The Rise of Target Date Funds and Stock Market Dynamics *

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Abstract

The rapid growth of Target Date Funds (TDFs) during the 2010's – 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 reduces 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 volatility. We show that TDFs rebalance in response to asset class movements according to prediction, and the rebalancing causes outflows from equity funds when the equity market does well that are proportionate to the TDF ownership share. Most of the rebalancing is attributed to TDFs close to equal equity-bond allocation, or those for investors in their 50s-70s, and flows from TDF investors do not offset the stabilizing strategies of the TDFs for this group. Finally, we document that TDF rebalancing leads to lower aggregate momentum in stock prices, in that stocks with higher TDF ownership experience lower market-beta adjusted returns after higher market-wide performance, and confirm this finding using the S&P 500 index inclusion as quasi-exogenous variation for TDF ownership. Further, the time series momentum in a portfolio formed with high-TDF stocks as well as that in the S&P 500 index declines from the pre-TDF to the post-TDF period, consistent with the rise of TDF dampening aggregate market fluctuations. Together, our results suggest the potentially large impact of TDFs on asset return dynamics that is expected to grow larger as the TDF market continues to expand.

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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 $1.1 trillion dollars (of the roughly 18 trillion mutual fund market) in 2018.[2]

In this paper, we document an important implication of this financial innovation on asset prices – that TDFs reduce aggregate market momentum and stabilize asset returns. Traditionally, retail investors either remain passive and let their portfolio share rise and fall with the returns on different asset classes,[3] or they trend-chase, reallocating their assets into better-performing asset classes, a behavior known as 'positive feedback trading' (de Long, Shleifer, Summers and Wardmann, 1990) or 'momentum trading' (Hong and Stein, 1999) that amplifies price fluctuations. In contrast, TDFs rebalance to maintain fixed, age appropriate, asset shares and pursue a contrarian investment strategy, reallocating out of better-performing asset classes and into lower-performing ones. We argue that the rise of TDFs turns a significant fraction of US retail investors from positive feedback traders into a countervailing force that trades against market movements and dampens asset momentum.

We start by deriving the formula for TDF rebalancing. A TDF seeks to maintain age-appropriate asset shares and thus rebalances after realized asset class returns. Intuitively,

[1] Following, for example, Merton (1969), Viceira (2001) and Cocco, Gomes and Maenhout (2005).

[2] ICI Factbook 2019, Figure 8.24 and Figure 2.1.

[3] See Agnew, Balduzzi, and Sunden (2003), and see Ameriks and Zeldes (2004) for evidence of rampant passivity, particularly in retirement accounts.

the direction of rebalancing is opposite to that of the difference in returns between the asset classes (e.g., sell equity when equity outperforms bond). The formula also predicts that more rebalancing is required when the asset return difference is larger and when the equity share approaches 50% . The reason for the latter is that the rebalancing formula turns out to be a quadratic function of the equity share: In the extreme cases when TDF assets are invested entirely in one asset class or the other (TDFs for the very young or very old cohorts), the portfolio weights would fluctuate minimally when returns move and rebalancing would not be necessary; however, TDFs with moderate allocations need to engage in more rebalancing for a given unit of asset class return difference. We expect the greatest amounts of contrarian trades from TDFs with moderate allocations, and these in the data represent the TDFs for investors around their 60s.

First, bringing the formula to the data, we confirm that the aggregate dollar amounts of TDF rebalancing in equity and fixed income mutual funds fit well the formula predictions. During 2008-2018, when the equity market moves up by 10% in excess of the bond market, TDFs in aggregate sell equity funds by $ 3 billion and buy fixed income funds by $ 3 billion in the concurrent quarter. These magnitudes rise to $ 10 billion each during 2014-2018 when the total TDF assets are larger. A response to the previous quarter's asset returns is also present but weaker, implying that most rebalancing occurs more rapidly than three months.[4] For each dollar of predicted rebalancing, the estimated rebalancing in the same quarter is about 51 cents and in the following quarter is about 24 cents. In addition, consistent with the formula prediction, more than 70% of the aggregate rebalancing is attributed to TDFs with moderate allocations, i.e., equity shares between 25% and 75% .[5]

We investigate whether investor flows into TDFs offset the rebalancing trades. A general trend during our sample is massive investor inflows into TDFs after the PPA of 2006. If the inflows correlate with stock-market returns, the allocations of flows can offset rebalancing and hinder the abilities by TDFs to dampen equity market fluctuation. However, we find

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

[5]This group accounts for half of all TDF assets. The TDFs with equity shares below 25% are rare, and those with equity share above 75% constitute the remainder 30% of the aggregate dollar rebalancing.

this to be a problem only for the TDFs with aggressive allocations where the rebalancing trades are weak to start with and even further muted by strong flows to TDFs from the young cohorts.[6] In the group of TDFs with moderate allocations, rebalancing trades are strong and not offset by flows. The 'total trades'— the sum of both rebalancing and flow-driven trades— for the moderate-allocation TDFs exhibit robust contrarian patterns and are expected to influence asset return dynamics.

Second, we contrast the TDF trades with retail flows and show that the impact of TDFs are quantitatively significant for both aggregate and individual fund flows. During 2008-2018, for an equity market return of 10% in excess of the bond market, 30 billion dollars flow into retail shares of domestic equity mutual funds in the concurrent quarter. As quoted above, TDFs sell $ 3 billion of this class of mutual funds, thus offsetting 10% of the aggregate trend-chasing by retail investors. We further find that TDF investments have a significant impact on the micro-level flows to the mutual funds held by the TDFs. While the average retail fund's quarterly flows correlate with the concurrent excess returns of the stock market,[7] we find that this relationship is reduced by one fifth for the mutual funds with a 10% TDF ownership (the mean percent held by TDFs among mutual funds with non-zero TDF ownership). Thus, 'positive feedback' flows to mutual funds with TDF investment are mitigated, and the resulting alleviation in flow pressure can pass on to the stocks held by these mutual funds.

Third, we ask how the rise of TDFs affects stock market dynamics. Since the demand associated with TDFs rebalancing is contrarian, stocks indirectly held by TDFs experience selling/buying pressure after high/low equity market performance. This predicts that returns of TDF-invested stocks should be negatively correlated with the preceding market returns, conditional on the CAPM beta. We find evidence supporting this prediction. In cross sections of stock returns, we find that the market-risk-adjusted returns of stocks with higher ultimate TDF ownership have lower correlation with the recent monthly or quarterly market returns. Our estimate suggests that when the excess equity return is 10% in a month,

[6]ICI Factbook 2019, Figure 8.12, shows that 401(k) participants in their twenties have close to 50% of their 401(k) account balances allocated to target-date funds as of 2016.

[7]This result is in line with the findings of Warther (1995) and Edelen and Warner (2001) who show a positive relationship between mutual fund flows and concurrent monthly, weekly, or daily market returns.

stocks one standard deviation (0.3%) higher in TDF ownership have 0.28% lower return in the following month. This effect is robust after controlling for month-by-month industry shocks and stock fixed effects. The coefficient estimate shrinks but remains significant when we directly control for the effect of market capitalization, suggesting that though size is a major determinant for TDF ownership, the TDF effect on stock returns is not purely due to a size factor.

To address the possible endogeneity that TDF investments may be correlated with other stock characteristics that drive the result, we exploit the quasi-exogenous variation in TDF ownership surrounding inclusion into the S& P 500 index.[8] The identifying assumption is that conditional on observables, selection into the S& P 500 index is uncorrelated with the main outcome variable, i.e., the stock return sensitivity to recent market returns. We create a matched sample of stocks included and not included in the index, using propensity score matching based on market capitalization, trading volume, industry, and profitability. In this sample of similar stocks, we find that being included in the S& P 500 index is associated with significantly lower sensitivity of the monthly alpha to the lagged stock market return, consistent with an increase in TDF ownership once included.

Lastly, At the aggregate level, the group of TDF-invested stock portfolio should have lower return autocorrelation, or 'time series momentum' (Moskowitz, Ooi and Pedersen 2012), due to the contrarian trading strategy by TDFs. To test this hypothesis, we sort stocks into quintiles based on the average TDF ownership during the last five years of our sample 2014-2018. Forming a value-weighted portfolio using stocks in the top quintile of TDF ownership (the 'high TDF portfolio'), we find a significant reduction in its time series momentum from the pre-PPA period 1986-2005 to the period 2010-2019 that has a sizable TDF market. Using the S& P 500 portfolio as an ex ante approximation for the high TDF portfolio gives similar results.

The market of TDFs is a burgeoning area of academic research. Mitchell and Utkus (2020)

[8] Morningstar 2019 TDF Landscape Report, Exhibit 12, shows that the sub asset class with the most TDF allocation is "US large cap" . We tabulate the benchmarks of the domestic equity funds held by TDFs and find the S& P 500 to be the most popular benchmark index. As presented later in Figure 2, the inclusion in or deletion from the S& P 500 index significantly increases or decrease the likelihood that a stock ranks high in TDF ownership.

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 makes a sizable impact on the portfolios of the adopters. Related, Chalmers and Reuter (2019) use TDFs to construct counterfactual portfolios of retail investors in absence of financial advice. On the competition in the TDF market, Balduzzi and Reuter (2018) 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 this financial 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 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, suggesting a price impact. Da, Larrain, Sialm, and Tessada (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 focuses on aggregate, not cross-sectional, momentum, and it complements the literature by studying the effects of contrarian flows.

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 size of TDFs has risen dramatically over the past 15 years due to financial innovation and financial regulation. The financial industry designed and developed TDFs following the proscriptive work of academics as well as practitioner calculations. 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 \$ 1.1 trillion at the end of 2018. The specific timing of the rise in 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 half of that invested in target date mutual funds as of 2018. 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. The CITs are negotiated between plan sponsors and providers and are usually at lower cost compared with TDFs. Since CITs follow almost identical strategies as TDFs, we underestimate the total impact of all target date products. 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

We provide the general formulae for rebalancing by TDFs with respect to market moves. First, we assume zero net flows to the TDF. Second, we consider a general case of rebalancing with simultaneous flow-driven trades (investor purchases or redemptions allocated pro rata to existing positions). The rebalancing trades in these two cases turn out to be the same. Total trades in the second case include both rebalancing and flow-driven trades.

Table 1 presents the derivation. 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.

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.

While the actual frequency of rebalancing is not observed, Table 1 panel B also illustrates that TDFs experiencing continuous inflows or redemptions can rebalance frequently through allocating the flows. One may expect that TDFs rebalance infrequently to reduce transaction costs. However, the incremental cost of rebalancing can be low if a TDF needs to invest or redeem its flows regardless. Panel B shows that as long as $FS - S(1-S)\left(R^S - R^B\right)$ has the same sign as F ($R^S - R^B$ is small relative to F), rebalancing can be achieved simply by allocating the net flows to new positions instead of adjusting existing positions, thus, the marginal cost of rebalancing can be negligible.

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 do not omit any active rebalancing by retail investors in opposition to the rebalancing trades of TDFs. In practice, we find that our results are cleaner with rebalancing trades but are robust with total trades. 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.[9] Mitchell and Utkus (2020) demonstrate that most flows in and out of TDFs 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.

[9]Two thirds are held in 401(k) plans and 19% are held through IRAs (19%). See ICI Factbook 2019 Figure 8.24.

3 Data

We construct a dataset connecting TDFs, the underlying mutual funds, and stocks. 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 then obtain from CRSP the quarterly holdings of the TDFs. TDFs are funds of funds, thus most holdings are other mutual fund share classes which can be directly linked to the CRSP mutual fund database using the CUSIP, allowing the categorization of each holding as domestic equity, foreign equity, or fixed income. To reduce data errors, we drop the observations where the value of a holding is larger than the total asset size of the mutual fund share class, or if the sum of holdings exceeds 110% of the size of the TDF. Due to the quality of TDF holdings data in CRSP, we restrict the sample period to 2008Q2-2018Q4.[10] 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. TDFs on average hold 15 mutual funds. The average equity weight is 74% , out of which 49% is in domestic equity and 25% in foreign equity, and the fixed income weight is 26% . The fund flow rate to TDFs suggests high growth during this period – the average TDF grows by 6% each quarter in excess of fund returns.

We obtain quarterly data on the underlying mutual funds during 2008 to 2018 from CRSP and combine different share classes of the same fund to the fund level. The sample comprises of 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

[10] The quality and coverage of the CRSP holdings data vary and are problematic for several quarters. Figure A.2 plots the 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 start the sample period in 2008Q2, where the value of holdings as a fraction of total assets rises from 57% in the previous quarter to 78% and stays at that level. We also exclude 2010Q2-2010Q3 and 2015Q2 due to unusually low ratio of holdings to total assets that can be seen from Figure A.2. The quarters following these are subsequently excluded when lagged holdings are used as an input into calculations.

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-quarter experiences an outflow of 0.12% of lagged assets.[11] The sample average of TDF ownership is low (0.4%) due to many zeros (only 5% of mutual funds have positive TDF ownership). Among the mutual funds which TDFs invest in, the mean TDF ownership is 8% and the median is 2% .

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. Roughly 20% of the stock-monthly observations belong to 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 0.77% . We will show in Section 6 that significant variation exists in TDF ownership across stocks, which we exploit to estimate the impact of TDFs on stock return dynamics.

4 TDF rebalancing

4.1 Aggregate rebalancing as expected

We start by demonstrating that TDFs indeed rebalance as expected. Our research question assumes that TDF rebalancing is mechanical and formula-driven, thus their trading strategy is unlikely to be correlated with future expected returns. However, if we find dramatic deviations from the formula, TDF trades could no longer be assumed to be mechanical and would become no different from those of other FoFs. Thus, though automatic rebalancing is usually emphasized by TDF providers as a key product feature,[12]

[11] The retail fund market experiences a downward trend which is partially attributable to an industry adjustment that moves broker-advised investor accounts into Registered Investment Advisors (RIAs) that invest in institutional mutual funds (Boyson 2019).

[12] 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.'https://retirementplans.vanguard.com/VGApp/pe/pubeducation/bank/targetdate/PowerBehindTRF.jsf?SelectedSe

it is important for us to verify it empirically.

Testable predictions are derived from Table 1 applied to an aggregate TDF. 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. With these caveats, we test whether the aggregate TDF sells equity funds and buys fixed income funds when the stock market goes up relative to the bond market. Since rebalancing can be implemented with a delay, we estimate the following specifications:

$$\Sigma_k Rebalancing\,(Equity)_{kt} = \gamma_S^{Agg}\left(R_t^S - R_t^B\right) + \zeta_S^{Agg}\left(R_{t-1}^S - R_{t-1}^B\right) + \epsilon_t \quad (1)$$

$$\Sigma_k Rebalancing\,(FixedIncome)_{kt} = \gamma_B^{Agg}\left(R_t^S - R_t^B\right) + \zeta_B^{Agg}\left(R_{t-1}^S - R_{t-1}^B\right) + \epsilon_t \quad (2)$$

The aggregate rebalancing measure sums up the individual trades from a panel dataset of holdings at the TDF by mutual fund share class level. In the calculation, we further assume all rebalancing trades are made at the end of each period after returns are realized and before the fund reports its portfolio. First, we calculate the dollar amount of '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, Total Trad$e_{ckt} = MV_{ckt} - MV_{ckt-1}\left(1 + r_{ct}\right)$ 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 *To*tal Trade_{kjt} where j stands for either equity or fixed income. We combine both domestic equity and foreign equity into one 'equity' class, because most glide paths are based on an equity-fixed income allocation without specifying separate weights for the domestic–foreign allocation, which implies that TDFs may not rebalance within the equity asset class. Third, we calculate the 'flow-driven trade' by a TDF of an asset class as the dollar flow to the TDF[13]

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[13]We follow the formula commonly used in the literature to impute net fund flows: , where is the total net

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., $RebalTrade_{kjt} = TotalTrade_{kjt} - FlowDrivenTrade_{kjt}$. Last, we aggregate up the individual rebalancing trades to obtain an aggregate time series. The measures of R^S and R^B come from the value weighted total return of the US stock market and the US bond market return that is approximated by the pre-fee return on the Vanguard Total Bond Market Index Fund.[14]

Table 3, panels A and B, present the estimates of equations 1 and 2 using aggregate data.[15] Panel A, columns 1 and 5 using full sample data during 2008-2018 suggest that if the equity market moves up by 10% in excess of the bond market, the aggregate TDF sells equity funds by \$ 3 billion and buys fixed income funds by \$ 3 billion in the concurrent quarter. The symmetric responses in equity and fixed income are expected given our derived formula. These effects shrink to about \$ 1 billion each in the following quarter and become statistically insignificant, suggesting that most of the rebalancing takes place within 3 months but some may take longer to implement. In columns 2 and 6, we limit the sample period to the latest 5 years 2014Q1-2018Q4 when the total TDF assets are larger. We find that the dollar amounts of TDF rebalancing are larger during this later sample: When $R^S - R^B$ is $\pm$ 10% , TDFs sell or buy \$ 10 billion of equity funds. We contrast these magnitudes of TDF rebalancing trades with retail fund flows in Section 5 and argue that the rise of TDFs has had a substantial impact on aggregate flows.

A further hypothesis based on Table 1 concerns the heterogeneity across TDFs. The magnitude of the predicted rebalancing trade $S\left(1-S\right)\left(R^S - R^B\right)$ 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 3-4 and 7-8, we split the TDF sample by equity share before aggregating the rebalancing trades,

assets of TDF in quarter and is the net return of the TDF.

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

[15]In Table A.1, we present similar results using a disaggregate TDF-quarterly dataset, and the findings are consistent with the aggregate outcomes.

and expect that the group with equity share in the range between 0.25 and 0.75 (which we call ‘moderate allocation”) should exhibit greater rebalancing than the group with equity share either below 0.25 or above 0.75 (‘conservative or aggressive allocation’). The results are consistent with this prediction. We find that more than 70% ($\approx 21/29$) of the aggregate rebalancing is attributable to the group of TDFs with moderate asset allocations. Though roughly equal in size, rebalancing by TDFs with aggressive or conservative equity allocations is economically smaller and statistically insignificant.

In panel B of Table 3, we replace the dependent variables in equations 1 and 2 with the ratios of dollar rebalancing over the lagged total holdings. This matches the setup in Table 1 where the AUM of the TDF is assumed to be \$ 1. Overall, the results are similar as those in panel A though they are interpreted as fractions of portfolio value. When stocks outperform bonds by 10% , the aggregate TDF sells equity by 11% of its portfolio value and buys fixed income by the same amount. Since rebalancing is normalized by the overall TDF size, the full sample and the recent sample give similar estimates. In addition, we observe more rebalancing in the TDFs with equity shares between 0.25 and 0.75.

Lastly, we compare the actual rebalancing with the prediction by estimating the following equations:

$$\begin{aligned}\Sigma_k Rebalancing\,(Equity)_{kt} = {} & \beta_{S1}^{Agg} S_{t-1}^{Agg}\left(1 - S_{t-1}^{Agg}\right)\left(R_t^S - R_t^B\right) + \\ & \beta_{S2}^{Agg} S_{t-1}^{Agg}\left(1 - S_{t-1}^{Agg}\right)\left(R_{t-1}^S - R_{t-1}^B\right) + \epsilon_t \qquad (3)\\ \Sigma_k Rebalancing\,(FixedInc)_{kt} = {} & \beta_{B1}^{Agg} S_{t-1}^{Agg}\left(1 - S_{t-1}^{Agg}\right)\left(R_t^S - R_t^B\right) + \\ & \beta_{B2}^{Agg} S_{t-1}^{Agg}\left(1 - S_{t-1}^{Agg}\right)\left(R_{t-1}^S - R_{t-1}^B\right) + \epsilon_t \qquad (4)\end{aligned}$$

The main independent variable is $S_{t-1}^{Agg}\left(1 - S_{t-1}^{Agg}\right)\left(R_t^S - R_t^B\right)$. Under perfect rebalancing, our model would predict $\beta_{S1}^{Agg} = -1$ and $\beta_{B1}^{Agg} = 1$. The estimated $\widehat{\beta_{S1}^{Agg}}$ and $\widehat{\beta_{B1}^{Agg}}$ may be closer to zero for several reasons. First, due to the cost of rebalancing, a TDF manager may leave the portfolio weights fluctuate and deviate from the target without intervention, especially under small movements in asset class returns. Second, TDFs may rebalance with a time lag, or the proscribed rebalancing may be smoothed out over time. To account for this possibility, we also include a lagged regressor $S_{t-1}^{Agg}\left(1-S_{t-1}^{Agg}\right)\left(R_{t-1}^{S}-R_{t-1}^{B}\right)$, to allow for an adjustment in the following quarter. Third, the target equity allocation is approximated by S_{t-1}^{Agg}, the lagged aggregate equity weight, and thus measured with noise. One reason is that the realized weight at $t-1$ may deviate from the target; the other is that given the high rate of inflows from young investors, the aggregate investor mix may shift toward a younger group over time and the 'target' may evolve as a result. These measurement errors can attenuate the estimates.

Panel C of Table 3 presents the estimates of equations 3 and 4. Our estimate of $\widehat{\beta_{S1}^{Agg}}$ is between 0.51 in the full sample and 0.58 in the most recent sample, suggesting that for each dollar of predicted rebalancing, the actual rebalancing is about 50$\sim$ 60 cents in the current quart. The adjustment to the previous quarter's predicted amount is about 24$\sim$ 46 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 than the rest do. This is intuitive as the former group tend to see greater deviations from the target allocations under a same amount of asset market fluctuations and have relatively smaller discretion over rebalancing.

4.2 Effect of investor flows on TDF trades

The above results show that TDF rebalancing across asset classes is strongly contrarian. Now we turn to examine the TDF total trades that further include the effect of investor flows, because inflows and outflows also affect the demand for different assets by the TDFs. If the inflows and outflows are correlated with asset class returns, they can reduce the ability by TDFs to dampen market fluctuations. As discussed in Section 2, we have reasons to believe that flows to TDFs are unlikely to be trend-chasing. However, our sample period covers a decade-long stock market boom with massive inflows into TDFs, and we want to make sure investor flows do not outweigh the rebalancing against market movements during this special period. In other words, while TDFs on average sell equity during this period out of rebalancing, flows to TDFs, if driven by sign-ups by the young cohort, result in buying equity. Thus, the total trades by TDFs may be less stabilizing than in a period with average market growth. Even if so, the total TDF trades may still be more contrarian than the counterfactual fund flows had TDFs not existed and investors stayed passive or trend-chasing. By using the total trades to approximate for the next effect of TDFs on flows, we make the conservative assumption that the counterfactual flows have zero return-chasing tendency.

In Table 4, we examine the relationship between the aggregate TDF total trades and asset class returns. The variables in this table are the same as those in Table 3, except that the dependent variables are calculated using the total, instead of rebalancing, trades. Compared with Table 3, we observe that all coefficients are shifted toward the positive direction, due to flow-driven trades and $R^S - R^B$ both being positive during the period: the contrarian results in equity become weaker, but in fixed income become stronger than those of rebalancing alone. Breaking down the TDFs into two groups based on equity share, we find that the overall trading by the TDFs with moderate allocations remains significantly contrarian despite the inflows, but that the rebalancing by the TDFs with aggressive or conservative allocations is offset by inflows and appears weakly trend chasing. This is intuitive, as the first group is responsible for most of rebalancing and experiences steady inflows, whereas the second group consists of TDFs with weak rebalancing and strong inflows during this period. For this reason, when measuring TDF investments in later sections, we also construct two versions based on either the ownership by all TDFs or those with moderate allocations and expect the latter to more accurately capture the effect of contrarian trades.

5 Effect of TDFs on fund flows

Section 4 illustrates that TDFs trade against market movements. In this section, we put the magnitude of TDF trades into perspective. The literature assumes retail investors to be positive feedback traders who can amplify return momentum (De Long et al. (1990); Hong and Stein (1999)). How much of the trend chasing of retail flows do TDFs offset? We answer this question by examining both aggregate data and mutual fund level flow patterns.

Table 5 contrasts the aggregate TDF trades in U.S. equity with flows to retail mutual funds in that category. 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 mutual fund share classes that are classified as retail, where the quarterly 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 net quarterly return of the fund share class.[16] We then regress the aggregate quarterly trades by TDFs and retail investors on the equity-fixed income return difference, allowing separate coefficients for these two series. Since stock market shocks are common to both series, we cluster the standard errors by time (year-quarter).

In column 1 of Table 5, the TDF series represents the sum of dollar rebalancing by all TDFs (same as in Table 3). The result suggests that when $R^S - R^B$ is 10%, 30 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 $3 billion of equity funds under the same market move out of rebalancing, and this is the same magnitude as documented in Table 3. Thus, during 2008-2018, TDFs offset about 10% 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 6.5%, while the rest of the TDFs reduce it by another 3.5%. In columns 3 and 4, we examine the total TDF trades which include the effect of flows. Overall, we observe that the net flows from the TDFs become less contrarian when we add in the flow-driven trades, however, it remains robust that TDFs in aggregate trade equity funds in the opposite

[16]Sometimes TDFs invest in retail share classes, so we deduct the TDF trades from retail flows before aggregating the latter.

direction as retail investors do despite inflows and outflows to the TDFs. The net coefficient for TDF in column 3 suggests that the overall total trades by all TDFs reduce the retail flow sensitivity to $R^S - R^B$ by about 3% which is not statistically significant. Breaking into the two subsamples of TDFs in column 4, we find that the total trades by moderate-allocation TDFs reduce the retail sensitivity by 4%, significant at 10%, but those by the aggressive- or conservative-allocation TDFs actually weakly increase retail trend-chasing by 1%. Overall, Table 5 implies that the aggregate fund flows from TDFs, especially those with moderate allocations, can be a market-stabilizing force.

Next, we turn to dis-aggregate data and investigate whether TDFs exert similar effects on flows to individual mutual funds, with the hypothesis that mutual funds with high TDF ownership receive lower flows following high market performance. The regression specification follows:

$$\begin{aligned} FundFlow_{jt} &= AssetClassRet_t + AssetClassRet_t \times Frac.TDF_{jt-1} + \\ AssetClassRet_{t-1} &+ AssetClassRet_{t-1} \times Frac.TDF_{jt-1} + Frac.TDF_{jt-1} + X_{jt} + \epsilon_{jt} \end{aligned} \tag{5}$$

The dependent variable is the fund flow rate measured as the growth rate in fund assets in excess of the realized fund return. We explore two versions of the asset class return. 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.[17] Equation 5 allows the flow sensitivity to asset class return to vary by TDF ownership. For the TDF ownership measure, we calculate the fraction of the mutual fund's

[17]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.

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 6 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 return of the equity market over bonds and most of the response is in the current quarter. The coefficients on the interaction terms with TDF ownership suggest that the trend-chasing relationship is significantly reduced for the small fraction of funds with TDF ownership. For example, if 8% 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 ($0.0355*0.8/0.179 \approx 16\%$). In column 2, we add time fixed effects. Coefficients on the asset class return can no longer be estimated, but those on the interaction terms with TDF ownership measures remain almost unchanged, suggesting the baseline result is not driven by the time periods. Columns 3-4 introduce an alternative TDF ownership measure that is based on holdings by TDFs with equity shares between 25% and 75% only. As shown in section 4, this group of TDFs are responsible for most of the rebalancing. Consistent with that result, here we find the magnitude of the TDF effect roughly doubles when the investment is measured for the moderate-allocation TDFs only. In columns 5-8 of Table 6, 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 1-4, confirming that TDF investment reduces the individual fund flow sensitivity to the stock market excess return.[18]

[18] For this reason and because common asset pricing tests are based on excess returns, in our subsequent analysis on the effect of TDFs on stock returns, we mainly examine the sensitivity to past market excess. The results are similar if we instead look at $R^S - R^B$ 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 contrarian trading patterns by TDFs documented above impact asset price dynamics. The literature has documented the effect of mutual fund trading pressure on asset prices (Warther (1995), Edelen and Warner (2001), Coval and Stafford (2007), Lou (2012)). Since mutual funds with high TDF ownership receive lower flows after positive market shocks, they exert lower upward pressure on the stocks in their portfolios than other mutual funds without TDF investment. Thus, the stocks with high actual or expected TDF ownership should exhibit lower "momentum" relative to recent market performance and realize 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 (e.g., Jegadeesh and Titman (1993), 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 Cross-Sectional TDF ownership and market momentum

We begin by documenting the dispersion of TDF ownership among stocks. The demand for low fees by plan fiduciaries implies that TDFs should prefer broad-market-based low-cost funds such as S&P 500 index funds for their equity allocations.[19] Consequently, we expect market capitalization to directly affect stock-level TDF ownership.

Figure 2 shows the distribution of TDF ownership by market capitalization. The key measure for TDF influence at the stock level is the ultimate TDF ownership, calculated 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

[19] 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

holdings data are from Thomson Reuters which are linked to the CRSP mutual fund dataset using MFLINKS.[20] We find that larger stocks have significantly higher TDF ownership, though there is some misalignment between the two, which we exploit below to estimate the effect of the TDFs that is separate from a size effect.

We now investigate the hypothesis that stocks that have higher TDF ownership exhibit lower market momentum. To test this hypothesis, we calculate the market risk adjusted monthly returns for stocks during 2010-2019 (which we call the post-TDF period) and regress them on both the lagged excess return of the market and that interacted with TDF ownership. For risk adjustment, we use the pre-TDF period as the estimation window to measure the market betas to avoid endogeneity. The results are presented in Table 7. In panel A, the lagged market return is measured with a 1-month horizon, and in panel B, it is measured with a 3-month horizon.

Our baseline estimate in panel A, column 1, suggests that a one-standard-deviation (0.3%) increase in TDF ownership is associated with a 0.027 decline in the sensitivity of stock return to lagged market return. In other words, when the market rises by 10% in a month, stocks one standard deviation higher in TDF ownership have 0.27% lower return in the following month. This result is consistent with TDF rebalancing in the opposite direction as market movements. Columns 2-4 suggest that the result is robust when we control for time fixed effects, monthly industry shocks, and stock fixed characteristics. In columns 5-6, we allow the lagged market return to affect the current month's CAPM alpha differentially by market cap in the pre-period or the change in market cap from the pre- to the post-period, thus directly controlling for the effect of size. Unsurprisingly, the coefficient on the interaction term with TDF shrinks because size is an important variation in TDF ownership. However, we find that the effect of TDF ownership remains significant in reducing the sensitivity of stock return to lagged market performance. Finally, we provide additional robustness test in column 8 that the TDF effect remains robust if we control for the post-period market beta, even though the post-betas themselves can be

[20]The holdings data of Thomson Reuters appear to have better coverage than the mutual fund holdings data from CRSP. However, MFLINKS do not have good coverage of TDFs, thus, to examine the TDF holdings described earlier, we rely on CRSP. The MFLINKS data we downloaded cover up to December 2017, thus our stock panel ends in 2017.

affected by TDF ownership.

6.2 Identification using index inclusion

While the result above using actual TDF ownership suggests that TDF investments put price pressure on stocks in the opposite direction as recent market performance, it does not answer whether the reduced momentum is indeed caused by TDF investments or TDFs happen to invest in types of stocks with certain return patterns. To establish causality, we rely on inclusion into the S&P 500 Index as a quasi-exogenous source of variation for TDF ownership. S&P 500 index funds are a common choice for equity allocation in TDF portfolios,[21] and Figure 3 shows that being included to or deleted from the S&P 500 is associated with increased or decreased TDF ownership. We define the quarter in which a stock is added to or deleted from the S& P 500 index as the event quarter and trace the TDF ownership around the change. Figure 3 panel A focuses on index inclusions which are associated with an increase in TDF investments. From one quarter before the inclusion to two quarters afterwards, we observe a 5-basis-point increase in raw TDF ownership, a 5 percentile improvement in the ranking, and a nearly 10% increase in the likelihood that the stock ranks in the top quintile of TDF ownership. The raw data plot may reflect a general time trend, but the rankings are less affected by this problem. In panel B of Figure 2, we examine events where a stock is deleted from the S&P 500 index. Raw data a sharp drop of 10 basis points in TDF ownership in the quarter of deletion, followed by a quick rebound. In addition to reflecting a time trend, the bounce back may also reflect the mechanism documented in this paper: TDFs increase their holdings after low stock performance (the reason for dropping out of the index) when other investors pull out. Switching to rankings, we again observe a sudden drop followed by a small recovery, but the drops appear more permanent. From one quarter before to two quarters after the index deletion, the TDF ownership ranking drops by 10 percentiles and the likelihood of being in the top quintile drops by 10%. Together, the evidence in Figure 3 suggests that S&P 500 index inclusion

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

captures important variation in stock-level TDF ownership.

We predict that if a stock is included in the S&P 500 index, it experiences an increase in TDF investment and will start to respond less to market movements, compared with similar stocks that are not included in the index, and test this prediction in a matched panel of treated and control stocks. The S&P 500 index composition is determined by the "index committee" at S&P Global. A necessary-but-not-sufficient condition is the satisfaction of S&P's eligibility criteria, mainly, included stocks need to be US-domiciled, trade on an eligible exchange (NYSE, NASDAQ, and Cboe), have positive profits, and pass a market-capitalization threshold which fluctuates with the market. Having passed the eligibility criteria,[22] constituent selection is at the discretion of the index committee, and a sector balance is considered. For our empirical strategy to identify the causal impact of TDF ownership, we need to assume that based on observables, selection into the S&P 500 index is orthogonal to the stock return sensitivity to market returns.

Given the considerations for S&P 500 index inclusion, we restrict the sample to firms incorporated in the United States and traded on the NYSE or NASDAQ. In each month we predict the S&P 500 status based on stock characteristics that are relevant for index inclusion, including market capitalization, trading volume, industry, and book profitability (return on assets) using a linear model and calculate the propensity scores for being included in the index. We then match stocks in the S&P 500 with those not included using propensity-score-based nearest neighbor matching. Finally, we estimate the sensitivity of stock return to lagged market return in the matched narrow sample, allowing separate coefficients for the S&P-included stocks and their matched controls.

Table 8 examines the effect of S&P 500 index inclusion on the sensitivity of monthly stock returns to lagged market performance during 2010-2019. In each month we predict the S&P 500 status based on stock characteristics including market capitalization, trading volume, industry, and book return-on-assets (ROA) using a linear model and calculate the propensity scores for being included in the index. The matching procedure uses propensity-score-based nearest neighbor matching with no replacement, and the caliper is

[22] See https://us.spindices.com/documents/methodologies/methodology-sp-us-indices.pdf.

set at 0.2 times the standard deviation of the propensity score. The regressions include only the matched pairs of observations. Columns 1-3 include the entire sample and Columns 4-6 include only the marginal stocks whose S&P 500 statuses change during the sample period. Across various specifications, we observe that the inclusion into the S&P 500 index significantly reduces the sensitivity of CAPM-adjusted stock return to recent market performance, relative to a control group of similar stocks. This is consistent with S&P 500 inclusion leading to an increase in TDF ownership and contrarian trading in the affected stocks.

6.3 Reduction in time series momentum in the TDF era

Lastly, we predict that the value-weighted portfolio of stocks with high TDF ownership will exhibit lower 'time series momentum' relative to a portfolio of stocks with low TDF ownership. We sort stocks into quintiles based on the average percentage TDF ownership during 2014-2019. The top quintile is defined as 'high TDF ownership' or the 'treated' group, and the bottom two quintiles are defined as 'low TDF ownership' or the 'control' group. We then form two value-weighted portfolios using the treated and control stocks and estimate the time series correlation in each. The results are presented in Table 9. Through various specifications, we find a significant and robust reduction in the time series momentum for the high-TDF portfolio from the pre-TDF period to the TDF period: While there is no relationship between the past 12- or 3-month return and the current 1-month return for this high TDF portfolio during 1986-2005, this relationship becomes significantly negative during 2010-2019, suggesting a medium-term return reversal. There is no such change in the low TDF portfolio (the control). We also examine ex ante approximations for TDF ownership using large-cap indices, namely the S&P 500 and the Russell 1000. Stocks in these large-cap indices are likely to have high TDF ownership, but since they are pre-determined, they allow us to mitigate selection bias. The results confirm our hypothesis that time series momentum has come down for the TDF portfolio.

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 ultimately the momentum and volatility in stock returns. As the TDF market continues to grow, we expect the effects documented in this paper to become more pronounced and continue to reshape asset return dynamics.

Figure 1 The Rise of TDF Assets

This figure plots the total net assets (TNA) of TDFs by target retirement year over time. 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. For this plot, 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).

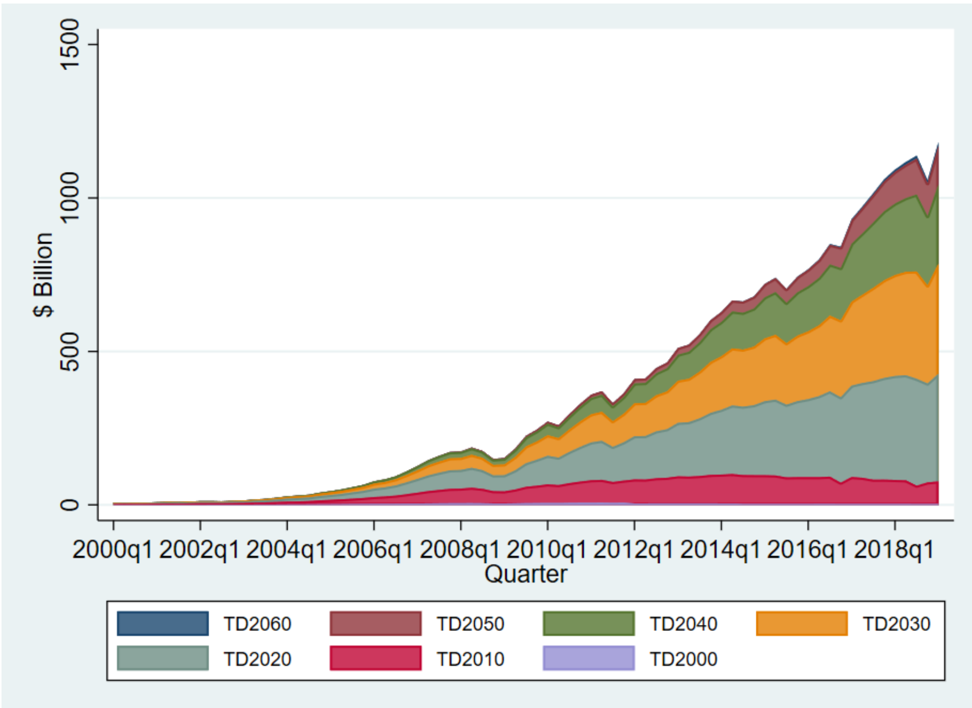
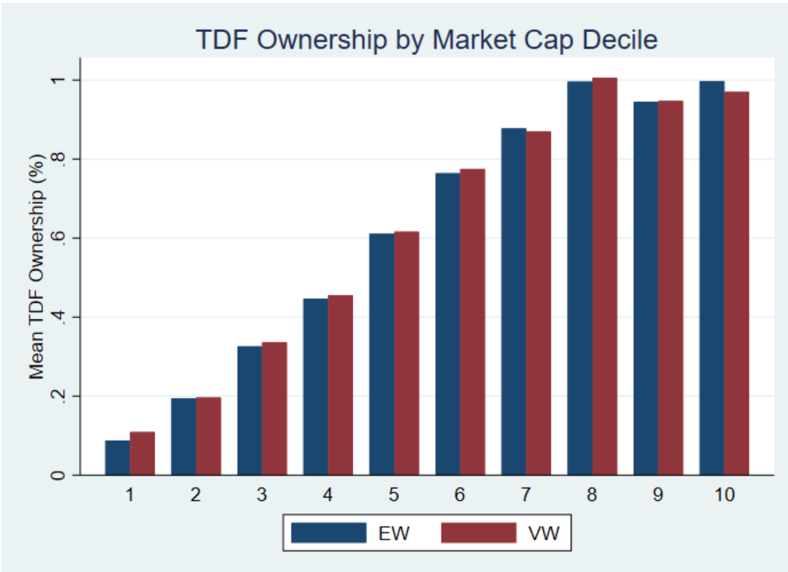


Figure 2 Distribution of TDF ownership and market capitalization

Panel A shows the distribution of TDF ownership by stock size in one collapsed cross section. The TDF ownership and market cap for each stock is calculated as the average during the latest five years of available data, i.e., 2014Q1-2018Q4. Bin 10 indicates the largest market cap. Panel B plots a two-way histogram of market cap deciles and TDF ownership.

A.



B.

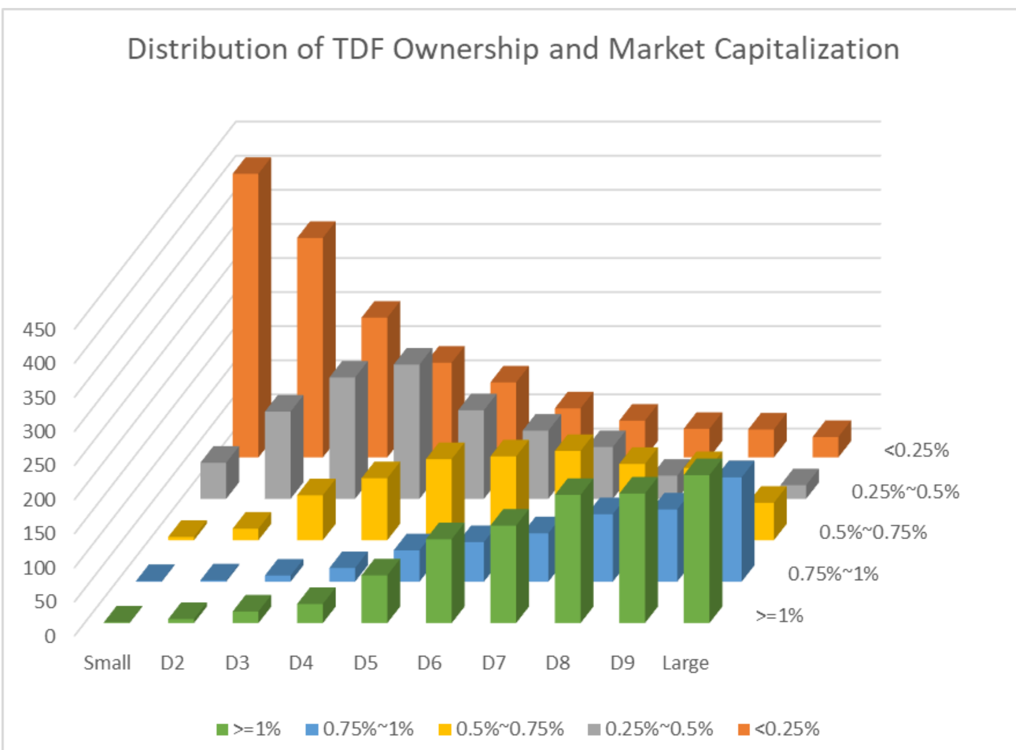
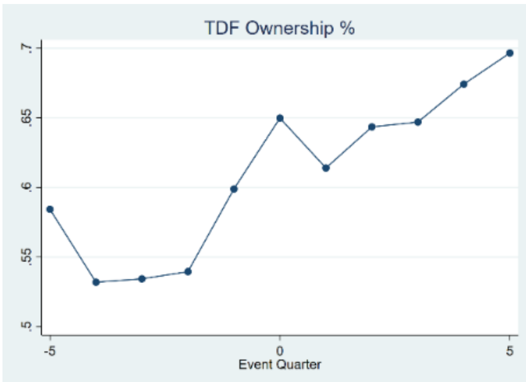
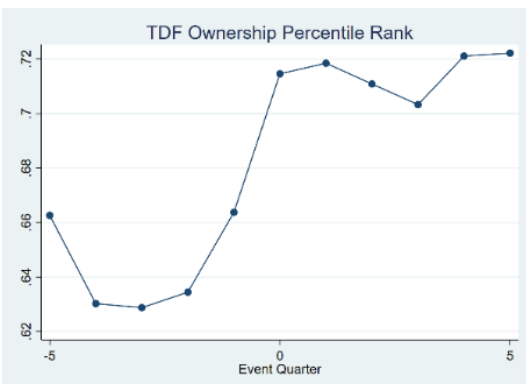


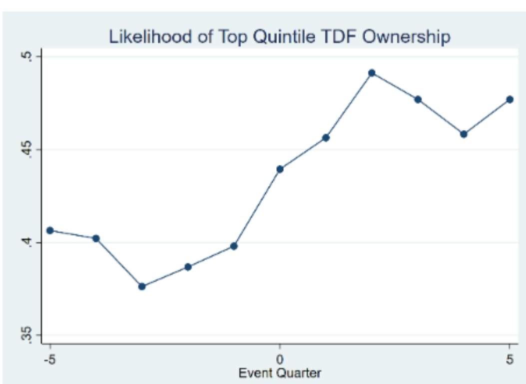
Figure 3 TDF Ownership around S&P 500 Inclusion and Deletion

This figure plots the average TDF ownership around S&P500 index inclusion (Panel (a)) and deletion (Panel (b)). The outcome variable is measured with raw TDF ownership, the cross-sectional percentile rank of TDF ownership, and an indicator for TDF ownership ranking in the top quintile. The mean outcome variable is plotted as a function of the event quarter. The inclusion and deletion events occur between -1 and 0.

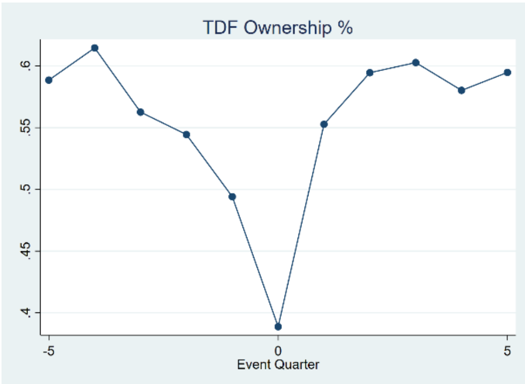
Panel (a) S&P 500 Index Inclusion

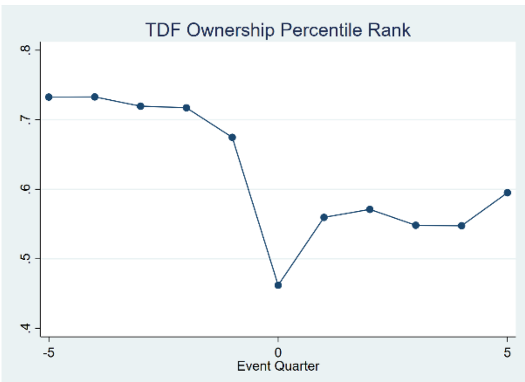






Panel (b) S&P 500 Index Deletion





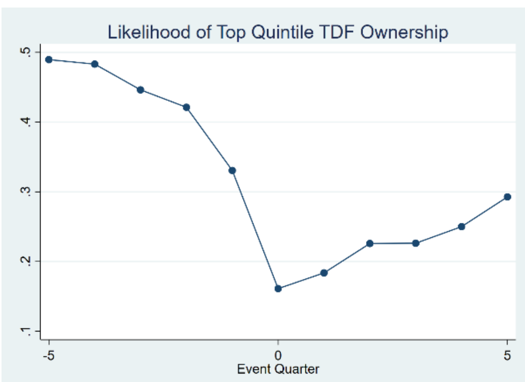


Table 1 TDF rebalancing model

A. Case of zero net flow to TDF

	Weight	Asset class return	Value w/o rebalancing	Allocation according to glide path	**Rebalancing trade**
Equity fund	S	R^S	$S(1+R^S)$	$[1+R^B+S(R^S-R^B)]S$	$\boldsymbol{-S(1-S)(R^S-R^B)}$
Bond fund	$1-S$	R^B	$(1-S)(1+R^B)$	$[1+R^B+S(R^S-R^B)](1-S)$	$\boldsymbol{S(1-S)(R^S-R^B)}$
Total	1		$1+R^B+S(R^S-R^B)$	$1+R^B+S(R^S-R^B)$	**0**

B. Case of non-zero net flow to TDF

	Weight	Asset class return	Value w/o rebalancing	Allocation according to glide path	**Total trade**	Flow-driven trade	**Rebalancing trade**
Equity fund	S	R^S	$S(1+R^S)$	$[1+R^B+S(R^S-R^B)+F]S$	$\boldsymbol{FS-S(1-S)(R^S-R^B)}$	FS	$\boldsymbol{-S(1-S)(R^S-R^B)}$
Bond fund	$1-S$	R^B	$(1-S)(1+R^B)$	$[1+R^B+S(R^S-R^B)+F](1-S)$	$\boldsymbol{F(1-S)+S(1-S)(R^S-R^B)}$	$F(1-S)$	$\boldsymbol{S(1-S)(R^S-R^B)}$
Net TDF flow			F				
Total	1		$1+R^B+S(R^S-R^B)+F$	$1+R^B+S(R^S-R^B)+F$	$\boldsymbol{F}$	F	**0**

Table 2 Summary statistics 2008-2018

2008-2018

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
# Funds held	9,016	15.9	9	15	21	8.6
Frac. TNA 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. TNA 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
Total trade in equity, t / Total holding, t-1	9,016	0.049	-0.016	0.018	0.069	0.168
Total trade in fixed income, t / Total holding, t-1	9,016	0.018	-0.001	0.009	0.027	0.058
Mutual fund quarterly	N	Mean	p25	p50	p75	SD
Fund flow rate (%)	47,668	-0.12	-4.67	-1.73	1.92	14.50
Fund size ($ billion)	47,668	2.1	0.1	0.3	1.2	11.4
Fund family size ($ billion)	47,668	256.4	2.8	29.1	134.4	598.2
Fund age (year)	47,668	19.1	10.0	16.0	24.0	14.0
Expense ratio (%)	47,668	1.17	0.91	1.19	1.44	0.46
Return volatility (%)	47,668	4.21	2.73	3.83	5.40	1.97
Frac. held by TDFs (%)	47,668	0.38	0.00	0.00	0.00	3.56
Frac. held by TDFs (%) among non-zero	2,225	8.16	0.39	1.92	8.87	14.40
Frac. held by moder. alloc. TDFs (%)	47,668	0.17	0.00	0.00	0.00	1.84
Frac. held by moder. alloc. TDFs (%) among non-zero	1,825	4.32	0.17	0.81	4.72	8.40
Stock monthly	N	Mean	p25	p50	p75	SD
Monthly excess return (%)	230,592	1.06	-4.66	0.80	6.19	11.34
CAPM beta	230,592	0.95	0.43	0.77	1.28	0.74
Monthly CAPM alpha (%)	230,592	0.02	-5.18	-0.12	4.73	10.79
S&P 500 membership	230,592	0.19	0.00	0.00	0.00	0.39
Market cap ($ billion)	230,592	8.49	0.18	0.97	4.14	33.35
Volume (million)	230,592	32.44	1.02	5.75	23.69	149.51
TDF ownership (%)	230,592	0.77	0.34	0.68	1.03	0.63

Table 3 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. Observations are at quarterly frequency. The dependent variable in panel A is the sum of rebalancing trades across all TDFs in the specific asset class and quarter, where the rebalancing trade of each TDF is calculated as the total trade in an asset class minus the flow-driven trade in that asset class. The dependent variable in panels B and C is calculated as 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 2008Q3-2018Q4. The 'last 5 years' sample includes 2014Q1-2018Q4. The time series under 'E shr [0.25, 0.75]' title aggregates only those TDFs with equity shares between 25% and 75%, and under 'E shr [0, 0.25) or (0.75, 1]' includes only those TDFs with equity shares below 25% or above 75%. *RS* represents the quarterly return of the total US stock market. *RB* 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 beginning of the quarter. Robust standard errors are in parentheses. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full	Last 5yrs	E shr [0.25, 0.75]	E shr [0, 0.25) or (0.75, 1]	Full	Last 5yrs	E shr [0.25, 0.75]	E shr [0, 0.25) or (0.75, 1]
A.	**$ Rebal (E), t**				**$ Rebal (FI), t**			
RS-RB, t	**-29.229****	**-99.169*****	**-21.257****	**-7.972**	**27.729*****	**85.900*****	**20.315*****	**7.414***
	(13.098)	**(21.218)**	**(8.423)**	**(4.954)**	**(9.419)**	**(18.069)**	**(5.961)**	**(3.778)**
RS-RB, t-1	-12.073	-48.171	-6.993	-5.080	9.032	41.563	4.990	4.042
	(14.048)	(54.589)	(9.371)	(4.856)	(8.825)	(30.289)	(5.884)	(3.161)
Observations	34	17	34	34	34	17	34	34
R-squared	0.131	0.359	0.165	0.074	0.241	0.586	0.273	0.126
B.	**Rebal (E), t / Total Holding, t-1**				**Rebal (FI), t / Total Holding, t-1**			
RS-RB, t	**-0.107****	**-0.112*****	**-0.142*****	**-0.064**	**0.105*****	**0.091*****	**0.142*****	**0.056*****
	(0.040)	**(0.029)**	**(0.040)**	**(0.043)**	**(0.020)**	**(0.023)**	**(0.025)**	**(0.014)**
RS-RB, t-1	-0.051	-0.089	-0.054	-0.068	0.042	0.050	0.054	0.025
	(0.042)	(0.098)	(0.046)	(0.049)	(0.027)	(0.044)	(0.035)	(0.017)
Observations	34	17	34	34	34	17	34	34
R-squared	0.248	0.221	0.316	0.168	0.475	0.449	0.556	0.301
C.	**Rebal (E), t / Total Holding, t-1**				**Rebal (FI), t / Total Holding, t-1**			
S(1-S)(RS-RB), t	**-0.508****	**-0.579*****	**-0.583*****	**-0.431**	**0.510*****	**0.471*****	**0.592*****	**0.382*****
	(0.203)	**(0.152)**	**(0.166)**	**(0.271)**	**(0.098)**	**(0.122)**	**(0.100)**	**(0.082)**
S(1-S)(RS-RB), t-1	-0.239	-0.459	-0.232	-0.500	0.200	0.256	0.228	0.175
	(0.212)	(0.520)	(0.200)	(0.361)	(0.133)	(0.232)	(0.152)	(0.123)
Observations	34	17	34	34	34	17	34	34
R-squared	0.235	0.217	0.311	0.179	0.477	0.443	0.558	0.314

Table 4 Aggregate TDF total trades with respect to asset class movements

This table estimates the relationship between the aggregate time series of TDF total trades and asset class returns. Observations are at quarterly frequency. The dependent variable in panel A is the sum of total trades across all TDFs in the specific asset class and quarter. The dependent variable in panels B and C is calculated as the aggregate dollar amount of total trades 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 2008Q3-2018Q4. The 'last 5 years' sample includes 2014Q1-2018Q4. The time series under 'E shr [0.25, 0.75]' title aggregates only those TDFs with equity shares between 25% and 75%, and under 'E shr [0, 0.25) or (0.75, 1]' includes only those TDFs with equity shares below 25% or above 75%. RS represents the quarterly return of the total US stock market. RB 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 beginning of the quarter. Robust standard errors are in parentheses. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full	Last 5yrs	E shr [0.25, 0.75]	E shr [0, 0.25) or (0.75, 1]	Full	Last 5yrs	E shr [0.25, 0.75]	E shr [0, 0.25) or (0.75, 1]
A.	**$ Total trade (E), t**				**$ Total trade (FI), t**			
RS-RB, t	**-7.936**	**-40.330**	**-10.487**	**2.551**	**35.635*** **	**104.900*** **	**26.702*** **	**8.934** **
	(16.749)	**(36.777)**	**(8.273)**	**(10.235)**	**(10.704)**	**(20.464)**	**(7.077)**	**(3.907)**
RS-RB, t-1	-4.005	-80.892	-6.432	2.427	10.279	36.183	5.149	5.130
	(13.958)	(90.261)	(8.792)	(8.608)	(10.253)	(42.033)	(6.826)	(3.627)
Observations	34	17	34	34	34	17	34	34
R-squared	0.003	0.025	0.041	0.001	0.226	0.440	0.267	0.126
B.	**Total trade (E), t / Total holding, t-1**				**Total trade (FI), t / Total holding, t-1**			
RS-RB, t	**-0.044**	**-0.041**	**-0.079***	**0.013**	**0.135*** **	**0.113*** **	**0.183*** **	**0.073*** **
	(0.044)	**(0.048)**	**(0.042)**	**(0.053)**	**(0.022)**	**(0.029)**	**(0.027)**	**(0.017)**
RS-RB, t-1	-0.092	-0.136	-0.059	-0.144	0.050	0.042	0.066	0.027
	(0.068)	(0.131)	(0.050)	(0.098)	(0.031)	(0.060)	(0.040)	(0.019)
Observations	34	17	34	34	34	17	34	34
R-squared	0.107	0.033	0.141	0.110	0.526	0.325	0.597	0.351
C.	**Total trade (E), t / Total holding, t-1**				**Total trade (FI), t / Total holding, t-1**			
S(1-S)(RS-RB), t	**-0.207**	**-0.220**	**-0.325***	**0.112**	**0.659*** **	**0.585*** **	**0.761*** **	**0.497*** **
	(0.218)	**(0.246)**	**(0.171)**	**(0.334)**	**(0.108)**	**(0.152)**	**(0.109)**	**(0.104)**
S(1-S)(RS-RB), t-1	-0.426	-0.720	-0.251	-1.065	0.244	0.211	0.283	0.194
	(0.338)	(0.695)	(0.215)	(0.720)	(0.150)	(0.315)	(0.173)	(0.142)
Observations	34	17	34	34	34	17	34	34
R-squared	0.099	0.033	0.138	0.113	0.528	0.320	0.598	0.363

Table 5 Aggregate TDF vs. Retail Flows

This table contrasts aggregate time series of TDF trades in and retail fund flows to domestic equity funds during 2008-2018. 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. The retail series is constructed by summing up all dollar flows to retail domestic equity funds 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 fund 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. RS-RB 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 billions. 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	
RS-RB, t	308.048***	308.301***	308.682***	308.654***
	(92.392)	(91.486)	(90.442)	(90.418)
(RS-RB), t * TDF all	-337.588***		-317.917***	
	(87.470)		(88.276)	
Net coef for TDF all	*-29.540**		*-9.235*	
	(16.351)		*(14.167)*	
(RS-RB), t * TDF aggr. or conserv.		-318.548***		-305.075***
		(89.673)		(88.204)
(RS-RB), t * TDF moder.		-327.500***		-321.831***
		(87.728)		(90.876)
Net coef for TDF aggr. or conserv.		*-10.247*		*3.579*
		(6.613)		*(8.847)*
Net coef for TDF moder.		*-19.200**		*-13.177**
		(10.126)		*(7.299)*
TDF all	30.237***		55.814***	
	(9.954)		(12.764)	
TDF aggr. or conserv.		34.517***		53.872***
		(8.443)		(10.403)
TDF moder.		34.749***		48.252***
		(8.070)		(9.616)
ln (Total assets), t-1	-5.625	-2.776	1.518	1.200
	(3.482)	(1.783)	(4.239)	(2.203)
Observations	68	102	68	102
R-squared	0.633	0.674	0.655	0.685

Table 6 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' stands for asset-class return and indicates whether it is measured as the difference between equity and bond return or the excess return of equity over the risk-free rate. RS measures the quarterly return of the US equity market from CRSP, RB measures the pre-fee return of the Vanguard Total Bond Market Index Fund, and Rf is the quarterly return on the 1-month treasury. 'Frac. held by TDFs' is measured as the fraction of fund assets held by TDFs. 'Frac. held by moder. TDFs' is the fraction of fund assets held by TDFs with equity share between 25% and 75%. 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. Time (year-quarter) fixed effects are included in the even columns. Standard errors are clustered two ways by time and fund. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fund flow rate, t							
AC return	RS- RB				RS-Rf			
AC return, t	0.179***		0.178***		0.199***		0.199***	
	(0.046)		(0.046)		(0.047)		(0.047)	
AC return, t * frac. held by TDFs, t-1	-0.355***	-0.315***			-0.380***	-0.344***		
	(0.085)	(0.083)			(0.092)	(0.088)		
AC return, t * frac. held by moder. TDFs, t-1			-0.805***	-0.619***			-0.855***	-0.676***
			(0.217)	(0.178)			(0.241)	(0.200)
AC return, t-1	0.003		0.003		0.003		0.003	
	(0.029)		(0.028)		(0.033)		(0.033)	
AC return, t-1 * frac. held by TDFs, t-1	-0.164***	-0.191***			-0.206***	-0.240***		
	(0.043)	(0.042)			(0.052)	(0.054)		
AC return, t-1 * frac. held by moder. TDFs, t-1			-0.348***	-0.340***			-0.445***	-0.429***
			(0.112)	(0.094)			(0.149)	(0.125)
Frac. held by TDFs, t-1	0.026	0.028			0.033	0.035*		
	(0.022)	(0.022)			(0.024)	(0.020)		
Frac. held by moder. TDFs, t-1			0.051	0.041			0.067*	0.055
			(0.038)	(0.042)			(0.037)	(0.035)
ln (Fund size), t-1	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln (Fund family size), t-1	0.002**	0.002***	0.002**	0.002***	0.002**	0.002***	0.002**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln (Age), t	-0.025***	-0.024***	-0.025***	-0.024***	-0.025***	-0.024***	-0.025***	-0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Expense ratio, t	-1.845***	-1.924***	-1.844***	-1.924***	-1.827***	-1.925***	-1.826***	-1.924***
	(0.330)	(0.320)	(0.330)	(0.320)	(0.329)	(0.320)	(0.329)	(0.320)
Return volatility, t-1	-0.021	-0.154	-0.021	-0.155	-0.073	-0.154	-0.073	-0.154
	(0.140)	(0.208)	(0.140)	(0.208)	(0.141)	(0.208)	(0.141)	(0.208)
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	47,358	47,358	47,358	47,358	47,358	47,358	47,358	47,358
R-squared	0.036	0.047	0.036	0.047	0.037	0.047	0.037	0.047

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. The dependent variable is the market risk adjusted return in month t, where the market beta is estimated using monthly returns during a pre-TDF window of 1996-2005. Panel A considers the 1-month market return in t-1, and Panel B uses the 3-month market return during t-3 to t-1. TDF ownership is measured as an average during 2014-2019. Column (1) includes industry fixed effects but no time fixed effects. Column (2) adds time (year-month) fixed effects. Column (3) further includes size-by-time fixed effects, and Column (4) industry-by-time fixed effects. Column (5) controls for stock fixed effects. Standard errors are clustered two ways by time and stock.

A.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Mkt beta adj. return, t			
Mkt ret, t-1	0.062						
	(0.049)						
Mkt ret, t-1 * TDF ownership	**-9.039*****	**-8.753*****	**-6.945*****	**-8.766*****	**-6.303*****	**-3.111****	**-8.149*****
	(2.762)	**(2.833)**	**(2.550)**	**(2.824)**	**(2.318)**	**(1.519)**	**(2.794)**
Mkt ret, t-1 * Pct rank mktcap (pre)					-0.156***	-0.211***	
					(0.057)	(0.070)	
Mkt ret, t-1 * Δ Pct rank mktcap (post-pre)						-0.355**	
						(0.162)	
Mkt ret, t-1 * Mkt beta (post)							0.027
							(0.050)
Mkt ret, t * Mkt beta (post)							0.575***
							(0.057)
TDF ownership	0.495***	0.499***	0.474***		0.472***	0.146**	0.475***
	(0.084)	(0.086)	(0.086)		(0.083)	(0.060)	(0.083)
Pct rank mktcap (pre)	-0.004*	-0.004	-0.004*		-0.002	0.004	-0.002
	(0.002)	(0.002)	(0.002)		(0.003)	(0.003)	(0.003)
Δ Pct rank mktcap (post-pre)						0.038***	
						(0.006)	
Mkt beta (post)							-0.011***
							(0.002)
Industry FE	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	Y	Y	Y	Y
Time-by-industry FE	N	N	Y	N	N	N	N
Stock FE	N	N	N	Y	N	N	N
Observations	230,589	230,592	222,125	230,592	230,592	230,592	226,168
R-squared	0.006	0.032	0.200	0.045	0.032	0.034	0.043

B.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Mkt beta adj. return, t			
Mkt ret, t-3 to t-1	0.047						
	(0.033)						
Mkt ret, t-3 to t-1 * TDF ownership	**-5.900*****	**-5.665*****	**-4.216****	**-5.699*****	**-4.289****	**-1.743***	**-5.106*****
	(1.916)	**(2.000)**	**(1.776)**	**(1.990)**	**(1.678)**	**(0.948)**	**(1.869)**
Mkt ret, t-3 to t-1 * Pct rank mktcap (pre)					-0.088**	-0.131***	
					(0.038)	(0.049)	
Mkt ret, t-3 to t-1 * Δ Pct rank mktcap (post-pre)						-0.283**	
						(0.112)	
Mkt ret, t-3 to t-1 * Mkt beta (post)							-0.006
							(0.035)
Mkt ret, t * Mkt beta (post)							0.570***
							(0.056)
TDF ownership	0.590***	0.590***	0.536***		0.545***	0.169**	0.554***
	(0.106)	(0.110)	(0.106)		(0.102)	(0.069)	(0.105)
Pct rank mktcap (pre)	-0.004*	-0.004	-0.004*		-0.001	0.006*	-0.002
	(0.002)	(0.002)	(0.002)		(0.003)	(0.003)	(0.003)
Δ Pct rank mktcap (post-pre)						0.044***	
						(0.007)	
Mkt beta (post)							-0.011***
							(0.003)
Industry FE	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	Y	Y	Y	Y
Time-by-industry FE	N	N	Y	N	N	N	N
Stock FE	N	N	N	Y	N	N	N
Observations	230,589	230,592	222,125	230,592	230,592	230,592	226,168
R-squared	0.006	0.032	0.200	0.045	0.032	0.034	0.043

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 lagged market performance during 2010-2019. In each month we predict the S&P 500 status based on stock characteristics including market capitalization, trading volume, industry, and book return-on-assets (ROA) using a linear model and calculate the propensity scores for being included in the index. The matching procedure uses propensity-score-based nearest neighbor matching with no replacement, and the caliper is set at 0.2 times the standard deviation of the propensity score. The regressions include only the matched pairs of observations. Columns (1)-(3) include the entire sample and Columns (4)-(6) include only the marginal stocks whose S&P 500 statuses change during the sample period.

	(1)	(2)	(3)	(4)	(5)	(6)
	Mkt Beta Adj. Return, t					
	All			Marginal		
Mkt Ret, t-1	0.043			0.048		
	(0.035)			(0.038)		
Mkt Ret, t-1 * S&P 500, t-1	**-0.091****	**-0.096****	**-0.103*****	**-0.099****	**-0.100****	**-0.098****
	(0.038)	**(0.039)**	**(0.039)**	**(0.046)**	**(0.048)**	**(0.047)**
S&P 500, t-1	-0.018***	-0.018***	-0.032***	-0.021***	-0.021***	-0.021***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)
Time FE	N	Y	Y	N	Y	Y
Stock FE	N	N	Y	N	N	Y
Observations	28,772	28,772	28,594	17,947	17,947	17,768
R-squared	0.013	0.032	0.094	0.016	0.039	0.101

Table 9 Reduction in time series momentum in TDF era

Based on the average percentage TDF ownership during 2014Q2-2019Q1 (the sorting period), we sort stocks into quintiles. The top quintile is defined as 'high TDF ownership' or the 'treated' group, and the bottom two quintiles are defined as 'low TDF ownership' or the 'control' group. We then form two 'indices' using value-weighted excess returns of the treated and control stocks, and estimate the time series correlation in each index following $r_t = \alpha + \beta r_{t-h\ to\ t-1} + \epsilon_t$ during three subsamples: 1986-1995, 1996-2005 and 2010-2019. Monthly returns are net of 1-month treasury returns in all calculations. The table below presents the beta estimates. Each regression has 120 monthly observations. The 'all' sample uses all stocks in the treated and control groups to form the indices, the 'balanced sample' requires the stocks to be present throughout 1986-2019, and the 'large stock sample' restricts to stocks ranking in the top 40% of market capitalization during the sorting period. Finally, we include the coefficients of similar estimates using the S&P 500 and the Russell 1000 indices which we take for ex ante measures of TDF ownership.

	High TDF Ownership Index						Ex Ante Measures			
	All		Balanced Sample		Large Stock Sample		S&P 500		Russell 1000	
	12m	3m	12m	3m	12m	3m	12m	3m	12m	3m
1986-1995	-0.043	-0.045	-0.043	-0.050	-0.043	-0.046	-0.056	-0.044	-0.049	-0.040
	(0.035)	(0.053)	(0.035)	(0.053)	(0.035)	(0.053)	(0.036)	(0.054)	(0.035)	(0.053)
1996-2005	0.014	-0.029	0.011	-0.038	0.014	-0.030	0.029	-0.003	0.025	-0.003
	(0.028)	(0.057)	(0.028)	(0.056)	(0.028)	(0.057)	(0.024)	(0.054)	(0.024)	(0.054)
2010-2019	**-0.081****	**-0.113***	**-0.080****	**-0.100***	**-0.081****	**-0.113***	**-0.087****	**-0.113***	**-0.070***	**-0.098**
	(0.036)	**(0.061)**	**(0.035)**	**(0.060)**	**(0.036)**	**(0.061)**	**(0.038)**	**(0.061)**	**(0.035)**	**(0.060)**
	Low TDF Ownership Index									
1986-1995	-0.016	0.012	-0.017	0.024	-0.020	0.005				
	(0.029)	(0.050)	(0.028)	(0.050)	(0.029)	(0.051)				
1996-2005	-0.019	-0.033	-0.006	-0.016	-0.020	-0.022				
	(0.031)	(0.052)	(0.026)	(0.050)	(0.032)	(0.053)				
2010-2019	**-0.035**	**-0.067**	**-0.020**	**-0.033**	**-0.021**	**-0.048**				
	(0.030)	**(0.060)**	**(0.029)**	**(0.060)**	**(0.028)**	**(0.059)**				

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.

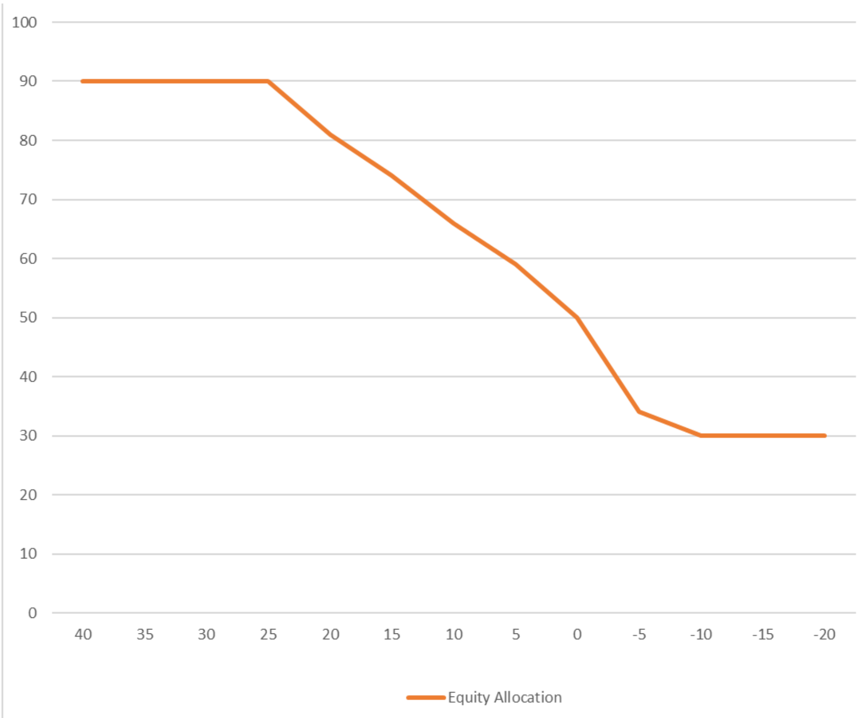


Figure A.2 TDF Holding Data Quality

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.

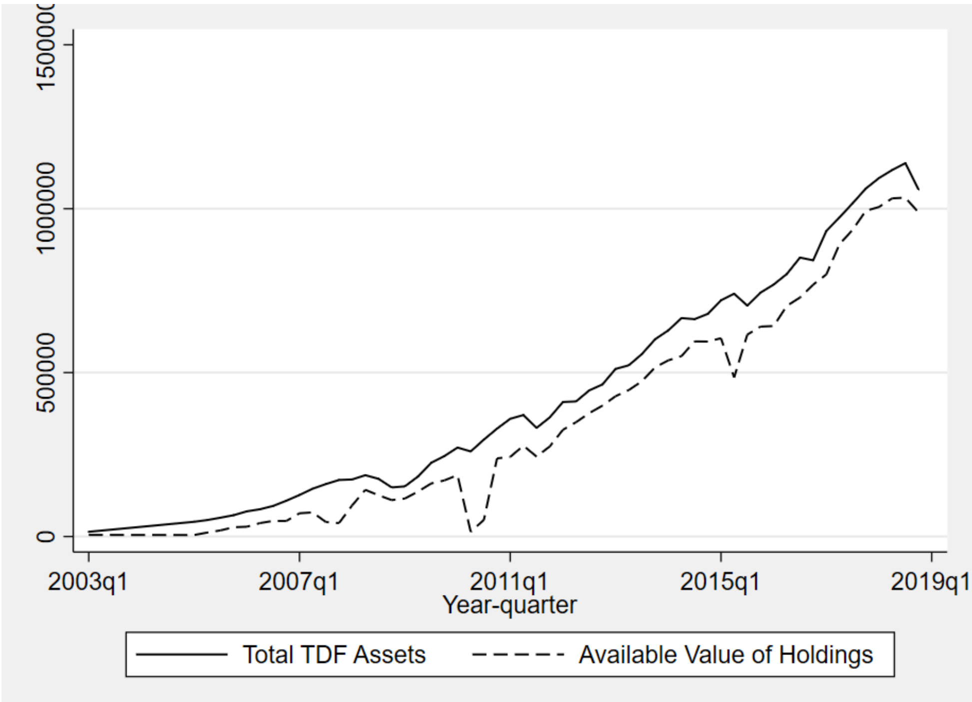


Table A.1 Individual TDF rebalancing with respect to asset class movements

This table provides the disaggregate version of Table 3, panels B and C, and estimates the relationship between the individual TDF rebalancing and asset class returns. The dependent variables are the ratios of rebalancing trades by a TDF in equity or fixed income in a quarter to the lagged total value of holdings of the TDF (including both equity and fixed income), and winsorized at 1% and 99%. The 'full' sample includes 2008Q3-2018Q4. The 'last 5 years' sample includes 2014Q1-2018Q4. The regressions under 'E shr [0.25, 0.75]' include only those TDFs with equity shares between 25% and 75%, and under 'E shr [0, 0.25) or (0.75, 1]' includes only those with equity shares below 25% or above 75%. *RS* represents the quarterly return of the total US stock market. *RB* 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 beginning of the quarter. 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)	(7)	(8)
	Full	Last 5yrs	E shr [0.25, 0.75]	E shr [0, 0.25) or (0.75, 1]	Full	Last 5yrs	E shr [0.25, 0.75]	E shr [0, 0.25) or (0.75, 1]
A.	**Rebal (E), t / Total Holding, t-1**				**Rebal (FI), t / Total Holding, t-1**			
RS-RB, t	**-0.080****	**-0.078****	**-0.121*****	**-0.042**	**0.056*****	**0.054****	**0.094*****	**0.021***
	(0.036)	**(0.027)**	**(0.038)**	**(0.035)**	**(0.017)**	**(0.024)**	**(0.026)**	**(0.011)**
RS-RB, t-1	-0.096*	0.031	-0.083	-0.105*	0.031**	0.034	0.035**	0.025
	(0.053)	(0.056)	(0.055)	(0.053)	(0.015)	(0.037)	(0.017)	(0.016)
TDF FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,002	5,238	3,681	4,290	7,932	5,210	3,681	4,219
R-squared	0.093	0.084	0.134	0.098	0.103	0.108	0.124	0.127
B.	**Rebal (E), t / Total Holding, t-1**				**Rebal (FI), t / Total Holding, t-1**			
S(1-S)(RS-RB), t	**-0.508****	**-0.579*****	**-0.583*****	**-0.431**	**0.510*****	**0.471*****	**0.592*****	**0.382*****
	(0.203)	**(0.152)**	**(0.166)**	**(0.271)**	**(0.098)**	**(0.122)**	**(0.100)**	**(0.082)**
S(1-S)(RS-RB), t-1	-0.239	-0.459	-0.232	-0.500	0.200	0.256	0.228	0.175
	(0.212)	(0.520)	(0.200)	(0.361)	(0.133)	(0.232)	(0.152)	(0.123)
TDF FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,002	5,238	3,681	4,290	7,932	5,210	3,681	4,219
R-squared	0.093	0.089	0.134	0.098	0.110	0.113	0.125	0.128

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