Reaching for Yield in Target Date Funds

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Abstract

Target date funds (TDFs) are widely perceived as passive "set-and-forget" investment vehicles that automatically rebalance for retirement savers according to a predetermined schedule. I challenge this view by showing that investors chase recent TDF performance and that managers, in turn, adjust their allocation schedules to reach for yield. Examining changes in the *glide path*, the fund's planned asset allocation, I find that managers systematically increase portfolio risk when interest rates are low, and that this tendency is more pronounced when they face greater pressure to attract flows. A lifecycle simulation shows that these adjustments generate economically meaningful welfare losses for households, equivalent to about 1.4% of retirement consumption.

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JEL Classification: G11, G23, G28.

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1 Introduction

Target date funds (TDFs), which automatically adjust portfolio allocations as investors approach their target retirement dates, have become a central component of the U.S. retirement system. Between 2000 and 2024, TDF assets increased from $9 billion to $3.8 trillion, accounting for approximately 13% of the mutual fund market.[1] Moreover, 59% of 401(k) assets are now invested in TDFs, reflecting their widespread adoption as the default option in employer-sponsored defined contribution (DC) plans. Despite their scale and central role in managing household retirement wealth, little is known about how and why TDF managers revise their pre-announced asset allocation schedules, known as *glide paths*, over time and the economic consequences of such revisions for investors.

This paper challenges the conventional "set-and-forget" view of TDFs, under which managers adhere to predetermined glide paths and investors would remain passive, rarely revisiting their TDF investment.[2] Contrary to this passive premise, I document that glide path adjustments are prevalent. Using a comprehensive sample of U.S. TDFs from 2006 to 2023, I show that 40.1% of funds have significantly altered their glide paths relative to their previous schedule. The average annual unconditional probability of such a shift is 12.1%, implying that one out of every eight funds changes its glide path in a given year.

The paper shows that competitive pressures play an important role in shaping managerial behavior. These pressures lead managers to "reach for yield," a behavior documented in many areas of finance, including corporate bonds, banks, insurance companies, structured products, and mutual funds (Becker and Ivashina, 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018; Célérier and Vallée, 2017; Vokata, 2023), but not in the context of TDFs. I show that managers systematically increase portfolio risk when inter-

[1] See Investment Company Fact Book (2025).

[2] The SEC has raised concerns that TDF marketing materials may mislead investors to believe that they would not need to monitor the portfolio allocations. As stated in its rule proposal, "Even though the marketing materials for target date funds ... included some information about associated risks, they often accompanied this disclosure with slogan-type messages ... encouraging investors to conclude that they can simply choose a fund without any need to ... monitor the fund over time." See SEC Release No. 33-9126, Investment Company Advertising: Target Date Retirement Fund Names and Marketing (2010).

est rates are low by shifting their glide paths in a riskier direction. The estimates indicate that a one–percentage-point lower level of the 10-year Treasury yield is associated with a one-percentage-point increase in the probability of a riskier glide path adjustment in the subsequent quarter, which corresponds to a 61.6% increase relative to the unconditional probability.

Cross-sectional evidence further underscores a flow-driven motive. Managers who have stronger incentives to attract flows are more likely to shift their portfolios toward riskier assets. Using low Morningstar ratings as proxies for flow pressure, I find that a one-star downgrade increases the probability of a subsequent equity share increase by 55.4%. Moreover, using the rating-induced flow shocks suggested by Adelino et al. (2023), I show that exogenous declines in flows lead managers to shift the glide path upward.

The premise of this mechanism is that TDF investors respond primarily to raw returns, since nominal performance is directly influenced by glide path adjustments whereas risk-adjusted performance is less sensitive to such changes. I find that TDF flows load strongly on nominal returns but not on the risks undertaken to produce them. A 10 percentage point increase in a fund's monthly return raises its subsequent monthly flow by 7.3 percentage points.[3] Moreover, DDC plan sponsors' replacement decisions are more sensitive to raw returns than to risk-adjusted performance. A decline in raw-return rankings from the 75th to the 25th percentile is associated with an increase in the probability of replacement of about 3.3 percentage points, while risk-adjusted return rankings do not significantly predict replacement.[4]

Given the prominence of TDFs in U.S. household retirement portfolios, evaluating the welfare implications of glide path adjustments is essential. Building on the methodological framework of Anarkulova et al. (2023), I develop a lifecycle simulation model to quantify

[3]Using Fama–MacBeth regressions in a horse race between raw and abnormal returns (Ben-David et al., 2022), I find that TDF flows respond to raw returns with a sensitivity comparable to that of U.S. domestic active equity funds.

[4]Anonymous TDF managers at a major provider have noted in private discussions that relationship managers frequently receive complaints from plan sponsors about underperformance relative to competitors, often accompanied by explicit demands to improve performance.

these consequences. The model abstracts from optimal consumption and savings choices in order to isolate the investment channel of TDFs, while incorporating realistic labor income dynamics, employment risk, and empirically grounded return processes for equities and bonds. Within this environment, I compare retirement consumption outcomes generated by a fixed baseline glide path to those produced by a rate-sensitive glide path calibrated to the empirical estimates in this paper. The simulation results show that the rate-sensitive glide path generates lower welfare than the baseline policy. Under the baseline calibration, households would require 1.41% higher constant retirement consumption to remain indifferent, indicating that yield-seeking glide path adjustments impose economically meaningful welfare costs on retirement savers.

Glide paths determine the long-horizon risk exposure of millions of households saving for retirement, yet the regulatory framework governing them remains relatively unconstrained. TDFs are regulated by the Securities and Exchange Commission (SEC) under a disclosure-based regime and overseen by the Department of Labor (DOL) through fiduciary process requirements under the Employee Retirement Income Security Act of 1974 (ERISA), but neither regulator prescribes a specific glide path shape, risk profile, or implementation approach. As a result, providers retain substantial discretion in managing and revising glide paths. The evidence in this paper indicates that such adjustments are systematic and economically meaningful, implying that participants' risk exposures may evolve in ways not fully anticipated by the current oversight structure. These findings underscore the importance of more transparent reporting and potentially greater scrutiny of glide path management.

This paper contributes to at least three strands of the literature. First, it contributes to the literature on the glide paths of TDFs by providing the first systematic evidence that TDF managers adjust their glide paths over time in response to market conditions and competitive pressures. Prior research has provided theoretical foundations for optimal lifecycle portfolio design (e.g., Merton, 1969; Samuelson, 1969; Bodie et al., 1992; Campbell and Viceira, 2002; Cocco et al., 2005; Gomes and Michaelides, 2005; Gomes et al., 2008;

Anarkulova et al., 2023), which motivate the general shape of the asset allocation schedules used by TDFs. Some researchers have examined rebalancing decisions or deviations from stated glide paths (e.g., Parker et al., 2023). Other studies have documented cross-sectional heterogeneity in glide paths (e.g., Tang and Lin, 2015; Balduzzi and Reuter, 2019). More related work provides suggestive evidence of glide path adjustments over time (e.g., Elton et al., 2015; Brown and Davies, 2024; Massa et al., 2020). This paper distinguishes itself from the existing literature by rigorously documenting glide path shifts and showing that these shifts are systematically related to interest rates and flow incentives, thereby identifying the economic forces that drive dynamic changes in risk exposure.

Second, this paper contributes to the reaching-for-yield literature by examining this behavior in the context of TDFs. Existing studies document that managers across various asset classes increase portfolio risk during low interest rate periods in response to performance incentives, investor demand, or market frictions (e.g., Becker and Ivashina, 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018; Célérier and Vallée, 2017; Vokata, 2023; Gomes et al., 2025). This paper shows that, in the TDF setting, yield-seeking behavior operates through adjustments to the glide path and is driven by investor preferences for higher nominal returns, which shape the flow–performance relationship.

This mechanism is related to, but distinct from, the one identified by Cortez et al. (2025), who show that performance-sensitive flows distort portfolio choices in defined contribution systems where investors actively reallocate across managers, such as in Chile and Peru. In the U.S. TDF market, however, allocations are delegated to plan sponsors rather than driven by individual investor switching, which implies that flow pressure operates indirectly yet still affects portfolio risk. In addition, I quantify the welfare consequences associated with this channel.

Finally, this paper contributes to the mutual fund literature on risk-taking incentives and flow competition (e.g., Chevalier and Ellison, 1997; Basak et al., 2007; Massa and Patgiri, 2009; Huang et al., 2011). Prior research highlights that competition for flows can induce

managers to increase portfolio risk, yet the welfare implications of such behavior are seldom quantified because the mapping from managerial decisions to household utility is typically unobservable. The TDF setting differs in this respect. These products are designed to facilitate lifetime consumption by delegating long-horizon portfolio decisions, which allows the lifecycle framework to be used directly to evaluate welfare effects. This paper provides one of the first empirical estimates of the welfare costs associated with flow-driven portfolio adjustments in delegated investment products.

The remainder of the paper proceeds as follows. Section 2 reviews the institutional background. Section 3 describes the data and measurement of key variables. Section 4 presents the empirical evidence on glide path adjustments and reaching-for-yield behavior. Section 5 develops the model and reports the simulation results. Section 6 concludes.

2 Institutional Background

2.1 The U.S. Retirement Savings System and TDFs

TDFs are diversified investment vehicles designed to simplify retirement saving by automatically adjusting their asset allocation over time. Each fund corresponds to an expected retirement year, its "target date", and follows a predetermined glide path that gradually shifts the portfolio from higher risk assets such as equities toward lower risk assets such as bonds as the target date approaches. By embedding lifetime portfolio management into a single investment product, TDFs offer households an age appropriate level of risk without requiring ongoing portfolio management.

TDFs are structured into *series*, each consisting of multiple funds targeting retirement years spaced at regular five year intervals (e.g., 2030, 2035, 2040). All vintages within a series share a common glide path and differ only in their current position along that path. A single portfolio management team typically oversees the entire series to ensure consistent implementation of the investment philosophy, risk assumptions, and capital market expec-

tations. Many fund families offer multiple series allowing plan sponsors to select the suite that best aligns with participant demographics and investment objectives.

The rise of TDFs is closely tied to the broader evolution of the U.S. retirement system. As employers shifted from defined benefit plans to defined contribution plans, individuals increasingly became responsible for their own investment decisions. The Pension Protection Act of 2006 encouraged automatic enrollment and established a set of Qualified Default Investment Alternatives (QDIA), among which TDFs quickly became the dominant default option.[5] Under automatic enrollment, participants who do not actively choose an investment are defaulted into a TDF whose target year matches their expected retirement date.

Because most 401(k) participants enter TDFs through default enrollment, plan sponsors' decisions to select, evaluate, and replace TDF suites play a significant role in determining flows. This delegated structure elevates the importance of performance at the series level, as a single mandate decision by a large plan sponsor can generate substantial inflows or outflows for a TDF family. Consequently, the TDF market functions within a framework in which fund managers, plan sponsors, and participants interact through layered incentives, and where perceptions of performance and suitability influence portfolio decisions.

2.2 Glide Path Design

Glide path design in TDFs is generally motivated by lifecycle investment theory, which recommends a gradual reduction in portfolio risk as an investor ages (e.g., Merton, 1969; Samuelson, 1969; Bodie et al., 1992; Campbell and Viceira, 2002; Cocco et al., 2005; Gomes and Michaelides, 2005; Gomes et al., 2008). In this framework, younger investors, whose human capital resembles a bond-like asset, hold a larger share of equities, while older investors shift toward fixed income assets as retirement approaches. Within a TDF series, this principle manifests along two dimensions: (i) the cross-sectional allocation differences across vintages with distinct target years, and (ii) the intertemporal trajectory that any given vintage follows

[5]The DOL describes the QDIA framework and the types of investment options that may qualify, including balanced funds and professionally managed accounts (QDIA Regulation Fact Sheet).

as it moves along the glide path toward retirement.

Glide paths are publicly disclosed in each fund's prospectus. These documents provide graphical representations of the glide path and report allocation schedules at both broad levels (for example, equity and fixed income) and more granular levels, including domestic equity, international equity, domestic bonds, international bonds, cash, and other asset classes. Although glide paths are intended as long-term strategic frameworks, they are not immutable. Fund managers retain discretion to revise these allocation schedules, and such adjustments appear in updated prospectuses.

Figure 1 illustrates these disclosures for *Fidelity Freedom Funds* using prospectus diagrams from 2010, 2015, and 2020. The sequence shows not only how asset allocations differ across vintages but also how the glide path itself can evolve over time. The 2015 and 2020 diagrams, in particular, incorporate a major glide path revision implemented in 2013, when Fidelity increased equity allocations across all near retirement vintages, an upward shift of roughly 10 percentage points. Fidelity attributed this change to expectations of lower long-term bond returns, rising longevity risk, and the need for higher equity exposure to support retirement consumption. Industry observers, however, offered a broader interpretation. At the time, Fidelity had been losing market share to competitors, whose glide paths relied more heavily on equities, and analysts suggested that competitive pressures may also have contributed to the adjustment.[6]

While fund families allow short term tactical deviations from the published glide path to accommodate market conditions or rebalancing needs, the empirical analysis in this paper focuses exclusively on revisions to the glide path. These revisions represent deliberate, long horizon shifts in risk exposure and carry meaningful implications for participants who rely on TDFs as the default investment option in their retirement plans.

[6]See https://www.cnbc.com/2013/10/23/fidelity-t-rowe-price-make-changes-to-target-date-funds.html.

2.3 Regulatory Environment

Despite their scale and importance, TDF glide paths are subject to little substantive regulation. The structure and evolution of glide paths are largely left to fund providers. The SEC regulates TDFs as mutual funds under a disclosure based regime, while the DOL oversees plan sponsors' fiduciary responsibilities under the ERISA. Neither regulator prescribes a specific glide path shape, risk profile, or implementation approach.

On the securities side, the SEC mandates clear disclosure of glide paths through portfolio holdings but does not regulate glide path structure. For example, the Commission has acknowledged the potential for investor confusion arising from industry naming and marketing practices for TDFs and has emphasized the importance of disclosure centered regulation rather than prescriptive asset allocation rules.[7]

On the retirement side, the DOL provides guidance for plan sponsors but similarly refrains from regulating asset allocation schedules. The department emphasizes the importance of understanding a fund's risk profile, monitoring how that profile changes over time, and evaluating whether the fund continues to meet participant needs.[8] By focusing on fiduciary process rather than asset allocation mandates, the DOL implicitly allows fund providers considerable latitude to adjust glide paths.

Taken together, the regulatory framework places few restrictions on how glide paths are designed or implemented. This flexibility creates an environment in which time0varying glide path changes are both feasible and consequential, and in which market conditions, fund family views, and competitive dynamics can meaningfully shape the evolution of TDF risk exposure.

[7]See SEC Release No. 33-9126, Investment Company Advertising: Target Date Retirement Fund Names and Marketing (2010) for more details.

[8]The DOL outlines fiduciary considerations for evaluating TDFs in its publication: Target Date Retirement Funds Tips for ERISA Plan Fiduciaries.

3 Data and Measurement

3.1 Target Date Funds Data

The TDF data are obtained from the CRSP Survivorship Bias-Free Mutual Fund Database, which provides time-series information on share-class-level fund characteristics and the historical portfolio holdings of the share classes. To identify TDFs within the database, I first construct a potential sample by selecting funds whose names include vintage years in five-year increments (2000, 2005, 2010, ..., 2065). I use *crsp_cl_grp*, a unique fund identifier in CRSP, as the baseline unit of analysis and aggregate share-class-level data to the fund level.

Other than identifying the correct TDFs, another important challenge is to systematically determine which TDF series each fund belongs to, as consistent series identifiers are not available in CRSP.[9] This classification is critical for the analysis, which reconstructs historical glide paths using the holdings of underlying funds within each TDF series. To address the lack of consistent series identifiers, I leverage large language models (LLMs), specifically ChatGPT-5, to classify TDFs into their respective series using historical fund names and CRSP fund identifiers (*crsp_cl_grp*). I assign unique series identifiers in cases where funds from different TDF series share identifiers while targeting the same vintage year, thereby capturing historical name changes. This automated classification is supplemented with manual verification to ensure accuracy. The final sample is restricted to TDF series whose constituent funds are uniquely identifiable across vintage years, as reported in Table A1.

Next, I compute the portfolio weights of each TDF to infer the implied glide path over time. Because most TDFs are structured as funds of funds, I link their holdings to underlying funds using CUSIP identifiers and aggregate characteristics to determine asset allocations. I classify underlying securities into three broad categories—equities, bonds, and others—and further subdivide these into domestic equity, international equity, corporate bonds, govern-

[9] A mutual fund family may manage multiple TDF series, so management-company-level identifiers in CRSP (e.g., *mgmt_cd* or *mgmt_name*) are not fully informative for series classification.

ment bonds, international bonds, cash, and other assets. Table A2 details the classification methodology used for TDF holdings.

Following Parker et al. (2023), I apply a series of sample restrictions to the TDF holdings data. First, I exclude observations where the reported value of a holding is either negative or exceeds the fund's total net assets (TNA), or where the sum of all holdings accounts for less than 90% or more than 110% of the TNA. Second, I remove cases in which a fund's TNA increases by more than 50% from the previous quarter to eliminate the influence of fund mergers. Third, I exclude small TDFs with TNAs below $10 million. A key difference from Parker et al. (2023) is that they exclude observations where the equity share of a TDF changes by more than ±5% from the previous quarter, as their analysis focuses on rebalancing activities and therefore omits potential glide path adjustment events. In contrast, I retain these observations because my primary interest lies in glide path adjustments. In addition to the restrictions, I exclude funds whose portfolio weight in the "Other" asset category exceeds 20% in a given period to mitigate potential measurement error.

3.2 Measuring Glide Path Shifts

To quantify glide path shifts, I first construct a glide path for each TDF series whenever holdings are available. Since a TDF series consists of multiple funds with discrete target years, I impute a glide path, $GlidePath_q$, by connecting the observed equity shares of all funds within the same series (Figure 2a).

As a validation exercise, I apply this procedure to the *Fidelity Advisor Freedom Funds* and plot the resulting historical glide paths from 2010 to 2023. The earlier paths prior to 2014 appear in orange, while the later paths appear in blue, which makes the timing of glide path changes visually clear (Figure 3). The figure shows a pronounced upward shift between 2013 and 2014, when equity allocations increased across most vintages. This change is consistent with the prospectus glide paths shown in Figure 1, where Fidelity documented

a series wide revision.[10] The close alignment between the interpolated glide paths and the prospectus based glide paths confirms that the holdings based method accurately captures meaningful adjustments in TDF glide paths through time.

Ideally, a shift in the glide path for a specific fund f would be measured by comparing its current-quarter equity share, $w_{f,q}$, to the equity share of a fund with a one-quarter shorter target date in the previous quarter, $w_{g,q-1}$. The difference $w_{f,q} - w_{g,q-1}$ would perfectly isolate the change in the planned allocation from the natural de-risking that occurs as the target date approaches (Figure 2b).

In practice, however, TDFs are typically offered in five-year increments rather than quarterly intervals. Therefore, I adapt the measure by comparing the current equity share of fund f with the equity share of a fund g that has a five-year shorter target date, measured twenty quarters earlier $w_{f,q} - w_{g,q-20}$. This comparison effectively captures structural shifts in the glide path while accounting for the discrete nature of target-date vintages (Figure 2c).

Finally, I refine the glide path adjustment measure using the fund's holdings from the previous quarter. Specifically, I introduce an indicator function that identifies cases in which the fund's own equity share changes by a meaningful amount (η) relative to the prior quarter (Figure 2d). The quarterly glide path adjustment measure is defined as

$$\Delta\text{Equity}_{f,q} = \mathbf{1}(|w_{f,q} - w_{f,q-1}| \geq \eta) \cdot (w_{f,q} - w_{g,q-20})\,. \tag{1}$$

This refinement serves two purposes. First, it ensures that the measure captures the correct timing of glide path shifts. Suppose a glide path adjustment occurs in quarter q, and the glide paths in quarters q and $q+1$ remain unchanged. Without using the previous-quarter holdings, the measure might incorrectly classify quarter $q+1$ as another adjustment. Anchoring the comparison to quarter $q-1$ prevents such false positives by ensuring that only genuine changes in the glide path are detected. Second, this approach mitigates the risk of

[10] *Fidelity Freedom Index Funds*, a related series under the same umbrella of Fidelity Freedom products but managed with index funds and a more stable portfolio strategy, displays the same pattern (see Figure B1).

misclassifying temporary portfolio rebalancing as a glide path adjustment. Conceptually, the threshold η represents the tolerance band within which managers can rebalance around their target allocations, consistent with the range-based rebalancing rules discussed in Harvey et al. (2025).

I set the threshold parameter η to 2.5% in my main analysis.[11] Harvey et al. (2025) study rule-based rebalancing strategies among institutional investors and show that, for a balanced 60/40 equity–bond portfolio, a threshold above 2.5% would imply rebalancing less than once per quarter, which is unlikely given institutional cash-flow and benchmark-tracking requirements. Because the sensitivity of portfolio weights to equity–bond return differences is symmetric between 60/40 and 40/60 allocations, the same 2.5% threshold implies a comparable rebalancing frequency—approximately once per quarter—for near-retirement TDFs with 40/60 target weights. For equity-heavy TDFs, such as those with a 90/10 allocation, portfolio weights drift more slowly due to the smaller bond share. In that case, a 2.5% threshold would correspond to substantially less frequent rebalancing, roughly equivalent to an annual adjustment.

It is also worth noting that this measure is unlikely to capture mechanical rebalancing or failures to rebalance under a calendar-based policy, which is the alternative strategy examined in Harvey et al. (2025), because TDF glide paths are generally structured around scheduled month-end or quarter-end allocations.

I then define a glide path shift at the fund level as

$$\text{Shift}_{f,q} = \mathbf{1}\big(|\Delta\text{Equity}_{f,q}| \geq \nu\big)\,, \tag{2}$$

where $\nu = 5\%$ in the baseline specification.[12] A positive (negative) glide path shift is

[11] Changing the threshold to 5% does not affect the results presented later.
[12] The results remain robust when ν is set to 4% or 6%.

identified when the equity allocation increases (decreases) by at least ν:

$$\text{PosShift}_{f,q} = \mathbf{1}[(w_{f,q} - w_{f,q-1} \geq \eta) \text{ and } (w_{f,q} - w_{g,q-20} \geq \nu)], \tag{3}$$

$$\text{NegShift}_{f,q} = \mathbf{1}[(w_{f,q-1} - w_{f,q} \geq \eta) \text{ and } (w_{g,q-20} - w_{f,q} \geq \nu)]. \tag{4}$$

At the series level, I measure coordinated glide path adjustments by aggregating fund-level indicators within each TDF series. A series is considered to experience a glide path shift when a majority of its underlying funds exhibit a shift of the same direction in a given quarter. This aggregation is applied separately for overall, positive, and negative shifts. Series-level measures are reported only when at least three underlying funds have valid fund-level shift observations, ensuring that the estimates reflect meaningful series-wide adjustments rather than isolated fund movements.

3.3 Morningstar Rating Data

Historical data on Morningstar star ratings, which range from one to five stars, are obtained from Morningstar Direct. I use CUSIP and ticker information to match *SecID*, Morningstar's unique share-class-level identifier, to *crsp_fundno*, the corresponding identifier in CRSP. Because star ratings are assigned at the share class level, discrepancies may arise across share classes within the same fund. To construct a consistent fund-level measure, I aggregate share class ratings by assigning the modal star rating in each period, weighted by the number of share classes and their TNA.

3.4 Defined Contribution Plan Data

I obtain DC plan data from Form 5500 filings, which cover 401(k) plans sponsored by U.S. public firms with at least 100 participants. For each plan, I identify the TDF series available in the investment menu.

3.5 Descriptive Statistics

The sample period spans from 2006 to 2023 for two reasons. First, coverage of TDF holdings in CRSP is relatively weak prior to 2006.[13] Second, restricting the sample to the post 2006 period helps mitigate confounding effects from the surge in TDF adoption following the Pension Protection Act of 2006, which encouraged employers to designate TDFs and similar vehicles as default investment options in retirement plans.

The final sample includes 46 fund families, 86 TDF series, and 737 individual TDFs, corresponding to 60,261 TDF-month observations, of which 30,763 contain portfolio holdings. Total net assets are expressed in December 2024 U.S. dollars.

Table 1 provides summary statistics for fund level variables in Panel A, series level variables in Panel B, portfolio holdings in Panel C, and glide path shift measures in Panel D.

Fund characteristics are defined as follows. *TNA* denotes the total net assets of the fund. *Family TDF TNA* is the sum of the TNAs of all TDFs managed by the same family, and *Family TNA* represents the total net assets of the fund complex across all products. *Fund Age* measures the number of years since the fund first appeared in CRSP. Returns are computed using CRSP net asset values, and *Quarterly Alpha* is derived from a regression of fund excess returns on benchmark factor returns. *Quarterly Flow* is defined as the percentage change in TNA net of capital gains. *Expense Ratio* and *Turnover Ratio* follow CRSP definitions. *Return Volatility* captures the standard deviation of raw returns during the previous 12 months. The fund characteristics are winsorized at the 1% and 99% levels within each period. The passive indicator equals one if a TDF is classified as passive in CRSP through either *index_fund_flag* or *et_flag*, or if its name contains passive fund keywords such as "INDEX," "IDX," or "ETF."

Panel A shows considerable variation in size. The median TDF manages 330 million dollars, while some funds exceed 50 billion dollars. Family level TNA exhibits even greater dispersion, reflecting the dominance of several large TDF providers. Target years cluster

[13] Thomson Reuters S12 provides even lower holdings coverage for TDFs.

around 2035, and the average fund has about 17 years remaining until its target date. Exposure to domestic and international equity benchmarks is sizable, while bond index loadings reflect the stabilizing role of fixed income allocations.

Series level variables in Panel B aggregate information across funds within the same series. *Series TNA* sums the TNAs of the underlying TDFs, and *Series Age* equals the maximum fund age within the series. The series level passive indicator equals the maximum of the corresponding fund level indicators. All other series level attributes, including returns, flows, expenses, turnover, and volatility, are computed as TNA weighted averages. A typical series contains about eight funds, and the median series manages nearly two billion dollars.

Panel C summarizes portfolio holdings for the observations in the sample. Most holdings are reported on a quarterly basis. Broad asset classes consist of *Equity*, *Bond*, and *Other*, while narrow classifications include *Domestic Equity*, *International Equity*, *Corporate Bond*, *Government Bond*, *International Bond*, *Other Bond*, *Cash*, and *Other*. Equity holdings account for about 70% of total assets on average, which is consistent with the typical structure of TDF glide paths. Variation in holdings across observations reflects differences in target year, provider investment philosophy, and the lifecycle allocation framework that underlies each series.

Panel D presents glide path shift measures. A *Quarterly Shift* indicator equals one when a TDF changes its strategic equity allocation relative to the previous quarter. *Quarterly Positive Shift* and *Quarterly Negative Shift* identify the direction of the adjustment, while *Positive Shift Magnitude* and *Negative Shift Magnitude* measure the corresponding percentage point change in equity allocation. Series level measures aggregate these indicators using TNA weights. Glide path adjustments occur in roughly five percent of fund quarter observations, consistent with the definitions of the shift variables. Positive shifts average almost 10 percentage points, and negative shifts are of similar size in the opposite direction, indicating that glide path revisions, when they occur, are economically meaningful.

4 Results

In this section, I present empirical evidence on how U.S. TDF managers revise their glide paths over time, emphasizing the role of interest rate conditions and flow incentives in shaping these adjustments.

4.1 Time-Varying Glide Path

I begin by documenting the prevalence of glide path changes over time. Figure 4 provides a visual illustration of how realized glide paths depart from the original glide path on average. The black dotted line plots the cross-sectional average pre-determined glide path as of 2010, where each point reflects the average equity share for funds with a given number of years remaining to the target date. The colored lines trace the realized glide paths for the 2050, 2040, 2030, 2020, and 2010 cohorts, computed as the cohort-level average equity share in each calendar year from 2010 to 2023. The shaded regions depict the interquartile range of equity exposures within each cohort, capturing the dispersion of realized allocations around the cohort average.

The divergence between the black dotted line and the colored realized paths provides clear evidence of time-varying glide paths. Put differently, the lifecycle portfolio that a TDF investor actually experiences increasingly deviates from the allocation schedule implied by the 2010 fund prospectus, reflecting systematic departures from originally stated glide path policies.

Frequency. Next, I show how frequently TDFs adjust their glide paths using the quarterly shift measures defined in Section 3.2. These indicators are designed to capture economically meaningful changes in equity exposure that reflect deliberate glide path adjustments.

The overall shift measure (Equation (2)) flags a glide path adjustment whenever a fund's equity allocation deviates from the series' implied glide path benchmark by at least five percentage points. The directional measures further distinguish whether the shift reflects

an upward (Equation (3)) or downward (Equation (4)) revision. A positive shift requires that the fund raise its equity share substantially relative to both the prior quarter and the benchmark, while a negative shift applies the analogous criteria to reductions in equity exposure. These definitions restrict attention to sizable, discretionary reallocations that are more likely to reflect glide path changes rather than routine rebalancing or market driven fluctuations.

Table 2 summarizes the prevalence of these adjustments across funds and series. Panel A shows that 40.1% of funds modify their glide path at least once during the sample period. Among these, 16.9% adjust once, 8.6% adjust twice, and fewer than 10% adjust more than three times. Downward adjustments occur slightly more frequently than upward adjustments.

To examine glide path revisions at the series level, I aggregate fund level indicators within each TDF series. A series is recorded as adjusting its glide path when a majority of its underlying funds exhibit a shift of the same direction in the same quarter. To ensure meaningful inference, a series level shift is recorded only when at least three constituent funds have valid observations in that quarter. Panel B presents the corresponding results at the series level, showing that about 44.4% of series exhibit at least one adjustment over the sample period.

Trends. Figure 5 plots the annual fraction of TDFs that record at least one positive or negative shift in a given year. Across the 2011–2023 period, the average annual unconditional probability of a positive glide path shift is 4.2%, while the corresponding probability for a negative shift is 6.2%. The average annual unconditional probability of any glide path adjustment is 12.1%, implying that roughly one out of every eight funds changes its glide path in a given year.

Positive glide path adjustments occur at varying levels over time. In most years, the share of funds increasing equity remains below 5%, with noticeable increases in 2013 and again in 2021–2022.

Negative glide path adjustments display greater variation over time. Between 2011 and 2013, the share of funds reducing equity is relatively modest, though it rises noticeably in 2013. From 2018 through 2020, the annual incidence of negative shifts stabilizes around 10–12%, before reaching its peak in 2020, when nearly one fifth of funds decrease their equity exposure.

Active vs. Passive. I compare glide path adjustments across active and passive TDFs. As noted by Parker et al. (2023), funds labeled as "passive" are not strictly passively managed in the traditional index-fund sense, because TDF providers retain discretion over allocation decisions. Instead, their defining feature is that they invest primarily in index funds or ETFs as underlying components. Nonetheless, both industry convention and practitioner discussions generally view these products as following a more passive investment approach than their actively managed counterparts.

Consistent with this characterization, passive TDFs adjust their glide paths less frequently than active TDFs, although neither group adheres to a fully static allocation policy. Figure 6 reports the quarterly probability of positive and negative shifts at both the fund level and the series level. At the fund level, active TDFs exhibit quarterly probabilities of 1.96% for positive shifts and 3.10% for negative shifts, compared with 0.72% and 2.06%, respectively, for passive funds. The differences are even larger at the series level.

Moreover, examining the ratio of positive to negative shifts shows that active TDFs are more likely to adjust their glide paths in a risk-increasing direction, conditional on making any adjustment. This pattern may reflect the more competitive environment faced by active TDFs relative to their passive counterparts.

Fund Characteristics. Figure 7 examines how glide path adjustments vary across TDF characteristics (Fund Size, TDF Sector Size, Family Size, Fund Age, Expense Ratio, Turnover Ratio, Flows, Raw Returns, and Alpha) by comparing High vs. Low groups for each variable.

Focusing on the ratio of positive to negative shifts, the figure shows that smaller funds,

smaller TDF complexes, and smaller fund families exhibit relatively more upward shifts conditional on making any adjustment. Younger funds and high-expense funds similarly display a disproportionate tendency toward positive shifts relative to negative ones. These patterns may reflect managerial incentives to increase portfolio risk by altering glide paths, in line with mechanisms documented in the mutual fund literature.

4.2 Interest Rates and Glide Path Shifts

I examine whether glide path adjustments respond systematically to interest rate conditions. In particular, I study how the likelihood that a TDF raises or lowers its target equity allocation varies with the prevailing yield environment. To do so, I estimate the following panel regressions:

$$\text{PosShift}_{f,t+3} = \alpha + \beta\,\text{Yield}_t + \gamma\,X_{f,t} + \delta_f + \delta_s + \delta_{\text{YTD}} + \varepsilon_{f,t}, \tag{5}$$

$$\text{NegShift}_{f,t+3} = \alpha' + \beta'\,\text{Yield}_t + \gamma'\,X_{f,t} + \delta'_f + \delta'_s + \delta'_{\text{YTD}} + \eta_{f,t}. \tag{6}$$

The dependent variables, $\text{PosShift}_{f,t+3}$ and $\text{NegShift}_{f,t+3}$, equal one if fund f increases or decreases its equity allocation at any point over the subsequent three months. The key explanatory variable is the three-month average 10-year Treasury yield at time t. The vector $X_{f,t}$ includes fund-level controls such as log TNA, log family TNA, log fund age, quarterly returns, flows, expense ratio, turnover ratio, and return volatility. All regressions include fund fixed effects, series fixed effects, and years-to-target-date fixed effects that absorb lifecycle patterns in risk-taking that vary with a fund's distance from its target date. Standard errors are clustered by time.

This empirical setup is similar to Gomes et al. (2025), who regress forward-looking portfolio adjustments on contemporaneous changes in interest rates. The key difference is that, whereas their setting focuses on households' short-run responses to rate shocks, I use the level of the three-month average 10-year Treasury yield to capture the broader rate regime

faced by TDF managers. This distinction reflects the institutional environment: households respond to marginal rate changes, while glide path revisions are infrequent and depend on the prevailing yield environment. Accordingly, the coefficient here captures state-dependent variation in the probability of a glide path adjustment.

Table 3 reports the results. Lower interest rates are associated with a meaningfully higher likelihood that TDFs increase equity exposure. In Columns (1) and (2), which model positive shifts—with Column (2) including fund-level controls—the coefficients on Yield_t are approximately -1.0 and statistically significant at the 1% level. A one–percentage-point decline in the 10-year Treasury yield corresponds to roughly one standard deviation of the yield distribution and increases the quarterly probability of a positive glide path shift by 1 percentage point. Given an unconditional probability of 1.62%, this effect represents an increase of about 61.6% relative to baseline.

The results for negative shifts exhibit a notably different pattern. Columns (3) and (4)—with Column (4) including fund-level controls—show that the coefficient β' on Yield_t is not statistically significant. Thus, higher yields do not predict reductions in equity exposure.

The findings indicate that interest rate conditions influence glide path adjustments in an asymmetric manner: lower yields prompt managers to increase equity exposure, whereas higher yields do not lead to correspondingly lower risk, consistent with reaching-for-yield behavior.

4.3 Flow Pressure and Glide Path Adjustments

Next, I examine whether glide path adjustments respond systematically to competitive pressure to attract flows. I use past flows and Morningstar ratings as proxies for flow-pressure incentives.

Past flows. To study the relationship between past flows and subsequent glide path

changes, I estimate:

$$\begin{aligned}\text{PosShift}_{f,t+3} = \alpha + \sum_{k\in\{0,3,6,\ldots,24\}} \beta_k \,\text{Flow}_{f,t-k} + \sum_{k\in\{0,3,6,\ldots,24\}} \gamma_k \,\text{Ret}_{f,t-k} \\ + \delta X_{f,t} + \theta_f + \theta_s + \theta_{t\times\text{TD}} + \varepsilon_{f,t},\end{aligned} \tag{7}$$

$$\begin{aligned}\text{NegShift}_{f,t+3} = \alpha' + \sum_{k\in\{0,3,6,\ldots,24\}} \beta'_k \,\text{Flow}_{f,t-k} + \sum_{k\in\{0,3,6,\ldots,24\}} \gamma'_k \,\text{Ret}_{f,t-k} \\ + \delta' X_{f,t} + \theta'_f + \theta'_s + \theta'_{t\times\text{TD}} + \eta_{f,t}.\end{aligned} \tag{8}$$

The dependent variables equal one if fund f increases or decreases its equity allocation over the subsequent three months. Flows and returns are measured at quarterly frequency with lags from zero to eight quarters. All regressions include fund fixed effects, series fixed effects, and time-by–target-date fixed effects. Fund fixed effects absorb time-invariant differences across funds, series fixed effects control for persistent differences across target-date vintages, and time-by–target-date fixed effects absorb shocks specific to a given cohort in each period. Identification therefore comes from within-period variation across funds that share the same target date. Standard errors are clustered at the fund level.

Table 4 presents the results. The coefficient on one-quarter lagged flows is economically large and statistically significant. In Columns (1) and (2), coefficients ranging from 0.121 to 0.125 imply that a 10% increase in flows raises the probability of a positive glide path shift by 1.21–1.25 percentage points, corresponding to a 75–77% increase relative to the mean probability. A similar pattern holds for negative shifts, although the estimated effects are somewhat smaller.

However, this relationship may be misleading. Glide path adjustments are often communicated to plan sponsors and intermediaries before they are fully reflected in publicly available data, allowing information about upcoming equity increases to diffuse into the marketplace. As a result, observed flows may partly respond to early signals of impending glide path changes. In this case, the positive coefficient on Flow_t may reflect anticipatory

flows rather than glide path adjustments responding to contemporaneous flow pressure.

Longer-horizon flows provide cleaner evidence on economic incentives. Several lagged flow coefficients at horizons of six, seven, eight, and nine quarters—Flow_{t-15}, Flow_{t-18}, Flow_{t-21}, and Flow_{t-24}—are negative and statistically significant in Columns (1) and (2). Aggregating these coefficients implies that a 10% decline in net flows over these horizons increases the probability of a positive glide path shift by approximately 8.0%[14]. This pattern is consistent with flow-driven managerial incentives: funds that have experienced persistently weak—or negative—net flows over the preceding six to nine quarters are more likely to increase their equity allocations. In contrast, the β'_k coefficients in the negative shift regressions are small in magnitude and rarely statistically significant.

Morningstar Ratings. Morningstar *star* ratings provide a proxy for flow pressure. Prior studies have used Morningstar ratings and their methodology as a driver of mutual fund flows (e.g., Del Guercio and Tkac, 2008; Reuter and Zitzewitz, 2021; Ben-David et al., 2022; Adelino et al., 2023). Because TDFs are evaluated under the same Morningstar rating scheme applied to traditional mutual funds, these ratings offer a timely and observable indicator of outflow risk faced by TDF managers. If glide path adjustments respond to flow-related pressure, shifts in asset allocation should be systematically related to Morningstar ratings.

To test this hypothesis, I estimate:

$$\text{PosShift}_{f,t+3} = \alpha + \beta\,\text{Rating}_{f,t} + \gamma\,X_{f,t} + \delta_f + \delta_s + \delta_{t\times\text{TD}} + \varepsilon_{f,t}, \tag{9}$$

$$\text{NegShift}_{f,t+3} = \alpha' + \beta'\,\text{Rating}_{f,t} + \gamma'\,X_{f,t} + \delta'_f + \delta'_s + \delta'_{t\times\text{TD}} + \eta_{f,t}. \tag{10}$$

The dependent variables are defined analogously to the flow regressions. The key explanatory variable is $\text{Rating}_{f,t}$, which ranges from one to five and corresponds to the fund's

[14]The sum of the statistically significant coefficients is $-0.001 - 0.006 - 0.005 - 0.001 = -0.013$. A 10% outflow therefore raises the shift probability by $(-0.013) \times (-0.10) = 0.0013$, or 13 basis points. Dividing by the unconditional probability of 1.62% yields $0.0013/0.0162 \approx 0.08$, corresponding to an 8.0% increase.

Morningstar rating. All specifications include fund, series, and time-by–target-date fixed effects, with standard errors clustered at the fund level. As before, identification comes from variation across funds within the same target date and period, after controlling for observable fund characteristics and unobservable heterogeneity across funds and vintages.

Table 5 shows a strong negative relation between Morningstar ratings and the likelihood of a positive glide path shift. In Columns (1) and (2), the coefficients on $\text{Rating}_{f,t}$ range from -0.009 to -0.011, indicating that a one-star decline increases the probability of a positive shift by 0.9 percentage points, which corresponds to 56–68 percent of the sample mean. The coefficients in the negative shift regressions are small and statistically insignificant, suggesting that Morningstar ratings play little role in prompting downward glide path revisions.

Taken together, the findings suggest that funds experiencing outflows or unfavorable ratings respond by increasing equity exposure, consistent with managers raising risk to counteract current or expected outflows by improving subsequent reported performance.

4.4 Interest Rates, Flow Pressure, and Glide Path Adjustments

The preceding results show that glide path deviations respond both to interest rate conditions and to fund-specific economic incentives. I now examine how these forces interact.

Interest Rates × Past Flows. I first test whether the tendency to reach for yield is dampened or amplified depending on past net-flow pressure. Because $\text{Flow}_{f,t}$ is measured as trailing 36-month *net* flow, it can take negative values, with negative flows (outflows) indicating heightened pressure and positive flows indicating relief. I estimate regressions that interact net flows with interest rates:

$$\text{PosShift}_{f,t+3} = \alpha + \beta\,\text{Flow}_{f,t} + \tau\,\text{Yield}_t + \phi\,(\text{Flow}_{f,t} \times \text{Yield}_t) + \gamma\,X_{f,t} + \delta_f + \delta_s + \delta_{\text{YTD}} + \varepsilon_{f,t}, \quad (11)$$

$$\text{NegShift}_{f,t+3} = \alpha' + \beta' \,\text{Flow}_{f,t} + \tau' \,\text{Yield}_t + \phi' \,(\text{Flow}_{f,t} \times \text{Yield}_t) + \gamma' \, X_{f,t} + \delta'_f + \delta'_s + \delta'_{\text{YTD}} + \eta_{f,t}. \tag{12}$$

$\text{Flow}_{f,t}$ denotes the trailing 36-month net flow, Yield_t is the quarterly average 10-year Treasury yield, and the interaction term captures whether the effect of net flows varies with the interest rate environment.

Table 6 reports the results. The interaction coefficient ϕ in Columns (1) and (2) is positive and statistically significant. This pattern indicates that the risk-taking response to outflows becomes stronger when interest rates are low.

The coefficient on net flows, β, is negative: holding yields constant, funds experiencing outflows are more likely to raise equity exposure, consistent with performance-related pressure inducing greater risk taking. The coefficient on Yield_t is also negative, reaffirming the baseline reaching-for-yield pattern whereby lower interest rates increase the likelihood of a positive glide path shift.

Although the interaction term for negative shifts in Column (4) is positive and statistically significant, it loses significance when fund controls are excluded (Column (3)), consistent with the earlier evidence showing no systematic relation between the economic drivers and the likelihood of a negative glide path shift.

Interest Rates × Morningstar Ratings. I next examine whether the effect of Morningstar ratings on glide path adjustments varies with the interest rate environment. If flow pressure interacts with the reaching-for-yield mechanism, the sensitivity of glide path changes to ratings should depend on the level of Treasury yields. To test this hypothesis, I estimate:

$$\begin{aligned} \text{PosShift}_{f,t+3} = \alpha + \beta \,(\text{Rating}_{f,t} \times \text{Yield}_t) + \tau \,\text{Rating}_{f,t} + \phi \,\text{Yield}_t \\ + \gamma \, X_{f,t} + \delta_f + \delta_s + \delta_{t\times\text{TD}} + \varepsilon_{f,t}. \end{aligned} \tag{13}$$

$$\begin{aligned} \text{NegShift}_{f,t+3} = \alpha' + \beta' \,(\text{Rating}_{f,t} \times \text{Yield}_t) + \tau' \,\text{Rating}_{f,t} + \phi' \,\text{Yield}_t \\ + \gamma' \, X_{f,t} + \delta'_f + \delta'_s + \delta'_{t\times\text{TD}} + \eta_{f,t}. \end{aligned} \tag{14}$$

Table 7 presents the results. In Columns (1) and (2), the interaction between ratings and yields is positive but only marginally significant. The main effect of the rating variable remains strongly negative: lower-rated funds are significantly more likely to increase equity exposure, consistent with performance pressure driving risk-taking behavior. Treasury yields also play a substantial role; lower yields are associated with a higher likelihood of positive glide path adjustments, in line with the reaching-for-yield mechanism documented earlier.

These estimates suggest that the sensitivity of glide path adjustments to Morningstar ratings weakens somewhat when interest rates are low. Nonetheless, the dominant pattern is that poorly rated funds are more inclined to raise equity exposure regardless of the interest rate environment. For negative shifts, neither ratings nor their interaction with yields exhibit economically or statistically meaningful effects.

Overall, these interaction results with past flows and ratings reveal a consistent pattern: fund-specific pressures interact with low interest rates in ways that reinforce the reaching-for-yield behavior of TDF managers.

4.5 Exogenous Flows and Glide Path Adjustments

To provide causal evidence on the effect of flow pressure on glide path adjustments, I follow the identification strategy developed by Adelino et al. (2023). The key insight is that Morningstar's overall star rating changes mechanically when a fund turns five years old. At that point, the 5-year Morningstar risk-adjusted return (MRAR) becomes available and is combined with the 3-year MRAR using a 60/40 weighting rule, rounded to the nearest integer

to produce the new overall rating.[15] [16] Because this re-weighting depends on performance realized three to five years in the past, variation in that distant performance affects overall ratings—and therefore investor flows—at the five-year mark even though it is orthogonal to contemporaneous fund fundamentals. This feature provides a predictable and plausibly exogenous source of variation in fund flows.

I adapt this identification logic to TDFs. For each fund f, I calculate the percentile rank of its 24-month MRAR measured over months $t-59$ to $t-36$, i.e., the two-year performance window ending three years before the fund's fifth anniversary. This measure, denoted MRAR[-59,-36] percentile$_f$, captures stale, risk-adjusted performance that affects the likelihood of a Morningstar rating change at the five-year threshold but is orthogonal to contemporaneous determinants of glide path decisions. I define an indicator Post5yr$_{f,t}$ that equals one in the quarter when fund f reaches five years of age and thereafter, and zero otherwise. The interaction of MRAR[-59,-36] percentile$_f$ with Post5yr$_{f,t}$ thus provides a continuous treatment intensity capturing the exogenous flow shock induced by the mechanical rating re-weighting.

[15] Morningstar computes the risk-adjusted returns (MRAR) over 3-, 5-, and 10-year horizons, ranks all share classes within each category by MRAR, and assigns discrete star ratings: the top 10% receive five stars, the next 22.5% four stars, the middle 35% three stars, and so forth. Overall ratings are then computed as weighted averages across horizons: a 3-year rating alone for funds younger than five years, a 60/40 weighted average of 5-year and 3-year ratings for funds aged 5–10 years (the "60/40 rule"), and a 50/30/20 weighting of 10-, 5-, and 3-year ratings for funds older than 10 years (the "50/30/20 rule"). The discontinuity for identification occurs at the five-year mark, when the 5-year MRAR is first introduced with a 60% weight, potentially causing a discrete jump in overall ratings unrelated to new information. See Adelino et al. (2023) for more institutional details.

[16] For a share class i at time t and horizon $T \in \{36, 60, 120\}$ months, MRAR is defined as:

$$\text{MRAR}_{i,t}(T) = \left[\frac{1}{T} \sum_{j=0}^{T-1} \left(1 + ER_{i,t-j}\right)^{-\gamma} \right]^{-12/\gamma} - 1,$$

where $ER_{i,t}$ denotes the excess return on share class i in month t, and $\gamma = 2$ is Morningstar's risk-aversion parameter.

Specifically, I estimate the following difference-in-differences specifications:

$$\begin{aligned}\text{PosShift}_{f,t} = \alpha + \beta \left(\text{MRAR[-59,-36]}_{f,t} \times \text{Post5yr}_{f,t}\right) \\ + \theta\, \text{MRAR[-59,-36]}_{f,t} + \phi\, \text{Post5yr}_{f,t} + \gamma\, X_{f,t} + \delta_f + \delta_t + \varepsilon_{f,t},\end{aligned} \tag{15}$$

$$\begin{aligned}\text{NegShift}_{f,t} = \alpha' + \beta' \left(\text{MRAR[-59,-36]}_{f,t} \times \text{Post5yr}_{f,t}\right) \\ + \theta'\, \text{MRAR[-59,-36]}_{f,t} + \phi'\, \text{Post5yr}_{f,t} + \gamma'\, X_{f,t} + \delta'_f + \delta'_t + \eta_{f,t}.\end{aligned} \tag{16}$$

The dependent variables, $\text{PosShift}_{f,t}$ and $\text{NegShift}_{f,t}$, indicate whether fund f increases or decreases its equity allocation at time t. All regressions include fund and time fixed effects, and standard errors are clustered at the fund level. Summary statistics for the estimation sample appear in Table B4.

Table 8 presents the estimates. In Columns (1)–(2), where the dependent variable is a positive glide path shift, the interaction coefficient β is negative and statistically significant at the 10% level. The point estimates range from -0.386 to -0.540, implying that higher stale performance—which predicts a mechanically higher rating at age five and therefore higher inflows—reduces the probability of an upward glide path adjustment. Because the percentile measure is scaled between 0 and 1, a one-half decrease (e.g., moving from the 25th to the 75th percentile) lowers the likelihood of a positive shift by approximately 19.3–27.0 percentage points. Columns (3)–(4) report the results for negative glide path shifts. In contrast to the positive shift results, the interaction coefficient β' is statistically indistinguishable from zero.

4.6 Return-Chasing Behaviors

Finally, I examine whether TDF investors respond more strongly to raw returns or to risk-adjusted returns. This question lies at the core of my argument: when investor flows are driven primarily by risk-unadjusted performance, managers face incentives to deviate from the planned asset allocation schedule in order to improve nominal returns.

To conduct a horse race between raw and risk-adjusted returns, I follow the approach

of Ben-David et al. (2022) and implement a Fama–MacBeth regression framework, which mitigates time-series confounding in the flow–performance relationship. Specifically, in each period t, I estimate the following Fama–MacBeth regression:

$$\text{Flow}_{f,t+1} = \alpha + \beta\,\text{RawRet}_{f,t} + \gamma\,\text{AbnormalRet}_{f,t} + \delta X_{f,t} + \varepsilon_{f,t}, \tag{17}$$

where the dependent variable $\text{Flow}_{f,t+1}$ represents net inflows to fund f in the subsequent period. Raw returns, $\text{RawRet}_{f,t}$, are defined as the fund's return in excess of the risk-free rate. Following Balduzzi and Reuter (2019), abnormal returns $\text{AbnormalRet}_{f,t}$ are computed as a monthly five-factor alpha based on the preceding 12 months of daily returns. The five-factor model includes daily returns on the CRSP U.S. Value-Weighted Market Index, MSCI World Index excluding the United States, Bloomberg U.S. Aggregate Bond Index, Bloomberg Global Aggregate ex-USD Index, and the S&P GSCI Commodity Index.[17] Control variables include fund TNA, family TNA, turnover ratio, expense ratio, return volatility, fund age, and annual flows.

Table 9 reports the results. Across all specifications, investor flows respond strongly to raw returns but not to risk-adjusted performance. In Columns (1) and (2), the coefficients on raw returns range from 0.730 to 0.783 and are statistically significant. Because both flows and returns are measured in percentage points, these coefficients imply that a 10 percentage point increase in monthly excess returns raises next-month flows by 7.30–7.83 percentage points. This magnitude is comparable to the findings in Ben-David et al. (2022), who conduct a similar analysis for U.S. actively managed domestic equity funds. By contrast, abnormal returns are neither statistically nor economically significant predictors of flows, indicating that investors predominantly chase raw returns.

These results differ from those of Balduzzi and Reuter (2019), who find that abnormal returns significantly predict flows into TDFs.[18] However, Ben-David et al. (2022) show that

[17] The Barclays U.S. Aggregate Bond Index and Global Aggregate ex-USD Index were renamed the Bloomberg U.S. Aggregate Bond Index and Bloomberg Global Aggregate ex-USD Index in August 2021.

[18] See also Del Guercio and Tkac (2002) and Sialm et al. (2015), who document that plan sponsors'

the pairwise horse-race regressions used in such studies, following Barber et al. (2016), can generate spurious evidence of investor sensitivity to alpha. Because the flow–performance relationship varies over time and is negatively related to market returns, pooled regressions overweight episodes with large market movements—precisely when the flow–performance sensitivity is weakest. This mechanical weighting bias inflates the apparent importance of alpha. When regressions are instead estimated using the Fama–MacBeth procedure, which equal-weights each cross-section, raw returns dominate in predicting flows.

To validate that this result is not an artifact of the Fama–MacBeth framework, I also estimate standard panel regressions—commonly used in the literature despite their limitations. As reported in Table B3, raw returns continue to outperform abnormal returns in the horse race, remaining a statistically meaningful predictor of flows. Although panel regressions are subject to the weighting issues discussed above, the fact that raw returns retain predictive power supports the more naive conclusion that investors respond to nominal performance.

Performance-Chasing by Plan Sponsors. Since TDFs are primarily held within DC retirement plans, I also examine whether plan sponsors—who decide whether to retain or replace a TDF series—exhibit similar return-chasing behavior. I estimate the following linear probability model:

$$\text{Replace}_{i,t+1} = \alpha + \beta\,\text{PerformanceRank}_{i,t} + \gamma\,X_{i,t} + \delta_i + \delta_t + \varepsilon_{i,t}, \tag{18}$$

where $\text{Replace}_{i,t+1} = 1$ if plan i removes its TDF series in year $t+1$. $\text{PerformanceRank}_{i,t}$ is the average percentile ranking of the underlying funds in the series, computed using annual raw returns (Column (1)) or annual alpha (Column (2)). Control variables include plan age, log plan size, log average account size, the number of funds offered in the plan, and the number of investment options.

Table 10 shows that DC plan sponsors place greater weight on raw performance than on risk-adjusted returns when making TDF replacement decisions. In Column (1), the

allocation decisions relate to risk-adjusted performance.

coefficient on the raw-return rank is -0.066 and statistically significant at the 5% level. Because the percentile-based rank is scaled between 0 and 1, a decline in the raw-return rank from the 75th to the 25th percentile increases the probability of replacement by 3.3 percentage points. Given that the unconditional annual replacement probability is 16.3%, this effect is economically meaningful. In contrast, performance ranks based on alpha are statistically insignificant (Column (2)), indicating that sponsors do not meaningfully respond to risk-adjusted performance when deciding which TDF series to retain.

5 Model and Simulations

The goal of this section is to quantify the welfare consequences for households when TDF managers increase portfolio risk in low interest rate environments. My approach builds on the methodological framework of Anarkulova et al. (2023), who emphasize that realistic asset return dynamics cannot be summarized by a small number of state variables and therefore cannot be handled reliably using traditional dynamic programming techniques. Instead, I adopt a Monte Carlo simulation design that preserves the empirical properties of asset returns while allowing glide path rules to be imposed exogenously.

In contrast to dynamic lifecycle models that jointly solve for consumption, savings, labor supply, and portfolio choice, my model isolates the investment channel of TDFs while incorporating realistic working-life income and employment risk. This design reflects the institutional features of DC plans and enables a welfare evaluation of rate-sensitive equity tilts without imposing strong parametric assumptions on household behavior.

I consider a standard CRRA investor who works from age 25 to 65, faces labor income and unemployment shocks during the working period, contributes to a retirement account when employed and eligible, and consumes accumulated wealth in retirement until age 95. The retirement account is managed according to one of two policies: a baseline glide path that is stationary over time, and a rate-sensitive glide path that exhibits a higher likelihood

of upward equity adjustments when risk-free rates are low. I then conduct a comparative welfare analysis across the two policies. The remainder of this section describes the model assumptions and simulation procedure in detail.

5.1 Lifecycle Structure

The household enters the model at age 25 and faces a lifecycle measured in monthly periods indexed by $t = 1, 2, \ldots, T$, where $t = 1$ corresponds to the first month of age 25. The retirement date is denoted T^* and is fixed at age 65, so that $T^* = 480$. The retirement phase lasts until age 95, yielding a total horizon of $T = 840$ months. Prior to retirement, the household is eligible to work, earn labor income, and contribute to a retirement account. After retirement, labor income ceases and the household finances consumption from accumulated retirement wealth.

During the working period ($t \leq T^*$), households may experience periods of unemployment. When employed, a household contributes a constant fraction $c = 10\%$ of labor income to its retirement account, and no contributions occur during periods of unemployment.[19] Following Anarkulova et al. (2023), households with annual labor income below $Y_{\min} = \$15{,}000$ do not make retirement contributions.

At retirement ($t = T^* + 1$), the household exits the labor force and finances consumption by withdrawing from accumulated retirement wealth according to the "4% rule" of Bengen (1994), which specifies a constant annual withdrawal equal to 4% of wealth at retirement.

5.2 Lifecycle Income

Labor income follows a standard permanent–transitory specification commonly used in the lifecycle literature (e.g., Cocco et al. (2005)). When employed, monthly log labor income

[19] Poterba et al. (2005) and Poterba et al. (2009) assume contribution rates of 9%, while Anarkulova et al. (2023) uses a 10% contribution rate.

evolves as

$$\log Y_t = \log \bar{Y}_t + v_t + \varepsilon_t, \tag{19}$$

where $\bar{Y}_t$ denotes a deterministic age–earnings profile, v_t is a permanent component evolving as

$$v_t = v_{t-1} + u_t, \tag{20}$$

and ε_t is a transitory shock. The innovations $u_t \sim \mathcal{N}(0, \sigma_u^2)$ and $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ are assumed to be independent over time and across components.

The deterministic income profile $\bar{Y}_t$ is calibrated to match age-specific median earnings in 2019 from the Bureau of Labor Statistics (BLS).[20] Specifically, annual median earnings are \$44,018 for ages 25–34, \$53,833 for ages 35–44, \$53,807 for ages 45–54, and \$53,014 for ages 55–64. These values are converted to monthly income and held constant within each age bin. I adopt benchmark annual income shock variances from Cocco et al. (2005), with permanent variance $\sigma_u^2 = 0.0738$ and transitory variance $\sigma_\varepsilon^2 = 0.0106$, and convert them to monthly frequency.

Employment follows a two-state Markov process. When unemployed, labor income is zero and retirement contributions cease, i.e., $Y_t = 0$ if $E_t = 0$. Let p_{EU} denote the monthly transition probability from employment to unemployment and p_{UE} the transition probability from unemployment to employment. Let u denote the steady-state unemployment rate and d the mean unemployment duration (in months). In a two-state Markov chain, these moments satisfy

$$d = \frac{1}{p_{UE}}, \qquad u = \frac{p_{EU}}{p_{EU} + p_{UE}}. \tag{21}$$

I calibrate the transition probabilities to match U.S. labor market conditions in 2019 using BLS data, targeting an average unemployment rate of $u = 2.95\%$ and an average unemployment duration of $d = 4.2$ months.

[20] I use 2019 data to remain consistent with the baseline glide path, which is calibrated using the 2019 average glide path. The choice of year does not materially affect the results.

Retirement contributions prior to retirement are given by

$$S_t = \begin{cases} c\,Y_t, & \text{if } E_t = 1 \text{ and } 12Y_t \geq Y_{\min}, \\ 0, & \text{otherwise,} \end{cases} \qquad t \leq T^*, \tag{22}$$

where the contribution rate is $c = 0.10$ and the annual income threshold is $Y_{\min} = \$15{,}000$.

5.3 Household Utility

Households derive utility from retirement consumption according to a standard CRRA utility function:

$$U = \sum_{t=T^*+1}^{T} \beta^{\,t-T^*-1} \frac{C_t^{1-\gamma}}{1-\gamma}, \tag{23}$$

where γ denotes the coefficient of relative risk aversion and β is the monthly subjective discount factor. Because pre-retirement consumption is not modeled, utility is evaluated only over the retirement period. I assume no bequest motive. If retirement wealth is exhausted, consumption is zero thereafter. Following Cocco et al. (2005), I set the annual discount factor to $\beta = 0.96$.

Let W_t denote financial wealth at time t. Prior to retirement, wealth evolves according to

$$W_{t+1} = (W_t + S_t)(1 + R_t^p), \qquad t \leq T^*. \tag{24}$$

After retirement, withdrawals reduce wealth:

$$W_{t+1} = (W_t - D_t)(1 + R_t^p), \qquad t > T^*. \tag{25}$$

Retirement withdrawals follow the 4% rule and are fixed at

$$D_t = \frac{0.04}{12} W_{T^*}, \qquad t > T^*, \tag{26}$$

so that retirement consumption equals withdrawals, $C_t = D_t$.

Portfolio returns are given by

$$R_t^p = w_t^{\mathrm{e}} R_t^{\mathrm{e}} + \left(1 - w_t^{\mathrm{e}}\right) R_t^{\mathrm{f}}, \tag{27}$$

where w_t^{e} is the equity share specified by the glide path, and R_t^{e} and R_t^{f} denote returns on the risky asset and the risk-free asset, respectively.

5.4 Glide Path Policies

Consistent with the sparse-attention framework of Gabaix (2014), I assume that households attend only to age when determining portfolio allocations. This assumption mirrors the design of TDFs, which implement lifecycle portfolio choices mechanically through age-based glide paths. I consider two glide path policies.

1. Baseline Glide Path. The baseline glide path is stationary and does not depend on any state variables. It is constructed by interpolating the 2019 average equity share across ages 25–65 and holding the equity share fixed at its age-65 value thereafter.[21] I use the 2019 average glide path because it lies outside the prolonged low interest rate environment in the sample period (2006–2023). Using alternative baseline glide paths from other periods with comparable interest rate conditions yields similar results.

2. Rate-Sensitive Glide Path. Motivated by empirical evidence that TDFs increase equity exposure in low interest rate environments, I introduce a rate-sensitive glide path that adjusts discretely at quarter-end dates. Let $w_t^{\mathrm{e,base}}$ denote the baseline equity share.

[21] The 2019 average glide path is defined over remaining years to retirement and the corresponding equity share as follows (remaining years, equity share): (36, 90.4%), (31, 89.0%), (26, 88.3%), (21, 83.4%), (16, 75.6%), (11, 65.9%), (6, 53.7%), (1, 45.9%), (−4, 41.4%), (−9, 35.4%), and (−14, 29.2%).

The rate-sensitive equity share is given by

$$w_t^{\text{e,rate}} = w_t^{\text{e,base}} + \Delta_t, \tag{28}$$

where Δ_t is a cumulative equity-level shift.

Let $\tilde{R}_t^{\text{f}}$ denote the quarterly risk-free rate, defined as

$$\tilde{R}_t^{\text{f}} = \frac{1}{m} \sum_{j=0}^{m-1} R_{t-j}^{\text{f}}, \tag{29}$$

with $m = 3$ months. Let $\bar{R}^{\text{f}}$ denote a benchmark level. In the baseline implementation, $\bar{R}^{\text{f}}$ is set to the path-specific mean of $\tilde{R}_t^{\text{f}}$ over the simulated lifecycle.

At each quarter-end month, the policy updates Δ_t in two steps:

1. **Upward shift:** if $\tilde{R}_t^{\text{f}} < \bar{R}^{\text{f}}$, the policy increases equity exposure with probability

$$p_t = p_0 + k\big(\bar{R}^{\text{f}} - \tilde{R}_t^{\text{f}}\big), \tag{30}$$

where $p_t \in [0, 1]$. Conditional on a positive shift, the equity increment is

$$d_t \sim \max\{0, \mathcal{N}(\mu_\Delta, \sigma_\Delta^2)\}, \tag{31}$$

and the cumulative shift updates as $\Delta_t \leftarrow \Delta_t + d_t$.

2. **Downward shift:** if $\tilde{R}_t^{\text{f}} \geq \bar{R}^{\text{f}}$, the cumulative shift reverts to zero, $\Delta_t \leftarrow 0$. This feature captures the idea that rate-driven risk taking unwinds when interest rates return to relatively high levels.

The quarter-end probability p_t consists of an intercept p_0 and a slope k, which governs how sensitively the likelihood of a positive glide path shift responds when the risk-free rate falls below its benchmark. I set $p_0 = 1.62\%$ per quarter, equal to the unconditional quarterly

probability of a positive glide path shift observed in the data (see Panel D of Table 1). I set $k = 0.1$, implying that a 10 basis point decline in the risk-free rate relative to its benchmark increases the probability of a positive glide path shift by 1 percentage point.[22] Conditional on a positive shift, the distribution of equity increments is calibrated to match the empirical distribution of observed glide path adjustments. The mean quarterly shift is $\mu_\Delta = 9.9\%$ and the standard deviation is $\sigma_\Delta = 4.25\%$ (see Panel D of Table 1). Together, these parameter choices map the empirically estimated effect of interest rates on upward glide path shifts into a parsimonious simulation rule.

Figure 8 illustrates how the empirically calibrated rate-sensitive rule generates higher equity exposure over the lifecycle relative to the baseline policy. The baseline glide path is shown as a black dotted line, while the mean rate-sensitive glide path across bootstrapped interest-rate environments is shown as a blue solid line. When risk-free rates fall below their benchmark, upward equity shifts accumulate; when rates rise back to or above the benchmark, these upward shifts are partially undone as the policy reverts toward the baseline. As a result, the rate-sensitive glide path lies persistently above the stationary baseline over most of the lifecycle. The shaded region indicates the interquartile range of the rate-sensitive equity share distribution, reflecting heterogeneity in interest-rate realizations and the timing of discrete adjustments. The rate-sensitive policy leads to a sustained upward shift in equity exposure of about 3.5 percentage points over the lifecycle on average.

5.5 Simulation Design

For each glide path policy $s \in \{\text{base}, \text{rate}\}$, I simulate N independent lifecycle paths according to the following steps:

1. Draw a bootstrap return series $\{R^{\text{e}}_t, R^{\text{f}}_t\}_{t=1}^{T}$.

2. Simulate a working-life path of income and employment $\{Y_t, E_t\}_{t=1}^{T^*}$.

[22] Table 3 shows that a one-percentage-point decline in the 10-year Treasury yield is associated with a one-percentage-point increase in the likelihood of a positive glide path shift. The 10-year Treasury yield and the monthly risk-free rate are strongly positively correlated and comove at approximately a ten-to-one ratio.

3. Simulate wealth accumulation from ages 25 to 65 given the glide path policy.

4. Simulate retirement withdrawals and consumption from ages 65 to 95.

5. Compute retirement utility $U_s^{(i)}$ using the CRRA utility function.

Asset returns are generated using a nonparametric procedure following Anarkulova et al. (2023). Instead of imposing a parametric model for returns, I employ a stationary block bootstrap that captures key empirical features of asset returns, including persistence, volatility clustering, and the comovement between equity and risk-free returns.

Let $\{R_t^{\mathrm{e}}, R_t^{\mathrm{f}}\}$ denote historical U.S. monthly returns on equity and the risk-free asset from 1926 to 2024. Each bootstrap return series is generated by drawing a random starting point from the historical sample and then appending consecutive return observations for a block whose length is drawn from a geometric distribution with mean 120 months. This procedure is repeated until a full 70-year return sequence is constructed. The stationary block bootstrap preserves serial correlation, volatility clustering, and the joint behavior of equity and risk-free returns without imposing a parametric state-space structure.

Expected utility under glide path s is given by

$$\mathbb{E}[U_s] = \frac{1}{N} \sum_{i=1}^{N} U_s^{(i)}. \tag{32}$$

In the baseline analysis, I set $N = 1{,}000{,}000$ simulated lifecycle paths.

5.6 Welfare Analysis

To compare welfare across glide path policies, I compute certainty-equivalent retirement consumption. Let CE_s denote the constant level of retirement consumption that yields the same expected discounted utility as the simulated consumption stream under policy s.

Welfare differences are summarized by the consumption-equivalent variation,

$$\lambda \equiv \frac{CE_{\text{rate}}}{CE_{\text{base}}} - 1, \tag{33}$$

which measures the proportional change in retirement consumption required to make households indifferent between the rate-sensitive and baseline glide path policies. A negative value of λ therefore indicates a welfare loss from the rate-sensitive policy.

Figure 9 plots $-\lambda$ as a function of the coefficient of relative risk aversion γ. For low levels of risk aversion ($\gamma < 1$), the rate-sensitive policy slightly improves welfare, reflecting higher expected returns from increased equity exposure. As risk aversion rises, this effect reverses sharply: households place greater weight on downside risk, and the additional volatility induced by rate-sensitive equity tilts dominates any return gains. The welfare loss increases rapidly around $\gamma = 1$ and then declines with diminishing sensitivity as γ increases, with the curve becoming progressively flatter at higher levels of risk aversion.

Under the baseline calibration $\gamma = 5$, the implied welfare loss is $\lambda = -0.0141$, meaning that households would require 1.41% higher retirement consumption under the baseline glide path to remain indifferent. This magnitude indicates that yield-seeking glide path adjustments impose economically meaningful welfare costs on retirement savers.

6 Conclusion

This paper challenges the conventional view of TDFs as passive "set-and-forget" investment vehicles by showing that managers actively revise their planned asset allocation schedules, the glide path. Using comprehensive data from 2006 to 2023, I document that glide path adjustments are prevalent and systematically related to conditions faced by TDF managers. When interest rates are low, managers substantially increase equity exposure, and this response is stronger among funds facing greater flow pressure.

A key mechanism behind these adjustments is investor behavior. I show that TDF

flows strongly chase raw returns but are largely insensitive to risk-adjusted performance. A similar pattern appears among retirement plan sponsors responsible for selecting and retaining TDF series. Because raw returns mechanically benefit from higher portfolio risk when interest rates are low, managers have incentives to raise equity shares in an effort to improve nominal performance, which in turn increases downside risk for investors.

To evaluate the implications of these adjustments for households, I develop a lifecycle simulation model that isolates the investment channel of TDFs while incorporating realistic asset return dynamics and working-life income risk. The model compares a fixed baseline glide path with a rate-sensitive glide path that endogenously increases equity exposure in low interest rate environments, calibrated to the empirical estimates in this paper. The simulation results indicate that the rate-sensitive policy generates economically meaningful welfare losses: households would require about 1.4% higher retirement consumption to remain indifferent between the two policies.

The findings in this paper highlight the need for greater scrutiny of glide path management. A more transparent framework for reporting and monitoring glide path changes could improve understanding of whether revisions to portfolio schedules are appropriate and whether they remain consistent with stated objectives and the long-term needs of retirement savers.

References

Adelino, M., Cheong, S. C., Choi, J., & Oh, J. Y. J. (2023). Mutual fund flows and the supply of capital in municipal financing. *National Bureau of Economic Research Working Paper No. 30980*.

Anarkulova, A., Cederburg, S., O'Doherty, M. S. (2023). Beyond the status quo: A critical assessment of lifecycle investment advice. *Available at SSRN 4590406*.

Balduzzi, P., Reuter, J. (2019). Heterogeneity in target date funds: Strategic risk-taking or risk matching? *The Review of Financial Studies*, 32(1), 300–337.

Barber, B. M., Huang, X., and Odean, T. (2016). Which factors matter to investors? Evidence from mutual fund flows. *Review of Financial Studies*, 29(10), 2600–2642.

Basak, S., Pavlova, A., & Shapiro, A. (2007). Optimal asset allocation and risk shifting in money management. *The Review of Financial Studies*, 20(5), 1583–1621.

Becker, B., Ivashina, V. (2015). Reaching for yield in the bond market. *The Journal of Finance*, 70(5), 1863–1902.

Ben-David, I., Li, J., Rossi, A., and Song, Y. (2022). Ratings-driven demand and systematic price fluctuations. *Review of Financial Studies*, 35, 2790–2838.

Ben-David, I., Li, J., Rossi, A., Song, Y. (2022). What do mutual fund investors really care about? *The Review of Financial Studies*, 35(4), 1723–1774.

Bengen, W. P. (1994). Determining withdrawal rates using historical data. *Journal of Financial Planning*, 7, 171–180.

Bodie, Z., Merton, R. C., Samuelson, W. F. (1992). Labor supply flexibility and portfolio choice in a life-cycle model. *Journal of Economic Dynamics and Control*, 16(3-4), 427–449.

Bordalo, P., Gennaioli, N., Shleifer, A. (2016). Competition for attention. *The Review of Economic Studies*, 83(2), 481–513.

Brown, D. C., & Davies, S. (2024). Off target: On the underperformance of target-date

funds. *Available at SSRN 3707755*.

Calvet, L. E., Célérier, C., Sodini, P., Vallée, B. (2023). Can security design foster household risk-taking? *The Journal of Finance*, 78(4), 1917–1967.

Campbell, J. Y., Viceira, L. M. (2002). *Strategic Asset Allocation: Portfolio Choice for Long-Term Investors*. Oxford University Press.

Célérier, C., Vallée, B. (2017). Catering to investors through security design: Headline rate and complexity. *The Quarterly Journal of Economics*, 132(3), 1469–1508.

Chevalier, J., Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy*, 105(6), 1167–1200.

Choi, J., Kronlund, M. (2018). Reaching for yield in corporate bond mutual funds. *The Review of Financial Studies*, 31(5), 1930–1965.

Choi, J. J., Laibson, D., Madrian, B. C., Metrick, A. (2004). For better or for worse: Default effects and 401(k) savings behavior. In *Perspectives on the Economics of Aging* (pp. 81–126). University of Chicago Press.

Choi, J. J., Laibson, D., Madrian, B. C. (2009). Reducing the complexity costs of 401(k) participation through quick enrollment. In *Developments in the Economics of Aging* (pp. 57–82). University of Chicago Press.

Cocco, J. F., Gomes, F. J., Maenhout, P. J. (2005). Consumption and portfolio choice over the life cycle. *The Review of Financial Studies*, 18(2), 491–533.

Cortez, B. G., Ivashina, V., Salomao, J. (2025). Performance capital flows in DC pensions. *NBER Working Paper No. w33693*.

Del Guercio, D., and Tkac, P. A. (2002). The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds. *Journal of Financial and Quantitative Analysis*, 37(4), 523–557.

Del Guercio, D., and Tkac, P. A. (2008). Star power: The effect of Morningstar ratings on mutual fund flow. *Journal of Financial and Quantitative Analysis*, 43(4), 907–936.

Di Maggio, M., Kacperczyk, M. (2017). The unintended consequences of the zero lower bound policy. *Journal of Financial Economics*, 123(1), 59–80.

Elton, E. J., Gruber, M. J., De Souza, A., Blake, C. R. (2015). Target date funds: Characteristics and performance. *Review of Asset Pricing Studies*, 5(2), 254–272.

Gabaix, X. (2014). A sparsity-based model of bounded rationality. *Quarterly Journal of Economics*, 129, 1661–1710.

Gaspar, J.-M., Massa, M., Matos, P. (2006). Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization. *The Journal of Finance*, 61(1), 73–104.

Gomes, F., Haliassos, M., Ramadorai, T. (2021). Household finance. *Journal of Economic Literature*, 59(3), 919–1000.

Gomes, F., Peng, C., Smirnova, O., Zhu, N. (2025). Reaching for yield: Evidence from households. *Journal of Financial Economics*, 168, 104057.

Gomes, F., Michaelides, A. (2005). Optimal life-cycle asset allocation: Understanding the empirical evidence. *The Journal of Finance*, 60(2), 869–904.

Gomes, F., Kotlikoff, L. J., Viceira, L. M. (2008). Optimal life-cycle investing with flexible labor supply: A welfare analysis of life-cycle funds. *American Economic Review*, 98(2), 297–303.

Harvey, C. R., Mazzoleni, M., Melone, A. (2025). The unintended consequences of rebalancing. *Fisher College of Business Working Paper No. 2025-03-001.*

Huang, J., Wei, K. D., Yan, H. (2007). Participation costs and the sensitivity of fund flows to past performance. *The Journal of Finance*, 62(3), 1273–1311.

Huang, J., Sialm, C., & Zhang, H. (2011). Risk shifting and mutual fund performance. *The Review of Financial Studies*, 24(8), 2575–2616.

Kahneman, D., Wakker, P. P., Sarin, R. (1997). Back to Bentham? Explorations of experienced utility. *The Quarterly Journal of Economics*, 112(2), 375–406.

Lian, C., Ma, Y., Wang, C. (2019). Low interest rates and risk-taking: Evidence from

individual investment decisions. *The Review of Financial Studies*, 32(6), 2107–2148.

Madrian, B. C., Shea, D. F. (2001). The power of suggestion: Inertia in 401(k) participation and savings behavior. *The Quarterly Journal of Economics*, 116(4), 1149–1187.

Massa, M., Moussawi, R., & Simonov, A. (2020). The unintended consequences of investing for the long run: Evidence from target date funds. *Available at SSRN 3729750*.

Massa, M., & Patgiri, R. (2009). Incentives and mutual fund performance: higher performance or just higher risk taking? *The Review of Financial Studies*, 22(5), 1777–1815.

Merton, R. C. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. *The Review of Economics and Statistics*, 51(3), 247–257.

Parker, J. A., Schoar, A., and Sun, Y. (2023). Retail financial innovation and stock market dynamics: The case of target date funds. *The Journal of Finance*, 78(5), 2673–2723.

Poterba, J. M., Rauh, J., Venti, S. F., and Wise, D. A. (2005). Utility evaluation of risk in retirement savings accounts. In D. A. Wise (Ed.), *Analyses in the Economics of Aging* (pp. 13–52). University of Chicago Press.

Poterba, J. M., Rauh, J., Venti, S. F., and Wise, D. A. (2009). Life-cycle asset allocation strategies and the distribution of 401(k) retirement wealth. In D. A. Wise (Ed.), *Developments in the Economics of Aging* (pp. 15–50). University of Chicago Press.

Reuter, J., and Zitzewitz, E. (2021). How much does size erode mutual fund performance? A regression discontinuity approach. *Review of Finance*, 25, 1395–1432.

Samuelson, P. A. (1969). Lifetime portfolio selection by dynamic stochastic programming. *The Review of Economics and Statistics*, 51(3), 239–246.

Sialm, C., Starks, L. T., and Zhang, H. (2015). Defined contribution pension plans: Sticky or discerning money?. *The Journal of Finance*, 70(2), 805–838.

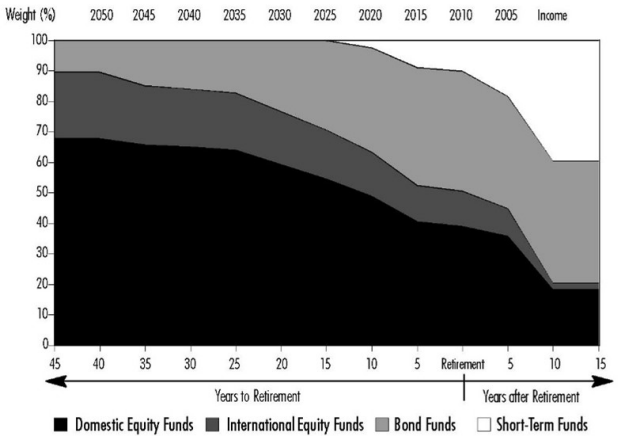
Sirri, E. R., Tufano, P. (1998). Costly search and mutual fund flows. *The Journal of Finance*, 53(5), 1589–1622.

Tang, N., & Lin, Y. T. (2015). The efficiency of target-date funds. *Journal of Asset Man-*

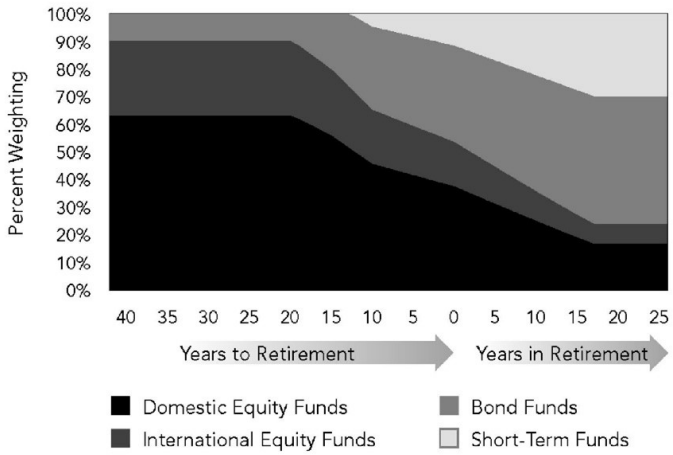
agement, 16(2), 131–148.

Vokata, P. (2023). Salient attributes and household demand for security designs. *Fisher College of Business Working Paper No. 2023-03-007*.

(a) 2010 Glide Path



(b) 2015 Glide Path



(c) 2020 Glide Path

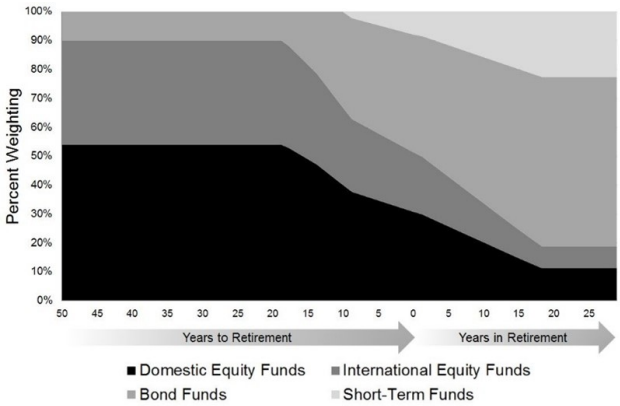


Figure 1: **Prospectus Glide Paths for Fidelity Freedom Funds**
This figure presents excerpts from Fidelity Freedom Fund prospectuses in 2010 (a), 2015 (b), and 2020 (c). The boundary between "International Equity Funds" and "Bond Funds" represents the glide path examined in this paper, corresponding to the total portfolio weight invested in domestic and international equities combined. The illustrations reflect a glide path shift that raised the equity allocation by approximately 10 percentage points at the end of 2013.

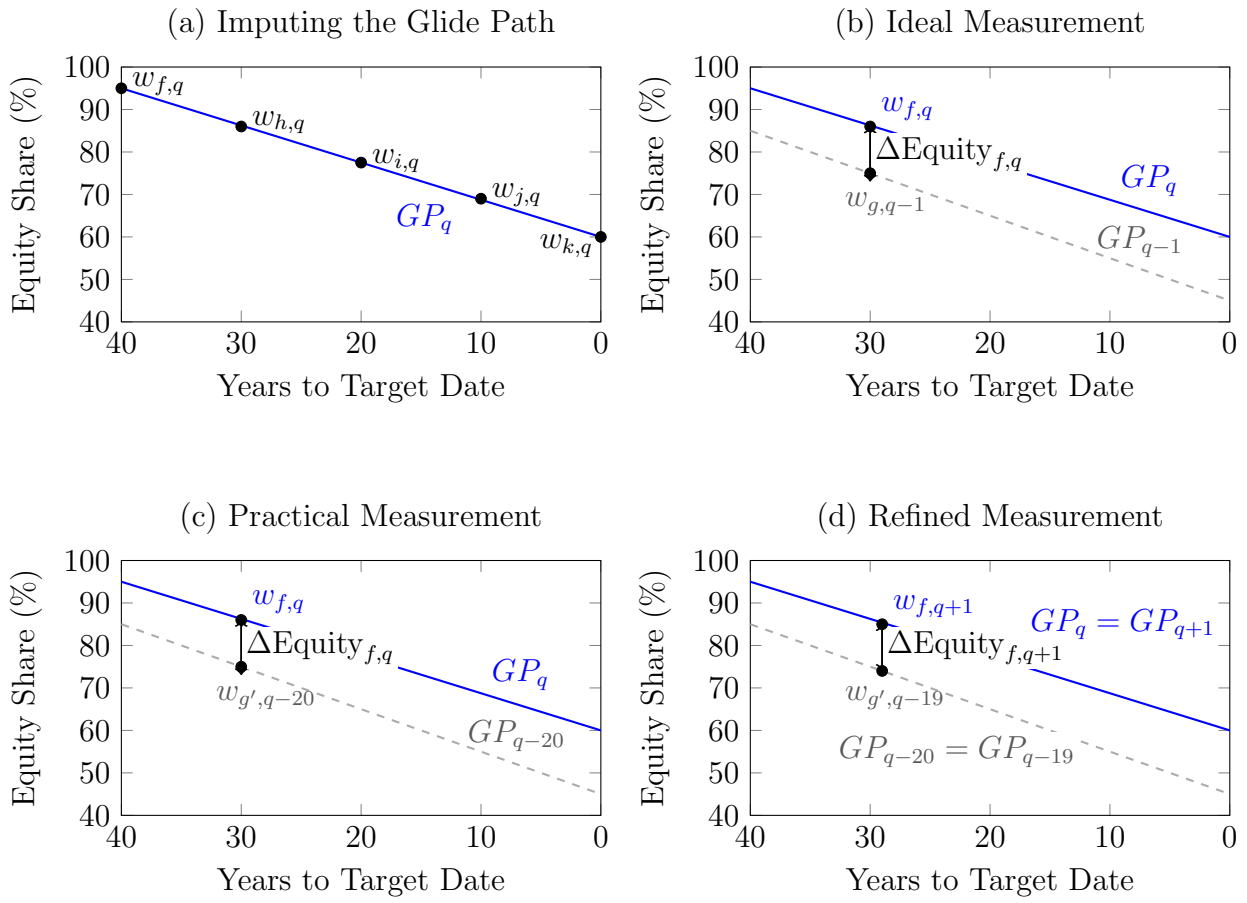


Figure 2: **Measuring Glide Path Shifts**
This figure illustrates the four-step process for measuring a glide path shift for a TDF series. Panel (a) shows how the glide path in quarter q is imputed from the equity weights of the underlying TDFs (f, h, i, j, and k) in the same series. Panel (b) presents the ideal glide path shift measure, defined as the difference between the equity weight of TDF f at time q and that of TDF g at time $q-1$, where the target date of g is one quarter earlier than that of f. Panel (c) describes the practical implementation necessitated by the typical five-year spacing of TDFs, which compares the equity weight of TDF f in quarter q with that of TDF g' twenty quarters (five years) earlier, where the target date of g' is five years earlier than that of f. Panel (d) shows the final, refined measure, which excludes stale shifts and avoids conflating glide path changes with failures to rebalance.

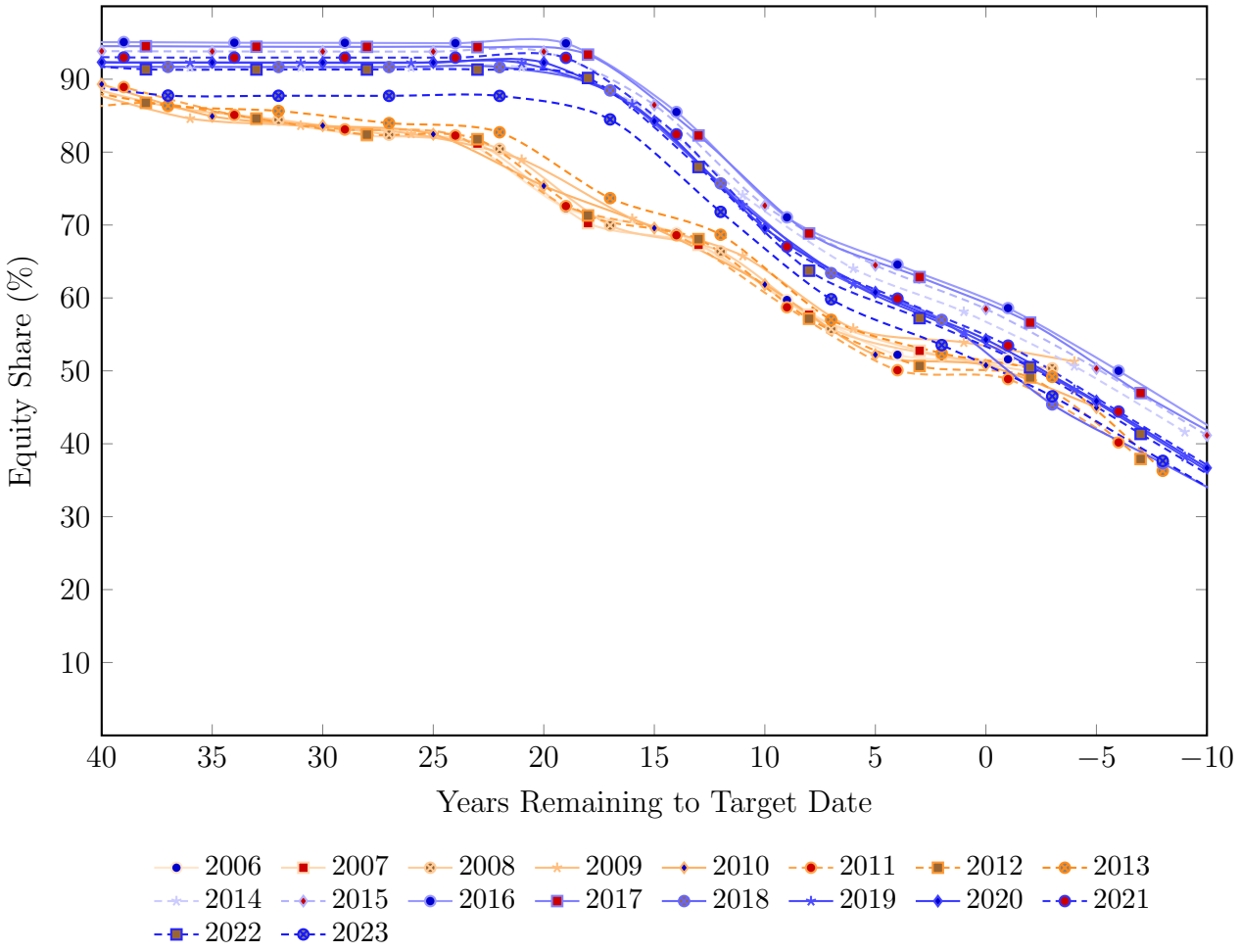


Figure 3: **Historical Glide Paths of *Fidelity Advisor Freedom Funds***
This figure presents the annual historical glide paths of *Fidelity Advisor Freedom Funds* from 2006 to 2023. Each glide path is constructed from the average equity weights (shown as dots) of the underlying TDFs using CRSP holdings data for the corresponding year. Glide paths from 2006 to 2013 are shown in orange, and those from 2014 to 2023 are shown in blue. The sharp increase between 2013 and 2014 reflects a shift in Fidelity's glide path during that period, consistent with the prospectus glide paths shown in Figure 1.

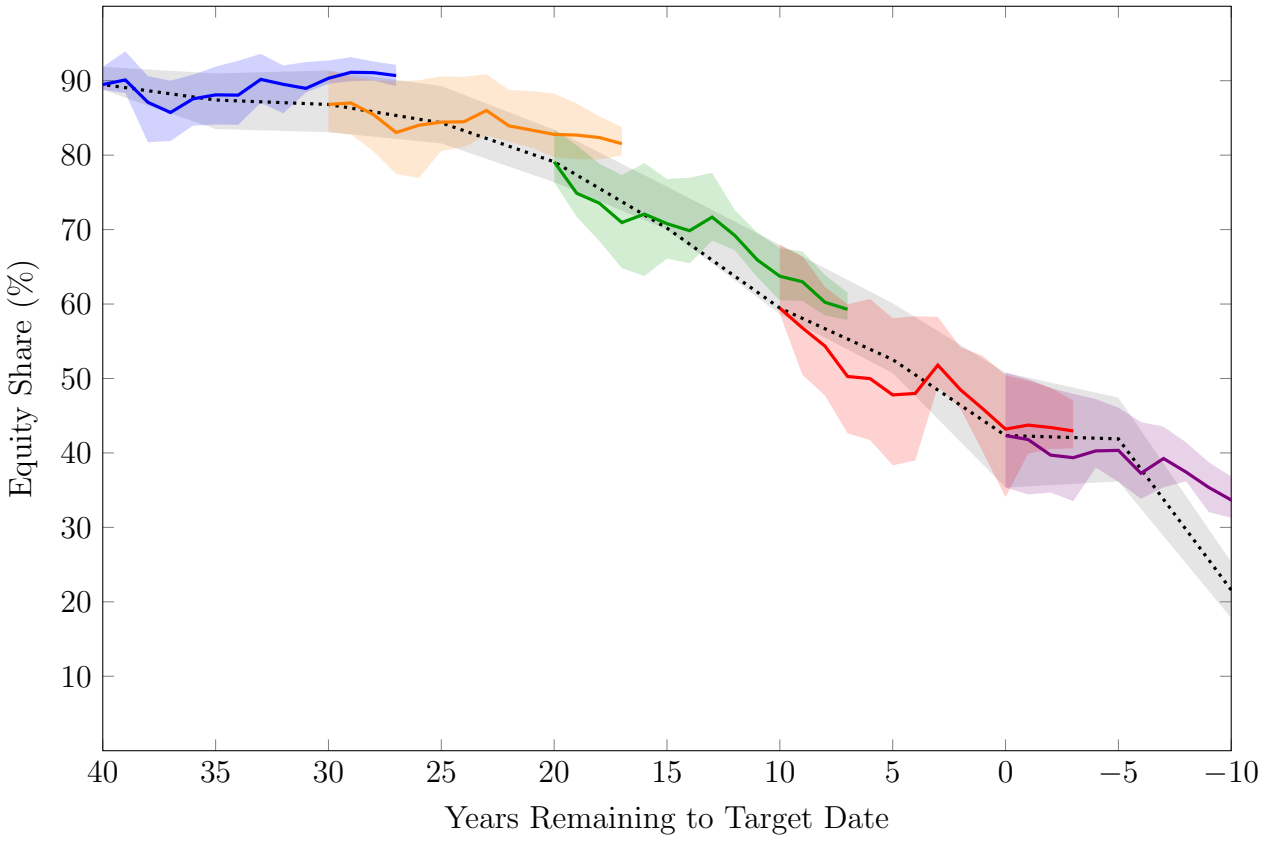


Figure 4: **Pre-determined vs. Realized Glide Paths**
This figure shows the pre-determined and realized glide paths for TDF cohorts. The black dotted line represents the average pre-determined glide path as of 2010. For each target date cohort, the average equity share in 2010 is plotted against the years remaining to the target date. The colored lines trace the realized glide paths for each target date, computed as the cohort's average equity share in each calendar year from 2010 to 2023. Specifically, the blue line corresponds to Target Date 2050, the orange line to Target Date 2040, the green line to Target Date 2030, the red line to Target Date 2020, and the violet line to Target Date 2010. The shaded areas indicate the interquartile range (25th–75th percentile) of equity shares. Divergence between the black line and the colored lines reflects portfolio drift from the 2010 pre-determined path, consistent with glide path shifts over time.

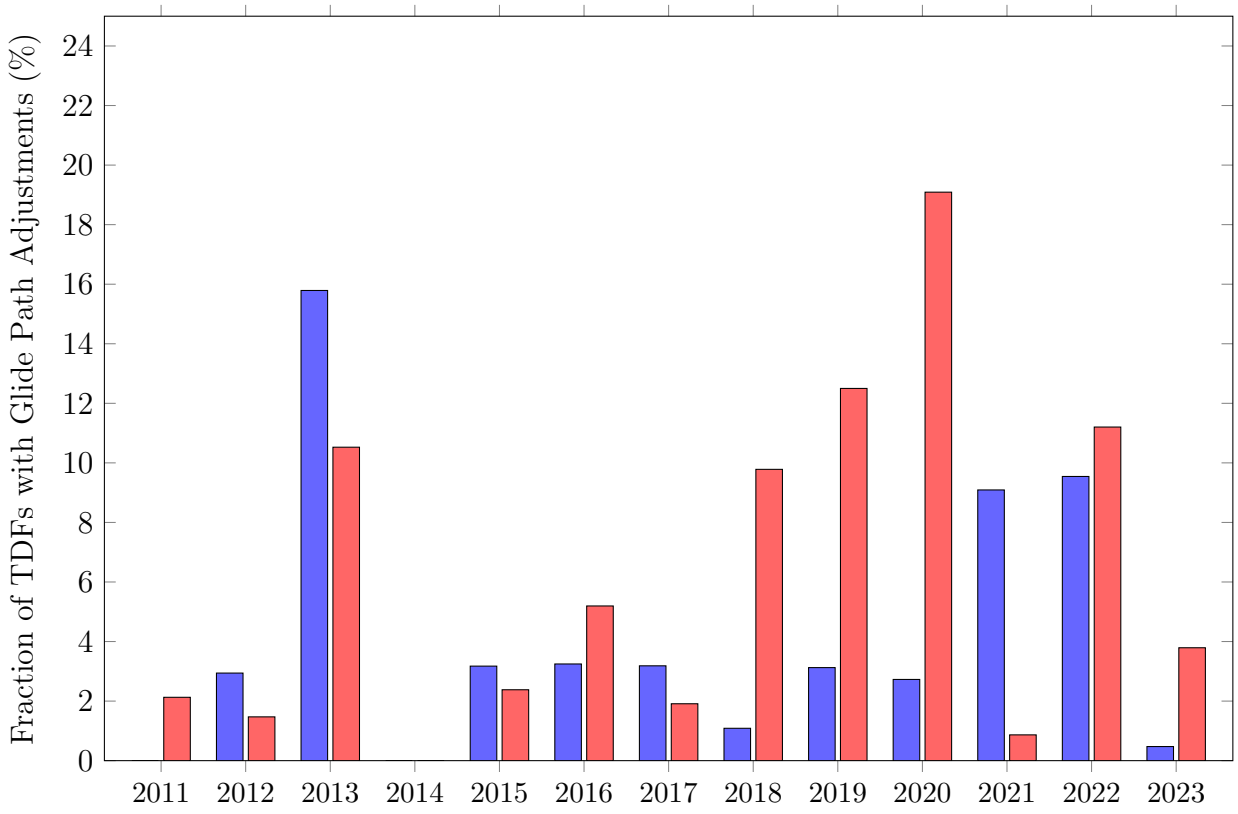


Figure 5: **Trends in Glide Path Adjustments**
This figure shows the annual trend in the percentage of TDFs that made glide path adjustments between 2011 and 2023. The blue bars show the percentage of TDFs that recorded at least one positive glide path shift—an increase in the target equity share—based on $\text{PosShift}_{f,q}$ (Eq. (3)). The red bars show the percentage of TDFs that recorded at least one negative glide path shift— a decrease in the target equity share—based on $\text{NegShift}_{f,q}$ (Eq. (4)).

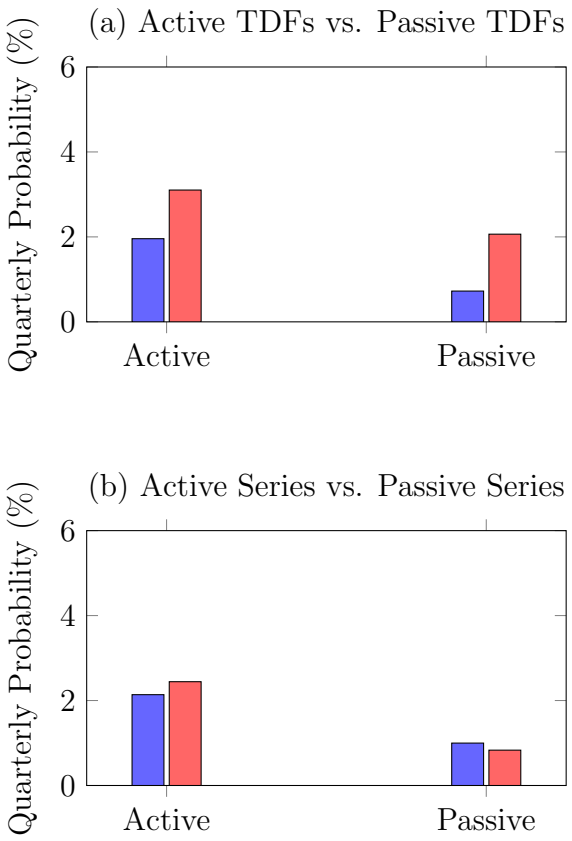


Figure 6: **Glide Path Adjustments: Active TDFs vs. Passive TDFs**
This figure shows the probability of glide path shifts conditional on whether funds (or series) are classified as active or passive. Panel (a) reports fund-level results, and Panel (b) reports series-level results. The blue bars denote the quarterly probability of positive glide path adjustments, while the red bars denote the quarterly probability of negative adjustments. For active TDFs (series), the quarterly probabilities of positive shifts are 2.0% (2.1%) and those of negative shifts are 3.1% (2.4%). For passive TDFs (series), the quarterly probabilities of positive shifts are 0.7% (1.0%) and those of negative shifts are 2.1% (0.8%).

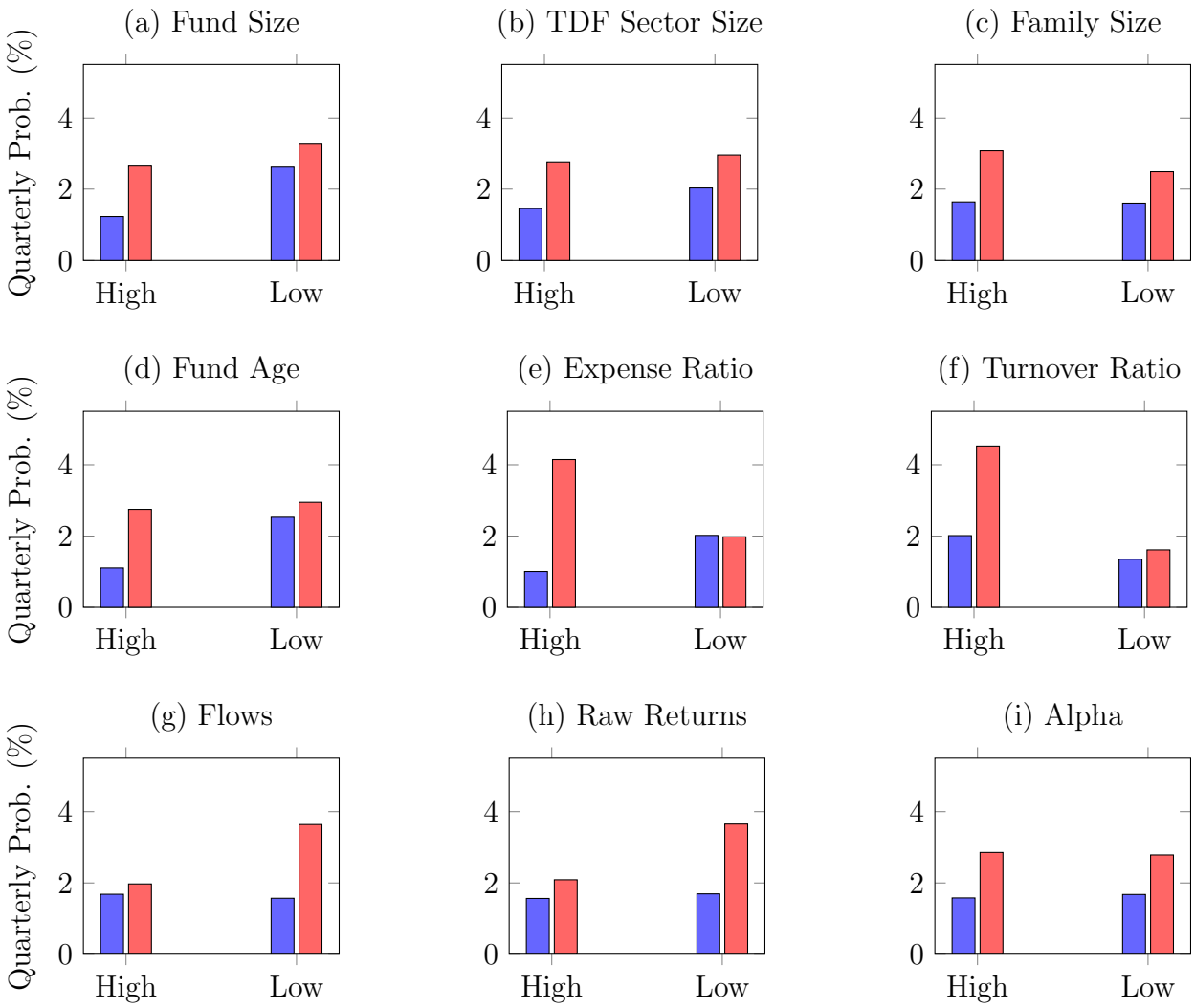


Figure 7: **Glide Path Adjustments Across Fund Characteristics**
This figure presents the probability of glide path shifts for High versus Low groups across several TDF characteristics: (a) Fund Size, (b) TDF Sector Size, (c) Family Size, (d) Fund Age, (e) Expense Ratio, (f) Turnover Ratio, (g) Flows, (h) Raw Returns, and (i) Alpha. The blue bars show the quarterly probability of positive glide path adjustments, while the red bars show the probability of negative adjustments.

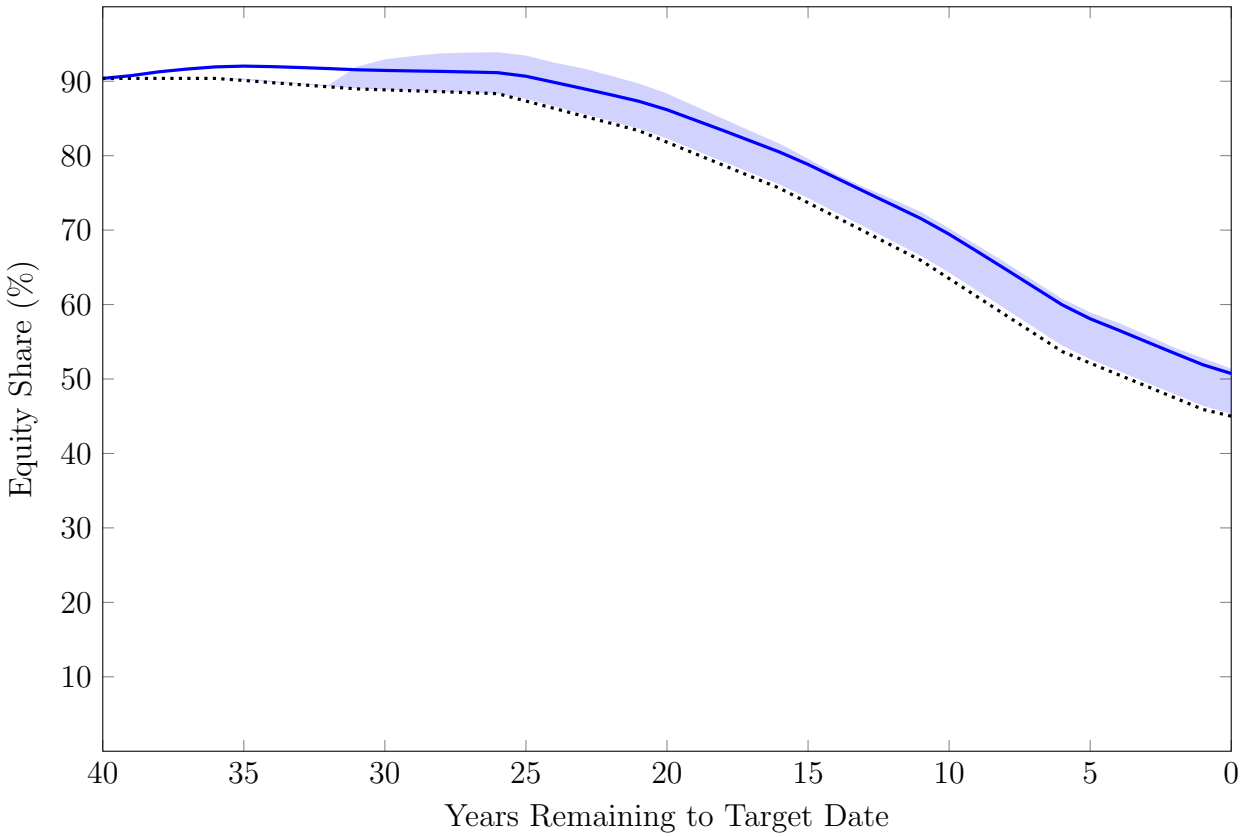


Figure 8: **Baseline vs. Rate-Sensitive Glide Paths**
This figure plots the baseline glide path and the rate-sensitive glide paths from the simulations. The baseline glide path, extrapolated from the 2019 average glide path, is shown as a black dotted line. The mean rate-sensitive glide path across block-bootstrapped interest-rate environments is shown as a blue solid line. The shaded region indicates the interquartile range (25th–75th percentiles) of the rate-sensitive equity share distribution at each remaining-year horizon. On average, the mean rate-sensitive glide path allocates about 3.5 percentage points more to equities than the baseline glide path.

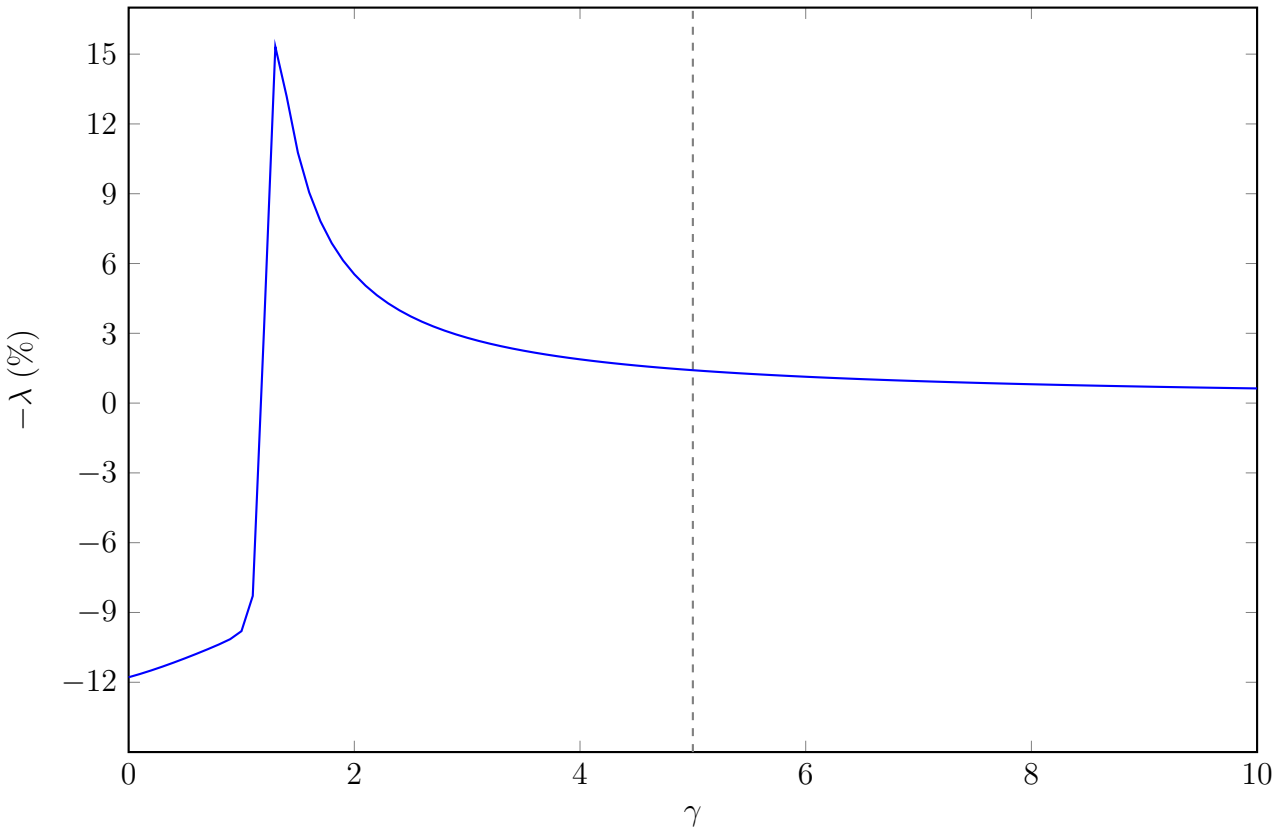


Figure 9: **Welfare Cost by Risk Aversion**
This figure plots $-\lambda$ as a function of the coefficient of relative risk aversion γ, where λ is defined by $CE_{\text{rate}} = (1+\lambda)\, CE_{\text{base}}$. The measure $-\lambda$ represents the welfare loss from the rate-sensitive glide path, interpreted as the proportional increase in baseline retirement consumption required to make households indifferent between the rate-sensitive and baseline policies. The vertical dashed line marks the baseline calibration $\gamma = 5$, under which the implied welfare cost equals 1.41% of retirement consumption.

Table 1: **Summary Statistics**
This table reports summary statistics for the sample, which comprises 46 fund families, 86 TDF series, and 737 individual TDFs, corresponding to 60,261 fund-month observations (Panel A), 8,440 series-month observations (Panel B), 30,771 TDF-month holdings (Panel C), and 16,865 glide path shift observations (Panel D) over the period 2006–2023. TDF characteristics are constructed as follows: *Family TDF TNA* is the sum of the TNAs of all TDFs managed by the same fund family; *Return Volatility* is measured as the standard deviation of raw returns over the previous 12 months; all other variables are constructed in a standard manner. TDF characteristics—including *TNA*, *Family TNA*, *Fund Age*, *Return*, *Flow*, *Expense Ratio*, *Turnover Ratio*, and *Return Volatility*—are winsorized at the 1st and 99th percentiles within each period. TDF series characteristics are computed as follows: *Series TNA* is the sum of the TNAs of the underlying TDFs; *Series Age* is the maximum fund age among the underlying TDFs; and the *Passive Indicator* equals the maximum of the corresponding fund-level indicators. All other variables are calculated as TNA-weighted averages across the constituent TDFs. Glide path shift measures are constructed using portfolio holdings data. See Section 3.2 for further details. *Shift Magnitude* denotes the change in equity allocation resulting from a glide path adjustment, expressed in percentage points. *Average Shift Magnitude* is the mean of the corresponding TDF-level measures.

Panel A. TDF Characteristics

Variable	N	Mean	Std Dev	Min	25th Pctl	Median	75th Pctl	Max
TNA ($ billion)	60,261	2.05	5.20	0.01	0.08	0.33	1.47	52.35
Family TDF TNA ($ billion)	60,261	58.13	97.77	0.03	2.19	14.13	56.55	726.90
Family TNA ($ trillion)	60,261	0.86	1.16	0.00	0.10	0.34	1.01	8.45
Target Year	60,261	2033.13	14.78	2000	2020	2035	2045	2065
Years Until Target Date	60,261	17.14	14.31	-18.00	6.00	17.00	29.00	48.00
Fund Age (years)	60,261	7.81	5.00	0.92	3.95	6.68	10.51	30.76
Quarterly Return (%)	60,261	1.40	6.03	-38.87	-1.02	2.10	4.58	31.81
Quarterly Alpha (%)	60,261	-0.50	1.19	-11.93	-1.17	-0.43	0.20	8.99
Factor Loadings								
CRSP U.S. Market Index	60,261	0.62	0.20	-0.17	0.49	0.67	0.78	1.24
MSCI World ex. U.S. Index	60,261	0.11	0.05	-0.23	0.07	0.10	0.14	0.46
Bloomberg U.S. Agg. Bond Index	60,261	0.23	0.26	-0.30	0.09	0.19	0.33	4.33
Bloomberg Global Agg. ex. U.S. Index	60,261	0.01	0.04	-0.76	-0.02	0.01	0.04	0.53
S&P GSCI Commodity Index	60,261	0.01	0.02	-0.08	-0.01	0.00	0.01	0.30
Quarterly Flow (%)	60,261	3.70	9.82	-75.63	-1.98	2.10	7.56	72.00
Expense Ratio (%)	60,261	0.32	0.27	-0.06	0.11	0.24	0.48	1.41
Turnover Ratio (%)	60,261	31.21	27.47	0.00	14.00	23.00	38.00	210.00
Return Volatility (%)	60,261	3.13	1.64	0.33	1.90	2.83	4.08	10.35
Morningstar Rating	50,403	3.10	1.10	1	2	3	4	5
Passive	60,261	0.24	0.42	0	0	0	0	1
Interest Rate Environment								
10-Year Treasury Yield (%)	60,261	2.47	0.92	0.65	1.83	2.36	2.98	5.10

Table 1: **Summary Statistics (continued)**

Panel B. TDF Series Characteristics

Variable	N	Mean	Std Dev	Min	25th Pctl	Median	75th Pctl	Max
No. of Underlying TDFs	8,440	8.28	2.97	1.00	6.00	9.00	11.00	13.00
Series TNA ($ billion)	8,440	14.66	37.69	0.01	0.46	1.99	8.94	264.13
Series Age (years)	8,440	9.16	6.18	0.92	4.33	7.75	12.55	30.76
Quarterly Return (%)	8,440	1.30	5.90	–38.51	–1.05	2.09	4.42	29.79
Quarterly Alpha (%)	8,440	–0.50	1.19	–8.25	–1.17	–0.44	0.20	8.02
Quarterly Flow (%)	8,440	3.00	8.97	–50.70	–1.98	1.47	5.95	59.82
Expense Ratio (%)	8,440	0.35	0.28	–0.04	0.12	0.27	0.53	1.41
Turnover Ratio (%)	8,440	32.77	28.69	0.31	14.92	24.21	38.34	193.73
Return Volatility (%)	8,440	3.01	1.50	0.33	1.86	2.72	3.90	10.02
Passive	8,440	0.23	0.42	0.00	0.00	0.00	0.00	1.00

Panel C. TDF Holdings

Variable	N	Mean	Std Dev	Min	25th Pctl	Median	75th Pctl	Max
Broad Asset Class								
Equity (%)	30,771	69.97	20.99	0.00	53.62	75.38	89.03	100.00
Bond (%)	30,771	27.04	20.08	0.00	9.91	21.22	42.31	100.00
Other (%)	30,771	2.98	4.63	0.00	0.00	0.43	4.37	20.00
Narrow Asset Class								
Domestic Equity (%)	30,771	45.24	15.64	0.00	33.90	47.71	57.42	100.00
International Equity (%)	30,771	24.81	11.94	0.00	16.87	24.59	31.13	73.68
Corporate Bond (%)	30,771	17.06	14.62	0.00	5.09	12.77	27.63	91.60
Government Bond (%)	30,771	4.14	5.98	0.00	0.00	1.86	5.72	59.07
International Bond (%)	30,771	1.56	2.61	0.00	0.00	0.20	2.07	27.58
Other Bond (%)	30,771	2.01	10.55	0.00	0.00	0.00	0.00	100.00
Cash (%)	30,771	1.30	3.41	0.00	0.00	0.14	1.14	94.60
Other (%)	30,771	2.98	4.63	0.00	0.00	0.43	4.37	20.00

Panel D. Glide Path Shifts

Variable	N	Mean	Std Dev	Min	25th Pctl	Median	75th Pctl	Max
TDF-Level Shift								
Quarterly Shift	16,865	0.06	0.23	0.00	0.00	0.00	0.00	1.00
Quarterly Positive Shift	16,865	0.02	0.13	0.00	0.00	0.00	0.00	1.00
Quarterly Negative Shift	16,865	0.03	0.17	0.00	0.00	0.00	0.00	1.00
Positive Shift Magnitude (%)	274	9.90	4.25	5.06	7.00	8.28	12.33	25.79
Negative Shift Magnitude (%)	476	-9.82	4.95	-29.21	-11.13	-8.19	-6.42	-5.01
TDF Series-Level Shift								
Quarterly Shift	2,238	0.05	0.21	0.00	0.00	0.00	0.00	1.00
Quarterly Positive Shift	2,238	0.02	0.13	0.00	0.00	0.00	0.00	1.00
Quarterly Negative Shift	2,238	0.02	0.14	0.00	0.00	0.00	0.00	1.00
Avg. Positive Shift Magnitude (%)	41	7.17	4.16	3.45	5.19	5.46	5.80	18.78
Avg. Negative Shift Magnitude (%)	45	-9.43	5.71	-27.25	-11.30	-8.08	-5.96	-2.98

Table 2: **Frequency of Glide Path Adjustments Among TDFs**
This table reports the distribution of TDFs by the number of glide path shifts over the period 2011–2023. Panel A presents the distribution at the fund level, and Panel B at the series level. In Panel A, *All Shifts* represents the fraction of funds that have shifted n times over their lifetimes, based on the shift measure $\text{Shift}_{f,q}$ defined in Eq. (2). *Positive (Negative) Shifts* represent the fraction of funds with n upward (downward) lifetime adjustments using $\text{PosShift}_{f,q}$ ($\text{NegShift}_{f,q}$), as defined in Eq. (3) (Eq. (4)). The series-level definitions of these shift measures follow the methodology described in Section 3.2. Overall, 40.1% of TDFs and 44.4% of TDF series adjust their glide paths at least once during their lifetimes.

Panel A: Fund Level

Number of Shifts	All Shifts (%)	Positive Shifts (%)	Negative Shifts (%)
0	59.9	82.8	75.5
1	16.9	10.2	13.8
2	8.6	2.9	5.7
3	6.5	3.4	1.6
4	3.9	0.5	1.8
5	1.8	0.3	1.3
6	1.8	0.0	0.3
7	0.0	0.0	0.0
8	0.3	0.0	0.0
9	0.3	0.0	0.0
Total	100.0	100.0	100.0

Panel B: Series Level

Number of Shifts	All Shifts (%)	Positive Shifts (%)	Negative Shifts (%)
0	55.6	75.6	73.3
1	26.7	17.8	24.4
2	13.3	6.7	0.0
3	2.2	0.0	2.2
4	0.0	0.0	0.0
5	2.2	0.0	0.0
Total	100.0	100.0	100.0

Table 3: **Interest Rates and Glide Path Adjustments**
This table reports coefficient estimates from the panel regressions:

$$\text{PosShift}_{f,t+3} = \alpha + \beta\,\text{Yield}_t + \gamma\,X_{f,t} + \delta_f + \delta_s + \delta_{\text{YTD}} + \varepsilon_{f,t},$$

$$\text{NegShift}_{f,t+3} = \alpha' + \beta'\,\text{Yield}_t + \gamma'\,X_{f,t} + \delta'_f + \delta'_s + \delta'_{\text{YTD}} + \eta_{f,t}.$$

The dependent variable $\text{PosShift}_{f,t+3}$ equals one if fund f increases its equity allocation at any time during the subsequent three months ($t+1$ to $t+3$). $\text{NegShift}_{f,t+3}$ equals one if the fund decreases its equity allocation over the same horizon. The key explanatory variable is the three-month average of the 10-year Treasury yield at time t. Columns (2) and (4) include fund-level controls: log TNA, log family TNA, log fund age, quarterly returns, quarterly flows, expense ratio, turnover ratio, and return volatility. All regressions include fund fixed effects, series fixed effects, and years-to-target date fixed effects. Standard errors are clustered by time, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.:	$\text{PosShift}_{f,t+3}$		$\text{NegShift}_{f,t+3}$	
Yield_t	-1.010***	-1.000***	-0.680	-0.368
	(-3.808)	(-3.835)	(-1.102)	(-0.577)
$X_{f,t}$				
$\text{Log TNA}_{f,t}$		-0.005		0.011
		(-1.104)		(1.551)
$\text{Log Family TNA}_{f,t}$		0.016**		-0.042***
		(2.266)		(-2.843)
$\text{Log Fund Age}_{f,t}$		0.020		-0.089*
		(1.012)		(-1.874)
$\text{Return}_{f,t}$		-0.090**		-0.031
		(-2.406)		(-0.465)
$\text{Flow}_{f,t}$		0.074*		0.112***
		(1.926)		(2.942)
$\text{Expense Ratio}_{f,t}$		-4.626***		2.809
		(-2.786)		(1.265)
$\text{Turnover Ratio}_{f,t}$		0.044***		0.134***
		(2.924)		(4.979)
$\text{Return Volatility}_{f,t}$		-0.132		-0.406
		(-0.710)		(-1.236)
Observations	17,335	17,335	17,335	17,335
Adjusted R^2	0.109	0.115	0.091	0.105
Fund FE	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes
Years to Target Date FE	Yes	Yes	Yes	Yes

Table 4: **Past Flows and Glide Path Shifts**
This table reports coefficient estimates from the panel regressions:

$$\text{PosShift}_{f,t+3} = \alpha + \sum_{k\in\{0,3,6,\ldots,24\}} \beta_k \,\text{Flow}_{f,t-k} + \sum_{k\in\{0,3,6,\ldots,24\}} \gamma_k \,\text{Ret}_{f,t-k} + \delta X_{f,t} + \theta_f + \theta_s + \theta_{t\times\text{TD}} + \varepsilon_{f,t},$$

$$\text{NegShift}_{f,t+3} = \alpha' + \sum_{k\in\{0,3,6,\ldots,24\}} \beta'_k \,\text{Flow}_{f,t-k} + \sum_{k\in\{0,3,6,\ldots,24\}} \gamma'_k \,\text{Ret}_{f,t-k} + \delta' X_{f,t} + \theta'_f + \theta'_s + \theta'_{t\times\text{TD}} + \eta_{f,t}.$$

The dependent variable $\text{PosShift}_{f,t+3}$ equals one if fund f increases its equity allocation at any time between months $t+1$ and $t+3$. $\text{NegShift}_{f,t+3}$ equals one if the fund decreases its equity allocation over the same horizon. Flows and returns are measured at quarterly frequency with lags of 0, 3, 6, ..., 24 months. Coefficient estimates for the lagged quarterly returns are omitted for brevity but are reported in Table B1. Columns (2) and (4) include fund-level controls: log TNA, log family TNA, log fund age, expense ratio, turnover ratio, and return volatility. All regressions include fund fixed effects, series fixed effects, and time-by-target date fixed effects. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.:	$\text{PosShift}_{f,t+3}$		$\text{NegShift}_{f,t+3}$	
Flow_t	0.125***	0.121***	0.078**	0.065*
	(2.809)	(2.843)	(2.080)	(1.669)
Flow_{t-3}	-0.000	-0.000*	0.001	0.000
	(-1.252)	(-1.717)	(1.503)	(0.719)
Flow_{t-6}	-0.000	-0.000*	0.001**	0.000
	(-1.227)	(-1.918)	(1.990)	(1.176)
Flow_{t-9}	-0.000	-0.000	0.001	0.001
	(-1.116)	(-1.239)	(1.474)	(1.427)
Flow_{t-12}	-0.000	-0.000	0.001	0.001**
	(-1.470)	(-1.049)	(1.313)	(2.051)
Flow_{t-15}	-0.001*	-0.001*	0.003	0.003
	(-1.731)	(-1.696)	(1.369)	(1.475)
Flow_{t-18}	-0.006**	-0.006**	0.015	0.013
	(-2.362)	(-2.421)	(1.553)	(1.443)
Flow_{t-21}	-0.005***	-0.005***	0.000	-0.001
	(-2.834)	(-2.811)	(0.217)	(-0.447)
Flow_{t-24}	-0.001**	-0.001**	-0.000	-0.001
	(-2.255)	(-2.250)	(-0.033)	(-0.663)
Observations	16,518	16,518	16,518	16,518
Adjusted R^2	0.120	0.124	0.179	0.190
Controls ($\text{Ret}_{f,t-k}$)	Yes	Yes	Yes	Yes
Controls ($X_{f,t}$)	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes
Time × Target Date FE	Yes	Yes	Yes	Yes

Table 5: **Morningstar Ratings and Glide Path Shifts**
This table reports coefficient estimates from the panel regressions:

$$\text{PosShift}_{f,t+3} = \alpha + \beta\,\text{Rating}_{f,t} + \gamma\,X_{f,t} + \delta_f + \delta_s + \delta_{t\times\text{TD}} + \varepsilon_{f,t},$$

$$\text{NegShift}_{f,t+3} = \alpha' + \beta'\,\text{Rating}_{f,t} + \gamma'\,X_{f,t} + \delta'_f + \delta'_s + \delta'_{t\times\text{TD}} + \eta_{f,t}.$$

The dependent variable $\text{PosShift}_{f,t+3}$ equals one if fund f increases its equity allocation at any time during the subsequent three months ($t+1$ to $t+3$). $\text{NegShift}_{f,t+3}$ equals one if the fund decreases its equity allocation over the same horizon. The key explanatory variable is $\text{Rating}_{f,t}$, which ranges from one to five and corresponds to the fund's Morningstar *star* rating. Columns (2) and (4) include fund-level controls. All regressions include fund fixed effects, series fixed effects, and time-by-target date fixed effects. Standard errors are clustered at the fund level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.:	$\text{PosShift}_{f,t+3}$		$\text{NegShift}_{f,t+3}$	
$\text{Rating}_{f,t}$	-0.009***	-0.011***	0.000	-0.001
	(-3.485)	(-3.805)	(0.128)	(-0.214)
$X_{f,t}$				
Log $\text{TNA}_{f,t}$		-0.003		0.008
		(-0.535)		(1.172)
Log Family $\text{TNA}_{f,t}$		0.009		-0.024**
		(0.955)		(-2.048)
Log Fund $\text{Age}_{f,t}$		-0.039		-0.079
		(-1.021)		(-1.274)
Raw $\text{Return}_{f,t}$		0.437		0.001
		(1.316)		(0.003)
$\text{Alpha}_{f,t}$		-0.714**		0.232
		(-2.065)		(0.657)
$\text{Flow}_{f,t}$		0.142***		0.067*
		(3.360)		(1.790)
Expense $\text{Ratio}_{f,t}$		-2.497**		1.639
		(-2.233)		(0.858)
Turnover $\text{Ratio}_{f,t}$		0.033**		0.118***
		(2.358)		(4.587)
Return $\text{Volatility}_{f,t}$		-0.744		0.288
		(-0.745)		(0.220)
Observations	16,544	16,544	16,544	16,544
Adjusted R^2	0.107	0.112	0.181	0.190
Fund FE	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes
Time × Target Date FE	Yes	Yes	Yes	Yes

Table 6: **Flows, Interest Rates, and Glide Path Adjustments**
This table reports coefficient estimates from the panel regressions:

$$\text{PosShift}_{f,t+3} = \alpha + \beta\,\text{Flow}_{f,t} + \tau\,\text{Yield}_t + \phi\,(\text{Flow}_{f,t} \times \text{Yield}_t) + \gamma\,X_{f,t} + \delta_f + \delta_s + \delta_{\text{YTD}} + \varepsilon_{f,t},$$

$$\text{NegShift}_{f,t+3} = \alpha' + \beta'\,\text{Flow}_{f,t} + \tau'\,\text{Yield}_t + \phi'\,(\text{Flow}_{f,t} \times \text{Yield}_t) + \gamma'\,X_{f,t} + \delta'_f + \delta'_s + \delta'_{\text{YTD}} + \eta_{f,t}.$$

The dependent variable $\text{PosShift}_{f,t+3}$ equals one if fund f increases its equity allocation during the next three months ($t+1$ to $t+3$), and $\text{NegShift}_{f,t+3}$ equals one if it decreases its equity allocation. The key explanatory variables are $\text{Flow}_{f,t}$, the net flow of fund f over the previous 36 months, Yield_t, the quarterly average 10-year Treasury yield, and their interaction. Columns (2) and (4) include fund-level controls. All regressions include fund, series, and years-to-target date fixed effects. Standard errors are clustered at the fund level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.:	$\text{PosShift}_{f,t+3}$		$\text{NegShift}_{f,t+3}$	
$\text{Flow}_{f,t} \times \text{Yield}_t$	0.015**	0.016**	0.008	0.011**
	(2.215)	(2.385)	(1.520)	(2.116)
$\text{Flow}_{f,t}$	-0.000**	-0.001**	-0.000	-0.000
	(-2.199)	(-2.464)	(-0.848)	(-1.382)
Yield_t	-1.013***	-1.042***	-0.860**	-0.462
	(-4.616)	(-4.051)	(-2.439)	(-1.368)
$X_{f,t}$				
Log $\text{TNA}_{f,t}$		-0.006		0.009
		(-1.051)		(1.320)
Log Family $\text{TNA}_{f,t}$		0.016**		-0.042***
		(2.005)		(-3.831)
Log Fund $\text{Age}_{f,t}$		-0.011		-0.057
		(-0.327)		(-1.289)
Expense $\text{Ratio}_{f,t}$		-5.251***		3.333
		(-3.976)		(1.597)
Turnover $\text{Ratio}_{f,t}$		0.046***		0.143***
		(3.094)		(5.057)
Return $\text{Volatility}_{f,t}$		-0.152		-0.391**
		(-0.776)		(-2.231)
Observations	16,582	16,582	16,582	16,582
Adjusted R^2	0.110	0.117	0.089	0.104
Fund FE	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes
Years to Target Date FE	Yes	Yes	Yes	Yes

Table 7: **Morningstar Ratings, Interest Rates, and Glide Path Adjustments**
This table reports coefficient estimates from the panel regressions:

$$\text{PosShift}_{f,t+3} = \alpha + \beta\,(\text{Rating}_{f,t} \times \text{Yield}_t) + \tau\,\text{Rating}_{f,t} + \phi\,\text{Yield}_t + \gamma\,X_{f,t} + \delta_f + \delta_s + \delta_{\text{YTD}} + \varepsilon_{f,t},$$

$$\text{NegShift}_{f,t+3} = \alpha' + \beta'\,(\text{Rating}_{f,t} \times \text{Yield}_t) + \tau'\,\text{Rating}_{f,t} + \phi'\,\text{Yield}_t + \gamma'\,X_{f,t} + \delta'_f + \delta'_s + \delta'_{\text{YTD}} + \eta_{f,t}.$$

The dependent variable $\text{PosShift}_{f,t+3}$ equals one if fund f increases its equity allocation during the next three months ($t+1$ to $t+3$), and $\text{NegShift}_{f,t+3}$ equals one if it decreases its equity allocation. The key explanatory variables are the Morningstar *star* rating $\text{Rating}_{f,t}$, the quarterly average 10-year Treasury yield Yield_t, and their interaction. Columns (2) and (4) include fund-level controls. All regressions include fund, series, and years-to-target-date fixed effects. Standard errors are clustered at the fund level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.:	$\text{PosShift}_{f,t+3}$		$\text{NegShift}_{f,t+3}$	
$\text{Rating}_{f,t} \times \text{Yield}_t$	0.295*	0.267	-0.261	-0.372
	(1.792)	(1.562)	(-0.947)	(-1.437)
$\text{Rating}_{f,t}$	-0.015***	-0.016***	0.009	0.010*
	(-3.351)	(-3.289)	(1.446)	(1.707)
Yield_t	-1.989***	-1.880***	0.055	0.812
	(-3.263)	(-2.893)	(0.051)	(0.805)
$X_{f,t}$				
Log $\text{TNA}_{f,t}$		-0.005		0.008
		(-0.897)		(1.274)
Log Family $\text{TNA}_{f,t}$		0.017**		-0.042***
		(2.183)		(-3.939)
Log Fund $\text{Age}_{f,t}$		0.004		-0.056
		(0.145)		(-1.262)
$\text{Return}_{f,t}$		-0.095***		-0.024
		(-2.952)		(-0.937)
$\text{Flow}_{f,t}$		0.107***		0.066*
		(2.734)		(1.902)
Expense $\text{Ratio}_{f,t}$		-3.839***		3.102
		(-3.358)		(1.488)
Turnover $\text{Ratio}_{f,t}$		0.043***		0.143***
		(2.981)		(5.108)
Return $\text{Volatility}_{f,t}$		-0.205		-0.394**
		(-1.072)		(-2.305)
Observations	16,682	16,682	16,682	16,682
Adjusted R^2	0.105	0.111	0.089	0.103
Fund FE	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes
Years-to-Target-Date FE	Yes	Yes	Yes	Yes

Table 8: **Exogenous Flows and Glide Path Adjustments**
This table reports coefficient estimates from difference-in-differences panel regressions using rating-induced flow shocks. The estimation sample consists of funds that reach the five-year mark, using a one-year pre-period and a one-year post-period.

$$\begin{aligned}\text{PosShift}_{f,t} = \alpha + \beta \left(\text{MRAR[-59,-36]}_{f,t} \times \text{Post5yr}_{f,t}\right) \\ + \theta\, \text{MRAR[-59,-36]}_{f,t} + \phi\, \text{Post5yr}_{f,t} + \gamma\, X_{f,t} + \delta_f + \delta_t + \varepsilon_{f,t}.\end{aligned}$$

$$\begin{aligned}\text{NegShift}_{f,t} = \alpha' + \beta' \left(\text{MRAR[-59,-36]}_{f,t} \times \text{Post5yr}_{f,t}\right) \\ + \theta'\, \text{MRAR[-59,-36]}_{f,t} + \phi'\, \text{Post5yr}_{f,t} + \gamma'\, X_{f,t} + \delta'_f + \delta'_t + \eta_{f,t}.\end{aligned}$$

The dependent variable in Columns (1)–(2) is $\text{PosShift}_{f,t}$, an indicator equal to one if fund f increases its equity share (a positive glide path shift) at time t. Columns (3)–(4) use $\text{NegShift}_{f,t}$, an indicator for a decrease in the equity share. $\text{MRAR[-59,-36]}_{f,t}$ is the percentile rank of Morningstar's risk-adjusted return (MRAR) measured 59–36 months before the five-year mark within the fund's target-date peer group; this stale performance affects the overall rating mechanically at age five but is orthogonal to contemporaneous portfolio decisions. $\text{Post5yr}_{f,t}$ equals one in the month a fund turns five and thereafter. Columns (2) and (4) include fund-level controls: log TNA, log family TNA, log fund age, quarterly raw return, quarterly flow, expense ratio, turnover ratio, and return volatility. All regressions include fund and time fixed effects. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.:	$\text{PosShift}_{f,t}$		$\text{NegShift}_{f,t}$	
$\text{MRAR[-59,-36]}_f \times \text{Post5yr}_{f,t}$	-0.386*	-0.540*	0.081	-0.068
	(-1.810)	(-1.956)	(1.359)	(-0.741)
MRAR[-59,-36]_f	-0.001	0.160	0.064	0.118*
	(-0.006)	(0.907)	(1.434)	(1.994)
$\text{Post5yr}_{f,t}$	0.260*	0.230	-0.068	0.001
	(1.905)	(1.694)	(-1.476)	(0.021)
Observations	282	282	282	282
Adjusted R^2	0.350	0.375	0.586	0.610
Controls	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table 9: **Flow–Performance Sensitivity of TDF Investors**
The table reports coefficient estimates from Fama-MacBeth regressions:

$$\text{Flow}_{f,t+1} = \alpha + \beta\,\text{RawRet}_{f,t} + \gamma\,\text{AbnormalRet}_{f,t} + \delta X_{f,t} + \varepsilon_{f,t},$$

where $\text{Flow}_{f,t+1}$ is next-month net flow for fund f. $\text{RawRet}_{f,t}$ denotes the fund's excess return over the risk-free rate. $\text{AbnormalRet}_{f,t}$ is computed as a monthly five-factor alpha based on the preceding 12 months of daily returns. The five-factor model includes daily returns on the CRSP U.S. Value-Weighted Market Index, MSCI World Index excluding the United States, Bloomberg U.S. Aggregate Bond Index, Bloomberg Global Aggregate ex-USD Index, and the S&P GSCI Commodity Index. $X_{f,t}$ includes log fund TNA, log family TNA, log fund age, expense ratio, turnover ratio, and return volatility. The number of groups corresponds to the number of monthly cross-sectional regressions. R^2 values report the average cross-sectional R^2 from the monthly regressions. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dep. Var.: $\text{Flow}_{f,t+1}$		
$\text{Raw Return}_{f,t}$	0.730***	0.783*
	(2.959)	(1.744)
$\text{Abnormal Return}_{f,t}$	0.105	0.080
	(0.324)	(0.194)
$X_{f,t}$		
$\text{Log TNA}_{f,t}$		-0.003**
		(-2.477)
$\text{Log Family TNA}_{f,t}$		0.003***
		(4.643)
$\text{Log Fund Age}_{f,t}$		-0.028***
		(-10.614)
$\text{Expense Ratio}_{f,t}$		-0.111
		(-0.146)
$\text{Turnover Ratio}_{f,t}$		-0.022***
		(-4.036)
$\text{Return Volatility}_{f,t}$		0.068
		(0.153)
Observations	60,013	60,013
Number of groups	216	216
R-squared	0.069	0.268

Table 10: **TDF Replacement Decisions of 401(k) Sponsors**
The table reports coefficient estimates from the linear probability model:

$$\text{Replace}_{i,t+1} = \alpha + \beta\,\text{PerformanceRank}_{i,t} + \gamma X_{i,t} + \delta_i + \delta_t + \varepsilon_{i,t},$$

where $\text{Replace}_{i,t+1}$ equals one if plan i drops a TDF series in year $t+1$. $\text{PerformanceRank}_{i,t}$ denotes the average performance rank of the underlying TDFs in year t, based on annual raw returns or annual alpha in year t. Performance ranks are computed within peer groups of TDFs sharing the same target date. Column (1) uses raw-return ranks, and Column (2) uses alpha ranks. $X_{i,t}$ includes plan age, log plan size, log average account size, the number of funds offered in the plan, and the number of investment options. All regressions include plan fixed effects and year fixed effects. Standard errors are clustered at the plan level. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dep. Var.: $\text{Replace}_{i,t+1}$	Raw Return Rank	Alpha Rank
$\text{Performance Rank}_{i,t}$	-0.066**	-0.052
	(-2.151)	(-1.600)
$X_{i,t}$		
$\text{Plan Age}_{i,t}$	-0.002	-0.002
	(-0.391)	(-0.379)
$\text{Log Plan Size}_{i,t}$	-0.059*	-0.059*
	(-1.952)	(-1.941)
$\text{Log Avg. Account Size}_{i,t}$	0.047	0.047
	(1.009)	(0.993)
$\text{Number of Funds}_{i,t}$	0.002	0.002
	(1.409)	(1.304)
$\text{Log Option Size}_{i,t}$	-0.006	-0.006
	(-0.751)	(-0.747)
Observations	4,133	4,133
Adjusted R^2	0.127	0.126
Controls	Yes	Yes
Plan FE	Yes	Yes
Year FE	Yes	Yes

Appendix A Data Construction

Table A1: **List of Target Date Fund Series**
This table lists the TDF series included in the final sample, ranked by their latest available TNA at the series level. Series names were initially generated using ChatGPT-5 from historical fund names of potential TDF candidates and subsequently verified through manual review. Each TDF series is uniquely defined such that its underlying funds do not share overlapping *crsp_cl_grp* identifiers with those of another series. Only series that satisfy the filtering criteria described in Section 3 remain in the list. Because the identification relies on historical fund names, the reported series names may not correspond to their most recent branding.

TDF Series	TNA ($ billions)	TDF Series	TNA ($ billions)
American Funds Target Date Retirement	258.51	Ing Retirement Solution	0.78
Fidelity Freedom	188.71	Guidestone MyDestination	0.59
Fidelity Freedom Index	138.36	Great–West Lifetime I	0.57
Vanguard Institutional Target Retirement	113.92	Franklin LifeSmart	0.55
T Rowe Price Retirement	82.34	Manning & Napier Target Series Target	0.46
Vanguard Target Retirement	70.04	BMO Target Retirement	0.43
T Rowe Price Retirement I	64.24	Deutsche LifeCompass	0.40
BlackRock LifePath Index	60.38	PGIM Target	0.34
TIAA–CREF Lifecycle Index	53.85	Transamerica ClearTrack	0.33
TIAA–CREF Lifecycle	35.10	Russell Strategy	0.32
JPMorgan I Smartretirement	24.40	Great–West Securefoundation Lifetime	0.27
Principal LifeTime	22.41	AllianzGI Retirement	0.24
Fidelity Advisor Freedom	18.93	AIM Balanced–Risk Retirement	0.22
State Street Target	15.69	One Choice Blend+	0.21
JPMorgan I Smartretirement Blend	15.14	Columbia Retirement Plus	0.21
Fidelity Advisor Freedom Blend	13.04	Zero Coupon	0.18
One Choice	11.02	Invesco Peak Retirement	0.17
Kp Retirement Path	10.63	John Hancock Ret. Living Through II	0.16
State Farm LifePath	8.94	Harbor Target Retirement	0.15
Massmutual Select T Rowe Price Ret.	6.97	NestEgg	0.14
Great–West Lifetime II	6.44	T Rowe Price Retirement Income	0.14
Great–West Lifetime III	6.30	BlackRock LifePath Active	0.14
John Hancock Retirement	5.65	db X–trackers Target Date	0.14
Vantagepoint Milestone	4.72	PIMCO RealPath	0.14
Schwab Target Index	4.57	Natixis Sustainable Future	0.13
Schwab Target	4.33	Seligman TargetFund	0.10
Principal LifeTime Hybrid	4.08	Fidelity Advisor Simplicity RMD	0.10
USAA Target Retirement	3.73	iShares S&P Target Date	0.09
T Rowe Price Target	3.64	Wells Fargo Dynamic Target	0.07
MFS LifeTime	3.54	Fidelity Flex Freedom	0.06
PIMCO RealPath Blend	3.01	Fidelity Advisor Managed Retirement	0.06
Wells Fargo LifePath	2.33	Goldman Sachs Target Date	0.06
AB Retirement Strategy	1.37	Putnam Retirement	0.04
Massmutual Retiresmart	1.28	DWS Target	0.04
John Hancock Retirement Living Through	1.24	Federated Target	0.04
Barclays Global Investors LifePath	1.20	Goldman Sachs Retirement Strategy	0.04
Nationwide Destination	1.16	1290 Retirement	0.03
MainStay Retirement	1.01	John Hancock Retirement Income	0.03
Hartford Target Retirement	1.00	JPMorgan IV Smartretirement Blend	0.01
Putnam RetirementReady	0.99	Fidelity Advisor Income Replacement	0.01
AB Multi–Manager Select	0.98	PNC Target	0.01
T Rowe Price Retirement Blend	0.96	Legg Mason Target Retirement	0.01
Oppenheimer Transition	0.80	Columbia Adaptive Retirement	0.01

Table A2: **Description of Broad and Narrow Asset Classifications**
This table describes the rules used to assign individual holdings to narrow and broad asset categories. The Narrow Asset Class divides holdings into Domestic Equity, International Equity, Corporate Bond, Government Bond, International Bond, Other Bond, Cash, and Other based on fund or security characteristics. The Broad Asset Class aggregates these categories into three main groups: Equity, Bond, and Other. Portfolio weights for each narrow and broad category are computed in each period when fund-level holdings are available.

Description	**Narrow Asset Class**	**Broad Asset Class**
CRSP objective code begins with "ED"	Domestic Equity	Equity
PERMNO available	Domestic Equity	Equity
CRSP objective code begins with "EF"	International Equity	Equity
CRSP objective code begins with "IC"	Corporate Bond	Bond
Lipper objective code $\in$ {A, BBB, HY, SII, SID, IID}	Corporate Bond	Bond
CRSP objective code begins with "IG"	Government Bond	Bond
CRSP objective code begins with "IF"	International Bond	Bond
Bond coupon rate or date of bond maturity is available	Other Bond	Bond
CRSP objective code begins with "IM"	Cash	Bond
Security name contains "CASH" or "REPO" & (number of shares $-$ market value)/market value < 0.10	Cash	Bond
Otherwise	Other	Other

Appendix B Robustness Check

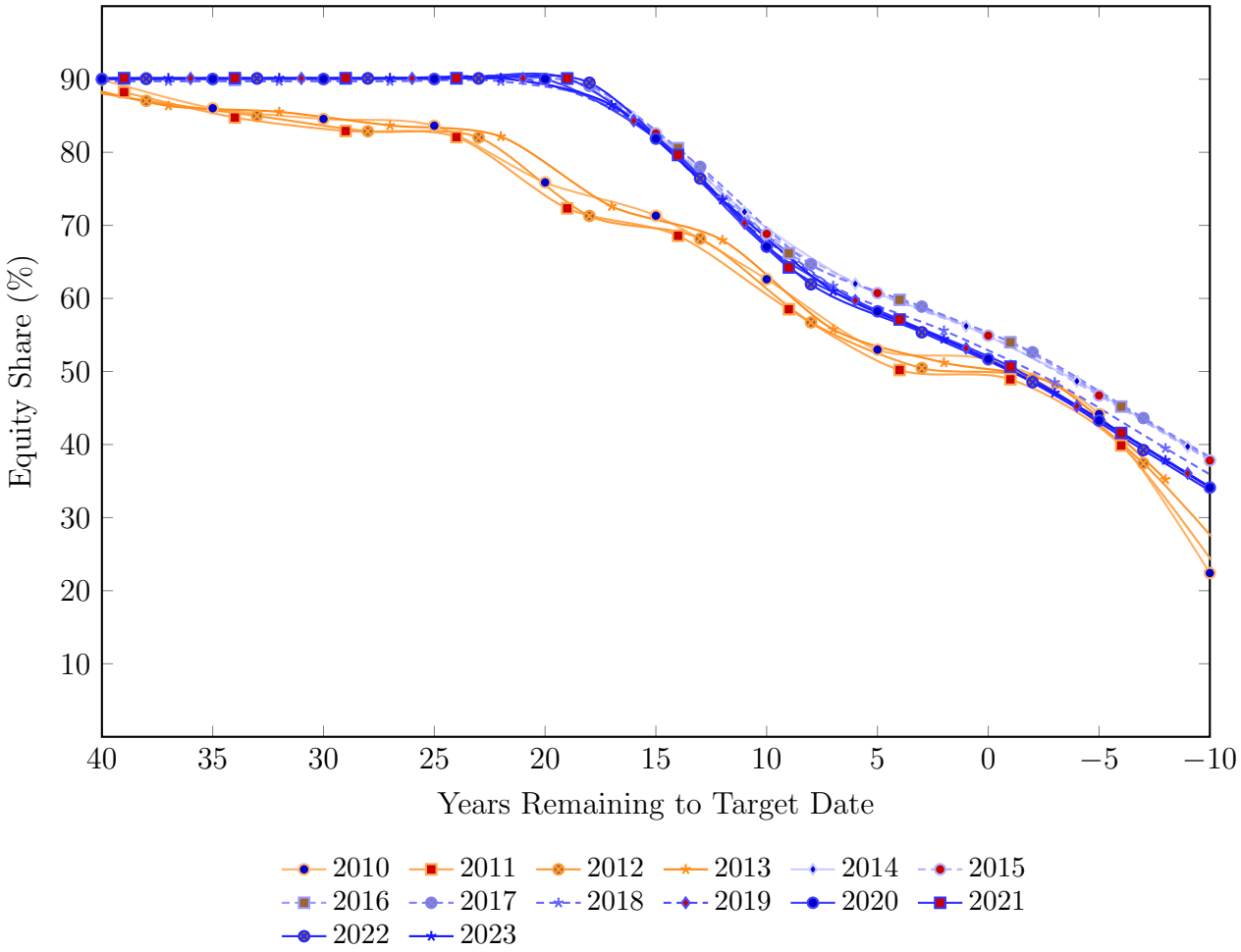


Figure B1: **Historical Glide Paths of *Fidelity Freedom Index Funds***
This figure presents the annual historical glide paths of *Fidelity Freedom Index Funds* from 2010 to 2023. Each glide path is constructed from the average equity weights of the underlying TDFs using CRSP holdings data for the corresponding year. Glide paths from 2010 to 2013 are shown in orange, and those from 2014 to 2023 are shown in blue. The sharp increase between 2013 and 2014 reflects a shift in Fidelity's glide path during that period.

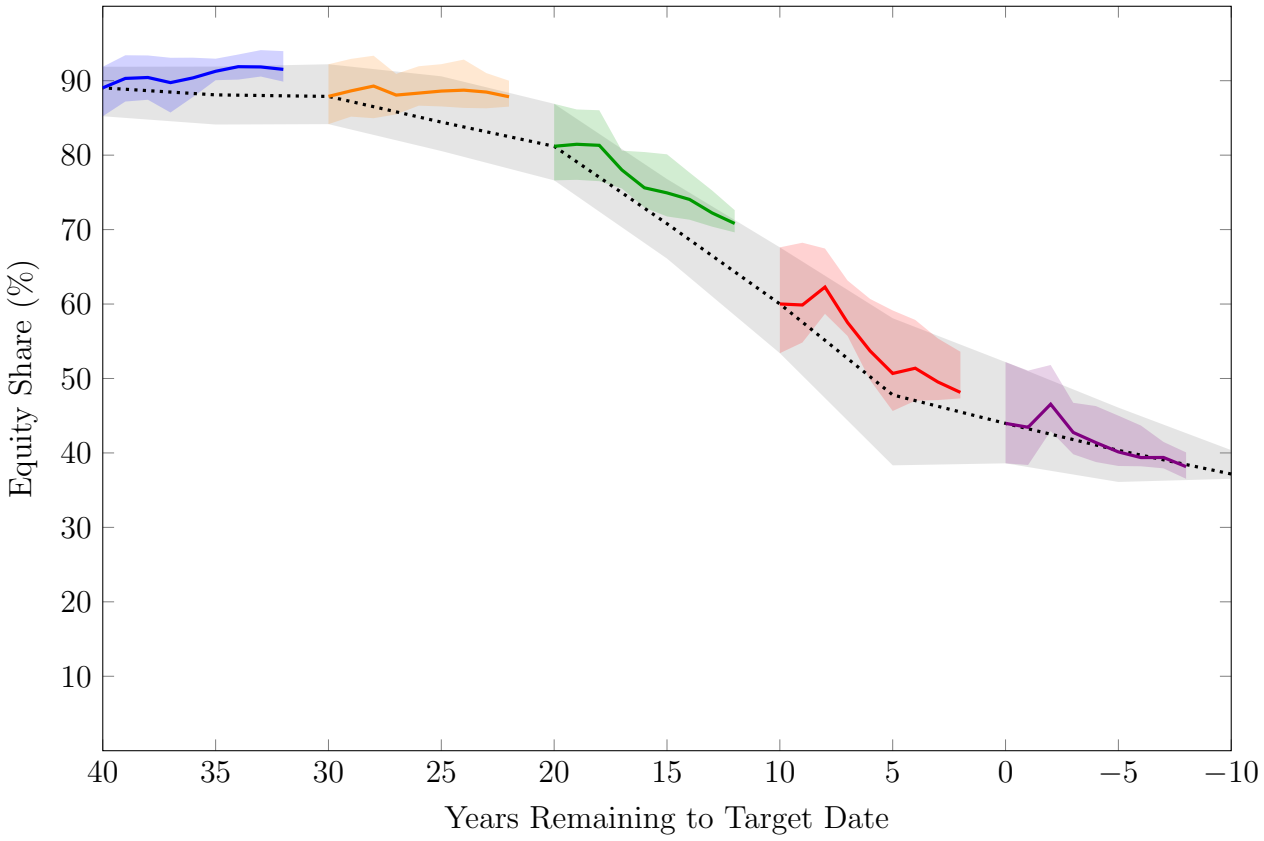


Figure B2: **Pre-determined vs. Realized Glide Paths (2015 Baseline)**
This figure shows the pre-determined and realized glide paths for TDF cohorts. The black dotted line represents the average pre-determined glide path as of 2015. For each target date cohort, the average equity share in 2015 is plotted against the years remaining to the target date. The colored lines trace the realized glide paths for each target date, computed as the cohort's average equity share in each calendar year from 2015 to 2023. Specifically, the blue line corresponds to Target Date 2055, the orange line to Target Date 2045, the green line to Target Date 2035, the red line to Target Date 2025, and the violet line to Target Date 2015. The shaded areas indicate the interquartile range (25th–75th percentile) of equity shares. Divergence between the black line and the colored lines reflects portfolio drift from the 2015 pre-determined path, consistent with glide path shifts over time.

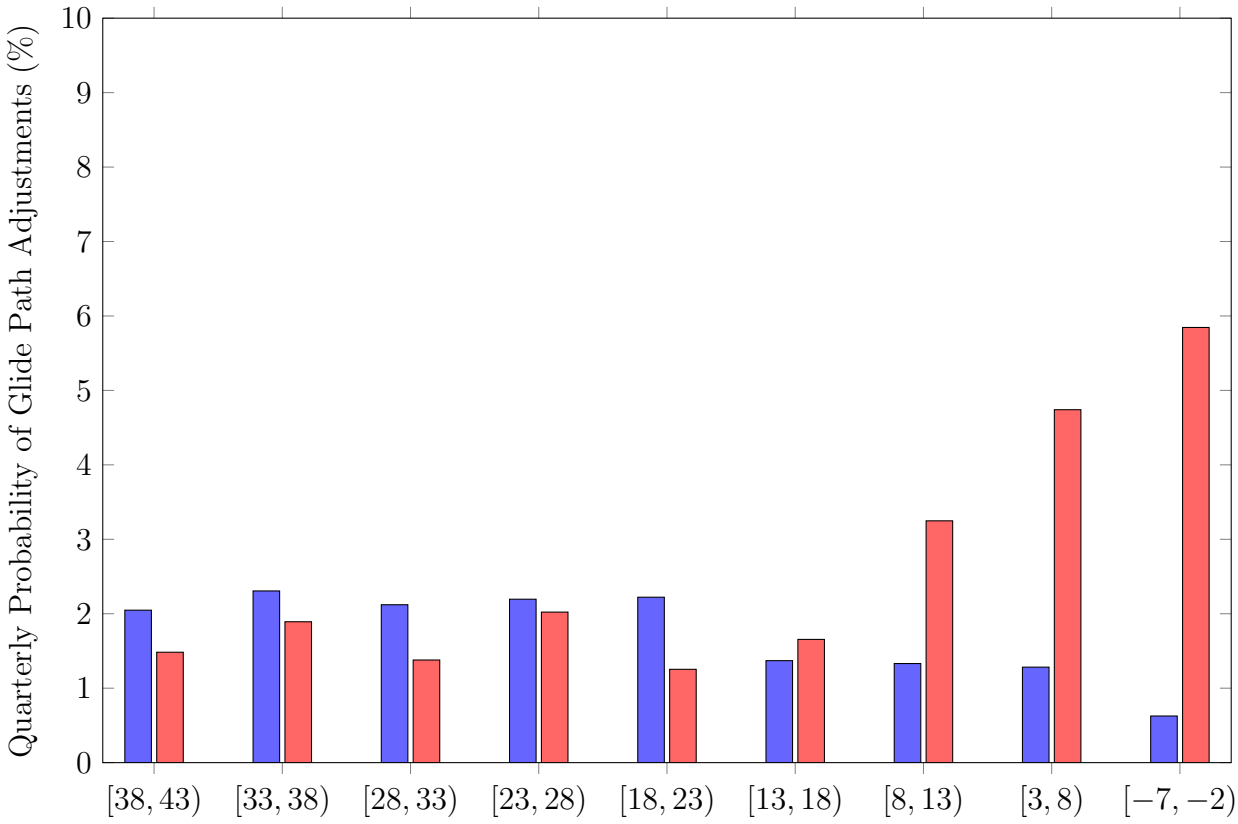


Figure B3: **Glide Path Adjustments by Years to Target Date**
This figure shows the quarterly probability of glide path adjustments by remaining years until retirement. The horizontal axis displays bins of remaining years (e.g., $[-7, -2)$ represents 7–2 years before retirement, and $[3, 8)$ represents 3–8 years after retirement). The blue bars show the quarterly probability of positive glide path shifts within each bin, measured by $\text{PosShift}_{f,q}$ (Eq. (3)), and the red bars show the quarterly probability of negative glide path shifts, measured by $\text{NegShift}_{f,q}$ (Eq. (4)). Only bins containing more than 50 unique funds with non-missing quarterly shift measures are reported.

Table B1: **Past Flows and Glide Path Shifts (Full Coefficients for Returns)**
This table reports the coefficient estimates for lagged quarterly returns from the panel regressions presented in Table 4. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.:	$\text{PosShift}_{f,t+3}$		$\text{NegShift}_{f,t+3}$	
Flow_t	0.125***	0.121***	0.078**	0.065*
	(2.809)	(2.843)	(2.080)	(1.669)
Flow_{t-3}	-0.000	-0.000*	0.001	0.000
	(-1.252)	(-1.717)	(1.503)	(0.719)
Flow_{t-6}	-0.000	-0.000*	0.001**	0.000
	(-1.227)	(-1.918)	(1.990)	(1.176)
Flow_{t-9}	-0.000	-0.000	0.001	0.001
	(-1.116)	(-1.239)	(1.474)	(1.427)
Flow_{t-12}	-0.000	-0.000	0.001	0.001**
	(-1.470)	(-1.049)	(1.313)	(2.051)
Flow_{t-15}	-0.001*	-0.001*	0.003	0.003
	(-1.731)	(-1.696)	(1.369)	(1.475)
Flow_{t-18}	-0.006**	-0.006**	0.015	0.013
	(-2.362)	(-2.421)	(1.553)	(1.443)
Flow_{t-21}	-0.005***	-0.005***	0.000	-0.001
	(-2.834)	(-2.811)	(0.217)	(-0.447)
Flow_{t-24}	-0.001**	-0.001**	-0.000	-0.001
	(-2.255)	(-2.250)	(-0.033)	(-0.663)
Return_t	-0.439*	-0.389	-0.124	0.015
	(-1.790)	(-1.615)	(-0.622)	(0.071)
Return_{t-3}	-0.255	-0.224	-0.387*	-0.315
	(-1.482)	(-1.316)	(-1.679)	(-1.350)
Return_{t-6}	-0.003	-0.013	-0.791***	-0.831***
	(-0.013)	(-0.055)	(-3.758)	(-4.111)
Return_{t-9}	-0.840***	-0.863***	0.034	-0.043
	(-3.297)	(-3.317)	(0.137)	(-0.179)
Return_{t-12}	0.330*	0.341*	-0.678***	-0.659***
	(1.688)	(1.739)	(-2.732)	(-2.764)
Return_{t-15}	0.391	0.408	0.099	0.156
	(1.499)	(1.556)	(0.270)	(0.426)
Return_{t-18}	-0.540*	-0.478	-0.072	0.085
	(-1.783)	(-1.555)	(-0.209)	(0.263)
Return_{t-21}	-0.927***	-0.866***	-0.177	-0.030
	(-4.584)	(-4.370)	(-0.460)	(-0.077)
Return_{t-24}	-0.252	-0.188	0.018	0.115
	(-1.016)	(-0.747)	(0.058)	(0.364)
Observations	16,518	16,518	16,518	16,518
Adjusted R^2	0.120	0.124	0.179	0.190
Controls	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes
Time × Target Date FE	Yes	Yes	Yes	Yes

Table B2: **Dynamics of Glide Path Adjustments: Positive vs. Negative Shifts**
This table reports panel regressions relating future glide path adjustments to contemporaneous shifts. Panel A estimates the effect of current positive shifts on future negative shifts:

$$\text{NegShift}_{f,t+h} = \alpha + \beta\,\text{PosShift}_{f,t} + \gamma X_{f,t} + \delta_f + \delta_s + \delta_{t\times\text{TD}} + \varepsilon_{f,t},$$

while Panel B estimates the effect of current negative shifts on future positive shifts:

$$\text{PosShift}_{f,t+h} = \alpha' + \beta'\,\text{NegShift}_{f,t} + \gamma' X_{f,t} + \delta'_f + \delta'_s + \delta'_{t\times\text{TD}} + \eta_{f,t}.$$

For both panels, the forecast horizons are $h \in \{3, 6, 9, \ldots, 24\}$ months. All regressions include fund fixed effects, series fixed effects, and time×target-date fixed effects. Controls—including log TNA, log family TNA, log fund age, quarterly returns, quarterly flows, expense ratio, turnover ratio, and return volatility—are included in all specifications. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Future Negative Shifts on Current Positive Shift

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	$\text{NegShift}_{f,t+3}$	$\text{NegShift}_{f,t+6}$	$\text{NegShift}_{f,t+9}$	$\text{NegShift}_{f,t+12}$	$\text{NegShift}_{f,t+15}$	$\text{NegShift}_{f,t+18}$	$\text{NegShift}_{f,t+21}$	$\text{NegShift}_{f,t+24}$
$\text{PosShift}_{f,t}$	0.003	-0.021	-0.051**	0.002	0.019	0.014**	0.007	0.010
	(0.141)	(-1.115)	(-2.537)	(0.124)	(0.988)	(2.075)	(1.248)	(1.583)
Observations	14,798	13,979	13,424	12,780	12,050	11,440	10,794	10,201
Adjusted R^2	0.221	0.206	0.226	0.224	0.229	0.204	0.230	0.263
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time × Target Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Future Positive Shifts on Current Negative Shift

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	$\text{PosShift}_{f,t+3}$	$\text{PosShift}_{f,t+6}$	$\text{PosShift}_{f,t+9}$	$\text{PosShift}_{f,t+12}$	$\text{PosShift}_{f,t+15}$	$\text{PosShift}_{f,t+18}$	$\text{PosShift}_{f,t+21}$	$\text{PosShift}_{f,t+24}$
$\text{NegShift}_{f,t}$	-0.025***	-0.005	-0.004	-0.026***	-0.020***	-0.020***	-0.030***	0.044*
	(-3.281)	(-0.493)	(-0.868)	(-2.770)	(-3.080)	(-2.846)	(-2.934)	(1.654)
Observations	14,798	13,979	13,424	12,780	12,050	11,440	10,794	10,201
Adjusted R^2	0.103	0.113	0.105	0.131	0.109	0.096	0.108	0.126
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time × Target Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table B3: **Flow–Performance Sensitivity of TDF Investors: Panel Regressions**
This table reports coefficient estimates from the panel regressions:

$$\text{Flow}_{f,t+1} = \alpha + \beta\,\text{RawRet}_{f,t} + \gamma\,\text{AbnormalRet}_{f,t} + \delta\,X_{f,t} + \varepsilon_{f,t},$$

where $\text{Flow}_{f,t+1}$ is next-month net flow for fund f. $\text{RawRet}_{f,t}$ denotes the fund's excess return over the risk-free rate, and $\text{AbnormalRet}_{f,t}$ is the fund's abnormal return, computed as a five-factor alpha based on the preceding 12 months of daily returns. $X_{f,t}$ includes log fund TNA, log family TNA, log fund age, expense ratio, turnover ratio, and return volatility. All regressions include fund and time fixed effects. As discussed in Section 4.6, panel regressions that jointly include raw returns and alphas may overstate investor sensitivity to alphas due to mechanical correlations between the two measures. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dep. Var.: $\text{Flow}_{f,t+1}$		
$\text{Raw Return}_{f,t}$	0.261*	0.353**
	(1.796)	(2.564)
$\text{Abnormal Return}_{f,t}$	0.601***	0.372**
	(3.448)	(2.150)
$X_{f,t}$		
$\text{Log TNA}_{f,t}$		-0.030***
		(-4.990)
$\text{Log Family TNA}_{f,t}$		0.025***
		(3.917)
$\text{Log Fund Age}_{f,t}$		-0.009
		(-0.613)
$\text{Expense Ratio}_{f,t}$		2.402**
		(2.437)
$\text{Turnover Ratio}_{f,t}$		-0.013***
		(-3.477)
$\text{Return Volatility}_{f,t}$		-0.358
		(-1.373)
Observations	59,911	59,911
Adjusted R-squared	0.004	0.013
Fund FE	Yes	Yes
Time FE	Yes	Yes

Table B4: **Summary Statistics: Difference-in-Differences Sample**
This table reports summary statistics for the sample used in the difference-in-differences analysis of exogenous flows and glide path shifts in Table 8. The sample consists of 19 TDF series, 38 individual TDFs, and 329 fund–month observations for which glide path shift measures are available. All TDF characteristics are defined as described in Section 3.2.

Variable	N	Mean	Std Dev	Minimum	25th Pctl	Median	75th Pctl	Maximum
TNA ($ billion)	329	1.71	3.85	0.01	0.08	0.33	1.00	21.50
Family TDF TNA ($ billion)	329	49.24	76.73	0.80	8.01	25.77	55.56	482.71
Family TNA ($ trillion)	329	1.20	1.20	0.03	0.23	0.65	2.01	6.09
Target Year	329	2043.30	16.51	2005	2030	2050	2060	2065
Years to Target Date	329	25.44	15.68	-10.00	9.00	33.00	39.00	44.00
Fund Age (years)	329	5.34	0.68	3.75	4.83	5.51	5.92	6.25
Quarterly Return (%)	329	2.09	5.67	-16.30	-1.23	2.90	5.65	18.60
Quarterly Alpha (%)	329	-0.43	0.96	-3.70	-0.89	-0.28	0.13	2.55
Quarterly Flow (%)	329	6.18	7.68	-21.96	0.92	5.35	10.75	35.28
Expense Ratio (%)	329	0.19	0.24	0.00	0.06	0.10	0.14	1.14
Turnover Ratio (%)	329	20.39	14.52	3.00	12.00	18.00	26.00	112.00
Return Volatility (%)	329	3.50	1.47	0.68	2.35	3.38	4.37	7.17
Morningstar Rating	322	3.11	1.05	1	2	3	4	5
Passive	329	0.43	0.50	0	0	0	1	1
MRAR[-59,-36] Pctl Rank	329	0.53	0.27	0.03	0.31	0.54	0.77	0.97
Post-5yr Indicator	329	0.71	0.45	0	0	1	1	1
Quarterly Shift	329	0.09	0.29	0	0	0	0	1
Quarterly Positive Shift	329	0.05	0.22	0	0	0	0	1
Quarterly Negative Shift	329	0.03	0.16	0	0	0	0	1

Table B5: **Flow Responses to Glide Path Adjustments**
This table reports panel regressions of future flows on contemporaneous glide path shifts. Panel A estimates the effect of a positive equity shift on future fund flows:

$$\text{Flow}_{f,[t+h,t+h+2]} = \alpha + \beta\,\text{PosShift}_{f,t} + \gamma X_{f,t} + \delta_f + \delta_s + \delta_{t\times\text{TD}} + \varepsilon_{f,t},$$

and Panel B estimates the effect of a negative equity shift:

$$\text{Flow}_{f,[t+h,t+h+2]} = \alpha' + \beta'\,\text{NegShift}_{f,t} + \gamma' X_{f,t} + \delta'_f + \delta'_s + \delta'_{t\times\text{TD}} + \eta_{f,t}.$$

Forecast horizons correspond to $h \in \{1, 4, 7, \ldots, 22\}$ months. All specifications include fund fixed effects, series fixed effects, and time×target date fixed effects. Controls—including log TNA, log family TNA, log fund age, quarterly returns, expense ratio, turnover ratio, and return volatility—are included in all columns. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Flow Responses to Positive Glide Path Shifts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	$\text{Flow}_{f,[t+1,t+3]}$	$\text{Flow}_{f,[t+4,t+6]}$	$\text{Flow}_{f,[t+7,t+9]}$	$\text{Flow}_{f,[t+10,t+12]}$	$\text{Flow}_{f,[t+13,t+15]}$	$\text{Flow}_{f,[t+16,t+18]}$	$\text{Flow}_{f,[t+19,t+21]}$	$\text{Flow}_{f,[t+22,t+24]}$
$\text{PosShift}_{f,t}$	-0.016***	-0.015***	-0.010*	-0.014**	-0.001	-0.013***	0.003	0.014**
	(-3.577)	(-3.324)	(-1.686)	(-2.424)	(-0.226)	(-3.704)	(0.563)	(2.420)
Observations	16,518	16,346	16,122	15,576	14,920	14,239	13,555	12,959
Adjusted R^2	0.623	0.621	0.606	0.595	0.599	0.587	0.603	0.583
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time×TD FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Flow Responses to Negative Glide Path Shifts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	$\text{Flow}_{f,[t+1,t+3]}$	$\text{Flow}_{f,[t+4,t+6]}$	$\text{Flow}_{f,[t+7,t+9]}$	$\text{Flow}_{f,[t+10,t+12]}$	$\text{Flow}_{f,[t+13,t+15]}$	$\text{Flow}_{f,[t+16,t+18]}$	$\text{Flow}_{f,[t+19,t+21]}$	$\text{Flow}_{f,[t+22,t+24]}$
$\text{NegShift}_{f,t}$	0.011**	0.015***	0.011***	-0.005	-0.017***	0.007*	0.008	0.006
	(2.015)	(3.274)	(3.216)	(-1.371)	(-3.637)	(1.652)	(1.619)	(0.589)
Observations	16,518	16,346	16,122	15,576	14,920	14,239	13,555	12,959
Adjusted R^2	0.623	0.621	0.606	0.594	0.600	0.586	0.603	0.583
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time×TD FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes