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Abstract

This study explores the effect of security returns on subsequent sales and purchases of securities by investment funds, and examines the potential of fund-related characteristics to amplify the elevated and procyclical sales of under-performing securities by funds. The study finds significant variations in investment behavior across different asset classes using unique data on trades by retail funds and non-retail hedge funds. The study then demonstrates how the financial fragility of funds increases their sensitivity to decreasing security returns, leading to increased sales of under-performing securities by funds.

Abstrakt

Studie zkoumá vliv výnosů z cenných papírů na následné prodeje a nákupy cenných papírů investičními fondy. Dále zkoumá charakteristiky fondů posilující zvýšené a procyklické prodeje méně výkonných cenných papírů fondy. Nachází významné rozdíly v obchodování napříč různými třídami aktiv s využitím jedinečných údajů o obchodech retailových fondů a fondů kvalifikovaných investorů. Studie pak ukazuje, jak finanční křehkost fondů zvyšuje jejich citlivost na klesající výnosy držených cenných papírů, což vede ke zvýšenému prodeji méně výkonných cenných papírů ze strany fondů.

JEL Codes: G11, G23.

Keywords: Asset management, emerging markets, externalities, interconnectedness, investment behavior.

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1. Introduction

Do fund managers contribute to stabilizing asset prices by limiting sales and increasing purchases of underperforming securities? Or do their investments promote a downward spiral of asset prices and tighten financial conditions by aggressively selling and curbing the purchase of securities whose prices have decreased? How does the trading behavior of funds differ for various asset classes? And to what extent is this behavior affected by the fund's vulnerability, such as investor flows, total returns, or liquid buffers? The considerable growth of assets under the management of mutual funds[1] and their potential to affect the global financial system's stability necessitate an exploration of fund managers' trading behavior. This study seeks to address these questions and provide insights into the role of fund managers in asset pricing and financial stability.

This study is grounded in the literature on limits to arbitrage, which examines the conditions under which certain financial institutions cannot act as stabilizing forces in asset markets (Shleifer and Vishny, 1997; Gromb and Vayanos, 2002). According to this literature, institutions with relatively stable funding can help to mitigate fluctuations in asset prices, while those with less stable funding may amplify adverse market conditions through procyclical investment behavior (Stein, 2009). For instance, several studies have pointed to the countercyclical investment behavior of insurance companies thanks to their stable, long-term liabilities, which can insulate them from market shocks (Chodorow-Reich et al., 2020; de Haan and Kakes, 2011).[2] Hanson et al. (2015) show the traditional banks as contrarian traders since they load on illiquid bonds during stress periods owing to their "sleepy" liabilities as government deposit insurance makes depositors insensitive to the value of the banks' assets.

On the other side of the spectrum, open-ended funds are assumed to be the opposite of contrarian traders. The principal-agent problems (Raddatz and Schmukler, 2012; Rajan, 2006) and the fact that investors in open-ended funds can pull out their claims on demand may incite fund managers to act as momentum investors (Grinblatt et al., 1995). It is thus assumed that fund managers tend toward procyclical investment behavior, i.e. selling as prices fall and purchasing as they grow. Empirical evidence of procyclical behavior based on security-level data was recently presented by Czech and Roberts-Sklar (2019) and Timmer (2018). However, the literature has focused on government and corporate bonds and has yet to explore fully the drivers of funds' investment behavior. This study aims to address this gap by examining the impact of security returns on fund managers' subsequent sales and purchases of securities across a more diverse set of securities. The study also explores potential fund-related drivers which may amplify the behavior. Both goals are approached by drawing on unique supervisory data covering retail open-ended funds as well as non-retail hedge funds. The study reveals considerable heterogeneity in investment behavior, which is not always procyclical.

Of particular interest is the contrast between sales of corporate bonds and shares in bond funds held by fund managers, both representing exposures to the same asset class but with different liquidation costs. The results show on average that the funds studied sold corporate bonds countercyclically: a one percentage point decrease in returns on corporate bonds was associated with an almost 7% decrease in their sales volumes. The results show that fund managers limit their

[1] The 2020 International Monetary Fund Global Financial Stability Report estimated that mutual funds owned more than 40% of high-yield bonds.

[2] Apicella et al. (2022) also study the asset allocation of insurers' unit-linked portfolios which, like open-ended funds, are closely affected by the decisions of policyholders who can redeem their unit-linked policies at short notice. The authors show that insurers do not act as shock absorbers for assets relating to unit-linked policies as investments from these portfolios behave procyclically.

sales of corporate bonds whose returns have declined, as if attempting to limit directly-borne liquidation costs and avert an amplification of potential downward price spirals. This relationship between sales and corporate bond returns is found for less liquid speculative-grade corporate bonds and persists even after controlling for issuer-time fixed effects. The addition of the fixed effects is necessary to account for potential time-varying differences across issuers that can affect both the returns and trading behavior of funds.

In contrast, shares held in bond funds were sold procyclically, with a one percentage point decrease in their returns leading to an 18.3% increase in their sales volumes (a 13% increase in the sales of shares in high yield bond funds). The results suggest that fund managers exploit the increased liquidity provided by significant liquidity transformation in the balance sheets of other funds. This transformation allows fund managers to reduce exposure to less liquid assets, such as high-yield bonds, while transferring the liquidation costs associated with direct bond trading to another fund.

However, this liquidity provision comes at the expense of the remaining, potentially less sophisticated co-investors, who experience losses resulting from portfolio adjustments following redemptions from sophisticated and return-sensitive investors, such as fund managers (Jin et al., 2021). Therefore, these results highlight financial stability concerns about intra-sectoral linkages and potential fire-sale risks (Jiang et al., 2022; Coval and Stafford, 2007). The return-sensitive reaction function suggests that investment funds, which have become non-negligible investors in and of themselves[3], may significantly contribute to the strategic complementarities among investors and can generate fragility in financial markets, see Chen et al. (2010).

Evidence of procyclical sales of fund managers' exposures to other investment funds is also found for managers' sales of shares in equity funds. Specifically, I also investigate sales and purchases of shares in mutual funds investing in small and mid-cap equities, which are generally associated with higher liquidation costs due to their relatively lower liquidity. The analysis reveals that managers' sales of these equity funds exhibit a procyclical pattern among managers of retail funds, i.e. funds that are more sensitive to capital withdrawals from investors due to their shorter redemption terms. In contrast, hedge fund managers who cater to qualified investors tend to act as countercyclical investors by purchasing small and mid-cap equity funds in greater volumes when returns on these equity funds plunge.

The results also show that funds traded government bonds procyclically while controlling for issuer-time fixed effects. This is presumably due to the higher liquidity of government bonds and their role in funds' liquid buffers (Ma et al., 2022). Another reason might be their frequent use as collateral in derivative and repo transactions, which could provide additional impetus for procyclical trading patterns caused by liquidity spirals (Brunnermeier and Pedersen, 2009). Such procyclical government bond sales can exacerbate financial stress, as was recently demonstrated in the UK government bond market in September 2022 (Bank of England, 2022).

The final part of this study delves into the drivers of fund managers' cyclical investment behavior, examining whether fragility in funds' financing and liquidity risk encourage more procyclical sales by their fund managers. Since fund managers are obliged to manage their funding liquidity that is significantly determined by investor flows, investor flows can shape managers' investment behavior through funding constraints and capital withdrawals. While previous studies have examined the impact of various risk factors on funds' funding needs resulting from redemption

[3] According to statistics from the ECB, the share of investment fund and money market fund shares and units held by EMU investment funds grew from 6% to 18% of total assets over the last two decades.

requests and weakened investor inflows (Goldstein et al., 2017; Ben-David et al., 2022; Hodula et al., 2022), there is limited empirical evidence linking these factors to funds' security-level sales.

To fill in the gap, I investigate the impact of liquidity risk and fragility in funds' financing on their investment behavior. I group funds based on their vulnerability to liquidity risk and compare their reactions in terms of securities sales and purchases to previous security returns between the groups and for various asset classes. My results indicate that funds in the vulnerable group, i.e. funds which have negative total returns, negative net investor flows, or are held by less sophisticated investors, exhibit more cyclical sales of investment fund shares compared to funds in the less stressed and less vulnerable group. Similarly, funds with lower cash buffers engage in more aggressive return-based trading. The results are profound for sales of government bonds and shares in small and mid-cap equity funds.

With this study I add to the growing stream of empirical literature that studies detailed security level proprietary data and the trading activity of financial institutions (Abbassi et al., 2016; Timmer, 2018; Barbu et al., 2021; Czech and Roberts-Sklar, 2019; Fache Rousová and Giuzio, 2019). I build on unique monthly supervisory security holding data collected from 2011 to April 2021 which cover retail and non-retail funds including hedge funds domiciled in the Czech Republic and holdings running the gamut from advanced market securities to less liquid emerging market bonds and equities. This breadth of coverage distinguishes the data set used in this study from previous data sets used in similar studies, making the insights gained from this analysis particularly valuable.

The analysis offers new insights into the drivers of fund managers' cyclical investment behavior. I highlight the critical role of liquidity risk and financing fragility in incentivizing mostly procyclical but relatively heterogeneous investment behavior across different types of securities. My results provide valuable contributions to the development of theoretical models of fund manager behavior and have significant implications for policymaking in financial markets, particularly with regards to the design of regulatory frameworks and stress tests aimed at mitigating and measuring systemic risk (Fricke and Fricke, 2021; Sydow et al., 2021). Notably, the stress tests assume a homogeneous and pro-rata way of selling securities from a manager's portfolio, which may not accurately reflect the behavior of fund managers as shown by the results of this study.

The study also contributes to the limited literature on funds from emerging markets, where non-bank financial intermediaries are experiencing substantial growth (Arora and Kashiramka, 2023).[4] Despite similarities in the incentives and vulnerabilities likely driving the investment behavior of fund managers across countries, fund managers from emerging markets often manage money from individual investors with different sensitivities to performance stemming from different wealth, risk appetites, and financial literacy (Khorana et al., 2005). This, in turn, may influence managers' investment behavior and lead to global spillovers due to their exposures to securities from advanced markets.

Importantly, funds from emerging markets are faced with the challenge of investing abroad due to less developed local capital markets and limited investment opportunities. At the same time, these funds usually disclose their returns in the domestic currency and are predominantly held by domestic investors. The reach for foreign assets creates exchange rate risks in managers' portfolios and leads to exchange rate movements forming an essential part of realized returns. Therefore, in

[4] For example, the Czech funds studied here grew by 400% over the last ten years, representing one of the most dynamic growth rates among EU countries.

this study I also investigate the impact of exchange rates on sales and purchases of foreign currency-denominated assets. The results reveal that exchange rate movements do not generally explain managers' trade volumes in foreign currency assets, possibly due to the hedging of exchange risk. However, the study shows that exchange rate movements can intensify procyclical sales of shares in bond funds, with a nearly two-fold larger effect for risk-seeking hedge funds that might bet on exchange rate movements to boost their returns.

Overall, I build on the literature on incentives for asset managers to behave procyclically (Chen and Qin, 2017; Chen et al., 2010; Rajan, 2006; Shek et al., 2018; Timmer, 2018; Franzoni and Giannetti, 2017; Giannetti and Kahraman, 2018; Ryan, 2022) and structural vulnerabilities in the fund sector stemming from the interconnectedness of funds studied in Fricke and Wilke (2020) and Fricke et al. (2022). It also follows the literature on funds' liquidity management practices and the joint behavior of investors and fund managers (Chernenko and Sunderam, 2016; Jiang et al., 2021; Ma et al., 2022; Szabo, 2022; Fricke and Fricke, 2021).

The remainder of this paper is organized as follows. Section 2 develops hypotheses. Section 3 describes the data and provides a summary of the statistics. Section 4 comprises multiple subsections, starting with the research design and identification strategy, followed by a presentation of the empirical results. Finally, Section 5 concludes the study.

2. Theoretical Background and Testable Hypotheses

In this section, I develop two hypotheses. The first hypothesis explores the potential heterogeneity in trading behavior caused by inherent differences among various securities, while the second examines how fragile funding, low liquid buffers, large investor outflows, and other factors may incentivize fund managers to trade more procyclically. By testing these hypotheses, I aim to provide a better understanding of the factors that shape fund managers' trading behavior and contribute to the literature on the dynamics of financial markets.

Inherent differences among various asset classes may result in class-specific trading behavior by fund managers. For instance, open-ended investment fund shares/units offer high liquidity due to their daily redeemability. The increased liquidity, combined with the first-mover advantage, can fuel a significant tendency to trade these mutual fund shares cyclically, particularly if used to obtain indirect exposure to less liquid assets, such as corporate or municipal bonds. In other words, the holdings of shares in other funds often represent the pursuit of higher returns while limiting direct commitments to illiquid assets and costs induced by their trading. Recent research by Fricke et al. (2022) indicates that investment funds are the main contributors to flow externalities as they tend to react more strongly to past returns than households or insurance companies.

Moreover, the NAV of bond funds may be extremely stale, resulting in substantial dilution risk for buy-and-hold investors, see Choi et al. (2022). Opportunistic investors who withdraw capital from overvalued funds thus exploit staleness in NAV. On the other hand, cyclical trading of directly held bonds, especially less liquid corporate bonds, can be less intense or possibly turned contrarian. This is because bond trades come with the actual liquidity costs borne by the buyer/seller, which tend to grow with the volume traded and momentary price volatility.

Next, within-asset-class differences may induce heterogeneity in fund managers' investment behavior. For instance, managers seem to consider the liquidity of individual bonds, as shown by Ma et al. (2022). The authors show that funds follow the pecking order by first selling liquid assets such as high-quality corporate bonds and Treasuries. A study by Choi et al. (2020) shows that investors sell more liquid bonds during market-wide shocks because of the lower search friction of liquid bonds. Scholes (2000) observes that during a crisis, investors first unwind their portfolios by selling the most liquid securities. Finally, various assets play different roles in the fund's portfolio. The instability of UK government bond markets in September 2022 highlighted the role of government bonds in derivatives and repo transactions, which can result in cyclical sales as a response to margin and collateral calls (Brunnermeier and Pedersen, 2009).

Based on this, I construct the first hypothesis:

H1: *There is heterogeneity in fund managers' cyclicity of sales and purchases owing to the different roles, characteristics, and trade easiness of various securities in funds' holdings.*

The second hypothesis explores the drivers of fund managers' cyclical investment behavior. Fund managers are forced to manage their funding liquidity provided from individual investors. Their ability to meet cash obligations due to redemption requests shapes their investment behavior in a specific way. The literature offers a wealth of evidence demonstrating intensifiers for funding fragility. Specifically, Chen et al. (2010), Chen and Qin (2017) and Goldstein et al. (2017) illustrate the convex (concave) flow-performance relationship for equity (bond) funds.[5] Moreover, equity- and bond-investing funds adopt different approaches to liquidity management as studied by Lou (2012), Chernenko and Sunderam (2016), Jiang et al. (2021), and Szabo (2022), resulting in varying run-like dynamics of investors as shown by Zeng (2017). The impact of a fund's liquid buffers on trading behavior has also been examined using aggregated data. For instance, Shek et al. (2018) observes discretionary sales (sales larger than what is required to meet redemptions) by emerging market funds, while Szabo (2022) finds equity funds engaging in dash-to-cash as a response to investor outflows. Franzoni and Giannetti (2017) argues that hedge funds with stable funding are more willing to take risks, thereby investing in less liquid and more volatile stocks.

The second hypothesis therefore proposes that fund managers' sales are driven by their need to manage their vulnerable funding:

H2*: Funds facing large redemption requests, funds with negative total returns, funds with small cash buffers, and funds with large shares of retail investors are predicted to be more return-sensitive their sales owing to their more fragile financing.*

Finally, to help understand the terminology used in this study, there are two types of mutual funds in the Czech Republic, both contained in the data that will be introduced in the next section. Czech regulation, based on EU regulation, recognizes retail investment funds and funds for qualified investors, also referred to as non-retail alternative investment funds (AIFs). Retail investment funds are characterized by daily redeemability and are commonly perceived as well-regulated, diversified, and non-speculative investments.

[5] The flow-performance relationship in investment funds refers to the correlation between the investment performance of an investment fund and the inflows or outflows of investor funds into or out of the fund. This relationship is based on the belief that investors are more likely to invest in investment funds that have performed well in the past and redeem their shares from funds that have performed poorly.

3. Data

This study draws on mandatory monthly fund-level security-holding data collected by the Czech National Bank, which provides a survivorship bias-free database of mutual funds' holdings. Available from the beginning of 2011 to April 2021, the data include an identifier, exposure amount expressed in its market value (after conversion to CZK), nominal values in the denomination currency for each debt security, and held quantities for stocks and shares in other mutual funds. Splits in securities are effective from the day of the split and incorporated into reported quantities. The study only includes securities with valid International Securities Identification Numbers (ISINs), which resulted in the exclusion of real estate and private equity funds that predominantly hold unlisted shares identified with a company registration number. Short positions, which are very rare in the sample (0.07% of the unique ISIN monthly holdings of securities in funds), were omitted. Historical prices and other security-specific characteristics were obtained from the Centralized Securities Database (CSDB), Refinitiv Eikon, and Morningstar. Monthly returns were constructed using historical prices and winsorized at the top and bottom 0.5% levels separately for each asset class to reduce the effect of outliers and minimize the impact of extreme values in the dataset.

Trading activity in the reported holdings is identified from the monthly differences in the split-adjusted[6] quantities and nominal values. The differences (expressed in two incomparable units) were converted into currency units to enable the simultaneous comparison of trades among bonds and stocks.[7] The conversion is done by multiplying the differences by the CZK price per unit of nominal value or quantity, at month-end, for a given security. The derived outputs can be interpreted as CZK trading-induced net cash flows for a given security, assuming that all transactions during a given month were realized at the end of the month, i.e. in a spirit similar to Shek et al. (2018) or Ben-David et al. (2012).

I split the trading-induced net flows by their sign as shown in Equation 1 for each security traded by a given fund in a given month (indices omitted for brevity now). Both amounts are then log-transformed and regressed separately.

$$\begin{aligned} \text{Buy Amount} &= \text{Trade-induced Net Cash-flow} && \text{if flow} > 0 \\ \text{Sell Amount} &= -1 \times \text{Trade-induced Net Cash-flow} && \text{if flow} < 0 \end{aligned} \tag{1}$$

An alternative approach to measuring sales and purchases could be to express trades of bonds by the differences in the log nominal values, as done by Timmer (2018). However, this transformation leads to the exclusion of observations where the nominal value is zero in one of the consecutive months and could potentially bias the estimates: complete sell-offs are fully omitted from the study despite their potential relation to security returns, similarly for brand new bond purchases. The loss of trades in the studied sample for government and corporate bonds would be substantial with 47% for sales and 41% for purchases. Finally, this transformation would not make sense and would be impossible to compare to other asset classes which are reported using quantities.

Holdings of securities were combined with other supervisory full census data, such as net investor flows, total net assets, and share of retail investors, all aggregated from class level to fund level.

[6] Information about split dates and split factors is obtained from the financial data providers. Without the adjustment, splits in stocks would be falsely recorded as a trading activity due to changes in split quantities.
[7] Besides that, it would be inappropriate to use quantities of shares held to express trades for stocks and shares in mutual funds due to incomparable prices per quantity.

Balance-sheet information available at the fund level was used to obtain funds' cash buffers, which consisted of holdings in current accounts and short-term repos. It should be noted that end-of-month cash buffers are only available at a quarterly frequency for non-retail alternative investment funds.

3.1 Summary Statistics

Over 116,000 transactions in matched securities by 367 unique mutual funds were identified from 726,655 monthly unique security holdings of funds, see Table 1. Non-retail funds executed approximately 31% of these transactions. Shares in mutual funds were the most frequently traded asset class, followed by stocks, corporate bonds, and government bonds. This active trading of holdings in mutual funds by fund managers highlights the relevance of intra-sector exposures among funds and its importance for interconnectedness and financial stability, also highlighted by Fricke and Wilke (2020). I also note that all the trades of investment funds' shares were filtered for open-ended funds only, but only a small number of trades was omitted. It shows that fund managers, at least those studied here, strongly prefer open-ended structures to closed-ended ones when investing in other investment funds.

Table 1: Summary Statistics for Monthly Returns of Traded Securities (in %)

Security type	Mean	Median	Q10	Q90	SD	Count
Panel A: Asset Class						
Corporate Bond	0.08	0.14	-2.13	1.81	2.65	11,709
Government Bond	-0.01	0.03	-1.23	1.24	1.65	7,789
Stock	0.52	0.46	-8.96	9.94	7.59	38,174
Mutual Fund	0.44	0.29	-4.02	4.90	4.22	59,190
Panel B: Strategy of Mutual Funds Traded						
Equity Fund	0.61	0.89	-5.66	6.22	5.11	36,119
Bond Fund	0.21	0.08	-1.29	1.94	1.72	17,183
Other	0.09	0.13	-2.94	2.98	3.15	5,888
Panel C: Investment Focus of Bond Mutual Funds Traded						
Corporate Bond	0.18	0.00	-0.74	1.33	1.27	4,703
Government Bond	0.29	0.00	-1.08	2.16	1.57	2,845
High Yield Bond	0.36	0.35	-1.48	2.13	1.58	2,776
Unknown	0.14	0.08	-1.06	1.67	1.65	2,430
Other	0.13	0.16	-1.79	2.46	2.25	4,429

Note: This table summarizes returns (in %) for identified trades broken down by asset class (Panel A). For trades of shares in mutual funds, I supply a detailed split of the shares by investment strategy (Panel B) with additional details for shares in bond funds (Panel C). SD, Q10 and Q90 stand for standard deviations, and 10th and 90th percentiles.

Table 1 further reveals that trades of shares in mutual funds mainly consist of equity mutual funds. The "Other" fund strategy mainly comprises mixed funds, hedge funds, real estate funds, etc. Additionally, the table shows a detailed split for identified trades of shares in bond funds by selected investment strategies.[8]

[8] Here, the "Other" category consists of bond funds that provide exposures in both corporate bonds and government bonds or follow an exotic and less represented investment strategy, such as ESG-oriented. There are also bond funds for which I could not obtain a detailed investment strategy from the data providers ("Unknown"). All the

Table 2 shows that 40% of total transactions are sales and 60% are purchases, which reflects the growth in the Czech investment fund sector over the last decade. Government bonds have the highest average transaction volumes, likely due to the large size of several government bond funds in the sample. On the other hand, equities have the lowest average monthly net trading volumes, which is consistent with the highly diversified portfolios of funds investing in equities.

Table 2: Summary Statistics of Individual Net Buy and Sell Amounts

Transaction	Class of Security	Mean	Median	Q10	Q90	SD	Count	Skewness
Sell	Corp. B.	-21.98	-10.61	-48.31	-2.66	50.52	4,331	-20.10
Sell	Mutual Fund	-15.16	-4.23	-35.34	-0.28	42.40	23,521	-13.47
Sell	Gov. B.	-43.73	-17.93	-108.80	-3.41	70.18	3,442	-4.24
Sell	Stock	-8.20	-3.27	-15.71	-0.80	26.01	16,179	-18.51
Buy	Corp. B.	19.59	10.80	2.70	47.13	26.29	7,378	4.29
Buy	Mutual Fund	12.10	3.20	0.24	27.43	36.83	35,669	20.59
Buy	Gov. B.	53.83	25.79	4.05	122.98	92.46	4,347	7.54
Buy	Stock	7.62	3.08	0.74	14.70	21.14	21,995	14.99

Note: This summary table shows statistics for net buy and sell amounts calculated as the monthly difference in quantity held or nominal value and converted to the currency units as described in Section 3. The amounts are broken down by the main asset classes. SD, Q10 and Q90 stand for standard deviation, and 10th and 90th percentile. Amounts in CZK million.

Table 3 presents 367 unique mutual funds, 43% of which are non-retail funds. Retail funds are usually larger than non-retail funds but typically achieve lower raw returns due to more conservative investments and restricted leverage (Molestina Vivar et al., 2020). Non-retail funds generally experience more volatile net flows, although the redemption period is much longer, and redemption requests are typically noticed in advance. Non-retail funds maintain larger cash buffers, with a twice larger standard deviation than retail funds. Some of the cash holdings of non-retail funds can be held as temporary dry powder. Households are the main funding source for Czech funds; however, several *retail* funds predominantly source their funding from institutional investors. I combine retail funds whose share of institutional investors is greater than 75% with the non-retail funds in the rest of the study because both are sought by rather sophisticated/institutional investors. Investors in non-retail AIFs must invest at least EUR 125,000 and meet other requirements related to financial background, investment objectives, expert knowledge, and investment experience. Therefore, similarly to the study by Calvet et al. (2009), I assume these households to be more sophisticated financially.

4. Empirical Analysis

The following subsections present the core of this study. First, I present the identification strategies. I then analyze the investment behavior for sales and purchases of shares in mutual funds. Afterwards, I study the investment behavior for sales and purchases of directly held corporate and government bonds. Lastly, I examine the drivers and intensifiers of procyclical sales by fund managers.

results shown later are robust to omitting these unmatched funds completely or merging them into one category with the “Other“ category.

Table 3: Summary Statistics of the Studied Funds

	Mean	Median	Q10	Q90	SD
Retail Funds					
Share of Household Investors (% TNA)	75.52	98.85	5.07	100.00	35.50
Total Net Assets	1.83	0.80	0.15	3.99	3.07
Returns (%)	0.20	0.20	-2.25	2.65	2.82
Net Investor Flows (% TNA)	1.45	0.15	-2.08	5.08	6.59
Cash Buffer (% TNA)	8.46	6.58	1.43	16.2	8.85
Non-retail Funds					
Share of Household Investors (% TNA)	53.53	73.21	0.00	100.00	46.43
Total Net Assets	0.75	0.37	0.08	1.71	1.32
Returns (%)	0.34	0.30	-1.98	3.01	4.95
Net Investor Flows (% TNA)	3.04	0.00	-0.94	8.75	10.31
Cash Buffer (% TNA)	14.8	13.2	1.16	29.4	16.3

Note: This summary table shows statistics for the retail and non-retail funds studied. Non-retail funds consist of funds for qualified investors (non-retail AIFs). Total net assets (TNA) in CZK billion. Net investor flows are in % of lagged TNA. All statistics are calculated from the monthly data except for the cash buffers for the non-retail funds which are available quarterly. SD, Q10 and Q90 stand for standard deviation, and 10th and 90th percentile.

4.1 Research Design and Identification Strategy

In a similar spirit to the studies by Czech and Roberts-Sklar (2019) and Timmer (2018), the aim of this study is to show how fund managers react by their sales and purchases to securities returns while paying greater attention to the heterogeneity in the response function across different securities and fund-related vulnerabilities. To achieve this, it is important to be particularly cautious about time-variant information on individual securities, which may also affect trading behavior. In other words, the critical idea for the testability of the two hypotheses is to distinguish between return-induced trades and fundamentals-driven trades. In this section, various identification strategies are developed to capture the effects of returns on sales and purchases controlled for here.

In order to examine fund managers' investment behavior, I estimate various linear models built on Equation 2 using the ordinary least squares (OLS) fixed effects technique. This baseline equation measures the log of the amount of net buy/sell ($Amount^{Buy/Sell}_{f,s,t}$) for the sth security by fth fund during month t. The upper index indicates that the dependent variable is regressed separately for sales and purchases, see Equation 1. The natural log of the dependent variable is taken to ease the interpretation of the results. Note that the estimated parameters then report a percentage change in the trade-induced net cash flows of securities after an appropriate transformation.

$$\begin{aligned} \log Amount^{Buy/Sell}_{f,s,t} = {} & \beta_1 R_{s,t-1} + \gamma \Delta CZK_{s,t-1} + \\ & Controls_{f,t-1} + \alpha_s + \alpha_f + \varepsilon_{f,s,t} \end{aligned} \tag{2}$$

$R_{s,t-1}$ represents the lagged return for the sth security in decimals and the denomination currency. By lagging the returns by one month, possible reverse causality caused by the trading activity to asset returns is prevented, and trading activity executed before the manager observes the end-of-month security return is ruled out.[9]

Furthermore, to investigate the impact of exchange rate on investment behavior in foreign currency-denominated assets (Camanho et al., 2022), I add the variable $\Delta CZK_{s,t-1}$ to the regression equations. This variable stands for the end-of-month change in the CZK exchange rate against the currency denomination of the given security s (in decimals, higher values mean appreciation of the foreign currency against CZK). The use is motivated by the fact that the studied funds report returns after conversion to CZK and are predominantly held by domestic investors, who calculate their yields in domestic currency. $\Delta CZK_{s,t-1}$ is naturally always zero for CZK denominated securities.

The fund's fixed effect a_f is added to account for any unobserved fund-specific heterogeneity. Additionally, other time-variant fund-specific factors are included using a set of fund control variables ($Controls_{f,t-1}$) consisting of the fund's total net assets (TNA) and net investor flows, each lagged by one period.[10] For some models duly marked for the reader, I also include funds' cash buffers to the controls. As an alternative, one could add time-fixed effects or use combined fund-month fixed effects to capture time-variant unobserved fund-related heterogeneity. However, this comes at the cost of over-controlling some of the effects of interest. Aggregate month-specific factors, such as an overall decrease in financial asset prices, would be discarded in that specification. Nonetheless, the results remain essentially unchanged even in the presence of *combined* fund-month fixed effects.

Another potential control variable available in the data are funds' total returns. However, as they are the sole weighted-average of returns realized on funds' individual securities, one might run into multicollinearity issues for the main β parameter of the study's interest. Interestingly, this is especially an issue for funds investing in other equity funds only, and adding funds' total returns into the controls does not change other results.[11] The reason is that these "funds of equity funds" usually act as an intermediary for investments in only a small number of index equity funds making their total returns correlate strongly with the returns on their individual holdings.

However, the main focus of this study is the heterogeneity of investment behavior due to natural differences between various types of securities. To this end, I will usually interact $R_{s,t-1}$ with sets of dummy variables that divide securities into different groups. This effectively enables me to explore group-wise slope estimates: How is the β parameter different for various types of securities? To demonstrate this, allow me to focus the proposed identification on a subset of securities consisting of traded shares in mutual funds only (for consistency, each share is denoted by s) and use dummy variables such as $BondFund_s$, which takes unity if the given share s represents sales/purchases of holdings of shares in a bond fund, see Equation 3. The β_b parameter then reports how fund managers react to changes in returns of shares in bond funds; β_e then provides information on the return elasticity related to traded shares in equity funds.

[9] The lagged form is also necessary because the end-of-month return was used to calculate the left-hand-side variable.

[10] I note that any time-variant fund-level exchange rate risk hedging would not be captured by the fund fixed effects, which may attenuate exchange rate movement elasticity and hence bias the respective γ estimate toward zero.

[11] The results with total returns included in the controls are available upon request.

$$
\begin{aligned}
\log Amount^{Buy/Sell}_{f,s,t} = \beta_b R_{s,t-1} \times BondFund_s + \\
\cdots + \beta_e R_{s,t-1} \times EquityFund_s + \gamma \Delta CZK_{s,t-1} + \\
Controls_{f,t-1} + \alpha_s + \alpha_f + \varepsilon_{f,s,t}
\end{aligned}
\tag{3}
$$

The same β-interaction terms logic is used to propose various models covering different types of securities in the following subsections. All the models also employ security fixed effects (α_s) to account for unobserved, time-invariant characteristics of securities, such as embedded options, coupon rates for bonds, covenants, or redemption terms for shares in mutual funds. The idiosyncratic error term, $\varepsilon_{f,s,t}$, is assumed to be correlated within the fund and security and potentially heteroskedastic (Petersen, 2009).

Nonetheless, time-variant information about the security, which may also affect trading behavior, is often unobservable and thus a potential and persisting source of endogeneity bias, especially for bonds and equities. The critical idea in controlling for any time-varying security-level information that might drive managers' sale and purchase decisions is to make it possible to distinguish between return-induced trades and fundamentals-driven trades.

Alternative specifications are proposed to mitigate endogeneity concerns, which might be especially strong for trades of bonds and stocks. The first adjustment to the baseline specification relies on many bond issuers having multiple outstanding bond issues. With bond issuers assumed as the primary source of unobserved heterogeneity, adding issuer-time fixed effects is expected to mitigate most endogeneity concerns. The second identification strategy relies on comparing the trading behavior of the two groups of funds with the grouping based on fragility sources, which are assumed to incentivize managers to behave more procyclically. This identification then allows for the introduction of combined security-time fixed effects. However, the gain in robustness comes at the cost of changing the interpretation of the β parameters. The parameters now report the difference in elasticity between the groups. Therefore, I leave a detailed description to Section 4.4 where the study strives to examine the fund-related risk factors for heterogeneity in managers' investment behavior.

Time-variant security-specific unobserved heterogeneity may not be a major concern when using Equation 3 to analyze trades of investment fund shares. This is because total returns of the held funds are assumed to be a sufficient criterion for managers' investment decisions (Ben-David et al., 2022). Fund managers may not have the ability or willingness to screen individual investments intermediated through mutual fund holdings, as such information is often disclosed with a significant lag, or such screening would be too costly due to the large number of intermediated exposures. Therefore, I start studying trades of funds' exposures to other mutual funds in the following subsection.

4.2 Baseline Results

I start with Equation 4 which focuses on managers' trades of shares held in mutual funds. Because these holdings can act as an intermediary for exposures to various assets, see also Carvalho (2022), I interact $R_{s,t-1}$ with a set of dummy variables in order to separate β for the main types of mutual funds: sales/purchases of equity funds, bond funds, and other[12].

[12] Consisting of hedge funds, mixed funds, etc. Less compressed results are available but no additional statistically-important relationships were found.

$$\log Amount^{Buy/Sell}_{f,s,t} = \beta_1 R_{s,t-1} \times BondFund_s + \beta_2 R_{s,t-1} \times EquityFund_s + \beta_3 R_{s,t-1} \times OtherFund_s + \gamma \Delta CZK_{s,t-1} + Controls_{f,t-1} + \alpha_s + \alpha_f + \varepsilon_{f,s,t} \tag{4}$$

The results in Table 4 reveal an economically and statistically significant relationship between lagged returns and sales of shares in bond funds. When $R_{s,t-1}$ decreased by one percentage point, fund managers increased the next month's sales of shares in the given bond fund by more than 6.3%, on average.[13] This effect is significant for both retail and non-retail funds, with a particularly large parameter estimated for a subset of non-retail funds.

Table 4: Results for Sales and Purchases of Shares in Mutual Funds

Dependent Variables:	log Sales			log Purchases		
Model:	(Total)	(Retail)	(Non-retail)	(Total)	(Retail)	(Non-retail)
Variables						
$R_{s,t-1} \times BondFund_s$	-6.49***	-5.48***	-10.2***	-1.03	-0.950	-2.00
	(1.69)	(1.84)	(3.34)	(1.63)	(1.53)	(3.54)
$R_{s,t-1} \times EquityFund_s$	-1.45***	-1.52**	-1.44*	-1.85***	-1.78**	-1.96*
	(0.552)	(0.664)	(0.804)	(0.664)	(0.800)	(1.07)
$R_{s,t-1} \times OtherFunds_s$	-0.720	-0.005	-1.59	0.997	0.229	2.10
	(1.33)	(1.69)	(1.63)	(1.29)	(1.19)	(2.41)
$\Delta CZK_{s,t-1}$	-0.288	-0.071	-1.15	-0.667	-0.552	-0.968
	(1.04)	(1.17)	(2.01)	(1.01)	(1.07)	(1.95)
log TNA$_{f,t-1}$	0.744***	0.855***	0.633***	0.525***	0.651***	0.318***
	(0.047)	(0.077)	(0.076)	(0.039)	(0.054)	(0.074)
Net flows$_{f,t-1}$	-0.732**	-1.68***	0.387	0.902***	1.44***	0.267
	(0.286)	(0.619)	(0.308)	(0.176)	(0.382)	(0.197)
Cash Buffer$_{f,t-1}$		0.373			0.341	
		(0.573)			(0.496)	
Fit Statistics						
Adjusted R^2	0.73	0.69	0.76	0.78	0.79	0.76
Observations	22,417	14,806	7,611	32,537	21,488	11,049

Note: This table reports regressions of the logarithm of trade-induced cash flows (sales and purchases separately) on securities' lagged returns. Only trades of shares in funds were included, and their strategies interacted with their lagged returns, see Equation 4. All specifications include listed fund controls, Fund and ISIN fixed effects, and cash buffers for retail funds only due to data limitations (column 2 and 5). Clustered (ISIN & Fund) standard errors in parentheses, ISIN & Fund fixed effects included. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Similar but weaker procyclical sales occur between lagged returns and sales of shares in equity funds. On average, when $R_{s,t-1}$ decreased by one percentage point, fund managers increased the next month's sales of held shares in the given equity fund by almost 1.5%. However, in addition to procyclical sales, there is also evidence of countercyclical purchases of shares in equity funds. Fund managers tended to increase their purchases of shares in equity funds whose returns previously decreased, as shown in the second half of the table. Moreover, the magnitude of the parameters is

[13] Given the log-level models, the reported parameters have to be converted using $100(e^{\beta \cdot \Delta x} - 1)$ before being interpreted as a percentage change.

greater for countercyclical purchases than procyclical sales for this type of security. The results are therefore rather mixed at this point.

Furthermore, the results are consistent with the intuitive assumption that larger funds trade higher volumes ($\log TNA_{f,t-1}$). Net investor inflows lead to an increase in purchase volumes and a decrease in sales, both of which are consistent with the liquidity management practices studied in Szabo (2022). Notably, the impact of investor flows is only statistically significant for retail funds. This is likely due to their generally less sophisticated investor base and shorter redemption terms, which work to amplify fragility in funds' funding and the flow-performance relationship (Goldstein et al., 2017). To save space, estimated parameters for the individual fund controls are omitted in subsequent tables, as the patterns are either persistent or become statistically insignificant in other specifications. A better-suited identification strategy and a wider set of securities will be used later in Section 4.4 to further explore the influence of these fund-specific variables on manager's trading behavior in particular.

Table 5: Results for Sales and Purchases of Shares in Bond Funds

Dependent Variables:		log Sales			log Purchases	
Model:	(Total)	(Retail)	(Non-retail)	(Total)	(Retail)	(Non-retail)
Variables						
$R_{s,t-1}$ × Strategy$_s$ = Corp. Bond	-20.3***	-18.2**	-28.2**	-1.28	-2.59	1.62
	(7.51)	(7.97)	(11.1)	(4.34)	(4.27)	(6.85)
$R_{s,t-1}$ × Strategy$_s$ = Gov. Bond	-3.16*	-2.89**	-2.57	1.13	0.101	1.31
	(1.61)	(1.43)	(5.60)	(3.09)	(2.18)	(10.6)
$R_{s,t-1}$ × Strategy$_s$ = HY Bond	-13.4***	-7.05	-27.9**	4.10	4.88	3.62
	(5.00)	(4.50)	(11.9)	(3.47)	(3.72)	(7.49)
$R_{s,t-1}$ × Strategy$_s$ = Unknown	0.210	-0.646	0.757	-5.37*	-6.61**	-3.65
	(1.78)	(2.25)	(2.81)	(2.94)	(2.74)	(4.15)
$R_{s,t-1}$ × Strategy$_s$ = Other	-4.99***	-3.46*	-13.2***	-3.11	-1.82	-7.02
	(1.72)	(1.97)	(2.81)	(2.35)	(2.09)	(4.95)
$\Delta CZK_{s,t-1}$	-6.06***	-4.55*	-9.76**	-1.35	-0.502	-2.25
	(2.19)	(2.59)	(3.69)	(1.70)	(1.73)	(2.74)
Fund Controls & Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fit Statistics						
Adjusted R^2	0.59	0.62	0.53	0.71	0.76	0.61
Observations	6,361	4,499	1,862	9,539	6,526	3,013

Note: This table reports regressions of the logarithm of trade-induced cash flows (sales and purchases separately) on securities' lagged returns. Only trades of shares in bond funds are included and their strategies interacted with lagged returns: $\log Amount^{Buy/Sell}_{f,s,t} = \beta R_{s,t-1} \times Strategy_s + \gamma \Delta CZK_{s,t-1} + Controls_{f,t-1} + \alpha_s + \alpha_f + \varepsilon_{f,s,t}$, where $Strategy_s$ indicates a set of dummy variables based on the investment strategy of the traded bond fund. For instance, *HY Bond* stands for shares in bond funds whose investment focus is on investing in high yield bond funds. All specifications include fund controls and fixed effects; cash buffers are included for retail funds only (columns 2 and 5). Clustered (ISIN & Fund) standard errors are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

In order to further investigate managers' investment behavior related to investments in bond funds, I focus on trades of these securities only and interact previous month's returns with a set of new dummy variables capturing the detailed investment strategy of the given traded bond funds. As shown in Table 5, the results reveal pronounced cyclical sales of shares in bond funds with corporate and high-yield investment strategies (see column 1). Fund managers increased sales of the given bond fund by more than 18% and almost 13% respectively on average when its previous month's returns decreased by one percentage point.[14] Importantly, HY and corporate bond funds are largely involved in considerable liquidity transformation (Falato et al., 2021).

Sales of holdings in government bond funds also increase with a decline in their returns but the size of the relation is much lower compared to the previous estimates, with the relevant β equal to 3.2. Finally, the results based on a subset consisting of sales of bond funds indicate a statistically and economically significant decrease when the denomination currency of sold bond funds appreciates to CZK, meaning the CZK return of the given holding increases ceteris paribus. Depreciation of the denomination currency increases the sales symmetrically. Additionally, the fact that the γ parameter is not equal to zero may suggest that some fund managers entering the data are not fully hedging the exchange rate risk as their sales volumes are associated with exchange rate movements.

Table 6: Baseline Results for Sales and Purchases of Directly Traded Corporate Bonds

Dependent Variables:	log Sales			log Purchases		
Model:	(Total)	(Retail)	(Non-retail)	(Total)	(Retail)	(Non-retail)
Variables						
$R_{s,t-1} \times \text{Grade}_{s,t-1} = \text{Investment}$	0.710	0.941	21.1***	1.61	1.69	-1.92
	(1.44)	(1.80)	(6.25)	(1.23)	(1.09)	(9.39)
$R_{s,t-1} \times \text{Grade}_{s,t-1} = \text{Not Rated}$	0.822	1.12	-0.363	0.377	0.098	1.68
	(1.86)	(1.45)	(3.85)	(0.802)	(0.942)	(1.77)
$R_{s,t-1} \times \text{Grade}_{s,t-1} = \text{Speculative}$	6.40***	5.45***	12.0**	0.057	-0.116	7.57**
	(1.84)	(1.54)	(5.88)	(1.08)	(1.11)	(3.43)
log Days to Maturity$_{s,t-1}$	-0.433***	-0.316***	-0.594***	-0.319**	-0.227	-0.674**
	(0.080)	(0.091)	(0.206)	(0.136)	(0.140)	(0.269)
log Days from Issuance$_{s,t-1}$	0.587***	0.638***	0.588*	0.176**	0.154*	0.246
	(0.162)	(0.167)	(0.302)	(0.085)	(0.087)	(0.168)
$\Delta CZK_{s,t-1}$	-1.13	-1.46	8.69***	1.88**	2.22***	2.37
	(1.40)	(1.52)	(3.29)	(0.769)	(0.783)	(2.99)
Fund Controls & Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fit Statistics						
Adjusted R^2	0.81	0.82	0.76	0.86	0.87	0.84
Observations	3,974	3,126	844	6,689	5,334	1,341

Note: This table reports regressions of the logarithm of trade-induced cash flows (sales and purchases separately) on securities' lagged returns. Only trades of corporate bonds are included and their rating grades interacted with their lagged returns: $\log Amount^{Buy/Sell}_{f,s,t} = \beta R_{s,t-1} \times Grade_{s,t-1} + \gamma \Delta CZK_{s,t-1} + \delta_1 \log DaysFromIssuance_{s,t-1} + \delta_2 \log DaysToMaturity_{s,t-1} + Controls_{f,t-1} + \alpha_s + \alpha_f + \varepsilon_{f,s,t}$, where $Grade_{s,t-1}$ indicates a set of dummy variables based on the rating grade of the corporate bonds traded. All specifications include fund controls and fixed effect; cash buffers are included for retail funds only (Column 2 and 5). Clustered (ISIN & Fund) standard errors are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

The question then arises whether this cyclical investment behavior is also present in the directly traded corporate bonds which are relatively iliquid assets (Bao et al., 2011), and where the liquidation costs cannot be easily avoided as is the case for sales of open-ended bond funds. To answer this question, I employ the same identification strategy at the risk of endogeneity bias and estimate a linear model with a set of dummy variables isolating the potential source of heterogeneity within corporate bonds – its rating grade (Ambastha et al., 2010). In addition, I include bond-related control variables to capture some of the time-related heterogeneity for the

[14] I also note that the results stay unchanged even if I omit ETF funds, which can be presumably traded more aggressively with a limited risk to financial stability (Antoniewicz and Stahel, 2020).

given corporate bonds: the natural logarithm of residual maturity (in days), and the natural logarithm of days from the bond's issuance.

Because of the limited number of corporate bonds which have no rating, I effectively estimate the three slope parameters shown in Table 6. The results suggest that speculative grade corporate bonds are subject to *countercyclical* investment behavior, which is statistically and economically significant (see Column 1). In addition, note that there is a relatively limited number of sales conducted by non-retail funds (Column 3), and the estimated parameters for this subset should be regarded with some caution. Nonetheless, the estimated parameters can be biased by time-variant unobserved bond-related heterogeneity. The next subsection attempts to control for endogeneity bias by using issuer-time fixed effects.

Table 7: Results for Sales and Purchases of Shares in Equity Funds

Dependent Variables:	log Sales			log Purchases		
Model:	(Total)	(Retail)	(Non-retail)	(Total)	(Retail)	(Non-retail)
Variables						
$R_{s,t-1}$ × Strategy$_s$ = Large Cap	-0.970	-0.653	-1.72	-1.87**	-1.64	-2.39
	(0.612)	(0.731)	(1.06)	(0.855)	(1.05)	(1.53)
$R_{s,t-1}$ × Strategy$_s$ = Unknown	-0.974	-1.48*	-0.344	-2.28***	-2.18***	-2.55**
	(0.690)	(0.761)	(1.20)	(0.608)	(0.724)	(1.08)
$R_{s,t-1}$ × Strategy$_s$ = Other	-1.36**	-1.49**	-1.49*	-1.23***	-1.70***	0.398
	(0.531)	(0.712)	(0.892)	(0.358)	(0.390)	(0.649)
$R_{s,t-1}$ × Strategy$_s$ = Small & Mid-cCap	-3.35**	-5.01***	-1.77	-4.08**	-3.65	-5.11***
	(1.54)	(1.85)	(2.60)	(1.64)	(2.76)	(1.30)
$\Delta CZK_{s,t-1}$	0.547	0.459	-0.190	-1.14	-1.09	-1.49
	(1.09)	(1.15)	(2.43)	(1.02)	(1.04)	(2.19)
Fund Controls & Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fit Statistics						
Adjusted R^2	0.78	0.73	0.83	0.83	0.82	0.84
Observations	14,008	8,955	5,053	19,528	12,893	6,635

Note: This table reports regressions of the logarithm of trade-induced cash flows (sales and purchases separately) on securities' lagged returns. Only trades of shares in equity funds are included and their strategies interacted with lagged returns: $\log Amount^{Buy/Sell}_{f,s,t} = \beta R_{s,t-1} \times Strategy_s + \gamma \Delta CZK_{s,t-1} + Controls_{f,t-1} + \alpha_s + \alpha_f + \varepsilon_{f,s,t}$, where $Strategy_s$ indicates a set of dummy variables based on the investment strategy of the traded equity fund. All specifications include fund controls and fixed effects. Cash buffers are included for retail funds only (column 2 and 5). Clustered (ISIN & Fund) standard errors are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Before that, Table 7 takes a closer look at sales and purchases of shares in equity funds. The table shows that β is significantly larger in absolute value for sales of small and mid-cap investing equity funds than for sales of shares in large-cap investing equity funds. Interestingly, retail funds (the second column) trade small and mid-cap equity funds cyclically, with no statistically significant relationship found for purchases. On the other hand, non-retail funds which have presumably more stable funding (Franzoni and Giannetti, 2017) traded these equity funds countercyclically with the relationship visible for purchases only (the last column).

4.3 Controlling for Issuer-Time Fixed Effects

This subsection builds on different identification that adds issuer-time fixed effects. The core idea is that many bond issuers have multiple outstanding bond issues. Assuming that the main source of unobserved heterogeneity comes from bond issuers, adding issuer-time fixed effects $\alpha_{i,t}$ should control for unobserved time-variant heterogeneity and mitigate endogeneity bias. Note that I retain the bond-specific maturity-based controls introduced in the previous section.

$$\begin{aligned} \log Amount^{Buy/Sell}_{f,s,t} &= \beta R_{s,t-1} + \gamma \Delta CZK_{s,t-1} + \\ \delta_1 \log DaysToMat_{s,t-1} &+ \delta_2 \log DaysFromIssuance_{s,t-1} + \\ &Controls_{f,t-1} + \alpha_s + \alpha_f + \alpha_{i,t} + \varepsilon_{f,s,t} \end{aligned} \tag{5}$$

Table 8 reports estimates for the linear model shown in Equation 5 using sales and purchases of government bonds only.[15] Note that the time frequency of the issuer fixed effects is set to quarterly due to the limited number of observations for government bonds.[16] The results show an economically and statistically significant cyclical increase in sales of government bonds followed by a decrease in bond returns. The β parameter is statistically and economically insignificant for managers' purchases of government bonds. Interestingly, adding cash buffers as a control variable (at the cost of losing some observations) yielded statistically significant and economically appealing parameters (Columns 2 and 4). The results show that lower cash buffers lead to an increase in sales of government bonds.

Using the same identification strategy to study sales of corporate bonds by fund managers, Table 9 confirms the countercyclical sales of speculative grade corporate bonds. Cash buffers are included in fund controls in Column 2 and 4 (the parameters are negative, but statistically insignificant and hence not printed to save space). Moreover, for robustness, I report the estimates with issuer-semester fixed effects in Columns 3 and 4 because issuer-year-quarter fixed effects may be too dense and data-demanding. The countercyclical sales of directly held corporate bonds remain in notable contrast to the sales of the bond funds held, which increase with decreasing returns. The results for purchases are provided in the Appendix.

4.4 Exploring the Effects of Fragility on Funds' Investment Behavior

The final subsection examines the drivers and intensifiers of procyclical sales by fund managers and draws on an even more comprehensive set of securities than in the previous subsections. Previously estimated parameters for fund controls indicate the potential effect of liquidity risk on managers' investment behavior, which is consistent with the findings of other authors. For instance, decreasing fund returns followed by increased investor outflows and depleted cash buffers have been shown to push fund managers to hoard cash and conduct discretionary sales of securities, see Shek et al. (2018) or Szabo (2022).

To mitigate the endogeneity concerns discussed in Section 4.1, this subsection employs an identification strategy that enables month-security fixed effects ($\alpha_{s,t}$). This allows us to examine trades of stocks held as well. Equation 6 presents the model specification, where the combined month-security fixed effects, $\alpha_{s,t}$, and a new dummy variable, $Vulnerable_{f,t-1}$, are used. The $Vulnerable_{f,t-1}$ variable splits the universe of funds according to the sources of vulnerabilities introduced later. If a fund is identified as vulnerable, this dummy variable takes the value of unity;

[15] The results are reported for the whole sample consisting of retail and non-retail funds. I omit reporting results for non-retail funds because of their small number of trades.

[16] Using issuer-month fixed effects yields a negative parameter -3.2, which is statistically significant at the 88% confidence level (p-value of 12%) and not reported in the table.

Table 8: Results for Government Bonds

Dependent Variables:	log Sales		log Purchases	
Model:	(1)	(2)	(3)	(4)
Variables				
$R_{s,t-1}$	-4.03**	-4.36**	0.346	0.457
	(1.72)	(1.92)	(1.75)	(1.86)
log Days to Maturity$_{s,t-1}$	-0.386**	-0.398**	-0.381	-0.301
	(0.194)	(0.198)	(0.233)	(0.217)
log Days from Issuance$_{s,t-1}$	-0.270	-0.314	-0.034	-0.028
	(0.285)	(0.308)	(0.104)	(0.107)
Cash Buffer$_{f,t-1}$		-1.56**		1.46**
		(0.687)		(0.661)
$\Delta CZK_{s,t-1}$	3.83*	4.40**	-0.092	-0.231
	(2.00)	(2.11)	(1.56)	(2.20)
Fund Controls	Yes	Yes	Yes	Yes
Fixed Effects				
ISIN	Yes	Yes	Yes	Yes
Issuer-Year-Quarter	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes
Fit Statistics				
Adjusted R^2	0.82	0.82	0.85	0.86
Observations	3,161	2,982	4,016	3,691

Note: This table reports regressions of the logarithm of trade-induced cash flows (sales and purchases separately) on securities' lagged returns, see Equation 5. Only trades of government bonds were included. All specifications include standard fund controls (TNA, fund investor flows) and fixed effects as listed in the Table. Cash buffers are added to fund controls in Column 2 and 4. Clustered (ISIN & Fund) standard errors are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

it takes the value of zero if it is not. The β parameter reports the degree to which the vulnerable group is more return-sensitive than funds from the less vulnerable group, thereby exploring heterogeneity in the return elasticity between the two groups. In addition, the slope parameter can also be interacted with other dummy variables to separate individual βs as done in previous sections. The lag by one month set for the vulnerability dummy variable rules out trades executed before the given fund f had become vulnerable. In addition, note that the fixed effect $\alpha_{s,t}$ perfectly spans change in the exchange rate as well as any other observable or unobservable security-time effects except for the interacted security returns.

$$\begin{aligned}\log Amount_{f,s,t}^{Buy/Sell} = {} & \beta R_{s,t-1} \times Vulnerable_{f,t-1} + \\ & \text{Controls}_{f,t-1} + \alpha_{s,t} + \alpha_f + \varepsilon_{f,s,t}\end{aligned} \tag{6}$$

Four different versions of the $Vulnerable_{f,t-1}$ dummy are proposed and estimated separately. One version is based on the fund's investor flows. Funds that experienced net investor outflows in the previous month are assigned to the vulnerable group. Another version groups by funds' performance, with the vulnerable group consisting of funds that experienced negative total returns.

Table 9: Results for Corporate Bonds (Sales)

Dependent Variable:	log Sales			
Model:	(1)	(2)	(3)	(4)
Variables				
$R_{s,t-1}$ × Grade$_{s,t-1}$ = Investment	7.14	6.92	-0.154	-0.710
	(8.98)	(9.89)	(4.43)	(4.80)
$R_{s,t-1}$ × Grade$_{s,t-1}$ = Not Rated	0.823	0.191	-0.716	-1.03
	(2.18)	(2.12)	(1.40)	(1.51)
$R_{s,t-1}$ × Grade$_{s,t-1}$ = Speculative	6.58***	5.87**	8.79***	8.58***
	(2.43)	(2.77)	(2.33)	(2.19)
log Days to Maturity$_{s,t-1}$	0.212*	0.214	0.224**	0.259***
	(0.122)	(0.134)	(0.086)	(0.091)
log Days from Issuance$_{s,t-1}$	0.146	0.199	0.145	0.158
	(0.172)	(0.193)	(0.096)	(0.105)
$\Delta CZK_{s,t-1}$	0.112	0.252	-0.623	-0.274
	(2.22)	(2.52)	(2.07)	(2.25)
Fund controls	Yes	Yes	Yes	Yes
Fixed Effects				
Issuer-Year-Quarter	Yes	Yes		
Issuer-Year-Semester			Yes	Yes
Fund	Yes	Yes	Yes	Yes
Fit Statistics				
Adjusted R^2	0.85	0.85	0.82	0.82
Observations	3,782	3,357	3,782	3,357

Note: This table reports regressions of the logarithm of trade-induced cash inflows on corporate bonds' lagged returns: $\log Amount^{Sell}_{f,s,t} = \beta R_{s,t-1} \times Grade_{s,t-1} + \gamma \Delta CZK_{s,t-1} + \delta_1 \log DaysFromIssuance_{s,t-1} + \delta_2 \log DaysToMaturity_{s,t-1} + Controls_{f,t-1} + \alpha_s + \alpha_{i,tt} + \alpha_f + \varepsilon_{f,s,t}$, where $Grade_{s,t-1}$ indicates a set of dummy variables based on the rating grade of the bonds sold, and $\alpha_{i,tt}$ is the issuer-time fixed effect (tt for year-quarter or year-semester). All specifications include standard fund controls (TNA, fund investor flows) and fixed effects as listed in the Table. Cash buffers are added to fund controls in Column 2 and 4. Clustered (ISIN & Fund) standard errors are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

A split of funds into groups according to cash holdings is also used. First, I calculate monthly 25th percentiles for the studied funds grouped by their investment strategy (equity, bond, mixed, etc.). The group-wise percentiles are preferred because managers of bond funds usually hold larger cash buffers than equity funds making their cash buffers incomparable.[17] I then assign funds with cash buffers below the first quartile to the vulnerable group. Finally, funds are split by investor base. Retail funds are assigned to the vulnerable group due to their less sophisticated investors and short-term redemption terms.

Table 10 shows sales results with detail on various asset classes: corporate bonds, government bonds, stocks, and shares in mutual funds, which are broken down by their investment strategies. The results for sales of corporate bonds (first row) report positive and economically significant parameters in Columns 1 and 2, which is additionally statistically significant in the latter. Hence, a one percentage point (pp) decrease in corporate bonds sold led to approximately 4% lower sales by funds that experienced investor net outflows in the previous month compared to funds with positive net investor flows.

[17] Nonetheless, the results are very similar even if simple monthly cross-sectional percentiles are used.

Table 10: Effects of Risk Factors on Investment Behavior

Dependent Variable:	log Sales			
Vulnerability:	(Total return)	(Flows)	(Cash Buffer)	(Investors)
Variables				
$R_{s,t-1} \times \text{Class}_s = \text{Corporate Bond}$	3.94	4.00***	-1.45	1.38
	(2.97)	(1.50)	(2.48)	(1.29)
$R_{s,t-1} \times \text{Class}_s = \text{Government Bond}$	-3.96	-1.71	-3.97**	5.79**
	(4.42)	(1.78)	(1.83)	(2.86)
$R_{s,t-1} \times \text{Class}_s = \text{Stock}$	-0.837	0.366	0.459	-0.266
	(0.666)	(0.320)	(0.337)	(0.414)
$R_{s,t-1} \times \text{Class}_s = \text{Bond Fund}$	-7.87*	-0.662	-7.28	-2.67
	(4.75)	(1.80)	(4.57)	(2.64)
$R_{s,t-1} \times \text{Class}_s = \text{Equity Fund}$	-5.12***	-2.78***	-5.16*	-1.72**
	(1.65)	(1.05)	(2.98)	(0.782)
$R_{s,t-1} \times \text{Class}_s = \text{Other Fund}$	-7.31*	-0.723	-4.99**	0.370
	(3.83)	(1.28)	(2.41)	(2.87)
Fund Controls	Yes	Yes	Yes	Yes
Fixed Effects				
ISIN-Month	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes
Fit Statistics				
Adjusted R^2	0.92	0.92	0.92	0.92
Observations	45,185	45,185	37,872	45,185

Note: This table reports regressions of the logarithm of trade-induced cash *in*flows on lagged returns: $\log Amount^{Sell}_{f,s,t} = \beta R_{s,t-1} \times Vulnerable_{f,t-1} \times Class_s + Controls_{f,t-1} + \alpha_{s,t} + \alpha_f + \varepsilon_{f,s,t}$, where $Class_s$ indicates a set of dummy variables based on type of s security, and $Vulnerable_{f,t-1}$ is a dummy variable, which equals to one if the given fund f belongs to the vulnerable group (see table header). There are four types of vulnerabilities estimated separately and indicated in the header of the table. All specifications include standard fund controls (TNA, fund investor flows). Cash buffers are added to fund controls in Column 3 only. Clustered (ISIN & Fund) standard errors are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Regarding government bonds, the results report mostly negative β parameters. Interestingly, there is a statistically significant relationship between government bond sales and the level of funds' cash buffers (see Column 3). Funds with low cash buffers reacted with a 4% larger sales volume of government bonds to a 1 pp decrease in returns compared to funds with relatively larger cash buffers. The fourth column that compares retail and non-retail funds should be read with some caution for sales of government bonds because of the limited number of observations available for non-retail funds to inform the estimates of the related β parameter.

The results for sales of directly held stocks do not show a statistically or economically significant relationship. Nevertheless, focusing on actively traded shares in investment funds, another reappearance of mostly negative and economically significant parameters is provided. Given the strong evidence of the effects of vulnerabilities on sales of shares in equity funds, the model is estimated for the subset of sales of shares in equity funds while exploring heterogeneity in the return elasticity for the different investment focuses of the equity funds sold.

Table 11: Effects of Risk Factors on Investment Behavior on Shares in Equity Funds

Dependent Variable:	log Sales			
Vulnerability:	(Total return)	(Flows)	(Cash Buffer)	(Investors)
Variables				
$R_{s,t-1}$ × Strategy$_s$ = Large Cap	-3.93*	-2.14	-4.10	-0.631
	(2.12)	(1.41)	(4.35)	(1.35)
$R_{s,t-1}$ × Strategy$_s$ = Unknown	-1.77	-2.85**	-6.92***	-1.20
	(1.11)	(1.30)	(1.04)	(0.861)
$R_{s,t-1}$ × Strategy$_s$ = Other	-1.82	1.89**	4.50**	2.39*
	(1.51)	(0.920)	(2.27)	(1.33)
$R_{s,t-1}$ × Strategy$_s$ = Small & Mid-cap	-7.11**	-4.96**	-11.2***	-2.41*
	(2.90)	(2.05)	(3.69)	(1.27)
Fund Controls	Yes	Yes	Yes	Yes
Fixed Effects				
ISIN-Month	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes
Fit Statistics				
Adjusted R^2	0.94	0.94	0.94	0.94
Observations	14,008	14,008	10,800	14,008

Note: This table reports regressions of the logarithm of trade-induced cash *in*flows on lagged returns: $\log Amount^{Sell}_{f,s,t} = \beta R_{s,t-1} \times Vulnerable_{f,t-1} \times Strategy_s + Controls_{f,t-1} + \alpha_{s,t} + \alpha_f + \varepsilon_{f,s,t}$, where $Class_s$ indicates a set of dummy variables based on type of s security, and $Vulnerable_{f,t-1}$ is a dummy variable, which equals to one if the given fund f belongs to the vulnerable group. There are four types of vulnerabilities estimated separately and indicated in the header of the table. Only sales of shares in equity mutual funds are used. All specifications include standard fund controls (TNA, fund investor flows). Cash buffers are added to fund controls in Column 3 only. Clustered (ISIN & Fund) standard errors are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 11 shows that the most prominent parameters appear once again for sales of small and mid-cap equity funds. The difference between groups is considerable when one constructs the split based on cash buffers. A 1 pp decrease in the price of a small & mid-cap equity fund held leads to 11% more aggressive sales by funds with relatively small cash buffers compared to sales of funds with larger cash buffers.

5. Conclusion

In conclusion, this paper makes a significant contribution to the literature by examining the procyclical investment behavior of fund managers, particularly their propensity to sell securities as prices decline and buy them when they increase. The study leverages unique monthly supervisory data to construct the individual sales and purchases of a wide range of securities. The results demonstrate that fund managers tend to engage in procyclical sales of securities, though the intensity of this behavior varies considerably. For illiquid assets, such as speculative-grade corporate bonds, fund managers exhibit countercyclical behavior, while exposures to less liquid assets through holdings of shares in bond funds result in profoundly procyclical sales. Moreover, procyclical investment behavior is prevalent in shares of small and mid-cap equity funds or government bonds.

The study also investigated the role of liquidity risk and other vulnerabilities in amplifying procyclical sales of securities. The findings reveal that funds in the vulnerable group, such as those with negative total returns, negative net investor flows, or held by less sophisticated investors, are more prone to exhibit cyclical sales of various assets compared to the less-stressed and less vulnerable group. Specifically, funds with low cash buffers tend to off-load government bonds in response to a decrease in bond returns.

The results also raise concerns about the financial stability implications of intra-sector exposures, where funds hold other funds. Although mutual funds provide an attractive way for fund managers to gain exposure to less liquid assets, sophisticated and informed managers seem to be encouraged to sell these holdings very aggressively. These cyclical sales of shares in mutual funds may strongly contribute to strategic complementarities, which generate the damaging "run" dynamic across investors. Overall, our study highlights the need for careful monitoring of investment fund behavior and the risks posed by their actions to the financial system.

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Appendix A: Additional Tables

Table A1: Results for Corporate Bonds (Purchases)

Dependent Variable:	log Purchases			
Model:	(1)	(2)	(3)	(4)
Variables				
$R_{s,t-1} \times \text{Grade}_{s,t-1} = \text{Investment}$	3.01	4.20*	-0.215	0.648
	(2.48)	(2.44)	(1.50)	(1.23)
$R_{s,t-1} \times \text{Grade}_{s,t-1} = \text{Not Rated}$	-1.21	-1.36	-0.913	-1.13
	(0.846)	(0.927)	(0.902)	(0.988)
$R_{s,t-1} \times \text{Grade}_{s,t-1} = \text{Speculative}$	-0.974	-0.683	0.058	0.278
	(3.51)	(3.82)	(2.61)	(2.81)
log Days to maturity$_{s,t-1}$	0.396***	0.397***	0.386***	0.417***
	(0.094)	(0.098)	(0.070)	(0.069)
log Days from issuance$_{s,t-1}$	-0.218**	-0.206**	-0.271***	-0.252***
	(0.095)	(0.099)	(0.066)	(0.073)
$\Delta CZK_{s,t-1}$	1.39	2.02	0.619	1.06
	(1.98)	(1.71)	(1.23)	(1.13)
Fund controls	Yes	Yes	Yes	Yes
Fixed-Efects				
Issuer-Year-Quarter	Yes	Yes		
Fund	Yes	Yes	Yes	Yes
Issuer-Year-Semester			Yes	Yes
Fit Statistics				
Adjusted R^2	0.88	0.88	0.85	0.85
Observations	6,420	5,828	6,420	5,828

Note: This table reports regressions of the logarithm of trade-induced cash outflows on corporate bonds' lagged returns: $\log Amount^{Buy}_{f,s,t} = \beta R_{s,t-1} \times Grade_{s,t-1} + \gamma \Delta CZK_{s,t-1} + \delta_1 \log DaysFromIssuance_{s,t-1} + \delta_2 \log DaysToMaturity_{s,t-1} + Controls_{f,t-1} + \alpha_s + \alpha_{i,tt} + \alpha_f + \varepsilon_{f,s,t}$, where $Grade_{s,t-1}$ indicates set of dummy variables based on rating grade of sold bonds, and $\alpha_{i,tt}$ is issuer-time fixed effect (*tt* for year-quarter or year-semester). All specifications include standard fund controls (TNA, fund investor flows, fund return) and fixed effects as listed in the Table. Cash buffers added to fund controls in Column 2 and 4. Clustered (ISIN & Fund) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

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