the period of 2009–2010 to 0.11 (0.05) in the period of 2018-2019, implying a reduction in the heterogeneity of TDF systematic risk.

In the subsample of the TDF series that spans the full period of 2009-2019, 16 (out of 30) series have shifted the empirical glide path downward by more than 5 percentage points from the period of 2009-2010 to that of 2018-2019, while only four series have elevated the glide path. In contrast, based on the reported glide path information extracted from fund prospectuses, only five (out of 30) series have indicated a downward shift of the reported glide path from 2009 to 2019. Therefore, the evolution of the average empirical glide path is not simply driven by those that have reported an updated glide path. In the group of TDF series that have not disclosed a major change in the reported glide path, we find that the equal-weighted (value-weighted) average E_0 has reduced by 5.7 (7.2) percentage points from the period of 2009-2010 to that of 2018-2019.

To demonstrate that the structural change in the average glide path renders significant performance implications, we compare returns of TDFs at maturity in both periods after controlling for the US equity market returns. We predict and confirm that TDFs from the series of downward shifters exhibit significantly lower (higher) returns in the later than the early period when the aggregate equity market experiences similar levels of gains (losses). As the downward shifters dominate others in the TDF market, TDFs deliver higher returns on average during the COVID-19 market sell-off. In addition, we compare the distribution of TDF returns in both periods after controlling for the market returns. We find that the cross-sectional standard deviation of TDF returns is much smaller in the later period than in the early period, implying a convergence in TDF returns.

We explore two explanations for why TDFs shift the glide path downward. Overall, we document evidence best in line with the catering hypothesis that the TDF series reduce equity allocation to cater to the market demand for lower aggregate equity exposure after the 2008 crisis. The finding that fund flows are negatively correlated with TDF equity betas in the years immediately after the 2008 crisis is consistent with the market demand for reduced risk, possibly triggered by a heightened risk aversion among TDF investors. In addition, we document that TDFs with a more aggressive initial glide path shift the glide path more downward, forcing the industry-average glide path distribution to move to the left and become more concentrated. However, we do not find evidence corroborating the risk-taking hypothesis that TDF shifters substitute equity allocations with high-idiosyncratic-risk assets. Collectively, the evidence suggests that the TDF market has exhibited a reduction in the heterogeneity of systematic risk-taking after 2008, which has led to a smaller return dispersion across TDFs.

Overall, our paper contributes to the growing literature on pension fund investments and TDFs (e.g., Sandhya, 2012; Elton et al., 2015; Balduzzi and Reuter, 2019). We extend the work by Balduzzi and Reuter (2019), who document an increase in TDF return heterogeneity contributed by small and post-Pension Protection Act of 2006 (PPA) TDF families that take high idiosyncratic risk to compete for a higher market share. In contrast to their findings based on comparing the pre-PPA with the post-PPA period, we show a reduction in TDF systematic risk heterogeneity during the period of 2009–2019. Another related study is by Mao and Wong (2020), who show that managerial commitment helps explain the heterogeneity of TDFs in idiosyncratic risk-taking. Our findings complement the literature on pension investments by underscoring dynamics in TDFs' systematic risk-taking and their implications for return dispersion. Further, small variations in the glide path greatly affect cumulative returns of TDFs in the long run and thus matter for investors who rely on TDFs for retirement support.

In addition, our findings add to discussions on the classical topic of optimal portfolio choice over the lifecycle (e.g., Merton, 1969; Bodie et al., 1992; Balduzzi and Lynch, 1999; Lynch, 2001; Cocco et al., 2005; Benzoni et al., 2007; and Bagliano et al., 2013). As different models and their underlying assumptions lead to different guidance on the best equity and bond allocations for people within certain age groups, extreme market conditions such as a crisis can affect how agents reflect on and revise their optimal choices. Although whether and to what extent TDF families should cater to the market demand can only be ad-

[3] For example, according to the summary prospectus of American Funds, their TDFs are expected to invest assets within a range that deviates no more than 10% above or below the glide path for each asset class (https://www.sec.gov/Archives/edgar/data/1380175/000005193117002353/aftd2060497k.htm).

dressed using an appropriate theoretical framework, our study documents a dynamic evolution of the industry solution of optimal lifecycle asset allocation in practice. Therefore, our work calls for further theoretical and empirical research to provide insight into the recommended approach for dynamically optimizing the investment mandate.

Finally, our paper sheds light on the design of options in defined contribution (DC) plans (e.g., Madrian and Shea, 2001; Agnew et al., 2003; Elton et al., 2006; Pool et al., 2016). TDFs are promoted as default options to benefit plan participants who lack sufficient attention or financial knowledge required for pension savings (Mitchell and Utkus, 2021). However, the wide dispersion in the investment approach or the glide path mandate across different TDF families implies a wide distribution of expected investment outcomes. The evidence that various TDF glide paths converge over time to the market median is consistent with the increased awareness by plan sponsors and participants who reference industry benchmarks when selecting specific TDF series in the DC plan menu.

The rest of the paper is organized as follows. We provide the institutional background and research question in Section 2. Section 3 introduces the sample and measures of the glide path. We present the results in Section 4 and investigate the economic channels for the shifting behavior in Section 5. Section 6 concludes the paper.

2. Institutional background and research question

2.1. TDF market and investment mandate

The popularity of TDFs has grown tremendously since Wells Fargo Investment Advisors introduced the first TDF in 1994. The rise of the TDF market is mainly due to its adoption as one qualified default investment alternative in the defined contribution 401(k) plans by the PPA. The total assets of target-date mutual funds and collective investment trusts exceeded 2 trillion USD in 2019.[4]

Though the inclusion of TDFs in pension plan menus helps boost participants' equity shares and reduce idiosyncratic risk (Mitchell and Utkus, 2021),[5] TDFs are not without their critics. The 2008 GFC put TDFs and the underlying strategies under scrutiny when some close-to-retirement TDFs lost over 30% of their value. Following a joint hearing by the Security and Exchange Commission (SEC) and Department of Labor on Examining Target Date Funds in 2009, the SEC, in 2010, proposed various rules to enhance information disclosure by TDFs, including the asset allocation details.

The common investment mandate for TDFs is to progressively become more conservative as the target retirement date approaches by shifting investors' wealth from return-seeking assets to capital-preserving assets, such as from equities to bonds. More specifically, each TDF series designs its equity glide path to govern the strategic asset allocation at each point in time, aiming to strike a balance between funding the retirement needs of investors and reducing the portfolio's volatility. On average, the equity share of TDFs declines from 80 to 90% to 30–40% during the period from 25 years before the target year to the target year.[6] Variations in the glide path across the TDF series contribute to the heterogeneity of TDF risk and return profiles. The two common types of TDF series—to-series and through-series—differ in their equity allocation schedule. Since the through-series assumes that participants withdraw money gradually after the target date, its equity allocation continues to decrease. Conversely, the equity share for the to-series stays constant once the target date is reached, assuming that investors withdraw most of the money at retirement. According to Morningstar's 2019 statistics, to-series and through-series constituted 28% and 72% of the market, respectively.

2.2. Research question

This study aims to answer why TDFs performed relatively better during the COVID-19 selloff compared to the 2008 selloff by investigating the evolution of the TDF equity glide path, both in the cross-section and time series. Since the investment mandate and active management jointly determine the asset allocation of a TDF, the better performance of TDFs during the COVID-19 selloff could indicate changes in TDF investment mandates toward more conservative strategies or active risk management decisions by fund managers without changing the mandate. On the one hand, exploring the heterogeneity in the investment mandate (i.e., the glide path) across the TDF series helps shed light on the relative performance of the TDF series and the underlying determinants. On the other hand, we analyze alternative explanations of the equity glide path dynamics and examine the alignment of the mandate design with fund family and management incentives. Balduzzi and Reuter (2019) document that the strategic risk-taking behavior of small and post-PPA TDF series has led to an increase in TDF idiosyncratic risk and more dispersed TDF returns; our study complements theirs by extending the sample period to more recent time and focusing on the systematic risk-raking behavior of TDFs.

3. Data and TDF glide path

3.1. Sample construction

We select and manually verify all TDFs from the CRSP Survivor-Bias-Free US Mutual Fund Database based on the target year information contained in fund names. We use fund characteristics in the database, including total net assets (TNA), return, inception date, expense ratio, and turnover ratio. In the case of TDFs with multiple share classes, we aggregate TNA across all share classes and calculate the TNA-weighted return, expense ratio, and turnover ratio. Fund flow is calculated as the change in TNA not caused by fund returns. Fund age is derived based on the inception date of the oldest share class.

We then supplement the data with glide path information contained in the fund prospectus. We download annual prospectuses of all TDF series and manually collect the equity share target where available. Our final sample comprises 89 TDF series from 2007 to 2019.[7] We also construct the subsample of 30 surviving series that cover all years from 2009 to 2019, which allows investigating the risk dynamics of the same TDF series from the year post the 2008 GFC to the year before the COVID-19 crisis. Because the TDF glide path typically begins to decline at approximately 25 years before

[4] According to the 2019 Investment Company Institute Fact Book, 68% of 401(k) plans offered TDFs, covering 75% of 401(k) plan participants at 2016 year-end. Participants' use of TDFs increased from 19 to 52% between 2006 and 2016. In Q1 2019, TDF assets under management and the fraction of mutual fund assets in DC plans invested in TDFs reached 1.2 trillion USD and 18%, respectively.

[5] Plan participants tend to be subject to biases and make suboptimal decisions (e.g., Benartzi and Thaler 2001; Agnew, Balduzzi, and Sunden, 2003; Huberman and Sengmueller, 2004). Mitchell and Utkus (2021) show that including TDFs in retirement saving menus can help overcome individuals' bias, such as reducing cash and company stock holdings.

[6] See Appendix B for examples of the glide path reported by the top three TDF families (Fidelity, T. Rowe Price, and Vanguard).

[7] Appendix C summarizes our sample from 2007–2019. We find that the total assets managed by our sample funds have increased from about 184 billion USD to about 1.4 trillion USD. In addition, the market share of the top three fund families (Fidelity, Vanguard, and T. Rowe Price) has dropped from 81.20% to 68.12%, which suggests a reduction in market concentration.

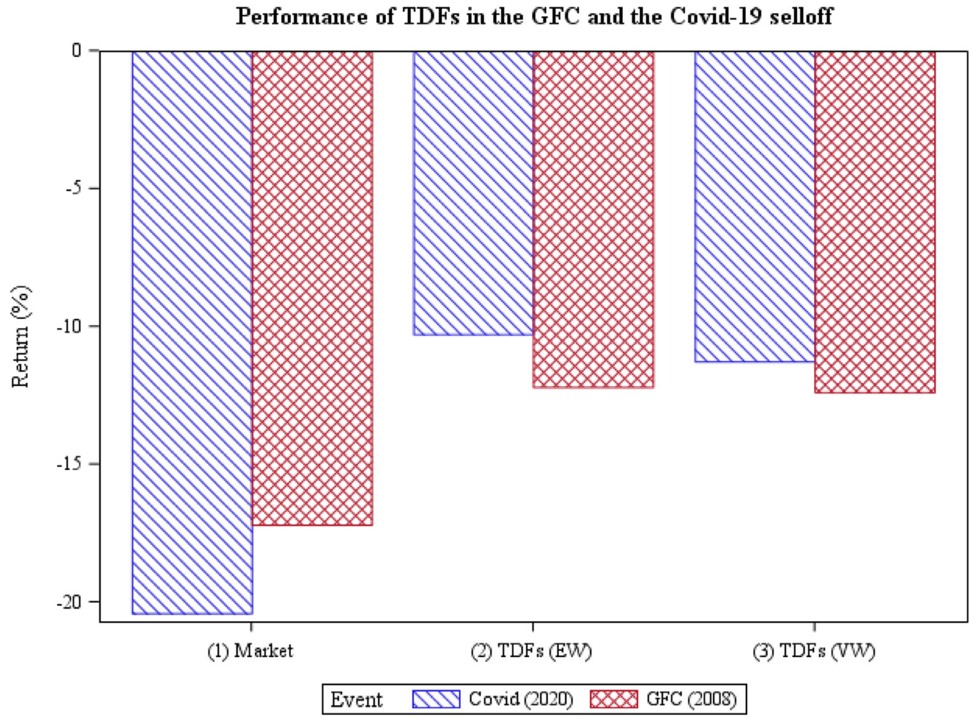


Fig. 1. Performance of TDFs during the 2008 and COVID-19 crises. This figure compares the equity market's performance and TDF performance in October 2008 and the period of February to March 2020. Column (1) presents the cumulative equity market returns. Equity market returns are proxied by the value-weighted excess returns on all NYSE, AMEX, and NASDAQ stocks. Columns (2) and (3) report the equal-weighted (EW) average return and value-weighted (VW) average return (using the fund series' total net assets as the weight) of 2010 TDFs in the 2008 crisis and 2020 TDFs in the COVID-19 crisis.

the target date, our tests focus on TDFs that have not reached their retirement target dates and whose retirement target dates are less than 25 years from the examined point in time.

3.2. Empirical measure of TDF glide path

We apply a two-step approach to estimate the equity, fixed income, and commodity exposures of each TDF series. First, in each year and for each fund, we follow Balduzzi and Reuter (2019) to regress daily returns of the TDF on the US equity, international equity, US bond, international bond, and commodity return factors to estimate the corresponding betas; second, in each year and for funds belonging to the same TDF series, we perform a cross-sectional regression of the estimated betas on the distance to the target date. This process generates the empirical glide path measures for each TDF series at annual frequencies, enabling both the time-series and cross-sectional comparisons.[8]

Step 1: The time-series regression.

$$\begin{aligned} Daily\_Returns_{i,t} &= \alpha_i + \beta_{i,US\,Equity} MKTRF_t + \beta_{i,\,US\,Bond} AGG_t \\ &+ \beta_{i,Int\,Equity} MSCI_t + \beta_{i,Int\,Bond} GDSB_t \\ &+ \beta_{i,Commodity} GSCI_t + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

where $Daily\_Returns_{i,t}$ is the excess return earned by TDF i on day t. $MKTRF_t$ is the value-weighted excess return on all NYSE, AMEX, and NASDAQ stocks. AGG_t is the excess return of the S&P US Aggregate Bond Index. $MSCI_t$ is the excess return of the MSCI World Index excluding the US. $GDSB_t$ is the excess return of the S&P Global Developed Sovereign Bond Index excluding the US. $GSCI_t$ is the excess return of the GSCI Commodity Index. We follow the literature on fund style analysis (Sharpe, 1992; Shoven and Walton, 2020) to restrict the sum of betas to be one so that the beta estimates can approximate relative allocations to different asset classes. Assuming a TDF's equity, bond, and commodity exposures remain stable within a year, we estimate the model each year to get the measures of equity, bond, and commodity betas at the fund-year level.[9]

Step 2: The cross-sectional regression.

$$beta_{Agg\,Equity,\,i,j} = E_{0,j} + E_{step,j} Years\_to\_retirement_{i,j} + \varepsilon_{i,j} \tag{2}$$

where $beta_{Agg\,Equity,\,i,j}$ is the aggregate equity beta of TDF i from the TDF series j, which is derived as the sum of the US and international equity betas; and $Years\_to\_retirement_{i,j}$ is the distance to the target date of TDF i from the series j. We conduct the regression each year for TDFs belonging to the same TDF series and estimate the empirical glide path. The intercept, $E_{0,j}$, is the estimated aggregate equity beta at the target date by the TDF series j, while the slope, $E_{step,j}$, is the estimated annual change of the equity beta along the glide path. Moreover, we define the estimated aggregate equity beta at 25 years before the target date as $E_{25,j}$.[10] Similarly, we derive $USE_{0,j}$, $IE_{0,j}$, $USFI_{0,j}$, $IFI_{0,j}$, and $C_{0,j}$, which represent the estimated US equity, international equity, US bond, international bond, and commodity betas in the target year, respectively.

4. Main results

We start by comparing the performance of TDFs during the 2008 selloff and COVID-19 selloff. We choose the event windows of October 2008 and February to March 2020, during which the aggregate US equity market performances have comparable magnitudes.[11] We focus on 2010 and 2020 TDFs, which represent the

[8] Balduzzi and Reuter (2019) question the reliability of CRSP equity holdings data as they find many missing data on TDF allocations to equity, bond, and cash. They also document significant inconsistencies in datasets downloaded at different points in time. Therefore, we choose to infer asset allocations from the factor loadings.

[9] The average adjusted R-squared of the five-factor regressions is 0.96.

[10] $E_{25,j}$ is derived as $E_{0,j} + 25 \times E_{step,j}$.

[11] We use the value-weighted excess return on all NYSE, AMEX, and NASDAQ stocks as a proxy of US equity market performance.

Table 1
Dynamics of TDF glide path. This table presents the equal-weighted and value-weighted (using the fund series' total net assets as the weight) summary statistics of the empirical glide path measures. Panel A reports the average values of the equity schedule measures year by year. E_0 and E_{25} are the estimated aggregate equity betas in the target year and 25 years before the target year, respectively. E_{step} is the estimated annual change of equity beta along the glide path. Panel B reports the cross-sectional standard deviations of the equity schedule measures. The sample covers 89 TDF series from 2007 to 2019. Standard errors of the mean difference tests are double clustered by the series and time levels. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A						
	Equal-weighted average			Value-weighted average		
	E_0	E_{step}	E_{25}	E_0	E_{step}	E_{25}
2007	0.543	0.017	0.972	0.553	0.016	0.945
2008	0.509	0.015	0.896	0.528	0.015	0.914
2009	0.515	0.015	0.892	0.555	0.015	0.930
2010	0.500	0.014	0.861	0.543	0.014	0.904
2011	0.452	0.016	0.853	0.505	0.015	0.889
2012	0.468	0.015	0.851	0.511	0.015	0.883
2013	0.466	0.016	0.866	0.517	0.015	0.899
2014	0.470	0.016	0.881	0.530	0.017	0.947
2015	0.464	0.016	0.865	0.528	0.016	0.926
2016	0.478	0.017	0.909	0.556	0.016	0.965
2017	0.459	0.016	0.853	0.519	0.015	0.898
2018	0.428	0.017	0.845	0.482	0.016	0.889
2019	0.430	0.017	0.864	0.484	0.017	0.905
2009 to 2010 (a)	0.507	0.015	0.877	0.548	0.015	0.915
2018 to 2019 (b)	0.429	0.017	0.854	0.483	0.017	0.898
(b) - (a)	−0.078***	0.002***	−0.023			

Panel B						
	Equal-weighted standard deviation			Value-weighted standard deviation		
	E_0	E_{step}	E_{25}	E_0	E_{step}	E_{25}
2007	0.163	0.007	0.087	0.077	0.003	0.035
2008	0.133	0.006	0.102	0.063	0.002	0.043
2009	0.140	0.005	0.117	0.069	0.003	0.047
2010	0.143	0.005	0.162	0.078	0.003	0.058
2011	0.138	0.006	0.169	0.095	0.003	0.078
2012	0.140	0.006	0.151	0.092	0.003	0.083
2013	0.117	0.005	0.118	0.088	0.003	0.076
2014	0.119	0.006	0.131	0.081	0.003	0.067
2015	0.110	0.005	0.112	0.078	0.003	0.050
2016	0.135	0.005	0.116	0.076	0.003	0.056
2017	0.126	0.005	0.104	0.057	0.002	0.056
2018	0.116	0.004	0.093	0.050	0.003	0.041
2019	0.100	0.004	0.101	0.053	0.003	0.043
2009 to 2010 (a)	0.142	0.005	0.140	0.073	0.003	0.052
2018 to 2019 (b)	0.108	0.004	0.097	0.051	0.003	0.042

closest-to-retirement TDFs corresponding to each period. Though more remote TDFs would exhibit more losses when the market falls due to their higher equity allocations by design, the closest-to-retirement TDFs have a more imminent impact on investors who rely on those savings to support their post-retirement lifestyle. Fig. 1 shows that the aggregate equity market returns and average returns of the 2010 TDFs are respectively −17.25% and −12.22% in October 2008, while the market returns and average returns of the 2020 TDFs are respectively −20.43% and −10.31% from February to March 2020. Despite the worse market performance in the later period, the corresponding closest-to-retirement TDFs have a higher return on average, which implies an overall lower return sensitivity to the equity market. The finding remains similar in column (3), which reports the value-weighted average returns of TDFs.

4.1. Evolution of the TDF glide path

Table 1 summarizes the empirical glide path for the entire sample, consisting of 89 TDF series. Panel A presents the averages of the equity glide path measures annually from 2007 to 2019. Comparing the equal-weighted (value-weighted) average measures in the periods of 2009-2010 and 2018-2019, we find that the E_0 and E_{25} have reduced by 0.08 (0.07) and 0.02 (0.02), respectively, while the E_{step} has increased by 0.002 (0.002). The evidence implies a downward shift of the TDF glide path and an increase in the equity risk reduction rate along the path, which collectively suggest a trend toward more conservative equity allocation strategies in the TDF market, especially for close-to-retirement funds. Panel B reports the cross-sectional heterogeneity of the equity glide path measures. It shows that the equal-weighted standard deviation of E_0 has decreased from 0.14 in the period of 2009-2010 to 0.11 in the period of 2018-2019. The pattern is consistent in the value-weighted results, implying a convergence in TDF glide paths. Overall, Table 1 shows the reductions of the average and the standard deviation of E_0 from 2009 to 2019, which demonstrate a reduction in the level and cross-sectional dispersion of TDF systematic risk.[12]

[12] In Appendix D, we find that TDF bond and international equity exposures have significantly increased from 2009–2019, which demonstrates a shift toward more conservative and more diversified asset allocation strategies by TDFs after the GFC. In Appendix E, we show that our results are consistent in a subsample of 30 TDF series that exist during the full period of 2009–2019.

Table 2

TDF glide path shifters and non-shifters. Panel A summarizes the count of glide path shifters and non-shifters. Prospectus changers (PC) are defined as those that have increased or decreased the equity allocation target at retirement by at least 0.05. Empirical glide path shifters (ES) are defined as those that have increased or decreased E_0 by at least 0.05. Panel B reports the annual average E_0 for the groups of upward, downward, and non-changers based on the reported information (PC_{up}, PC_{down}, and $PC_{non\text{-}changer}$). E_0 is the estimated aggregate equity beta at the target year. The sample covers 30 TDF series that span the period of 2009–2019. Standard errors of the mean difference tests are double clustered by the series and time levels. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A			
	PC_{down}	$PC_{non\text{-}changer}$	PC_{up}
ES_{up}	0	1	3
$ES_{non\text{-}shifter}$	0	10	0
ES_{down}	5	11	0

Panel B			E_0			
	Equal-weighted average			Value-weighted average		
	PC_{up}	PC_{down}	$PC_{non\text{-}changer}$	PC_{up}	PC_{down}	$PC_{non\text{-}changer}$
2009	0.279	0.517	0.524	0.271	0.532	0.561
2010	0.306	0.477	0.496	0.264	0.510	0.554
2011	0.343	0.441	0.463	0.239	0.546	0.525
2012	0.327	0.448	0.474	0.285	0.538	0.534
2013	0.340	0.437	0.490	0.276	0.534	0.541
2014	0.348	0.427	0.493	0.242	0.509	0.543
2015	0.334	0.432	0.490	0.241	0.494	0.537
2016	0.349	0.449	0.511	0.285	0.535	0.564
2017	0.408	0.412	0.496	0.343	0.489	0.529
2018	0.449	0.358	0.454	0.460	0.401	0.484
2019	0.416	0.338	0.453	0.458	0.353	0.486
2009 to 2010 (a)	0.293	0.497	0.510	0.266	0.521	0.557
2018 to 2019 (b)	0.432	0.348	0.454	0.459	0.375	0.485
(b) - (a)	0.140***	−0.149***	−0.057***			

4.2. TDF shifters and non-shifters

We now examine the heterogeneity of equity glide path dynamics among TDF series. We focus on the subsample of 30 TDF series that spans the full period of 2009–2019. To measure the series-specific glide path dynamics, we define prospectus changers (PC) as those series whose prospectuses have explicitly described a change in the target equity exposure at retirement over the sample period. We term those as empirical glide path shifters (ES) if the measured E_0 has changed by more than 0.05 in the period of 2009-2010 to that of 2018-2019.[13] The prospectus changers and empirical shifters are further classified as upward (downward) changers and shifters if the equity exposure has increased (decreased).

As shown in Panel A of Table 2, only eight out of 30 TDF series are prospectus changers, of which three are upward and five are downward changers. We find that all prospectus changers have shifted the equity exposure, which is consistent with the declared direction. Of the other 22 series, 12 are identified as empirical shifters, with 11 being downward shifters. Since the change of equity exposure by an allowed amount reflects the discretion of TDF managers, the evidence is consistent with the proposition that the management of a large proportion of TDFs has applied considerable discretion without explicitly updating the glide path mandate. Panel B presents the measured E_0 year by year for the three groups of TDF series based on the reported glide path (i.e., upward changers (PC_{up}), downward changers (PC_{down}), and non-changers ($PC_{non-changer}$)). We find that both the second and third groups demonstrate a significant reduction in E_0 during the sample period. For example, the equal-weighted (value-weighted) average E_0 have reduced by 0.15 (0.15) and 0.06 (0.07) respectively for PC_{down} and $PC_{non-changer}$. The results show that the asset allocation strategy of those series is adjusted toward a more conservative one. When the change is implicit rather than formally disclosed in a prospectus, investors in those TDFs could unnoticeably bear the corresponding impact.[14]

4.3. Implications of glide path change on TDF performance and performance dispersion

Next, we study the implications of glide path shift on fund performance by comparing fund daily returns in the two-year windows of 2009-2010 and 2018-2019. Assuming the same magnitude of market losses (gains) in both periods, we predict that downward shifters would perform better (worse) in the later period due to the reduction in equity exposure. The opposite should hold for upward shifters.

When studying the implications of glide path shift on fund returns, it is critical to control for market returns. We combine the two windows and sort days into six groups based on the distribution of the US equity market daily returns. Group 1 (6) consists of days on which the market returns fall into the left (right) tail of the distribution. Each group corresponds to the spectrum of one standard deviation on the return distribution. As shown in Panel A of Table 3, the differences in the average daily market returns between the two periods are statistically indifferent from zero for all groups, enabling the comparison of TDF performance during the days when the market exhibits similar returns in the early and later periods. Moreover, to ensure a fair comparison, we need to find TDFs with the same distance to the target year. Since TDFs are

[13] Our results are similar if we use different thresholds, such as 0.07 or 0.10.

[14] Appendix F presents the initial equity and bond exposures for the TDF series with different inception dates. Among the post-PPA fund series, we find that those introduced in the later period allocate less to equities at inception.

Table 3

Equity market returns and TDF performance. This table reports the average TDF performance matched with different levels of equity market returns. Panel A compares the distribution of daily equity market returns for the periods of 2009–2010 and 2018–2019. Daily equity market returns are sorted into six groups based on the distance to the mean (in several standard deviations). Group 1 (6) contains the days with the lowest (highest) equity market returns during the period. Panels B and C report the average daily returns of the hypothetical TDFs at maturity in each period and each group. PC_{up}, PC_{down}, and $PC_{non\text{-}changer}$ denote upward changers, downward changers, and non-changers based on the reported glide path in the prospectus. ES_{up}, ES_{down}, and $ES_{non\text{-}shifter}$ denote those based on the empirical glide path. The sample covers 30 TDF series that span the period of 2009–2019. Standard errors of the mean difference tests are clustered by the time level. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A		Market return (%)		
	Definition	2009–2010	2018–2019	Diff
Group 1	Mean −2 Std to Mean −3 Std	−3.014	−2.900	0.114
Group 2	Mean −1 Std to Mean −2 Std	−1.672	−1.740	−0.069
Group 3	Mean to Mean −1 Std	−0.388	−0.350	0.038
Group 4	Mean to Mean +1 Std	0.563	0.540	−0.024
Group 5	Mean +1 Std to Mean +2 Std	1.784	1.648	−0.137
Group 6	Mean +2 Std to Mean +3 Std	3.024	3.110	0.086

Panel B	Returns of PC_{up} (%)			Returns of PC_{down} (%)			Returns of $PC_{non\text{-}changer}$ (%)		
	2009–2010	2018–2019	Diff	2009–2010	2018–2019	Diff	2009–2010	2018–2019	Diff
Group 1	−0.677	−0.898	−0.220**	−1.380	−0.719	0.661***	−1.404	−0.961	0.443***
Group 2	−0.369	−0.615	−0.247***	−0.734	−0.471	0.263***	−0.774	−0.626	0.149***
Group 3	−0.077	−0.116	−0.039*	−0.147	−0.090	0.057***	−0.160	−0.128	0.032
Group 4	0.172	0.202	0.030	0.282	0.157	−0.125***	0.283	0.210	−0.073***
Group 5	0.500	0.568	0.068	0.853	0.449	−0.404***	0.874	0.596	−0.278***
Group 6	0.644	1.073	0.428***	1.375	0.894	−0.480***	1.384	1.180	−0.204

Panel C	Returns of ES_{up} (%)			Returns of ES_{down} (%)			Returns of $ES_{non\text{-}shifter}$ (%)		
	2009–2010	2018–2019	Diff	2009–2010	2018–2019	Diff	2009–2010	2018–2019	Diff
Group 1	−0.727	−0.894	−0.167**	−1.483	−0.896	0.587***	−1.333	−0.953	0.380***
Group 2	−0.377	−0.609	−0.232***	−0.812	−0.581	0.231***	−0.739	−0.622	0.117***
Group 3	−0.071	−0.116	−0.045***	−0.167	−0.116	0.051***	−0.154	−0.129	0.026***
Group 4	0.173	0.199	0.026**	0.302	0.195	−0.106***	0.267	0.210	−0.057***
Group 5	0.498	0.564	0.065*	0.919	0.557	−0.362***	0.837	0.589	−0.248***
Group 6	0.735	1.073	0.338***	1.485	1.111	−0.374***	1.275	1.158	−0.117

typically offered with target dates with five- or ten-year intervals, we use the interpolation method to derive the return of a hypothetical at-maturity fund[15] for each series and on each day. For example, in 2018, we derive the daily returns of a hypothetical 2018 fund as only 2015 and 2020 funds are available in the market.

Panel B of Table 3 reports the performance of the three groups based on the reported glide path. Supporting our conjecture, the downward changers earn higher returns in the later period than in the early period when the market returns are below the mean (Groups 1, 2, and 3) and earn lower returns when the market returns are above the mean (Groups 4, 5, and 6). The pattern is similar for the third group, implying that those series that have not explicitly documented changes in the prospectus have also shifted to more conservative equity allocation strategies. On the other hand, the pattern is the opposite for upward changers, which is consistent with the increased equity exposure. Panel C separates TDFs into upward, downward, and non-shifters based on the empirical glide path, where similar results are found. Overall, the evidence suggests that shifts in glide path can translate into significant consequences for TDF performance. Since the downward shifters dominate the others in the market, they drive the overall TDF market to be less exposed to big swings in equity market returns.[16]

Next, we examine whether the reduction in the heterogeneity of TDF systematic risk would affect the dispersion in TDF returns. Fig. 2 reports the average daily cross-sectional standard deviations of the returns of TDFs at maturity for groups 1–6 formed based on market returns as described above. The U-shaped pattern suggests that TDF returns are more dispersed when the market condition is more extreme. More interestingly, after controlling for market returns, we find that TDF returns are less dispersed in the later period than in the early period. For example, the average cross-sectional standard deviation of TDF returns for group 1 is 0.5% in the early period and 0.3% in the later period. The result is consistent across all market conditions, implying that the reduction in the dispersion of TDF systematic risk results in convergence in TDF returns.

5. Why do TDFs shift the glide path downward?

The next step is to understand the incentives of TDF fund companies and management to shift the equity glide path. We propose two explanations and test them accordingly. First, we explore the catering hypothesis that TDFs cater to the market demand for lower equity exposure. We predict that the incentives are more salient in the years just after the 2008 crisis owing to large losses by aggressive TDFs and the associated negative publicity. The incentives to cater to investor needs are well documented in the mutual fund literature. For example, managed funds hold stocks with high sustainability scores to attract investors who care about socially responsible investing (e.g., Starks et al., 2017; Hartzmark and Sussman, 2019). Christoffersen and Simutin (2017) show that mu-

[15] For TDFs belonging to the same series and for each day, we regress daily return on the distance to the target date and measure the daily return for the hypothetical at-maturity fund using the estimated intercept. Our approach assumes a linear relationship between return and the distance to the target date for TDFs, within the same series and on each day. Overall, these regressions have a good fit to the data, with an average R-squared of 0.84.

[16] The distance to the target date differs for 2010 funds in 2008 and 2020 funds in 2020 by a small amount. In an unreported test, we compare the average returns of the hypothetical 2008 funds in 2008 and the actual 2020 funds in 2020. We find that the better performance of the at-maturity TDFs during the COVID market downturn compared with the 2008 market downturn remains robust.

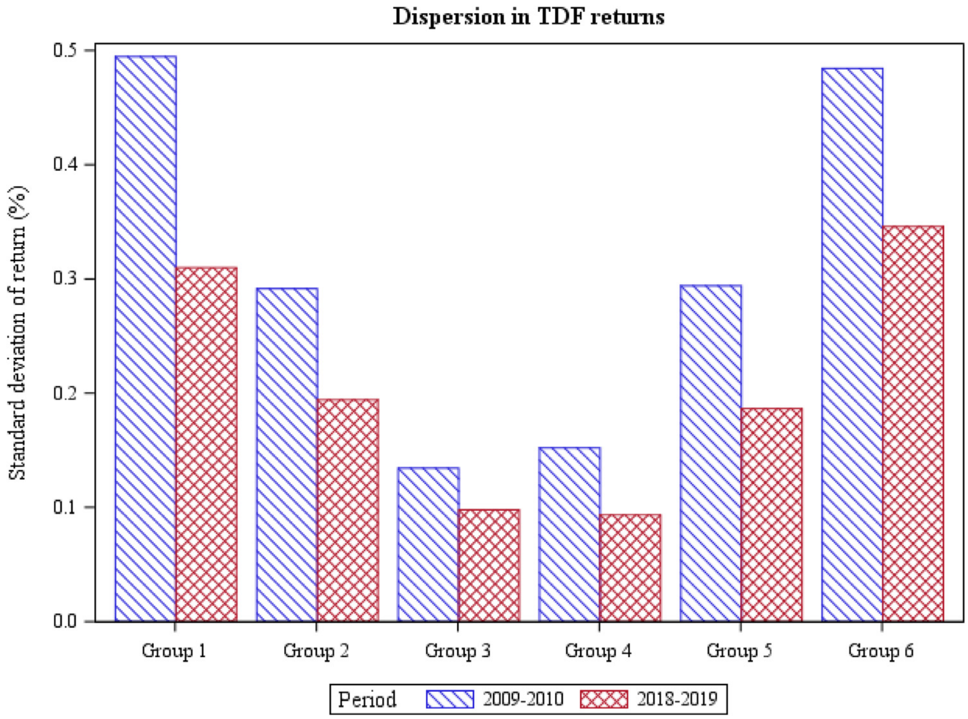


Fig. 2. Dispersion in TDF returns. This figure shows the dispersion in TDF returns under different market conditions. Daily equity market returns are sorted into six groups based on the distance to the mean (in several standard deviations). Group 1 (6) contains the days with the lowest (highest) equity market returns during the period. The columns report the average cross-sectional standard deviation of daily returns of the hypothetical TDFs at maturity for each group in the period of 2009–2010 and 2018–2019. The sample covers 89 TDF series.

tual funds respond to benchmarking pressure from pension plan sponsors by tilting the holdings toward high-beta stocks. In our setting, we test whether flows to TDFs are affected by their equity exposure relative to industry peers.

Second, changing the glide path could reflect managerial incentives for more idiosyncratic risk-taking. Similar to conventional mutual funds, which face incentives for excessive risk-taking (Chevalier and Ellison, 1997; Sirri and Tufano, 1998), TDFs are more likely to be selected by pension plan sponsors if they deliver higher risk-adjusted performance. Therefore, the tendency to take more idiosyncratic risk is an important agency issue for TDF managers (Balduzzi and Reuter, 2019; Mao and Wong, 2020). If TDF managers substitute equity investment with nonstandard asset classes, such as real estate and commodity funds (Elton et al., 2015), this could result in a reduction in equity market risk and an increase in idiosyncratic risk. To test this explanation, we explore whether TDF shifters exhibit different levels of idiosyncratic volatility and return heterogeneity than non-shifters.

5.1. The catering hypothesis

We conduct regressions of the year t fund flows on year t-1 fund aggregate equity beta to examine the market preference for TDF equity exposure. Other controls include lagged fund flows, annualized five-factor alphas, systematic returns,[17] expense ratio, turnover, fund size, and age. We also employ year-by-target-date fixed effects to ensure that we compare TDFs with the same target date in the same year.

Table 4 presents the results of the regressions. Columns (1)–(3) report the subsample results for the periods of 2009–2012, 2013–2016, and 2017–2019, respectively. We find that TDFs with lower aggregate equity exposure attract more inflows during the period of 2009–2012, consistent with a heightened risk aversion among TDF investors after the GFC. Conversely, fund flows are not sensitive to the equity exposure during the other periods. Column (4) reports the regression results for the entire period of 2009–2019. The coefficient on year t-1 fund flow is positively significant, suggesting that fund flow exhibits a strong autocorrelation. The coefficient on fund alpha suggests that TDFs with higher risk-adjusted returns attract more inflows. The finding is consistent with Del Guercio and Tkac (2002) and Sialm et al. (2015), who document that pension fund flows are sensitive to risk-adjusted returns. In summary, the significant sensitivities of fund flow to TDF equity exposure and risk-adjusted return demonstrate market incentives for TDF managers to adjust the investment strategy to cater to investors' demands. In particular, the downward shift of the glide path is consistent with the market pressures on TDFs to reduce equity exposure after the 2008 financial crisis.[18]

In the cross-section of the TDF series, those with higher initial equity allocation should react more to catering incentives if investors favor the series with lower equity exposure. To verify the prediction, Panel A of Fig. 3 illustrates the average E_0 for each TDF series in the early period of 2009–2010 and the later period of 2018–2019 against its E_0 rank in the early period. It shows that TDF series with relatively high (low) E_0 in the early period are more likely to reduce (increase) their equity exposure over time. None of the TDF series with higher than the median E_0 in the early period exhibit an increase in equity exposure. Panel B presents the cross-sectional histograms of E_0 in both periods. We find that the

[17] We follow Barber et al., (2016) and Balduzzi and Reuter (2019) to calculate systematic returns as the product of betas and factor realization.

[18] In an unreported regression test, we examine the relationship between fund flows and activeness. The sample covers 61 TDF series from Morningstar's 2019 TDF Landscape report. Fund activeness is measured by the proportion of actively managed funds in a TDF's portfolio in 2019. Overall, our results remain similar after controlling for activeness, and we find no evidence that activeness is related to fund flows. The results are available on request.

Table 4

Determinants of TDF flows. This table presents the results of the regressions that investigate the determinants of fund flows. The dependent variable is the year *t* fund flow. The independent variable of interest is year *t-1* fund equity beta. Columns (1)–(3) present the subsample results for the periods of 2009–2012, 2013–2016, and 2017–2019, respectively. Column (4) presents the result for the period of 2009–2019. The sample covers 89 TDF series from 2009 to 2019. Variable definitions are in Appendix A. Standard errors (in parentheses) are double clustered at the series and time levels. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	2009–2012 (1)	2013–2016 (2)	2017–2019 (3)	2009–2019 (4)
	Flow	Flow	Flow	Flow
$Beta_{Agg\ equity}$, year t-1	−0.890**	0.323	0.049	−0.074
	(0.166)	(0.564)	(0.447)	(0.298)
Flow, year t-1	0.035	0.111	0.274*	0.152**
	(0.058)	(0.143)	(0.069)	(0.062)
Alpha, year t-1	0.849	4.716	0.715	2.036*
	(1.931)	(3.339)	(1.189)	(1.029)
Systematic return, year t-1	−0.929	2.552	0.223	2.234*
	(0.441)	(3.140)	(1.896)	(1.049)
Flow, year t-2	0.005*	−0.005	0.011	0.002
	(0.002)	(0.005)	(0.006)	(0.003)
Alpha, year t-2	2.512	1.929	−2.689	1.170
	(1.334)	(1.531)	(2.630)	(1.132)
Systematic return, year t-2	0.278	5.251	2.336	3.008*
	(1.083)	(2.973)	(2.787)	(1.603)
Log (size), year t-1	−0.029	−0.152	−0.025	−0.089
	(0.018)	(0.096)	(0.011)	(0.050)
Expense ratio, year t-1	0.012	−0.441	−0.228	−0.285*
	(0.115)	(0.307)	(0.133)	(0.142)
Log (Turnover), year t-1	−0.130	−0.008	−0.050	−0.085**
	(0.056)	(0.038)	(0.025)	(0.029)
Age, year t-1	−0.023*	−0.006	−0.010	−0.006
	(0.009)	(0.013)	(0.005)	(0.006)
Target date-by-time fixed effect	Yes	Yes	Yes	Yes
Observations	445	602	599	1646
R-squared	0.32	0.25	0.54	0.23

Table 5

Determinants of E_0 dynamics. This table presents the results of the regressions that investigate the relationship between the level and change of E_0, which is the estimated aggregate equity beta in the target year for a TDF series. The dependent variables include the change of E_0 from year t to $t+1$ (ΔE_0) and the difference between the average E_0 in the periods of 2009–2010 and 2018–2019 ($E_{0,2018-2019}$ - $E_{0,2009-2010}$). The independent variables of interest are the E_0 in year t, the average E_0 from 2009 to 2010 ($E_{0,2009-2010}$), and the dummy variables that indicate whether E_0 is in the second or third tercile of the distribution. The definitions of other variables are in Appendix A. The sample covers 30 TDF series that span the period of 2009–2019. Standard errors (in parentheses) are double clustered at the series and time levels for the first two columns. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	ΔE_0	ΔE_0	$E_{0,2018-2019}$ - $E_{0,2009-2010}$	$E_{0,2018-2019}$ - $E_{0,2009-2010}$
E_0	−0.123***			
	(0.034)			
E_0 in the third tercile?		−0.028***		
		(0.006)		
E_0 in the second tercile?		−0.019***		
		(0.007)		
$E_{0,2009-2010}$			−0.562***	
			(0.168)	
$E_{0,2009-2010}$ in the third tercile?				−0.111**
				(0.041)
$E_{0,2009-2010}$ in the second tercile?				−0.113**
				(0.051)
Post-2006	−0.005	−0.006	0.008	0.005
	(0.007)	(0.006)	(0.034)	(0.034)
Log (Family size)	0.002	0.001	0.010	0.006
	(0.002)	(0.001)	(0.008)	(0.010)
Constant	0.034	−0.000	0.144	−0.022
	(0.021)	(0.015)	(0.098)	(0.087)
Time-fixed effect	Yes	Yes	No	No
Observations	297	297	30	30
R-squared	0.18	0.16	0.44	0.27

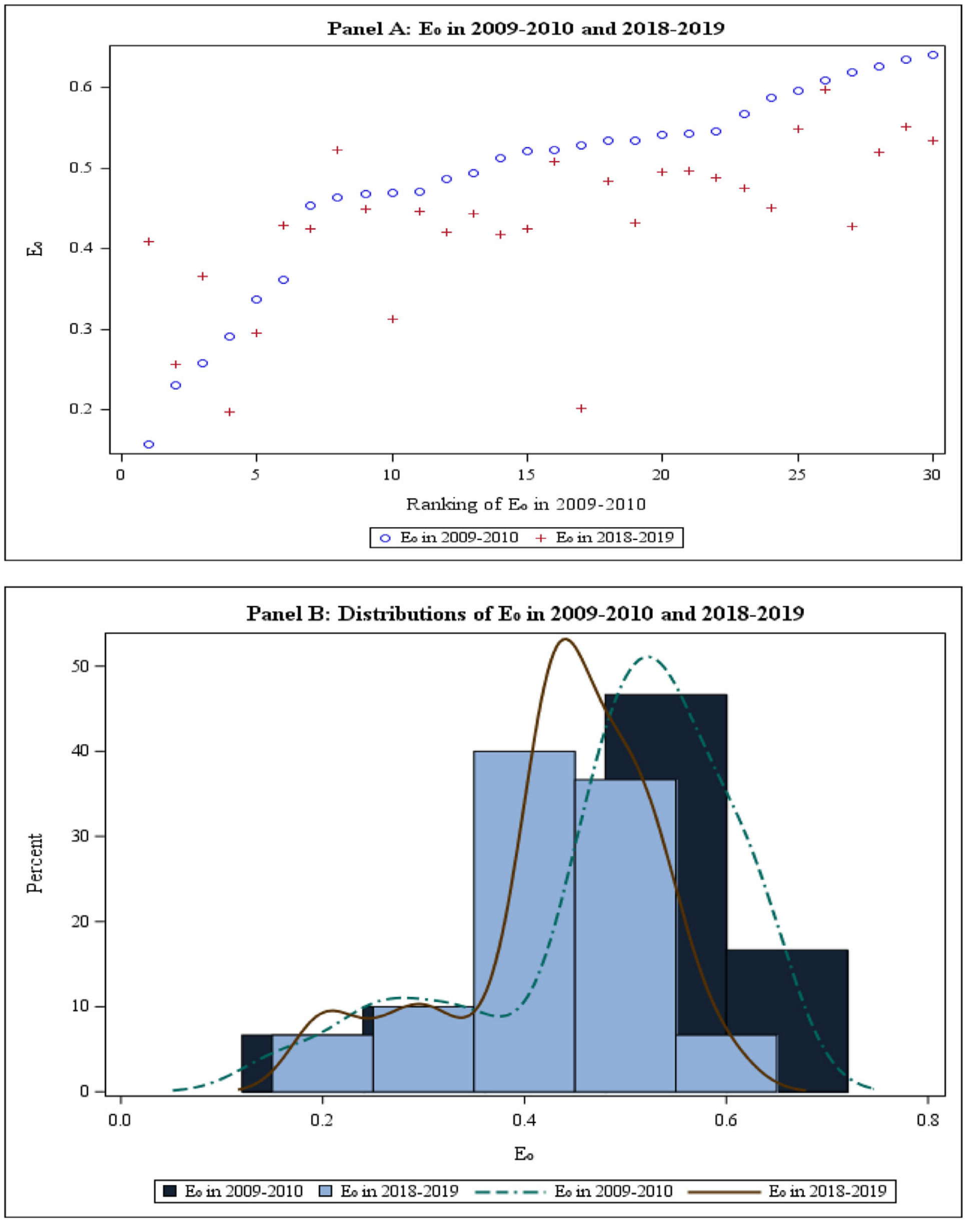


Fig. 3. Cross-section distributions of E_0. This figure reports the cross-sectional distributions of E_0 in the periods of 2009–2010 and 2018–2019. E_0 is the estimated aggregate equity beta in the target year for the TDF series. Panel A presents the average E_0 for each TDF series during the two periods against its E_0 rank in the early period. Panel B presents the histograms of E_0 in each of the two periods. The sample covers 30 TDF series that span the period of 2009–2019.

right tail of the distribution is shifted to the left while the left tail remains similar. Overall, the evidence confirms the prediction that the relatively more aggressive TDF series in the early period have reduced equity market risk exposure over time, driving the industry's average exposure downward. As the TDF series move to benchmark industry standards in the glide path design, the heterogeneity of the glide path mandate across the TDF series has been reduced over time.[19]

To further validate our findings, we conduct multivariate regressions and report the results in Table 5. The dependent variable in columns (1) and (2) is the change of E_0 from year t to $t + 1$. Both columns include time-fixed effects so we compare different TDF series at a given point in time. *Post-2006* in an indicator variable taking the value of one if the fund family enters the market after the PPA, or zero otherwise. As shown in column (1), the coefficient of E_0 is negative and statistically significant at the 1% level, which implies a mean-reverting pattern. Column (2) further shows that relative to the most conservative TDF series, those in the middle and top E_0 terciles exhibit a reduction in E_0 by about 0.02 and 0.03 per year, respectively. In columns (3) and (4), we report the results of the cross-sectional regression that compares the average E_0 in the early period and that in the later period after controlling for the average family size in the early period and the *Post-2006* dummy. Columns (3) and (4) reconfirm the mean-reverting pattern over the longer horizon. In particular, relative to the bottom $E_{0,2009-2010}$ tercile, TDF series in the middle and top terciles experience a cumulative decrease in E_0 by 0.11 between the two periods.[20]

[19] Appendix G compares the cross-sectional distributions of $E_{0,2009-2010}$ and $E_{0,2018-2019}$ for the subsamples of To-series and Through-series as well as for active and passive TDF series. The results are qualitatively indifferent from that in Fig. 2.

[20] The average $E_{0,2009-2010}$ and $E_{0,2018-2019}$ for series in the bottom $E_{0,2009-2010}$ tercile are 0.348 and 0.366, respectively. This is consistent with the pattern shown in

Table 6
Idiosyncratic risk-taking of TDF shifters and non-shifters. This table compares the idiosyncratic risk between TDF shifters and non-shifters. Panels A and B report the summary statistics of the idiosyncratic risk measures and regression results, respectively. The dependent variables of the regressions include annual measures of *Dispersion in return, Dispersion in alpha, R-squared*, and *Idiosyncratic volatility. Dispersion in return* is the squared difference between TDF *i*'s annual return and the average annual return of TDFs with the same retirement target date; *Dispersion in alpha* is the squared difference between TDF *i*'s annual abnormal return and the average annual abnormal return of TDFs with the same retirement target date; and *Idiosyncratic volatility* and *R-squared* are the annualized volatility of the residuals and the R^2 from a five-factor model. The independent variables of interest are ES_{up} and ES_{down}, which are the indicator variables for upward shifters and downward shifters based on the empirical glide path, respectively. All regressions control for target date-by-time fixed effect. Standard errors (in parentheses) are double clustered at the series and time levels. Variable definitions are in Appendix A. The sample covers 30 TDF series that span the period of 2009–2019. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A

	Mean	Std. Dev.	P1	Median	P99
Dispersion in return (%)	5.137	11.117	0	1.457	73.084
Dispersion in alpha (%)	2.781	6.562	0	0.680	46.314
R-squared	0.956	0.065	0.595	0.976	0.994
Idiosyncratic volatility (%)	1.873	0.917	0.863	1.650	6.630

Panel B

	(1)	(2)	(3)	(4)
	Dispersion in return	Dispersion in alpha	R-squared	Idiosyncratic volatility
ES_{up}	0.899	−1.168	−0.006	0.294
	(2.756)	(1.629)	(0.029)	(0.381)
ES_{down}	−0.625	−0.755	0.009	0.017
	(1.353)	(0.967)	(0.016)	(0.153)
Post-2006	0.950	1.422	−0.019	0.277
	(1.505)	(0.828)	(0.015)	(0.167)
Log (Family size)	−0.767**	−0.695**	0.007*	−0.078*
	(0.341)	(0.221)	(0.003)	(0.037)
Target date-by-time fixed effect	Yes	Yes	Yes	Yes
Observations	2089	2089	2089	2089
R-squared	0.19	0.18	0.24	0.36

5.2. The risk-taking hypothesis

Next, we explore the risk-taking hypothesis by differentiating TDF shifters from non-shifters in the level of idiosyncratic risk-taking. Following Balduzzi and Reuter (2019), we measure the idiosyncratic risk of a TDF in two ways. One captures time-series return variations and the return co-movements with the aggregate US and global equity and bond indices, measured by the R-squared and residual volatility of the five-factor regression in Eq. (1). The other is the squared difference between a TDF's annual (abnormal) return and the average annual (abnormal) return of TDFs with the same retirement target date, namely, the cross-sectional dispersion in (alpha) return. Cross-sectional dispersion measures quantify a TDF's deviation from its peers and its contribution to the heterogeneity in the TDF market. We compute the annual measures of idiosyncratic risk-taking for each TDF. Panel A of Table 6 reports the summary statistics of the idiosyncratic risk measures. On average, we find that TDFs deviate from the average return and abnormal return of their peers with the same target date by approximately 2.27% and 1.67%, respectively.[21] In addition, the average R-squared and idiosyncratic volatility of our sample TDFs are 0.96 and 1.87%.

In Panel B of Table 6, we compare the idiosyncratic risk-taking between TDF shifters and non-shifters. The dependent variables are the idiosyncratic risk measures. The independent variables of interest are ES_{up} (ES_{down}), which take the value of one if the average E_0 of a TDF series in the period of 2018–2019 is larger (smaller) than that of 2009–2010 by 0.05, or zero otherwise. The year-by-target-date fixed effects are included to ensure that we compare TDFs with the same target date at the same time.

As shown in Table 6, all coefficients of ES_{up} and ES_{down} are statistically insignificant, which suggests that TDF shifters do not exhibit different levels of idiosyncratic risk-taking or return heterogeneity than non-shifters. The finding does not corroborate the explanation that TDF shifters substitute systematic risk with idiosyncratic risk; it implies that management's variations of the glide path do not reflect agency incentives for idiosyncratic risk-taking. Moreover, the results show that fund family size is negatively associated with return heterogeneity, which is consistent with more risk-taking incentives by smaller fund families as documented by Balduzzi and Reuter (2019). Combined with the results on the systematic risk-taking by TDFs, the evidence here suggests a net effect of reduced volatility in realized returns for an average TDF series.

6. Conclusion

Our study highlights that the systematic risk of TDFs has been reduced over the past decade, leading to an average lower sensitivity of TDF performance to equity market fluctuations. A fair evaluation of whether the phenomenon is a sign of market improvement depends on the appropriate equity exposure guidance using a lifecycle investment model and underlying assumptions. Since TDFs are designed to balance investors' needs of wealth creation and wealth preservation, our study cautions that a decision to alter the glide path should consider potential consequences for both aspects. Market selloffs and the resulting low investor sentiment may trigger incentives to reduce equity exposure at the cost of sacrificing the opportunity for long-term capital appreciation.

Fig. 2 and implies that more conservative TDF series face less incentives to alter the glide path compared to the others.

[21] These are calculated as the square root of the mean cross-sectional dispersion in return and the mean cross-sectional dispersion in alpha.

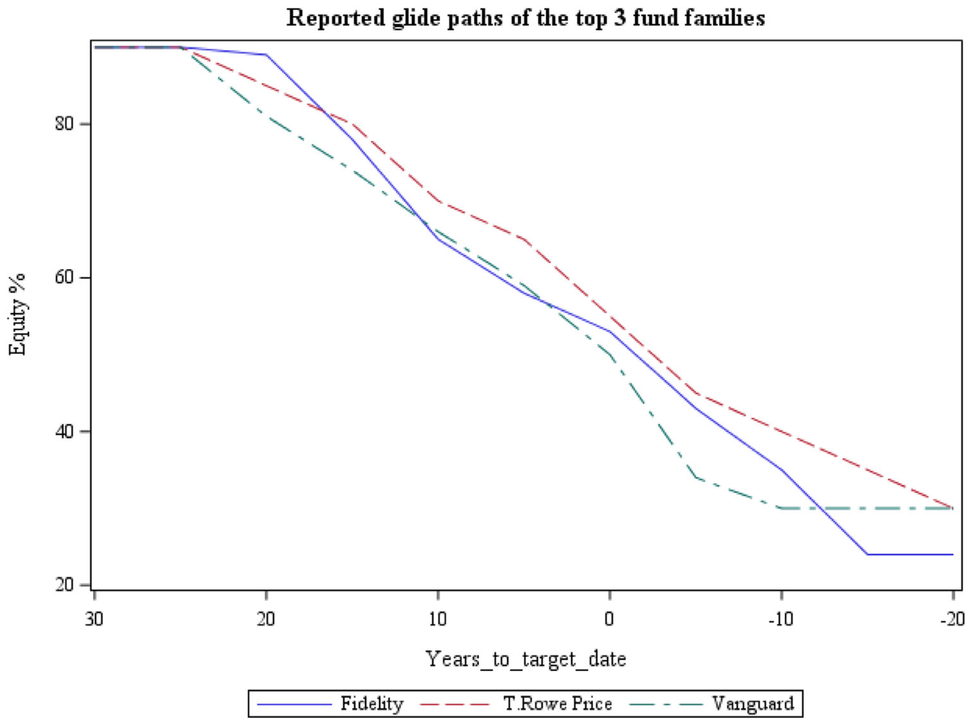
Overall, we document a reduction in the heterogeneity of systematic risk-taking across TDF series during the decade after the 2008 GFC. The findings can potentially generate implications beyond the market of only TDFs. For example, future research can study the management of other investment vehicles with similar types of mandates and uncover the economic forces that can lead to a permanent or temporary deviation from the mandates by managers.

Appendix A. Variable definitions

Variable	Definition
TDF fund-level measures	
$beta_{Agg\ equity}$	The sum of the estimated US and international equity betas in the five-factor model
$beta_{Agg\ bond}$	The sum of the estimated US and international bond betas in the five-factor model
Systematic return	Product of betas and factor realizations of the five-factor model estimation
Alpha	Abnormal return of the five-factor model estimation
R-squared	R^2 of the five-factor model estimation
Idiosyncratic volatility	The annualized standard deviation of residual returns
Dispersion in return	Squared difference between a TDF's annual return and the average annual return of TDFs with the same target date
Dispersion in alpha	Squared difference between a TDF's annual abnormal return and the average annual abnormal return of TDFs with the same target date
Post-2006	An indicator variable taking the value of one if the fund family entered the TDF market after the PPA (2006), and zero otherwise
Log (family size)	The logarithm of the aggregated total net assets (TNA) of each TDF fund family
Log (size)	The logarithm of the aggregated TNA of each TDF
Flow	Net change in the TNA excluding growth in TNA as a result of fund returns
Age	Number of years since fund inception (calculated using the oldest share class)
Expense	Expense ratio in percentage
Log (Turnover)	The logarithm of the turnover ratio
TDF series-level measures	
E_0	Estimated $beta_{Agg\ equity}$ in the target year on the empirical equity glide path
E_{step}	The speed of change (one year) in $beta_{Agg\ equity}$ on the empirical equity glide path
E_{25}	Estimated $beta_{Agg\ equity}$ at 25 years before the target year on the empirical equity glide path
USE_0	Estimated $beta_{US\ equity}$ in the target year on the empirical US equity glide path
IE_0	Estimated $beta_{Int\ equity}$ in the target year on the empirical international equity glide path
$USFI_0$	Estimated $beta_{US\ bond}$ in the target year on the empirical US bond glide path
IFI_0	Estimated $beta_{Int\ bond}$ in the target year on the empirical international bond glide path
C_0	Estimated $beta_{commodity}$ in the target year on the empirical commodity glide path
PC_{up}	An indicator for upward changers, which takes the value of one if the equity allocation target at retirement reported on the fund prospectus in 2019 is larger than that in 2009 by at least 0.05, and zero otherwise
PC_{down}	An indicator for downward changers, which takes the value of one if the equity allocation target at retirement reported on the fund prospectus in 2019 is smaller than that in 2009 by at least 0.05, and zero otherwise
ES_{up}	An indicator for upward shifters, which takes the value of one if the average E_0 during the period of 2018–2019 is larger than that of 2009–2010 by at least 0.05, and zero otherwise
ES_{down}	An indicator for downward shifters, which takes the value of one if the average E_0 during the period of 2018–2019 is smaller than that of 2009–2010 by at least 0.05, and zero otherwise

Appendix B. Equity glide paths of the top three TDF families in 2019

The figure presents the reported equity glide paths of Fidelity, T. Rowe Price, and Vanguard from Morningstar's 2019 TDF Landscape report.



Appendix C. Summary of TDFs

The table summarizes TDFs from 2007 to 2019 in the sample. Columns (1)–(6) report the number of funds by target dates. Columns (7) and (8) report the aggregate total net assets (TNA) and market share of the top three fund families (Fidelity, Vanguard, and T. Rowe Price), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Below 2015	2015 and 2020	2025 and 2030	2035 and 2040	2045 and 2050	Above 2050	TNA (million)	Top three families
2007	61	59	56	54	36	2	184,005.20	81.20%
2008	73	79	76	75	59	3	159,013.60	79.40%
2009	82	87	83	82	67	5	255,441.70	76.98%
2010	77	85	83	82	69	14	340,607.50	75.83%
2011	73	87	87	86	78	25	376,929.10	75.10%
2012	78	97	98	97	94	33	486,354.40	74.35%
2013	78	99	101	101	99	41	622,009.40	72.96%
2014	83	107	111	111	108	62	708,849.80	71.14%
2015	85	114	119	119	116	82	771,810.80	70.03%
2016	82	112	122	121	120	94	889,373.00	69.99%
2017	82	115	128	127	127	110	1,116,897.80	70.08%
2018	77	111	126	125	125	111	1,095,661.20	68.57%
2019	75	107	123	122	122	121	1,381,315.70	68.12%

Appendix D. TDF exposure to the equity, bond, and commodity factors

This table presents the estimated equity, bond, and commodity exposures of TDFs. Panel A reports the equal-weighted averages of the estimated US equity beta (USE_0), international equity beta (IE_0), US bond beta ($USFI_0$), international bond beta (IFI_0), and commodity beta (C_0) for TDFs at the target year in the periods of 2009–2010 and 2018–2019. Panel B reports the averages of the estimated betas for TDFs that are 25 years before the target year.

Panel A					
	USE_0	IE_0	$USFI_0$	IFI_0	C_0
2009 to 2010 (a)	0.455	0.053	0.437	0.034	0.021
2018 to 2019 (b)	0.353	0.076	0.525	0.040	0.007
(b) - (a)	−0.101***	0.023***	0.087***	0.006	−0.014***
Panel B					
	USE_{25}	IE_{25}	$USFI_{25}$	IFI_{25}	C_{25}
2009 to 2010 (a)	0.787	0.089	0.062	0.035	0.026
2018 to 2019 (b)	0.706	0.149	0.085	0.055	0.006
(b) - (a)	−0.081***	0.059***	0.023	0.020***	−0.020***

Appendix E. Dynamics of TDF glide path

This table presents the equal-weighted and value-weighted (using the fund series' total net assets as the weight) summary statistics of the empirical glide path measures. Panel A reports the average values of the equity schedule measures year by year. E_0 and E_{25} are the estimated aggregate equity betas in the target year and 25 years before the target year, respectively. E_{step} is the estimated annual change of equity beta along the glide path. Panel B reports the cross-sectional standard deviations of the equity schedule measures. The sample covers 30 TDF series that exist during the full period of 2009–2019. Standard errors of the mean difference tests are double clustered by the series and time levels. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A						
	Equal-weighted average			Value-weighted average		
	E_0	E_{step}	E_{25}	E_0	E_{step}	E_{25}
2007	0.511	0.018	0.958	0.552	0.016	0.943
2008	0.485	0.017	0.904	0.526	0.015	0.913
2009	0.499	0.016	0.900	0.554	0.015	0.929
2010	0.474	0.015	0.854	0.544	0.014	0.906
2011	0.447	0.016	0.842	0.515	0.015	0.900
2012	0.455	0.016	0.848	0.524	0.015	0.900
2013	0.465	0.016	0.870	0.532	0.015	0.916
2014	0.467	0.017	0.884	0.533	0.016	0.940
2015	0.465	0.016	0.864	0.528	0.016	0.921
2016	0.485	0.017	0.901	0.558	0.016	0.960
2017	0.473	0.015	0.850	0.526	0.015	0.904
2018	0.438	0.017	0.858	0.484	0.016	0.896
2019	0.430	0.017	0.865	0.485	0.017	0.912
2009 to 2010 (a)	0.486	0.016	0.877	0.549	0.015	0.918
2018 to 2019 (b)	0.434	0.017	0.862	0.485	0.017	0.904
(b) - (a)	−0.052***	0.001**	−0.015			
Panel B						
	Equal-weighted standard deviation			Value-weighted standard deviation		
	E_0	E_{step}	E_{25}	E_0	E_{step}	E_{25}
2007	0.138	0.006	0.070	0.073	0.003	0.028
2008	0.102	0.005	0.090	0.059	0.002	0.041
2009	0.122	0.005	0.112	0.064	0.003	0.045
2010	0.136	0.005	0.168	0.079	0.002	0.057
2011	0.130	0.006	0.188	0.095	0.003	0.075
2012	0.123	0.005	0.169	0.089	0.003	0.078
2013	0.113	0.004	0.132	0.084	0.003	0.071
2014	0.115	0.005	0.146	0.074	0.003	0.064
2015	0.107	0.004	0.127	0.072	0.002	0.048
2016	0.132	0.005	0.145	0.074	0.002	0.056
2017	0.105	0.004	0.126	0.051	0.002	0.060
2018	0.098	0.004	0.108	0.040	0.003	0.044
2019	0.101	0.004	0.127	0.046	0.003	0.045
2009 to 2010 (a)	0.129	0.005	0.140	0.071	0.003	0.051
2018 to 2019 (b)	0.100	0.004	0.118	0.043	0.003	0.045

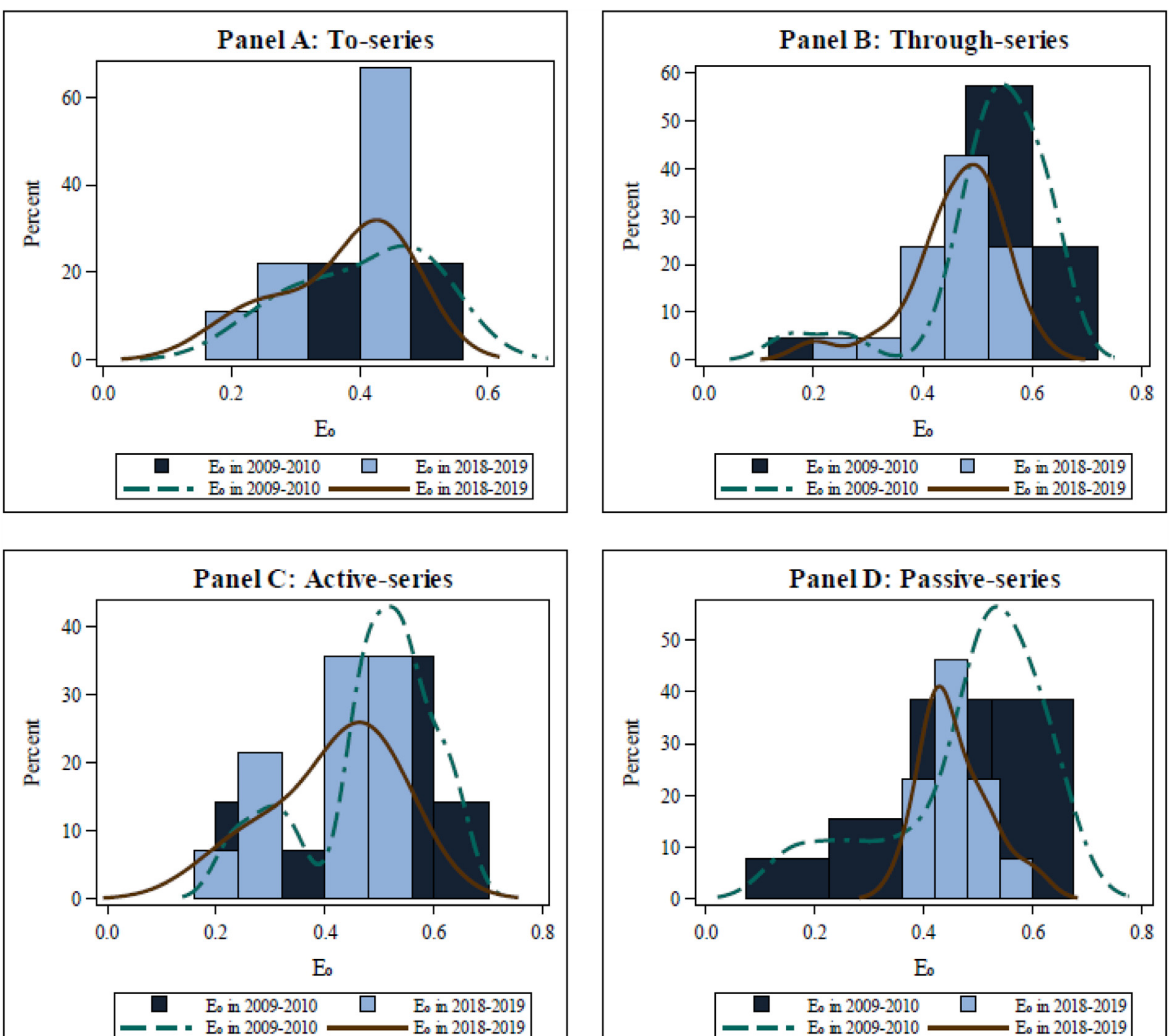
Appendix F. Empirical glide path measures at inception

This table presents the summary statistics of the inception-year empirical glide path measures. The inception year of a series is calculated using its oldest share class from CRSP's record. If daily returns are not available in the reported inception year, the earliest year that enables us to calculate the glide path measures is used. Panel A reports the aggregate equity schedule measures. E_0 and E_{25} are the estimated aggregate equity betas in the target year and 25 years before the target year, respectively. E_{step} is the estimated annual change of aggregate equity beta along the glide path. Panel B reports USE_0, IE_0, $USFI_0$, IFI_0, and C_0, which represent the estimated US equity, international equity, US bond, international bond, and commodity betas in the target year. The sample covers 89 TDF series. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A						
Inception year	E_0	E_{step}	E_{25}	N		
Before 2006 (a)	0.420	0.016	0.823	16		
2006 to 2009 (b)	0.532	0.015	0.907	33		
2010 to 2014 (c)	0.464	0.016	0.858	19		
2015 to 2019 (d)	0.435	0.017	0.858	21		
(d) - (b)	−0.097**	0.002	−0.048			
Panel B						
Inception year	USE_0	IE_0	$USFI_0$	IFI_0	C_0	N
Before 2006 (a)	0.369	0.052	0.554	0.021	0.005	16
2006 to 2009 (b)	0.459	0.073	0.429	0.022	0.017	33
2010 to 2014 (c)	0.403	0.061	0.512	0.006	0.017	19
2015 to 2019 (d)	0.356	0.079	0.531	0.024	0.011	21
(d) - (b)	−0.104***	0.006	0.101**	0.002	−0.007*	

Appendix G. Cross-sectional distribution of E0

This figure compares the cross-sectional distributions of E_0 in the periods of 2009–2010 and 2018–2019. E_0 is the estimated aggregate equity beta in the target year for the TDF series. Panels A–D report the results for the samples of To-series, Through-series, Active-series, and Passive-series, respectively. The activeness of a TDF series is measured by the proportion of actively managed funds in its portfolio in 2019. We classify TDF series that are more (less) active than the sample median as active (passive) series. The sample covers 30 TDF series that span the entire period of 2009–2019.



CRediT authorship contribution statement

Mike Qinghao Mao: Conceptualization, Methodology, Supervision, Writing – review & editing. **Ching Hin Wong:** Investigation, Data curation, Formal analysis, Writing – original draft.

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