Retail Financial Innovation and Stock Market Dynamics: The Case of Target Date Funds *

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Abstract

This paper shows that rapid growth of Target Date Funds (TDFs) during the past 15 years – driven by financial innovation and the subsequent regulatory approval of TDFs as default options in retirement plans – has moved a substantial share of retail investors into a contrarian trading strategy that has reduced stock market momentum. Because TDFs maintain fixed (age appropriate) portfolio shares of different asset classes, they actively rebalance into (out of) asset classes that underperform (outperform). Historically, in contrast, retirement investors were primarily passive or trend-chasing, either letting their portfolio shares vary with the returns on different asset classes or reallocating into better-performing asset classes, and so amplifying return fluctuations. We show that a) TDFs rebalance following excess returns as we predict, b) this causes inflows and outflows for equity funds in proportion to their TDF ownership shares, c) investors do not trade to offset these flows, and d) these flows lead to lower aggregate momentum in stock prices in three ways. First, stocks with higher TDF exposure experience lower returns after higher market-wide performance. Second, this correlation appears to be causal based on using the S&P 500 index inclusion as a quasi-exogenous source of variation for TDF ownership. Third, consistent with the rise of TDFs dampening aggregate market fluctuation, the time series momentum in the S&P 500 index declines from the pre-TDF to the post-TDF period. Together, our results suggest that continued growth in the market share of TDFs will further increase market stability.

JEL codes: G12; G23; G51

Keywords: target date funds; contrarian strategies; mutual fund flow pressure; time series momentum; market stability

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One of the most important innovations for the typical American investor in the last two decades has been the rise of target date funds (TDFs, also called lifecycle funds). TDFs are funds of funds (FoFs) that maintain a given portfolio share of assets invested in different asset classes, where the shares change with the number of years until the 'target date,' the expected retirement date of the investor. A typical TDF allocates 80 to 90 percent of assets to diversified equity funds and the remainder to bond funds until 25 years before retirement date, at which point the equity share declines roughly linearly until reaching 30 to 40 percent 10 years after retirement. The direct benefits of these funds are that they provide investors with some (generally) low-fee cross-class asset reallocation based on the proscription of calibrated microeconomic models of optimal portfolio choice.[1] Facilitated by the by the Pension Protection Act (PPA) of 2006 which qualified TDFs as default options in defined contribution retirement saving plans, TDFs have risen from managing less than $8 billion dollars in 2000 to more than $2.3 trillion dollars (of the roughly $21 trillion mutual fund market) in 2019.[2]

In this paper, we document an important implication of this financial innovation on asset prices: TDFs have reduced aggregate stock market momentum and fluctuations. Traditionally, retail investors either remain passive and let their portfolio share rise and fall with the returns on different asset classes, or they trend-chase, reallocating their assets into better-performing asset classes, a behavior known as 'positive feedback trading' or 'momentum trading' that amplifies price fluctuations.[3] In contrast, TDFs trade against market movements. That is, they rebalance to maintain age-appropriate, asset shares, which implies a contrarian investment strategy that reallocates out of better-performing asset classes and into lower-performing ones.

We show that, though not an original intention of this financial innovation, the rise of TDFs has turned a significant fraction of US retail investors from positive feedback

[1] Following, for example, Merton (1969), Viceira (2001), Cocco et al. (2005).

[2] This figure includes $0.9 trillion in target date collective investment trusts (CITs) which, for data reasons are not in our analysis, but which presumably have similar market impact. CITs invest like TDFs but have lower fees than the equivalent mutual funds. Dollar amounts are from the Investment Company Institute (2020, figure 8.20 and figure 2.2) and (Morningstar (2020)).

[3] See Agnew et al. (2003) and Ameriks and Zeldes (2004) for evidence of rampant passivity, particularly in retirement accounts, and De Long et al. (1990) and Hong and Stein (1999) for discussions of the effects of momentum on stock returns.

traders into a countervailing force that trades against market movements. We show that TDFs sell equity following high equity returns, that this trading this causes inflows and outflows for equity funds in proportion to their TDF ownership shares, and that other investors do not trade to offset these flows. Further, TDFs stabilize stock prices: stocks with higher TDF exposure experience lower returns after higher market-wide performance. This correlation appears to be causal. Stocks included in the S&P 500 index have higher shares of TDF ownership than similar stocks that are not included. We observe the same return differential between these stocks, but only in the recent period following the rise of TDFs. Finally, consistent with the rise of TDFs dampening aggregate market fluctuation, the time series momentum in the S&P 500 index declines from the pre-TDF to the post-TDF period.

We start by identifying the effects of TDF allocation strategies on their trading behavior. TDFs with different target dates have different desired equity shares. This variation implies different trading behavior in response to market movements. Specifically, the rebalancing formula is a quadratic function of the desired equity share. A fund with a desired equity share of 50% is most sensitive to returns on the stock market. When the stock market returns 20% more than the bond market, such a fund needs to convert 4.5% of portfolio from stocks to bonds. In contrast, for a TDF invested entirely in one asset class or the other (TDFs designed for very young for example), stock market returns would cause the portfolio weights to fluctuate minimally and so the amount of rebalancing required would be minimal.

Our first result is that TDFs rebalance across equity and fixed income mutual funds exactly as predicted by their desired equity shares given realized asset returns. Using quarterly data on TDF holdings during 2008-2018, we show that when the equity market returns exceed those on the bond market in a given quarter, the average TDF sells some of its holdings of equity mutual funds and increases its holdings of fixed income mutual funds in the same quarter. They also trade in the same direction in the following quarter, but by less, implying that most rebalancing occurs more rapidly than three months.[4] Consistent

[4]Based on our conversations with practitioners, in order to avoid any expected price impact being exploited by arbitrageurs, TDFs do not employ fixed trading schedules and do not tightly adhere to target allocations. While they maintain an allocation within a narrow band around the target allocation, many

with the quadratic form of the formula, we observe a greater magnitude of rebalancing in the group of TDFs with moderate allocations, i.e., equity shares between 25% and 75%. In addition, for each dollar of rebalancing predicted by the model, the estimated rebalancing in the current quarter is 50 cents and in the following quarter is about 45 cents.

Second, we show that the contrarian trading of TDFs is a quantitatively significant part of mutual funds flows. At the fund level, the rebalancing by TDFs has a significant impact on the flows to individual mutual funds. The average retail fund's quarterly flows correlate with the concurrent excess returns of the stock market.[5] But this relationship is reduced by one sixth for mutual funds with a 6% TDF ownership, which is the mean percent held by TDFs among mutual funds with non-zero TDF ownership. At the aggregate level, during 2008-2018, for a quarterly equity market return of 10% in excess of the bond market, 30 billion dollars flow into retail shares of domestic equity mutual funds during the concurrent quarter. At the same time, TDFs sell $3 billion of retail shares of mutual funds, thus offsetting about 10% of the aggregate trend-chasing by retail investors. TDFs with moderate allocations provide the majority of the offsetting effect. In sum, at both the individual and aggregate level, 'positive feedback' flows to mutual funds with TDF investments are mitigated by TDF contrarian trading.

Our third result is that this contrarian trading by TDFs dampens the price and return dynamics of individual stocks, and so presumably the price and return dynamics of the overall market. Greater TDF (indirect) ownership is associated with lower returns of individual stocks following higher stock market returns in recent months. Specifically, when the excess equity return is 10% in a month, stocks one standard deviation (0.6%) higher in TDF ownership have 0.57% lower return in the following month. This effect is robust to controlling for month-by-month industry shocks and stock fixed effects. However, many stock characteristics also correlate with the share held by TDF funds. Most notably, both cross-sectionally and longitudinally, the fraction of shares owned by TDFs increases with the size (market value) of the stock, but imperfectly. Conditioning on market capitalization interacted with past return, the estimated relationship between greater TDF ownership

funds make use of continuous inflows and outflows to rebalance through flow allocation when possible.

[5]This finding is consistent with Warther (1995) and Edelen and Warner (2001) which show a positive relationship between mutual fund flows and concurrent monthly, weekly, or daily market returns.

and lagged market returns is smaller but still significant. In addition, this relationship is robust to controlling for stock return exposures to current or lagged performance of the size, book-to-market, and momentum factors. As a falsification test, we conduct our analysis using data before the Pension Protection Act of 2006 that triggered the growth of the TDF market. The falsification tests reveal that stocks with recent high TDF investments did not behave differently in the earlier periods, but the results are unique to the TDF era.

To provide further evidence that these price dynamics are driven by TDF ownership rather than other correlated factors, we show that stocks that are included in the S&P 500 index have both a discretely higher TDF ownership and have a lower sensitivity of their returns to lagged market performance than otherwise similar stocks. The S& P 500 index is the most common benchmark among TDF-invested mutual funds. Further, S&P 500 membership is based on a set of eligibility criteria, but the index committee at S&P has discretion at the margin (for example, an industry balance of the index is considered). We assume that this discretionary component of inclusion is uncorrelated with the specific return sensitivity to market performance other than through the response of TDFs. We match a sample of S&P 500 stocks to 'control' stocks that are matched on industry, size and liquidity.

Among these (large-cap) stocks with matched characteristics, being included in the S&P 500 leads to a reduction in the stock return sensitivity to lagged market performance. With a 10% excess return on the market in a month, the index stocks have a 0.9% lower return in the following month compared with similar non-index stocks. This effect does not seem to be a feature of S&P 500 inclusion through other channels than TDF ownership because being included in the S&P 500 did not exhibit similar pattern during the pre-PPA period that lacked a sizable TDF market.[6]

Lastly, we examine the pricing effect of TDFs in the aggregate. The index inclusion result implies that the rise of the TDF market and its contrarian trading strategies can lead to negative time series correlations in the S&P 500 index. In line with this prediction, we find a significant negative time series correlation in the S&P 500 during 2010-2019 which

[6]While existing research has documented that index inclusion affects the price level of a stock (Shleifer, 1986) and its co-movement (Barberis et al., 2005) with other stocks in the index, those effects are present even in the earlier period, whereas the lowered momentum effect that we document is unique to the TDF period.

has a sizable TDF market, which is in sharp contrast with the lack of predictability in the index returns during 1986-1995 or 1996-2005.

The market of TDFs is a burgeoning area of academic research. Mitchell and Utkus (2020) use data from one large 401(k) provider to study the take-up of TDFs in retirement plans. They show that plan-level features, such as autoenrollment, are key drivers for adoption, and that the introduction of TDFs into 401(k) plans serves as advice to plan participants and makes a sizable impact on the portfolios of the adopters. Related, Chalmers and Reuter (forthcoming) use TDFs to construct counterfactual portfolios of retail investors in absence of financial advice. On the competition in the TDF market, Balduzzi and Reuter (2019) document the dispersion in the risk and return profiles even among TDFs with similar target retirement dates and attribute the heterogeneity to risk-taking by market followers. In this literature, our paper is the first to study the impact of the TDF innovation on asset prices.

Our paper is also closely related to the literature on fund flows and market stability. Warther (1995) finds that aggregate unexpected flows in and out of mutual funds are positively associated with concurrent monthly and weekly returns on market indices, arguing that the phenomenon can be explained by price pressure or information. Using daily flow data, Edelen and Warner (2001) show that flows respond to returns with a one-day lag, but within a trading day, returns appear to respond to flows. Da et al. (2018) use defined contribution pension data from Chile to show that asset allocation advice from a major financial adviser significantly affects stock prices and increases return volatility. On cross-sectional trading pressure and momentum, Coval and Stafford (2007) demonstrate that flow-driven fire sales by mutual funds lead to a price impact followed by a reversal. Lou (2012) documents the price impact of flow-induced trading and offers a flow-based explanation for the smart money effect and the momentum effect, and Vayanos and Woolley (2013) derive a model with delegated management and slow-moving flows to explain the momentum and value effects. Our paper complements the literature by studying the effects of contrarian flows that counteract the price pressure from retail flows. Moreover, our focus is on the aggregate, or 'time series' momentum (Moskowitz et al. (2012)), instead of cross-sectional momentum.

1 Target date funds

While mutual funds have helped retail investors become more diversified, they mostly hold only one asset class, such as domestic stocks or foreign bonds. In contrast, TDFs are funds-of-funds that invest in other mutual funds, and which maintain given portfolio shares in different asset classes according to stated goals. TDFs rebalance in response to market movements in order to maintain their desired portfolio shares, and they rebalance over time as their desired portfolio shares change. A TDF typically starts with a large desired share of equity – on the order of 90 percent – and moves more into fixed income over time as the fund approaches and passes its target retirement year. Figure A.1 presents the proscribed equity share over the life cycle, or 'glide path,' for the Vanguard TDF series (which have a roughly 40% market share). TDFs typically invest primarily in domestic equity, foreign equity and fixed income mutual funds. Mitchell and Utkus (2020) offer a detailed description on the workings of TDFs.

The use of TDFs has risen dramatically over the past 15 years due to financial innovation and financial regulation. Figure 1 plots the size of TDF assets by quarter. Total assets invested in TDFs increased from less than $8 billion dollars in 2000, to $109 billion at the end of 2006, and to $1.4 trillion at the end of 2019. The financial innovation that is TDFs followed from research by academics and practitioner on the optimal lifecycle portfolio choice. The specific timing of the rise of TDFs follows the passage of the Pension Protection Act in August of 2006 which qualified target-date funds to be used as default options (Qualified Default Investment Alternative, or 'QDIA') in 401(k) retirement saving plans. A breakdown of assets by retirement year indicates that the largest components are TDFs with retirement years in 2020-2040.

Most TDFs are structured as mutual funds or collective investment trusts (CITs). According to Morningstar estimates, total assets invested in CITs are about 60% of that invested in target date mutual funds as of 2019 and are growing rapidly. The CITs are negotiated between plan sponsors and providers and are usually at lower cost compared with TDFs. We focus on target date mutual funds in this paper due to data availability and use TDFs to refer to target date mutual funds exclusively. Since CITs follow almost identical strategies

as TDFs, we underestimate the investment of all target date strategies. Portfolio funds held by TDFs include both open-end mutual funds and exchange-traded funds (ETFs). For the simplicity of reference, we call both 'mutual funds' henceforth.

2 Mechanism of TDF rebalancing

This section formally shows that he amounts of trading that a TDFs has to do in response to excess stock market returns in order to maintain its desired equity share is quadratic in its desired equity share with a maximum at a 50% equity share. We first assume zero net flows to the TDF. We then consider a general case of rebalancing with simultaneous flow-driven trades (investor purchase or redemption allocated pro rata to existing positions) and show that rebalancing trades in these two cases are the same.

Table 1 shows that TDFs rebalancing in response to excess stock market returns is heterogeneous in desired equity share. Consider a TDF with \$1 of assets, weight S invested in an equity index fund, and weight $1-S$ invested in bond funds, and stock and bond asset returns of R^S and R^B respectively. In the case of no investor flows (panel A), the total portfolio value becomes $1+R^B+S\left(R^S-R^B\right)$ after the realized asset class returns. To restore the original asset allocation, the TDF needs to bring the equity and bond fund values to $\left[1+R^B+S\left(R^S-R^B\right)\right]S$ and $\left[1+R^B+S\left(R^S-R^B\right)\right](1-S)$ respectively. Thus, the TDF needs to sell the equity fund in the amount of $-S(1-S)\left(R^S-R^B\right)$, and buy the bond fund in the amount of $S(1-S)\left(R^S-R^B\right)$. The two rebalancing trades sum up to zero in dollar amounts due to zero net flows. The important result is that the amounts of trading is quadratic in desired equity share, with a maximum at an equity share of 50%.

Panel B considers the case of rebalancing when the TDF receives a net flow of F from investors at the same time as the stock market realizes a return of R. In this case, the total portfolio value becomes $1+R^B+S\left(R^S-R^B\right)+F$. Like in Panel A, we can calculate the target dollar allocation according to proscribed portfolio shares and the necessary total net trades to restore that allocation. Note that here the sum of the total net trades is F , which includes both rebalancing trades (that sum up to zero) and flow-driven trades (that sum up to net flow F). For the purpose of allocating net flows only, the TDF would trade FS in

equity and $F(1-S)$ in fixed income. Subtracting the flow-driven trades from the total net trades, we can back out the rebalancing trades, which turn out to be the same as those in panel A, and thus are also quadratic with a with a maximum at an equity share of 50%. It is important to note that while TDFs experiencing inflows or redemptions can rebalance through allocating the flows, the net effect of TDF ownership on asset demand is still given by Table 1 panel B.

One issue that affects our analysis is that TDFs do not rebalance continuously to maintain their desired equity share exactly. In fact, according to conversations with asset managers (confirmed in our later findings), they tend to trade back to their desired equity shares over a month or two in order to reduce transaction costs relative to more exact tracking of their targets. This savings from slower adjustment can be substantial if inflows allow rebalancing purely from re-directing purchases. As shown in Panel B, as long as $FS - S(1-S)\left(R^S - R^B\right)$ has the same sign as F (that is, $R^S - R^B$ is small relative to F), rebalancing can be achieved simply by allocating the net flows to new positions instead of adjusting existing positions.

In our subsequent analysis, we analyze both the rebalancing trades (as in panel A) and the total trades (as in panel B). The advantage of the rebalancing trades is that they remove trading driven automatically by auto-enrollment, incomes, auto-escalation, withdrawals, and menu choice decisions that change flows over time. However, our central argument is that rebalancing by TDFs drives fund flows and ultimately stock prices. If investors actively reallocated out of TDFs when they and/or the stock market performed poorly, then the rebalancing would not be representative of the change in demand for stock by these investors. Thus, we also analyze total trades. While these include the 'noise' associated with institutional changes across funds and plans just described, they also include any active decisions by retail investors in opposition to the rebalancing trades of TDFs. Our baseline results include only rebalancing trades, but are similar when we use total trades instead. This is consistent with the fact that the vast majority of TDF assets are held through defined contribution retirement plans and IRAs where switching decisions by investors are infrequent.[7] Mitchell and Utkus (2020) demonstrate that most flows in and out of TDFs

[7] $734 billion out of the $1.1 trillion TDF assets are held in 401(k) plans (67%) and $213 billion are held

are explained by plan sponsor actions combined with passive plan participant behavior rather than past returns. Finally, in our conversations with practitioners, they believe that investors defaulted into TDFs are less likely to trade in response to market movements than those defaulted into other types of funds.

3 Data

We construct a dataset of TDFs, the underlying mutual funds they hold, and, the individual stocks held by TDFs through these underlying mutual funds.

At the TDF level, we obtain fixed characteristics and quarterly total net assets (TNA) from the CRSP Mutual Fund Database. TDFs in the database are identified from fund names containing target retirement years at five-year intervals ranging from 2000 to 2065, then manually cleaned using the TDF series names listed in the Morningstar annual TDF research reports.

We obtain the quarterly holdings of the TDFs from CRSP. TDFs are funds of funds, thus most holdings are other mutual fund share classes, which we link to the CRSP mutual fund database using the CUSIP code. We use this matching to categorize each holding as domestic equity, foreign equity, or fixed income. The match or data do not appear to be perfect, and we drop a few observations where the value of a holding is larger than the total asset size of the mutual fund share class, or where the sum of holdings exceeds 110% of the TNA of the TDF. Further, the quality and coverage of the CRSP holdings data vary across time and are problematic for several quarters. Figure A.2 plots the aggregate total value of TDF holdings that can be mapped to mutual fund share classes, and as a reference, it also shows the total assets under management of TDFs over time. We base the sample selection on the ratio of total holdings to total assets and restrict the main sample period to 2008Q3-2018Q4.[8] We also drop the holding data in quarters 2010Q2, 2010Q3 and 2015Q2 due to unusually low ratio of holdings to total assets that can indicate data errors. The

through IRAs (19%). See ICI Factbook 2019 Figure 8.24.

[8]The value of available holdings as a fraction of total assets rises from 60% in 2008Q1 to 80% in 2008Q2 and stays around 80% afterwards. We start the sample in 2008Q3 to allow one quarter of lagged TDF holdings data.

quarters immediately following these are subsequently excluded when lagged holdings are used as an input into calculations. Further, we exclude small TDFs with TNA below $ 10 million.

Table 2 panel A presents the summary statistics on the TDFs in our sample. The mean asset size is $ 2.2 billion while the median is $ 276 million, implying a high degree of market concentration. Each TDF on average holds 16 mutual funds. The average equity weight is 73% , out of which 49% is in domestic equity and 24% in foreign equity, and the fixed income weight is 27% . The fund flow rate to TDFs suggests high growth during this period – the average TDF grows by 6% per quarter from net inflows.

To measure the effect of TDFs on funds, we also construct a quarterly dataset on the underlying mutual funds from CRSP. We combine different share classes of the same fund to the fund level. We focus on domestic equity mutual funds that can be classified as retail, that is, those where the fraction of assets invested through retail share classes is above 50%. For each mutual fund, we calculate the percent ownership by TDFs as the sum of TDF holdings across all share classes of the fund divided by the total fund size.

Table 2 panel B shows the mutual funds' summary statistics. The average mutual fund experiences a quarterly inflow at 1.3% of lagged assets, while the median fund experiences an average quarterly outflow of 1.7%. The sample average of TDF ownership is low (0.5%) due to many zeros (only 8% of mutual fund quarterly observations have positive TDF ownership). Among the mutual funds which TDFs invest in, the mean TDF ownership is 6.4% and the median is 1%.

Lastly, we assemble a panel dataset of monthly stock return, price, volume and market capitalization from CRSP, and S& P 500 membership from Compustat, the summary statistics of which are presented in panel C of Table 2. The sample contains stocks traded on the New York Stock Exchange, NASDAQ, and American Stock Exchange. Roughly 18% of the stock-monthly observations represent S& P 500 stocks. We calculate stock-level TDF ownership as the total fraction of shares outstanding that are held by TDFs through mutual funds, and the average TDF ownership is 0.54%. We will show in Section 6 that significant variation exists in TDF ownership across stocks, which we then employ to estimate the impact of TDFs on stock return dynamics.

4 TDF rebalancing

4.1 Aggregate rebalancing as expected

We start by establishing both that TDFs rebalance as predicted and that they do so within two quarters. If we found significant deviations in behavior from our quantitative predictions for rebalancing, TDFs might be pursuing other cross-asset class strategies such as momentum or market timing and so would be no different from the trades of any other funds and those of other FoFs. Thus, though automatic rebalancing is usually emphasized by TDF providers as a key product feature, we to verify it.[9]

We empirically evaluate whether TDFs rebalance according to the formulae derived from Table 1. Because funds can trade continuously and one can observe portfolio holdings only at discrete (quarterly) intervals, the formulae in Table 1 are only approximations. Specifically, while we can in theory observe asset returns daily, we do not observe when funds trade during the period nor exactly when inflows occur. Instead, we assume all rebalancing trades are made at the end of each period after returns are realized and before the fund reports its portfolio.

Our first exercise focuses on the directions of rebalancing and tests whether the average TDF sells equity funds and buys fixed income funds when the stock market goes up relative to the bond market, and vice versa. Since rebalancing can be implemented with a delay, we estimate the following specifications with both the current quarter and the lagged quarter's asset returns:

$$Rebalancing_{Skt} = \gamma_S \left(R_t^S - R_t^B\right) + \zeta_S \left(R_{t-1}^S - R_{t-1}^B\right) + \epsilon_{Skt} \tag{1}$$

$$Rebalancing_{Bkt} = \gamma_B \left(R_t^S - R_t^B\right) + \zeta_B \left(R_{t-1}^S - R_{t-1}^B\right) + \epsilon_{Bkt} \tag{2}$$

The dependent variable, the rebalancing trade in either equity or fixed income by TDF

[9]For example, Vanguard describes on its website, 'Target Retirement Funds represent an alternative for investors who want a broadly diversified portfolio for their retirement savings but don't want to do the rebalancing themselves. A Target Retirement Fund will—automatically—rebalance over time via its glide path. This is the key behind a Target Retirement Fund.' retirementplans.vanguard.com

k in quarter t, is constructed using a panel dataset of holdings at the TDF by mutual fund share class level and calculated in three steps. First, we calculate the dollar amount of the 'total trade' for each TDF and fund share class pair as the change in the value of holdings in excess of the value predicted by the quarterly share class return, that is, $TotalTrade_{ckt} = MV_{ckt} - MV_{ckt-1}(1 + r_{ct})$ where k indicates the TDF, c stands for a mutual fund share class, and t represents a quarter. The calculation includes the cases of investment initiations (where $MV_{ckt-1} = 0$) and terminations (where $MV_{ckt} = 0$). Second, we aggregate the observations from each holding to the TDF-by-asset-class level and obtain $TotalTrade_{jkt}$ where j stands for either the equity or the fixed income asset class. We combine both domestic equity and foreign equity into 'equity', because most glide paths are based on an equity-fixed income allocation without specifying separate weights for the domestic–foreign allocation. Third, we calculate the 'flow-driven trade' by a TDF of an asset class as the dollar flow to the TDF[10] allocated pro rata to lagged portfolio weight of the asset class (Frazzini and Lamont (2008)), and subtract it from the total trade to obtain the 'rebalancing trade', i.e., $Rebalancing_{jkt} = TotalTrade_{jkt} - FlowDrivenTrade_{jkt}$. The measures of R^S and R^B come from the value weighted total return of the US stock market obtained from CRSP and the US bond market return that is approximated by the pre-fee return on the Vanguard Total Bond Market Index Fund.[11]

Table 3 present the estimates of equations 1 and 2 using quarterly rebalancing at the individual TDF-by-asset-class level during 2008-2018.[12] To match the setup in Table 1 where the AUM of the TDF is assumed to be one dollar, we normalize the dollar rebalancing trades by the lagged total dollar holdings of the TDF. Panel A, columns 1 and 4 use the entire sample of TDFs. The coefficient on $(R^S - R^B)_t$ suggests that if the equity market moves up (down) by 10% in excess of the bond market in a quarter, the average TDF sells

[10] We follow the formula commonly used in the literature to impute net fund flows: $DollarFlow_{kt} = TNA_{kt} - TNA_{kt-1}(1 + r_{kt})$, where TNA_{kt} is the total net assets of TDF k in quarter t and r_{kt} is the net return of the TDF.

[11] Using the US stock market return to approximate for R^S introduces measurement errors when a fraction of the aggregate TDF holding is in foreign equity. We have verified that our results are similar if we calculate a weighted average R^S based on the weights in domestic equity and foreign equity. Since the focus of this paper is to understand the return dynamics in the US stock market, we present the results only using the US stock market returns as R^S.

[12] We present a similar table using aggregate data in Table A.1. The aggregate results essentially put higher weights on larger TDFs.

(buys) equity funds by 0.8% of the lagged portfolio value in the same quarter and buys (sells) fixed income funds by 0.6% of the lagged portfolio value at the same time. The coefficients on $(R^S - R^B)_{t-1}$ further imply that the rebalancing continues in the following quarter. However, the delayed effect has lower statistical significance, suggesting that the most concentrated action of TDF rebalancing occurs more rapidly than a quarter.

We can consider the magnitudes of these effects in the context of the total asset size under management by in the TDF market. Take $2.3 trillion as the total asset size invested in target date strategies (including both TDFs and target date CITs) at the end of 2019, the estimate in column 1 suggests that TDFs on aggregate should purchase around $40 billion ($0.08 \times 22\% \times 2300$) of equity funds in the first quarter of 2020 when the stock market drops by around 22% relative to the bond market.

A further prediction from Table 1 relates to the cross-sectional heterogeneity across TDFs. The magnitude of the predicted rebalancing trade $S(1-S)(R^S - R^B)$ is a concave quadratic function of the target equity share S. Thus, for a given $R^S - R^B$, the expected rebalancing should be higher for TDFs with equity shares close to the vertex, or 0.5. In columns 2-3 and 5-6, we split the TDF sample by equity share, and expect that the group with equity share in the range between 0.25 and 0.75 (which we call 'moderate allocation TDFs') to exhibit greater rebalancing than the group with equity share either below 0.25 or above 0.75 ('conservative or aggressive allocation TDFs'). The results are consistent with this prediction: For an equity market return that exceeds the fixed income market by 10%, the moderate allocation TDFs on average sell equity holdings by 1.2% of portfolio value, significant at the 0.01 level, while the conservative or aggressive allocation TDFs sell equity holdings by 0.4%, which is statistically insignificant. In addition, the rebalancing by the latter group appears more delayed compared with the former group, and an explanation is that the same magnitude of equity market shock throws the TDFs with moderate allocations off their glide paths by more and that is more likely to exceed the TDF manager's discretion.

In panel B of Table 3, we compare the actual rebalancing with the predicted values by estimating the following equations:

$$Rebalancing_{Skt} = \eta_S S_{t-1}(1-S_{t-1})\left(R_t^S - R_t^B\right) + \pi_S S_{t-1}(1-S_{t-1})\left(R_{t-1}^S - R_{t-1}^B\right) + \epsilon_{Skt} \quad (3)$$

$$Rebalancing_{Bkt} = \eta_B S_{t-1}(1-S_{t-1})\left(R_t^S - R_t^B\right) + \pi_B S_{t-1}(1-S_{t-1})\left(R_{t-1}^S - R_{t-1}^B\right) + \epsilon_{Bkt} \quad (4)$$

The main independent variable is $S_{t-1}(1-S_{t-1})(R_t^S - R_t^B)$, the predicted magnitude of rebalancing. Perfect rebalancing predicts $\eta_S = -1$ and $\eta_B = 1$. However, the estimated $\widehat{\eta_S}$ and $\widehat{\eta_B}$ may be closer to zero for several reasons. First, due to the cost of rebalancing, a TDF manager may leave the portfolio weights temporarily deviate from the target without intervention, especially when the market movement is small. Second, TDFs may rebalance with a time lag, or the predicted rebalancing may be smoothed out over time. To account for this possibility, we also include the lagged predicted value $S_{t-1}(1-S_{t-1})(R_{t-1}^S - R_{t-1}^B)$, to allow for any adjustment with a one-quarter delay. Third, the target equity share is approximated by $\widehat{S_{t-1}}$, the observed lagged aggregate equity weight, and thus is measured with noise. One reason is that the realized weight at $t-1$ may deviate from the target; the other is that the target allocation may evolve from $t-1$ to t along the glide path. These measurement errors can attenuate the estimated coefficients.

As Table 3, panel B indicates, our estimate of $\widehat{\eta_S}$ is about 0.5, suggesting that for each dollar of predicted rebalancing, the actual rebalancing is about 50 cents in the current quarter. The adjustment to the previous quarter's predicted amount is about 45 cents but cannot be precisely estimated. When separating the TDFs by the target equity weight, we find that the group of moderate allocation TDFs follow the formula more closely than the rest do. This is again intuitive as the former group tend to see greater deviations from the target allocations under a same amount of asset market fluctuations, making rebalancing more imminent.

5 Effect of TDFs on fund flows

Section 4 illustrates that TDFs trade against market movements. In this section, we contrast the magnitude of TDF trades with that of retail fund flows. The literature assumes

that retail investors are positive feedback traders who can amplify return momentum (e.g. De Long et al., 1990; Hong and Stein, 1999). How much of the trend chasing of retail flows do TDFs offset? In this section, we answer the question with both aggregate and mutual fund level evidence.

Table 4 contrasts the aggregate TDF trades in U.S. equity mutual funds with retail flows to those funds during our sample 2008Q3-2018Q4. We track both aggregate series along market cycles and compare their sensitivities to the excess return of the U.S. equity market. We explore several ways of aggregating the TDF trades as explained below. The retail series is constructed by summing up all dollar flows to retail share classes of U.S. domestic equity mutual funds. The quarterly flow to a share class is calculated as the increase in assets above the level implied by fund return, that is $TNA_t - TNA_{t-1}(1 + r_t)$ where r_t is the net quarterly return of the fund share class. In cases where TDFs also invest in retail share classes, we deduct those TDF trades from retail flows before aggregating the latter. We then regress the aggregate quarterly trades by TDFs and retail investors on the return difference between equity and fixed income ($R^S - R^B$), allowing separate coefficients for TDFs and retail flows. Since stock market shocks are common to both series, we cluster the standard errors by time (year-quarter).

In column 1 of Table 4, the TDF series represents the sum of dollar rebalancing by all TDFs. The result suggests that when $R^S - R^B$ is 10%, 30.7 billion dollars flow into retail shares of domestic equity mutual funds in the concurrent quarter, confirming the positive-feedback trading of retail investors. The trades by TDFs of equity funds significantly differ from the retail flows. A calculation of the net coefficient for the TDF series using the delta method suggests that TDFs sell roughly $2.8 billion of equity funds under the same market move out of rebalancing. Thus, during the sample period, TDFs offset about 9% of the aggregate trend-chasing by retail investors. In column 2, we instead separate the TDFs into those with equity share above 75% or below 25% (aggressive or conservative allocation) and those with equity share between 25% and 75% (moderate allocation). The net coefficients for these suggest that the moderate-allocation TDFs reduce retail feedback trading by about 7%, while the rest of the TDFs reduce it by another 2%. The contrast between these two TDF series echoes the result in Table 3 the moderate allocation group

rebalance at a greater magnitude for the same amount of asset market movement.

In column 3, we examine the total TDF trades which include both rebalancing and the effect of investor flows to the TDFs. Overall, we observe that the net flows from the TDFs appear less contrarian when we add in the flow-driven trades, and Column 4 suggests this is mainly driven by the TDFs with aggressive or conservative allocations. Given the existing evidence on sticky investor behavior in TDF accounts (e.g., Mitchell and Utkus (2020)), one should be careful not to conclude that columns 3-4 imply flows to TDFs are trend-chasing. Rather, a likely interpretation is that the recent growth in the TDF market also corresponded with a period of relatively strong stock market growth. Further, it is important to note that despite the investor inflows, the behavior of total TDF trades differ significantly from that of retail flows. This suggests that the increasing use of TDFs as an intermediary by retail investors can alter the flow pressure on the underlying assets. Our later analysis of the impact of TDFs on the underlying mutual funds and stocks confirms this prediction.

Next, we turn to dis-aggregate data and investigate whether TDFs exert similar effects on individual mutual funds. Our hypothesis is that because of TDF rebalancing, mutual funds with high TDF ownership receive lower flows following high market performance. With quarterly mutual fund data, we estimate the following specification:

$$FundFlow_{jt} = \beta_1 AssetClassRet_t + \beta_2 AssetClassRet_t \times Frac.TDF_{jt-1} + \beta_3 AssetClassRet_{t-1} + \beta_4 AssetClassRet_{t-1} \times Frac.TDF_{jt-1} + \gamma Frac.TDF_{jt-1} + X_{jt} + \epsilon_{jt} \quad (5)$$

The dependent variable is the fund flow rate measured as the growth rate in assets in excess of the realized fund return. We explore two versions of the asset class returns. Though TDF trades respond to $R^S - R^B$, the difference between U.S. stock and bond market returns, it is unclear that retail mutual fund flows react to this performance measure, thus, we also examine $R^S - R^f$, the excess return of the stock market, as an alternative. Further, we allow flows to respond to both the current quarter and the lagged quarter's asset class

performance.[13] Equation 5 allows the flow sensitivity to asset class return to vary by TDF ownership, and we expect $\widehat{\beta_2}$ and $\widehat{\beta_4}$ to be negative. For the TDF ownership measure, we calculate the fraction of the mutual fund's assets that are held by TDFs at the end of the previous quarter. Control variables X_{jt} include the common fund characteristics that affect fund flows, including fund size, fund family size, fund age, expense ratio, and return volatility. To allow for the correlations in errors in cross sections and within the same fund over time, we cluster standard errors two-ways by time and fund.

Table 5 presents the results. Column 1 estimates the baseline specification. We find that in a mutual fund without TDF investments, fund flows significantly chase the excess equity market return over bonds – for an $R^S - R^B$ of 10%, the average retail fund experiences about 2.5% inflow – and that most of the response is in the current quarter. The coefficients on the interaction terms with TDF ownership ($\widehat{\beta_2}$ and $\widehat{\beta_4}$) suggest that the trend-chasing relationship is significantly reduced for the small fraction of funds with TDF ownership. For example, if 6% of a mutual fund's assets are held by TDFs (the mean in the subsample with positive TDF investment), the return-chasing tendency is reduced by about one sixth ($0.645 \times 0.06/0.250 \approx 16\%$). In column 2, we add time fixed effects, thus, coefficients on the asset class return can no longer be estimated. The coefficients on the interaction terms with TDF ownership shrink but remain economically and statistically significant, suggesting the difference between mutual funds with and without TDF investment is significant within cross-sections.

In columns 3-4 of Table 5, we measure the asset class return as the excess return of the equity market over the risk-free rate. The estimates stay similar as those in columns 1-2 and imply that TDF investment reduces the individual fund flow sensitivity to the stock market excess return. For this reason and because common asset pricing tests are based on excess returns, we focus on the sensitivity of stock returns to past market excess returns in

[13] The mutual fund flow literature has largely focused on the within asset-class excess performance. On cross-sectional raw return or market-adjusted return, see Chevalier and Ellison (1997), Sirri and Tufano (1998), Bergstresser and Poterba (2002). On asset-pricing model adjusted return, see Barber et al. (2016) and Berk and van Binsbergen (2016). On the role of rating agencies, see Del Guercio and Tkac (2008), Evans and Sun (forthcoming) and Ben-David et al. (2019). Studies on the flow sensitivity to asset class performance are fewer. Cooper et al. (2005) and Greenwood and Nagel (2009) show that investors respond to hot investment styles (subsets of the equity asset class), which impacts fund strategies. Bailey et al. (2011) show that trend chasing is correlated with proxies for investor biases.

the subsequent section, but our results are similar if we instead examine the sensitivity to $R^S - R^B$ which is the variable directly implied by our model.

6 TDF ownership and stock return dynamics

In the last part of the paper, we analyze whether the rebalancing trades by TDFs impact asset price dynamics. The literature has documented the effect of mutual fund flow-driven pressure on asset prices (Warther (1995), Edelen and Warner (2001), Coval and Stafford (2007), Lou (2012)). However, we argue that such flow pressure is reduced in the mutual funds with high TDF ownership. Specifically, stocks with high actual or expected TDF ownership should exhibit lower 'momentum' with respect to recent market performance, in that they generate lower returns after market rises. Note that this notion of 'momentum' is different from the cross-sectional momentum that is widely documented in the literature (see, for example, Jegadeesh and Titman (1993) and Jegadeesh and Titman (2001)) which refers to the phenomenon that cross-sectional winner stocks are likely to continue outperforming in the medium term. Instead, we focus on the sensitivity of stock returns to recent aggregate market (more precisely, the aggregate TDF portfolio) performance. In this sense, our study is more similar to the 'time series momentum' documented in Moskowitz et al. (2012).

6.1 Determinants for TDF ownership

We begin by documenting the distribution of TDF ownership across stocks in order to identify the set of stocks that are most affected by TDF rebalancing. Given the demand for low fees by plan fiduciaries[14] and the common usage of broad-market-based low-cost funds such as S&P 500 index funds in TDF portfolios, we expect size to be a main factor affecting stock-level TDF ownership.

Figure 2 examines the relationship between TDF ownership and market capitalization.

[14] In 2013, DOL issued a set of tips to plan fiduciaries for the selection of TDFs, which include an emphasis on low fees. See https://www.dol.gov/sites/dolgov/files/EBSA/about-ebsa/our-activities/resource-center/fact-sheets/target-date-retirement-funds.pdf

We measure TDF ownership at the stock level as $TDFpct_{it} = \Sigma_{jk} a_{ijt} b_{jkt}$ for stock i in quarter t where a_{ijt} is the fraction of stock i held by mutual fund j and b_{jkt} is the fraction of mutual fund j held by TDF k. Quarterly mutual fund holdings data are from Thomson Reuters which are linked to the CRSP mutual fund dataset using MFLINKS. Figure 2 represents the collapsed cross section of stocks during our sample 2008Q3-2018Q4. For each stock, we calculate the average market capitalization and TDF ownership during this period. Then we sort the stocks into deciles based on the average market capitalization. In panel A, we plot the equal-weighted and value-weighted average TDF ownership by market-cap decile, and find that TDF ownership is the highest among the top four deciles of stocks, where the TDF ownership is three times the level of the other deciles. In panel B, we provide a two-way histogram on the joint distribution between market capitalization and TDF ownership. While confirming a positive correlation between the two variables, panel B also illustrates that TDF ownership is not perfectly co-linear with size, which we later exploit to estimate the effect of the TDFs that is separate from a size effect. Further, we later hypothesize that rule- or index-based investment strategies of TDFs may contribute to the dispersion in TDF ownership among stocks of similar size.

Now we rely on regression analysis to confirm the result from Figure 2. Table 6 estimates the determinants for TDF ownership using observations at the stock-by-quarter level. The dependent variable is the time varying ultimate TDF ownership expressed in percentages, calculated by $TDFpct_{it} = \Sigma_{jk} a_{ijt} b_{jkt}$ where a_{ijt} is the fraction of stock i held by mutual fund j in quarter t, and b_{jkt} is the fraction of mutual fund j held by TDF k. First, we examine the dispersion in TDF ownership across all stocks. Column 1 controls for time fixed effects but no stock fixed effects, thus focusing on the cross-sectional dispersion in TDF investment. The result suggests that a 10% increase in size (measured by market capitalization) is associated with a 1.2 basis point increase in the stock-level TDF ownership. In column 2 which controls for stock fixed effects, we see that longitudinally, an increase in market capitalization of 10% in the same stock implies a 1 basis point higher TDF ownership. These rates of increases appear small as they represent the average among all stocks.

Next, we ask whether rules, such as index inclusion into the S&P 500, affect stock-level TDF ownership. S&P 500 index funds are a common choice for equity allocation in TDF

portfolios.[15] The S&P 500 inclusion rule is based on a set of eligibility criteria, including domicile, stock exchange, years since IPO, financial viability, market capitalization, and liquidity. After the eligibility criteria are satisfied, the 'index committee' at S&P Global has discretion over the selection, in particular, a 'sector balance' is considered.[16] However, it is conceivable that in a group of stocks similarly eligible for the index, the actual inclusion decisions are uncorrelated with expected TDF ownership or stock return dynamics. Under this assumption, index inclusion into the S&P 500 among a set of similar stocks offers plausibly exogenous variation in the extent of TDF ownership.

To understand whether being included in the S&P 500 index leads to an increase in TDF ownership and consequently different return dynamics, we construct a group of control stocks for stocks in the S&P 500, following the methodology in Denis et al. (2003). First, based on the eligibility criteria, we screen the full sample of stocks and restrict to stocks that are domiciled in the U.S., traded on the eligible exchanges, at least one year from the IPO, and have positive sum of earnings in the recent four quarters as well as positive earnings in the most recent quarter. Second, in each of the 12 Fama-French industry portfolios, we first divide the stocks into 3 groups based on terciles of market capitalization, with equal numbers of stocks in each group, and then further divide each industry and size group into another three based on liquidity (defined as the annual trading volume divided by the number of shares outstanding). This way we obtain 108 portfolios. Third, we map the S&P 500 stocks to the 108 portfolios (multiple S&P stocks can be mapped to the same portfolio) and use the other stocks in the corresponding portfolios that are not included in the index as a control for the index-included stocks. Throughout the sample period, 53 out of the 108 portfolios can be matched with S&P 500 stocks.

The regressions in columns 3-4 of Table 6 use the sample of stocks in the portfolios that can be matched with S&P 500 stocks, i.e., the S&P 500 stocks and control stocks that are matched on industry, market capitalization and liquidity. We mainly exploit the changes in S&P 500 status by including stock fixed effects in these two columns. In addition, column 4

[15] According to our tabulation, the amount of TDF assets allocated to S&P 500 index funds is the highest among the common S&P and Russell indices and 1.5 times higher than that invested in Russell 1000-based index funds, the second popular option.

[16] Please refer to https://us.spindices.com/documents/methodologies/methodology-sp-us-indices.pdf /: for more details.

further includes the narrow peer portfolio by time fixed effects, thus controlling for time varying impacts of stock characteristics. The result suggests that being added to the S&P 500 index leads to a 0.13% to 0.19% increase in TDF ownership (or about 20% of the mean TDF ownership in the matched subsample), relative to similar stocks that are not included in the index.

6.2 Effect of TDF investment on stock returns

6.2.1 Cross-sectional TDF investment and stock returns

In this section, we investigate the hypothesis that stocks with higher TDF ownership exhibit lower momentum with respect to market returns. We start by estimating the sensitivity of monthly stock returns to the lagged market return, allowing the sensitivity to vary by TDF ownership. The regression specification follows:

$$Ret_{it} = \gamma Mkt_{t-1} \times TDFOwnership_{it} + TDFOwnership_{it} + \theta_t + X_{it} + \epsilon_{it} \tag{6}$$

The baseline sensitivity of monthly stock return to the lagged market excess return among the stocks not invested by TDFs is absorbed by the inclusion of time fixed effects, and the key parameter of interest is γ, the differential sensitivity to market momentum by different levels of TDF ownership. Given the TDF trading pressure that is opposite to market movements, we expect $\hat{\gamma}$ to be negative. For the estimation, we use monthly stock returns during 2010-2019 to allow for a substantial size and impact of the TDF market. The dependent variable is the raw monthly return winsorized at 1% and 99%. Market return is measured as the monthly excess return of the market over the risk-free rate. Since TDF holdings are available only quarterly, TDF ownership is measured at the latest quarter end. The control variables include the natural logarithms of lagged market value and lagged trading volume. The analysis clusters the standard errors two-ways by time (year-month) and stock.

In Table 7, panel A, column 1, our baseline specification, we find that higher TDF

ownership is associated with lower market momentum. Stocks with one standard deviation (0.6%) higher TDF ownership is associated with a 0.057 (0.6×0.095) reduction in the sensitivity of the stock return to the lagged market return. That is, when the market rises by 10% in a month, stocks one standard deviation higher in TDF ownership have 0.57% lower return in the following month. Columns 2 shows that this result is robust when we control for time-by-industry (measured by Fama French 12 industry classification) shocks.

Our main prediction about the TDF trading pressure concerns raw stock returns. If stocks with different characteristics have different propensities for TDF investment, that is part of the variation we want to capture. However, it is also important to rule out that the result on differential sensitivity to market momentum may simply be driven by stock characteristics. Columns 3, 5 and 6 of Table 7 provide robustness checks that assess these concerns. In column 3, we allow the baseline sensitivity to market momentum to be different for stocks with different size and trading volume. Unsurprisingly, the coefficient on the interaction term with TDF ownership shrinks because size is an important source of variation in TDF ownership (Table 6). However, we find that the effect of TDF ownership in reducing the sensitivity of stock return to the lagged market performance remains robust. In addition, size appears to have a separate but marginally insignificant effect on the return sensitivity that is in the same direction as TDF ownership.[17]

In columns 5-6, we consider whether factor exposures of stocks may explain our finding. Since factor betas may be directly influenced by TDF investments, we use an estimation window of 1996-2005 to estimate the exposures of stocks to the Fama-French three factors and the momentum factor. In column 5, the 4 factor exposures are estimated using concurrent stock returns and factor returns, i.e., $r_{it} - r_t^f = \alpha_i + \beta_{i1}(r_t^m - r_t^f) + \beta_{i2} r_t^{SMB} + \beta_{i3} r_t^{HML} + \beta_{i4} r_t^{MOM} + \epsilon_{it}$, where in each regression we use monthly returns during the estimation window and require at least 60 observations. The regression subsequently includes controls for these beta estimates multiplied by the factor returns in the same month as the stock return measure. This is similar to using the 4-factor alpha as the dependent variable. Next, we control for the possibility that the returns of certain stocks may be systematically correlated

[17] The specification in column 4 is only estimated for panel B but not panel A, because the large number of fixed effects make the estimation infeasible in the full sample.

with lagged factor returns, which may drive our results. Again using a window of 1996-2005, we estimate the exposures of stocks to returns of the 4 factors in the previous month, following: $r_{it} - r_t^f = \alpha_i + L\beta_{i1}(r_{t-1}^m - r_{t-1}^f) + L\beta_{i2}r_{t-1}^{SMB} + L\beta_{i3}r_{t-1}^{HML} + L\beta_{i4}r_{t-1}^{MOM} + \epsilon_{it}$. Then we include the $L\beta$ estimates multiplied by the previous month's factor returns as controls in the regression in column 6. If TDFs simply hold stocks with low $L\beta$ with respect to the lagged market factor, the coefficient on the interaction term between the lagged market factor and TDF ownership will be explained away once we directly control for $L\hat{\beta}_{i1}$ times the lagged market factor. However, column 6 suggests that this is not the case. In fact, the estimated effect of the TDFs is unaffected by the inclusion of the additional controls.

To show that the high-TDF-ownership stocks do not always respond negatively to recent market performance, we conduct falsification tests using two earlier periods 1996-2005 and 1986-1995 before the PPA of 2006 set off the growth of the TDF market. Using TDF ownership measured as the average during 2010-2018, we track these stocks to the earlier periods and test whether the high-TDF stocks in the later period already behaved differently in the earlier periods even without the actual impact of TDF investments. The falsification test results in columns 7-8 suggest that this is not the case: we find that before the PPA of 2006, the high- and low-TDF stocks exhibit similar sensitivity to the lagged market performance. These results suggest that the results documented in Table 7 are unique to the TDF era.

Finally, in panel B of Table 7, we repeat the analysis in panel A in a matched sample containing S&P 500 stocks matched to their peer groups based on industry, size, and liquidity. Most estimations in panel B control for time-by-peer-group fixed effects, thus controlling for time-varying shocks to stocks within narrow ranges of characteristics. We also estimate an additional specification in column 4 which includes stock fixed effects interacted with the lagged market excess return, thus controlling for the average sensitivity of the stock to the market and only exploiting the changes in TDF ownership. This specification strengthens our results. In panel B, size no longer has an independent effect on the sensitivity to market momentum, which is as expected since we compare stocks with highly similar characteristics. However, the magnitudes of the estimated TDF effect are similar to those in panel A, which reassures us that our results in this table capture a

TDF effect by itself which is separate from a size effect.

6.2.2 S&P 500 index inclusion study

Though the battery of robustness tests help us alleviate concerns over mechanical explanations for the results in Table 7, it does not fully answer whether the reduced stock-level sensitivity to market momentum is indeed caused by TDF investments or only driven by TDF selection into certain types of stocks. To shed light on the causal relationship, we now rely on inclusion into the S&P 500 Index as a quasi-exogenous source of variation for TDF ownership. To identify the causal impact of TDF ownership on stock returns, we use the matching procedure explained in section 6.1 to form a control group for the S&P 500 stocks which are matched on industry, size, and liquidity. We then estimate:

$$Ret_{ipt} = \gamma Mkt_{t-1} \times S\&P500_{it-1} + S\&P500_{it-1} + \theta_{pt} + X_{it} + \epsilon_{ipt} \tag{7}$$

where i stands for a stock, p refers the peer group that the stock belongs to, and t indexes time (year-month). Equation 7 estimates a difference-in-differences specification that compares the responses of two groups of stocks to market shocks. The S&P 500 stocks are the treated group with higher TDF ownership, and the non-S&P stocks with similar characteristics serve as a control. With the inclusion of the peer group by time fixed effects θ_{pt}, the identifying assumption is that within each peer group, the treated and control stocks would have behaved similarly in response to market shocks if they had not been affected by TDF investments. This assumption is likely to be satisfied. As explained and shown in section 6.1, conditional on the eligibility criteria, the decision to include a stock into the S&P 500 index is plausibly orthogonal to the expected stock return dynamics, but leads to a discrete and sizable increase in TDF ownership.

Table 8 presents the index inclusion results for the matched sample. Column 1 suggests that compared with peer stocks matched on characteristics, being included in the S&P 500 leads to a 0.09 reduction in the sensitivity to market momentum, which implies that when the market rises by 10% in a month, the index stocks have 0.9% lower return in the

following month compared with similar non-index stocks. Column 2 adds in time-by-peer portfolio fixed effects, thus ensuring that the estimate is driven by within peer group comparisons. Columns 3-6 show that the results are robust under various controls for the impact of stock characteristics including factor exposure on the return sensitivity to market momentum. In columns 3, 5, and 6, we observe that in the matched sample, controlling for the effect of size no longer reduces the estimated TDF effect. In column 4, we see the effect doubles in magnitude if we control for time-invariant return sensitivity at the stock level, which suggests that our results are driven by the switches into and out of the S&P 500 index. Finally, in the falsification tests conducted using data over 1996-2005 and 1986-1995, we find that being included in the S&P 500 did not lower the sensitivity to market momentum in those early periods, instead, it is a phenomenon only present in our main sample period that has a substantial TDF market. This suggests that the documented index inclusion effect is indeed likely to be driven by TDFs.[18]

A growing literature documents the many potential impacts of index inclusion on the return dynamics of stocks. For example, the demand effect leads to an increase in price (e.g., Harris and Gurel (1986),Shleifer (1986), Wurgler and Zhuravskaya (2002), and Chang et al. (2015)), co-movement (Barberis et al. (2005) and Boyer (2011)), excess daily return volatility due to exchange-traded fund (ETF) trading (Ben-David et al. (2018)). A recent study Bennett et al. (2020) shows that joining the S&P 500 alters the investment and financial policies of firms, leading to a long-term negative impact. Our analysis controls for the return level effect of the inclusion and focuses on the sensitivity of stock return to the market momentum. This sensitivity is distinct from co-movement, in that it concerns the relationship between stock return and the lagged market performance, whereas co-movement concerns the correlation between contemporaneous stock return and market performance. If the market return follows a random walk, co-movement does not generate any prediction on the effect of index inclusion on the stock-level return sensitivity to lagged market performance. If the market return is serially positively correlated, for example due to positive feedback trading, co-movement predicts an increase in the sensitivity to market

[18]In Table A.2, we present a two-stage least squares estimate of the effect of TDFs using S&P 500 membership as an instrumental variable for TDF ownership. However, we acknowledge that the analysis in Table A.2 is subject to the weak instrument problem.

momentum in index-included stocks. However, our result shows the opposite, cannot be explained by co-movement, and is in line with the contrarian effect of TDFs. Our result is also distinct from the ETF-induced excess volatility. Our conversations with practitioners suggest that TDFs rebalance at much lower frequency than the trading strategies of ETFs. Instead of examining volatility at the daily level, we consider the monthly return dynamics of stocks in response to the recent market performance. Since TDF-invested stocks exhibit lower sensitivity to market momentum, our result works in the direction of dampening low-frequency market fluctuations at the aggregate level.

6.3 Aggregate market return predictability during TDF era

We now examine the pricing effect of TDFs in the aggregate. The results in section 6.2 suggest that S&P 500 stocks have higher TDF ownership and negatively respond to recent market performance. This implies that the rise in the TDF market can lead to negative time series correlations in the S&P 500 index.

In Table 9, we report the time series correlations in the S&P 500 index during three 10-year periods 1986-1995, 1996-2005 (before the PPA of 2006), and 2010-2019. The first two periods had limited impact from the TDFs, and the third period represents an era when TDF investments have a sizable impact. The regressions follow:

$$r_t^{SP} = \alpha + \beta_h r_{t-h \text{ to } t-1}^{SP} + \epsilon_t^{SP} \tag{8}$$

where r_t is the monthly return of the S&P 500 index in month t and $r_{t-h \text{ to } t-1}$ represents the lagged cumulative return of the S&P 500 during the h months ending in month $t-1$. We explore h values of 1, 3, 6, and 12.

The result in column 1 of Table 9 shows that before the rise of the TDFs, there was weakly positive but insignificant time series correlation between in monthly returns of the S&P 500 index from one month to the next, in line with a lack of predictability in the equity market returns (e.g., Fama (1970) and Malkiel (1973)).[19] However, during 2010-2019

[19] Moskowitz et al. (2012) show a violation of the efficient market hypothesis and a persistence in the

which had a sizable TDF market, the monthly returns of the S&P 500 show a significant negative time series correlation, which is consistent with the findings in Table 8. Columns 2-4 confirm that the time series reversal observed for the S&P 500 index during 2010-2019 is robust under cumulative measures of lagged performance calculated over 3-month, 6-month, or 12-month horizons. Overall, the results in Table 9 are consistent with the rise of TDFs altering aggregate stock market dynamics.

7 Concluding remarks

The target date fund innovation shifts life-cycle investment problems from ill-equipped retirement plan participants to professional money management companies. Since the 2006 Pension Protection Act which qualified TDFs to serve as default options in 401(k) plans, the TDF market has seen exponential growth. Today 90% of employers offer TDFs as the default options in their retirement plans. Many retirement plan investors are thus moved into an investment vehicle that holds automatically rebalanced portfolios with optimal debt-equity allocation.

This paper draws attention to an important implication of TDFs on the financial asset market. We show that TDFs rebalance portfolios by buying low and selling high, which enables them to become a market-stabilizing force. In the past 15 years, the growth of TDFs has significantly changed the patterns of fund flows and the time series dynamics in stock returns. As the TDF market continues to grow, we expect the effects documented in this paper to become more pronounced.

monthly returns at 1 to 12 month horizons for a collection of asset classes. For the equity asset class, they use data on nine equity index futures. With data on the S&P 500 index only, we do not observe a significant positive serial correlation even when replicating the Moskowitz et al. (2012) methodology.

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Figure 1: Growth of TDF assets

This figure plots the total net assets (TNA) of TDFs during 2000Q1-2019Q4 broken down by target retirement years. TDFs in the CRSP mutual fund database are identified from fund names containing target retirement years at five-year intervals ranging from 2000 to 2065, then manually cleaned using the TDF series names listed in the Morningstar annual TDF research reports. TDFs with target retirement years that are in the middle of a decade (20x5) are grouped together with the TDFs with target retirement years at the beginning of the decade (20x0). The TD2010- category in this figure includes TD2000 and TD2010. The TD2050+ category includes TD2050 and TD2060.

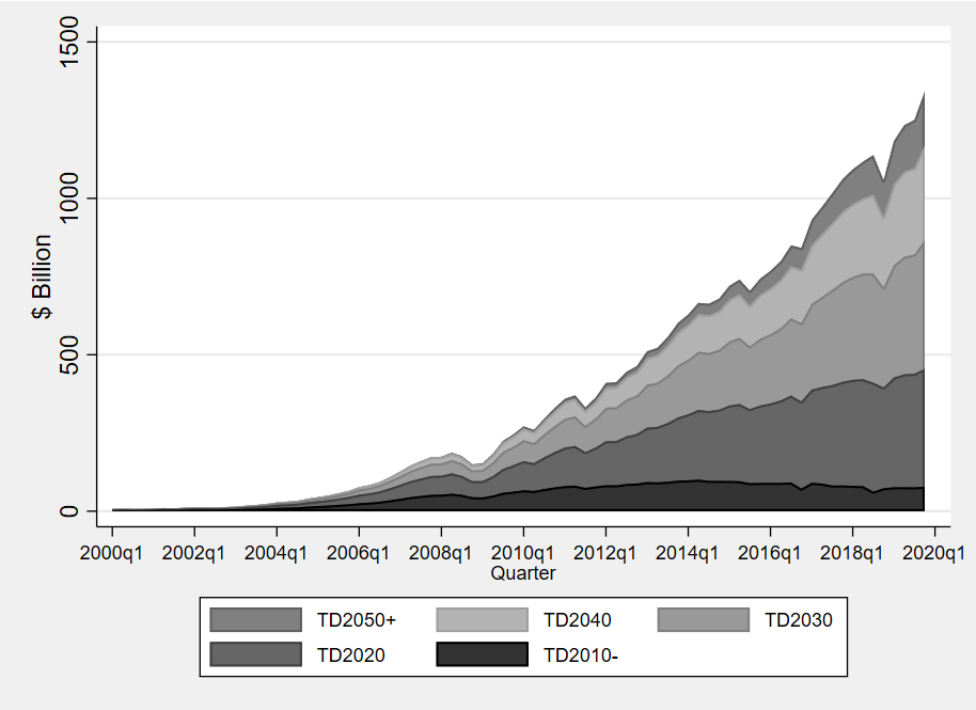
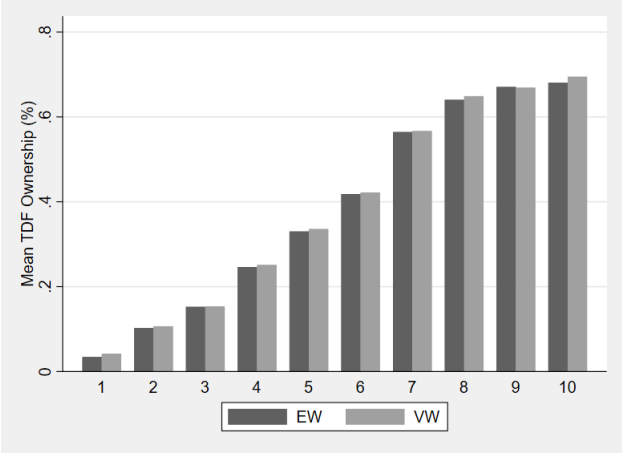
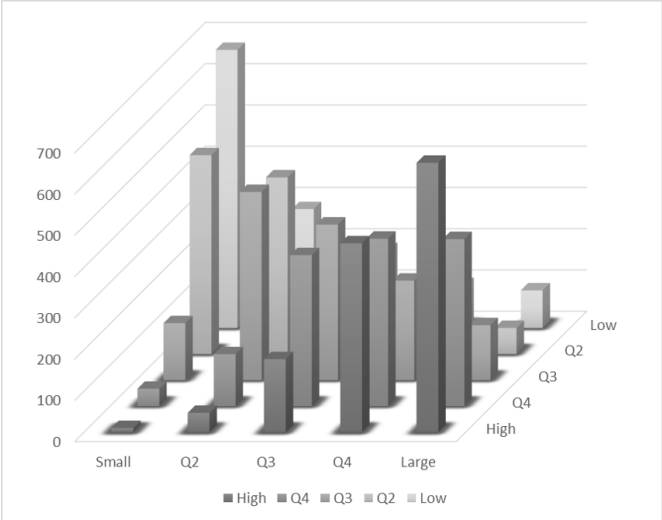


Figure 2: Distribution of size and TDF ownership

This figure illustrates the relationship between stock-level size measured by market capitalization and TDF ownership. Both the market capitalization and the TDF ownership for each stock are calculated as averages during our sample 2008Q3-2018Q4. Panel A plots both the equal-weighted and value-weighted averages of TDF ownership expressed in percentages by size decile, where decile 10 represents the largest stocks. Panel B plots a two-way histogram for the number of stocks in each of 25 cells, where the cells are constructed from the market capitalization quintiles (large, Q4, Q3, Q2, small) and TDF ownership quintiles (high, Q4, Q3, Q2, low).



(a) TDF ownership by market cap decile



(b) Two-way histogram by size and TDF ownership

Table 1: TDF rebalancing formulae

This table derives the rebalancing formulae by which a TDF restores the target asset allocation after realized asset class returns R^S and R^B for equity and bond, respectively. Panel A concerns the case of zero net flow to the TDF. Panel B considers non-zero net flow to the TDF. The TDF asset value at the beginning of the period before the asset class returns are realized is normalized to \$1.

A.	Wt.	Return	Value w/o re-balancing	Alloc. accord. to glide path	Re-balancing trades
Equity	S	R^S	$S(1+R^S)$	$[1+R^B+S(R^S-R^B)]S$	$-S(1-S)(R^S-R^B)$
Bond	$1-S$	R^B	$(1-S)(1+R^B)$	$[1+R^B+S(R^S-R^B)](1-S)$	$S(1-S)(R^S-R^B)$
Total	1		$1+R^B+S(R^S-R^B)$	$1+R^B+S(R^S-R^B)$	0

B.	Wt.	Return	Value w/o re-balancing	Alloc. accord. to glide path	Total net trades	Flow alloc.	Re-balancing trades
Equity	S	R^S	$S(1+R^S)$	$[1+R^B+S(R^S-R^B)+F]S$	$FS-S(1-S)(R^S-R^B)$	FS	$-S(1-S)(R^S-R^B)$
Bond	$1-S$	R^B	$(1-S)(1+R^B)$	$[1+R^B+S(R^S-R^B)+F](1-S)$	$F(1-S)+S(1-S)(R^S-R^B)$	$F(1-S)$	$S(1-S)(R^S-R^B)$
TDF net flow			F				
Total	1		$1+R^B+S(R^S-R^B)+F$	$1+R^B+S(R^S-R^B)+F$	F	F	0

Table 2: Summary statistics

The sample period is 2008Q3-2018Q4. Target year is extracted from fund name containing target retirement years from 2000 to 2065 at five-year intervals. No. funds held represents the number of mutual funds held by a TDF in a given quarter. The fractions of portfolios invested in equity and fixed income are imputed from TDF holdings data, where the classifications of the underlying mutual funds are identified using the CRSP objective codes. Flow to TDF is calculated as the dollar growth in the TDF assets in excess of the growth that would have occurred given the investment return. Rebalancing trade in an asset class is calculated as the total trade in the asset class, measured by the change in the value of holding in excess of the value predicted by the returns of the underlying mutual funds, minus the flow-driven trade, measured by the dollar flow to the TDF allocated proportionally to the lagged asset class weight. Fund flow rate is measured at the mutual fund level as the quarterly growth rate in assets in excess of the growth that would have occurred given the investment return. Return volatility is calculated as one-year standard deviation in the monthly returns up to a given quarter. Fraction held by TDFs is calculated as the total value of TDF holdings of a fund divided by the fund TNA. Stock-level monthly excess return is the monthly raw return minus the risk-free rate. S&P 500 membership equals one if a stock is included in the S&P 500 in a month. TDF ownership refers to the fraction of a stock ultimately owned by TDFs.

A. TDF quarterly	N	Mean	p25	p50	p75	SD
Target year	9,016	2031.8	2020	2030	2045	14.6
Total net assets ($ million)	9,016	2185.9	63.2	276.2	1513.8	4896.2
No. funds held	9,016	15.9	9	15	21	8.6
Frac. portfolio in equity	9,016	0.734	0.588	0.778	0.899	0.185
- Domestic equity	9,016	0.486	0.389	0.508	0.597	0.143
- Foreign equity	9,016	0.248	0.172	0.240	0.306	0.113
Frac. portfolio in fixed income	9,016	0.266	0.101	0.222	0.412	0.185
Flow to TDF, t / TNA, t-1	9,016	0.060	-0.007	0.031	0.084	0.126
Rebal. trade in equity, t / Total holding, t-1	9,016	-0.011	-0.022	-0.008	0.002	0.067
Rebal. trade in fixed income, t / Total holding, t-1	9,016	0.004	-0.003	0.003	0.012	0.030

B. Mutual fund quarterly	N	Mean	p25	p50	p75	SD
Fund flow rate (%)	58,200	1.27	-4.64	-1.69	1.99	32.16
Fund size ($ billion)	58,200	2.1	0.1	0.3	1.2	11.2
Fund family size ($ billion)	58,200	249.8	2.9	28.9	130.8	579.7
Fund age (year)	58,200	18.9	10.0	16.0	23.0	14.0
Expense ratio (%)	58,200	1.18	0.91	1.19	1.45	0.46
Return volatility (%)	58,200	4.29	2.84	4.00	5.50	1.91
Frac. held by TDFs (%)	58,200	0.52	0.00	0.00	0.00	4.05
Frac. held by TDFs (%) among non-zero	4,669	6.43	0.19	1.05	5.45	12.90
C. Stock monthly	N	Mean	p25	p50	p75	SD
Monthly excess return (%)	274,167	0.89	-5.36	0.63	6.57	12.51
S&P 500 membership	274,167	0.18	0.00	0.00	0.00	0.38
Market capitalization ($ billion)	274,167	6.89	0.13	0.72	3.22	27.89
Volume (million)	274,167	33.73	0.90	5.39	23.07	173.92
TDF ownership (%)	274,167	0.54	0.10	0.40	0.73	0.62

Table 3: TDF rebalancing with respect to asset class movements

This table estimates the relationship between the individual TDF rebalancing and asset class returns during 2008Q3-2018Q4. Observations are at TDF-by-quarter frequency. The dependent variables are the ratios of rebalancing trades by a TDF in equity or fixed income in quarter t divided by the total value of holdings of the TDF including both equity and fixed income in quarter $t-1$, and winsorized at 1% and 99%. The full sample includes all TDFs. The 'moderate' sample includes only the TDFs with equity shares between 25% and 75%, and under the 'aggressive or conservative' sample includes only those with equity shares below 25% or above 75%. R^S represents the quarterly return of the total US stock market. R^B is measured as the pre-fee quarterly return of the Vanguard Total Bond Market Index Fund. S is the equity share for each TDF and is measured as the fraction of the TDF portfolio invested in equity at the end of quarter $t-1$. All regressions include TDF fixed effects. Standard errors are clustered two ways by TDF and quarter. *p $<$ .1; **p $<$ .05; ***p $<$ .01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full	Moder.	Aggr. or conserv.	Full	Moder.	Aggr. or conserv.
A.	Rebal (E), t / Total holding, t-1			Rebal (FI), t / Total holding, t-1		
$(R^S - R^B)_t$	-0.080**	-0.121***	-0.042	0.056***	0.094***	0.021*
	(0.036)	(0.038)	(0.035)	(0.017)	(0.026)	(0.011)
$(R^S - R^B)_{t-1}$	-0.096*	-0.083	-0.105*	0.031**	0.035**	0.025
	(0.053)	(0.055)	(0.053)	(0.015)	(0.017)	(0.016)
TDF FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,002	3,681	4,290	7,932	3,681	4,219
R-squared	0.093	0.134	0.098	0.103	0.124	0.127
B.	Rebal (E), t / Total holding, t-1			Rebal (FI), t / Total holding, t-1		
$S(1-S)(R^S - R^B)_t$	-0.498**	-0.516***	-0.443	0.369***	0.409***	0.241**
	(0.189)	(0.164)	(0.286)	(0.105)	(0.115)	(0.095)
$S(1-S)(R^S - R^B)_{t-1}$	-0.453	-0.357	-0.837	0.152*	0.153**	0.154
	(0.293)	(0.238)	(0.521)	(0.080)	(0.074)	(0.132)
TDF FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,002	3,681	4,290	7,932	3,681	4,219
R-squared	0.093	0.134	0.098	0.110	0.125	0.128

Table 4: Aggregate TDF vs. retail flows

This table contrasts aggregate time series of TDF trades in and retail fund flows to domestic equity funds during 2008Q3-2018Q4. Observations are at quarterly frequency. The TDF series in columns 1-2 is calculated as the sum of all rebalancing trades by TDFs and in columns 3-4 is calculated as the sum of all total trades by TDFs. For each TDF-quarter, the rebalancing trade is the total trade minus the flow-driven trade. The retail series is constructed by summing up all dollar flows to retail domestic equity fund share classes in a quarter, where the flow to a share class is the increase in assets above the level implied by fund return and calculated as $TNA_t - TNA_{t-1}(1 + r_t)$ and r_t is the quarterly net return of the share class. In the case that any retail share class is traded by TDFs, the TDF trades are deducted before aggregating up the retail flows. $R^S - R^B$ represents the return of the US equity market from CRSP minus the pre-fee return of the Vanguard Total Bond Market Index Fund. Columns 1 and 3 contrast the retail flows with one aggregate TDF series that is the sum of all TDFs. Columns 2 and 4 contrast retail flows with two TDF series, one 'aggressive or conservative' that is based on TDFs with equity shares below 25% or above 75%, and the other 'moderate' that is based on TDFs with equity shares between 25% and 75%. 'TDF all', 'TDF aggressive or conservative', and 'TDF moderate' are indicators and total assets are measured as the sum of assets of the respective data series in billion dollars. Standard errors are clustered by time (year-quarter). *p $<$ .1; **p $<$ .05; ***p $<$ .01.

	(1)	(2)	(3)	(4)
	Dollar flow, t			
TDF measure	Rebalancing		Total	
$R^S - R^B$, t	306.598***	306.598***	306.598***	306.598***
	(86.563)	(86.761)	(86.563)	(86.761)
$R^S - R^B$, t × TDF all	-334.416***		-309.498***	
	(87.045)		(85.328)	
Net coef for TDF all	*-27.818**		*-2.899*	
	(14.397)		*(16.229)*	
$R^S - R^B$, t × TDF aggr. or conserv.		-312.458***		-299.331***
		(88.192)		(86.081)
$R^S - R^B$, t × TDF moder.		-328.557***		-316.765***
		(85.261)		(85.626)
Net coef for TDF aggr. or conserv.		*-5.860*		*7.267*
		(6.761)		*(9.950)*
Net coef for TDF moder.		*-21.959***		*-10.167*
		(8.417)		*(8.120)*
TDF all	39.753***		50.610***	
	(5.320)		(6.100)	
TDF aggr. or conserv.		40.687***		48.700***
		(5.410)		(5.897)
TDF moder.		40.734***		43.578***
		(5.238)		(5.435)
Observations	74	111	74	111
R-squared	0.618	0.667	0.649	0.681

Table 5: Effect of TDF ownership on mutual fund flows

This table estimates the effect of TDF ownership on the mutual fund flow-performance relationship. Observations are at the mutual-fund-by-quarter level. The sample is restricted to retail domestic equity mutual funds where the fraction of assets invested in retail share classes is above 50%. The dependent variable is the quarterly fund flow rate, defined as the growth rate in fund assets in excess of the realized fund return. Observations where the lagged asset size is less than $10 million, and where the flow rate is larger than 1,000% or smaller than -90%, are dropped. The header 'AC return measure' stands for asset-class return and indicates whether it is measured as the difference between equity and bond market returns $R^S - R^B$ or the excess return of equity over the risk-free rate $R^S - R^f$. R^S is the quarterly return of the US equity market from CRSP, R^B is the pre-fee return of the Vanguard Total Bond Market Index Fund, and R^f is the quarterly return on the 1-month treasury. 'Frac. held by TDFs' is measured as the fraction of fund assets held by TDFs. The control variables include log of the lagged fund size and fund family size, log of fund age measured for the oldest share class, the annual expense ratio, and the lagged yearly standard deviation of monthly returns measured with rolling window. Standard errors are clustered two ways by time and fund. *p $<$ .1; **p $<$ .05; ***p $<$ .01.

	(1)	(2)	(3)	(4)
	Fund flow rate, t			
AC return measure	$R^S - R^B$		$R^S - R^f$	
AC return, t	0.250***		0.256***	
	(0.078)		(0.067)	
AC return, t × frac. held by TDFs, t-1	-0.645***	-0.368*	-0.682***	-0.440**
	(0.182)	(0.194)	(0.180)	(0.188)
AC return, t-1	0.075		0.097	
	(0.059)		(0.081)	
AC return, t-1 × frac. held by TDFs, t-1	-0.282*	-0.132	-0.344*	-0.118
	(0.160)	(0.202)	(0.198)	(0.250)
Frac. held by TDFs, t-1	0.023	0.037	0.033	0.042*
	(0.021)	(0.024)	(0.021)	(0.022)
ln (Fund size), t-1	-0.014***	-0.015***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
ln (Fund family size), t-1	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
ln (Age), t	-0.022***	-0.019***	-0.021***	-0.019***
	(0.003)	(0.004)	(0.003)	(0.004)
Expense ratio, t	-1.588***	-1.705***	-1.563**	-1.706***
	(0.575)	(0.579)	(0.581)	(0.579)
Return volatility, t-1	0.320	-0.048	0.243	-0.048
	(0.325)	(0.251)	(0.317)	(0.251)
Time FE	N	Y	N	Y
Observations	57,828	57,828	57,828	57,828
R-squared	0.016	0.049	0.016	0.049

Table 6: Determinants for TDF ownership at stock level

This table shows the determinants for stock-level TDF ownership. Observations are at stock-by-quarter level during 2008Q3-2018Q4. Columns 1-2 include the full sample. Columns 3-4 include the matched sample of S&P 500 stocks and their benchmark stocks within the same industry-by-size-by-liquidity peer group. The peer groups are obtained in each quarter by sorting on market capitalization and annual trading volume divided by shares outstanding within each Fama-French-12 industry. The dependent variable is the fraction (expressed in percentages) of the stock ultimately owned by TDFs and calculated for each stock i in quarter t as $TDFpct_{it} = \Sigma_{jk} a_{ijt} b_{jkt}$ where a_{ijt} is the fraction of stock i held by mutual fund j in quarter t, and b_{jkt} is the fraction of mutual fund j held by TDF k. S&P 500 is an indicator that equals one if the stock is included in the S&P 500 index in the corresponding quarter and zero otherwise. Standard errors are clustered by stock.

	(1)	(2)	(3)	(4)
	TDF Ownership (%), t			
	All stocks		S&P 500 matched sample	
S&P 500, t			0.134**	0.190**
			(0.064)	(0.074)
ln (Market cap, t-1)	0.120***	0.099***	-0.033	-0.098
	(0.004)	(0.007)	(0.053)	(0.061)
ln (Volume, t-1)	0.003	-0.005	0.019	0.005
	(0.004)	(0.004)	(0.047)	(0.046)
Time FE	Y	Y	Y	Y
Stock FE	N	Y	Y	Y
Time-by-matched peer group FE	N/A	N/A	N	Y
Observations	122,009	121,791	7,949	7,910
R-squared	0.216	0.600	0.614	0.675

Table 7: TDF ownership and stock return sensitivity to lagged market performance

This table examines the relationship between TDF ownership and stock returns in response to recent market performance. Panel A uses the full sample of all stocks traded on the NYSE, NASDAQ, and AMEX. Panel B uses the matched sample of S&P 500 stocks and their benchmark stocks within the same industry-by-size-by-liquidity peer group. The peer groups are obtained in each quarter by sorting on market capitalization and annual trading volume divided by shares outstanding within each Fama-French-12 industry. The main sample includes monthly stock returns during 2010-2018. The dependent variable is the raw monthly return winsorized at 1% and 99%. TDF ownership is measured as of the end of the previous quarter and expressed in percentages. Industry dummies are defined by Fama-French 12 industries. Exposures to current and lagged factors are estimated using monthly returns during 1996-2005. The falsification tests use data of 1996-2005 and 1986-1995. TDF ownership in the falsification tests is measured as an average during 2010-2018. Standard errors in this table are clustered two ways by time and stock.

A. Full sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Net return, t 2008-2018				Falsification 1996-2005	Falsification 1986-1995
Mkt ret, t-1 × TDF ownership (%), q-1	-0.095***	-0.080***	-0.040***		-0.045***	-0.048***	-0.018	0.003
	(0.025)	(0.025)	(0.015)		(0.016)	(0.017)	(0.028)	(0.023)
Mkt ret, t-1 × ln (Market cap, t-1)			-0.040		-0.055**	-0.049	-0.082*	-0.101***
			(0.027)		(0.027)	(0.030)	(0.044)	(0.032)
Mkt ret, t-1 × ln (Volume, t-1)			-0.002		0.014	0.009	0.035	0.045*
			(0.031)		(0.027)	(0.032)	(0.046)	(0.024)
TDF ownership (%), q-1	0.004***	0.003***	0.003***		0.002***	0.002***	0.010***	0.005***
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
ln (Market cap, t-1)	0.002*	0.001*	0.002**		0.001	0.001	-0.006***	-0.003***
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.002)	(0.001)
ln (Volume, t-1)	-0.001*	-0.001	-0.001		-0.001	-0.001	0.003	0.003***
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.002)	(0.001)
Time FE	Y	Y	Y		Y	Y	Y	Y
Time-by-industry FE	N	Y	N		N	N	N	N
Ctrls. for exp. to current factors × Factor returns, t	N	N	N		Y	N	N	N
Ctrls. for exp. to lagged factors × Factor returns, t-1	N	N	N		N	Y	N	N
Observations	400,728	400,720	400,728		226,132	226,132	314,121	161,877
R-squared	0.123	0.148	0.123		0.154	0.148	0.116	0.120

B. Matched sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Net return, t 2008-2018				Falsification 1996-2005	1986-1995
Mkt ret, t-1 × TDF ownership (%), q-1	-0.041*	-0.039*	-0.040*	-0.098**	-0.068***	-0.068***	0.031	0.096
	(0.021)	(0.021)	(0.021)	(0.049)	(0.022)	(0.022)	(0.063)	(0.276)
Mkt ret, t-1 × ln (Market cap, t-1)			0.000	0.101	-0.013	-0.011	0.031	0.137
			(0.024)	(0.107)	(0.022)	(0.023)	(0.066)	(0.197)
Mkt ret, t-1 × ln (Volume, t-1)			-0.014	-0.059	-0.010	-0.012	-0.031	-0.283*
			(0.022)	(0.061)	(0.020)	(0.020)	(0.063)	(0.161)
TDF ownership (%), q-1	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.006)
ln (Market cap, t-1)	-0.003***	-0.005***	-0.005***	-0.051***	-0.004***	-0.004***	-0.019***	-0.010
	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)	(0.003)	(0.007)
ln (Volume, t-1)	0.000	0.001	0.001	0.003	0.001	0.001	0.009***	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.006)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Time-by-matched peer group FE	N	Y	Y	Y	Y	Y	Y	Y
Mkt ret, t-1 × Stock FE	N	N	N	Y	N	N	N	N
Ctrls. for exp. to current factors × Factor returns, t	N	N	N	N	Y	N	N	N
Ctrls. for exp. to lagged factors × Factor returns, t-1	N	N	N	N	N	Y	N	N
Observations	28,171	27,659	27,659	27,659	18,543	18,543	15,810	1,204
R-squared	0.235	0.360	0.360	0.430	0.406	0.405	0.306	0.422

Table 8: S&P 500 inclusion and stock return sensitivity to lagged market performance

This table examines the effect of S&P 500 index inclusion on the sensitivity of monthly stock returns to recent market performance. The sample includes matched S&P 500 stocks and their benchmark stocks within the same industry-by-size-by-liquidity peer group. The peer groups are obtained in each quarter by sorting on market capitalization and annual trading volume divided by shares outstanding within each Fama-French-12 industry. The main sample includes monthly stock returns during 2010-2018. The dependent variable is the raw monthly net return winsorized at 1% and 99%. S&P 500, t-1 equals one if a stock is included in the S&P 500 index in month t-1, and zero otherwise. Exposures to current and lagged factors are estimated using monthly returns during 1996-2005. The falsification tests use data of 1996-2005 and 1986-1995. Standard errors in this table are clustered two ways by time and stock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Net return, t 2010-2018				Falsification 1996-2005	1986-1995
Mkt ret, t-1 × S&P 500, t-1	-0.090**	-0.088**	-0.114***	-0.234**	-0.115***	-0.114***	0.040	0.139
	(0.035)	(0.034)	(0.039)	(0.092)	(0.032)	(0.031)	(0.080)	(0.437)
Mkt ret, t-1 × ln (Market cap, t-1)			0.022	0.083	0.011	0.012	-0.001	0.071
			(0.024)	(0.098)	(0.021)	(0.021)	(0.063)	(0.209)
Mkt ret, t-1 × ln (Volume, t-1)			-0.003	-0.033	0.001	-0.001	-0.019	-0.257*
			(0.021)	(0.058)	(0.019)	(0.019)	(0.056)	(0.152)
S&P 500, t-1	-0.001	-0.002	-0.001	-0.001	-0.002	-0.002	0.017***	0.013
	(0.001)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.004)	(0.013)
ln (Market cap, t-1)	-0.002*	-0.004***	-0.004***	-0.047***	-0.003***	-0.003***	-0.021***	-0.013*
	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)	(0.003)	(0.008)
ln (Volume, t-1)	-0.000	0.001	0.001	0.002	0.000	0.001	0.007***	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.006)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Time-by-matched peer group FE	N	Y	Y	Y	Y	Y	Y	Y
Mkt ret, t-1 × Stock FE	N	N	N	Y	N	N	N	N
Ctrls. for exp. to current factors × Factor returns, t	N	N	N	N	Y	N	N	N
Ctrls. for exp. to lagged factors × Factor returns, t-1	N	N	N	N	N	Y	N	N
Observations	28,171	27,659	27,659	27,659	18,543	18,543	15,810	1,204
R-squared	0.255	0.379	0.379	0.442	0.426	0.425	0.311	0.423

Table 9: Time series correlation in the S&P 500 index

This table reports the estimated time series correlations for the S&P 500 index, following $r_t^{SP} = \alpha + \beta_h r_{t-htot-1}^{SP} + \epsilon_t^{SP}$ during three subsamples: 1986-1995, 1996-2005 and 2010-2019, where r_t^{SP} represents the monthly excess return of the S&P 500 index in month t and $r_{t-htot-1}^{SP}$ represents the 1-month, 3-month, 6-month, or 12-month cumulative excess return of the index ending in month $t-1$. The beta coefficients and their standard errors are reported. Each regression has 120 monthly observations.

	(1) 1m	(2) 3m	(3) 6m	(4) 12m
1986-1995	0.035	-0.028	-0.056	-0.056
	(0.092)	(0.052)	(0.043)	(0.036)
1996-2005	0.039	-0.006	0.012	0.029
	(0.092)	(0.053)	(0.039)	(0.024)
2010-2019	-0.161*	-0.096	-0.123**	-0.087**
	(0.091)	(0.060)	(0.048)	(0.037)

Figure A.1: Vanguard glide path

This figure plots the equity allocation of Vanguard Target Retirement Funds as a function of years to retirement. Data come from the fund's prospectus.

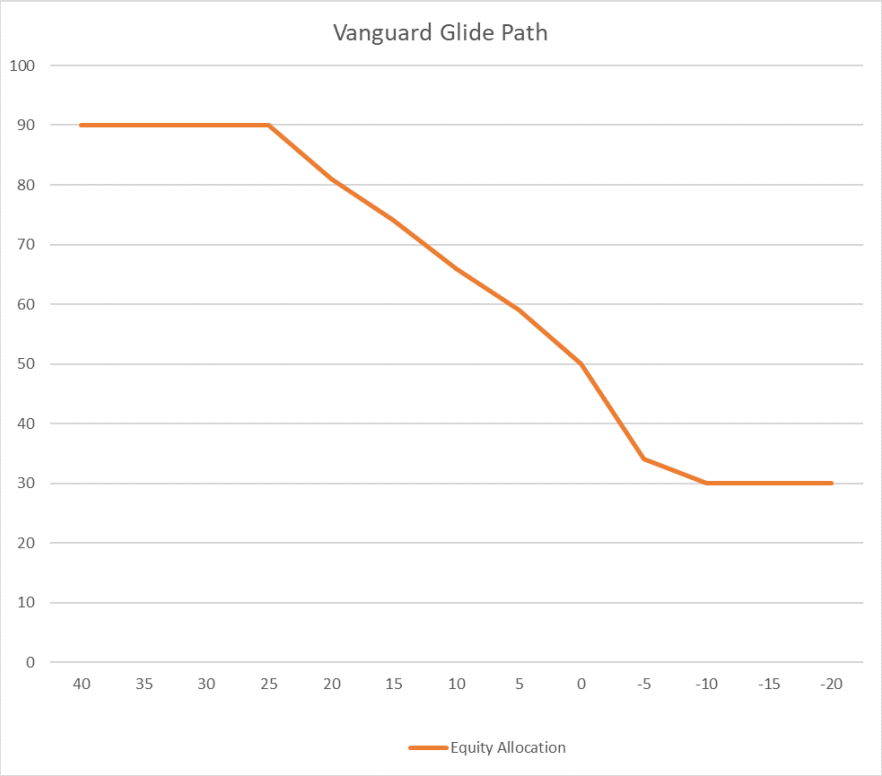


Figure A.2: TDF holding data quality

The solid line represents the total AUM of TDFs over time. The dotted line shows the total value of TDF holdings from the CRSP holdings dataset that can be matched to mutual funds in CRSP.

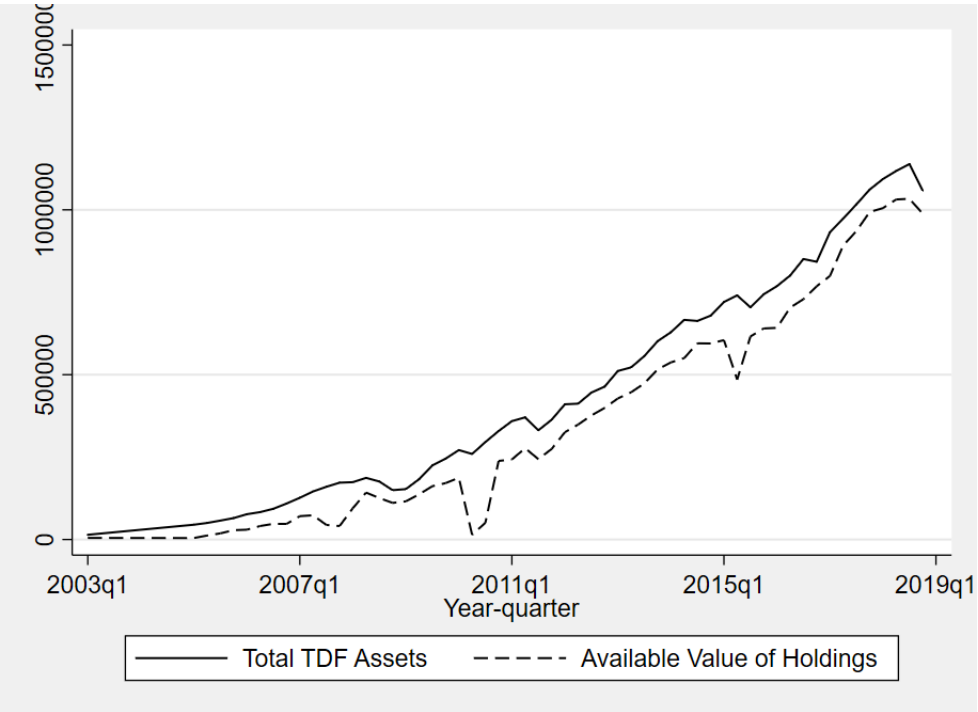


Table A.1: Aggregate TDF rebalancing with respect to asset class movements

This table estimates the relationship between the aggregate time series of TDF rebalancing and asset class returns during 2008Q3-2018Q4. Observations are at quarterly frequency. The dependent variable is the aggregate dollar amount of rebalancing divided by the lagged sum of portfolio values across all TDFs. The largest and smallest values of the time series are winsorized, equivalent to winsorizing at 5% and 95%. The full sample includes all TDFs. The 'moderate' sample aggregates only the TDFs with equity shares between 25% and 75%, and under the 'aggressive or conservative' sample includes only those with equity shares below 25% or above 75%. R^S represents the quarterly return of the total US stock market. R^B is measured as the pre-fee quarterly return of the Vanguard Total Bond Market Index Fund. S is the aggregate equity share and is measured as the fraction of the aggregate TDF portfolio invested in equity at the end of quarter $t-1$. Robust standard errors are in parentheses. *p $<$ .1; **p $<$ .05; ***p $<$ .01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full	Moder.	Aggr. or conserv.	Full	Moder.	Aggr. or conserv.
A.	Rebal (E), t / Total holding, t-1			Rebal (FI), t / Total holding, t-1		
$(R^S - R^B)_t$	-0.107**	-0.142***	-0.064	0.105***	0.142***	0.056***
	(0.040)	(0.040)	(0.043)	(0.020)	(0.025)	(0.014)
$(R^S - R^B)_{t-1}$	-0.051	-0.054	-0.068	0.042	0.054	0.025
	(0.042)	(0.046)	(0.049)	(0.027)	(0.035)	(0.017)
Observations	34	34	34	34	34	34
R-squared	0.248	0.316	0.168	0.475	0.556	0.301
B.	Rebal (E), t / Total holding, t-1			Rebal (FI), t / Total holding, t-1		
$S(1-S)(R^S - R^B)_t$	-0.508**	-0.583***	-0.431	0.510***	0.592***	0.382***
	(0.203)	(0.166)	(0.271)	(0.098)	(0.100)	(0.082)
$S(1-S)(R^S - R^B)_{t-1}$	-0.239	-0.232	-0.500	0.200	0.228	0.175
	(0.212)	(0.200)	(0.361)	(0.133)	(0.152)	(0.123)
Observations	34	34	34	34	34	34
R-squared	0.235	0.311	0.179	0.477	0.558	0.314

Table A.2: 2SLS estimate of stock return sensitivity to lagged market performance

This table uses S&P 500 membership at the end of the previous quarter as an instrument for the TDF ownership at the end of the previous quarter and estimates the relationship between TDF ownership and stock returns in response to recent market performance using a two-stage least squares procedure. The sample includes the matched sample of S&P 500 stocks and their benchmark stocks within the same industry-by-size-by-liquidity peer group. The peer groups are obtained in each quarter by sorting on market capitalization and annual trading volume divided by shares outstanding within each Fama-French-12 industry. The dependent variable is raw monthly net return winsorized at 1% and 99%. TDF ownership is predicted following Table 6 column 4. Exposures to current and lagged factors are estimated using monthly returns during 1996-2005. Standard errors in this table are block-bootstrapped with clustering by time and stock.

	(1)	(2)	(3)	(4)	(5)
			Net return, t 2010-2018		
Mkt ret, t-1 × Pred. TDF ownership (%), q-1	-0.492**	-0.595**	-1.011**	-1.014***	-1.004***
	(0.220)	(0.263)	(0.410)	(0.343)	(0.327)
Mkt ret, t-1 × ln (Market cap, t-1)			0.024	0.013	0.015
			(0.029)	(0.028)	(0.028)
Mkt ret, t-1 × ln (Volume, t-1)			0.018	0.016	0.015
			(0.026)	(0.025)	(0.024)
Pred. TDF ownership (%), q-1	-0.012	-0.015	-0.011	-0.016	-0.016
	(0.011)	(0.012)	(0.012)	(0.011)	(0.011)
ln (Market cap, t-1)	-0.000	-0.002**	-0.002***	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln (Volume, t-1)	0.000	0.001*	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time FE	Y	Y	Y	Y	Y
Time-by-matched peer group FE	N	Y	Y	Y	Y
Mkt ret, t-1 × Stock FE	N	N	N	N	N
Ctrls. for exp. to current factors × Factor returns, t	N	N	N	Y	N
Ctrls. for exp. to lagged factors × Factor returns, t-1	N	N	N	N	Y
Observations	22,424	21,856	21,856	14,485	14,485
R-squared	0.249	0.378	0.378	0.421	0.420