Target Allocation Funds, Strategic Complementarities, and Cross-Market Fragility*

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Abstract

Target date funds and other funds with target allocations (TAFs) rebalance in a predictable manner: when equities plunge, TAFs redeem bond fund shares and purchase equity fund shares, transmitting equity market shocks to the bond market. This introduces a new form of cross-market fragility: when equities fall and TAFs are expected to rebalance out of bond mutual funds, *other* investors also redeem strategically, since liquidation costs are borne by the remaining mutual fund investors. These strategic runs are particularly pronounced among illiquid bond mutual funds, where liquidation costs are large and therefore payoff complementarities are strong. Together, TAF rebalancing and the associated runs explain half of aggregate bond fund outflows and a significant share of Treasury and corporate yield dislocations during COVID-19. The growth of TAFs contributes to the rise in stock-bond correlation and weakens the traditional role of bonds as safe-haven assets.

Keywords: target allocation, strategic complementarity, stock-bond correlation

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1 Introduction

There has been a secular rise in target allocation strategies. Among registered investment funds, assets under management by target date funds and other funds with explicit allocation targets—henceforth target allocation funds (TAFs)—have more than doubled over the past decade and now exceed $2 trillion. To maintain target allocations, TAFs rebalance in a predictable manner: when equities underperform bonds, they sell bonds and buy equities. This behavior has important implications for market dynamics. Notably, Parker et al. (2023); Parker and Sun (2023) show that, following equity-market declines, TAFs provide contrarian inflows into equities, dampening shocks to equity prices. In this paper, we study the other side of the coin: while TAF rebalancing dampens shocks *within* a market, it also transmits shocks *across* markets.

The COVID-19 crisis provides a salient illustration of these market dynamics. During the crisis, the bond market experienced severe turmoil (Haddad et al., 2021), and a major contributor was historic outflows from bond mutual funds (Falato et al., 2021; Vissing-Jorgensen, 2021). Specifically, there were in total $178 billion of net outflows from bond mutual funds in 2020Q1 alone, as shown in Panel A of Figure 1. Why were there large outflows from bond mutual funds? The red bars in Panel A of Figure 1 show that TAFs redeemed $59 billion worth of bond fund shares, accounting for 33% of the total outflows. Panel B of Figure 1 shows that, in percentage terms, TAFs redeemed 12% of their bond fund shares during COVID-19, about four times the redemption rate of other investors. The reason behind TAFs' redemptions is evident from Panel A of Figure 2, which shows that TAFs simultaneously redeemed bond fund shares and purchased equity fund shares during the COVID-19 crisis. During COVID-19, equity values fell sharply by 21%, while bond values changed much less. Absent rebalancing, this shift in relative valuations would have substantially increased the portfolio weight of bonds. To maintain target allocations, TAFs

withdrew capital from bond funds and redirected it to equity funds.[1]

These market dynamics are further complicated by the fact that most TAFs are funds of funds. Rather than trading equities or bonds directly, TAFs trade shares of equity or bond mutual funds, which not only provide diversified exposure but also, crucially, liquidity transformation. Specifically, while the underlying assets such as corporate bonds can be quite illiquid, bond mutual funds allow TAFs to purchase and redeem fund shares at net asset values that are largely insulated from market liquidity. When equities decline and TAFs need to rebalance by redeeming from bond mutual funds, bond mutual funds need to sell underlying bonds to meet redemptions, which may incur significant transaction costs especially when there is limited liquidity in the bond market, such as during the COVID-19 crisis. However, the transaction costs are not fully borne by the redeeming investors—i.e., the TAFs—but are instead borne by investors who remain in the fund. As a result, this liquidity transformation generates strategic complementarity among mutual fund investors and, as we will show, can lead to run-like behavior. We refer to this mechanism as *cross-market fragility*.

We have three main findings. First, TAFs make highly predictable rebalancing trades given realized returns, and the trades are influenced by the costs of liquidating underlying assets and whether the costs are internalized at the fund family level. Second, when equities experience large declines – such as those during the COVID-19 crisis – predictable redemptions by TAFs trigger strategic runs by *other* non-TAF bond mutual fund investors, because liquidation costs are not borne by the redeemers but instead by the remaining investors. This strategic complementarity is particularly salient for bond mutual funds holding illiquid bonds, and we rule out alternative explanations by analyzing holdings by *individual* bond mutual fund investors. Lastly, Treasury and investment-grade corporate bonds with greater exposure to TAFs exhibit stronger comovement with equity market returns. We estimate

[1]Contemporaneous work by Foley-Fisher and Lee (2025) also demonstrates this rebalancing behavior.

that TAFs' rebalancing activities and the associated runs they trigger account for 17% of the rise in stock-bond correlation over the past decade. As target date funds and other target allocation vehicles continue to grow, the dynamics we document may play an even bigger role in future crises.

We begin by showing that TAFs make predictable rebalancing trades conditional on lagged holdings and realized returns. Most TAFs are funds of funds, and a typical TAF's allocation to a fund remains remarkably stable over time (Parker et al., 2023). We confirm that these funds do exhibit sticky allocation targets. Building on this allocation rigidity, we characterize the theoretical rebalancing trades a TAF would conduct in response to realized returns on its portfolio funds. These theoretical rebalancing-induced trades (RIT) represent the adjustments required to keep the TAF exactly at its target allocations, using public information available to all market participants in real time. We show that there is a near one-for-one relationship between RIT and TAFs' actual trades. During COVID-19, most of the bond fund redemptions and equity fund purchases can be explained by RIT.

Focusing on bond funds, we find that the near one-for-one relationship between theoretical and actual rebalancing is influenced by illiquidity. Among affiliated bond funds within the same fund families, TAFs trade illiquid bond funds less than one-for-one with RIT, especially during illiquid periods such as the COVID-19 crisis. This behavior suggests that, when redeeming from affiliated bond funds, TAFs internalize the transaction costs of liquidating the underlying bonds. Consistent with this interpretation, such a liquidity pecking order is not observed for unaffiliated bond funds, where the liquidation costs are fully external. Using this liquidity adjustment, we refine the calculation of RIT and reaffirm its predictive power for actual TAF trades in the cross section of bond mutual funds.

Because TAFs' rebalancing activities are highly predictable based on lagged holdings and realized returns – which are publicly available to market participants in real time – other fund investors can react strategically. As shown by Chen et al. (2010) and Goldstein

et al. (2017), for U.S. mutual funds, when some investors request redemptions, the costs associated with liquidating the underlying bonds are borne by the *remaining* investors. This is because these funds allow investors to redeem at the current NAV, which does not factor in subsequent liquidation costs through mechanisms such as swing pricing. Therefore, when TAFs are expected to redeem their bond fund shares, other investors are incentivized to also redeem in order to avoid bearing the liquidation costs.

We show strong evidence of this strategic complementarity in the cross section of bond mutual funds during the COVID-19 crisis. For each bond mutual fund in each period, we aggregate predicted rebalancing trades by all TAFs, accounting for liquidity adjustment based on fund affiliation. We find that bond mutual funds facing higher rebalancing-induced redemptions by TAFs experienced significantly larger outflows from *other* non-TAF bond fund investors. Specifically, when a bond mutual fund is expected to experience 1% higher rebalancing-induced redemption from its TAF investors, it simultaneously experiences 0.681% higher outflows from other investors. Consistent with theory prediction, this coordinated run is much more pronounced for bond mutual funds holding illiquid bonds, where liquidation costs are large and therefore payoff complementarities are more salient. We show robustness of our results with respect to various alternative measures of illiquidity.

To further rule out alternative explanations, such as endogenous selection by unobserved rebalancers, we analyze a subset of investors for which we observe granular holdings at the *individual* investor level, including non-TAF mutual funds and insurance companies. By including investor fixed effects, we purge out the heterogeneity across investors and zoom in on the same investor's trading across different bond mutual funds. With this investor-level data, we find similar comovement with TAF rebalancing-induced trading: non-TAF mutual funds and insurance companies withdrew more from TAF-exposed bond mutual funds compared to other bond mutual funds they held, during COVID-19. Based on the coefficient magnitudes, institutional investors exhibited much stronger run coordination than

the average investor. This investor-level analysis provides further confirmation on presence of strategic complementarity.

It is important to distinguish the direct effect of returns from their indirect effect through rebalancing. While we directly control for contemporaneous and lagged returns in all regressions, we demonstrate the robustness of our results by constructing a version of RIT that relies exclusively on equity fund returns and is therefore orthogonal to bond funds' own returns. Our main results hold when using this equity-return-induced rebalancing measure, highlighting that it is the negative shocks to equity markets that trigger the strategic bond mutual fund runs we document.

Strategic runs from other investors amplify the rebalancing-induced redemptions by TAFs. Using the estimates from our cross-sectional regression, we estimate that the aggregate amount of strategic redemptions by other investors during COVID-19 was $27 billion. Rebalancing by TAFs and the associated runs by other investors explain $86 billion, or 48%, of the total outflows from bond mutual funds during the COVID-19 crisis. This amplification gives rise to a concave relationship between equity-market returns and flows to TAF-exposed bond mutual funds. When equity markets experience large negative returns, TAF rebalancing triggers strategic runs by other investors, whereas this coordination is absent for mild or positive equity returns.

Turning to asset pricing implications, we show that TAFs transmit equity market shocks to the bond market, particularly during crisis periods. For identification, we exploit cross-sectional variation in Treasury and corporate bonds' exposure to TAF rebalancing. We take a bottom-up approach and aggregate two layers of intermediation: purchases and redemptions of bond funds by a given TAF, and buying and selling of bonds by a given bond fund. For each layer, we carefully adjust for liquidity pecking order, using the same approach as Ma et al. (2022). Our rebalancing exposure is a significant predictor of how bond returns comove with the aggregate equity market. During the COVID-19 stock market crash, bonds with

higher exposure to TAF rebalancing experienced much more negative returns.

Lastly, we provide evidence that TAF rebalancing contributes significantly to the rise in aggregate stock-bond correlation over the past decade. To do this, we calculate aggregate TAF rebalancing-induced trades on equities and bonds, incorporating the amplifying trades by other investors due to strategic complementarity. We then multiply these aggregate trades by existing estimates of aggregate price multipliers (Gabaix and Koijen, 2021; Ma et al., 2022) to arrive at rebalancing-induced returns. By subtracting these rebalancing-induced returns from actual returns, we derive the counterfactual aggregate stock-bond correlation absent TAF rebalancing. The results show that, without TAF rebalancing-induced trades, aggregate stock-bond correlation would have decreased from 0.11 to -0.01 at year-end 2023, eliminating 17% of its rise over the past decade.

Our findings have important implications for market stability and the safe-haven role of bonds. The same contrarian rebalancing that stabilizes equity markets can destabilize bond markets. When this rebalancing is implemented through open-end bond mutual funds, it can generate redemption externalities and trigger run-like dynamics. This mechanism works against the traditional flight-to-safety pattern: during downturns, investors typically reallocate toward safe government bonds and highly rated corporate bonds, putting upward pressure on bond prices (Baele et al., 2019). TAFs mechanically rebalance in the opposite direction, from safe-haven assets toward risky assets. As target date funds and other target allocation funds continue to grow, this reverse-flight-to-safety channel can weaken the hedging role of bonds and increase stock-bond comovement.

1.1 Literature

This paper contributes to the understanding of target allocation strategies and their unintended consequences (Balduzzi and Reuter, 2018; Massa et al., 2022; Parker et al., 2023;

Parker and Sun, 2023; Andonov et al., 2024; Lu and Wu, 2025; Harvey et al., 2025). Parker et al. (2023) study the secular growth of target date funds and show that their predictable contrarian rebalancing increases stock-market resilience: when equities underperform bonds, target date funds buy equities to restore their target allocations, thereby partially reversing the initial equity shock. Parker and Sun (2023) extend this analysis to the COVID-19 crisis, showing that target date funds provided important stabilizing demand during the pandemic crash. Although the authors also document the bond leg of rebalancing, their central insight is that TAFs provide stabilizing demand to the equity market. We complement their analysis by showing that TAF rebalancing does not make equity-market shocks disappear; rather, it spreads them across other markets, stabilizing equities while generating redemption pressure in bond funds and price pressure in bonds. We do so by constructing a refined measure of rebalancing-induced trading (RIT) that captures return heterogeneity at the fund level, and by accounting for liquidity pecking order through two layers of intermediation: TAFs tend to prioritize redeeming more liquid bond funds, and bond funds tend to prioritize selling more liquid bonds. Most importantly, we show that predictable TAF redemptions trigger strategic responses from *other* bond fund investors: because early redeemers avoid liquidation costs that are borne by remaining investors, other investors also redeem, amplifying the direct rebalancing shock through the first-mover advantage in open-end mutual funds.

Harvey et al. (2025) develop market-level proxies for portfolio rebalancing and show that predictable rebalancing has significant effects on both aggregate equity returns and aggregate bond returns. We provide complementary evidence by developing rebalancing-induced trading (RIT) for each individual TAF in our sample, and show that this measure predicts comovement with equity-market downturns in the cross section of Treasury and corporate bonds. We also provide evidence that TAF rebalancing explains a sizable fraction of the rise in stock-bond correlation over the past decade. More importantly, both papers document strategic behavior in response to predictable rebalancing. Harvey et al. (2025) focus on arbitrageurs' incentives to front-run rebalancers and profit from the price impact of

predictable rebalancing trades. Our mechanism is different. We focus on investors who co-invest with TAFs in the same open-end mutual funds. When TAFs are expected to redeem from bond mutual funds, other investors also redeem to avoid bearing liquidation costs, due to the first-mover advantage created by open-end fund liquidity transformation.

Second, we contribute novel evidence on strategic complementarity in liquidity transformation vehicles. The classic insight of Diamond and Dybvig (1983) is that liquidity provision against illiquid assets can generate run incentives because investors' withdrawal decisions are strategic complements. To test strategic complementarity, existing studies focus on redemptions in response to worsening fundamentals, based on the prediction of Goldstein and Pauzner (2005). Chen et al. (2024) show evidence for banks, while Chen et al. (2010) and Goldstein et al. (2017) show evidence for equity and bond mutual funds. This paper complements existing studies with a more direct test of strategic complementarity. In our setting, plausibly exogenous equity-market shocks induce TAFs to redeem from bond mutual funds because of their investment mandates. These predictable redemptions impose liquidation-cost externalities on remaining bond fund investors, giving other investors an incentive to redeem strategically to avoid bearing the costs. Thus, mandated rebalancing by one class of investors allows us to identify run-like behavior by other investors in the same liquidity-transformation vehicle.

Finally, our paper contributes to the understanding of bond market turmoil during the COVID-19 crisis. Unlike previous crises in which Treasury yields fell as investors engaged in flight to safety (Baele et al., 2019), March 2020 featured severe selling pressure and puzzling yield spikes in U.S. Treasuries (Haddad et al., 2021), calling into question their role as safe-haven assets. Duffie (2020); Duffie et al. (2023) show that limited dealer intermediation capacity constrained the Treasury market's ability to absorb selling pressure. Falato et al. (2021); Vissing-Jorgensen (2021); Ma et al. (2022) show that bond mutual funds were an important source of the selling pressure, as unprecedented outflows forced these funds to

liquidate underlying bonds. We further uncover an origin of bond fund outflows: mechanical rebalancing by TAFs.

Contemporaneous work by Foley-Fisher and Lee (2025) uses daily flow data and similarly shows that rebalancing trades by funds of funds account for a third of total bond fund outflows. Our contribution is to derive a theoretical measure of rebalancing-induced trading (RIT) that matches observed TAF trading nearly one-for-one. More importantly, we show that rebalancing-induced redemptions by TAFs are significantly amplified by strategic runs from other bond fund investors, and these dynamics together account for close to half of the total bond fund outflows during COVID-19. As target date funds and other funds with target allocations continue to grow relative to the bond market, the mechanisms we document will likely become even more important in future crises.

2 Background and Data

We study registered investment funds with explicit allocation targets (henceforth TAFs).[2] Figure A1 shows examples of the TAFs in our sample. For instance, the prospectus of Fidelity Asset Manager 60% Fund describes its principal investment strategies as: "Maintaining a neutral mix over time of 60% of assets in stocks, 35% of assets in bonds, and 5% of assets in short-term and money market instruments." When equities and bonds realize different returns and their relative values change, the fund would need to rebalance: buy equities and sell bonds, or vice versa, such that the target allocations are restored.

One important group of TAFs that we focus on are target date funds (TDFs). These funds have target allocations that slowly adjust over time. For example, the prospectus of Fidelity

[2]There are other investors that also follow target allocation strategies, such as defined-benefit pension funds, endowments, and collective investment trusts. We focus on funds registered under the Investment Company Act of 1940 because they report granular data on portfolio holdings, allowing us to measure rebalancing-induced trades directly.

Freedom 2055 Fund describes its principal investment strategies as: "Investing primarily in a combination of Fidelity U.S. equity funds, international equity funds, bond funds, and short-term funds... Allocating assets according to a neutral asset allocation strategy shown in the glide path below that adjusts over time..." According to the glide path, copied in Figure A1, the fund initially targets 90% equities and 10% bonds, which slowly shift to 20% equities and 80% bonds over several decades. Parker et al. (2023) show that, at quarterly frequency, TDFs are effectively TAFs. Panel A of Figure A2 shows that the total AUM of TAFs has more than doubled from less than $1 trillion in 2011 to $2.4 trillion in 2023. The growth mainly comes from TDFs, which have overtaken conventional target allocation funds in size since 2014. One important driver is the 2006 Pension Protection Act, which designated TDFs as a qualified default investment option in 401(k) plans (Mitchell and Utkus, 2021).

Most TAFs are funds of funds, meaning that they invest in other mutual funds and not directly in bonds or equities. This way, the asset-class-level allocation decision is separated from the individual asset-level portfolio decision: the TAF focuses on broad asset allocation by rebalancing between specialized funds, and the specialized funds focus on picking individual stocks or bonds. Apart from diversified exposure, mutual funds also perform liquidity transformation, allowing TAFs to transact fund shares without incurring the underlying costs of transacting bonds or equities. As we will elaborate, this liquidity transformation generates strategic complementarity between TAFs and other fund investors.

Most TAFs, especially TDFs, target allocations to a broad set of asset classes, not just equities versus bonds. Panel B of Figure A2 shows that TAFs invest almost half of their equity portfolio in international equity funds, i.e. funds that invest in stocks of foreign corporations. International equities can have meaningfully different returns from domestic equities. This is an important motivation for our bottom-up rebalancing measure in Equation 1, which captures heterogeneity in returns across styles within an asset class.

Panel C of Figure A2 shows that TAF assets are managed by a broad set of fund families,

the biggest of which include Vanguard, Fidelity and American Funds. Consistent with Balduzzi and Reuter (2018); Massa et al. (2022), Panel D of Figure A2 shows that TAFs mostly invest in affiliated funds. As we will show later, investing in affiliated funds facilitates the internalization of liquidation costs.

2.1 TAF rebalancing during the COVID-19 crisis

The COVID-19 crisis serves as a great illustration of TAFs' rebalancing activities. In the first quarter of 2020, the S&P 500 declined by 21% from 3258 to 2585. Over the same period, the Bloomberg Aggregate Bond Index (AGG) rose 5%. A fund with 60-40 allocation between equities and bonds would see the portfolio move to 52-48, without rebalancing. To restore the 60-40 target allocation, the fund needs to sell bonds, which have appreciated in values, and buy equities, which have declined in values. In other words, a TAF engages in contrarian trading (Parker et al., 2023).

This contrarian trading is indeed what happened during the COVID-19 crisis. Panel A of Figure 2 shows that, during the COVID-19 crisis, TAFs redeemed large quantities of bond funds and simultaneously purchased large quantities of equity funds in nearly equal amounts. The magnitude of bond fund shares redeemed is massive, at $59 billion, which accounts for 33% of the total outflows from bond funds during COVID-19, as shown in Panel A of Figure 1.

Panel B of Figure 2 shows that this contrarian behavior is remarkably consistent throughout the past decade, not limited to COVID-19. The solid and dash lines show returns to equity funds and bond funds that are held by TAFs. Equity returns are much more volatile than bond returns and drive most of the variation in their differences. The bars show TAF net purchases of equity funds (blue) and bond funds (red). Whenever equity returns turn negative, TAFs reallocate from bond funds to equity funds. The graph also shows that the

absolute amounts of these rebalancing trades have grown substantially over time, mirroring the rapid growth of TAFs.

2.2 Sample and data sources

Our data on target allocation funds and bond mutual funds come from CRSP and Morningstar. The data contain total net assets (TNA), returns, expense ratios, and rear loads for each fund at monthly frequency. We identify fund family affiliation using management company names, following Dannhauser and Spilker (2023).[3] For both TAFs and the bond mutual funds they hold, we aggregate share class information to the fund level.

Importantly, CRSP and Morningstar provide quarterly snapshots of fund holdings at the CUSIP level.[4] This means that we can link the CUSIPs to the bond mutual funds that they belong to and obtain a database of TAFs' holdings of bond mutual funds. We manually correct any anomalies we observe in the holdings data. Common data errors include missing share classes[5], duplicate holdings[6], and look-through holdings[7], which we detect and correct manually. Over our sample period, 324 TAFs are merged into other TAFs, and we manually examine each merger to ensure that the resulting changes in holdings are not mistakenly treated as purchases or sales.[8] These data cleaning procedures are crucial for us to accurately

[3]We take into account mergers between fund families. For example, Nuveen funds are assigned under TIAA after 2014.

[4]Some funds report monthly holdings, but over 30% of the TAFs in our sample report holdings only at quarterly frequency. For funds that do not report at quarter-end, we use the reporting dates closest to quarter-end. Specifically, if a fund reports holdings on January, April, July and October, we will assign those holdings to Q4 of previous year, Q1, Q2 and Q3, respectively.

[5]For example, almost all of the share classes held by T. Rowe Price TAFs after March 2020 are missing from CRSP, such as T. Rowe Price Equity Index 500 Z TRHZX 779552504. We manually download these share classes from Morningstar and link them to the corresponding CRSP funds.

[6]For example, almost all American Funds TAFs report duplicated positions in 2021Q4 and 2022Q1 (e.g. on Intermediate Bond Fund of America R-6 RBOGX 45880981). We detect these cases using the sum of portfolio weights and delete the duplicate holdings.

[7]For example, each of Vanguard Institutional Target Retirement Funds reports thousands of positions in equities and bonds in 2019Q2, whereas in other periods they typically report only several positions of fund shares.

[8]For example, Vanguard Institutional Target Retirement 2025 Fund was merged into Vanguard Target

compute net purchases by TAFs and subsequently infer net flows from non-TAF investors.

As mentioned above, we consider both conventional target allocation funds and target date funds, which effectively have fixed allocation targets in the short run. We identify these funds as those whose Lipper Classification Code starts with "MTA" or "MAT" and Morningstar Category contains "Allocation" or "Target-Date". We focus on TAFs domiciled in the United States. We exclude tactical allocation funds and target volatility funds, which do not have allocation targets and tend to have the opposite trading behavior to TAFs. Most TAFs are funds of funds, and we exclude TAFs whose fund holdings are below 50% of their total holdings. We include variable annuity funds, and excluding these funds does not alter our main results.

We focus on TAFs' trading of bond mutual funds, identified by Lipper Objective Code.[9]. We exclude exchange-traded funds, which represent a negligible fraction of TAF holdings (Panel B of Figure A2) and are less subject to strategic complementarity (Falato et al., 2021). Following Ma et al. (2022), for each bond fund in each quarter, we measure the illiquidity of its holdings by average credit rating, where AAA is 1, AA+ is 2, ..., and CCC- is 19. For each bond, we take the median rating across S&P, Moody's and Fitch. Our sample period starts in 2012Q4, when rating agencies began publicly disclosing all of their ratings according to SEC Rule 17g-7. For robustness, we also consider measuring portfolio illiquidity by average bid-ask spread, share of corporate bonds, or share of high-yield bonds.[10]

To define illiquid periods, we use the average corporate bond bid-ask spread. Specifically, we calculate each corporate bond's bid-ask spread on each date as the difference between dealer-to-customer (buy) prices and customer-to-dealer (sell) prices, normalized by deal-to-

Retirement 2025 in 2022Q1.

[9]We include government bond funds (GUS, GUT, IUG, IUT, SIU, SUS, SUT), investment-grade bond funds (A, ARB, BBB, CPB, GB, IID, SID, SII, USO), high-yield bond funds (FLX, HY, LP, MSI, SFI, SHY), and international bond funds (EMD, EML, GHY, GLI, INI, SWM). We exclude municipal bond funds due to differential tax treatments.

[10]Cash and cash equivalents (e.g. shares of money market funds) are assigned AAA rating and zero bid-ask spread.

dealer prices, following Kargar et al. (2021). We then take the average of bid-ask spreads across corporate bonds for each date. To ensure comparability over time, we focus on BBB-rated corporate bonds with a rounded duration of 5 years. To address the secular decline in bid-ask spreads, we residualize the data with respect to a linear time trend. We define a period to be illiquid if the residualized corporate bond bid-ask spread in that period is in the upper quartile of the time series distribution.

S&P 500 aggregate returns are from CRSP. Bloomberg Aggregate Bond Index returns are from Bloomberg. Data on Treasury bonds are from CRSP Treasury Database. Data on U.S. corporate bonds are from Mergent FISD and TRACE.

2.3 Measuring flow variables

We are interested in *flow* variables such as trading by TAFs and flows to bond mutual funds. However, our datasets contain *stock* variables such as total net assets and holdings. To make the conversion, we need to exclude returns. Net flows to mutual fund i during quarter t is measured as:

$$NetFlow_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + Return_{i,t}) - M\&A_{i,t}$$

where $M\&A$ captures acquisitions of other funds, which do not represent inflows of new capital.

Net purchases – or trading – by TAF i of bond mutual fund j during quarter t is similarly measured as:

$$Trading_{i,j,t} = Holding_{i,j,t} - Holding_{i,j,t-1}(1 + Return_{j,t})$$

where *Return* includes both NAV changes and distributions.

3 Predictability of TAF Rebalancing

This section shows that target allocation funds (TAFs) make rebalancing trades in a highly predictable manner. We begin by verifying that TAFs indeed have allocations that are sticky in the short run and maintained at the fund level. Given target allocations, we construct a measure called rebalancing-induced trading (RIT) that predicts how TAFs trade using lagged holdings and realized fund returns, which are publicly available to all market participants in real time. We confirm that there is a near one-for-one relationship between RIT and TAFs' actual trading of individual bond funds. At the same time, the relationship is influenced by illiquidity for affiliated bond funds. After liquidity adjustment, RIT almost exactly predicts actual TAF trading in the cross section of bond funds.

3.1 Allocation stickiness

As elaborated in Section 2, TAFs have explicit mandates on asset-class-level allocations, which are either fixed or, in the case of TDFs, slowly adjust over time according to some predetermined glide path. Panel A of Figure 3 confirms that the asset-class-level allocation is indeed very sticky at the quarterly frequency, for both conventional TAFs or TDFs. Specifically, allocation to bond funds this quarter is often identical to allocation to bond funds last quarter, even though there can be large positive or negative returns that shrink or expand bond fund allocation absent rebalancing. Such asset-class-level allocation stickiness has also been shown by Parker et al. (2023) and Foley-Fisher and Lee (2025).

Perhaps surprisingly, TAFs seem to also target allocations at the individual fund level. Panel B of Figure 3 shows that, within the bond fund portfolio, allocation to an *individual* bond fund also tends to remain identical from previous quarter to current quarter. This stickiness exists for both conventional TAFs and TDFs. There are two explanations for

this fund-level target allocation. First, a typical TAF holds a small number of funds, each representing a sub-asset-class style. For example, Figure A3 shows that Vanguard Target Retirement 2025 Fund – the largest TAF in our sample – holds only 5 funds. Within bond funds, it holds a domestic bond fund and an international bond fund, and this sub-asset class allocation is also specified in the fund's investment mandate.

More generally, maintaining portfolio weights with respect to external shocks is a prevalent portfolio management practice that goes beyond TAFs. For example, there is pervasive evidence that mutual funds proportionally scale up or down their portfolios in response to inflows or outflows (Edmans et al., 2012; Lou, 2012). When equity funds experience large returns and a TAF needs to rebalance by scaling up or down its bond funds, this is akin to inflow or outflow to the TAF's bond fund portfolio. Rather than trading its bond funds in an arbitrary manner, the TAF would likely trade proportional to their existing portfolio weights, so that there is minimal distortion to its investment strategy.

3.2 Rebalancing-induced trading

Suppose that TAF i targets portfolio weight $w^*_{i,j}$ in fund j, which is achieved at $t-1$. We can derive the exact amount of trading required in order to maintain target allocation $w^*_{i,j}$ from $t-1$ to t:

$$\begin{aligned} & A_{i,t}w^*_{i,j} - A_{i,t-1}w^*_{i,j}R_{j,t} \\ &= (A_{i,t-1}(\sum_k w_{i,k,t-1}R_{k,t}) + F_{i,t})w^*_{i,j} - A_{i,t-1}w^*_{i,j}R_{j,t} \\ &= \underbrace{A_{i,t-1}w^*_{i,j}(\sum_k w_{i,k,t-1}R_{k,t} - R_{j,t})}_{\textbf{RIT}} + \underbrace{F_{i,t}w^*_{i,j}}_{\textbf{FIT}} \end{aligned} \tag{1}$$

On the first line, the first term is the target dollar allocation to fund j, and the second term is the realized dollar allocation to fund j before portfolio adjustment. The second line applies the law of motion for AUM, where changes in AUM can come from both returns

$\{R_{k,t}\}$ and flows $F_{i,t}$. The third line re-arranges terms and shows the two components of trading to maintain target allocation: rebalancing-induced trading (RIT) and flow-induced trading (FIT).

FIT arises because of inflows or outflows (Edmans et al., 2012; Lou, 2012). When a TAF experiences inflows or outflows, it needs to buy or sell fund j proportionally, so that its allocation in the portfolio remains the same. The opposite applies for outflows.

RIT arises because of return differences across funds held. If all funds have the same return, then no rebalancing is required. If fund j experiences more negative return than other funds, its portfolio weight would shrink more, and the TAF needs to redeem other funds to purchase shares of fund j to restore its target allocation. The opposite applies for positive return. Effectively, TAFs engage in contrarian trading. Importantly, RIT depends on the returns of *all* funds in the portfolio. For example, even if a fund experiences zero return, its RIT would be negative if other funds have negative returns.

Compared to Parker et al. (2023), who focus on equity-vs-bond rebalancing, our calculation of RIT captures the heterogeneity across funds, which can be economically meaningful. As shown in Panel B of Figure A2, almost half of TAFs' equity funds specialize in international equities, a fact also documented in Andonov et al. (2024). The returns to these international equity funds can be meaningfully different from domestic equity returns. By incorporating this heterogeneity, our approach provides more accurate predictions of rebalancing trades at the fund level. At the same time, returns on individual funds are publicly available to all market participants in real time, just like aggregate market returns, so our measure is not subject to look-ahead bias.

Similar to Parker et al. (2023), we measure $w^*_{i,j}$ by lagged portfolio weight $w_{i,j,t-1}$. The previous subsection shows that portfolio weights are very sticky over quarterly horizon, affirming that TAFs adhere to their target allocations. Since target date funds' allocations

drift over time, we also conduct robustness analysis by measuring their target allocations using linear extrapolation, and our main results are virtually unchanged.[11]

We calculate $RIT_{i,j,t}$ on each bond or equity fund j held by each TAF i in each quarter t. To emphasize, these rebalancing trades are predicted by lagged portfolio holdings and realized fund returns, all of which are publicly available to all market participants in real time, and we do not use any information on TAFs' actual trading. Figure 4 shows TAFs' aggregate trading and RIT on bond funds (Panel A) and equity funds (Panel B). Our RIT measure is able to predict almost all of TAFs' bond fund redemptions and equity fund purchases during the COVID-19 crisis in 2020Q1.

To formally assess the accuracy of our RIT measure in predicting TAF trading, we estimate the following regression:

$$Trading_{i,j,t} = \beta RIT_{i,j,t} + \gamma Controls + FE + \epsilon_{i,j,t} \tag{2}$$

where $Trading_{i,j,t}$ denotes actual trading by TAF i of bond fund j during quarter t, RIT our measure of rebalancing-induced trading according to Equation 1, and FE TAF-by-quarter fixed effects as well as bond-fund-by-quarter fixed effects, which purge out common trading of all bond funds by a TAF and common trading of a bond fund across TAFs. Both actual and predicted trading are normalized by lagged holdings. To avoid the influence of small positions, we estimate the regression using weighted least squares, with holding amounts as weights. Standard errors are three-way clustered by TAF i, by bond fund j and by quarter t.

Column 1 of Table 2 shows the results. There is a near one-for-one relationship between actual bond fund trades by TAFs and rebalancing-induced trades based on lagged holdings and realized returns. Specifically, for each dollar of RIT, the actual trading is 0.998 dollar.

[11] Specifically, for each TDF in each quarter, we fit a regression line between observed allocations and time over the past 8 quarters, and define current target allocation as the predicted value.

Column 2 separates the negative and the positive component of RIT and shows that the near one-for-one relationship applies to both rebalancing-induced redemptions and purchases. The coefficient on negative RIT is noticeably smaller, meaning that actual redemption appears to be smaller than negative RIT, and we will show below that this is driven by liquidity concerns on affiliated bond funds.

3.3 Liquidity adjustment

Transaction costs should play a role in TAFs' rebalancing.[12] TAFs may deviate more from theoretical rebalancing for illiquid assets, where the cost per unit of trading is higher. Following Ma et al. (2022), we define the illiquidity rank of bond fund j in TAF i's portfolio as:

$$IlliquidityRank_{i,j,t} = \sum_{k} w_{i,k,t} \mathbb{1}[Illiquidity_{k,t} < Illiquidity_{j,t}] + \frac{1}{2} w_{i,j,t} \tag{3}$$

where the illiquidity of a bond fund is measured by the average credit rating (AAA = 1, CCC- = 19) of its bond holdings. This illiquidity rank measure goes from 0 to 1. The higher the value its illiquidity rank, the more illiquid the bond fund is relative to other bond funds in the TAF's portfolio. We augment Regression 2 with interaction terms between RIT, illiquidity rank, and illiquid period:

$$Trading_{i,j,t} = \beta RIT_{i,j,t} \times IlliquidityRank_{i,j,t-1} \times IlliquidPeriod + \gamma Controls + FE + \epsilon_{i,j,t} \tag{4}$$

There is an interesting dichotomy between affiliated and unaffiliated bond funds. Column 3 of Table 2 shows that illiquidity significantly affects the relationship between RIT and actual TAF rebalancing for affiliated bond funds. For the most liquid bond funds ($IlliquidityRank = 0$), TAFs redeem almost exactly one dollar for each dollar of nega-

[12] For example, Vanguard Research (2024) explicitly mentions transaction costs in its rebalancing strategies.

tive RIT. However, this one-for-one relationship is significantly dampened for illiquid bond funds. For the most illiquid bond funds ($IlliquidityRank = 1$), the relationship is reduced by 0.092, and additional 0.199 during illiquid periods, when bid-ask spreads on bonds are large. This liquidity effect is absent for positive RIT.

In contrast, Column 4 shows that the coefficients on the interaction terms are insignificant for unaffiliated bond funds. In fact, the coefficients are positive, meaning that unaffiliated illiquid bond funds appear to be redeemed *more* than one-for-one with RIT, especially during illiquid periods. In other words, whereas TAFs follow a liquidity pecking order for affiliated bond funds, they follow a *reverse* pecking order on liquidity for unaffiliated bond funds.

What explains the liquidity adjustment and its asymmetric effect on affiliated versus unaffiliated bond funds? Ma et al. (2022) show that bond mutual funds avoid selling illiquid bonds that may incur high liquidation costs. However, TAFs do not invest in illiquid bonds directly. They invest in bond mutual funds that in turn invest in illiquid bonds. Because bond mutual funds provide liquidity transformation, TAFs are insulated from the liquidation costs of selling illiquid underlying bonds. In the case of affiliated bond funds, TAFs can internalize the downstream liquidation costs, and therefore avoid incurring redemptions in the upstream. This is consistent with the findings in Bhattacharya et al. (2013), who show that funds of funds provide liquidity insurance to affiliated funds with the same fund families. For unaffiliated bond funds, however, the liquidation costs are entirely external to the TAFs, which therefore do not need to follow a liquidity pecking order.

Panel B and C of Table 2 show that the predictability of rebalancing is similar for conventional TAFs and TDFs. For both types of TAFs, there is a near one-for-one relationship between RIT and actual trading, which is dampened by illiquidity for affiliated bond funds, where liquidation costs can be internalized within fund families.

Based on the evidence above on liquidity adjustment, we refine the prediction of rebalancing-

induced trading as:

$$\widetilde{RIT}_{i,j,t} = \begin{cases} RIT_{i,j,t} \times (1 - \hat{\beta} \times IlliquidityRank_{i,j,t-1}) & , \ RIT_{i,j,t} < 0 \ \& \ IlliqPeriod = 1 \ \& \ j \in Aff \\ RIT_{i,j,t} & , \ \text{otherwise} \end{cases} \tag{5}$$

where unadjusted RIT comes from Equation 1, illiquidity rank is based on Equation 3, and illiquid periods are those with upper-quartile corporate bond bid-ask spreads. $\hat{\beta}$ is the estimated coefficient on the triple interaction term between the negative component of RIT, illiquidity rank and illiquid period indicator from Regression 4. To avoid look-ahead bias, we estimate $\hat{\beta}$ using only the data prior to t. For example, to estimate $\hat{\beta}$ and use it to adjust RIT during 2020Q1, we train Regression 4 using the data prior to 2020. For the remainder of the paper, we will refer to this liquidity-adjusted version of RIT simply as RIT.

4 Strategic Complementarity

The previous section shows that TAFs make rebalancing trades that are highly predictable based on lagged holdings and realized returns. This section shows that predictable rebalancing-induced redemptions by TAFs trigger strategic redemptions by *other* non-TAF bond mutual fund investors.

The mechanism is a mutual-fund version of the classic Diamond and Dybvig (1983) logic: when financial intermediaries provide liquidity transformation, withdrawals by some investors reduce the payoff to investors who remain, making withdrawal decisions strategic complements. As shown by Chen et al. (2010) and Goldstein et al. (2017), this strategic complementarity exists not only for bank deposits but also for open-end mutual funds that invest in illiquid assets. Specifically, to meet redemption requests, a mutual fund may need to liquidate underlying assets, which can be costly because of illiquidity, such as the large

bid-ask spreads on Treasury and corporate bonds during COVID-19 (Fleming and Ruela, 2020; Kargar et al., 2021). In the U.S. and other jurisdictions without swing pricing, these liquidation costs are not fully charged to redeeming investors because funds allow redemptions at the current NAV. Instead, these costs are borne by investors who remain in the fund. Therefore, when TAFs are expected to redeem their bond fund shares, other investors are incentivized to redeem as well in order to avoid bearing the liquidation costs.

This strategic complementarity is what contributes to fragility. Redemptions by some investors impose negative externalities on the remaining investors, increasing their incentives to redeem as well. This kicks off a vicious cycle, as more redemptions create stronger incentives to redeem. Consequently, an initially small shock can eventually lead to a large redemption wave, resulting in a fragile system.

Typically, runs on liquidity transformation vehicles are triggered by worsening fundamentals, and it is difficult to separate the direct effect of worsening fundamentals from the amplifying effect due to strategic complementarity. In an ideal experiment, we want to have some investors randomly decide to redeem their mutual fund shares, which create liquidation costs for the other investors, and we can test if *other* investors indeed choose to exit to avoid bearing the liquidation costs. TAFs provide a laboratory that closely resembles such an experiment. Large negative returns in the equity market lead to mechanical rebalancing by TAFs, which predictably redeem from bond mutual funds. This behavior is largely driven by equity market shocks, orthogonal to fundamentals of the bond market. We show that other investors redeem more when they expect larger TAFs rebalancing-induced redemptions, providing a clean test of the existence of strategic complementarity.

Mutual funds use cash buffers and liquid assets to mitigate liquidation costs (Chernenko and Sunderam, 2016; Choi et al., 2020; Ma et al., 2022). In practice, however, cash holdings by bond mutual funds are generally less than 5% of TNA, and even liquid assets such as Treasury notes and bonds can become quite illiquid during crisis periods such as COVID-

19 (Fleming and Ruela, 2020). More importantly, Morris et al. (2017); Jiang et al. (2021) show that funds tend to maintain or even hoard cash when they are uncertain about future redemption risks. Emphasizing this forward-looking aspect, Zeng (2017) shows that depleting cash today may raise expectations of future liquidation costs, exacerbating strategic complementarity. Our results below confirm that, despite liquidity management, significant liquidation externalities remain in open-end bond mutual funds.

There are important conceptual differences between the strategic complementarity we document and the front-running behavior studied by Harvey et al. (2025). To front-run rebalancers, an arbitrageur trades equities or bonds in advance, waits for the rebalancing-induced price pressure to materialize, and then unwinds its position at more favorable prices. The profitability of this strategy depends on the magnitude of price impact: the more inelastic market demand is, the larger the front-running profit. Our mechanism is different. The relevant decision-makers are existing mutual fund investors, not outside arbitrageurs, and their incentive is to avoid bearing the transaction costs, such as bid-ask spreads, imposed by TAF redemptions. Thus, even though both mechanisms involve anticipatory trading, the assumptions differ: conventional front-running requires predictable price impact, whereas the strategic complementarity we document requires only transaction costs, which are arguably a less stringent condition.[13]

4.1 Fund-level evidence

To test strategic complementarity, we exploit the cross section of bond mutual funds. Some bond funds are expected to experience larger TAF rebalancing-induced redemptions compared to other bond funds: these bond funds may be held more by TAFs, the TAF holders'

[13] As an illustrative example, consider a highly illiquid corporate bond with a highest bid of \$90, a lowest ask of \$110, and a fair value of \$100. Buying or selling this bond involves a transaction cost of 10% relative to fair value because of the bid-ask spread, even if the trade does not move the fair value itself. Bid-ask spreads alone can generate the strategic complementarity we describe, whereas conventional front-running requires an additional assumption of price movement.

equity funds may experience worse returns than the average equity funds, or they have lower illiquidity rank in their TAF holders' portfolios. We hypothesize that these bond mutual funds experience higher redemptions by *other* non-TAF investors, due to strategic complementarity.

We first reaffirm the predictability of TAF trading in the cross section of bond mutual funds:

$$\frac{\sum_i Trading_{i,j,t}}{TNA_{j,t-1}} = \beta \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} + FE + \epsilon_{j,t} \tag{6}$$

The dependent variable is total trading of bond fund j by all TAFs. The main independent variable is the sum of liquidity-adjusted rebalancing-induced trading according to Equation 5. We exclude fund-quarter observations with zero TAF ownership. Table 3 shows that our RIT measure moves nearly one-for-one with actual TAF trading in both the single period of 2020Q1 during COVID-19 and throughout all sample periods. RIT alone accounts for 0.789 (0.531) of the R-squared of the cross section of actual TAF trading during 2020Q1 (all sample periods), which is close to the maximum R-squared achievable at 0.936 (0.682) by adding a host of other observable variables and fixed effects.

Having validated the predictability of TAF trading, we examine the strategic interaction between TAFs and other investors using the cross section of bond mutual funds:

$$\frac{Flow_{j,t} - Flow_{j,t}^{TAF}}{TNA_{j,t-1} - TNA_{j,t-1}^{TAF}} = \beta \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} + \gamma Controls + FE + \epsilon_{j,t} \tag{7}$$

The dependent variable measures net flows from *other* investors – excluding net flows from TAFs – normalized by lagged TNA held by these other investors. The regressor of interest is the sum of rebalancing-induced trading across TAFs, according to Equation 5, normalized by the bond mutual fund's TNA. For simplicity, we refer to this variable as RIT. Following Goldstein et al. (2017), we control for contemporaneous return, lagged return, lagged flow, log TNA, log age, expense ratio, and rear load. We include Lipper-Object-Code-by-quarter fixed

effects to zoom in on the comparison between similar bonds at the same time. Standard errors are clustered by Lipper Object Code in each quarter. To avoid the influence of small funds, we estimate the regression using weighted least squares, with non-TAF TNA as weights.

We first focus on the single quarter of 2020Q1, i.e. the COVID-19 crisis. Panel A of Table 4 shows the baseline results. In Column 1, the coefficient on RIT is positive, statistically significant, and economically large. 1% rebalancing-induced redemptions by TAFs is associated with 0.681% redemptions by *other* non-TAF investors.

The degree of liquidation costs should play a role: compared to those investing in Treasuries, bond mutual funds investing in illiquid corporate bonds or foreign bonds should have higher liquidation costs and therefore exhibit more strategic complementarity. In Panel B of Table 4, we estimate the same regression separately for different styles of bond mutual funds, sorted by illiquidity. Whereas β is insignificant for Treasury bond funds, it is larger and statistically significant for investment-grade bond funds that invest in not only Treasury bonds but also agency MBS and corporate bonds, which have significant illiquidity. β is even larger for more illiquid mutual funds that invest in high-yield bonds and international bonds. The estimate is not statistically significant because of the lack of statistical power – most of these funds have small exposure to TAFs and therefore there is small cross-sectional variation in RIT.

To investigate the effect of illiquidity more formally, we augment the baseline regression with an interaction term with fund illiquidity:

$$\frac{Flow_{j,t} - Flow_{j,t}^{TAF}}{TNA_{j,t-1} - TNA_{j,t-1}^{TAF}} = \beta \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} \times IlliquidFund_{j,t} + \gamma Controls + FE + \epsilon_{j,t} \qquad (8)$$

We measure fund illiquidity by the average credit rating (AAA = 1, CCC- = 19) across its holdings, weighted by par amount held. To ease interpretation, we focus on an indicator variable of whether the bond mutual fund's portfolio illiquidity is above median among all

funds in each period. Both the interaction term and its components are included in the regression.

Column 2 of Panel A of Table 4 shows the result. The coefficient on the interaction term is also significantly positive, meaning that the comovement between RIT and trading by other investors is stronger for illiquid bond funds. In fact, the comovement is nearly *twice* as large for the illiquid bond mutual funds (0.443 + 0.386) compared to the average ones (0.443). This result further strengthens the strategic-complementarity interpretation, because illiquid bond funds are precisely where liquidation costs are largest and the incentive to redeem strategically is strongest. For liquid bond funds, it is relatively cost-free to liquidate the underlying assets (e.g. Treasury bills), so redemptions by TAFs would not trigger run incentives for the other investors. For most bond mutual funds during COVID-19, liquidating underlying bonds was costly, as even Treasury notes and bonds and investment-grade bonds exhibited substantial illiquidity (Fleming and Ruela, 2020; Haddad et al., 2021).

Panel C of Table 4 shows robustness with alternative measures of fund illiquidity, including average bid-ask spread of portfolio bonds, portfolio share of corporate bonds, and portfolio share of high-yield (BB+ or worse) bonds. The identified illiquid funds are largely the same, and the regression results are remarkably similar to the baseline ones.

Having analyzed the COVID-19 crisis, we turn to the full panel data from 2017Q4 to 2023Q4. Our sample starts in 2017Q4 because the estimation of $\hat{\beta}$ for $\widetilde{RIT}$ requires sufficient number of prior quarters, and the underlying data on credit ratings do not start until 2012Q4. Table 5 shows the results. Following Goldstein et al. (2017), we separately analyze cases with rebalancing-induced purchases ($RIT \geq 0$) versus with rebalancing-induced redemptions ($RIT \leq 0$). Column 1 and 2 show that the coefficient on RIT is negative, especially for illiquid funds during illiquid period, suggesting that other investors tend to redeem from bond funds that receive rebalancing inflows from TAFs. This is consistent with our hypothesis: either selling or buying illiquid bonds incurs transaction costs, TAFs impose these costs

on other investors, which create incentives for these investors to redeem. However, the coefficients are not statistically significant, consistent with the fact that a bond fund receiving inflows is not forced to buy bonds at a cost, limiting the externality on other investors.

Column 3 focuses on the observations where RIT is negative – that is, when TAF investors are predicted to rebalance out of the bond fund. Similar to the COVID-19 crisis analysis, the coefficient on RIT is positive. The interaction with the illiquid period indicator is positive and statistically significant, meaning that: when TAFs are expected to redeem more, other non-TAF investors also redeem more, particularly during illiquid periods, where liquidation costs are elevated.

Column 4 adds further interaction with an indicator for illiquid bond mutual funds, defined as those whose bond holdings have above-median illiquidity in each quarter. The coefficient on the triple interaction term is significant, meaning that the strategic coordination is mainly driven by illiquid bond funds, where liquidation costs are particularly high.

While we have focused on how equity market shocks transmit to bond fund outflows, a natural question is whether negative bond market shocks can generate similar cross-market fragility, particularly on equity mutual funds that invest in illiquid small and international equities. Panel B of Figure 2 plots the average returns to equity funds (solid line) and the average returns to bond funds (dash line) held by TAFs. It is clear that TAFs' equity fund returns are much more volatile than their bond fund returns, and none of the negative bond fund returns are nearly as severe as the negative equity fund returns.

4.2 Investor-level evidence

The analyses so far pool all non-TAF investors together. In this subsection, we examine bond mutual fund trading at the individual investor level. This helps ruling out an important al-

ternative explanation: some non-TAF investors are also rebalancers, they are attracted to the same bond mutual funds that are held more by TAFs, so the comovement with TAF rebalancing is not strategic complementarity but rather simultaneous rebalancing from unobserved rebalancers. To rule out this endogeneity concern, we analyze a subset of investors for which we directly observe holdings. Effectively, we examine whether *a given investor* tilts away from TAF-exposed bond funds, which is free from the selection bias aforementioned.

The investors for which we have investor-level portfolio holdings data include 55 non-TAF mutual funds and 98 insurance companies.[14] We require the investors to have at least $100K holdings in at least 2 unaffiliated bond funds as of year-end 2019. Analogous to Regression 8, we examine the comovement between trading by these non-TAF investors $\{k\}$ and RIT by TAFs:

$$\frac{Trading_{k,j,t}}{Holding_{k,j,t-1}} = \beta \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} \times IlliquidFund_{j,t} + FE + \epsilon_{k,j,t} \tag{9}$$

The dependent variable is trading of bond mutual fund j by non-TAF investor k, normalized by lagged holding. The independent variables are the same as Regression 8. Crucially, FE includes investor-by-time fixed effects, which effectively zoom in on the variation of trading across bond funds by *the same investor at the same time*. Standard errors are clustered by each investor k in each quarter t. To avoid the influence of small positions, we estimate the regression using weighted least squares, with holdings as weights. Due to data limitation, we focus on the single period of 2020Q1 during the COVID-19 crisis.

Table 6 shows the results. Column 1 includes non-TAF mutual funds only, Column 2 includes insurance companies only, and Column 3 includes both. Similar to Regression 8, the coefficients on RIT and the interaction with illiquid fund indicator are both positive throughout and, in Column 3 where we include both investor groups, statistically significant.

[14] We obtain insurers' holdings from their Schedule D reports filed with National Association of Insurance Commissioners (NAIC). Although a large fraction of insurers' fund holdings are in separate accounts, we focus on insurers' general account holdings because separate account holdings are mostly determined by rules described in variable life or variable annuity policies, not discretionary investments.

Importantly, with investor fixed effects, the interpretation sharpens to: a typical non-TAF fund redeems more (or purchases less) bond funds with more expected TAF withdrawals, particularly for bond funds with illiquid holdings. In terms of magnitude, one-percentage-point-of-TNA higher rebalancing-induced redemption is associated with additional net sales at 0.598% of holdings by the fund or insurer holder. This number increases an additional 1.529% of holdings for illiquid bond mutual funds, consistent with stronger strategic complementarity at larger liquidation costs. These coefficients, especially the one on the interaction term with illiquid fund, are much larger than those the fund-level regression in Table 4, suggesting that the strategic behavior we hypothesize is more salient for institutional investors than for the average investors, which also include retail investors.

It is worth emphasizing that the comovement between non-TAF investor trading and TAF trading is in the cross section. In aggregate, insurance companies actually increased holdings of bond mutual funds during COVID-19, consistent with the fact that insurers acted as one of the only liquidity providers during the bond market selloffs in COVID-19 (Brown and Davies, 2024). Our regression suggests that, across bond mutual funds, insurers avoided purchasing the ones sold by TAFs.

4.3 Robustness excluding bond fund returns

The construction of RIT on a bond fund includes the bond fund's own returns (Equation 1). Therefore, non-TAF investors' response to TAFs' RIT can be contaminated by these investors' response to the bond fund return itself. For example, investors may flee from the bond funds with negative returns due to the usual flow-performance relationship (Ben-David et al., 2022), instead of responding to TAF rebalancing. Although we directly control for both contemporaneous and lagged bond fund returns in all regressions, we further address this concern by focusing on the component of RIT that is orthogonal to bond funds' own

returns.

Panel B of Figure 2 shows that most of the return differences between equity funds and bond funds are driven by the equity side. For example, in 2020Q1, the equity funds held by TAFs had an average return of -23%, whereas the bond funds held by TAFs had a positive return of 0.8%. As a result, RIT is mainly driven by equity fund returns, and our strategy is to construct a version of RIT using only equity fund returns, so it is orthogonal to bond fund returns. Specifically, when calculating RIT through Equation 1, we set all bond fund returns to zero. We call this measure equity-return-induced trading ($ERIT$). We apply the same liquidity adjustment to $ERIT$ through Equation 5 to account for the liquidity pecking order. We then rerun Regressions 7, 8 and 9 using $ERIT$ as the main explanatory variable.

Table 7 shows the results. Panel A shows that, when there are larger expected redemptions from TAFs solely due to the large negative returns on equity funds, other non-TAF investors redeemed more, especially for illiquid bond mutual funds where the cost of liquidating bonds to meet TAF redemptions is high. Panel B focuses on the subset of non-TAF investors for which we directly observe holdings and shows that, for the same investor, there are more sales or less purchases of bond mutual funds with larger TAF redemptions that are solely expected from equity fund returns. These results are very similar to our baseline results, providing reassurance to our interpretation that redemptions from bond mutual funds are responding strategically to TAF rebalancing, not the underlying bond fund returns themselves.

4.4 Amplifying effects

The analyses above show that TAFs' rebalancing-induced trading is amplified by trading by other investors due to strategic complementarity. While we have shown the *direct* contribution of TAF trades to aggregate COVID-19 outflows in Figure 1, how much of the outflows

was attributable to the *amplification* of TAF trades due to strategic complementarity? To answer that question, we use the panel estimates of Regression 8 in Table 5. Specifically, for each bond fund j that experiences *negative* TAF rebalancing-induced redemptions in each *illiquid* quarter t, the amplifying dollar flows are calculated as:

$$(0.451 + 0.214 \times IlliquidFund_{j,t}) \times \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} \times (TNA_{j,t-1} - TNA^{TAF}_{j,t-1}) \qquad (10)$$

where 0.451 and 0.214 are directly from Column 4 of Table 5.

Figure 5 shows that the amplifying outflows from other investors in response to expected TAF rebalancing total $27 billion during the COVID-19 crisis in 2020Q1. As a result, the sum of direct redemptions by TAFs and the indirect redemptions by other investors reacting to TAF rebalancing is $86 billion – or 48% – of the total outflows from bond mutual funds during 2020Q1.

Existing research has studied the link between bond fund returns and bond mutual fund outflows (Goldstein et al., 2017). Due to TAF rebalancing, a new form of flow-performance relationship arises, where equity market returns affect bond fund outflows. Moreover, according to our analyses above, negative equity market returns induce TAF redemptions that further trigger additional strategic outflows from other investors. Positive equity market returns, on the other hand, do not trigger symmetric inflows, as liquidation costs do not apply. Figure 6 shows this concave bond-fund-flow-to-equity-market-return relationship. Each dot plots the average bond fund flows (normalized by TNA) against the S&P 500 stock return in a quarter. To ensure apples-to-apples comparison, we residualize bond fund flows against the known determinants, including return, size, expense ratio and rear loads. Bond funds with high exposure to TAFs (defined as 10% or more TAF ownership) exhibit a salient concave flow to equity market return relationship: good equity returns are associated with inflows to these bond funds, but their outflows associated with bad equity returns are much larger.

In contrast, for other bond funds, there is no visible relationship between their flows with equity market returns.

5 Cross-Market Shock Transmission

The previous analyses establish that TAFs redeem bond funds to buy equity funds when the equity market under-performs, and these actions are amplified by coordinated trading from other investors due to strategic complementarity. This section shows direct evidence that TAFs transmit equity market shocks to bond returns. Moreover, a counterfactual exercise suggests that TAFs explain a large fraction of the increase in *aggregate* stock-bond correlation over the last decade.

5.1 Cross-sectional evidence

We exploit the heterogeneity in exposure to TAF rebalancing in the cross section of bonds. This heterogeneity comes from two layers: some bond mutual funds are held more by TAFs, and some bonds are held more by these bond mutual funds. In both layers, the ranking of illiquidity should matter: Section 3 shows that TAFs prioritize redeeming liquid affiliated funds, and Ma et al. (2022) show that bond funds prioritize selling liquid bonds. Taking all of these into account, our rebalancing exposure measure for bond b at time t is given by:

$$Exposure_{b,t} = \sum_i \sum_j E[\widetilde{RIT}_{i,j,t+1} | R^E_{t+1} - R^B_{t+1} = 1\%] w_{j,b,t} (b_0 + b_1 IlliquidityRank_{j,b,t}) \quad (11)$$

The calculation is looped over all TAFs $\{i\}$ and all bond mutual funds $\{j\}$. Within the loop, the first term $E[\cdot]$ gives expected rebalancing-induced trading by TAF i of fund j if the equity market has 1% higher return than the bond market. The calculation is based on

Equation 5, where next period's returns on all equity funds are set to 1% and returns on all bond funds set to 0%.

The rest of the term $w(b_0 + b_1 IlliquidityRank)$ calculates how much bond mutual fund j would sell of bond b, conditional on \$1 of outflow. The first component w is straightforward: if the bond accounts for a larger share of the portfolio, it would get liquidated more, assuming that the fund proportionally liquidates all holdings. Ma et al. (2022) show that bond funds do not liquidate all holdings perfectly proportionally in response to outflows. Instead, bond funds follow a liquidity pecking order to avoid liquidation costs on illiquid bonds, captured by b_0 and b_1. Illiquidity rank of bond b in bond fund j's portfolio is constructed in the same way as Ma et al. (2022), and we also use b_0 and b_1 directly from their paper.

To sum up, Equation 11 provides a bottom-up approach to predict the time t exposure of bond b to TAFs' rebalancing activities if there is 1 p.p. discrepancy between equity market return and bond market return in period $t+1$. We now examine whether this exposure has actual power in predicting bond return sensitivity to contemporaneous equity market returns.

We estimate the following panel regression using a panel of bond-month observations:

$$R_{b,m} = \beta(R^E_m - R^B_m) \times Exposure_{b,q-1} + \gamma Controls + FE + e_{b,m} \tag{12}$$

$R_{b,m}$ denotes the return of bond b in month m. $(R^E_m - R^B_m)$ denotes the difference between aggregate equity market return and aggregate bond market return in month m. $Exposure_{b,q-1}$ measures bond b's exposure to rebalancing-induced trading as of the immediate quarter before, measured by Equation 11. To ease interpretation, we normalize *Exposure* to have unit standard deviation. Control variables include bond characteristics such as credit rating, duration, and bid-ask spread.

Panel A of Table 8 shows the results for Treasury bond returns.[15] We include CUSIP fixed effects and rounded maturity-by-month fixed effects. Effectively, we compare Treasury bonds with the same years to maturity at the same time. In both columns, the coefficient on *Exposure* is not statistically different from zero, confirming that rebalancing exposure itself does not correlate with risk or other determinants of returns.

In Column 1, the coefficient on the interaction term is positive, although not statistically significant. When the equity market has 1% higher return than the bond market , bonds with one-standard-deviation higher exposure to TAF rebalancing are associated with 0.193 basis points of higher returns. Column 2 adds a triple interaction with an indicator for the COVID-19 period in March 2020. It shows that, conditional on the same exposure to TAF rebalancing, the comovement between bond returns and $(R^E - R^B)$ was substantially stronger during COVID-19 than during other periods, by a statistically significant 1.089 basis points. There are two explanations. First, RIT was particularly large and the market was particularly illiquid during COVID-19, which triggers more strategic complementarity, as we have shown in the previous section. Second, arbitrage capital from dealers and hedge funds was particularly constrained (O'Hara et al., 2025).

Panel B of Table 8 shows the results for investment-grade corporate bond returns.[16] We include credit rating letter-by-month fixed effects, rounded maturity-by-month fixed effects and Fama-French 12 industry-by-month fixed effects. Effectively, we compare corporate bonds with the same credit rating, same maturity and issued by firms in the same industry and at the same time, purging out a large set of unobserved confounding effects.

The results are qualitatively similar to those of Treasury bonds: when there is 1% increase in equity market returns relative to bond market returns, corporate bonds with higher exposure to TAF rebalancing experience higher returns, particularly during the COVID-19

[15] We include Treasury notes and bonds. We exclude bills, floating-rate notes, TIPS, and strips.

[16] We include U.S. dollar bonds issued by non-financial U.S. firms and eligible to be reported in TRACE. We focus on straight bonds and exclude convertible bonds, preferred securities and putable bonds.

crisis. The coefficients are significantly larger than those of Treasury bond returns, consistent with the fact that corporate bonds are less liquid and subject to larger price impacts per unit of liquidity shock.

To further illustrate the price impacts, we follow Ma et al. (2022) and examine yields on different portfolios of bonds during COVID-19. Relative to Ma et al. (2022) – who show that bonds with higher exposure to mutual fund outflows experienced larger yield increases during COVID-19 – we add an additional layer of sorting based on our rebalancing exposure measure. Effectively, we compare bonds with similar exposure to mutual funds, but those whose mutual funds had larger exposure to TAF rebalancing versus those mutual funds did not.

Figure 7 shows yields on bonds with above-median versus below-median rebalancing exposure, *conditional* on the bonds with upper-quartile mutual fund ownership. Yields are measured as relative to their rating-duration-matched peers.[17] Panel A and B show the results for Treasury bonds and investment-grade corporate bonds, respectively. In both cases, bonds with higher rebalancing exposure had much higher yield increases during COVID-19 than those with lower rebalancing exposure, even though both are at the upper quartile of mutual fund ownership. In other words, exposure to TAF rebalancing is an important driver behind the price impact of mutual fund exposure documented in Ma et al. (2022).

5.2 Aggregate stock-bond correlation

The cross-sectional analysis above uses granular fixed effects to compare near-identical bonds. Although this approach facilitates identification, it may under-state the aggregate effect. In particular, recent literature shows that investors are less elastic at more aggregate levels (Li and Lin, 2022; Chaudhary et al., 2025). This means that the cross-sectional estimate, which

[17]Specifically, for a given bond, its peers are designated as those with the same rating letter (AAA, AA, A, BBB, BB, B, CCC) and with the same duration bucket (1-3Y, 3-5Y, 5-10Y, 10+Y).

reflects elasticity at the individual bond level, may under-estimate the effects on aggregate bond returns. This section directly quantifies the price impacts of TAF rebalancing-induced trading using aggregate elasticity estimates from existing literature.

We begin by aggregating rebalancing-induced trading from Equation 5 for all equity funds and all bond funds in each quarter. They are shown by the navy bars and the maroon bars in Figure 8. Our analyses in Section 4 show that there is significant amplification by other investors, due to strategic complementarity. To be conservative, we assume that strategic complementarity only occurs for bond funds, and the sizes of the amplifying trades are given by Equation 10 and shown in Figure 5. For simplicity, we assume that these purchases and redemptions of equity funds and bond funds translate one-for-one to purchases and sales of the aggregate equity market and the aggregate bond market.

The price impacts are the product of the size of these purchases and sales (relative to the size of the market) and the price multiplier, which is the reciprocal of market elasticity.[18] Gabaix and Koijen (2021) estimate that the aggregate equity market has a price multiplier of 5, meaning that \$1 of purchase would lead to \$5 increase in the value of the aggregate stock market. Ma et al. (2022) estimate that the aggregate bond market has a price multiplier of 1.37. We call these price impacts – due to TAF rebalancing-induced trades and the additional strategic trades they trigger – rebalancing-induced returns.

To quantify the contribution of TAF rebalancing on stock-bond correlation, we perform a simple counterfactual analysis. We ask: what would the stock-bond correlation have looked like, if the TAFs did not rebalance at all? This is achieved by subtracting the calculated rebalancing-induced returns from the actual returns, separately for equities and for bonds. We then compare the 5-year rolling-window stock-bond correlation for the actual returns versus for the counterfactual returns, where rebalancing-induced returns are subtracted.

[18] Aggregate equity market size is given by the total market capitalization of S&P 500 stocks (TOTVAL) from CRSP Stock Database. Aggregate bond market size is given by the total amount of Treasury notes and bonds outstanding (TMPUBOUT) from CRSP Treasury Database.

The results are shown by the two lines in Figure 8. The black line is the actual stock-bond correlation. It was *negative* at -0.58 at the beginning of 2010 and increased by 0.69 to *positive* 0.11 by the end of 2023. The green line is the counterfactual stock-bond correlation without TAF rebalancing-induced trades and the amplifying trades by other investors. The counterfactual correlation is visibly lower than the actual one. In fact, our analysis shows that stock-bond correlation would have still stayed negative in 2023 if there were no TAF rebalancing. The gap between the actual and the counterfactual correlation is the contribution by TAF rebalancing. The contribution was initially small – because TAFs were still small relative to the market – but has steadily increased over time and reached 0.12 by 2023. In other words, TAF rebalancing and the amplifying trades by other investors have contributed to 17% (0.12 / 0.69) of the increase in stock-bond correlation over the past decade.

In recent years, more and more 401(k) plans have switched their menu options from mutual funds to collective investment trusts (CITs), which have similar portfolio holdings as mutual funds but face less regulation and therefore charge less fees (Shnitser, 2025). Therefore, our estimated rebalancing trades by target allocation mutual funds overlooks similar activities by target allocation CITs and under-states the total magnitude of rebalancing.[19] To deal with limited data on holdings by CITs, for each target allocation CIT, we match it to the target allocation mutual funds in the same fund family with the same Morningstar Category and assume that it conducts the exact same rebalancing trades relative to AUM. Using data on target allocation CITs' AUM, we can then calculate the dollar amount of rebalancing trades by CITs. After incorporating CITs' activities, the contribution of rebalancing-induced trading to stock-bond correlation is even bigger, at 0.18.[20] In other words, rebalancing by target allocation mutual funds and CITs explain 26% of the rise in stock-bond correlation

[19]Target allocation CITs invest in other CITs, not mutual funds. Therefore, our *RIT* measure for each bond mutual fund is not subject to omitted rebalancing by CITs.

[20]We take the conservative approach and assume that other investors do not strategically respond to rebalancing by target allocation CITs. Whether there is strategic complementarity or not depends on the exact redemption policy set by the bond CITs. Whereas bond mutual funds are required to meet redemptions at current NAV, bond CITs can implement alternative policies, e.g. swing pricing.

over the last decade.

6 Conclusion

This paper documents a new source of fragility for the bond market: equity-market shocks can trigger redemptions from bond mutual funds through TAF rebalancing. When equities experience large negative returns, TAFs redeem bond fund shares and purchase equity fund shares to keep their equity-bond allocations on target. These predictable redemptions induce other bond mutual fund investors to redeem strategically in order to avoid bearing liquidation costs, amplifying the redemptions initiated by TAFs. To meet these redemptions, bond mutual funds sell underlying bonds, transmitting shocks from the equity market to Treasury and corporate bond returns. TAFs—in particular, TDFs—are expected to grow even larger relative to the size of the bond market. As a result, the cross-market transmission mechanism we document may become more important in future crises.

Our results point to a policy trade-off. One way to reduce cross-market fragility is to allow TAFs to rebalance less mechanically and predictably. This would reduce the direct redemptions from bond funds after equity declines. However, it would also weaken TAFs' ability to maintain target allocations and may forgo the benefits of contrarian trading during crisis periods (Parker and Sun, 2023).

Another direction to address fragility is to re-design the vehicles through which TAFs obtain bond exposure. Strategic complementarity arises because open-end bond mutual funds offer redemptions at NAV while holding assets that can be costly to liquidate. Swing pricing can reduce liquidation externalities by charging transaction costs to transacting investors (Capponi et al., 2020; Jin et al., 2022), but operational hurdles have limited its use in the United States; so far, no U.S. mutual fund has adopted swing pricing (U.S. Securities and

Exchange Commission, 2022). Cash buffers and other liquid assets can also help funds meet redemptions, but they are imperfect shock absorbers: funds hold limited cash because of performance drag, and prior work shows that funds may preserve or even hoard cash when future redemption risk is high (Morris et al., 2017; Jiang et al., 2021). Finally, the ongoing shift from mutual funds toward exchange-traded funds and collective investment trusts may reduce the open-end mutual fund run channel. These alternative vehicles can provide similar asset-class exposure with less NAV-based liquidity transformation or more flexible liquidity policies. They do not eliminate price pressure from rebalancing, but they may reduce the first-mover advantage that amplifies redemptions in open-end mutual funds.

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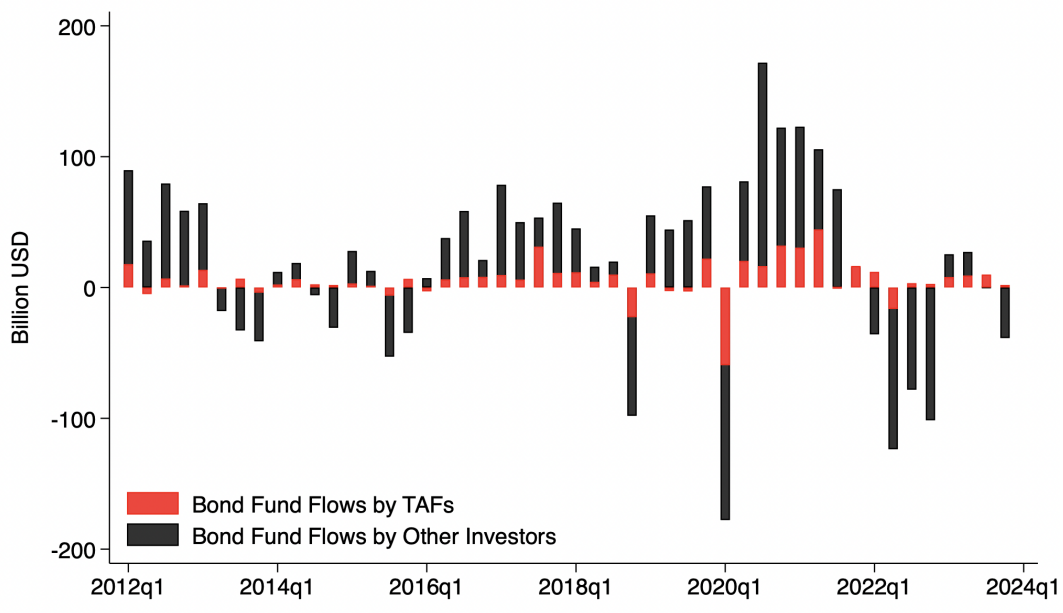
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Figures

Figure 1: **Aggregate Flows to Bond Mutual Funds.** These figures show aggregate quarterly net flows to bond mutual funds from target allocation funds (red) and other investors (black). Panel A plots flows in billion dollars. Panel B plots flows as percentage of holdings.

Panel A: Bond Fund Flows in Billion Dollars



Panel B: Bond Fund Flows as Percentage of Holdings

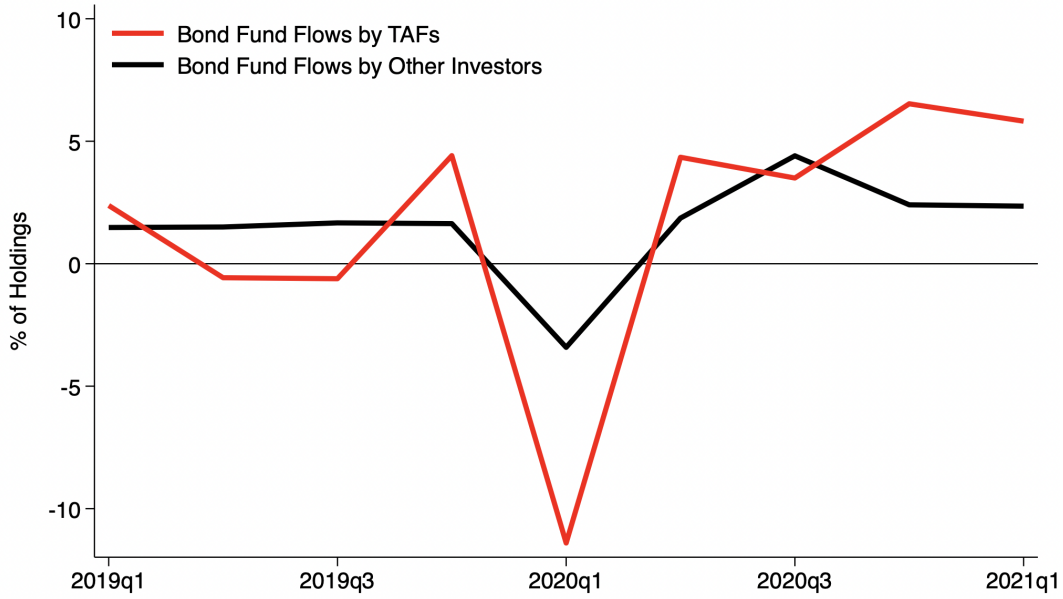
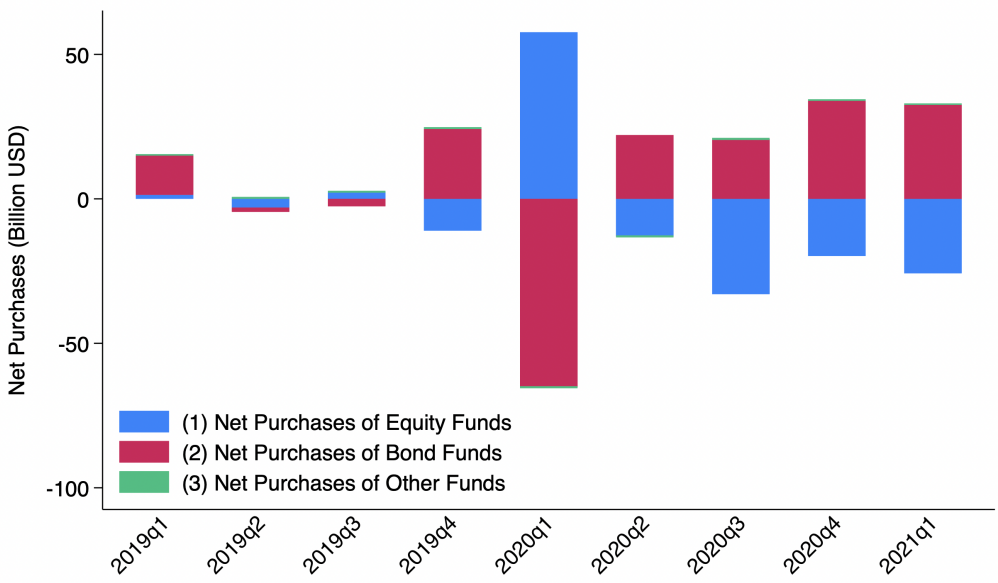


Figure 2: **Aggregate Trading by Target Allocation Funds.** These figures plot aggregate quarterly trading by target allocation funds around the COVID-19 crisis (Panel A) and over all sample periods (Panel B).

Panel A: COVID-19



Panel B: All Periods

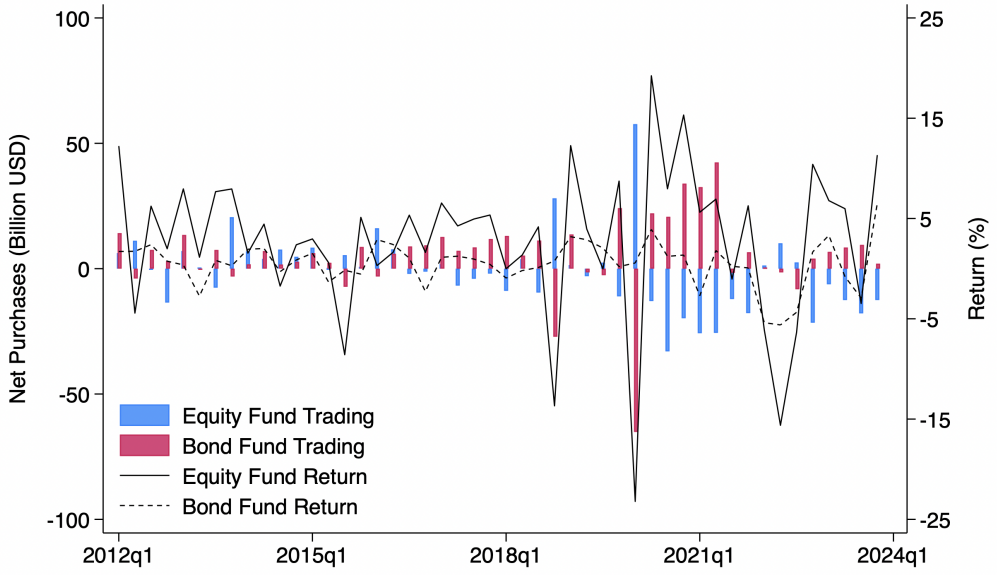
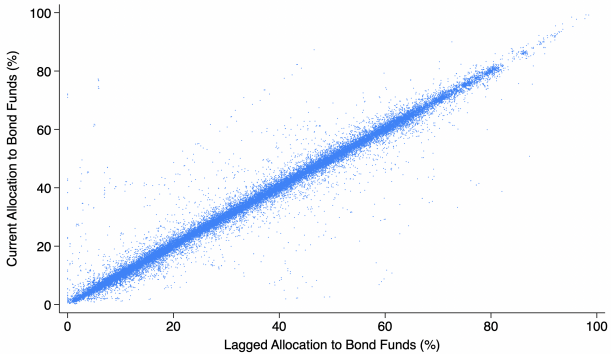


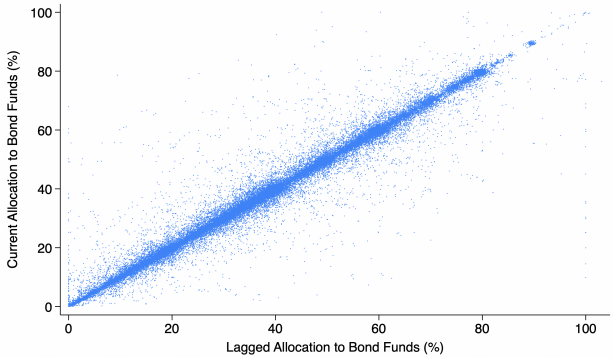
Figure 3: **Allocation Stickiness.** These figures show stickiness in TAFs' bond fund allocations at the quarterly frequency. Panel A shows current versus lagged total allocation to bond funds ($\frac{TotalBondFundHolding}{TotalHolding}$), where each observation represents TAF-quarter. Panel B shows current versus lagged allocation to individual funds within the bond portfolio ($\frac{IndividualBondFundHolding}{TotalBondFundHolding}$), where each observation represents TAF-bond fund-quarter.

Panel A: Asset Class Level ($\frac{TotalBondFundHolding}{TotalHolding}$)

Target Date Funds

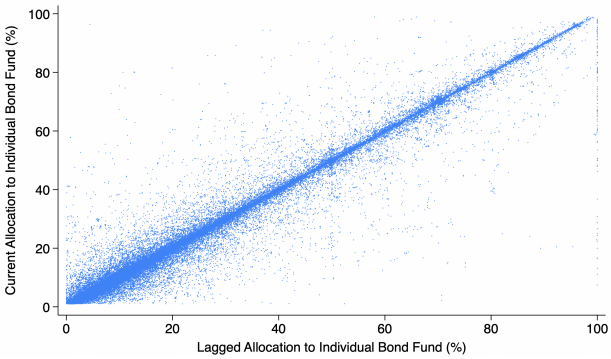


Conventional Target Allocation Funds



Panel B: Individual Fund Level ($\frac{IndividualBondFundHolding}{TotalBondFundHolding}$)

Target Date Funds



Conventional Target Allocation Funds

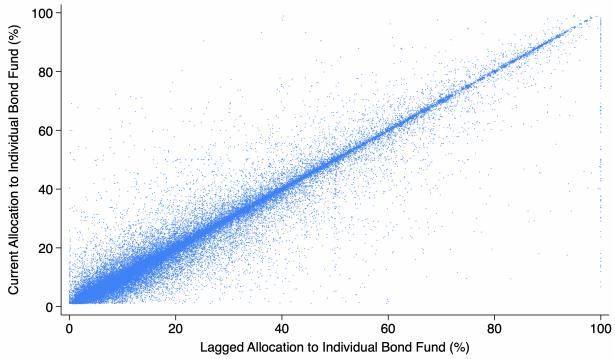
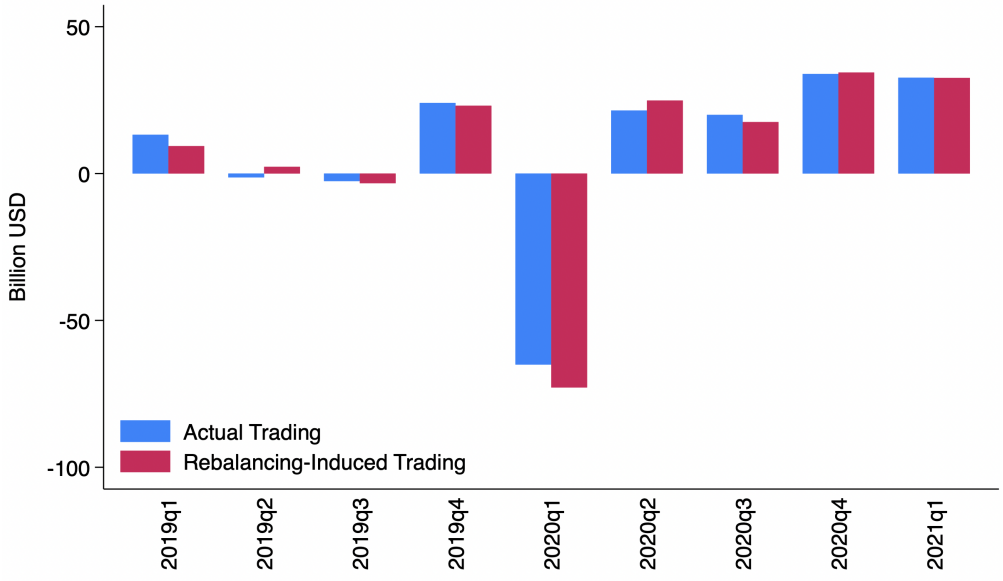


Figure 4: **Actual v.s. Predicted TAF Trading.** These figures show aggregate trading of bond mutual funds (Panel A) and equity mutual funds (Panel B) by TAFs. The blue bars show actual trading. The red bars show rebalancing-induced trading (without liquidity adjustment) predicted by lagged holdings and realized returns, according to Equation 1.

Panel A: TAF Trading of Bond Mutual Funds



Panel B: TAF Trading of Equity Mutual Funds

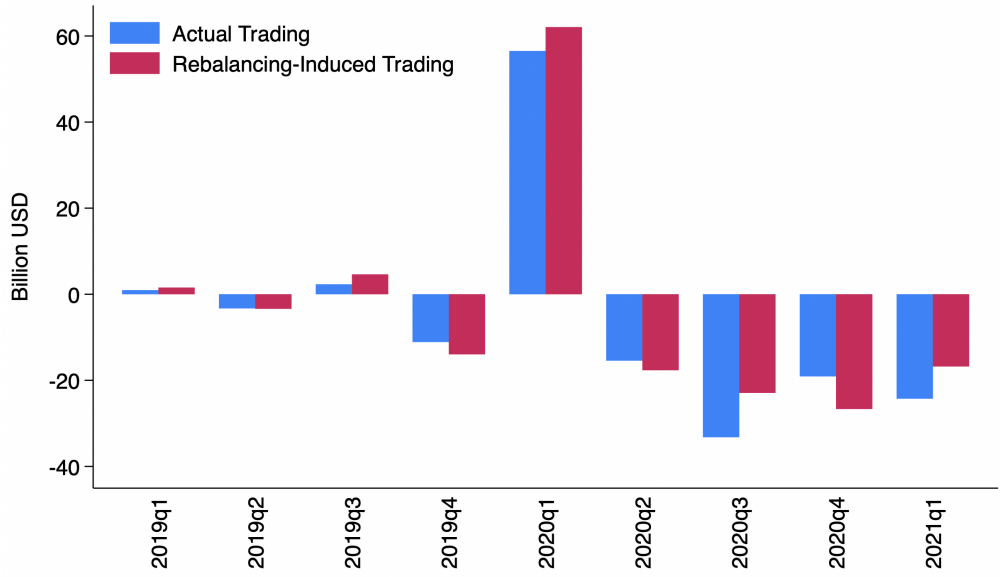


Figure 5: **Amplification of Bond Fund Outflows due to Strategic Complementarity.** This figure shows a decomposition of aggregate net flows to bond mutual funds. The dark red bars show flows due to direct trading by TAFs. The bright red bars show strategic flows from other investors in response to TAF rebalancing, estimated from Equation 10. The black bars show the residual flows.

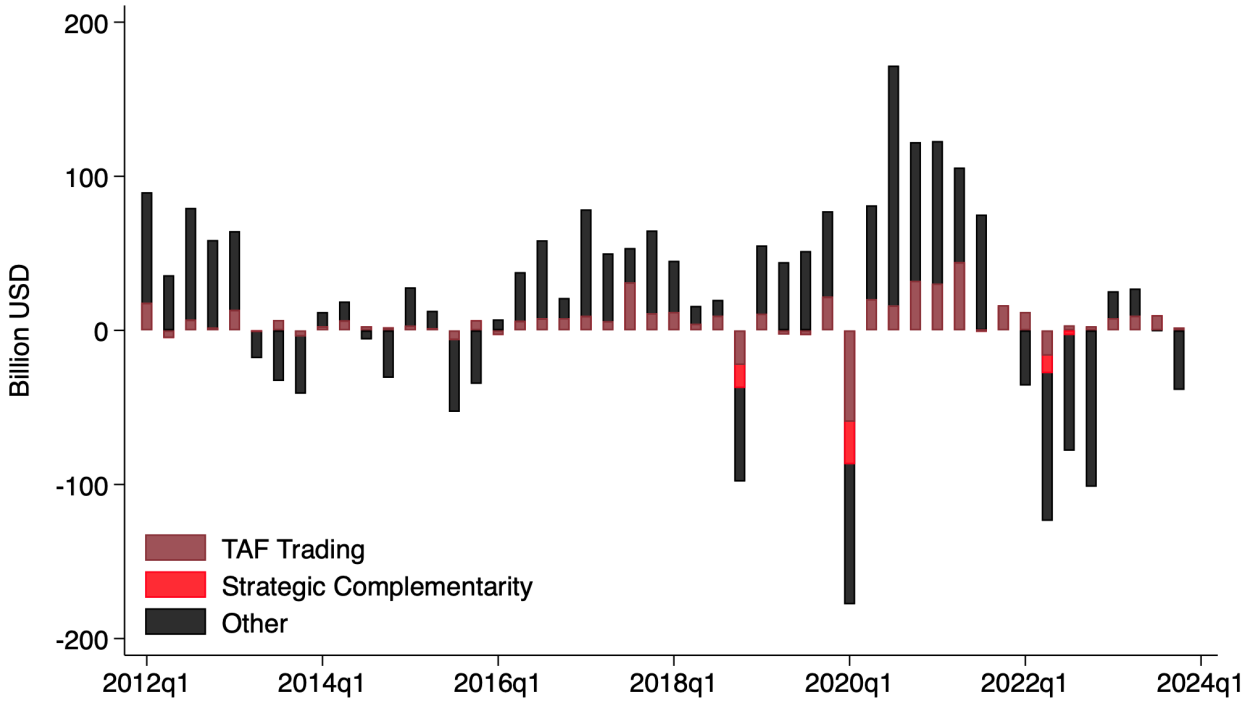


Figure 6: **Concave Bond Fund Flow to Equity Market Performance Relationship.** This figure plots average bond mutual fund flows binned by equity market returns. Flows are residualized against returns, lagged flows, log TNA, log age, expense ratio, and rear load. The red dots show bond mutual funds with more than 10% of ownership by TAFs. The blue dots show other bond mutual funds with zero or small ownership by TAFs. The lines are fitted from kernel-weighted local polynomial regression.

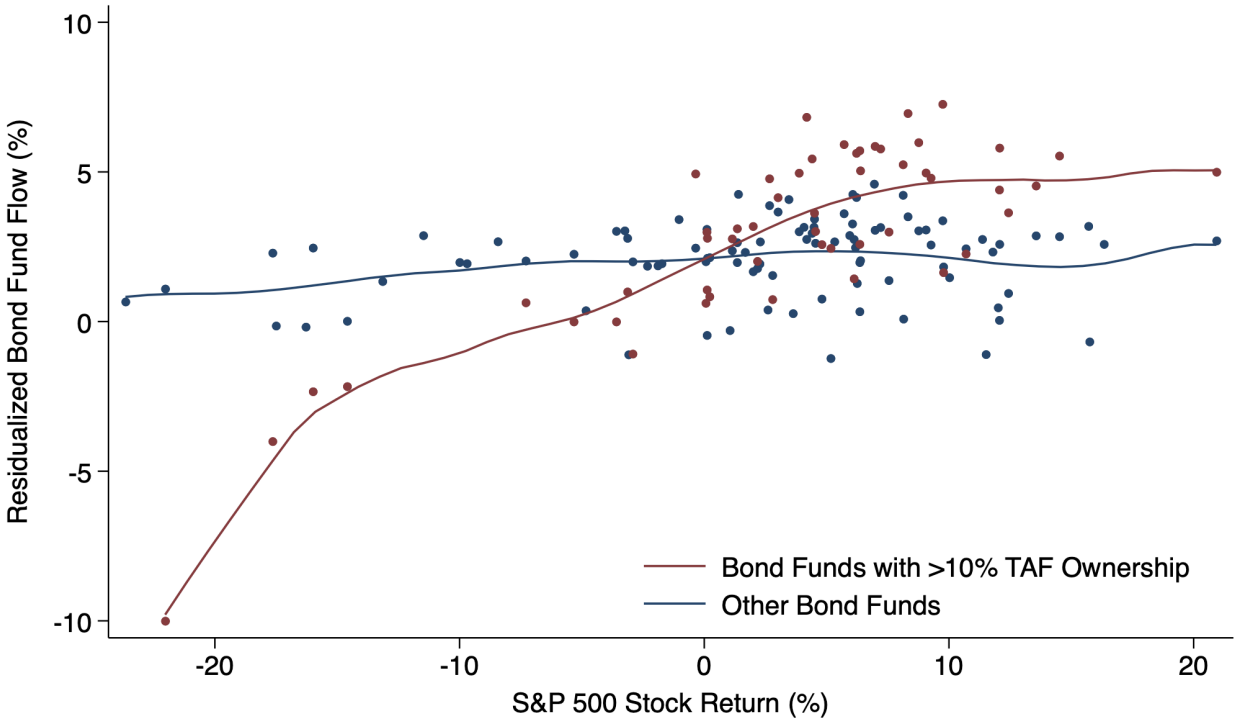
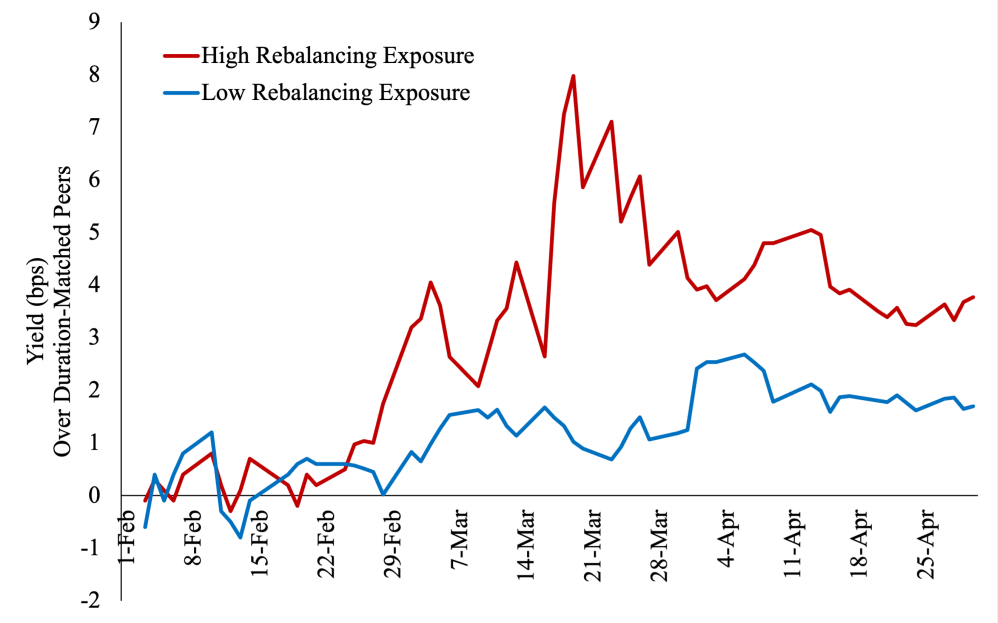


Figure 7: **Rebalancing Exposure and Bond Yields during the COVID-19 crisis.** These figures show yield dynamics for Treasury bonds (Panel A) and investment-grade corporate bonds (Panel B) whose mutual fund ownership are at the upper quartile of the distribution as of January 2020. These high-mutual-fund-ownership bonds are further sorted into two groups, based on their exposure to TAF rebalancing (Equation 11). For each bond on each date, its yield is normalized by the average across its peers with the same rating letter and the same duration bucket.

Panel A: Yields on Treasury Bonds with High Mutual Fund Ownership



Panel B: Yields on Corporate Bonds with High Mutual Fund Ownership

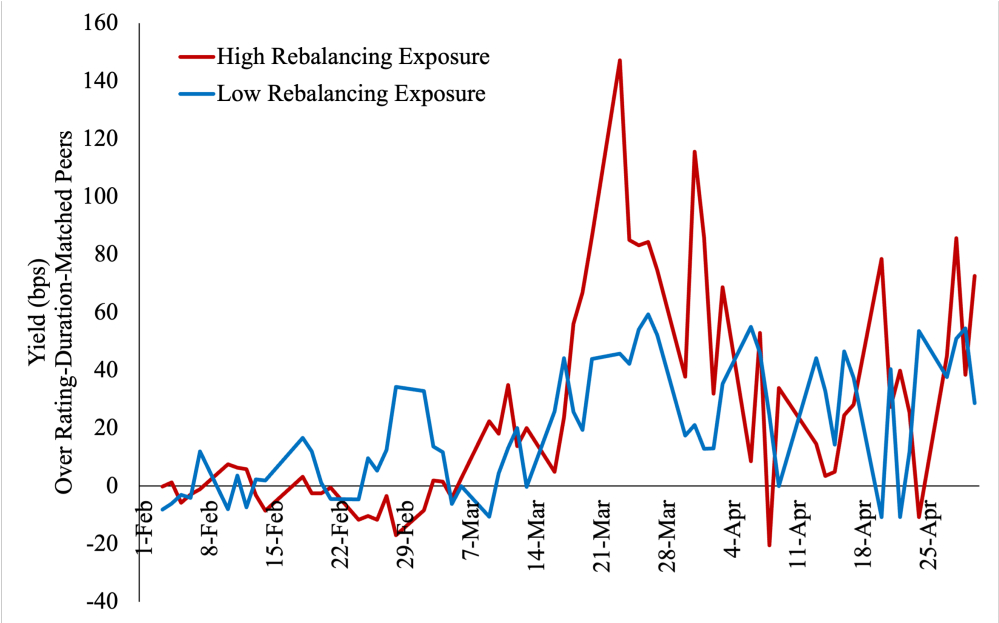
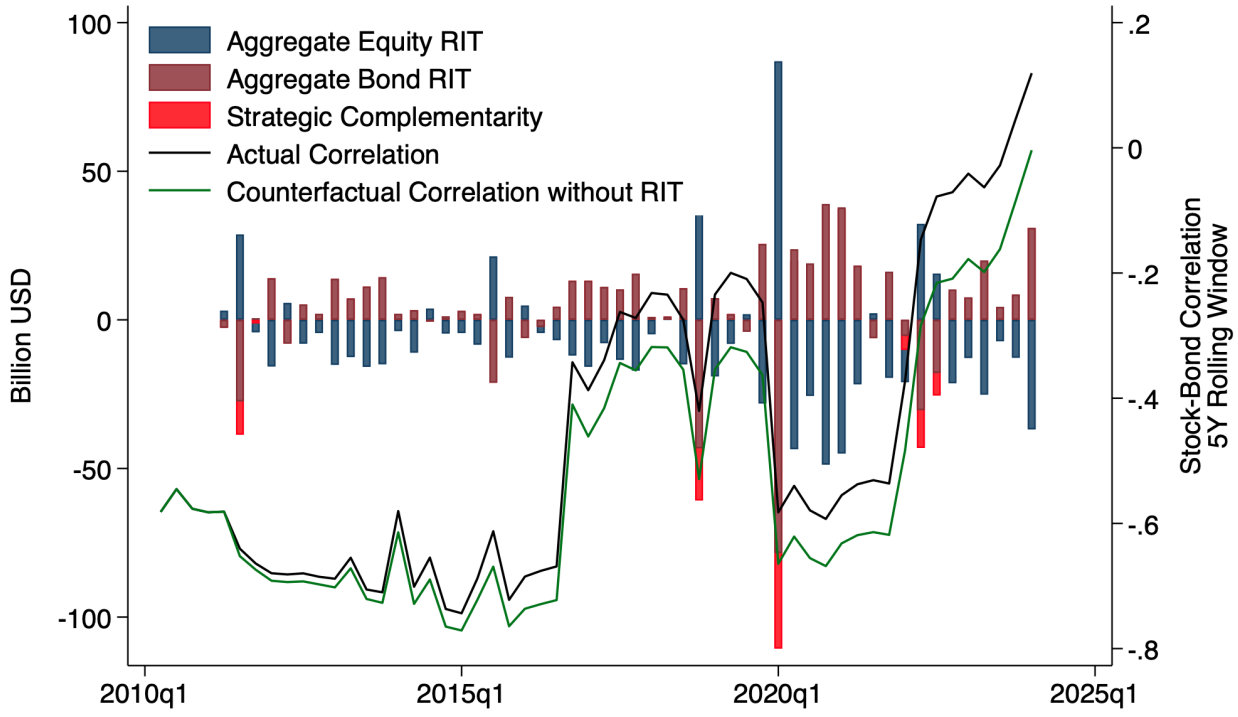


Figure 8: **TAF Rebalancing and Aggregate Stock-Bond Correlation.** This figure shows aggregate rebalancing-induced trading and its impact on aggregate stock-bond correlation. The navy (maroon) bars show rebalancing-induced trading of equity (bond) mutual funds by TAFs. The red bars show strategic flows from other investors in response to TAFs' rebalancing of bond mutual funds. The black line shows actual quarterly correlation between S&P 500 Index returns and Bloomberg Aggregate Bond Index returns, measured using 20-quarter rolling window. The green line shows correlation between counterfactual equity and bond market returns that subtract the price impacts of rebalancing-induced trading, estimated from Section 5.2.



Tables

Table 1: **Summary Statistics.** These tables show summary statistics of target allocation funds (Panel A) and bond mutual funds (Panel B). The data are quarterly from 2012Q4 to 2023Q4.

Panel A: Target Allocation Fund Statistics

	N	Mean	SD	P10	P50	P90
TNA (mn $)	35021	1946	5325	15	303	4644
Return (%)	35021	1.70	5.78	-5.64	2.40	7.39
Flow (% of TNA)	35021	3.46	15.36	-4.50	-0.01	13.19
Holdings of Bond Mutual Funds:						
Number of Distinct Funds	35021	4.53	2.84	1.00	4.00	8.00
Share of Overall Portfolio (%)	35021	32.83	21.45	6.96	30.97	62.72
Credit Rating (AAA = 1, CCC- = 19)	35021	4.68	2.09	2.48	4.42	7.17
Share of Affiliated (%)	35021	82.16	34.34	0.00	100.00	100.00

Panel B: Bond Mutual Fund Statistics

	N	Mean	SD	P10	P50	P90
TAF Ownership (% of TNA)	52473	7.40	20.23	0.00	0.00	26.19
Rebalancing-Induced Trading (% of TNA)	52473	0.01	2.07	-0.08	0.00	0.04
TAF Trading (% of TNA)	52473	0.08	3.40	-0.02	0.00	0.01
Flow (% of TNA)	52473	0.96	16.38	-10.26	-0.55	12.43
Flow ex TAF (% of TNA ex TAF)	52473	0.86	18.44	-10.96	-0.59	13.41
Credit Rating (AAA = 1, CCC- = 19)	52473	6.04	4.13	1.00	5.08	12.93
Return (%)	52473	0.51	3.35	-3.02	0.65	3.62
TNA (mn $)	52473	2712	11460	29	406	5259
Age (year)	52473	15.72	11.96	2.50	13.33	31.00
Expense Ratio (annualized, %)	52473	0.68	0.36	0.22	0.66	1.09
1[Rear Load]	52473	0.20	0.40	0.00	0.00	1.00

Table 2: **Actual v.s. Predicted TAF Trading.** These tables examine the predictability of TAFs' trading of bond mutual funds through Regression 4:

$$Trading_{i,j,t} = \beta RIT_{i,j,t} \times IlliquidityRank_{i,j,t-1} \times IlliquidPeriod_t + \gamma Controls + FE + \epsilon_{i,j,t}$$

$Trading_{i,j,t}$ denotes TAF i's actual trading of bond mutual fund j in quarter t, normalized by lagged holdings. $RIT_{i,j,t}$ measures TAF i's rebalancing-induced trading (Equation 1) of bond mutual fund j in quarter t, normalized by lagged holdings. $IlliquidityRank_{i,j,t-1}$ measures bond mutual fund j's illiquidity rank in TAF i's portfolio in quarter $t-1$ (Equation 3). $IlliquidPeriod_t$ is an indicator of whether the average corporate bond bid-ask spread in quarter t is in the upper quartile of its time series distribution. Panel A includes all TAFs, Panel B focuses on TDFs, and Panel C focuses on conventional TAFs. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: All Target Allocation Funds

Dependent Variable:	Actual Trading (% of Holding)			
			Affiliated	Unaffiliated
	(1)	(2)	(3)	(4)
Rebalancing-Induced Trading	0.998***			
(% of Holding)	(23.882)			
Negative RIT		0.925***	1.009***	0.963***
		(12.978)	(5.870)	(7.953)
× Illiquidity Rank			-0.092	-0.032
			(-1.138)	(-0.181)
× Illiquidity Rank × 1[Illiquid Period]			-0.199**	0.161
			(-2.033)	(1.199)
Positive RIT		1.122***	1.109***	0.943***
		(17.674)	(7.921)	(10.883)
× Illiquidity Rank			0.079	0.208
			(0.454)	(1.548)
× Illiquidity Rank × 1[Illiquid Period]			-0.002	0.122
			(-0.008)	(0.537)
TAF FE × Quarter FE	Y	Y	Y	Y
Bond Fund FE × Quarter FE	Y	Y	Y	Y
Controls	flow-induced trading, illiquidity rank × illiquid period			
Standard Errors	clustered by TAF, by bond fund, by quarter			
Observations	151963	151963	116372	30682
R2	0.865	0.866	0.873	0.864
Distinct TAFs	1537	1537	1335	680
Distinct Bond Funds	1156	1156	848	579

Panel B: Target Date Funds

Dependent Variable:	Actual Trading (% of Holding)			
			Affiliated	Unaffiliated
	(1)	(2)	(3)	(4)
Rebalancing-Induced Trading	1.065***			
(% of Holding)	(18.357)			
Negative RIT		1.033***	1.120***	0.974***
		(14.467)	(6.600)	(3.617)
× Illiquidity Rank			-0.017	-0.167
			(-0.081)	(-1.415)
× Illiquidity Rank × 1[Illiquid Period]			-0.248**	0.207
			(-2.390)	(1.257)
Positive RIT		1.103***	0.974***	1.047***
		(10.132)	(4.306)	(7.006)
× Illiquidity Rank			0.278	-0.428
			(0.916)	(-1.645)
× Illiquidity Rank × 1[Illiquid Period]			0.151	0.624
			(0.449)	(0.880)
TAF FE × Quarter FE	Y	Y	Y	Y
Bond Fund FE × Quarter FE	Y	Y	Y	Y
Controls	flow-induced trading, illiquidity rank × illiquid period			
Standard Errors	clustered by TAF, by bond fund, by quarter			
Observations	85807	85807	71414	11848
R2	0.884	0.884	0.889	0.920
Distinct TAFs	875	875	823	310
Distinct Bond Funds	478	478	391	153

Panel C: Conventional Target Allocation Funds

Dependent Variable:	Actual Trading (% of Holding)			
			Affiliated	Unaffiliated
	(1)	(2)	(3)	(4)
Rebalancing-Induced Trading (% of Holding)	0.947*** (15.744)			
Negative RIT		0.851*** (9.149)	1.053*** (5.247)	0.919*** (7.845)
× Illiquidity Rank			0.040 (0.424)	-0.009 (-0.036)
× Illiquidity Rank × 1[Illiquid Period]			-0.266* (-1.916)	0.159 (0.432)
Positive RIT		1.151*** (12.976)	1.236*** (6.964)	0.982*** (7.255)
× Illiquidity Rank			-0.188 (-0.950)	0.237 (1.139)
× Illiquidity Rank × 1[Illiquid Period]			-0.156 (-0.308)	-0.047 (-0.139)
TAF FE × Quarter FE	Y	Y	Y	Y
Bond Fund FE × Quarter FE	Y	Y	Y	Y
Controls	flow-induced trading, illiquidity rank × illiquid period			
Standard Errors	clustered by TAF, by bond fund, by quarter			
Observations	65307	65307	44228	18704
R2	0.879	0.879	0.885	0.870
Distinct TAFs	662	662	512	370
Distinct Bond Funds	1061	1061	736	531

Table 3: **Actual v.s. Predicted TAF Trading across Bond Mutual Funds.** This table examines the predictability of total TAF trading across bond mutual funds through Regression 6:

$$\frac{\sum_i Trading_{i,j,t}}{TNA_{j,t-1}} = \beta \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} + \gamma Controls + FE + \epsilon_{j,t}$$

$\widetilde{RIT}$ denotes rebalancing-induced trading predicted using real-time returns and accounts for illiquidity adjustment according to Equation 5. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Dependent Variable:	Actual TAF Trading (% of TNA)			
Sample:	2020Q1		All Periods	
	(1)	(2)	(3)	(4)
Rebalancing-Induced Trading	0.950***	0.991***	1.013***	1.046***
(% of TNA)	(12.990)	(24.222)	(14.960)	(16.549)
Contemporaneous Return (%)		0.010		0.002
		(0.483)		(0.302)
Lagged Return (%)		-0.018		0.006
		(-1.220)		(1.300)
Lagged Flow (% of TNA)		0.006***		0.001**
		(2.764)		(2.288)
Log TNA		-0.135***		-0.055
		(-3.179)		(-1.599)
Log Age		0.155		0.064
		(1.230)		(0.641)
Expense Ratio (%)		-0.355		0.255
		(-1.446)		(1.571)
1[Rear Load]		0.052		-0.054
		(0.438)		(-1.018)
Style FE		Y		
Bond Fund FE				Y
Style FE × Quarter FE				Y
Observations	702	702	29245	29245
R2	0.789	0.936	0.531	0.682

Table 4: **TAF Rebalancing and Strategic Flows from Other Investors, COVID-19.** These tables examine the relationship between predicted rebalancing by TAFs and flows from other non-TAF bond mutual fund investors during the COVID-19 crisis in 2020Q1, based on Regression 8:

$$\frac{Flow_{j,t} - Flow_{j,t}^{TAF}}{TNA_{j,t-1} - TNA_{j,t-1}^{TAF}} = \beta \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} \times IlliquidFund_{j,t} + \gamma Controls + FE + \epsilon_{j,t}$$

$\widetilde{RIT}$ denotes rebalancing-induced trading predicted using real-time returns and accounts for illiquidity adjustment according to Equation 5. $IlliquidFund_{j,t}$ is an indicator of whether bond mutual fund j has above-median illiquidity in quarter t, measured by average credit rating of bond holdings. Panel A shows the baseline results. Panel B examines subsamples of bond mutual funds, sorted by illiquidity. Panel C shows robustness with alternative definitions of illiquid bond mutual funds. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Baseline

Dependent Variable:	2020Q1 Flow ex Trading by TAF (% of 2019Q4 TNA ex Holding by TAF)	
	(1)	(2)
Rebalancing-Induced Trading (% of TNA)	0.681***	0.443***
	(3.354)	(3.080)
1[Fund Illiquidity > Median]	-1.150	-0.628
	(-0.942)	(-0.519)
RIT × 1[Illiquid Fund]		0.386**
		(2.201)
Contemporaneous Return (%)	0.273	0.244
	(1.577)	(1.429)
Lagged Return (%)	0.336	0.333
	(1.139)	(1.133)
Lagged Flow (% of TNA)	0.022	0.022
	(0.700)	(0.695)
Log TNA	-0.897**	-0.882*
	(-2.083)	(-2.021)
Log Age	1.558	1.577
	(1.355)	(1.383)
Expense Ratio (%)	-3.684	-3.595
	(-1.211)	(-1.203)
1[Rear Load]	1.536	1.583
	(1.662)	(1.694)
Style FE	Y	Y
Standard Errors	clustered by Lipper style	
Observations	1193	1193
R2	0.334	0.337

Panel B: Subsamples of Bond Mutual Funds

Dependent Variable:	2020Q1 Flow ex Trading by TAF (% of 2019Q4 TNA ex Holding by TAF)			
Sample:	Government Bond Funds	Investment-Grade Bond Funds	High-Yield Bond Funds	International Bond Funds
Rebalancing-Induced Trading (% of TNA)	0.174	0.457***	1.326	0.982*
	(0.330)	(6.517)	(1.008)	(1.892)
Controls	contemporaneous return, lagged return, lagged flow, log TNA, log age, expense ratio, rear load, illiquidity			
Style FE	Y	Y	Y	Y
Standard Errors	clustered by Lipper style			
Observations	122	571	319	181
R2	0.434	0.356	0.496	0.379

Panel C: Alternative Liquidity Measures

Dependent Variable:	2020Q1 Flow ex Trading by TAF (% of 2019Q4 TNA ex Holding by TAF)			
Illiquidity Measure:	Average Credit Rating	Average Bid-Ask Spread	Share of Corporate Bonds	Share of High-Yield Bonds
Rebalancing-Induced Trading (% of TNA)	0.443***	0.359**	0.492***	0.588***
	(3.080)	(2.641)	(2.945)	(3.305)
RIT × 1[Illiquid Fund]	0.386**	0.584**	0.383*	0.202*
	(2.201)	(2.392)	(1.956)	(1.909)
Controls	contemporaneous return, lagged return, lagged flow, log TNA, log age, expense ratio, rear load, illiquidity			
Style FE	Y	Y	Y	Y
Standard Errors	clustered by Lipper style			
Observations	1193	1193	1193	1193
R2	0.337	0.336	0.337	0.334

Table 5: **TAF Rebalancing and Strategic Flows from Other Investors, All Periods.** This table examines the relationship between predicted rebalancing by TAFs and flows from other non-TAF bond mutual fund investors using the full panel data from 2017Q4 to 2023Q4, based on Regression 8:

$$\frac{Flow_{j,t} - Flow_{j,t}^{TAF}}{TNA_{j,t-1} - TNA_{j,t-1}^{TAF}} = \beta \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} \times IlliquidFund_{j,t} \times IlliquidPeriod_t + \gamma Controls + FE + \epsilon_{j,t}$$

$\widetilde{RIT}$ denotes rebalancing-induced trading predicted using real-time returns and accounts for illiquidity adjustment according to Equation 5. $IlliquidFund_{j,t}$ is an indicator of whether bond mutual fund j has above-median illiquidity in quarter t, measured by average credit rating of bond holdings. $IlliquidPeriod_t$ is an indicator of whether the average corporate bond bid-ask spread in quarter t is in the upper quartile of its time series distribution. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Dependent Variable:	Flow ex Trading by TAF (% of TNA ex Holding by TAF)			
Sample:	RIT ≥ 0		RIT ≤ 0	
	(1)	(2)	(3)	(4)
Rebalancing-Induced Trading (% of TNA)	-0.043	-0.022	0.179	0.269
	(-0.136)	(-0.103)	(0.829)	(0.850)
RIT × 1[Illiquid Fund]		0.266		-0.058
		(0.526)		(-0.056)
RIT × 1[Illiquid Period]	-0.277	-0.215	0.540**	0.451**
	(-0.798)	(-0.605)	(2.381)	(2.005)
RIT × 1[Illiquid Period] × 1[Illiquid Fund]		-0.322		0.214*
		(-0.599)		(1.953)
Fund FE	Y	Y	Y	Y
Style FE × Quarter FE	Y	Y	Y	Y
Controls	contemporaneous return, lagged return, lagged flow, log TNA, log age, expense ratio, rear load, illiquidity			
Standard Errors	clustered by Lipper style × quarter			
Observations	23953	23768	24812	24631
R2	0.478	0.481	0.412	0.414

Table 6: **Rebalancing-Induced Strategic Complementarity, Investor-Level Evidence.** This table examines rebalancing-induced strategic complementarity using holdings by individual non-TAF mutual funds and individual insurance companies, based on Regression 9:

$$\frac{Trading_{k,j,t}}{Holding_{k,j,t-1}} = \beta \frac{\sum_i \widetilde{RIT}_{i,j,t}}{TNA_{j,t-1}} \times IlliquidFund_{j,t} + \gamma Controls + FE + \epsilon_{k,j,t}$$

$Trading_{k,j,t}$ ($Holding_{k,j,t}$) denotes net purchases (holdings) by investor k of bond mutual fund j in quarter t. $\widetilde{RIT}$ denotes rebalancing-induced trading predicted using real-time returns and accounts for illiquidity adjustment according to Equation 5. $IlliquidFund_{j,t}$ is an indicator of whether bond mutual fund j has above-median illiquidity in quarter t, measured by average credit rating of bond holdings. FE includes investor-by-quarter fixed effects. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Dependent Variable:	2020Q1 Trading (% of 2019Q4 Holding)		
Sample:	Non-TAF Mutual Funds	Insurance Companies	Funds + Insurers
	(1)	(2)	(3)
Rebalancing-Induced Trading	0.600	0.561**	0.598**
(% of TNA)	(1.301)	(2.278)	(2.007)
RIT × 1[Illiquid Fund]	0.796**	1.660*	1.529**
	(2.062)	(1.715)	(2.198)
Controls	contemporaneous return, lagged return, lagged flow, log TNA, log age, expense ratio, rear load, illiquidity		
Fund / Insurer FE	Y	Y	Y
Style FE	Y	Y	Y
Standard Errors	clustered by fund / insurer		
Observations	296	461	763
R2	0.767	0.760	0.744
Distinct funds / insurers	55	98	153
Distinct bond mutual funds	177	238	341

Table 7: **Robustness with Equity-Return-Induced Trading by TAFs.** These tables provide robustness to Regressions 7, 8 and 9 by using equity-return-induced trading, which is constructed from Equation 1 with all bond fund returns set to 0. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Fund Level

Dependent Variable:	2020Q1 Flow ex Trading by TAF (% of 2019Q4 TNA ex Holding by TAF)	
	(1)	(2)
Equity-Return-Induced Trading (% of TNA)	0.852***	0.411**
	(3.013)	(2.388)
ERIT × 1[Illiquid Fund]		0.676**
		(2.335)
Controls	contemporaneous return, lagged return, lagged flow, log TNA, log age, expense ratio, rear load, illiquidity	
Style FE	Y	Y
Standard Errors	clustered by Lipper style	
Observations	1193	1193
R2	0.337	0.343

Panel B: Investor Level

Dependent Variable:	2020Q1 Trading (% of 2019Q4 Holding)		
Sample:	Non-TAF Mutual Funds	Insurance Companies	Funds + Insurers
	(1)	(2)	(3)
Equity-Return-Induced Trading (% of TNA)	0.757	0.844*	0.794
	(1.322)	(1.877)	(1.562)
ERIT × 1[Illiquid Fund]	0.897**	1.541	0.923**
	(2.268)	(1.303)	(2.021)
Controls	contemporaneous return, lagged return, lagged flow, log TNA, log age, expense ratio, rear load, illiquidity		
Fund / Insurer FE	Y	Y	Y
Style FE	Y	Y	Y
Standard Errors	clustered by fund / insurer		
Observations	296	461	763
R2	0.767	0.760	0.749
Distinct funds / insurers	55	98	153
Distinct bond mutual funds	177	238	341

Table 8: **Rebalancing Exposure and Cross-Sectional Bond Return Sensitivity to Equity Market Shocks.** These tables examine how exposure to TAF rebalancing (Equation 11) affects comovement with equity market returns in the cross section of Treasury bonds (Panel A) and investment-grade corporate bonds (Panel B), based on Regression 12:

$$R_{b,m} = \beta(R^E_m - R^B_m) \times Exposure_{b,q-1} + \gamma Controls + FE + e_{b,m}$$

t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Treasury Bond Returns

Dependent Variable	Treasury Bond Return (bps)	
	(1)	(2)
(1) $R^E - R^B$ (%)		
(2) Rebalancing Exposure	0.007	0.003
	(0.246)	(0.186)
(1) × (2)	0.193	0.096
	(1.408)	(1.032)
(1) × (2) × 1[COVID]		1.089*
		(1.903)
Controls	duration, bid-ask spread, lagged return	
CUSIP FE	Y	Y
Maturity FE × Month FE	Y	Y
Standard Errors	clustered by month	
Observations	24892	24892
R2	0.986	0.988

Panel B: Investment-Grade Corporate Bond Returns

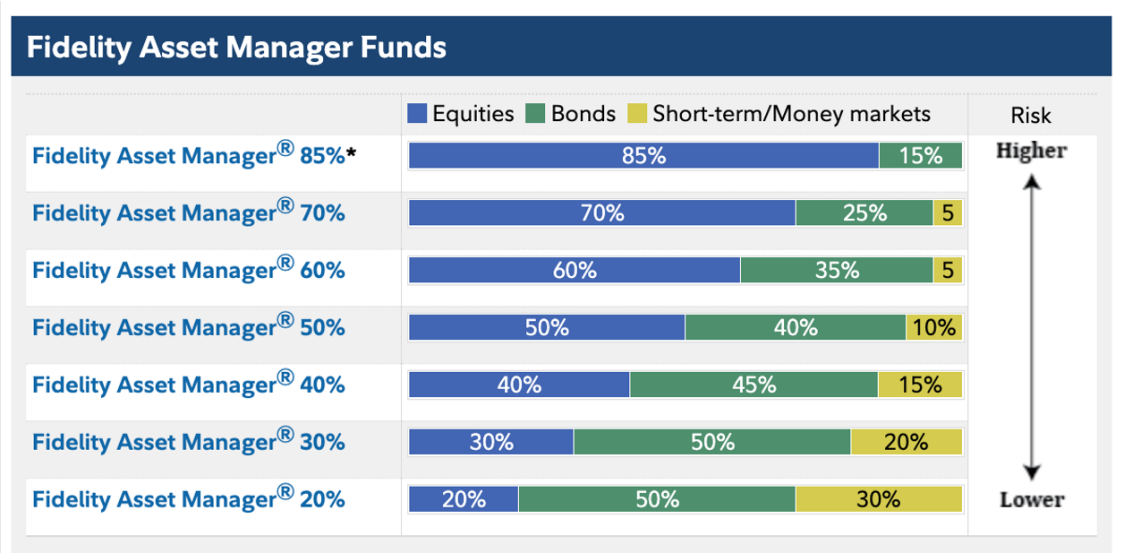
Dependent Variable	Corporate Bond Return (bps)	
	(1)	(2)
(1) $R^E - R^B$ (%)		
(2) Rebalancing Exposure	-0.001	0.000
	(-0.107)	(0.084)
(1) × (2)	0.927	0.394
	(1.615)	(1.375)
(1) × (2) × 1[COVID]		5.902**
		(2.035)
Controls	credit rating, duration, bid-ask spread, lagged return	
CUSIP FE	Y	Y
Rating FE × Month FE	Y	Y
Maturity FE × Month FE	Y	Y
Industry FE × Month FE	Y	Y
Standard Errors	clustered by month	
Observations	203942	203942
R2	0.638	0.641

Internet Appendix

A Additional Figures

Figure A1: **Examples of Target Allocation Funds.** These figures show examples of conventional target allocation funds (Panel A) and target date funds (Panel B).

Fidelity Asset Manager Funds



Fidelity Freedom 2055 Fund

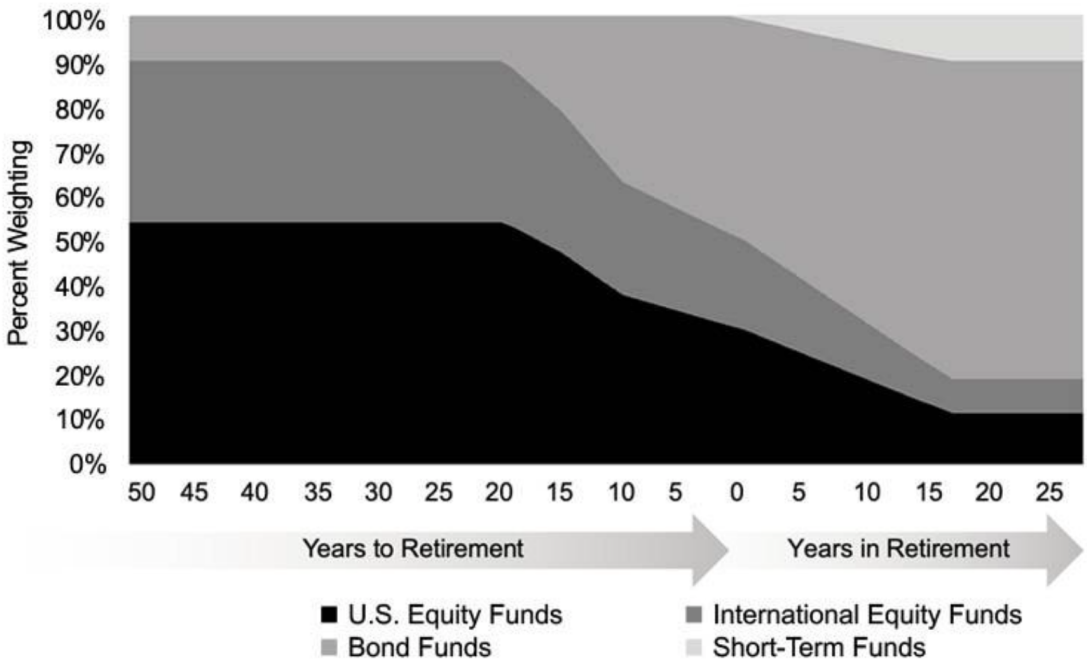
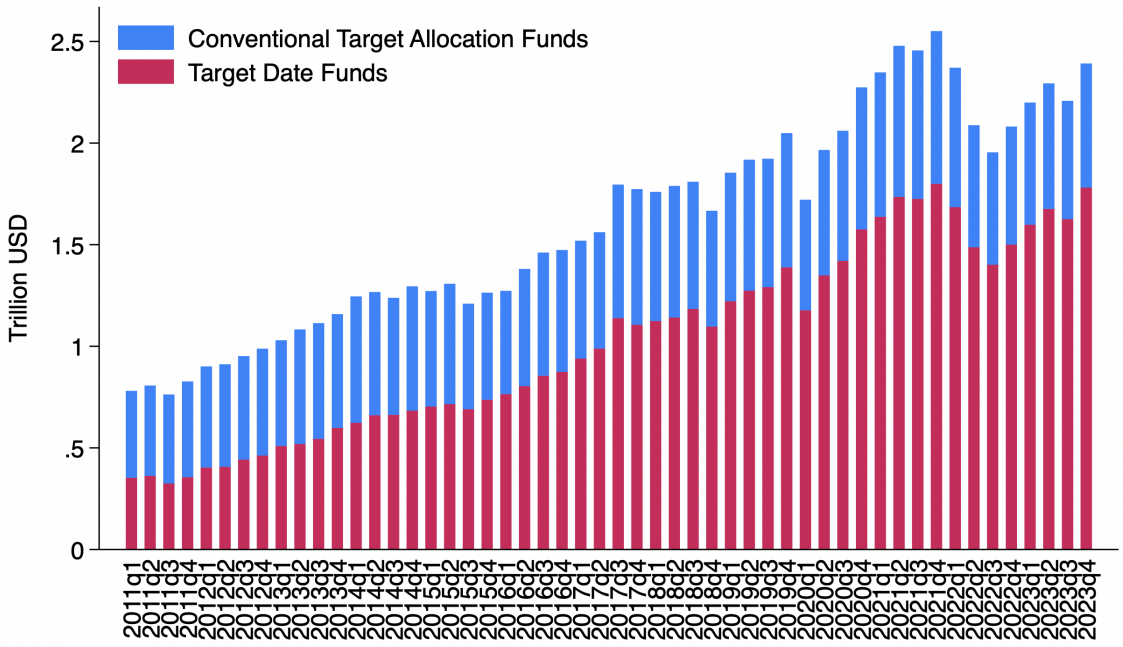
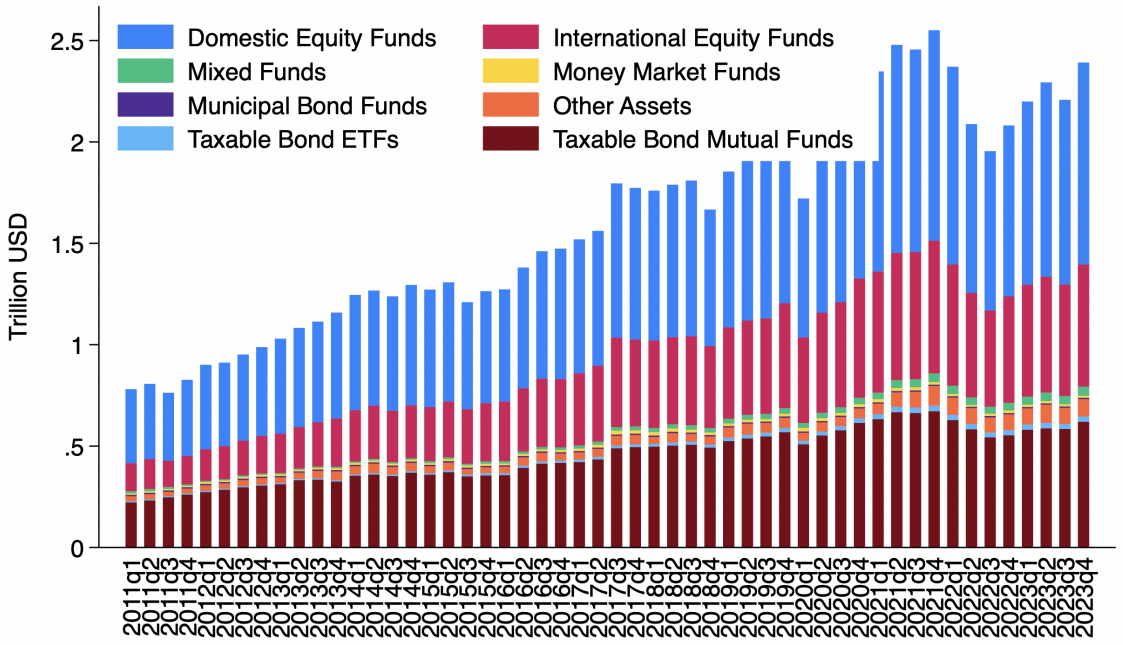


Figure A2: **Aggregate Statistics of Target Allocation Funds.**

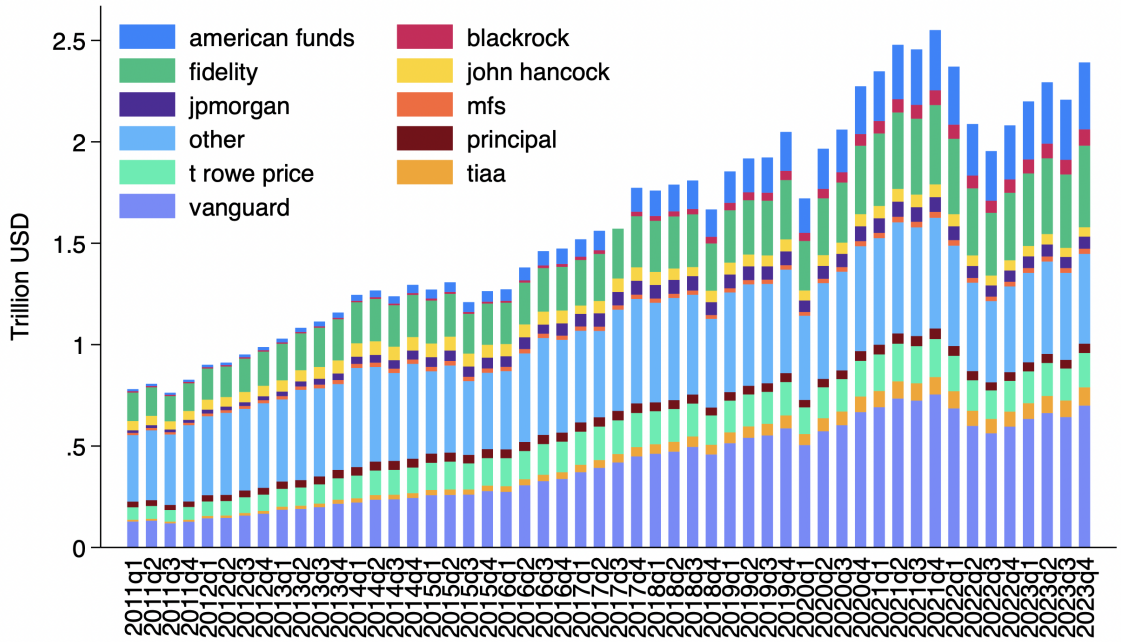
Panel A: By TAF Strategy



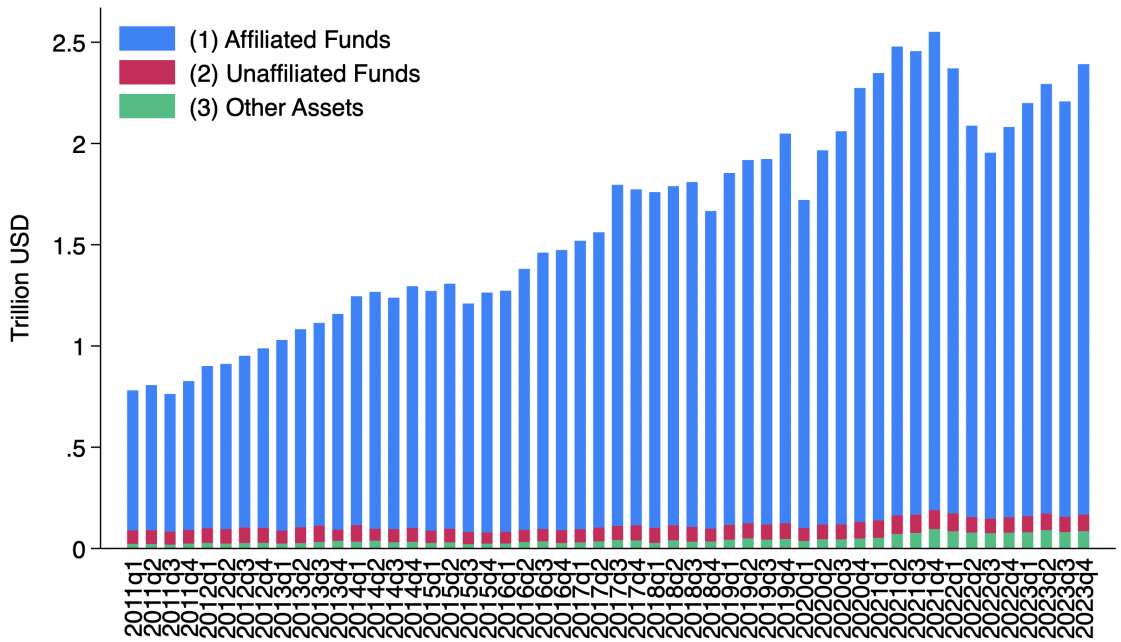
Panel B: By Asset Class of Funds Held



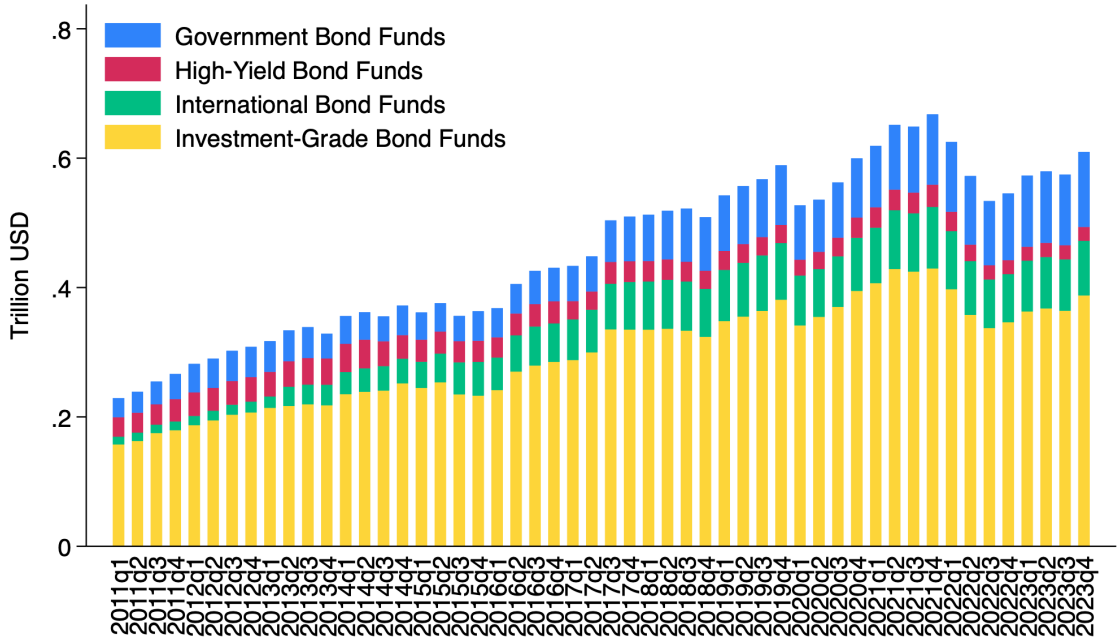
Panel C: By TAF Fund Family



Panel D: By Affiliation of Funds Held



Panel E: By Styles of Bond Funds Held



Panel F: By Activeness of Bond Funds Held

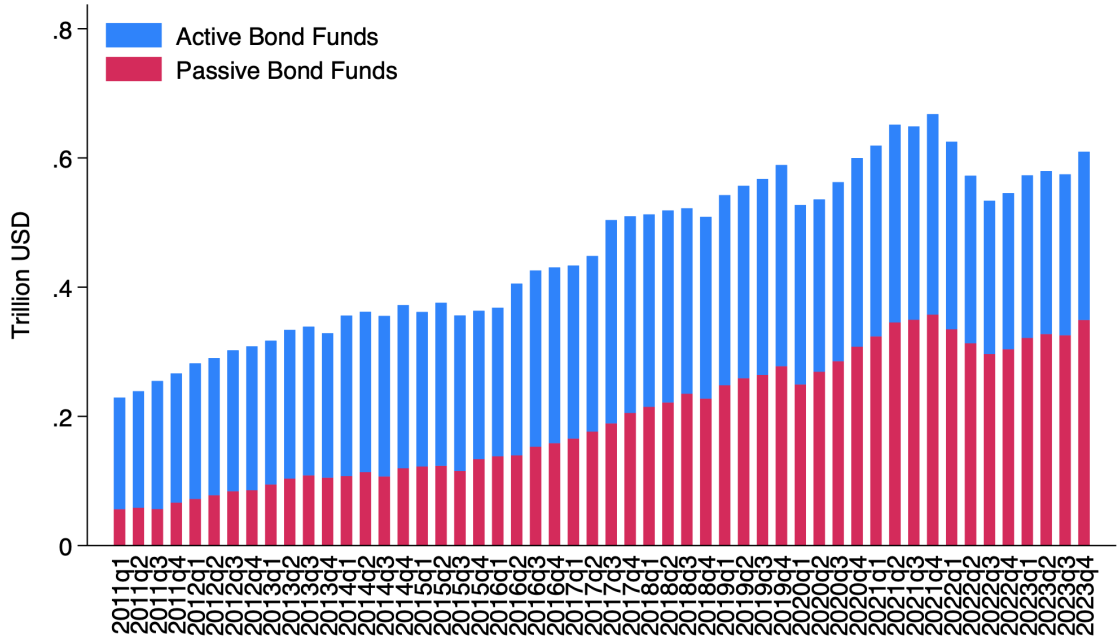


Figure A3: **Example of TAF Portfolio Holdings.** This table shows the portfolio holdings of Vanguard Target Retirement 2025 Fund, the largest TAF in our sample, at quarter-end 2019Q4 and at quarter-end 2020Q1.

report_dt	security_rank	percent_tna	market_val	security_name	cusip
31-Dec-19	1	36.41	1.70E+10	Vanguard Total Stock Market Index Fund;Investor	92290830
31-Dec-19	2	27.77	1.30E+10	Vanguard Total Bond Market II Index Fund;Investor	92203C10
31-Dec-19	3	24.51	1.14E+10	Vanguard Total International Stock Index Fund;Inv	92190960
31-Dec-19	4	11.32	5.28E+09	Vanguard Total International Bond Index Fund;Inv	92203J10
31-Dec-19	5	0.00	29262	CMT Market Liquidity Rate	
...	...	...	...	...	...
31-Mar-20	1	36.01	1.43E+10	Vanguard Total Stock Market Index Fund;Investor	92290830
31-Mar-20	2	27.79	1.11E+10	Vanguard Total Bond Market II Index Fund;Investor	92203C10
31-Mar-20	3	24.33	9.67E+09	Vanguard Total International Stock Index Fund;Inv	92190960
31-Mar-20	4	11.75	4.67E+09	Vanguard Total International Bond Index Fund;Inv	92203J10
31-Mar-20	5	0.11	45537662	CMT Market Liquidity Rate	