Target Date Funds as Asset Market Stabilizers: Evidence from the Pandemic

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Abstract

Target Date Funds (TDFs) provide retirement investors, many of whom are unsophisticated or inattentive, with age-appropriate exposures to different asset classes like stocks and bonds. To maintain exposures, TDFs trade actively against market returns, buying stock funds when the stock market does poorly, and selling when the market does well (Parker, Schoar, and Sun, 2023). This paper shows that trading by TDFs was a significant stabilizing force in US equity markets during the unprecedented economic volatility of the COVID-19 pandemic period. Specifically, TDFs – now comprising a quarter of all 401(k) plan assets – caused significant contrarian investment flows across asset classes, flows that were not undone by enrollment of TDF investors or by discretionary actions by TDF managers. Mutual funds with large ownership by TDFs had more stable funding through the pandemic, and stocks that had greater indirect ownership by TDFs had lower co-movement with the market and lower volatility during the pandemic period.

JEL codes: G12; G23; G51

Keywords: target date funds; retirement saving accounts; contrarian strategies; mutual fund flows; COVID-19 pandemic; market volatility; market stability

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The transition from defined benefit to defined contribution plans has placed significant financial responsibilities on retirement savers. Out of concern that many retirement investors do not have the time or financial literacy required to make sound investment decisions, the past few decades have seen both the development of innovative financial products and the widespread adoptions of default options designed to improve the behavior of investors by replacing potentially erroneous retirement saving and portfolio choices with those based on robustly optimal rules derived from quantitative finance theory.

However, when retirement savers are defaulted into these financial products and stay due to inertia, the rules behind these products change not only the outcomes of many investors individually, but also the behavior of a large amount of capital in the economy and so potentially national saving rates, interest rates, and asset returns. For example, a retirement plan feature that increases the saving of retirees can lower interest rates and lead to more capital accumulation and economic growth. But in practice, the impact of these defaults and products on retirement saving rates, and thus interest rates, has been minimal. In contrast, the impact on the stock and bond allocations of typical retirees appears to have been dramatic (Parker et al., 2022).

This paper focuses on one of the most important products automating such portfolio choices for retirement investors, Target Date Funds (TDFs), also known as life-cycle funds. TDFs are funds-of-funds that invest primarily in equity and fixed-income mutual funds to maintain specific proportions of their assets in different asset classes, such as stocks and bonds, based on the investor's expected retirement date. Most importantly for our purposes, in maintaining these specific proportions, 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 show that this contrarian trading by TDFs (and TDF-like entities) stabilized the funding of equity funds and even stabilized the prices of the underlying stocks that TDFs held (indirectly) during the COVID-19 period of unprecedented economic volatility. Though this was not the primary intent of the product design of TDFs, which was simply to improve the individual-level portfolio choices of inattentive or unsophisticated retail investors, the contrarian behavior of TDFs has started to generate market-wide impacts.

These mechanisms were proposed in Parker, Schoar, and Sun (2023) (PSS), which shows that from 2008 to 2018, TDF trading has been macro-contrarian: after high stock market returns, TDFs sell stocks to return to their prescribed asset allocations within a short period of time, and that as a result TDFs stabilized markets during a period of rapid growth in TDFs.

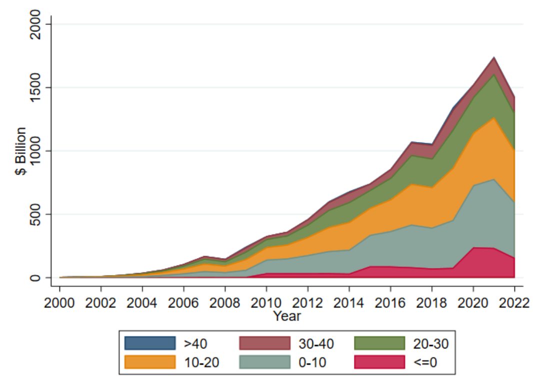
TDFs have a significant effect on fund flows and individual stock prices in the pandemic because they now manage a lot of money. The capital invested in TDFs and other balanced funds (BFs) rose from under \$8 billion in 2000 to almost \$6 trillion in 2021, then fell to \$4.7 trillion in 2022 due to negative returns in that year, as shown in Figure 1(a).[1] The share of 401(K) plan mutual fund assets invested in TDFs increased from 3% in 2005 to about one quarter in 2022 (also Figure 1(a), right axis). Figure 1(b) shows that the largest growth in TDF assets is driven by TDFs with fewer than 20 years to retirement date, funds which mostly hold more than 40% of their assets in each of stocks and bonds. According to Vanguard (2022), 95% of plans offered TDFs in their investment options at end of 2021, up from 84% in 2012. Further, 81% of all participants used TDFs and 69% of participants that owned a TDF had their entire account invested in a single TDF.

The growth of TDFs was facilitated by the Pension Protection Act (PPA) of 2006, which qualifies both TDFs and BFs as default options in defined-contribution retirement saving plans (see Parker et al., 2022). But similar strategies that automatically stabilize the share of an investor's portfolio in different asset classes have recently been incorporated into a broader set of investment products, such as some automated advisory programs (e.g. model portfolios).

To summarise, retail investors move their money across funds in ways that appear to be stabilizing during the COVID-19 pandemic, in contrast to the trend-chasing behavior that we observe during previous periods. Our first main finding is that this change in flow patterns is significantly but far from solely due to the rebalancing by TDFs and TDF-like funds that trade mutual funds against market movements. Our second main finding is

[1] Of the \$4.7 trillion, \$2.8 trillion was in TDFs including \$1.3 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 *Morningstar Target Date Strategy Landscape 2023*.

Figure 1: The Rise of assets in TDFs and TDF-like funds



(a) Dollars (left axis) and as a fraction of 401(k) (right axis)

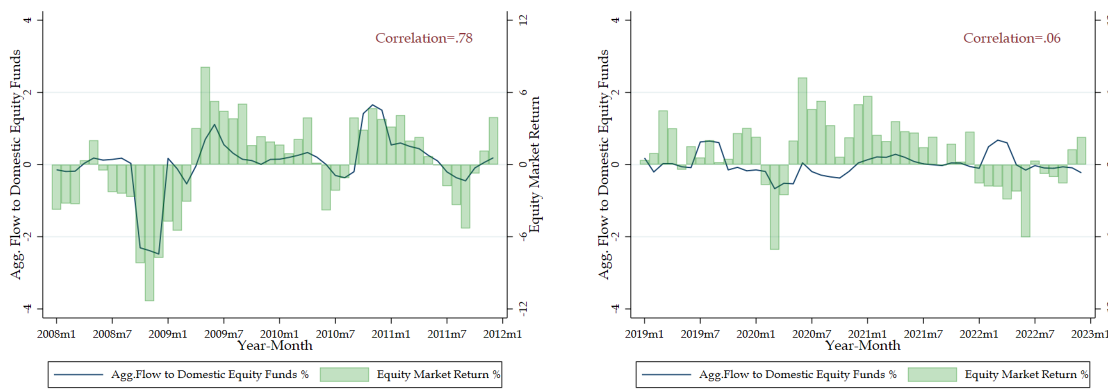
(b) TDF assets by years to retirement

Note: Panel (a) plots the sum of total net assets of target date funds (TDFs), target date collective investment trusts (CITs) and balanced funds (BFs) during 2000Q1-2022Q4 (left axis) and TDF assets as a fraction of total 401(k) assets in mutual funds (right axis). Assumed 67% of TDF investment is through 401(K) plans, following the ICI Factbook, 2022, Figure 8.20. Panel (b) plots the sum of total net assets (TNA) of TDFs broken down by years to retirement (grouped by ten years).
Source: Assets in TDFs and BFs are estimated using *CRSP*. Assets in CITs are collected from annual *Morningstar* TDF research reports. Total assets for 401(k) plans from ICI Quarterly Retirement Market data.

that stocks with higher TDF ownership (through the mutual funds held by TDFs) have lower returns after higher market performance, consistent with TDFs selling equity funds which then pass on the flow pressure to the prices of underlying stocks. Further, stocks with higher TDF holdings before the pandemic period show lower overall volatility during the subsequent market fluctuations during the pandemic, which suggests that TDFs and similar rebalancing investment vehicles that overlap with TDFs' holdings dampened stock price volatility during the pandemic.

Our first main result is partly summarized by the aggregate flow to performance relationships for U.S. equity funds shown in Figure 2. Panel A shows the financial crisis period and its aftermath, during 2008-2011. Flows to U.S. domestic equity funds track the equity market returns closely during this period. The correlation between flows and returns is 0.78, implying possible de-stabilizing effects. Panel B focuses on the COVID-19 pandemic period and shows different flow patterns. Strikingly, flows appear to be much

Figure 2: Equity returns and fund flows during financial crisis and pandemic periods



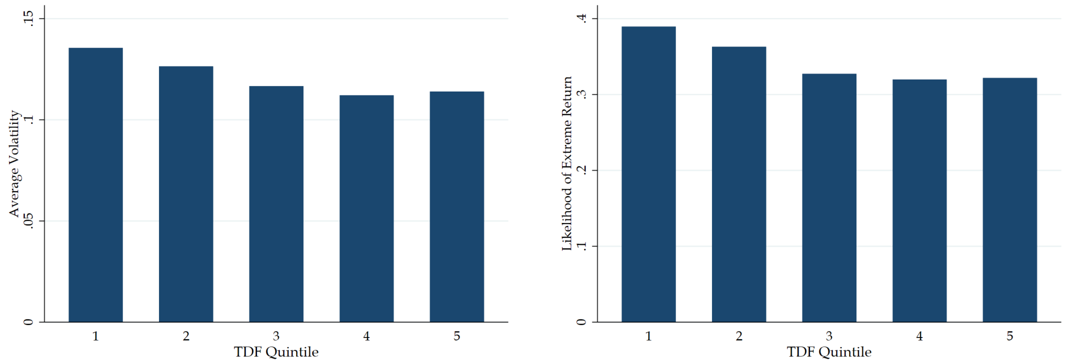
(a) Financial crisis period 2008.1-2011.12 (b) Pandemic period 2019.1-2022.12

Note: this figure shows aggregate flows to U.S. domestic equity funds during 2008.1-2011.12 (Panel A) and 2019.1-2022.12 (Panel B) (left axis) and the U.S. total equity market returns (right axis). Aggregate dollar flows are smoothed using 3-month moving averages and normalized by total assets with a 3-month lag. Returns are shown as 3-month moving averages.
Source: CRSP

less trend chasing during this period. We observe only mild outflows during the market decline of February to March 2020 and a lack of inflows during the rally in 2021. Moreover, we observe inflows to equity funds during the bear market of 2022. Of course, part of the reason for the new shape of flow sensitivity could be some trend-chasing flows have left mutual funds, for example, retail investors have started engaging more in direct stock trading during this period. However, retail investor behavior cannot explain the fund inflow during 2022, which is more likely to be caused by funds of funds like TDFs which buy equity funds after market declines depress their equity share to below the desired level.

Our second main finding is previewed by Figure 3 which shows that stocks that have (indirect) ownership by TDFs have lower volatility during the pandemic and are less likely to have extreme returns. We sort stocks into quintiles based on the fractions of their shares outstanding that are held (indirectly) by TDFs before the pandemic (averaged over the four quarters of 2018), and plot their subsequent volatility during the pandemic

Figure 3: Correlation between TDF investment and stock-level volatility



(a) Raw Return Volatility (b) Likelihood of Extreme Returns

Note: This figure plots the average raw monthly return volatility and the likelihood of extreme returns of stocks during 2019-2022 by levels of TDF investment in 2018. Stocks are sorted into quintiles according to their average indirect TDF ownership during 2018. Raw return volatility is the standard deviation of the monthly stock returns during 2019.1-2022.12. To reduce the influence of outliers, we winsorize stock returns at 1% and 99% before calculating the standard deviation. Likelihood of extreme returns is the fraction of months during 2019.1-2022.12 where a stock's monthly return is larger than 10% or smaller than -10%. We require stocks to have observable monthly returns for at least 24 months during the four-year window. Regression evidence with stock-level controls are shown in Table VII.

period, 2019-2022. Panel A plots the volatility of the monthly returns during the 48-month period. Stocks with the lowest TDF holding at the beginning of the period on average had a standard deviation of monthly returns of 14%, as opposed to a volatility of 11% for stocks with high TDF holdings (quintiles 5 and 4). Panel B plots the likelihood of extreme returns (monthly returns with magnitudes larger than $\pm 10\%$) out of all monthly observations. Stocks in the lowest-TDF quintile had these large swings in returns in 39% of the stock-month observations, while the fraction is at 32% for stocks with the highest TDF holdings. Of course, these are simply correlations and not adjusted for stock characteristics. In Section IV, we show that these relationships between TDF ownership and both volatility and extreme returns also hold in regression analysis that controls for a large set of other determinants of returns.

Historically, a majority of retirement investors have been either passive — letting their portfolio shares rise and fall with the returns on different asset classes — or active but re-allocating into asset classes or funds with better past performance, a behavior known as positive feedback trading or momentum trading that can amplify price fluctuations. Complementing evidence in PSS, this paper points out that due to the adoption of TDFs and TDF-like funds as default options in defined contribution plans and their mechanical trading rules, retirement savers have been moved from being passive or trend-chasing to contrarian traders who reduce market fluctuations even in times of extreme market stress and volatility.[2]

The expected magnitude of rebalancing by TDFs and TDF-like funds is the greatest with a target equity share of 50%, in contrast, funds with 0% or 100% equity share do not experience allocation distortions under differential asset class returns and do not need to rebalance (an important result we review in Section I). Therefore, the effects of rebalancing that we document both in PSS and in this paper are expected to grow, not only with continued growth of assets in TDF-like funds, but also as the younger workforce that are defaulted into TDFs get older and their portfolios are gradually shifted toward a more equal balanced between stocks and bonds by the glide paths of the TDFs.

Related Literature The most important pre-cursor to our paper is PSS, and we refer the reader to that paper for a broader discussion of the literature that it build on. We note here that there is a substantial amount of evidence that the rise of TDFs followed from financial innovation and regulatory changes and altered investor portfolio behavior. In particular, Mitchell and Utkus (2021), using data from one large 401(k) provider, shows that plan-level features, such as auto-enrollment, are key drivers of TDF adoption, and make a sizable impact on the portfolios of the adopters (see also Chalmers and Reuter, 2020; Parker et al., 2022; Zhang, 2022). And there is substantial work on the differences across TDFs and its causes and impact on investors (Balduzzi and Reuter, 2019; Shoven and Walton, 2020; Brown and Davies, 2020; Massa, Moussawi, and Simonov, 2020). A few recent papers also propose improvements to the glide path design of TDFs to consider realistic household characteristics and heterogeneity (Duarte et al. (2021)), as well as the time variation in the

[2]The literature has also shown that changes in the rules behind information providers such as the mutual fund ratings by Morningstar can change the trend-chasing behavior of fund flows (Evans and Sun, 2021; Ben-David et al., 2021).

expected equity premium (Gomes, Michaelides, and Zhang (2022)).

Our study also complements the literature on flows to mutual funds through defined contribution (DC) plans. For example, Sialm, Starks, and Zhang (2015a) and Sialm, Starks, and Zhang (2015b) show that menu adjustments by plan sponsors generate flows among equity and fixed income mutual funds that are more sensitive both to idiosyncratic performance and to macroeconomic shocks than flows outside of DC plans. In contrast, our paper studies the indirect flows to and from mutual funds through the trading by mixed-asset-class funds in DC plans like TDFs and balanced funds. These flows are counter-cyclical, thus offsetting the trend-chasing in the rest of the DC plans (i.e., direct listings of equity and bond funds). We do not have data on the menus or default options of DC plans, so we cannot speak to whether menu adjustments with respect to TDFs contribute to or reduce their main contrarian effect. However, our findings suggest that any discretionary decisions by plan sponsors, investors, or TDFs themselves do not cancel out the main rebalancing effect of the TDFs.

I. Summary of evidence on TDF rebalancing

This section summarizes the evidence that TDFs rebalance within a few months after differential asset class returns to restore the desired asset-class allocations. We describe the evidence from PSS that documents how the actual rebalancing trades of TDFs across asset classes match what one would expect given asset-class returns and the stated fund strategies.

First, how should we expect TDFs to rebalance? 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) during the period. As shown in the second panel of Table I, following equity and bond asset returns of R^E and R^B, 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 (row 2). These same quadratic patterns holds when

Table I: TDF Rebalancing in Response to Asset Class Returns

	Equity funds	Bond funds	Total
Initial and desired portfolio shares	S^*	$1 - S^*$	
Asset class return	R^E	R^B	
(0) Post-return value pre-trades and flows	$S^*(1 + R^E)$	$(1 - S^*)(1 + R^B)$	$1 + R^B$ $+S^*(R^E - R^B) \equiv V$
(1) Desired holdings	VS^*	$V(1 - S^*)$	V
(2) Total net purchases, $(1) - (0)$	$-S^*(1 - S^*)(R^E - R^B)$	$S^*(1 - S^*)(R^E - R^B)$	0

Note: This table shows the formula for 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. The formula in this table assumes zero net flow to the TDF. V denotes the value of the portfolio before trades and flows, or $1 + R^B + S^*(R^E - R^B)$.
Source: Parker, Schoar, and Sun (2023).

there are fund inflows or outflows, or when there are more than two asset classes.[3]

The rebalancing formulae – the last row of Table I – show that the better an asset class performs, the more the TDF must sell of that asset class and buy of the other asset class to rebalance. That is, TDF strategies are contrarian at the level of asset classes.

Importantly for testing, these formulae predict how different TDFs should rebalance: the amount of equity or bonds that a given TDF must sell in response to a positive excess return on that asset class is a quadratic function of its desired equity share, with a maximum for a TDF with a 50% desired equity share. This result is intuitive: for the same amount of differential asset class moves ($R^E - R^B$), a TDF with 100% or 0% equity share has no need to rebalance, and a TDF with 50% equity share faces the largest distortion to its asset allocation.

Second, do TDFs actually rebalance as predicted? While TDFs have some discretion

[3]See PSS, which shows that when the TDF experiences inflows or outflows at the same time as the differential asset class returns, it can rebalance through flows, purchasing the asset class that it needs more of with fund inflows or selling the asset class it needs less of to satisfy redemptions, but the cumulative net effect of TDF rebalancing trades is given by the same quadratic equation.

over rebalancing across asset classes, the answer is that TDF rebalancing is contrarian and quadratic as predicted. Further, one can measure the timing of the rebalancing. PSS shows that TDFs rebalance within a couple of months with passive funds rebalancing rapidly and more active funds rebalancing more slowly.[4]

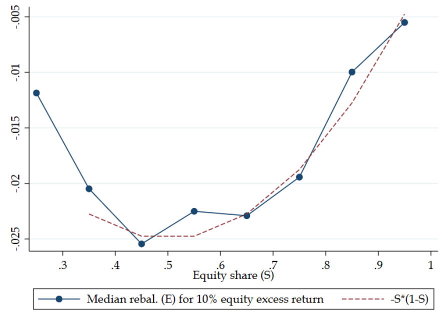
PSS develops a relatively standard method to measure rebalancing trades by TDFs, but we describe it precisely here because we use the same measures later in our paper. Given holdings data of the underlying mutual funds by TDF k in quarter q, define the dollar amount of the "total trade" for each share class (c) as the change in the value of holdings in excess of the value predicted by the quarterly share class return, that is, $TotalTrade_{ckq} = MV_{ckq} - MV_{ck,q-1}(1 + r_{cq})$. The observations from each holding to the TDF-by-asset-class level are aggregated to obtain $TotalTrade^{y}_{kq}$ where y stands for either the equity (E) or the fixed income (B) asset class. Given these amounts, the "flow-driven trade" by a TDF of an asset class is measured as the dollar flow to the TDF allocated pro rata to lagged portfolio weight of the asset class. Finally, the "rebalancing trade" is the difference: $Rebalancing^{y}_{kq} = TotalTrade^{y}_{kq} - FlowDrivenTrade^{y}_{kq}$. To match the formulae in Table I, where the total assets of the TDF are assumed to be one dollar, the dollar rebalancing trades are normalized by the lagged total assets of the TDF.[5] The return on equity, R^E, is the average return on domestic equity and foreign equity weighted using lagged TDF portfolio weights, thus is TDF-specific.

Before quantifying the relationship between predicted and actual rebalancing at the TDF level, Figure 4, reproduced from PSS, shows in broad terms that the rebalancing trades are contrarian at the asset-class level and that they match the quadratic pattern of the simple formula quite well. For each range of stated equity share, the median rebalancing across periods and TDFs with that stated equity share in response to a 10% excess return on equity in a quarter fits the quadratic function well for equity and slightly less well for

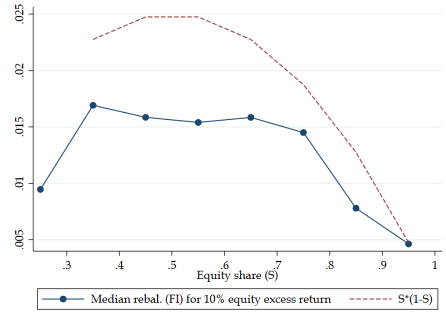
[4]In the bond market, rebalancing is typically not as strong as predicted, spread out over a couple of months, and has significant heterogeneity across funds as we discuss below.

[5]This calculation includes the cases of investment initiations (where $MV_{ck,q-1} = 0$) and terminations (where $MV_{ckq} = 0$). Note that this 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.

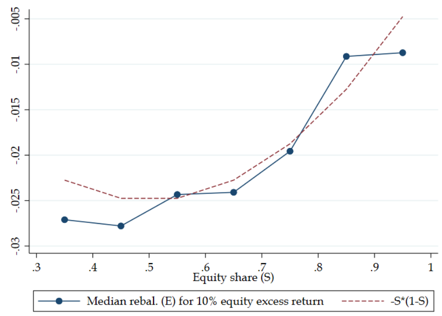
Figure 4: Median rebalancing by equity share



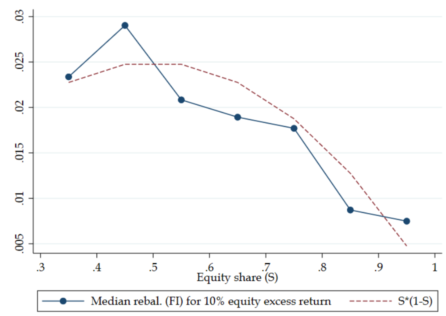
(a) Equity rebalancing - all TDFs



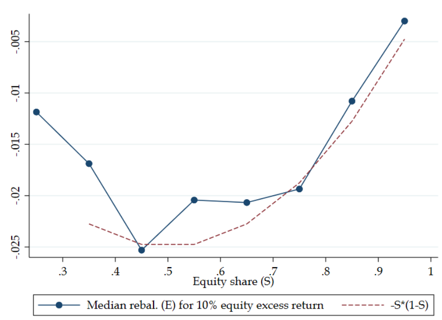
(b) Bond rebalancing - all TDFs



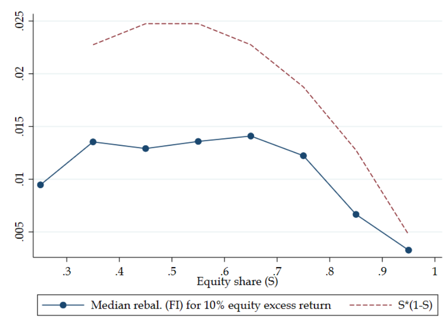
(c) Equity rebalancing - passive TDFs



(d) Bond rebalancing - passive TDFs



(e) Equity rebalancing - active TDFs



(f) Bond rebalancing - active TDFs

Note: The connected lines plot the median ratio of rebalancing by TDFs in each stated equity-share group: greater then 90%, greater then 80% up to 90%, . . . but the bin centered at 0.25 includes all TDFs whose equity share is at or below 30%. The outcome variable is the amount of rebalancing trade (in equity or bonds) scaled to show the amount of rebalancing for each 10% movement in $R^E - R^B$. 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.
Source: Parker, Schoar, and Sun (2023)

bonds (Panels (a) and (b) of Figure 4). For example, when $R^E - R^B = 10\%$, a TDF with 0.65 equity share is expected to sell 2.3% of its portfolio value in stocks, which is also what the median fund sells. Rebalancing with respect to bonds also has a quadratic shape, but the magnitude is lower than predicted. Panels (c)-(f) shows the results for passive and active TDFs separately. The smaller magnitude in bond rebalancing is due to active TDFs.

It is worth noting that TDFs designed for young and old investors engage in different degrees of this counter-cyclical rebalancing. Most TDFs start with a large desired share of equity – on the order of 90 percent - until roughly 25 years before retirement. The desired equity share declines smoothly over time to reach roughly 40 percent ten years after the target date. Therefore, an aging population (such as for the U.S.) can generate stronger counter-cyclical rebalancing demand, according to life cycle models, than a young population does.

To be more precise (and not limit analysis to the median TDF in each group), Table II presents a subset of the results on rebalancing contained in PSS and highlights three key findings in PSS about TDF rebalancing. First, during a quarter, TDFs rebalance roughly 80% of the amount predicted by the rebalancing formulae. Columns 1-2 show that TDFs rebalance 44%, 70%, and 83% of the predicted amount of equity in the same month as the return differential (row 1), by one month after the reurn (row 2), and by two months after (row 3) respectively. These coefficients trace out the monthly speed of rebalancing for the average TDF in equity funds. Control variables (added in column 2) make little difference to the estimated coefficients.

Second, passive TDFs rebalance more rapidly and more completely than active TDFs do. Splitting the sample of TDFs according to whether the majority of assets are invested in index funds or actively managed funds, column 3 shows that 50% of the predicted rebalancing is implemented within the same month for passive TDFs, and 85% by the end of the quarter. In contrast, column 4 shows that only about 40% is implemented by active TDFs within the same month, an amount which is not statistically significant. Similarly, passive TDFs completely return to desired shares within the same quarter, while active TDFs still have 27% of the way to go at the end of the quarter. As expected, portfolios of

Table II: TDF Rebalancing as a fraction of predicted rebalancing, 2008-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Rebal(E)_q$ / TNA_{q-1}				$Rebal(FI)_q$ / TNA_{q-1}			
	All		Passive	Active	All		Passive	Active
$Pred.rebal_{q,m=3}$	0.442**	0.436**	0.503***	0.408	0.179	0.087	-0.081	0.284**
	(0.215)	(0.193)	(0.116)	(0.260)	(0.151)	(0.220)	(0.335)	(0.126)
$Pred.rebal_{q,m=2}$	0.695***	0.727***	0.762***	0.710**	0.778***	0.660***	1.085***	0.398***
	(0.185)	(0.200)	(0.114)	(0.270)	(0.169)	(0.144)	(0.210)	(0.136)
$Pred.rebal_{q,m=1}$	0.829***	0.831***	0.852***	0.818***	0.694***	0.597***	0.883***	0.390***
	(0.139)	(0.128)	(0.092)	(0.166)	(0.160)	(0.143)	(0.159)	(0.120)
$Pred.rebal_{q-1}$	0.213*	0.218*	0.116	0.272*	0.190*	0.183	0.383**	0.013
	(0.111)	(0.117)	(0.070)	(0.151)	(0.112)	(0.121)	(0.188)	(0.070)
Controls	no	yes	yes	yes	no	yes	yes	yes
TDF FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	4,670	4,670	1,539	3,131	4,670	4,670	1,539	3,131
R-squared	0.228	0.235	0.434	0.214	0.260	0.266	0.439	0.221

This table presents a subset of results in estimating the relationship between actual rebalancing by TDFs in quarter q and the predicted values of rebalancing given the TDFs' equity shares and realized differential asset-class returns during the third, second, and first months of quarter q and during $q-1$ in the period 2008Q3-2018Q4. Observations are at the TDF quarterly level. $Rebal(E)_q$ / TNA_{q-1} ($Rebal(FI)_q$ / TNA_{q-1}) in columns 1-4 (5-8) is TDF-level rebalancing trade in quarter q with respect with equity (bond), divided by $TDF\ TNA$ in quarter $q-1$ and winsorized at 1% and 99%. $Pred.rebal_{q,m=t}$ stands for predicted rebalancing in response to the realized return of the tth month of quarter $qPred.rebal_{q-1}$ stands for the value of predicted rebalancing in response to the realized return of quarter $q-1$. R^E is approximated by the weighted average between total U.S. and foreign equity market return. Control variables include lagged quarter's log $TDF\ TNA$, log $Series\ size$, $Cash\ share$, and current quarter's $TDF\ flow\ rate$, $TDF\ quarterly\ return$, and $Years\ to\ retirement$. Standard errors are clustered two ways by TDF and quarter. *p < .1; **p < .05; ***p < .01.
Source: Table 3 of Parker, Schoar, and Sun (2023).

passive TDFs track their desired asset allocations more closely than active TDFs.

Third, smaller and less statistically significant coefficients in columns 5-8 suggest that TDF rebalancing in fixed income is weaker and slower. However, this finding may not reflect true economic exposure over time because TDFs' use cash and derivatives to rebalance fixed income exposures.[6]

We now turn to describing that data that we use in our analysis of the role of TDFs in stabilizing the equity market during the pandemic.

[6] PSS also examines the fit of the rebalancing model by provider and finds that TDF providers vary significantly in how closely they follow their prescribed glide paths.

II. Data on TDFs, funds, stocks, and returns

To maintain consistency, our use of data largely follows PSS.

TDFs We obtain quarterly fund characteristics and holdings of TDFs from the *CRSP Mutual Fund Database*. TDFs are identified from fund names containing target retirement years at five-year intervals ranging from 2000 to 2070, then manually cleaned using the TDF series names listed in the *Morningstar* annual TDF research reports. Most holdings of TDFs are other mutual funds which we link to the *CRSP Mutual Fund Database* using the CUSIP codes of the share classes. We use this matching to categorize each holding as domestic equity, foreign equity, or fixed income.

Equity mutual funds Using *CRSP*, we construct a dataset on the underlying mutual funds that focuses on domestic equity mutual funds (CRSP objective codes starting in ED). We use funds sold both to retail and institutional investors, and aggregate different share classes to the fund level. For each mutual fund, the percent ownership by TDFs is the total of TDF holdings (across all share classes) by the total assets of the fund.

Individual stocks Our panel dataset of monthly stock return, price, volume, and market capitalization is built from *CRSP* and financial data from *Compustat*. We include all stocks traded on the New York Stock Exchange, NASDAQ, and American Stock Exchange. We use Thomson Reuters and MFLINKS to measure stockholding by TDFs through mutual funds. For concerns over lack of liquidity, we drop stocks with market capitalizations that place them in the bottom 5% of NYSE stocks or with beginning-of-month prices below $5 (penny stocks), following Jegadeesh and Titman (2001).

In Table III, we present the summary statistics on TDFs, equity mutual funds, and stocks in our sample period 2019-2022. Compared with the earlier period of 2008-2018 studied in PSS, TDFs have higher but more volatile returns during the more recent period and have a reduced cash share. There are more passive TDFs in the new sample and the underlying mutual funds are more likely to be passive. We also observe that TDF ownership at the fund level and its indirect ownership at the stock level are both higher than in the earlier sample period. At the fund level, the average TDF ownership increased from 10% to 13%. At the stock level, TDF indirect ownership is doubled, from 0.64% to 1.28%.

Table III: Summary statistics of TDFs, equity mutual funds, and stocks, 2019-2022

Panel A. TDFs quarterly, N=7,498	Mean	p25	p50	p75	SD
Total net assets ($ billion)	2.621	0.032	0.214	1.211	7.396
Target year	2037.3	2025	2035	2050	16.0
Years to retirement	16.8	4	16	30	16.0
TDF quarterly return (%)	2.107	-1.325	3.715	7.165	8.354
Cash share (%)	1.406	0.060	0.870	2.500	3.188
Series size ($ billion)	41.596	0.482	4.096	20.271	107.766
Passive TDF	0.385	0	0	1	0.487
Panel B. Mutual fund monthly, N=17,218	Mean	p25	p50	p75	SD
Fund flow rate (%)	-0.31	-1.50	-0.45	0.64	3.55
Index fund	0.37	0.00	0.00	1.00	0.48
Frac. held by TDFs (%)	13.19	0.11	1.58	15.86	22.66
Fund size ($ billion)	17.0	0.6	1.8	8.6	72.9
Fund family size ($ billion)	934.2	63.3	249.5	821.4	1666.1
Fund age (year)	20.7	10.0	18.0	24.0	15.7
Expense ratio (%)	0.56	0.20	0.61	0.85	0.36
Return volatility (%)	5.47	4.35	5.42	6.70	1.55
Panel C. Stock monthly, N=48,928	Mean	p25	p50	p75	SD
Monthly return (%)	1.31	-5.03	1.20	7.08	11.73
4-Factor alpha (%)	0.18	-5.66	-0.16	5.50	10.70
TDF ownership (%)	1.28	0.90	1.10	1.47	0.68
Mutual fund ownership (%)	20.83	14.93	20.65	26.69	8.18
Market capitalization ($ billion)	21.18	0.96	3.04	12.11	94.96
Monthly volume/Shares out.	0.18	0.09	0.13	0.20	0.30

Note: For TDFs, *Target year* is the target retirement year stated in the fund name. *Years to retirement* is *Target year* minus current year. *Series size* is total size across TDFs in a series (a collection of TDFs with the same manager(s) but different target retirement years). *Passive TDFs* are those with more than 50% of their assets invested in index funds. For mutual funds, *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 *Fund size*. *Fund family size* is the total size of funds managed by a management company. *Fund age* is the years since inception of the oldest share class of a fund. *Expense ratio* is the weighted-average net expense ratio across share classes. *Return volatility* is the one-year standard deviation in the monthly returns. For stocks, *Monthly return* is the monthly total return of a stock. *4-Factor market beta* is the monthly return adjusted for market, SMB, HML, and momentum factor returns using betas estimated with the pre-window (1996-2005, requiring 24 monthly return observations). *TDF ownership* refers to the fraction of a stock owned indirectly by TDFs through mutual funds. *Mutual fund ownership* is the fraction of a stock owned by equity mutual funds that have no investment from TDFs. *Market capitalization* is total shares outstanding times the share price. *Monthly volume/Shares out.* is monthly trading volume normalized by the number of shares outstanding.
Source: CRSP.

Market excess returns We study monthly returns during from January 2019 to December 2022 inclusive. We measure equity returns as the total return of the U.S. equity from CRSP, and bond returns as the pre-fee return on the Vanguard Total Bond Market Index Fund.

Figure 5: Cumulative return of the stock market in excess of the bond market, 2019-2022

The cumulative excess return of the value-weighted monthly total U.S. equity market (R^E, solid line) less the Vanguard Total Bond Market Index Fund ($R^E - R^B$, dashed line) during 2019.1-2022.12. Both index levels are normalized to 1 at the start of 2019.
Source: CRSP.

Figure 5 plots of the cumulative returns of the U.S. equity market and the differential returns between equity and bonds during this pandemic period.

Following a sharp drop of 20% in the equity market during February-March 2020, the market experienced a rapid recovery, followed by strong performance in 2021, and a correction period with high volatility in 2022. Equity and bond returns have a correlation of 0.34 during this period, thus both the run-up in 2021 and the correction in 2022 appear smaller for the differential asset class return $R^E - R^B$ than for R^E.

III. The stabilizing effects of TDF ownership on equity mutual funds during the pandemic

The extreme stock market volatility during the COVID-19 pandemic period of 2019-2022 provides a useful window into the stabilizing effects of TDFs as well as a test of this effect during a crisis. The unprecedented volatility of the economy during the pandemic changed lots of economic relationships, and TDFs may have delayed rebalancing or even changed strategies. Similarly, retirement investors may have moved money out of TDFs in response to poor performance. Either of these changes would have made TDFs less market contrarian and reduced their stabilizing effects. This section builds on the evidence that we presented in Figure 2 and shows that, in fact, TDFs acted as stabilizer during the pandemic; they sold stock funds when the stock market did relatively well and bought them when it did poorly. For example, following the stock market crash of March 2020, we observe significant investment by TDFs into equity mutual funds during March and April of 2020, consistent with 70% of TDF rebalancing in equity being completed within the contemporaneous month and month following a differential asset class return (Table II).

Quantifying and generalizing this example in steps, we first study fund flows to equity mutual funds with different levels of TDF ownership during the months in which the difference in return between equity and bonds exceeded 8%. The fund flow rate for mutual fund j in month m is measured as the growth rate (in percent) in assets in excess of the realized net fund return, or $\frac{TNA_{j,m}-TNA_{j,m-1}(1+r_{j,m})}{TNA_{j,m-1}}$ where $TNA_{j,m}$ is total net assets and $r_{j,m}$ is net return. We sort equity funds into high-TDF and low-TDF groups using the average TDF investment in 2018.

Table IV shows that during the months of the pandemic with extreme returns, domestic equity funds with higher TDF exposure experience higher flows when equity under-performs bonds, and vice versa.[7] Means tests between the two groups show that several differences are statistically significant based on data for that one month alone. For example, during March 2020 when equity under-performed bonds by 12.7%, equity funds that had low TDF investments (measured in 2018) saw an outflow of 4.2% of assets, while those with high TDF investment experienced 2.9% outflow. The difference is statistically significant with a p-value of 0.03. Similarly, most differences in the flows in the other months are aligned with the predicted signs and are often statistically significant. Thus, TDFs do appear to offer counter-cyclical flows to the underlying mutual funds during the pandemic period in months when the stock market crashed or boomed.

[7] Due to space limitations, we present the months where the excess equity return over bonds is larger than $\pm 8\%$, or in the top or bottom fifth percentiles of the return distribution during the sample period.

Table IV: Flows to equity funds with high and low TDF ownership during months with extreme market returns

			High TDF		Low TDF			
		N		196		196		
		Mean TDF (%)		31.69		0.54		
		(SE)		(32.92)		(0.55)		
			Fund Flow (%)					
Month	$(RE-RB)_m$	$(RE-RB)_{m-1}$	N	Mean (SE)	N	Mean (SE)	High-Low	p-value
2019-05	-8.57%	4.12%	184	-0.589 (0.201)	192	-0.935 (0.244)	0.346	0.277
2020-02	-9.73%	-2.11%	175	-0.286 (0.197)	186	-0.902 (0.218)	0.616	0.038**
2020-03	-12.69%	-9.73%	177	-2.881 (0.400)	185	-4.159 (0.408)	1.278	0.026**
2020-04	11.94%	-12.69%	166	-0.256 (0.376)	180	1.021 (0.435)	-1.277	0.028**
2020-08	8.65%	4.22%	170	-0.815 (0.173)	182	-0.928 (0.242)	0.113	0.707
2020-11	11.36%	-1.49%	168	0.107 (0.219)	179	0.314 (0.294)	-0.207	0.577
2022-10	9.42%	-4.99%	155	-0.629 (0.197)	174	0.003 (0.255)	-0.632	0.055*

Note: Fund flow rates in percentages to equity mutual funds with high and low TDF holdings in months during 2019.1-2022.12 where differential return between equity and bond is larger than ±8%. Subsamples based on average TDF investments in funds in 2018 above and below median and do not include funds not held by TDFs. Differences in means between sub-samples and two-sided p-values are reported.
Source: CRSP

Second, to quantify the average effects of TDFs on fund flows, we estimate 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) using data from the entire pandemic period. We run the following regression:

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

In the equity fund sample, because retail investors typically invest more into equity funds when the stock market does well, we expect β_1 and β_3 to be positive for equity funds

(Warther, 1995; Edelen and Warner, 2001; Ben-Rephael, Kandel, and Wohl, 2011). But, because TDFs equity funds and buy bond funds when the stock market does well, we expect the main coefficients of interest, β_2 and β_4, to be negative. These coefficients measure the contemporaneous (β_2) and lagged (β_4) effect of greater TDF investment on fund flows following a positive return on the asset class of the fund. Equation (1) 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 sample of bond funds, we expect the reverse response to excess returns on the stock market because TDFs rebalance into bonds when equity outperforms. That is β_2 and/or β_4 should be positive for bond funds.[8]

We estimate equation (1) using only mutual funds with some TDF ownership at some point during the sample to avoid a large number of zeros in the regressions (with similar results using the entire sample). Further, since percent flow rates are noisy, especially for smaller funds, we drop observations below 1% or above 99% within the distribution for each asset class. Control variables $X_{j,m}$ include fund characteristics that have previously been found to affect fund flows, specifically fund size, fund family size, fund age, net 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 V shows that TDF ownership stabilized inflows and outflows from mutual funds during the pandemic period. Table V, columns 1-2 presents the estimates from equation (1) without and with fund fixed effects for all domestic equity funds in our sample. First note that the inclusion of fund fixed effects has little impact on the estimated coefficients, suggesting that the flow sensitivity to cross-sectional differences in returns and TDF ownership is similar as that to time-series changes in returns and changes in TDF holdings. Second, the coefficients on $(R^E - R^B)_m$, $(R^E - R^B)_{m-1}$ and on their interactions with *Index*

[8]To our knowledge, the bond fund literature has not established how bond fund flows respond to asset class returns. Goldstein, Jiang, and Ng (2017) and Chen and Qin (2017) both show that bond fund flows are sensitive to risk-adjusted returns, and Chen and Qin (2017) further shows that flows to bond funds follow the return of the aggregate bond market, however, these papers do not answer how bond fund flows respond to returns of the equity market.

Table V: Effect of TDF ownership on mutual fund flows, 2019-2022

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fund flow, m							
	Domestic equity funds				Corporate bond funds			
	All		Index	Active	All		Index	Active
$(R^E - R^B)_m$	0.046	0.055*	0.084***	0.047	0.094***	0.082**	0.124**	0.082**
	(0.030)	(0.030)	(0.029)	(0.030)	(0.035)	(0.035)	(0.047)	(0.036)
$(R^E - R^B)_m \times$ *Frac. by* $TDFs_{q-1}$	-0.109**	-0.107**	-0.194***	-0.073	0.027	0.022	-0.037	0.054
	(0.042)	(0.041)	(0.059)	(0.044)	(0.051)	(0.052)	(0.086)	(0.057)
$(R^E - R^B)_{m-1}$	0.022	0.034	0.038*	0.031	0.049*	0.046*	0.058*	0.052*
	(0.025)	(0.024)	(0.022)	(0.024)	(0.027)	(0.027)	(0.032)	(0.028)
$(R^E - R^B)_{m-1} \times$ *Frac. by* $TDFs_{q-1}$	-0.152***	-0.154***	-0.189***	-0.138***	0.241***	0.232***	0.271**	0.218***
	(0.038)	(0.038)	(0.066)	(0.036)	(0.060)	(0.062)	(0.111)	(0.068)
$(R^E - R^B)_m \times$ Index fund	0.022	0.016			0.053*	0.042		
	(0.018)	(0.017)			(0.027)	(0.028)		
$(R^E - R^B)_{m-1} \times$ Index fund	0.007	0.002			0.029	0.025		
	(0.014)	(0.014)			(0.024)	(0.021)		
Frac. by $TDFs_{q-1}$	-0.008**	-0.009	-0.024	-0.005	-0.004	-0.015	-0.075*	-0.010
	(0.003)	(0.007)	(0.017)	(0.008)	(0.004)	(0.014)	(0.038)	(0.014)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Fund FE	no	yes	yes	yes	no	yes	yes	yes
Time FE	no	no	no	no	no	no	no	no
Observations	17,200	17,200	6,342	10,858	4,804	4,804	1,385	3,419
R-squared	0.043	0.136	0.109	0.127	0.094	0.189	0.151	0.193

Note: The dependent variable $Fund\ flow$ is the growth rate in fund assets in excess of the realized net fund return. $R^E - R^B$ is the excess return of the U.S. total stock market over the U.S. total bond market. The sample in columns 1-4 (5-8) includes retail and institutional domestic equity funds (corporate bond funds) which are held by any TDF during the sample period. $Frac.by\ TDFs$ is measured as the fraction of fund assets held by TDFs, measured at the end of the previous quarter. Control variables include the lagged month's log *Fund size*, log *Fund family size*, current month's log *Fund age*, *Expense ratio*, and lagged *Return volatility*. Standard errors are clustered two ways by time and fund. *p $<$ .1; **p $<$ .05; ***p $<$ .01.
Source: CRSP

suggest that equity fund flows chase equity market performance and slightly more so in index funds.[9] For the typical non-index equity fund that has no holding by TDFs, a ten percent decline in the stock market is associated with an outflow of 0.46% of assets under management ($\widehat{\beta_1}$) in the month of the return and an additional outflow of 0.22% of assets under management ($\widehat{\beta_3}$) the following month, based on estimates in column 1.

Our key result however is that this trend-chasing behavior is significantly reduced for funds with higher TDF ownership. The coefficients on the interaction terms with TDF ownership, $\widehat{\beta_2}$ implies that, in response to a decline in the stock market, the associated outflow is reduced by 24% in the month of the return (1.09$\times$0.1/0.46) for each 10% of the

[9]See also Dannhauser and Pontiff (2019) which documents differential flow-performance relationships in actively managed funds and index funds.

mutual fund that is owned by TDFs, and by a total of 38% ((1.09+1.52)×0.1/(0.46+0.22) = 0.261/0.68 = 0.38) on average over the month of and following the stock market decline. The estimates imply that the average TDF rebalances by a similar amount in the month of the return and the month after ($\widehat{\beta_2}$ and $\widehat{\beta_4}$ respectively), consistent with the timing of rebalancing by TDFs in the period prior to the pandemic (Section I).

This contrarian trading behavior is stronger for index funds that are held by TDFs than it is for actively managed funds (as seen in Columns 3 and 4). Rebalancing in index funds is also faster. Column 3 shows that rebalancing in index funds is stronger in the contemporaneous month as the return shock, while column 4 shows that rebalancing in actively managed funds is stronger in the following month. The greater and more rapid rebalancing in index funds almost surely reflects differences in TDFs rather than differences in rebalancing across funds within TDFs. The Vanguard TDFs for example hold index funds (and derivatives) and rebalance to desired equity exposure on a daily level, while Fidelity TDFs that tend to invest more in active funds and also have more discretion and allow equity share to vary over time to seek higher total returns and to save on trading costs.

For corporate bond mutual funds, Table V also shows that rebalancing by TDFs into bond funds when equity outperforms is passed on to the underlying fund level, and mainly in the following month (in columns 5-8, $\widehat{\beta_4}$ is consistently positive and significant).

In sum, we find that TDF ownership in mutual funds had a significant contrarian effect on equity fund flows during the pandemic. Thus, even in this time of extreme economic disruption, neither a reduction in rebalancing by TDFs nor active rebalancing out of TDFs by retirement investor undid the automatic TDF rebalancing that is documented in the pre-pandemic period by PSS. The typical automatic rebalancing by TDFs and inertial behavior by TDF investors respectively meant that TDFs continued to produce contrarian flows to equity funds. Did these funds stabilize the stock and bond markets during the pandemic? We turn next to evidence on the effect of TDFs on return differentials across stocks.

IV. TDF ownership and stock returns during the pandemic

This section shows that, because TDFs buy stock funds when the overall stock market does poorly and sell stock funds when the stock market does well, they affect both the co-movement between stocks and market and the individual volatility of stocks.

A. TDFs lower stock return sensitivity to recent market performance

Because TDFs have a contrarian effect on fund flows which then put counter-cyclical pressure on stock prices, we expect stocks with higher *indirect* holdings by TDFs – through the mutual funds that TDFs invest in – to have lower sensitivity to systemic shocks that move the stock or bond markets. PSS shows evidence in line with this hypothesis during the decade before the pandemic, and hypothesized an increasingly important role for TDFs and TDF-like strategies. Here we use the pandemic market movements to test this hypothesis.

We estimate the impact of TDF trading on monthly "alphas," which are monthly returns in excess of the returns one would expect based on their historical correlation with standard systemic risk factors and the realizations of these risk factors (described in more details below). We run the following regression using monthly data from 2019 to 2022, a period with both sizable TDF assets and high market volatility:

$$\begin{aligned} Alpha_{iml} = {} & \lambda_1 (R^E - R^B)_m \times TDF_{iq-1} + \lambda_2 (R^E - R^B)_{m-1} \times TDF_{iq-1} + \gamma TDF_{iq-1} + \\ & \xi X_{im} + \delta_1 X_{im} \cdot (R^E - R^B)_m + \delta_2 X_{im} \cdot (R^E - R^B)_{m-1} + \\ & Return_{im-1} + Return_{i,m-6 \text{ to } m-2} + \theta_{ml} + \epsilon_{im} \end{aligned} \tag{2}$$

where i indexes the stocks, m represents a month, l refers to the three-digit SIC industry classification, and $(R^E - R^B)_m$ and $(R^E - R^B)_{m-1}$ are the current and lagged months' excess return of equity over bonds. The coefficients λ_1 and λ_2 measure the effect of TDF ownership on stock returns by measuring differences in risk-adjusted returns among stocks that are held in different amounts (indirectly) by TDFs. These are the coefficients on the asset class returns interacted with lagged percentage of indirect TDF ownership at the stock level, calculated as $TDF_{i,q-1} = \Sigma_{jk} a_{ij,q-1} b_{jk,q-1}$ 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. Our analysis also controls for the typical co-movement of stock returns within industries by including industry(3-digit SIC)-by-time fixed effects (θ_{ml}). If TDFs stabilize stock returns, then λ_1 and λ_2 should be negative. The analysis clusters the standard errors two-ways by time (year-month) and stock.[10]

In addition to controls directly included in equation (2), we control for typical differences in returns for different stock by using the risk-adjusted monthly return of the stocks as the dependent variable rather than the raw return. We follow a standard four-factor risk adjustment model, which includes Market-rf (the excess return of the total equity market over the risk-free rate), small-minus-big (SMB or the size factor), high-minus-low (HML or the value factor) (Fama and French, 1993), and momentum (Carhart, 1997). An issue with this risk adjustment is that TDF trading can directly affect the sensitivity of a stock's return to the performance of the market, 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 require at least 24 observations for each beta estimate and winsorize the alphas at 1% and 99% to account for the fat tails due to extreme movements unrelated to TDF trading.

Table VI shows that higher TDF ownership is associated with lower sensitivity to market momentum. That is, when the overall stock market does well, stocks that have a large indirect TDF ownership perform worse than they should have given their (pre-TDF-period) risk-factor exposure and the movement in these risk factors. This lower return is consistent with their under-performance because they are being disproportionately sold by TDFs when the overall stock market return is relatively high. In column 1, a specification without controls, the coefficient on $(R^E - R^B)_m \times TDF_{iq-1}$ indicates that a 1% higher TDF

[10] We can roughly infer the different effects of passive and active TDFs from differences between $\hat{\lambda}_1$ and $\hat{\lambda}_2$. As shown in Table V, passive TDFs contribute to the contemporaneous month effect λ_1, while both passive and active TDFs contribute to the next month effect λ_2. Because the holdings of active and passive TDFs are highly correlated at the stock level, we cannot estimate separate coefficients on the interaction terms with holdings by passive and active TDFs.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				4-Factor alpha, m			
Beta window			1996-2005			2006-2015	2009-2018
$(R^E - R^B)_m \times TDF_{q-1}(\%)$	-0.051**	-0.062**	-0.053**	-0.057**	-0.049*	-0.009	-0.006
	(0.024)	(0.025)	(0.024)	(0.026)	(0.027)	(0.020)	(0.018)
$(R^E - R^B)_{m-1} \times TDF_{q-1}(\%)$	-0.027**	-0.030**	-0.028**	-0.020*	-0.021*	-0.032***	-0.027**
	(0.013)	(0.013)	(0.011)	(0.010)	(0.012)	(0.008)	(0.011)
$TDF_{q-1}(\%)$	-0.000	0.001*	0.001	0.001	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ret, m-1			-0.070***		-0.069***		
			(0.021)		(0.019)		
Ret, m-6 to m-2			-0.005		-0.005		
			(0.007)		(0.007)		
Controls	no	yes	yes	yes	yes	no	no
Characteristics $\times$ $R^E - R^B$	no	no	no	yes	yes	no	no
Time-by-industry FE	yes	yes	yes	yes	yes	yes	yes
Observations	48,626	45,036	43,575	45,036	43,575	67,877	78,925
R-squared	0.268	0.280	0.292	0.283	0.295	0.218	0.179

Note: This table examines the relationship between indirect TDF ownership and monthly stock return sensitivity to differential asset class performance during 2019-2022. The dependent variable *4-factor alpha* is the risk-adjusted return winsorized at 1% and 99%, where the factors include Market-rf, SMB, HML (Fama and French, 1993), and momentum (Carhart, 1997). The beta loadings are estimated using monthly stock returns during 1996-2005 in columns 1-5, 2006-2015 in column 6, and 2009-2018 in column 7. Each estimation requires 24 monthly return observations. $TDF_{q-1}(\%)$ is the share of a stock indirectly owned by TDFs measured at the end of the previous quarter expressed in percentage points. Control variables include log of lagged values of *Market capitalization*, *Monthly volume/Shares out.*, *Market-to-book ratio*, and lagged values of *Dividend yield 12m*, *ROE*, *Investment*, *Illiquidity*, and *Mutual fund ownership*. Standard errors in this table are clustered two ways by time and stock. *p $<$ .1; **p $<$ .05; ***p $<$ .01.
Source: CRSP

ownership of a stock implies a 0.051 lower sensitivity of the 4-factor alpha of that stock to the contemporaneous market return. We offer an interpretation of the magnitude below.

We also find that TDF ownership significantly stabilizes the returns on a stock the month after the market return: the coefficient on $(R^E - R^B)_{m-1} \times TDF_{iq-1}$, which was not precisely estimated in PSS, is significant and just over half the size of the contemporaneous effect during the pandemic period. The fact that there is a large and measurable lagged effect – consistent with the delayed rebalancing documented in the previous section – may be due to the larger size of TDFs or the larger size of the market movements in this more recent period than in the period studied by PSS.

When adding stock characteristics in column 2 as controls, the estimated effect of TDF ownership becomes slightly stronger. In column 3, we further control for the stock return lagged by one month and the cumulative return from month $m-6$ to $m-2$ to account for both short-term reversal and medium-term momentum in the stock returns. We observe a strong negative coefficient on the one-month lagged return, consistent with the well-known reversal effect. However, controlling for lagged returns does not change our estimates of the TDF effect in the contemporaneous month.

Controlling for interactions of market returns with stock-level characteristics does not alter the estimated TDF effect, implying that the TDF effect is distinct from the potential effects of other stock characteristics on return dynamics. Columns 4 and 5 shows the main coefficients when we include the full set of stock characteristics interacted with both $(R^E - R^B)_m$ and $(R^E - R^B)_{m-1}$. The set of characteristics include log of lagged market capitalization, trading volume, the market-to-book ratio, lagged trailing-twelve-month dividend yield, ROE, investment, illiquidity, and the holdings by mutual funds that are not held by TDFs. If our results were entirely driven by the different characteristics of TDF-held stocks, we would expect the main coefficients on the interaction terms between differential asset class returns and indirect TDF investment to disappear in this specification. In fact, the effects of TDFs remains significant.

One possible concern is the use of the period 1996-2005 to estimate the stock betas and so to infer risk-adjusted returns, our alphas in equation 2. For example, if betas varied dramatically over time, our measure would then be poor and possibly introduce bias. In addition, the mechanical requirement for a stock to be traded during the pre-window excludes a large fraction of observations which may be important for testing our hypothesis. Below we offer several pieces of evidence to alleviate these concerns.

First, the stock betas do not move much in a way that is correlated with (indirect) TDF ownership. Though stock betas have on average risen over time, the change is not dramatic relative to the standard deviation within each estimation window.[11] The table also shows that the lowest-TDF quintile is the most affected by the mechanical data restriction

[11]Appendix Table A.1 presents summary statistics of betas estimated using alternative windows, in groups sorted by TDF holdings in 2018 (one year before our sample). In fact, the subgroup with the highest TDF holdings sees a slight decline in market beta, which is consistent with the role of TDFs in decreasing the stock return sensitivity to asset class movements.

problem, thus the procedure mostly excludes "control" stocks which are less affected by TDFs. Further, the newer firms that were not traded during the earlier window are tilted toward technology companies, so these companies which had abnormal performance during our period are actually under-represented in our sample and so are not driving our results.[12]

Our results are also somewhat robust to some plausible alternative ways of calculating the betas used in risk adjusting stock returns. In columns 6-7 of Table VI, we report results using the alternative windows 2006-2015 and 2009-2018. As expected, the estimated same-month TDF effect ($\hat{\lambda}_1$) becomes much smaller and statistically insignificant, because estimated betas in these more recent windows absorb some of the TDF effect.[13] However, the effect of the lagged $R^E - R^B$ ($\hat{\lambda}_2$, not taken out by the estimated beta) is almost the same as in the other columns. This result reassures that the main effect of using the early pre-2006 window for beta is to prevent the TDF effect from being taken out by the risk adjustment, thus allowing the estimation of $\hat{\lambda}_1$.

B. How much did TDFs cushion the market decline during February-March 2020?

We now take the estimates above to do a back-of-the-envelope exercise to approximately quantify i) how much the rebalancing policy by TDFs offset fund outflows at the onset of the pandemic (February and March 2020, when the equity market dropped relative to bonds by 9.7% and 12.7%, respectively), and ii) how much TDFs may have cushioned these stock price declines.

First, from the coefficients in Table V column 2, during the two-month period including and following a return, TDFs offset roughly 38% of fund flows in our sample of funds and about 19% of flows of all domestic equity funds. We calculate the first number based on our result that for any excess equity market return $(R^E - R^B)_m$ in month m, the aggregate domestic equity fund would experience a total net flow of $(R^E - R^B)_m \times 0.089$ during both

[12] That is, one might argue that our results are more convincing because we excluded the stocks of these companies from the study.

[13] Though the estimation windows precede the sample period, TDF holdings are persistent.

m and $m+1$ had there been zero TDF investment. We obtain 0.089 by summing up the flow sensitivity to both the current month return (0.055) and the lagged month return (0.034). Then, using the coefficients on the interaction terms with fractions held by TDFs and the fact that the average fund in our sample has a 13% TDF ownership, TDFs affect fund flows by $-(R^E - R^B)_m \times (0.107 + 0.154) \times 13\% = -(R^E - R^B)_m \times 0.034$ in months m and $m+1$. This results then leads to our conclusion that TDFs offset roughly $0.034/0.089 = 38\%$ of fund outflows in a two-month period.[14] Note that our regression sample includes only domestic equity funds that are held by TDFs during our sample. Those funds account for around 50% of all fund assets, so that, scaling down the fraction by half, TDFs offset about 19% of fund flows of all domestic equity funds.

Turning to the effect on asset prices, the coefficients in Table VI suggest that for the average stock that is held 1.3% (indirectly) by TDFs (Table III), TDFs can cushion return changes by $(0.051 + 0.027) \times 1.3(R^E - R^B)_m$, or $0.1014(R^E - R^B)_m$ in months m and $m+1$, for an excessive equity return $(R^E - R^B)_m$ in month m. Therefore, during the 21% drop in the first two months of the COVID crisis, TDFs should have pushed up the average stock price by $0.1014 \times 21\% = 2.13\%$, or about one-tenth of the aggregate decline.

This effect on asset prices may seem large, given that indirect TDF holdings account for a small fraction of the shares outstanding of the typical stock. However, as we discuss above, TDF trades can offset a greater fraction of the flow-induced trades by mutual funds, so the impact of TDFs may be big from a flow perspective.[15] In addition, our measure of indirect TDF holdings almost surely picks up TDF-like funds that rebalance in a similar contrarian manner. We discuss other rebalancing funds in Section D.

Our calculation above also illustrates how the growth of TDFs can change the flow and price dynamics during crisis periods, which may contribute to some of the stark contrast in asset price movements between the 2020 COVID period and the 2008 financial crisis (although there are many other sources of differences too). Interestingly, the estimated

[14]Specifically using the cumulative excess equity return during February-March 2020 ($-21\% = (1 - 0.097) \times (1 - 0.127) - 1$), the average domestic equity fund in our sample would have experienced an outflow of 1.9% ($21\% \times 0.089$), but TDFs bought in 0.71% ($21\% \times 0.034$).

[15]This result is also consistent with recent studies showing that small shifts in the demand for stocks can lead to large price changes, see, for example Gabaix and Koijen (2020).

coefficients of TDF effects, which are scaled by TDF holdings of mutual funds or stocks, have similar magnitudes in PSS and in the current paper, suggesting that each unit of TDF has a similar effect during the COVID crisis and the earlier periods. The main difference between the periods is then the assets in TDFs. That is, the growth in TDF and TDF-like funds leads them to account for a larger fraction of ownership of domestic equity funds and stocks and so have a bigger impact. We estimate that TDFs held at most 0.2% of the aggregate assets in domestic equity funds during the financial crisis in 2008,[16] compared with at least 5% before the pandemic. Therefore, the effects of TDFs both on fund flows and asset prices should have been minimal during 2008, consistent with Figure 2.

C. TDFs lower return volatility

We next examine whether TDF ownership of a stock is associated with lower volatility of the returns on that stock during the pandemic period. For this analysis, we collapse the stock panel to one cross section by calculating the standard deviation of monthly returns during the period and the likelihood of extreme returns (monthly returns higher than 10% or lower than -10%). We then examine whether these volatility measures are negatively related to TDF investments in the stocks. To avoid the regressors being affected by the dependent variables, we take the TDF indirect ownership from 2018 by averaging the four quarters. Table VII Panel A shows the summary statistics of the stock-level volatility measures. The average monthly return standard deviation during this four-year period is about 13%, and in 37% of the monthly observations, a stock has an "extreme return" where the absolute magnitude of the monthly return is larger than 10%, confirming the overall high volatility during this period.

Figure 3 in the Introduction shows that stocks in higher quintiles of TDF indirect ownership in 2018 had lower stock return volatility during the pandemic period. Column 1 in Panel B of Table VII shows a continuous regression version of this result: stocks with greater ex ante TDF ownership have lower raw return volatility during the turbulent markets of 2019-2022. Column 4 also shows that they have a lower likelihood of extreme

[16] The holdings data of TDFs is noisy before 2009, thus this is a very rough estimate.

Table VII: TDF ownership and stock return volatility

A. N=2,791	Mean	p25	p50	p75	SD	
SD Monthly Return (%)	12.96	9.16	11.99	16.10	5.15	
Likelihood of Extreme Return (%)	37.34	23.81	35.42	50.00	18.00	
Frac. by TDFs (%)	1.15	0.60	0.94	1.45	0.88	
Frac. By MFs (%)	18.14	10.33	17.94	25.72	10.33	
B.	(1)	(2)	(3)	(4)	(5)	(6)
	SD Monthly Return (%)			Likelihood Extreme Return (%)		
Frac. by TDF (%), 2018	-1.298***	-0.946***	-0.398***	-4.173***	-3.389***	-1.641***
	(0.117)	(0.117)	(0.115)	(0.398)	(0.406)	(0.359)
Frac. by MF (%), 2018		-0.063***	-0.043***		-0.141***	-0.077*
		(0.010)	(0.011)		(0.036)	(0.041)
Constant	14.447***	15.193***	26.067***	42.121***	43.781***	82.050***
	(0.178)	(0.240)	(0.830)	(0.601)	(0.805)	(3.285)
Controls	No	No	Yes	No	No	Yes
Observations	2,791	2,791	1,944	2,791	2,791	1,944
R-squared	0.049	0.061	0.373	0.041	0.046	0.347

Note: Panel A presents summary statistics of the cross section of stocks with volatility measures based on 2019-2022. Panel B examines the relationship between TDF ownership and stock return volatility. *SD Monthly Return (%)* measures the standard deviation of monthly returns during the four year window expressed in percentages. *Likelihood of Extreme Returns (%)* is the fraction of months where the absolute value of the stock return is larger than 10%, expressed in percentages. *Frac. by TDFs (%)* is the percentage of a stock indirectly owned by TDFs measured as an average during 2018. *Frac. by MFs (%)* is the percentage of a stock owned by mutual funds with zero TDF investment measured as an average during 2018.Control variables include logs of *Market capitalization*, *Monthly volume/Shares out.*, *Market-to-book ratio*, and *Dividend yield 12m*, *ROE*, *Investment*, and *Illiquidity*, all measured as an average during 2019. Robust standard errors are reported. *p < .1; **p < .05; ***p < .01.
Source: CRSP

returns. But this pattern could be due to the different characteristics of stocks that TDFs choose to own. To address this possibility, we run a cross-sectional regression with a full set of controls for stock characteristics that have been found to be associated with differential returns.

Focusing first on the role of TDFs that are unrelated to general mutual fund ownership (columns 2 and 5), we still find that stocks with greater ex ante TDF ownership have both lower raw return volatility and lower likelihood of extreme returns, but both relationships are slightly smaller. Second, in columns 3 and 6, we control for log of market capitalization, trading volume, the market-to-book ratio, and trailing-twelve-month dividend yield, ROE, investment, and illiquidity, all measured with 2018 values. The coefficient on TDF ownership drops in half again, but, even with this full set of controls, remains highly statistically significant.

To conclude, even based on the smallest estimates in columns 3 and 6, those with all controls, a 1% higher TDF ownership share is associated with 0.4% lower standard deviation of return volatility and 1.6% lower likelihood of realizing extreme returns.

D. Mis-measurement due to other TDF-like investors

A concern with our results so far is that our measure of TDF ownership at the stock level could be picking up holdings of other funds with fixed asset allocations. If these funds pursued identical strategies to the TDF sector, then we would be underestimating rebalancing flows (in the previous section), accurately measuring the effect of these strategies on stock returns (in the analysis above), but underestimating the true ownership share by investors with TDF-like strategies. If for example there were as much money outside of TDFs pursuing the same strategies as inside TDFs, then the main coefficients in Table VI and Table VII (and their standard errors) would be biased upward by a factor of two. On the other hand, our calculation of the effect on a stock's return or volatility of moving one standard deviation in TDF ownership would be an unbiased estimate but would measure the effect of moving one standard deviation in both TDF and other funds ownership.

Alternatively, other funds pursuing TDF-like strategies might hold portfolios of stocks that are uncorrelated with and unrelated to the portfolios of stocks held by the TDF sector. In this alternative extreme case, our estimates of the stock-level impact of TDFs would be completely unbiased. But for any randomly chosen stock, there would be reduction in stock volatility coming from these other funds that we would not measure in addition to the effect of TDFs that we would measure.

The truth probably lies somewhere between these two extremes. An additional complication is that the investors in these funds could respond to the pandemic or market movements by taking money in and out of these other funds, unlike TDF investors who do not on net reallocate much even in response to the economic disruption of the pandemic.

In sum, it is likely that our main measure of TDF ownership at the stock level has measurement error due to other funds or strategies that invest in a way that is contrarian at the asset-class level in a way that is similar to TDFs. Below we follow PSS and discuss these other types of funds to consider how their strategies might interact with our analysis.[17]

Model portfolios Model portfolios are fund-of fund strategies that mostly hold mutual funds and exchange-traded funds and that follow prescribed strategies. They include i) robo-advisors, ii) financial advisors, broker-dealers, and home offices that provide fund advisory or allocation programs that make or advise automated re-allocations, and iii) some mutual fund companies that provide strategists or model platforms. Model portfolios have the feature of TDFs in that they try to maintain fixed allocations and provide some automatic rebalancing. Model portfolios managed roughly $4 trillion in 2019.[18] Given the similarity in investment objectives and overlap in sponsors between TDFs and the providers of model portfolios (e.g. companies like Fidelity), model portfolios and TDFs may seek to hold similar portfolios and so may have highly correlated holdings within the equity space at the stock level. The trading behavior of portfolios managed by model portfolios may therefor have substantial similarity to the trading behavior of assets held in TDFs at the stock level, as in our first example above.[19]

Hedge funds The global hedge fund industry does not appear to pursue similar trading strategies to those of TDFs and in fact many funds tend to try to be market nuetral, so that their returns at the asset-class level are unaffected by the return on the asset class. Grinblatt et al. (2020) shows evidence that two thirds of the hedge funds pursue cross-sectional contrarian strategies, quite different than the market-contrarian trades of TDFs. However there is one hedge fund strategy that is more akin to the trading behavior of TDFs: "risk parity," which seeks to maintain a desired risk level and therefore may sell an asset class that has relatively high returns. But these strategies are typically not pursued at the asset class level and we know of no such hedge funds strategies that try to maintain an explicit target asset allocation.

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[17]See Lu and Wu (2023), which uses data from FactSet (which is primarily based on 13F filings) to estimate the rebalancing demand at the asset manager level.

[18]See "the Rise of Model Portfolios", broadridge.com; "Model Portfolios Surging as Advisers Seek Quick Ways to Invest Client Money", *Wall Street Journal*, 12/4/2020. According to Morningstar ("2021 Model Portfolio Landscape"), the vast majority of model portfolios provide equity shares between 50% and 70%.

[19]For example, when BlackRock adjusted its model portfolios in 2021, the underlying funds (ETFs) experience massive flows within a week. See "BlackRock Tweaked Some Models. It Triggered a Wave of Buying and Selling", *Wall Street Journal*, 7/9/2021.

Pension funds and endowments Pension funds, foundations, family offices and endowments tend to pursue rebalancing strategies at much lower frequencies and, while the sometimes do have target allocations at the level of the asset class, these are often revised at the same (annual or lower) frequency at which managers might seek to return to target. That is, pensions and similar institutions do state target allocations at the level of the asset class. However, these funds have more discretion over portfolio balance after initial investment, have much greater freedom to deviate from any explicit desired balance, and often adjust the targets in response to market movements (Andonov and Rauh (2020)). In sum, rebalancing of pensions and endowments may provide some aggregate contrarian fund flows that complement those from TDFs, but probably rebalance much more slowly and less completely..

V. Returns from trading before or with TDFs

One question one might ask is whether the stabilizing effect of TDFs might in the future be eliminated by other strategies that trade against these funds. Put differently, have TDFs made retirement investors “smarter” investors with the additional benefit of stabilizing stock prices, or have TDFs made retail investors more exploitable by other traders with more sophisticated strategies?

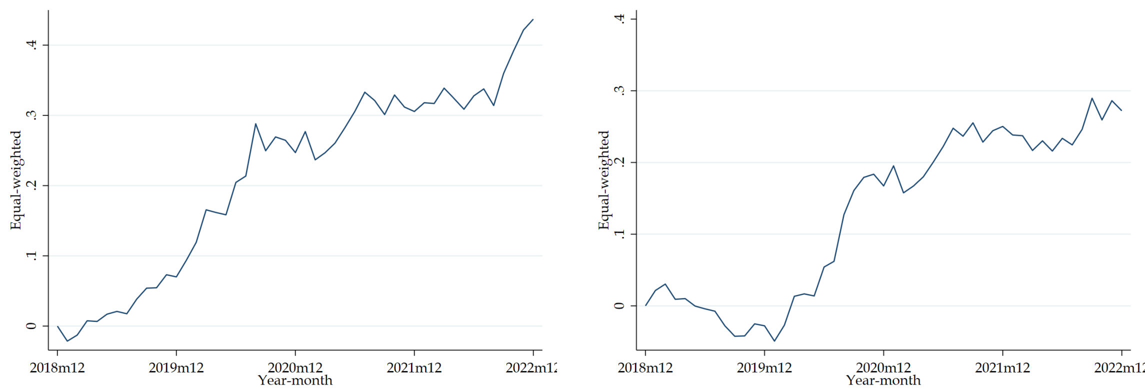
While a full answer to these questions requires a complete model and correct understanding of these investors’ goals, a partial answer comes from studying whether the TDF trading strategy was profitable during the pandemic, or whether trading against the automatic rebalancing in these retirement funds would have been profitable. PSS investigates this before the pandemic, when retail investors were moving money into equity funds in response to positive excess returns on the stock market. In this case, one might expect sophisticated arbitrage capital to trades against these general retail/institutional flows and alongside TDFs, suggesting that TDF strategies might produce better risk-adjusted returns. However, during the pandemic retail investors traded in the opposite direction as in normal times, buying the pandemic dip, for example. In this case, TDFs and retail investors would have traded together in a macro-contrarian manner, and one might reasonably ask whether sophisticated capital was trading against or alongside TDFs and whether doing so would have produced better risk-adjusted returns over this period.

Following PSS, we consider one long-short strategy that (infeasibly) trades and holds for the month of an asset-class return (and the contemporaneous TDFs rebalancing), and one long-short strategy that (feasible) trades and holds for the month following the returns (and so trades alongside slower TDF rebalancing). To trade alongside TDFs, both of these strategies short high-TDF stocks and buy low-TDF stocks (at the start of the month in question) when the stock market return is high and take the opposite position when the market return is low (and hold for a month). The profit of these strategies approximates the profit from the aggregate rebalancing trading by TDFs while using stocks with low TDF exposure as a hedge. As before, we sort stocks into quintiles based on TDF ownership in each quarter and then form portfolios every month based on the sign of the excess equity market return.

Consider the first strategy that 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. This strategy is impossible in practice because it requires knowledge of aggregate returns during a month at the start of the month. It also involves risk. Figure 6 panel A shows that the cumulative risk-adjusted return of this strategy is 40% over the four years 2019-2022, or about 83 bps per month on average. We interpret this excess return as (infeasible) upper bound to the profit of a cross-sectional trading strategy that trades in the same direction, but ahead of, TDFs.

Consider the second strategy that trades along with TDFs in the month following a return, month m: 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 $(R^E - R^B)_{m-1} < 0$. Because this strategy trades the month after a return, it is feasible. This strategy trades alongside the slower rebalancing TDFs, which we show are primarily the *active* TDFs. Panel B of Figure 6 shows that this strategy of trading along with active TDFs still generates positive profits. In fact, somewhat surprisingly it is only slightly less profitable than the infeasible

Figure 6: Returns From TDF-Based Long-Short Trading Strategy



(a) Current-Return Strategy

(b) Lagged-Return Strategy

Note: This figure shows the cumulative 4-factor alphas 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 (panel (a)) or previous month (panel (b)) is negative, and the reverse when the excess stock market return is positive. 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. Stocks are sorted into quintiles according to their average indirect TDF ownership in 2018.

strategy that trades ahead of TDFs. That said, the key point for us is that sophisticated capital would not have been able to exploit predictable rebalancing by TDFs during this period: feasibly trading against TDFs would have generated a loss of 30% return over four years.

In sum, the TDF rebalancing the month after a return seems to be profitable in a cross-sectional sense during the pandemic period. It does not seem to be profitable to trade against TDFs based on the previous month return. Thus arbitrage capital should not be allocating funds to trading strategies that would reduce the cross-section price impact of TDF trading going forward.

VI. Concluding remarks

Target date funds have become an important financial instrument for retail investors, largely following the 2006 Pension Protection Act which qualified TDFs to serve as default options in 401(k) retirement plans. At present, 90% of employers offer TDFs as the default options in their retirement plans, and TDFs manage one quarter of all 401(k) plan assets.

But while TDFs were designed to be optimal for households taking returns as given, they have had an unintended and significant stabilizing impact on mutual fund flows and on stock returns during the period of market volatility around the pandemic. Because TDFs rebalance portfolios by selling stocks when the stock market rises and buying stocks when the market falls, they have acted as a market-stabilizing force. These findings complement and extend the evidence of Parker, Schoar, and Sun (2023) based on the period before the pandemic when TDFs were growing and economic outcomes were more typical. We show that even during the unprecedented volatility of the last few years, TDFs have stabilized the funding of the mutual funds that they disproportionately invest in, and they have stabilized the prices of stocks that they (indirectly) disproportionately hold.

If the amount of funds invested through TDFs continues to grow, or as the population ages and remains in TDFs so that more TDF assets are near a 50% equity share implying maximum rebalancing, the contrarian trading of these types of funds may start to have greater effects on aggregate market returns. By putting downward pressure on stock prices after market increases and upward pressure after market drops, contrarian strategies are likely dampening overall stock market fluctuations. That said, at the moment these market-wide effects cannot be measured well given market volatility, a reasonable estimate of the elasticity of the level of the overall stock market to TDF trading, and the size of the TDF sector at the moment. TDF macro-contrarian trading is also likely affecting the serial correlation of returns, and increasing the correlation between stock and bond returns, but again in ways too small to evaluate or quantify to date.

Finally, we should emphasize that any stabilizing effect of TDFs on the stock market may or may not be beneficial for the stock market, the economy, or even the TDF investor. If a given stock market movement is an inefficient, transitory fluctuation in market prices, then trading by TDFs may increase market efficiency by reducing the deviation of prices from their efficient fundamental values. Alternatively, if a fluctuation is instead an efficient response to fundamentals (e.g. a permanent change in aggregate dividends), then trading by TDFs may decrease market efficiency (and/or TDFs would lose some returns to arbitrage capital that trades to restore fundamental prices).

An alternative design choice for TDFs that would not require a stand on whether fluctuations are or are not efficient would be to take a *macro-optimal* perspective and structure the TDFs to hold a portfolio comprised of an age-dependent combination of a risk-free asset and the market portfolio of all risky assets (consisting of whatever share of stocks and bonds there are in the market portfolio). As people aged, the TDF would have them hold more of the risk free asset and less of the market portfolio, but as the stock market fluctuated, the TDF would only adjust the balance between all risky assets – stocks and bonds – and risk-free short term debt.

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Appendix: Additional Results

Table A.1: Summary statistics of beta estimates

A.	β using monthly returns 1996-2005				
TDF holding quintile	Obs.	Missing	Mean	Median	SD
5	287	46.4%	0.99	0.93	0.59
4	329	38.5%	1.02	0.95	0.61
3	332	37.9%	1.02	0.91	0.61
2	277	48.2%	0.87	0.80	0.66
1	178	66.8%	0.82	0.70	0.69
B.	β using monthly returns 2006-2015				
TDF holding quintile	Obs.	Missing	Mean	Median	SD
5	414	22.6%	0.95	0.96	0.54
4	446	16.6%	1.03	1.02	0.48
3	432	19.3%	1.04	1.02	0.46
2	402	24.9%	0.98	0.89	0.58
1	283	47.2%	0.97	0.90	0.67
C.	β using monthly returns 2009-2018				
TDF holding quintile	Obs.	Missing	Mean	Median	SD
5	487	9.0%	0.98	0.95	0.49
4	493	7.9%	1.04	1.06	0.67
3	493	7.9%	1.05	1.02	0.48
2	480	10.3%	1.01	0.93	0.59
1	366	31.7%	0.96	0.88	0.70

Note: This table reports the summary statistics of betas estimated using different time windows for stocks observed during 2018 that satisfy the sample selection procedure described in II. TDF holding quintiles are sorted based on the average indirect TDF ownership in 2018. Beta estimates use monthly returns during 1996-2005 in Panel A, 2006-2015 in Panel B, and 2009-2018 in Panel C. Each beta estimation requires 24 observations in the respective window. The number of non-missing beta values, fraction of observations with missing betas, mean, median, and standard deviations of betas are reported for each quintile of stocks are reported.
Source: CRSP