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Determinants of Corporate Bond Mutual Fund Flows

Vanessa Jeske

University of Stuttgart

Abstract

This paper examines the determinants of investor flows into U.S. corporate bond mutual funds, with a focus on monetary policy and fund-specific characteristics during the COVID-19 crisis. These funds, as non-bank financial intermediaries, are vulnerable to sudden investor redemptions due to liquidity mismatches. Using monthly data from 2001 to 2021, the analysis applies panel regressions with fund style and time fixed effects to assess how monetary policy, fund characteristics, and market conditions influence investor behavior. Results show that higher effective federal funds rates are significantly associated with reduced fund flows. Past flows and performance rankings are strong predictors of current flows, while fund cash holdings matter mainly in riskier fund types. During the COVID-19 crisis, flow sensitivity to interest rate changes intensified. Although Federal Reserve policy announcements in spring 2020 coincided with a quick return of inflows, the findings emphasize ongoing structural fragility. By analyzing flow dynamics alongside macroeconomic factors and policy responses, this research contributes to understanding the determinants of corporate bond mutual fund flows and the complex role of central bank actions during periods of systemic stress.

Keywords: corporate bond mutual funds; COVID-19 crisis; federal reserve policy; fund flows; liquidity risk

1. Introduction

US bond mutual funds have expanded significantly over the last decade and gained importance. By 2021, they captured $5.6 trillion of the US economy, i.e., 10% of the US bond market, and received $2.6 trillion in net new cash flow (see Figure 1).

Corporate bond mutual funds (CBMF) make up a substantial portion of that bond market. Corporate bonds themselves are a pivotal tool for corporate debt financing yet tend to be highly illiquid.[1] Since CBMFs are not associated with banks, they are classified as non-bank financial intermediaries (NBFI) which are less strictly regulated than banks and have a crucial macroeconomic role. Indeed, in 2021 the Global Monitoring Report on Non-Bank Financial Intermediation documented that NBFIs captured $14.7 trillion (62% of the US GDP) and, worryingly, considered them vulnerable to runs.[2] This run risk is based on a fundamental liquidity mismatch as most CBMFs offer daily withdrawal schedules and therefore continuously engage in major liquidity transformations. The liquidation costs are internalized by the fund, encouraging a first-mover effect. Consequently, CBMFs raise concerns regarding their systematic financial fragility and market resilience.

The COVID-19 crisis provided a global stress test as it led to a corporate bond liquidity crisis in March 2020. Adam Lollos from Citigroup Inc. reflected: " 'The 2008 financial crisis was a car crash in slow motion,' … 'This was like, 'Boom!' "[3] The corporate bond market experienced extreme

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[1] Bao et al. (2011), p. 911 f.

[2] cp. Financial Stability Board (2024a), URL see References

[3] cp. Baer (2020), URL see References

[4] cp. Investment Company Institute (2022), p. 59.

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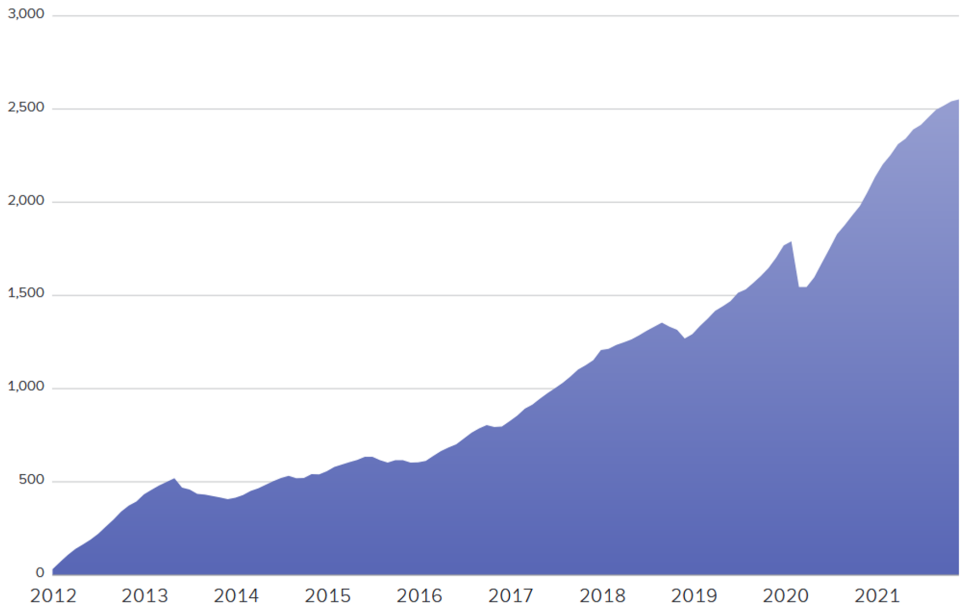

Figure 1: US bond mutual funds net inflows[4]

liquidity strains and transaction costs.[5] Combined with extreme selling pressures, the Bank of America considered the bond market " 'basically broken' ".[6] The economic situation remained dire until the Federal Reserve System (Fed) committed $75 billion of equity for corporate credit facilities aimed at supporting the bond market.[7] The medium-term effects of the Fed's policy intervention require further study.

The existing literature on CBMF flows is far less comprehensive than similar research on equity funds. This research gap is slowly being bridged; however, authors primarily focus on the isolated influence of fund-specific or macro factors on the performance by way of the flow-performance relationship. Additionally, few macro determinants have been extensively studied. Fund flow dynamics themselves have not received much focused attention with their systematic liquidity risk being potentially neglected. Conversely, researchers comprehensively investigated the COVID-19 corporate bond liquidity crisis, providing ample insights into bond evolution during the immediate pandemic. Since relevant studies were chiefly published in 2020 and 2021, they could only analyze short-term effects. Research on the medium-term implications becomes possible as time passes, but literature with data sample periods up to the year-end of 2021 or beyond is still few and far between. Currently, few papers integrate fund characteristics, macro conditions, monetary policy, and pandemic crisis in one cohesive study.

This thesis aims to fill this gap and asks: First, what are the determinants of corporate bond mutual fund flows, with a particular focus on the effective federal funds rate, effective federal funds rate change, and cash ratio; second, how do fund styles affect these determinants; and third, how did the COVID-19 crisis influence CBMF flows in the medium term? First, I investigate the influence of fund-specific and macro factors on fund flows in a systematic fund flows analysis spanning 20 years in order to explore, confirm or reject well-studied correlations. Then, I explore if the impact of these determinants varies within fund styles, e.g., high-yield vs. corporate vs. nontraditional bond mutual funds. Finally, I want to study the short-term and, notably, the medium-term impact of the COVID-19 pandemic on fund flows using data extending up to December 2021. Since the pandemic was an exogenous stress event, I focus the pandemic dedicated case study on the influence of the macro factors.

The thesis continues in chapter 2 with an explanation of the underlying theory. Firstly, subchapter 2.1 presents the fundamentals of CBMFs. Secondly, subchapter 2.2 establishes the theoretical framework of fund flows and the fragility of financial systems. Lastly, subchapter 2.3 introduces the macro perspective and chronicles the corporate bond market liquidity crisis. Chapter 3 reviews the current state of research, examining the current relevant literature on corporate bond mutual fund flows and how they were impacted by the pandemic. Chapter 4 describes the data and methodology used, namely the construction of the CBMF data sample, summary statistics of the fund information and macro data and the preparation and calculation of the independent and dependent variables. Chapter 5 presents the core analysis and results of the thesis. Subchapter 5.1 begins with an examination of systematic fund flow dynamics through Ordinary Least Squares (OLS) and Fixed Effects (FE) regressions. Subchapter 5.2 delves deeper into the systematic dynamics by conducting a split-sample analysis based on fund styles. Finally, subchapter 5.3 offers a case study of the COVID-19 pandemic's impact on CBMFs. Chapter 6

[5] cf. O'Hara and Zhou (2021), p. 46 f.
[6] cp. Idzelis (2020), URL see References
[7] cp. Board of Governors of the Federal Reserve System (2020c), URL see References

concludes the thesis with a summary and brief discussion of future considerations.

2. Theory

This chapter explores the theoretical foundations surrounding US CBMFs and their role in the US financial market. An overview of the fundamentals is provided. It dives deeper into the theory behind fund flow dynamics and financial fragility and proceeds with illuminating the influence of the macro condition by means of macro factors and central bank policy on CBMFs. Finally, the state of the corporate bond market during the COVID-19 crisis is summarized.

2.1. Corporate Bond Mutual Funds: Fundamentals

2.1.1. Essentials, Risks and Fund Styles

A corporate bond is a debt security issued by a company to raise funding for business operations, capacity, or investments.[8] Investors can bundle their funds in professionally managed mutual funds which use the aggregated capital to purchase diversified bond portfolios. Most mutual funds are open-end, i.e., they can issue unlimited shares and grant their investors daily withdrawal rights. Many funds have a distinct investment profile and fund style, which allows investors to select funds matching their own requirements.

Corporate bonds can be vulnerable to default, interest rate, economic, liquidity and inflation risks. Default risk or credit risk describes the probability of the bond issuer defaulting, e.g., through insolvency, while liquidity risk describes the potential difficulty bondholders might have in selling and converting the bond value to cash at will.[9] Interest rate risk occurs when market interest rates rise, new bonds offer better terms to investors, making the existing bond prices lose value; inflation risk describes the danger that rising inflation reduces the effective value of the bond coupons and lowers purchasing power of consumers, potentially lowering the profits of bond issuers. Finally, the economic risk is the risk of economic turmoil inducing investors to shift to assets with higher credit ratings and sell a majority of their bond holdings.[10] These risks, which influence the capital allocations of investors and thereby fund flows, differ between fund categories.

Over time, many different CBMF fund styles have emerged to suit investors performance, stability, and risk needs. To permit a more detailed analysis of the influence of the fund style on the fund flows, we will first be differentiating between the nine different categories of CBMFs as assigned by Morningstar. US high-yield (HY) bond funds invest in "lower-quality bonds" and thus "generally offer higher yields [...] but they are also more vulnerable to economic and credit risk".[11] US short-term bond funds "invest primarily in corporate and other investment-grade U.S. fixed-income issues and have durations of one to 3.5 years" and are "less sensitive to interest rates," which satisfies more risk-averse investors.[12] In sum, short-term bond funds have a low interest rate and credit risk compared to other fund styles and, due to the short maturation duration, little liquidity risk.

US intermediate core Bond Funds mostly consist of "investment-grade U.S. fixed-income issues ... and typically hold less than 5% in below-investment-grade exposures" with an intermediate "effective duration of the Morningstar Core Bond Index", which are "a measure of interest-rate sensitivity".[13] Similarly, US intermediate core-plus bond funds also consist of intermediate investment-grade (IG) bonds but have "greater flexibility".[14]

US corporate bond funds are composed of "investment-grade bonds issued by corporations in US dollars, which tend to have more credit risk than government or agency-backed bonds".[15] Additionally, corporate bonds may have a significant inflation and economic risk as the issuing corporations' successes rely on the economic health of their consumers and their purchasing power. In a global or sector-wide economic downturn, the economic risk would be significant as investors globally try to shift to less risky assets. Of course, investors of this category may be motivated by non-economic factors, notably a belief in a corporation or sector, to incorporate this bond type in their portfolio. US multisector bond funds have diversified their investments across a wide range of domestic and foreign fixed-income sectors.[16] Due to their larger credit risk, they tend to offer higher total returns but suffer significant losses during equity market stress periods.[17] US long-term bond funds primarily hold "corporate and other investment-grade U.S. fixed-income issues" and have durations of six years or more, making them prone to interest rate risk.[18]

US nontraditional bond funds consist of funds with disparate strategies and flexible mandates, e.g., absolute return portfolios which aim to produce returns independently from the bond market, unconstrained portfolios which boast very high flexibility and allocation size and minimum volatility portfolios which seek to reduce volatility despite high credit risk and potentially high return investments.[19] Their goal is to outperform specific benchmarks or focus on other benchmarks. Finally, US bank loan funds invest in "floating-rate bank loans and other floating-rate securities" and "in exchange for their credit risk ... , these loans offer higher interest rates that typically float above a common short-term

[8] cf. U.S. Securities and Exchange Commission (2013a), URL see References
[9] cf. U.S. Securities and Exchange Commission (2013b), URL see References
[10] cf. U.S. Securities and Exchange Commission (2013a), URL see References
[11] cf. Morningstar (2025b), URL see References
[12] cf. Morningstar Office (2023e), URL see References
[13] cp. Bush (2019b), URL see References
[14] cp. Bush (2019b), URL see References
[15] cf. Morningstar (2025a), URL see References
[16] cf. Morningstar Office (2023c), URL see References
[17] cf. Bush (2019a), URL see References
[18] cp. Morningstar Office (2023b), URL see References
[19] cp. Morningstar Office (2023d), URL see References

benchmark".[20] This synopsis of the different fund categories forms the conceptual foundation of the Morningstar Category split sample analysis in subchapter 5.2 and allows for a substantive interpretation of the fund style as an independent variable.

2.1.2. Financial Intermediaries and Investors

CBMFs invest primarily in corporations. After bonds have been issued and sold on the primary market, investors use over-the-counter (OTC) brokerages to purchase and trade bonds and mutual fund shares.[21] When an investor wants to redeem their investment, they receive the total return after fees are deducted. These OTC dealers are classified as NBFIs with the potential to carry systematics risks if engaged in liquidity transformations.[22] Liquidity transformation in mutual funds describes the process of converting non-liquid assets like bonds and stocks to cash, mostly to satisfy daily investor withdrawals.

The Global Monitoring Report on Non-Bank Financial considers fixed-income funds to be vulnerable to runs.[23] This is because the liquidation costs accompanying investor redemptions are not paid by the exiting investors but instead internalized by the fund, which reduces the return of the remaining investors and creates a first-mover incentive.[24] Thus, investors who expect share sales are motivated to sell first to become advantageous first movers, which turns large redemptions into a self-fulfilling prophecy. Corporate bond funds especially suffer from a perpetual liquidity mismatch because their main asset category, corporate bonds, are generally illiquid: They are traded much more rarely than stocks, can have substantial transaction costs and have a higher credit risk than e.g., government bonds.[25] To combat these risks, mutual funds are likely to have a high level of cash on hand, a so-called cash buffer. Nevertheless, such measures are only effective if they satisfy the fund investors.

CBMF fund investors are typically rather conservative, desiring low risk and a higher predictability, thus being satisfied with moderate returns. With the advent of better and more accessible technology, the number of financial intermediaries and retail investors increased.[26] Consequently, their behavior and psychology gained prominence in analyzing and predicting fund flow movements. Human behavior is known to diverge from the ideal financial agent, *homo economicus*, following detrimental behavioral patterns such as overreactions, heuristic simplification, and loss aversion (which often translates to risk aversion).[27] In times of economic uncertainty and distress, investors often engage in flight-to-liquidity and flight-to-quality behaviors. Flight-to-liquidity is the capital allocation towards assets with higher liquidity like US Treasury bonds and cash.[28] Meanwhile, flight-to-quality or flight-to-safety refers to investors moving their capital from higher-risk to lower-risk assets.[29] Reverse flight-to-quality occurs when investors sell higher-rated assets first to acquire liquidity or because they are unable to sell lower-rated assets.[30] These behavioral phenomena shape fund flows and often align with the distinctive fund styles. To understand the nuances of these dynamics, it is necessary to explore the diverse fund categories. Next, the dependent variable, i.e., the fund flow, will be considered.

2.2. Fund Flows: Theoretical Framework and Financial Fragility

The fund flow needs to be calculated in accordance with the literature standard to be comparable with other published fund flow studies. Thus, I follow the calculation method of Sirri and Tufano and Chevalier and Ellison:[31]

$$Flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + r_{i,t})}{TNA_{i,t-1}} \tag{1}$$

The current flows of fund i, $Flows_{i,t}$, are calculated as the difference between the current total net assets, $TNA_{i,t}$, and the prior total net assets, $TNA_{i,t-1}$, multiplied by the returns relative to the current total net returns, $r_{i,t}$. Investor flow dynamics are known to be affected by a variety of factors, the most prominent of which are persistence and performance chasing. Persistence or momentum describes the phenomenon of past flows predicting current flows, i.e., funds with past inflows receiving more inflows.[32] This leads to a highly significant and strong correlation between the recent and current flows. Next, investors who chase performance value the best return performance and continuously reallocate their capital to the best performing funds in their pursuit. These winner funds receive disproportionately large inflows, and accordingly, loser funds experience disproportionately large outflows. For this reason, the return performance, proxied by the fund alpha or performance rank, has a highly significant and large effect on fund flows. Furthermore, fund flows are known to be driven by fund size, fund age, and return volatility, while the influence of the expense ratio is reportedly negative.[33] Another key characteristic of a given fund is its flow-performance relationship. CBMFs have been shown to have a more concave flow-performance relation which suggests that bond investors are particularly responsive to poor fund performance and penalize it with disproportionate outflows but are not as sensitive to superior

[20] cp. Morningstar Office (2023a), URL see References
[21] cf. Kramer (2024), URL see References
[22] cf. Financial Stability Board (2024b), URL see References
[23] cp. Financial Stability Board (2024a), URL see References
[24] cp. Q. Chen et al. (2010), p. 597
[25] cf. Q. Chen et al. (2010), p. 597
[26] cf. PIMCO (n.d.), URL see References
[27] cf. Hirshleifer (2015), p. 137–144
[28] cf. Longstaff (2004), p. 512 f.
[29] cf. Beber et al. (2009), p. 925
[30] cf. Ma et al. (2022), p. 4674 f.
[31] cf. Chevalier and Ellison (1997), p. 1173 and cp. Sirri and Tufano (1998), p. 1594
[32] cf. Sirri and Tufano (1998), p. 1619
[33] cf. Sirri and Tufano (1998), p. 1599, cf. Q. Chen et al. (2010), p. 406, cf. Goldstein et al. (2017), 602

performance. This leads to an inherent instability in the bond market which raises the question of financial fragility.

Financial fragility is defined as the propensity of a system to falter due to small liquidity demand shocks leading to disproportionately large disruptions, e.g., high asset-price volatility and bank defaults.[34] More generally, it describes the susceptibility and vulnerability of a financial system or market to a financial crisis.[35] The bigger the system, the bigger the potential emergency. Complementarily, financial stability or resilience describes the ability to absorb and weather these shocks without outsize impact. As NBFIs, the growing corporate bond debt markets and mutual funds constitute a key component of the bond financial system and, due to its inherent liquidity mismatch, liquidity shocks would be especially dangerous. This raises concerns about their financial fragility as a liquidity demand shock in response to mass redemptions during a macro crisis seems inevitable. Evidently, the macro conditions play a crucial role for CBMF resilience.

2.3. Macroeconomic Determinants of Fund Flow Dynamics

2.3.1. Macroeconomic Conditions and Monetary Policy Transmission Channels

The returns of CBMFs are dependent on multiple macro factors. As corporate bonds carry a higher credit risk than Treasury bills, investors expect to be compensated with a higher return. This is operationalized as the yield spread, which is calculated as the difference between two different bonds of the same maturity but different credit ratings. Therefore, it is dependent on the performance of baseline rates of safer investments like the 4-week Treasury bill, 3-month Treasury bill for short-term bonds or the intermediate government index. Additionally, bonds carry interest rate risks and thus are impacted by the implied stock market volatility index (VIX), which measures the aggregate market liquidity. For risk-tolerant investors, the default spread is also relevant as it measures the excess return of high-yield bonds compared to the intermediate government bond index. Finally, companies often issue stocks in addition to bonds, which is why their bonds are also impacted by the performance of the stock market index. In short, any macro variable that influences the CBMF yield spread could be relevant for fund flow analyses.[36]

As discussed, investors tend towards loss and risk aversion. Central banks can influence investor behavior through monetary policy transmission channels (MPTC), e.g., their policy decisions can affect markets indirectly by influencing interest rates, credit supply and rate expectations.[37] The interest rate channel theory examines the effects of monetary tightening and loosening. The credit channel theory asserts that debt financing costs caused by “informational frictions ... worsen” during illiquid periods and thereby amplify the impact of monetary policies.[38] Therefore, these MPTCs influence the benefits of higher-risk assets such as CBMFs and are relevant for interpreting investor flows. As the US-American central bank and maker of national monetary policies, the Fed is a vital player in these transmission channels. The Federal Reserve Bank of New York, a supporting reserve bank, publishes the daily effective federal funds rate (FEDFUNDS).[39] This rate affects the lending costs of loans among domestic depository institutions like banks.[40] These borrowing costs indirectly trickle down to other liquidity costs and thus can impact debt financing instruments across the board. This matters particularly during a financial crisis like the COVID-19 liquidity crisis.

2.3.2. The Corporate Bond Market during the COVID-19 Liquidity Crisis

By early March, the COVID-19 pandemic had fully disrupted the US and global financial markets. In fixed-income markets, the extreme instability and uncertainty led to extreme yield spreads in corporate bonds as corporations struggled to operate during imposed restrictions and lockdowns (see Figure 2).[41] This chain of events included an extreme bond price crash and liquidity strain in corporate bond markets.[42]

The bond crisis peaked within three weeks as fixed-income markets inevitably became highly illiquid, and investors turned desperate.[43] IG bond funds suffered especially. Two primary reasons were selling pressures and lacking liquidity. Selling pressures increased immensely as mutual funds in desperate need of cash sold Treasury securities worth $266 billion in a reverse flight-to-quality while liquidity provision faltered as OTC dealers were unable (due to full capacity) or unwilling to take bonds into inventory and supply liquidity.[44] At this point, the Fed directly entered the corporate bond market as a “market maker of last resort” and bought illiquid assets through its newly created corporate credit facilities.[45] The chronology is as follows: On March 23, the Fed announced the PMCCF and SMCCF with their initial term sheets: The PMCCF’s role was to act as a liquidity backstop for corporate debt by buying bonds directly from and providing loans to eligible issuers, while the SMCCF’s purpose was to purchase secondary market corporate bonds from eligible issuers.[46] This served as a liquidity backstop for US corporations in severe need of liquid funds to continue operating. On April 9, the Fed increased the Treasury capital to $50 billion and $25 billion of equity and included HY CBMFs.[47]

[34] cf. Allen and Gale (2004), p. 1027
[35] cf. Lagunoff and Schreft (2001), p. 220
[36] cf. Y. Chen and Qin (2017), pp. 7 f.
[37] cf. European Central Bank (2025), URL see References
[38] cf. Mishkin (1995), p. 4, cf. Bernanke and Gertler (1995), p. 35
[39] cf. Board of Governors of the Federal Reserve System (2025), URL see References
[40] cf. Federal Reserve Bank of New York (2025), URL see References
[41] cf. O’Hara and Zhou (2023), p. 56 f.
[42] cp. O’Hara and Zhou (2023), p. 57
[43] cf. O’Hara and Zhou (2023), p. 58
[44] cf. O’Hara and Zhou (2021), p. 57
[45] cf. O’Hara and Zhou (2021), p. 46
[46] cf. Board of Governors of the Federal Reserve System (2020a, 2020b, 2020d), URL see References
[47] cf. Board of Governors of the Federal Reserve System (2020c), URL see References

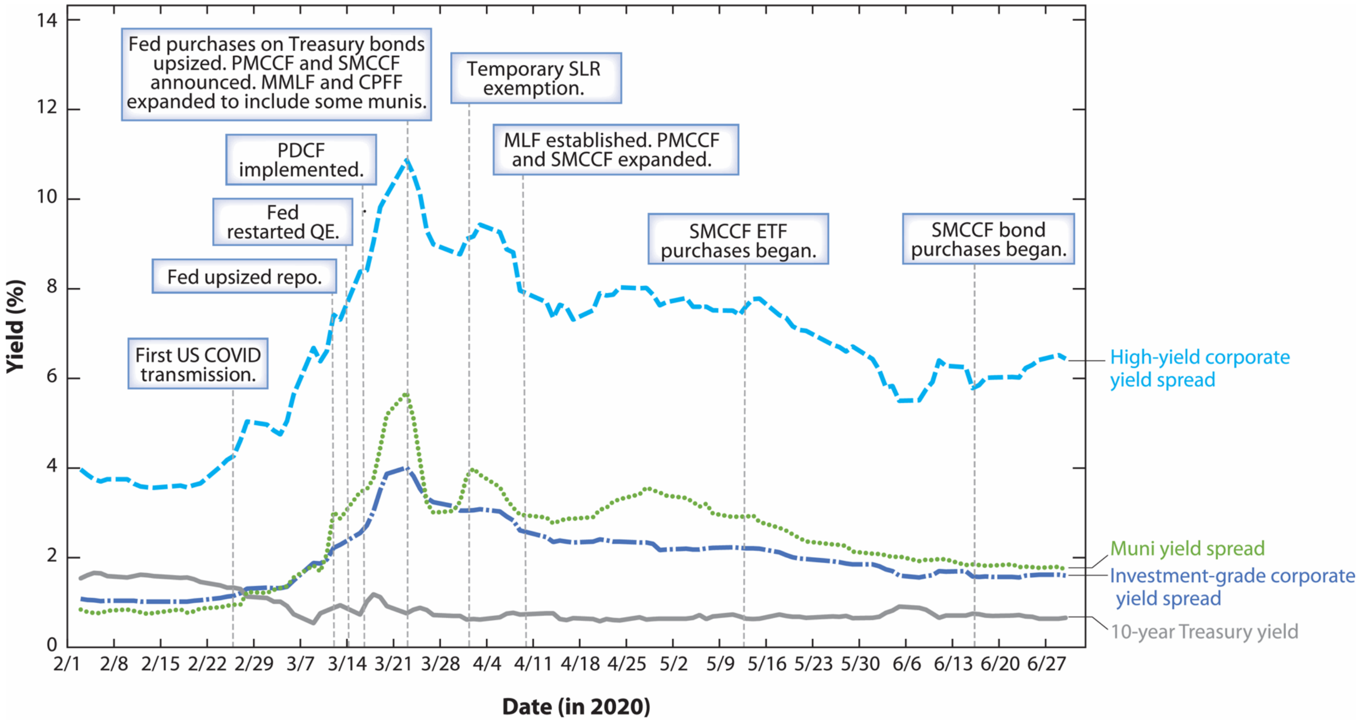

Figure 2: US COVID-19 liquidity crisis evolution and US macro policy responses[48]

The PMCCF launched on June 29 and the SMCCF launched on May 12; both had ceased operations by December 13, 2020.[49] Through these actions, the Fed improved aggregate bond market liquidity. Regarding the liquidity demands placed on mutual funds, the Fed proved most effective as the SMCCF announcement reversed outflows, in particular for more fragile funds.[50] These effects continued and created "positive spillovers to primary bond markets and to other funds holding similar assets".[51]

3. Literature Review

This chapter reviews the relevant, existing literature on CBMF flows, focusing on the determinants and performance relationships identified by Chen and Qin and Goldstein et al. (2017) as well as the impact of macro factors explored by Kuong et al. (2024). Additionally, it examines the effects of the COVID-19 pandemic on bond market flows, drawing insights from studies by Falato et al. (2021), Boyarchenko et al. (2022) and O'Hara and Zhou (2021). These analyses provide a comprehensive understanding of the dynamics influencing CBMFs. Lastly, it will situate the research question within existing research.

[48] cp. O'Hara and Zhou (2023), p. 57
[49] cf. Federal Reserve Bank of New York (2020), URL see References
[50] cf. Falato et al. (2021), p. 37
[51] cf. Falato et al. (2021), p. 37

3.1. Systematic Fund Flow Dynamics

3.1.1. Influence of Macroeconomic Variables on Fund Flows

The macro influence on CBMF flows is a central theme across many studies. Chen and Qin study the determinants of CBMF flows and their flow-performance relation, confirming for the first time in academic literature the sensitivity of investor flows to the recent macro conditions. They find a positive association between the BOND, default spread, OPTION factor, stock market return and VIX index and the money flows, respectively. The correlation to the three-month Treasury bill rate is negative. Their results suggest that rising short-term rates reduce inflows into corporate bond funds.[52]

Kuong et al. expand the literature on the influence of macros on CBMF flows and aggregate fund fragility by exploring the impact of changes in the Federal Funds Target rate (ΔFFTar). Firstly, they document that aggregate bond outflow (inflow) increases (decreases) correspond to FFTar raises (cuts). Secondly, they regress annual and monthly fund flows as dependent variable on FFTar changes and macro controls like the logarithm of the VIX index, default risk changes and a temporal dummy variable for the COVID-19 crisis, among others. The results show a highly significant correlation. Hence, Kuong et al. put forth the following mechanism: Market participants anticipate the decrease in net asset value when learning of planned FFTar increases before FOMC meetings and thus redeem their shares, which suffer from stale overpricing, at an increased rate both before

[52] cf. Y. Chen and Qin (2017), pp. 1-17

and after those meeting dates. They term this phenomenon outflow–ΔFFTar sensitivity.[53]

Goldstein et al. analyze investor flow dynamics into CBMFs and study the flow-performance relationship. They establish the escalating effects of asset and corporate bond market illiquidity, two mechanisms behind bond liquidity mismatches. Namely, they assess the impact of high bond market illiquidity, i.e., high VIX index, and fund liquidity, estimated as fund cash assets. In summary, while Chen and Qin emphasize a broad range of macro factors, Kuong et al. propose the outflow–ΔFFTar sensitivity mechanism with its direct connection to monetary policy, and Goldstein et al. explore how bond market volatility exacerbates fund flow dynamics during periods of economic stress. All provide valuable background for the cash ratio, FEDFUNDS and FEDFUNDS-CHG interpretations.[54]

3.1.2. Influence of Fund Characteristics on Fund Flows

The relationship between fund flows and performance is another key area of investigation in these studies. Chen and Qin find that investor flows chase past fund performance but determine the flow-performance relationship to be non-convex and thus differ from that of equity funds. Also, they conclude that investor flows also predict fund performance. Goldstein et al. similarly study flow-performance relation and find it to be more concave, which implies investor outflows are more sensitive to inferior performance than inflows are to good fund performance. They confirm this finding's robustness across fund age, aggregate fund flow level, fund, and month fixed effects. Together, these studies show that investor behavior in CBMFs is highly sensitive to poor performance, which can decrease a fund's liquidity as investors leave.

The fund and market liquidity also play a pivotal role across fund flow studies. Chen and Qin incorporate aggregate market liquidity factors, i.e., VIX, and find that it positively correlates with CBMF flows. However, fund-level liquidity is not integrated into their analysis. Goldstein et al. examine the influence of fund and market liquidity on investor flows. They find that illiquidity exacerbates fund outflows on both the fund and market level. Also, they discuss the resulting potential financial fragility of markets and suggest remedies in the form of cash buffers or regulations. Kuong et al. explore liquidity in further regressions which indicate that market illiquidity and the staleness of fund share prices amplify the outflow-ΔFFTar sensitivity, which they consider to be novel findings. Thus, they determine a MPTC affecting corporate bond fund flow patterns. Together, these studies emphasize the significance of liquidity in CBMF dynamics. Goldstein et al. highlight the risks of liquidity mismatches, while Kuong et al. provide novel insights into how liquidity interacts with monetary policy to shape investor behavior.

[53] cf. Kuong et al. (2024), pp. 1–19

[54] cf. Goldstein et al. (2017), pp. 592–613

3.2. Impact of COVID-19 on Fund Flows and Corporate Bond Markets

The COVID-19 crisis profoundly affected corporate bond fund flows, with studies examining how flows evolved during this period and identifying key factors driving these changes. Falato et al. examine corporate bond fund flows during and in the wake of the COVID-19 crisis, which they define as the period from February to April 2020. They use a regression analysis to estimate the relationship between fund flows and the various pandemic stages by utilizing the chronological dummy variables Crisis (February – April 2020), Peak (March 13 – 23, 2020), First Response (March 23 – April 9, 2020) and Second Response (April 9 – 17, 2020). The latter two dummies refer to the Fed policy announcements regarding the PMCCF and SMCCF on March 23 and their endowment with $75 billion on April 9. Outflows peaked during mid-to-late March, the height of the crisis. The authors show that, on average, funds experienced an unprecedented 10% cumulative outflow. Then, they explore the effect of and the mechanism behind the Fed policy announcements and bond purchase program, which improved fragility by supplying a liquidity backstop in a liquidity drained market. They conclude with an analysis of the Fed's lasting effect on flows and liquidity after the crisis (April – August 2020), finding that cumulative inflows rebounded remarkably quickly to an average of 9%. Afterward, Falato et al. assess sources of fragility and identify three main sources: asset illiquidity, fire-sales vulnerability, and sector exposure. They find that illiquid funds experienced preemptive and more extreme outflows relative to other funds.[55]

Boyarchenko et al. similarly examine fund flows during this period but focus on the effect of the Federal Reserve Bank of New York corporate credit facilities, i.e., PMCCF and SMCCF on corporate bond markets in the wake of the COVID-19 pandemic.[56] The PMCCF was created as a "funding backstop" and the SMCCF as a provider of "market liquidity for corporate bonds".[57] Ultimately, they find that aggregate liquidity on the secondary debt market was improved mainly through announcement effects.[58]

O'Hara and Zhou investigate the COVID-19 corporate bond liquidity crisis, which they define as the liquidity crunch and its repercussions for liquidity and transaction costs and bond pricing in the weeks before the PMCCF and SMCCF creation. They find that the interventionist actions established the Fed as "market maker of last resort, ... willing to buy assets directly or to facilitate such buying by taking such assets as collateral" who injected liquidity back into the corporate bond market. This market improvement was already effective through announcements alone, which preceded the actual implementation, leading to a speedy resolution of the liquidity crisis.[59] All three papers agree that the Fed's an-

[55] cf. Falato et al. (2021), pp. 35–52

[56] cf. Boyarchenko et al. (2022), pp. 695–731

[57] cp. Federal Reserve Bank of New York (2020), URL see References

[58] cf. Boyarchenko et al. (2022), p. 707

[59] cf. O'Hara and Zhou (2021), pp. 46–68

nouncements significantly calmed investors and improved corporate bond market stability. Together, these findings demonstrate the scale of outflows during the COVID-19 crisis and the pivotal role of the Fed's interventions in restoring stability to corporate bond markets.

3.3. Datasets and Methodologies in Fund Flow Studies

The datasets and methodologies employed by these studies vary and provide valuable suggestions for this thesis's analysis. Chen and Qin construct their dataset from US corporate bond funds information from 1991-2014 and cover 418 unique bond funds, consisting of 229 HY and 189 IG bonds. They then conduct fund-level time-pooled and cross-sectional regressions of the net fund flows on the fund characteristics controls and macro variables. The latter consist of the bond-related BOND, STK, DEF, OPTION, TB3 and VIX factors.[60]

Goldstein et al. use a larger data sample consisting of corporate bond data from January 1992 to December 2014 with 4679 unique fund share classes and 1660 unique corporate bond funds. Their fund-level analyses regress the corporate bond's net flow on the fund alpha variable and fund characteristics controls using multiple estimations, enabling them to study flow-performance dynamics and liquidity mismatches in depth.[61]

Kuong et al. use a more recent dataset of 3182 unique funds and 6251 unique share classes, covering the years 2009 to 2023, composed of FFTar from the Federal Reserve Economic Data (FRED), Federal Open Market Committee dates and Futures related information. Their analyses include event studies and cross-sectional time-series regressions, allowing them to capture the impact of FFTar changes and crises like COVID-19 on fund flows.

Falato et al. construct their dataset from US corporate bond high-frequency real-time daily fund flows and returns data from January 2010 to April 2020 as well as fund characteristics information, all from Morningstar. In summary, they observe 1511 unique funds and 1511 unique share classes. First, they determine the scale of the impact on funds flows during the pandemic by documenting the change in flow patterns during the crisis in graphical and statistical analyses. Then, they conduct a multiple regression analysis with crisis-stage dummy variables to study the evolution of fund flows during the pandemic and the effectiveness of Fed policy actions.[62]

Boyarchenko et al. use bond issuance, dealer, trade, and daily bond information spanning 2020. They regress various spreads on the secondary market against differently-rated corporate bonds and dummy variables indicating the timeline around facility announcements. Their analysis highlights the effects of the PMCCF and SMCCF on differently rated bonds, emphasizing the role of announcement effects in stabilizing the market.[63]

O'Hara and Zhou assemble their sample from corporate bond transaction data, characteristics, and dealer information, spanning February 1, 2020, to May 19, 2020. They analyze the microstructure of liquidity provision by measuring the corporate bond illiquidity proxied by trading transaction costs across bond categories. Moreover, they study primary and non-primary dealers and their ability and efficaciousness as liquidity providers. They employ a variety of regressions with trading volume, dealer inventory changes, transaction costs and market liquidity as dependent variables and control for industry and trade size fixed effects.[64]

3.4. Formulation of Research Question

Chen and Qin focus on only a select few macro factors. Furthermore, Kuong et al. elaborate on this question by focusing on the impact changes in the Federal Funds Target rate while Goldstein et al. focus on the influence of general fund characteristics and analyze the flow-performance relationship. Building on this, the present thesis seeks to reduce that research gap by focusing on the effective federal funds rate and rate change. These factors present a novel opportunity to examine two macro factors which are closely tied to the Fed.

While Falato et al. study the evolution of corporate bond fund flows during the COVID-19 crisis, Boyarchenko et al. examine the impact of the Fed interventions on credit spreads in corporate bond markets. Additionally, O'Hara and Zhou analyze the liquidity provision during the COVID-19 crisis. This thesis builds on and expands their findings by focusing on the medium-term impact of COVID-19 on CBMF flows until December 2021. Moreover, the cash ratio could be another key variable. As a potential liquidity buffer, it may protect CBMFs against investor withdrawals and associated liquidation costs. Hence, I plan to analyze whether investors reward fund-level liquidity, inspecting the correlation between the cash ratio and fund flows.

Like Chen and Qin, this thesis employs monthly cross-sectional and time-pooled regressions, with and without time and fund style fixed effects. The same macro variables are included (BOND, VIX, STK, DEF, OPTION and TB3). Also, I use subsets of variables to improve the robustness of my findings. Once again similar to Chen and Qin, I differentiate between fund styles in my analysis, but conversely to them, I analyze every Morningstar Category to extract more nuanced fund style results. Following Falato et al. and O'Hara and Zhou, this thesis incorporates time dummy variables and interaction terms in the COVID-19 crisis case study to delineate the pandemic phases. This analysis includes interaction terms with the cash ratio, the performance rank, and changes in the effective federal funds rate. In summary, this thesis examines the determinants of CBMF flows with a special focus

[60] cf. Y. Chen and Qin (2017), pp. 2 ff.
[61] cf. Goldstein et al. (2017), p. 598 ff.
[62] cf. Falato et al. (2021), p. 38 ff.
[63] cf. Boyarchenko et al. (2022), p. 695 ff.
[64] cf. O'Hara and Zhou (2021), p. 51 ff.

on the effective federal funds rate, rate changes, and cash ratio. Then it proceeds with a fund style split sample analysis. Finally, it investigates the medium-term effects of the COVID-19 crisis on the CBMF flows in a dedicated case study.

4. Data and Methodology

This chapter outlines the data sources and methodology used for the analysis of CBMF flows. The primary dataset is monthly US CBMF information from Morningstar (2001-2021). Additionally, macro factors are extracted from Bloomberg and FRED databases. The methodology focuses on constructing the main variables. The chapter also discusses the descriptive statistics of both the fund and macro data.

4.1. Corporate Bond Mutual Fund and Macroeconomic Data

The primary data is monthly US corporate bond mutual fund information from Morningstar: fund identification, share class identification, total raw returns, inception date, Morningstar category, asset allocation, expense ratio, date, and net assets, with the data spanning the years from August 2001 to December 2021. Fund turnover information was included initially, but its poor data availability reduced the sample by tens of thousands of observations, which would have weakened the analysis. Multiple comparative studies also proceed without turnover data.[65] Consequently, the data was removed from this analysis. The original data includes 721 unique funds and 2814 unique share classes. In the final sample, share classes are aggregated to fund level, leaving 681 unique funds. As funds consist of share classes with unique flows, returns and expense ratios, I use asset-weighted net fund flows, total returns and net expense ratios by calculating weighted averages of the aggregated share classes relative to the corresponding fund's total net assets (TNA).[66] I then perform a monthly 90% winsorization of the flows, returns and expense ratios by winsorizing them at the 5^{th} and 95^{th} percentiles. The final cumulative net flow is plotted in Figure 3. Noticeably, the funds in the sample received inflows of tens of billions of US dollars which aligns with the expanding US bond market.

Each fund has a minimum average bond asset allocation of 40% over the sample period and is thus classified as a CBMF. The cash ratio, bond ratio, equity ratio and other ratio (the remaining percentage) are taken from the asset allocations. The cash ratio, bond ratio and equity ratio over time are visualized in Figure 4. The cash and bond lines show that CBMFs hold the majority of their assets in bonds and only a small percentage in cash. Of the bond holdings, roughly 40% consist of corporate bonds, however, the median corporate bond ratio sways between 50% to 70% percent (see Figure 4). This negative skew suggests that some funds hold fewer corporate bonds, lowering the average.

The expense ratio is backfilled for the preceding months of the year since funds report it at end of the fiscal year. The fund age is calculated as the difference between the current date and the fund inception age in years, under the assumption that the minimum inception age applies to all share classes.[67] Funds differ in their reporting frequency: Some report their current asset allocation monthly, while others report each quarter. Therefore, the gaps between reports are filled by assigning the prior date's asset allocation forward until the next date, unless the next date is the last date. The volatility is the current date's standard deviation of the cumulative monthly returns in the prior 12 months. Finally, Morningstar assigns each Morningstar Category to each fund. The nine Morningstar Categories are (in decreasing sample frequency): US Fund High-Yield Bond (280 funds), US Fund Intermediate Core Bond (111 funds), US Fund Short-Term Bond (102 funds), US Fund Multisector Bond (70 funds), US Fund Corporate Bond (54 funds), US Fund Intermediate Core-Plus Bond (47 funds), US Fund Nontraditional Bond (29 funds), US Fund Long-Term Bond (29 funds), and US Fund Bank Loan (9 funds).

Table 1 shows the summary statistics for the sample's fund characteristics. The average fund has \$1.357 billion total net assets, is 14.424 years old, with an asset allocation of 88.459% bonds and 7.558% cash. Its net inflows are 0.469% with 0.421% total returns, 1.382 volatility and a net expense ratio of 0.823%. In comparison, the median fund has \$298.392 million total net assets, is 12.217 years old and allocates more assets to bonds with a 91.661% bond ratio and only 4.806% cash ratio.

It experiences a slight net outflow at the median but has higher returns and a lower volatility and net expense ratio. This suggests a positive skew of the total net assets, fund age, volatility, net expense ratio and cash ratio. The percentiles of the total net assets show a heterogeneous, wide distribution. In comparison, the fund age difference of 2.207 years is relatively small. The distribution of fund flows includes firmly positive and negative percentiles, which indicates quite heterogeneous fund flows. More than half of the funds must experience small-to-substantial net outflows. The total returns and bond ratio are negatively skewed. The contrast between the mean fund and median fund is unexpected as it implies that investor flows may not conform to traditional risk-return tradeoff expectations. However, the standard deviations of the flows, volatility, expense ratio and returns encompass these ratios. Consequently, the sample is considered robust enough for further analysis.

The macro data is drawn from both the Bloomberg and FRED databases. The Barclays aggregate bond index, intermediate government bond index, US corporate high yield index, S&P 500 index and GNMA index are extracted from Bloomberg. The indices here and hereafter refer to the to-

[65] cf. Choi et al. (2020), p. 435, cf. Y. Chen and Qin (2017), p. 2 f., cf. Goldstein et al. (2017), p. 598, cf. Q. Chen et al. (2010), p. 244 f.

[66] cf. Pástor et al. (2015), p. 31

[67] cf. Pástor et al. (2015), p. 31

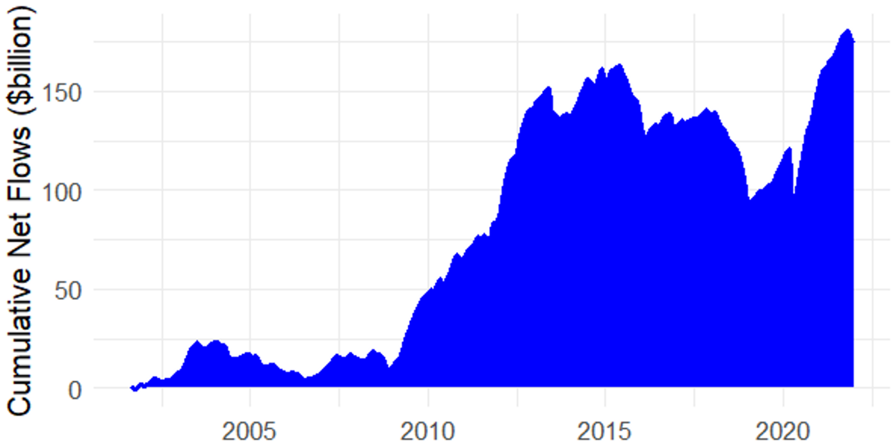

Figure 3: Cumulative net flow of the data sample in percent

This graph plots the cumulative net flows of all funds in the sample in the sample period, August 2001 to December 2021.

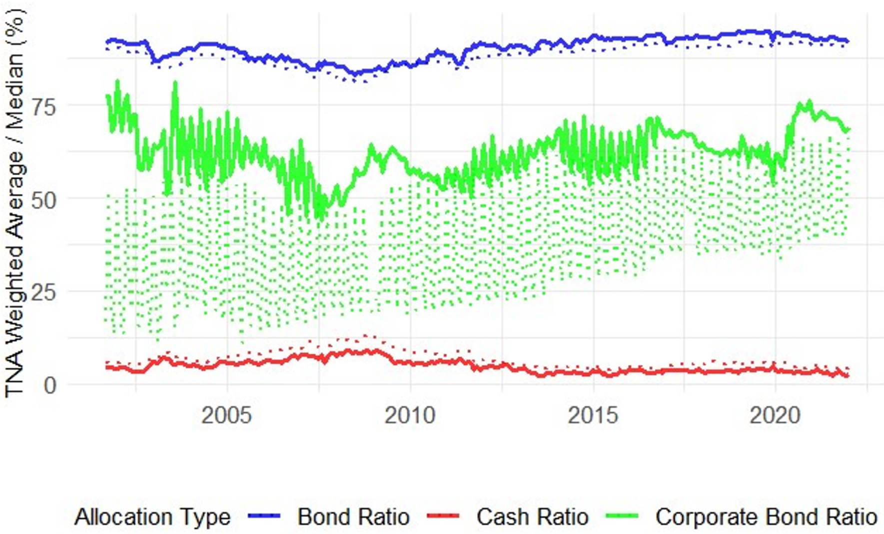

Figure 4: TNA weighted average and median of the sample cash, bond, and corporate bond ratios

This graph plots the time series of the sample's bond ratio, cash ratio and corporate bond ratio. The solid line shows the TNA-weighted median, and the dotted line represents the TNA-weighted average.

tal return index with gross dividends. The FEDFUNDS, effective federal funds rate change (FEDFUNDS-CHG, in percent), three-month Treasury bill secondary market rate (TB3MS) and four-week Treasury bill secondary market rate are downloaded from FRED. The market volatility index (VIX), "measuring implied volatilities in stock market", is obtained from the Chicago Board Options Exchange.[68] Since the volatility index is reported daily, each month's arithmetic VIX average is used.

4.2. Construction of Main Variables

The fund flow is the main dependent variable. The independent variables include both fund characteristics and macro factors. All independent variables are lagged by one month. The fund controls include the logarithm of fund age, of fund size, i.e., total net assets, as well as the volatility, expense ratio, the past month's flows, and the performance rank. The performance rank is a fund's fractional rank based on its cumulative monthly returns in the prior 12 months relative to other funds in the same Morningstar Category.[69] The better a fund's percentile performance, the higher its assigned rank, ranging from 0 to 1. The cash asset allocation ratio held by CBMFs represents the approximate fund-level liquidity.[70]

[68] cp. Goldstein et al. (2017), p. 595

[69] cf. Y. Chen and Qin (2017), p. 5

[70] cf. Goldstein et al. (2017), p. 599

Table 1: Descriptive statistics: fund characteristics

Variable	N	Mean	SD	P5	P25	P50	P75	P95
Total net assets [$ million]	93198	1357.417	3758.315	12.721	78.593	298.392	1017.033	6116.023
Fund age [year]	93198	14.424	11.000	1.000	5.610	12.217	20.660	35.306
Net fund flows [%]	92771	0.469	3.534	–4.481	–1.277	–0.011	1.619	7.303
Total returns [%]	92771	0.421	1.806	–2.008	–0.169	0.438	1.170	2.811
Volatility [%]	92263	1.382	1.110	0.279	0.701	1.100	1.661	3.579
Net expense ratio [%]	93198	0.823	0.383	0.148	0.607	0.800	1.035	1.474
Cash Ratio [%]	93197	7.558	9.058	0.258	2.366	4.806	9.236	24.101
Bond Ratio [%]	93197	88.459	11.214	67.156	85.564	91.632	95.391	98.685
Equity Ratio [%]	93197	0.889	3.528	0.000	0.000	0.000	0.325	4.390
Other Ratio [%]	93197	3.092	5.060	0.000	0.141	1.420	3.968	11.059

This table shows the summary statistics for the sample's fund characteristics: N, mean, standard deviation, and the 5th, 25th, 50th (median), and the 95th percentiles.

Additionally, the BOND, DEF, OPTION and STK factors are calculated. BOND is the return spread between the Barclays aggregate bond index and the 4-week Treasury bill rate, DEF is the "return spread between the high-yield bond index and the intermediate government bond index", OPTION is the "return spread between the GNMA index and the intermediate government bond index" and STK is the stock market return spread between the S&P 500 index and the 4-week Treasury bill rate.[71] Finally, I use a second liquidity measure: The aggregate corporate bond market illiquidity is proxied by the implied market volatility index, VIX.[72] I assign the BOND, DEF, OPTION, STK and VIX factors as macro controls. Table 2 shows the summary statistics for the macro factors. On average, the BOND factor is -0.779%, the FEDFUNDS is 1.269 with a rate change of -0.012%, the VIX index is 19.254, the STK factor is -0.241%, the DEF factor is 0.357%, the OPTION factor is 0.046% and the three-month Treasury bond index is 1.162. At the median, the BOND factor is -0.483%, the FEDFUNDS is 0.650 with a rate change of 0.000%, the VIX index is 17.273, the STK factor is -0.042%, the DEF factor is 0.566%, the OPTION factor is 0.093% and the three-month Treasury bond index is 0.510.

5. Analysis and Results

This chapter outlines the analysis of the fund flow determinants using regression models and the results, focusing on both systematic dynamics and the impact of the COVID-19 pandemic. First the systematic fund flow regressions are presented. Next, a comprehensive fund style split sample analysis is conducted, and the results are compared. Finally, the impact of the COVID-19 on CBMF flows is investigated.

[71] cp. Y. Chen and Qin (2017), p. 5

[72] cf. Goldstein et al. (2017), p. 599, cf. Kuong et al. (2024), p. 15

5.1. Systematic Fund Flow Dynamics: Regression Models and Results

I estimate the influence of the fund characteristics and macro factors with pooled time-series and cross-sectional linear regressions, namely OLS regressions without fixed effects and FE regressions with fixed time and fund style effects similar to Chen and Qin.[73] The fund flow remains the dependent variable for all regressions. The time fixed effects control for the year and month, and the fund style fixed effect controls for the Morningstar Category. The effective federal funds rate, its change, the VIX index, the BOND factor, the cash lag, and the performance rank are of particular interest. The remaining fund characteristics, i.e., the logarithm of the fund age and total net assets, the return volatility, the expense ratio and the previous month's flows are fund control variables. Similarly, the three-month Treasury bill rate and the STK, DEF, OPTION factors are macro controls. These variables were selected to estimate the fund flow correlations accurately as they are standard in published fund flow studies like Elton et al. and Chen and Qin.[74] Using heteroskedastic and autocorrelation consistent standard errors is also the standard in published flow studies. This is because financial market time series data is known to exhibit heteroskedasticity and have time-varying standard deviations for predictor variables.[75] Additionally, financial market time series data often exhibits autocorrelation. For example, fund returns have been shown to be positively correlated.[76] Furthermore, daily fund flows have also been proven to be significantly autocorrelated.[77] Consequently, a studentized Breusch-Pagan-

[73] cf. Y. Chen and Qin (2017), p. 6f.

[74] cf. Elton et al. (1995), 1234, 1241, cf. Y. Chen and Qin (2017), p. 8

[75] cf. Investopedia (2025), URL see References

[76] cf. Choi et al. (2020), p. 297

[77] cf. Edelen and Warner (2001), p. 199 f., cf. Rakowski and Wang (2009), 2104 f.

Table 2: Descriptive statistics: macroeconomic condition

Variable	N	Mean	SD	P5	P25	P50	P75	P95
BOND [%]	87160	–0.779	1.606	–4.191	–1.593	–0.483	0.317	1.309
FEDFUNDS [%]	87160	1.269	1.501	0.080	0.120	0.650	1.910	5.020
FEDFUNDS-CHG [%]	87160	–0.012	0.158	–0.280	–0.010	0.000	0.020	0.170
VIX	87160	19.254	8.242	11.062	13.678	17.273	22.374	34.05
STK [%]	87160	–0.241	4.554	–8.795	–2.680	–0.042	2.422	6.846
DEF [%]	87160	0.357	2.874	–3.522	–0.556	0.566	1.485	4.229
OPTION [%]	87160	0.046	0.428	–0.743	–0.182	0.093	0.309	0.694
TB3MS [%]	87160	1.162	1.400	0.020	0.080	0.510	1.760	4.720

This table shows the summary statistics for the macroeconomic factors during the sample period: N, mean, standard deviation, and the 5th, 25th, 50th (median), and the 95th percentiles.

Test is performed for each regression. The test has two hypotheses: The null hypothesis is that homoscedasticity is present, the complementary hypothesis is that heteroskedasticity is present. If the test statistic output's ("BP") corresponding p-value indicates significance, the null hypothesis must be rejected, and heteroskedasticity is present. Therefore, OLS standard errors may be less dependable. Consequently, Newey-West standard errors are calculated, which have the advantage of being both heteroskedasticity and autocorrelation consistent.

First, I analyze the influence of the macro condition on the fund flows by performing iterative regressions. In OLS regression 1, I regress the fund flows on the fund and macro variables (see equation 2). α represents the regression intercept, β the coefficients and $\varepsilon_{i,t}$ the residual error term.

$$\begin{aligned} Flows_{i,t} = \alpha &+ \beta_1 \times cash\ ratio_{i,t-1} \\ &+ \beta_2 \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_3 \times performance\ rank_{i,t-1} \\ &+ \beta_4 \times Controls_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

In OLS regression 2, I repeat the regression while limiting the independent variables to the macroeconomic factors (see equation 3).

$$\begin{aligned} Flows_{i,t} = \alpha &+ \beta_1 \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_2 \times Controls_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

In FE regression 3, I conduct a regression on all independent variables while controlling for style fixed effects (see equation 4). η_i describes the control term for style fixed effects.

$$\begin{aligned} Flows_{i,t} = \alpha &+ \beta_1 \times cash\ ratio_{i,t-1} \\ &+ \beta_2 \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_3 \times performance\ rank_{i,t-1} \\ &+ \beta_4 \times Controls_{i,t-1} + \eta_i + \varepsilon_{i,t} \end{aligned} \tag{4}$$

Time fixed effects are excluded as the macro conditions primarily change with transitory time and hence could lose informative value. Performing the Breusch-Pagan test reveals highly significant results for all three regressions (see Table 3) with p-values $< 2.2e^{-16}$. Accordingly, the null hypothesis is rejected, heteroskedasticity is present, and I calculate Newey-West standard errors. Then, I further analyze the influence of the fund characteristics on the fund flows by performing iterative regressions. In the FE Regression 4, I regress the fund flows on the fund variables while controlling for style and time fixed effects (see equation 5). λ_t is the control term for the time fixed effects.

$$\begin{aligned} Flows_{i,t} = \alpha &+ \beta_1 \times cash\ ratio_{i,t-1} \\ &+ \beta_2 \times performance\ rank_{i,t-1} \\ &+ \beta_3 \times Controls_{i,t-1} + \eta_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{5}$$

Table 3: Breusch-Pagan test results for the regression models 1-4

Model	Statistic	p-value
Regression 1	4092.193***	$< 2.2e^{-16}$
Regression 2	2518.826***	$< 2.2e^{-16}$
Regression 3	4666.439***	$< 2.2e^{-16}$
Regression 4	8261.537***	$< 2.2e^{-16}$

This table shows the Breusch-Pagan test results for regressions 1-4. Stars signify statistical significance: *** p < 0.001, ** p < 0.01, * < 0.05, respectively.

I also conduct Breusch-Pagan tests (see Table 3) with highly significant results (p-value $< 2.2e^{-16}$) that confirm heteroskedasticity and calculate the Newey-West standard errors. I then proceed with the different regression analyses. Table 4 presents the results.

The expected correlation between FEDFUNDS and FEDFUNDS-CHG to fund flows is negative as a high FEDFUNDS

Table 4: OLS and style FE regressions 1-4

	Dependent variable: flows			
	All vars.	**Macro. vars.**	**All vars.**	**Fund vars.**
	OLS	OLS	Style FE	Time FE
	Newey-West	*Newey-West*	*Newey-West*	*Newey-West*
	(1)	(2)	(3)	(4)
volatility	–0.056***		–0.009	–0.113***
	(0.016)		(0.019)	(0.022)
	t = –3.379		t = –0.480	t = –5.060
log(fund age)	–0.414***		–0.427***	–0.408***
	(0.019)		(0.020)	(0.019)
	t = –21.295		t = –21.400	t = –21.292
past flows	0.372***		0.369***	0.373***
	(0.008)		(0.008)	(0.008)
	t = 47.526		t = 47.123	t = 48.629
log(TNA)	0.017*		0.015	0.016
	(0.008)		(0.009)	(0.008)
	t = 2.061		t = 1.726	t = 1.956
expense ratio	0.003		0.090	0.006
	(0.048)		(0.052)	(0.049)
	t = 0.069		t = 1.749	t = 0.118
performance rank	1.077***		1.086***	1.079***
	(0.046)		(0.047)	(0.045)
	t = 23.229		t = 23.317	t = 23.757
cash ratio	0.005**		0.003	0.005**
	(0.002)		(0.002)	(0.002)
	t = 2.642		t = 1.667	t = 2.779
BOND	0.153***	0.212***	0.153***	
	(0.012)	(0.013)	(0.012)	
	t = 12.441	t = 15.853	t = 12.451	
FEDFUNDS	–0.266***	–0.204	–0.250***	
	(0.070)	(0.106)	(0.070)	
	t = –3.777	t = –1.921	t = –3.560	
FEDFUNDS-CHG	0.046	0.030	0.035	
	(0.110)	(0.143)	(0.110)	
	t = 0.416	t = 0.208	t = 0.316	

This table reports the fund-level regression results for the coefficient estimates of the independent variables. Fund flow is the dependent variable while fund characteristics and macro factors are the independent variables. Column (1) shows the OLS regression results for all variables. Column (2) shows the OLS regression estimates for macro variables. Column (3) shows the FE fund style regression for all variables. Column (4) shows the FE time regression for the fund variables. "Time FE" denotes time, i.e., year and month, fixed effects, and "Style FE" above Column (3) denotes fund style fixed effects. The Newey-West standard error sits below the coefficient in parentheses. The t-value, designated "t", is below it. Stars indicate statistical significance: *** $p < 0.001$, ** $p < 0.01$, * < 0.05, respectively.

Table 4 — continued

STK	0.019***	0.014**	0.019***	
	(0.005)	(0.005)	(0.004)	
	t = 4.217	t = 3.065	t = 4.191	
VIX	0.051***	0.056***	0.048***	
	(0.003)	(0.004)	(0.003)	
	t = 18.243	t = 14.206	t = 16.622	
TB3MS	0.412***	0.405***	0.402***	
	(0.078)	(0.117)	(0.078)	
	t = 5.304	t = 3.469	t = 5.178	
DEF	0.009	0.100***	0.006	
	(0.008)	(0.009)	(0.008)	
	t = 1.185	t = 11.133	t = 0.769	
OPTION	0.089**	0.067	0.085**	
	(0.031)	(0.035)	(0.031)	
	t = 2.882	t = 1.885	t = 2.759	
Intercept	–0.648***	–0.831***	–0.886**	1.515***
	(0.168)	(0.080)	(0.339)	(0.280)
	t = –3.857	t = –10.360	t = –2.616	t = 5.408
Observations	87,160	87,160	87,160	87,160
R^2	0.206	0.027	0.208	0.252
Adjusted R^2	0.206	0.027	0.208	0.250

and its increases exacerbate liquidity costs by making borrowing money more costly.[78] Thereby, investor flows into funds should decrease.[79] As hypothesized, FEDFUNDS is consistently negative but varies in significance: highly significant in regression 1 and 3, but not significant in regression 2.

This implies that investors invest less during high effective federal rate conditions, which is highly economically plausible and significant as the factor loadings amount to roughly half of the average net fund flows of 0.469%. The decreased net flows across fund styles could suggest divestment from CBMFs of all fund styles when the FEDFUNDS rises, potentially indicating fire sales.[80] In contrast, the FEDFUNDS-CHG and flow relationship is positive, small and statistically insignificant across regressions and style fixed effects. Comparing this to Kuong et al., where the ΔFFTar correlates strongly and significantly (1.276 at the 1% level) with monthly bond outflows, offers two key insights:[81] First, they support the hypothesis that investors closely consider macro factors tied to the FEDFUNDS. Second, they underscore the importance of the Fed as monetary policy maker and its transmission channels between corporate bond markets and monetary policy.[82] Unlike Kuong et al., who determine the ΔFFTar to be the key factor, this analysis finds that FEDFUNDS, and not FEDFUNDS-CHG, is more significant.[83]

The DEF coefficients are positive, slightly above zero, and not significant, except in regression 2, where it is 0.100 and highly significant. These results agree with Chen and Qin, who also find the DEF factor to be consistently small and positive for all funds and IG funds.[84] A positive DEF is economically plausible, as more investors tend to engage in flight-to-safety behavior during periods of higher default risk, favoring bonds over stocks.[85] The implied market volatility index coefficients 1-3 are highly significant with only minimal variation: 0.051, 0.056 and 0.048. Chen et al. receive similar results and Kuong et al. estimate $\Delta\log(\text{VIX}) = -0.179$ which equals VIX ≈ 0.836.[86] Akin to investor behavior during times of higher default risk, the risk associated with higher stock market volatility, i.e., higher VIX, might also cause investors to prefer bond investments and lead to inflows.[87]

78 cf. Goldstein et al. (2017), p. 611 f.
79 cf. Kuong et al. (2024), p. 5
80 cf. Falato et al. (2021), p. 3145
81 cf. Kuong et al. (2024), p. 6
82 cf. Kuong et al. (2024), p. 5
83 cf. Kuong et al. (2024), p. 6
84 cf. Y. Chen and Qin (2017), p. 8
85 cf. Y. Chen and Qin (2017), p. 7 f.
86 cf. Y. Chen and Qin (2017), p. 8, cf. Kuong et al. (2024), p. 6
87 cf. Y. Chen and Qin (2017), p. 7 f.

The BOND coefficients are highly significant, ranging between 0.125 (regression 1 and 3) and 0.212. This is reasonable as higher excess returns on the aggregate bond index result in higher investor margins and are therefore more profitable, thereby attracting investors and net inflows across all fund styles. This finding is validated by Chen and Qin, who calculate BOND factors close to 0.2 for all, IG and HY funds.[88] The other macro controls, STK (significant to highly significant), OPTION (not significant to significant) and TB3MS (highly significant) have a consistently positive correlation to flow. These macro correlations are corroborated by Chen and Qin; however, the positive TB3MS correlation diverges from their findings as it would imply that rising interest rates, which lower the comparative bond yield spread, still lead to fund inflows.[89]

Funds with higher cash ratios, i.e., better liquidity, should attract inflows from investors who value asset liquidity due to presumably lower liquidation and redemption costs. In fact, Chen et al. show that funds with lower liquidity tend to conduct costly liquidations to satisfy withdrawals.[90] Depending on the priorities of the overall investor population, I expect the correlation between cash ratio and fund flows to be positive to neutral. This expectation is met as the regression coefficients are near zero. This might indicate that flows are largely unrelated to the cash ratio, however, considering their varied significance, a firm conclusion cannot be drawn. While this suggests a limited economic significance of the cash ratio due to the coefficients' exceedingly small size, the correlation is statistically significant in some regressions (e.g., 0.005 in regression 1 and 0.003 in regression 3, though not significant). This aligns with Jiang et al., who suggest that funds often scale down liquid and illiquid holdings proportionally during financial strain to maintain their portfolio ratio, making cash ratio changes largely irrelevant to investors.[91]

The association of the fund controls log(fund age), log(TNA), past flows and performance rank is expected to be negative, negative, positive and positive, respectively.[92] The past flow and especially the performance rank should be highly significant and have a larger effect as investors are hypothesized to strongly prioritize fund performance and recent flows. These correlations are confirmed by the results across regressions, style, and time fixed effects. The log(fund age), past flows and performance rank correlations behave very consistently and are economically significant due to their large size relative to the fund flows average and median.

The performance rank coefficients are highly significant and noticeably large in regressions 1, 3 and 4, i.e., the regressions involving all or the fund variables: They exceed 1. As such, they are larger than the results the studies of Chen and Qin and Chen et al. (0.77 and 0.016), however, they remain below the Rakowski and Wang performance rank coefficient, 1.693.[93] Overall, this implies strong performance chasing from fund investors as the fund flows increase by more than 1 for every one-unit increase in the performance rank. This behavior is economically significant as the inflow is more than double the average fund flow, raising the question of investor overreactions.

The log(TNA) coefficient is marginally significant at 0.017 regression 1 but not robust to controlling for style or time fixed effects – in any case it is too small to be economically significant. This agrees with Goldstein et al., Rakowski and Wang and Chen and Qin.[94] The expense ratio correlations are slightly positive and not significant. Due to their lack of significance and large Newey-West standard errors, the results are not dependable. Otherwise, the positive correlation would be unusual as expenses were incorporated to control for the reportedly negative effect on fund flows.[95]

The volatility is negative and generally highly significant as expected, indicating that increasing return volatility deters fund inflows which is validated by literature.[96] However, this result is not robust to controlling for style and too small to be economically significant. The adjusted coefficient of determination, adjusted R^2, shows how much of all variation in fund flows is explained by the incorporated variables. When employing all variables, it is broadly 21% (regression 1). It falls to 2.7% when the regression is confined to macro variables and controlled for style (regression 2). The maximum explanatory power is 25.2% when the regression is focused on fund variables and includes all FEs (regression 4). Broadly, this aligns with Chen and Qin who have adjusted R^2 values around 20%.[97]

5.2. Systematic Fund Style Split Sample Analysis: Regression Models and Results

In FE regression 5, I conduct regressions on the fund variables and controls for each fund style by constructing individual and separate fund samples per Morningstar category while controlling for month fixed effects. The non-HY funds were not aggregated to an investment-grade sample because the goal is to examine the fund category's individual profile. The estimated model specification is (see equation 6):

$$\begin{aligned} Flows_{i,t} = \alpha &+ \beta_1 \times cash\ ratio_{i,t-1} \\ &+ \beta_2 \times performance\ rank_{i,t-1} \\ &+ \beta_3 \times Controls_{i,t-1} + \eta_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

[88] cf. Y. Chen and Qin (2017), p. 8
[89] cf. Y. Chen and Qin (2017), p. 7 f.
[90] cf. Q. Chen et al. (2010), p. 258
[91] cf. Jiang et al. (2021), p. 1625
[92] cf. Bergstresser and Poterba (2002), p. 405, cf. Y. Chen and Qin (2017), p. 8, cf. Sirri and Tufano (1998), p. 1599, cf. Pástor et al. (2015), p. 25
[93] cf. Y. Chen and Qin (2017), p. 6, 8, cf. Q. Chen et al. (2010), p. 248, cf. Rakowski and Wang (2009), p. 2107
[94] cf. Goldstein et al. (2017), p. 602, cf. Rakowski and Wang (2009), p. 2107, cf. Y. Chen and Qin (2017), p. 6
[95] cf. Sirri and Tufano (1998), p. 1612
[96] cf. Rakowski and Wang (2009), p. 227 f.
[97] cf. Y. Chen and Qin (2017), p. 6, 8

I confirm heteroskedasticity with Breusch-Pagan test (see Table 5) and calculate Newey-West standard errors. Table 6 presents the results of the regression results for each Morningstar Category. The factor loadings for the **cash ratio** range from slightly above zero to slightly below zero and are not significant across most Morningstar Category fund styles, i.e., short-term, intermediate core, intermediate core-plus, corporate, multisector, long-term and nontraditional bond funds.

This indicates that the cash ratio has no significant impact on fund flows in these categories, suggesting that these investors do not prioritize or reward larger cash buffers. There are multiple potential explanations for this finding. Short-term, intermediate core, intermediate core-plus, corporate, and long-term bond funds already primarily invest in investment-grade securities with low credit risk ratings. Hence, their investors might be less concerned with potential defaults, less likely to engage in flight-to-safety and thus less likely to suddenly withdraw. Nontraditional bond fund investors aim for specific objectives, e.g., absolute returns or lower volatility, which is why they likely deprioritize stability-focused measures such as the cash ratio. Another potential reason might be Jiang et al. showing that during times of financial stress, funds sell liquid and illiquid asset classes proportionally to maintain their original portfolio proportions.[98] Thus a higher cash ratio would not translate into lower internal redemption costs and be of little benefit for investors.

On the opposite end of the spectrum, the coefficients in high-yield bond funds and bank loan funds are marginally significant with 0.010 and 0.084, respectively. This implies a weak but positive association with the net fund flows with low economic significance due to their small size relative to the fund average of 0.469%. The explanation might be similar for both HY and bank loan funds. High-yield bond funds have an inherently bigger default and liquidity risk, as the underlying issues are rated as higher-risk securities with a bigger default risk and therefore are less easy to sell. During crises, they would be more vulnerable to fire sales and sudden redemptions.[99] Like high-yield bond funds, bank loan fund investments are also generally illiquid, as floating-rate debt is harder to shift due to its higher interest rate risk. This might motivate investors to allocate their funds in bank loan funds with larger liquidity buffers to safeguard their withdrawal rights and the funds‘ financial stability during economic downturns and lower interest rate environments.[100]

Thus, investors might value HY bond and bank loan funds with larger cash ratios, since these liquidity buffers could mitigate their financial fragility in case of liquidity demand shocks by way of large redemptions or macro financial crises and economic downturns. However, Choi and Kronlund show that funds which tend to reach for yield, e.g., high-yield and bank loan funds, tend to practice less careful liquidity management, i.e., hold fewer liquid assets.[101] For this reason, the very small, marginally statistically significant and economically insignificant positive correlation could suggest that these fund investors do not place much importance on the cash ratio. Funds scaling down their liquid and illiquid assets proportionally offer a possible explanation.

Their magnitude is in line with Sirri and Tufano, who determine the performance rank coefficient to be 1.693, nearly twice as large as the rank coefficient results from Chen et al.[102] The single outlier is the long-term bond fund category with the only negative and insignificant performance rank. Altogether, this clearly shows that performance rank and return momentum are a primary driver of fund flows: First, despite the typical investor heterogeneity of the fund styles, the majority of investors engage in significant performance chasing and allocate their capital in the recently high-performing funds. Second, the fact that the performance coefficient has the biggest effect of all variables shows that investors are highly sensitive to performance rank and prioritize it above all else. This conclusion is supported in prior studies from Chen et al. and Goldstein et al.[103] The largest coefficient is observed in nontraditional bond funds, which is plausible as nontraditional fund investors seek to fulfill specific goals in exchange for the atypical investment profile and are therefore immediately willing to shift if the fund disappoints their expectations. High-yield, short-term and multisector bonds all exhibit a similarly high investor responsivity to performance rank which is logical as high-yield fund investors prioritize yield in exchange for higher credit and liquidity.

Additionally, this aligns with Goldstein et al. finding that illiquid funds have a higher performance sensitivity. This potentially applies to nontraditional, high-yield and multisector bonds, which are all considered higher risk.[104] Short-term and multisector funds attract investors more interested in liquidity and diversification, respectively, and potentially use high performance as a marker of quality or success. Interestingly, the intermediate core and core-plus performance rank coefficients differ significantly: While the formers' is the lowest of all categories, the latter's is bigger by nearly half. This clearly shows that investors who chose intermediate-core plus funds with their bigger flexibility and higher credit and economic risk expect to be compensated with better performances and higher returns. Their sister category likely attracts more conservative investors who prioritize stability and other benchmarks compared to the other fund styles. The same can be hypothesized about corporate bond fund investors who have a similarly low performance coefficient at 0.634. Investors might value stability and believe in the long-term success of the underlying corporations or industries instead of being focused on immediate high returns.

The most surprising result is the small, negative, and not significant performance rank coefficient for long-term bond

[98] cf. Jiang et al. (2021), p. 1625
[99] cf. Choi and Kronlund (2018), p. 1959
[100] cf. Jiang et al. (2021), p. 1625
[101] cf. Choi and Kronlund (2018), p. 1960
[102] cf. Sirri and Tufano (1998), p. 1559, cf. Q. Chen et al. (2010), p. 248
[103] cf. Q. Chen et al. (2010), p. 247, cf. Goldstein et al. (2017), p. 605
[104] cf. Goldstein et al. (2017), p. 605

Table 5: Breusch-Pagan test results for the regression model 5 for each fund style

Split Sample Morningstar Category	Statistic	p-value
US Fund Corporate Bond	929.868***	$< 2.2e^{-16}$
US Fund Nontraditional Bond	554.967***	$< 2.2e^{-16}$
US Fund Multisector Bond	955.450***	$< 2.2e^{-16}$
US Fund High Yield Bond	4190.997***	$< 2.2e^{-16}$
US Fund Short-Term Bond	1517.569***	$< 2.2e^{-16}$
US Fund Intermediate Core Bond	866.684***	$< 2.2e^{-16}$
US Fund Long-Term Bond	555.690***	$< 2.2e^{-16}$
US Fund Intermediate Core-Plus Bond	853.275***	$< 2.2e^{-16}$
US Fund Bank Loan	323.488**	0.001

This table shows the Breusch-Pagan test results for regression 5 for each fund style as indicated by the Morningstar Category. Stars denote statistical significance: *** $p < 0.001$, ** $p < 0.01$ and * < 0.05.

funds, -0.019. Long-term bonds have maturation durations of more than six years, making them more susceptible to interest rate risk and similar macro factors than comparable categories. Thus, their investors likely value long-term income stability instead of short-term performance and make their asset allocation decisions independent of the fund's relative rank.

The **fund age** correlations behave as expected for most bond fund categories, i.e., they are highly statistically significant and negative, ranging from -0.3 to -0.5. This implies that older high-yield, short-term, intermediate core, intermediate core-plus, corporate bond, and multisector bonds receive less net fund flows in a significant economic magnitude. Bank loan and nontraditional bond funds are the exception as both have statistically and economically less significant age coefficients, showing that fund age has no material impact on fund flows. Bank loan and nontraditional investors likely focus on other metrics like performance rank instead of age. They may also be more sophisticated in their niches and less likely to fall prey to recency and marketing biases. In sum, the log(fund age) correlation is in line with Bergstresser and Poterba, Chen et al., Goldstein et al., Chen and Qin, and Rakowski and Wang, who also determine the association to be negative.[105]

The **expense ratio** coefficients are near zero and not significant for high-yield, short-term, intermediate core, intermediate core-plus, corporate, bank loan and nontraditional bond funds, suggesting that expenses do not influence investor fund flow patterns, statistically, and would be too small to be economically significant even if they did. These results agree with Sirri and Tufano and the investment-grade and complete sample coefficients from Chen and Qin but are far from the findings of Goldstein et al. with -0.200.[106] Additionally, Chen and Qin find a HY expense ratio correlation of -0.153, which is much bigger than this analysis's result, -0.002.[107]

The outliers are long-term bond funds whose coefficient is -1.045 and multisector bond funds whose coefficient is 1.002. Both are highly statistically significant at the 0.1% level and very large, making them highly economically significant. Investors in long-term funds are likely highly averse to any factors that might erode their payments in addition to their high interest rate risk. In turn, it is plausible that they might also be highly cost-sensitive and penalize higher expense ratios harshly. Still, the extremely positive association between the expense ratio and net fund flows for multisector funds is untypical and economically implausible, as this would make expenses the second-strongest determinant of fund inflows after performance rank. Possibly higher expenses indicate a higher standard of quality regarding active managers and asset selections. However, such an excellent multisector bond manager could be expected to manage larger funds, resulting in a similarly significant and large fund size coefficient. This is not the case, as the log(TNA) coefficient is insignificant, small, and negative. Furthermore, at an absolute value of 1, the long-term and multisector expense correlations exceed all comparative analyses. At this point, it would be prudent to repeat the analysis with a larger sample and larger sample period to assess the robustness of the result.

The effect of the **recent past flows** on the net fund flows is highly significant, positive, ranges between 0.2 and 0.5 and aligns with literature. This indicates a momentum or persistence in flows, i.e., past flows predict current flows. The more flexibility the fund style allows and the higher the focus on performance, the bigger the past flow coefficient is: Indeed, the top categories are bank loan, nontraditional, intermediate core-plus and multisector bond funds. Overall, the past flow coefficient magnitude is moderately larger compared to

[105] cf. Bergstresser and Poterba (2002), cf. Q. Chen et al. (2010), p. 248, cf. Goldstein et al. (2017), p. 602, cf. Y. Chen and Qin (2017), p. 6, cf. Rakowski and Wang (2009), p. 2107

[106] cf. Y. Chen and Qin (2017), p. 6

[107] cf. Y. Chen and Qin (2017), p. 6

Table 6: Fund-specific time FE regression 5 for fund styles

	Dependent variable: fund flows								
Fund style	**High-Yield**	**Short-Term**	**Intermediate Core**	**Intermediate Core-Plus**	**Corporate Bond**	**Multisect or**	**Long-Term**	**Nontraditional**	**Bank Loan**
	Time FE	Time FE	Time FE	Time FE	Time FE	Time FE	Time FE	Time FE	Time FE
	Newey-West	*Newey-West*	*Newey-West*	*Newey-West*	*Newey-West*	*Newey-West*	*Newey-West*	*Newey-West*	*Newey-West*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
volatility	–0.519***	–0.376***	–0.211	–0.047	0.321*	–0.034	–0.585*	0.040	–0.361
	(0.071)	(0.113)	(0.116)	(0.128)	(0.127)	(0.084)	(0.269)	(0.152)	(0.457)
	t = –7.273	t = –3.340	t = –1.824	t = –0.364	t = 2.532	t = –0.400	t = –2.179	t = 0.264	t = –0.791
log(fund age)	–0.419***	–0.370***	–0.413***	–0.385***	–0.520***	–0.567***	–0.329**	–0.146	0.037
	(0.033)	(0.047)	(0.054)	(0.074)	(0.065)	(0.052)	(0.107)	(0.130)	(0.304)
	t = –12.803	t = –7.806	t = –7.681	t = –5.177	t = –8.046	t = –10.894	t = –3.091	t = –1.124	t = 0.121
past flows	0.297***	0.377***	0.342***	0.496***	0.369***	0.478***	0.287***	0.496***	0.539***
	(0.012)	(0.016)	(0.022)	(0.026)	(0.024)	(0.023)	(0.030)	(0.035)	(0.064)
	t = 25.455	t = 22.944	t = 15.567	t = 18.866	t = 15.569	t = 20.967	t = 9.730	t = 14.315	t = 8.445
log(TNA)	–0.008	0.035	0.016	0.030	0.090***	–0.011	–0.043	–0.094	–0.431*
	(0.015)	(0.018)	(0.027)	(0.029)	(0.026)	(0.022)	(0.039)	(0.072)	(0.185)
	t = –0.527	t = 1.892	t = 0.587	t = 1.027	t = 3.440	t = –0.489	t = –1.096	t = –1.319	t = –2.334
expense ratio	–0.002	0.059	–0.025	0.212	–0.013	1.001***	–1.045***	–0.244	0.666
	(0.089)	(0.149)	(0.137)	(0.189)	(0.145)	(0.179)	(0.299)	(0.287)	(0.439)
	t = –0.022	t = 0.395	t = –0.184	t = 1.118	t = –0.089	t = 5.580	t = –3.496	t = –0.851	t = 1.516
performance rank	1.247***	1.248***	0.604***	1.107***	0.634***	1.248***	–0.019	1.327***	0.909***
	(0.077)	(0.121)	(0.109)	(0.123)	(0.133)	(0.125)	(0.197)	(0.235)	(0.350)
	t = 16.279	t = 10.328	t = 5.538	t = 9.020	t = 4.764	t = 10.020	t = –0.094	t = 5.638	t = 2.598
cash ratio	0.010*	0.002	0.006	–0.001	0.013	–0.005	0.025*	0.002	0.084*
	(0.004)	(0.004)	(0.006)	(0.006)	(0.008)	(0.003)	(0.011)	(0.007)	(0.038)
	t = 2.381	t = 0.448	t = 1.150	t = –0.195	t = 1.788	t = –1.889	t = 2.353	t = 0.257	t = 2.219
Intercept	2.775***	2.127**	1.111	2.927*	0.060	2.206	3.569***	2.300	6.562
	(0.506)	(0.783)	(0.603)	(1.178)	(0.811)	(1.302)	(0.945)	(1.506)	(3.948)
	t = 5.482	t = 2.717	t = 1.842	t = 2.485	t = 0.073	t = 1.694	t = 3.777	t = 1.528	t = 1.662
Observations	35,304	13,737	11,165	7,195	6,894	7,706	2,336	2,093	730
R^2	0.294	0.281	0.208	0.387	0.299	0.425	0.264	0.448	0.585
Adjusted R^2	0.289	0.268	0.189	0.365	0.273	0.406	0.175	0.373	0.369

This table reports the fund-level regression 5 results for the coefficient estimates of the fund specific variables. Fund flow is the dependent variable while fund characteristics and macro factors are the independent variables. “Time FE” above the columns denotes time, i.e., year and month, fixed effects. The Newey-West standard errors sits below the coefficient in parentheses. The t-value, designated “t”, is below the standard deviation. Stars show statistical significance: *** $p < 0.001$, ** $p < 0.01$, * < 0.05, respectively.

Goldstein et al. (0.152) and Chen et al. (0.14 – 0.24) and Chen and Qin who determine the lagged flow coefficients to be 0.210 for HY and 0.258 for all bond funds.[108] The results align for the latter's IG lagged flow coefficient, 0.362, which is similar to the fund styles that primarily invest in IG.[109]

The **volatility** factor loadings vary across fund styles with meaningful implications for the net fund flows. First, the HY and short-term bond fund volatility coefficients are highly significant and negative at -0.519 and -0.379, respectively. On the one hand, this makes them much larger in absolute value than the volatility coefficients Chen and Qin determine: -0.134 for all, 0.000 for IG and -0.212 for HY bond funds.[110] On the other hand, Sirri and Tufano find significant volatility coefficients of -1.043 and -1.068, which is more than twice as big.[111] Still, their magnitude relative to the average net fund flows of 0.469% makes them economically significant. This suggests that investors sell these funds shares during periods of high return volatility which could indicate economic turmoil. They are likely motivated by other reasons: HY investors potentially sell their shares with high credit, liquidity, and economic risk to reduce their exposure and minimize losses, engaging in typical flight-to-safety behavior. This potentially also applies to long-term bond fund flows with a marginally significant but large -0.585 coefficient: Long-term bond investments suffer especially during periods of changing market conditions and subsequent return volatilities and hence receive less fund flows and are sold. Therefore, their investors engage in flight-to-safety away from interest rate and economic risk. In contrast, short-term investors probably sell their low-risk shares in order to generate liquidity in a reverse flight-to-liquidity pattern. Nonetheless, the volatility has little impact on fund flows for intermediate core, intermediate core-plus, multisector, bank loan and nontraditional bond funds as the coefficients are insignificant and near zero. Chen and Qin validate this finding as their volatility coefficients are also insignificant.[112]

Finally, the **fund size** has no significant impact on most fund styles as the coefficients are very small and not significant. Only the corporate bond fund category has a highly significant, positive association of 0.090, indicating that these investors place minimal importance on the fund's size when allocating their capital. The standard literature is divided on the influence the fund size on the net fund flows: Chen and Qin, Goldstein et al. and Rakowski and Wang determine the coefficient to range between 0.000 and 0.001.[113] Sirri and Tufano show the coefficient to be slightly negative at -0.048.[114] Neither coefficient is large enough to be economically significant, even if it were statistically significant. Hence, the fund size is not a significant consideration for bond fund investors.

5.3. COVID-19 Pandemic Case Study: Regressions with a Macroeconomic Focus

The impact of the COVID-19 crisis on bond funds is clear when looking at the net new fund flows of bond mutual funds over the past two decades (see Figure 5): New bond fund flows experienced a severe drop and fell to less than -10%. To illuminate the impact of the pandemic on the fund flows, I operationalize the pandemic stages in three dummy variables: Crisis, Recovery and PostCovid. Crisis applies from February to April 2020 and represents the onset and peak of the pandemic, its impact on the financial markets and the funds' resilience to the crisis.[115] Recovery applies from May to June 2020 and tracks the recovery of the corporate bond market.

Finally, PostCovid applies from July 2020 onward; its purpose is to indicate the medium-term impact of the pandemic. The sample period remains unchanged to guarantee a comparable level of explanatory power regarding the independent and dependent variables. The VIX index is excluded, as the market volatility is highly correlated with the Crisis indicator variable and as such, it would likely create disadvantageous multicollinearity in the model. To study the association between cash ratio, performance rank and FEDFUNDS-CHG and the pandemic stages, the estimation uses interactions between these three variables and the Crisis, Recovery and PostCovid dummies, respectively. I estimate the following regression models: The net fund flows continue as dependent variable. OLS regression 6 includes all macroeconomic and fund variables and controls (see equation 7).

$$
\begin{aligned}
Flows_{i,t} = \alpha &+ \beta_1 \times cash\ ratio_{i,t-1} \\
&+ \beta_2 \times FEDFUNDS\text{-}CHG_{i,t-1} \\
&+ \beta_3 \times performance\ rank_{i,t-1} \\
&+ \beta_4 \times Crisis_t + \beta_5 \times Recovery_t \\
&+ \beta_6 \times PostCovid_t \\
&+ \beta_7 \times Crisis_t \times cash\ ratio_{i,t-1} \\
&+ \beta_8 \times Crisis_t \times FEDFUNDS\text{-}CHG_{i,t-1} \\
&+ \beta_9 \times Crisis_t \times performance\ rank_{i,t-1} \\
&+ \beta_{10} \times Recovery \times cash\ ratio_{i,t-1} \\
&+ \beta_{11} \times Recovery \times FEDFUNDS\text{-}CHG_{i,t-1} \\
&+ \beta_{12} \times Recovery \times performance\ rank_{i,t-1} \\
&+ \beta_{13} \times PostCovid \times cash\ ratio_{i,t-1} \\
&+ \beta_{14} \times PostCovid \times FEDFUNDS\text{-}CHG_{i,t-1} \\
&+ \beta_{15} \times PostCovid \times performance\ rank_{i,t-1} \\
&+ \beta_{16} \times Controls_{i,t-1} + \varepsilon_{i,t}
\end{aligned} \tag{7}
$$

[108] cf. Goldstein et al. (2017), p. 602, cf. Y. Chen and Qin (2017), p. 6
[109] cf. Y. Chen and Qin (2017), p. 6
[110] cf. Y. Chen and Qin (2017), p. 6
[111] cf. Sirri and Tufano (1998), p. 1599
[112] cf. Y. Chen and Qin (2017), p. 6, 8
[113] cf. Y. Chen and Qin (2017), p. 6, cf. Goldstein et al. (2017), p. 602, cf. Rakowski and Wang (2009), p. 2107
[114] cf. Sirri and Tufano (1998), p. 1599
[115] cf. Falato et al. (2021), p. 41 f.

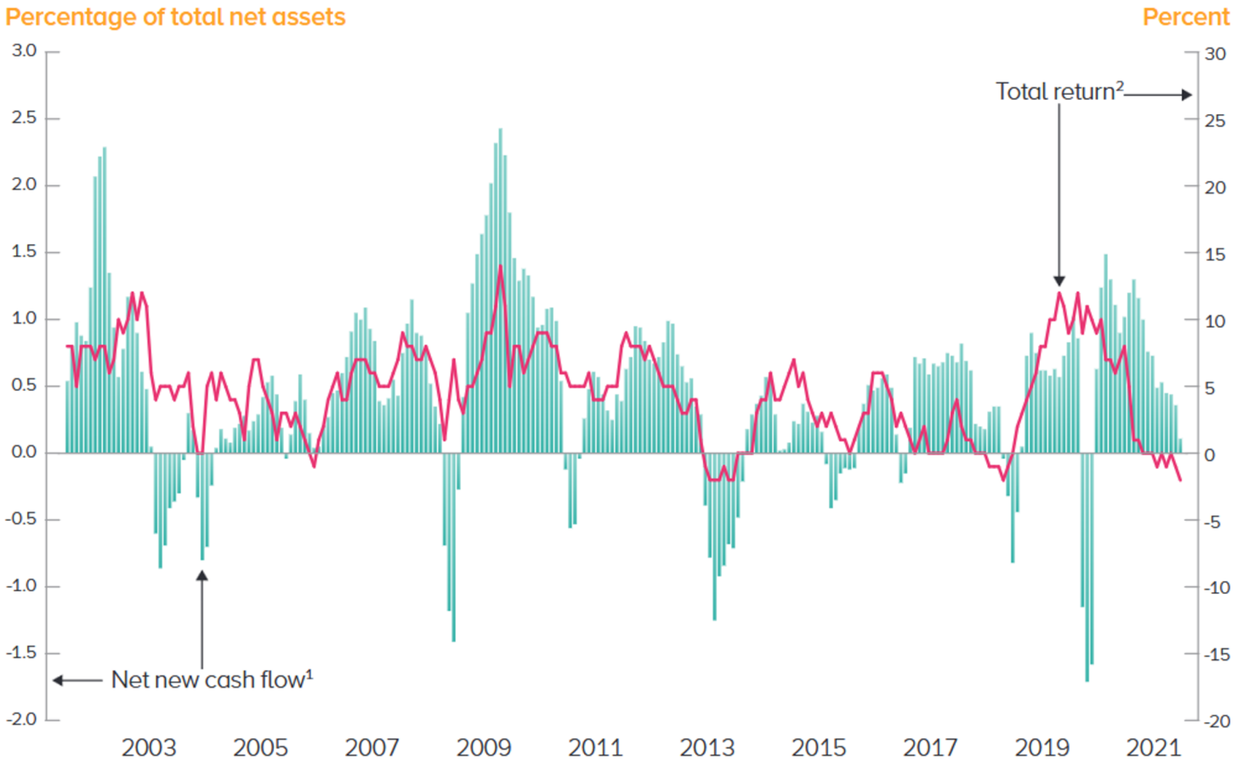

Figure 5: US bond mutual funds net new cash flows and total returns[116]

OLS regression 7 focuses on the macro variables (see equation 8).

$$\begin{aligned} Flows_{i,t} = \alpha &+ \beta_1 \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_2 \times Crisis_t + \beta_3 \times Recovery_t \\ &+ \beta_4 \times PostCovid_t \\ &+ \beta_5 \times Crisis_t \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_6 \times Recovery \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_7 \times PostCovid \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_8 \times Controls_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{8}$$

In FE regression 8, the macroeconomic variables are evaluated in a regression with Morningstar Category fixed effects (see equation 9).

$$\begin{aligned} Flows_{i,t} = \alpha &+ \beta_1 \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_2 \times Crisis_t + \beta_3 \times Recovery_t \\ &+ \beta_4 \times PostCovid_t \\ &+ \beta_5 \times Crisis_t \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_6 \times Recovery \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_7 \times PostCovid \times FEDFUNDS\text{-}CHG_{i,t-1} \\ &+ \beta_8 \times Controls_{i,t-1} + \eta_i + \varepsilon_{i,t} \end{aligned} \tag{9}$$

Similarly to regressions 1-5, Breusch-Pagan tests confirm heteroskedasticity in regressions 6-8 (see Table 7) and Newey-West standard errors are calculated. Table 8 presents the regression results for regression 6-8.

Table 7: Breusch-Pagan test results for the regression models 6-8

Model	Statistic	p-value
Regression 6	3981.882***	$< 2.2e^{-16}$
Regression 7	1129.492***	$< 2.2e^{-16}$
Regression 8	1573.222***	$< 2.2e^{-16}$

This table shows the Breusch-Pagan test results for regressions 6-8. Stars signify statistical significance: *** $p < 0.001$, ** $p < 0.01$, * < 0.05, respectively.

The COVID-19 pandemic was a notable global stressor that affected the real economy with likely lasting impacts. For this reason, I expect the dummy regression coefficients and interaction effects to be highly significant. First, the Crisis coefficient should be negative and have a high magnitude depending on the shock on, and subsequent outflows of, the corporate bond market. Second, the Recovery dummy signals the recovery of the corporate bond market, investor trust and outlook thanks to the Fed policy interventions effectively calming the markets through the interest rate monetary

[116]cp. Investment Company Institute (2022), p. 56

policy channel.[117] Therefore, the correlation should have a smaller absolute value than the Crisis's by a wide margin, being either significantly less negative or even positive. Third, the PostCovid coefficients could indicate that markets are still actively recovering after the crisis, have largely recovered or carry a long-term impact. It would depend on their size and sign.

The correlation between the Crisis indicator variables and the fund flows is noticeably strong, i.e., highly significant with large coefficients around -2.5. This confirms that the flows decreased starkly during the crisis by up to -2.659 with style FE. These results are both larger and smaller than other studies as Falato et al. estimate the Crisis coefficient to be -0.29 and Kuong et al. determine the correlation to fund outflows to be 4.247 – still, both find that the pandemic crisis had materially decreased bond fund flows.[118] Overall, the Crisis coefficients still align with both studies' conclusions: Bond funds experienced large outflows during the pandemic months which were driven by liquidity demand shocks.

Table 8 presents the OLS and style FE regressions for models 6 – 8.The Recovery coefficients are initially negative, but positive when focusing on macro variables and never significant. They have no clear trends since the coefficients are not significant and switch from negative to positive. This would suggest that there was no substantial difference between the fund flow dynamics before the crisis and during the recovery months, indicating a stabilization of investor behavior. A possible contributor could be the PMCCF and SMCCF policy interventions which reassured investors.[119] With such decisive actions, investors gained confidence, and the corresponding outflows reversed.[120] The PostCovid factor loadings are initially positive and significant but lose their significance when focusing on macro variables or controlling for fund style fixed effects. Their insignificance suggests there is no major difference between fund flows before and after COVID-19. This result would corroborate the interpretation that the Fed's credit facilities calmed investors long-term, and that no negative effects remain, resonating with Falato et al., who show that investor flow dynamics normalized relatively quickly after the Fed's interventions.

Overall, the net fund flows' evolution over the Crisis, Recovery and PostCovid period mirrors the evolution of transaction costs in bond markets over the course of the pandemic, as O'Hara and Zhou show: first, the liquidity crisis at the start and height of the pandemic caused exorbitant transaction costs, then the Fed intervened with their credit facility policy and offered a liquidity backstop, leading to a quick resolution and normalized markets[121]

Additionally, Falato et al. also find that COVID-related outflows were most extreme during the height of the crisis, halved in the weeks after the first Fed PMCCF and SMCCF announcement and normalized to pre-crisis levels following the second Fed announcement which communicated the expansion to $75 billion.[122] These parallel behaviors support the validity of the findings of this thesis. Considering the interaction terms allows for a more differentiated interpretation of the effective federal funds rate and rate change. The FEDFUNDS-CHG interaction terms with the pandemic dummies behave as follows: the interaction between FEDFUNDS-CHG and Crisis has exceedingly negative and highly significant factor loadings in regressions 6 – 8. In contrast, FEDFUNDS-CHG and Recovery have a highly significant positive association in regressions 7 and 8. Lastly, the FEDFUNDS-CHG and PostCovid coefficients are not significant, negative and highly changeable across regressions: -0.607, 2.962 and 2.951. Hence, a one-unit increase in FEDFUNDS-CHG during the crisis leads to a decrease of at least -5.63 (= -0.813 – 4.823) in fund flows across fund styles. This finding is extremely economically significant, as this encompasses more than 45% of the net flow range (P5-P50). Next, the FEDFUNDS-CHG coefficient is 0.042 (= -1.592 + 1.634) and highly significant during Recovery.

Finally, the coefficient is 1.359 (= -1.592 + 2.951) and not significant in the months after the crisis. That shows that increases in the effective federal fund rate changes were correlated with a significant decrease in fund flows during the crisis and slight increases during the Recovery phase, possibly because the Fed rate policy actions restored investor trust. Post pandemic, the PostCovid and FEDFUNDS-CHG correlation has become relatively large. However, since it is, first, not statistically significant, and second, exceeded by its Newey-West standard error, the most that can be concluded is: there is no substantial difference in the correlation between FEDFUNDS-CHG and fund flows before the COVID-19 crisis and in the years that followed. The individual effective federal funds rate change coefficients are highly significant and negative. The FEDFUNDS factor loadings are smaller in size but still highly significant. The DEF and TB3MS factors have a highly significant, positive correlation to flows. This former's correlation is validated while the latter's is contradicted by literature.[123] The OPTION coefficients are slightly below zero and none are significant. This finding is not supported by Chen and Qin who estimate the OPTION factor to range between 0.028 and 0.352.[124] The adjusted R^2 is 0.207 in regression 6, which includes all variables, and falls drastically with the macro focus. Similarly to coefficients of determination in regressions 1-4, roughly 21% of the flow variation is explained by all variables and less than 3% by macro variables only. Still, the regression 6 adjusted R^2 is validated by Chen and Qin.[125]

[117] cf. Falato et al. (2021), p. 37
[118] cf. Falato et al. (2021), p. 41, cf. Kuong et al. (2024), 6
[119] cf. O'Hara and Zhou (2021), p. 47
[120] cf. Falato et al. (2021), p. 37
[121] cf. O'Hara and Zhou (2021), p. 66
[122] cf. Falato et al. (2021), p. 43, cf. Board of Governors of the Federal Reserve System (2020c), URL see References
[123] cf. Y. Chen and Qin (2017), p. 7
[124] cf. Y. Chen and Qin (2017), p. 8
[125] cf. Y. Chen and Qin (2017), p. 6, 8

Table 8: OLS and style FE regression 6-8

	Dependent variable: flows		
	All vars.	**Macro. vars.**	**Macro vars.**
	OLS	OLS	Style FE
	Newey-West	*Newey-West*	*Newey-West*
	(6)	(7)	(8)
volatility	0.070***		
	(0.016)		
	t = 4.417		
log(fund age)	–0.397***		
	(0.019)		
	t = –20.361		
past flows	0.378***		
	(0.008)		
	t = 47.430		
log(TNA)	0.004		
	(0.009)		
	t = 0.422		
expense ratio	–0.047		
	(0.049)		
	t = –0.964		
performance rank	1.057***		
	(0.049)		
	t = 21.442		
cash ratio	0.010***		
	(0.002)		
	t = 4.797		
BOND	0.237***	0.320***	0.321***
	(0.013)	(0.014)	(0.014)
	t = 18.812	t = 22.399	t = 22.607
FEDFUNDS	–0.375***	–0.497***	–0.493***
	(0.073)	(0.109)	(0.108)
	t = –5.134	t = –4.571	t = –4.553
FEDFUNDS-CHG	–0.813***	–1.570***	–1.592***
	(0.108)	(0.148)	(0.148)
	t = –7.523	t = –10.578	t = –10.741
STK	–0.016***	–0.028***	–0.029***
	(0.005)	(0.005)	(0.005)
	t = –3.418	t = –5.194	t = –5.405
TB3MS	0.542***	0.722***	0.726***
	(0.081)	(0.120)	(0.120)
	t = 6.686	t = 6.017	t = 6.074
DEF	0.036***	0.139***	0.141***
	(0.008)	(0.010)	(0.010)
	t = 4.588	t = 13.849	t = 14.080

This table reports the fund flow regression results. Column (6) shows the OLS regression results for all variables. Column (7) shows the OLS regression for macro independent variables. Column (8) shows the FE fund style regression for macro variables. "Style FE" denotes style fixed effects. The Newey-West standard errors (in parentheses) are below. Stars show statistical significance: *** $p < 0.001$, ** $p < 0.01$, * < 0.05.

Table 8 — continued

OPTION	–0.046	–0.029	–0.029
	(0.031)	(0.036)	(0.036)
	t = –1.482	t = –0.799	t = –0.792
Crisis	–2.659***	–2.482***	–2.516***
	(0.278)	(0.150)	(0.149)
	t = –9.555	t = –16.591	t = –16.847
Recovery	–0.180	0.336	0.310
	(0.296)	(0.192)	(0.191)
	t = –0.608	t = 1.751	t = 1.623
PostCovid	0.221*	0.151*	0.127
	(0.088)	(0.070)	(0.070)
	t = 2.513	t = 2.140	t = 1.816
cash ratio x Crisis	–0.030*		
	(0.013)		
	t = –2.256		
performance rank × Crisis	0.642		
	(0.433)		
	t = 1.484		
FEDFUNDS-CHG × Crisis	–4.823***	–3.722***	–3.721***
	(0.344)	(0.315)	(0.315)
	t = –14.012	t = –11.822	t = –11.827
cash ratio × Recovery	–0.012		
	(0.012)		
	t = –0.983		
performance rank × Recovery	1.048*		
	(0.426)		
	t = 2.458		
FEDFUNDS-CHG × Recovery	0.414	1.621***	1.634***
	(0.464)	(0.405)	(0.404)
	t = 0.891	t = 4.005	t = 4.039
cash ratio × PostCovid	–0.008		
	(0.006)		
	t = –1.335		
performance rank × PostCovid	–0.098		
	(0.134)		
	t = –0.735		
FEDFUNDS-CHG × PostCovid	–0.607	2.962	2.951
	(2.668)	(3.072)	(3.066)
	t = –0.228	t = 0.964	t = 0.962
Intercept	0.431**	0.306***	0.329
	(0.164)	(0.034)	(0.433)
	t = 2.634	t = 8.891	t = 0.760
Observations	87,160	87,160	87,160
R^2	0.207	0.022	0.026
Adjusted R^2	0.206	0.022	0.026

6. Conclusion

The aim of this thesis was to investigate the influence of fund-specific and macro variables on CBMF flows. This first required an analysis of the systematic fund flow dynamics with all variables, then with the macro and fund variables. A fund style split sample analysis was performed to inspect the individual fund flow determinants for each Morningstar Category. Finally, the impact of COVID-19 on fund flows was explored based on a dedicated case study. These made it possible to confirm well-studied correlations in one comprehensive analysis, expanding the literature by testing less-studied macro determinants, i.e., the effective federal funds rate and its change, and conducting a different pandemic case study.

In the analysis of the systematic fund flow dynamics, the effective federal funds rate showed a statistically and economically significant negative correlation to fund flows across all regressions, showing that higher rates deter investor flows due to increased liquidity costs. The corresponding rate changes, however, exhibited an insignificant relationship, indicating that the absolute level, not the changes, primarily influence fund flows. Among the fund variables, the performance rank and past flows emerged as the strongest drivers of the fund flows, highlighting strong performance chasing and flow persistence with coefficients exceeding 1. The fund style split sample analysis differentiated these results according to Morningstar Category and highlighted the different investor profiles based on investment objectives and risk tolerance. Again, performance rank was the dominant determinant across nearly all fund styles, reflecting performance-chasing behavior. Conversely, the cash ratio had minimal significance except for bank loan and high-yield funds, implying a higher responsivity to default and liquidity risk.

Finally, the COVID-19 pandemic case study uncovered that bond mutual funds experienced severe outflows during the crisis months, consistent with large liquidity demands due to sudden investor withdrawals. The recovery period was marked by a quick fund flow stabilization indicated by materially smaller and often statistically insignificant Recovery correlations, likely due to the Fed's interventionist PMCCF and SMCCF announcements and implementations. This development continued into the Post-Covid phase, which showed normalized behavior with no substantial fund flow difference compared to the pre-crisis period. The pandemic stage interaction terms with the changes in the effective federal funds rate revealed a heightened sensitivity during the crisis. This implies that any increases in the effective federal funds rate discourage investors and lead to more outflows. However, similar to the evolution of the pandemic, these effects dissipated during the Recovery and Post-Covid period, potentially indicating restored investor confidence and the stabilizing effect of Fed interventions.

The insignificance of the cash ratio was surprising, raising the question of if and how funds can pacify investors during financial crises. After all, as long as CBMFs must perform critical liquidity transformations to satisfy daily investor withdrawal rights, they will remain financially fragile. Since they continue to grow in size and in importance as non-bank financial intermediaries, their vulnerability remains a macro concern. Considering the macro factors, the significance of the VIX and BOND factor highlights the role of the macro market condition for fund flow dynamics; this thesis supports adding the effective federal funds rate as an important determinant. A principal limitation is the inability to model concrete key dates as I used monthly fund information. Therefore, the explanatory power of my pandemic dummies and their interaction terms is constrained, and significant fund flow movements potentially remained unobserved. Next, testing and comparing multiple liquidity measures as complementary analyses would have increased the robustness of the results, which could have been especially valuable for the analysis of the cash ratio. Indeed, the fund-level liquidity could have been calculated as bid-ask spread or Roll measure while the aggregate liquidity could be estimated using the TED factor or DFL factor.[126] Finally, future research includes extending the literature on macro determinants by testing other macro determinants and other countries. Also, green funds could be explored as Fatica et al. find that green bonds experienced lower sales during the pandemic.[127]

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[126]cf. Falato et al. (2021), p. 43, cf. Goldstein et al. (2017), p. 604
[127]cf. Fatica and Panzica (2024), p. 18

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