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RETAIL FINANCIAL INNOVATION AND STOCK MARKET DYNAMICS: THE CASE OF TARGET DATE FUNDS

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ABSTRACT

The rise of Target Date Funds (TDFs) has moved a significant share of retail investors into contrarian strategies that rebalance between stocks and bonds to maintain age-appropriate portfolio shares. We show that i) TDFs actively rebalance within a few months following differential asset-class returns according to mandate, ii), this rebalancing drives contrarian flows across funds held by TDFs, and iii) these flows affect stock returns: stocks with greater (indirect) TDF ownership have lower risk-adjusted returns when equity outperforms bonds and vice versa. Continued growth in TDFs may dampen stock market volatility and increase the transmission of shocks across asset classes.

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Over the past two decades, one of the most important financial innovations for the typical American investor has been the rise of Target Date Funds (TDFs, also called life-cycle funds). Unlike a typical mutual fund that invests in only one asset class like stocks or bonds, a TDF invests in multiple asset classes. The fraction of its assets invested in each asset class is set by the TDF's "glide path" and is a function of the time until the fund's "target date," typically the expected retirement year of its investors. After differential asset class returns, TDFs are expected to rebalance back to their prescribed asset allocation within a short period of time, typically one or two months. As time passes (and its investors age), a TDF reduces risk by reallocating across asset classes, typically out of stocks and into bonds, as proscribed by many partial-equilibrium models of optimal portfolio choice.[1] A closely related product is a balanced fund (BF) which simply maintains a constant share of its asset in each asset class. Most TDFs merge into balanced funds at the end of their glide paths.

Facilitated by the Pension Protection Act (PPA) of 2006, which qualifies both TDFs and BFs as default options in defined-contribution retirement saving plans, investment in these funds has risen dramatically. TDF holdings rose from less than \$8 billion in 2000 to more than \$2.3 trillion in 2019.[2] Although less concentrated in retirement accounts, holdings of balanced funds grew simliarly over this period so that TDFs and BFs together held more than \$4 trillion of the roughly \$21 trillion in US mutual funds in 2019.

This paper shows that, while possibly not an original intention of this financial innovation, the rise of TDFs and BFs has 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 retirement and retail investors were either passive – letting their portfolio shares rise and fall with the returns on different asset classes – or they were active and tended 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

[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 life cycle portfolio problem.

[2] The \$2.3 trillion in TDFs includes \$0.9 trillion in target date collective investment trusts (CITs) which invest like TDFs but have lower fees than the equivalent mutual funds and are primarily used by large employers. 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

to maintain age-appropriate asset allocations, TDFs trade against excess returns in each asset class, selling stocks and buying bonds when the stock market outperforms the bond market, and vice versa.

We have three main findings. First, we show that following high (low) excess equity returns, TDFs sell (buy) equity to move their portfolios back towards their desired equity-bond mix within a few months, consistent with their mandates. Second, following high equity returns relative to bond returns, equity funds with larger TDF ownership experience lower net inflows than equity funds with smaller or nonexistent TDF ownership. Thus, TDF ownership reduces the inflows that typically follow contemporaneous and past asset class out-performance, conferring some funding stability in response to market returns on these funds. Third, we find evidence that stocks with higher TDF ownership (through the mutual funds held by TDFs) have lower returns after higher market performance, consistent with TDFs altering the return dynamics of individual stocks.

Our first result is based on the fact that desired equity shares differ across TDFs with different target dates, but do not depend either on the composition of the market portfolio or on past or expected future returns on different asset classes. A typical TDF initially 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. These shares are independent of market performance, so that differences in desired shares imply differences in trading behavior across TDFs in response to differential asset class returns. The amount of rebalancing by a TDF is a quadratic function of the desired equity share with a maximum at 50%. When the stock market returns 20% more than the bond market, a fund with a 50% desired equity share 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.

Using quarterly data on TDF holdings during 2008-2018, we find that TDFs rebalance across equity and fixed income mutual funds within a few months and behave as predicted by their desired equity shares given realized asset returns. For each dollar of rebalancing we

investors in retirement accounts. In contrast, Calvet, Campbell, and Sodini (2009) shows that retail investors in Sweden rebalance against idiosyncratic returns to offset about half of the passive changes in asset shares. De Long et al. (1990), Hong and Stein (1999), Lou (2012), and Vayanos and Woolley (2013) discuss the effects of momentum trading on stock returns.

expect based on a TDFs equity share and the differential return between broad asset classes, the actual rebalancing in the concurrent quarter is 50 cents, and most rebalancing occurs within the same quarter as a market movement.[4] Passive TDFs (TDFs with more than 50% of assets invested in index funds) rebalance more aggressively. 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. These are also the TDFs that have the most assets under management, since this asset allocation applies to older people.

Second, we show that the market-contrarian trading of TDFs has become a quantitatively significant part of equity fund flows. For an excess return on the stock market of 10% in a month, the average equity mutual fund receives additional investment flows that increase its size by 0.6% in that month. Using differences across funds in the degree of TDF ownership, this relationship is reduced by 40% for mutual funds with a 20% 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 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 decreases (increases) returns on the stocks that they hold more of following positive (negative) excess returns on the stock market. Given the share of each fund held by TDFs and the stocks held by each fund, we calculate the (indirect) stock level holdings by TDFs. Looking across all stocks, greater TDF ownership is associated with lower individual stock returns in the same month as high stock market returns and in the following month. Specifically, when the excess return of the equity asset class is 1% in a month, stocks with a one standard deviation (0.7%) higher share of TDF ownership have a 3.8 basis point lower four-factor adjusted return in the same month. The timing of the price effect is consistent with the speeds at which different types of TDFs rebalance; some large passive TDFs (which hold index funds in their portfolios) tend to rebalance within a day, while active TDFs (which hold actively managed funds)

[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 inflows and outflows to rebalance through flow allocation when possible.

can rebalance over a month or two.

Two pieces of evidence suggest that this price impact is not driven by other characteristics of stocks that are correlated with TDF ownership share. First, we control for the effects of size and general mutual fund ownership (that is not through TDFs) on the sensitivity of stock returns to asset class movements. Second, we find that there is no correlation between our measure of TDF ownership share (during 2008 to 2018) and individual stock returns following aggregate market returns in a similar length period prior to the PPA and so prior to the rise of TDFs.

We also identify the stock-level price impact of TDF trading using only variation in TDF ownership driven by inclusion in the S&P index, but these effects are statistically weak. Stocks that are included in the S&P 500 index have both discretely higher TDF ownership (statistically significant) and lower returns following excess stock market returns (statistically insignificant) than stocks not included in the index that are otherwise similar (matched on industry, size and liquidity). We report these results for completeness.

The price impact of TDBF trading that we find is large relative to previous studies of the impact of demand on individual stock prices. We estimate a demand elasticity of -0.3, implying that when a TDF demands an additional dollar of a stock, the price of that stock rises by 30 cents (a Gabaix and Koijen (2020) price multiplier of 0.3). We consider several potential explanations. First, many other investors, such as pension funds or endowments, may have similar target allocations and rebalance alongside the TDFs, thus contributing to the measured price impact. We view this as an unlikely source of bias, because these other funds rebalance much more slowly and likely hold quite different portfolios than TDFs. Second, TDFs affect a large number of similar stocks, and therefore trading against the TDF price impact would entail taking on systematic risk.

Our third explanation, which we view as the most likely, is that TDFs trade against the price pressure from trend-chasing retail investors and are therefore pursuing a profitable strategy. To evaluate this hypothesis, we consider a long-short strategy that buys low-TDF stocks and shorts high-TDF stocks when equity has outperformed bonds in the previous month, which is trading in the same direction as the TDFs. This strategy earns a risk-adjusted cumulative profit of 20% during 2011-2018, which implies that it is not profitable (in a risk-factor-adjusted return sense) to trade against TDFs. Thus arbitrage capital should not be dampening the price impact of TDF trades, whereas it may be in settings in which previous research has found a smaller elasticity of an individual stock price to demand.

Our findings have several implications. First, by selling stocks after stock market increases and buying stocks after stock market declines, TDBFs dampen stock market fluctuations. A back-of-the-envelope calculation suggests that this effect is around 6% of excess returns, and therefore currently too small to be statistically detected. However, if TDBFs continue to grow, the size of this effect may grow. In that case, TDBFs may increase market efficiency by smoothing out sentiment-driven fluctuations but might worsen market efficiency by dampening price responses to dividend news. A corollary of this effect would be that TDBFs would lower aggregate stock market price multipliers by reducing the price response to asset-class-specific changes in demand from other sources.

Second, 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. Again, this effect is likely very small at the moment but would increase if TDBFs continue to grow.

Finally, 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 disappeared) as more retail investor money follows market-contrarian strategies. Of course all of these effects may be mitigated by the responses of other investors or by TDBFs themselves as they adopt more sophisticated investment strategies and/or respond to changing return dynamics.

Related Literature Our paper contributes to the literature documenting that mutual fund flows can have a large impact on equity prices. Our work is the most closely related to studies on aggregate fund flows and prices. Earlier works by Warther (1995) and Edelen and Warner (2001) find a positive relationship between aggregate mutual fund flows and concurrent monthly, weekly, or daily market returns. Using daily fund flows data from Israel, Ben-Rephael, Kandel, and Wohl (2011) shows that mutual fund flows create temporary price pressure that reverses in the short term. Moreover, 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.

Apart from studies on a market-level price impact, Peng and Wang (2021) and Ben-David et al. (2021) show that mutual fund flows affect factor returns. Furthermore, at the level of individual stocks, 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 price pressure from fund flows contributes to the cross-sectional momentum effect. Dou, Kogan, and Wu (2020) presents evidence that fund managers hedge against common flow shocks and stocks with high flow beta earn a risk premium.

The type of fund flows examined in our paper is distinct from the literature in several dimensions. First, while the existing literature studies net fund flows that combine decisions by all investors, we focus on one cause of mutual fund flows which is the trading by funds-of-funds. To our knowledge, trading of mutual funds by funds-of-funds has so far received little attention in the literature. Second, TDFs rebalance following mechanical rules, which causes flows in the underlying mutual funds that are "exogenous," driven only by the target asset allocation and realized asset class returns, which means they are unlikely to be correlated with expected future returns. The mechanical nature of the rebalancing flows allows us to separate the effect of flows from expectations or sentiment that drive flows.[5] Third, the rebalancing flows we study are contrarian and work against the effect of typical mutual fund flows (i.e., momentum) which have been the focus of the previous literature.

Our paper is also broadly related to the literature on demand system asset pricing which argues that aggregate demand is inelastic, and therefore shifts in institutional demand can generate large price impacts. Basak and Pavlova (2013) and Vayanos and Woolley (2013) model how the incentives of institutional investors shape asset prices, Koijen and Yogo (2019) models and tests heterogeneous characteristic-based institutional demand, and Gabaix and Koijen (2020) shows that because of the inelasticity of institutional demand, fund flows have a large impact on prices and aggregate fluctuations. In a current study, Haddad, Huebner, and Loualiche (2021) argues that the rise of passive investing lowers the elasticity of aggregate demand.

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 and performance of TDFs. Mitchell and Utkus (2021), using data from one large 401(k) provider,

[5] Da et al. (2018), Evans and Sun (2021), and Ben-David et al. (2019) discuss the role of rating agencies in causing mechanical fund flows.

shows that plan-level features, such as auto-enrollment, are key drivers of TDF 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 (2020) 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. On the performance of TDFs, 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, and Brown and Davies (2020) shows that TDFs underperform portfolios replicated using ETFs. In this literature, our paper is the first to study the impact of TDFs on asset prices.

1 Target date funds and other fixed-allocation funds

This section describes the working of TDFs and other similar investment vehicles in the United States. Our analysis focuses on the rebalancing behavior of TDFs because their equity holdings can be measured well, because they have risen dramatically over the last two decades, and because they seem to have changed the investment behavior of trillions of dollars of assets held by retail investors (as discussed in the previous section). But there are also other mixed-asset-class funds which have predetermined asset allocations to equity and bonds, which we refer to as "fixed-share funds." These other fixed-share funds need to engage in rebalancing following market returns in order to restore the desired asset allocations; some with similarity to TDFs while others with significant differences. As we discuss, many rebalance at much lower frequencies and many are affected more by inflows and outflows so that their impact on investor demand across asset classes is unclear (or minimal). However, if these other fixed-allocation funds hold the same type of mutual funds or securities that the TDFs hold, then the flows and price effects that we document can also be affected by these funds, a fact we take into account when calculating price multipliers in Section 5.

1.1 Target date funds

While mutual funds (and exchange traded funds) have helped retail investors become more diversified, they mostly hold only one asset class, such as domestic stocks or foreign bonds. In contrast, target date funds are funds-of-funds that invest in equity and fixed income mutual funds, primarily domestic but with a small fraction international. Target date funds seek to maintain given portfolio shares in different asset classes, with the shares based on the time to "target date." Most 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 smoothly over time to reach roughly 40 percent ten years after the target date.[6] 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.

While the financial innovation that is TDFs reflects research by academics and practitioners on optimal portfolio choice, the rise of TDFs followed the passage of the Pension Protection Act (PPA) in August of 2006. The PPA qualifies TDFs to be used as default options (Qualified Default Investment Alternative, or "QDIA") in 401(k) retirement saving plans. As shown in Figure 1 panel A, total assets invested in TDFs increased from less than $8 billion 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. 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).

TDFs can be classified into "active" or "passive," based on characteristics of the underlying mutual funds. Figure 2 plots the distribution of fractions of index funds in TDF portfolios. About 21% of the TDFs are purely index and hold 100% of their assets in index funds. Meanwhile, about 25% are purely active, holding 100% of assets in actively managed funds. However, the rest of TDFs (about half of all observations) are "hybrid," meaning that they hold a mixture of index funds and actively managed funds. Following the terminology in the industry, we classify a TDF as "passive" if more than 50% of its assets are invested in index funds, and "active" if less than 50% of its assets are in index funds. However, active TDFs can have index fund holdings, and vice versa. We distinguish between active

[6] Appendix Figure B.1 presents the desired equity share over the life cycle, or "glide path," for the Vanguard Target Retirement Fund series.

and passive TDFs when examining the speeds of rebalancing. Our conversations with practitioners suggest that passive TDFs stick closer to their glide paths and rebalance faster than active TDFs do.

1.2 Other cross-asset-class, fixed-share funds

Collective investment trusts Target date products can be structured either as mutual funds or as collective investment trusts (CITs). While mutual funds are usually available to most retirement plans as well as retail investors, many CITs are offered only to certain retirement plans. Large plan sponsors (employers) can negotiate with providers for lower fees or other customization, and CITs allow for these plan-specific fee arrangements. 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.

Unlike mutual funds which are regulated by the Securities and Exchange Commission (SEC) under the Investment Company Act of 1940, CITs are not subject to SEC regulation and do not file annual reports with the SEC. As a result, data on CITs are generally difficult to obtain. However, the large target-date CITs are simply lower-fee versions of their mutual fund counterparts, and we make the assumption that holdings of CITs overlap with those of TDFs. As indicated in Figure 1 panel B, the total assets in TDFs and CITs stood at 2.3 trillion dollars at the end of 2019.

Balanced funds Balanced funds (BFs) hold equity and bonds with fixed weights, but do not adjust the weights during the life-cycle. The most common allocation by a balanced fund is 60% equity and 40% fixed income. Figure 1 panel B shows that the total assets invested in TDFs, target date CITs, and BFs together were at slightly more than $4 trillion by the end of 2019.

A large degree of heterogeneity exists across BFs. Some BFs are funds-of-funds investing in other mutual funds. Figure B.2 panel A shows that about $0.7 trillion of the $3 trillion of BF assets in 2018 are in funds-of-funds (defined as those with more than 80% of assets invested in mutual funds). This group tends to behave in a similar way as the TDFs do. Indeed, many TDFs turn into balanced funds-of-funds after reaching the bottom of their glide paths and behave much like their TDF "parent" funds. Other BFs invest directly in stocks and bonds, or hold a combination of mutual funds and individual securities, and while these BFs also need to rebalance after excess asset class returns, their rebalancing involves endogenous security selection, and thus the price impact can be different from that of TDFs. Although we later conduct a back-of-the-envelope calculation which scales the behavior of TDFs to all BFs, it is an aggressive assumption given the heterogeneity in BF products. We will use the term "TDBFs" when referring to TDFs, target date CITs, and BFs combined.

Other retail products In addition to TDFs and BFs, retail investments through college saving accounts follow similar life cycle strategies and financial planners and robo-advisers allocate investor money according to personalized target allocations. About $370 billion and $330 billion were invested in 529 plans and robo advisers, respectively, as of 2019, and about $4 trillion are in rule-based "model portfolios" managed by financial advisers.[7] These products are not included in our study, but they mainly allocate assets among mutual funds and engage in rebalancing in similar ways as the TDFs.

Pension funds and endowments The above products are financial innovations in the retail space that enable retail investors to follow proscribed asset allocations. Although institutional investors are less prone to biases, pension funds, foundations, and endowments likewise often specify target allocations as part of their investment objectives, which indicates they also need to periodically rebalance. The difference between the institutional funds and retail products is that the institutional managers often have much greater flexibility - they often follow ranges of asset shares instead of precise targets - as well as more discretion over the target allocations (Andonov and Rauh (2020)). Overall, we believe the behavior of pensions and endowments contributes to the aggregate contrarian fund flows which are in the background of our data but at a much lower frequency. However, we do not have data to quantify the rebalancing trades by these institutional investors, nor is that a focus of our paper.

[7] Based on the Fed's Enhanced Financial Accounts data, Business Insider (Chatenay, 2020), and Wall Street Journal (Lim, 2020).

2 Data

Our analyses and data are organized around three levels: the TDFs, the underlying mutual funds they hold, and the individual stocks held by TDFs through these underlying mutual funds.

TDFs We obtain quarterly fund characteristics from the CRSP Mutual Fund Database. TDFs 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. CRSP also provides quarterly holdings data of mutual funds. TDFs are funds-of-funds, thus most holdings are other mutual funds (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, we exclude small TDFs with TNA below \$ 10 million. Figure B.3 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 select the main sample period to be 2008Q3-2018Q4.[8] In our analysis of TDF trading (Section 3), to avoid mis-measurement, we further restrict the TDF sample to TDFs for which we can measure holdings (including cash) of at least 95% of the assets of the TDF. We do not impose these restrictions in Sections 4 and 5 in order to have the best possible measure of TDF ownership of mutual funds and stocks.

Table 1 presents the summary statistics on the TDFs in the regression sample which requires that at least 95% of assets are known holdings. 36% of the TDFs in our panel are classified as passive and have more than 50% of their assets invested in index funds. The mean asset size is \$ 2.8 billion while the median is \$ 424 million, implying a high degree of market concentration. Each TDF on average holds 15 mutual funds. The average equity

[8]Figure B.3 suggests several quarters have lower coverage of holdings data, mainly 2010Q2, 2010Q3, and 2015Q2. Results in this paper are similar whether we include or drop these quarters. We also assessed the quality of holdings data of the balanced funds. Figure B.2 panel B suggests that the coverage of BF holdings is worse than that of TDFs, which is another reason we do not include the BFs in our main analyses, but results on BFs are available upon request.

weight is 75% , out of which 50% is in domestic equity and 25% in foreign equity, and the fixed income weight is 25% . The fund flow rate to TDFs suggests high growth during this period – the average TDF grows by 7% per quarter from net inflows. The allocations of new flows have an impact on TDF trading, and as will be explained in Section 3, we subtract "flow-driven" trades by TDFs from their total trades to calculate the trades that are due to rebalancing.

Mutual Funds In order to measure the effect of TDFs on funds, we construct a quarterly dataset on the underlying mutual funds from CRSP. We focus on domestic equity mutual funds that are sold to retail and institutional investors, and combine different share classes to the fund level.[9] 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.

Panel A of Table 2 shows summary statistics at monthly frequency for our sample of domestic equity funds which are held by any TDF at the start of each quarter.[10] The average mutual fund experiences a monthly net flow of 0.08% of lagged assets, but the standard deviation in the monthly flow rate is large (4.7%). The average of TDF ownership among TDF-held funds is 20%. While we omit summary statistics on the mutual funds which are not held by TDFs, we find that the TDF-held sample contains larger funds from larger fund families, consistent with industry concentration in the TDF market.

Individual Stocks We assemble our 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 B of Table 2. The sample contains stocks traded on the New York Stock Exchange, NASDAQ, and American Stock Exchange. Following Jegadeesh and Titman (2001), we drop stocks with market capitalizations that place them in the bottom 5% of NYSE stocks, or with beginning-of-month prices below $5, due to the lack of liquidity. We calculate stock-level TDF ownership as the total fraction of shares outstanding that are held by TDFs through mutual funds. Quarterly mutual

[9] While one might think it useful to contrast behavior across institutional and retail share classes, Boyson (2019) shows that dual-registered investment advisers have steadily converted clients' investments from retail share classes to institutional share classes since 2007. Thus, we combine retail and institutional share classes in our analysis, however, our results are similar if we restrict the sample to retail funds only.

[10] TDF-invested mutual funds are rising and range between 5% and 11% of observations during the time period, however, they account to between 13% and 47% of total assets in domestic equity funds.

fund holdings data are from Thomson Reuters which are linked to the CRSP mutual fund dataset using MFLINKS. The average TDF ownership is 0.83%, and this indirect holding by TDFs is roughly equally split between holdings through index funds and actively managed funds that are underlying in the TDF portfolios. We calculate stock-level mutual fund ownership as the percentage owned by mutual funds which are not held by TDFs. [11]

Returns 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 bonds as an asset class, R^B, as the pre-fee return on the Vanguard Total Bond Market Index Fund. We measure the return on the portfolio held by each TDF from the returns of the funds underlying it (last three rows of Table 1).

3 TDF rebalancing

3.1 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 derive this result by first assuming no net inflows or outflows to the TDF and then for a general case with flow-driven trades (investor purchase or redemption allocated pro rata to existing positions).

Table 3 shows that TDFs rebalancing in response to excess stock market returns is quadratic in the desired equity share, S^*, with a maximum at 50 percent. 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 its target allocation at the beginning of the period and that the target shares do not change (no move along the glide path) by the period end. Assuming no investor flows, column (1) in Table 3 panel A shows that the total portfolio value is $1 + R^B + S^* \left(R^E - R^B\right)$ following equity and bond asset returns of R^E and R^B respectively. Note that R^E and R^B incorporate the assumption that all dividends paid out by the underlying mutual funds are reinvested by the TDF, and all

[11] On average 20% of a stock's market capitalization is held by these mutual funds that are unrelated to TDFs.

dividends declared by the TDF are reinvested, consistent with TDF and retirement investor common practice.[12]

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 same amount of the bond fund (column 3). The important result is that the amount of trading is quadratic in desired equity share, with a maximum at an equity share of 50%.

Panel B of Table 3 considers the case of rebalancing when the TDF receives a net flow of F from investors following the returns. In this case, the excess stock market return causes the total portfolio value to become $1 + R^B + S^* \left(R^E - R^B\right)$ (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 in S^* 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 3 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), while some TDFs rebalance daily, others 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,

[12] TDFs have the option to automatically reinvest dividends in the underlying mutual funds. We learned from practitioners that in almost every instance, TDFs choose to dividend-reinvest. Moreover, practitioners told us that 99% of investors in TDFs dividend-reinvest at the TDF level due to 401(k) plans automatically reinvesting dividends.

$R^E - R^B$ 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 the effect of TDF trading driven by automatic rebalancing and exclude trading driven by inflows and outflows because these latter flows are driven by factors such as auto-enrollment, incomes, auto-escalation, withdrawals, and retirement menu choices that are potentially spuriously correlated with market returns. We find that the automatic rebalancing by TDFs is passed through to mutual funds and has a significant impact on the net mutual fund flows. Thus investor flows to and from TDFs do not wash out the effect of automatic rebalancing, 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.[13]

3.2 Calculation of rebalancing trades

We use our panel dataset of quarterly holdings at the TDF-by-mutual-fund-share-class level to calculate rebalancing trades in equity and fixed income by TDF k in quarter q in three steps. Our calculation assumes all rebalancing trades are made at the end of each period after returns are realized and before the fund reports its portfolio. First, we calculate the dollar amount of 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, $TotalTrade_{ckq} = MV_{ckq} - MV_{ck,q-1}(1 + r_{cq})$ where k indicates the TDF, c stands for a mutual fund share class, and q represents a quarter. The calculation includes the cases of investment initiations (where $MV_{ck,q-1} = 0$) and terminations (where $MV_{ckq} = 0$). Second, we aggregate the observations from each holding to the TDF-by-asset-class level and obtain $TotalTrade^y_{kq}$ where y stands for either the equity (E) or the fixed income (B) asset class. 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

[13]For example, Mitchell and Utkus (2021) 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.

the asset class (as in Frazzini and Lamont, 2008).[14] We calculate "rebalancing trade" from the difference: $Rebalancing_{kq}^{y} = TotalTrade_{kq}^{y} - FlowDrivenTrade_{kq}^{y}$. To match the setup in Table 3, where the total assets of the TDF are assumed to be one dollar, we normalize the dollar rebalancing trades by the lagged total assets of the TDF. It is important to note that our calculation assumes that all residual trades by TDFs apart from the allocations of flows are rebalancing trades. However, this measure also includes other active trading strategies pursued by TDFs as well as the move along the glide paths. Therefore, we compare the residual trades with predicted rebalancing in the next subsection.

Table 1 presents summary statistics on the quarterly total trades and rebalancing trades by TDFs during 2008-2018. While the mean and median total trades are positive during the sample period, rebalancing trades are much smaller in magnitudes. During the period, TDFs on average sell equity and buy bond funds net of the flow-driven allocations (i.e., for rebalancing purpose), which makes sense given the strong growth in the equity market. The statistics also show that subtracting flow-driven trades significantly reduces the standard deviations in the TDF trades' measures, suggesting that investor flows are noisy.

3.3 Actual vs. predicted rebalancing

While TDF providers sell age-appropriate portfolios as a key product feature, some TDFs, especially active 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.[15] This subsection establishes that TDFs in fact do rebalance to their desired equity shares as in Table 3, and that they do so within a quarter of a market movement.

We compare the actual rebalancing with the predicted values by estimating the follow-

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

[15] The discretion for TDFs to pursue these other short-term strategies is called "tactical allocations". TDFs with tactical allocations have to keep the asset class shares within a range (e.g., $\pm$ 5% or $\pm$ 10%) around the shares indicated by the glide path. The tactical allocation feature is usually present for active TDFs, though some passive TDFs allow such deviations as well.

ing equations:

$$\begin{aligned}Rebalancing^{E}_{kq} &= \eta^{E} S_{kq}\left(1-S_{kq}\right)\left(R^{E}-R^{B}\right)_{q} \\ &\quad + \pi^{E} S_{kq}\left(1-S_{kq}\right)\left(R^{E}-R^{B}\right)_{q-1} + \theta^{E}\mathbf{X}_{kq} + \delta_{k} + \epsilon^{E}_{kq} \qquad (1)\\ Rebalancing^{B}_{kq} &= \eta^{B} S_{kq}\left(1-S_{kq}\right)\left(R^{E}-R^{B}\right)_{q} \\ &\quad + \pi^{B} S_{kq}\left(1-S_{kq}\right)\left(R^{E}-R^{B}\right)_{q-1} + \theta^{B}\mathbf{X}_{kq} + \delta_{k} + \epsilon^{B}_{kq} \qquad (2)\end{aligned}$$

where S_{kq} measures (possibly with error) the desired equity share of TDF k and is measured in quarter $q-2$.[16] The coefficients of interest are η and π which measure the effect of the predicted magnitude of rebalancing in response to current and lagged quarters' asset price movements, $S(1-S)(R^E - R^B)$ in q and $q-1$ respectively. X denotes other control variables and θ is the column vector of their coefficients.

Several assumptions are worth noting. First, our main focus is on rebalancing in the contemporaneous quarter, because our data of TDF holdings are available at quarterly frequency, and because our conversations with practitioners suggest that the time frames for rebalancing range between a day to a few months, or depending on whether the actual allocation hits a "threshold" away from the target. If all rebalancing is implemented within the same quarter, we expect $\eta^E = -1$ and $\eta^B = 1$. However, we also include the lagged predicted value of rebalancing, because for a return shock that is late in a quarter, the action of rebalancing can spill into the following quarter. If there is inertia driven by fixed costs of adjustment, our model will suggest partial adjustment (the absolute values of η^E and η^B will be less than one).

Second, while R^E and R^B in the derivation in Section 3.1 refers to TDF-specific returns on the equity and bond portfolios of the TDF, we choose to focus on broad asset-class level returns (total U.S. equity market and bond market returns) in our empirical analysis. The reason is that broad asset-class returns are exogenous to the portfolio selection problem of the TDF. This approximation makes no difference for passive TDFs, where asset-class returns are close to the actual portfolio returns. For active TDFs, the actual returns are different due to investment style specialization and/or stock selections. While idiosyncratic

[16] If TDFs do not fully return to their targets each period, equity share measured in $q-1$ would be biased, the direction of which would be the same as $(R^E - R^B)_{q-1}$. Thus, we take the equity share measure with a two-period lag to mitigate this bias.

returns also predict rebalancing, the implications of that for mutual fund flows and stock prices are unclear because of the endogenous selection by active TDFs.[17] Hence, we report rebalancing results using both measures of returns but use only broad asset class returns for R^E and R^B in the subsequent sections of this paper.

Third, we control for TDF fixed effects and time-varying characteristics. While the predicted rebalancing amount does not depend on these controls, our measure of rebalancing includes other trading strategies by TDFs such as moving along the glide paths and/or cross-sectional stock selections. The inclusion of fixed effects and co-variates helps control for these other strategies. The control variables include the sizes of the TDF and the TDF series, current and lagged overall TDF return, current and lagged investor net flow to the TDF, years to retirement, and the cash share in the TDF portfolio.

To minimize measurement errors due to incomplete holdings data, we restrict the regression sample to TDFs where the value of available holdings (including cash) is larger than 95%. The dependent variable is the rebalancing trade in quarter q divided by the TDF asset size in quarter $q-1$ winsorized at 1% and 99%. In columns 1-4, predicted rebalancing is calculated using the broad asset class returns, and R^E and R^B are based on the total returns of the U.S. stock and bond markets. In columns 5-8, we use TDF-specific returns of R^E and R^B based on the actual equity and bond holdings. Standard errors are clustered two ways by TDF and quarter.

Table 4 presents the estimates of equation (1) and conveys three main findings. First, comparing columns 1-4 and columns 5-8, we see that, unsurprisingly, the fit with the model is better when we predict rebalancing with actual returns than with broad asset returns. The actual rebalancing is about 50 cents for each dollar of predicted rebalancing based on broad asset returns, but about 80 cents on the dollar for predictions using actual portfolio returns. The actions are concentrated in the concurrent quarter and there is no spillover into the following quarter, suggesting that TDFs rebalance within the same quarter as the return shock. The results suggest that TDFs rebalance with respect to both asset class returns and idiosyncratic returns. Moreover, although our approximation using aggregate returns is imperfect, it allows us to capture the majority of the actions of rebalancing. This

[17] If an active TDF owns an outperforming sector or stock, it is unclear that the active TDF will sell this winner sector/stock during rebalancing because it has an allowance to pursue cross-sectional momentum strategies. Moreover, the selections by different TDFs may be in different directions and may cancel out once the trades are aggregated to the stock level.

reassures that aggregate return shocks matter for TDF rebalancing and supports the focus on the aggregate shocks moving forward. As discussed above, the advantages of using aggregate asset class returns are that they are orthogonal to the portfolio selection decisions of the TDFs and that they affect all TDFs in the same direction, which means the trades will not cancel each other out at the stock level.

Second, in columns 3-4 and 7-8, we contrast the behavior of passive and active TDFs. The sample is split according to whether the majority of assets are invested in index funds or actively managed funds. Columns 3-4 suggest that in response to the same market movements, passive TDFs rebalance by more than active TDFs do, though this could be driven by asset class returns being more accurately approximated for passive TDFs. Columns 7-8 address this issue by using TDF-specific equity and bond returns, which eliminate the measurement errors for both passive and active TDFs, and the results confirm that passive TDFs stick to their target asset allocations more closely than active TDFs do.

Third, adding control variables (comparing columns 1 and 5 with 2 and 6) improves the fit between actual and predicted rebalancing, which is as expected as the control variables can be related to other trading strategies by TDFs which are (incorrectly) classified as rebalancing trades in our data. Among the control variables, cash holdings appears to have a significant positive correlation with the dependent variable. A possible explanation is that TDFs with higher cash holdings are also those in retirement, where the glide paths are flat rather than downward-sloping, so that all else equal, these funds do not sell equity as much as prime-age TDFs do.[18]

Table B.1 presents the same set of estimates for TDF rebalancing into bonds. The specification follows equation (2). The results suggest that TDFs rebalance into bonds when $R^E - R^B > 0$ and the magnitudes are as expected. The coefficients are slightly smaller than those for equity, especially in the subsample of active TDFs. A possible reason is that TDFs sometimes hold individual fixed income securities, such as treasuries, which are missing from our data, thus, trades into bonds can be understated. In contrast, TDFs' equity holdings are predominantly through equity mutual funds and therefore are properly measured.

We also turn to a graphical exercise to establish the quadratic relationship between the

[18]In unreported results, we obtain similar results normalizing both the dependent variable and the predicted amounts of rebalancing by the actual return of the TDF, thereby measuring the "passive change in risky share" (as in Calvet, Campbell, and Sodini, 2009) which the TDF needs to undo.

magnitude of rebalancing and the target equity share in Figure 3. The rebalancing formula implies that the ratio between rebalancing (per dollar of assets) and the differential asset class return $R^E - R^B$ should be $-S^*(1-S^*)$ for equity and $S^*(1-S^*)$ for bonds, where S^* stands for the target equity share. To assess the fit of the rebalancing formula, we divide the TDF-quarterly level observations into groups based on the equity share (for example, (0.4, 0.5], (0.5, 0.6]), calculate the ratio of rebalancing to $R^E - R^B$ for all observations, and plot the median ratio (multiplied by 0.1 so as to show the amount of rebalancing for each 10% movement in $R^E - R^B$) of each group as a function of the equity share. The median in each bin is taken across time and across TDFs. As a reference, we also plot the quadratic functions $S^*(1-S^*)$ and $-S^*(1-S^*)$ as the predicted values for equity and bonds.

Panels (a) and (b) of Figure 3 use the entire sample and show equity and bond rebalancing respectively. The median rebalancing with respect to equity fits the quadratic function well. For example, when $R^E - R^B = 10\%$, a TDF with 0.65 equity share is expected to sell equity at 2.3% of its portfolio value, and the median fund sells 2.1%. Rebalancing with respect to bonds also has a quadratic shape, but the magnitude is lower than predicted. In panels (c)-(f), we break down the TDF sample by passive and active TDFs. The results suggest that the smaller magnitude in bond rebalancing is driven by the active TDFs where unobserved trades in bond securities may be a problem.

4 The effect of TDFs on net flows to equity mutual funds

In this section, we look across equity mutual funds with different levels of TDF ownership to measure how the contrarian trades by TDFs influence total fund flows, both at the level of the mutual fund and at the level of the entire market. We show 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.

We use our monthly panel of mutual fund flows, as described in Section 2, from July 2008 to December 2018 to match the time period of available TDF holdings data. Section 3.3 shows that TDFs typically implement equity rebalancing within the same quarter as realized asset class returns. We therefore examine the sensitivity of fund flows to both the current month and the lagged month's differential asset class performance in proportion to the fraction of the mutual fund that is held by TDFs (at the end of the previous quarter). Our regression specification is:

$$\begin{aligned}FundFlow_{jm} = \beta_1(R^E - R^B)_m + \beta_2(R^E - R^B)_m \times Frac.TDF_{j,q-1} \\ + \beta_3(R^E - R^B)_{m-1} + \beta_4(R^E - R^B)_{m-1} \times Frac.TDF_{j,q-1} + \gamma Frac.TDF_{j,q-1} \\ + \beta_5(R^E - R^B)_m \times Index_j + \beta_6(R^E - R^B)_{m-1} \times Index_j + \theta X_{jm} + \xi_j + \epsilon_{jm}\end{aligned} \tag{3}$$

where the dependent variable is the fund flow rate for mutual fund j in month m measured as the growth rate in assets in excess of the realized net fund return, or $\frac{TNA_{jm} - TNA_{j,m-1}(1+r_{jm})}{TNA_{j,m-1}}$ where TNA_{jm} refers to the total net assets and r_{jm} refers to net return.

The main 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. Based on TDFs' trading behavior, we expect β_2 and β_4 to be negative. In contrast, we expect β_1 and β_3 to be positive because flows are on average trend-chasing (Warther, 1995; Edelen and Warner, 2001; Ben-Rephael, Kandel, and Wohl, 2011).[19] Equation (3) further allows the differential asset class returns to interact with an indicator for index funds to allow for potential different return-chasing dynamics in index funds and actively managed funds.

In the average cross section, TDFs have positive holdings in 9% of the equity mutual fund observations which account for 35% of total assets of equity funds. We estimate equation (3) in the subsample of funds which have non-zero TDF ownership to avoid a large number of zeros in the regressions (with similar results using the entire sample). Control variables X_{jm} 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.

Table 5, columns 1-3 present the estimates of equation (3). First note that the coefficients on $(R^E - R^B)_m$, $(R^E - R^B)_{m-1}$ and on their interactions with $Index$ suggest that equity fund flows chase equity market performance and slightly more so in index funds (but the difference is not statistically significant). An $R^E - R^B$ of 10% leads to a higher monthly net

[19]The literature also suggests that fund flows chase trends at style level (Cooper, Gulen, and Rau, 2005; Greenwood and Nagel, 2009) as well as with respect to individual funds' excess returns (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Bergstresser and Poterba, 2002).

flow at about 0.6% of the lagged size of the fund or about 1% higher in index funds.

More importantly, these trend-chasing relationships are significantly reduced for funds with higher TDF ownership. The coefficients on the interaction terms with TDF ownership ($\widehat{\beta_2}$ and $\widehat{\beta_4}$) suggest that if 20% of an actively managed mutual fund's assets are held by TDFs (the mean in the sample with positive TDF investment), the same-month return-chasing tendency is reduced by about 40% ($0.145 \times 0.2/0.067$). Fund flows are negative following a positive excess return on the stock market for funds with TDF ownership exceeding 50%, which applies to about 15% of the observations in the regression sample.

The result that TDF ownership in mutual funds has a significant contrarian effect on fund flows implies that investor flows in and out of TDFs do not undo the automatic TDF rebalancing that we documented in the previous section. This is not a guaranteed result, because if investor flows had been highly trend-chasing, forcing TDFs to allocate the trend-chasing flows, net fund flows to TDF-held funds would not be contrarian. Moreover, a comparison between the coefficients on the interaction terms with $(R^E - R^B)_m$ and $(R^E - R^B)_{m-1}$ suggests that the strongest contrarian effect from TDFs is in the same month as the realized differential asset class return, but a weaker effect continues in the following month. This is consistent with the timing of rebalancing by TDFs that we found in the previous section.

In columns 2-3, we split the mutual fund sample by index and actively managed funds. Two findings from the comparison are interesting. First, the contrarian effect is stronger in index funds than in actively managed funds. Second, rebalancing in index funds is faster, entirely in the contemporaneous month as the return shock, while rebalancing in actively managed funds is spread out in the contemporaneous month and the following month. These differences are consistent with index funds being more likely to be held by passive TDFs which rebalance faster and stick closer to the mandated asset allocations, while active TDFs have more discretion and rebalance more gradually.

Columns 4-6 show that a large majority of predicted rebalancing is passed through to — and so is observable in — mutual fund flows. As in the previous Section, given the differential asset class return $R^E - R^B$ in a month, we predict the magnitude of each TDFs rebalancing based on the equity share of that TDFs and the rebalancing formula. We then allocate the rebalancing trades by each TDF into the underlying equity mutual funds based on the weights of the mutual funds in the TDF's equity portfolio. Formally, let TNA_{km}

and TNA_{jm} stand for the total net assets of TDF k and mutual fund j in month m, and let the equity share of TDF k at time m be S_{km} and the share of the equity portion invested in mutual fund j be V_{jkm}.[20] Total predicted rebalancing trade in mutual fund j due to return shock $(R^E - R^B)_m$, in dollar amount, is given by:

$$Pred.Rebal_{jm} = \Sigma_k [V_{jkm} S_{km} (1 - S_{km}) TNA_{k,m-1}] (R^E - R^B)_m \tag{4}$$

And we measure the speed at which automatic rebalancing driven by asset-class returns passes through to mutual funds using the following regression specification:

$$\begin{aligned} FundFlow_{jm} = {} & \gamma_1 Pred.Rebal_{jm} + \gamma_2 Pred.Rebal_{j,m-1} + \beta_1 (R^E - R^B)_m + \beta_2 (R^E - R^B)_{m-1} \\ & + \lambda_1 (R^E - R^B)_m \times Index_j + \lambda_2 (R^E - R^B)_{m-1} \times Index_j + \theta X_{jm} + \xi_j + \epsilon_{jm} \end{aligned} \tag{5}$$

Table 5 columns 4-6 show that roughly 100% of the predicted TDF rebalancing implied by aggregate excess return $R^E - R^B$ is passed through to the net flows of the underlying equity mutual funds after two months. The split between index funds and actively managed funds again suggests faster rebalancing by passive TDFs.[21]

Are these fund-level flows important for *aggregate* flows to and from the stock market through mutual funds? Returning to quarterly data to match the frequency of TDF tradings data, we calculate the aggregate dollar net flows to all domestic equity mutual funds as the sum of flows to both retail and institutional share classes. In cases where TDFs also invest in a retail or institutional share class, we deduct those TDF trades before taking the aggregate. We also calculate aggregate TDF trades in domestic equity funds as the sum of rebalancing trades across all TDFs.[22]

Figure 4, panel A, shows that a positive excess return on the stock market in a quarter, $R^E - R^B$, is associated with increased inflows to domestic equity funds by retail investors in that same quarter (including those investing through institutional share classes, such

[20] Therefore, the weight of mutual fund j in TDF k's total portfolio is $W_{jkm} = S_{km} V_{jkm}$.

[21] Why do we obtain a higher ratio of the actual effect of rebalancing relative to the predicted effect than implied earlier by the TDF rebalancing result in Table 4? One possible reason is that the holdings of CITs and balanced funds overlap with those of TDFs (target date CIT portfolios in particular are almost copies of TDFs), therefore, the effect of TDF rebalancing on mutual fund flows is "amplified" due to trading behavior (rebalancing) by those other mixed-asset vehicles that have fixed asset allocations. If this is the case, the amplification is quite limited since the extent of passthrough that is estimated to occur is not that different.

[22] Note that in Section 3, TDF equity trades included those in both domestic equity and foreign equity.

as investors in advised accounts). In contrast, as panel B of Figure 4 shows, aggregate TDF rebalancing trades move in the opposite direction as $R^E - R^B$: high $R^E - R^B$ leads to significant outflows from domestic equity funds by TDFs. The different right-hand-side scales on the two panels differ by a factor of 10. Roughly, in aggregate, TDFs offset more than one tenth of aggregate fluctuations in fund flows.

To be more precise, we calculate the share of aggregate return-chasing flows that are offset by TDF trading from regressions that account for the changing relative size of the two types of funds. We regress flows to domestic equity mutual funds (in percent) on current and lagged returns for three measures of flows: all aggregate retail flows (as a percent of all domestic mutual funds assets), total rebalancing flows from TDFs (as a percent of TDF assets), and all flows from TDFs (as a percent of TDF assets).[23] We estimate:

$$AggFlowPct_q = \gamma_1(R^E - R^B)_q + \gamma_2(R^E - R^B)_{q-1} + \delta + \epsilon_q \tag{6}$$

and report the results in Table 6.[24]

Table 6, Column 1 shows that when the excess return, $R^E - R^B$, is 10%, net aggregate flows to equity mutual funds through retail investors is higher by 1% of aggregate fund assets in the same quarter and higher by 0.3% in the following quarter. Column 2 uses the aggregate rebalancing trades of TDFs as the dependent variable and shows that when $R^E - R^B$ is 10%, TDFs sell 1% of their lagged asset value in equity mutual funds. Taking 2019 as our base year, the total asset size of domestic equity mutual funds is at \$12 trillion, 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 \$120 billion (=12,000×1%) higher than the baseline, but TDFs trade against the retail flows at the amount of \$15 billion (=1,400×1.1%), thereby offsetting about 13% of the trend-chasing tendency of retail flows in the same quarter as the realized asset class returns. This fraction is in line with that implied by Figure 4. If we assume that all \$4 trillion of TDBF assets rebalance in a similar way, we can infer that together they offset almost 40% of the aggregate mutual fund flows. Including trading in the subsequent quarter, TDF rebalancing trades offsets 18% (=1,400×2%)/(12,000×1.3%))

[23] We normalize the fund flows and TDF trades by their respective asset sizes because the TDF market grew at a much faster pace than the equity mutual fund sector during the period, as is somewhat visible in Figure 4.

[24] Standard errors are estimated using the Huber-White heterokedasticity-consistent approach. A constant term is included in all regressions but its coefficient is omitted from the table.

of total retail flows.

Column 3 of Table 6 examines the aggregate total trades of TDFs, which include any active movement by retail investors into and out of TDFs rather than just the TDFs' rebalancing trades. Including the investor flows makes aggregate trades by TDFs less contrarian in the concurrent quarter and more contrarian the following quarter (reducing the estimates' current quarter offset by two thirds and the cumulative offset by one fifth).

5 TDF ownership and stock returns

In this section we show that rebalancing by the TDF sector affects the returns on the stocks that TDFs (indirectly) overweight or underweight in their holdings. Specifically, stocks with higher TDF ownership exhibit lower "market momentum" or sensitivity to recent market performance, which we interpret as because TDFs trade against differential asset-class returns and counteract the well-documented trend-chasing price pressure from other mutual fund flows. It is important to note that our notion of market momentum is different from the cross-sectional momentum that is widely documented in the literature, which refers to the phenomenon that stocks that outperform in the cross-sectional are likely to continue outperforming in the medium term (as in Jegadeesh and Titman, 1993, 2001).[25] Following this section, Section 6 shows that the price effects that we estimate are large relative to other research on the price response of individual stocks to changes in demand. Section 7 presents a potentially important reason for this large price impact: that a long-short strategy that trades in the opposite direction of TDFs would make slightly negative risk-adjusted returns. Thus, arbitrageurs may (on average) trade along with TDFs (and against market momentum), not dampening the price impact of TDFs and possibly amplifying it. Finally, Section 8 shows economically larger price effects but without much statistical significance using only variation in TDF ownership driven by inclusion in the S&P 500 index.

Given that TDFs impact individual stock prices, one might ask whether they are also altering asset-class returns. We expect that any effect on aggregate stock market returns is probably still too small to detect because TDFs currently hold only about 1.5% of the U.S.

[25] The concept of market momentum is more similar to the "time series momentum" documented in Moskowitz, Ooi, and Pedersen (2012).

stock market capitalization (2.4% including CITs, see Figure B.4). However, we speculate about their potential growing aggregate price impact in the next section.

Before turning to our analysis, we note two important points about our tests. First, as noted earlier, a TDF's need to rebalance is driven both by asset class returns and by the returns on the stocks that they overweight and underweight. We focus only on the impact of asset class returns, because it is unrelated to the stock picking by TDFs and the funds that they invest in, and therefore is unrelated to the over-weighting and under-weighting that we are studying the price effect of.

Second, the stocks over-weighted by other fixed-share funds — primarily CITs but also balanced funds and the other funds discussed in Section 1.2 — though unmeasured by our data, may overlap with those over-weighted by TDFs, which would bias upward some of our estimated coefficient on TDF ownership. That is, to the extent that other fixed-share funds hold similar portfolios to those of TDFs, the price impact of a given asset class return would be driven by the larger differences in ownership across all fixed-share funds rather than just the differences across TDFs. This overlap is likely large for CITs, significant for balanced funds, and likely minimal for the other (somewhat) fixed-share funds discussed in Section 1.2. Though it is not possible to quantify this bias precisely, we factor in the size of CITs and BFs when interpreting the magnitude of our estimated price effect.

We study monthly individual stock returns from 2010 to 2018, a period with sizable and growing assets in TDFs. Following Jegadeesh and Titman (2001), we drop stocks with market capitalizations that place them in the bottom 5% of NYSE stocks, or with beginning-of-month prices below $5, due to the lack of liquidity. Because rebalancing occurs *after* realized asset class return shocks (motivating our use of the term "market momentum"), the speed at which TDFs rebalance varies significantly across TDFs. Large passive TDFs currently mostly rebalance by the end of every day (the lag is a few hours), while other TDFs, especially the active ones, can take a month or two before restoring their target asset allocations. Therefore, we study the price effect during the same month as the market returns to allow for the effect of the majority of TDFs to be captured. We also look at the effect during the subsequent month when active TDFs that do more of the (indirect) over-weighting and under-weighting of individual stocks are still trading.[26] Finally, as we

[26]Though passive and active TDFs rebalance at different speeds, their holdings are highly correlated at the stock level (Figure B.6), making it impossible to identify their effects separately with any degree of statistical precision.

focus on later, the stock holdings of the TDF sector deviate from the market portfolio (e.g. Figure B.5 shows the role of stock size).

We identify price impacts from the variation in TDF investments across stocks by running the following regression:

$$
\begin{aligned}
Alpha_{im} = {} & \lambda_1 (R^E - R^B)_m \times TDF_{iq-1} + \lambda_2 (R^E - R^B)_{m-1} \times TDF_{iq-1} + \delta_1 (R^E - R^B)_m \times MF_{iq-1} \\
& + \delta_2 (R^E - R^B)_{m-1} \times MF_{iq-1} + \gamma TDF_{iq-1} + \eta MF_{iq-1} + \xi X_{im} + \theta_m + \epsilon_{im} \qquad (7)
\end{aligned}
$$

where i indexes the stocks and m represents a month. TDF ownership at the stock level is calculated as $TDFpct_{i,q-1} = \Sigma_{jk} a_{ij,q-1} b_{jk,q-1}$ for stock i in the lagged quarter $q-1$, where $a_{ij,q-1}$ is the fraction of stock i held by mutual fund j and $b_{jk,q-1}$ is the fraction of mutual fund j held by TDF k. $(R^E - R^B)_m$ and $(R^E - R^B)_{m-1}$ represent the current and lagged months' excess return of equity over bonds. The key parameters of interest, λ_1 and λ_2, measure the differential sensitivity to market momentum across stocks with different levels of TDF ownership. Since TDFs sell following strong stock market performance, we expect $\hat{\lambda}_1$ and $\hat{\lambda}_2$ to be negative.

The main dependent variable is the Fama-French-Carhart four-factor alpha, the return on the stock in a month in excess of that predicted by the Fama-French-Carhart four-factors. We risk-adjust the returns to control for stocks' intrinsic sensitivity to market movements (market beta) and to take out the direct effect of stock characteristics (size, growth/value orientation, and momentum) on returns. However, an issue with this risk adjustment is that TDF trading can directly affect the sensitivity of stock return to market performance, that is, TDFs lower the market beta of stocks, which is the main effect we want to measure. To alleviate this problem, we estimate the factor betas using the period 1996-2005 which is before the PPA of 2006, so that the betas are (largely) free of TDF impact. We windsorize the alphas at 1% and 99% to account for the fat tails due to extreme movements unrelated to TDF trading. Using the pre-TDF window to calculate the intrinsic betas is not perfect and it would be concerning if TDF-invested stocks have lower market betas and this drives their lower sensitivity to excess equity market returns. However, if anything, high-TDF stocks have higher market betas than low-TDF stocks do (see table B.2).

Equation (7) controls for the amount of ownership of the stock by non-TDF mutual funds by including the sum of holdings by mutual funds that are not held by TDFs and that measure interacted with current and lagged excess equity return. These controls allow the general mutual fund ownership to affect the stock's sensitivity to asset class returns, and could capture the effect of mutual fund flows on asset prices (e.g., Coval and Stafford, 2007; Lou, 2012). Other control variables include the natural logarithms of lagged market value and lagged trading volume. In some specifications, to account for stock return dynamics that are driven by characteristics — the lead-lag effect documented by Lo and MacKinlay (1990) for example — we further include the equity excess returns interacted with stock size. Lastly, our analysis controls for the typical co-movement of stock returns with the market excess return by including time fixed effects (θ_t), and we include stock fixed effects in some specifications. The analysis clusters the standard errors two-ways by time (year-month) and stock.

Table 7 shows that higher TDF ownership is associated with lower market momentum. In Column 1, the coefficient on $(R^E - R^B)_t \times TDF$ indicates that a one standard deviation (0.7%) higher TDF ownership of a stock implies a 0.038 (=0.7×0.055) lower sensitivity of the return (four-factor alpha) of that stock to the contemporaneous market return. That is, if the market rises by 1% in a month relative to bonds, a one standard deviation higher level of TDF ownership implies a 3.8 basis point lower return on that stock in the same month. The coefficient on the interaction term between TDF ownership and lagged returns suggests there continues to be a TDF effect on returns in the subsequent month, though that is weaker than the same-month effect. The concentration of the price effect in the contemporaneous month is consistent with the fact that the majority of TDFs rebalance within one to two months in response to excess asset class return shocks.

Column 2 shows that the estimate is highly similar when we include stock fixed effects thus controlling for the time-invariant reasons that TDFs select into certain stocks. In columns 3-4, we further control for differential asset class returns interacted with stock size, to allow for the possibility that large and small stocks may have different responses to aggregate return shocks. The magnitude of the result shrinks, which is unsurprising because size is a key determinant for TDF investment (see again Figure B.6), however, the results show that TDFs affect prices beyond the effect of size.

As another approach to checking whether these results are indeed driven by the trading of TDFs, we conduct falsification tests using an earlier period 1987-2005, before the PPA of 2006 set off the growth of the TDF (and balanced funds) market.[27] Of course, the rise of rebalancing vehicles 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.[28] That said, using TDF ownership measured as the average during 2010-2018, we conduct our falsification analysis in the earlier period. The result, presented in columns 5, suggests that stocks that would have high TDF ownership in the most recent period did not have lower market momentum before the PPA. Before 2006, the high- and low-TDF stocks exhibit similar sensitivity to the current and lagged market performance. While this test is again not perfect because of the many differences between the pre-TDF period and the TDF period, these results show that the results documented in Table 7 are unique to the TDF era.

6 Discussion of magnitude of price impact

In this subsection, we show that the price response to changes in the demand for a stock implied by our findings is large relative to the price responses estimated by previous researchers in response to different sources of changes in demand for individual stocks. We then discuss several reasons why these estimated price responses are larger.

To estimate the price elasticity implied by our estimates, we need to make an assumption about the total asset value of the funds following market contrarian strategies and with similar holdings to those of the TDFs that we can accurately measure. As noted, indirect ownership by TDFs likely aligns closely with unmeasured ownership by target date CITs that have almost identical portfolios as the TDFs, as well as with ownership by balanced funds. Therefore, for our calculation of the demand elasticity, we assume that both these types of retail fixed-allocation funds (TDBFs) have similar holdings to those of the TDFs, and thus scale up our measure of TDF ownership proportionally across stocks by about four times to account for those funds. While this assumption is in some ways aggressive, in other ways it is not. For example, it omits funds managed by advisory firms, robo advisers,

[27] The choice of 1987 as the beginning of the period used for the falsification test is that our measure of R^B, based on returns of the Vanguard Total Bond Market Index Fund, is only available starting then.

[28] 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.

and endowments, some of which may trade in similar ways (but we expect hold quite different portfolios).

Using the estimated price effect in Table 7, column (4) (the coefficient -0.04 on $R^E - R^B, t \times TDF(\%)$), and the scaling by a factor of four to account for all TDBFs, we estimate a demand elasticity of -0.3 (details in Appendix A). That is, when TDBFs demand an additional dollar of stock, the price of that stock rises by three dollars. This estimated price response is in line with Gabaix and Koijen (2020) which reports an estimate that an additional dollar of demand for stocks increases the value of the stock market by three to eight dollars. But our estimated individual stock-level price impact is much higher than (or our estimated elasticity is significantly lower in absolute magnitude than) estimates in the previous literature.[29] What accounts for the difference?

First, could we be omitting more funds that have holdings and trade like TDFs? Our calculation would imply a smaller price response per dollar if we included in our calculation the funds held by institutional investors such as pensions and endowments. However, we believe this is an unlikely source of the difference. These funds likely have different holdings and certainty trade to rebalance much more slowly than TDFs.

Second, previous studies have looked at idiosyncratic changes in demand for one stock as compared to similar stocks. In contrast, we are looking at systematic changes in demand for a set of similar stocks. Therefore, if there were profits to front-running TDFs, equity traders would have to bear systematic risk to profit from trading against the TDF price impact. Consistent with this argument, our estimate is quantitatively more similar to the asset-class level estimates of Da et al. (2018) and Gabaix and Koijen (2020).

However, the third explanation seems most likely. As we will show now, trading against TDFs is not actually a profitable trade. Thus, the greater price impact that we estimate may be because there is no arbitrage capital working to reduce the predictable price movement.

7 Returns from trading before or with TDFs

This section presents evidence that trading against TDFs is not profitable, implying that arbitrage capital is unlikely to be trading against the TDF price impact. Instead, arbitrage

[29]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).

capital may be trading against general retail flows. In other words, they may already be trading in the same direction as the TDFs. Thus the cross-sectional price impact of TDF trading that we find may be large relative to other situations because in other situations arbitrage capital may be trading against and mitigating the price impact while for TDFs they are not.

Based on our findings in Section 5, we consider two long-short strategies, one that (infeasibly) trades before TDFs and one that trades along with them. Because, stocks high in TDF investments have lower returns during and after high equity market performance, we consider a strategy that shorts high-TDF stocks and buys low-TDF stocks when the equity market is return is high and takes the opposite position when the market is low as follows. In each quarter and within each size group based on market capitalization (the size groups are defined according to NYSE size breakpoints that are at 5-percentile increments), we sort stocks into quintiles based on (non-TDF) mutual fund ownership, and then within each mutual fund quintile, sort again based on TDF ownership. We then form portfolios every month based on the sign of the excess equity market return and the predicted direction of TDF trades.

First, an infeasible trading strategy that trades ahead of TDFs is profitable. This strategy takes its position prior to the asset class return during a month: if $R^E - R^B, m < 0$, it goes long the highest TDF quintile of stocks and shorts the lowest TDF quintile at the beginning of month m and holds until the end of the month. If $R^E - R^B, m > 0$, the strategy takes the opposite long-short position. Figure 5, panels (a) and (b), shows that the cumulative raw and risk-adjusted returns of this first strategy are positive. A strategy that uses equal-weighting among long and short stocks (solid line) produces a steady positive return (both in raw and risk-adjusted terms) that amounts to a cumulative 30% return in the period we plot (2011-2018). The strategy that weights stocks in the strategy according to their market capitalization (dashed line) is less stable, and one possible reason is that size weighting puts more weight on stocks that have recently gone up in size (momentum stocks).

Second, a feasible, similar strategy that trades along with TFDs is less profitable, which suggests that the opposite long-short strategy, i.e. trading against TDFs, would have negative risk-adjusted return. This second strategy is based on the previous month's return: if $R^E - R^B, m-1 > 0$, go long the highest TDF quintile of stocks and short the lowest quintile during month m, and the reverse when $R^E - R^B, m-1 < 0$. Panels (c) and (d) of Figure 5 show that this feasible strategy of trading along with TDFs is, like the first infeasible strategy, also a profitable strategy, but less so. The more important point however is that the *reverse* of this second strategy does not have positive profits and in fact would have generated a loss of 20% return over eight years (steadily for the equally-weighted strategy). This result could be due to the price impact of active TDFs which are slower to rebalance, or the mean reversion in asset-class returns. In sum, it is not be profitable to trade against TDFs based on the previous month return, so arbitrage capital should not be reducing the cross-sectional price impact of TDF trading.

8 Evidence from S&P 500 index inclusion

We have shown that the pattern of returns across stocks and time is consistent with that predicted by TDF trading following positive returns. However, while we have controlled for four major cross-sectional patterns of stock returns using the standard 4 four factor model, as always there is the possibility that some other perhaps undiscovered factor besides the one we model generates the particular pattern of returns across time and stocks that we attribute to TDFs. In this section, we focus on a narrow source of variation in TDF ownership: inclusion in the S&P500 index. We first show that there is a preference among TDFs to hold equity by investing in S&P 500 index funds during our sample period. Second, identifying the price impact of TDFs only from variation in holdings by TDFs that is driven by index inclusion and comparing similar stocks included and not included in the index, we find an economically larger but statistically much weaker effect of TDF trading on individual stock returns.

This approach relies on there being otherwise similar stocks included and not included in the S&P 500 index. The S&P 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 composition of the index, and in particular, considers a "sector balance."[30] We assume that in a group of stocks similarly eligible for the index, the actual inclusion decisions are otherwise uncorrelated with TDF ownership.

We construct a group of control stocks for stocks in the S&P 500, following the method-

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

ology in Denis et al. (2003), which constructs comparison groups based on 12 industries, terciles of market capitalization (in the range of the S&P 500), and terciles of liquidity. Appendix C contains further details. Throughout the sample period, 53 out of the 108 portfolios can be matched with S&P 500 stocks.

To measure the extent to which TDFs overweight S&P 500 stocks, we estimate the following stock-level regression using quarterly data on the matched sample of S&P 500 stocks and their controls:

$$TDF(\%)_{ipq} = \beta S\&P500_{iq} + \lambda X_{iq} + \theta_{pq} + \alpha_i + \epsilon_{ipq} \tag{8}$$

where p indexes the 53 peer groups that contain "similar" stocks, the dependent variable is stock-level indirect TDF ownership expressed in percentages, S&P 500 is an indicator $\in \{0, 1\}$ for being included in the S&P 500. We include as control variables, X_{iq}, stock size, trading volume, and the market-to-book ratio. The matched-peer-group by quarter fixed effects θ_{pt} imply that the result comes from comparing stocks in and out of the S&P 500 index in that quarter conditional on industry, size, and liquidity.[31]

Table 8 shows that being included in the S&P 500 index is associated with 0.16% higher TDF ownership (or about 20% of the mean), relative to similar stocks that are not included in the index (column 1). This effect is primarily due to holdings of index funds (column 2) and primarily driven by active TDFs (column 5), although the effect only through actively managed funds is (economically similar but) imprecisely estimated (column 3).[32] There is also a strong relationship between flows to individual S&P 500 index funds and their TDF ownership, similar to our findings for all equity mutual funds in Section 4 (see Table C.1 in Appendix C).

Second, we estimate how individual stock returns vary both with market-level excess

[31] We include stock fixed effects α_i, so that we only exploit the variations from stocks that are included in the index in some periods during the sample. Stocks that are always included in or excluded from the index do not affect our estimate.

[32] These patterns are consistent with the strategies of large passive and active TDFs, and that many active TDFs, such as T. Rowe Price, hold the S&P 500 index fund as a large building block in their equity portfolios (in addition to actively managed equity funds). While the largest passive TDFs use total market index funds for their equity allocations, the TDF sector historically over-weighted the S&P, especially early in our sample. See Figure B.7.

returns and inclusion in the S&P index, using the following regression:

$$
\begin{aligned}
Alpha_{ipm} &= \gamma_1(R^E - R^B)_m \times S\&P500_{i,m-1} + \gamma_2(R^E - R^B)_{m-1} \times S\&P500_{i,m-1} + \eta S\&P500_{i,m-1} \\
&+ \beta_1(R^E - R^B)_m \times MF_{i,q-1} + \beta_2(R^E - R^B)_{m-1} \times MF_{i,q-1} + \lambda MF_{i,q-1} + \xi X_{im} + \theta_{pm} + \epsilon_{ipm}
\end{aligned} \tag{9}
$$

where p index peer group and m month and again θ_{pm} is the key fixed effect that implies that we are only comparing stocks within their peer group. $S\&P500_{i,m-1}$ equals one if a stock is included in the S&P 500 index in month t-1, and zero otherwise. $MF_{i,q-1}$ stands for the percentage of a stock owned by equity mutual funds that have no investment from TDFs, measured at quarterly frequency and at the end of the previous quarter. The reason for including the interactions between $MF_{i,q-1}$ and current and lagged returns is that index inclusion may lead to an increase in the investment by mutual funds that are unrelated to TDFs, which can also impact return dynamics. Equation (9) estimates the key coefficients γ_1 and γ_2 from a difference-in-differences type specification that compares, within each peer group, the responses to market return of i) the return on stocks included in the S&P 500 index which have higher TDF ownership, to ii) the return on stocks not included in the index which have lower TDF ownership.

Table 9 shows that, consistent with price impact from TDF trading, when the market rises by 1% in a month, stocks that are included in the S&P 500 index have a similar return in the contemporaneous month but a 9 basis point lower risk-adjusted and raw returns in the following month compared with similar non-index stocks. Could other features of S&P index inclusion be driving these results? On the one hand, effects documented in previous research do not seem related to the market momentum effect that we are measuring.[33] On the other hand, we are not directly evaluating the effect of TDF ownership.

To evaluate the economic and statistical significance of TDF ownership directly, we estimate a two-stage least squares regression in which we estimate how TDF ownership

[33]Previous research has documented other features of stock dynamics that change when a stock when is included in the S&P 500 index. Notably, 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). None of these effects would seem to contaminate or bias our estimate of the price impact of TDFs associated with S&P index inclusion, although we discuss them further in Appendix C.

interacts with market momentum — as in our main results in Table 7 — but using only variation in TDF ownership driven by inclusion in the S&P 500 index. We relegate the complete description of this analysis to Appendix C because nothing is statistically significant. As shown in Table C.2, point estimates are much larger than in our main results in Section 5 but standard errors are larger than the coefficients.

In sum, while the evidence in this section identifies prices effects using only the more exogenous variation in TDF ownership share driven by S&P inclusion, it is statistically weak. As such, it provides at best evidence that the market-contrarian trading strategies of TDFs have changed the price dynamics of the stocks they hold.

9 Speculation about aggregate stock market dynamics

The goal of our paper is to document that the rise of TDBFs is having an impact on mutual fund flows and on individual stock returns. A natural question is whether the rise of TDBFs has also impacted aggregate stock market dynamics.

Given their current size, TDBFs still likely have quite limited effects on aggregate dynamics. However, if the fraction of rebalancing traders continues to grow, the influence of market contrarian strategies on aggregate prices may become more pronounced. Below we lay out some market-wide implications that may follow from further growth of TDBFs.

Market stability By putting downward pressure on prices after market increases and upward pressure after market drops, TDBFs can dampen market fluctuations. However, any impact on volatility would require a substantial dollar amount of rebalancing trades in order to be statistically detectable. Suppose $R^E - R^B = 10\%$ in a period, at the current holdings of 4% of the U.S. equity market, TDBFs trade -0.12% of the market ($= -.7 * .3 * 10\% * 4\%/.7$), assuming the equity share of the aggregate TDBF is 70%. Even if we aggressively assume that all rebalancing is implemented within the same period and the aggregate "price multiplier" is 5 (Gabaix and Koijen (2020)), TDBFs can reduce the excess equity return by 0.6%, or from 10% to 9.4%, which is statistically undetectable (given the sample size to date). However, if stocks held by rebalancing investors were to grow to 20% of the market, the return would be reduced by 30% (from 10% to 7%).[34]

[34] This dampening effect would also grow if TDFs start to condition equity shares on forecasts of future market returns, as suggested by Gomes, Michaelides, and Zhang (2021).

This dampening can either decrease or increase market efficiency. Roughly half of stock market fluctuations are transitory fluctuations in prices, and by trading against these, TDBFs may increase market efficiency (depending on your preferred theory). The other half of stock market fluctuations is driven by permanent changes in dividends, which should lead to permanent changes in the effective amount of equity relative to bonds. TDBFs trade against these fundamental changes in value as well as the transitory returns. That is, because TDBFs have a *micro-optimal* view of portfolio choice: TDBFs do not adjust equity shares to permanent changes in the market portfolio. If they instead held a *macro-optimal* view of portfolio choice, they would hold the market portfolio and a risk-free asset in age-dependent proportions and thus hold more equity when equity comprised more of the market portfolio.

Price predictability TDFs can generate a negative autocorrelation at horizons that match the time interval between price changes and the completion of rebalancing. We find that the majority of TDFs' rebalancing occurs in the contemporaneous month but also a substantial amount the following month (both because some return shocks occur toward the end of the month and because some TDFs are slower at rebalancing). At the aggregate level, this rebalancing can create reversal in monthly returns.[35] To investigate this possibility, consider the regression:

$$r_m = \alpha + \beta_1 r_{m-1} + \beta_2 r_{m-1} \times TD(B)F_{y-1} + \gamma TD(B)F_{y-1} + \epsilon_m \tag{10}$$

where r_m is the monthly return of the U.S. equity market in month m, either as the raw return or as the excess return relative to the U.S. bond market, and $TD(B)F_{y-1}$ measures the fraction of the market held by TD(B)Fs at the end of the previous year.[36]

The results in Table 10 suggest that the rise of TDBFs has been accompanied by a reduction in the aggregate momentum or an increase in stock market reversal. When TDBFs hold 4% of the market, the implied autocorrelation is $0.29 - 9 * 4\% = -0.07$. Because the rise of TDFs is relatively recent, the time series that we can investigate is

[35]If we examine longer time intervals, the majority of TDFs would finish rebalancing in period t (e.g., a quarter) in response to a return shock in the same period. Therefore, TDFs play little role in reversal in lower-frequency data. In contrast, if TDFs trade against price movements due to dividend innovations, they may generate aggregate momentum in slow-moving data by slowing down the adjustment of prices to fundamental values.

[36]Some specifications rely on the total ownership of TDBFs, and the size of CITs are only available yearly.

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, so there is no way to cleanly separate the effects of TDFs from other changes in investment strategies, financial regulation and so forth.[37]

The correlation between stock and bond returns Finally, as TDBFs grow larger, they may affect the comovement between stock and bond returns. Interest rate declines — such as pursued by quantitative easing — may lead to stronger stock market responses, as an increasingly large amount of funds invested in TDBFs trades out of bonds and into stocks. Similarly, excess stock returns lead TDBFs to purchase bonds and stock market booms may lower interest rates. Because TDBFs increase linkages across asset classes, their continued growth may increase return correlations across asset classes.

Of course all of these speculative points may be mitigated or mediated by changes in trading behavior of other market participants. The responses, and the general equilibrium effects in general, may provide interesting fodder for testing models of asset price dynamics.

10 Concluding remarks

Target date funds are an important financial innovation for retail investors. Since the 2006 Pension Protection Act qualified TDFs to serve as default options in 401(k) plans, the TDF market has experienced substantial growth. Today 90% of employers offer TDFs as the default options in their retirement plans and TDFs manage trillions of dollars of retirement savings. Retail investors that invest in TDFs do not have to monitor or choose the relative shares of stock funds and bond funds in their portfolios. Instead, they delegate these choices to TDFs that make these allocations based on automatic, age-dependent rules designed by professional money management companies. As a result, many retirement plan investors have moved from passive or trend-chasing behavior to investment vehicles that automatically rebalance their portfolios across asset classes to undo compositional changes due to differences in returns across asset classes.

This paper points out a quantitatively important implication of the rise of this household finance innovation for the dynamics of asset markets. TDFs rebalance portfolios by selling

[37] Martin (2021) discusses other explanations for the negative autocorrelation in market returns in the recent period.

stocks when the stock market rises and buying stocks when the market falls, and so act as a market-stabilizing force. We find that in the past 15 years, the growth of TDFs has changed the patterns of fund flows across mutual funds and the cross-sectional pattern of returns across stocks. In addition, we speculate that if the amount of funds invested through TDFs continues to grow, the contrarian trading of TDBFs will start to have noticeable effects on aggregate stock market returns.

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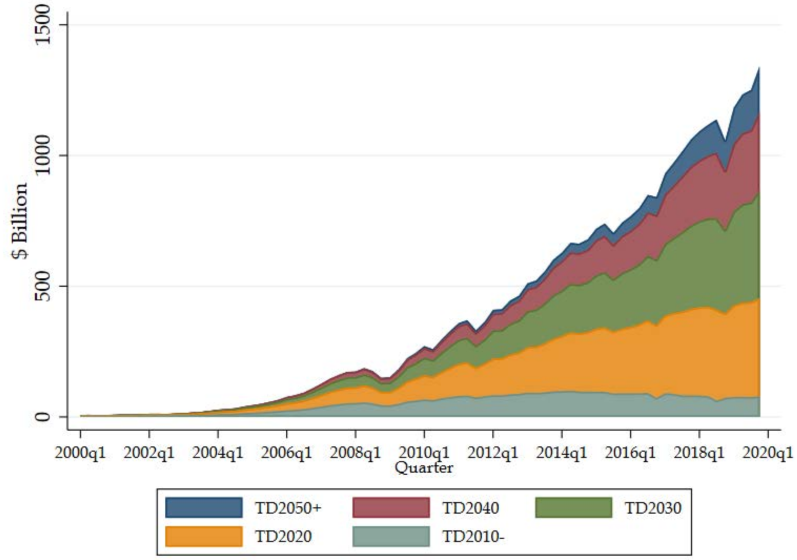
Figure 1: Size of assets in TDFs, target date CITs, and balanced funds by year

Panel A plots the sum of total net assets (TNA) of TDFs during 2000Q1-2019Q4 broken down by target retirement years. 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. Panel B shows the total assets in balanced mutual funds and target date collective investment trusts (CITs) in additional to those in TDFs. Balanced funds are identified in the CRSP Mutual Fund Database using Lipper classifications including B (balanced funds), MTAA/MTAC/MTAG/MTAM (mixed-asset target allocation aggressive/conservative/growth/moderate), MTRI (retirement income), and MATJ (mixed-asset target today). Assets in CITs are collected from Morningstar TDF research reports.

A. Growth of TDF assets



B. Growth of assets in TDFs, CITs and balanced funds

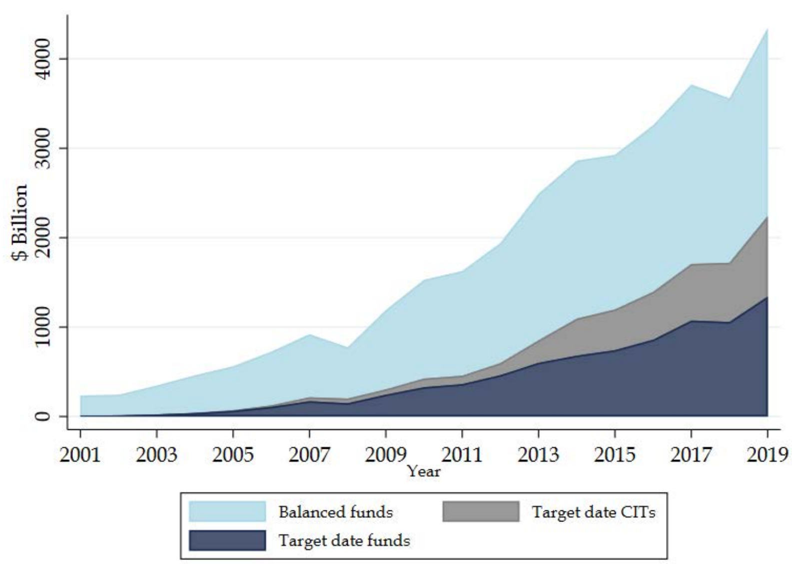
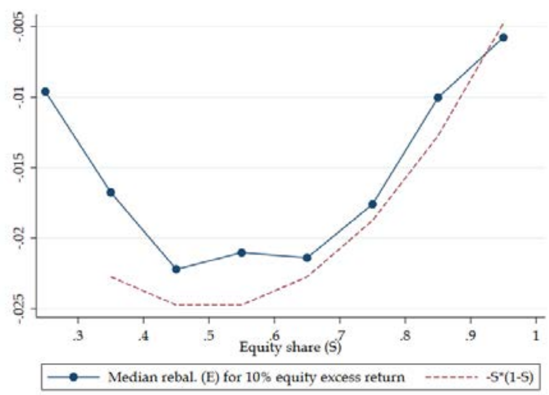


Figure 2: Distribution of index fund share in TDF portfolios

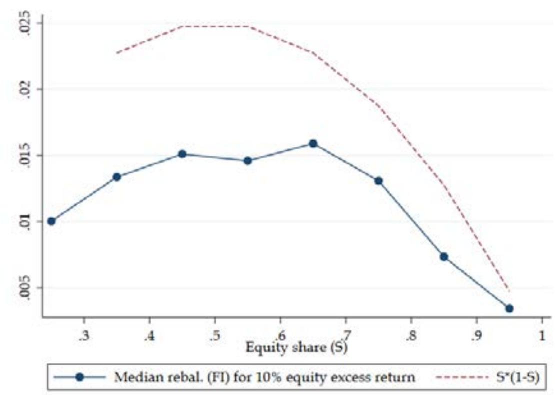
This figure presents a histogram of the fractions of TDF portfolios invested in index mutual funds. Observations are for each TDF-quarter and include only TDFs where the value of available holdings (including cash) is larger than 95% of fund assets at beginning of quarter.

Figure 3: Median rebalancing by equity share

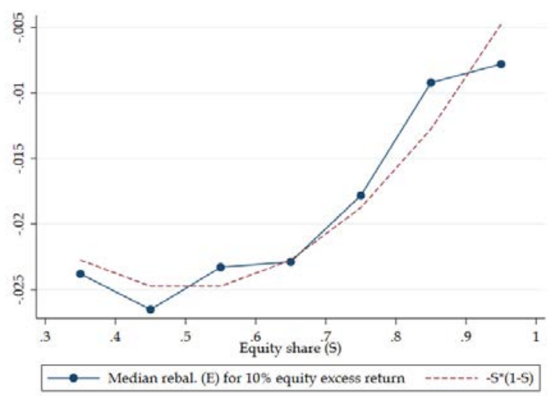
The connected line plots the median ratio of rebalancing for each equity-share-based bin. The outcome variable is calculated as the amount of rebalancing (in equity or bonds) for each dollar of TDF holding divided by $R^E - R^B$ and multiplied by 0.1 so as to show the amount of rebalancing for each 10% movement in $R^E - R^B$. Each bin represents the interval with a length of 0.1, and the median is taken across time and across TDFs. The bin that centers at 0.25 includes all TDFs whose equity share is at or below 30% (several bins are combined into one due to small numbers of observations). The dotted line represents the theoretical predicted magnitude of the ratio at the midpoint of each interval. (a) and (b) use the full sample, (c) and (d) use the sample of passive TDFs whose holdings in index mutual funds are at least 50% of their portfolio values, and (e) and (f) use the sample of active TDFs whose holdings in index funds are less than 50% of their portfolio values.



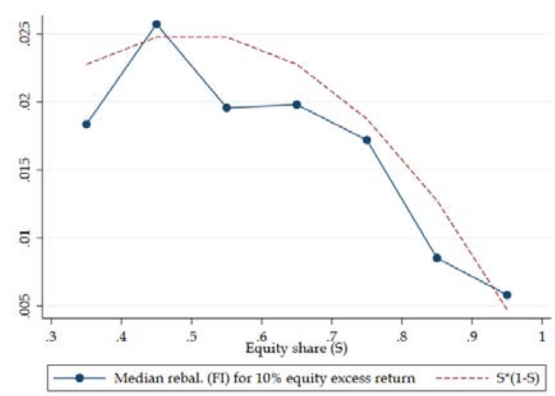
(a) Equity rebalancing - all TDFs



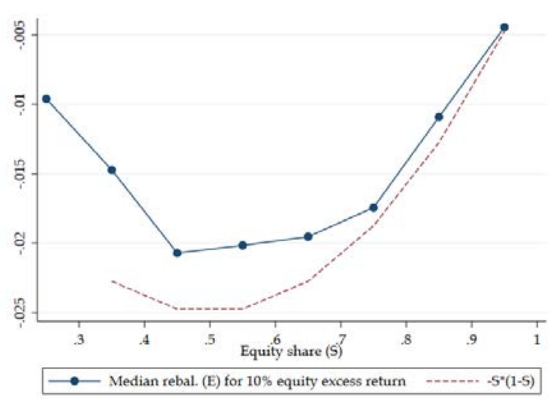
(b) Bond rebalancing - all TDFs

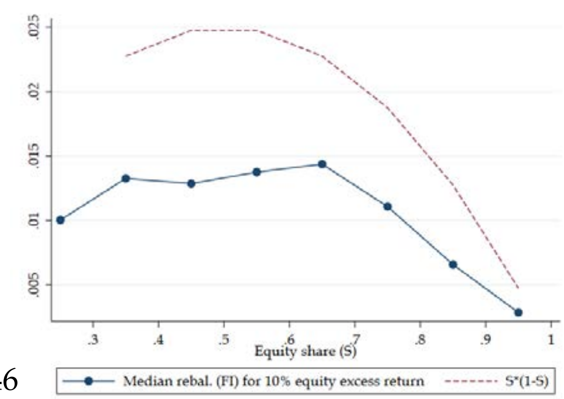


(c) Equity rebalancing - passive TDFs



(d) Bond rebalancing - passive TDFs





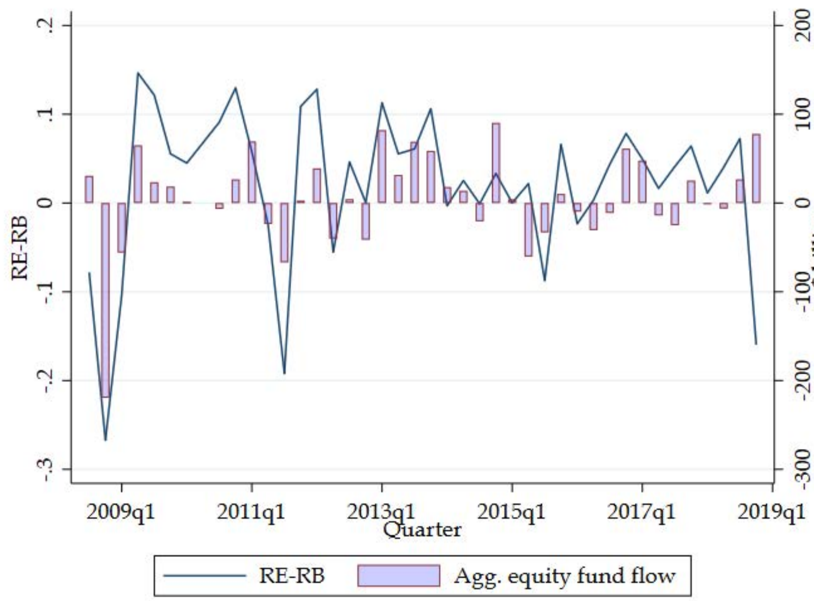
(e) Equity rebalancing - active TDFs

(f) Bond rebalancing - active TDFs

Figure 4: Aggregate retail/institutional 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 and institutional share classes (panel A.) and TDF rebalancing (panel B.) during 2008Q3-2018Q4.

A. Aggregate retail and institutional flows



B. Aggregate TDF rebalancing trades

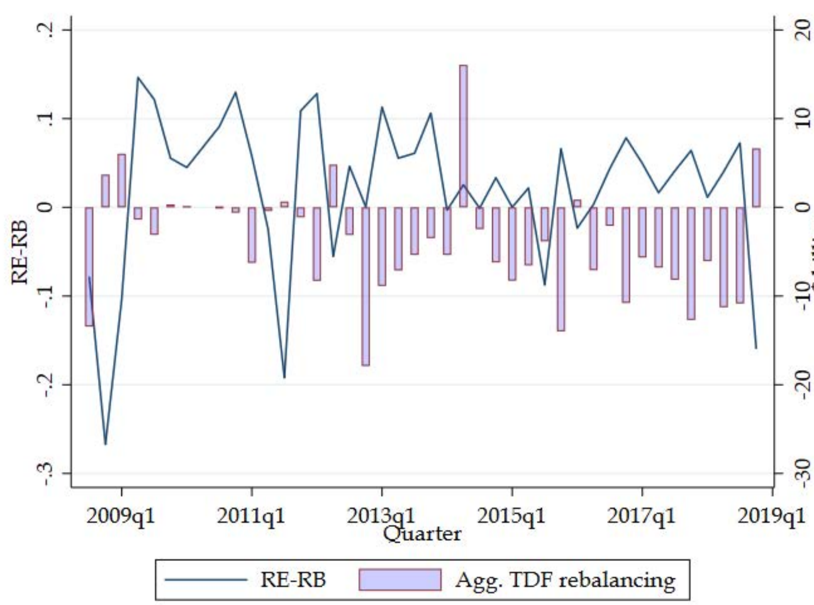
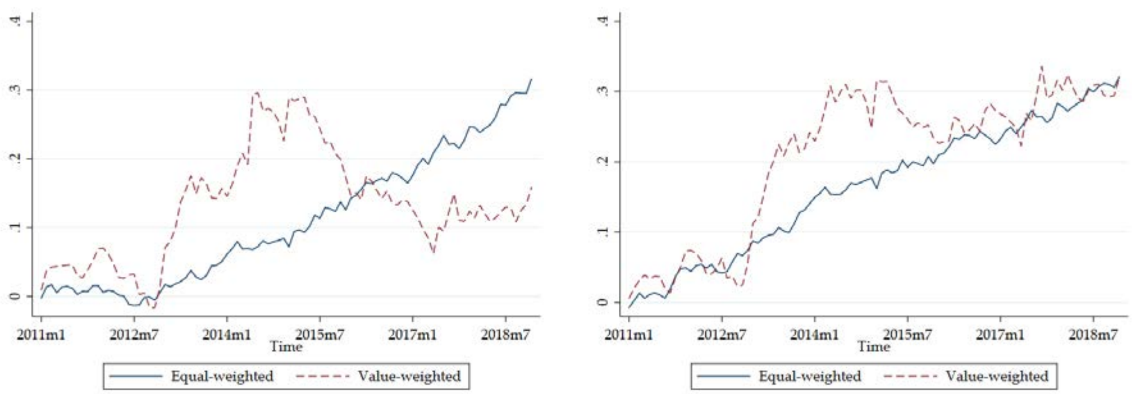
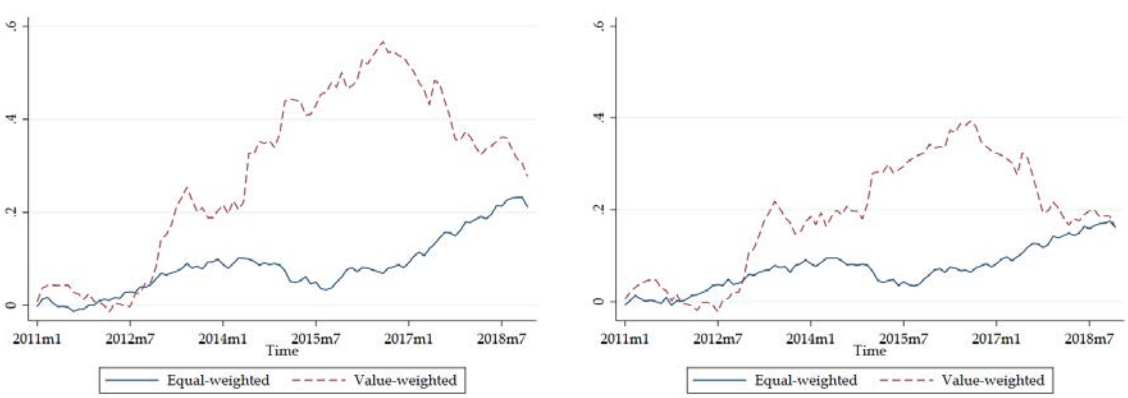


Figure 5: Returns from TDF-based long-short trading strategy

This figure shows the cumulative returns from investing in a portfolio of stocks with the highest TDF ownership and shorting a portfolio with the lowest TDF ownership when the excess stock market return in the current month (panels (a) and (b)) or previous month (panels (c) and (d)) is positive, and the reverse when the excess market return is negative. The sample includes NYSE-, NASDAQ-, and AMEX-traded stocks with market capitalizations that are above the fifth percentile on the NYSE and with beginning-of-month prices above five dollars. In each quarter and within each size group based on market capitalization (the size groups are defined according to NYSE size breakpoints that are at 5-percentile increments), stocks are sorted two-ways into quintiles, first by mutual fund ownership (calculated as the sum of ownership by mutual funds which are not held by TDFs), and second by TDF ownership. The trading strategy in the top panels (bottom panels) invests in the highest TDF portfolio and shorts the lowest TDF portfolio in month t if $R_t^E - R_t^B < 0$ ($R_{t-1}^E - R_{t-1}^B > 0$) and takes the reverse positions (long the lowest TDF portfolio and short the highest TDF portfolio) if $R_t^E - R_t^B < 0$ ($R_{t-1}^E - R_{t-1}^B < 0$). Panels (a) and (c) show the cumulative raw returns and (b) and (d) show the Fama-French-Carhart four-factor adjusted returns of the respective strategies.



(a) Current-return (infeasible strategy) , raw return (b) Current-return (infeasible strategy), 4-factor alpha



(c) Lagged-return strategy, raw return (d) Lagged-return strategy, 4-factor alpha

Table 1: Summary statistics on TDFs

This table presents statistics on TDF-level quarterly observations. TDF holdings are classified using the CRSP objective codes of the underlying mutual funds. Passive TDFs are those with more than 50% of their assets invested in index funds. 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. S stands for the equity share of a TDF and is measured with a two-quarter lag.

TDF quarterly	N	Mean	p25	p50	p75	SD
Passive TDF	4,772	0.36	0.00	0.00	1.00	0.48
Target year	4,772	2033.4	2020	2035	2045	14.9
TDF total net assets ($ million)	4,772	2803.4	78.6	423.8	2270.0	5788.9
Series total assets ($ million)	4,772	52429.0	1158.3	6993.7	102436.5	85305.5
No. funds held	4,772	15.0	7	15	22	8.4
Frac. assets held in mutual funds	4,772	0.963	0.948	0.984	0.999	0.058
Frac. cash	4,772	0.031	0.002	0.017	0.041	0.051
Frac. portfolio in equity funds	4,772	0.750	0.614	0.806	0.900	0.178
- Domestic equity	4,772	0.495	0.407	0.521	0.600	0.130
- Foreign equity	4,772	0.255	0.189	0.260	0.308	0.092
Flow to TDF, t / TNA, t-1	4,772	0.067	-0.007	0.032	0.091	0.179
Total trade in equity, t / TNA, t-1	4,772	0.047	-0.012	0.017	0.066	0.187
Total trade in bonds, t / TNA, t-1	4,772	0.015	-0.001	0.008	0.023	0.055
Rebal. trade in equity, t / TNA, t-1	4,772	-0.009	-0.015	-0.006	0.002	0.039
Rebal. trade in bonds, t / TNA, t-1	4,772	0.003	-0.002	0.003	0.010	0.018
$R^E - R^B$	4,772	0.022	0.000	0.040	0.064	0.068
$S(1-S)(R^E - R^B)$	4,772	0.004	0.000	0.004	0.010	0.013
TDF quarterly return	4,772	0.016	0.001	0.021	0.043	0.046
TDF equity portfolio return	4,772	0.020	0.005	0.026	0.053	0.058
TDF bond portfolio return	4,772	0.008	-0.002	0.009	0.019	0.018

Table 2: Summary statistics on mutual funds and stocks

This table presents statistics on equity mutual funds and stocks. The mutual fund sample contains domestic equity mutual funds which are held by any TDF in the lagged quarter. The stock sample includes NYSE-, NASDAQ-, and AMEX-traded stocks with market capitalizations that are above the fifth percentile on the NYSE and with beginning-of-month prices above five dollars. Mutual fund flow rate is the quarterly growth rate in assets in excess of that implied by net fund return. Fraction held by TDFs is the total value of TDF holdings of a fund divided by the fund total net assets. Expense ratio is the net annual expense ratio. Return volatility is the one-year standard deviation in the monthly returns. Predicted rebalancing is calculated for each mutual fund as follows: *i)* predicted rebalancing at monthly frequency is calculated for each TDF according to formula and realized differential asset class return; *ii)* predicted rebalancing by each TDF is allocated to the underlying mutual funds in proportion to lagged weights in the TDF's equity portfolio; and *iii)* rebalancing trades in a mutual fund are summed up across TDFs and divided by the lagged assets of the mutual fund. Month 4-factor alpha is calculated following the Fama-French-Carhart 4-factor model, where beta loadings on the four factors are estimated using monthly stock returns during the window 1996-2005. TDF ownership refers to the fraction of a stock owned by TDFs through mutual funds. TDF ownership through index funds and active funds are fractions of a stock owned by TDFs through index funds and actively managed funds, respectively. Mutual fund ownership is the fraction of a stock owned by equity mutual funds that have no investment from TDFs. Market capitalization is measured in billion dollars, and trading volume is normalized by the number of shares outstanding.

A. Mutual fund monthly	N	Mean	p25	p50	p75	SD
Fund flow rate (%)	23,023	0.075	-1.13	-0.14	0.86	4.68
Index fund	23,023	0.20	0.00	0.00	0.00	0.40
Frac. held by TDFs	23,023	0.20	0.01	0.05	0.25	0.30
Fund size ($ billion)	23,023	10.0	0.6	1.5	5.5	36.9
Fund family size ($ billion)	23,023	455.8	45.1	126.9	491.1	755.2
Fund age (year)	23,023	17.9	8.0	14.0	21.0	15.8
Expense ratio (%)	23,023	0.77	0.55	0.82	1.02	0.36
Return volatility (%)	23,023	3.97	2.71	3.67	5.00	1.71
$R^E - R^B$	23,023	0.007	-0.012	0.008	0.033	0.041
Pred. rebalancing (%)	23,023	0.037	-0.002	0.002	0.051	0.324

B. Stock monthly	N	Mean	p25	p50	p75	SD
Monthly raw return (%)	152,550	1.38	-3.76	1.22	6.19	9.72
Monthly 4-factor alpha (%)	152,550	0.35	-4.25	0.21	4.59	8.61
TDF ownership (%)	152,550	0.83	0.39	0.65	1.04	0.74
TDF ownership (%) through index funds	152,550	0.38	0.28	0.40	0.52	0.21
TDF ownership (%) through active funds	152,550	0.44	0.05	0.20	0.53	0.66
Mutual fund ownership (%)	152,550	20.48	13.36	20.84	28.04	11.11
Market capitalization ($ billion)	152,550	10.90	0.69	1.98	6.66	35.54
Volume	152,550	0.19	0.09	0.14	0.22	0.18
$R^E - R^B$	152,550	0.010	-0.010	0.010	0.033	0.039

Table 3: TDF rebalancing formulae

This table derives the one-period formula of rebalancing that restores the target asset allocation 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 allocation at the beginning of the period and to reinvest all dividends paid out by the underlying mutual funds. Dividends declared by the TDF are assumed to be reinvested by investors. 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 4: TDF rebalancing out of equity

This table estimates the relationship between TDF rebalancing with respect to equity holdings and the predicted magnitudes of rebalancing. The sample is restricted to TDFs where the value of available holdings (including cash) is larger than 95% of fund assets at beginning of quarter. Observations are at the TDF-quarterly level. Rebalancing trades are calculated as the sum of changes in positions in equity mutual funds minus TDF flow-driven trades in equity. The dependent variable is the rebalancing trade in quarter q divided by the TDF asset size in quarter $q-1$, and winsorized at 1% and 99%. $S(1-S)(R^E - R^B)_q$ and $S(1-S)(R^E - R^B)_{q-1}$ stand for the magnitudes of predicted equity rebalancing trades in quarters q and $q-1$, in columns 1-4 are calculated using quarterly returns of the total U.S. stock market and bond market, and in columns 5-8 are calculated as the TDF-specific actual returns on the equity and bond portfolios. S is the fraction of a TDF portfolio (or the aggregate TDF portfolio) invested in equity, measured at $q-2$. Standard errors are clustered two ways by TDF and quarter. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Net rebalancing in q into equity as a faction of total holdings in $q-1$							
	Broad asset class returns				Actual returns			
	All	All	Passive	Active	All	All	Passive	Active
$S(1-S)(R^E - R^B)_q$	-0.347***	-0.461***	-0.627***	-0.344**	-0.491***	-0.797***	-0.897***	-0.726***
	(0.113)	(0.127)	(0.138)	(0.152)	(0.123)	(0.114)	(0.214)	(0.123)
$S(1-S)(R^E - R^B)_{q-1}$	0.013	0.086	-0.007	0.142	0.057	0.233	0.023	0.330**
	(0.159)	(0.152)	(0.204)	(0.153)	(0.180)	(0.153)	(0.228)	(0.160)
ln (TDF size), q-1		-0.003	-0.002	-0.005*		-0.003	-0.001	-0.005*
		(0.003)	(0.005)	(0.003)		(0.003)	(0.005)	(0.003)
ln (TDF series size), q-1		-0.000	0.000	-0.004		-0.001	0.000	-0.004
		(0.003)	(0.004)	(0.004)		(0.003)	(0.004)	(0.004)
TDF return, q		0.034	0.083	-0.011		0.084***	0.126**	0.046
		(0.034)	(0.056)	(0.044)		(0.029)	(0.061)	(0.046)
TDF return, q-1		-0.031	0.066	-0.089		-0.050	0.066	-0.112**
		(0.053)	(0.066)	(0.060)		(0.047)	(0.069)	(0.052)
TDF flow, q		-0.016	-0.024	-0.016		-0.017	-0.023	-0.016
		(0.018)	(0.017)	(0.023)		(0.018)	(0.017)	(0.023)
TDF flow, q-1		0.008	0.014	0.005		0.008	0.015	0.005
		(0.006)	(0.009)	(0.005)		(0.006)	(0.009)	(0.005)
Year to retirement, q		-0.002	-0.002	-0.001		-0.002	-0.002	-0.001
		(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)
Cash share, q-1		0.208***	0.215**	0.187*		0.215***	0.228**	0.193*
		(0.076)	(0.101)	(0.110)		(0.073)	(0.102)	(0.107)
TDF FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	4,722	4,722	1,684	3,038	4,722	4,722	1,684	3,038
R-squared	0.136	0.155	0.176	0.159	0.142	0.166	0.187	0.169

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 monthly level. The sample is restricted to domestic equity mutual funds which are held by any TDF in the lagged quarter. The dependent variable is the monthly 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 are dropped, and the dependent variable is winsorized at 1% and 99%. R^E is the monthly return of the US equity market from CRSP. R^B is the monthly return of the US bond market approximated with the pre-fee return of the Vanguard Total Bond Market Index Fund. Frac. held by TDFs is measured as the fraction of fund assets held by TDFs, measured at the end of the previous quarter. Predicted rebalancing in month m is calculated as the predicted amount of rebalancing at the TDF level, given monthly $R^E - R^B$, allocated to equity mutual funds in the TDF according to weights of the funds in the equity portfolio of the TDF. 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)	(5)	(6)
	Fund flow in month m					
	All	Index	Active	All	Index	Active
$R^E - R^B$, m × Frac. by TDFs, q-1	-0.145***	-0.228***	-0.132**			
	(0.050)	(0.080)	(0.052)			
$R^E - R^B$, m-1 × Frac. by TDFs, q-1	-0.089*	-0.139	-0.081*			
	(0.048)	(0.095)	(0.049)			
Pred. rebalancing, m				-0.637***	-0.977***	-0.561***
				(0.194)	(0.277)	(0.211)
Pred. rebalancing, m-1				-0.416**	-0.482	-0.401**
				(0.171)	(0.312)	(0.178)
$R^E - R^B$, m	0.067*	0.112***	0.065*	0.070*	0.116***	0.066*
	(0.038)	(0.036)	(0.038)	(0.038)	(0.035)	(0.038)
$R^E - R^B$, m × Index fund	0.036			0.036		
	(0.028)			(0.028)		
$R^E - R^B$, m-1	0.026	0.071*	0.025	0.028	0.068*	0.028
	(0.023)	(0.038)	(0.023)	(0.022)	(0.036)	(0.022)
$R^E - R^B$, m-1 × Index fund	0.039			0.039		
	(0.025)			(0.025)		
Frac. by TDFs, q-1	0.005	0.006	0.005	0.004	0.004	0.005
	(0.007)	(0.015)	(0.008)	(0.007)	(0.015)	(0.008)
ln (Fund size), m-1	-0.026***	-0.027***	-0.026***	-0.026***	-0.026***	-0.026***
	(0.005)	(0.010)	(0.005)	(0.005)	(0.009)	(0.005)
ln (Fund family size), m-1	0.009**	0.005	0.010**	0.009**	0.005	0.009**
	(0.004)	(0.012)	(0.004)	(0.004)	(0.012)	(0.004)
ln (Age), m	-0.005	0.007	-0.006	-0.005	0.006	-0.006
	(0.006)	(0.012)	(0.006)	(0.006)	(0.011)	(0.006)
Expense ratio, m	1.159	-2.361	1.343	1.052	-2.323	1.240
	(0.965)	(3.288)	(1.000)	(0.958)	(3.310)	(0.992)
Return volatility, m-1	-0.120	-0.078	-0.134*	-0.121	-0.083	-0.134*
	(0.075)	(0.102)	(0.078)	(0.075)	(0.101)	(0.078)
Fund FE	yes	yes	yes	yes	yes	yes
Time FE	no	no	no	no	no	no
Observations	22,745	4,443	18,302	22,745	4,443	18,302
R-squared	0.153	0.124	0.158	0.153	0.125	0.158

Table 6: Aggregate retail and institutional vs. TDF flows to U.S. equity funds

Column 1 shows the correlations between aggregate flows to U.S. domestic equity funds in quarter q, through retail and institutional share classes, and the excess performance of the equity market in q and $q-1$. The dependent variable is calculated as the aggregate dollar flows to retail and institutional share classes of domestic equity funds in quarter q, divided by the total assets under management in those share classes in quarter $q-1$. TDF trades are deducted before aggregating up the retail and institutional flows. Columns 2 and 3 show the correlations between aggregate TDF trades (rebalancing or total) of domestic equity funds and the excess performance of the equity market. The dependent variables are aggregate dollar trades by TDFs in quarter q divided by the total size of TDFs in quarter $q-1$. $R^E - R^B$ 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. The sample period is 2008Q3-2018Q4. 2010Q2 is dropped due to insufficient TDF trading data. Robust standard errors are reported. *p $<$ .1; **p $<$ .05; ***p $<$ .01.

	(1)	(2)	(3)
	Retail flow, q	TDF rebal. trades, q	TDF total trades, q
$R^S - R^B$, q	0.100***	-0.109**	-0.034
	(0.035)	(0.041)	(0.038)
$R^S - R^B$, q-1	0.032**	-0.087	-0.128*
	(0.013)	(0.056)	(0.068)
Observations	41	41	41
R-squared	0.577	0.259	0.208

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

This table examines the relationship between TDF ownership and monthly stock return sensitivity to differential asset class performance during 2010-2018. The sample includes NYSE-, NASDAQ-, and AMEX-traded stocks with market capitalizations that are above the fifth percentile on the NYSE and with beginning-of-month prices above five dollars. The dependent variable is the Fama-French-Carhart four-factor-adjusted alpha, where beta loadings on the four factors are estimated using monthly stock returns during the window 1996-2005. The dependent variable is winsorized at 1% and 99%. TDF (%) is the percentage of a stock indirectly owned by TDFs. MF other (%) is the percentage of a stock owned by equity mutual funds that have no investment from TDFs. TDF(%) and MF other (%) are available at quarterly frequency and measured at the end of the previous quarter. The falsification test uses a time period of 1987-2005 and calculates factor betas using the window 1985-2005. TDF(%) and MF other (%) in the falsification test are measured as averages during 2010-2018. Other control variables include the natural logarithm of market capitalization measured in millions and the natural logarithm of trading volume normalized by the number of shares outstanding. Standard errors in this table are clustered two ways by time and stock.

	(1)	(2)	(3)	(4)	(5)
	4-Factor alpha, m				
	Main sample: 2010-2018				Falsification
$R^E - R^B$, m $\times$ TDF (%)	-0.055***	-0.058***	-0.037**	-0.040**	0.000
	(0.018)	(0.018)	(0.018)	(0.018)	(0.005)
$R^E - R^B$, m-1 $\times$ TDF (%)	-0.020	-0.023*	-0.022	-0.024*	-0.012
	(0.014)	(0.014)	(0.014)	(0.014)	(0.012)
$R^E - R^B$, m $\times$ MF other (%)	-0.002	-0.002	-0.002**	-0.003**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$R^E - R^B$, m-1 $\times$ MF other (%)	0.000	0.000	0.000	0.000	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$R^E - R^B$, m $\times$ ln(Mktcap, m-1)			-0.048***	-0.048***	-0.015**
			(0.010)	(0.010)	(0.007)
$R^E - R^B$, m-1 $\times$ ln(Mktcap, m-1)			0.009	0.006	-0.017**
			(0.008)	(0.008)	(0.007)
TDF (%)	0.001	0.000	0.001	0.000	0.003***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
MF other (%)	-0.000*	-0.000**	-0.000	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Mktcap, m-1)	-0.002***	-0.032***	-0.002***	-0.031***	-0.003***
	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)
ln(Vol, m-1)	-0.003***	-0.004***	-0.003***	-0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Stock FE	no	yes	no	yes	no
Time FE	yes	yes	yes	yes	yes
Observations	152,528	152,516	152,528	152,516	306,900
R-squared	0.013	0.050	0.014	0.051	0.015

Table 8: Relationship between S&P 500 index inclusion and TDF investment

This table estimates the effect of S&P 500 index inclusion on stock-level TDF ownership. Observations are at stock-by-quarter level during 2010Q1-2018Q4, and the sample contains S&P 500 stocks and control stocks matched on industry, size, and liquidity, following Denis et al. (2003). In each quarter, stocks are sorted by market capitalization and annual trading volume (divided by shares outstanding) within each Fama-French-12 industry. The dependent variable in column 1 is the indirect ownership by all TDFs through mutual funds, in column 2 the indirect ownership by all TDFs through index funds, in column 3 the indirect ownership by passive TDFs through index funds, in column 4 the indirect ownership by active TDFs through index funds, and in column 5 the indirect ownership by all TDFs through actively managed funds. ln(Market cap) is the natural logarithm of market capitalization in million dollars. ln(Vol) is the natural logarithm of monthly trading volume normalized by shares outstanding, and ln(Market-to-book) measures the natural logarithm of the ratio between market and book values of equity. S&P 500 is an indicator that equals one if the stock is included in the S&P 500 index quarter q and zero otherwise. Standard errors are clustered by stock.

	(1)	(2)	(3)	(4)	(5)
	TDF total	TDF $\rightarrow$ index	TDF $\rightarrow$ active	Passive TDF $\rightarrow$ index	Active TDF $\rightarrow$ index
S&P 500, q	0.158*	0.071***	0.087	0.004	0.067***
	(0.080)	(0.012)	(0.077)	(0.011)	(0.004)
ln (Market cap, q-1)	-0.063	0.008	-0.071	0.008	0.000
	(0.069)	(0.010)	(0.068)	(0.009)	(0.002)
ln (Volume, q-1)	0.017	-0.002	0.019	-0.001	-0.000
	(0.024)	(0.004)	(0.023)	(0.004)	(0.001)
ln (Market-to-book, q-1)	-0.030	-0.016	-0.014	-0.013	-0.003
	(0.054)	(0.010)	(0.051)	(0.009)	(0.002)
Time-by-matched peer group FE	yes	yes	yes	yes	yes
Stock FE	yes	yes	yes	yes	yes
Observations	8,901	8,901	8,901	8,901	8,901
R-squared	0.694	0.911	0.644	0.905	0.936

Table 9: S&P 500 inclusion and stock return sensitivity to market performance

This table examines the effect of S&P 500 index inclusion on the sensitivity of monthly stock returns to recent market performance. Observations are at stock-by-month level during 2010.1-2018.12, and the sample contains S&P 500 stocks and control stocks matched on industry, size, and liquidity, following Denis et al. (2003). The dependent variable is the Fama-French-Carhart four-factor-adjusted alpha, where beta loadings on the four factors are estimated using monthly stock returns during the window 1996-2005, and winsorized at 1% and 99%. S&P 500, m-1 equals one if a stock is included in the S&P 500 index in month $m-1$, and zero otherwise. MF other (%) is the percentage of a stock owned by equity mutual funds that have no investment from TDFs, measured at quarterly frequency and at the end of the previous quarter. The falsification test uses a time period of 1987-2005 and calculates factor betas using the window 1985-2005. MF other (%) in the falsification test is measured as an average for each stock during 2010-2018. Other control variables include the natural logarithm of market capitalization measured in millions and the natural logarithm of trading volume normalized by the number of shares outstanding. Standard errors in this table are clustered two ways by time and stock.

	(1)	(2)	(3)
	4-Factor alpha, t		
	2010-2018		Falsification
$R^E - R^B$, m × S&P 500, m-1	-0.018	-0.015	-0.041
	(0.064)	(0.066)	(0.050)
$R^E - R^B$, m-1 × S&P 500, m-1	-0.094***	-0.087***	0.047
	(0.029)	(0.032)	(0.056)
$R^E - R^B$, m × MF other (%), q-1	-0.003	-0.003	0.001
	(0.003)	(0.003)	(0.004)
$R^E - R^B$, m-1 × MF other (%), q-1	-0.002	-0.002	-0.001
	(0.002)	(0.002)	(0.003)
S&P 500, m	-0.002	-0.012**	0.006
	(0.002)	(0.005)	(0.009)
MF other (%), q-1	-0.000	-0.000*	
	(0.000)	(0.000)	
ln (Market cap, m-1)	-0.004***	-0.049***	-0.051***
	(0.001)	(0.005)	(0.005)
ln (Volume, m-1)	-0.001	-0.002	-0.002
	(0.002)	(0.003)	(0.004)
Time-by-peer group FE	yes	yes	yes
Stock FE	no	no	yes
Observations	18,529	18,529	16,153
R-squared	0.233	0.282	0.263

Table 10: TDFs and aggregate return autocorrelation

This table reports the autocorrelation in monthly returns of the U.S. equity market as a function of the fraction of the market held by TD(B)Fs. The dependent variable is the raw monthly return of the U.S. stock market (R^E) in columns 1-2 and the excess return of equity over bonds ($R^E - R^B$) in columns 3-4. TDF (TDBF) fraction stands for the fraction of the U.S. equity market held by TDFs (TDBFs) measured at the end of the previous year. Standard errors are estimated using the Newey-West method, with one lag in the error structure.

	(1)	(2)	(3)	(4)
	Return, m			
	R^E		$R^E - R^B$	
Return, m-1	0.293**	0.329**	0.252**	0.284**
	(0.129)	(0.151)	(0.121)	(0.140)
Return, m-1 × TDF fraction, y-1	-37.198**		-33.449**	
	(14.500)		(13.447)	
Return, m-1 × TDBF fraction, y-1		-9.745**		-8.861**
		(4.479)		(4.193)
TDF fraction, y-1	1.080**		1.195**	
	(0.541)		(0.569)	
TDBF fraction, y-1		0.347**		0.385**
		(0.173)		(0.183)
Constant	-0.001	-0.004	-0.004	-0.007
	(0.005)	(0.006)	(0.005)	(0.006)
Observations	228	228	228	228
F	2.721	2.301	2.547	2.439
DF residual	224	224	224	224
DF model	3	3	3	3