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

Jonathan A. Parker
MIT and NBER

Antoinette Schoar
MIT and NBER

Yang Sun
Brandeis University

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Abstract

The rise of Target Date Funds (TDFs) has moved a significant share of retail investors into contrarian trading strategies that rebalance between stocks and bonds so as to maintain age-appropriate portfolio shares. We show that *i*) TDFs actively rebalance within a few months following differential asset-class returns to maintain stable portfolio shares, *ii*), this rebalancing drives contrarian rebalancing flows across funds held by TDFs, *iii*) investors do not move funds into or out of TDFs to offset these flows, and *iv*) these flows impact the prices of stocks. Across otherwise similar stocks, those with higher (indirect) TDF ownership experience lower returns after higher market-wide performance, a results that holds when looking only at variation in TDF ownership driven by S&P index inclusion. Consistent with this price impact, the stock market exhibits more reversion at the monthly frequency during the recent TDF era. Together, our results suggest that continued growth in TDFs may affect return dynamics and the relation between stock and bond returns.

JEL codes: G12; G23; G51

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Parker: Sloan School of Management, MIT, 100 Main Street, Cambridge, MA 02142, japarker@mit.edu; Schoar: Sloan School of Management, MIT, 100 Main Street, Cambridge, MA 02142, aschoar@mit.edu; Sun: Brandeis University International Business School, 415 South Street, Waltham, MA 02453, yangs@brandeis.edu.

Over the past two decades, one of the most important financial innovations for people investing their retirement saving has been the rise of target date funds (TDFs, also called lifecycle funds). TDFs are designed to provide investors with an age-appropriate portfolio of stocks and bonds that depends on the investor's expected retirement date – or 'target date' – following the proscriptions of partial-equilibrium models of optimal portfolio choice.[1] Thus, over time and as their investors age, a TDF slowly reduces risk by rebalancing across asset classes, out of stocks and into bonds. More importantly for our purposes, to maintain the age-appropriate share of stocks relative to bonds, TDFs actively rebalance to undo changes in this share that are caused by differential returns across these asset classes. 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 in US mutual funds) in 2019.[2]

This paper shows that, while possibly not an original intention of this financial innovation, TDFs have moved a significant fraction of US retail investors to an actively 'market-contrarian' trading strategy that trades against aggregate stock market momentum and fluctuations. Traditionally, many retail investors are either passive – letting their portfolio shares rise and fall with the returns on different asset classes – or they are active and tend to reallocate their assets into asset classes or funds with better past performance, a behavior known as 'positive feedback trading' or 'momentum trading' that can amplify price fluctuations.[3] In contrast, by rebalancing to maintain age-appropriate asset allocations, TDFs trade against excess returns in each asset class, stocks or bonds.

We have three main findings. First, following high returns in an asset class, funds in that asset class experience outflows in proportion to their TDF ownership shares, which reduces the relationship between past fund performance and inflows to that fund. Importantly, investors do not move funds into or out of TDFs to offset these flows. Second, stocks with

[1] Merton (1969), Viceira (2001), Cocco, Gomes, and Maenhout (2005) study the characteristics of the optimal mix of stocks and bonds as people age. Campbell (2016) Section 5.1 discusses some of the benefits and pitfalls of TDFs as a solution to the lifecycle portfolio problem.

[2] This number 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 Investment Company Institute (2020), figures 2.2 and 8.20, and Morningstar (2020).

[3] Agnew, Balduzzi, and Sunden (2003) and Ameriks and Zeldes (2004) show widespread passivity of retail investors in retirement accounts, and Calvet, Campbell, and Sodini (2009) and De Long et al. (1990) and Hong and Stein (1999) discuss of the effects of momentum trading on stock returns.

higher TDF exposure (through the funds held by TDFs) have lower returns after higher market performance, consistent with TDFs altering the return dynamics of individual stocks. We show that this correlation appears to be driven by TDFs' price impact, and is not simply the result of TDFs investing in stocks that have less exposure to market momentum. Specifically, stocks included in the S&P 500 index have higher shares of TDF ownership than otherwise similar stocks that are not included (e.g. for reasons of index 'balance' across industries). Consistent with price pressure from TDF rebalancing, we find lower returns following high equity market returns for stocks included in the S&P Index relative to similar stocks not in the Index. This return differential does not exists in previous decades prior to the rise of TDFs. Finally, the time series momentum in the S&P 500 index declines from the pre-TDF to the post-TDF period, a change that we speculate could by partly due to the rise of TDFs dampening aggregate market fluctuation.

We reach these findings by first confirming that the trading behavior of TDFs follows their stated allocation strategies across asset classes. TDFs with different target dates have different desired equity shares. A typical TDF allocates 80 to 90 percent of its assets to diversified equity funds and the remainder to bond funds until 25 years before the target retirement date, at which point the equity share typically starts to decline smoothly over time to reach 30 to 40 percent 10 years after the target date. This variation implies different trading behavior by different TDFs in response to market returns. Specifically, the amount of rebalancing by a TDF 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 its portfolio from stocks to bonds. In contrast, a TDF invested entirely in one asset class or the other would not have to rebalance at all. Importantly for our purpose, the share of its assets that a TDF invests in each asset class depends only on the calendar year relative to the target date, and so does not depend either on the composition of the market portfolio or on past or expected future returns on different asset classes.

Our first result is that TDFs rebalance across equity and fixed income mutual funds within a few months and behave almost exactly as predicted by their desired equity shares given realized asset returns. Using quarterly data on TDF holdings during 2008-2018, we show that in quarters when the equity market returns exceed those on the bond market, 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 and in the following quarter. For each dollar of rebalancing predicted by their strategies, the actual rebalancing in the current quarter is 50 cents and in the following quarter is (less precisely estimated) 45 cents, implying that most rebalancing occurs within the first three months of a market movement.[4] Consistent with the quadratic relationship between desired equity share and required rebalancing, we observe a greater magnitude of rebalancing in the group of TDFs with more equal allocations between equity and bonds, i.e., equity shares between 25% and 75%. These are also the TDFs that have most assets under management, since this asset allocation applies to older people.

Second, we show that the market-contrarian trading of TDFs is a quantitatively significant part of equity fund flows. For an excess return on the stock market of 10% in a quarter, the average equity mutual fund receives additional investment flows that increase its size by 2.5% in that quarter. Using differences across funds in the degree of TDF ownership, 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, we estimate that TDF rebalancing offsets about 20% of this 'aggregate trend-chasing' by retail investors in mutual funds in 2019. In sum, at both the individual and aggregate level, flows to mutual funds in response to market returns are mitigated by TDF contrarian trading.

Our third result is that this contrarian trading by TDFs dampens the sensitivity of individual stock returns to recent market performance. Given the share of each fund held by TDFs and the stocks held by each funds, we calculate the (indirect) stock level holdings of each TDF. Looking across all stocks, greater (indirect) TDF ownership is associated with lower returns in the months following higher stock market returns. Specifically, when the excess return of the equity asset class is 10% in a month, stocks with one standard deviation (0.6%) higher share of TDF ownership have 0.24% lower return in the following month. Given the size of the TDF sector, this is a large price effect. However, several pieces of evidence suggest that this price impact is not driven by other characteristics of stocks that are correlated with TDF ownership share. Specifically, our findings are unchanged when

[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.

we measure the effect using only variation in TDF ownership for the same stock over time, when comparing stocks only to others within the same industry (including stock fixed effects and including month-by-industry fixed effects), and when controlling for risk factor exposures. We also conduct a falsification test and find that there is no correlation between (later) TDF ownership share and stock returns following aggregate market returns prior to the PPA and so prior to the rise of TDFs.

To provide further evidence on the price impact of rebalancing by TDFs, we show that once stocks are included in the S&P 500 index they have a discretely higher TDF ownership. Subsequently their momentum returns go down, i.e. their returns are less sensitive to lagged market performance compared to otherwise similar stocks not included in the index.[5] Membership in the S&P 500 is set by an index committee based not only on a set of eligibility criteria related to size but also on other considerations such as industry balance. We assume that these other considerations are uncorrelated with the specific return sensitivity to market performance other than through the trading of TDFs. Among a set of (large-cap) stocks matched on industry, size and liquidity, being included in the S&P 500 leads to a reduction in the stock return sensitivity to lagged market performance. Following a 10% excess return on the stock market in a month, the index stocks have a 1% lower return in the following month compared with similar non-index stocks. Again, a falsification test finds no similar effect before the rise of TDFs.[6]

Lastly, and most speculatively, our findings on fund flows and individual stock returns raise the possibility that the market-contrarian strategies of TDFs that lead TDFs to sell stock funds and buy bond funds following positive stock market returns actually affect stock market prices and returns. Focusing on the S&P 500, there is a significant negative time series correlation in monthly returns during 2010-2019 that is not present in the periods 1986-1995 or 1996-2005. As a rough calculation, if the value of the stock market decreases by $5 when TDFs sell a dollars of the market, as Gabaix and Koijen (2020) estimate, then the rise of TDFs can account for a tenth to a fifth of this change in the time-series momentum of the stock market.

Our findings have several implications. First, our estimates imply a large response of

[5]The S&P 500 index is a common benchmark for TDF-invested equity funds.

[6]While existing research has documented that index inclusion affects the price level of a stock (Shleifer, 1986) and its co-movement (Barberis, Shleifer, and Wurgler, 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.

market prices to the stock trading by TDFs. A back of the envelope calculation implies that an increase of demand for a stock of 0.1% of its market capitalization by ETFs raises the price by roughly 0.7%, which implies a price 'multiplier' in the sense of Gabaix and Koijen (2020) of 7 which is much larger than previous estimates, although these estimates are based on changes in idiosyncratic demand for stocks. Our paper further implies that TDFs, by trading across asset classes, reduce the price response to asset-class-specific changes in demand from other sources. That is, TDFs lower price multipliers.

Second, our results suggest that to the extent that momentum or other anomalies are (or were) due to trend-chasing by retail investors, these anomalies may disappear (or may have already) as more retail investor money follows market-contrarian strategies. A related implication is that as TDF assets increase, they may lead to different anomalies or even to persistent mis-pricing, because simple rebalancing rules of this type do not account for changes in the market portfolio. Of course, TDFs may adopt more sophisticated strategies and/or other investors may change their trading behavior in response.

Finally, because TDFs actively re-balance between stocks and bonds, they add to co-movement in returns between these markets. An implication of this is that TDFs propagate movements in interests rates from bond markets to stock markets. Thus, TDFs automatically transmit expansionary policies such as quantitative easing from the bond market to the stock market.

Related Literature Our paper builds on the previous literature documenting that mutual fund flows can alter return dynamics and affect market volatility. Warther (1995) and Edelen and Warner (2001) find a positive relationship between aggregate mutual fund flows and concurrent monthly, weekly, or daily market returns. Da et al. (2018) uses 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. Coval and Stafford (2007) demonstrates that flow-driven fire sales by mutual funds lead to a price impact followed by a reversal, and Lou (2012) shows that the momentum effect could be caused by a significant price impact of retail flows to mutual funds. Vayanos and Woolley (2013) and Gabaix and Koijen (2020) develop models that show how changes in asset demand can cause substantial price effects due to financial frictions. Our paper adds causal evidence on price effects, focuses on contrarian rather than momentum trading, and ultimately on 'time series' rather than cross-sectional momentum.

We also add to a smaller literature studying TDFs that measures the effect of retirement plans, of retail financial advice, and of competition among funds on the rise of TDFs. Mitchell and Utkus (2020), using data from one large 401(k) provider, shows that plan-level features, such as auto-enrollment, 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 (forthcoming) uses TDFs to construct counterfactual portfolios of retail investors in absence of financial advice. On the competition in the TDF market, Balduzzi and Reuter (2019) documents 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. Shoven and Walton (2020) shows that returns on lower-cost TDFs tend to track their performance benchmarks, while returns on higher-cost TDFs tend to under-perform their benchmarks. In this literature, our paper is the first to study the impact of the TDF innovation on asset prices.

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 domestic equity, foreign equity and fixed income mutual funds. TDFs seek to maintain given portfolio shares in different asset classes, with the shares based on the time to 'target date.' TDFs typically start with a large desired share of equity – on the order of 90 percent – until roughly 25 years before retirement, at which point the desired equity share declines linearly over time to each roughly 40 percent ten years after the target date. 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). Not only do TDFs have to rebalance as their target equity shares change over time, but they have to rebalance in response to market movements to maintain their proscribed shares of given asset classes.[7]

The use of TDFs has risen dramatically over the past 15 years due to financial innovation and financial regulation. As shown in Figure 1, total assets invested in TDFs increased

[7] See Mitchell and Utkus (2020) for further details on TDFs.

from less than $8 billion dollars in 2000, to $109 billion at the end of 2006, and then rapidly increased to $1.4 trillion at the end of 2019. TDFs with retirement years in 2020-2040 account for the majority of this increase.

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 however 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. In 2019, $942 billion out of the $1.4 trillion TDF assets are held in 401(k) plans (67%) and $260 billion are held through IRAs (19%) (ICI Factbook, 2020, Figure 8.20).

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 Desired equity shares and TDF rebalancing

This section shows that the amount of equity that a TDF must sell in response to a positive excess return on the stock market is quadratic in its desired equity share with a maximum at a 50% equity share. We first derive this result assuming no net flows to the TDF. We then consider a general case of rebalancing with 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, S^*. Consider a TDF with $1 of assets, a target weight of S^* invested in equity funds and a target weight of $1 - S^*$ invested in bond funds. Further assume that the TDF is at target allocations at the beginning of the period and that the target shares do not change (move along the glide path) by the period end. Assume no investor flows (panel A). Following equity and bond asset returns of R^E and R^B respectively, the total portfolio value is $1 + R^B + S^* \left(R^E - R^B\right)$ (column 1). To restore the original asset allocation, the TDF needs to bring the equity and bond fund values to $\left[1 + R^B + S^* \left(R^E - R^B\right)\right] S^*$ and $\left[1 + R^B + S^* \left(R^E - R^B\right)\right] (1 - S^*)$ respectively (column 2). Thus, the TDF needs to sell the equity fund in the amount of $-S^* (1 - S^*) \left(R^E - R^B\right)$, and buy the bond fund in the amount of $S^* (1 - S^*) \left(R^E - R^B\right)$ (column 3). 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 following the returns. In this case, the total portfolio value becomes $1 + R^B + S^* \left(R^E - R^B\right)$ (column 1) and the fund then receives a net flow of F. Following the same procedure as in Panel A, we calculate the desired holding as shares S^* and $1 - S^*$ of the total value of the fund including fund flows (column 2), and the necessary total net trades to restore that allocation (column 3). As shown in column 4, for the purpose of allocating net flows only, the TDF only needs to allocate new flows to asset classes in proportion to its desired holdings by buying FS^* in equity (or selling $-FS^*$ if $F < 0$) and $F (1 - S^*)$ in fixed income. Subtracting these flow-driven trades from the total net trades, we can back out the rebalancing trades, which are 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 trades 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 $FS^* - S^* (1 - S^*) \left(R^E - R^B\right)$ has the same sign as F (that is, $R^E - R^B$ is small relative to F, a case that is more prevalent for large TDFs), rebalancing can be achieved simply by allocating the net flows to new positions instead of adjusting existing positions.

In our subsequent analysis, we focus on rebalancing trades (as in panel A) but also report results for total trades (as in panel B). We focus on rebalancing trades because they do not include trades driven automatically by auto-enrollment, incomes, auto-escalation, withdrawals, and menu choice decisions that change flows over time. Rebalancing trades also omit flows to and from TDFs, and so do not include potentially spurious co-movement between these flows and market returns such as from the trend of positive inflows to TDFs the strong average performance of the stock market and economy. However, we also present results for total trades which represent the net change in demand for assets through TDFs, with the caveat that total trade measures can potentially be biased and noisy. In practice we find similar point estimates with both measures, consistent with investors in TDF funds not actively rebalancing in response to market movements. However, the estimates for total flows are less statistically significant, consistent with the greater noise in this series. This lack of active investor flows to and from TDFs is consistent with existing evidence that the vast majority of TDF assets are held through defined contribution retirement plans and IRAs where switching decisions by investors are infrequent. For example, Mitchell and Utkus (2020) demonstrates that most flows in and out of TDFs are explained by plan sponsor actions combined with passive plan participant behavior rather than past returns. In addition, 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 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

[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.

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. Quarterly mutual fund holdings data are from Thomson Reuters which are linked to the CRSP mutual fund dataset using MFLINKS. 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.

Finally, we measure the return on stocks as an asset class, R^E, as the value weighted total return of the US stock market obtained from CRSP, and the return on on bonds as an asset class, R^B, as the pre-fee return on the Vanguard Total Bond Market Index Fund.[9]

4 TDF rebalancing

While TDF providers sell age-appropriate portfolios as a key product feature, some TDFs might also be pursuing other cross-asset class strategies such as momentum or market timing, and so their trades might be no different than those of any other fund. This section establishes that TDFs in fact do rebalance to their desired equity shares as in Table 1, and that they do so within two quarters of a market movement.

We use our panel dataset of holdings at the TDF-by-mutual-fund-share-class level to calculate rebalancing trades in equity and fixed income by TDF k in quarter t in three steps. First, we calculate the dollar amount of the 'total trade' for each pair of TDF and fund share class 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

[9]Using the US stock market return to approximate for the return of the equity asset class R^E introduces measurement errors when a fraction of the TDF holdings is in foreign equity. We have verified that our rebalancing results are similar if we calculate a weighted average R^E 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^E.

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 $TotalTrade^y_{kt}$ where y stands for either the equity (E) or the fixed income (B) asset class.[10] Third, we calculate the 'flow-driven trade' by a TDF of an asset class as the dollar flow to the TDF allocated pro rata to lagged portfolio weight of the asset class (as in Frazzini and Lamont, 2008).[11] We calculate 'rebalancing trade' from the difference: $Rebalancing^y_{kt} = TotalTrade^y_{kt} - FlowDrivenTrade^y_{kt}$.[12] To match the setup in Table 1, where the total assets of the TDF are assumed to be one dollar, we normalize the dollar rebalancing trades by the lagged total dollar holdings of the TDF.

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:

$$Rebalancing^E_{kt} = \gamma^E \left(R^E - R^B\right)_t + \zeta^E \left(R^E - R^B\right)_{t-1} + \theta_i + \epsilon^E_{kt} \tag{1}$$

$$Rebalancing^B_{kt} = \gamma^B \left(R^E - R^B\right)_t + \zeta^B \left(R^E - R^B\right)_{t-1} + \theta_i + \epsilon^E_{kt} \tag{2}$$

where we include TDF fixed effects, θ_i, to account for the different and unknown desired equity shares of different TDFs.

Table 3 present the estimates of equations (1) and (2) using quarterly rebalancing at the individual TDF-by-asset-class level during 2008-2018. Panel A, columns 1 and 4 use the entire sample of TDFs. The coefficient on $(R^E - R^B)_t$ suggests that if the equity market moves up (down) by 10% in excess of the bond market in a quarter, the average TDF sells (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 $(R^E - R^B)_{t-1}$ further imply that the rebalancing continues in the following

[10]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.

[11]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.

[12]Because funds can trade continuously and one can observe portfolio holdings only at discrete (quarterly) intervals, the formulae in Table 1 are only approximations. We are assuming all rebalancing trades are made at the end of each period after returns are realized and before the fund reports its portfolio.

quarter. However, the delayed effect has lower statistical significance, suggesting that the most concentrated action of TDF rebalancing occurs during the quarter of the return.

A further prediction from Table 1 relates to the cross-sectional heterogeneity across TDFs. The magnitude of the predicted rebalancing trade $S^*(1 - S^*)(R^E - R^B)$ is a concave quadratic function of the target equity share S^*. Thus, for a given $R^E - R^B$, the expected rebalancing should be greater 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'). Since we do not observe the target equity shares, we classify funds based on the observed equity shares at $t - 1$, or S_{t-1}. The results are consistent with this prediction: For an equity market return that exceeds the fixed income market by 10%, the TDFs with moderate allocations on average sell equity holdings by 1.2% of portfolio value, significant at the 0.01 level, while TDFs with conservative or aggressive allocations 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. At the bottom of panel A, we report the cumulative effect which is still stronger for the TDFs with moderate allocations. 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.

Table 3 panel B presents the effect of rebalancing on TDF trades at the aggregate level. The aggregate estimate puts higher weights on larger TDFs. The result suggests stronger rebalancing in response to current quarter performance compared with panel A and implies that larger TDFs rebalance at higher frequency than smaller TDFs do, consistent with their rebalancing through flow allocations. We also observe more equal magnitudes in the trading of equity and bond funds in panel B, which indicates that larger TDFs adhere closer to the rebalancing formula. We can consider the magnitudes of these effects in the context of the total asset size under management by in the TDF market. Given the $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 panel B column 1 suggests that TDFs on aggregate should purchase around $81 billion ($0.16 \times 22\% \times 2300$) of equity funds and sell around the same amount of bond funds in the first two quarters of 2020 as the stock market dropped by around 22% relative to the bond market in 2020Q1.

In Table 4, we compare the actual rebalancing with the predicted values by estimating the following equations based on Table 1:

$$Rebalancing^E_{kt} = \eta^E S_{kt-1}\left(1-S_{kt-1}\right)\left(R^E-R^B\right)_t + \pi^E S_{kt-1}\left(1-S_{kt-1}\right)\left(R^E-R^B\right)_{t-1} + \epsilon^E_{kt}$$
$$Rebalancing^B_{kt} = \eta^B S_{kt-1}\left(1-S_{kt-1}\right)\left(R^E-R^B\right)_t + \pi^B S_{kt-1}\left(1-S_{kt-1}\right)\left(R^E-R^B\right)_{t-1} + \epsilon^E_{kt}$$

where S_{kt-1} measures (possibly with error) the desired equity share of TDF k. The independent variables $S(1-S)(R^E-R^B)$ in t and $t-1$ are the predicted magnitude of rebalancing in the current and subsequent quarter respectively. Immediate rebalancing predicts $\eta^E = -1$ and $\eta^B = 1$, and $\pi^E = 0$ and $\pi^B = 0$. However, the estimates, $\widehat{\eta^E}$ and $\widehat{\eta^B}$, may be closer to zero for several reasons. First, rebalancing may not be immediate. TDFs may rebalance with a time lag, for example to save costs by re-allocating inflows until the desired equity share is reached. The lagged terms, $S_{t-1}(1-S_{t-1})(R^E-R^B)_{t-1}$, allow for and measure such delayed adjustment. If complete adjustment occurs withing the two quarters, then π and η should sum to one. Second, due to the cost of rebalancing, a TDF manager may allow the portfolio weights deviate from the target without intervention, especially when the market movement is small.[13] Third, we approximate the desired equity share by S_{t-1}, with the observed lagged equity share. If the observed share at $t-1$ is not equal to the desired share or if the desired allocation changes as proscribed by the glide path, then S_{t-1} measures the true desired equity share with noise. These three reasons for measurement error suggest that our estimates of π and η may be attenuated and so may sum to less than one.

Table 4 panel A uses TDF level data and shows that $\widehat{\eta^E}$ is about 0.5, suggesting that for each dollar of predicted rebalancing, the actual rebalancing is about 50 cents in the current quarter. The estimated fraction of predicted rebalancing done in the subsequent quarter is about 45 cents per dollar, but is not be precisely estimated. The sum of the coefficients (reported in 'cumulative effect') is below one, but quite close to one. When we split TDFs by the target equity weight, we find that the group of moderate allocation TDFs follow the formula more closely than the rest do. The same result is seen in panel

[13] That is, if there is inertia driven by fixed costs of adjustment, partial adjustment models such as ours tend underestimate adjustment.

B estimated with aggregate data. This pattern is consistent with TDFs not responding to small deviations from desired equity shares since TDFs with extreme desired equity shares see only small movements away from their target allocations for the same asset market fluctuations, making rebalancing less important.

5 The Effect of TDFs on net flows to equity mutual funds

Section 4 illustrates that TDFs trade against market movements. In this section, we look across equity mutual funds with different levels of TDF ownership to measure how these TDF trades influence total retail fund flows, both at the level of the mutual fund and at the level of the entire market.

We base our analysis on the hypothesis that, because of TDF rebalancing, mutual funds with high TDF ownership receive lower net inflows following good returns in their asset class relative to mutual funds in the same asset class with low TDF ownership. To focus on retail investor behavior, we restrict our sample to mutual funds with the majority of assets held through retail share classes. Using quarterly data at the mutual fund level from 2008Q3-2018Q4, we estimate the following specification

$$\begin{aligned} FundFlow_{jt} = \beta_1 ExcessEquityRet_t + \beta_2 ExcessEquityRet_t \times Frac.TDF_{jt-1} + \beta_3 ExcessEquityRet_{t-1} \\ + \beta_4 ExcessEquityRet_{t-1} \times Frac.TDF_{jt-1} + Frac.TDF_{jt-1} + X_{jt} + \epsilon_{jt} \end{aligned} \tag{3}$$

where the dependent variable is the fund flow rate for mutual fund j in quarter t measured as the growth rate in assets in excess of the realized net fund return. We allow flows to respond to both the current quarter and the lagged quarter's asset class performance in proportion to the fraction of their shares owned by TDFs. The coefficients of interest are those on the two interaction terms which measure the contemporaneous (β_2) and lagged (β_4) effect of greater TDF ownership on fund flows following a positive return on the asset class of the fund. Our hypothesis, based on TDF trading behavior, is that β_2 and β_4 are negative.

We explore two versions of the excess equity returns for the following reason. While TDF trades respond to the difference between U.S. stock and bond market returns, $R^E - R^B$, retail flows to equity mutual funds may react to different aggregate performance metrics, such as simply stock market performance. Thus, we examine the response not just to, $R^E - R^B$, which is the right measure for TDFs trades, but also to $R^E - R^f$, which may be the right measure of retail investor flows.[14]

To measure TDF ownership, 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 fund characteristics that have previously been found to affect fund flows, specifically 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.

Column 1 of Table 5 presents the estimates of equation (3) using the excess return, $R^E - R^B$, as our measure of returns. Fund flows significantly chase equity asset class returns. For an equity mutual fund that is not held by TDFs, an $R^E - R^B$ of 10% leads to a higher net flow at about 2.5% of the lagged size of the fund in the contemporaneous quarter and an additional 0.75% in the following quarter relative to when $R^E - R^B$ is zero. 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 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 contemporaneous return-chasing tendency is reduced by about one sixth ($0.645 \times 0.06/0.250 \approx 16\%$).[15] In column 2, we replace the variables that vary only with time with time fixed effects. The coefficients on the interaction terms with TDF ownership shrink slightly but remain economically and statistically significant. Retail flows to mutual funds are related to their ownership by TDFs as predicted.

In columns 3-4 of Table 5, we measure the excess equity return as the return of the equity market less the risk-free rate. The estimates are quite 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

[14]The mutual fund flow literature has largely focused on the within asset-class abnormal 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, Huang, and Odean (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, Gulen, and Rau (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, Kumar, and Ng (2011) shows that trend-chasing is correlated with proxies for investor biases.

[15]Fund flows are negative following a positive excess return on the stock market for funds with TDF ownership exceeding 38%, which applies to only 0.25% of the observations.

excess returns over the risk-free rate, we focus on the sensitivity of stock returns to past market excess returns in the subsequent section, but our results are similar if we instead examine the sensitivity to $R^E - R^B$ which is the variable directly implied by our model.

Are these fund-level flows important for *aggregate* flows to and from the stock market through mutual funds? We calculate the total dollar net flow to each fund by all retail investors as the increase in assets above the level implied by that fund's return, $TNA_t - TNA_{t-1}(1 + r_t)$ where r_t is the net quarterly return of the share class. In cases where TDFs also invest in retail share classes, we deduct those TDF trades from retail flows. We sum all such flows into or out of all retail share classes of all U.S. domestic equity mutual funds to construct a measure of aggregate retail investor trades as follows. We compare these aggregate flows with aggregate TDF trades measured as the aggregate dollar rebalancing trades by TDFs in domestic equity funds.[16]

Excess returns on the stock market in a quarter are associated with increased inflows to domestic equity funds by retail investors, but to significant *outflows* from domestic equity funds by TDFs. Figure 2 shows these contrarian flows by plotting the aggregate dollar amounts of retail flows (Panel A) and TDF flows (Panel B) to and from domestic equity funds by quarter along with the concurrent excess stock market return over the bond market, $R^E - R^B$. TDF rebalancing trades in domestic equity funds move in the opposite direction as $R^E - R^B$. The different right-hand-side scales on the two Panels which differ by a factor of 5, suggesting that TDFs offset roughly a fifth of retail investor flows.[17]

To more precisely quantify the relative magnitudes of trend-chasing trades by retail investors and the market-contrarian trades by TDFs, we regress aggregate retail and TDF flows in quarter t, normalized by their respective assets under management in quarter $t - 1$, on the return difference between equity and fixed income ($R^E - R^B$) in both quarter t and quarter $t - 1$.[18] Table 6 panel A shows that TDF rebalancing, especially by those

[16]Note that the aggregate time series for TDF rebalancing analyzed here are slightly different from the rebalancing trades in equity studied in Table 3. Here we sum up only the trades in domestic equity mutual funds while Table 3 includes the trades in foreign equity also.

[17]Figure 2, panel A also suggests that retail flows are negative in most quarters during the sample period, consistent with Boyson (2019), which documents that dual-registered investment advisers have converted clients' investments from retail share classes to institutional share classes since 2007. We present an alternative version of Figure 2 in Figure A.3, where we combine flows through retail and institutional share classes. Our result remains unchanged that the retail/institutional mutual fund flows are trend-chasing, while TDFs are contrarian.

[18]The regressions estimate a constant term which is omitted from the table. Standard errors are estimated using the Huber-White heterokedasticity-consistent approach.

TDFs with moderate equity shares, offsets a significant fraction of the trend-chasing in retail mutual fund flows. When the excess return, $R^E - R^B$, is 10%, net aggregate flows to equity mutual funds through retail investors is 1.2% higher than the baseline, measured as a fraction of lagged assets held by this investor type (column 1). Meanwhile, TDF trades of equity mutual funds out of rebalancing is 0.9% lower, measured as a fraction of lagged asset size of TDFs (column 2).

To interpret these results in dollar amounts, we can apply these flow ratios to the assets outstanding in retail share classes and TDFs in 2019. According to our calculation, the total asset size of retail share classes of domestic equity mutual funds is at $5 trillion in the fourth quarter of 2019, and the total asset size managed by TDFs is at $1.4 trillion. Therefore, for a 10% excess performance of the equity market, retail flows are $60 billion(=5000×1.2%) higher than the baseline, but TDF rebalancing trades are $12 billion(=1400×0.9%) lower, thereby offsetting about 20% of the trend-chasing tendency of retail flows in the same quarter as the realized asset class returns. The cumulative effects –the sum of the two quarters effect reported in the final row of the Table – further suggest that TDF rebalancing trades offset $(1400 \times 20.7\%)/(5000 \times 13.6\%) = 42\%$ of the retail flows by the end of the following quarter.

An important point is that these TDF trades are not offset by investors buying and selling TDFs in a pattern related to past returns. In Panel B of Table 6, we replicate Panel A but, in columns 2-4, we include in TDF trades any active movement by retail investors into and out of TDFs rather than just their rebalancing trades. Overall, TDF net flows including flow-driven trades from TDF investors is less contrarian in the concurrent quarter, and columns 3-4 suggest this is mainly driven by the TDFs with more extreme desired equity shares.[19] The cumulative effects, on the other hand, show similar magnitudes as those in panel A, but with more noise. Thus, even including investor flows into and out of TDFs, the behavior of total TDF trades differ significantly from that of retail flows and is contrarian. In the next section 6.3 we investigate whether this contrarian trading by TDFs alters applies flow-driven price pressure on the underlying assets and affects stock returns.

[19] This could be because these investors are more active or because of a correlation between TDF investments by young investors corresponding with periods of relatively strong stock market growth.

6 TDF ownership and stock returns

In this section, presents evidence that the contrarian trading of TDFs that we have documented impacts stock prices and returns. The first subsection documents two major determinants of stock ownership by TDFs: their size as measured by their market capitalization and whether they are included in the S&P 500 index. The second subsection shows that stocks with high actual or expected TDF ownership exhibit lower 'market momentum' or sensitivity to recent market performance, in that they generate lower returns after market rises, consistent with TDF rebalancing putting downward price pressure on the stocks that they hold following high stock returns. Note that our notion of market momentum is with respect to recent market performance, and so is different from the cross-sectional momentum that is widely documented in the literature, which refers to the phenomenon that cross-sectional winner stocks are likely to continue outperforming in the medium term (as in Jegadeesh and Titman, 1993, 2001).[20] Note further that the cross-sectional pattern of market momentum could be driven by other characteristics correlated with TDF ownership (e.g. factors correlated with size) rather than by trading by TDFs. So, in the last subsection of this section, we show that we find a reduced momentum for stocks included in the S&P index relative to similar stocks that are not and for stocks when they are included the index relative to when they are not.

6.1 Determinants of 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 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.[21]

Figure 3 examines the relationship between TDF ownership and market capitalization. We measure TDF ownership at the stock level as $TDFpct_{it} = \Sigma_{jk} a_{ijt} b_{jkt}$ for stock i in quarter

[20] In focusing on the sensitivity of stock returns to recent aggregate market (or more precisely, the aggregate TDF portfolio) performance, our study is more similar to the 'time series momentum' documented in Moskowitz, Ooi, and Pedersen (2012).

[21] 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

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 and take the average market capitalization and TDF ownership during our sample 2008Q3-2018Q4 for each stock. Figure 3 panel A plots the equal-weighted and value-weighted average TDF ownership by these market-cap deciles and shows 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 3. Table 7 estimates the determinants for TDF ownership using observations at the stock-by-quarter level. The dependent variable is the time varying indirect TDF ownership, 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. $TDFpct_{it}$ is expressed in percentages. 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 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. 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.[22] However, it is

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

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 7 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 further includes the 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 TDF ownership and stock returns following market movements

In this subsection, we show that stocks with higher TDF ownership exhibit lower market momentum by estimating the extent to which the sensitivity of monthly stock returns to the lagged market return varies by level of TDF ownership. We then estimate the extent to which this relationship is plausibly causal using variation in TDF ownership driven by inclusion in the S&P 500 index in the following subsection.

Using our dataset of monthly stock returns from 2010 to 2018, we run the following regression at the individual stock level:

$$\begin{aligned} Ret_{it} = \gamma(r^{MKT} - r^f)_{t-1} \times TDFOwnership_{iq-1} + (r^{MKT} - r^f)_{t-1} \times X_{it} \\ + TDFOwnership_{iq-1} + X_{it} + \theta_t + \epsilon_{it} \end{aligned} \quad (4)$$

where i indexes the stocks and t represents a month. $(r^{MKT} - r^f)_{t-1}$ represents the lagged market excess return. The key parameter of interest is γ, the differential sensitivity to market momentum by different levels of TDF ownership. TDF trading pressure is opposite to recent market movements, so if it has an effect on stock prices, we expect $\hat{\gamma}$ to be negative. We windsorize the dependent variable, raw monthly return, at 1% and 99% to account for the fat tails due to extreme movements unrelated to TDF trading. 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 indexed as $q - 1$. Our analysis controls for the typical co-movement (or sensitivity) of stock return to the lagged market excess return among the stocks by including time fixed effects (θ_t). The control variables in the main specification include the natural logarithms of lagged market value and lagged trading volume. Moreover, it is important to note that we include the market excess return $(r^{MKT} - r^f)_{t-1}$ interacted with these control variables to allow the baseline market momentum to vary by these characteristics. In other words, we estimate the TDF effect beyond the selection into different characteristics. The analysis clusters the standard errors two-ways by time (year-month) and stock.

In Table 8, 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 0.024 (=0.6×0.04) 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 0.24% lower return in the following month. In addition, size appears to have a separate but marginally insignificant effect on the return sensitivity that is in the same direction as that of TDF ownership.

Column 2 shows that the baseline result is robust when we control for time-varying, industry-specific shocks measured at the level of Fama-French 12 industry classifications.

Our main prediction about the TDF trading pressure applies to raw (not risk-adjusted) stock returns. If stocks with different risk factor exposures have different propensities for TDF investment, that is part of the variation we want to capture. However, if stocks with different factor risks have differential sensitivity to market momentum due to their factor loadings rather than TDF ownership, that would invalidate our inference. In columns 3-4, we show that differences in the factor exposures of stocks do not explain the way differences in market momentum are related to TDF ownership, at least according to two sets of factor exposure estimates based on current and lagged 4 factor returns. In column 3, we control for the exposures of stock returns to the contemporaneous Fama-French three factors and the momentum factor, which are estimated using a pre-TDF window. That is, using an estimation window of 1996-2005, we run the regression $r_{it} - r^f_t = \alpha_i + \beta_{i1}(r^{MKT} - r^f)_t + \beta_{i2} r^{SMB}_t + \beta_{i3} r^{HML}_t + \beta_{i4} r^{MOM}_t + \epsilon_{it}$, where in each regression we use monthly returns during the estimation window and require at least 60 observations.[23] We then include these beta estimates multiplied by the factor returns in the same month as the stock return measure in equation (4) as controls. This procedure is similar to using the 4-factor alpha as the dependent variable. In column 5, we control for the exposures of stock returns to the *lagged* Fama-French three factors and momentum factor. Again using a window of 1996-2005, we estimate the exposures of stocks to returns of the 4 factors in the previous month, following: $r_{it} - r^f_t = \alpha_i + L\beta_{i1}(r^{MKT} - r^f)_{t-1} + L\beta_{i2} r^{SMB}_{t-1} + L\beta_{i3} r^{HML}_{t-1} + L\beta_{i4} r^{MOM}_{t-1} + \epsilon_{it}$. Then we include the $L\beta$ estimates multiplied by the previous month's factor returns as controls in equation (4). If TDFs simply hold stocks with low betas with respect to the contemporaneous or lagged market factor, the coefficient on the interaction term between the market return and TDF ownership would be explained away once we directly control for estimated betas multiplied by the contemporaneous or lagged market factors. Columns 3-4 suggest that this is not the case. The estimated effect of TDF ownership is unaffected by the inclusion of these additional controls.

As another approach to checking whether these results are indeed driven by the trading of TDFs, we conduct falsification tests using two earlier periods 1996-2005 and 1986-1995

[23]The numbers of observations in columns 3-4 drop significantly from those in columns 1-2 because the use of a pre-TDF estimation window restricts the sample to older stocks.

before the PPA of 2006 set off the growth of the TDF market. Of course, the rise of TDFs is not the only change that occurred in financial markets over this period and so other factors may account for differences between the pre- and post-TDF periods.[24] That said, using TDF ownership measured as the average during 2010-2018, we conduct our analysis in these two earlier periods. Columns 5-6 suggest that stocks that would have high TDF ownership stocks in the modern period did not have lower market momentum before the PPA. Before 2006, the high- and low-TDF stocks exhibit similar sensitivity to the lagged market performance. While this test is again not perfect because of the many differences between the first two periods and the third, these results show that the results documented in Table 8 are unique to the TDF era.

A back-of-the-envelope calculation using the estimated coefficient on $(r^{MKT} - r^f)_{t-1} \times TDFOwnership$ in Table 8 (detailed in the next paragraph), implies that each dollar of TDF rebalancing moves a stock's total outstanding value (market capitalization) by about 6.6 dollars. Put differently, these estimates imply a demand elasticity of other investors of -0.15. This elasticity is substantially lower (or price impact higher) than the micro elasticity documented by the previous literature.[25] But there is a substantial difference between these previous studies and ours. Previous studies have looked at idiosyncratic changes in demand for one stock as compared to similar stocks. We are looking at systematic changes in demand for a set of similar stocks (as shown in Section 6.1). This may explain why our estimate is quantitatively more similar to the asset-class level estimates of Gabaix and Koijen (2020). Another possible explanation for the difference is that our TDF trades are actually trading in the same direction as arbitrageurs who are trading against general retail flows. In this case, there is no arbitrage working against TDF trades to lower the price impact. A final possibility for large price impact is that arbitrageurs have not (yet) noticed and traded against the TDF price impacts that we document.

The calculation of the price multiplier is as follows. Consider a 10% increase in the U.S. equity market in month $t-1$, and suppose stock i has X% TDF ownership. To

[24] Although the rise of TDFs is one of the largest changes for retail investors, there have been other strategies newly offered by retail funds, and momentum strategies in particular might interact with the dynamics we are measuring. However relative to TDFs, these are small. To date, funds pursuing momentum strategies only amount to roughly $25 billion under management in 2019.

[25] See Wurgler and Zhuravskaya (2002) and Gabaix and Koijen (2020) for a summary and discussion of the stock demand elasticity literature. The majority of this literature examines index inclusions as a laboratory and reports an elasticity of around -1 (e.g., Shleifer, 1986; Chang, Hong, and Liskovich, 2015).

calculate $\Delta\%Price$ in the numerator, we start with $\hat{\gamma}$ from Table 8, which measures the incremental return (or change in price) due to each 1% of TDF ownership, -0.04. We divide this coefficient by 1.6 to account for the fact that CITs that have identical portfolios and strategies as the TDFs, and hold 60% of the assets of the TDFs (and are not accounted for in our $TDF(\%)$ measure). We use 1996-2005 as the base period for the counterfactual with no TDFs, which provides us with $\hat{\gamma} = -0.018$ which is the value that would occur for reasons other than trading by TDFs. These two adjustments yield an adjusted-$\hat{\gamma}$ of $(-0.04 - (-0.018))/1.6 = -0.014$. This coefficient implies that the return of stock i is $-0.014 \times 10\% \times X$ lower in month t due to TDF trading. For $\Delta\%Demand$ in the denominator, we estimate that for the same increase in the equity market, the aggregate TDF sells equity at $-0.7 \times 0.3 \times 10\% = -2.1\%$ of its portfolio value (the aggregate fraction of TDF assets invested in equity is about 70%). Suppose the TDF sells all stocks in its portfolio in proportion to portfolio weights, then it sells -2.1% of its holding of stock i. The multiplier is therefore $(-0.014 \times 10\% \times X)/(-2.1\% \times X/100) = (0.14\% \times 100)/2.1\% = 6.6$.

Table 9 shows that we find the same effect of TDF ownership as we showed in Table 8 but only comparing similar stocks in our matched sample of S&P 500 stocks matched to their peer groups based on industry, size, and liquidity, as described in subsection 6.1. All regressions 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 (not in Table 8) 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.[26] The within-stock comparison yields slightly larger magnitude for the TDF effect. Throughout Table 8, size no longer has an independent effect on the sensitivity to market momentum, because identification comes from differences in dynamics among stocks with highly similar characteristics. However, even though these stocks are quite similar, TDF ownership still affects stock returns following market returns. The magnitudes of the estimated TDF effect displayed in Table 9 are similar to those displayed in Table 8, providing further evidence that these stock price dynamics are driven by TDF ownership rather than by correlated other factors like size, industry, or liquidity.

[26] The specification in column 4 is not estimated for Table 8, because the large number of fixed effects make the estimation infeasible in the full sample.

6.3 Evidence from S&P 500 index inclusion

Though the above tests alleviate many mechanical explanations for the results in Table 8, they do not completely eliminate the possibility that reduced stock-level sensitivity to market momentum is at least partly driven by TDF selection into certain types of stocks. To further shed light on the causal relationship, we use inclusion into the S&P 500 Index as a quasi-exogenous source of variation for TDF ownership. We assume that, ceteris paribus, TDF funds prefer stocks that are included in the S&P 500 Index because, as noted, it is a common benchmark. Further, we assume that, among similar stocks, inclusion in the index is partly determined by index-specific factors (such as industry balance) that are unrelated with differences in return dynamics relative to similar stocks. Lastly, we assume that the other things that vary with inclusion S&P Index – discussed at the end of this subsection – either are also driven by TDF ownership or do not affect the sensitivity of the stock return to market momentum.

Using 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 estimate the causal impact of TDF ownership on stock returns with the regression:

$$\begin{aligned} Ret_{ipt} = \gamma(r^{MKT} - r^{f})_{t-1} \times S\&P500_{it-1} + (r^{MKT} - r^{f})_{t-1} \times X_{it} \\ + S\&P500_{it-1} + X_{it} + \theta_{pt} + \epsilon_{ipt} \end{aligned} \tag{5}$$

where i stands for a stock, p refers the peer group that the stock belongs to, and t indexes time (year-month). Equation 5 estimates γ from a difference-in-differences type specification that compares the responses of stocks with different levels of treatment, within each industry-size-liquidity group. The highly-treated group are the stocks included in the S&P 500 Index, which as shown in Section 6.1, have higher TDF ownership. The less-treated group are the stocks not included in the Index, which have relatively lower TDF ownership. With the inclusion of the peer group by time fixed effects θ_{pt}, the identifying assumption is that within each peer group, stocks with different levels of treatment (TDF ownership) would have behaved similarly in response to market shocks if they had not been affected by TDF investments. The plausibility of this assumption was discusssed 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 10 presents the index inclusion results for the matched sample. Column 1 shows that, compared with peer stocks matched on characteristics, being included in the S&P 500 leads to a 0.11 reduction in the sensitivity to market momentum, which implies that when the market rises by 10% in a month, the index stocks have 1.1% lower return in the following month compared with similar non-index stocks. Columns 2-3 show that the result is robust to controlling for the impact of risk factor exposure on the return sensitivity to market momentum. In column 4, we see the effect doubles in magnitude if we control for time-invariant return sensitivity at the stock level and exploit only the changes in S&P 500 status within the same stock. This suggests that our results are driven by the switches into and out of the S&P 500 index. Finally, we conduct a falsification tests using data over 1996-2005 and 1986-1995, when TDFs were not a significant presence in the stock market. Being included in the S&P 500 did not lower the sensitivity to market momentum in those early periods. Thus, it is a phenomenon only present in our main sample period that has a substantial TDF market.

In sum, the evidence in this section – using only variation in TDF ownership share driven by S&P inclusion – provides further evidence that the market-contrarian trading strategies of TDFs have changed the price dynamimcs of the stocks they hold.[27] However, a lot of things may change for a stock when it is included in the S&P 500 Index. Consistent with S&P membership leading to greater demand for the stock (e.g. from S&P 500 Index funds), index inclusion leads to an increase in price (Harris and Gurel, 1986; Shleifer, 1986; Wurgler and Zhuravskaya, 2002; Chang, Hong, and Liskovich, 2015). It also leads to excess daily return volatility due to exchange-traded fund (ETF) trading (Ben-David, Franzoni, and Moussawi (2018)), to more co-movement with other stocks in the Index (Barberis, Shleifer, and Wurgler, 2005; Boyer, 2011), and to changes the investment and financial policies of the firm (for the worse) (Bennett, Stulz, and Wang, 2020).

Our analysis focuses on a different dimension of returns than the above papers: Our analysis of the sensitivity of stock return to the lagged market returns would be unaffected by any return-level effect of inclusion in the Index. Thus, our results are very unlikely to be driven by a general increase in demand for a stock on inclusion in the Index. Our

[27]In Table A.1, 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. It is relegated to the Appendix because the instruments are quite weak.

results is also quite 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, motivating our choice of monthly rather than daily returns. Finally, co-movement concerns the correlation between contemporaneous stock return and market performance, while we focus on the relation with lagged market returns. Obviously, 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 market momentum. If the market return were serially positively correlated, then co-movement would predict an increase in the sensitivity to market momentum in index-included stocks rather than the negative effect we find. However, we find, only in the recent period with TDFs, that the S&P Index has negative serial correlation, as we discuss in the next section.

7 Stock market return predictability during TDF era

In this final section, we speculate about whether the market-contrarian trading strategies of TDFs are affecting aggregate stock market returns. Because the rise of TDFs is relatively recent, the time series that we can investigate is relatively short and statistical power is relatively low. Further, the rise of TDFs is far from the only change in equity markets during the period we study relative to earlier periods, so there is no way to cleanly separate the effects of TDFs from other changes in investment strategies, financial regulation and so forth. However, our results in section 6 show that individual stock that have the greatest TDF ownership respond negatively to recent market returns.

Keeping these caveats in mind, we study the time series of S&P 500 returns since these large cap stocks have the greatest TDF ownership. We investigate changes in stock market momentum, or serial correlation in returns, by estimating the following simple regression:

$$r_t^{SP} = \alpha + \beta_h r_{t-h\,\mathrm{to}\,t-1}^{SP} + \epsilon_t^{SP} \tag{6}$$

where r_t is the monthly return of the S&P 500 index in month t and $r_{t-h\,\mathrm{to}\,t-1}$ 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.

Consistent with the hypothesis that the rise of TDFs has lead to negative time series correlations in the S&P 500 index returns, S&P monthly returns respond negatively to the medium-term lagged performance within the most recent period and not before. Table 11 reports the estimated $\widehat{\beta_h}$ for 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. Column 1 shows that before the rise of the TDFs, there was weakly negative but insignificant time series correlation between the 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; Malkiel, 1973). However, during 2010-2019 which had a sizable TDF market, the monthly returns of the S&P 500 show a borderline significant negative time series correlation, which is consistent with the findings in Table 10. 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. Thus, there is statistically weak evidence that rejects the null hypothesis that there was no change in serial correlation of aggregate returns, as well as the potential for other factors to have altered the stochastic process for returns.

That said, how much of the change in the aggregate return dynamics of the S&P 500 index estimated in Table 11 (point estimates) can be attributed to TDF trading? For a given return of the U.S. equity market, Table 1 implies a corresponding quantitative difference in demand for equity in the world with TDF rebalancing and the world without following the same return. Gabaix and Koijen (2020) shows that aggregate demand by other investors is price inelastic, and estimate that the aggregate price multiplier is about 5: \$1 additional investment in the stock market increases the aggregate value of the market by about \$5. Taking the Gabaix-Koijen multiplier and the current size of the TDFs, we estimate that about one tenth to one fifth of the change that we observe in Table 11 can be attributed to TDFs.

We obtain the above estimates with the following calculation. According to our data, TDF owns about 1% of the total market capitalization of the S&P 500 stocks (on average during 2010-2018). Since our dataset only includes the target-date mutual funds, we increase the aggregate TDF ownership by 60% (to 1.6%) to account for CITs that are offered by the same fund families and follow the same target-date investment strategies (see Section 1). The equity share in the aggregate TDF portfolio is about 70%, implying that rebalancing trades would amount to -0.034% ($= -1.6\% \times 0.7 \times 0.3 \times 10\%$) of the market capitalization of the S&P 500 index after a 10% increase in the market, assuming zero return in the bond market. Applying a price multiplier of 5, this suggests that after a 10% increase in the equity market, S&P 500 return would be $0.034\% \times 5 = 0.17\%$ lower in the subsequent period in a world with TDFs compared with a world without. The estimates in Table 11, columns 1-2 imply that after a 10% increase in the S&P 500 index over month $t-1$ or months $t-3$ to $t-1$, the index return in month t is 1.5% or 0.9% lower in the most recent period than in the previous periods.[28] Therefore, between $0.17\%/1.5\% = 11\%$ and $0.17\%/0.9\% = 19\%$ of these changes may be explained by the rise of the TDFs. Given the large standard errors in Table 11, this range should be interpreted as a rough estimate.

8 Concluding remarks

Target date funds are an important financial innovation for retail investors saving for retirement. They relieve retail investors of the burden of choosing the relative shares of stock funds and bond funds in their portfolios, replacing this decision with an automatic age-dependent rule designed by 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. As a result, many retirement plan investors are holding investment vehicles that automatically rebalance their portfolios across asset classes to age-appropriate allocations.

This paper points out an important implication of TDF investment strategies: TDFs rebalance portfolios by selling stocks when the stock market goes down and buying stocks when the market rises, and so acting as a market-stabilizing force. We find that 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. If, as expected, the amount of funds invested through TDFs continues to grow, their market stabilizing effects may become more pronounced. We argued that TDFs may weakening momentum in aggregate stock prices caused by trend-chasing.

[28] We focus on backward-looking returns over 1 month and 3 months because most TDF rebalancing is implemented within the same quarter as the realized asset class returns.

However, TDFs may also create anomalies or mispricing. Roughly half of stock market fluctuations are driven by permanent changes in dividends, which can lead to persistent changes in the effective amount of equity relative to bonds. TDFs trade against these fundamental changes in value also. That is, because TDFs have a micro-optimal view of portfolio choice, they do not adjust equity shares to permanent changes in the market portfolio.

Finally, by investing across stock and bond markets, TDFs may change the relationship between the returns on these two markets and thus change the way in which changes in interest rates that raise bond prices – such as pursued by quantitative easing – operate. Interest rate declines may lead to stronger stock market responses, as an increasingly large amount of funds invested in TDFs trades out of bonds and into stocks.

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Figure 1: Growth of TDF assets

This figure plots the sum of 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. TDFs with target retirement years at the middle of a decade (20x5) are grouped together with 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.

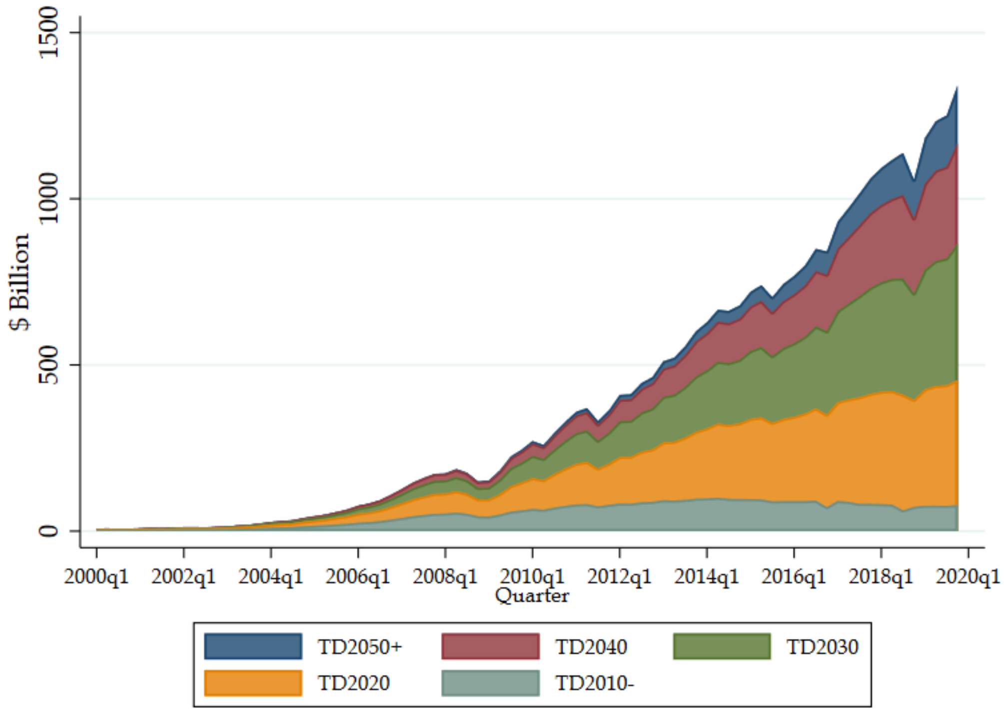
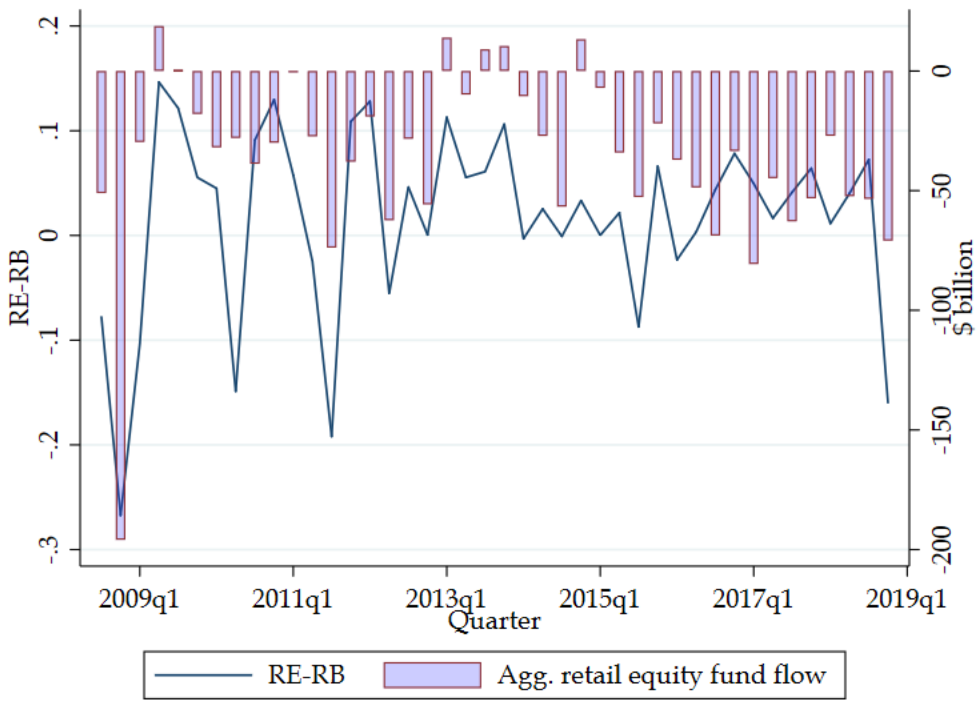
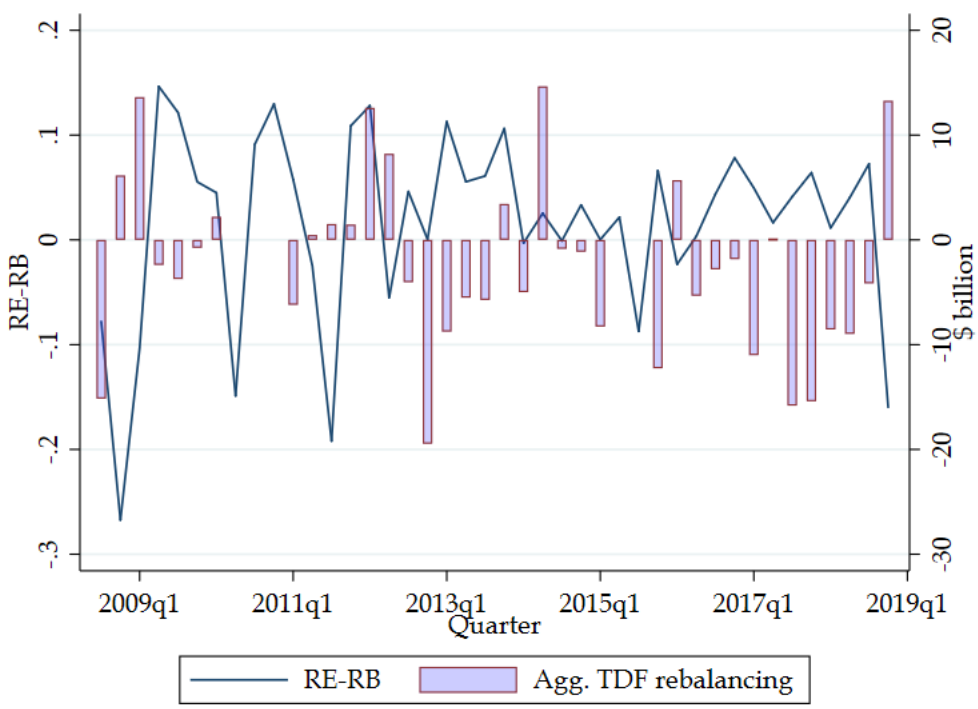


Figure 2: Aggregate retail flows and TDF flows to U.S. domestic equity funds

This figure plots the aggregate quarterly dollar flows to U.S. domestic equity mutual funds through retail share classes (panel A) and TDF rebalancing (panel B) during 2008Q3-2018Q4.



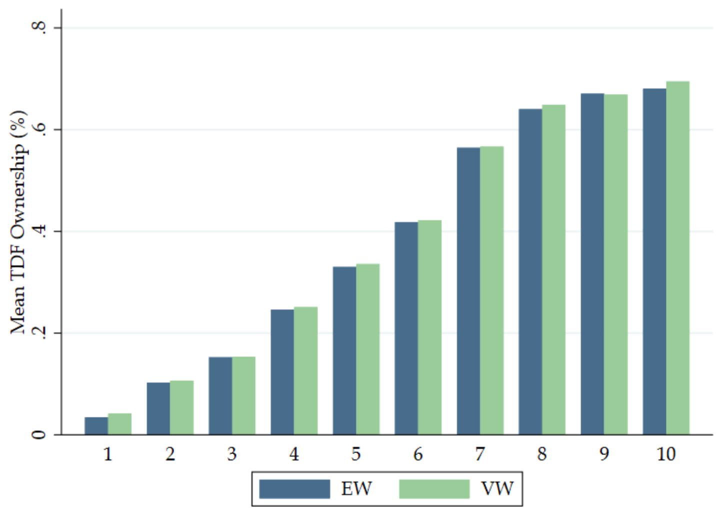
(a) Aggregate retail flows



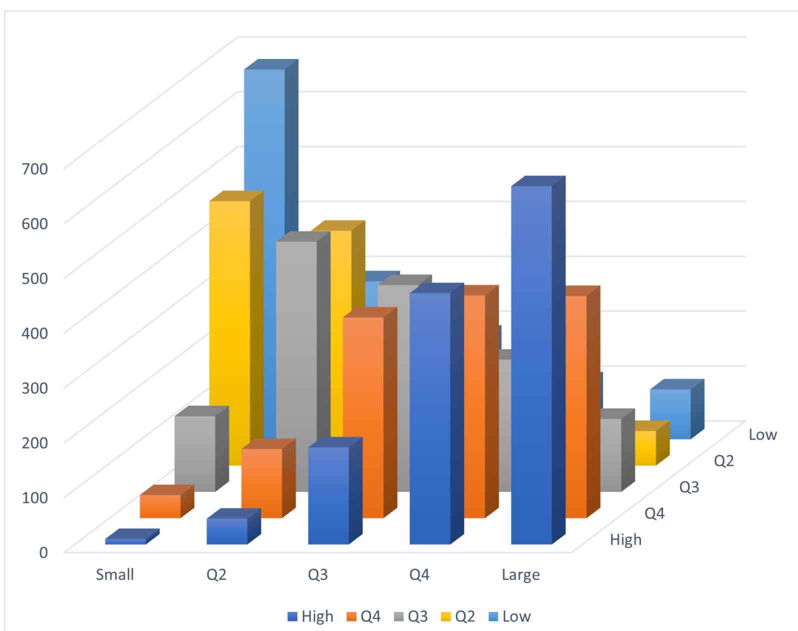
(b) Aggregate TDF rebalancing trades

Figure 3: Stock-level distribution of size and TDF ownership

This figure illustrates the relationship between market capitalization and TDF ownership (both variables calculated as averages during 2008Q3-2018Q4) at the stock level. Panel A plots the average TDF ownership expressed in percentages by size decile among all stocks traded on the NYSE, NASDAQ and AMEX, where decile 10 represents the largest stocks. Panel B presents a two-way histogram for the number of stocks in each of 25 cells constructed by combining 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 one-period rebalancing formulae that restore the target asset allocations of a TDF after realized asset class returns R^E (equity) and R^B (bond). The target equity share is S^* and the target bond share is $1 - S^*$. The TDF is assumed to hold the target allocations at the beginning of the period. TDF asset value at the beginning of the period before the asset class returns is normalized to $1. Panel A represents the case of zero net flow to the TDF. Panel B considers non-zero net flow to the TDF.

	Weight	Asset class return	(1) Value before trades and flows	(2) Desired holdings	(3) Total net trades	(4) Flow-driven trades	(5) Re-balancing trades
A. No fund flows							
Equity Fund	S^*	R^E	$S^*(1+R^E)$	$[1+R^B+S^*(R^E-R^B)]S^*$	$-S^*(1-S^*)(R^E-R^B)$	0	$-S^*(1-S^*)(R^E-R^B)$
Bond Fund	$1-S^*$	R^B	$(1-S^*)(1+R^B)$	$[1+R^B+S^*(R^E-R^B)](1-S^*)$	$S^*(1-S^*)(R^E-R^B)$	0	$S^*(1-S^*)(R^E-R^B)$
Total	1		$1+R^B+S^*(R^E-R^B)$	$1+R^B+S^*(R^E-R^B)$	0	0	0
B. With fund flows of F							
Equity Fund	S^*	R^E	$S^*(1+R^E)$	$[1+R^B+S^*(R^E-R^B)+F]S^*$	$FS^*-S^*(1-S^*)(R^E-R^B)$	FS^*	$-S^*(1-S^*)(R^E-R^B)$
Bond Fund	$1-S^*$	R^B	$(1-S^*)(1+R^B)$	$[1+R^B+S^*(R^E-R^B)+F](1-S^*)$	$F(1-S^*)+S^*(1-S^*)(R^E-R^B)$	$F(1-S^*)$	$S^*(1-S^*)(R^E-R^B)$
Total	1		$1+R^B+S^*(R^E-R^B)$	$1+R^B+S^*(R^E-R^B)+F$	F	F	0

Table 2: Summary statistics

This table presents statistics on quarterly data on TDFs (panel A) and mutual funds (panel B), and on monthly data on stocks (panel C). In panel A, TDF holdings are classified using the CRSP objective codes. Flow to TDF is calculated as the dollar growth in TDF assets in excess of the growth that would have occurred given the net return. Rebalancing trade in an asset class is calculated as *i)* the total trade, measured as the change in the value in excess of the value implied by the returns of the underlying mutual funds, less *ii)* the flow-driven trade, measured as the flow into the TDF allocated to the asset class based on the lagged share in that asset class. In panel B, fund flow rate is the quarterly growth rate in assets in excess of that implied by net fund return. Return volatility is one-year standard deviation in the monthly returns. Fraction held by TDFs is calculated as the total value of TDF holdings of a fund divided by the fund total net assets. In panel C, monthly excess return is the monthly 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, and zero otherwise. TDF ownership refers to the fraction of a stock owned by TDFs through mutual funds.

	N	Mean	p25	p50	p75	SD
A. TDF quarterly						
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						
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						
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 in response to asset class movements

This table estimates the relationship between TDF rebalancing and asset class returns during 2008Q3-2018Q4. Panel A uses TDF quarterly observations. The dependent variable in columns 1-3 (columns 4-6) is the ratio of rebalancing trade of a TDF in equity (fixed income) in quarter t divided by the total value of holdings (sum of equity and fixed income) of this TDF in quarter $t-1$, and winsorized at 1% and 99%. Panel B uses aggregate quarterly observations. The dependent variable in columns 1-3 (columns 4-6) is the aggregate dollar amount of rebalancing trades in equity (fixed income) in quarter t divided by the aggregate portfolio value of all TDFs in quarter $t-1$. The largest and smallest values of the aggregate time series are winsorized, equivalent to winsorizing at 5% and 95%. R^E represents the quarterly return of the total U.S. stock market from CRSP. R^B is the quarterly return of the U.S. bond market, measured as the pre-fee return of the Vanguard Total Bond Market Index Fund. Equity share S is measured as the fraction of a TDF portfolio invested in equity at the end of quarter $t-1$. Standard errors in panel A are clustered two ways by TDF and quarter and in panel B are estimated following the Huber-White heterokedasticity-consistent approach. Cumulative effect reports the sum of coefficients on $(R^E - R^B)_t$ and $(R^E - R^B)_{t-1}$ and its standard errors are calculated using the delta method. *p $<$ .1; **p $<$ .05; ***p $<$ .01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Rebalancing into Equity			Rebalancing into Bonds		
A. TDF quarterly	Rebal (E), t / Total holding, t-1			Rebal (B), t / Total holding, t-1		
Equity share (S)	All	[.25, .75]	[0, .25)(.75,1]	All	[.25, .75]	[0, .25)(.75,1]
$(R^E - R^B)_t$	-0.080**	-0.121***	-0.042	0.056***	0.094***	0.021*
	(0.036)	(0.038)	(0.035)	(0.017)	(0.026)	(0.011)
$(R^E - R^B)_{t-1}$	-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
Cumulative effect	-0.176**	-0.204**	-0.147*	0.086***	0.129***	0.046**
	(0.078)	(0.082)	(0.078)	(0.024)	(0.033)	(0.022)
B. Aggregate quarterly	Rebal (E), t / Total holding, t-1			Rebal (B), t / Total holding, t-1		
Equity share (S)	All	[.25, .75]	[0, .25)(.75,1]	All	[.25, .75]	[0, .25)(.75,1]
$(R^E - R^B)_t$	-0.107**	-0.142***	-0.064	0.105***	0.142***	0.056***
	(0.040)	(0.040)	(0.043)	(0.020)	(0.025)	(0.014)
$(R^E - R^B)_{t-1}$	-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
Cumulative effect	-0.158**	-0.196***	-0.131	0.146***	0.196***	0.081***
	(0.065)	(0.065)	(0.078)	(0.035)	(0.047)	(0.019)

Table 4: TDF rebalancing relative to prediction

This table estimates the relationship between actual TDF rebalancing and the predicted rebalancing magnitude following Table 1. Panel A uses TDF quarterly observations. The dependent variable in columns 1-3 (columns 4-6) is the ratio of rebalancing trade of a TDF in equity (fixed income) in quarter t divided by the total value of holdings (sum of equity and fixed income) of this TDF in quarter $t-1$, and winsorized at 1% and 99%. Panel B uses aggregate quarterly observations. The dependent variable in columns 1-3 (columns 4-6) is the aggregate dollar amount of rebalancing trades in equity (fixed income) in quarter t divided by the aggregate portfolio value of all TDFs in quarter $t-1$. The largest and smallest values of the aggregate time series are winsorized, equivalent to winsorizing at 5% and 95%. R^E represents the quarterly return of the total U.S. stock market from CRSP. R^B is the quarterly return of the U.S. bond market, measured as the pre-fee return of the Vanguard Total Bond Market Index Fund. Equity share S is measured as the fraction of a TDF portfolio or the aggregate TDF portfolio invested in equity at the end of quarter $t-1$. Standard errors in panel A are clustered two ways by TDF and quarter and in panel B are estimated following the Huber-White heterokedasticity-consistent approach. Cumulative effect reports the sum of coefficients on $S(1-S)(R^E-R^B)_t$ and $S(1-S)(R^E-R^B)_{t-1}$ and its standard errors are calculated using the delta method. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Rebalancing into Equity			Rebalancing into Bonds		
A. TDF quarterly	Rebal (E), t / Total holding, t-1			Rebal (B), t / Total holding, t-1		
Equity share (S)	All	[.25, .75]	[0, .25)(.75,1]	All	[.25, .75]	[0, .25)(.75,1]
$S(1-S)(R^E-R^B)_t$	-0.498**	-0.516***	-0.443	0.369***	0.409***	0.241**
	(0.189)	(0.164)	(0.286)	(0.105)	(0.115)	(0.095)
$S(1-S)(R^E-R^B)_{t-1}$	-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
Cumulative effect	-0.951**	-0.872**	-1.280*	0.521***	0.562***	0.395*
	(0.427)	(0.356)	(0.712)	(0.146)	(0.145)	(0.197)
B. Aggregate quarterly	Rebal (E), t / Total holding, t-1			Rebal (B), t / Total holding, t-1		
Equity share (S)	All	[.25, .75]	[0, .25)(.75,1]	All	[.25, .75]	[0, .25)(.75,1]
$S(1-S)(R^E-R^B)_t$	-0.508**	-0.583***	-0.431	0.510***	0.592***	0.382***
	(0.203)	(0.166)	(0.271)	(0.098)	(0.100)	(0.082)
$S(1-S)(R^E-R^B)_{t-1}$	-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
Cumulative effect	-0.747**	-0.815***	-0.931*	0.710***	0.820***	0.557***
	(0.333)	(0.276)	(0.516)	(0.170)	(0.197)	(0.126)

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 net 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. Asset-class return is measured as the difference between equity and bond market returns $R^E - R^B$ in columns 1-2, and the excess return of equity over the risk-free rate $R^E - R^f$ in columns 3-4. R^E is the quarterly return of the US equity market from CRSP. R^B is the quarterly return of the US bond market approximated with the pre-fee return of the Vanguard Total Bond Market Index Fund. 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 logs of the lagged fund size and fund family size, log of fund age measured for the oldest share class of a fund, the annual expense ratio, and the lagged yearly standard deviation of monthly returns. Standard errors are clustered two ways by time and fund. *p $<$ .1; **p $<$ .05; ***p $<$ .01.

	(1)	(2)	(3)	(4)
	Fund flow rate, t			
Asset-class return measure:	$R^E - R^B$		$R^E - R^f$	
Asset-class return, t	0.250***		0.256***	
	(0.078)		(0.067)	
Asset-class return, t × frac. held by TDFs, t-1	-0.645***	-0.368*	-0.682***	-0.440**
	(0.182)	(0.194)	(0.180)	(0.188)
Asset-class return, t-1	0.075		0.097	
	(0.059)		(0.081)	
Asset-class 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: Aggregate retail vs. TDF flows to U.S. equity funds

This table presents the regression coefficients of net aggregate flows to US equity funds in quarter t on the excess performance of the equity market in quarters t and $t-1$, by retail investors, all TDFs and subsets of TDFs at quarterly frequency over 2008Q3-2018Q4. The dependent variable in column 1 is the aggregate dollar flows to retail share classes of domestic equity funds in quarter t divided by the total assets under management in retail share classes in quarter $t-1$ and is the same in panel A and panel B. In cases that any retail fund share class is traded by TDFs, the TDF trades are deducted before aggregating up the retail flows. The dependent variable in column 2 is the aggregate dollar trades of domestic equity funds in quarter t divided by the total assets of TDFs in quarter $t-1$. The aggregate TDF dollar trades are measured as rebalancing trades in panel A and as total trades in panel B. The dependent variables in columns 3 and 4 are constructed using the subsamples of TDFs with equity shares between 25% and 75% and equity shares below 25% or above 75%, respectively. $R^E - R^B$ represents the quarterly return differential between equity and fixed income, and is calculated as the US total equity market return from CRSP minus the pre-fee return of the Vanguard Total Bond Market Index Fund. Robust standard errors are reported. Cumulative effect reports the sum of coefficients on $(R^E - R^B)_t$ and $(R^E - R^B)_{t-1}$ and its standard errors are calculated using the delta method. *p $<$ .1; **p $<$ .05; ***p $<$ .01.

Panel A	(1)	(2)	(3)	(4)
Flows series	Retail	TDF rebalancing trades		
		All	S[0.25,0.75]	S[0,0.25)(0.75,1]
$R^S - R^B$, t	0.119***	-0.092**	-0.114***	-0.066
	(0.041)	(0.042)	(0.041)	(0.042)
$R^S - R^B$, t-1	0.017	-0.115	-0.118	-0.109
	(0.021)	(0.079)	(0.081)	(0.075)
Observations	37	37	37	37
R-squared	0.562	0.276	0.326	0.228
Cumulative effect	0.136**	-0.207**	-0.233**	-0.175*
	(0.050)	(0.101)	(0.102)	(0.097)

Panel B	(1)	(2)	(3)	(4)
Flows series	Retail	TDF total trades		
		All	S[0.25,0.75]	S[0,0.25)(0.75,1]
$R^S - R^B$, t	0.119***	-0.049	-0.074*	-0.012
	(0.041)	(0.044)	(0.042)	(0.050)
$R^S - R^B$, t-1	0.017	-0.136	-0.126	-0.162
	(0.021)	(0.098)	(0.090)	(0.113)
Observations	37	37	37	37
R-squared	0.562	0.209	0.252	0.187
Cumulative effect	0.136**	-0.184	-0.200*	-0.174
	(0.050)	(0.121)	(0.112)	(0.138)

Table 7: 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 control stocks within the same industry-by-size-by-liquidity peer group. Following Denis et al. (2003), the peer groups are obtained in each quarter by sorting stocks 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 through mutual funds 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. ln(Market cap) is the log of market capitalization in billion dollars. ln(Vol) is the log of monthly trading volumne in million shares. S&P 500 is an indicator that equals one if the stock is included in the S&P 500 index quarter t 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 8: TDF ownership and stock return sensitivity to lagged market performance

This table examines the relationship between TDF ownership and monthly stock return sensitivity to recent market performance during 2010-2018 in the full sample of stocks. The dependent variable is the raw monthly return winsorized at 1% and 99%. TDF (%), the fraction of a stock indirectly owned by TDFs and expressed in percentages, is available at quarterly frequency and measured at the end of the previous quarter. Industry dummies are defined by Fama-French 12 industries. Exposures to current and lagged factors are estimated using monthly returns during 1996-2005. Controls for current factors include estimated betas on current factor returns multiplied by the factor returns in month t. Controls for lagged factors include estimated betas on lagged factor returns multiplied by the factor returns in month $t-1$. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Net return, t 2010-2018				Falsification	
					1996-2005	1986-1995
Mkt, t-1 × TDF (%), q-1	-0.040***	-0.029*	-0.045***	-0.048***	-0.018	0.003
	(0.015)	(0.015)	(0.016)	(0.017)	(0.028)	(0.023)
Mkt, t-1 × ln (Mktcap, t-1)	-0.040	-0.040	-0.055**	-0.049	-0.082*	-0.101***
	(0.027)	(0.026)	(0.027)	(0.030)	(0.044)	(0.032)
Mkt, t-1 × ln (Vol, t-1)	-0.002	-0.002	0.014	0.009	0.035	0.045*
	(0.031)	(0.029)	(0.027)	(0.032)	(0.046)	(0.024)
TDF (%), q-1	0.003***	0.003***	0.002***	0.002***	0.010***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln (Mktcap, t-1)	0.002**	0.002**	0.001	0.001	-0.006***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
ln (Vol, t-1)	-0.001	-0.001	-0.001	-0.001	0.003	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Time FE	Y	Y	Y	Y	Y	Y
Time-by-industry FE	N	Y	N	N	N	N
Controls for current factors	N	N	Y	N	N	N
Controls for lagged factors	N	N	N	Y	N	N
Observations	400,728	400,720	226,132	226,132	314,121	161,877
R-squared	0.123	0.148	0.154	0.148	0.116	0.120

Table 9: TDF ownership and stock return sensitivity to lagged market performance in matched sample

This table examines the relationship between TDF ownership and stock return sensitivity to recent market performance in a matched sample of S&P 500 stocks with control stocks. The dependent variable is the raw monthly return winsorized at 1% and 99%. TDF (%), the fraction of a stock indirectly owned by TDFs and expressed in percentages, is available at quarterly frequency and measured at the end of the previous quarter. Exposures to current and lagged factors are estimated using monthly returns during 1996-2005. Controls for current factors include estimated betas on current factor returns multiplied by the factor returns in month t. Controls for lagged factors include estimated betas on lagged factor returns multiplied by the factor returns in month $t-1$. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Net return, t 2010-2018				Falsification 1996-2005	1986-1995
Mkt, t-1 × TDF (%), q-1	-0.040*	-0.068***	-0.068***	-0.098**	0.031	0.096
	(0.021)	(0.022)	(0.022)	(0.049)	(0.063)	(0.276)
Mkt, t-1 × ln (Mktcap, t-1)	0.000	-0.013	-0.011	0.101	0.031	0.137
	(0.024)	(0.022)	(0.023)	(0.107)	(0.066)	(0.197)
Mkt, t-1 × ln (Vol, t-1)	-0.014	-0.010	-0.012	-0.059	-0.031	-0.283*
	(0.022)	(0.020)	(0.020)	(0.061)	(0.063)	(0.161)
TDF (%), q-1	0.001	0.001	0.001	0.001	0.001	-0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)
ln (Mktcap, t-1)	-0.005***	-0.004***	-0.004***	-0.051***	-0.019***	-0.010
	(0.001)	(0.001)	(0.001)	(0.006)	(0.003)	(0.007)
ln (Vol, t-1)	0.001	0.001	0.001	0.003	0.009***	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.006)
Time FE	Y	Y	Y	Y	Y	Y
Time-by-peer group FE	Y	Y	Y	Y	Y	Y
Controls for current factors	N	Y	N	N	N	N
Controls for lagged factors	N	N	Y	N	N	N
Mkt, t-1 × Stock FE	N	N	N	Y	N	N
Observations	27,659	18,543	18,543	27,659	15,810	1,204
R-squared	0.360	0.406	0.405	0.430	0.306	0.422

Table 10: 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 the matched sample of S&P 500 stocks with control stocks. 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. Standard errors in this table are clustered two ways by time and stock.

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

Table 11: Time series correlation in the S&P 500 index

This table reports the estimated time series correlations in the returns of the S&P 500 index during three subsamples: 1986-1995, 1996-2005 and 2010-2019. The regressions follow $r_t^{SP} = \alpha + \beta_h r_{t-h \text{ to } t-1}^{SP} + \epsilon_t^{SP}$, where r_t^{SP} represents the monthly excess return of the S&P 500 index in month t and $r_{t-h \text{ to } t-1}^{SP}$ 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.

Lagged return measure	(1) 1m	(2) 3m	(3) 6m	(4) 12m
1986-1995	-0.020	-0.044	-0.056	-0.056
	(0.092)	(0.054)	(0.043)	(0.036)
1996-2005	-0.018	-0.003	0.012	0.029
	(0.092)	(0.054)	(0.039)	(0.024)
2010-2019	-0.172*	-0.113*	-0.123**	-0.087**
	(0.091)	(0.061)	(0.048)	(0.037)