London School of Economics and Political Science

ESSAYS IN ASSET MANAGEMENT

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Declaration

I certify that the thesis I have presented for examination for the Ph.D. degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I confirm that Chapter 2 is jointly co-authored with Li An, Shiyang Huang, and Dong Lou. I contributed 25% of this work.

I confirm that Chapter 3 is jointly co-authored with Jiaxing Tian. I contributed 50% of this work.

I declare that the thesis consists of 31,157 words.

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Abstract

This thesis contains three essays on the trading behavior and product market innovation of asset managers.

The first chapter finds that political beliefs shape professional investors' interpretations of fiscal policy and, consequently, their asset allocation decisions. Using daily data on Congressional Budget Office cost releases for U.S. legislative proposals, I find that fixed-income mutual fund managers who oppose the current president's party trade more aggressively and pessimistically in response to news of anticipated rising federal budget deficits. Compared to politically aligned managers, they reduce their positions in long-term Treasury and corporate bonds more significantly while increasing their holdings in Treasury Inflation-Protected Securities. This partisan-driven trading exerts a temporary price impact on Treasury securities and long-term corporate bonds.

The second chapter (with Li An, Shiyang Huang, and Dong Lou) documents that despite the removal of all regulatory barriers by 1997, long-short equity mutual funds have seen disappointing growth over the past two decades. We shed new light on this puzzle by documenting a novel set of facts: long-short mutual funds: 1) hold a substantial amount of cash (in excess of cash-collateral requirements) and have an average market beta of 0.6; 2) generate a 5% annual alpha on risky holdings but do not outperform their long-only peers in total returns; and 3) face much higher flow-performance sensitivities and more volatile flows, and use cash buffers more aggressively. These findings challenge prevailing explanations for this puzzle—such as client restrictions, lack of short-selling skills, or high short-selling costs and risks—and motivate a new framework centered on investor clientele and flow responses.

The third chapter (with Jiaxing Tian) investigates the decline of traditional mutual funds, focusing on the substitution of mutual funds by collective investment trusts (CITs) in the 401(k) pension investment, and offers insights from both demand and supply sides. Employing several datasets, we demonstrate that CITs are adopted due to their lower fees, comparable returns, and customized nature, aligning with investor preferences sensitive to cost rather than financial transparency. Moreover, mutual fund companies with positive

signals, such as past returns and ratings, are incentivized to introduce CITs to reduce auditing costs and gain market shares in 401(k)s. The surge of CITs in 401(k) menus has implications for pension plan governance, with better-governed plans more likely to incorporate CITs. Our findings suggest potential welfare improvements in this delegated asset management model, with investors benefiting from lower total investment costs and mutual fund companies gaining inflow stability. Overall, our research contributes to understanding the dynamics of non-mutual fund investments and their implications for financial markets and investors.

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Chapter 1

Partisan Bias and Federal Budget Deficit: Evidence from Mutual Funds

Political beliefs shape professional investors' interpretations of fiscal policy and, consequently, their asset allocation decisions. Using daily data on Congressional Budget Office cost releases for U.S. legislative proposals, I find that fixed-income mutual fund managers who oppose the current president's party trade more aggressively and pessimistically in response to news of anticipated rising federal budget deficits. Compared to politically aligned managers, they reduce their positions in long-term Treasury and corporate bonds more significantly while increasing their holdings in Treasury Inflation-Protected Securities. This partisan-driven trading exerts a temporary price impact on Treasury securities and long-term corporate bonds.

1.1 Introduction

Political polarization in the U.S. has increased over the past two decades, with growing evidence from political science literature indicating that individuals hold biased economic beliefs and tend to become more pessimistic when the opposing party holds office (Bartels, 2002; Gerber and Huber, 2009; Gerber and Huber, 2010; Prior et al., 2015; McGrath et al., 2017; Brady et al., 2022). Meeuwis et al. (2022) shows that Democratic households exhibited greater risk aversion and shifted into safe assets following the 2016 presidential election. This partisan disagreement effect extends beyond individuals to professionals in financial markets (Cassidy and Vorsatz, 2021; Kempf and Tsoutsoura, 2021; Dagostino et al., 2023; Rice, 2024). However, little is known about what drives this partisan effect and why individuals feel more optimistic about the economy when their ideology aligns with the sitting president's party. This paper proposes a unique economic mechanism underlying this divergence in opinion: heterogeneous interpretations of fiscal policy outcomes. I find that following news of potentially rising federal budget deficits, fixed-income mutual fund managers who disagree with the party in power exhibit greater pessimism, reduce more of their holdings of long-term bonds, and increase more of their allocation to Treasury Inflation-Protected Securities (TIPS), compared to the managers supporting the president's party.

With the increasing tendency of politicians to criticize the opposing party as fiscally irresponsible[1], the federal budget deficit has become one of the most divisive issues for voters from the two parties.[2] Partisans differ in how they attribute blame for government overspending, reacting more severely to fiscal expansion under the opposing party (Rudolph, 2003; Rudolph, 2006; Kane and Anson, 2023).[3] Although it is well docu-

[1]For instance, back in 2008, Presidential Candidate Barack Obama criticized government overspending, stating, "Bush added $4 trillion to our national debt, so that we now have over $9 trillion of debt that we are going to have to pay back – $30,000 for every man, woman, and child." During the 2016 election, Presidential Candidate Donald Trump similarly spoke about Obama's overspending: "The budget is no better. President Obama has almost doubled our national debt to more than $19 trillion, and growing." Years later, President Joe Biden criticized the budgetary impact of Trump's administration, noting, "This isn't going to be anything like my predecessor, whose unpaid tax cuts and other spending added nearly $8 trillion in his four years to the national debt."

[2]In the 2024 presidential election, a Gallup poll indicates a 29% difference between Republican and Democratic voters regarding the importance of the federal budget deficit in their voting decisions.

[3]For example, A 2010 Pew Research Center showed that 85% of Democrats had confidence in President Obama to handle the federal budget deficit effectively, while only 17% of Republicans shared this view. In contrast, a Gallup poll on public opinion regarding President Trump's tax cuts found that 71%

mented that reductions in national surpluses lead to higher inflation (Sargent et al., 1981; Cochrane, 2001; Hilscher et al., 2022; Cochrane, 2023) and declines in government debt values (Berndt et al., 2012; Campbell et al., 2023; Gomez Cram et al., 2023), individuals must estimate the quantitative outcomes of fiscal expansions based on their personal priors, which are often influenced by their political ideology—even among financial professionals.[4] While capturing individuals' differing interpretations of fiscal policy consequences based on political views outside of survey data is challenging, fixed-income asset managers provide an ideal setting for this study. These professionals must make investment decisions based on their own predictions of economic policy outcomes and have strong incentives to make accurate forecasts. Moreover, with actively managed fixed-income mutual funds overseeing assets under management (AUM) totaling \$3.5 trillion by the end of 2023, these fund managers play a significant role in the U.S. bond market, and their portfolio choices may influence underlying asset prices.

This paper documents substantial differences in portfolio choices among fixed-income mutual fund managers based on their ideological alignment with the current president's party in response to news of anticipated increases in federal budget deficits. I determine managers' partisan alignment based on their lifetime political contributions (Hong and Kostovetsky, 2012; Lee et al., 2014; Rice, 2024). A comprehensive sample spanning 2003 to 2023 enables me to capture the trading behavior of both Republican and Democratic managers when they align with or oppose the current president. To understand how policies may contribute to the federal budget deficit, I follow Gomez Cram et al. (2023) and Gomez Cram et al. (2024) and collect cost estimates from the nonpartisan Congressional Budget Office (CBO), which provides spending and revenue projections for each legislative proposal. As shown in Figure 1.1, most of these bills, if enacted, are projected to increase the federal deficit.

I find that fund managers opposing the president's party tend to adopt a more pessimistic outlook after CBO estimates of rising deficits, anticipating sharper declines in long-term Treasury bond prices and higher inflation. In response, compared to ideologi-

of Republicans believed the cuts would reduce the federal deficit in the long run, while 77% of Democrats expected an increase.

[4]For instance, an economist who consistently donates to the Republican Party expressed optimism about President Trump's tax cuts in 2017. Conversely, during the 2024 election cycle, while this Democratic economist argued that there was no need to panic about the budget deficit, a Republican asset manager harshly criticized President Biden's spending policies.

cally aligned managers, these misaligned managers reduce their Treasury bond holdings further and increase their investments in TIPS. A one-standard-deviation increase in the quarterly projected deficit-to-GDP ratio contributed by bills is associated with a 6.5% additional reduction in long-term Treasury holdings and a 10% additional increase in TIPS holdings, relative to their original positions. Anticipating sharper inflation increases, misaligned managers also reduce their holdings in long-term corporate bonds, particularly investment-grade bonds, which are more sensitive to discount rate changes. In contrast, both types of managers show no significant differences in their positions in short-term bonds. The results remain consistent across a series of rigorous robustness tests, including controls for an extensive set of fund and manager characteristics, high-dimensional fixed effects, and alternative definitions of key variables. These findings are not driven by any specific subperiod or by managers affiliated with a particular party.

I further analyze these legislative bills by their sponsors and the intended use of the deficit, finding that fund managers consider both the deficit size and the specific details of the bills. Legislative proposals may be introduced by members of either the president's party or the opposition. I show that politically misaligned managers more significantly reduce their long-term Treasury and corporate bond positions in response to deficit increases associated with bills introduced by politicians from the president's party. I then decompose bill-level deficit increases into those driven by higher government spending and those resulting from reduced government revenues, and regress fund trading on estimates of these two bill types. I uncover that managers trade Treasury bonds and TIPS similarly, but sell more long-term corporate bonds only in response to bills that increase government spending. This is because bills that reduce federal revenues through tax cuts tend to benefit firms, potentially offsetting the negative impact of inflation on long-term corporate bonds.

Since personal attributes can influence individuals' inflation expectations (D'Acunto et al., 2023, Binetti et al., 2024), I classify funds into two groups based on fund manager characteristics. Consistent with Malmendier and Nagel (2016), my results suggest that the effect of political misalignment is more pronounced among fund managers with longer experience in the mutual fund industry, as they are more likely to recall the high inflation periods and sharp rises in Treasury yields before the 2000s. Although the findings are less robust due to the relatively small sample size, I also observe that political bias appears to have a smaller effect on management teams with female members and those with PhDs.

Next, I employ a local projection approach (Jordà, 2005) to examine whether the effects of partisan views and shifts in federal deficits on fund trading behavior persist over time. Compared to managers aligned with the president, those with opposing views are more likely to continue reducing Treasury bond holdings for up to three quarters following projections of increasing deficits, while their purchases in TIPS and sales of long-term corporate bonds are smaller in size and reverse earlier. These findings suggest that fund managers interpret CBO deficit projections as signals of both increased Treasury supply (Gomez Cram et al., 2024) and rising inflation (Cochrane, 2023), with Treasury bond trades reflecting both concerns, while TIPS and corporate bond trades are driven primarily by inflation expectations. To further understand how partisan views influence fund managers' trading decisions, I extend this test to all asset classes held by the funds. I find that misaligned managers primarily rebalance into agency MBS and municipal bonds, likely as substitutes for long-term Treasury bonds.

After establishing that politically misaligned managers trade more actively in response to CBO forecasts of rising federal deficits, I turn to the asset pricing effects of this partisan-influenced behavior. Applying Fama-MacBeth regressions with controls for various Treasury characteristics, I find that on days with highly negative cash flow projections from the CBO, trades by politically misaligned managers lead to an additional 6.8% decline in the prices of Treasury bonds they predominantly hold. Additionally, compared to managers supporting the president's party, these misaligned managers gradually increase their TIPS holdings, which in turn generates a positive price impact for these securities.

I then examine the asset pricing implications for corporate bonds. Given the relative infrequency of corporate bond transactions, I test the price impact of trading by misaligned funds on a quarterly basis. After controlling for a comprehensive set of high-dimensional fixed effects, I find that a 1 percentage point increase in the quarterly projected deficit-to-GDP ratio contributed by bills is associated with a 3.74 bps increase in the yield spread of long-term corporate bonds fully held by misaligned funds. This effect reverts after two quarters, suggesting that the rise in yield spread is driven by partisan trading from misaligned funds rather than by changes in the fundamental value of these corporate bonds.

My final set of tests examines whether partisan-driven trading decisions influence fund flows and impact fund value. I find no significant response in investment flows to the political affiliation of managers, regardless of whether quarters include large CBO cost estimates. However, misaligned managers generate lower CAPM alpha in the quarters following high deficit announcements, while differences in other return measures remain insignificant. Interestingly, misaligned funds show higher average returns, although this advantage declines and loses statistical significance after accounting for maturity and mortgage factors.

My findings indicate that fund managers with partisan views opposing the president's party tend to adopt a more pessimistic outlook following CBO projections of rising deficits, anticipating sharper increases in Treasury supply and higher inflation. Therefore, they trade more aggressively based on this biased prediction of fiscal expansion consequences, leading to temporary price impacts in Treasury and corporate bond markets. Collectively, this paper offers an economic mechanism explaining the divergence in opinions between individuals from opposing parties: the varied interpretations of fiscal policy outcomes.

Related Literature. This study contributes to multiple strands of literature. First, it relates to research that examines the impact of political alignment between investors and the government on capital allocation decisions. Meeuwis et al. (2022) finds that Democratic households become more pessimistic and reduce equity holdings following the 2016 U.S. presidential election. Similarly, Cassidy and Vorsatz (2021) documents comparable behavior among Democratic U.S. equity mutual fund managers. [5] The underlying drivers of increased risk aversion among investors who disagree with the party in power remain an open question. This work contributes to the literature by studying the economic mechanisms behind the effects of partisan alignment. Specifically, it provides

[5]These studies examine the political alignment between investors and the U.S. government. Other research explores the effects of political alignment on portfolio choices in various contexts, including between mutual fund management teams (Evans et al., 2025), between fund managers and firms (Wintoki and Xi, 2020), and between managers and foreign governments (Kempf et al., 2023).

evidence that heterogeneous interpretations of fiscal policies drive the divergent trading behaviors observed between investors from opposing parties.

More broadly, this work is also related to the growing literature on political beliefs and sophisticated professionals, including sell-side equity analysts (Jiang et al., 2016; Cassidy and Vorsatz, 2021), credit rating analysts (Kempf and Tsoutsoura, 2021), bankers (Dagostino et al., 2023; Chu, 2024), regulators (Engelberg et al., 2023a), inventors (Engelberg et al., 2023b), and firm executives (Lee et al., 2014; Babenko et al., 2020; Knill et al., 2022; Rice, 2024). Research on U.S. equity mutual funds shows that partisanship shapes fund managers' non-pecuniary beliefs, including attitudes toward socially responsible companies (Hong and Kostovetsky, 2012), the COVID-19 pandemic (Vorsatz, 2022; Sheng et al., 2024), climate change, and health care (Wang, 2024). This study contributes to the literature in two key ways. First, to the best of my knowledge, it is among the first to examine how political polarization influences fixed-income mutual fund managers' portfolio choices, thereby affecting asset prices in the Treasury and corporate bond markets. Second, it demonstrates that political preferences also shape fund managers' pecuniary beliefs when forecasting the consequences of economic policies. These findings suggest that the impact of partisan bias on professional investors may be even greater than previously documented.

This paper also extends the literature on partisanship and inflation expectations. Survey evidence consistently suggests that individuals have lower inflation expectations when their preferred party is in power (Bachmann et al., 2021; Mian et al., 2023; Binder, 2023; Kamdar and Ray, 2023; Binder et al., 2024). Surveys conducted in 2023–2024, during a Democratic presidency, show that Republicans report higher inflation perceptions and are more likely to attribute inflation to government spending and debt (Binetti et al., 2024; Stantcheva, 2024). Instead of relying on survey data, this study uses fund holdings and trading data to demonstrate that political preferences influence investors' inflation expectations and their portfolio choices based on these perceptions, thereby providing additional evidence to this stream of literature.

Finally, this paper adds to the literature on the ways professional investors make asset allocation decisions based on macroeconomic information. Huang and Wang (2014) and Hong et al. (2023) examine the macro timing abilities of government bond funds, while

Ceballos and Xiao (2023) finds that corporate bond mutual funds forecast inflation risks and adjust their portfolio exposures accordingly. Becker and Ivashina (2015), Di Maggio and Kacperczyk (2017), and Choi and Kronlund (2018) show that managers tend to reach for yield during periods of low-interest rates in insurance companies, money market funds, and corporate bond funds, respectively. Further, recent studies examine the influence of scheduled Federal Open Market Committee (FOMC) announcements on fixed-income mutual fund flows, returns, and portfolio compositions (Brooks et al., 2018; Fang, 2023; Kuong et al., 2024; Xiao, 2024). Unlike these works on monetary policy effects, this study uncovers that asset managers' political biases shape their interpretations of fiscal policy, suggesting that partisan misaligned managers are more prone to view fiscal expansion as a negative signal for Treasury supply and inflation, which sheds new light on how investors process macroeconomic information.

1.2 Data Descriptions

In this section, I first describe the construction of the mutual fund sample used for analysis (Section 1.2.1), followed by an introduction to the data on CBO cost estimates (Section 1.2.2) and mutual fund partisanship, including summary statistics for each party (Section 1.2.3). I then discuss the remaining data sources for Treasury securities and corporate bonds in Section 1.2.4. Detailed definitions of all variables are provided in Appendix Table 1.A.1.

1.2.1 Mutual fund sample

I collect data on U.S. actively managed fixed-income mutual funds from Morningstar, covering fund characteristics and quarterly holdings from January 2003 to December 2023.[6] Following Huang et al. (2025), I apply a series of filters to construct the mutual fund sample from the Morningstar mutual fund universe: (1) keep funds with domicile in the U.S., with Morningstar global board category group of "Fixed Income", and with

[6] I start the sample from 2003, as the data on corporate bond transactions from TRACE starts in 2002.

U.S. category group of "Taxable Bond";[7] (2) exclude funds that focus on a single strategy with strict investment mandates;[8] (3) drop index funds, fund-of-funds, and small funds with beginning-of-quarter TNAs below \$5 million; (4) exclude funds that never invest in U.S. Treasuries, corporate bonds, or any bonds with maturities longer than 10 years during the sample period. I obtain a total of 1,586 unique mutual funds after applying these filters.

Since Morningstar provides fund characteristics at the share-class level, I aggregate net assets across all share classes to calculate fund-level total net assets (TNAs). Additionally, I compute value-weighted averages across share classes to obtain fund returns, turnover ratio, and expenses. I calculate monthly fund gross returns as monthly fund net returns plus 1/12 of the annual expense ratio. Finally, I aggregate monthly gross returns to obtain quarterly gross returns. In addition, I calculate quarterly fund flows as follows,

$$Flow_{f,q\to q+1} = \frac{TNA_{f,q+1} - TNA_{f,q} \times (1 + Ret_{f,q\to q+1})}{TNA_{f,q}} \tag{1.1}$$

Further, using fixed-income mutual fund holding data from Morningstar, I calculate how fund managers trade across different asset classes and maturity baskets each quarter. For each fund f from quarter q to $q+1$, I define the fund's active trading of asset type I as,

$$\Delta Holdings^{I}_{f,q\to q+1} = \sum_{i\in I} \frac{(Shares_{i,f,q+1} - Shares_{i,f,q}) \times P_{i,q}}{TotalValue_{f,q}} \tag{1.2}$$

where $Shares_{i,f,q}$ is the share amount of asset i held by fund f at quarter q, $P_{i,q}$ is the price of asset i at q, and $TotalValue_{f,q}$ is the sum of overall holdings of fund f at q.[9] $\Delta Holdings^{I}_{f,q\to q+1}$ measures the percentage change in a fund's position within an asset type relative to the fund's beginning-of-quarter total investments. By using the initial price at q, I control for the potential influence of price changes on portfolio weight

[7] I focus on taxable bonds, as many legislative bills increase deficits by reducing taxation, which will also influence the flows, returns, and trading strategies of tax-free bonds

[8] Specifically, I exclude funds within Morningstar categories containing any of the following keywords: "bank loan", "high yield", "money market", "mortgage", "muni", "inflation", "government", and "preferred". I exclude high-yield funds, as they typically do not invest in U.S. Treasuries, and are less subject to inflation risk. I also remove inflation-protected funds, money market funds, and government bond funds, as these funds either have strict mandates limiting investments to specific asset classes and maturity ranges, or their positions in Treasury securities are largely driven by flow-induced trades.

[9] For a few funds with both long and short positions, I focus only on the long side. The short side primarily consists of net unsettled trades, which reflect the market value of future trade commitments, as fixed-income funds may invest in less liquid assets that require longer transaction times to settle.

adjustments. Similarly, when classifying assets by maturity and credit ratings, I use the beginning-of-quarter characteristics in forming $\Delta Holdings^{I}_{f,q\to q+1}$ to avoid mechanical portfolio rebalancing.

1.2.2 CBO cost estimates

Following the introduction of each legislative proposal by Congress, the CBO releases the projected federal budgetary impact for current year and the next five or ten years, detailing the direct spending, discretionary spending (spending subject to appropriations), and revenues resulting from the bill.[10] The CBO provides XML links to all historical cost estimates on its website[11], from which I retrieve each cost estimate in PDF format for the 108th (2003–2004) to 118th (2023–2024) Congresses, totaling 13,668 files. Focusing only on the impact of large bills, I apply the process detailed in Appendix 1.A.2.1 and obtain 1,374 files with effects on the surplus or deficit exceeding \$1 billion.[12]

Following Gomez Cram et al. (2023) and Gomez Cram et al. (2024), for legislative proposal p with cost estimates releases in current year y, I estimate the budgetary impact as,

$$
\begin{aligned}
\Delta Surplus^{p}_{y} &= \mathbb{E}_t\left[\sum_{i=y}^{y+h} v^{h}\frac{\Delta Revenue^{p}_{y+i}-\Delta Spending^{p}_{y+i}}{GDP_{y+i}}\right]\\
\Delta Deficit^{p}_{y} &= -\Delta \mathrm{Surplus}^{p}_{y}
\end{aligned}
\tag{1.3}
$$

where $\Delta Revenue^{c}_{y+i}$ measures the increase in federal revenues in future year $y+i$ if the bill is passed, $\Delta Spending^{p}_{y+i}$ accounts for the effects in year $y+i$ from both direct spending and discretionary spending, h takes the value of 5 or 10 for CBO estimation periods, and GDP_{y+i} is the yearly nominal GDP forecast from the latest CBO Budget and

[10]Direct or mandatory spending is controlled by laws, so it can occur immediately once a bill is passed and enacted as public law. Discretionary spending, on the other hand, comes from authority granted in appropriation acts. Although it depends on further actions by the House or Senate Appropriations Committees, a bill may also impact future financial commitments through discretionary spending. Therefore, I include both types of spending when calculating the overall budgetary effects of legislative bills. I report bill-level cash flow contributions from direct spending and reduced revenues and from discretionary spending subject to appropriations in Appendix Figure 1.A.2 Panel C. For more details on how the CBO addresses these two types of spending, see `https://www.cbo.gov/about/products/ce-faq`.

[11]Available at `https://www.cbo.gov/cost-estimates/xml`.

[12]For comparison, the U.S. GDP in 2003 was \$11,456.5 billion, so omitting small bills with budgetary impacts below \$1 billion does not affect the results.

Economic Outlook report prior to the cost estimate of proposal p. Following Gomez Cram et al. (2023), the annual discount rate v is set to 0.96, representing the inflation-adjusted average return for aggregated Treasury securities. I further merge the cost estimates with data from https://www.congress.gov/ to obtain information on the bill sponsor and legislative status. Figure 1.1 plots the estimated deficit-to-GDP ratio $\Delta Deficit_y^p$, categorizing by the bill sponsors' parties in Panel B, and decomposing bill-level deficit increases into those that raise government spending and those that reduce government revenues in Panel C. If passed, the majority of bills increase the federal budget deficit. Bills that significantly expand the deficit are more likely to be sponsored by politicians from the president's party. A large proportion of bills raise the deficit through higher government spending, while some contribute by reducing taxation, which lowers federal revenues.

Finally, to study the effect of the federal budget deficit on mutual fund quarterly trading, I calculate the quarterly deficit impact by summing all cost estimates published in the current quarter,[13]

$$\Delta Deficit_{q \to q+1} = \sum_{p \in q} \Delta Deficit^p \tag{1.4}$$

this measure serves as the main independent variable of interest in my analysis.

1.2.3 Fund manager partisanship

I combine data from Morningstar's biographies of mutual fund managers with political contribution records from the Center for Responsive Politics (CRP) to create a measure of fund manager partisanship.

Morningstar provides detailed personal information on mutual fund managers, including full names, work experience, educational degrees, gender, and years in the industry. The CRP database includes records of individual donations and political action committee (PAC) contributions since the 1990 election cycle. I merge these databases by matching individuals based on full name, address, inferred gender, and occupation. The

[13] For duplicate or recurrent bill estimates, I use the incremental value in getting $\Delta Deficit_{q \to q+1}$ with the process discussed in Appendix 1.A.2.1.

full matching procedure is outlined in Appendix 1.A.2.2. An individual may contribute to both candidates and PACs. I label each donation as either Republican or Democratic based on the candidate's party affiliation. For contributions to PACs, I classify the contribution as Republican or Democratic only if the PAC allocates more than 90% of its funds in an election cycle to causes aligned with the Republican or Democratic party. After the matching process, I identify 22,453 donations from 1,198 out of 4,913 managers.[14] The detailed number of partisan managers and funds by year is reported in Appendix Figure 1.A.4.

Following the prior literature (Hong and Kostovetsky, 2012; Lee et al., 2014; Wintoki and Xi, 2020; Rice, 2024), I use each manager's overall donation history to infer their political orientation, minimizing measurement errors under the assumption that an individual's political stance remains stable in adulthood, shaped during their formative years (Green et al., 2004). I define the Republican index for each manager as

$$Rep_i = \frac{R_i - D_i}{R_i + D_i} \tag{1.5}$$

where R_i represents manager i's lifetime donations to the Republican party, and D_i to the Democratic party. By construction, Rep_i ranges from -1 (donating exclusively to Democrats) to 1 (donating exclusively to Republicans). Table 1.1 Panel A presents summary statistics for the matched managers. Consistent with existing literature, fund managers tend to lean Republican. Republican-leaning managers are less likely to be female, less likely to hold a PhD, and have more years of experience in the mutual fund industry. I also report the lifetime dollar amounts donated to both parties, averaged across managers. While managers do contribute to the opposing party, these contributions make up only about $2-3\%$ of their total political donations.

I then aggregate the manager partisanship measure at the fund level. For funds with multiple managers, I average each manager's Republican index to determine the fund-level political affiliation measure,

$$Rep_{f,q} = \frac{1}{N_{f,q}} \sum_i Rep_i \tag{1.6}$$

[14] The match quality is comparable to similar datasets in the literature for equity fund managers (Hong and Kostovetsky, 2012; Vorsatz, 2022; Sheng et al., 2024).

where $N_{f,q}$ is the number of managers in fund f at quarter q. Since funds may add new managers or see existing managers depart, $Rep_{f,q}$ varies over time. For managers who are not matched to the CRP database or who only contribute to PACs without specific political affiliations, I set Rep_i to zero in calculating $Rep_{f,q}$.[15] Table 1.1 Panel B reports the panel distribution of fund characteristics by each partisan group. Republican funds refer to those with positive $Rep_{f,q}$, Democratic funds refer to those with negative $Rep_{f,q}$, and funds are labeled as "gray" if the measure is zero. On average, the "gray" funds have a lower TNA (\$1,574M relative to \$2,544M for Republican and \$2,959M for Democratic funds), so my partisan measure covers a relatively large fraction of the total fixed-income fund market. Compared to Democratic funds, Republican funds have a slightly lower annual turnover ratio (1.63 vs. 1.84), charge a similar expense ratio (0.75% vs. 0.71%), and have similar fund age (13.87 vs. 14.21), returns (4.41% vs. 4.26%), and flows (0.16 vs. 0.17). Additionally, funds from both political affiliations have similar asset compositions, as shown in Appendix Figure 1.A.5, with approximately 14% of assets invested in Treasury securities and 36% in corporate bonds.

Finally, I construct the ideological misalignment measure between the fund and the party of the president as,

$$Misalign_{f,q} = \frac{|Rep_{f,q} - Rep_{president,q}|}{2} \tag{1.7}$$

where $Rep_{president,q}$ is the party of the president in quarter q, takes the value of 1 if the president affiliates to the Republican party. Following Kempf and Tsoutsoura (2021), I use the party of the newly elected president at the end of a presidential election quarter, when the election results are known by quarter-end. $Misalign_{f,q}$ varies from 0 to 1, with a value of 0 if the fund is fully aligned with the president's party, and 1 if all managers of the fund are completely opposed to the president's party.

[15]Including managers without political donations or with equal donations to both parties allows me to capture the trading activity of both polarized and moderate funds, resulting in a more balanced panel.

1.2.4 Treasury and corporate bond characteristics

I obtain data on U.S. Treasury securities from the Center for Research in Security Prices (CRSP), which collects Treasury information from GovPX, ICAP, and the U.S. Treasury Department. CRSP provides detailed Treasury characteristics, including issue date, maturity date, daily price, coupon rate, amount of shares publicly held, and bid-ask spread. I merge CRSP with Morningstar holdings data by CUSIP, resulting in 2,722 unique Treasury securities, of which 95 are TIPS. The daily return for bond j is calculated as,

$$Ret_{j,t-1\to t} = \frac{P_{j,t} + AI_{j,t} + C_{j,t}}{P_{j,t-1} + AI_{j,t-1}} - 1 \tag{1.8}$$

where $P_{j,t}$ is the clean price of bond j at the end of day t, $AI_{j,t}$ is the accrued interests and $C_{j,t}$ is the coupon payments. For TIPS, I adjust daily accrued interest and coupon payments by multiplying them by the inflation index ratio provided by CRSP.[16]

I obtain data on corporate bond prices from the Trade Reporting and Compliance Engine (TRACE) enhanced database and merge it with the Mergent FISD database, which provides bond information including issue and maturity dates, ratings, and coupon rates. I follow the standard data cleaning process in the literature (Dick-Nielsen, 2014; Dickerson et al., 2023), limiting the sample to corporate bonds only[17] and excluding those issued under the 144A rule, floating-rate bonds, bonds not traded in U.S. dollars, as well as convertible, asset-backed, pay-in-kind, or unit deal bonds. I identify 19,901 corporate bonds from 4,368 issuers held by mutual funds in my sample. I use codes from Open Source Bond Asset Pricing to calculate bond returns in the same way as Eq. (1.8) and to compute bond characteristics, including yield-to-maturity, duration, and yield spread over duration-matched Treasuries. Finally, I merge the corporate bond information with the Compustat database to access control variables at the bond issuer level (e.g., book-to-market, Tobin's Q, leverage ratio), following Fang (2023).

[16] The daily TIPS index ratio (TDIDXRATIO) is calculated as the reference CPI of the current date divided by the reference CPI of the original issue date.

[17] I require bond types to be "CDEB (US Corporate Debentures)," or "CMTN (US Corporate MTN)," or "CMTZ (US Corporate MTN Zero)," or "CZ (US Corporate Zero)" in the Mergent FISD database.

1.3 Main Results

This section presents the main results. In Section 1.3.1, I show that when managers' political ideology diverges from the president's party, they respond more aggressively to news of rising federal budget deficits. Specifically, they sell long-term Treasury securities and corporate bonds while increasing holdings in TIPS. This result is robust across various estimation methods, subsamples, and alternative variable definitions. In Section 1.3.2, I document the price effects of managers' partisan trading on Treasuries and corporate bonds. Lastly, Section 1.3.3 examines whether fund managers' portfolio choices induced by political views affect fund flows and returns.

1.3.1 Partisan view and fund trading

Fiscal expansion raises the supply of government bonds (Gomez Cram et al., 2024) and increases the inflation rate (Cochrane, 2023), which decreases the valuation of fixed-income assets, with pronounced effects on those with longer maturities (Gomez Cram et al., 2023). However, there is a considerable lag between legislative proposals, CBO cost projections, bill enactment, and the eventual increase in long-term government bond supply.[18] Consequently, in anticipation of fiscal policy changes, managers must revise their expectations regarding future Treasury supply and their inflation forecasts based on personal views. Managers whose partisan beliefs differ from the president's party may adopt a more pessimistic outlook following CBO projections of rising deficits, foreseeing steeper declines in Treasury bond prices and elevated inflation. This section examines the impact of partisan bias on managers' trading behavior in response to federal deficit changes, using the following regression specification to test this relationship:

$$\begin{aligned}\Delta Holdings^{I}_{f,q\to q+1} = \beta_0 + \beta_1 \times \mathbf{Misalign_{f,q}} \times \mathbf{\Delta Deficit_{q\to q+1}} + \beta_2 Misalign_{f,q} \\ + \Gamma Controls + \lambda_f + \lambda_q + \epsilon_{f,q} \qquad (1.9)\end{aligned}$$

[18] For example, during the initial COVID-19 response from March to July 2020, the U.S. government increased spending amounting to 11.9% of GDP (Romer, 2021), while inflation began to surge in the spring of 2021, and the U.S. Treasury expanded long-term bond auction sizes starting in 2023.

where the dependent variable $\Delta Holdings^I_{f,q\rightarrow q+1}$ measures the fund's active trading in asset type I, $Misalign_{f,q}$ is the level of political mismatch between the fund and the president's party as defined in Eq. (1.7), and $\Delta Deficit_{q\rightarrow q+1}$ represents the quarterly aggregate of the estimated deficit-to-GDP ratio contributed by legislative bills with CBO projections issued in the current quarter. The main independent variable of interest is the interaction term between $Misalign_{f,q}$ and $\Delta Deficit_{q\rightarrow q+1}$, which captures whether funds with a political ideology aligned or misaligned with the president respond differently to legislative bills that may reduce federal budget surpluses. I control for beginning-of-quarter fund characteristics, including past returns ($Annual\ Return_{f,q-4\rightarrow q}$), expense ratio ($Expenses_{f,q}$), fund size ($Log(TNA)_{f,q}$), turnover ratio ($Turnover_{f,q}$), fund age ($Log(Fund\ Age)_{f,q}$), and the initial position in the asset type of interest ($\%Initial\ Treasury_{f,q}$ or $\%Initial\ Corp\ Bond_{f,q}$). Additionally, I control for fund manager characteristics, including the percentage of female managers ($\%\ Female_{f,q}$), the percentage with a PhD degree ($\%\ PhD_{f,q}$), and the longest tenure in the mutual fund industry ($Log(Experience)_{f,q}$) within the team. I also control for contemporaneous fund flows ($Flow_{f,q\rightarrow q+1}$) to rule out proportional mechanical trading driven by these flows. Finally, I control for fund fixed effects (λ_f) and year-quarter fixed effects (λ_q), which subsume $\Delta Deficit_{q\rightarrow q+1}$. Standard errors are double clustered at the fund level and year-quarter level.

Specifically, I examine active trading driven by partisan views on Treasury securities with maturities shorter than 10 years and those with maturities of 10 years or longer. If a fund manager holds a more pessimistic view—due to political bias—on how the government will finance fiscal expansion proposals, she may anticipate a larger increase in long-term Treasury bond issuance and, as a result, require higher compensation to hold these bonds. Similarly, if the manager believes that large CBO deficit projections from legislative bills will lead to severe long-run inflation, particularly when these bills are introduced by an administration from the opposing party, she may increase more of her holdings in TIPS and reduce more of her position in long-term corporate bonds, compared to managers supporting the president's party. However, since mutual funds typically invest in corporate bonds with shorter maturities (Bretscher et al., 2023; Butler et al., 2023), I classify short-term and long-term corporate bonds based on the median maturity of corporate bond holdings by funds in the sample at the beginning of the quarter.[19] As previously discussed, β_1 is expected to be negative for long-term Treasuries and corporate bonds, positive or insignificant for short-term bonds, and positive for TIPS.

1.3.1.1 Baseline results

Table 1.2 presents the results of Eq. (1.9). Panel A displays fund active trading percentages in Treasury securities: column (1) shows results for Treasuries with maturities of 10 years or more, column (2) for TIPS, and column (3) for Treasuries with maturities under 10 years as a comparison. The findings indicate that fund managers politically misaligned with the president trade more aggressively in response to deficit increases following CBO releases, reducing positions in long-term Treasuries and increasing holdings in TIPS. With all fund characteristics and fixed effects controlled, the regression coefficient β_1 is -2.191 (t-statistic = -2.81) for long-term Treasuries, and 1.680 (t-statistic = 3.06) for TIPS. This effect is both statistically significant and economically meaningful: for a fund with managers whose political views are entirely opposed to those of the president's party ($Misalign = 1$), a one-standard-deviation increase in $\Delta Deficit$[20] corresponds to a greater reduction in long-term Treasury holdings equivalent to 0.13% of the fund's total assets, and a larger increase in TIPS holdings of 0.10% as a share of the fund's total assets, compared with managers fully aligned with the president's party. For reference, funds on average hold 2% of their total investments in Treasury bonds and 1% in TIPS in the sample period.

Note that these quarterly regression estimates tend to underestimate the sharp reactions of misaligned managers to CBO announcements of rising deficits. Gomez Cram et al. (2023) demonstrates that Treasury values decline substantially on CBO announcement dates with significant negative surplus projections, while Jansen et al. (2024) finds that mutual funds exhibit notably high demand elasticity for Treasury securities. This indicates that fund managers may partially recover their Treasury positions following an initial price drop, resulting in a more moderate position by the end of the quarter.[21] In

[19]Specifically, I first calculate the time-to-maturity of each fund's corporate bond holdings in each quarter, weighted by the number of shares outstanding, and then obtain the median across funds. This median maturity fluctuates slightly over time, with a mean of 7.1 years and a standard deviation of 0.3 years.

[20]The standard deviation of quarterly $\Delta Deficit$ measure is 5.88%.

[21]Although some funds voluntarily report monthly positions to Morningstar, fewer than 45% did so

Appendix Table 1.A.4, I re-estimate the main regression from Eq. (1.9) without controlling for time fixed effects—which would subsume $\Delta Deficit$—and instead control for macroeconomic variables that may influence fund investment in long-term bonds: GDP growth, CPI, and changes in the federal funds target rate, unemployment rate, and VIX. The results show that managers politically aligned with the president's party even increase their positions in long-term Treasuries and reduce investments in TIPS by quarter-end, potentially drawn by the better yields following negative CBO surplus projections.

Panel B of Table 1.2 reveals similar effects for corporate bonds. The regression coefficient β_1 is -1.779 (t-statistic = -2.37) for all corporate bond holdings with maturities above the sample median, as shown in column (1). Breaking down these holdings, I further analyze investment-grade (IG) and high-yield (HY) bonds in columns (2) and (3), where the coefficients are -1.454 (t-statistic = -2.30) and -0.325 (t-statistic = -1.82), respectively. Column (4) presents the effect for short-term corporate bonds with maturities below the sample median, which is small in magnitude (β_1 = -0.411) and statistically insignificant (t-statistic = -0.27). These results reinforce the finding that politically misaligned managers tend to reduce their long-term bond holdings more than aligned managers, anticipating inflationary pressures driven by increased government spending. The overall relative impact on corporate bonds is smaller compared to Treasury securities, reflecting that mutual funds, on average, allocate less than 15% to Treasuries and over 36% to corporate bonds. This difference arises because misaligned managers reduce more of their Treasury bond holdings in response to anticipated increases in Treasury supply and expected inflation, whereas their transactions in long-term corporate bonds primarily reflect future inflation expectations. Additionally, managers with political views opposed to the president's party sell more IG bonds than HY bonds following CBO estimates of rising budget deficits, as bonds with higher credit quality are more sensitive to anticipated inflation increases.

In Figure 1.2, I further break down fund quarterly bond trading by beginning-of-quarter maturity buckets (shorter than 2 years, 2–4 years, 4–6 years, 6–8 years, 8–10 years,

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during my sample period (2003–2023), and most began monthly reporting relatively late, so analyses are conducted at the quarterly level. Additionally, the effect of managers recovering positions after an initial price drop would remain even with monthly data. Nevertheless, the results in Table 1.2 indicate that, despite potentially attractive Treasury yields following deficit announcements, misaligned managers still hold smaller long-term Treasury positions and larger TIPS positions at the quarter end.

longer than 10 years, and TIPS for Treasury securities in Panel A) and plot the regression coefficients β_1. Bar charts categorized by both corporate bond maturity and credit ratings are displayed in Appendix Figure 1.A.6. The plots align with the findings in Table 1.2, showing that, compared to managers supporting the president's party, ideologically misaligned fund managers reduce long-term bond holdings more significantly, with no comparable reduction in short-term bonds following deficit increases in CBO releases. They also rebalance more heavily into TIPS, reflecting heightened inflation expectations.

1.3.1.2 Robustness

Appendix Table 1.A.5 presents a series of additional robustness tests for the main regression in Eq. (1.9). For brevity, only the regression coefficient and t-statistics of the interaction term β_1 are reported. Unless otherwise specified, all control variables and regression specifications are the same as those in Table 1.2.

The first part of Panel A presents results from alternative estimation methods, which remain similar in magnitude and statistically significant. To address concerns that a specific type of fund may drive the effects, specification (1) includes controls for both fund-level and Morningstar category × time fixed effects, while specification (3) clusters standard errors by Morningstar category × time. Recognizing that fiscal expansions may also affect fund fundamentals, specification (3) includes both the original control variables and their interaction terms with $\Delta Deficit$.[22]

The second part of Panel A presents a series of subsample analyses to demonstrate that the main results are not solely driven by specific periods or particular funds. In specification (4), I exclude election years, and in specification (5), I omit periods encompassing the global financial crisis and the COVID-19 pandemic. The results remain consistent and are even stronger in some specifications. Although retaining non-partisan funds in the sample provides a more balanced panel, in specification (6), I show that excluding non-partisan funds with $Misalign = 1/2$ does not affect the main results. Another concern is the lack of data on who makes primary investment decisions in team-managed

[22] Some effects are slightly weaker for HY bonds, as mutual fund positions in HY bonds fluctuate over time, depend heavily on the credit environment, and may remain at zero for several quarters for numerous funds. However, the overall regression coefficient of interest for long-term corporate bonds remains statistically significant across various estimation methods.

funds. To address this, in specifications (7) to (9), I limit the sample to funds with a single manager, funds with no more than two managers, and funds with no more than three managers, respectively. The results are robust and particularly strong for single-manager funds with politically misaligned managers, which show more aggressive selling of long-term Treasuries (coefficient = -4.086, t-statistic = -3.72).[23]

The first part of Panel B reports results with alternative definitions of $\Delta Deficit$. For example, in specification (10), I use the original CBO cost estimates for all bills without adjusting for duplicated or recurrent bill estimates when constructing the quarterly $\Delta Deficit$, while I adjust for duplicated bills but retain the original estimates for recurrent bills (the National Defense Acts) in (11). One concern regarding this measure is that, although certain legislative bills increase discretionary spending, this spending is still subject to further appropriation even if the bills are enacted. In specification (12), I exclude deficit increases arising from spending subject to appropriation (i.e., I account only for deficit changes due to mandatory spending and reductions in revenue, which are certain if the bill passes), and the results are unaffected. Another concern is that using GDP estimates available beforehand may overlook the effect of fiscal expansion on future GDP. In specification (13), to construct $\Delta Deficit$, I use the latest GDP estimates available after the CBO cost release. As various media sources are likely to refer to CBO projections as the total deficit dollar amounts rather than deficit-to-GDP ratios,[24] in specification (14), I calculate $\Delta Deficit$ by directly summing the annual deficits attributed to the bill, in trillions of U.S. dollars, as reported by media sources. The results are robust across different variable construction methods.

Finally, in the second part of Panel B, I present results using alternative definitions of $Misalign$, drawing on various strands of the partisanship literature. In specification (15), based on Sheng et al. (2024), I assign a misalignment dummy to each manager, set to 0 if the manager donates more to the president's party and 1 otherwise. I then

[23]The effect is milder for IG bonds, as single-manager funds are typically core-plus bond funds with greater flexibility and a higher allocation of HY bonds, resulting in a reduced net selling effect in IG bonds during quarters with increased CBO deficit projections. This outcome is consistent with Fang et al. (2014), which finds that fund families tend to allocate their most skilled managers to HY-focused sectors, and these managers are more likely to manage funds independently. Nonetheless, the results remain statistically significant and show an even larger magnitude for overall long-term corporate bonds in the single-manager fund sample compared to Table 1.2.

[24]For example, see "What's in the $3 Trillion HEROES Act?", and "Biden signs $886 billion US defense policy bill into law".

calculate an equal-weighted average of this dummy within each fund, confirming that the main results are robust. In specification (16), I weight managers within funds according to their contribution amounts, as in Wintoki and Xi (2020). In specification (17), using the approach from Evans et al. (2025), I construct the original misalignment measure based on manager donation amounts up to quarter q, rather than lifetime donations. As suggested by Vorsatz (2022), Sheng et al. (2024), and Massa and Zhang (2024), in specification (18), I relax the classification criteria for PACs, assigning a PAC to a party if it spends more than two-thirds of its funds on that party's candidates. All results are consistent with Table 1.2 for Treasury bonds, TIPS, and overall long-term corporate bonds.

Furthermore, the effects of partisan bias on fund portfolio choices are not limited to managers from a single political party. In Appendix Table 1.A.6, I replicate the analysis of Eq. (1.9) across subsample periods under Republican presidents and Democratic presidents. Panel A reports results for long-term Treasury bonds and TIPS, which align with the main findings: fund managers from both parties react more sharply to negative federal surplus news when their political views differ from those of the current administration. Panel B presents the subsample analysis for corporate bonds, where the effects are statistically significant only during periods with a Democratic president. This may be partly because, in the sample period, Democratic presidents tended to increase federal budget deficits through higher government spending, while Republican presidents often increased deficits by reducing government revenues, primarily through tax cuts,[25] which may be beneficial to firms to a certain extent. The impacts of increasing government spending versus decreasing revenues will be discussed further in Section 1.3.1.3. Taking together the results for both Treasury securities and corporate bonds, the table suggests that managers from both parties adopt a more pessimistic outlook on Treasury supply and inflation following deficit announcements when their political views oppose those of the president's party.

[25]For example, the Jobs and Growth Tax Relief Reconciliation Act of 2003 by President George W. Bush, and the Tax Cuts and Jobs Act by President Donald Trump.

1.3.1.3 Decomposing bill types

Legislative proposals can be introduced by Congress members from either the president's party or the opposition. For example, a series of COVID relief bills were introduced by Democratic politicians during Donald Trump's presidency in 2020, as shown in Figure 1.1 Panel B. Fund managers supporting the opposition party may respond less actively to changes in federal budget deficits resulting from bills sponsored by their affiliated party. I test this hypothesis in Table 1.3 by categorizing the bills based on their sponsors. The results for Treasury securities are displayed in Panel A, with Treasury bonds in column (1) and TIPS in column (3). For long-term corporate bonds, the results are shown in Panel B, with overall corporate bonds in column (1), IG bonds in column (3), and HY bonds in column (5). The effects of bills from the president's party versus the opposition are partially mixed. Ideologically misaligned managers reduce their positions in long-term Treasury and corporate bonds more sharply in response to deficit increases from bills sponsored by politicians of the president's party than from those of their affiliated party (regression coefficients: -2.416 vs. -1.850 for Treasury bonds, -2.532 vs. -0.659 for long-term corporate bonds). However, they increase their purchases of TIPS in response to bills sponsored by politicians from both parties (1.766 vs. 1.552). Taken together, the overall effects suggest that managers who are politically misaligned with the president's party may to a limited extent be less opposed to bills introduced by their own party.

In the second set of tests in Table 1.3, bill-level deficit increases are decomposed into those that increase government spending and those that reduce government revenues. The results for Treasury bonds and TIPS are reported separately in Panel A columns (2) and (4). Misaligned managers respond to both types of bills by writing off Treasury bonds and purchasing TIPS, anticipating higher Treasury supply and future inflation. Notably, these managers only significantly decrease their long-term corporate bond positions in response to CBO estimates indicating increased government spending (coefficient = -1.891, t-statistics = -2.08), while the coefficients are insignificant for CBO estimates of reduced federal revenues (coefficient = -1.512, t-statistics = -1.45). As discussed in Section 1.3.1.2, legislative proposals decrease federal revenues through tax cuts, which benefit firms and may partially offset the negative impact of inflation on long-term corporate bonds.

Overall, the results in Table 1.3 from decomposing bill types suggest that, although partisan bias influences fund managers' investment behavior, they consider factors beyond deficit figures, including the sponsor's party and the intended use of the deficit. Since the CBO typically publishes cost estimates following the introduction of legislative bills rather than the enactment of related laws (Gomez Cram et al., 2023), I also report results categorized by whether the bill ultimately passes in Appendix Table 1.A.7. The regression coefficients are large in magnitude and statistically significant only for bills that will eventually be approved for both Treasury securities and long-term corporate bonds. However, this does not necessarily imply that managers possess predictive power regarding a bill's likelihood of approval; rather, they may have access to additional information on the legislative process (e.g., debates, amendments, voting outcomes) by the end of the quarter, which is reflected in the dependent variable $\Delta Holdings_{q\rightarrow q+1}$.

1.3.1.4 Manager experience

A natural and interesting question arises as to whether certain personal attributes of fund managers influence their political biases and, consequently, their trading behavior in response to deficit changes. D'Acunto et al. (2023) and Binetti et al. (2024) suggest that factors such as age, gender, and education can affect individuals' inflation expectations. Malmendier and Nagel (2016) shows that individuals tend to overweight inflation experiences from their lifetimes; for example, the high inflation periods of the 1980s, when President Ronald Reagan added over \$1.6 trillion to the U.S. national debt.

I test the effect of manager experience in Table 1.4. Since Morningstar does not provide sufficient information to infer fund managers' ages,[26] I instead use the number of years they have worked in the mutual fund industry as a proxy, assuming that managers with longer work experience are more likely to be older and to have a stronger recollection of the periods with high inflation, elevated government spending, and sharp increases in Treasury yields before the 2000s.[27] In each quarter, I calculate the median years of

[26]Although the equity fund literature (Kostovetsky, 2017, Bai et al., 2019) suggests inferring manager age based on their college graduation years, most managers in my sample report only their college names and degrees, with fewer than 30% also reporting graduation years.

[27]Although not empirically proven, it is widely believed among practitioners that "bond vigilantes" exist in the bond market (Spiegel and Rose, 2024). These individuals protest against monetary or fiscal policies perceived as inflationary by selling bonds, thereby increasing yields. For instance, they reacted

industry experience among fund managers and classify funds into a short experience group (presented in the left part of Table 1.4) and a long experience group (presented in the right part of Table 1.4), based on the longest experience within each fund's management team.[28] I then re-estimate the main regression in Eq. (1.9) separately for these two groups of funds. The results in Table 1.4 support the hypothesis that managers with longer industry experience and stronger resistance to the current president's party predict a larger Treasury supply (Treasury bond coefficient = -3.002, t-statistic = 2.64) and higher inflation expectations (TIPS coefficient = 2.430, t-statistic = 3.78; long-term corporate bond coefficient = -2.047, t-statistic = 2.34). In contrast, the regression coefficients are insignificant for the shorter experience group.

I also consider additional manager characteristics, including gender and education, and report the results in Appendix Table 1.A.8. Given the relatively low proportions of female managers and PhD holders in the sample, I classify funds into two groups based on the presence of female managers and the presence of PhD holders within the management team. Most effects are stronger for all-male manager teams and teams without PhDs. However, this does not necessarily imply that female or PhD managers are less influenced by political bias in investment decisions, as their sample sizes are relatively small.

to the Fed's dovish monetary policies during a period of rising inflation in the early 1980s by selling government bonds. They also pushed back against significant government spending under the Clinton administration in the early 1990s, driving yields on 10-year Treasuries from around 5% to 8% within a year to pressure the government to reduce deficits. Since then, whenever government spending is expected to increase, practitioners caution about the potential return of the "bond vigilantes", see "The bond vigilantes are back, and Trump better pay attention" and "Fear of Inflation Finds a Foothold in the Bond Market", among others. Consistent with the inflation memory suggested by Malmendier and Nagel (2016), fund managers with longer industry experience and stronger opposition to the current government may more readily recall the memory of "bond vigilantes," leading them to demand higher compensation for holding long-term government bonds in anticipation of an increased federal deficit.

[28]Following Ding and Wermers (2012) and Luo et al. (2022), I classify each fund based on the longest experience within its management team. The results remain robust when using the average industry experience for classification. Although the manager with the longest experience may not necessarily hold a lead position in decision-making, this measure better captures the influence of inflation experience from the 1980s. For example, consider two management teams in 2020: one with two managers, each having 15 years of industry experience, and another with one junior manager who recently joined the industry and a senior manager with 30 years of experience. While both teams have an average experience of 15 years, both managers in the first team were likely in their childhood during periods of high inflation, whereas the senior manager in the second team likely experienced high inflation firsthand while already working in the financial industry.

1.3.1.5 Persistence of the effects

Following Brooks et al. (2018) and Fang (2023) to examine whether the effect of partisan views and changes in the federal deficits on fund trading behavior persists over time. I repeat the regression analysis in Eq. (1.9) extending the dependent variable up to four quarters forward,

$$\Delta Holdings^{I}_{f,q \rightarrow q+h} = \beta_0 + \beta_1 \times \mathbf{Misalign_{f,q}} \times \mathbf{\Delta Deficit_{q \rightarrow q+1}} + \beta_2 Misalign_{f,q} + \Gamma Controls + \lambda_f + \lambda_q + \epsilon_{f,q} \tag{1.10}$$

where $h = 1, 2, 3, 4$, $\Delta Holdings^{I}_{f,q \rightarrow q+h}$ measures cumulative position change of asset type I for fund f sine quarter q.

Figure 1.3 plots the regression coefficient β_1 over time. Compared to managers aligned with the president's party, those with opposing views are more likely to continue reducing their Treasury bond positions following CBO releases that project decreased national surpluses, with this effect persisting for more than three quarters. These managers also reverse their active purchases of TIPS after three quarters and reduce their selling of long-term corporate bonds after two quarters, gradually tapering off the selling activity in subsequent quarters. The results again suggest that fund managers interpret deficit news from CBO projections as signaling both an increase in Treasury supply and rising inflation. Their investment decisions in Treasury bonds reflect concerns about both effects, while their trading in TIPS and long-term corporate bonds appears to be driven solely by rising inflation expectations. For comparison, I also plot the effects on short-term Treasury securities and corporate bonds in Appendix Figure 1.A.7 Panel A, where all regression coefficients are statistically insignificant and considerably smaller in magnitude.

1.3.1.6 Rebalancing into other asset classes

To gain a more comprehensive understanding of how partisan views affect fund managers' trading decisions in response to projected changes in the federal budget deficit, I repeat the analysis in Eq. (1.10) for asset classes beyond Treasuries and corporate bonds. The results are presented in Figure 1.4. Misaligned fund managers primarily rebalance into agency MBS, with some reallocations into municipal bonds. I find no evidence of rebalancing into other asset classes, such as other MBS, agency debts, CMOs, asset-backed securities, or preferred stocks.

Agency MBS pass-throughs are fully guaranteed by U.S. government agencies, have a large and relatively liquid market,[29] and a long time-to-maturity, which may make them suitable substitutes for long-term Treasury bonds, with municipal bonds potentially serving a similar role.[30] Trading behaviors in other asset classes also reinforce my main finding that politically mismatched managers tend to interpret declining national surpluses as indicating both an expanding Treasury supply and rising inflation.[31]

1.3.2 Partisan ownership and asset returns

After confirming that politically misaligned managers trade more aggressively in response to CBO releases forecasting increased federal deficits, this section examines the asset-pricing implications of such partisanship-induced investment behavior. Following Sheng et al. (2024), I calculate the misaligned ownership for each bond as the weighted average of fund-level misalignment, with weights determined by each fund's relative holding amount in the bond,

$$\%Misalign\ Holding_q^b = \frac{\sum_{f=1}^{F} Shares_{f,q}^b \times Misalign_{f,q}}{\sum_{f=1}^{F} Shares_{f,q}^b} \tag{1.11}$$

where $Shares_{f,q}^b$ is the par value amount of bond b held by fund f at quarter q, and $Misalign_{f,q}$ is defined in Eq. (1.7). By construction, $\%Misalign\ Holding_q^b$ ranges from 0 to 1 and equals 1 if all fixed-income fund managers holding the bond are entirely opposed

[29] As of December 31, 2023, agency MBS constituted 27% of the Bloomberg US Aggregate Bond Index, making them the second-largest segment of the U.S. bond market.

[30] For examples of practitioners considering agency MBS as substitutes for long-term Treasury bonds, see https://doubleline.com/wp-content/uploads/2022/05/Advantages-of-Agency-MBS.pdf and https://www.franklintempleton.ch/articles/2024/western-asset/the-advantages-of-agency-mortgage-backed-securities. For discussion of municipal bonds and Treasuries, see https://www.nuveen.com/en-us/insights/municipal-bond-investing/municipal-market-update.

[31] Note that I do not find specific evidence of fund managers rebalancing into short-term asset classes; one potential explanation is that mutual fund mandates typically provide detailed guidelines on the permissible maturity ranges of their investments (Choi and Kronlund, 2018, Li and Yu, 2021, Bai et al., 2023, and Bretscher et al., 2023).

to the president's party.[32] In this section, I test the implications for Treasury securities and corporate bonds separately.

1.3.2.1 Treasury returns

Although I present quarter-level evidence of partisan investments by funds, the highly liquid nature of the US Treasury market makes it unlikely that mutual fund trading will have a lasting price impact on Treasury securities through quarter-end. To more precisely measure the stronger reactions of misaligned managers to CBO projections of rising deficits, I focus exclusively on days when deficits reach the 95th, 97th, and 99th percentiles of all deficit releases.[33] Following Gomez Cram et al. (2023), days with large deficit announcements that fall within a 3-day window of FOMC meeting days are excluded. On the remaining days with CBO releases indicating exceptionally high deficits, I run the following Fama and MacBeth (1973) regressions to study the effect of politically misaligned mutual fund ownership on Treasury security returns,

$$ExRet^b_{t\to t+h} = \beta_0 + \beta_1 \times \%\mathbf{Misalign\,Holding^b_{q-1}} + \Gamma Controls + \epsilon^b_t \tag{1.12}$$

where $ExRet^b_{t\to t+h}$ is the cumulative daily returns for Treasury in excess of the risk-free rate in basis points, aggregated from the event day t, through day one, or day three post-event. The key independent variable, $\%Misalign\,Holding^b_{q-1}$, measures the position of bond b held by ideologically mismatched funds at the end of the prior quarter before day t. I also control for the time-to-maturity of the Treasury security ($Maturity$), the coupon rate ($Coupon$), on-the-run dummy (*On-the-run*, a dummy variable that equals to 1 if the Treasury is the most recently issued in its maturity class, and 0 otherwise), the logarithm of publicly held shares outstanding in millions of dollars ($Log(Shares)$), and the average bid-ask spread (*Bid-ask spread*) of quarter $q-1$. All control variables are defined in Appendix Table 1.A.1. I compute Newey and West (1987) standard errors corrected by serial dependence of four lags.

[32] To better capture the effect of political polarization, I exclude "gray" funds that exhibit non-partisanship from the measure. The results remain consistent when these funds are included.

[33] The daily projected deficit-to-GDP ratio contributed by bills measure reaches 2.86% at the 95th percentile, 3.81% at the 97th percentile, and 5.61% at the 99th percentile.

Table 1.5 presents the regression results from Eq. (1.12), with columns (1)-(3) reporting the effects for long-term Treasury bonds. The coefficient β_1 is -1.953 (t-statistic = -2.46) on the event days with 95th percentile deficit releases and becomes more pronounced as deficit projections increase, reaching -3.788 (t-statistic = -2.35) when the deficit releases are at or above the 99th percentile. For reference, as shown in Appendix Table 1.A.9, Treasury bond prices decline by an average of 55.670 bps on days when $\Delta Deficit$ reach or exceed the 99th percentile.[34] Thus, on days with the most extreme CBO cost estimates that increase federal deficits, trading by politically mismatched fund managers contributes to 6.8% (= 3.788/55.670) additional price decline for Treasury bonds heavily held by these funds.

The results for TIPS are presented in columns (4)-(6) of Table 1.5. The effects are insignificant on event days with large deficit announcements; however, the regression coefficient becomes positively significant for the cumulative returns of the event day and the following day, suggesting that misaligned managers increase their TIPS purchases following large CBO deficit releases. One potential explanation for these mixed results is that, although TIPS offers inflation protection, their prices still comove with the broader Treasury market. As revealed in Appendix Table 1.A.9, TIPS values also decline on days with large deficit projections.

For robustness, I also conduct a series of placebo tests, as reported in Appendix Table 1.A.10. Panel A shows the effect of misaligned fund ownership on Treasury returns on days without large deficit projections, where regression coefficients are insignificantly different from zero across all types of Treasury securities. Panel B repeats the test for Treasury bills and notes on days with large deficit announcements, again yielding insignificant results.

If the observed return effect results from price pressure due to excess trading by politically misaligned funds, rather than changes in the fundamental value of Treasury securities, I expect the temporary price movements around event days with large CBO deficit projections to eventually revert. To test this, I repeat the regression in Eq. (1.12),

[34]Although using a different sample period (2020–2023), Gomez Cram et al. (2024) shows that on days when the deficit-to-GDP ratio contributed by bills exceeds the 99th percentile, the overall Treasury value decreases by 20.67 bps. Since the Treasury value measure in Gomez Cram et al. (2024) includes all Treasury bills, notes, and bonds, my return magnitudes are comparable to their results.

now using the cumulative excess returns from the event day t to $t+30$ as the dependent variables. The coefficients on misaligned mutual fund ownership are plotted in Figure 1.5 for days with deficit releases that are equal to or exceed the 95th percentile. For long-term Treasury bonds, the initial negative, significant relationship between excess returns and misaligned fund ownership converges toward zero and becomes insignificant within 25 trading days. For TIPS, the regression coefficient gradually increases over time, peaking at a significant 20 bps above zero, and gradually returns to zero after 30 trading days. These results reinforce my findings that fund managers interpret CBO releases indicating reduced national surpluses as signaling both an expansion in Treasury supply and heightened inflation, as suggested by Gomez Cram et al. (2023). Managers more ideologically opposed to the current president's party respond more aggressively to these projections. Although my estimates for the cumulative return response to politically mismatched ownership become noisy as the return horizon extends, the overall pattern aligns with a complete reversal within 30 days.[35]

1.3.2.2 Corporate bond returns

Unlike highly liquid Treasuries, corporate bond transactions are relatively sparse, and funds do not necessarily trade corporate bonds on days of large deficit announcements. Therefore, in this section, I examine the price impact of trading by misaligned funds at the quarterly level. Specifically, I conduct a regression similar to the main test in Eq. (1.9),

$$\begin{aligned} \Delta Yield\,Spread^{b}_{q\rightarrow q+1} = {} & \beta_0 + \beta_1 \times \%\,\mathbf{Misalign\,Holding^{b}_{q}} \times \mathbf{\Delta Deficit_{q\rightarrow q+1}} \\ & + \beta_2 \times \%\,Misalign\,Holding^{b}_{q} + \Gamma_1 Controls \\ & + \Gamma_2 Controls \times \Delta Deficit_{q\rightarrow q+1} + \lambda_b + \lambda_{mat,q} + \lambda_{rat,q} + \epsilon^{b}_{q} \end{aligned} \tag{1.13}$$

[35] Note that the results in Figure 1.5 do not necessarily imply that the pricing effect from misaligned funds persists for 30 trading days. In the U.S., numerous macroeconomic announcement events (e.g., changes in nonfarm payrolls, initial jobless claims, CPI MoM) may influence Treasury prices. Given the small sample size (only 57 days with deficit releases at or above the 95th percentile), it is not feasible to exclude all such days. Consequently, as the return horizon extends, Treasury prices are increasingly likely to be affected by these events, introducing greater noise into the estimates over time.

where the main independent variable of interest is the interaction term between $\% Misalign\,Holding^b_q$, the percentage of shares held by misaligned mutual funds, and $\Delta Deficit_{q\to q+1}$, the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. The independent variable $\Delta Yield\,Spread^b_{q\to q+1}$ measures the change in the yield spread from quarter q to $q+1$ for bond b in percentage terms. Control variables include issuer firm characteristics (ROA, leverage ratio, cash%, the logarithm of book equity, book-to-market ratio, Tobin's Q), and bond characteristics (duration, rating number, yield, bid-ask spread) at the end of the previous quarter, defined in Appendix Table 1.A.1. Following Zhu (2021),Meeuwis et al. (2022), and Fang (2023), I further include interaction terms between control variables and $\Delta Deficit_{q\to q+1}$ to capture the potential effect of fiscal expansions on issuer fundamentals, and control for bond fixed effects, maturity-notch (shorter than 2, 2–4, 4–6, 6–8, 8–10, longer than 10 years) $\times$ time, and rating-notch (AAA, AA, A, BBB, or HY) $\times$ time fixed effects.

Table 1.6 presents separate results for overall, IG, and HY corporate bonds with maturities at or above the sample median. As shown in column (1), the coefficient of the interaction term is 0.374 (t-statistic = 3.37) for overall long-term bonds, suggesting that for bonds fully held by misaligned funds (i.e., $\% Misalign\,Holding = 1$), a 1 percentage point increase in $\Delta Deficit$ is associated with a 3.74 bps rise in yield spread. The effects are also significant for long-term IG bonds, with a 1 percentage point increase in $\Delta Deficit$ linked to a 2.97 bps climb in yield spread. However, although the coefficient is also positive for long-term HY bonds, the effect is insignificant, possibly because HY bonds are less sensitive to inflation, leading misaligned managers to be less inclined to divest these bonds, as shown in the main results in Table 1.2.

Given that the rise in yield spread stems from partisan trading by misaligned funds rather than changes in the fundamental value of these corporate bonds, the temporal price effects are expected to decline over time. To examine this, I conduct the test in Eq. (1.13) again, now using $\Delta Yield\,Spread^b_{q\to q+h}$ as the dependent variable. This variable measures the change in the yield spread for bond b, calculated as the yield spread at quarter $q+h$ minus the yield spread at q, where $h = 1, 2, 3, 4$. Figure 1.6 illustrates the regression coefficients for the interaction term in Eq. (1.13). The yield spread rises by the end of the first quarter, gradually declines over time, and returns to approximately zero by the fourth quarter, consistent with Figure 1.3, which shows that misaligned funds reduce their selling of long-term corporate bonds after two quarters. For robustness, I also repeat this test for short-term corporate bonds with maturities below the sample median. The coefficients, plotted in Appendix Figure 1.A.7 Panel B, remain insignificantly different from zero across all four quarters in response to partisan trading and CBO cost estimates. Viewed collectively, the findings indicate that politically misaligned managers, compared to those aligned with the president's party, reduce their positions in long-term corporate bonds more sharply in response to large deficit releases, resulting in a moderate decline in corporate bond value that diminishes after one year.

1.3.3 Partisan trading, fund flows, and returns

Current findings suggest that fund managers affiliated with the opposing party of the president tend to adopt more pessimistic investment strategies following large deficit estimates from the CBO, likely anticipating an increased Treasury supply and higher inflation due to fiscal expansion—expectations less commonly shared by politically aligned managers. This raises a natural question: does their pessimistic interpretation of fiscal expansions enhance or diminish value? Vorsatz (2022) demonstrates that investors can identify politically polarized fund managers and tend to divest from these funds during periods of turmoil. Besides, the works of Geczy et al. (2021) and Sheng et al. (2024) find that if fund managers are primarily motivated by non-pecuniary interests, such behavior may negatively impact fund performance. I therefore conduct two sets of tests to examine whether partisan-driven portfolio choices impact fund flows and returns.

In Table 1.7 Panel A, I regress fund flows on the interaction term between misalignment and changes in deficits based on CBO estimates. Since investors can only observe fund holdings at the end of each quarter, I use contemporaneous flows in the first two columns and flows from the following quarter in columns (3) and (4). The model includes the same control variables as in Table 1.2, including past annual returns, along with past annual flows for each fund. The regression coefficients for both the interaction term and the misalignment measure are insignificantly different from zero for both periods of flows, indicating that investor flows are not expected to be influenced by fund partisanship. My findings differ from Vorsatz (2022), which observes that investors preferred non-partisan funds during COVID-19. One potential reason for this difference is that Vorsatz (2022) focuses on active equity funds, where investors can more easily understand fund holdings. In contrast, my sample consists of fixed-income funds with thousands of investments, making it more challenging for investors to evaluate managers' portfolio decisions and, therefore, less likely to respond to partisan-driven trading.

In Table 1.7 Panel B, I regress fund risk-adjusted returns on the interaction term between $Misalign$ and $\Delta Deficit$ to examine whether the investment decisions of politically mismatched funds impact fund performance. Since fund holdings at the end of the current quarter may also influence future returns, I present the effects on contemporaneous performance in the upper part of the panel and on next-quarter performance in the lower part. I begin with net quarterly returns in excess of the risk-free rate in column (1) (*ExRet*) and then add risk factors incrementally across the subsequent columns. Column (2) controls for market returns (*CAPM*); column (3) adds the maturity factor (*CAPM+Maturity*); column (4) incorporates the credit factor (*3F*); column (5) includes the mortgage spread (*3F+Mortgage*); and column (6) further controls for equity market returns alongside all previously mentioned factors (*3F+Mtg.+Equity*).[36] The regression coefficients for $Misalign \times \Delta Deficit$ across most returns and alphas are not statistically significant, while negatively significant for the next quarter CAPM alpha, so it remains unclear whether partisan-driven trading by misaligned funds following deficit releases will adversely impact fund performance. An interesting finding is that the coefficients of $Misalign$ for CAPM alphas and three-factor alphas are significantly positive but become statistically insignificant after controlling for the maturity and mortgage factors. This suggests that politically misaligned funds have lower exposure to the credit factor while having higher exposure to the maturity and mortgage factors in general. Consistent with this, Figure 1.4 shows that misaligned funds indeed rebalance more into agency MBS in response to increasing deficit projections from the CBO.

[36] I first estimate rolling fund betas using the past 24 months of return data (requiring at least one year of complete data), then compute each fund's monthly alpha based on beginning-of-quarter betas, and aggregate these monthly alphas to obtain quarterly alphas. Following Goldstein et al. (2017), I use the Vanguard Total Bond Market Index Fund and the CRSP value-weighted market return as proxies for aggregate bond and stock market returns. The maturity, credit, and mortgage factors are constructed according to Chen et al. (2010b), as detailed in Appendix Table 1.A.1.

1.4 Conclusion

Political polarization is a prominent social issue in the modern U.S., deeply affecting people's beliefs about the state of the economy. A large body of literature discusses the tendency for individuals to become more pessimistic when the opposing party holds power (Kempf and Tsoutsoura, 2021, Meeuwis et al., 2022, Dagostino et al., 2023, Engelberg et al., 2023b). This paper provides an economic mechanism for the divergence of opinions between individuals from the two parties: the heterogeneous interpretation of fiscal policy consequences.

Using unique daily-level CBO cost estimate data for legislative proposals, I document distinct trading patterns among fixed-income mutual fund managers based on their ideological alignment with the current president's party. Specifically, following CBO projections of increasing federal budget deficits, fund managers who contribute more to the opposition party further reduce their holdings in long-term Treasury bonds and corporate bonds, particularly in investment-grade corporate bonds, which are more sensitive to changes in discount rates. Conversely, compared to managers aligned with the president's party, they increase their investments in Treasury Inflation-Protected Securities (TIPS). The results hold under a series of stringent robustness tests and are not driven by any specific subperiod or managers aligned with a particular party. Fund managers distinguish between different legislative bills, reacting less strongly in corporate bond trading to bills that reduce taxes. The effect of political misalignment is more pronounced for fund managers with longer experience in the mutual fund industry, as they are more likely to remember the high inflation periods and sharp increases in Treasury yields before the 2000s. These findings indicate that fund managers with misaligned partisan beliefs tend to adopt a more pessimistic outlook after CBO projections of rising deficits, anticipating sharper declines in Treasury bond prices and heightened inflation.

Partisan-driven trading has real effects. On days with extremely negative cash flow projections from the CBO, trading by politically misaligned fund managers contributes to an additional 6.8% price decline for Treasury bonds heavily held by these funds. Long-term corporate bonds, predominantly held by politically misaligned funds, also experience a greater increase in yield spreads during quarters with larger deficit estimates.

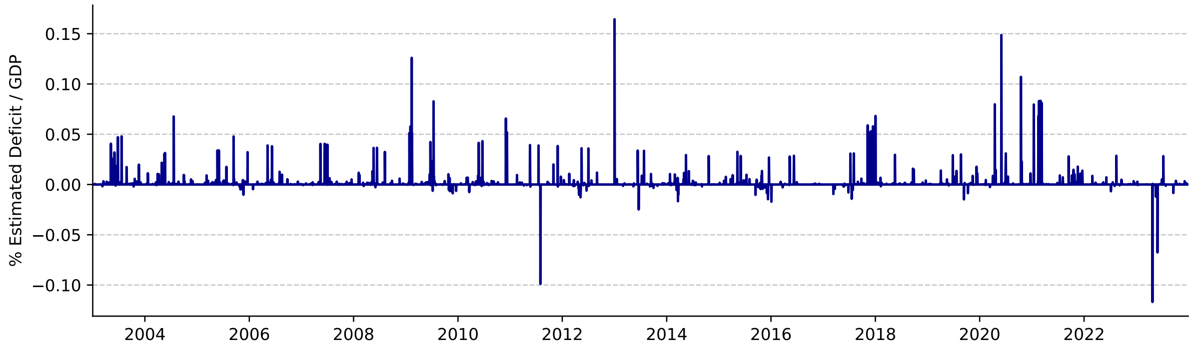
With political polarization on the rise in the U.S. and even globally, this paper contributes to the social finance literature and may hold practical implications for investors and policymakers. When politicians use national debt as a tool for criticism, even professional investors can be influenced by such political messaging. This raises the question: would partisan bias affect the government's ability to effectively communicate fiscal policy to citizens—a question for future research to explore.

Figures

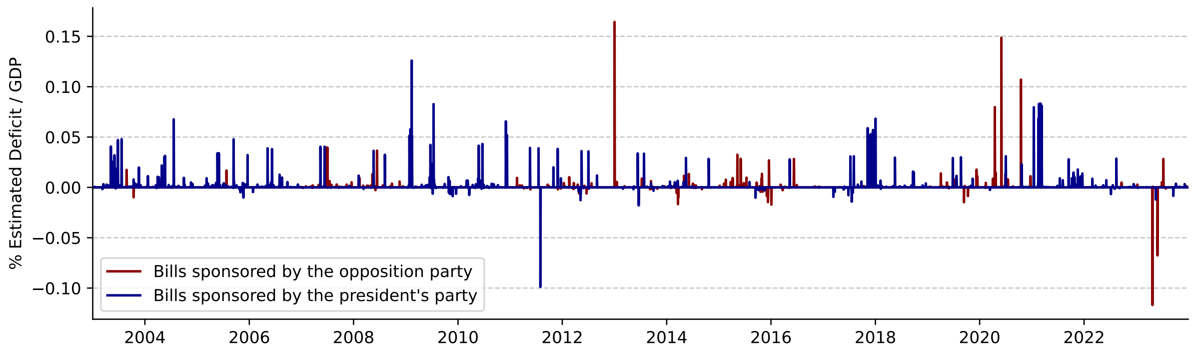
Figure 1.1: CBO Cost Estimates

This figure illustrates the estimated deficit-to-GDP ratio contributed by each bill. For CBO estimates released on the same date, I aggregate them on a daily basis. Panel A presents overall contributions at the bill level. Panels B and C categorize these contributions by bill type. Panel B distinguishes contributions based on the sponsoring party: the blue line represents cash flows from bills sponsored by members of the president's party, while the red line represents flows from the opposition party. Panel C breaks down bill-level deficit increases into those that raise government spending (blue line) and those that reduce government revenues (red line).

Panel A: Bill contributions to the budget deficit



Panel B: Bill contributions by sponsor party



Panel C: Bill contributions by decreasing revenues or increasing spending

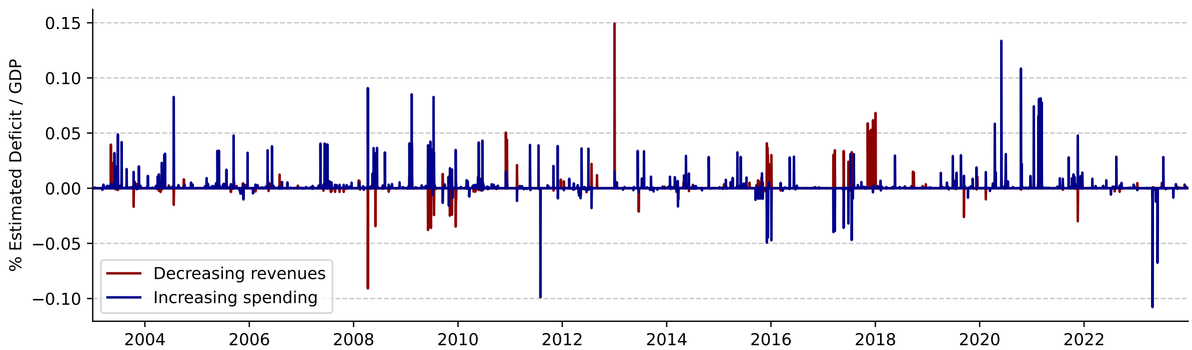
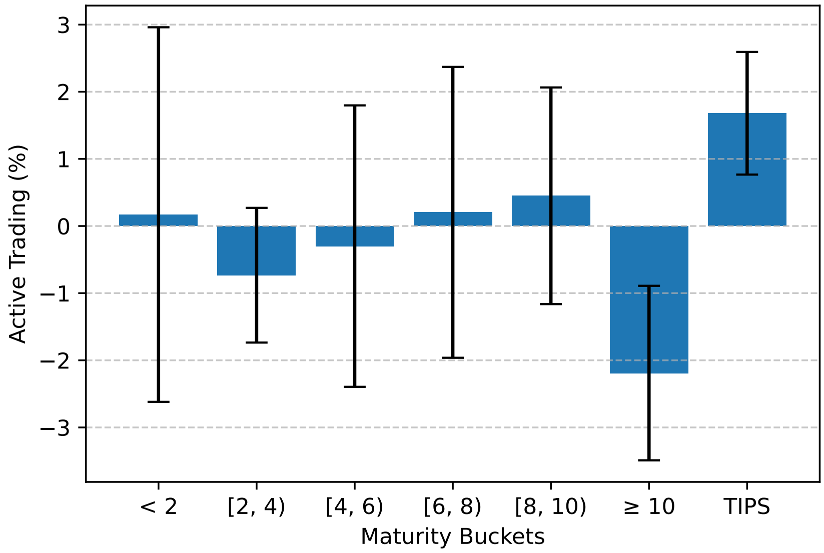


Figure 1.2: Partisan View and Fund Trading by Maturity Buckets

This figure plots regression coefficients of fund quarterly trading in Treasuries and corporate bonds by maturity buckets on ideological misalignment and the deficit increases from CBO releases. The dependent variable is the fund's active trading in Treasury securities in Panel A and in corporate bonds in Panel B. In the last bar of Panel A, I also show the effect on Treasury inflation-protected securities (TIPS). The independent variable of interest is the interaction term between $Misalign$ and $\Delta Deficit$. $Misalign$ measures the level of political misalignment between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. All regression specifications are identical as in Table 1.2. The error bars indicate the 90% confidence interval.

Panel A: Trading in Treasury securities



Panel B: Trading in corporate bonds

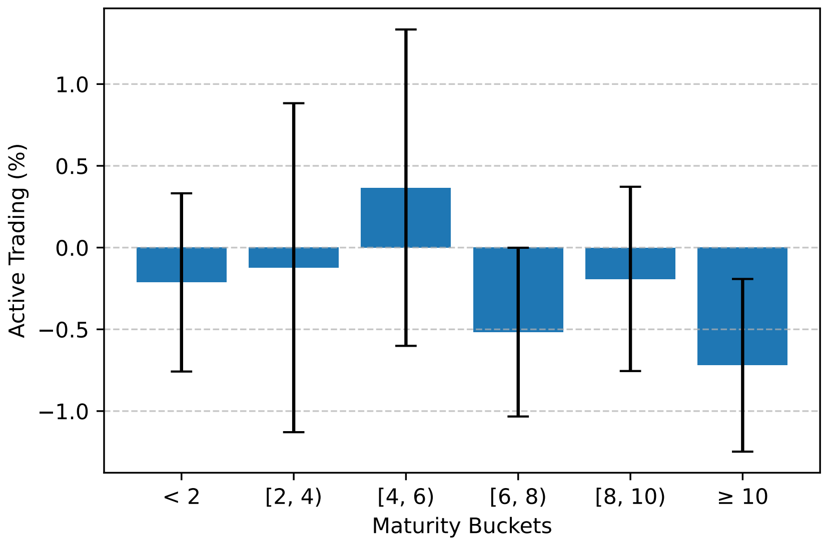


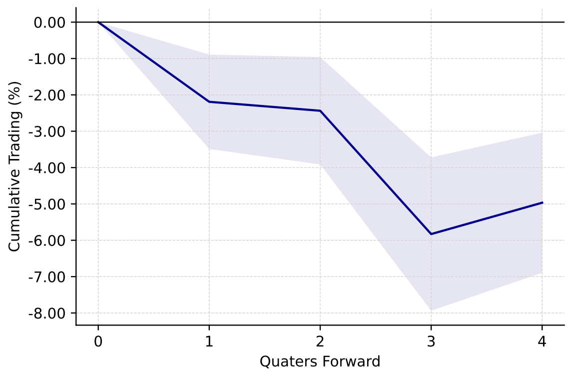
Figure 1.3: Partisan View and Fund Trading: Persistence of the Effects

This figure plots regression coefficient β_1 of Eq. (1.9) up to four quarters forward,

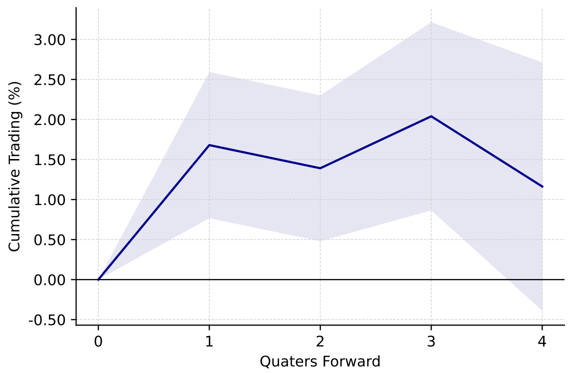
$$\Delta Holdings^{I}_{f,q\to q+h} = \beta_0 + \beta_1 \mathbf{Misalign_{f,q}} \times \mathbf{\Delta Deficit_{q\to q+1}} + \beta_2 Misalign_{f,q}$$
$$+ \Gamma Controls + \lambda_f + \lambda_q + \epsilon_{f,q}.$$

The dependent variable is the fund's active trading in Treasury securities in Panel A and in long-term corporate bonds in Panel B. The independent variable of interest is the interaction term between $Misalign$ and $\Delta Deficit$. All regression specifications are identical as in Table 1.2. The x-axis shows h, the number of quarters forward since q. I set the coefficient for $h = 0$, the beginning of the current quarter q, to be 0. The light blue area illustrates the 90% confidence interval.

Panel A: Trading in Treasury securities

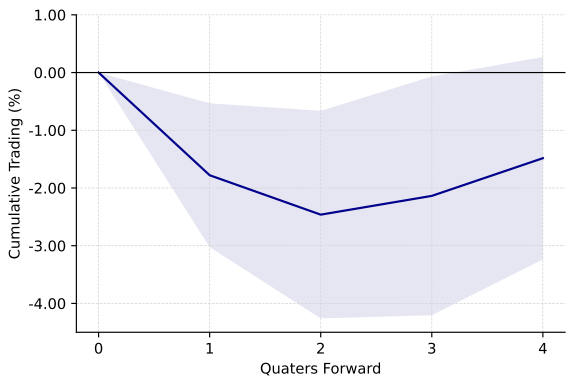


(1) Treasury maturity $\geqslant$ 10

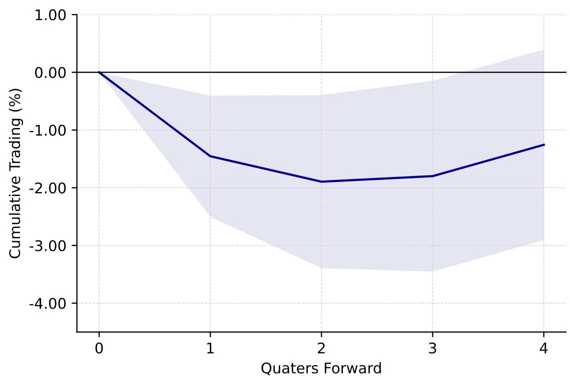


(2) TIPS

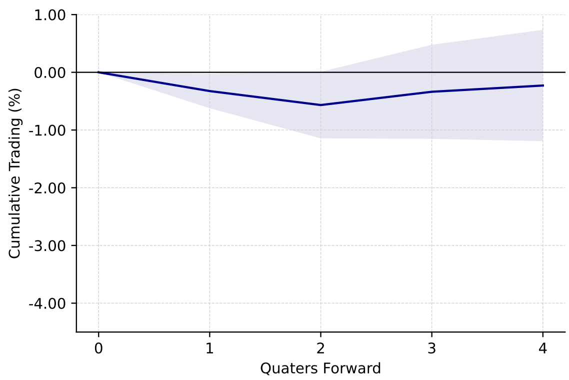
Panel B: Trading in corporate bonds



(1) Corporate bond maturity $\geqslant$ median



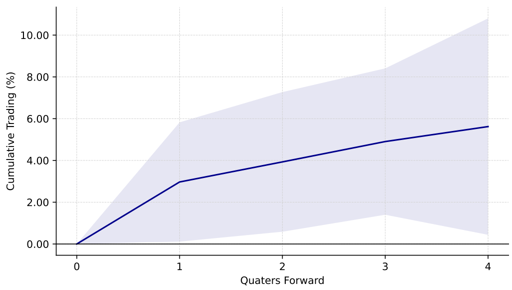
(2) Investment grade maturity $\geqslant$ median



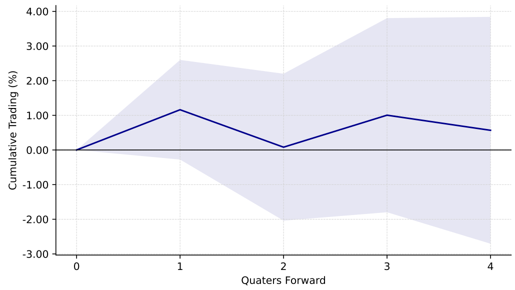
(3) High yield maturity $\geqslant$ median

Figure 1.4: Partisan View and Fund Trading: Other Asset Classes

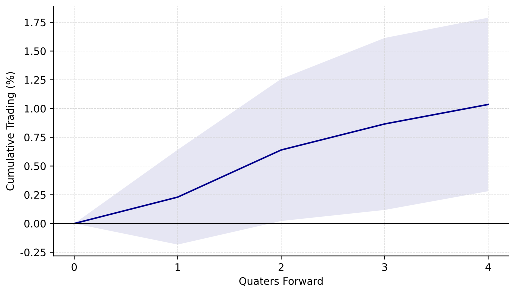
This figure plots regression coefficient β_1 of Eq. (1.9) up to four quarters forward. The dependent variable is the fund's active trading in all the other asset classes held by the fund. The independent variable of interest is the interaction term between $Misalign$ and $\Delta Deficit$. All regression specifications are identical as in Table 1.2. The x-axis shows h, the number of quarters forward since q. I set the coefficient for $h = 0$, the beginning of the current quarter q, to be 0. The light blue area illustrates the 90% confidence interval.



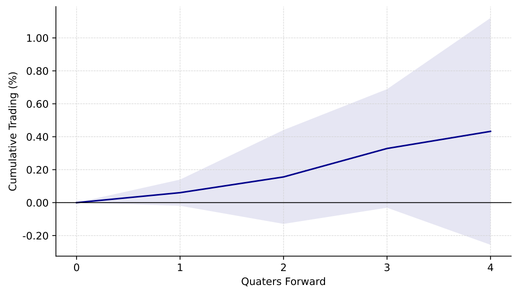
(1) Agency MBS pass-through



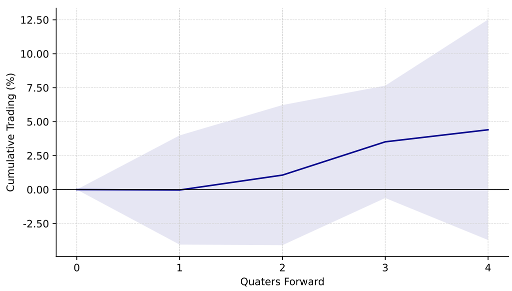
(2) Other MBS



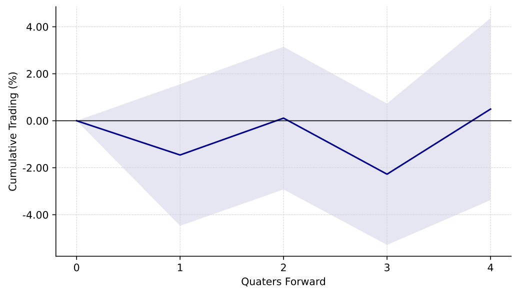
(3) Municipal bonds



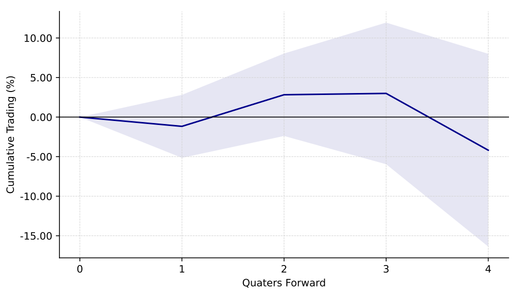
(4) Bank loans



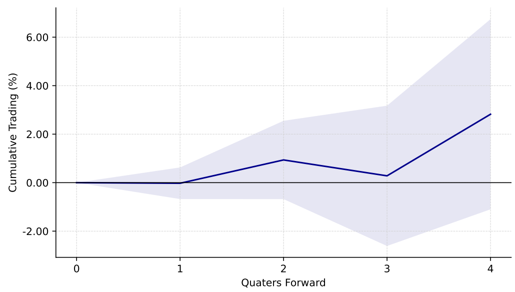
(5) Agency debts



(6) Collateralized mortgage obligations



(7) Asset-backed securities

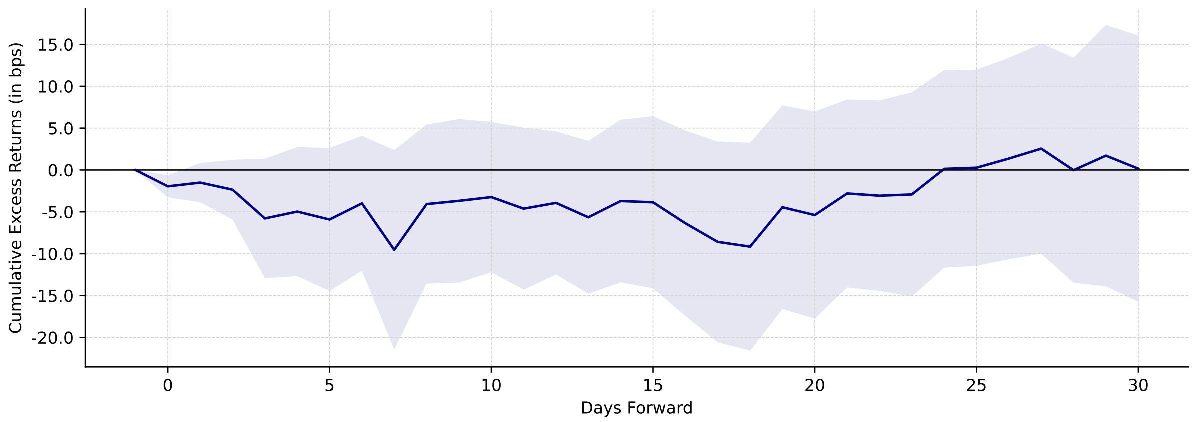


(8) Preferred stocks

Figure 1.5: Misaligned Partisan Ownership and Treasury Returns: Cumulative Effects

This figure plots the coefficients of *% Misalign Holding* on $ExRet_{t \to t+h}$, the cumulative excess returns for Treasury from day t to day $t+h$, where day t represents days with deficit releases that are equal to or exceed the 95th percentile of all deficit releases. Days with large deficit announcements that fall within a 3-day window of FOMC meeting days are excluded. All independent variables are defined in Table 1.5. Panel A reports the effect of misaligned partisan ownership on the returns for Treasury with maturities of 10 years or more, while Panel B reports that on Treasury inflation-protected securities (TIPS) returns. The x-axis shows the number of trading days forward since day t. I set the coefficient for $h = -1$, the day before the deficit release day, to be 0. The light blue area illustrates the 90% confidence interval.

Panel A: Long-term Treasury returns



Panel B: Treasury inflation-protected security returns

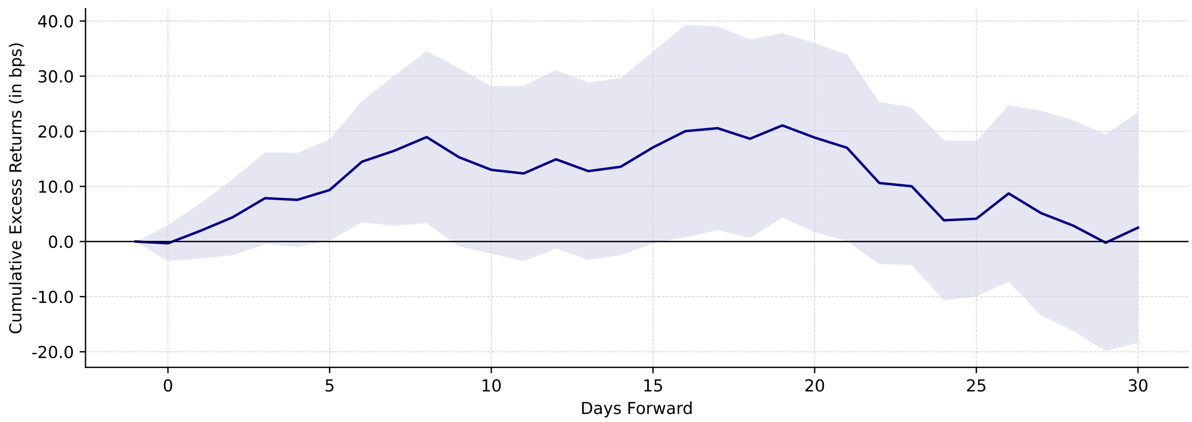
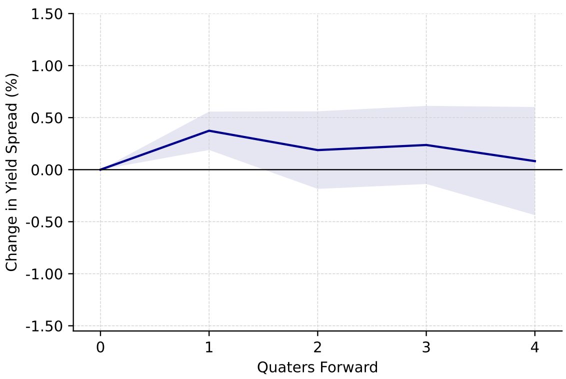


Figure 1.6: Misaligned Partisan Ownership and Corporate Bond Returns: Cumulative Effects

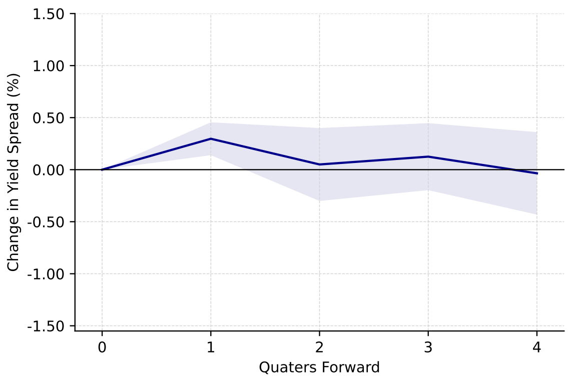
This figure plots regression coefficient β_1 of Eq. (1.13) up to four quarters forward,

$$\begin{aligned}\Delta Yield\,Spread^b_{q\to q+h} = {} & \beta_0 + \beta_1 \times \%\,\mathbf{Misalign\,Holding^b_q} \times \mathbf{\Delta Deficit_{q\to q+1}} \\ & + \beta_2 \times \%\,Misalign\,Holding^b_q + \Gamma_1 Controls \\ & + \Gamma_2 Controls \times \Delta Deficit_{q\to q+1} + \lambda_b + \lambda_{mat,q} + \lambda_{rat,q} + \epsilon^b_q\end{aligned}$$

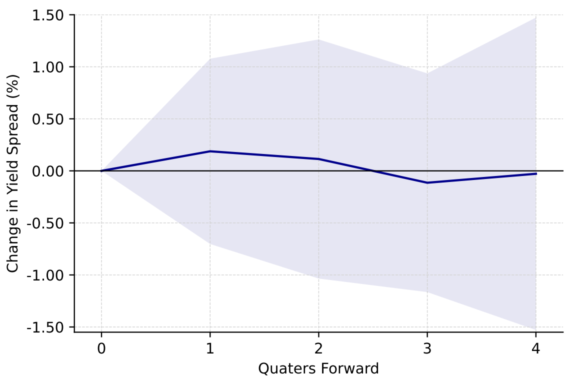
The independent variable of interest is the interaction term between $\%\,Misalign\,Holding$ and $\Delta Deficit$. $\%\,Misalign\,Holding$ is the percentage of shares held by misaligned mutual funds as defined in Eq. (1.11). $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. The dependent variable measures the change in the yield spread from the beginning to the end of the quarter. All regression specifications are identical as in Table 1.6. The x-axis shows h, the number of quarters forward since q. I set the coefficient for $h = 0$, the beginning of the current quarter q, to be 0. The light blue area illustrates the 90% confidence interval.



(1) Corporate bond maturity $\geqslant$ median



(2) Investment grade maturity $\geqslant$ median



(3) High yield maturity $\geqslant$ median

Tables

Table 1.1: Manager and Fund Characteristics

This table presents summary statistics for fund managers and funds, categorized by partisanship.

Panel A reports the distribution of fund managers by political affiliation. A manager is classified as Republican if they donate more to Republican causes, and as Democratic if they donate more to Democratic causes. "Gray" managers are those who either contribute equal amounts to both parties or only donate to political action committees (PACs) without a clear partisan preference. I report the number of unique managers in each party, along with the proportion of female managers and those holding a PhD degree. For each party, I report the average years the managers work in the mutual fund industry (*# Years in the industry*), calculated by averaging each manager's industry tenure over the sample period. *Average donations to Republican ($)* shows the mean total lifetime donation by managers to the Republican party, while *Average donations to Democrats ($)* shows that to the Democratic party. I also report *Average overall donations ($)*, which represents the mean total political donations by each manager to both parties and PACs without clear partisan affiliations.

Panel B reports the panel distribution of fund characteristics by each partisan group. A fund is classified as Republican if the average Republican index of its managers, $Rep_i = (R_i - D_i)/(R_i + D_i)$, is positive; Democratic if the index is negative; and "gray" if the index is zero. This panel shows the total net assets (TNA), expense ratio, turnover ratio, fund age, annual return, and annual flows to the fund. The table reports the mean, the median, and the 5th, 25th, 75th, and 95th percentiles.

Panel A: Fund Manager Characteristics

	Republican	Democrats	Gray
# of Obs	520	407	271
% Female	5.96%	17.94%	8.12%
% PhD	3.27%	3.93%	7.38%
# Years in the industry	10.19	8.06	9.66
Average donations to Republican ($)	50,475.49	723.86	32.10
Average donations to Democrats ($)	1,585.74	16,895.48	32.10
Average overall donations ($)	74,764.08	20,934.21	4,881.69

Panel B: Fund Characteristics

	Mean	5th	25th	50th	75th	95th
TNA($ Million)						
Rep	2,543.71	19.88	122.84	430.54	1,426.19	9,086.33
Dem	2,959.39	26.89	145.31	489.71	1,600.26	12,010.45
Gray	1,573.83	19.86	91.62	294.70	1,087.19	6,473.71
Expenses						
Rep	0.75%	0.20%	0.51%	0.71%	0.95%	1.42%
Dem	0.71%	0.30%	0.51%	0.66%	0.87%	1.26%
Gray	0.69%	0.19%	0.49%	0.67%	0.87%	1.24%
Turnover						
Rep	1.63	0.20	0.50	0.95	2.17	5.16
Dem	1.84	0.22	0.55	1.06	2.36	6.27
Gray	1.36	0.19	0.45	0.81	1.62	4.51
Fund Age						
Rep	13.87	1.42	6.25	12.25	19.58	31.92
Dem	14.21	1.25	6.00	12.67	21.00	31.75
Gray	15.10	1.33	6.17	13.25	21.75	34.67
Annual Return						
Rep	4.41%	-5.25%	1.35%	4.17%	7.38%	14.66%
Dem	4.26%	-5.82%	1.12%	4.05%	7.38%	14.32%
Gray	3.81%	-5.95%	1.09%	3.67%	6.82%	13.10%
Annual Flow						
Rep	0.16	-0.38	-0.14	-0.01	0.19	1.18
Dem	0.17	-0.38	-0.13	0.00	0.19	1.20
Gray	0.15	-0.39	-0.15	-0.01	0.19	1.20

Table 1.2: Partisan View and Fund Trading

This table regresses fund quarterly trading on political misalignment and the deficit increases from CBO releases. Panel A reports the fund's active trading in Treasuries with maturities of 10 years or more, Treasury Inflation-Protected Securities (TIPS), and Treasuries with maturities under 10 years in columns (1)-(3) separately. Panel B reports the effect on corporate bonds. Column (1) shows that for all bonds with maturities at or above the sample median, columns (2) and (3) break down the effect by investment-grade (IG) and high-yield (HY) bonds, while column (4) presents trading in bonds with maturities below the sample median. $Misalign$ measures the level of political mismatch between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. Control variables are defined in Appendix Table 1.A.1. Time and fund fixed effects are included. Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading in Treasury securities

DepVar =	$\Delta\, Treasury\ Holdings_{f,q+1}$ (*in* %)		
	Maturity $\geqslant$ 10 (1)	TIPS (2)	Maturity $<$ 10 (3)
$Misalign_{f,q} \times \Delta Deficit_{q\to q+1}$	**-2.191*** **	**1.680*** **	**-0.862**
	(0.781)	**(0.549)**	**(3.492)**
$Misalign_{f,q}$	0.086*	-0.091**	-0.002
	(0.047)	(0.042)	(0.221)
$Annual\ Return_{f,q-4\to q}$	-0.401*	-0.145	0.723
	(0.218)	(0.118)	(1.019)
$Expenses_{f,q}$	0.004	-0.021	-0.235
	(0.048)	(0.027)	(0.276)
$Log(TNA)_{f,q}$	0.008	0.003	-0.157***
	(0.008)	(0.004)	(0.046)
$Turnover_{f,q}$	0.006	0.005	0.157***
	(0.008)	(0.005)	(0.040)
$Log(Fund\ Age)_{f,q}$	0.044	0.017	0.537***
	(0.034)	(0.015)	(0.145)
$\%Initial\ Treasury_{f,q}$	-0.009***	-0.004***	-0.148***
	(0.001)	(0.001)	(0.007)
$Flow_{f,q\to q+1}$	1.291***	0.343***	6.333***
	(0.127)	(0.037)	(0.505)
$\%\,Female_{f,q}$	0.002	-0.024	0.017
	(0.036)	(0.027)	(0.241)
$\%\,PhD_{f,q}$	-0.065	-0.090	0.831**
	(0.088)	(0.069)	(0.330)
$Log(Experience)_{f,q}$	0.007	0.005	-0.061
	(0.013)	(0.010)	(0.071)
Time FE	Y	Y	Y
Fund FE	Y	Y	Y
# of Obs	52,669	52,669	52,669
Adj R^2	0.038	0.020	0.119

Panel B: Trading in corporate bonds

DepVar =	Δ *Corporate Bond Holdings*$_{f,q+1}$ (*in* %)			
	Maturity $\geqslant$ 50th			Maturity < 50th
	All (1)	IG (2)	HY (3)	All (4)
$Misalign_{f,q} \times \Delta Deficit_{q\rightarrow q+1}$	**-1.779****	**-1.454****	**-0.325***	**-0.411**
	(0.750)	**(0.631)**	**(0.179)**	**(1.501)**
$Misalign_{f,q}$	0.088	0.057	0.031*	-0.061
	(0.060)	(0.051)	(0.017)	(0.089)
$Annual\ Return_{f,q-4\rightarrow q}$	0.228	-0.157	0.385***	-0.814
	(0.330)	(0.313)	(0.091)	(0.673)
$Expenses_{f,q}$	0.064	-0.024	0.088***	0.022
	(0.084)	(0.075)	(0.025)	(0.089)
$Log(TNA)_{f,q}$	-0.041***	-0.034***	-0.007*	-0.000
	(0.014)	(0.013)	(0.004)	(0.020)
$Turnover_{f,q}$	0.001	0.001	-0.000	0.009
	(0.008)	(0.007)	(0.002)	(0.011)
$Log(Fund\ Age)_{f,q}$	0.019	0.046	-0.027*	-0.041
	(0.051)	(0.044)	(0.014)	(0.064)
$\%Initial\ Corp\ Bond_{f,q}$	-0.004***	-0.004***	0.000*	-0.022***
	(0.001)	(0.001)	(0.000)	(0.002)
$Flow_{f,q\rightarrow q+1}$	2.214***	1.929***	0.285***	5.100***
	(0.150)	(0.132)	(0.031)	(0.300)
$\%\ Female_{f,q}$	-0.094	-0.098	0.004	-0.107
	(0.089)	(0.082)	(0.024)	(0.104)
$\%\ PhD_{f,q}$	0.093	0.085	0.008	-0.081
	(0.105)	(0.093)	(0.029)	(0.121)
$Log(Experience)_{f,q}$	-0.011	-0.004	-0.007	0.011
	(0.024)	(0.023)	(0.006)	(0.035)
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	52,669	52,669	52,669	52,669
Adj R^2	0.183	0.159	0.190	0.207

Table 1.3: Partisan View and Fund Trading: by Bill Types

This table regresses fund quarterly trading on political misalignment and the deficit increases from CBO releases, categorized by the types of bills. *Misalign* measures the level of political mismatch between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. In the first two rows of each panel, bill-level deficit increases are separated based on whether the bill is sponsored by politicians from the president's party or the opposition party. In the second set of tests in each panel, bill-level deficit increases are decomposed into those that increase government spending and those that reduce government revenues. Panel A reports the fund's active trading in Treasuries with maturities of 10 years or more in columns (1) and (2), and in Treasury Inflation-Protected Securities (TIPS) in columns (3) and (4). Panel B reports the effect on corporate bonds with maturities at or above the sample median. Columns (1) and (2) show that for all bonds, columns (3) and (4), (5) and (6) break down the effect by investment-grade (IG) and high-yield (HY) bonds separately. I control for the same sets of control variables as in Table 1.2, defined in Appendix Table 1.A.1. Time and fund fixed effects are included. Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading in Treasury securities

DepVar =	Δ *Treasury Holdings (in %)*			
	Maturity $\geqslant$ 10		TIPS	
	(1)	(2)	(3)	(4)
Misalign × Δ*Deficit*	-2.416**		1.766**	
from President's Party	(1.025)		(0.761)	
Misalign × Δ*Deficit*	-1.850		1.552**	
from Opposition Party	(1.197)		(0.594)	
Misalign × Δ*Deficit*		-1.877**		1.732***
from Spending (+)		(0.738)		(0.588)
Misalign × Δ*Deficit*		-2.939**		1.546**
from Revenues (-)		(1.279)		(0.761)
Misalign	0.087*	0.087*	-0.091**	-0.091**
	(0.047)	(0.046)	(0.042)	(0.042)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	52,669	52,669	52,669	52,669
Adj R^2	0.038	0.038	0.020	0.020

Panel B: Trading in corporate bonds

DepVar =	Δ *Corporate Bond Holdings (in %)*					
	All		IG		HY	
	(1)	(2)	(3)	(4)	(5)	(6)
Misalign × Δ*Deficit*	-2.532**		-1.990**		-0.542**	
from President's Party	(1.102)		(0.953)		(0.255)	
Misalign × Δ*Deficit*	-0.659		-0.655		-0.004	
from Opposition Party	(0.468)		(0.445)		(0.109)	
Misalign × Δ*Deficit*		-1.891**		-1.582**		-0.309
from Spending (+)		(0.909)		(0.795)		(0.187)
Misalign × Δ*Deficit*		-1.512		-1.147		-0.365
from Revenues (-)		(1.038)		(0.902)		(0.223)
Misalign	0.089	0.087	0.058	0.056	0.031*	0.031*
	(0.059)	(0.060)	(0.050)	(0.050)	(0.017)	(0.017)
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
# of Obs	52,669	52,669	52,669	52,669	52,669	52,669
Adj R^2	0.183	0.183	0.159	0.159	0.191	0.191

Table 1.4: Partisan View and Fund Trading: by Manager Experience

This table regresses fund quarterly trading on political misalignment and the deficit increases from CBO releases, categorized by manager experience tenure. Funds are classified into two groups: the short-experience group, which includes funds where the longest manager tenure in the industry is below the quarterly median of all sample managers, and the long-experience group, comprising funds with the longest manager tenure above the quarterly median. Panel A reports the fund's active trading in Treasuries with maturities of 10 years or more in columns (1) and (3), and in Treasury Inflation-Protected Securities (TIPS) in columns (2) and (4). Panel B reports the effect on corporate bonds with maturities at or above the sample median. Columns (1) and (4) show that for all bonds, columns (2) and (5), (3) and (6) break down the effect by investment-grade (IG) and high-yield (HY) bonds separately. $Misalign$ measures the level of political mismatch between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. I control for the same sets of control variables as in Table 1.2, defined in Appendix Table 1.A.1. Time and fund fixed effects are included. Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading in Treasury securities

DepVar =	Δ *Treasury Holdings (in %)*			
	Short Experience		Long Experience	
	Maturity $\geqslant$ 10	TIPS	Maturity $\geqslant$ 10	TIPS
	(1)	(2)	(3)	(4)
Misalign × Δ*Deficit*	-1.274	0.688	-3.002***	2.430***
	(0.870)	(0.581)	(1.137)	(0.642)
Misalign	0.037	-0.046	0.117*	-0.125*
	(0.069)	(0.041)	(0.059)	(0.066)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	26,542	26,542	26,100	26,100
Adj R^2	0.032	0.018	0.049	0.028

Panel B: Trading in corporate bonds

DepVar =	Δ *Corporate Bond Holdings (in %)*					
	Maturity $\geqslant$ 50th					
	Short Experience			Long Experience		
	All	IG	HY	All	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
Misalign $\times$ Δ*Deficit*	-1.401	-1.395	-0.005	-2.047**	-1.402*	-0.645**
	(1.020)	(0.990)	(0.162)	(0.876)	(0.765)	(0.258)
Misalign	-0.038	-0.043	0.005	0.138*	0.090*	0.048*
	(0.083)	(0.075)	(0.016)	(0.078)	(0.049)	(0.028)
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
# of Obs	26,542	26,542	26,542	26,100	26,100	26,100
Adj R^2	0.179	0.151	0.195	0.218	0.197	0.219

Table 1.5: Misaligned Partisan Ownership and Treasury Returns

This table reports the results from Fama-MacBeth regressions of US Treasury excess returns on ideologically mismatched fund holdings during days with large deficit releases. The dependent variable is the cumulative daily excess returns for Treasury in basis points, aggregated from the event day, through day one, or day three post-event. The independent variable $\% Misalign\, Holding$ is the percentage of shares held by misaligned mutual funds as defined in Eq. (1.11). Columns (1)-(3) report the effects for long-term Treasury securities, while columns (4)-(6) show results for Treasury Inflation-Protected Securities (TIPS). The three parts of the table show the effects on days with deficits at or above the 95th, 97th, and 99th percentiles of all deficit releases separately. Days with large deficit announcements that fall within a 3-day window of FOMC meeting days are excluded. Control variables include Treasury time-to-maturity, coupon rate, on-the-run dummy, the logarithm of publicly held shares outstanding, and the bid-ask spread at the beginning of the current quarter, defined in Appendix Table 1.A.1. T-statistics based on standard errors with Newey-West correction are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

DepVar =	*Cumulative Excess Returns (in bps)*					
	Maturity $\geqslant$ 10			TIPS		
	[0]	[0, 1]	[0, 3]	[0]	[0, 1]	[0, 3]
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Deficit \geqslant$ 95th (# of Days = 57)						
% Misalign Holding	-1.953**	-1.504	-5.787	-0.322	1.932	7.861
	(-2.46)	(-1.08)	(-1.36)	(-0.17)	(0.64)	(1.58)
Controls	Y	Y	Y	Y	Y	Y
# of Obs	2,343	2,343	2,343	1,755	1,755	1,755
Adj R^2	0.802	0.792	0.841	0.790	0.786	0.762
$\Delta Deficit \geqslant$ 97th (# of Days = 34)						
% Misalign Holding	-2.486**	-1.835	-8.714	0.527	7.352**	7.811
	(-2.32)	(-0.77)	(-1.32)	(0.23)	(2.28)	(1.67)
Controls	Y	Y	Y	Y	Y	Y
# of Obs	1,386	1,386	1,386	1,082	1,082	1,082
Adj R^2	0.802	0.811	0.841	0.757	0.776	0.702
$\Delta Deficit \geqslant$ 99th (# of Days = 17)						
% Misalign Holding	-3.788**	-5.750	-13.405	2.054	15.151*	8.865
	(-2.35)	(-1.31)	(-1.25)	(1.18)	(2.19)	(1.34)
Controls	Y	Y	Y	Y	Y	Y
# of Obs	803	803	803	614	614	614
Adj R^2	0.754	0.804	0.917	0.699	0.786	0.699

Table 1.6: Misaligned Partisan Ownership and Corporate Bond Returns

This table reports the results of changes in corporate bond yield spreads on ideologically mismatched fund holdings and the deficit increases from CBO releases. The independent variable $\% Misalign\, Holding$ is the percentage of shares held by misaligned mutual funds as defined in Eq. (1.11). $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. The dependent variable measures the change in the yield spread from the beginning to the end of the quarter. Column (1) reports the effects on all corporate bonds with maturities at or above the sample median, while columns (2) and (3) report the effects on investment-grade (IG) and high-yield (HY) bonds separately. Control variables include issuer firm characteristics (ROA, leverage ratio, cash%, the logarithm of book equity, book-to-market ratio, Tobin's Q), and bond characteristics (duration, rating number, yield, bid-ask spread) at the beginning of the current quarter, defined in Appendix Table 1.A.1. The interaction terms between control variables and $\Delta Deficit$ are included. Bond, maturity-notch × time, and rating-notch × time fixed effects are controlled. Standard errors clustered at both the time and bond levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

DepVar =	Δ *Corporate Bond Yield Spread (in %)*		
	Maturity ⩾ 50th		
	All	IG	HY
	(1)	(2)	(3)
% Misalign Holding ×Δ*Deficit*	0.374***	0.297***	0.188
	(0.111)	(0.095)	(0.535)
% Misalign Holding	0.005	-0.012	0.109*
	(0.009)	(0.009)	(0.056)
Controls	Y	Y	Y
Controls × ΔDeficit	Y	Y	Y
Bond FE	Y	Y	Y
Maturity Notch × Time FE	Y	Y	Y
Rating Notch × Time FE	Y	Y	Y
# of Obs	130,106	113,627	16,479
Adj R^2	0.607	0.642	0.568

Table 1.7: Effects on Fund Flows and Returns

This table presents the effects of fund partisan trading on fund flows and returns, separately shown in Panel A and Panel B. The independent variable of interest is the interaction term between $Misalign$ and $\Delta Deficit$ in both panels. $Misalign$ measures the level of political mismatch between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. In Panel A, the dependent variables are fund flows expressed in percentage terms. Columns (1) and (2) report flows from the current quarter q to the end of the quarter, while columns (3) and (4) report flows during the following quarter. Additionally, I control for prior annual flows in columns (2) and (4). In Panel B, the dependent variables are various measures of quarterly returns and alphas in percentage terms. Column (1) reports excess returns (*ExRet*), while column (2) shows CAPM alphas (*CAPM*). Column (3) presents alphas adjusted for market and maturity factors (*CAPM + Maturity*), and column (4) adjusts alphas further with credit factors (*3F*). Column (5) includes adjustments for mortgage factors (*3F + Mortgage*), and column (6) adds equity market factors to the previous adjustments (*3F + Mtg. + Equity*). The first part of Panel B reports contemporaneous effects on returns and alphas from quarter q to $q+1$, while the second part reports effects for the following quarter. I control for the same sets of control variables including past annual returns as in Table 1.2, defined in Appendix Table 1.A.1. Time and fund fixed effects are included. Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effects on fund flows

DepVar =	$Flow_{f,q\rightarrow q+1}(\%)$		$Flow_{f,q+1\rightarrow q+2}(\%)$	
	(1)	(2)	(3)	(4)
$Misalign_{f,q} \times \Delta Deficit_{q\rightarrow q+1}$	-4.800	-2.909	1.329	3.457
	(6.217)	(6.529)	(7.929)	(7.804)
$Misalign_{f,q}$	0.149	0.064	0.046	-0.087
	(0.575)	(0.488)	(0.572)	(0.516)
$Annual\ Flow_{f,q-4\rightarrow q}(\%)$		0.040***		0.026***
		(0.003)		(0.002)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	52,669	52,084	52,189	51,605
Adj R^2	0.162	0.203	0.163	0.178

Panel B: Effects on fund returns

Contemporaneous Effects

DepVar =	$Alpha_{f,q \to q+1}$					
	ExRet	*CAPM*	*CAPM + Maturity*	*3F*	*3F + Mortgage*	*3F + Mtg. + Equity*
	(1)	(2)	(3)	(4)	(5)	(6)
$Misalign_{f,q} \times \Delta Deficit_{q \to q+1}$	0.366	-0.347	-1.015	-5.507	-9.166	-9.243
	(1.257)	(0.854)	(1.321)	(4.456)	(7.336)	(6.359)
$Misalign_{f,q}$	0.198**	0.124*	0.071	0.843*	1.068	0.712
	(0.077)	(0.065)	(0.097)	(0.435)	(0.665)	(0.573)
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
# of Obs	52,464	52,464	52,464	52,464	52,464	52,464
Adj R^2	0.602	0.444	0.470	0.464	0.456	0.366

Future Effects

DepVar =	$Alpha_{f,q+1 \to q+2}$					
	ExRet	*CAPM*	*CAPM + Maturity*	*3F*	*3F + Mortgage*	*3F + Mtg. + Equity*
	(1)	(2)	(3)	(4)	(5)	(6)
$Misalign_{f,q} \times \Delta Deficit_{q \to q+1}$	-0.643	-1.141**	0.878	-1.616	-3.695	-3.365
	(0.545)	(0.500)	(1.809)	(2.327)	(3.298)	(3.140)
$Misalign_{f,q}$	0.210***	0.171***	0.255	0.704	0.833	0.538
	(0.076)	(0.063)	(0.249)	(0.427)	(0.614)	(0.570)
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
# of Obs	51,860	51,860	51,860	51,860	51,860	51,860
Adj R^2	0.598	0.443	0.412	0.448	0.450	0.365

1.A Appendix

1.A.1 Variable definition

Table 1.A.1: Variable Definition

Variable	Definition
Main dependent variables	
$\Delta Holdings^{I}_{f,q\rightarrow q+1}$	The quarterly active trading of asset type I by fund f, calculated as $\Delta Holdings^{I}_{f,q\rightarrow q+1} = \sum_{i\in I}[(Shares_{i,f,q+1} - Shares_{i,f,q}) \times P_{i,q}]/TotalValue_{f,q}$, where $Shares_{i,f,q}$ is the share amount of asset i held by fund f at quarter q, $P_{i,q}$ is the price of asset i at q, and $TotalValue_{f,q}$ is the sum of overall holdings of fund f at q.
$ExRet^{b}_{t\rightarrow t+h}$	The cumulative daily returns for Treasury in excess of the risk-free rate in basis points, aggregated from the event day t, through day h post-event.
$\Delta Yield\,Spread^{b}_{q\rightarrow q+1}$	The change in the yield spread for bond b from quarter q to $q+1$, expressed in percentage terms. The yield spread is calculated as the difference between the bond's yield-to-maturity and the yield of duration-matched zero-coupon Treasuries. The bond's duration is matched to Treasury durations using linear interpolation between the two Treasuries with the closest durations to the bond.
Main independent variables	
$\Delta Deficit^{p}$	The deficit-to-GDP contribution at the legislative proposal level, calculated as the projected future increase in government spending minus the decrease in federal revenue, divided by the latest available projected GDP. All values are discounted to present terms.
$\Delta Deficit_{q\rightarrow q+1}$	The quarterly deficit impact from all cost estimates published during the current quarter, calculated as the sum of $\Delta Deficit^{p}$, with adjustments for incremental values applied to duplicate and recurrent bills.
$Misalign_{f,q}$	The level of political mismatch between the fund and the president's party. I first calculate each manager's Republican index as the $Rep_i = (R_i - D_i)/(R_i + D_i)$ based on their contribution to each party, then average this measure within the fund. $Misalign_{f,q} = \lvert Rep_{f,q} - Rep_{president,q}\rvert/2$.
$\%Misalign\,Holding^{b}_{q}$	The misaligned ownership for each bond, calculated as the weighted average of fund-level misalignment, with weights determined by each fund's relative holding amount in the bond, $\%Misalign\,Holding^{b}_{q} = (\sum_{f=1}^{F} Shares^{b}_{f,q} \times Misalign_{f,q})/(\sum_{f=1}^{F} Shares^{b}_{f,q})$, where $Shares^{b}_{f,q}$ is the par value amount of bond b held by fund f at quarter q.
Control variables at the fund-time level	
Annual Return	Fund cumulative return of previous one year.
$Log(TNA)$	The natural logarithm of fund total net assets across all share classes.
Expenses	Annual expense ratio reported by the end of the most recent fiscal year.
Turover	Annual turnover ratio reported by the end of the most recent fiscal year.
$Log(Fund\,Age)$	The natural logarithm of fund age, measured in years as the difference between the start date of the fund's oldest share class and the current date.

Variable	Definition
Control variables at the fund level (continued)	
%Initial Treasury	Fund overall Treasury position over total value of its holdings at the beginning of the current quarter.
%Initial Corp Bond	Fund overall corporate bond position over total value of its holdings at the beginning of the current quarter.
Flow	Quarterly fund flow, calculated as the proportion of the difference between the current TNA and the return-adjusted beginning-of-quarter TNA to the beginning-of-quarter TNA. Annual fund flow is similarly calculated using TNA and returns from one year prior.
% Female	The number of female managers divided by the total number of managers for the fund.
% PhD	The number of managers with a PhD degree divided by the total number of managers for the fund.
% Log(Experience)	The natural logarithm of the longest tenure in the mutual fund industry (in years) among all managers within the team for the fund.
Control variables at the bond level	
Maturity	The years between the quarter-end and maturity date.
Coupon	The annual coupon rate. For TIPS, the stated rate is used without inflation adjustments.
On-the-run	A dummy variable that equals 1 if a Treasury is the most recently issued Treasury of a specific maturity and 0 otherwise.
Log(Shares)	The natural logarithm of publicly held shares outstanding, measured at face value in millions of USD.
Bid-ask spread	The average difference between the previous quarter's bid and ask prices.
Rating Number	The numerical credit rating of the bond, 1=AAA, 2=AA+,..., 21=C, 22=D.
Duration	The duration of the bond.
Yield	The yield-to-maturity of the bond.
ROA	Income before extraordinary items (Compustat: IBQ; Unless otherwise specified, all issuer firm information in this section is sourced from Compustat) divided by total assets (ATQ).
Leverage Ratio	Total liabilities (LTQ) divided by total assets (ATQ).
Cash%	Cash and Short-Term Investments (CHEQ) divided by total assets (ATQ).
Log(BE)	The natural logarithm of book equity, calculated as stockholders' equity (SEQQ) plus deferred taxes and investment tax credit (TXDITCQ) minus total preferred stocks (PSTKQ). If stockholders' equity is missing, use common equity (CEQQ) plus preferred stocks (PSTKQ) instead. If still missing, use total assets (ATQ) minus total liabilities (LTQ) instead.
Book-to-Market	Book equity divided by market cap (CRSP: SHROUT $\times$ |PRC|).
Tobin's Q	Total assets (ATQ) plus market cap (CRSP: SHROUT $\times$ |PRC|) minus book equity divided by total assets.

1.A.2 Details on sample construction

1.A.2.1 Congressional Budget Office cost estimates

I discuss how I construct the data of CBO cost estimates in this part, mainly following Gomez Cram et al. (2023) and Gomez Cram et al. (2024).

The CBO provides XML links to all historical cost estimates on its website[1], from which I obtain each cost estimate in PDF format for the 108th to 118th Congresses, totaling 13,668 files. For bills involving relatively small spending or revenue changes, the CBO typically includes only a paragraph discussing the cost or a brief table showing projected costs, as shown in Figure 1.A.1 Panel A. For bills that may have a notable effect on the deficit or surplus, the CBO provides more detailed projections with extended text descriptions and multiple tables as in Figure 1.A.1 Panel B. Since I focus only on large bills with effects on the surplus or deficit exceeding $1 billion, I apply the following filtering process:

(1) Exclude files without any tables, leaving 7,413 files.[2]

(2) Keep all files containing the keyword "billion" or those with "million" that include numbers longer than three digits, leaving 2,108 files.

(3) Manually check the remaining files and collect information on bill numbers and titles, estimated revenues, direct (mandatory) spending, and discretionary spending (spending subject to appropriations). The net increase in the deficit is calculated as the sum of direct and discretionary spending minus revenues. This step results in 1,374 files with a total budgetary impact greater than $1 billion.

I further merge the cost estimates from previous steps with data from `https://www.congress.gov/` using congress and bill numbers to obtain information on the bill sponsor and legislative status. Figure 1.A.2 Panel A shows bill-level cash flow contributions based on whether the bill ultimately passes.[3]

[1] Available at `https://www.cbo.gov/cost-estimates/xml`.

[2] Gomez Cram et al. (2023) suggests that smaller bills, typically those below the median in size, usually do not include a detailed table. My file count after this step is consistent with their findings.

[3] The figure may not be fully accurate for the 118th Congress, as some recent bills are still in the legislative process.

When aggregating the budgetary effects of bills at the quarterly level, I adjust for duplicated or recurrent bill estimates. The CBO may provide multiple estimates for the same bill as it progresses through the legislative process, and Congress may update the same bill under different bill numbers.[4] I identify these cases by Congress, bill numbers, and titles. For each bill's initial cost estimate, I use the original value and apply only the incremental changes for later releases. I also apply these adjustments to the National Defense Authorization Act (NDAA) each year, as it requires reauthorization yearly. The results of these updates are reported in Figure 1.A.2 Panel B.

Finally, Table 1.A.2 provides details on the top 20 legislative bills that increase or decrease the federal budget deficit, ranked by the main deficit measure, $\Delta Deficit$.[5] These bills are generally more likely to increase deficits than to contribute to surpluses.

[4] An example of H.R. 6800/H.R. 925, the Heroes Act in the 116th Congress can be found in Heroes Act (H.R. 6800/H.R. 925): Selected Consumer Loan Provisions.

[5] I also report the total sum of yearly deficit contributions in dollar amounts. A bill may have a large total amount but a smaller $\Delta Deficit$ if it involves larger cash flows in later years.

Figure 1.A.1: Examples of Congressional Budget Office Cost Estimates

This figure provides examples of Congressional Budget Office cost estimates. Panel A shows cost estimates for S.1425 - the Satellite Cybersecurity Act, a bill involving deficits or surpluses less than $1 billion. Panel B presents cost estimates for H.R. 6800 - the Heroes Act, a bill that increases budget deficits of more than $1 billion.

Panel A: Congressional Budget Office Cost Estimate for S. 1425

Congressional Budget Office
Cost Estimate

June 12, 2023

S. 1425 would require the Cybersecurity and Infrastructure Security Agency (CISA) to disseminate information on cyber safety measures to operators of commercial satellites. Under the bill, CISA would collect security recommendations from the private sector and other federal agencies with expertise in satellite operations.

Using information from CISA about similar information sharing efforts, CBO anticipates that the agency would need six full-time employees to create and manage an online database with cybersecurity resources for satellite operators. CBO estimates that staff salaries and technology costs to publish safety materials would total $3 million annually. Accounting for the time needed to hire new employees and prepare the database, CBO estimates that implementing the bill would cost $14 million over the 2023-2028 period; such spending would be subject to the availability of appropriated funds.

The costs of the legislation, detailed in Table 1, fall within budget function 050 (national defense).

Table 1.
Estimated Increases in Spending Subject to Appropriation Under S. 1425

	By Fiscal Year, Millions of Dollars						
	2023	2024	2025	2026	2027	2028	2023-2028
Estimated Authorization	0	2	3	3	3	3	14
Estimated Outlays	0	2	3	3	3	3	14

The CBO staff contact for this estimate is Aldo Prosperi. The estimate was reviewed by Chad Chirico, Director of Budget Analysis.

Panel B: Congressional Budget Office Cost Estimate for H.R. 6800

CBO Estimate for H.R. 6800, the Heroes Act, as Passed by the House of Representatives on May 15, 2020

Table 1. Summary of Estimated Budgetary Effects — **Revised June 1, 2020**

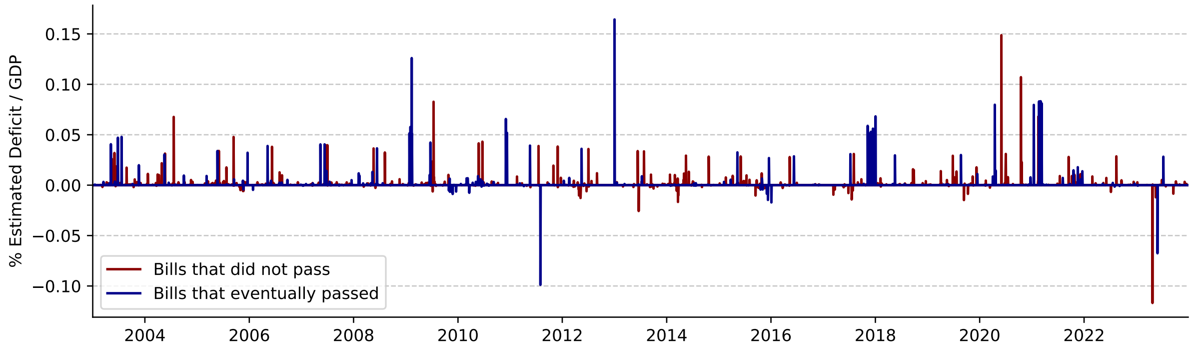
By Fiscal Year, Billions of Dollars

	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2020-2025	2020-2030
INCREASES OR DECREASES (-) IN DISCRETIONARY APPROPRIATIONS (Division A)													
Estimated Budget Authority	1,512	1	0	0	0	0	0	0	0	0	0	1,513	1,513
Estimated Outlays	706	562	103	60	54	16	9	1	*	0	0	1,501	1,511
INCREASES OR DECREASES (-) IN REVENUES (Div. A, Subsection 10607(d) and Divisions B through T)													
Estimated Revenues	-178	-179	-43	10	-5	-7	2	20	22	24	24	-403	-310
INCREASES OR DECREASES (-) IN DIRECT SPENDING (Div. A, Subsection 10607(d) and Divisions B through T)													
Estimated Budget Authority	1,043	494	29	29	-6	-9	11	10	11	11	11	1,578	1,632
Estimated Outlays	835	690	38	24	-7	-9	11	10	11	11	11	1,570	1,624
NET INCREASE OR DECREASE (-) IN THE DEFICIT													
Total	1,719	1,431	183	74	52	14	18	-9	-12	-13	-13	3,475	3,445
On-Budget	*1,719*	*1,431*	*183*	*74*	*53*	*14*	*18*	*-8*	*-12*	*-13*	*-13*	*3,475*	*3,448*
Off-Budget	*	*	*	*	*	*	*	*	*	*	*	*-1*	*-2*

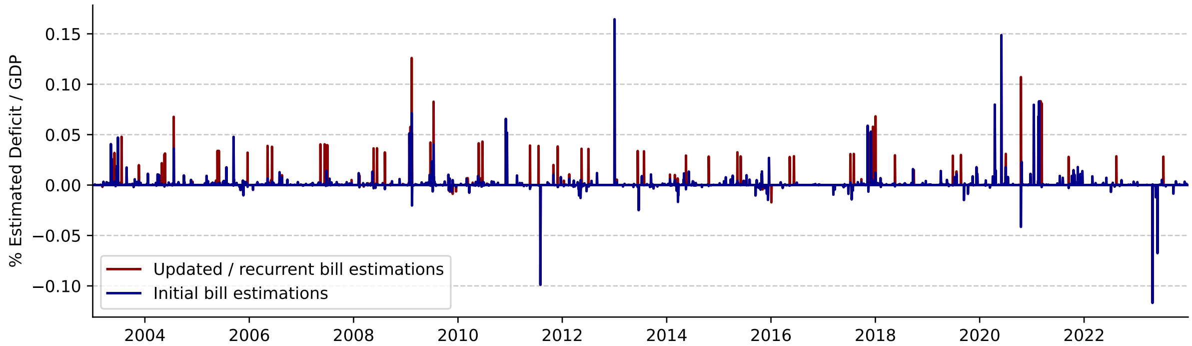
Figure 1.A.2: CBO Cost Estimates by Bill Types

This figure breaks down the bill-level estimated deficit-to-GDP ratio by types of legislative bills. For CBO estimates released on the same date, I aggregate them on a daily basis. Panel A shows deficits contributed by bills that did not pass (red line) and those that eventually passed (blue line). Panel B displays cost estimates for bills appearing in the CBO for the first time (blue line) and for recurring or duplicate bills (red line). Panel C reports bill-level cash flow contributions from direct spending and reduced revenues (blue line) and from discretionary spending subject to appropriations (red line).

Panel A: Bill contributions based on whether the bill eventually passes



Panel B: Bill contributions based on whether the bill estimation is initial



Panel C: Bill contributions from direct or discretionary spending

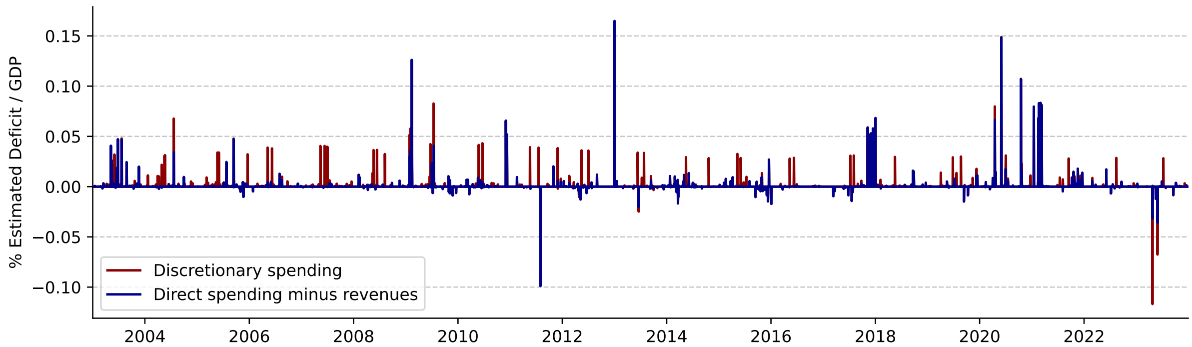


Table 1.A.2: Top 20 Legislative Bills Increasing or Decreasing the Federal Budget Deficits

This table reports the top 20 legislative bills that increase or decrease the federal budget deficits by the estimated deficit to GDP ratio in Panel A and Panel B, respectively. I show the first date of CBO projections for bills with multiple CBO releases and exclude the annual National Defense Authorization Act. $Amt(\$B)$ is the total sum of yearly deficits contributed by the bill in billion US dollars, and $\Delta Deficit$ is the bill-level estimated deficit to GDP ratio. The negative $Amt(\$B)$ and $\Delta Deficit$ in Panel B suggest reductions in deficits. I also report the sponsor party of each bill in the last column.

Panel A: Top 20 bills increasing the deficits

Congress	Bill Number	Date	Amt ($B)	$\Delta Deficit$	Bill Title	Sponsor
112	H.R. 8	2013/1/1	3,961.28	16.44%	American Taxpayer Relief Act of 2012	Rep
116	H.R. 925	2020/6/1	3,444.00	14.87%	Heroes Act	Dem
116	H.R. 748	2020/4/16	1,721.00	7.98%	CARES Act	Dem
117	H.R.1319	2021/2/20	1,920.00	8.31%	American Rescue Plan Act of 2021	Dem
111	H.R. 4853	2010/12/2	1,505.00	6.56%	Middle Class Tax Relief Act of 2010	Dem
115	H.R. 1	2017/11/8	1,671.00	5.89%	Tax Cuts and Jobs Act	Rep
111	H.R. 4853	2010/12/10	857.81	5.18%	Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010	Dem
111	H.R. 1	2009/1/26	815.90	5.14%	American Recovery and Reinvestment Act of 2009	Dem
109	H.R. 3304	2005/9/13	995.80	4.78%	Growing Real Ownership for Workers Act of 2005	Rep
116	H.R. 133	2021/1/14	1,042.69	4.73%	Consolidated Appropriations Act, 2021	Dem
108	H.R. 1	2003/6/26	968.80	4.71%	Medicare and Prescription Drug Modernization Act of 2003	Rep
117	S. Con. Res. 5	2021/2/15	923.66	4.15%	Concurrent Resolution on the Budget for Fiscal Year 2021	Ind
108	H.R. 2	2003/5/8	549.54	4.06%	Jobs and Growth Tax Relief Reconciliation Act of 2003	Rep
111	H.R.3200	2009/7/14	1,043.00	4.04%	America's Affordable Health Choices Act of 2009	Dem
108	H.R. 3821	2004/7/21	667.80	3.50%	Bipartisan Retirement Security Act of 2004	Rep
116	H.R. 133	2021/1/14	682.32	3.24%	Coronavirus Response and Relief Consolidated Appropriations Act, 2021	Dem
116	S. 178	2020/10/21	519.20	2.29%	Delivering Immediate Relief to America's Families, Schools and Small Businesses Act	Rep
114	H.R. 2029	2015/12/18	679.56	2.69%	Consolidated Appropriations Act, 2016	Rep
108	S. 1	2003/6/17	368.60	1.81%	Prescription Drug and Medicare Improvement Act of 2003	Rep
117	H.R. 5376	2021/11/18	367.12	1.78%	Build Back Better Act	Dem

Panel B: Top 20 bills decreasing the deficits

Congress	Bill Number	Date	Amt ($B)	$\Delta Deficit$	Bill Title	Sponsor
118	H.R. 2811	2023/4/25	-4,804.20	-11.69%	Limit, Save, Grow Act of 2023	Rep
112	S. 365	2011/8/1	-2,467.00	-9.88%	Budget Control Act of 2011	Dem
118	H.R. 3746	2023/5/30	-2,859.50	-6.76%	Fiscal Responsibility Act of 2023	Rep
113	S. 40	2014/3/21	-464.50	-1.67%	American Liberty Restoration Act	Rep
116	H.R. 860	2019/9/13	-524.68	-1.50%	Social Security 2100 Act	Dem
114	H.R. 3762	2015/12/11	-473.60	-1.47%	Restoring Americans' Healthcare Freedom Reconciliation Act	Rep
115	H.R. 1628	2017/7/19	-473.40	-1.42%	Obamacare Repeal Reconciliation Act of 2017	Rep
112	H.R. 5652	2012/5/8	-328.04	-1.28%	Sequester Replacement Reconciliation Act	Rep
115	H.R. 1628	2017/7/20	-420.10	-1.21%	Better Care Reconciliation Act of 2017	Rep
118	H.J.Res 45	2023/5/18	-315.61	-1.21%	Providing for congressional disapproval under chapter 8 of title 5, United States Code, of the rule submitted by the Department of Education relating to "Waivers and Modifications of Federal Student Loans"	Rep
113	S. 2122	2014/3/24	-284.50	-1.01%	Responsible Medicare SGR Repeal and Beneficiary Access Improvement Act of 2014	Rep
108	H.R. 3053	2003/10/14	-173.43	-0.99%	Sacrifice and Responsibility Act	Dem
115	H.R. 1628	2017/3/13	-336.60	-0.95%	American Health Care Act of 2017	Rep
116	H.R. 3	2019/10/11	-345.00	-0.87%	Lower Drug Costs Now Act of 2019	Dem
118	H.J.Res. 88	2023/9/18	-260.70	-0.81%	Providing for congressional disapproval under chapter 8 of title 5, United States Code, of the rule submitted by the Department of Education relating to "Improving Income Driven Repayment for the William D. Ford Federal Direct Loan Program and the Federal Family Education Loan (FFEL) Program"	Rep
112	H.R. 6684	2012/6/19	-236.61	-0.76%	Spending Reduction Act of 2012	Rep
113	S. 18	2013/6/19	-219.94	-0.74%	Sequester Replacement and Spending Reduction Act of 2013	Rep
111	H.R. 3962	2009/11/20	-138.00	-0.70%	Affordable Health Care for America Act	Dem
111	H.R. 4872	2010/3/21	-143.00	-0.67%	Reconciliation Act of 2010	Dem
111	H.R. 3590	2009/11/18	-129.00	-0.67%	Patient Protection and Affordable Care Act	Dem

1.A.2.2 Mutual fund manager political donations

I match mutual fund managers' personal information from Morningstar with the political contribution data from the Center for Responsive Politics (CRP) to obtain the manager's donation history.

Mutual fund managers voluntarily report their biographies to Morningstar, including their full name, work experience, educational degree, gender, and years in the industry. I collect the biographies for all active fixed-income fund managers in the sample from the Morningstar website, presented in Table 1.A.3 Panel A.[6] Since Morningstar typically reports manager work experience in a long paragraph, I upload this information to ChatGPT to convert the manager biographies into a standardized table with inferred years and firms, as displayed in Table 1.A.3 Panel B. Additionally, since the demographic information from Morningstar only includes each manager's latest experience in the mutual fund industry, I manually collect further information from LinkedIn for managers who have since left the industry. I also gather the locations of these firms from Morningstar and LinkedIn, supplementing this data by checking the firms' websites. Using the manager's full available work history, rather than just the period they served as a mutual fund manager, provides a more comprehensive understanding of the manager's political stance over their lifetime.

Following Wintoki and Xi (2020) and Evans et al. (2025), I obtain individual political contribution information since the 1990 election cycle from CRP, which collects and cleans the campaign finance data from the Federal Election Commission (FEC). [7] Figure 1.A.3 presents a screenshot from the FEC website, displaying the individual's name, address, occupation, employer, donation amount, and donation recipient. The CRP assigns identifiers to individual donors, infers donor genders, standardizes employer names, and provides links to contributions made by political action committees (PACs), simplifying the merging process compared to using the original FEC database.[8] I use the following

[6] To protect personal privacy, a specific name in the image has been redacted. The same applies to Figure 1.A.3, where the name has also been obscured.

[7] All contributions 1989 - 2014 will be reported by FEC if the reporting period amount is $200 or more, and all contributions since 2015 will be included by FEC if the election cycle-to-date amount is over $200 for contributions to candidate committees, or if the calendar year-to-date amount is over $200 for contributions to PACs and party committees. See https://www.fec.gov/campaign-finance-data/contributions-individuals-file-description/ for more details on the FEC reporting rules.

[8] The CRP data is available at https://www.opensecrets.org/open-data, and the data manual

algorithm to merge mutual fund managers with their political donations:

(1) Exact match by last name, exclude names with incorrect middle name and suffix (if available in both datasets). Require individuals to have the same inferred gender in both datasets.

(2) Use HMNI [9] to fuzzy match first name, as individuals may report both their nicknames and formal names to FEC, like Bob for Robert (Hong and Kostovetsky, 2012).

(3) For all names matched in steps 1 and 2, include additional observations that share the same *ContribeID* as identified by CRP. Exclude observations with unrelated occupations, such as artist, farmer, or salesperson.[10]

(4) Include all individuals employed at the same firm as the fund manager during the same period. To conduct fuzzy match on employer firm names, I first remove the common organization suffixes and general words for asset management companies, then convert all abbreviations to full company names (e.g., PGIM for Prudential, FMR or FIAM for Fidelity), and require a similarity score above 60% for matched firm pairs (Sheng et al., 2024). [11]

(5) For employees of small firms operating in a single state, retain only observations where the individual resides in the same state as the fund manager. Use that name mapping if the fund manager is matched to only one *ContribeID* after this step.

(6) For employees of large firms operating across multiple states, include all individuals working in the same state as the firm's asset management division headquarters, *or* those with the exact occupations listed in the fund manager's employment history. Use that name mapping if the fund manager is matched to only one *ContribeID* after this step.

(7) For common names, such as John Smith, with multiple possible matches, I require exact matches in employer name, location, and occupation. If this still results in multiple matches between the manager's name and *ContribeID*, I further require

including their cleaning process can be found at https://www.opensecrets.org/open-data/bulk-data-documentation.

[9] Available at https://github.com/Christopher-Thornton/hmni.

[10] I do not precisely require the occupation to be fund manager at this step, as individuals may sometimes vaguely file occupations. In Figure 1.A.3, the manager reports his occupation as "finance".

[11] Firm names can change due to mergers and acquisitions. I consider both pre- and post-M&A names in the matching process when possible. For example, since Invesco acquired AIM Investment in 1997, a match is considered valid if a fund manager from Invesco is linked to either Invesco or AIM.

an exact first name match (rather than using the fuzzy-matched first name from step 2).

(8) Search the rest of the CRP dataset for specific occupations like "asset manager", "portfolio manager", "mutual fund", "investor", and "fixed income". Manually check for missing matches from previous steps.

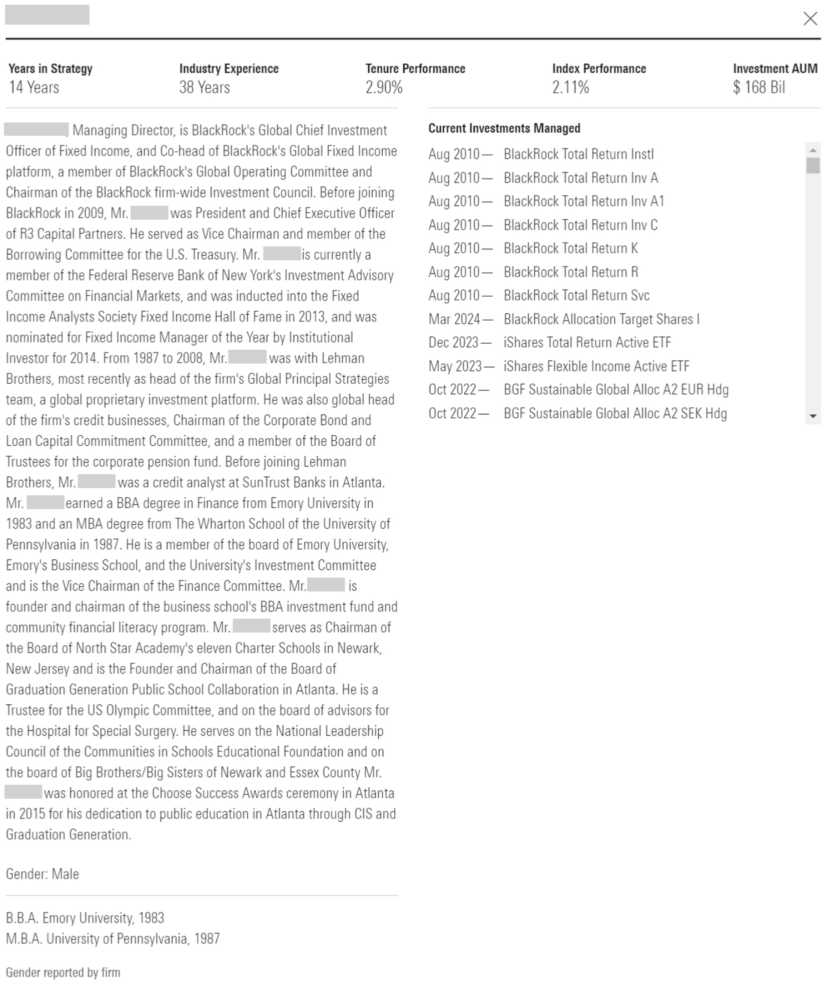
(9) Finally, manually check all matching results from the previous steps.

Combining the algorithm and hand audits, I identify 22,453 donations from 1,198 out of 4,913 managers. Figure 1.A.4 reports the detailed numbers of partisan fund managers and funds over time.

Table 1.A.3: An Example of Mutual Manager Biography from Morningstar

This figure presents a screenshot of the self-reported mutual manager biography from the Morningstar website in Panel A, and the standardized work and education experience output for the fund manager from ChatGPT in Panel B.

Panel A: Morningstar manager biography page



[redacted]

Years in Strategy	Industry Experience	Tenure Performance	Index Performance	Investment AUM
14 Years	38 Years	2.90%	2.11%	$ 168 Bil

[redacted], Managing Director, is BlackRock's Global Chief Investment Officer of Fixed Income, and Co-head of BlackRock's Global Fixed Income platform, a member of BlackRock's Global Operating Committee and Chairman of the BlackRock firm-wide Investment Council. Before joining BlackRock in 2009, Mr. [redacted] was President and Chief Executive Officer of R3 Capital Partners. He served as Vice Chairman and member of the Borrowing Committee for the U.S. Treasury. Mr. [redacted] is currently a member of the Federal Reserve Bank of New York's Investment Advisory Committee on Financial Markets, and was inducted into the Fixed Income Analysts Society Fixed Income Hall of Fame in 2013, and was nominated for Fixed Income Manager of the Year by Institutional Investor for 2014. From 1987 to 2008, Mr. [redacted] was with Lehman Brothers, most recently as head of the firm's Global Principal Strategies team, a global proprietary investment platform. He was also global head of the firm's credit businesses, Chairman of the Corporate Bond and Loan Capital Commitment Committee, and a member of the Board of Trustees for the corporate pension fund. Before joining Lehman Brothers, Mr. [redacted] was a credit analyst at SunTrust Banks in Atlanta. Mr. [redacted] earned a BBA degree in Finance from Emory University in 1983 and an MBA degree from The Wharton School of the University of Pennsylvania in 1987. He is a member of the board of Emory University, Emory's Business School, and the University's Investment Committee and is the Vice Chairman of the Finance Committee. Mr. [redacted] is founder and chairman of the business school's BBA investment fund and community financial literacy program. Mr. [redacted] serves as Chairman of the Board of North Star Academy's eleven Charter Schools in Newark, New Jersey and is the Founder and Chairman of the Board of Graduation Generation Public School Collaboration in Atlanta. He is a Trustee for the US Olympic Committee, and on the board of advisors for the Hospital for Special Surgery. He serves on the National Leadership Council of the Communities in Schools Educational Foundation and on the board of Big Brothers/Big Sisters of Newark and Essex County Mr. [redacted] was honored at the Choose Success Awards ceremony in Atlanta in 2015 for his dedication to public education in Atlanta through CIS and Graduation Generation.

Gender: Male

B.B.A. Emory University, 1983
M.B.A. University of Pennsylvania, 1987

Gender reported by firm

Current Investments Managed

Aug 2010— BlackRock Total Return Instl
Aug 2010— BlackRock Total Return Inv A
Aug 2010— BlackRock Total Return Inv A1
Aug 2010— BlackRock Total Return Inv C
Aug 2010— BlackRock Total Return K
Aug 2010— BlackRock Total Return R
Aug 2010— BlackRock Total Return Svc
Mar 2024— BlackRock Allocation Target Shares I
Dec 2023— iShares Total Return Active ETF
May 2023— iShares Flexible Income Active ETF
Oct 2022— BGF Sustainable Global Alloc A2 EUR Hdg
Oct 2022— BGF Sustainable Global Alloc A2 SEK Hdg

Panel B: ChatGPT formatted output for the manager biography

Work Experience		
Year	**Firm**	**Occupation**
2009 - 2024	BlackRock	Chief Investment Officer
2008 - 2009	R3 Capital Partners	President and Chief Executive Officer
1987 - 2008	Lehman Brothers	Head of the firm's Global Principal Strategies team
1983 - 1987	SunTrust Banks in Atlanta	Credit analyst
Education Experience		
Year	**School**	**Degree**
1987	University of Pennsylvania	M.B.A.
1983	Emory University	B.B.A.

Figure 1.A.3: An Example of Individual Political Contribution Information

This figure presents a screenshot of individual political contribution data obtained from the Federal Election Commission website. The contribution database contains the individual name, address, occupation, employer, donation amount, and the donation recipient.

Source information

Name	
City, state and ZIP code	NEW YORK, NY 10017-3216
Occupation	FINANCE
Employer	AQR CAPITAL
Year to date	$0.00

Receipt information

Amount	$10,000.00
Receipt date	December 31, 2023
Report year	2024
Memo	
Reported on	Form 3X on line 12
Election type	PRIMARY

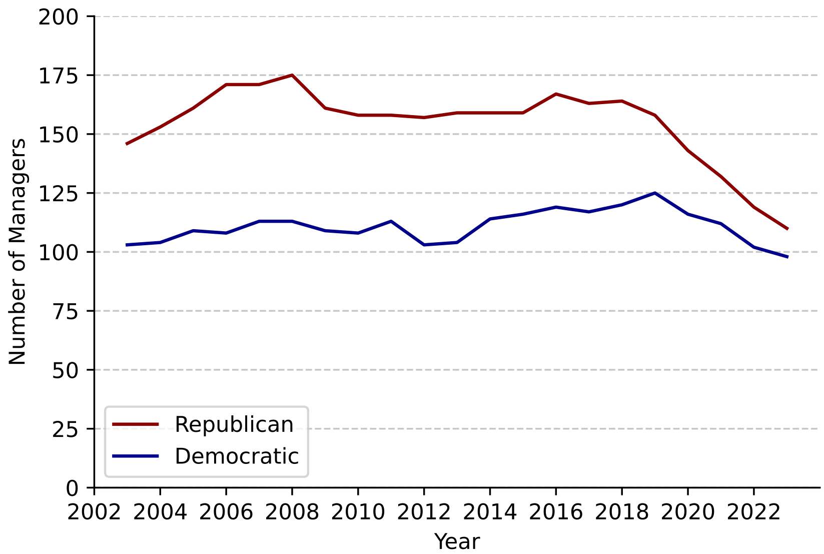
Recipient information

Committee	REPUBLICAN FEDERAL COMMITTEE OF PENNSYLVANIA
Political party	REPUBLICAN PARTY
Type	Party - Qualified
State	Pennsylvania

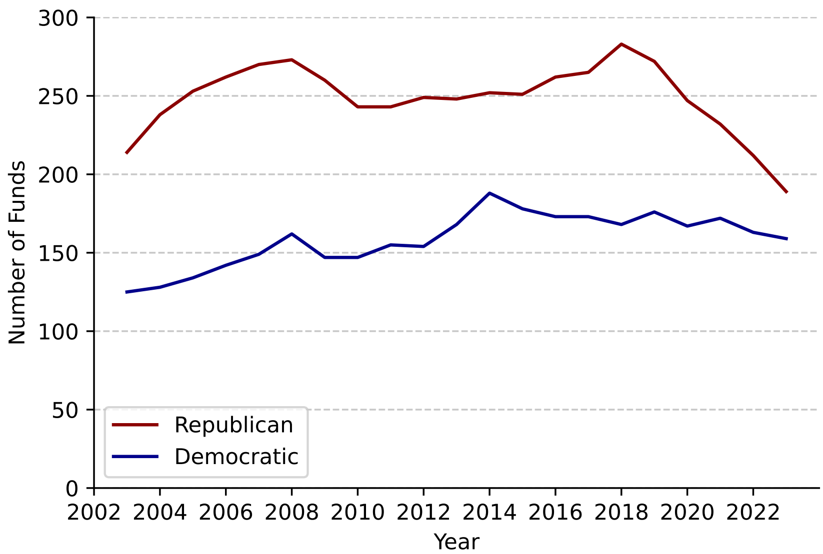
Figure 1.A.4: Number of Managers and Funds by Party over Time

This figure reports the number of unique fund managers per year in each party in Panel A, and the partisan number of funds over time in Panel B. A manager is classified as Republican if they donate more to Republican causes, and as Democratic if they donate more to Democratic causes. A fund is classified as Republican if the average Republican index of its managers, $Rep_i = (R_i - D_i)/(R_i + D_i)$, is positive, and Democratic if the index is negative.

Panel A: Number of fund managers by party over time



Panel B: Number of funds by party over time



1.A.3 Additional figures

Figure 1.A.5: Mutual Fund Holdings by Asset Types

This figure decomposes mutual fund holdings by asset types and partisanship. The red bar indicates the average portfolio weights for Republican funds and the blue bar for Democratic funds. I report the portfolio weights of U.S. Treasury securities, corporate bonds, agency mortgage-backed securities (MBS), other MBS, agency debts, collateralized mortgage Obligations (CMO), asset-backed Securities (ABS), municipal bonds, bank loans, preferred stocks, cash, and other holdings, respectively.

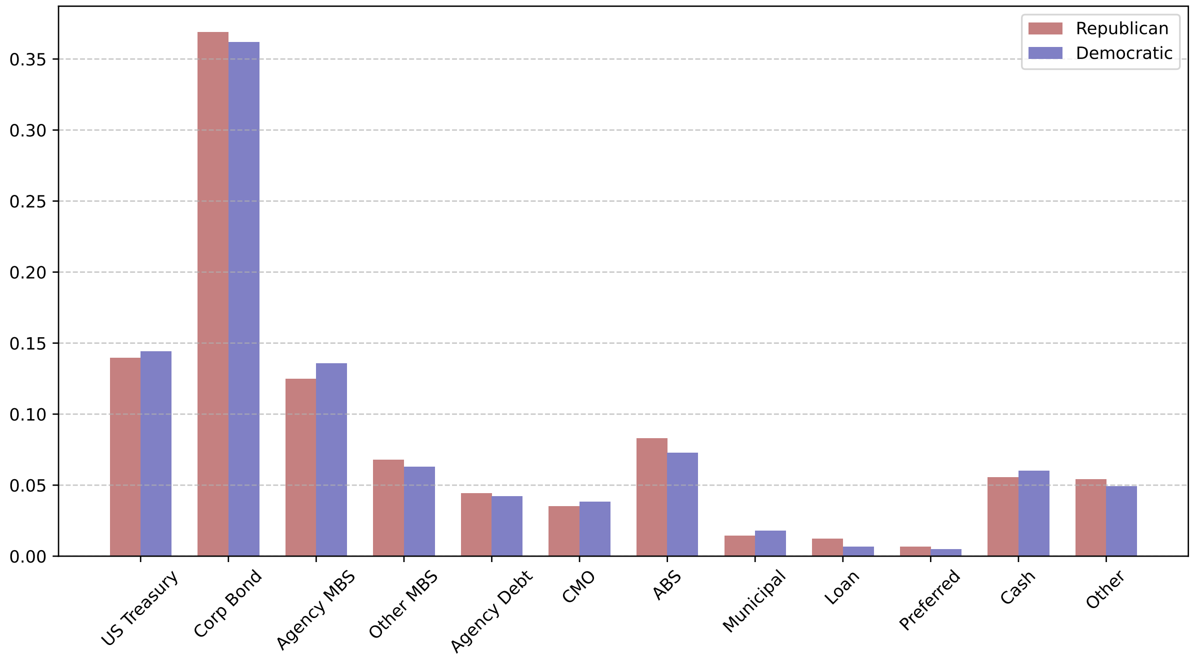
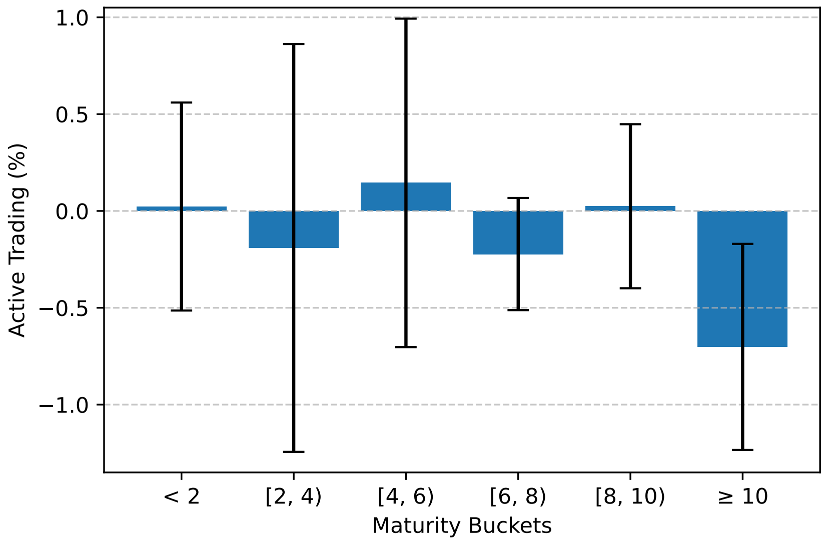


Figure 1.A.6: Partisan View and Fund Trading by Maturity Buckets: Breaking down Corporate Bond Credit Ratings

This figure plots regression coefficients of fund quarterly trading in corporate bonds on ideological misalignment and the deficit increases from CBO releases by maturity buckets and by bond credit ratings. The dependent variable is the fund's active trading in investment-grade bonds in Panel A and in high-yield bonds in Panel B. The independent variable of interest is the interaction term between $Misalign$ and $\Delta Deficit$. $Misalign$ measures the level of political misalignment between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. All regression specifications are identical as in Table 1.2. The error bars indicate the 90% confidence interval.

Panel A: Trading in investment-grade bonds



Panel B: Trading in high-yield bonds

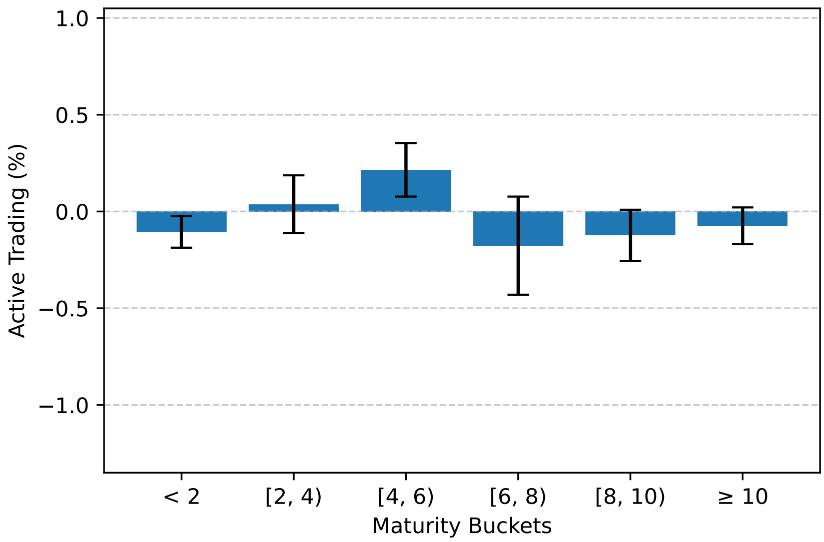


Figure 1.A.7: Effects on Short-Term Bonds

This figure reports the effects on short-term bonds for fund trading and changes in yield spreads up to four quarters forward.

Panel A plots regression coefficient β_1 of Eq. (1.9) for short-term bonds,

$$\Delta Holdings^{I}_{f,q\to q+h} = \beta_0 + \beta_1 \times \mathbf{Misalign_{f,q}} \times \mathbf{\Delta Deficit_{q\to q+1}} + \beta_2 Misalign_{f,q} + \Gamma Controls + \lambda_f + \lambda_q + \epsilon_{f,q}$$

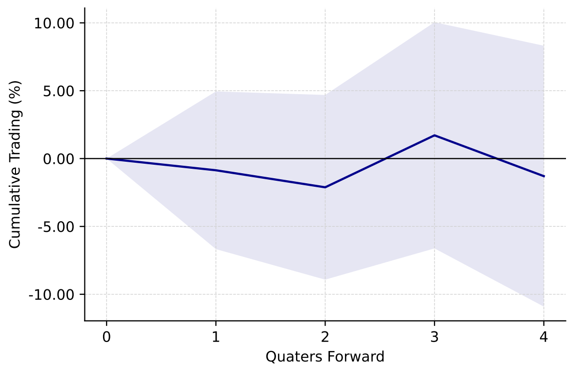
The dependent variable is the fund's active trading in Treasury securities with maturities of less than 10 years on the left, and in short-term corporate bonds with maturities below the sample median on the right. The independent variable of interest is the interaction term between $Misalign$ and $\Delta Deficit$. All regression specifications are identical as in Table 1.2.

Panel B plots regression coefficient β_1 of Eq. (1.13) up to four quarters forward for short-term corporate bonds with maturities below the sample median,

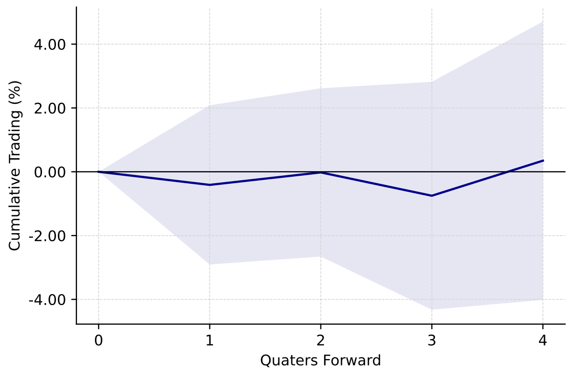
$$\Delta Yield\,Spread^{b}_{q\to q+h} = \beta_0 + \beta_1 \times \%\,\mathbf{Misalign\,Holding^{b}_{q}} \times \mathbf{\Delta Deficit_{q\to q+1}} + \beta_2 \times \%\,Misalign\,Holding^{b}_{q} + \Gamma_1 Controls + \Gamma_2 Controls \times \Delta Deficit_{q\to q+1} + \lambda_b + \lambda_{mat,q} + \lambda_{rat,q} + \epsilon^{b}_{q}$$

The independent variable of interest is the interaction term between $\%\,Misalign\,Holding$ and $\Delta Deficit$. All regression specifications are identical as in Table 1.6. The x-axis shows h, the number of quarters forward since q. I set the coefficient for $h = 0$, the beginning of the current quarter q, to be 0. The light blue area illustrates the 90% confidence interval.

Panel A: Trading in short-term securities

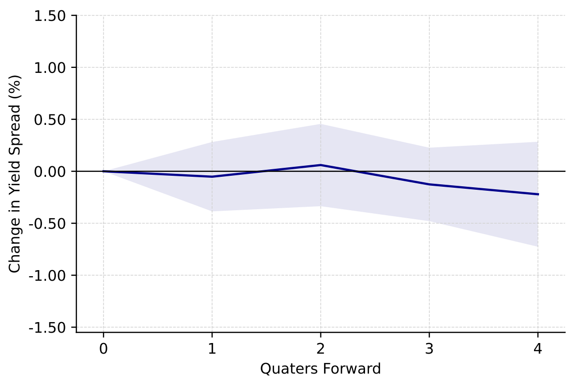


(1) Treasury maturity < 10



(2) Corporate bond maturity < median

Panel B: Changes in yield spreads for short-term corporate bonds



1.A.4 Additional tables

Table 1.A.4: Partisan View and Fund Trading: without Time Fixed Effects

This table repeats the analyses in Table 1.2, but not controls for time fixed effects. The left part includes the fund's active trading in Treasury securities, with Treasuries with maturities of 10 years or more in column (1) and Treasury Inflation-Protected Securities (TIPS) in column (2). The right part shows the effect on corporate bonds with maturities at or above the sample median. Column (3) displays that for all bonds, columns (4) and (5) break down the effect by investment-grade (IG) and high-yield (HY) bonds separately. $Misalign$ measures the level of political mismatch between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. I include the same set of control variables as in Table 1.2, along with macroeconomic variables: GDP growth, CPI, and changes in the federal funds target rate, unemployment rate, and VIX. Fund fixed effects are included. Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

DepVar =	Δ *Holdings (in %)*				
	Treasury		Maturity $\geqslant$ 50th Corp Bond		
	Maturity$\geqslant$10	TIPS	All	IG	HY
	(1)	(2)	(3)	(4)	(5)
Misalign* $\times$ Δ*Deficit	**-2.161*****	**1.501*****	**-1.452****	**-1.007***	**-0.445****
	(0.761)	**(0.531)**	**(0.671)**	**(0.547)**	**(0.219)**
Misalign	0.098**	-0.083*	0.165***	0.113***	0.052**
	(0.049)	(0.042)	(0.055)	(0.034)	(0.020)
Δ*Deficit*	1.066**	-1.162***	-0.133	-0.080	-0.053
	(0.463)	(0.358)	(0.338)	(0.295)	(0.096)
Controls	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y
# of Obs	52,669	52,669	52,669	52,669	52,669
Adj R^2	0.032	0.011	0.147	0.126	0.166

Table 1.A.5: Partisan View and Fund Trading: Robustness

This table conducts the robustness tests for the main regression,

$$\Delta Holdings^{I}_{f,q+1} = \beta_0 + \beta_1 \mathbf{Misalign_{f,q}} \times \mathbf{\Delta Deficit_{q+1}} + \beta_2 Misalign_{f,q} + \Gamma Controls + \lambda_f + \lambda_q + \epsilon_{f,q}$$

$Misalign$ measures the level of political mismatch between the fund and the president's party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. I report only the regression coefficient and t-statistics of β_1 for brevity. The left part of each panel includes the fund's active trading in Treasury securities, with Treasuries with maturities of 10 years or more in column (1) and Treasury Inflation-Protected Securities (TIPS) in column (2). The right part of each panel shows the effect on corporate bonds with maturities at or above the sample median. Column (3) displays that for all bonds, columns (4) and (5) break down the effect by investment-grade (IG) and high-yield (HY) bonds separately. Unless specified, I control for the same sets of control variables as in Table 1.2, defined in Appendix Table 1.A.1. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A reports the results from alternative estimation methods and subsample analyses. In specification (1), I control for both the fund-level and Morningstar category $\times$ time fixed effects. Specification (2) clusters standard errors by Morningstar category $\times$ time. In specification (3), I include both the original control variables and the interaction term of these control variables with $\Delta Deficit$. In specification (4), I exclude election years (2004, 2008, 2012, 2016, 2020). In specification (5), I exclude the periods covering the global financial crisis (2007Q3 – 2009Q2) and the COVID-19 pandemic (2020 – 2021). In specification (6), I drop non-partisan funds with $Misalign = 1/2$. In specifications (7) to (9), I include only funds with a single manager, funds with no more than two managers, and funds with no more than three managers, respectively.

Panel B presents the results with alternative variable definitions. In specification (10), I use the original CBO cost estimates for all bills without adjusting for duplicated or recurrent bill estimates when constructing the quarterly $\Delta Deficit$, while I adjust for duplicated bills but retain the original estimates for recurrent bills (the National Defense Acts) in (11). In specification (12), I exclude deficit increases from spending subject to appropriation. In specification (13), when constructing the deficit-to-GDP measure, I use the latest GDP estimates available after the CBO cost releases rather than the GDP estimates available beforehand. In specification (14), I calculate $\Delta Deficit$ by directly summing the yearly deficits attributed to the bill in trillion U.S. dollars. In specification (15), I assign a misalignment dummy to each manager, set to 0 if the manager donates more to the president's party and 1 otherwise. I then calculate an equal-weighted average of this dummy within each fund. In specification (16), I weigh managers within funds by their contribution amounts. In specification (17), I construct the original misalignment measure using manager donation amounts up to quarter q instead of the manager's lifetime donations. In specification (18), I relax the classification criteria for political action committees (PACs), assigning a PAC to a party if it spends more than two-thirds of its funds on that party's candidates.

Panel A: Alternative estimations

DepVar =	Δ *Holdings (in %)*				
	Treasury		Maturity ⩾ 50th Corporate Bond		
	Maturity ⩾ 10	TIPS	All	IG	HY
	(1)	(2)	(3)	(4)	(5)
Alternative estimation methods					
(1) Control for fund FE and Morningstar category × time FE	-1.974**	1.636***	-1.501**	-1.218*	-0.283**
	(0.825)	(0.554)	(0.715)	(0.633)	(0.135)
(2) Cluster by Morningstar category × time	-2.191***	1.680***	-1.779***	-1.454**	-0.325**
	(0.744)	(0.551)	(0.689)	(0.644)	(0.148)
(3) Interact all control variables with $\Delta Deficit$	-2.039***	1.674***	-1.714**	-1.401**	-0.313*
	(0.757)	(0.534)	(0.792)	(0.661)	(0.182)
Subsample analyses					
(4) Exclude election years	-2.672**	1.290**	-3.048**	-2.296**	-0.752**
	(1.063)	(0.582)	(1.317)	(1.082)	(0.326)
(5) Exclude financial crisis and COVID-19 period	-2.002**	1.653***	-2.694**	-2.234**	-0.460**
	(0.867)	(0.535)	(1.188)	(0.962)	(0.224)
(6) Exclude gray funds	-2.235***	1.652***	-1.662**	-1.426**	-0.236*
	(0.791)	(0.554)	(0.728)	(0.633)	(0.140)
(7) Include single manager fund only	-4.086***	1.837**	-1.740*	-1.098	-0.642**
	(1.098)	(0.766)	(1.022)	(0.955)	(0.276)
(8) Include funds with no more than two managers only	-2.335***	1.445**	-1.575**	-1.112*	-0.464**
	(0.852)	(0.557)	(0.736)	(0.612)	(0.211)
(9) Include funds with no more than three managers only	-2.093***	1.479***	-1.891***	-1.581**	-0.310**
	(0.720)	(0.501)	(0.658)	(0.606)	(0.155)

Panel B: Alternative variable constructions

DepVar =	Δ *Holdings (in %)*				
	Treasury		Maturity $\geqslant$ 50th Corporate Bond		
	Maturity $\geqslant$ 10	TIPS	All	IG	HY
	(1)	(2)	(3)	(4)	(5)
Alternative definition of $\Delta Deficit$					
(10) Use unadjusted $\Delta Deficit$	-1.828**	1.369***	-1.641**	-1.352**	-0.289*
	(0.725)	(0.507)	(0.670)	(0.578)	(0.150)
(11) Use $\Delta Deficit$ with original Defense Acts	-1.387**	1.336**	-1.621**	-1.317**	-0.304*
	(0.655)	(0.530)	(0.738)	(0.625)	(0.181)
(12) Exclude deficit increases from spending subject to appropriation	-2.005**	1.854***	-1.990**	-1.635**	-0.355*
	(0.876)	(0.596)	(0.844)	(0.697)	(0.202)
(13) Use GDP estimates after CBO cost releases for $\Delta Deficit$	-2.154***	1.654***	-1.755**	-1.438**	-0.318*
	(0.747)	(0.532)	(0.737)	(0.617)	(0.178)
(14) Use the sum of yearly deficit amounts ($ trillion) as $\Delta Deficit$	-0.076**	0.056**	-0.066**	-0.054**	-0.012**
	(0.029)	(0.025)	(0.032)	(0.027)	(0.005)
Alternative definition of $Misalign$					
(15) Assign misalignment dummy to each manager	-2.066***	2.123***	-1.620***	-1.324**	-0.296*
	(0.627)	(0.618)	(0.612)	(0.530)	(0.152)
(16) Value weight within funds by contribution amount	-0.470**	0.702***	-0.640**	-0.566**	-0.075
	(0.217)	(0.259)	(0.276)	(0.272)	(0.096)
(17) Use contributions up to today	-3.094***	0.870**	-0.868**	-0.821**	-0.047
	(0.897)	(0.409)	(0.380)	(0.361)	(0.082)
(18) Relax PAC classification requirement	-1.806**	1.493***	-1.492**	-1.268**	-0.224*
	(0.713)	(0.483)	(0.617)	(0.517)	(0.125)

Table 1.A.6: Partisan View and Fund Trading: by the President's Party

This table presents a subsample analysis of fund quarterly trading regressed on political misalignment and deficit increases from CBO releases, segmented by the president's party. The left part of each panel includes the subsample for periods with a Republican president (2003–2008, 2017–2020), while the right part includes the subsample for periods with a Democratic president (2009–2016, 2021–2023). Panel A reports the fund's active trading in Treasuries with maturities of 10 years or more in columns (1) and (3), and in Treasury Inflation-Protected Securities (TIPS) in columns (2) and (4). Panel B reports the effect on corporate bonds with maturities at or above the sample median. Columns (1) and (4) show that for all bonds, columns (2) and (5), (3) and (6) break down the effect by investment-grade (IG) and high-yield (HY) bonds separately. $Misalign$ measures the level of political mismatch between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. I control for the same sets of control variables as in Table 1.2, defined in Appendix Table 1.A.1. Time and fund fixed effects are included. Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading in Treasury securities

DepVar =	Δ *Treasury Holdings (in %)*			
	Republican		Democratic	
	Maturity $\geqslant$ 10 (1)	TIPS (2)	Maturity $\geqslant$ 10 (3)	TIPS (4)
Misalign $\times$ Δ*Deficit*	-1.744*	1.563**	-2.440***	1.938**
	(0.927)	(0.622)	(0.939)	(0.912)
Misalign	0.008	-0.086*	0.197**	-0.099*
	(0.123)	(0.049)	(0.081)	(0.054)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	24,563	24,563	28,081	28,081
Adj R^2	0.024	0.009	0.045	0.017

Panel B: Trading in corporate bonds

DepVar =	Δ *Corporate Bond Holdings (in %)*					
	Maturity $\geqslant$ 50th					
	Republican			Democratic		
	All (1)	IG (2)	HY (3)	All (4)	IG (5)	HY (6)
Misalign $\times$ Δ*Deficit*	-0.611	-0.468	-0.143	-2.703***	-2.243**	-0.460**
	(0.796)	(0.715)	(0.153)	(1.003)	(0.955)	(0.230)
Misalign	-0.084	-0.085	0.001	0.089	0.060	0.029
	(0.104)	(0.093)	(0.024)	(0.115)	(0.104)	(0.031)
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
# of Obs	24,563	24,563	24,563	28,081	28,081	28,081
Adj R^2	0.156	0.143	0.151	0.224	0.193	0.234

Table 1.A.7: Partisan View and Fund Trading: by whether the Bill Eventually Passes

This table regresses fund quarterly trading on political misalignment and the deficit increases from CBO releases, categorized by whether the bill eventually passes. *Misalign* measures the level of political mismatch between the fund and the president's party, which is equal to 1 if the fund managers are entirely from the president's opposing party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. I separate bill-level deficit increases based on whether the bill eventually passes. Since bills from the 118th Congress (2023–2024) may still be in the legislative process, I exclude these bills on the right side of each panel. Panel A reports the fund's active trading in Treasuries with maturities of 10 years or more in columns (1) and (3), and in Treasury Inflation-Protected Securities (TIPS) in columns (2) and (4). Panel B reports the effect on corporate bonds with maturities at or above the sample median. Columns (1) and (4) show that for all bonds, columns (2) and (5), (3) and (6) break down the effect by investment-grade (IG) and high-yield (HY) bonds separately. I control for the same sets of control variables as in Table 1.2, defined in Appendix Table 1.A.1. Time and fund fixed effects are included. Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading in Treasury securities

DepVar =	Δ *Treasury Holdings (in %)*			
	All Bills		Exclude 118th Congress	
	Maturity $\geqslant$ 10 (1)	TIPS (2)	Maturity $\geqslant$ 10 (3)	TIPS (4)
Misalign × Δ*Deficit*	-2.666***	1.805**	-2.559***	1.831***
from Passed Bills	(0.927)	(0.875)	(0.927)	(0.516)
Misalign × Δ*Deficit*	-1.296	1.446	-0.567	2.067*
from Bills not Pass	(1.395)	(1.407)	(1.540)	(1.067)
Misalign	0.083*	-0.090**	0.055*	-0.099**
	(0.047)	(0.042)	(0.029)	(0.044)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	52,669	52,669	49,878	49,878
Adj R^2	0.038	0.020	0.034	0.020

Panel B: Trading in corporate bonds

DepVar =	*Delta Corporate Bond Holdings (in %)*					
	Maturity ⩾ 50th					
	All Bills			Exclude 118th Congress		
	All	IG	HY	All	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
Misalign × Δ*Deficit*	-2.532**	-2.072**	-0.459	-2.578**	-2.105**	-0.473
from Passed Bills	(1.218)	(0.946)	(0.327)	(1.212)	(0.944)	(0.327)
Misalign × Δ*Deficit*	-0.374	-0.298	-0.076	-0.698	-0.546	-0.152
from Bills not Pass	(1.057)	(0.893)	(0.316)	(1.083)	(0.913)	(0.364)
Misalign	0.081	0.051	0.030*	0.091	0.059	0.032*
	(0.058)	(0.050)	(0.017)	(0.060)	(0.052)	(0.018)
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
# of Obs	52,669	52,669	52,669	49,878	49,878	49,878
Adj R^2	0.183	0.159	0.191	0.185	0.162	0.194

Table 1.A.8: Partisan View and Fund Trading: by Manager Personal Characteristics

This table regresses fund quarterly trading on political misalignment and the deficit increases from CBO releases, categorized by manager personal characteristics. Funds are classified into two groups in each panel. The first part of each panel categorizes funds based on the presence of female managers, while the second part categorizes funds based on the presence of managers with a PhD degree. Panel A reports the fund's active trading in Treasuries with maturities of 10 years or more in columns (1) and (3), and in Treasury Inflation-Protected Securities (TIPS) in columns (2) and (4). Panel B reports the effect on corporate bonds with maturities at or above the sample median. Columns (1) and (4) show that for all bonds, columns (2) and (5), (3) and (6) break down the effect by investment-grade (IG) and high-yield (HY) bonds separately. *Misalign* measures the level of political mismatch between the fund and the president's party. $\Delta Deficit$ represents the quarterly aggregate of the deficit-to-GDP ratio contributed by bills. I control for the same sets of control variables as in Table 1.2, defined in Appendix Table 1.A.1. Time and fund fixed effects are included. Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading in Treasury securities

DepVar =	Δ *Treasury Holdings (in %)*			
	By Manager Gender			
	Without Female		With Female	
	Maturity $\geqslant$ 10 (1)	TIPS (2)	Maturity $\geqslant$ 10 (3)	TIPS (4)
Misalign $\times$ Δ*Deficit*	-2.349***	1.853***	-0.490	1.384***
	(0.783)	(0.606)	(1.468)	(0.415)
Misalign	0.077	-0.102**	-0.024	-0.063
	(0.049)	(0.048)	(0.098)	(0.052)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	40,890	40,890	11,762	11,762
Adj R^2	0.038	0.023	0.042	0.004
	By Manager Education			
	Without PhD		With PhD	
	Maturity $\geqslant$ 10 (1)	TIPS (2)	Maturity $\geqslant$ 10 (3)	TIPS (4)
Misalign $\times$ Δ*Deficit*	-2.331***	1.749***	0.575	1.089
	(0.804)	(0.621)	(2.478)	(1.023)
Misalign	0.084	-0.088*	-0.061	-0.112
	(0.051)	(0.045)	(0.144)	(0.072)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	48,106	48,106	4,551	4,551
Adj R^2	0.039	0.018	0.075	0.093

Panel B: Trading in corporate bonds

DepVar =	Δ *Corporate Bond Holdings (in %)*					
	Maturity $\geqslant$ 50th					
	By Manager Gender					
	Without Female			With Female		
	All	IG	HY	All	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
Misalign $\times$ Δ*Deficit*	-1.713**	-1.402**	-0.311*	-2.557	-2.191	-0.366
	(0.740)	(0.715)	(0.170)	(1.594)	(1.445)	(0.388)
Misalign	0.041	0.023	0.019	0.238	0.174	0.064
	(0.054)	(0.046)	(0.018)	(0.167)	(0.147)	(0.040)
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
# of Obs	40,890	40,890	40,890	11,762	11,762	11,762
Adj R^2	0.191	0.167	0.201	0.189	0.166	0.205
	By Manager Education					
	Without PhD			With PhD		
	All	IG	HY	All	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
Misalign $\times$ Δ*Deficit*	-1.796**	-1.449**	-0.347**	-0.639	-0.768	0.129
	(0.743)	(0.645)	(0.167)	(1.663)	(1.439)	(0.739)
Misalign	0.071	0.047	0.025	0.280*	0.174*	0.106
	(0.059)	(0.052)	(0.016)	(0.154)	(0.094)	(0.085)
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
# of Obs	48,106	48,106	48,106	4,551	4,551	4,551
Adj R^2	0.184	0.161	0.190	0.238	0.196	0.289

Table 1.A.9: Treasury Returns during Days with Large Deficit Releases

This table reports the average US Treasury excess returns on days with large deficit releases and the rest of the days. Column (1) shows the average returns for long-term Treasuries with maturities of 10 years or more, Column (2) reports those for Treasuries with maturities under 10 years, and Column (3) for Treasury Inflation-Protected Securities (TIPS). The first three rows show average returns on days with deficits at or above the 95th, 97th, and 99th percentiles of all deficit releases separately, while the last row shows returns on all other days. Days with large deficit announcements within a 3-day window of FOMC meeting days are excluded. T-statistics clustered at the fund level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Maturity $<$ 10 (1)	Maturity $\geqslant$ 10 (2)	TIPS (3)
$\Delta Deficit \geqslant$ 95th (# of Days = 57)	-1.252***	-12.636***	-5.533***
	(-8.04)	(-12.01)	(-4.53)
$\Delta Deficit \geqslant$ 97th (# of Days = 34)	-4.798***	-35.581***	-10.120***
	(-21.27)	(-20.50)	(-4.91)
$\Delta Deficit \geqslant$ 99th (# of Days = 17)	-5.893***	-55.670***	-24.000***
	(-18.51)	(-25.78)	(-7.13)
Other Days	0.329***	1.216***	-0.190**
	(15.97)	(10.85)	(-2.24)

Table 1.A.10: Misaligned Partisan Ownership and Treasury Returns: Placebo Tests

This table replicates the analyses of Table 1.5 as a series of placebo tests under varying scenarios. Panel A presents the results from Fama-MacBeth regressions of US Treasury excess returns on ideologically mismatched fund holdings on days without large deficit releases. The dependent variable is the daily Treasury returns in basis points. The independent variable $\%MisalignHolding$ is the percentage of shares held by misaligned mutual funds as defined in Eq. (1.11). Column (1) shows the regression coefficients for long-term Treasuries with maturities of 10 years or more, Column (2) reports those for Treasuries with maturities under 10 years, and Column (3) for Treasury Inflation-Protected Securities (TIPS). Panel B shows the results from the same sets of regressions during days with large deficit releases for Treasuries with maturities under 10 years. The dependent variable is the cumulative Treasury excess returns, aggregated from the event day, through day one, or day three post-event. The three parts of the table report the effects on days with deficits at or above the 95th, 97th, and 99th percentiles of all deficit releases separately. Days with large deficit announcements that fall within a 3-day window of FOMC meeting days are excluded. All control variables are defined in Table 1.5. T-statistics based on standard errors with Newey-West correction are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Treasury returns on days without large deficit releases

DepVar =	*Excess Returns (in bps)*		
	Other days		
	Maturity $<$ 10	Maturity $\geqslant$ 10	TIPS
	(1)	(2)	(3)
% Misalign Holding	0.027	-0.075	-0.328
	(0.67)	(-0.56)	(-1.10)
Controls	Y	Y	Y
# of Obs	1,044,317	216,346	161,310
Adj R^2	0.751	0.772	0.803

Panel B: Misaligned partisan ownership and short-term Treasury returns

DepVar =	*Cumulative Excess Returns (in bps)*		
	Maturity < 10		
	[0]	[0, 1]	[0, 3]
	(1)	(2)	(3)
$\Delta Deficit \geqslant$ 95th (# of Days = 57)			
% Misalign Holding	0.151	-0.423	0.186
	(0.48)	(-0.52)	(0.23)
Controls	Y	Y	Y
# of Obs	11,414	11,414	11,414
Adj R^2	0.791	0.719	0.763
$\Delta Deficit \geqslant$ 97th (# of Days = 34)			
% Misalign Holding	0.292	-1.247	0.627
	(0.82)	(-1.21)	(0.52)
Controls	Y	Y	Y
# of Obs	6,857	6,857	6,857
Adj R^2	0.769	0.689	0.799
$\Delta Deficit \geqslant$ 99th (# of Days = 17)			
% Misalign Holding	0.739	0.166	1.350
	(1.20)	(0.16)	(0.91)
Controls	Y	Y	Y
# of Obs	4,004	4,004	4,004
Adj R^2	0.766	0.686	0.824

Chapter 2

Why Don't Most Mutual Funds Short Sell

Co-authored with Li An, Shiyang Huang, Dong Lou

Despite the removal of all regulatory barriers by 1997, long-short equity mutual funds have seen disappointing growth over the past two decades. We shed new light on this puzzle by documenting a novel set of facts: long-short mutual funds: 1) hold a substantial amount of cash (in excess of cash-collateral requirements) and have an average market beta of 0.6; 2) generate a 5% annual alpha on risky holdings but do not outperform their long-only peers in total returns; and 3) face much higher flow-performance sensitivities and more volatile flows, and use cash buffers more aggressively. These findings challenge prevailing explanations for this puzzle—such as client restrictions, lack of short-selling skills, or high short-selling costs and risks—and motivate a new framework centered on investor clientele and flow responses.

2.1 Introduction

The last four decades have witnessed tremendous growth of the mutual fund industry. The total net assets (TNA) of US equity funds, for example, reached \$10 trillion in recent years from less than \$250 billion in 1980.[1] There has also emerged a new class of mutual funds in which the short-sale constraint of traditional long-only funds is relaxed – the so-called "active extension" or 1X/X (e.g., 120/20, 130/30, 150/50) funds. These hedge-fund-like products are designed to exploit mispricing both on the long side and short side, thus bringing the benefit of "hedged" investment returns – previously available only to the ultra-wealthy and large institutions – to the public. Some industry experts predicted imminent dominance of these long-short products. As reported by Financial Times, "back in the heady days of 2007, Merrill Lynch confidently predicted that newly fashionable 130/30 funds – a breed of long/short equity funds – would reach \$1tn in assets by 2012. Not to be outdone, Tabb Group, a consultancy, raised the stakes to \$2tn by 2010."[2] Lo and Patel (2008) went as far as calling the 130-30 funds the "new long-only."

To the surprise of many advocates, the 1X/X class of equity funds has had disappointing growth in the last twenty years. Far from dominating the mutual fund industry, the 1X/X sector's total TNA peaked at less than \$150B, accounting for a small fraction of the mutual fund industry to this day.[3] This is puzzling for at least two reasons. First, virtually all regulatory restrictions on mutual fund short selling had been lifted by the turn of the century (most notably, with the 1996 relaxation of leverage requirements on mutual funds and the 1997 repeal of the "short-short" rule in the US tax code).[4] Indeed, although nearly 50% of all equity funds after 2000 explicitly allow for short selling in their SEC filings, less than 10% have actually engaged in short selling (e.g., Agarwal et al., 2009). Second, there are strong theoretical arguments for the popularity of long-short equity funds, as the ability to short sell affords managers a larger toolkit to exploit mispricing. Consistent with this view, prior research documents that long-short equity funds

[1] See, for example, https://www.ici.org/research/stats.

[2] See, https://www.ft.com/content/fdbf6284-b724-11e2-841e-00144feabdc0.

[3] The total TNA of long-short equity funds is comparable to that of equity closed-end funds, which managed around \$100B at their peak.

[4] See Almazan et al. (2004), Agarwal et al. (2009), and Chen et al. (2013a) for a discussion of the history of regulations on mutual fund short selling, which we summarize in Section 2.2.

outperform their long-only peers by 1-2% a year on a risk-adjusted basis.

To shed new light on this puzzling observation and, more generally, on mutual funds' short-selling activity, we conduct the first systematic analysis of long-short equity funds' cash holdings, portfolio compositions and risks, and capital flows. In particular, we collect detailed data on mutual funds' long-short equity positions directly from SEC filings. We then classify all actively managed mutual funds in each quarter into four groups: 1) G00 includes all funds that are self-refrained from short selling (roughly 50% of our sample); 2) G01 includes mutual funds that can short sell but do not have any short positions in the previous eight quarters (slightly over 40% of the sample); 3) G1 includes "casual" long-short funds whose short positions account for less than 20% of the funds' TNA in the past eight quarters (5% of the sample); and 4) G2 includes "aggressive" long-short funds whose short positions account for more than 20% of their TNA in the previous eight quarters (the remaining 3% of our sample).[5] Consistent with short-selling being potentially risky, G2 funds hold well-diversified portfolios: the typical G2 fund has over 200 long positions and 150 short positions.

The most striking pattern emerging from the data is the large heterogeneity in cash holdings. The traditional view of long-short funds is that "a [1X/X] fund's portfolio can be viewed as a long-only portfolio plus a market-neutral portfolio with long and short exposures that are [X%] of the long-only portfolio's market value" (Lo and Patel, 2008), so the fund has a market beta close to one and little cash holdings.[6] Contrary to this conventional view, the average G2 fund invests 109% of its TNA in long equity positions, has short equity positions worth 52% of its total assets, and has 37% in cash and cash equivalents. This is in sharp contrast to the well-known result that long-only mutual funds keep less than 5% of their TNA in cash and cash equivalents (which we also confirm in our sample).

Note that the cash holdings of G2 funds far exceed brokers' cash-collateral requirements, as institutional short sellers with diversified long-short portfolios face a cash-

[5]We use mutual funds' short-selling activity in the previous eight quarters in our classification to avoid any look-ahead bias. We choose a weight cut-off of 20% because most long-short equity funds are self-declared as 120/20, 130/30 and 150/50 funds. Other cutoffs, such as 10%, 15% and 25%, yield very similar results.

[6]For details of 1X/X funds, see, for example, A Strategy Aiming to Pump Returns Gains Clout but May Be 'No Free Lunch', Some Managers Show Knack for 130/30s.

collateral requirement much lower than 71% (=37%/52%).[7] Indeed, a non-trivial fraction – around 15% – of all funds in G2 follow a strict 1X/X strategy with little cash holdings, which confirms that mutual funds can use their long stock holdings as collateral for their short positions. Moreover, in our analysis of within-fund variation, for a 1% increase in short positions of a mutual fund, its cash holdings increase by merely 0.2% and its long positions by 0.8%, indicating a cash-collateral requirement of roughly 20%. Finally, the cash-holding result is not driven by a small subset of long-short funds that pursue a market-neutral strategy (less than 10% of the G2 sample); the average cash-to-short ratio remains economically large at 61% after we exclude from our sample all funds that use cash (or Treasuries) as the benchmark.[8]

We next examine the impact of cash holdings on long-short funds' risk exposures and performance. In our sample, the average market beta of mutual funds in groups G00 and G01 is 1.06. For a typical fund in G2, its risky holdings have a market beta of 1.05, but due to the 40% cash holdings, its overall fund beta is 0.63. Because the vast majority the mutual funds in G2 are benchmarked against long-only equity indices (e.g., S&P 500, Russell 2000), a market beta of 0.63 leads not only to a lower average return but also a larger tracking error.[9]

We next turn to the average performance of the various mutual fund groups. Long-only funds (those in G00 and G01) and occasional long-short funds (those in G1) are unable to beat the market. In contrast, G2 funds produce significant abnormal returns. For instance, the risky holdings of G2 funds earn a Fama-French-Carhart four-factor (or Fung and Hsieh seven-factor) alpha of nearly 5% a year, with a t-statistic of 4.[10]

[7]In many private conversations with prime brokers and asset managers, they confirm that the cash-collateral requirement for diversified long-short institutions is around 20% of the short position value. In other words, G2 funds hold an excess cash position of 26% (37%-52%×20%), over and beyond the cash-collateral requirement.

[8]The cash-holding result is nearly identical for the subset of G2 funds that do not trade derivative contracts at all, so are not subject to further margin requirements.

[9]Out of the 457 unique long-short equity funds in our sample, only seven of them report benchmarks that are the weighted average of an equity index and a Treasury index. We provide details of these seven long-short funds in Appendix Table 2.A.2. The AQR long-short equity fund is the only one that lists the weighted average of two indices as its primary benchmark; for the remaining six, the primary benchmark is an equity index, while the secondary benchmark is the weighted average of two indices.

[10]We zoom in on a subset of aggressive long-short mutual funds that share common managers with one or more long-only mutual funds and observe similar return patterns: risky holdings of aggressive long-short funds outperform those of the comanaged long-only funds by about 5% a year. Although this result does not rule out the selection channel – that managers of long-short funds are inherently more skilled – it is more consistent with the view that the capability to short broadens fund managers'

Interestingly, only 40% of this alpha is produced by G2 funds' short equity positions and the remaining 60% by their long equity positions.[11] The former can be attributed to their information advantage on the short side (see Hwang et al., 2019) and the latter to the hedging benefit of short selling (i.e., fund managers can now leverage their positive information to a larger extent by hedging out industry/factor risk on the short side).

This return pattern also holds for CRSP mutual fund returns. The typical fund in G2 has an annual alpha (with respect to various risk benchmarks) of around 3% with a t-statistic of 3 (the reduction in alpha from 5% above to 3% here is, again, due to cash dilution). A perhaps surprising result is that in terms of raw fund returns (before adjusting for risk factors), aggressive long-short mutual funds underperform traditional long-only products by 50bps a year before management fees and by over 1% a year after fees (albeit statistically insignificant). This is almost entirely due to long-short funds' smaller market exposures, which lower their average returns by more than 3% a year given an annual equity risk premium of 8-9% in our sample.

In our final set of analyses, we link long-short equity funds' cash-hoarding behavior to their capital flow patterns. Our first key finding is that capital flows to long-short mutual funds are much more sensitive to funds' past performance than flows to long-only funds. This result holds true after controlling for fund age, size and return volatility. For example, the regression coefficients of quarterly flows on lagged fund returns (with various risk adjustments) for G2 funds are two to four times larger than those of G00 and G01 funds. This is consistent with the view that G2 is a new class of mutual funds which attracts more attentive, sophisticated investors.

Our second result, related to the first one, is the large heterogeneity in the contemporaneous relation between a fund's quarterly changes in cash holdings and its capital flows. Long-short mutual funds are much more likely to use cash to absorb flows. For example, the regression coefficient of changes in cash and cash equivalents on contemporaneous capital flows is 0.23 for G2 but a mere 0.04 for G00 and G01. This contrast is even starker for outflows: the same regression coefficient for the outflow sample is 0.27 for G2 and 0.03 for G00 and G01. One plausible interpretation is that because a) funds

opportunity set to produce abnormal returns.

[11] The long and short portfolio returns of each fund are weighted by their respective portfolio weights so that the overall portfolio return = the long portfolio return + the short portfolio return.

in G2 face a much stronger flow-performance sensitivity and thus more volatile capital flows (the flow volatility of G2 is more than twice that of G00 and G01), and b) their liquidation trades involve opening/closing both long and short positions (so more costly than long-only funds), G2 funds optimally hoard cash to absorb short-term capital flows and minimize flow-induced liquidation costs (e.g., Coval and Stafford, 2007; Lou, 2012).

To recap, our analyses reveal several novel facts about long-short mutual funds. First, aggressive long-short equity funds hold a substantial amount of cash, nearly 40% of their TNA (much higher than their cash-collateral requirement), and have a market beta substantially below one. Second, these funds earn a large abnormal return of nearly 5% a year from their equity holdings, but do not outperform long-only products in total returns yet have a much higher tracking error. Finally, long-short equity funds face substantially stronger flow-performance sensitivities and more volatile flows, and are much more likely to use cash to absorb capital flows compared to their long-only peers.

Our results, put together, suggest that mutual funds' reluctance to short is not due to their lack of shorting skills; aggressive long-short funds are able to generate a large positive alpha but are unable to grow their assets under management.[12] The lack of growth is also unlikely driven by the downside risks associated with short selling. Long-short mutual funds are well diversified with low gross leverage exposures (less than 200%), so the risks of short-squeeze and of suffering large losses from individual short positions are not a major concern.

Our results instead point to a novel (albeit partial) explanation for the disappointing growth of long-short equity funds. On the one hand, long-short mutual funds can better leverage their information advantage and hedge their industry/factor risks, thereby achieving higher abnormal returns. On the other hand, they face substantially more volatile flows – a result of their attracting more attentive clienteles – and higher flow-induced liquidation costs. Long-short equity funds thus hoard cash to absorb capital flows, which adversely affects their overall performance.

Meanwhile, mutual fund investors rely primarily on benchmark-adjusted – rather than

[12]Note that the superior performance of long-short funds' risky holdings is primarily driven by their long holdings rather than short positions, underscoring the hedging benefit of short selling. This pattern persists even among long-short and long-only funds managed by the same fund managers.

risk-adjusted – fund returns in their allocation decisions (e.g., Ben-David et al., 2022). Long-short mutual funds, which are typically benchmarked against long-only indices, do not outperform their long-only peers in terms of total or benchmark-adjusted returns. As a result, long-short funds are unable to attract capital away from traditional long-only products.

In the final section of the paper, we write down a stylized model to capture the various tradeoffs highlighted above. We further quantitatively estimate our model with reasonable parameter values to demonstrate that our proposed mechanism can have a meaningful impact on mutual funds' portfolio choice. For example, our model suggests that long-only funds optimally choose to fully invest in risky assets while long-short funds, despite their better alpha-generating technology, choose to leave nearly 30% of their net assets in cash.

Related Literature

Our paper contributes to the vast literature on the short-sale constraint and its implications for asset prices. For example, Chen et al. (2002) argue and show that short-sale constraints can prevent the revelation of negative news in prices, resulting in significant return predictability on the downside. Stambaugh et al. (2012) document that for many asset pricing anomalies, the short leg is much more profitable than the corresponding long leg, especially after periods of buoyant investor sentiment, again suggesting that the short-sale constraint is binding for many important investors. These prior studies start with the premise that some investors face binding short-sale constraints and then study the implications of such constraints. Our paper, on the other hand, drills down on the sources of the short-sale constraint faced by one of the most important investor groups in the market – equity mutual funds. The novel empirical facts we document challenge the prevailing explanations for the limited use of short selling by mutual funds—such as regulatory constraints, client-imposed restrictions, the lack of short-selling skills in mutual fund industry, or the high costs and risks typically associated with short selling. Instead, we propose a new framework centered on the differences in investor clientele and flow responses.

Our paper also contributes to the existing literature on mutual fund short selling activity. Almazan et al. (2004), Agarwal et al. (2009), and Chen et al. (2013a) show that a large fraction of mutual funds explicitly allow for short selling in their SEC N-SAR filings but only a small fraction actually engage in short selling. Moreover, drawing on answers to Question 70 in the N-SAR form that asks whether the fund actually uses short selling in a given quarter, prior studies show that short-selling funds outperform long-only funds by 1%–2% a year on a risk-adjusted basis.[13] Our first contribution is to separate occasional short sellers (G1) from aggressive short sellers (G2) by exploiting comprehensive data on their short positions and show that only the latter are able to produce large positive abnormal returns. Second and more importantly, our paper is the first to systematically analyze mutual funds' cash holdings, long-short equity positions, portfolio betas, and capital flows, which allows us to uncover a set of novel findings about long-short equity funds.

More broadly, our paper relates to the literature on the use of nontraditional financial tools/securities by mutual funds. Koski and Pontiff (1999), Deli and Varma (2002) study whether and how mutual funds use derivatives to speculate and hedge, and find that mutual funds that use derivatives do not outperform those that do not. Unlike the detailed short-position data that we collect in this study, information on mutual funds' derivatives holdings is limited and noisy before 2019. The SEC started to require mutual funds to report granular information on derivatives holdings in Form N-PORT only after the Investment Company Reporting Modernization Reforms, first adopted in 2016 and later revised in 2017 and 2019 (see Jiang et al., 2021; Kaniel and Wang, 2025).

Our paper also contributes to the growing literature on mutual fund cash and liquidity management. Chernenko and Sunderam (2016), Girardi et al. (2017), Jiang et al. (2020) and Choi et al. (2020) show that mutual funds use cash and cash equivalents to accommodate capital flows to minimize flow-induced liquidation costs; this tendency is

[13] Chen et al. (2013a) also analyze mutual funds' long-short equity holdings over a short three-year period (2003-2006) reported by the CRSP mutual fund database (which has incomplete coverage of both long-short equity funds and their short positions). More recently, in a contemporaneous paper, Gao and Wang (2023) examine long-short equity funds' portfolio holdings using Morningstar data. First, our data are more comprehensive, which combine Morningstar holdings with our manually collected fund holdings from SEC filings. Second, we separate occasional short sellers (G1) from aggressive short sellers (G2). Third and most importantly, our focus is on long-short equity funds' surprisingly large cash holdings, the implications for fund risks and performance, and the potential drivers of this cash-hoarding behavior.

particularly strong for funds with illiquid holdings and during times of heightened uncertainty.[14] In our setting, long-short equity funds face substantially more volatile capital flows and need to trade on both the long and short legs to accommodate flows. Drawing on insights from prior research on mutual fund liquidity management, we argue that long-short equity funds hoard cash, at least partly, to reduce their flow-induced liquidation costs.

Finally, our paper is related to a large literature on closed-end funds (e.g., Lee et al., 1991; Pontiff, 1996). Although the closed-end structure is more conducive to betting against long-term mispricing (as it shields managers from short-term capital flows that often chase recent fund performance), it is not a popular organizational structure in the mutual fund industry, accounting for less than 3% of the industry's total TNA (Giannetti and Kahraman, 2018).[15] In a similar spirit, although short selling can expand managers' investment opportunity set and improve fund performance, it is not widely used by mutual funds. Given that all the hard restrictions on mutual fund short selling had been lifted more than two decades ago, it is at least worth thinking about the equilibrium forces that prevent mutual funds from engaging in short selling.

2.2 The Institutional Background

In this section, we describe the history of regulations that limit mutual fund short selling. Contrary to the narrative that mutual funds are not allowed to short, there is in fact no regulation that directly prohibits mutual funds from short selling. Instead, regulatory restrictions are imposed on the use of leverage. Section 18 of the Investment Company Act of 1940 prohibits any registered investment company from issuing any class of senior securities that represents indebtedness, including short sale borrowings, unless the investment company has an asset coverage ratio of at least 300% immediately after such issuance. This means that a mutual fund with TNA of $100 from equity investors can

[14] A recent literature (e.g., Franzoni and Giannetti, 2019; Jin et al., 2022; Agarwal et al., 2023b) examines various alternative ways through which mutual funds mitigate liquidation costs. There is also a literature that studies the financial fragility induced by mutual funds' liquidations (e.g., Chen et al., 2010a; Goldstein et al., 2017).

[15] Stein (2005) argues that this is a natural outcome of a competitive equilibrium: fund managers adopt the open-end structure, which is costlier than the closed-end structure, to signal that they are skilled.

short sell (or borrow) up to \$50; therefore, the fund's net equity value plus the market value of securities sold short is three times that market value, making it a typical 150/50 fund.

This requirement of a 300% asset coverage ratio was later relaxed to 100% in the 1979 SEC Release IC-10666; however, to fulfill the full coverage requirement, qualified collateral is restricted to cash and high-grade debt obligations. The Release notes that if an investment company issues a senior security, "the Division of Investment Management has determined that the issue of compliance with section 18 will not be raised with the Commission if the investment company 'covers' the senior security by establishing and maintaining certain 'segregated accounts.' ... The Commission believes that only liquid assets, such as cash, U.S. government securities or other appropriate high-grade debt obligations, should be placed in such segregated accounts."

The restriction on qualified collateral was further eased in an SEC staff no-action letter in 1996: "Staff agreed not to recommend enforcement action under section 18 if a fund covers its obligations, that may otherwise be deemed to be senior securities, by maintaining a segregated account on the books of its custodian, and including in that segregated account cash or liquid securities (regardless of type) having an aggregate value, measured on a daily basis, at least equal to the amount of the covered obligations." From 1996 onward, a fund is deemed compliant if it maintains full coverage of its short positions using liquid securities, including stocks.

Another set of regulations that have important implications for the use of short selling is corporate tax rules. IRS Code §851 (b)(3), also known as the "short-short" rule, requires that mutual funds generate less than 30% of their revenues from the sale of securities held for less than three months (including short sales); otherwise, the fund's entire gain would be subject to the corporate tax rate. This provision, as part of a 1936 tax law, was intended to restrict short-term churning by mutual funds. The Taxpayer Relief Act of 1997 repealed this "short-short" rule and made it much less expensive for mutual funds to short sell. In sum, virtually all regulatory restrictions on short selling had been lifted by 1997.

2.3 Data Descriptions

We construct a novel dataset of actively managed mutual funds' long/short equity positions from several data sources.[16] Investment companies are required by the SEC to disclose their entire portfolios, including short positions, in their annual/semi-annual shareholder reports (N-CSR) and quarterly holdings reports (N-Q).[17] We manually collect mutual funds' quarterly short positions from these reports. We then supplement this dataset with short positions from Morningstar and the CRSP US mutual fund database. As pointed out by Schwarz and Potter (2016), these databases contain voluntarily reported positions not in the SEC filings but also miss many positions available in the SEC filings.

We combine the three sources on mutual fund holdings by matching both fund family and fund names; we then apply the following criteria to improve matching quality: For a fund to be matched between any two databases, the number of stocks reported in the two databases for the same fund in the same quarter should not differ by more than 100% (i.e., 0.5 < the number of stocks reported in database A/the number of stocks reported in database B < 2). Also, the number of shares held in each stock should not differ by more than 25% (i.e., 0.8 < shares of stock reported in database A/shares of stock reported in database B < 1.25). Our sample covers the period June 2004, the year in which mutual funds started to report holdings on a quarter frequency, through December 2016. In total, we have a sample of 1,274 distinct long-short mutual funds with 11,171 fund-quarter observations.

We next obtain information on mutual fund long positions from Thomson Reuters' mutual fund holdings database and supplement it with long positions from CRSP and Morningstar. This completes the information on stock holdings by long-short mutual funds. As a benchmark group, we also include long-only equity funds in our sample. We further obtain mutual funds' cash holdings from Morningstar and CRSP.

For most of our analysis, we focus on the universe of actively managed, US domestic

[16]The typical go-to database of mutual fund positions, the Thomson Reuters institutional holdings database, contains mutual funds' long positions but not short positions (Schwarz and Potter, 2016).

[17]SEC: Shareholder Reports and Quarterly Portfolio Disclosure of Registered Management Investment Companies, https://www.sec.gov/rules/final/33-8393.htm.

equity mutual funds using common screening criteria in the literature. Specifically, we require that 1) the investment objective code (IOC) reported by Thomson Reuters is in the set of aggressive growth, growth, growth and income, unclassified, and missing; 2) the fund's long portfolio invests more than 75% in US equity; and 3) the fund's TNA is above 5 million USD at the end of the previous quarter. After applying all these screening criteria, we end up with a sample of 3,555 distinct domestic equity funds (including both long-only and long-short funds) with 102,764 fund-quarter observations.

In all subsequent return-based tests, where we compare fund returns inferred from quarter-end holdings (with the assumption that mutual funds do not trade intra-quarter) and actual fund returns reported by CRSP, we further exclude mutual funds whose CRSP fund returns and holding-based returns have a correlation below 0.5. This filter weeds out cases in which fund-return information and holdings information diverge, potentially due to data errors, incomplete records, and/or significant uses of derivatives (which we do not observe in our sample period). We lose roughly 10% of our sample with this filter.

In addition to detailed information on mutual funds' portfolio holdings, our analysis also requires information on mutual funds' investment policies. Question 70-R in SEC form N-SAR specifically asks whether the fund's investment policy permits short selling. We manually extract the answers to this question from the N-SAR form and then link this information to our main dataset based on fund names.

Information on mutual fund characteristics and monthly fund returns is obtained from Morningstar and CRSP. For funds with multiple share classes, we sum up the TNA across all share classes to calculate the total fund TNA; for other fund characteristics, we take the TNA-weighted average across all share classes. Monthly fund gross returns are calculated as net returns plus 1/12 of annual fees and expenses.

Finally, information on fund manager characteristics is also from Morningstar and CRSP. For information on comanagement, we obtain fund manager names from CRSP; following Agarwal et al. (2023a), we drop managers that simultaneously manage more than four mutual funds to avoid pseudo-managers (those with a name attached to multiple funds without really managing any of these funds). We obtain information on managers' biographies and education from Morningstar.

2.4 Main Results

Section 2.4.1 presents basic statistics. Sections 2.4.2 and 2.4.3 compare the cash holdings and risk exposures of different types of mutual funds. Section 2.4.4 examines the performance of long-short versus long-only mutual funds and the impact of cash holdings on fund performance. Finally, Section 2.4.5 studies the sensitivity of fund flows to fund performance and the association between fund flows and cash holdings.

2.4.1 Summary statistics: long-short mutual funds

Table 2.1 shows the total number, aggregate TNA, and aggregate short positions of long-short equity funds—as well as those of long-only funds—year by year. The left-hand side of the table reports the number of long-short funds—with all investment objectives—as well as a breakdown of funds in each of the investment categories. The total number of long-short funds increased from 157 in 2004 to 453 in 2016, out of which 30%–40% were US equity funds (the rest included balanced funds, international equity funds, and other unclassified funds). In all our empirical analyses, we focus on US equity funds.

The right-hand side of the table shows the distribution of funds within the US equity fund universe. In our sample, nearly 50% of all US equity funds explicitly permit short selling in their SEC N-SAR filings; however, the fraction of funds that actually engaged in short selling only increased modestly from 2% in 2004 to 8% in 2016. At the end of our sample, the total TNA of long-short US equity funds is approximately 100 billion USD, less than 3% of that of US equity funds. Their aggregate short positions amounted to 15 billion USD, roughly 2% of the aggregate short interest.

To aid our empirical analyses, we group all US equity funds into four categories in each quarter based on information in N-SAR filings and short selling activity in the previous eight quarters: 1) funds that are not permitted to short (G00); 2) funds that are permitted to short but that did not engage in short selling in the previous eight quarters (G01); 3) casual short sellers, whose average short positions in the previous eight quarters accounted for less than 20% of the fund's TNA (G1); and 4) aggressive short sellers, whose short positions in the previous eight quarters accounted for more than 20% of their TNA (G2). (As can be seen from Table 2.1, the number of G2 funds rose from 14 in 2004 to 86 in 2016.) It is worth noting that we use information from the previous eight quarters in our classification to avoid any look-ahead bias. Mutual funds' short selling activity, and therefore their classification, is persistent over time: for example, out of all mutual funds in group G2 in year t, over 80% remain in G2 after two years, 8% are reclassified to group G1, and the remaining 10% are defunct.

Panels A and B of Appendix Table 2.A.1 list Lipper fund style classifications for casual long-short funds (G1) and aggressive long-short funds (G2), respectively. Funds in G1 cover a wide range of investment objectives; in contrast, funds in G2 are much more concentrated in style categories that clearly indicate short selling activity. For example, "long-short equity," "equity market natural," "extended large-cap core," "specialty diversified equity," and "alternative-event driven" are the five most popular style categories for G2 funds; they collectively account for 75% of all funds in G2.

Panels A and B of Table 2.2 report summary statistics of fund and manager characteristics of different fund groups, respectively. There is no discernible difference among groups G00, G01, and G1. In contrast, aggressive long-short funds (G2), relative to long-only funds, are significantly smaller ($360M vs. $1.4B), have higher monthly portfolio turnover (21% vs. 7%), charge higher management fees (1.61% vs. 1.13%), and are younger (7 vs. 14 years). Panel B shows that G2 funds are also more likely to be managed by a team of managers as well as managers with a Ph.D. degree. Moreover, manager turnover is slightly higher for G2 funds than for funds in other groups (a turnover rate of 2.71% per quarter for G2 vs. 2.11% for G1 vs. 2.57% for G0).

In Panel C of Table 2.2, we report the distribution of holdings characteristics of aggressive long-short funds (G2). The portfolio of an average G2 fund contains 205 stocks on the long side and 155 stocks on the short side; in other words, it is well diversified on both legs. We also report the distribution of the equal-weighted and value-weighted average short interest of stocks in the short leg. For both weighting schemes, the mean and median short interest is approximately 6%, in the ballpark of the average short interest of the CRSP stock universe. This suggests that long-short mutual funds do not concentrate their short positions on a small number of stocks with abnormally high shorting demand.

Appendix Table 2.A.3 further reports stock characteristics of fund holdings. Relative to G1 and G0 funds, G2 funds on average hold stocks of larger size and with higher past one-year returns; meanwhile, the three groups of mutual funds hold stocks with similar book-to-market ratios.

2.4.2 Cash holdings

We next turn to portfolio compositions of different mutual fund groups, that is, how mutual funds allocate capital across long equity positions, short equity positions, and cash and cash equivalents. We define long%, short%, and cash% as the ratio of the total value of stocks in the long leg, the absolute value of stocks in the short leg, and the value of cash and cash equivalents to fund TNA, respectively. By construction, long% - short% + cash% approximately equals 100%.

Conventional wisdom suggests that mutual funds have little incentive to hold cash other than for liquidity management purposes (Chernenko and Sunderam, 2016). This view applies to both long-only funds and long-short funds. Our results reveal a striking pattern—aggressive long-short funds keep a large amount of cash, substantially more than funds in other groups. Panels A, B, and C of Table 2.3 report the time-series averages of cross-sectional distributions of long%, cash%, and short% for different fund groups. For example, the portfolio of a typical long-only fund (G00 and G01) consists of 92% long equity positions, 0% short positions, and 2%–3% cash. The average G1 fund (with short% between 0 and 20%) holds 106% of its TNA in long equity positions and 6% in cash. The average G2 fund—having short positions worth 52% of its TNA—invests 109% of its TNA in long equity positions and 37% in cash. Put differently, the average "150/50 fund" does not invest 150% of its TNA in long equity positions; instead, it has 109% in long equity positions, 37% in cash, and 52% in short positions.

Importantly, the large amount of cash positions far exceeds brokers' cash-collateral requirement on short selling. First, institutional short sellers with diversified long-short portfolios face a cash-collateral requirement that is much lower than the observed cash-to-short ratio of 71% (=37%/52%). In many private conversations with prime brokers, they confirm that the cash-collateral requirement for diversified long-short institutions is around 20% of the short position value (our later analysis in Table 2.3 Panel D shows consistent result). To gauge the magnitude of excess cash holdings of long-short mutual funds, we report in the bottom two rows of Table 2.3 Panel B G2 funds' actual cash holdings minus 20% (or 30% to be very conservative) of their short position value. Under these two benchmarks, the average G2 fund holds 26% (21%) of its TNA in cash *in excess of* the cash-collateral requirement.

Second, a non-trivial fraction (between 10% and 20%) of the G2 funds follow a classic 1X/X strategy (i.e., 1X% of TNA in long and X% of TNA in short positions, with little cash holdings in their portfolios). This suggests that it is feasible for mutual funds to use risky holdings as collateral for shorting.

Moreover, exploring within-fund variation of portfolio compositions, we find that when a long-short fund increases its short positions, most of this change is absorbed by an accompanying increase in long positions rather than a rise in cash holdings. Specifically, Panel D of Table 2.3 reports panel regressions of the relations between long%, cash%, and short%. The main independent variable in these regressions is a fund's short% in each quarter; the dependent variable in columns (1)–(3) is long%, and that in columns (4)–(6) is cash% in the same quarter. Given the add-up constraint that long% - short% + cash% is close to 100%, the coefficient from the long% regression and that from the cash% regression should roughly add up to 1.[18]

We first explore cross-sectional variation by including only quarter-fixed effects. As reported in columns (1) and (4), for a 1% increase in short%, the long% increases by 0.29% and cash% by 0.76%, which is consistent with heterogeneity in cash holdings across different groups of mutual funds. We next turn to time-series variation in portfolio composition *within* each fund by including fund-fixed effects in columns (2) and (5), and both time- and fund-fixed effects in columns (3) and (6). Once fund-fixed effects are included, the relation between cash% and short% becomes much weaker: the coefficients in columns (5) and (6) are 0.206 and 0.207, respectively. These estimates suggest that for a 1% increase in short positions of a mutual fund, its cash holdings increase by merely 0.2%, consistent with the view that the cash-collateral requirement is roughly 20% of the

[18]For this empirical exercise, we further impose the restriction 0.5 ¡ long% + cash% - short% ¡ 1.5 to weed out apparent data errors.

short position value. At the same time, the relation between long% and short% becomes much stronger: the coefficients in columns (2) and (3) rise to 0.765 and 0.764, respectively. In sum, the results in Panel D, exploiting both across-fund and within-fund variation, suggest that long-short equity funds keep a large amount of cash on the side (a decision that is largely independent of the fund's actual short selling activity) and then engage in pairs-trading in their daily operations (so that long% and short% move in tandem).

Motivated by the strong contemporaneous correlation between long% and short% (see columns 3 and 4), we further examine whether such a strong correlation arises, at least partially, because of long-short funds engaging in industry-neutral pairs trading in one form or other (see Panel E of Table 2.3). Specifically, we conduct fund-quarter-industry-level regressions where the dependent variable is the value of long positions in each industry divided by the fund's total TNA, and the independent variable is the value of short positions in the same industry as a percentage of the fund's TNA. Columns (1) and (2) include all industries, while columns (3) and (4) exclude industries in which the fund has zero holdings (long or short) in that quarter. We control for fund×industry-fixed effects in columns (1) and (3) and additionally for quarter-fixed effects in columns (2) and (4). For all specifications, the relation between changes in long positions and changes in short positions within the same industry is close to one-for-one, suggestive of industry-neutral pairs-trading activities.

An alternative interpretation of the cash result is that long-short funds may also have derivatives positions requiring cash collateral. To address this concern, we exclude funds that report using derivatives in each quarter (based on their answers to Question 70 in SEC form N-SAR) and repeat our analysis in Table 2.3. As shown in Table 2.5 Panels A1–A3, our results remain virtually unchanged after excluding funds that use derivatives: the remaining funds in G2 have, on average, 109% of their TNA in long equity positions, 53% in short equity positions, and 38% in cash, leading to a cash-to-short ratio of 72%.

Another concern is that the large cash holdings of G2 funds are driven by a small number of market-neutral funds that are typically benchmarked against cash-like instruments (such as Treasury bills). Table 2.3 Panels B1–B3 repeats the exercise for G2 excluding all market-neutral funds (roughly 10% of the G2 sample). The results are qualitatively similar. The remaining funds in G2 have, on average, 113% of their TNA in long equity positions, 44% in short positions, and 27% in cash. The cash-to-short ratio remains economically large at 61%, much higher than the 20% cash-collateral requirement. Taken together, our results suggest that long-short funds' large cash holdings are not primarily driven by hard collateral constraints.[19]

2.4.3 Risk exposures (portfolio beta)

Given this surprising variation in mutual funds' cash holdings, we next examine its impact on funds' risk exposures. A 1X/X fund's equity portfolio can be viewed as a long-only portfolio plus a market-neutral portfolio with long and short exposures that are X% of the long-only portfolio's market value; in other words, the market exposure of the risky holdings of a 1X/X mutual fund should be similar to that of a traditional long-only product. To compare risk exposures of different types of mutual funds, we calculate their market betas based on both quarter-end holdings and actual fund returns. The risky-holdings-based beta is defined as the weighted average beta of all stocks in the portfolio, where stock betas are calculated using a three-year rolling window of monthly returns. The return-based fund beta is calculated using monthly fund returns in the 12 months after the short% classification.

Panel A of Table 2.4 reports the time-series average of cross-sectional distributions of market betas. As shown in the top half of Panel A, the average risky-holdings-based beta of long-short funds (G2) is 1.05, similar to that of long-only funds. Interestingly, the average fund beta of G2, as shown in the lower half of the same Panel, is 0.63. For reference, the fund return beta of G0 is slightly above 1. Since over 90% of mutual funds in G2 are benchmarked against long-only indices (e.g., S&P 500, Russell 2000), a market beta of 0.6 mechanically leads to 1) a large tracking error, and 2) a relatively low expected return given a positive equity risk premium.

In Table 2.5 Panels A4 and B4, we repeat this exercise for subsamples of long-short equity funds that exclude derivatives users and market neutral funds, respectively. The results remain nearly identical: the average G2 fund has a risky-holdings-based beta of

[19]In untabulated results, we show that our finding of excessive cash holdings by G2 funds holds true both during and outside of the global financial crisis (2007-2008).

1.04 for both subsamples, and a fund return beta (diluted by cash) of 0.63 and 0.68, respectively.[20]

Next, we conduct a panel regression to show that the difference in beta between long-only and long-short funds is largely explained by their cash holdings (Panel B of Table 2.4). The dependent variable in columns (1)–(3) is the risky-holdings–based beta, and that in columns (4)–(6) is the fund return beta. As shown in columns (1)–(3), the risky-holdings–based beta has zero correlation with short%, consistent with our earlier result that long-short funds are holding stocks similar to those of long-only funds. As for the fund return beta (which is naturally affected by cash holdings), the coefficient is significantly negative in column (4). This negative correlation between fund return beta and short% (together with the weak relation between risky-holdings-based beta and short%) reflects the difference in cash holdings between aggressive long-short funds and other funds. Once we turn to within-fund variation by including fund-fixed effects, this negative relation is no longer statistically significant, consistent with our earlier result of a weak within-fund relation between cash% and short%.

The substantial cash holdings by G2 funds affect not only their market exposures but also their idiosyncratic risk and return skewness. In Appendix Table 2.A.4, we report idiosyncratic volatility, total volatility, and return skewness calculated from both funds' risky holdings and their total returns. Based on risky holdings alone, G2 funds on average have higher idiosyncratic volatility but similar total volatility and return skewness compared to the other two groups of funds. After incorporating the impact of cash dilution, the overall returns of G2 funds have smaller idiosyncratic volatility, smaller total volatility, and less negative return skewness than G0 and G1 funds.

2.4.4 Fund performance

We next examine the performance of mutual funds in various short% groups, with two measures of fund returns: 1) hypothetical portfolio returns, inferred from mutual funds' quarter-end stock holdings (assuming no intra-quarter trading) and not affected by their

[20] We provide a detailed discussion of the low average fund beta, as well as the dispersion in fund beta, of long-short equity funds in Section 2.A.1 of the Appendix.

cash holdings, and 2) total fund returns as reported by the CRSP mutual fund database. A comparison of these two measures of fund returns helps uncover the impact of cash holdings on fund performance.

Panel A of Table 2.6 reports raw returns (without risk adjustments) of the various mutual fund groups. As shown in column (1), in terms of risky-holdings-based performance, G2 funds have an average monthly return of 1.1% and outperform long-only funds by nearly 40 bps per month (t-statistic = 3.3). Perhaps surprisingly, column (5) shows that G2 funds have a monthly total fund return (as reported by CRSP) of 65 bps, which is not statistically different from that of long-only funds. The difference between risky-holdings-based returns and total fund returns can be attributed to long-short funds' cash holdings; indeed, long-short funds' average fund returns are in line with their risky-holdings returns multiplied by (1 - cash%).

In Panel B of Table 2.6, we report the CAPM alpha of various mutual fund groups. As can be seen from column (1), G2 funds are the only ones whose risky holdings can produce significantly positive abnormal returns. For example, G00, G01, and G1 funds earn a CAPM alpha of 0.2 bps, -2 bps, and -0.7 bps per month, respectively, from their risky holdings. In contrast, G2 funds earn a monthly CAPM alpha of 41 bps (t-statistic = 3.62); the difference between G2's risky-holdings-based CAPM alpha and that of any other fund group is statistically significant at the 1% level.

We further explore the sources of the positive alpha of G2 funds. As proposed in prior research, the ability to short not only allows investors to exploit their information advantage on the downside but also helps hedge their industry/factor risks on the upside, thus allowing investors to leverage their positive information more aggressively (e.g., Huang et al., 2021; Hwang et al., 2019). To examine these two possibilities, we decompose the risky-holdings-based return into a long-stock-position return and a short-stock-position return, both of which are adjusted by their respectively portfolio weights (in other words, the risky-holdings-based return = long-stock-position return + short-stock-position return). As shown in columns (2) and (3) of Panel B, long and short stock holdings contribute roughly 60% and 40% of G2 funds' CAPM alpha; specifically, G2 funds earn 23 bps of CAPM alpha from their long positions and 18 bps from their short positions.[21] In other words, aggressive long-short mutual funds reap the benefits of short-selling on both sides of their portfolios.

In column (5), we report the CAPM alpha based on total fund returns. Long-short equity funds in G2 again are the only group with a positive CAPM alpha of 19 bps per month (t-statistic = 2.5). The difference in CAPM alpha based on total fund returns between G2 and any other fund group is again statistically significant. In column (4) of the same panel, we report risky-holdings-based CAPM alpha adjusted for funds' cash%. The difference in alphas between columns (4) and (5) for G2, which is roughly 7 bps per month, reflects mutual funds' unobserved intra-quarter trading activity as well as the transaction costs incurred in their trading (e.g., Kacperczyk et al., 2008).

We then repeat the same portfolio exercise with different risk models in Panels C–G, corresponding to the Fama-French three-factor model, the Fama-French-Carhart four-factor model, the Fama-French-Carhart four-factor plus Pastor-Stambaugh liquidity-factor model, the Fama-French five-factor model, and the Fung and Hsieh (2001) seven-factor model, respectively.[22] The results are virtually unchanged; after controlling for these risk models, long-short equity funds in G2 outperform long-only funds in G0 by roughly 40 bps per month in terms of risky-holdings-based returns and by about 25 bps per month in CRSP fund returns.

One potential concern with the above return pattern is that long-short equity funds and long-only funds differ along other fund characteristics, such as fund size and age, which are known to be associated with average fund returns (e.g., Chen et al., 2004; Pollet and Wilson, 2008). To address this concern, we conduct two additional tests. First, instead of reporting portfolio returns, we conduct Fama-MacBeth regressions of fund returns on short% group dummies, as well as a set of fund characteristics including the logarithm of fund TNA, fund age, turnover, and expense ratios. The time series of the coefficients on these short% group dummies then indicates the average monthly returns of these fund groups after controlling for various fund characteristics. As shown in Table 2.7, the results are nearly identical to those reported in Table 2.6. G2 funds outperform

[21] The excess returns of G2 funds' short positions are negative, as shown in Panel A; this is because short positions bet against the market and therefore lose out on the market risk premium. Indeed, after controlling for the market factor, the CAPM alpha of G2 funds' short positions is significantly positive.

[22] See Fung and Hsieh (2001) for details of the seven-factor model. We thank Fung and Hsieh for making their data available online: https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

long-only funds by more than 40 bps per month in terms of risky-holdings-based returns and by more than 20 bps in terms of CRSP fund returns. These return differences are statistically significant and robust to a range of risk adjustments.

In the second test, we use a matching procedure to account for nonlinear effects of fund size and age on fund performance. Specifically, for each long-short fund in G2, we select three long-only funds that 1) are launched in the two-year window around the inception date of the G2 fund, and 2) have the closest TNA to the G2 fund. As shown in Appendix Table 2.A.5, G2 funds once again outperform long-only funds with similar fund age and size by more than 40 bps per month in risky-holdings-based returns and by nearly 30 bps per month in CRSP fund returns.

There are two possible interpretations of the observed return differential between long-short equity funds and long-only funds. The first is a selection explanation: managers of long-short funds are inherently more skilled than those managing long-only funds, and it is this difference in skill that drives the performance gap. The second is a causal interpretation: the ability to short sell expands a manager's investment opportunity set, thereby directly contributing to higher abnormal returns. To help distinguish between these two possibilities, we compare the performance of long-short mutual funds with that of long-only funds that are managed concurrently by the same managers.

We find evidence consistent with the causal interpretation. As shown in Appendix Table 2.A.6, G2 funds' risk holdings significantly outperform those of their comanaged long-only counterparts. For example, the difference in Fama-French-Carhart four-factor alpha between long-short funds and their comanaged long-only funds is 47 bps per month (t-statistic = 2.93).[23] Although we cannot entirely rule out the selection channel, these results are more consistent with the view that short selling helps improve fund performance.[24]

In Appendix Table 2.A.8, we report two additional measures of fund performance.

[23] Consistent with Chen et al. (2013a), we also find that the long-only funds comanaged by long-short fund managers produce a marginally significant alpha of about 11 bps per month.

[24] One potential explanation for the results in Table 2.A.6 is that long-short funds charge higher management fees so fund managers are more incentivized to produce alphas in the long-short funds than the comanaged long-only funds. To show this is not the case, we conduct panel regressions of fund returns on expense ratios within the sample of comanaged funds. As shown in Appendix Table 2.A.7, expense ratios are insignificantly associated with future fund returns.

Column (1) reports the average Sharpe ratio of each mutual fund group. As cash holdings do not affect the Sharpe ratio, and G2 is the only group with a significantly positive alpha, long-short equity funds in G2 have a Sharpe ratio that is significantly higher than other groups. For example, the annualized Sharpe ratio of G0 is 0.54, and that of G2 is 0.696; the latter is more than 30% higher. For reference, the annualized stock market Sharpe ratio in our sample is 0.56. Column (2) then reports tracking errors of various mutual fund groups. Given a market beta of 0.6, G2 funds have an annual tracking error of over 10%; for comparison, the average annual tracking error in G0 and G1 is around 6%.

In sum, the results presented in Tables 2.6–2.7 show that aggressive long-short equity funds are able to generate significant abnormal returns in their risk holdings by exploiting both the information and hedging benefits of short selling. However, their large cash holdings (nearly 40% of their TNA) and low market beta (around 0.6) put a drag on their total performance. As a result, long-short funds underperform long-only funds in total fund returns by about 50 bps a year (albeit statistically insignificant). Coupled with the fact that G2 funds have an annual expense ratio that is 50 bps higher than that of G0 funds, the net-of-fee return difference between long-short funds and long-only funds is around 1% per year.

2.4.5 Flow-performance relations

In our final set of analyses, we link long-short equity funds' cash-hoarding behavior to their capital flow patterns and the ways in which mutual funds deal with capital flows. To start, we compare the flow-performance sensitivity across different mutual fund groups. The flow-performance sensitivity is defined as the regression coefficient of quarterly flows on lagged annual fund returns (measured against various asset pricing models) after controlling for fund flows in the previous four quarters.

Table 2.8 reports the regression results. Capital flows to long-short mutual funds are much more sensitive to funds' past performance than those of long-only mutual funds. For example, the regression coefficient of quarterly fund flows on lagged excess fund returns is 5.527 for G2 funds, 3.018 for G1 funds, and 2.154 for long-only funds (those in G00 and G01). This monotonically decreasing pattern remains strong if we instead use risk-adjusted returns as the performance measure.

We conduct additional tests to show that the results in Table 2.8 are not driven by observable fund characteristics. First, in Appendix Table 2.A.9, we follow the matching procedure in Table 2.A.5 and focus on G2 funds and long-only funds with similar fund size and age. We still observe that the flow-performance sensitivity of long-short funds is significantly higher than that of long-only funds after controlling for fund size and age. Second, to address the concern that long-short funds may have different fund return volatilities than long-only funds, we use the cross-sectional fund performance ranking instead of actual fund performance on the right-hand-side of the equation in Appendix Table 2.A.10, and find very similar results as those reported in Table 2.8.

One potential explanation for the large heterogeneity in the flow-performance sensitivity is the difference in the types of investors that long-only and long-short funds attract. This can be seen from mutual fund classifications used by gatekeeper platforms such as Morningstar and Lipper. Long-short equity mutual funds are often classified as extended core funds, long/short equity funds or alternative funds, while long-only funds are often classified as large-cap/small-cap/value/growth core funds. Consequently, one interpretation of our result is that investors of long-short funds are more sophisticated and therefore more attentive to past fund performance (in particular abnormal fund returns) relative to investors in long-only funds.

Our second analysis examines the contemporaneous relation between quarterly changes in a fund's cash holdings and its capital flows. More specifically, we conduct Fama-MacBeth regressions in which the dependent variable is the change in cash holdings from quarter $t-1$ to t scaled by the fund's TNA at the end of quarter $t-1$, and the independent variable of interest is the fund's capital flow in quarter t divided by the fund's TNA in quarter $t-1$. If mutual funds use only cash to absorb their quarterly capital flows, we expect to see a regression coefficient of 1; if, on the other hand, mutual funds deal with capital flows entirely by scaling up or down their risky holdings, we expect a coefficient of 0.

Table 2.9 reports the regression results. Aggressive long-short mutual funds are much more prone to use cash to absorb capital flows. For example, the sensitivity of cash holdings to capital flows is 0.23 for G2 funds, 0.08 for G1 funds, and 0.04 for G0 funds. This same declining pattern is even more pronounced for the outflow sample: the same regression coefficient becomes 0.27 for G2 funds, 0.07 for G1 funds, and 0.03 for G0 funds for fund-quarters with capital outflows.[25] Note that these coefficients likely understate the importance of cash in dealing with capital flows as we focus on quarterly flows; mutual funds rely much more on their cash holdings to absorb daily flows. Consequently, we think of these estimates as a lower bound of the sensitivity of cash to capital flows.

Based on our estimates of the cash-holdings-to-capital-flows sensitivity, we then gauge the economic significance of long-short equity funds' cash holdings in a back-of-the-envelope calculation. The typical G2 fund holds 37% of its TNA in cash and cash equivalents (Panel B of Table 2.3), and has a short position weight of 52%. Assuming a cash-collateral requirement of 20% (30%), long-short equity funds hold 26% (21%) excess cash. Meanwhile, G2 funds' quarterly flows have a standard deviation of 23%, so a one standard deviation move in capital outflows is associated with a 6% ($= 23\% \times 0.27$) reduction in cash holdings. Put differently, G2 funds hold sufficient cash to accommodate a three-to-four-standard-deviation increase in quarterly outflows.

One plausible interpretation of G2 funds' cash-hoarding behavior, based on the results in Tables 2.8 and 2.9, is that because a) funds in G2 face a much stronger flow-performance sensitivity and thus more volatile capital flows, and b) their liquidation trades involve opening/closing both long and short positions (and so are more costly than in the case of long-only funds), G2 funds optimally hoard cash to absorb short-term capital flows and therefore mitigate the associated liquidation costs.

[25] One potential explanation for the large cash holdings by G2 funds is that they cannot easily use long positions as collateral for their short positions due to high turnover. In Appendix Table 2.A.11, we show that this explanation is unlikely to drive our results as portfolio turnover has no impact on the relation between cash holdings and short positions of mutual funds.

2.5 A Coherent Framework for Thinking about the Results

In sum, our analyses reveal several novel facts about long-short mutual funds. First, aggressive long-short equity funds (i.e., those with significant short positions) hold a substantial amount of cash, nearly 40% of their TNA, and have a market beta substantially below one. Second, these funds earn a large abnormal return of 5% a year from their equity positions, but do not outperform long-only products in terms of total returns despite the much larger tracking error. Finally, long-short equity funds face substantially higher flow-performance sensitivities and more volatile flows; they are also much more likely to use cash to absorb temporary capital flows compared to their long-only peers.

Our results, taken together, are inconsistent with existing explanations for mutual funds' rare use of short selling: 1) regulatory constraints (virtually all were lifted by 1997), 2) client restrictions (nearly 50% of equity funds explicitly allow for short selling in their SEC filings), 3) the lack of short-selling skills in the mutual fund industry (G2 funds produce an average alpha of 5% a year through their risky holdings), and 4) large costs and risks associated with short selling (most G2 funds are well-diversified on both their long and short legs).[26]

We instead propose a novel (albeit partial) explanation for the disappointing growth of long-short equity funds. First, although the ability to short sell allows mutual funds to better leverage their information advantage and hedge their portfolio risk to achieve higher abnormal returns, long-short mutual funds also face substantially more volatile flows, in part because they attract more attentive clients. In response, long-short funds hoard cash to cushion capital flows and to mitigate liquidation costs; the resulting cash dilution adversely affects their returns. In balance, long-short funds do not outperform long-only funds in terms of total returns yet have a much larger tracking error.

Second, as shown in Ben-David et al. (2022), investors rely primarily on benchmark-adjusted, rather than risk-adjusted, fund returns in their mutual fund allocation decisions.

[26]We go into more details of these popular explanations for the lack of growth in the long-short fund sector in Section 2.A.2 of the Appendix.

Consequently, long-short funds, which are typically benchmarked against long-only indices (e.g., S&P 500), are unable to attract capital away from traditional long-only products.

2.5.1 A stylized model of funds' decision on cash holdings

In this subsection, we introduce a stylized model of a mutual fund optimally choosing its cash vs. risky-asset holdings. With reasonable parameters of the alpha-generating technology and flow-performance sensitivity, the model can generate varying levels of fund cash holdings and overall fund returns that quantitatively match those of G0 and G2 funds in our sample.

Risky asset positions and fund returns. The fund allocates a fraction w to risky assets and $1 - w$ to cash. Assume that the fund earns an abnormal return α from risky assets, so the fund's overall abnormal return is $w\alpha$. Further assume that $\alpha = \bar{\alpha} + \epsilon$, where $\bar{\alpha}$ is the expected alpha. For simplicity, ϵ follows a binary distribution, taking the value of $-A$ or A with an equal probability. We impose the condition $A > \bar{\alpha}$, so that alpha can be negative in the worse state, which may lead to investor redemptions.

Flow-performance sensitivity. Fund flow depends on both overall alpha and other factors: $f = b(w\alpha + v)$, where f is the fund flow, b is the flow-performance sensitivity (with $b > 0$ for all funds), and v captures residual factors affecting fund flows unrelated to alpha. To simplify the analysis, we assume $v \in \{-B,\ B\}$ with an equal likelihood.

Liquidation costs. When outflows exceed the fund's cash buffer $1 - w$, the fund must liquidate part of its risky portfolio to meet the redemption demand. Such forced liquidation incurs an additional quadratic cost $c > 0$.

Fund optimization problem. Taking both alpha and potential liquidation costs into account, the fund chooses w to solve the following maximization problem:

$$\max_{w} \mathbb{E}\left\{w\alpha - \mathbb{1}_{\{f+1-w<0\}} \cdot c \cdot (f+1-w)^2\right\}, \tag{2.1}$$

where $\mathbb{1}_{\{f+1-w<0\}}$ is an indicator function equal to 1 if $f+1-w<0$. In other words, the fund selects its risky asset weight w to maximize the expected overall alpha net of liquidation costs arising from outflow-induced liquidation. The quadratic liquidation cost term reflects the increasing marginal cost of selling under pressure: larger outflows impose disproportionately higher costs on the fund. This formulation aligns with a broad literature on the asset pricing effects of mutual fund fire sales (Coval and Stafford, 2007; Shleifer and Vishny, 2011; Dyakov and Verbeek, 2013; Huang et al., 2023a). Investor redemptions force mutual funds to liquidate risky assets, often at unfavorable prices. These forced sales can create temporary price pressure, pushing asset prices away from fundamentals for extended periods. Additionally, other market participants may anticipate and front-run such trades, further exacerbating liquidation costs.

We further assume that the outflow exceeds the fund's cash holdings only when both the noise component of alpha and the noise component of flow take negative values (i.e., with a probability of 1/4). Given these distributional assumptions, the fund's objective function can be written as:

$$\max_{w}\left\{w\bar{\alpha} - \frac{c}{4}\left[w\left(-1-bA+b\bar{\alpha}\right)+\left(1-bB\right)\right]^2\right\},$$

Let $F(w) = w\bar{\alpha} - \frac{c}{4}\left[w(-1-bA+b\bar{\alpha})+(1-bB)\right]^2$. Taking the first-order condition (FOC) with respect to $F(w)$, we have:

$$\bar{\alpha} - \frac{c}{2}\left[\left(1+bA-b\bar{\alpha}\right)w-1+bB\right]\left(1+bA-b\bar{\alpha}\right)=0 \tag{2.2}$$

Since $A>\bar{\alpha}$ and $c>0$, the left-hand side of Equation (2.2) is strictly decreasing with w, ensuring a unique solution to the fund's optimization problem. Specifically,

$$w_{FOC} = \frac{2\bar{\alpha}}{c\left(1+bA-b\bar{\alpha}\right)^2} + \frac{1-bB}{1+bA-b\bar{\alpha}}. \tag{2.3}$$

When $w = w_{FOC}$, $F(w)$ takes the maximum value.

Discussion. Taking the derivative of Equation (2.3) with respect to b, we have:

$$\begin{aligned} \frac{dw_{FOC}}{db} &= -\left[\frac{2\bar{\alpha}(A-\bar{\alpha})}{c(1+bA-b\bar{\alpha})^3} + \frac{(1-bB)(A-\bar{\alpha})}{(1+bA-b\bar{\alpha})^2} + \frac{B}{1+bA-b\bar{\alpha}}\right] \\ &= -\frac{A-\bar{\alpha}}{(1+bA-b\bar{\alpha})^2} \cdot \left[\frac{2\bar{\alpha}}{c(1+bA-b\bar{\alpha})} + 1 + \frac{B}{A-\bar{\alpha}}\right]. \end{aligned}$$

Since both $\frac{A-\bar{\alpha}}{(1+bA-b\bar{\alpha})^2} > 0$ and $\frac{2\bar{\alpha}}{c(1+bA-b\bar{\alpha})} + 1 + \frac{B}{A-\bar{\alpha}} > 0$ when $A > \bar{\alpha}$, $\frac{dw_{FOC}}{db}$ should always be negative. Therefore, an increase in b has two opposing effects. On the one hand, it raises the average level of fund flows through the term $b\alpha$, which can reduce expected liquidation costs. On the other hand, it amplifies the sensitivity of flows to performance noise ϵ, increasing expected costs due to larger and more volatile outflows. When A is sufficiently large, the second effect dominates. As a result, the fund optimally holds a larger cash buffer to hedge the heightened liquidation risk.

Proposition 1. *Under the assumptions above, higher flow-to-performance sensitivity leads the fund to allocate a larger proportion of its assets to cash.*

2.5.2 Estimation

This subsection discusses how we choose the parameters of the model, and their implications for the mutual fund's optimal cash holdings.

Expected alpha from risky assets $\bar{\alpha}$. For long-short funds, we use the CAPM alpha of risky assets reported in Table 2.6 Panel B column (1) (*Stock Holding Returns*) for G2 funds. Note that Table 2.6 reports monthly alpha, which is annualized to $\bar{\alpha} = 0.0490 (= 0.409\% \times 12)$. For long-only funds, we replicate the analysis in Table 2.6 using post-1975 data and restrict the sample to funds with at least five years of history to better reflect long-run performance. This yields an annual $\bar{\alpha}$ of 0.0092, which is consistent with the literature that the majority of U.S. equity mutual funds have net-of-fee alphas close to zero (Berk and Green, 2004; Barras et al., 2010).

Noise of alpha A. The standard deviation of α is 0.0317 for G0 funds and 0.0430 for G2 funds, based on the same calculations used for $\bar{\alpha}$. The noise term ϵ takes a value in $\{-A, A\}$ with a 50-50 probability, so A is intended to capture extreme deviations rather than the average dispersion, and we set A to three times the standard deviation of α. This implies $A = 0.0951$ for long-only funds and $A = 0.1291$ for long-short funds.

Flow-performance sensitivity $\boldsymbol{b}$. We use the regression coefficient (of quarterly fund flows on monthly fund alpha) from Table 2.8 Panel B column (2). We annualize both flows and returns, resulting in $b = 1.1487 (= 3.4462/3)$ for long-only funds and $b = 5.1218 (= 15.3653/3)$ for long-short funds.

Noise of flow $\boldsymbol{B}$. Fund flows are modeled by $f = b(w\alpha + v)$ and $v \in \{-B,\ B\}$ with equal probabilities, so the standard deviation of v equals B. This allows us to estimate B from the R^2 of a flow–performance regression. Specifically,

$$R^2 = \frac{\sigma^2_{w\alpha}}{\sigma^2_{w\alpha} + \sigma^2_v},$$

which implies

$$B^2 = \sigma^2_v = \frac{1 - R^2}{R^2}\sigma^2_{w\alpha}. \tag{2.4}$$

Prior studies report a wide range of R^2 values for flow–performance regressions. Chevalier and Ellison (1997) find R^2 values between 0.22 and 0.38; Coval and Stafford (2007) report values from 0.359 to 0.535; and Ben-David et al. (2022) document a range of 0.156 to 0.538. To avoid overestimating the noise component in fund flows, we adopt the upper bound of these estimates and set the R^2 to 0.5. Accordingly, under the specification in Equation (2.4), the noise factor is assumed to contribute equally to fund flows as fund performance, and B is therefore set to the same value as A.

Liquidation cost $\boldsymbol{c}$. Edelen et al. (2013) and Pástor et al. (2017) report a total annual trading cost of 1.44% for U.S. equity mutual funds, comprising commissions, bid-ask spreads, and price impact. Edelen et al. (2013) also estimate a per-unit trading cost ranging from 0.42% to 1.64%. Similarly, Busse et al. (2021) find per-unit execution shortfall of 0.480%, based on total costs standardized by an average annual turnover of

98%. Based on these prior results, we set the per-unit trading cost at 0.480% as a prudent estimate for long-only funds. For the typical 130/30 funds, which need to liquidate both long and short positions, the per dollar outflow of trading cost mechanically rises to $0.480\% \times 1.30 = 0.623\%$.

In our model in Section 2.5.1, c is defined as the coefficient on the quadratic cost of outflow, while the above estimates represent linear trading costs. To translate the linear cost into a quadratic specification, we divide the per-unit trading cost by the average outflow in our sample (6.075%). This yields $c = 0.0789$ for long-only funds and $c = 0.1026$ for long-short funds.

It is worth noting that using the average trading cost from the literature is a conservative estimate for liquidation cost in our model. In our setup, c applies specifically when funds are forced to sell risky assets to meet redemption beyond the cash buffer—a situation often associated with mutual fund fire sales. Such cases are often associated with severe price pressures. For example, Coval and Stafford (2007) show that stocks sold during fire sales by funds in the lowest performance decile suffer an average cumulative abnormal return of -15% during the event quarter, implying that actual liquidation costs in distressed scenarios may far exceed average trading costs.

Optimal cash holdings. Table 2.10 summarizes the parameter values and the estimated optimal risky asset weight w for two types of funds. For long-only funds, the computed w_{FOC} exceeds 1, and since $\frac{dF(w)}{dw} > 0$, these funds choose $w_{FOC} = 1$. In other words, long-only funds minimize cash holdings and allocate fully to risky assets to maximize overall fund alpha. In contrast, for long-short funds, the estimated $w_{FOC} = 0.7211$, consistent with the evidence in Table 2.3 that G2 funds hold nearly 40% of their net assets in cash. This elevated cash position reflects a strategy to offset increasing liquidation costs arising from potential redemption driven by their relatively higher flow-to-performance sensitivities.

2.5.3 Fund decisions on short selling and the equilibrium composition of fund types

Building on the stylized model outlined above, we now examine its implications for mutual funds' decisions on whether to engage in short selling. In equilibrium, mutual funds should be indifferent between adopting or not adopting short selling, leading to the coexistence of both long-only and long-short funds.

We start with the expected payoff of a fund when it takes the optimal weight of risky assets w_{FOC} in Equation (2.3):

$$\begin{aligned} F(w) &= w\bar{\alpha} - \frac{1}{2}c \cdot \left[w\left(-1 - bA + b\bar{\alpha}\right) + (1 - bB)\right]^2 \\ &= -\frac{1}{2}c\left(1 + bA - b\bar{\alpha}\right)^2 w^2 + \left[\bar{\alpha} - c\left(1 + bA - b\bar{\alpha}\right)(1 - bB)\right]w - \frac{1}{2}c(1 - bB)^2 \\ &= \frac{\bar{\alpha}^2}{2c(1 + bA - b\bar{\alpha})^2} + \frac{\bar{\alpha}(1 - bB)}{1 + bA - b\bar{\alpha}}. \end{aligned}$$

Denote $F(\alpha) = \frac{\alpha^2}{2c(1+bA-b\alpha)^2} + \frac{\alpha(1-bB)}{1+bA-b\alpha}$, taking the derivative with respect to α:

$$\begin{aligned} \frac{dF(\alpha)}{d\alpha} &= \frac{\alpha(1 + bA - b\alpha)^2 + b\alpha^2(1 + bA - b\alpha)}{c(1 + bA - b\alpha)^4} + \frac{(1 - bB)(1 + bA)}{(1 + bA - b\alpha)^2} \\ &= \frac{\left[\alpha + c(1 - bB)(1 + bA)\right](1 + bA - b\alpha) + b\alpha^2}{c(1 + bA - b\alpha)^3}. \end{aligned} \tag{2.5}$$

As shown in Table 2.10, the inequality $\alpha + c(1 - bB)(1 + bA) > 0$ holds for both long-only funds and long-short funds. Given that $A - \alpha > 0$, it follows that $\frac{dF(\alpha)}{d\alpha} > 0$, indicating that $F(\alpha)$ is increasing in α.

We normalize the total mass of mutual funds to 1. A fraction $\lambda \in [0, 1]$ of these funds choose to engage in short selling. Compared to long-only funds, short-selling funds earn a higher alpha but face greater flow-performance sensitivity. Let L and S denote long-only funds and long-short funds, respectively, such that $\alpha_S > \alpha_L$ and $b_S > b_L$.

In the economy, mutual funds face decreasing returns to scale (Chen et al., 2004), implying that $\alpha_S(\lambda)$ declines as λ increases. Since Equation (2.5) shows that $F(\alpha)$ is increasing in α, it follows that $F(\alpha_S(\lambda))$ is decreasing in λ. In equilibrium, the expected payoff of long-short funds must equal that of long-only funds. Therefore, a unique equilibrium share λ^* exists such that:

If $\lambda = 1$:

$$\frac{\alpha_S^2}{2c(1+b_S A - b_S\alpha_S)^2} + \frac{\alpha_S(1-b_S B)}{1+b_S A - b\alpha_S} > \frac{\alpha_L^2}{2c(1+b_L A - b_L\alpha_L)^2} + \frac{\alpha_L(1-b_L B)}{1+b_L A - b\alpha_L},$$

then the equilibrium is $\lambda^* = 1$;

If $\lambda = 0$:

$$\frac{\alpha_S^2}{2c(1+b_S A - b_S\alpha_S)^2} + \frac{\alpha_S(1-b_S B)}{1+b_S A - b\alpha_S} < \frac{\alpha_L^2}{2c(1+b_L A - b_L\alpha_L)^2} + \frac{\alpha_L(1-b_L B)}{1+b_L A - b\alpha_L},$$

then the equilibrium is $\lambda^* = 0$;

Otherwise, there is one unique interior solution λ^* satisfying:

$$\frac{\alpha_S^2}{2c(1+b_S A - b_S\alpha_S)^2} + \frac{\alpha_S(1-b_S B)}{1+b_S A - b\alpha_S} = \frac{\alpha_L^2}{2c(1+b_L A - b_L\alpha_L)^2} + \frac{\alpha_L(1-b_L B)}{1+b_L A - b\alpha_L}.$$

We now turn to examine how the flow-performance sensitivity of long-short funds, b_S, affects the equilibrium share λ^*. Let

$$G(\lambda, b_S) = \frac{\alpha_S^2}{2c(1+b_S A - b_S\alpha_S)^2} + \frac{\alpha_S(1-b_S B)}{1+b_S A - b\alpha_S}.$$

Taking the derivative with respect to b_S, we obtain:

$$\frac{\partial G}{\partial b_S} = -\frac{\alpha_S^2(A-\alpha_S)}{c(1+b_S A - b\alpha_S)^3} - \frac{\alpha_S(B+A-\alpha_S)}{(1+b_S A - b\alpha_S)^2}. \tag{2.6}$$

Since $A - \alpha_S > 0$, we have that $\frac{\partial G}{\partial b_S} < 0$.

We then have the following result:

Proposition 2. *In the interior equilibrium, a higher flow-to-performance sensitivity reduces the share of funds engaging in short selling. That is,* $\frac{d\lambda^*}{db_S} < 0$.

Proof: In the interior equilibrium, the expected payoff of long-short and long-only funds must be equal. That is,

$$G(\lambda, b_S) = \frac{\alpha_L^2}{2c(1 + b_L A - b_L \alpha_L)^2} + \frac{\alpha_L(1 - b_L B)}{1 + b_L A - b\alpha_L}. \tag{2.7}$$

From Equation (2.5), we have $\frac{\partial G}{\partial \lambda} < 0$, and from Equation (2.6), $\frac{\partial G}{\partial b_S} < 0$. Therefore, as b_S increases, λ must decrease in order to satisfy the equilibrium condition in Equation (2.7).

Discussion. To quantitatively estimate λ, we must impose strong assumptions on the functional form of $\alpha(\lambda)$, which is not directly observable. What we do observe is the equilibrium outcome—specifically, the value of α_L and α_S when a fraction λ^* of funds optimally choose to engage in short selling. In our earlier estimation, we use the observed equilibrium value of α_S to estimate the optimal cash holdings of long-short funds and find that the model's predictions are consistent with the observed cash levels.

In the data, although only a small fraction of mutual funds engage in short selling, long-short funds earn an average total return similar to that of long-only funds. To the extent that investor flows are driven by benchmark-adjusted—rather than beta-adjusted—returns (e.g., Ben-David et al., 2022), these empirical patterns support our proposed framework: most mutual funds do not engage in short selling in equilibrium, and those at the margin are indifferent between adopting and not adopting short selling.

2.6 Conclusion

Although all regulatory restrictions on mutual fund short-selling were lifted more than two decades ago, and despite all the benefits of short selling to both mutual fund investors and market efficiency, the class of long-short equity funds has had disappointing growth in the last 20 years. By 2016, while nearly 50% of all equity mutual funds explicitly allowed for short selling in their prospectuses and quarterly SEC filings, only 3% had meaningful short positions.

To shed light on this puzzling observation, we collect detailed data on mutual funds' long/short positions, cash holdings, and capital flows from public SEC filings. Our analyses reveal a number of novel facts about long-short mutual funds. First, long-short equity funds hold a substantial amount of cash (nearly 40% of their TNA) in their portfolios and have a market beta substantially below one. Second, aggressive long-short equity funds earn significant abnormal returns in their risky holdings. Third, because of the large cash holdings and small market beta, long-short equity funds do not outperform long-only funds in terms of total returns yet have a much higher tracking error. Finally, long-short equity funds face much stronger flow-performance sensitivities and are much more likely to use cash to absorb temporary capital flows.

We propose a novel way of thinking about these results: long-short equity funds hold a substantial amount of cash to absorb fluctuations in capital flows; this portfolio choice lowers their total returns, increases their tracking errors, and makes them less attractive to the broader public. We leave it to future research to further our understanding of why the flow-performance relation is so much more sensitive for long-short equity funds and why long-short funds (and/or their clients) are content with a market beta substantially below one. Answers to both questions require granular information on the investor clienteles in long-short equity funds.

Tables

Table 2.1: Summary Statistics

This table reports the total number, total net assets under management (TNA), total short positions of long-short funds, as well as those of the universe of US equity funds each year during our sample period from June 2004 to December 2016. The number of G2 funds each year is reported in parentheses after the number of US long-short equity funds.

Year	Number of Funds							Total Assets ($ Million)		
	Long-Short Funds					US Equity Funds	US Equity	US Equity Long-Short Funds		US Equity Funds
	Total	US Equity (# G2)	Balanced	Intl Equity	Others	Permitted to Short	Funds	TNA	Total Short Positions	TNA
2004	157	57 (14)	29	10	61	967	2,373	12,814	1,374	1,949,462
2005	161	65 (17)	36	8	52	1,049	2,362	11,914	2,571	2,221,290
2006	222	94 (19)	39	9	80	989	2,274	27,871	4,565	2,503,033
2007	282	113 (26)	63	15	91	1,114	2,562	31,707	7,376	2,636,604
2008	283	115 (36)	78	13	77	1,253	2,793	30,322	5,799	2,289,644
2009	265	100 (29)	79	17	69	1,161	2,638	27,393	7,479	1,950,401
2010	301	133 (47)	95	15	58	1,155	2,547	42,986	8,090	2,238,542
2011	318	136 (57)	132	17	33	1,056	2,289	53,880	8,712	2,623,638
2012	335	132 (57)	151	21	31	1,020	2,195	49,601	7,110	2,866,396
2013	347	135 (63)	149	29	34	974	2,078	67,831	9,446	3,463,929
2014	377	131 (72)	136	31	79	916	1,996	139,001	12,576	4,102,284
2015	450	154 (82)	161	24	111	879	1,947	118,477	12,666	4,127,552
2016	453	153 (86)	168	20	112	859	1,892	101,672	15,833	4,187,769

Table 2.2: Fund, Manager, and Holdings Characteristics

This table reports the panel distribution of fund, manager, and holdings characteristics of different types of US equity mutual funds. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-restrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. Panel A reports the characteristics of funds in each group, including *total net assets (TNA)*, *monthly turnover*, *annual expense ratio*, *fund age*, and *fund flow volatility*. Fund flow volatility is measured as the standard deviation of each fund's quarterly flows over the sample period. Panel B reports manager characteristics for each fund group. *No. of years with the current fund* measures how long the current fund managers have been managing the fund. *Team management* is a dummy variable that is equal to 1 if a fund is managed by more than one manager in the current quarter. *Fraction of Managers with a Ph.D. degree* is the fraction of managers who have a Ph.D. degree within each fund. Panel C reports the holdings characteristics of aggressive long-short funds in group G2. *Number of stocks* measures the number of stocks in long and short portfolios in each G2 fund. We also report the distribution of the average short interest for each G2 fund: equal-weighted short interest is the simple average of short interest within each fund, and the value-weighted short interest is weighted by the value of a stock's short position as a fraction of the fund's total short positions. The table reports the mean, the median, and the 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles.

Panel A: Fund characteristics

	Mean	5th	25th	50th	75th	95th
TNA ($ million)						
G00(=0)	1415.30	13.10	64.60	232.30	884.60	5317.40
G01(=0)	1483.74	13.60	75.40	292.50	1016.30	5717.70
G1(0-20%)	1713.99	10.90	51.00	209.10	1257.40	7674.70
G2(⩾20%)	362.51	9.70	38.10	97.20	324.60	1636.00
Monthly turnover						
G00(=0)	0.06	0.01	0.02	0.05	0.08	0.17
G01(=0)	0.08	0.01	0.03	0.05	0.09	0.20
G1(0-20%)	0.09	0.01	0.03	0.06	0.12	0.26
G2(⩾20%)	0.21	0.05	0.09	0.15	0.26	0.59
Annual expense ratio						
G00(=0)	1.12%	0.26%	0.85%	1.12%	1.38%	1.91%
G01(=0)	1.13%	0.39%	0.86%	1.10%	1.40%	1.87%
G1(0-20%)	1.25%	0.20%	0.81%	1.29%	1.62%	2.34%
G2(⩾20%)	1.61%	1.04%	1.30%	1.52%	1.85%	2.50%
Fund age						
G00(=0)	15.25	2.42	7.25	12.17	18.67	41.5
G01(=0)	13.41	2.42	6.58	10.75	16.92	30.92
G1(0-20%)	12.68	1.00	4.50	10.75	16.67	35.92
G2(⩾20%)	6.85	0.67	2.58	5.50	9.58	17.33

Panel A: Fund characteristics

Fund flow volatility						
G00(=0)	10.60%	1.03%	3.46%	7.32%	13.95%	30.13%
G01(=0)	10.94%	1.12%	3.49%	7.06%	14.02%	34.95%
G1(0-20%)	11.50%	0.65%	3.08%	7.44%	14.83%	37.32%
G2(⩾20%)	22.87%	1.90%	8.54%	20.88%	32.11%	52.22%

Panel B: Fund manager characteristics

	Mean	5th	25th	50th	75th	95th
No. of years with the current fund						
G00(=0)	7.20	1.33	3.33	5.83	9.58	17.83
G01(=0)	6.39	1.08	2.83	5.33	8.83	14.92
G1(0-20%)	5.10	1.08	2.33	4.08	7.00	12.33
G2(⩾20%)	4.84	0.83	2.33	4.08	6.83	10.33
Team management						
G00(=0)	0.58	0.00	0.00	1.00	1.00	1.00
G01(=0)	0.58	0.00	0.00	1.00	1.00	1.00
G1(0-20%)	0.55	0.00	0.00	1.00	1.00	1.00
G2(⩾20%)	0.66	0.00	0.00	1.00	1.00	1.00
Fraction of managers with a Ph.D. degree						
G00(=0)	0.03	0.00	0.00	0.00	0.00	0.33
G01(=0)	0.03	0.00	0.00	0.00	0.00	0.20
G1(0-20%)	0.05	0.00	0.00	0.00	0.00	0.33
G2(⩾20%)	0.07	0.00	0.00	0.00	0.00	0.67

Panel C: Long-short fund (G2) holdings characteristics

	Mean	5th	25th	50th	75th	95th
Number of stocks						
Long positions	204.71	32	80	135	215	553
Short positions	154.94	18	52	108	172	435
Short interest of stocks						
Equal weighted	6.69%	3.50%	4.81%	6.17%	7.92%	11.36%
Value weighted	6.69%	3.16%	4.68%	6.11%	8.06%	12.29%

Table 2.3: Portfolio Compositions: Long, Short, and Cash Holdings

This table reports the portfolio weights of long positions, cash holdings, and short positions of different types of US equity mutual funds. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-restrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. For each fund in each quarter, we define the long%, short%, and cash% as the ratio of total value of stocks in long positions, the absolute value of stocks in short positions, and the value of cash and cash equivalents to fund TNA, respectively. Panels A, B, and C report the time-series average of cross-sectional summary statistics of long%, cash%, and short% for different fund groups, respectively. Panel D reports panel regression results with fund-quarter-level observations that examine the contemporaneous association between long%, cash%, and short%. The main independent variable of interest is a fund's short% in each quarter; the main dependent variable in columns (1)-(3) is long%, and that in columns (4)-(6) is cash% in the same quarter. We control for time-fixed effects in columns (1) and (4), fund-fixed effects in columns (2) and (5), and both time and fund-fixed effects in columns (3) and (6). Long% is winsorized above at the value of 200%, short% is winsorized above at the value of 100%, and cash% is winsorized at the values of -90% and 90%. Panel E reports the results from panel regressions where the observations are at the fund-quarter-industry level. The dependent variable is the market value of long positions in each industry divided by the fund's total TNA (denoted as *long%* in this panel), and the independent variable of interest is the market value of short positions in the same industry divided by the fund's TNA (denoted as *short%* in this panel). Industries are defined using two-digit Standard Industrial Classification (SIC) codes. Variables are winsorized at the 1^{st} and 99^{th} percentiles within each quarter. Columns (1)-(2) include all industries, while columns (3)-(4) exclude industries in which the fund has no holdings either in the long leg or in the short leg in that quarter. We control for fund$\times$industry-fixed effects in columns (1) and (3), and both additionally time-fixed effects in columns (2) and (4). Standard errors clustered at both the time and fund levels are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cross-sectional distribution of long%

	Mean	5th	25th	50th	75th	95th
G00(=0)	92.51%	77.62%	88.83%	93.01%	96.00%	101.33%
G01(=0)	91.70%	75.50%	87.50%	92.26%	95.41%	100.89%
G1(0-20%)	106.22%	55.65%	87.03%	95.41%	110.03%	158.88%
G2(⩾20%)	108.96%	62.12%	85.80%	99.87%	124.22%	184.26%

Panel B: Cross-sectional distribution of cash%

	Mean	5th	25th	50th	75th	95th
G00(=0)	2.72%	-0.01%	0.29%	1.61%	3.62%	9.08%
G01(=0)	2.51%	-0.04%	0.26%	1.44%	3.45%	8.84%
G1(0-20%)	6.48%	-0.33%	0.29%	2.08%	6.76%	32.28%
G2(⩾20%)	36.91%	-0.43%	3.19%	25.66%	75.20%	90.00%
G2 - short%×0.2	26.45%	-15.37%	-3.66%	17.67%	61.98%	75.78%
G2 - short%×0.3	21.22%	-23.20%	-7.23%	14.30%	55.32%	68.99%

Panel C: Cross-sectional distribution of short%

	Mean	5th	25th	50th	75th	95th
G00(=0)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
G01(=0)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
G1(0-20%)	4.42%	0.00%	0.00%	0.16%	5.08%	21.39%
G2(⩾20%)	52.29%	13.64%	28.43%	46.75%	78.79%	95.39%

Panel D: Long positions, cash holdings, and short positions

DepVar =	*Long%*			*Cash%*		
	(1)	(2)	(3)	(4)	(5)	(6)
Short%	0.291***	0.765***	0.764***	0.755***	0.206***	0.207***
	(0.050)	(0.079)	(0.080)	(0.048)	(0.055)	(0.055)
Time FE	Y		Y	Y		Y
Fund FE		Y	Y		Y	Y
# of Obs	99,051	99,051	99,051	99,051	99,051	99,051
Adj. R^2	0.133	0.447	0.533	0.436	0.731	0.733

Panel E: Long positions and short positions by industry

	All Industries		Excluding Industries where Funds Have no Holdings	
DepVar=	*Long%*	*Long%*	*Long%*	*Long%*
	(1)	(2)	(3)	(4)
Short%	1.210***	1.201***	0.869***	0.853***
	(0.269)	(0.265)	(0.335)	(0.326)
Time FE		Y		Y
Fund×Industry FE	Y	Y	Y	Y
# of Obs	776,282	776,282	357,880	357,880
Adj. R^2	0.565	0.568	0.584	0.591

Table 2.4: Mutual Funds' CAPM Beta

This table reports the relation between short positions and funds' market beta. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-restrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. Panel A reports the time series average of Cross-sectional distribution of market betas based on funds' stock holdings (*Risky-Holdings-Based Beta*), as well as market betas of funds' overall returns (*Fund Return Beta*). The *Risky-Holdings-Based Beta* is defined as the weighted average beta of all stocks in the portfolio, where the stock beta is calculated using monthly returns in a rolling past-three-year window. The *Fund Return Beta* is calculated using CRSP monthly returns in the 12 months after the short% classification. Within each quarter, we winsorize market betas at the 1^{st} and 99^{th} percentiles. Panel B reports panel regressions that examine the relation between market beta and short%. The dependent variable in columns (1)-(3) is *Risky-Holdings-Based Beta*, and that in columns (4)-(6) is *Fund Return Beta*. The independent variable is the short% of the same fund in the same quarter. We winsorize short% above at the value of 100%. We control for time-fixed effects in columns (1) and (4), fund-fixed effects in columns (2) and (5), and both time and fund-fixed effects in columns (3) and (6). Standard errors clustered at both the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cross-sectional distribution of market beta

	Mean	5th	25th	50th	75th	95th
Risky-Holdings-Based Beta						
G00(=0)	1.124	0.799	0.978	1.104	1.259	1.515
G01(=0)	1.150	0.784	0.999	1.131	1.292	1.562
G1(0-20%)	1.111	0.789	0.976	1.080	1.227	1.502
G2(⩾20%)	1.046	0.669	0.847	1.046	1.228	1.460
Fund Return Beta						
G00(=0)	1.064	0.664	0.907	1.048	1.223	1.496
G01(=0)	1.098	0.670	0.926	1.075	1.256	1.599
G1(0-20%)	0.968	0.427	0.809	0.994	1.134	1.421
G2(⩾20%)	0.633	0.099	0.360	0.668	0.899	1.111

Panel B: Portfolio beta and short positions

DepVar =	*Risky-Holdings-Based Beta*			*Fund Return Beta*		
	(1)	(2)	(3)	(4)	(5)	(6)
Short%	-0.0688	-0.0644	-0.0498	-0.845***	-0.0313	-0.0221
	(0.045)	(0.073)	(0.081)	(0.087)	(0.057)	(0.055)
Time FE	Y		Y	Y		Y
Fund FE		Y	Y		Y	Y
# of Obs	101,077	101,077	101,077	94,090	94,090	94,090
Adj. R^2	0.070	0.546	0.610	0.096	0.411	0.473

Table 2.5: Excluding Funds with Derivative Holdings and Market-Neutral Funds

This table repeats the analyses of Panels A-C of Table 2.3 and Panel A of Table 2.4 but excludes all funds that report derivative holdings in SEC Form N-SAR or excludes all market neutral funds (those with "EMN" Lipper classification) separately. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-refrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. Panel A reports the analyses excluding funds that report derivative holdings, and Panel B reports that of funds excluding all market neutral funds.

Panel A1-A3 and Panel B1-B3 report the portfolio weights of long positions, cash holdings, and short positions. For each fund in each quarter, we define the long%, short%, and cash% as the ratio of total market value of stocks in long positions, the absolute market value of stocks in short positions, and the amount of cash and cash equivalents to fund TNA, respectively. Panels A1 (B1), A2 (B2) and A3 (B3) report the time-series average of cross-sectional summary statistics of long%, cash%, and short% for different fund groups excluding funds with derivative holdings (excluding market neutral funds).

Panel A4 and B4 report the time series average of Cross-sectional distribution of market betas based on funds' stock holdings (*Risky-Holdings-Based Beta*), as well as market betas of funds' overall returns (*Fund Return Beta*), excluding funds with derivative holdings, and excluding all market neutral funds respectively. The *Risky-Holdings-Based Beta* is defined as the weighted average beta of all stocks in the portfolio, where the stock beta is calculated using monthly returns in a rolling-past-three-year window. The *Fund Return Beta* is calculated using CRSP monthly returns in the 12 months after the short% classification. Within each quarter, we winsorize market betas at the 1^{st} and 99^{th} percentiles.

Panel A: Excluding funds with derivatives holdings

A1: Cross-sectional distribution of long%						
	Mean	5th	25th	50th	75th	95th
G00(=0)	92.57%	77.69%	88.88%	93.04%	96.06%	101.42%
G01(=0)	91.78%	76.54%	87.56%	92.25%	95.48%	100.96%
G1(0-20%)	106.59%	58.03%	86.88%	94.97%	110.43%	196.49%
G2(⩾20%)	108.88%	59.65%	86.33%	100.20%	124.39%	184.91%

A2: Cross-sectional distribution of cash%						
	Mean	5th	25th	50th	75th	95th
G00(=0)	2.72%	-0.01%	0.27%	1.59%	3.60%	9.07%
G01(=0)	2.46%	-0.01%	0.26%	1.45%	3.43%	8.51%
G1(0-20%)	6.38%	-0.30%	0.23%	2.07%	6.68%	31.61%
G2(⩾20%)	37.96%	-0.12%	2.99%	28.47%	77.14%	90.00%

A3: Cross-sectional distribution of short%						
	Mean	5th	25th	50th	75th	95th
G00(=0)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
G01(=0)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
G1(0-20%)	4.11%	0.00%	0.00%	0.14%	4.19%	21.57%
G2(⩾20%)	53.33%	13.12%	29.10%	49.51%	79.85%	96.05%

A4: Cross-sectional distribution of market beta						
	Mean	5th	25th	50th	75th	95th
Risky-Holdings-Based Beta						
G00(=0)	1.124	0.796	0.978	1.105	1.259	1.515
G01(=0)	1.154	0.776	1.002	1.135	1.296	1.580
G1(0-20%)	1.113	0.797	0.976	1.085	1.229	1.509
G2(⩾20%)	1.041	0.657	0.842	1.033	1.231	1.457
Fund Return Beta						
G00(=0)	1.065	0.664	0.907	1.049	1.223	1.500
G01(=0)	1.092	0.667	0.924	1.075	1.251	1.565
G1(0-20%)	0.980	0.442	0.840	1.005	1.139	1.419
G2(⩾20%)	0.632	0.111	0.346	0.674	0.897	1.104

Panel B: Excluding equity market neutral funds

B1: Cross-sectional distribution of long%

	Mean	5th	25th	50th	75th	95th
G00(=0)	92.51%	77.61%	88.83%	93.01%	96.00%	101.33%
G01(=0)	91.70%	75.50%	87.50%	92.26%	95.41%	100.89%
G1(0-20%)	106.23%	55.54%	87.07%	95.42%	109.97%	194.62%
G2(⩾20%)	113.36%	64.60%	89.83%	109.04%	128.27%	182.09%

B2: Cross-sectional distribution of cash%

	Mean	5th	25th	50th	75th	95th
G00(=0)	2.72%	-0.01%	0.29%	1.61%	3.62%	9.08%
G01(=0)	2.51%	-0.04%	0.26%	1.44%	3.45%	8.84%
G1(0-20%)	6.44%	-0.33%	0.29%	2.08%	6.78%	32.11%
G2(⩾20%)	27.33%	-5.05%	2.83%	15.65%	48.93%	88.34%

B3: Cross-sectional distribution of short%

	Mean	5th	25th	50th	75th	95th
G00(=0)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
G01(=0)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
G1(0-20%)	4.40%	0.00%	0.00%	0.16%	5.06%	21.39%
G2(⩾20%)	44.27%	12.00%	27.17%	37.17%	59.07%	93.94%

B4: Cross-sectional distribution of market beta

	Mean	5th	25th	50th	75th	95th
Risky-Holdings-Based Beta						
G00(=0)	1.124	0.798	0.978	1.104	1.259	1.515
G01(=0)	1.150	0.784	0.999	1.131	1.292	1.562
G1(0-20%)	1.111	0.789	0.976	1.080	1.227	1.503
G2(⩾20%)	1.037	0.683	0.839	1.029	1.215	1.429
Fund Return Beta						
G00(=0)	1.065	0.668	0.907	1.048	1.223	1.496
G01(=0)	1.098	0.670	0.926	1.075	1.256	1.599
G1(0-20%)	0.968	0.427	0.809	0.994	1.134	1.421
G2(⩾20%)	0.683	0.195	0.429	0.729	0.912	1.119

Table 2.6: Performance by Fund Groups

This table reports the equally weighted average fund performance of different groups of US equity mutual funds. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-restrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. We study several types of fund returns: a) monthly returns based on mutual funds' reported stock holdings, including those in both the long leg and short leg (*Stock Holding Returns*); b) cash-adjusted stock holding returns (*Stock Holding Returns* × *(1 - cash%)*); and c) fund overall returns as reported by CRSP (*Fund Returns*). We also decompose *Stock Holding Returns* into returns from long positions (*Long-Holding Returns*, weighted by portfolio weights) and those from short positions (*Short-Holding Returns*, also weighted by portfolio weights), so that *Stock Holding Returns = Long-Holding Returns + Short-Holding Returns*. To weed out data errors and incomplete records, we drop funds whose market value of long-leg holdings is smaller than that of short-leg holdings, as well as funds for which the correlation between *Stock Holding Returns* and *Fund Returns* is below 0.5. We report the returns in excess of risk-free rate in Panel A, CAPM alphas in Panel B, alphas adjusted by the Fama-French three factors in Panel C, alphas adjusted by Fama-French-Carhart four factors in Panel D, alphas adjusted by Fama-French-Carhart four factors plus the Pastor-Stambaugh liquidity factor in Panel E, alphas adjusted by Fama-French five factors in Panel F, and alphas adjusted by hedge fund seven factors in Panel G. T-statistics based on standard errors with Newey-West correction are reported in brackets. Estimates significant at the 5% level are indicated in bold.

Panel A: Excess returns

	Stock Holding Returns	Long-Holding Returns	Short-Holding Returns	Stock Holding Returns × (1 - Cash%)	Fund Returns (CRSP)
	(1)	(2)	(3)	(4)	(5)
G00(=0)	0.728%	0.728%		0.710%	0.697%
	[1.74]	[1.74]		[1.75]	[1.71]
G01(=0)	0.725%	0.725%		0.710%	0.713%
	[1.67]	[1.67]		[1.68]	[1.65]
G1(0-20%)	0.707%	0.748%	-0.041%	0.662%	0.631%
	[1.70]	[1.68]	[-1.51]	[1.71]	[1.69]
G2(⩾20%)	**1.097%**	**1.329%**	-0.232%	**0.801%**	**0.653%**
	[2.63]	**[2.08]**	[-1.05]	**[2.45]**	**[2.32]**
G2-G00	**0.369%**	**0.601%**		0.091%	-0.045%
	[3.36]	**[2.61]**		[0.72]	[-0.29]
G2-G01	**0.372%**	**0.604%**		0.091%	-0.060%
	[3.30]	**[2.82]**		[0.65]	[-0.35]
G2-G1	**0.389%**	**0.581%**	-0.191%	0.139%	0.022%
	[3.43]	**[2.82]**	[-0.97]	[1.18]	[0.17]

Panel B: CAPM alpha

	Stock Holding Returns	Long-Holding Returns	Short-Holding Returns	Stock Holding Returns × (1 - Cash%)	Fund Returns (CRSP)
	(1)	(2)	(3)	(4)	(5)
G00(=0)	0.002%	0.002%		0.004%	-0.009%
	[0.04]	[0.04]		[0.10]	[-0.18]
G01(=0)	-0.019%	-0.019%		-0.013%	-0.024%
	[-0.35]	[-0.35]		[-0.25]	[-0.43]
G1(0-20%)	-0.007%	-0.016%	0.009%	-0.007%	-0.008%
	[-0.14]	[-0.30]	[0.86]	[-0.15]	[-0.17]
G2(⩾20%)	**0.409%**	**0.231%**	**0.177%**	**0.261%**	**0.194%**
	[3.62]	**[2.16]**	**[2.05]**	**[2.95]**	**[2.51]**
G2-G00	**0.406%**	**0.229%**		**0.257%**	**0.203%**
	[3.58]	**[2.70]**		**[2.67]**	**[2.41]**
G2-G01	**0.427%**	**0.250%**		**0.274%**	**0.218%**
	[3.78]	**[3.02]**		**[2.81]**	**[2.55]**
G2-G1	**0.416%**	**0.247%**	**0.168%**	**0.269%**	**0.202%**
	[3.45]	**[2.80]**	**[2.00]**	**[2.60]**	**[2.22]**

Panel C: Fama-French three-factor alpha

	Stock Holding Returns	Long-Holding Returns	Short-Holding Returns	Stock Holding Returns × (1 - Cash%)	Fund Returns (CRSP)
	(1)	(2)	(3)	(4)	(5)
G00(=0)	0.011%	0.011%		0.013%	-0.001%
	[0.32]	[0.32]		[0.40]	[-0.02]
G01(=0)	-0.010%	-0.010%		-0.005%	-0.015%
	[-0.23]	[-0.23]		[-0.11]	[-0.34]
G1(0-20%)	-0.003%	-0.011%	0.008%	-0.004%	-0.005%
	[-0.08]	[-0.27]	[0.80]	[-0.12]	[-0.13]
G2(⩾20%)	**0.415%**	**0.247%**	**0.168%**	**0.264%**	**0.197%**
	[3.60]	**[2.42]**	**[2.71]**	**[2.94]**	**[2.62]**
G2-G00	**0.405%**	**0.236%**		**0.252%**	**0.198%**
	[3.90]	**[2.72]**		**[3.10]**	**[3.22]**
G2-G01	**0.425%**	**0.257%**		**0.269%**	**0.213%**
	[4.17]	**[3.07]**		**[3.32]**	**[3.44]**
G2-G1	**0.418%**	**0.258%**	**0.160%**	**0.269%**	**0.203%**
	[3.75]	**[2.89]**	**[2.58]**	**[2.98]**	**[2.69]**

Panel D: Fama-French-Carhart four-factor alpha

	Stock Holding Returns	Long-Holding Returns	Short-Holding Returns	Stock Holding Returns × (1 - Cash%)	Fund Returns (CRSP)
	(1)	(2)	(3)	(4)	(5)
G00(=0)	0.013%	0.013%		0.015%	0.002%
	[0.38]	[0.38]		[0.46]	[0.05]
G01(=0)	-0.007%	-0.007%		-0.002%	-0.012%
	[-0.15]	[-0.15]		[-0.04]	[-0.25]
G1(0-20%)	-0.004%	-0.011%	0.007%	-0.005%	-0.004%
	[-0.11]	[-0.25]	[0.67]	[-0.15]	[-0.11]
G2(⩾20%)	**0.399%**	**0.241%**	**0.159%**	**0.253%**	**0.192%**
	[3.58]	**[2.42]**	**[2.58]**	**[2.94]**	**[2.57]**
G2-G00	**0.386%**	**0.228%**		**0.238%**	**0.190%**
	[3.85]	**[2.71]**		**[3.07]**	**[3.11]**
G2-G01	**0.406%**	**0.248%**		**0.254%**	**0.204%**
	[4.11]	**[3.05]**		**[3.29]**	**[3.31]**
G2-G1	**0.403%**	**0.251%**	**0.152%**	**0.258%**	**0.196%**
	[3.73]	**[2.92]**	**[2.45]**	**[2.97]**	**[2.60]**

Panel E: Five-factor (Carhart 4F+liquidity) alpha

	Stock Holding Returns	Long-Holding Returns	Short-Holding Returns	Stock Holding Returns × (1 - Cash%)	Fund Returns (CRSP)
	(1)	(2)	(3)	(4)	(5)
G00(=0)	0.008%	0.008%		0.010%	-0.003%
	[0.30]	[0.30]		[0.40]	[-0.10]
G01(=0)	-0.013%	-0.013%		-0.007%	-0.018%
	[-0.35]	[-0.35]		[-0.21]	[-0.48]
G1(0-20%)	-0.007%	-0.014%	0.007%	-0.008%	-0.007%
	[-0.19]	[-0.36]	[0.71]	[-0.24]	[-0.20]
G2(⩾20%)	**0.384%**	**0.228%**	**0.155%**	**0.241%**	**0.181%**
	[3.99]	**[2.52]**	**[2.58]**	**[3.26]**	**[2.97]**
G2-G00	**0.375%**	**0.220%**		**0.230%**	**0.184%**
	[4.05]	**[2.69]**		**[3.18]**	**[3.31]**
G2-G01	**0.396%**	**0.241%**		**0.248%**	**0.199%**
	[4.23]	**[2.99]**		**[3.34]**	**[3.40]**
G2-G1	**0.391%**	**0.242%**	**0.148%**	**0.249%**	**0.189%**
	[4.03]	**[2.94]**	**[2.46]**	**[3.19]**	**[2.80]**

Panel F: Fama-French five-factor alpha

	Stock Holding Returns	Long-Holding Returns	Short-Holding Returns	Stock Holding Returns × (1 - Cash%)	Fund Returns (CRSP)
	(1)	(2)	(3)	(4)	(5)
G00(=0)	0.017%	0.017%		0.018%	0.009%
	[0.56]	[0.56]		[0.65]	[0.31]
G01(=0)	0.013%	0.013%		0.016%	0.009%
	[0.35]	[0.35]		[0.48]	[0.25]
G1(0-20%)	0.034%	0.025%	0.009%	0.033%	0.039%
	[1.07]	[0.74]	[0.84]	[1.05]	[1.16]
G2(⩾20%)	**0.383%**	**0.247%**	**0.136%**	**0.233%**	**0.156%**
	[3.70]	**[2.50]**	**[2.20]**	**[2.95]**	**[2.25]**
G2-G00	**0.366%**	**0.230%**		**0.215%**	**0.147%**
	[3.94]	**[2.72]**		**[3.01]**	**[2.56]**
G2-G01	**0.371%**	**0.234%**		**0.217%**	**0.147%**
	[4.08]	**[2.87]**		**[3.09]**	**[2.63]**
G2-G1	**0.349%**	**0.221%**	**0.128%**	**0.201%**	0.117%
	[3.63]	**[2.60]**	**[2.07]**	**[2.65]**	[1.70]

Panel G: Hedge fund seven-factor alpha

	Stock Holding Returns	Long-Holding Returns	Short-Holding Returns	Stock Holding Returns × (1 - Cash%)	Fund Returns (CRSP)
	(1)	(2)	(3)	(4)	(5)
G00(=0)	0.080%	0.080%		0.079%	0.067%
	[1.76]	[1.76]		[1.79]	[1.51]
G01(=0)	0.063%	0.063%		0.067%	0.058%
	[1.22]	[1.22]		[1.32]	[1.14]
G1(0-20%)	0.079%	0.075%	0.004%	0.072%	0.072%
	[1.25]	[1.13]	[0.51]	[1.16]	[1.25]
G2(⩾20%)	**0.497%**	**0.357%**	0.140%	**0.333%**	**0.259%**
	[5.44]	**[3.71]**	[1.86]	**[4.79]**	**[4.27]**
G2-G00	**0.417%**	**0.277%**		**0.254%**	**0.192%**
	[4.13]	**[3.57]**		**[2.94]**	**[2.48]**
G2-G01	**0.434%**	**0.294%**		**0.266%**	**0.201%**
	[4.19]	**[3.80]**		**[2.95]**	**[2.50]**
G2-G1	**0.418%**	**0.282%**	0.136%	**0.261%**	**0.187%**
	[3.63]	**[3.50]**	[1.81]	**[2.55]**	**[2.05]**

Table 2.7: Fund Performance Controlling for Fund Characteristics

This table reports the comparison of fund performance across different groups of US equity mutual funds. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-restrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. To control for fund characteristics and adjust for risk exposures, we take the following two steps in a similar spirit of Fama-MacBeth regressions. First, in each month, we run cross-sectional regressions of fund performance on fund group dummies, controlling for fund characteristics. The dependent variable is fund performance at month $t+1$, measured as *Stock Holding Returns* in Panel A, and as *Fund Returns* (as reported in CRSP) in Panel B. The key independent variables are three dummy variables indicating whether the fund belongs to G01, G1, or G2 group, respectively (G00 is omitted and serves as the baseline group). Control variables include the logarithm of fund age since inception, the logarithm of fund TNA at the end of last quarter, as well as turnover and expense ratios in the last quarter. The regression specification is as follows:

$$
\begin{aligned}
Return_{i,t+1} = & \sum_{n \in \{G01, G1, G2\}} \beta_{n,t} \cdot Dummy_{i,n,t} + \beta_{1,t} \cdot \log\left(Fund\ age_{i,t}\right) + \beta_{2,t} \cdot \log\left(TNA_{i,t}\right) \\
& + \beta_{3,t} \cdot Expense_{i,t} + \beta_{4,t} \cdot Turnover_{i,t} + \varepsilon_{i,t+1},
\end{aligned}
$$

where $\text{Dummy}_{i,n,t}$ is a dummy variable, which equals 1 if fund i belongs to group n ($n \in \{G01, G1, G2\}$) at month t and equals 0 otherwise. The estimate of $\beta_{n,t}$ represents the difference of monthly performance between funds in group n and funds in group G00, after controlling for fund characteristics. Meanwhile, the difference between the estimates of $\beta_{k,t}$ and $\beta_{l,t}$ represents the return difference of monthly performance between funds in groups k and l.In the second step, we run time-series regressions of estimates of $\beta_{n,t}$ on risk factors to obtain the difference of alphas between funds in different groups n and funds in group G00. We report the difference in excess returns in column (1), alphas adjusted by the market factor in column (2) (*CAPM*), alphas adjusted by the Fama-French three factors in column (3) (*FF 3F*), alphas adjusted by the Fama-French-Carhart four factors in column (4) (*Carhart 4F*), the Fama-French-Carhart four factors plus the Pastor-Stambaugh liquidity factor in column (5) (*4F+Liquidity*), alphas adjusted by the Fama-French five factors in column (6) (*FF 5F*), and alphas adjusted by the hedge fund seven factors in column (7) (*HF 7F*). To weed out data errors and incomplete records, we drop funds whose market value of long-leg holdings is smaller than that of short-leg holdings, as well as funds for which the correlation between *Stock Holding Returns* and *Fund Returns* is below 0.5. T-statistics based on standard errors with Newey-West correction are reported in brackets.

Panel A: Stock holding returns

	Excess Ret	CAPM	FF 3F	Carhart 4F	4F+Liquidity	FF 5F	HF 7F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
G2-G00	0.411%	0.489%	0.484%	0.470%	0.462%	0.428%	0.500%
	[3.18]	[3.75]	[4.73]	[4.67]	[4.82]	[4.46]	[4.10]
G2-G01	0.414%	0.506%	0.501%	0.484%	0.477%	0.429%	0.514%
	[3.06]	[3.85]	[4.81]	[4.71]	[4.79]	[4.51]	[4.10]
G2-G1	0.422%	0.485%	0.484%	0.471%	0.462%	0.396%	0.486%
	[3.29]	[3.66]	[4.37]	[4.35]	[4.56]	[3.70]	[3.75]

Panel B: Fund returns

	Excess Ret	CAPM	FF 3F	Carhart 4F	4F+Liquidity	FF 5F	HF 7F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
G2-G00	0.037%	0.324%	0.315%	0.309%	0.305%	0.242%	0.304%
	[0.19]	[2.97]	[4.17]	[3.98]	[3.97]	[3.86]	[3.05]
G2-G01	0.018%	0.333%	0.324%	0.314%	0.312%	0.237%	0.308%
	[0.08]	[2.98]	[4.01]	[3.78]	[3.75]	[3.75]	[2.99]
G2-G1	0.074%	0.296%	0.292%	0.285%	0.281%	0.183%	0.271%
	[0.45]	[2.77]	[3.54]	[3.37]	[3.41]	[2.64]	[2.59]

Table 2.8: Flow-Performance Sensitivity by Fund Groups

This table reports results from Fama-MacBeth regressions of fund flows on fund performance for different types of US equity mutual funds. We classify mutual fund/quarter observations into three groups: G0 includes all mutual funds that do not use short sales in any of the previous eight quarters (combining the previous G00 and G01); G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. For each group of funds (G0, G1, or G2), we run Fama-MacBeth regressions and estimate the flow-performance sensitivity with the following specification:

$$flow_{i,t+1} = \beta_{0,t} + \beta_{1,t} \cdot Performance\ Measure_{i,t} + \sum_{n=1}^{4} \gamma_{n,t} \cdot flow_{i,t+1-n} + \varepsilon_{i,t+1}.$$

The performance measure in quarter t is calculated as the average monthly excess returns (*ExRet*) in column (1), the alphas adjusted by CAPM model (*CAPM*) in column (2), the alphas adjusted by the Fama-French three factors (*FF 3F*) in column (3), the alphas adjusted by Fama-French-Carhart four factors (*Carhart 4F*) in column (4), the alphas adjusted by Fama-French-Carhart four factors plus the Pastor-Stambaugh liquidity factor (*4F+Liq*) in column (5), the alphas adjusted by Fama-French five factors (*FF 5F*) in column (6), and the alphas adjusted by the hedge fund seven factors in column (7) (*HF 7F*).
The dependent variable $flow_{i,t+1}$ is calculated as the net capital flow to the fund in quarter $t+1$ divided by the fund's TNA at the end of quarter t, and is winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles within each quarter. Panel A reports regression results that control for lagged capital flows over the previous four quarters, while Panel B presents results without controlling for past flows. We report the flow-performance sensitivity, defined as the time series average of the regression coefficient $\beta_{1,t}$, for each group of funds. The last row reports the difference between G2 funds and G0 funds. Standard errors with Newey-West correction are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Controlling for past flows

DepVar =				$Flow_{t+1}$			
	ExRet	CAPM	FF 3F	Carhart 4F	4F+Liq	FF 5F	HF 7F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
G0(=0)	2.154***	2.039***	2.116***	1.884***	1.692***	1.545***	1.136***
	(0.291)	(0.257)	(0.186)	(0.187)	(0.182)	(0.156)	(0.167)
G1(0-20%)	3.018***	3.564***	2.595***	2.291***	2.372***	1.574***	1.672***
	(0.720)	(0.775)	(0.614)	(0.621)	(0.543)	(0.463)	(0.455)
G2(⩾20%)	5.527***	10.587***	8.155***	8.205***	8.527***	3.939***	4.233***
	(1.560)	(2.434)	(2.544)	(2.589)	(2.568)	(1.472)	(1.359)
G2-G0	3.373**	8.548***	6.039***	6.321***	6.835***	2.394*	3.097***
	(1.643)	(2.485)	(2.479)	(2.434)	(2.325)	(1.369)	(1.130)

Panel B: Without controlling for past flows

DepVar =				$Flow_{t+1}$			
	ExRet	CAPM	FF 3F	Carhart 4F	4F+Liq	FF 5F	HF 7F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
G0(=0)	3.094***	3.446***	3.218***	2.759***	2.281***	2.014***	1.423***
	(0.499)	(0.410)	(0.271)	(0.264)	(0.221)	(0.257)	(0.178)
G1(0-20%)	6.085***	7.685***	6.196***	5.456***	4.677***	3.572***	3.113***
	(1.255)	(1.025)	(0.759)	(0.835)	(0.670)	(0.879)	(0.638)
G2(⩾20%)	7.221***	15.365***	12.004***	11.288***	10.535***	6.756***	4.704***
	(1.972)	(2.120)	(2.573)	(2.406)	(2.435)	(2.477)	(1.642)
G2-G0	4.127**	11.919***	8.786***	8.529***	8.254***	4.742**	3.281**
	(1.926)	(2.199)	(2.575)	(2.411)	(2.402)	(2.349)	(1.669)

Table 2.9: Cash Holdings and Fund Flows by Fund Groups

This table reports results from Fama-MacBeth regressions of changes in fund cash positions on quarterly fund flows for different types of US equity mutual funds. We classify mutual fund/quarter observations into three groups: G0 includes all mutual funds that do not use short sales in any of the previous eight quarters (combining the previous G00 and G01); G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (*TNA*) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. For each group of funds (G0, G1, or G2), we run Fama-MacBeth regressions of changes in fund cash positions on fund flows in the same quarter, and report the estimated coefficients (the sensitivity) for each fund group. The dependent variable, $\Delta\ Cash_t/TNA_{t+1}$, is the change of cash dollar amount from the end of quarter $t-1$ to the end of quarter t, scaled by TNA at the end of quarter $t-1$. The independent variable $flow_t$ is calculated as the net capital flow in quarter t divided by the fund's TNA at the end of quarter $t-1$. We also separate the fund-quarter observations into those with fund inflows (*Flow+*) and those with outflows (*Flow–*). The last row reports the difference in sensitivity between G2 funds and G0 funds. Fund flows and $\Delta Cash/TNA_{t+1}$ are winsorized at the 1^{st} and 99^{th} percentiles within each quarter. Standard errors with Newey-West correction and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

DepVar =	$\Delta Cash_t/TNA_{t-1}$		
	Flow	Flow+	Flow-
	(1)	(2)	(3)
G0(=0)	0.037***	0.038***	0.031***
	(0.002)	(0.003)	(0.003)
G1(0-20%)	0.081***	0.073**	0.074***
	(0.020)	(0.032)	(0.025)
G2(⩾20%)	0.230***	0.181***	0.269***
	(0.035)	(0.052)	(0.087)
G2-G0	0.193***	0.143***	0.238***
	(0.035)	(0.053)	(0.086)

Table 2.10: Parameter Values in the Model

This table reports the parameter values used in the model. The first column lists the parameter names; the second column shows their corresponding symbols; the third and fourth columns present the estimated parameter values for long-only and long-short funds, respectively.

Parameter	Symbol	Value	
		Long-only	Long-short
Average alpha	$\bar{\alpha}$	0.0092	0.0490
Noise of alpha	A	0.0951	0.1291
Flow-to-performance sensitivity	b	1.1487	5.1218
Noise of flow	B	0.0951	0.1291
Liquidation cost	c	0.0789	0.1026
Optimal risky asset weight	w_{FOC}	**1.0000**	**0.7211**

2.A Appendix

2.A.1 Dispersion in fund beta

Perhaps the most puzzling findings of our analyses are the low average fund beta and large beta dispersion of long-short mutual funds, as it is nearly costless to adjust a fund's market exposure using derivative contracts such as equity index futures. One possibility is that while the average fund beta is significantly below one, each fund family launches multiple long-short products with the same underlying long-short portfolio but different levels of market exposures to cater to different investors' needs. For example, a fund family may choose a beta that is close to 0 to cater to institutional clients who want a market-neutral alpha product, then a beta of 0.4 to 0.8 for corporate clients who want some market exposures on top of the alpha, and finally a beta of 1 for retail clients who evaluate mutual fund performance relative to long-only benchmarks.

In this section, we carefully examine the dispersion in fund beta. To start, we compare the characteristics of long-short mutual funds with different levels of market exposures. In Panel A of Online Appendix Table 2.A.12, we divide all aggressive long-short mutual funds into four equal groups (remember that the 25th, 50th, 75th percentile thresholds in the beta distribution are around 0.4, 0.6, and 0.9, respectively) and examine the differences in fund expenses, turnover, and retail shares across the four quartiles. There is no clear monotonic relation between market beta and any of these fund characteristics. Annual expenses are the highest for long-short mutual funds in the second quartile—with a beta between 0.4 and 0.6—at 1.89%. Monthly turnover is also the highest for the second quartile at slightly over 30%. Retail shares (defined as the TNA weight of retail share classes within each fund) peaks for mutual funds in the third quartile—with a beta between 0.6 and 0.9—at nearly 50%.

In Panel B of the same table, we classify all long-short mutual funds into two groups based on the sample median of fund beta and analyze the flow-performance sensitivities of the two groups. As can be seen from the panel, the regression coefficients of next-quarter capital flows on last-year fund performance, measured relative to various asset pricing models, are nearly identical. Together, the results shown in Panels A and B of

Appendix Table 2.A.12 suggest that there are no significant differences in clienteles across long-short funds with different levels of market exposures.

In Panel C, we analyze dispersion in fund beta within each fund family. If the catering story described above is true, we expect fund families to launch multiple, nearly identical products with different market exposures. We test this possibility by examining the correlations in residual returns—after controlling for the market factor—across long-short funds within the same family. More specifically, we divide all long-short products within a family into two halves: those with high and those with low market betas. For each long-short product in the low-beta group, we then match it to a long-short fund in the high-beta group with the largest residual correlation. Finally, we take the average of this maximum correlation for all funds in the low-beta group and report the distribution of this mean-max correlation across fund families.

As shown in the first row of Panel C, the average correlation in residual fund returns between the best matched pair of low-beta and high-beta funds within the same family is around 0.35, suggesting that these funds are unlikely pursuing identical strategies. In the second row, we impose a further restriction that the matched fund from the high-beta group must have a beta that is at least 0.3 larger than that of the low-beta fund; this is to ensure that we are comparing two funds with sufficiently different market exposures. The average correlation in residual fund returns drops to 0.24 in this case.

Combined, the evidence presented in Online Appendix Table 2.A.12 is largely inconsistent with the idea that fund families launch multiple long-short mutual funds—building on the same long-short active portfolio—to cater to different investor groups with differential needs for market exposures. We leave it to future research to shed additional light on exactly why long-short mutual funds choose an average market beta that is substantially below one.

2.A.2 Popular explanations for why most mutual funds do not short sell

One of the most natural, common explanations for the lack of growth of long-short equity funds is binding regulatory constraints. However, as discussed in Section 2.2, all regulatory restrictions on short selling had been lifted by 1997, so regulations are unlikely to have been an important deterrent to mutual fund short selling in the last two decades.

A related explanation is that although mutual funds are not legally barred from short selling, they are constrained from doing so due to client restrictions, which may be imposed for a number of reasons. First, some institutional clients (state pension funds for example) may face short-sale constraints themselves and, as a result, restrict their fund managers from short-selling. Second, given incomplete contracting or imperfect monitoring, investors worried about excessive risk-taking and portfolio turnover may find it optimal to restrain their managers from short selling. Third, there may be a broad, negative sentiment (social stigma) against short selling—after all, short sellers profit from others' misfortunes. To start, regardless of the underlying mechanism, this client-restriction view is hard to square with the fact that nearly half of all equity funds explicitly allow for short selling in their SEC filings—which suggests that the lack of shorting is unlikely due to their inability to short.[1] Moreover, the client-restriction view—particularly the optimal-contracting channel—has broader, interesting implications for the organization of the delegated portfolio management industry.

Another popular explanation is the lack of shorting ability among mutual fund managers, as smart managers with short-selling skills are immediately hired away by hedge funds. We show that long-short funds significantly outperform long-only funds on a risk-adjusted basis, and yet are unable to grow their assets under management. We further show that long-short equity funds outperform even long-only funds co-managed by the same managers, suggesting that the ability to short affords the managers a large oppor-

[1] In particular, more than 40% of equity funds allow for short selling in their public filings even though they never short in practice. If short selling is viewed as a "crime," why would any "innocent" long-only funds not pre-commit to never use short sales? It is equally difficult to understand why 5% of equity funds short a trivial amount in their portfolios. If the act of short selling is deemed a "crime" by some investors, these "casual" short sellers commit a "crime" without reaping much benefit (a 1% short position has virtually no impact on the fund's total returns).

tunity/tool set to generate abnormal returns. More broadly, this lack-of-talent argument, while unlikely to completely explain our empirical findings, raises interesting questions about the asset management industry. What are the implications of the current fee structures of mutual funds and hedge funds for the organization of the asset management industry? Do hedge funds attract all the talent and mutual fund compete on fees? What are the optimal compensation schemes for mutual funds and hedge funds? Should we perhaps allow mutual funds to also charge performance fees?

Finally, the rare use of shorting by mutual funds may be due to the large marginal costs and risks associated with short selling. As shown in Panel C of Table 2.2, long-short equity funds hold well-diversified portfolios, so the short-squeeze risk and the risk of a potentially unlimited loss for any particular short position is unlikely to have a big impact on the overall portfolio performance. Moreover, long-short equity funds do not seem to concentrate their short positions on a small number of stocks with abnormally high shorting demand, so the marginal shorting cost is also unlikely to explain our findings.

2.A.3 Additional tables

Table 2.A.1: Lipper Classifications of Long-Short Equity Funds

This table reports the Lipper classification of US equity long-short mutual funds. We classify US equity long-short mutual fund/quarter observations into two groups: G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA in the previous eight quarters. Panels A and B report the percentage of funds under each Lipper classification within groups G1 and G2, respectively.

Panel A: Lipper classification of G1 (0-20%)

Lipper Classification	Objective Class Name	% of G1
LSE	Long/Short Equity Funds	14.77%
LCCE	Large-Cap Core Funds	12.79%
MLCE	Multi-Cap Core Funds	7.97%
MCCE	Mid-Cap Core Funds	4.93%
LCVE	Large-Cap Value Funds	4.58%
ELCC	Extended U.S. Large-Cap Core Funds	4.20%
MLGE	Multi-Cap Growth Funds	4.02%
LCGE	Large-Cap Growth Funds	3.85%
SCGE	Small-Cap Growth Funds	3.14%
MCGE	Mid-Cap Growth Funds	2.78%
SCCE	Small-Cap Core Funds	2.73%
H	Health/Biotechnology Funds	2.65%
MLVE	Multi-Cap Value Funds	2.46%
EIEI	Equity Income Funds	2.41%
SPSP	S&P 500 Index Objective Funds	2.11%
MCVE	Mid-Cap Value Funds	2.05%
ABR	Absolute-Return Funds	1.97%
TK	Science & Technology Funds	1.86%
FX	Flexible Portfolio Funds	1.59%
SCVE	Small-Cap Value Funds	1.29%

Panel B: Lipper classification of G2 (⩾20%)

Lipper Classification	Objective Class Name	% of G2
LSE	Long/Short Equity Funds	37.73%
EMN	Equity Market Neutral Funds	13.96%
ELCC	Extended U.S. Large-Cap Core Funds	10.75%
SESE	Specialty Diversified Equity Funds	3.65%
MLCE	Multi-Cap Core Funds	3.62%
AED	Alternative Event Driven Funds	2.70%
DSB	Dedicated Short Bias Funds	2.65%
ABR	Absolute-Return Funds	2.53%
FX	Flexible Portfolio Funds	1.70%
AMS	Alternative Multi-Strategy Funds	1.48%
S	Specialty/Miscellaneous Funds	1.44%
LCCE	Large-Cap Core Funds	1.42%
MLVE	Multi-Cap Value Funds	1.29%
LCGE	Large-Cap Growth Funds	1.23%

Table 2.A.2: List of Long-Short Funds with Multiple Benchmarks

This table reports the US equity long-short mutual funds with multiple benchmarks. We report the fund names, primary prospectus benchmarks, and secondary prospectus benchmarks obtained from Morningstar for these funds. This field will be blank for the funds without a secondary benchmark.

Fund Name	Primary Prospectus Benchmark	Secondary Prospectus Benchmark
AQR Long-Short Equity	(MSCI World NR USD) 50.000% + (ICE BofA US 3M Treasury Bill TR USD) 50.000%	
Diamond Hill Long-Short	Russell 1000 TR USD	(Bloomberg US Treasury Bill 1-3 M TR USD) 40.000% + Russell 1000 TR USD 60.000%
Diamond Hill Financial Long-Short	Russell 3000 Ind/Financials TR USD	(Russell 3000 Ind/Financials TR USD) 80.000% + ICE BofA 0-3 M US Treasury Bill TR USD 20.000%
Diamond Hill Research Opportunities	Russell 3000 TR USD	(Russell 3000 TR USD) 75.000% + ICE BofA 0-3 M US Treasury Bill TR USD 25.000%
Easterly Snow Long/Short Opportunity	Russell 3000 Value TR USD	(Russell 3000 Value TR USD) 70.000% + ICE BofA US 3M Treasury Bill TR USD 30.000%
Nuveen Equity Long/Short	Russell 1000 TR USD	(Russell 1000 TR USD) 70.000% + ICE BofA US 3M Treasury Bill TR USD 30.000%
PGIM QMA Long-Short Equity	S&P 500 TR USD	(FTSE Treasury Bill 3 Mon USD) 50.000% + S&P 500 TR USD 50.000%

Table 2.A.3: Fund Holdings Characteristics

This table reports the panel distribution of fund holdings characteristics for different fund groups. Panel A shows firm size, book-to-market ratio, and cumulative stock returns in the past one year. For each fund in each quarter, we calculate the fund holdings characteristics as the average stock characteristics weighted by the market value of the stock's position (with short positions having negative signs) divided by the fund's total holdings value. Panel B reports the average liquidity of fund holdings based on three measures: the one-year average Amihud illiquidity measure, the effective bid-ask spread, and the Pastor-Stambaugh liquidity beta estimated using a 60-month rolling return regression. At the fund level, these measures are computed as the weighted average of stock-level liquidity metrics, with weights assigned based on the absolute value of a stock's portfolio weight relative to the sum of total long and short weights. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-refrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. The table reports the mean, the median, and the 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles.

Panel A: Fund holdings characteristics

	Mean	5th	25th	50th	75th	95th
Stock size ($ million)						
G00(=0)	44,172	1,213	4,767	36,983	74,990	118,021
G01(=0)	42,412	1,273	5,493	32,278	72,073	115,377
G1(0-20%)	59,373	1,517	19,147	58,818	91,944	127,841
G2(⩾20%)	55,760	1,871	22,334	50,749	84,864	126,554
Book-to-market ratio						
G00(=0)	0.592	0.268	0.379	0.498	0.652	1.050
G01(=0)	0.576	0.264	0.374	0.501	0.668	1.045
G1(0-20%)	0.571	0.266	0.401	0.516	0.647	1.070
G2(⩾20%)	0.598	0.145	0.446	0.562	0.704	1.171
Past one-year return						
G00(=0)	0.191	-0.200	0.073	0.182	0.299	0.572
G01(=0)	0.200	-0.209	0.071	0.188	0.316	0.606
G1(0-20%)	0.186	-0.207	0.064	0.183	0.293	0.567
G2(⩾20%)	0.260	-0.179	0.105	0.246	0.398	0.729

Panel B: Liquidity of fund holdings

	Mean	5th	25th	50th	75th	95th
Amihud illiquidity						
G00(=0)	0.0062	0.0000	0.0000	0.0001	0.0001	0.0004
G01(=0)	0.0062	0.0000	0.0000	0.0001	0.0001	0.0004
G1(0-20%)	0.0074	0.0000	0.0000	0.0000	0.0001	0.0003
G2(⩾20%)	0.0053	0.0000	0.0001	0.0001	0.0002	0.0006
Bid-ask spread						
G00(=0)	0.667%	0.282%	0.336%	0.385%	0.475%	0.573%
G01(=0)	0.683%	0.282%	0.342%	0.392%	0.484%	0.586%
G1(0-20%)	0.647%	0.280%	0.340%	0.381%	0.465%	0.553%
G2(⩾20%)	0.621%	0.317%	0.352%	0.405%	0.488%	0.559%
Pastor-Stambaugh liquidity beta						
G00(=0)	-0.015	-0.437	-0.302	-0.107	-0.043	-0.014
G01(=0)	-0.017	-0.437	-0.331	-0.121	-0.047	-0.017
G1(0-20%)	-0.018	-0.305	-0.157	-0.104	-0.042	-0.017
G2(⩾20%)	-0.017	-0.136	-0.092	-0.073	-0.040	-0.021

Table 2.A.4: Volatility and Skewness of Fund Returns

This table reports the distribution of idiosyncratic volatility, total volatility, and skewness of fund performance for different groups of US equity mutual funds respectively. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-restrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. For each fund in each quarter, we calculate annual idiosyncratic volatility against the CAPM model, annual total volatility, and return skewness using daily fund returns in the future one year after classification. We then report the time series average of cross-sectional mean and median for each group of funds. In Columns (1) and (2), the metrics are based on returns of funds' stock portfolio, calculated by value weighting returns of all stock holdings in each fund (*Stock Holding Returns*); in Columns (3) and (4), we report metrics calculated using overall fund returns from CRSP (*Fund Returns*). To weed out data errors and incomplete records, we drop funds whose market value of long-leg holdings is smaller than that of short-leg holdings, as well as funds for which the correlation between *Stock Holding Returns* and *Fund Returns* is below 0.5. All variables are winsorized at the 1^{st} and 99^{th} percentiles within each quarter.

	Stock Holding Returns		*Fund Returns*	
	Mean	Median	Mean	Median
Idiosyncratic Volatility				
G00(=0)	6.187%	5.492%	6.067%	5.343%
G01(=0)	6.842%	6.087%	6.780%	5.954%
G1(0-20%)	6.081%	5.373%	5.619%	5.024%
G2(⩾20%)	8.191%	7.266%	5.208%	4.449%
Total Volatility				
G00(=0)	19.458%	18.889%	18.862%	18.313%
G01(=0)	20.087%	19.420%	19.707%	18.885%
G1(0-20%)	19.211%	18.466%	17.263%	17.363%
G2(⩾20%)	19.621%	18.884%	13.547%	13.653%
Skewness				
G00(=0)	-0.195	-0.197	-0.207	-0.208
G01(=0)	-0.194	-0.200	-0.208	-0.213
G1(0-20%)	-0.196	-0.198	-0.203	-0.203
G2(⩾20%)	-0.193	-0.197	-0.176	-0.180

Table 2.A.5: Fund Performance:
Matched Sample Based on Fund Size and Age

This table repeats the analyses of Table 2.7 but focuses on a matched sample where the long-short funds (G2) and long-only funds (G0) are matched based on fund size and age. We classify mutual fund/quarter observations into three groups: G0 includes all mutual funds that do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. For each long-short fund in G2, we select three long-only funds in G0 that 1) are launched in a two-year window around the inception date of the G2 fund, and 2) have the closest TNA to the G2 fund. Within this matched sample, we then take the following two steps to control for fund characteristics and adjust for risk exposures, in a similar spirit of Fama-MacBeth regressions. First, in each month, we run cross-sectional regressions of fund performance on fund group dummies, controlling for fund characteristics. The dependent variable is fund performance at month $t+1$, measured as *Stock Holding Returns* in Panel A, and as *Fund Returns* (as reported in CRSP) in Panel B. The key independent variable is the dummy variable indicating whether the fund belongs to G2. Control variables include the logarithm of fund age since inception, the logarithm of fund TNA at the end of last quarter, as well as turnover and expense ratios in the last quarter. The regression specification is as follows:

$$\begin{aligned} Return_{i,t+1} = {} & \beta_t \cdot Dummy_{i,t} + \beta_{1,t} \cdot \log(Fund\ age_{i,t}) + \beta_{2,t} \cdot \log(TNA_{i,t}) + \beta_{3,t} \cdot Expense_{i,t} \\ & + \beta_{4,t} \cdot Turnover_{i,t} + \varepsilon_{i,t+1}, \end{aligned}$$

where $Dummy_{i,t}$ is a dummy variable, which equals one if fund i belongs to group G2 at month t and equals zero otherwise. The estimate of β_t represents the return difference of monthly performance between G2 funds and G0 funds, after controlling for fund characteristics. In the second step, we run time-series regressions of coefficient estimates of β_t on risk factors to obtain the difference of alphas between G2 funds and G0 funds. We report the difference in excess returns (*ExRet*) in column (1), the difference in alphas adjusted by the market factor in column (2) (*CAPM*), the difference in alphas adjusted by Fama-French Three Factors in column (3) (*FF 3F*), the difference in alphas adjusted by Fama-French Carhart Four Factors in column (4) (*Carhart 4F*), the difference in Fama-French-Carhart Four Factors plus the Pastor-Stambaugh liquidity factor in column (5) (*4F+Liq*), the difference in alphas adjusted by Fama-French Five Factors in column (6) (*FF 5F*), and finally the difference in alphas adjusted by the hedge fund seven factors in column (7) (*HF 7F*). To weed out data errors and incomplete records, we drop funds whose market value of long-holdings is smaller than that of short-leg holdings, as well as funds for which the correlation between *Stock Holding Returns* and *Fund Returns* is below 0.5. T-statistics based on standard errors with Newey-West correction are reported in brackets.

Panel A: Comparison of stock holding returns

	(1) ExRet	(2) CAPM	(3) FF 3F	(4) Carhart 4F	(5) 4F+Liq	(6) FF 5F	(7) HF 7F
G2-G0	0.440%	0.544%	0.550%	0.523%	0.513%	0.420%	0.515%
	[1.99]	[2.50]	[2.73]	[2.60]	[2.57]	[2.16]	[2.32]

Panel B: Comparison of fund returns

	(1) ExRet	(2) CAPM	(3) FF 3F	(4) Carhart 4F	(5) 4F+Liq	(6) FF 5F	(7) HF 7F
G2-G0	0.093%	0.360%	0.357%	0.349%	0.346%	0.231%	0.330%
	[0.44]	[2.44]	[2.56]	[2.46]	[2.42]	[1.92]	[2.24]

Table 2.A.6: Performance of Comanaged Long-Short Funds and Long-Only Funds

This table reports the comparison of fund performance between long-short mutual funds and long-only funds that are comanaged by the same managers. We first select long-short funds whose average short positions account for more than 20% of their TNA on average in the previous eight quarters (defined as G2 in Panel A), or those whose average short positions account for more than 20% of their TNA during the whole sample (defined as G2 in Panel B). For each long-short fund in G2, we then identify long-only equity mutual funds that share common managers with the long-short fund in the same quarter. For this exercise, we measure fund performance using monthly returns based on fund stock holdings (*Stock Holding Returns*). We also decompose *Stock Holding Returns* into returns from long positions (*Long-Holding Returns*, weighted by portfolio weights) and those from short positions (*Short-Holding Returns*, also weighted by portfolio weights), so that *Stock Holding Returns = Long-Holding Returns + Short-Holding Returns*. We report the returns in excess of risk-free rate (*ExRet*) in column (1), alphas adjusted by the market factor in column (2) (*CAPM*), alphas adjusted by the Fama-French three factors in column (3) (*FF 3F*), alphas adjusted by the Carhart four factors in column (4) (*Carhart 4F*), the Carhart four factors plus the Pastor-Stambaugh liquidity factor in column (5) (*4F+Liq*), alphas adjusted by the Fama-French five factors in column (6) (*FF 5F*), and the alphas adjusted by the hedge fund seven factors in column (7) (*HF 7F*). *T*-statistics based on standard errors with Newey-West correction are reported in brackets.

Panel A: Groups based on average short% in the previous 8 quarters

	ExRet (1)	CAPM (2)	FF 3F (3)	Carhart 4F (4)	4F+Liq (5)	FF 5F (6)	HF 7F (7)
Stock Holding Returns							
Long-Only Funds	0.766%	0.087%	0.107%	0.090%	0.090%	0.102%	0.138%
	[1.91]	[1.09]	[1.49]	[1.44]	[1.43]	[1.48]	[2.10]
Short Funds (G2)	1.247%	0.543%	0.564%	0.557%	0.536%	0.516%	0.650%
	[2.74]	[3.60]	[3.76]	[3.73]	[3.15]	[3.15]	[4.68]
Difference	0.481%	0.456%	0.457%	0.468%	0.446%	0.414%	0.512%
	[3.23]	[2.78]	[2.83]	[2.93]	[3.26]	[2.90]	[3.64]
Long-Holding Returns							
Long-Only Funds	0.766%	0.087%	0.107%	0.090%	0.090%	0.102%	0.138%
	[1.91]	[1.09]	[1.49]	[1.44]	[1.43]	[1.48]	[2.10]
Short Funds (G2)	1.449%	0.268%	0.321%	0.330%	0.312%	0.273%	0.460%
	[1.97]	[1.79]	[2.05]	[2.15]	[2.24]	[1.74]	[3.63]
Difference	0.684%	0.181%	0.214%	0.241%	0.222%	0.171%	0.322%
	[1.88]	[1.09]	[1.18]	[1.40]	[1.41]	[1.09]	[2.42]
Short-Holding Returns							
Short Funds (G2)	-0.202%	0.274%	0.243%	0.227%	0.223%	0.243%	0.190%
	[-0.65]	[2.06]	[2.27]	[2.20]	[2.12]	[2.54]	[1.43]

Panel B: Groups based on average short% in the whole sample

	ExRet (1)	CAPM (2)	FF 3F (3)	Carhart 4F (4)	4F+Liq (5)	FF 5F (6)	HF 7F (7)
Stock Holding Returns							
Long-Only Funds	0.722%	0.041%	0.054%	0.043%	0.038%	0.054%	0.131%
	[1.75]	[0.67]	[0.87]	[0.76]	[0.70]	[0.89]	[1.87]
Short Funds (G2)	1.229%	0.563%	0.578%	0.574%	0.553%	0.534%	0.680%
	[2.88]	[4.01]	[4.06]	[4.02]	[4.60]	[3.47]	[5.26]
Difference	0.507%	0.522%	0.524%	0.531%	0.515%	0.480%	0.549%
	[4.10]	[3.94]	[4.11]	[4.19]	[4.64]	[3.79]	[4.40]
Long-Holding Returns							
Long-Only Funds	0.722%	0.041%	0.054%	0.043%	0.038%	0.054%	0.131%
	[1.75]	[0.67]	[0.87]	[0.76]	[0.70]	[0.89]	[1.87]
Short Funds (G2)	1.412%	0.354%	0.392%	0.398%	0.385%	0.353%	0.546%
	[2.19]	[2.35]	[2.73]	[2.84]	[2.91]	[2.24]	[3.71]
Difference	0.691%	0.313%	0.338%	0.355%	0.347%	0.298%	0.415%
	[2.68]	[2.31]	[2.52]	[2.87]	[2.90]	[2.22]	[3.23]
Short-Holding Returns							
Short Funds (G2)	-0.184%	0.209%	0.186%	0.176%	0.168%	0.182%	0.134%
	[-0.74]	[1.56]	[1.85]	[1.82]	[1.81]	[2.18]	[1.02]

Table 2.A.7: Performance and Expense Ratios of Comanaged Funds

This table reports regression results of fund performance on fund expenses in a sample where long-short mutual funds and long-only funds are comanaged by the same managers (the same sample as in Table 2.A.6). The dependent variable is fund return (from CRSP) in month $t+1$. The key independent variable is the annual fund expense ratio at the end of last quarter. Control variables include the logarithm of fund TNA, the logarithm of fund age since inception, turnover ratio in the last quarter, and the logarithm of the number of funds that the manager works with. Columns (1)–(4) report panel regression results; we include time- and manager-fixed effects in column (1), time-, manager-, and fund-fixed effects in column (2), time×manager-fixed effects in column (3), and finally time×manager- and fund-fixed effects in column (4). Columns (5)–(6) report results from Fama-MacBeth regressions, and we include manager-fixed effects in column (6). Standard errors with Newey-West adjustment are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel Regressions				Fama-MacBeth	
DepVar =	*Fund Returns*	*Fund Returns*	*Fund Returns*	*Fund Returns*	*Fund Returns*	*Fund Returns*
	(1)	(2)	(3)	(4)	(5)	(6)
Expenses	0.056	0.037	0.060	0.023	0.029	0.054
	(0.046)	(0.143)	(0.046)	(0.079)	(0.057)	(0.047)
log(TNA)	-0.001***	-0.003**	-0.000***	-0.002***	-0.000***	-0.000***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
log(Fund Age)	0.001***	0.001*	0.000	0.001	0.000*	0.000*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Turnover	0.003	0.009**	-0.001	0.003	-0.002	-0.001
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)
log(No. of Funds the Manager Works with)	-0.001	-0.001			0.000	
	(0.001)	(0.001)			(0.000)	
Time FE	Y	Y				
Manager FE	Y	Y				Y
Time×Manager FE			Y	Y		
Fund FE		Y		Y		
# of Obs	171,825	171,825	171,825	171,825	171,825	171,825
Adj. R^2	0.313	0.308	0.248	0.240	0.041	0.752

Table 2.A.8: Sharpe Ratios and Tracking Errors by Fund Groups

This table reports the Sharpe ratio and tracking error of different groups of US equity mutual funds. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-refrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. The annual Sharpe ratio is calculated using monthly fund returns from CRSP. For comparison, we also report the annual Sharpe ratio of the market in the same sample period. The annualized tracking error for each fund is calculated using future 12-month returns after Short% classification; the benchmark market return is the value-weighted return of all CRSP firms listed on NYSE, AMEX, and NASDAQ. We then report the time-series average of cross-sectional mean within each group of funds.

	Sharpe Ratio	Tracking Error
G00(=0)	0.545	0.061
G01(=0)	0.533	0.069
G1(0-20%)	0.546	0.061
G2(⩾20%)	0.696	0.102
Market	0.558	

Table 2.A.9: Flow-Performance Sensitivity: Matched Sample Based on Fund Size and Age

This table repeats the analyses of Table 2.8 but focuses on a matched sample where the long-short funds (G2) and long-only funds (G0) are matched based on fund size and age. We classify mutual fund/quarter observations into three groups: G0 includes all mutual funds that do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. For each long-short fund in G2, we select three long-only funds (in G0) that 1) are launched in a two-year window around the inception date of the G2 fund, and 2) have the closest TNA to the G2 fund. For each group of funds in this matched sample, we run Fama-MacBeth regressions and estimate the flow-performance sensitivity with the following specification:

$$flow_{i,t+1} = \beta_{0,t} + \beta_{1,t} \cdot Performance\ Measure_{i,t} + \sum_{n=1}^{4} \gamma_{n,t} \cdot flow_{i,t+1-n} + \varepsilon_{i,t+1}.$$

The performance measure in quarter t is calculated as the average monthly excess returns (*ExRet*) in column (1), the alphas adjusted by CAPM model (*CAPM*) in column (2), the alphas adjusted by the Fama-French three factors (*FF 3F*) in column (3), the alphas adjusted by Fama-French-Carhart four factors (*Carhart 4F*) in column (4), the alphas adjusted by Fama-French-Carhart four factors plus the Pastor-Stambaugh liquidity factor (*4F+Liq*) in column (5), the alphas adjusted by Fama-French five factors (*FF 5F*) in column (6), and the alphas adjusted by the hedge fund seven factors in column (7) (*HF 7F*). The dependent variable $flow_{i,t+1}$ is calculated as the net capital flow to the fund in quarter $t+1$ divided by the fund's TNA at the end of quarter t, and is winsorized at the 1st and 99th percentiles within each quarter. Control variables include lagged capital flows in the previous four quarters. The last row reports the difference between G2 funds and G0 funds. Standard errors with Newey-West correction are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

DepVar =	$Flow_{t+1}$						
	ExRet	CAPM	FF 3F	Carhart 4F	4F+Liq	FF 5F	HF 7F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
G0(=0)	2.205***	2.739***	2.452***	2.750***	2.126**	2.022**	1.564***
	(0.350)	(0.412)	(0.496)	(0.517)	(0.735)	(0.350)	(0.413)
G2(⩾20%)	5.527***	10.587***	8.155***	8.205***	8.527***	3.939***	4.233***
	(1.560)	(2.434)	(2.544)	(2.589)	(2.568)	(1.472)	(1.359)
G2-G0	3.322**	7.848***	5.703**	5.455**	6.401***	1.916*	2.669**
	(1.664)	(2.287)	(2.413)	(2.437)	(2.068)	(1.125)	(0.953)

Table 2.A.10: Flow-Performance Sensitivity Based on Cross-Sectional Performance Ranking

This table repeats the analyses of Table 2.8 but uses cross-sectional rankings of fund performance instead of the direct performance measure. We classify mutual fund/quarter observations into three groups: G0 includes all mutual funds that do not use short sales in any of the previous eight quarters (combining the previous G00 and G01); G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. For each group of funds (G0, G1, or G2), we run Fama-MacBeth regressions and estimate the flow-performance sensitivity with the following specification:

$$\mathit{flow}_{i,t+1} = \beta_{0,t} + \beta_{1,t} \cdot \mathit{Performance\ Measure}_{i,t} + \sum_{n=1}^{4} \gamma_{n,t} \cdot \mathit{flow}_{i,t+1-n} + \varepsilon_{i,t+1}.$$

The performance measure in quarter t is calculated as the average monthly excess returns (*ExRet*) in column (1), the alphas adjusted by CAPM model (*CAPM*) in column (2), the alphas adjusted by the Fama-French three factors (*FF 3F*) in column (3), the alphas adjusted by Fama-French-Carhart four factors (*Carhart 4F*) in column (4), the alphas adjusted by Fama-French-Carhart four factors plus the Pastor-Stambaugh liquidity factor (*4F+Liq*) in column (5), the alphas adjusted by Fama-French five factors (*FF 5F*) in column (6), and the alphas adjusted by the hedge fund seven factors in column (7) (*HF 7F*). In each quarter, we rank funds into deciles based on their performance measures. Panel A reports the results where fund performance is ranked across all mutual fund groups, Panel B reports the results where fund performance is ranked within each fund group. The dependent variable $\mathit{flow}_{i,t+1}$ is calculated as the net capital flow to the fund in quarter $t+1$ divided by the fund's TNA at the end of quarter t, and is winsorized at the 1st and 99th percentiles within each quarter. Control variables include lagged capital flows in the previous four quarters. We report the flow-performance sensitivity, defined as the time series average of the regression coefficient $\beta_{1,t}$ for each group of funds. The last row reports the difference between G2 funds and G0 funds. Standard errors with Newey-West correction are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Performance ranking across all fund groups

DepVar =	$Flow_{t+1}$						
	ExRet	CAPM	FF 3F	Carhart 4F	4F+Liq	FF 5F	HF 7F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
G0(=0)	0.055***	0.053***	0.054***	0.047***	0.042***	0.045***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
G1(0-20%)	0.071***	0.072***	0.054***	0.043***	0.051***	0.041***	0.045***
	(0.017)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
G2(⩾20%)	0.165***	0.226***	0.150***	0.151***	0.153***	0.103***	0.121***
	(0.051)	(0.053)	(0.038)	(0.040)	(0.042)	(0.028)	(0.036)
G2-G0	0.110**	0.173***	0.095***	0.104***	0.111***	0.058**	0.085***
	(0.048)	(0.054)	(0.035)	(0.036)	(0.037)	(0.024)	(0.030)

Panel B: Performance ranking within each fund group

DepVar =	$Flow_{t+1}$						
	ExRet	CAPM	FF 3F	Carhart 4F	4F+Liq	FF 5F	HF 7F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
G0(=0)	0.055***	0.053***	0.054***	0.047***	0.042***	0.045***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
G1(0-20%)	0.066***	0.067***	0.056***	0.045***	0.050***	0.043***	0.043***
	(0.017)	(0.012)	(0.013)	(0.011)	(0.012)	(0.012)	(0.012)
G2(⩾20%)	0.138***	0.166***	0.144***	0.145***	0.150***	0.101***	0.115***
	(0.035)	(0.037)	(0.030)	(0.030)	(0.032)	(0.025)	(0.030)
G2-G0	0.083**	0.113***	0.090***	0.098***	0.108***	0.056***	0.079***
	(0.033)	(0.039)	(0.029)	(0.025)	(0.028)	(0.021)	(0.025)

Table 2.A.11: Turnover, Short Positions, and Cash

This table reports panel regression results that investigate the relation between funds' turnover, short positions, and their cash holdings. We classify mutual fund/quarter observations into four groups: G00 includes all mutual funds that are self-restrained from short selling; G01 includes mutual funds that are allowed to short sell but do not use short sales in any of the previous eight quarters; G1 includes long-short funds whose short positions account for less than 20% of the funds' total net assets (TNA) on average in the past eight quarters; G2 includes long-short funds whose short positions account for more than 20% of their TNA on average in the previous eight quarters. For each fund in each quarter, we calculate short% and cash% as the absolute value of stocks in short positions, and the value of cash and cash equivalents to its TNA, respectively. Short% is winsorized above at the value of 100%, and cash% is winsorized at the values of -90% and 90%. We run panel regressions where the dependent variable is cash%, and the independent variables include turnover, short%, and the interaction term between these two. In columns (1) and (2), turnover is measured as a dummy variable (*Turnover Dummy*) that is equal to 1 if a fund's turnover is above the median in each fund group in each quarter. In columns (3) and (4), turnover is measured as a ranking variable (*Turnover Rankings*) indicating turnover quintiles for each fund group in each quarter (the lowest turnover quintile takes the value of 1). We control for time-fixed effects in columns (2) and (4). Standard errors clustered at the time and fund levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Turnover Dummy		Turnover Rankings	
DepVar =	*Cash%*	*Cash%*	*Cash%*	*Cash%*
	(1)	(2)	(3)	(4)
Turnover × *Short%*	0.063	0.063	0.035	0.035
	(0.078)	(0.078)	(0.030)	(0.030)
Turnover	-0.002**	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.000)
Short%	0.716***	0.718***	0.637***	0.639***
	(0.069)	(0.069)	(0.120)	(0.120)
Time FE		Y		Y
# of Obs	99,051	99,051	99,051	99,051
Adj. R^2	0.435	0.437	0.436	0.438

Table 2.A.12: Long-Short Funds with Different Levels of Market Exposures

This table reports the characteristics of long-short (G2) mutual funds with different levels of market exposures. All analyses in this table focus on the sample of G2 funds. For each fund in each quarter, we estimate the rolling CAPM beta based on fund returns in the next 12 months after classification; we then obtain the time-series average of beta for each fund. In Panel A, we sort all G2 funds into four groups according to their beta and report the average fund characteristics including annual expenses, monthly turnover ratio, and the fraction of retail share class (*Retail Share*). *Retail Share* takes the value of 1 if a share class is retail and 0 otherwise, and we compute the fund-level measure by taking the TNA-weighted average across all share classes. In Panel B, we sort G2 funds into two groups and analyze the flow-performance sensitivity for each group (the same exercise as in Table 2.8). We run panel regressions where the dependent variable $flow_{i,t+1}$ is calculated as the net capital flow in quarter $t+1$ divided by the fund's total net assets at the end of quarter t, and is winsorized at the 1st and 99th percentiles in each quarter. The main independent variable, fund performance in quarter t, is calculated as the average monthly excess returns (*ExRet*) in column (1), the alphas adjusted by CAPM model (*CAPM*) in column (2), the alphas adjusted by the Fama-French three factors (*FF 3F*) in column (3), the alphas adjusted by Fama-French-Carhart four factors (*Carhart 4F*) in column (4), the alphas adjusted by Fama-French-Carhart four factors plus the Pastor-Stambaugh liquidity factor (*4F+Liquidity*) in column (5), the alphas adjusted by Fama-French five factors (*FF 5F*) in column (6), and the alphas adjusted by the hedge fund seven factors in column (7) (*HF 7F*). We control for lagged capital flows in the previous four quarters and year-quarter fixed effects in all regressions. T-statistics calculated using standard errors clustered at the year-quarter level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. Panel C analyzes the dispersion in fund beta within each fund family. We divide all long-short products within a family into two halves: those with high and those with low market betas. For each long-short product in the low-beta group, we then match it to a long-short fund in the high-beta group with the largest residual correlation—after controlling for the market factor. Finally, we take the average of this maximum correlation for all funds in the low-beta group and report the distribution of this mean-max correlation across fund families. In the second row of Panel C, we conduct the same procedure and additionally require that the difference of betas for each fund pairs to be higher than 0.3. The panel reports the mean, the median, and the 5th/25th/75th/95th percentiles.

Panel A: Fund characteristics

Beta Group	0th - 25th	25th - 50th	50th - 75th	75th - 100th
Annual Expenses	1.63%	1.89%	1.68%	1.44%
Monthly Turnover	0.277	0.314	0.136	0.139
Retail Share	0.405	0.406	0.481	0.307

Panel B: Flow-performance sensitivity

DepVar =	$Flow_{t+1}$						
	ExRet	CAPM	FF 3F	Carhart 4F	4F+Liq	FF 5F	HF 7F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low Beta	0.929	7.255***	8.309***	6.576***	6.142***	4.776**	3.990**
	[0.54]	[3.27]	[3.39]	[2.96]	[2.82]	[2.68]	[2.25]
High Beta	4.879**	11.55***	7.786***	7.058***	6.092***	6.168***	4.687***
	[2.25]	[5.61]	[4.03]	[3.49]	[3.23]	[3.59]	[4.33]

Panel C: Return correlation within fund families

	Mean	5th	25th	50th	75th	95th
Residual correlation	0.351	-0.201	0.100	0.355	0.616	0.885
Residual correlation (beta difference > 0.3)	0.239	-0.288	0.041	0.296	0.430	0.627

Chapter 3

Why Mutual Funds Decline in 401(k)s

Co-authored with Jiaxing Tian

This study investigates the decline of traditional mutual funds, focusing on the substitution of mutual funds by collective investment trusts (CITs) in the 401(k) pension investment, and offers insights from both demand and supply sides. Employing several datasets, we demonstrate that CITs are adopted due to their lower fees, comparable returns, and customized nature, aligning with investor preferences sensitive to cost rather than financial transparency. Moreover, mutual fund companies with positive signals, such as past returns and ratings, are incentivized to introduce CITs to reduce auditing costs and gain market shares in 401(k)s. The surge of CITs in 401(k) menus has implications for pension plan governance, with better-governed plans more likely to incorporate CITs. Our findings suggest potential welfare improvements in this delegated asset management model, with investors benefiting from lower total investment costs and mutual fund companies gaining inflow stability. Overall, our research contributes to understanding the dynamics of non-mutual fund investments and their implications for financial markets and investors.

3.1 Introduction

Traditional mutual funds have experienced declining market share in certain sectors.[1] This trend is particularly evident in pension investments, especially within 401(k) defined contribution plans. In 2009, mutual funds held over $1 trillion in 401(k) assets, accounting for approximately 47.1% of total plan assets. By the end of 2020, this share had declined to 39.3%, or $2.5 trillion.

The decline in mutual fund usage raises questions given the growth of passive investing and the historically strong role of mutual funds. A detailed analysis of the substitution process is needed to understand this shift. Explaining the decline in mutual fund investment and the corresponding rise in alternative vehicles is key to understanding investor behavior and institutional responses. Differentiating mutual funds from competing products helps clarify investor preferences and supports the development of more tailored financial offerings. On the supply side, understanding asset managers' motivations—such as markup opportunities, brand leverage, and managerial capacity—provides insight into product introduction decisions.

Despite the importance of this shift, there is limited empirical evidence on why alternative vehicles are gaining ground, largely due to data constraints. To identify potential causal mechanisms, it is important to study a market that captures both demand- and supply-side dynamics. While we do not attempt to establish causality, this paper provides empirical evidence from the 401(k) defined contribution market to document the substitution of mutual funds by collective investment trusts (CITs). Figure 3.1 presents the time series of 401(k) asset allocations: mutual fund assets grow slowly, while CITs expand steadily; other vehicle types remain relatively stable over the past decade.

In 401(k) plans, approximately 2.5% of mutual fund investments have been replaced by CITs, which reached $2.33 trillion in assets under management by the end of 2020. CITs

[1] Notably in target date products: assets in non-custom TDF portfolios fell from $3.25 trillion at the end of 2021 to $2.83 trillion at the end of 2022, marking a 13% decline.

offer lower management fees and expense ratios but are less financially transparent and highly customized. To study this substitution with granular data, we compile and merge multiple datasets to identify CIT-level returns and costs. We construct balance sheets and income statements for all CITs used in 401(k) plans and develop methods to infer their flows and potential holdings. Most CITs are managed by large mutual fund companies such as Vanguard and Fidelity, and over half have a twin mutual fund sharing similar names, management teams, benchmarks, portfolio holdings, and returns. However, unlike mutual funds, CITs are not audited by the Securities and Exchange Commission (SEC). To conduct a comparative analysis and explore potential causal mechanisms, we identify a set of CIT–mutual fund twin pairs.

Using this dataset, we examine the drivers of CIT adoption from both the demand and supply sides. On the demand side, CITs are, on average, 50% cheaper than comparable mutual funds and deliver similar returns. We decompose the CIT expense structure and find that the fee advantage arises from both lower disclosure/auditing requirements and reduced marginal investment costs. In 401(k) plans, investors are more sensitive to fees and less responsive to short-term returns—particularly in actively managed flows. Flow sensitivity to expenses is nearly five times higher than to returns, especially in CITs. Investors are also willing to forgo financial transparency and mitigate this by relying on twin mutual funds as signals when evaluating CITs.

On the supply side, the low sensitivity of flows to returns—but high sensitivity to fees—creates incentives for mutual fund companies to transition to CITs, which allow them to reduce compliance, administrative, and distribution costs. Mutual funds with stronger historical performance, higher ratings, and lower expenses are more likely to issue new CITs, as they are better positioned to send positive signals and distinguish themselves in a less transparent environment. A 1% increase in past returns raises the probability of CIT issuance by 0.52% unconditionally. These funds also tend to have lower marginal costs, allowing them to offer lower fees without reducing markups. We estimate that marginal costs account for less than 50% of reported expenses in these funds, and that markups are often underestimated. These findings contribute to a broader understanding of the mutual fund industry's structure, particularly cross-sectional variation in markups and marginal revenues.

Beyond supply and demand factors, the delegated nature of asset management in 401(k) plans suggests that CIT adoption also reflects broader governance considerations. Plan sponsors with stronger governance—proxied by practices such as third-party audits or greater participant bargaining power—are more likely to incorporate CITs into plan menus. Service providers, many of whom are also affiliated with mutual fund companies, experience lower turnover rates when CITs are present in the menu, indicating a preference for historical adoption and increased stability in provider relationships.

Finally, CIT adoption appears to improve welfare outcomes within the delegated agency framework. While investors are more responsive to direct costs when selecting CITs, they exhibit less sensitivity to indirect costs, such as service provider fees. Although mutual fund companies may relinquish some marginal revenue by transitioning to CITs, they are often compensated through revenue-sharing arrangements within 401(k) asset management services. Service providers, in turn, face lower turnover risk and receive higher fees when offering CITs. As a result, total investor costs—combining both direct and indirect components—decline. Mutual fund companies benefit from more stable flows and increased market share in the 401(k) channel, while service providers effectively break even by capturing greater compensation. Counterfactually, in the presence of reduced auditing and disclosure costs and sufficient signaling mechanisms, all three parties—investors, fund companies, and service providers—are likely to benefit.

Our research contributes to several strands of the literature, with a primary focus on understanding non-mutual fund investments. Prior studies have examined pooled separate accounts (PSAs), which lack singular ownership features and are typically operated by insurance companies.[2] While CITs and PSAs share certain characteristics, CITs generally charge lower fees and are not bundled with additional services. Nevertheless, both

[2]For a detailed discussion of PSA categories, see Evans et al. (2023).

exhibit sensitivity to expense ratios, turnover, and size (Elton et al., 2012).

Emerging evidence suggests that non-mutual fund products may outperform mutual funds due to superior managerial actions (Chen et al., 2017), size-related advantages (Jones et al., 2022), and greater factor exposures (Gerakos et al., 2021). Our findings add more generalizable evidence by highlighting the role of cost savings and selection on marginal costs.[3] Additionally, both mutual funds and non-mutual fund products are found to lack persistent alpha and exhibit return homogeneity (Busse et al., 2010). Institutional and sophisticated retail investors increasingly prioritize fees, driving the shift toward non-mutual fund products (Evans and Fahlenbrach, 2012; Beggs et al., 2022). High-skill managers may use strong performance to offset the costs associated with reduced transparency (Gervais and Strobl, 2020). In this context, the 401(k) market offers a strong institutional fit by matching sophisticated investors with managers seeking to optimize transparency and cost trade-offs.

Our research also aligns with the literature on demand-side preferences and behaviors in long-term investment. Previous studies, such as Wiedenbeck et al. (2012) and Shnitser (2023), show that a significant portion of assets are allocated to non-mutual fund products, which continue to receive stable flows (Akepanidtaworn et al., 2023), underscoring the importance of understanding investor behavior. Investors in delegated asset management settings are particularly responsive to soft factors and tend to trust their agents in most cases (Jenkinson et al., 2016). We demonstrate that such trust also depends on credible signals, which reduce the agency's turnover risk once trust is established. While our findings are closely related to existing research, we highlight marginal differences arising from the unique characteristics of CITs. For example, Chen et al. (2013b) finds that outsourced funds often underperform, indicating that investors are more sensitive to products managed by advisory firms. We show that investors are primarily fee-conscious and rely on stronger external signals when investing in products with potential conflicts of interest. This is consistent with the evidence in Ben-David et al. (2022).

[3] That said, some research has shown that non-mutual fund products may underperform due to higher active share and risk-taking behavior; see Cremers et al. (2019).

Understanding these non-mutual fund products helps clarify financial puzzles (Huang et al., 2023b) and improves the framework of delegated asset management. In our case, fee sensitivity may help explain why funds attempt to obscure costs through complex investment structures (DeHaan et al., 2021). While prior work shows that fiduciary duties can improve returns through enhanced compliance (Bhattacharya et al., 2019), we find that they may also prompt a wave of product innovation designed to avoid such compliance. These compliance costs are a primary driver of change, not only for asset management firms (Kalmenovitz, 2023), but also for plan sponsors.

This paper also contributes to the literature on 401(k) investment and menu choice. Prior studies often treat menu design as exogenous or focus on the bargaining outcomes between plan sponsors and asset managers (Huberman and Jiang, 2006; Davis and Kim, 2007; Cohen and Schmidt, 2009; Pool et al., 2016; Tang et al., 2010; Pool et al., 2022). Sialm et al. (2015) examine the determinants of 401(k) menu offerings and fund flows; we contribute by emphasizing the role of fees and past returns in shaping vehicle choice. Revenue-sharing arrangements in 401(k) plans are also central to our analysis.

Lastly, we contribute to the understanding of marginal costs and markups across investment vehicles. Ying Luo (2002) provides a foundational model of mutual fund fee-setting, and several empirical studies explore manager markups. An et al. (2023), for instance, use index provider payments to explain ETF markups. We show that marginal costs account for less than 50% of reported expenses, while marginal revenue exceeds reported levels due to revenue-sharing structures. Our results serve as a first step toward calibrating markups for large mutual fund teams, particularly when deciding whether to introduce CITs.

This paper is structured as follows: Section 3.2 introduces the institutional background. Section 3.3 describes the CIT data sources and the construction of key variables. Section 3.4 analyzes the demand and supply side factors that drive the substitution between mutual funds and CITs. Section 3.5 examines pension plan governance and evaluates the welfare implications of CIT adoption in a delegated asset management framework. Section 3.6 concludes.

3.2 The Institutional Background

Private pension plans are permitted by the Employee Retirement Income Security Act of 1974 (ERISA) to hold certain types of indirect investment vehicles. Those vehicles should file their annual returns in Form 5500 to the Department of Labor (DOL), so they are called "Direct Filing Entities" (DFEs). The DOL exempts pension plans that invest in them from providing detailed financial information on DFEs, which renders these DFEs much less transparent compared to other open-end investment vehicles (Wiedenbeck et al. (2012)). CITs – also known as collective funds, commingled funds, common funds, and common trust funds – make up a significant proportion of these DFEs. Subject to ERISA, only qualified retirement plans, including defined benefit plans and 401(k) plans, are eligible to invest in CITs during our 2009-2020 sample period.[4]

CITs are funds maintained by banks or trust companies, regulated at the federal and state level by the Office of the Comptroller of the Currency (OCC).[5] On the contrary, open-end mutual funds operate under the U.S. Securities and Exchange Commission (SEC) regulation, subject to the Securities Act of 1933 or the Investment Company Act of 1940. The OCC typically imposes less regulatory oversight than the SEC's comprehensive regulations on mutual funds, encompassing registration, operational procedures, disclosure, and reporting mandates, which partially account for the lower and more flexible cost structure associated with CITs. We present a detailed comparison between

[4]On March 5th 2024, the House of Representatives voted to permit CIT use in 403(b) plans. Although it is beyond the sample of this paper, this may provide some hints for future studies in the defined contribution plan investment vehicles.

[5]Although CITs must be maintained by a bank or trust company, asset management companies can still participate in this surging market in several ways. Fund families affiliated with bank conglomerates issued CIT products directly through their affiliated banks; some asset managers established their own fiduciary trust companies; others served as advisors to CITs issued by banks or trust companies. In September 2020, the SEC announced a settled administrative proceeding requiring banks or trust companies to exercise "substantial investment responsibility" when maintaining the CITs, see https://www.sec.gov/files/litigation/admin/2020/33-10869.pdf. No matter how banks or trust companies undertake their duty in managing CITs, it is common for traditional mutual fund families to serve as the investment managers for these CITs, a focus we will maintain throughout this paper.

mutual funds and CITs regarding regulations, disclosures, and investment costs in Table 3.1.

CITs have been mainly used by defined benefit plans since 1936, when Congress provided tax-exempt states to these trusts. Since 2000, CITs have started to be traded on the National Securities Clearing Corporation (NSCC) platform, offering daily valuation and trading akin to mutual funds, enabling this investment vehicle to gain popularity among defined contribution plans. The Pension Protection Act in 2006 allows 401(k) plans to use CITs as their qualified default investment alternatives (QDIAs),[6] again boosting the usage of CITs in the 401(k) menu. By the end of our sample period, since 2020, some CITs were permitted to have NASDAQ tickers and to share their market data on the platform.

3.3 Data Descriptions

This section introduces collective investment trusts (CITs) and outlines the associated data. Our main contribution is to collect and merge information on this high-volume vehicle in private pensions. Despite the opacity of CITs, we extract return and flow data from multiple public databases.

3.3.1 401(k) investments

Our primary data sources consist of the DOL Form 5500 filings and BrightScope Beacon. Defined contribution plan sponsors are required to file DOL Form 5500 annually. Especially plans with more than 100 participants by the end of the year must also file their detailed schedule of assets in the appendix of Form 5500 Schedule H. BrightScope Beacon, covering more than 90% of 401(k) defined contribution plans, consolidates plan-level

[6]QDIAs are the default investment options used when an employee makes contributions to the plan without designating how the funds should be allocated. Plans generally adopt target date strategies or other balanced investment vehicles as their QDIAs.

investment data from Schedule H and Form 5500's appendix. The cumulative investment across each option is aggregated across all plan participants. We obtain plan holdings from BrightScope Beacon, and other plan-level details from Form 5500 filings, including plan location and industry, employee contribution and employer matching scheme, and expenses charged by plan service providers.

Our sample period is from 2009 to 2020. We start the sample in 2009, as BrightScope Beacon had severe holding data missing in 2008, and DOL started requiring Form 5500 to be filed electronically on January 1st, 2009. BrightScope Beacon reports detailed types of investment options, including mutual funds, CITs, separate accounts, guaranteed investment contracts (GICs), etc. We exclude small plans with end-of-year total assets less than $1 million or less than 5 investment options in the menu. We also require the sum of all investment option balances over plan total assets greater than 90%. As our analysis focuses on 401(k) plans replacing mutual funds with CITs, we require the plans to hold at least one mutual fund or CIT over the entire sample period. This selection criteria results in a final sample of 487,783 plan-year observations with 78,680 unique plans.

3.3.2 Collective investment trusts

Our data on CITs comes from three sources: DOL Form 5500, BrightScope Beacon, and Morningstar Collective Investment Trust database. Direct filing entities, including CITs, must submit Form 5500 to DOL annually. They report the plans invested or participated in the DFEs in Schedule D Part II of Form 5500. We match these filings with the plan CIT holdings from BrightScope Beacon based on plan identifiers, holding balances, and CIT names. We then manually match CITs to Morningstar based on the trust names and their management companies. Like mutual funds, CITs may have multiple share classes reported to Morningstar. We compute the TNA-weighted average across all share classes to generate the trust-level returns and expenses. For CITs reporting their share class names, we can match them to Morningstar at the share class level.

For the remaining CITs, we match them to Morningstar at the trust level and use the aggregated trust-level characteristics from Morningstar. We obtain other CIT features, including investment category, index trust indicator, and turnover, from Morningstar as well. Although managers only have to report their CITs voluntarily to Morningstar, and we cannot entirely match the CIT holdings, the matched CITs with Morningstar identifiers account for more than 85% of total CIT assets held by 401(k) plans by the end of 2020.

Unlike mutual funds, which have fixed expenses for each share class, CITs are more flexible in their costs, and plans may negotiate with CIT managers to gain their own plan-specific expenses. As we are interested in the total expenses of a CIT paid by plan participants, we manually construct trust-plan-year expenses from Form 5500. CITs must report their financial information in Schedule H of Form 5500 and their investments in other DFEs in Schedule D Part I. We define the annual expenses of investing in CITs as the administrative expenses over the average of plan begin-of-year and end-of-year total assets, reported in the Income and Expense Statement in the CIT's Schedule H. However, a large proportion of CITs operate in a fund-of-fund or trust-of-trust structure, especially for target-date CITs. That is, they invest in other DFEs or mutual funds, charging two layers of expenses. We collect the CITs' holdings in DFEs from Schedule D and obtain their annual expenses similarly from their Form 5500 filings. For CITs holding mutual funds, we gather the underlying fund expenses from Morningstar. Following Brown and Davies (2020), the total annual expenses of a CIT paid by a certain plan are the sum of the trust-of-trust fees and the underlying assets' fees. For unmatched CITs or CITs with apparent data errors in the Form 5500 reported expenses, We supplement them with expenses from Morningstar. We also match the mutual fund holdings from BrightScope to Morningstar using tickers, fund names, and fund families and collect all essential mutual fund characteristics from Morningstar. We adjust the total expenses for fund-of-funds following the same process as for CITs.

Our next step of analysis is to identify twin CITs. Similar to Jones et al. (2022) and

Huang et al. (2023b), we start from the Morningstar identifier "Morningstar StrategyID" to identify mutual funds and CITs managed by the same fund managers and follow identical investment process. [7] We pair CITs with the corresponding mutual funds under the same investment strategy by matching StrategyID. For CITs without StrategyIDs, we manually match their mutual fund twins if they have identical portfolio managers and product names. If the CITs voluntarily report their returns to Morningstar, we then require a gross return correlation of 0.90 or greater throughout the history of the twins. [8] We yield 946 distinct CITs with twin mutual funds after the process.

3.4 Main Results

This section investigates the dual drivers behind the rise of CITs and the decline of mutual funds: investor demand and supply-side incentives. On the demand side, the shift reflects investor preferences in long-term retirement investment, particularly the trade-off between transparency and cost. On the supply side, financial firms leverage their comparative advantage to promote CITs, signaling pricing power and capturing associated gains. We treat demand as exogenous from the perspective of the supply side, forming the foundation of our analysis. Given investor preferences, providers have stronger incentives to offer CITs, which may also reveal information about their markups.

3.4.1 Shift from mutual funds to CITs

We begin by documenting the rise of CITs and the corresponding decline of mutual funds in 401(k) accounts. Figure 3.2 shows the investment category breakdown for both

[7] Morningstar describes the process of generating StrategyID as follows, *"The Morningstar identifier that links investments that follow the same investment process. Often investment management companies subadvise more than one mutual fund, and offer equivalent investment pools in separate accounts, collective investment trusts, or other vehicles. Following industry convention, Morningstar groups these substantively identical pools into a single strategy. Morningstar identifies strategies through surveying management companies, as well as performing quantitative and qualitative analysis. StrategyIds are currently available only for strategies that have been reported to our database."*

[8] Replacing the criterion to 0.95 following Evans and Fahlenbrach (2012) does not alter our results. The mean and median return correlations of CITs and mutual fund pairs are 0.994 and 0.999.

vehicles. Panel A indicates that mutual funds are primarily allocated to U.S. equity, although this share has declined over time, while target-date funds (TDFs) have gained prominence since 2012, following the ERISA fee disclosure regulation. By the end of 2020, U.S. equity and TDFs each account for roughly one-third of mutual fund assets.

Panel B reveals that CITs had a similar composition initially, but since 2016, an increasing number have been introduced as TDF-like products. By 2020, nearly half of CIT assets in 401(k) plans are in TDFs, totaling approximately $1.03 trillion in AUM. Despite differences in structure, both mutual funds and CITs in 401(k) plans are concentrated in TDFs and U.S. equity, which together comprise more than two-thirds of total assets.

This shift in composition suggests that CITs are replacing mutual funds, particularly in target-date products, and are also expanding in domestic equity. To provide empirical evidence, we analyze plan menu changes. Specifically, if investment vehicle f appears in plan i's menu at year $t-1$ but is removed by year t, and another vehicle g in the same Morningstar category is added to the plan by year t, we define this as a replacement of f by g.[9] For TDFs, we additionally require f and g to have identical target retirement dates.

Figure 3.3 shows the time series of replacement volumes and the share of total 401(k) assets affected. The blue bars and lines denote mutual fund to CIT replacements, which have risen steadily since 2012, reaching nearly $100 billion annually. Note that we only classify a replacement when deletion and addition occur within the same category-year, so the true number of deletions and additions may be higher. In contrast, reverse switches—CITs replaced by mutual funds—remain limited and stable, averaging $20 billion annually, or roughly 1 bp of total 401(k) assets. These cases likely reflect idiosyncratic factors, such as service provider turnover.

[9] We follow BrightScope Beacon's mandate win/lose convention. When a plan replaces vehicle f with g, it typically issues a fund change notice to participants and automatically transfers assets. For an example, see: https://www.nmpera.org/assets/uploads/downloads/deferred-compensation-performance-reports/PERA-NM-Fund-Change-Notice-March_April-2023_FINAL-draft.pdf.

3.4.2 Summary statistics

We continue our analysis by comparing mutual funds and CITs in 401(k) plans. Panel A of Table 3.2 presents basic characteristics and return-related statistics. We summarize twin CIT- and fund-year observations to ensure comparability. In general, CITs are highly customized for 401(k) plans. Over half of the CITs allocate more than 97% of their assets to 401(k)s, yet each trust serves a median of only 6 plans. In contrast, twin mutual funds allocate just 26% of assets to 401(k)s but typically serve 110 plans. CITs are smaller in size—just one-eighth the total net assets of their mutual fund counterparts (median TNA: 219 vs. 1,761 million USD)—and are younger in inception age (mean: 9.35 vs. 16.93 years).

CITs also exhibit lower turnover rates and, more importantly, lower expense ratios than their twin mutual funds. On average, the turnover rate is 15% lower in CITs (45.28% vs. 53.3%), though the gap narrows at the median. CITs maintain significantly lower expenses, which may reflect both lower transaction costs and reduced disclosure requirements. We explore this further in later sections.

In terms of performance, CITs outperform in net returns and display lower volatility and idiosyncratic volatility (IVOL). The 1-year return advantage of 25 bps largely reflects the 33 bps fee differential. Gross returns for mutual funds may be slightly higher—by 6 to 8 bps—but CITs show lower overall volatility and IVOL. Alphas are similar across both vehicles, with mutual funds marginally outperforming in four-factor alphas. However, there is no clear evidence that mutual funds achieve higher Sharpe ratios.

Despite significant differences in customization, size, age, and costs, most CITs have twin mutual funds and are otherwise similar in structure.[10] We classify CITs into five categories based on whether they have a mutual fund twin and whether they voluntarily report to Morningstar. For CITs without twins and without Morningstar data, we identify

[10]Appendix Table 3.A.1 shows that mutual funds with and without twin CITs differ in several characteristics, including fees and returns, while CITs with and without twins are largely indistinguishable.

plan-specific CITs—products tailored for a single plan, often including the plan name in the title and being exclusively held by that plan. Figure 3.4 plots the time series of CIT growth by type, which suggests that most CITs in our sample have twin mutual funds and voluntarily report to Morningstar. In the following sections, we examine why CITs with twins are more likely to be adopted, from both supply- and demand-side perspectives.

Panel B of Table 3.2 summarizes the 401(k) plans in our sample. The median plan has $12 million in assets and 300 participants. Our sample includes over 44,000 plans, most of which have participation rates above 80%, covering approximately 5% of the U.S. population. The average participant contributes $4,842 annually, with employers matching nearly half.

Focusing on the investment option of plans (shown in the lower two blocks of Panel B), over one-sixth of plans offer CIT options. These plans include a median of 26 menu options—15 mutual funds and 7 CITs. Other investment vehicles (see Section 3.3) play only a minor role. Most menus consist of just one or two types: mutual funds, CITs, or both. In terms of assets, mutual funds still hold roughly half, while CITs account for about 33%. Overall, CIT adoption in 401(k) plans is substantial and increasing.

3.4.3 Switching driven by fee savings

We now turn to fee differences, which are central to understanding the switching behavior—particularly given that most CITs have a twin mutual fund. We collect CIT expense data from Form 5500 and supporting sources, as outlined in Section 3.3, and decompose these fees for comparison with mutual fund expenses. Table 3.3 reports time-series averages of cross-sectional statistics. Each panel presents equal-weighted (EW) averages in the first row and value-weighted (VW) averages (weighted by 401(k) AUM) in the second row. The last columns show the share of each fee component as a percentage of total expenses.

Panel A shows that CIT expenses consist of three parts: professional fees, contract fees, and investment fees. Professional fees include payments for external accounting, actuarial, legal, and valuation services. Contract fees refer to payments to administrators handling plan-level operations. These two components are minimal—around 3 bps in the EW case, and even lower in the VW case. The majority of expenses stem from investment fees, which represent the cost of portfolio management and are analogous to mutual fund management fees. These fees average 25 bps (EW) and 9 bps (VW), accounting for about 90% of total CIT expenses. This level is substantially lower than in traditional vehicles.

Panel B decomposes mutual fund expenses into four parts. To improve comparability, we focus on the cheapest share class for each mutual fund, since most 401(k) assets are invested in these classes. The D&T component includes 12b-1 distribution fees, as well as transfer agent and custodian fees.[11] D&T fees average about 12 bps across all share classes and 7 bps in the cheapest classes, comprising 18% of total expenses. Most CITs avoid these costs through direct plan negotiations or revenue-sharing arrangements. Notably, many popular TDFs are offered as both mutual funds and CITs, allowing sponsors to reduce fees without changing the underlying product.

Regulatory fees (including registration, shareholder reporting, and board governance) and administrative fees (covering expenses related to accounting, auditing, legal services, insurance, and administration) are around 6–7 bps across weighting methods and share classes. These are comparable to the professional and contract fees of CITs. Regulatory and administrative costs account for roughly 13% (EW) to 30% (VW) of mutual fund expenses. Since CITs are exempt from these disclosure obligations, they save substantially—potentially reducing costs by 13–30%. Together with D&T savings, total cost reductions range from 30% to 50%.

Additional savings stem from lower investment costs. Mutual fund investment fees average 58–66 bps (EW) and 27–31 bps (VW), which are 50–60% higher than those for CITs. Because most CITs are recently created and linked to existing mutual funds, their

[11] These services are typically duplicated in mutual funds but are handled by plan providers in CITs. See https://crr.bc.edu/are-401k-plans-spending-1-billion-in-unnecessary-fees-to-mutual-funds/ for further discussion.

marginal management costs are lower. Typically, the same manager oversees both vehicles using identical strategies. In many cases, separate accounts or portfolios in 401(k) plans closely match mutual funds in returns and volatility, despite not being explicitly labeled as twins.

These findings suggest that the true marginal cost of mutual funds—especially those with twin CITs—is over 50% lower than reported. Thus, mutual fund markups may be even larger than previously estimated. While we acknowledge potential endogeneity and selection concerns, we treat these results as a first step in highlighting the (possibly substantial) pricing power embedded in mutual fund fees.

3.4.4 Demand-side preferences and flows

We now turn to the demand-side preferences in 401(k) asset management to explore the rationale behind the switch from mutual funds to CITs. While our analysis takes an ex-post perspective and does not establish causality, we identify necessary conditions for understanding the surge in CIT adoption. Specifically, we examine three aspects of investor behavior: flow sensitivity to fees, sensitivity to past returns, and the adoption of new CITs. These findings suggest that investors are willing to trade off financial transparency for lower-fee products, using these relatively opaque vehicles while still responding to performance signals.

3.4.4.1 Flow sensitivity

Panel A of Table 3.4 presents results on flow-return sensitivity in 401(k) plans, offering a general overview of investor anchoring in long-term pension investment. Following Sialm et al. (2015), we define 401(k) and non-401(k) flows to a given fund or CIT f at time t

as:

$$\begin{aligned} 401(k)Flow_{f,t} &= \frac{\sum_p AUM_{p,f,t} - \sum_p AUM_{p,f,t-1}(1+r_{f,t})}{\sum_p AUM_{p,f,t-1}(1+r_{f,t})} \\ Non-401(k)Flow_{f,t} &= Flow_{f,t} - 401(k)Flow_{f,t}. \end{aligned}$$

The regression specification is as follows:

$$Flow_{f,t} = \beta_1 Expense_{f,t-1} + \beta_2 Ret_{f,t-1} + \Gamma Controls_{f,t-1} + \theta_t + \phi_{fc} + \epsilon_{f,t}.$$

We use 3-year cumulative returns, CAPM alphas, and Fama-French-Carhart four-factor alphas as return measures. Vehicle fixed effects account for branding, while time fixed effects absorb market-wide shocks. Following Sialm et al. (2015), we also show the difference across groups.

We find substantial flow-fee sensitivity in 401(k) flows: a 1 bp decrease in fees leads to a 26.65 bps increase in flow, which is more than four times the flow-fee sensitivity observed for investments outside 401(k) plans. This result is consistent with the literature showing that pension investors are highly sensitive to investment costs (Badoer et al., 2020; Kronlund et al., 2021). Such sensitivity may be a key driver behind the shift from mutual funds to CITs in the pension market, as 401(k) flows respond far more strongly to cost than flows from other mutual fund investors. Return sensitivity is also evident: a 1% increase in annual return raises 401(k) flows by 0.17% and non-401(k) flows by 0.1%. This behavior aligns with the idea that 401(k) investors focus on performance signals but prioritize low-fee products when returns are comparable.

Panel B of Table 3.4 explores these sensitivities separately by vehicle type. For CITs, 401(k) investors respond strongly to fees but not returns, potentially due to the homogeneity of CIT returns or opacity of performance reporting. Most CIT flows come from 401(k) plans, with little activity from non-401(k) sources. For mutual funds, both fee and return sensitivity are observed, with higher responsiveness in 401(k) flows. The sensitivity to 4-factor alpha is stronger among 401(k) flows, possibly due to fiduciary responsibilities and delegated asset management structures.

We further separate flows into those driven by plan menu changes and those from participant choices. We define:

$$\begin{aligned} MenuFlow_{f,t} &= \frac{\sum\limits_{p \in Additions} AUM_{p,f,t} - \sum\limits_{p \in Deletions} AUM_{p,f,t-1}(1 + r_{f,t})}{\sum\limits_{p} AUM_{p,f,t-1}(1 + r_{f,t})} \\ Non - MenuFlow_{f,t} &= 401(k)Flow_{f,t} - MenuFlow_{f,t} \end{aligned}$$

Menu flows capture sponsor-driven changes, while non-menu flows reflect participant-driven investments in existing menu options. Panel C of Table 3.4 implements a piecewise linear regression following Sirri and Tufano (1998), focusing on twin mutual funds and CITs.[12] Vehicles are ranked by 3-year return within Morningstar categories and binned into 100 percentiles. We define:

$$\begin{aligned} LowRet_{f,t} &= \min(Rank_{f,t}, 0.2) \\ MidRet_{f,t} &= \min(Rank_{f,t} - LowRet_{f,t}, 0.6) \\ HighRet_{f,t} &= Rank_{f,t} - LowRet_{f,t} - MidRet_{f,t}, \end{aligned}$$

Menu flows in CITs show weak mid-range return sensitivity, suggesting menu inclusion depends more on extreme performance. In contrast, mutual fund menu flows are more responsive to mid-tier performance. Expense sensitivities are similar across both vehicle types, with CITs benefiting from governance signals via their mutual fund twins. Non-menu flows, driven by participant behavior, show little sensitivity to past performance or fees. This reflects inertia in 401(k) allocation decisions once products are included in the menu.

Figure 3.5 offers further support. Panel A reveals a monotonic relationship between mutual fund returns and flow, with CIT flows remaining stable even in low-return deciles. Panels B and C show similar patterns for CAPM and 4-factor alphas. In Panel D, fee

[12]Results are similar using the full sample.

sensitivity is monotonic for mutual funds but non-monotonic for CITs. While middle-fee CITs attract high flows, those in the highest fee deciles experience sharp declines, consistent with Table 3.2.

Sialm et al. (2015) highlight that additions and deletions by plan sponsors are the primary drivers of fund-level defined contribution (DC) flows, rather than reallocation by individual participants. Following this insight, Figure 3.6 investigates fund deletion behavior. Deletion rates are defined as the proportion of plan menus from which a given fund is removed in a given year. Across all deciles of past returns, CITs exhibit consistently lower deletion rates than mutual funds. In the lowest return decile, for example, CITs are approximately 22% less likely to be deleted than mutual funds. While mutual fund deletion rates increase monotonically as past returns decline, CIT deletion appears largely insensitive to performance history.

3.4.4.2 Plan adoption of new CITs

Table 3.5 analyzes the factors influencing the initial adoption of CITs by 401(k) plans. We estimate a series of logit regressions to predict the probability that a plan adopts a CIT for the first time:

$$Prob(CIT_{p,t} = 1) = \Lambda(\beta Characteristic_{p,t-1} + \Gamma Controls_{p,t-1} + \theta_t + \phi_k + \eta_j).$$

The dependent variable $CIT_{p,t}$ is an indicator equal to 1 if plan p includes no CITs up to year $t-1$ but adds one or more CITs in year t. The model includes time fixed effects θ_t, industry fixed effects ϕ_k, and location fixed effects η_j to account for time trends and geographic or industry-specific information diffusion.

The results show that plans with higher average expenses on existing vehicles—primarily mutual funds—are more likely to adopt CITs. This may reflect greater bargaining power to negotiate customized CITs or a stronger cost sensitivity among plan fiduciaries. These interpretations are aligned, and we cannot separately identify them. Given the long-term trend of declining mutual fund fees, the propensity to switch to CITs would likely increase further.

Several indicators of plan governance are significantly associated with CIT adoption. The presence of affiliated funds on the plan menu is negatively correlated with adoption, likely due to reduced incentives for service providers to shift assets away from affiliated products. Conversely, governance quality measures—such as having a third-party trustee or advisor, regular financial communication with participants, labor union involvement in plan design, and automatic enrollment—are all positively associated with CIT adoption. Among these, third-party advice and labor union bargaining power show the strongest marginal effects. Access to financial advice appears to reduce concerns about the opacity of CITs, while union involvement reflects increased scrutiny and legal compliance, potentially encouraging the use of lower-fee alternatives.[13]

In addition to governance, other plan characteristics influence CIT adoption. Plans that are large but relatively young, with lower average account balances but higher employee deferrals, are more likely to adopt CITs. These plans often originate from younger firms with high-earning, risk-tolerant employees who are open to new investment structures despite limited disclosure.

Menu structure also matters. Plans with small menus that already include vehicle types beyond mutual funds and CITs, and those with products from a broader set of fund providers, are more likely to adopt CITs. Although potentially endogenous, these characteristics may serve as proxies for plan openness and positive prior experiences with financial innovation.

3.4.5 Supply-side issuance decisions

To complement the demand-side analysis, we now turn to the supply side and examine asset managers' decisions to issue new CITs. Table 3.6 reports results from logit re-

[13]We find that after 2015, nearly one-third of 401(k) lawsuits are related to poor performance of menu products.

gressions predicting whether a management company issues a twin CIT for an existing mutual fund. The specification is given by:

$$Prob(TwinCIT_{f,t} = 1) \quad = \quad \Lambda(\beta Ret_{f,t-1} + \Gamma Controls_{i,t-1} + \theta_t + \phi_{fc}).$$

Performance-related variables—including cumulative 3- and 5-year returns, CAPM alphas, Fama-French-Carhart four-factor alphas, Morningstar overall ratings, and both 3- and 5-year rating scores—are significant predictors of CIT issuance. Strong historical performance, especially over longer horizons, increases the likelihood that a fund family issues a twin CIT. Among these metrics, 5-year returns have the largest marginal effect, suggesting that asset managers rely on long-term return stability when signaling product quality to the market. While we acknowledge that returns are endogenous in this context, we interpret them as proxies for unobservable factors such as managerial skill. We do not claim a direct causal link between return and issuance, but the results indicate that performance plays an important role in CIT issuance decisions.

Other fund characteristics also influence issuance. Funds affiliated with one of the Big 10 401(k) families, or those with large family-level market shares, are more likely to issue CITs—likely due to brand strength and the ability to mitigate investor concerns about opacity. In contrast, funds with higher expense ratios are less likely to issue twins. Lower-fee funds have lower marginal costs and can remain competitive even after cutting fees for the CIT version, whereas high-fee funds face profit compression in the CIT market.

Table 3.6 further shows that funds with lower return volatility, lower affiliated fund concentration, and higher 401(k) assets under management are more likely to issue CITs. These attributes may serve as quality signals. Index funds, on the other hand, are less likely to issue twin CITs due to already-low fees and dominant market share. Twin issuers also tend to be smaller funds from larger, younger fund families. These management teams may seek more stable inflows to support early-stage growth. Finally, the original fund's flow sensitivity to fees and returns does not predict issuance decisions. Asset managers appear indifferent to these sensitivities, suggesting that CIT issuance is not primarily driven by optimizing flow responsiveness to pricing or performance.

3.5 Plan Governance and Investment Costs

After examining both demand- and supply-side decisions surrounding CIT adoption, we now turn to the broader implications for 401(k) governance and investor welfare. Investors appear willing to accept reduced transparency in exchange for lower fees, particularly when asset managers benefit from cost savings and increased revenues. Within the delegated asset management structure, service providers—who serve as intermediaries—may receive higher compensation and face lower turnover risk, partially mitigating agency concerns. We focus on two dimensions in this section. First, we investigate whether adopting CITs affects the likelihood that a plan sponsor replaces its service provider, which reflects trust and delegation in plan governance. Second, we assess how participants respond to different components of investment costs—both direct (e.g., fund expenses) and indirect (e.g., service provider fees)—to evaluate cost sensitivity under reduced financial transparency.

3.5.1 CIT adoption and provider turnover

We test the hypothesis that plans adopting CITs are less likely to replace their service providers. In this setting, despite persistent agency frictions and indirect fees, both investors and asset managers may benefit: investors face lower total costs, while fund and trust companies reduce disclosure and regulatory burdens while maintaining acceptable markups. Accordingly, this section focuses on the actual investment costs borne by investors.

We begin by documenting that service providers offering CITs are less likely to be terminated, using an ex-post perspective. Table 3.7 presents results from a logit regression estimating the likelihood that a plan changes its main service provider:

$$Prob(Change\,Provider_{p,t} = 1) \quad = \quad \Lambda(\beta f(CIT_{p,t-1}) + \Gamma Controls_{i,t-1} + \text{Fixed Effects}).$$

The dependent variable Change Provider$_{p,t}$ equals 1 if plan p replaces its main service provider in year t. We define the main provider as the trustee or recordkeeper charging the highest service provider costs in that year. The function $f(CIT_{p,t-1})$ captures plan-level usage of CITs and related indicators in year $t-1$.

Columns (1) and (4) include a dummy variable equal to 1 if the plan menu includes any CITs in year $t-1$. While not intended as a causal estimate, this CIT indicator likely correlates with broader governance traits. Even after controlling for governance-related covariates, the presence of CITs is negatively associated with provider turnover. Unconditionally, CIT-using plans are 6.3% less likely to change their service provider. One explanation is that CITs are often customized and rely on firm-specific relationships; thus, switching providers imposes additional costs via menu disruptions.

The extent of CIT adoption also matters. Columns (2) and (5) compute the share of CIT options in plan p's menu, ranking plans into 100 bins and normalizing the highest to 1. Columns (3) and (6) perform the same ranking based on the share of assets invested in CITs. Both shares of CITs in the investment menu (*% CIT Option*) and shares of CIT value compared to overall plan assets (*% CIT Value*) are negatively correlated with provider turnover. These findings suggest that CIT adoption signals trust in both the service provider and plan sponsor, perhaps due to the opaqueness of CITs. This contradicts the alternative hypothesis that CIT adoption leads to higher provider turnover. Moreover, providers that offer CITs and broader product menus beyond mutual funds are less likely to be terminated—consistent with the interpretation that product expansion serves as a signal of value-added services and reduces the likelihood of dismissal. The most plausible explanation is that CITs align with investor welfare.

3.5.2 Fee sensitivity and investor welfare

As shown in Figure 3.7, service providers earn higher marginal revenue per dollar of assets managed. As they take on additional roles—such as endorsing and gatekeeping CITs—they also act as educators to plan sponsors and participants. Over the past decade, provider costs per $1 of 401(k) AUM have risen from 21 bps to 30 bps. Meanwhile, investor total costs declined from 82 bps to 76 bps, largely due to the adoption of passive and low-fee vehicles like CITs. Given that net-of-fee returns on CITs and twin mutual funds are nearly identical, investors may be better off in this equilibrium.

In Table 3.8, we examine investor response to indirect fees—specifically, service provider charges—when allocating capital. These fees are deducted at the plan level and not always visible to participants at the time of investment decisions. Hence, we expect limited responsiveness—or even a positive correlation—between flows and service provider fees. If higher fees are interpreted as a proxy for more comprehensive services, participants may allocate more to opaque products like CITs. The results support this view.

Panel A of Table 3.8 pools all investment vehicle types. Investor flows are positively associated with service provider fees per dollar ($Expense_{Service}$), but negatively related to fund-level expense ratios ($Expense_{Fund}$). These findings persist after controlling for past returns and their interactions with 3-year performance (Column 2). One explanation is that investors focus more on direct, visible fees, and interpret higher service fees as indicators of improved financial support. We combine fund expenses and provider fees into a "total cost" metric per invested dollar ($Expense_{Service} + Expense_{Fund}$). In Columns (5) and (6), investor flows show no sensitivity to total cost. Notably, a large portion of the service fee accrues to the asset managers: around half of all providers are asset managers, and the rest often share revenue with them (Pool et al., 2022). As illustrated in Figure 3.7, while investors face slightly lower total costs, asset managers earn more than the fees they forgo—maintaining stable 401(k) flows in the process.

Panel B of Table 3.8 separates CITs and mutual funds. For CITs, flows are unresponsive to expense ratios but positively related to provider fees (Columns 1–4). Given the already-low fees of CITs and their dependence on provider trust, this is expected. Plans with higher provider fees see greater CIT inflows, even after adjusting for performance. Overall, total cost remains irrelevant to flow decisions. Columns (5)–(8) focus on mutual funds. In contrast to CITs, investors are sensitive to fund-level expense ratios but not to total cost. This is consistent with mutual funds being substitutable within menus, where fee differences affect allocation. In contrast, CIT fees are often standardized and less salient.

These findings support a broader interpretation. Investors obtain modest cost savings—though smaller than headline fee reductions—while maintaining comparable pre-fee returns in a less transparent environment. Asset managers, especially those with strong reputations and low marginal costs, benefit from issuing CITs: they reduce disclosure obligations, expand 401(k) market share, and capture indirect fee revenue. Finally, service providers that introduce CITs face lower termination risk and are compensated for their expanded role. In this equilibrium, investors, asset managers, and providers all potentially gain.

3.6 Conclusion

By integrating multiple datasets, we document the substitution of mutual funds by collective investment trusts (CITs) in 401(k) defined contribution plans. We analyze the drivers of this transition from both the demand and supply sides. As a foundation for further research, our dataset provides a comprehensive overview of CITs—including balance sheets, returns, fees, and matched (twin) mutual funds.

Comparing mutual funds and CITs, we find that CITs charge lower fees while offering nearly identical products, particularly among large funds. The fee differential arises primarily from two sources: reduced disclosure and auditing costs, and lower marginal investment costs. Although CITs are generally less transparent due to their exemption from SEC regulation, asset management companies compensate by providing alternative signals to investors.

On the demand side, younger and wealthier investors are more willing to trade financial transparency for lower fees and greater customization. Their flows are more sensitive to expenses than to returns. CITs attract stable flows when returns are moderate, while mutual fund flows respond to returns across the full distribution. Investors selecting CITs also rely on positive signals. Plans with stronger governance are more likely to adopt CITs, as sponsors and service providers are better positioned to endorse such products.

On the supply side, asset management companies are more likely to issue CITs when they can credibly signal quality—through high third-party ratings or strong past performance. These firms benefit from cost savings and gain greater market share in the 401(k) space. The resulting profits exceed direct compensation, revealing real markups through indirect revenue channels.

From a social welfare perspective, investors appear better off, despite facing higher indirect fees. The total marginal cost of 401(k) investment declines relative to traditional investment expenses. Flows toward low-fee products are accompanied by rising service provider fees, reflecting compensation for additional responsibilities such as auditing and gatekeeping. Service providers with stronger governance are more likely to include CITs in plan menus, resulting in lower provider turnover and reduced compliance burden. Overall, all parties involved in the transition—investors, service providers, and asset managers—are likely to benefit.

This research has important implications for academics and policymakers, particularly the SEC. Although the transition has emerged from bottom-up market behavior, the SEC currently exercises limited oversight over CITs. Given the high regulation costs associated with mutual funds—borne by both asset managers and investors—the rise of CITs reflects a shift toward cost efficiency. This process provides valuable insight into asset managers' markups and investor preferences for future regulatory and academic work.

Figures

Figure 3.1: Investment Vehicle Types in 401(k)s

This figure reports the time series of 401(k) plan total assets by investment vehicle types from 2009 to 2020.

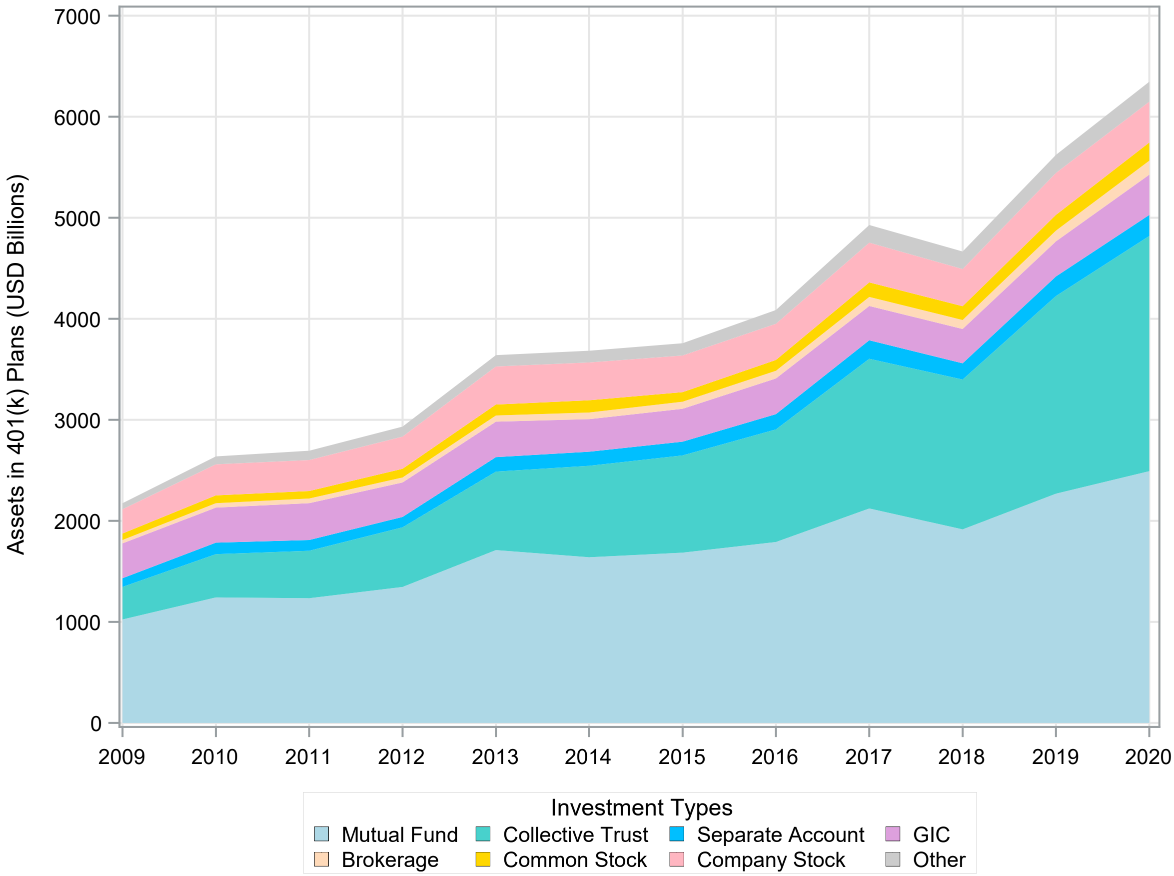
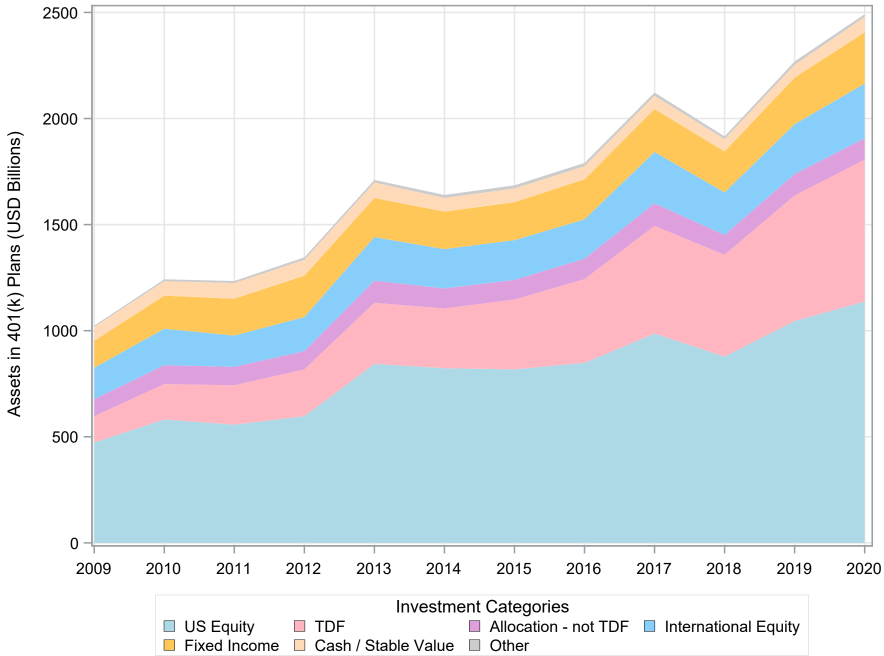


Figure 3.2: Investment Categories in 401(k)s for Mutual Funds and CITs

This figure reports the total value of 401(k) plan assets by investment category, with mutual funds in Panel A and CITs in Panel B. Allocation funds invest in a mix of fixed-income assets and equities. We report target-date funds separately from allocation funds without a specified retirement year.

Panel A: Investment categories for mutual funds



Panel B: Investment categories for CITs

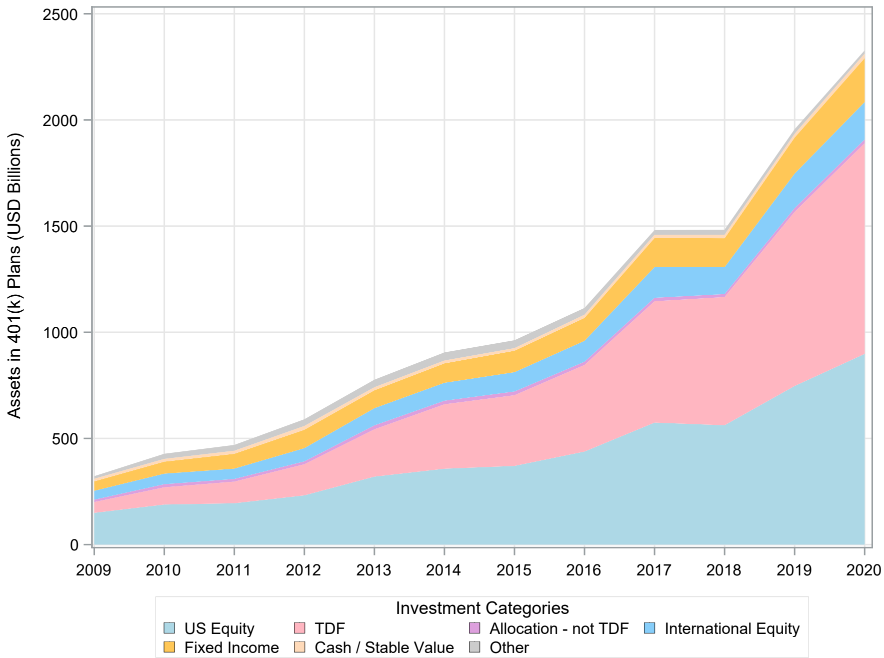


Figure 3.3: Mutual Fund and CIT Substitutions

This figure reports the investment vehicle substitutions in 401(k) assets. If investment vehicle f is included in plan i's menu at the end of year $t-1$ but is no longer in i's menu in year t, and another investment vehicle g from the same Morningstar category as f is added to i's menu by the end of year t, we define this as g replacing f in this plan-year observation. For target-date investments, we further require f and g to have identical target retirement dates. We aggregate option replacements between CITs and mutual funds for each year from 2010 to 2020. The figure includes all CITs and mutual funds, regardless of whether they have twin investment vehicles. We display the aggregated replaced asset values as bars and the replaced assets as a share of total investment vehicle assets as lines. The blue bars and lines represent mutual funds replaced by CITs, while the grey bars and lines represent CITs replaced by mutual funds.

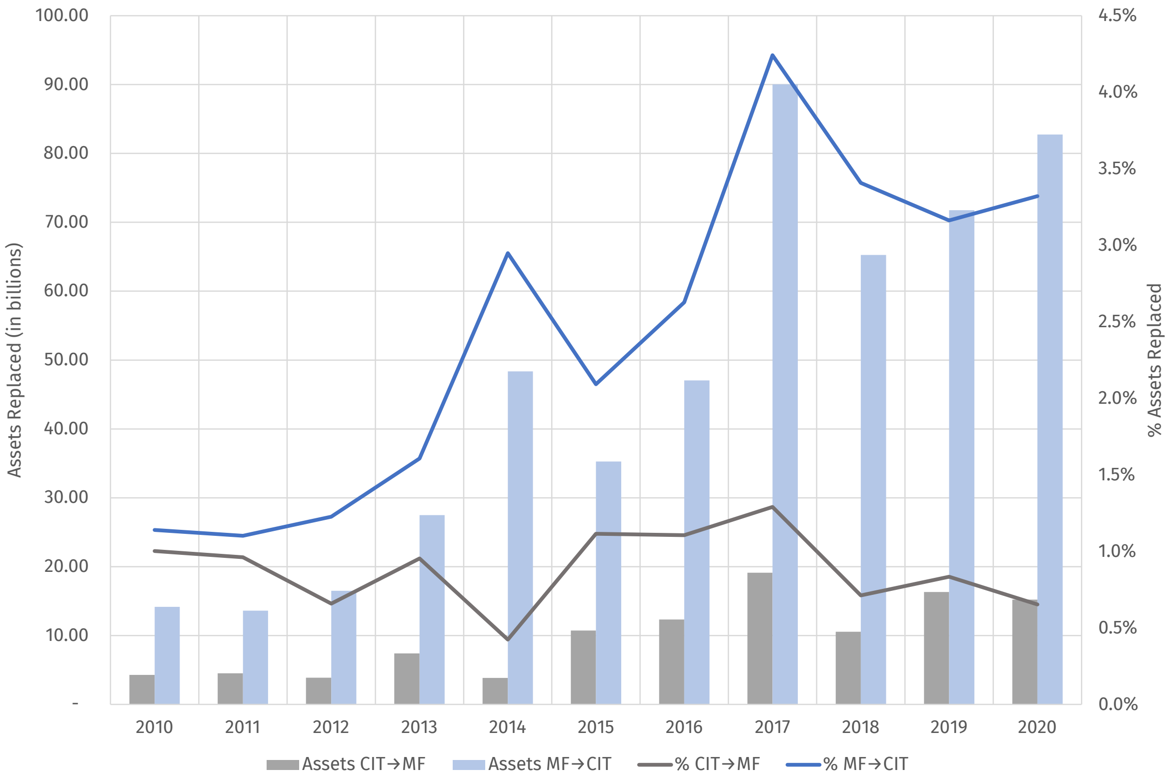


Figure 3.4: Growth of CITs by Category

This figure plots total 401(k) assets in CITs by category. We classify CITs into five subgroups based on whether they have twin mutual funds and whether they voluntarily report information to Morningstar. Among CITs without twin mutual funds that do not report to Morningstar, we further identify plan-specific CITs—products uniquely tailored to a particular plan, identifiable by plan names in their titles and exclusively invested in by the corresponding plan.

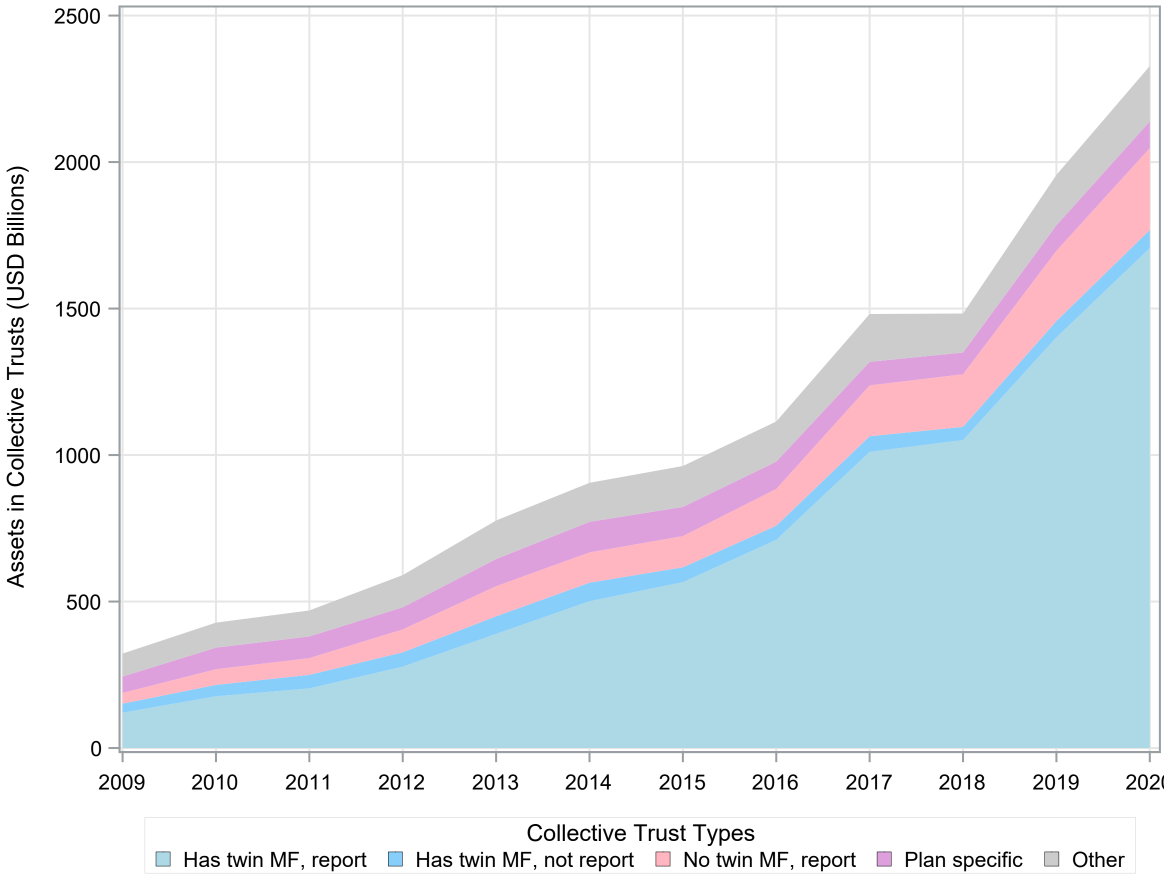
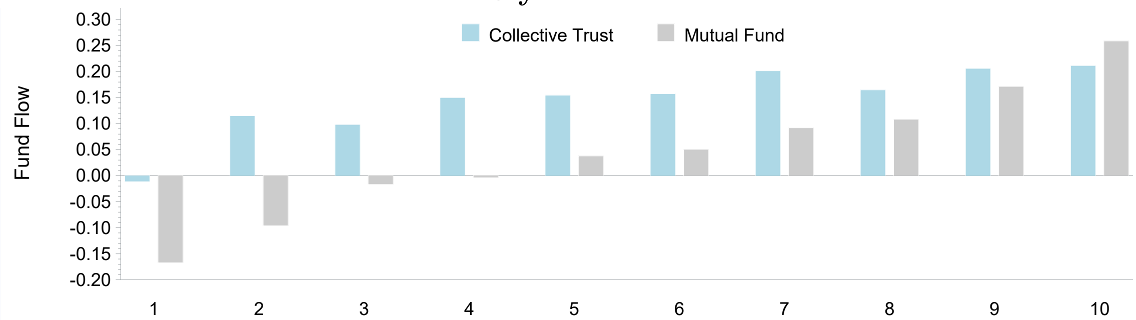


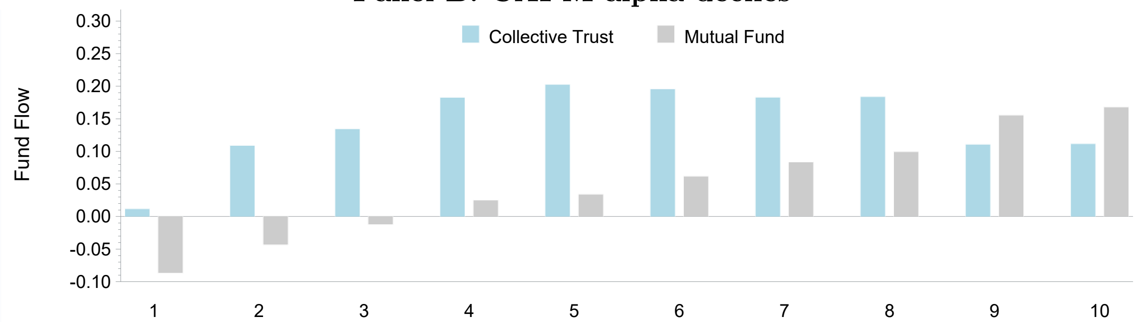
Figure 3.5: Flow-Performance Sensitivity of Mutual Funds and CITs

Each year, we rank CIT and mutual fund cumulative 3-year returns, CAPM alphas, and Fama-French-Carhart four-factor alphas, and fund expenses into 10 groups separately within each Morningstar category. We then compute the equal-weighted average 401(k) flows for each performance decile annually and take the average across years.

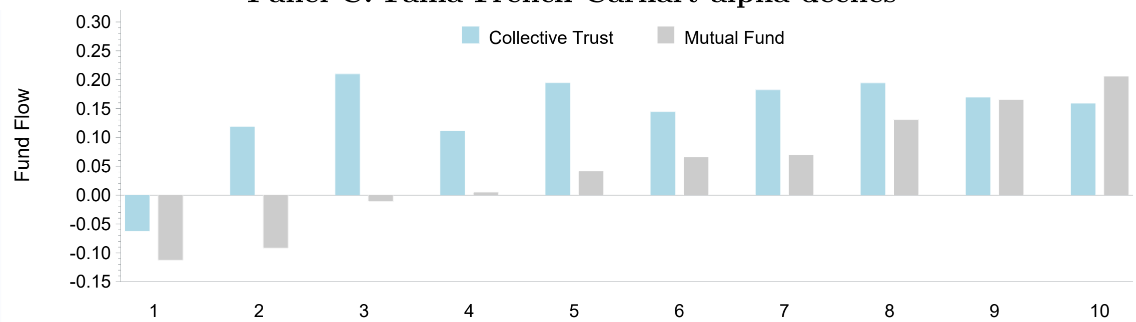
Panel A: 3-year return deciles



Panel B: CAPM alpha deciles



Panel C: Fama-French-Carhart alpha deciles



Panel D: Fund expense deciles

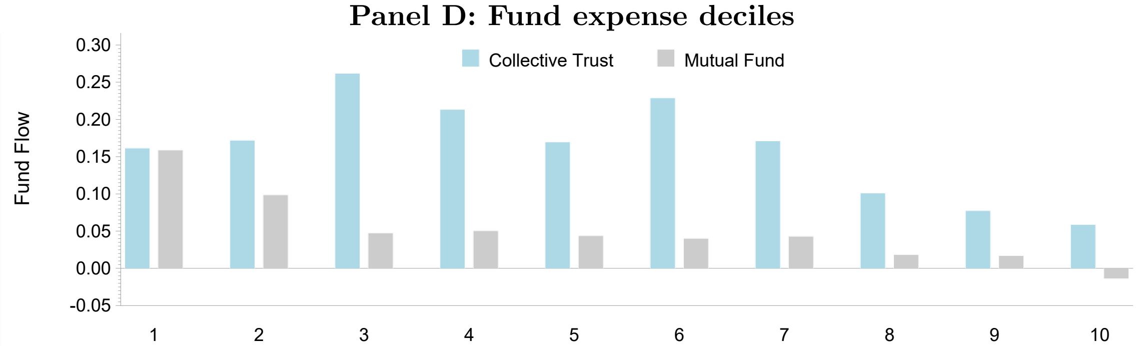
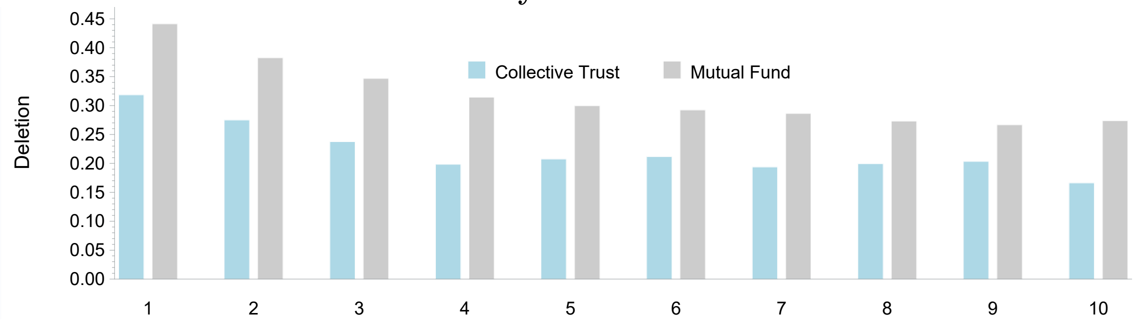


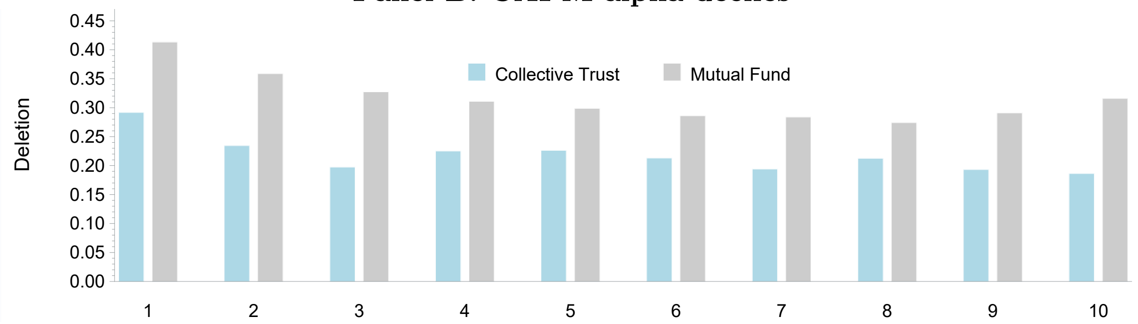
Figure 3.6: Deletion from 401(k) Menus for Mutual Funds and CITs

Each year, for each investment vehicle, we calculate the deletion rate as the number of plans the fund exited this year divided by the number of plans the fund participated in last year. We then rank CITs and mutual funds into 10 groups within each Morningstar category based on their cumulative 3-year returns, CAPM alphas, and Fama-French-Carhart four-factor alphas. Panels A, B, and C report the equal-weighted average deletion rate by investment vehicle type and performance decile, respectively.

Panel A: 3-year return deciles



Panel B: CAPM alpha deciles



Panel C: Fama-French-Carhart alpha deciles

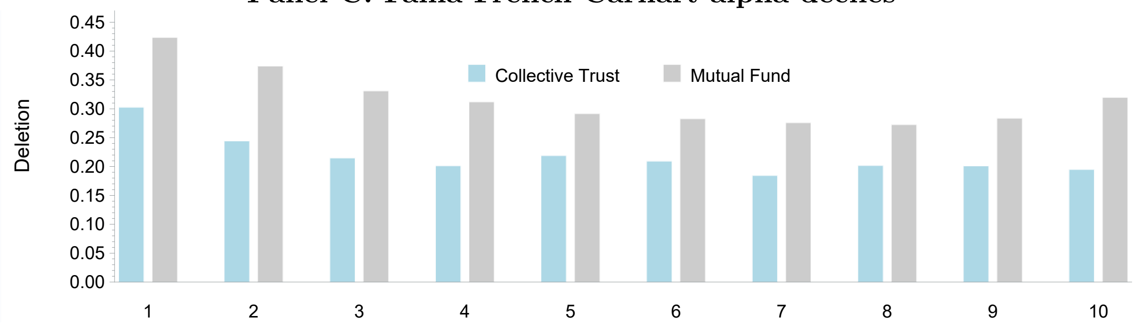
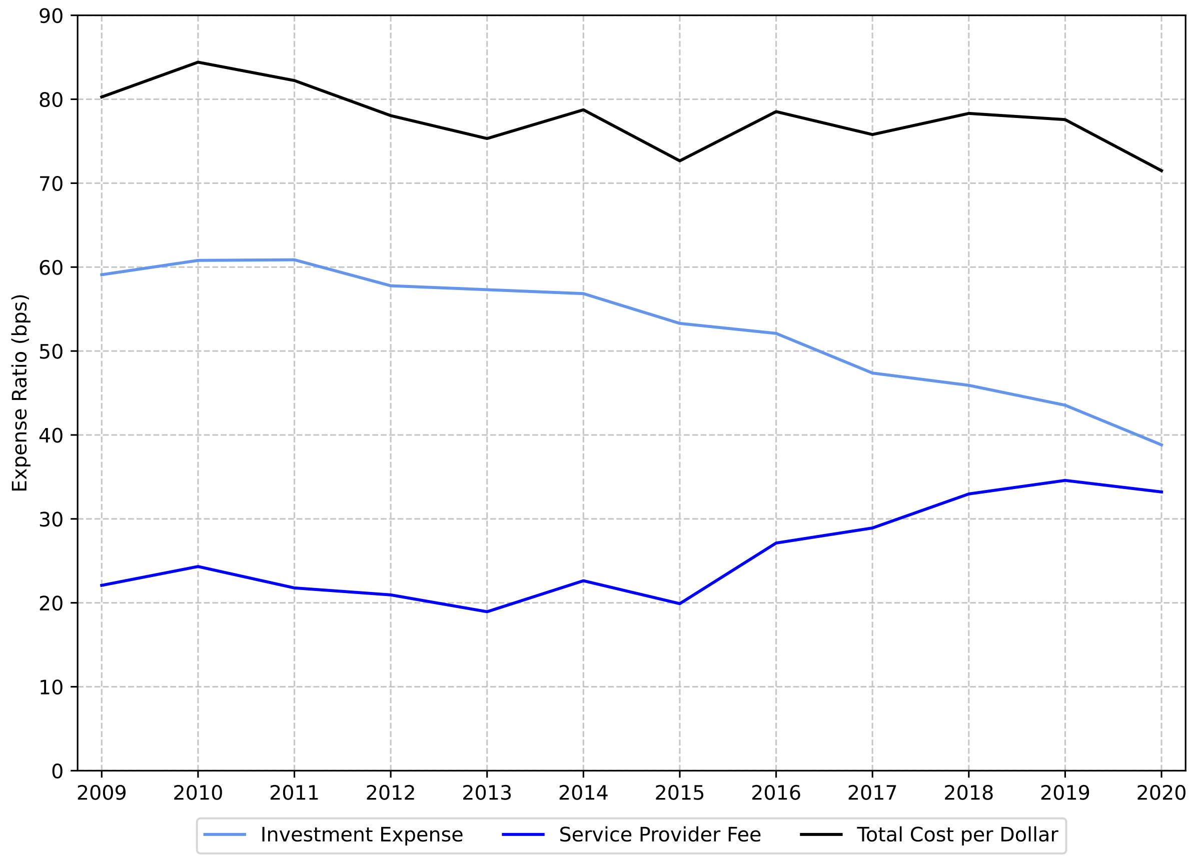


Figure 3.7: Cost of Investing One Dollar in 401(k)s

This figure reports the per-dollar cost paid by plans to investment vehicles (light blue line), service providers (deep blue line), and the total cost (black line).



Tables

Table 3.1: Institutional Details

	Mutual Funds	Collective Investment Trusts
Issuer	Asset management company	Bank or trust company
Regulation	SEC, Securities Act of 1933, Investment Company Act of 1940	The Office of the Comptroller of Currency (OCC) and Department of Labor (DOL)
ERISA Oversight	Not held to ERISA fiduciary standards	Subject to ERISA fiduciary standards
Public Information	Prospectus, detailed investment reports each quarter, historical records, ratings from all platforms	Limited voluntary disclosure to certain data vendors like Morningstar
Information to participants	All publicly available information	Declaration of trust, including performances and expenses
Liquidity	Daily value and daily traded on National Securities Clearing Corporation (NSCC)	Most provide daily value and daily traded on NSCC since 2000
Fee Structure	Have multiply share classes, fixed fee for a given share class	Have multiply share classes, potential for arranging negotiated pricing
Cost	May have a 12b-1 fee, transfer-agent fee, custodian fee, registration fee, shareholder reporting fee, board-of-directors fee, etc.	Generally do not have the fees listed for mutual funds
Availability	Open to most pension plans and general public	Exclusive to certain retirement plans

Table 3.2: Summary Statistics

This table reports the panel distribution of investment vehicles and 401(k) plans from 2009 to 2020. Panel A presents the characteristics of CIT and mutual fund twins. In the first part of Panel A, we report the fraction of assets in 401(k) relative to fund TNAs, the number of plans invested in the fund, TNA, fund age, annual turnover, the ratio of cash and cash equivalents holdings to fund TNA, and annual expenses. In the second part of Panel A, we report alphas, volatility, and idiosyncratic volatility, estimated from monthly gross or net returns over the past three years and standardized to an annual level. We include both CAPM alphas and alphas Adj for the Fama-French-Carhart four-factor model. The last two columns provide the coefficients and t-statistics from a t-test of the difference between CITs and their twin mutual funds. T-values are clustered at both the time and investment vehicle levels.

Panel B reports summary statistics for plan-year observations. In the first part of Panel B, we report plan total assets, number of participants, average account balance, employee contribution amount, employer match rate (defined as employer contribution divided by employee contribution amount), plan age, participation rate, the dummy variable that indicates if the plan automatically deducts deferrals from an employee's wages, and the indicator of whether the plan sets default investment options. The second and third parts of the panel show the distribution of investment options for plans with at least one CIT option 2009 - 2020. These parts separately report the number of investment options in the plan menu and the assets in each option over the plan's total assets.

Panel A: Summary statistics for CIT and mutual fund twins

		CIT (1)				Mutal Fund (2)				Diff (1) - (2)	
	N	Mean	25th	50th	75th	Mean	25th	50th	75th	Diff	t value
Fund Characteristics											
% assets in 401(k)	5,646	70.39%	36.40%	97.37%	100.00%	26.00%	3.52%	14.17%	41.01%	44.38%	29.79
Number of plans	5,648	64.53	2.00	6.00	27.50	729.75	22.00	110.00	677.00	-665.23	-10.07
TNA (million)	5,648	2,782.58	27.99	218.74	963.07	9,963.17	350.92	1,761.64	7,099.11	-7,180.59	-4.87
Log(Fund Age)	5,497	9.35	4.92	7.92	12.08	16.93	7.67	14.83	23.00	-7.58	-14.88
Turnover	4,322	45.28%	14.00%	29.00%	57.00%	53.30%	16.00%	33.00%	61.00%	-8.02%	-3.48
Cash%	3,510	3.37%	0.96%	2.31%	3.97%	3.37%	1.20%	2.56%	4.23%	0.00%	0.01
Expense (bps)	5,206	32.71	5.05	24.04	53.08	65.63	35.54	69.72	90.40	-32.92	-20.06
Performance Measures											
1-year gross return	4,050	11.48%	1.00%	10.64%	20.53%	11.54%	1.10%	10.48%	20.59%	-0.06%	-1.22
1-year net return	4,050	11.17%	0.73%	10.36%	20.10%	10.92%	0.58%	9.91%	19.96%	0.25%	6.59
3-year gross return	3,251	28.42%	14.96%	26.90%	39.05%	28.61%	14.83%	26.83%	39.27%	-0.19%	-1.29
3-year net return	3,251	27.38%	14.06%	25.72%	38.02%	26.46%	13.15%	24.92%	36.99%	0.92%	7.94
Gross CAPM alpha	3,557	-0.82%	-2.80%	-0.70%	0.91%	-0.63%	-2.72%	-0.72%	0.99%	-0.19%	-1.42
Net CAPM alpha	3,472	-1.09%	-3.06%	-0.98%	0.69%	-1.20%	-3.15%	-1.18%	0.50%	0.11%	0.84
Gross 4-factor alpha	3,557	-0.18%	-1.13%	-0.15%	0.70%	0.10%	-0.96%	-0.12%	0.85%	-0.28%	-3.05
Net 4-factor alpha	3,472	-0.45%	-1.35%	-0.34%	0.39%	-0.47%	-1.43%	-0.48%	0.26%	0.02%	0.26
Volatility	3,557	12.10%	8.03%	11.52%	15.60%	12.26%	8.16%	11.64%	15.65%	-0.16%	-4.10
IVOL	3,557	2.82%	0.97%	2.08%	3.75%	2.93%	0.97%	2.05%	3.69%	-0.11%	-2.18

Panel B: Summary statistics for 401(k) plans

	N	Mean	StdDev	25th	50th	75th
Full Sample						
Plan Characteristics						
Total Assets (million)	487,783	84	676	5	12	31
# Participants	487,783	1,492	10,599	178	308	727
Average Account Balance	487,783	60,044	46,859	27,974	47,082	77,080
Employee Contribution	487,783	4,842	2,829	2,801	4,162	6,252
Employer Match Rate	487,783	0.48	0.28	0.26	0.43	0.65
Plan Age	487,783	22.83	12.23	14.17	21.92	29.42
Participation Rate	487,783	0.75	0.24	0.60	0.83	0.95
Auto Enrollment	487,783	0.28	0.45	0.00	0.00	1.00
Default Investment	487,783	0.81	0.39	1.00	1.00	1.00
Plans with at least One CIT Option						
Number of Investment Options						
All Options	87,015	26.17	13.22	21.00	25.00	30.00
Mutual Fund	87,015	15.80	13.52	9.00	15.00	21.00
Collective Investment Trust	87,015	7.18	5.66	2.00	6.00	12.00
Pooled Separate Account	87,015	1.86	5.78	0.00	0.00	0.00
Guaranteed Investment Contract	87,015	0.90	0.88	1.00	1.00	1.00
Company Stock	87,015	0.12	0.63	0.00	0.00	0.00
% Assets in each Options						
Mutual Fund	87,015	0.50	0.31	0.21	0.54	0.78
Collective Investment Trust	87,015	0.33	0.29	0.07	0.23	0.55
Pooled Separate Account	87,015	0.05	0.16	0.00	0.00	0.00
Guaranteed Investment Contract	87,015	0.09	0.10	0.00	0.06	0.13
Company Stock	87,015	0.02	0.08	0.00	0.00	0.00

Table 3.3: Expense Decomposition of CITs and Mutual Funds in 401(k)s

In this table, we decompose CITs and their twin mutual funds' annual expenses and report the time-series average of cross-sectional summary statistics. The first row presents the equal-weighted (EW) average, while the second row shows the value-weighted (VW) average, weighted by the investment vehicle's 401(k) balance. The last several columns include percentage expenses, calculated as the detailed fee component divided by the overall expenses. To mitigate reporting errors, we require the sum of all detailed expenses divided by overall expenses to fall within the range [0.5, 1.5].

Panel A reports decomposed CIT annual expenses, consisting of three components: professional, contract, and investment fees. Professional fees include payments for external accounting, actuarial, legal, and valuation/appraisal services. Contract fees cover payments to a contract administrator for plan-related administrative services. Investment fees, defined as the remaining costs after deducting professional and contract fees, specifically relate to portfolio management.

Panel B reports decomposed mutual fund expenses. D&T fees include 12b-1 fees, which cover marketing and distribution costs, and transfer agent and custodian fees. Regulation fees comprise registration fees, shareholder reporting fees, and board-of-directors fees. Administrative fees cover expenses related to accounting, auditing, legal services, insurance, and administration. The table first presents detailed expenses aggregated at the fund level, followed by a separate report on expenses for the mutual funds' cheapest share class.

Panel A: Expense decomposition of CITs

CIT	Overall	Professional	Contract	Invest	% Professional	% Contract	% Invest
EW	0.29%	0.02%	0.01%	0.25%	14.68%	2.99%	82.34%
VW	0.10%	0.00%	0.00%	0.09%	3.89%	1.77%	94.34%

Panel B: Expense decomposition of mutual funds

	Overall	D&T	Regulation	Admin	Invest	%D&T	% Regulation	% Admin	% Invest
Fund Level									
EW	0.66%	0.12%	0.02%	0.05%	0.45%	18.48%	2.79%	10.62%	66.16%
VW	0.31%	0.07%	0.01%	0.05%	0.17%	22.98%	4.09%	26.96%	43.58%
Cheapest Share Class									
EW	0.58%	0.07%	0.02%	0.04%	0.44%	12.10%	2.85%	10.10%	72.37%
VW	0.27%	0.05%	0.01%	0.05%	0.16%	18.68%	4.25%	25.72%	47.81%

Table 3.4: Flow-Performance Sensitivity within and outside 401(k)s

This table compares flow sensitivity across various investment vehicle groups within and outside 401(k)s. All variables are winsorized at the 1st and 99th percentiles. Panel regressions are conducted by group to estimate flow sensitivity to performance and expenses using the following specifications:

$$Flow_{f,t} = \beta_1 Expense_{f,t-1} + \beta_2 Ret_{f,t-1} + \Gamma Controls_{f,t-1} + \theta_t + \phi_{fc} + \epsilon_{f,t}.$$

Panel A presents the regression results, where the dependent variables are 401(k) flows and non-401(k) flows in the first and second columns, respectively, and the difference in coefficients in the third column. The return measures include 3-year cumulative returns, CAPM alphas, and Fama-French-Carhart four-factor alphas. Control variables include volatility, turnover, fund assets within and outside 401(k), fund family size, fund age, an index fund indicator dummy, as well as year and fund Morningstar category fixed effects. Panel B replicates the analysis in Panel A but reports results separately for CITs (left panel) and mutual funds (right panel).

Panel C presents the regression coefficients for CIT and mutual fund twins, using menu flows (left panel) and non-menu flows (right panel) as the dependent variables. Each year, CIT and mutual fund cumulative 3-year returns are ranked separately within each Morningstar category into 100 groups, with the maximum return rank standardized to 1. The low, mid, and high return specifications are defined as follows: $Low_{f,t} = min(Rank_{f,t}, 0.2), Mid_{f,t} = min(Rank_{f,t} - Low_{f,t}, 0.6), High_{f,t} = Rank_{f,t} - Low_{f,t} - Mid_{f,t}$. We conduct the following piecewise linear regressions,

$$Flow_{f,t} = \beta_1 Low_{f,t-1} + \beta_2 Mid_{f,t-1} + \beta_3 High_{f,t-1} + \Gamma Controls_{i,t-1} + \theta_t + \phi_{fc} + \epsilon_{f,t}.$$

We control for annual expenses, volatility, turnover, fund assets within 401(k) plans, fund total asset under management (AUM_{Fund}), fund family size, fund age, and an index fund indicator dummy. A fund is classified as an affiliated fund for a plan if its management company also serves as the plan's trustee or recordkeeper. We define *% Affiliated* as the fund's total affiliated assets divided by its 401(k) assets. T-statistics, clustered at both the time and investment vehicle levels, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 401(k) flow v.s. non-401(k) flow

DepVar =	Mutual Fund + Collective Trust		
	401(k) Flow	*Non-401(k) Flow*	*Diff*
	(1)	(2)	(3)
Expense	-26.653***	-6.570***	-20.083***
	(-10.44)	(-4.30)	(-7.29)
3-Year Return	0.166***	0.098***	0.068*
	(4.75)	(3.51)	(2.07)
CAPM Alpha	-0.018	0.012	-0.030
	(-0.06)	(0.11)	(-0.11)
4-Factor Alpha	2.333***	1.770***	0.563**
	(5.13)	(5.56)	(2.47)
Volatility	-0.043	-0.077	0.034
	(-0.22)	(-0.39)	(0.18)
Turnover	-0.011	-0.009	-0.002
	(-1.26)	(-1.79)	(-0.24)
$Log(AUM_{401k})$	-0.057***	0.014**	-0.070***
	(-5.59)	(3.10)	(-7.28)
$Log(AUM_{Non-401k})$	0.038***	-0.044***	0.083***
	(4.60)	(-7.98)	(8.66)
$Log(AUM_{Family})$	0.017***	0.018***	-0.001
	(5.78)	(8.79)	(-0.40)
Log(Fund Age)	-0.136***	-0.101***	-0.035**
	(-13.02)	(-12.33)	(-2.85)
Index Fund	-0.142***	0.032*	-0.174***
	(-9.06)	(1.85)	(-6.91)
Time FE	Y	Y	Y
Fund Category FE	Y	Y	Y
# of Obs	39,844	39,844	39,844
Adj. R^2	0.087	0.073	0.053

Panel B: CITs v.s. mutual funds

DepVar =	Collective Trust			Mutual Fund		
	401(k) Flow	*Non-401(k) Flow*	*Diff*	*401(k) Flow*	*Non-401(k) Flow*	*Diff*
	(1)	(2)	(3)	(4)	(5)	(6)
Expense	-22.771***	-8.561	-14.210**	-23.580***	-11.671***	-11.910***
	(-5.87)	(-1.66)	(-2.06)	(-7.79)	(-7.86)	(-5.09)
3-Year Return	0.199	-0.013	0.212*	0.160***	0.106**	0.054
	(1.42)	(-0.13)	(1.86)	(4.99)	(3.15)	(1.52)
CAPM Alpha	-0.611	0.585	-1.197	-0.082	0.039	-0.121
	(-0.78)	(0.78)	(-1.45)	(-0.27)	(0.37)	(-0.54)
4-Factor Alpha	2.366**	1.595	0.770	2.414***	1.770***	0.644**
	(2.40)	(1.25)	(0.65)	(5.03)	(5.63)	(2.96)
Volatility	-0.255	0.347	-0.602	-0.014	-0.059	0.045
	(-0.32)	(0.72)	(-0.84)	(-0.08)	(-0.31)	(0.25)
Turnover	-0.045	0.013	-0.057	-0.008	-0.010*	0.001
	(-1.21)	(0.85)	(-1.62)	(-0.88)	(-1.97)	(0.19)
$Log(AUM_{401k})$	-0.096***	0.063***	-0.158***	-0.063***	0.014***	-0.078***
	(-5.61)	(4.30)	(-6.36)	(-6.50)	(3.35)	(-9.92)
$Log(AUM_{Non-401k})$	0.069***	-0.087***	0.156***	0.049***	-0.049***	0.098***
	(4.56)	(-5.24)	(6.10)	(6.36)	(-10.04)	(12.67)
$Log(AUM_{Family})$	0.033*	0.010	0.024	0.019***	0.015***	0.004
	(2.05)	(0.77)	(1.31)	(7.03)	(8.41)	(1.23)
Log(Fund Age)	-0.170***	-0.090**	-0.079	-0.135***	-0.104***	-0.031**
	(-4.11)	(-2.29)	(-1.36)	(-11.60)	(-15.12)	(-2.61)
Index Fund	0.002	0.100	-0.098	-0.179***	0.011	-0.190***
	(0.03)	(0.98)	(-1.08)	(-8.48)	(0.77)	(-7.41)
Time FE	Y	Y	Y	Y	Y	Y
Fund Category FE	Y	Y	Y	Y	Y	Y
# of Obs	3,791	3,791	3,791	36,053	36,053	36,053
Adj. R^2	0.091	0.054	0.086	0.091	0.100	0.064

Panel C: Menu flow v.s. non-menu flow

DepVar=	*Menu Flow*			*Non-Menu Flow*		
	CIT	MF	Diff	CIT	MF	Diff
	(1)	(2)	(3)	(4)	(5)	(6)
Low Return	0.892*	0.402	0.490	0.264	0.317	-0.053
	(1.98)	(0.80)	(0.96)	(1.18)	(1.75)	(-0.17)
Mid Return	0.067*	0.451***	-0.384***	0.065	-0.005	0.071
	(2.08)	(7.35)	(-6.07)	(0.85)	(-0.15)	(0.72)
High Return	0.687**	0.418	0.270	-0.163	0.315*	-0.478
	(2.64)	(1.79)	(0.69)	(-0.58)	(2.04)	(-1.41)
Expense	-11.456*	-15.245**	3.789	-1.881	-7.092	5.211
	(-2.19)	(-2.71)	(0.54)	(-0.60)	(-1.37)	(0.72)
Volatility	-0.633	-0.376	-0.256	0.615	0.399	0.216
	(-1.12)	(-0.86)	(-0.34)	(1.54)	(1.24)	(0.65)
Turnover	0.052*	-0.008	0.060*	-0.012	-0.016	0.004
	(2.02)	(-0.78)	(2.17)	(-0.96)	(-1.45)	(0.24)
$Log(AUM_{401k})$	-0.023	-0.052***	0.029	-0.029**	-0.046***	0.016
	(-1.36)	(-4.96)	(1.32)	(-2.66)	(-3.74)	(1.07)
$Log(AUM_{Fund})$	-0.016	0.041***	-0.057**	0.043***	0.005	0.038**
	(-0.85)	(3.90)	(-2.89)	(5.36)	(0.41)	(2.69)
$Log(AUM_{Family})$	0.016	0.016**	-0.001	0.005	0.023**	-0.018
	(1.05)	(2.52)	(-0.06)	(0.59)	(2.46)	(-1.12)
Log(Fund Age)	-0.096**	-0.118***	0.022	0.016	0.006	0.010
	(-3.17)	(-5.09)	(0.53)	(0.73)	(0.30)	(0.39)
% Affiliated	0.079	-0.090**	0.169**	-0.090**	-0.086***	-0.004
	(1.71)	(-2.41)	(2.60)	(-2.59)	(-3.81)	(-0.10)
Index fund	0.086	-0.187***	0.273***	0.047	0.016	0.030
	(1.68)	(-3.78)	(3.46)	(1.74)	(0.27)	(0.46)
Time FE	Y	Y	Y	Y	Y	Y
Fund Category FE	Y	Y	Y	Y	Y	Y
# of Obs	3,491	5,000	8,491	3,491	5,000	8,491
Adj. R^2	0.032	0.095	0.066	0.075	0.125	0.101

Table 3.5: CIT Adoption Decisions by 401(k) Plans

This table presents results from logit regressions predicting the likelihood of plans adopting CITs,

$$Prob(CIT_{p,t} = 1) \quad = \quad \Lambda(\beta Characteristic_{p,t-1} + \Gamma Controls_{p,t-1} + \theta_t + \phi_k + \eta_j).$$

$CIT_{p,t}$ is a dummy variable equal to 1 if plan p has never included any CITs in its menu up to year $t-1$ but begins adding CITs in year t. *Expense* represents the per-dollar investment cost for plan p in year $t-1$. A fund is classified as an affiliated fund for a plan if its management company also serves as the plan's trustee or recordkeeper. We define *% Affiliated* as the plan's total affiliated assets divided by its total assets.

Third-Party Trustee and *Third-Party Advisor* are dummy variables equal to 1 if the plan hires trustees or advisors beyond its main service providers. *Communication* is a dummy variable indicating whether the plan incurs service provider fees related to participant communication. *Collective Bargaining* is a dummy variable equal to 1 if the plan engages in collective bargaining. *Auto-Enrollment* is a dummy variable indicating whether the plan automatically deducts deferrals from employees' wages.

Control variables include company stock fractions, average account balance, plan size, average employee deferral rate (measured as employee contributions relative to their account balance), employee participation rate, plan age, an indicator for whether the plan sets default investment options, the number of options in the menu, the number of investment vehicle types, and the number of fund families in the plan menu. We also control for time, plan industry, and plan location fixed effects. T-statistics clustered at the plan level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

DepVar =	$Prob(CIT_{p,t} = 1)$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expense	-10.965**								-17.405***
	(-2.52)								(-3.92)
% Affiliated		-0.323***							-0.329***
		(-9.33)							(-9.29)
Third-Party Trustee			0.099***						0.058*
			(2.97)						(1.67)
Communication				0.118***					0.092**
				(2.64)					(1.99)
Third-Party Advisor					0.233***				0.221***
					(8.67)				(8.18)
Collective Bargaining						0.223***			0.256***
						(5.34)			(6.10)
Auto-Enrollment							0.178***		0.176***
							(7.08)		(6.92)
Contribution								-0.013	-0.004
								(-0.55)	(-0.18)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Plan Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Plan Location FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
# of Obs	285,156	285,185	285,185	285,185	285,185	285,185	285,185	285,185	285,156
Pseudo R^2	0.0242	0.0252	0.0242	0.0242	0.0249	0.0244	0.0247	0.0241	0.0272

Table 3.6: Twin CIT Issuing Decisions by Mutual Fund Families

This table presents results from logit regressions predicting whether an asset management company will issue a twin CIT for a mutual fund,

$$Prob(TwinCIT_{f,t} = 1) \quad = \quad \Lambda(\beta Ret_{f,t-1} + \Gamma Controls_{i,t-1} + \theta_t + \phi_{fc}).$$

$TwinCIT_{p,t}$ is an indicator variable equal to 1 in the first year a twin CIT is introduced to mutual fund f and 0 otherwise. The return measures include cumulative 3-year or 5-year returns, CAPM and Fama-French-Carhart four-factor alphas, Morningstar overall ratings, and 3-year or 5-year ratings in year $t-1$.

Big 10 Family is a dummy variable equal to 1 if the fund family's AUM ranks in the top 10. *Family Share* measures the asset management company's CIT assets as a proportion of total 401(k) assets within the Morningstar category. Sensitivity to expenses or returns is the yearly univariate regression coefficient of 401(k) flow on fund expenses or returns within each Morningstar category.

Control variables include the mutual fund f's expense ratio, turnover, volatility, affiliated investment fraction (as defined in Table 3.4), an index fund indicator dummy, fund assets within and outside 401(k) plans, fund family size, fund age, and fund family CIT market share (measured as the CIT AUM of the family relative to its total AUM). Year and fund Morningstar category fixed effects are also included. T-statistics clustered at the fund level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

DepVar=	$Prob(TwinCIT_{p,t} = 1)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
3-Year Return	0.410*** (2.62)						
5-Year Return		0.574*** (3.37)					
CAPM Alpha			0.341** (2.18)				
4-Factor Alpha				0.391** (2.51)			
Rating					0.210*** (4.35)		
Rating (3-Year)						0.183*** (4.34)	
Rating (5-Year)							0.245*** (5.07)
Big 10 Family	0.331** (2.27)	0.409** (2.56)	0.304** (2.13)	0.303** (2.13)	0.333** (2.25)	0.310** (2.10)	0.501*** (2.97)
Family Share	0.964*** (5.24)	1.069*** (5.38)	0.946*** (5.28)	0.950*** (5.31)	0.938*** (5.05)	0.940*** (5.07)	1.030*** (4.95)
Expense	-0.653*** (-3.65)	-0.632*** (-3.22)	-0.602*** (-3.49)	-0.595*** (-3.45)	-0.610*** (-3.42)	-0.573*** (-3.23)	-0.510*** (-2.60)
Turnover	-0.081 (-1.57)	-0.108* (-1.82)	-0.092* (-1.77)	-0.091* (-1.75)	-0.078 (-1.56)	-0.078 (-1.55)	-0.119* (-1.89)
Volatility	-2.436** (-2.02)	-3.053** (-2.32)	-1.622 (-1.42)	-1.505 (-1.31)	-1.285 (-1.04)	-1.510 (-1.23)	-1.660 (-1.19)
% Affiliated	-0.851*** (-5.13)	-0.980*** (-5.32)	-0.808*** (-5.05)	-0.807*** (-5.04)	-0.792*** (-4.70)	-0.834*** (-4.95)	-0.913*** (-4.77)
Index Fund	-1.033*** (-4.82)	-0.892*** (-3.91)	-1.052*** (-5.02)	-1.045*** (-4.99)	-1.038*** (-4.72)	-1.071*** (-4.89)	-0.921*** (-3.81)
$Log(AUM_{401k})$	0.464*** (12.82)	0.494*** (12.94)	0.460*** (13.33)	0.460*** (13.35)	0.450*** (12.57)	0.456*** (12.83)	0.482*** (12.36)
$Log(AUM_{Non-401k})$	0.047 (0.95)	0.045 (0.80)	0.051 (1.08)	0.049 (1.05)	0.048 (1.08)	0.063 (1.45)	0.038 (0.76)
$Log(AUM_{Family})$	-0.164*** (-4.75)	-0.192*** (-5.16)	-0.166*** (-4.90)	-0.166*** (-4.92)	-0.163*** (-4.63)	-0.162*** (-4.63)	-0.204*** (-5.24)
Log(Fund Age)	-0.299*** (-3.64)	-0.232** (-2.36)	-0.323*** (-4.30)	-0.318*** (-4.23)	-0.304*** (-3.73)	-0.303*** (-3.75)	-0.220** (-2.15)
Market Share	-0.525 (-0.67)	-0.164 (-0.21)	-0.967 (-1.21)	-0.913 (-1.14)	-0.400 (-0.50)	-0.406 (-0.51)	0.195 (0.24)
Sensitivity-to-Exp	-0.004 (-1.26)	-0.005 (-1.57)	-0.003 (-0.93)	-0.003 (-0.85)	-0.003 (-1.07)	-0.003 (-1.06)	-0.005 (-1.53)
Sensitivity-to-Ret	0.028 (0.54)	0.021 (0.39)	0.027 (0.54)	0.029 (0.58)	0.028 (0.54)	0.029 (0.55)	0.015 (0.27)
Time FE	Y	Y	Y	Y	Y	Y	Y
Fund Category FE	Y	Y	Y	Y	Y	Y	Y
# of Obs	34,143	30,669	35,215	35,215	33,606	33,606	28,121
Pseudo R^2	0.138	0.153	0.135	0.135	0.140	0.140	0.155

Table 3.7: Service Provider Turnover and CIT Adoption

This table reports results from the following logit regressions that predict if the plan changes its main service provider conditional on plan CIT usage,

$$Prob(Change\,Provider_{p,t} = 1) \quad = \quad \Lambda(\beta f(CIT_{p,t-1}) + \Gamma Controls_{i,t-1} + \text{Fixed Effects}).$$

$Change\,Provider_{p,t}$ is an indicator variable equal to 1 if plan p changes its main service provider in year t and 0 otherwise. The main service provider is defined as the trustee or recordkeeper that incurs the highest service provider costs in year t. $f(CIT_{p,t-1})$ represents plan usage of CITs in year $t-1$. In columns (1) and (4), we use a dummy variable equal to 1 if the plan includes CITs in its menu in year $t-1$. In columns (2) and (5), we compute the ratio of CIT options in plan p's menu to total investment options, ranking them into 100 categories and standardizing the highest rank to 1. In columns (3) and (6), we calculate the share of plan p's assets invested in CITs relative to total plan assets and rank them similarly. *# Vehicle Types* denotes the number of investment vehicle types in plan p's menu. *# Plans Served* measures the number of plans the service provider manages. We control for the same plan-year level variables as in Table 3.5, along with time fixed effects, plan industry, and plan location fixed effects in columns (1) to (3), and plan fixed effects in columns (4) to (6). T-statistics clustered at the plan level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

DepVar=	$Prob(Change\,Provider_{p,t} = 1)$					
	(1)	(2)	(3)	(4)	(5)	(6)
CIT Dummy	-0.063***			-0.063*		
	(0.020)			(0.034)		
% CIT Option		-0.076**			-0.265***	
		(0.035)			(0.060)	
% CIT Value			-0.069**			-0.330***
			(0.034)			(0.059)
# Vehicle Types	-0.142***	-0.158***	-0.159***	-0.302***	-0.262***	-0.237***
	(0.029)	(0.028)	(0.028)	(0.052)	(0.050)	(0.050)
# Plans Served	-0.172***	-0.172***	-0.172***	-0.179***	-0.179***	-0.179***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
Controls	Y	Y	Y	Y	Y	Y
TIME FE	Y	Y	Y	Y	Y	Y
Cross Sectional FE	Industry Location	Industry Location	Industry Location	Plan	Plan	Plan
# of Obs	362,616	362,616	362,616	142,806	142,806	142,806
Pseudo R^2	0.0321	0.0321	0.0321	0.0328	0.0330	0.0332

Table 3.8: Flow Sensitivity to Total Investment Expenses

This table reports estimated coefficients from plan-fund-year level regressions examining two expense measures: $Expense_{Service}$, the fee per dollar of investment paid to service providers, and $Expense_{Fund}$, the investment vehicle cost per dollar. We include interaction terms between each expense measure and past three-year returns. $Expense_{Service}$ is computed from Form 5500 as total payments to the main service provider divided by beginning-of-year total assets. Panel A uses the full 401(k) sample; each column corresponds to a separate regression. Panel B splits the sample into mutual funds and CITs as indicated. All regressions include the control variables from Table 3.4, along with time and plan fixed effects. All variables are winsorized at the 1st and 99th percentiles. T-statistics clustered at both the time and fund levels are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: All investment vehicles

DepVar =	$Flow$	$Flow$	$Flow$	$Flow$
	(1)	(2)	(3)	(4)
$Expense_{Service}$	0.134***	0.145***		
	(4.72)	(4.34)		
$Expense_{Fund}$	-0.367***	-0.389***		
	(-5.20)	(-4.14)		
$Expense_{Service} \times Ret$		-0.094		
		(-0.68)		
$Expense_{Fund} \times Ret$		0.189		
		(0.64)		
$Expense_{Service} + Expense_{Fund}$			0.038	0.032
			(1.31)	(0.83)
$(Expense_{Service} + Expense_{Fund}) \times Ret$				0.060
				(0.33)
Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
# of Obs	8,025,669	8,025,669	8,025,669	8,025,669
Adj. R^2	0.037	0.037	0.037	0.037

Panel B: CITs v.s. mutual funds

	Collective Trust				Mutual Fund			
DepVar =	*Flow*	*Flow*	*Flow*	*Flow*	*Flow*	*Flow*	*Flow*	*Flow*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Expense_{Service}$	0.299***	0.364***			0.125***	0.133***		
	(3.22)	(5.09)			(4.32)	(3.79)		
$Expense_{Fund}$	-0.691	-0.664			-0.355***	-0.376***		
	(-1.17)	(-1.06)			(-5.54)	(-4.30)		
$Expense_{Service} \times Ret$		-0.678				-0.069		
		(-1.04)				(-0.47)		
$Expense_{Fund} \times Ret$		-0.371				0.179		
		(-0.31)				(0.58)		
$Expense_{Service} + Expense_{Fund}$			0.157	0.201*			0.035	0.027
			(1.37)	(1.90)			(1.15)	(0.68)
$(Expense_{Service} + Expense_{Fund}) \times Ret$				-0.469				0.065
				(-0.98)				(0.33)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y
# of Obs	362,129	362,129	362,129	362,129	7,663,526	7,663,526	7,663,526	7,663,526
Adj. R^2	0.045	0.046	0.044	0.044	0.037	0.037	0.036	0.036

3.A Appendix

3.A.1 Additional tables

Table 3.A.1: Comparison between Mutual Funds (CITs) with and without Twins

This table compares the characteristics of investment vehicles with and without twins. Panel A presents the distribution of mutual funds, while Panel B reports the distribution of CITs. In each panel, the first section includes the index fund indicator, the fraction of assets in 401(k) relative to fund TNA, the number of plans invested in the fund, total net assets (TNA), fund age, annual turnover, the ratio of cash and cash equivalents to fund TNA, and annual expenses. The second section reports alphas, volatility, and idiosyncratic volatility, computed using monthly gross or net returns from the past three years and standardized to an annual level. We present both CAPM alphas and alphas adjusted for the Fama-French-Carhart four factors.

Panel A: Mutual fund characteristics

	MFs without twin CIT					MFs with twin CITs				
	N	Mean	25th	50th	75th	N	Mean	25th	50th	75th
Fund Characteristics										
Index fund	62,927	0.16	0.00	0.00	0.00	5,647	0.14	0.00	0.00	0.00
% assets in 401(k)	62,895	14.81%	0.19%	1.71%	10.10%	5,646	26.00%	3.52%	14.17%	41.01%
Number of plans	62,938	74.31	2.00	7.00	34.00	5,648	729.75	22.00	110.00	677.00
TNA	62,938	1798.57	77.30	349.90	1217.60	5,648	9963.17	350.92	1761.64	7099.11
Fund age	62,587	14.42	6.08	12.17	20.08	5,497	16.93	7.67	14.83	23.00
Turnover	54,481	77.67%	23.00%	47.00%	87.00%	4,322	53.30%	16.00%	33.00%	61.00%
Cash%	49,570	5.79%	1.23%	2.88%	5.90%	3,510	3.37%	1.20%	2.56%	4.23%
Expense (bps)	61,628	90.03	58.00	88.00	115.90	5,206	65.63	35.54	69.72	90.40
Performance Measures										
1-year gross return	56,757	11.06%	0.66%	8.68%	20.04%	4,050	11.54%	1.10%	10.48%	20.59%
1-year net return	56,757	10.11%	0.07%	7.81%	18.96%	4,050	10.92%	0.58%	9.91%	19.96%
3-year gross return	52,385	25.45%	8.44%	22.55%	39.80%	3,251	28.61%	14.83%	26.83%	39.27%
3-year net return	52,385	22.18%	5.90%	19.56%	36.17%	3,251	26.46%	13.15%	24.92%	36.99%
Gross CAPM alpha	53,142	-0.05%	-2.26%	0.13%	2.20%	3,557	-0.63%	-2.72%	-0.72%	0.99%
Net CAPM alpha	52,928	-0.93%	-3.11%	-0.56%	1.31%	3,472	-1.20%	-3.15%	-1.18%	0.50%
Gross 4-factor alpha	53,142	0.15%	-1.24%	0.14%	1.65%	3,557	0.10%	-0.96%	-0.12%	0.85%
Net 4-factor alpha	52,928	-0.73%	-2.10%	-0.49%	0.75%	3,472	-0.47%	-1.43%	-0.48%	0.26%
Volatility	53,142	13.17%	7.05%	12.30%	18.18%	3,557	12.26%	8.16%	11.64%	15.65%
IVOL	53,142	4.34%	1.57%	3.20%	5.46%	3,557	2.93%	0.97%	2.05%	3.69%

Panel B: Collective investment trust characteristics

	CITs without Twin MF					CITs with Twin MFs				
	N	Mean	25th	50th	75th	N	Mean	25th	50th	75th
Fund Characteristics										
Index fund	7,337	0.16	0.00	0.00	0.00	5,647	0.12	0.00	0.00	0.00
% assets in 401(k)	7,335	64.60%	23.53%	82.90%	100.00%	5,646	70.39%	36.40%	97.37%	100.00%
Number of plans	7,337	26.25	2.00	5.00	16.00	5,648	64.53	2.00	6.00	27.50
TNA	7,337	734.35	17.32	86.57	414.32	5,648	2782.58	27.99	218.74	963.07
Fund age	7,242	9.76	3.92	7.17	12.50	5,497	9.35	4.92	7.92	12.08
Turnover	5,771	48.86%	14.08%	26.18%	62.60%	4,322	45.28%	14.00%	29.00%	57.00%
Cash%	5,535	6.25%	1.11%	3.08%	5.99%	3,510	3.37%	0.96%	2.31%	3.97%
Expense (bps)	7,050	31.24	4.66	21.69	48.00	5,206	32.71	5.05	24.04	53.08
Performance Measures										
1-year gross return	5,937	9.90%	0.89%	9.17%	16.84%	4,050	11.48%	1.00%	10.64%	20.53%
1-year net return	5,937	9.63%	0.75%	8.91%	16.46%	4,050	11.17%	0.73%	10.36%	20.10%
3-year gross return	4,876	24.02%	12.03%	22.94%	34.30%	3,251	28.42%	14.96%	26.90%	39.05%
3-year net return	4,876	23.12%	11.21%	21.94%	33.23%	3,251	27.38%	14.06%	25.72%	38.02%
Gross CAPM alpha	5,296	-1.01%	-2.83%	-0.95%	0.42%	3,557	-0.82%	-2.80%	-0.70%	0.91%
Net CAPM alpha	5,226	-1.25%	-3.12%	-1.30%	0.26%	3,472	-1.09%	-3.06%	-0.98%	0.69%
Gross 4-factor alpha	5,296	-0.35%	-1.03%	-0.20%	0.36%	3,557	-0.18%	-1.13%	-0.15%	0.70%
Net 4-factor alpha	5,226	-0.59%	-1.32%	-0.44%	0.17%	3,472	-0.45%	-1.35%	-0.34%	0.39%
Volatility	5,296	10.43%	5.84%	9.58%	14.13%	3,557	12.10%	8.03%	11.52%	15.60%
IVOL	5,296	2.02%	0.81%	1.31%	2.41%	3,557	2.82%	0.97%	2.08%	3.75%

Table 3.A.2: Comparison between Plans with and without CITs

This table compares the characteristics of 401(k) plan-year observations with at least one CIT option and those without any CIT option. The first section reports plan total assets, number of participants, average account balance, employee contribution amount, employer match rate (defined as employer contributions divided by employee contributions), plan age, participation rate, an indicator for whether the plan automatically deducts deferrals from employees' wages, and an indicator for whether the plan sets default investment options. The second and third sections present the number of investment options in the plan menu and the distribution of assets across investment options as a fraction of total plan assets, respectively.

	With CITs		Without CITs	
	Mean	StdDev	Mean	StdDev
Plan Characteristics				
Total Assets (in Millions)	293	1,544	38	167
# Participants	4,147	23,883	916	3,320
# Participants with Account Balance	3,212	16,969	655	2,143
Average Account Balance	67,208	53,457	58,523	45,189
Employee Contribution	5,093	2,945	4,788	2,801
Employer Match Rate	0.50	0.28	0.47	0.28
Plan Age	23.75	13.30	22.63	11.97
Participation Rate	0.77	0.24	0.75	0.24
Auto Enrollment	0.37	0.48	0.26	0.44
Default Investment	0.83	0.38	0.81	0.40
Number of Investment Options				
All Options	26.17	13.22	27.22	12.23
Mutual Fund	15.80	13.52	20.90	13.88
Collective Investment Trust	7.18	5.66	0.00	0.00
Pooled Separate Account	1.86	5.78	5.37	12.40
GIC	0.90	0.88	0.72	0.58
Company Stock	0.12	0.63	0.04	0.35
% Investment Vehicle to Total Assets				
Mutual Fund	0.50	0.31	0.74	0.36
Collective Investment Trust	0.33	0.29	0.00	0.00
Pooled Separate Account	0.05	0.16	0.16	0.33
GIC	0.09	0.10	0.08	0.11
Company Stock	0.02	0.08	0.01	0.07

Table 3.A.3: Time Series Changes of CIT Expenses

This table reports the decomposition of CIT expenses from 2009 to 2020. CIT expenses consist of three parts: professional, contract, and investment fees. The professional fees are the total fees paid by the CIT for outside accounting, actuarial, legal, and valuation/appraisal services. The contract fees are paid to a contract administrator for performing administrative services for the plan. The investment fees are those specially related to portfolio management, defined as the rest of overall costs other than professional or contract fees. We require the sum of all detailed expenses divided by overall expenses to be in [0.5, 1.5] to eliminate data errors in reporting. We report the overall and decomposed annual expenses in the first four columns, and the percentage expenses, defined as the detailed fee component divided by the overall expenses, in the last three columns.

Year	Overall	Professional	Contract	Invest	% Professional	% Contract	% Invest
2009	0.38%	0.04%	0.01%	0.33%	11.12%	5.07%	83.80%
2010	0.38%	0.03%	0.00%	0.35%	13.11%	0.80%	86.09%
2011	0.44%	0.03%	0.01%	0.40%	9.59%	1.81%	88.61%
2012	0.38%	0.03%	0.01%	0.35%	11.65%	2.10%	86.25%
2013	0.38%	0.03%	0.00%	0.35%	10.95%	1.31%	87.74%
2014	0.35%	0.02%	0.01%	0.32%	11.07%	3.26%	85.67%
2015	0.39%	0.02%	0.01%	0.36%	11.31%	2.16%	86.54%
2016	0.39%	0.03%	0.01%	0.35%	9.97%	2.58%	87.45%
2017	0.34%	0.03%	0.01%	0.31%	11.41%	2.22%	86.37%
2018	0.35%	0.03%	0.01%	0.31%	12.18%	4.33%	83.49%
2019	0.30%	0.02%	0.01%	0.27%	10.98%	3.13%	85.89%
2020	0.28%	0.02%	0.01%	0.26%	9.32%	2.96%	87.72%

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