Asset market liquidity, strategic complementarity, and bond fund flows

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ABSTRACT

We examine the role of asset liquidity in explaining the strategic redemption decisions of open-end bond fund investors. In the U.S., bond mutual funds have a concave relation between flow and performance. However, why we observe this phenomenon is less clear. While Chen, Goldstein, and Jiang (2010) provide rich predictions on the role of investor payoff complementarities in a fund run, no clear causal links have been established. In this paper, we identify an exogenous shock to the liquidity of the Chinese bond market that affects the level of complementarities, and this change helps us evaluate the causal impact of the underlying asset market liquidity on investor flow decisions. Using this setup, first, we demonstrate that in China, where the overall bond market liquidity is higher, bond funds have a convex flow-performance relation. Second, we show causal evidence that when the advantage of frontrunning other investors is removed, the sensitivity of outflows to poor fund performance significantly diminishes. Overall, our evidence documents that the illiquidity of corporate bonds and consequent payoff complementarities generate a first-mover advantage in a fund run, particularly among investors in illiquid U.S. bond funds.

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1 Introduction

Capturing investor flows and maintaining the optimal assets under management (AUM) are the primary objectives of mutual fund families. Understanding the dynamics behind the investor's capital allocation decision to mutual funds has been a topic of acute interest for academics and industry professionals. For better or worse, mutual fund investors observe past fund performance and direct their money to better-performing funds (see Sirri and Tufano (1998)). However, empirically, the manner in which investors withdraw their money from poor-performing funds differs by fund type. Equity mutual funds have a convex relationship between flows and performance, indicating a lower sensitivity of outflows to poor performance; in contrast, the relationship in corporate bond funds is concave, indicating a stronger sensitivity of outflows to poor performance (see Goldstein, Jiang, and Ng (2017)).

Understanding the factors causing this difference is crucial, as coordinated outflows can generate fragility in the financial markets (see Diamond and Dybvig (1983)). Goldstein et al. (2017) argue that the structure of open-ended mutual funds and the underlying illiquidity of the United States (U.S.) corporate bond market create payoff complementarities among corporate-bond-fund investors, thereby yielding the concave flow-performance relation. The central idea is that corporate-bond-mutual funds face a maturity and liquidity mismatch between their assets and liabilities. Their assets, corporate bonds, are less liquid and have a medium- to long-term investment horizon. In contrast, their liabilities are akin to a demand deposit. Following poor fund performance, when some investors redeem their fund units, the remaining investors in the fund bear the cost of selling illiquid bonds. Therefore, there is a first-mover advantage on the part of bond-fund investors. Such a situation is concerning as the complementary investor strategy can lead to large redemptions followed by asset fire sales and self-fulfilling runs.

In this paper, we empirically test whether the liquidity of the underlying asset market indeed affects investors' payoff complementarities and, in turn, their allocation decisions. We use data from the Chinese bond market to study this research question. Existing tests that claim the role of asset liquidity in a first-mover advantage show that following a month of bad performance, bond funds holding fewer liquid bonds see greater outflows. Gallagher and Hu (2021) argue that such evidence is not conclusive as return-sensitive investors (an investor type) can self-select into specific categories of bond funds that hold illiquid assets, such as high yield and emerging market bond funds, and lead to outflows post underperformance. Therefore, the strong flow-performance relation in funds that hold fewer liquid assets is more a story of selection bias than asset liquidity. Moreover, Gallagher and Hu (2021) use estimates from a structural VAR to argue that the U.S. bond markets are not so illiquid as to create a first-mover advantage in the redemption process.

The Chinese bond market provides an ideal setting to examine the role of asset liquidity for two distinct reasons. First, the Chinese bond markets, overall, are significantly more liquid than their U.S. counterpart. Chen, Chen, He, Liu, and Xie (Forthcoming, Table A1) perform a detailed comparison of the liquidity in the two bond markets. The Chinese bond market displays a significantly higher level of asset turnover and a lower price impact from trading as proxied by Amihud (2002) measure.[1] Second, using a global-game framework, Chen, Goldstein, and Jiang (2010) show that, in equilibrium, an investor's choice to withdraw money from poorly performing funds monotonically depends on the level of complementarities. Furthermore, they state, "*Finding proxies in the data for the level of complementarities and for the relative size of the players, one can then identify the causality implied by the predictions of the model.*" Using the Chinese data affords us the opportunity to use an exogenous shock to the liquidity of the bond market and, hence, the level of complementarities. This shock helps us identify the causal impact of the underlying asset market liquidity on investor flow decisions.

[1] We discuss below that China has two distinct places where the bonds are traded: the interbank market and the exchange market. The reported average turnover ratio, calculated by dividing the total number of bonds traded by the number of bonds outstanding, for the Chinese interbank sample is 0.01212. This statistic is more than eight times larger than the corresponding ratio for the U.S. market, which is 0.0015. For the exchange market, the turnover ratio is more modest at 0.00099. Similarly, the Amihud illiquidity measure for the Chinese interbank market is 0.00016. The corresponding number for the U.S. bond market is 0.4881, implying a far lower level of liquidity.

Using the Chinese bond mutual fund data from 2003-2022, we first show that fund flow is a convex function of past fund performance. Our results are robust to a variety of performance metrics and in a battery of sub-sample analyses. The convexity exists among young and old funds, small and large funds, and during low and high aggregate industry inflows. These results starkly contrast with the seminal findings of Goldstein et al. (2017), who document a concave flow-performance relation in the U.S. bond mutual funds. To explain our result, we hypothesize that the improved liquidity in the Chinese bond market diminishes the level of payoff complementarity. In other words, the presence of market liquidity and lower transaction cost mitigates any significant gains from the early redemption after observing poor fund performance. We use a distinct exogenous event in the Chinese bond market to identify the causal impact of market liquidity on fund flows.

We believe the July 2017 introduction of the new trading platform, *Bond Connect*, by the People's Bank of China (PBOC) provides an ideal setup to identify the causal effect. *Bond Connect* linked the Shanghai exchange to the exchange in Hong Kong and permitted all foreign investors to invest in the Chinese interbank bond market. During the early part of the last decade, the participation of offshore investors in the Chinese bond market was very restrictive. Investors had to qualify initially through the Qualified Foreign Institutional Investor (QFII) program and later through the Renminbi Qualified Foreign Institutional Investor (RQFII) program to participate. The approval was strictly controlled by the PBOC, which preferred institutions with a long-term investment mandate. In addition, there were limits on the size of holdings (quotas) and restrictions on the repatriation of the money (lock-up period).

As *Bond Connect* commenced its operations, trading quotas, lock-up periods, and registration became obsolete. The participation of institutional investors, including commercial lenders, insurance companies, securities firms, and asset managers, dramatically increased. Notably, the market liquidity substantially improved as the offshore investors and the investors in mainland China could now invest in each other's bond markets. Mo and Subrahmanyam (2020, Table 11) present causal evidence and document that the introduction of this platform dramatically changed the level of market liquidity in the Chinese bond market. Furthermore, Mo and Subrahmanyam (2020) identify this reform as the most important of all the policies introduced by China to liberalize their bond markets.

Using a difference-in-difference estimator, we show that an improvement in the bond market liquidity substantially reduces the propensity of investors to withdraw their investments after observing poor fund performance. We perform a few placebo tests to ensure that we are capturing the treatment effects of an improvement in liquidity. We also show that when market liquidity diminishes, symmetrically, the complementarity in investors' strategy increases. We use the Covid-19 pandemic and the Evergrande debt crisis as exogenous events to show this evidence. In addition, we utilize the mutual fund holdings data and find our results consistent with the model presented in Chen et al. (2010). The sensitivity of outflows to bad past performance is stronger for funds that hold more illiquid bonds and for funds that display lower institutional ownership. Overall, we find strong support for the thesis that the underlying asset market liquidity has a causal impact on the level of investors' payoff complementarities and, hence, the shape of the flow-performance relation.

This paper makes an important contribution by underscoring a key area where policy makers can make a difference. Recent runs on Silicon Valley Bank (SVB) and Signature Bank have highlighted the fragility of financial markets. Schmidt, Timmermann, and Wermers (2016) show that mutual funds are also vulnerable to such runs. Clearly, some of the vulnerability is due to the structure of open-ended funds and the floating net asset value (NAV) guaranteed at redemption. However, our evidence shows that by merely improving on one dimension of the problem, liquidity of corporate bond market, we can experience significant positive externalities, as evidenced by the Chinese bond markets.

Our results also contribute to studies that tie managerial risk-taking decisions to the patterns of mutual fund flows (see Brown, Harlow, and Starks (1996)). Choi and Kronlund (2018) show that to attract higher flows, corporate bond mutual funds tilt their portfolios toward bonds with yields higher than their benchmarks, i.e., "*reaching for yields*." In the context of money market funds, Kacperczyk and Schnabl (2013) show that managers take on additional risk as fund inflows are highly responsive to fund yields.[2] Although some of these risk-taking incentives are moderated by market illiquidity, it would be important to understand whether these risks are exacerbated by the improvement in asset liquidity or whether market efficiency reduces such arbitrage opportunities. Alternatively, managerial contracts could also evolve to moderate risk taking behavior (see Lee et al. (2019)). An investigation of this interaction could provide a new direction for the literature.

Finally, it is also vital for the fund families to understand the causal role of market illiquidity on the investors' concerns and their strategic redemption decision. In designing the managerial contracts, fund families carefully choose the benchmark of comparison and the compensation structure to extract the most effort and the optimal portfolio risk (see Li and Tiwari (2009)). Although the competition for flows is primal, understanding the exogenous role of market liquidity and the ensuing complementarities, however, can help reduce benchmark hacking, design better managerial contracts, and build investor confidence (see Sensoy (2009), and Mullally and Rossi (2022)).

The remainder of the paper is organized as follows. In Section 2, we describe some of the details regarding the bond market in China as this supports the design of our study. In Section 3, we describe the data that we use in our empirical analysis and discuss some of the highlights. We present our hypothesis and the supporting empirical evidence in Section 4. In Section 5, we perform a series of robustness checks and present further evidence. Finally, we present our concluding arguments in Section 6.

[2] In addition, Kacperczyk and Schnabl (2013) document that as a consequence of reaching for yield, these funds also suffered runs.

2 Institutional background

2.1 Chinese mutual fund

The Chinese open-end mutual fund industry started in 2001, and the first bond fund was launched in September 2002. The market has experienced exponential development in the past two decades, from being virtually non-existent in 2001 to having 25,747 CNY billion ($3.7 trillion) under management by the end of 2022.[3] We plot the market size of the Chinese mutual fund industry in Figure 1. There were only 110 mutual funds in China in 2003, among which 11 were fixed income funds. As of December 2022, there were 10,491 mutual funds having more than 17,000 share classes. Among them, 1,995 were equity funds, 3,124 were fixed-income funds, and 4,316 were hybrid funds (mixed funds). Only 25 funds were close-ended. We observe a strong increasing trend in the growth of equity funds in the post 2008-2009 financial crisis era. This trend continued until July 2015, when the Chinese stock market crashed and halted the growth of equity funds. Since then, bond funds, hybrid funds and money market funds have outweighed the equity funds in China.

[Insert Table 1 here]

2.2 Onshore Chinese bond market

The fast growth of the Chinese bond mutual funds is highly related to the development of its bond market in the past 20 years. The overall bond market size increased from 3.04 CNY trillion in 2001 to 141.35 CNY trillion by the end of 2022, which is 117% of China's GDP in 2022, the second largest globally. Based on issuing entities, we can group Chinese bonds into three broad categories: government bonds, financial bonds, and corporate bonds. Often, financial and corporate bonds are collectively referred to as "Credit Bonds." Government bonds include instruments issued by the Ministry of Finance (Treasury bonds), local governments (Municipal bonds), and policy banks. Financial bonds are fixed-income

[3] At the end of 2022, one USD could be exchanged for approximately 6.95 CNY.

securities issued by financial institutions like commercial banks, cooperative banks, and insurance companies. A large fraction of financial institutions in China are still state-owned, and, therefore, the bonds issued by them come with an implicit government guarantee. Corporate bonds cover all fixed-income securities issued by non-financial firms. The non-governmental, non-financial debt instruments include enterprise bonds (EBs), non-financial enterprise debt financing instruments (e.g., short-term commercial papers and medium-term notes), private placement notes (PPN), private-placed corporate bonds (PCB), asset-backed securities (ABS), and convertible corporate bonds. Of the total bond market, 42.78% are Treasury bonds and Municipal bonds, 9.98% are interbank Certificates of Deposit (CDs), 23.87% are financial bonds issued by policy banks and other financial institutions, 18.89% are corporate debt securities issued by non-financial institutions, and 4.48% are other bonds. Note, with regard to the total debt outstanding, the Chinese corporate bond market, which is the focus of our paper, is the second largest in the world. However, in terms of new corporate bond issuance, China surpassed the U.S. for the year 2022.[4]

2.3 Bond trading venues and market liquidity

In China, bonds are traded in two distinct and broadly segmented markets.[5] First is an over-the-counter (OTC) based Chinese Interbank Bond Market (CIBM). The interbank bond market in China resembles the one in the U.S. as it is a quote-driven market where wholesale transactions typically take place. PBOC is the main regulator of the interbank market and the trades are executed through the China Foreign Exchange Trading System (CFETS). Commercial banks, credit cooperatives, mutual funds, insurance companies, and other non-banking financial institutions are the main participants in this market. This is a decentralized market where a trade typically begins with an inquiry and ends with bilateral bargaining done through market makers.

[4] https://markets.businessinsider.com/news/bonds/china-us-yuan-dollar-corporate-debt-sales-central-banks-fed-2022-9

[5] We discuss some prominent features of this market below. However, see Mo and Subrahmanyam (2020), He and Wei (2022), and Amstad and He (2022) for a more detailed description of the Chinese bond market.

Second is an order-driven bond exchange, which resides within the Shanghai and Shenzhen stock exchanges. This centralized exchange is governed by the China Securities Regulatory Commission (CSRC). In this market, the typical investors are non-banking financial institutions, corporate investors, and high net-worth retail individuals. Currently, in the U.S., there is no equivalent bond market of this type.

There are inherent differences between the two Chinese bond markets. The exchange market has more trades but lacks depth. The interbank market has fewer trades, but the volume is significantly higher than the exchange market. Chen et al. (Forthcoming, Figure A1) show that, in 2019, over 95% of the number of trades took place in the exchange market. However, the exchange market contributes slightly less than 4% of the dollar volume of trades. Overall, these markets collectively provide a venue for all types of investors to participate in the price discovery process, making the market more efficient and liquid.

2.4 Hypothesis development

In the U.S., a key distinction between corporate bond funds and equity funds is that they have a different flow-performance relation. Bonds funds hold far more illiquid assets (bonds) and are subject to higher transaction costs when liquidity is demanded. Following poor fund performance, when some investors desire to redeem their units, they get the net asset value as of the day of redemption. However, depending on the speed of liquidation, significant costs are borne by the remaining fund investors, making every investor want to move before others. This complementarity in the investors' strategy, stemming from the bond market illiquidity, is believed to be causing a concave relation between fund flow and fund performance. Chen et al. (2010) provide a model consistent with this prediction. However, equity mutual funds have a convex relation as they primarily invest in equity instruments, which are significantly more liquid than bonds.

An important feature of the Chinese bond market is that it is considerably more liquid than its U.S. counterpart. The increased liquidity diminishes the incentive of Chinese investors to move first and leads to the first hypothesis.

Hypothesis 1. Corporate bond funds in China do not exhibit a strong sensitivity of outflows to bad performance, leading to a more convex flow-to-performance relation.

If true, the above hypothesis only confirms an association between a country having higher market liquidity and it having a convex flow-performance relation. A multitude of reasons could influence why we observe such a phenomenon (see Gallagher and Hu (2021)).[6] One way to assert the causality is to find an exogenous event that affects the investment strategy only through the market liquidity channel. Such a shock changes the complementarity in the investor's strategy, helps us pin down the causal factor, and rules out the alternative explanation(s). This leads us to our second hypothesis.

Hypothesis 2. Corporate bond funds exhibit lower (higher) sensitivity of outflows to low past performance because of an exogenous increase (decrease) in bond market liquidity.

The previous hypothesis deals with the causal effect of changes in market liquidity over time. In addition, Chen et al. (2010) predict that the degree of complementarity changes, in the cross-section, by the amount of illiquid assets the fund owns and the level of institutional ownership. In our final hypothesis, we predict that such variation should also exist among Chinese investors.

Hypothesis 3. Corporate bond funds with more illiquid assets and lower institutional ownership exhibit greater sensitivity of outflows to low past performance.

[6] The source of investor payoff complementarities in Chen et al. (2010) is the underlying asset liquidity; in contrast, the self-selection explanation of Gallagher and Hu (2021) argues that investors' style preferences and return sensitivity drive the complementarities. An exogenous shock to market liquidity and the consequent change in the payoff dependencies helps us make a distinction between these two arguments.

We now describe our data and the empirical methodology used to test these hypotheses.

3 Data and Summary Statistics

3.1 Sample

The Wind database (Wind) is our primary source of data on Chinese mutual funds. It provides detailed information on mutual fund returns, bond market index returns, fund classification, fund styles, fund characteristics, and top ten fund holdings, among other things. Other financial information about funds and aggregate stock market returns comes from the China Stock Market & Accounting Research Database (CSMAR). Based on the investment strategy and performance benchmark stated in the fund prospectus, Wind categorizes mutual funds into the following classifications: equity funds, bond funds, hybrid (mixed) funds, money market funds, alternative investment funds, Qualified Domestic Institutional Investor (QDII) funds, and fund of funds (FOF). By definition, equity funds need to hold more than 60% of their assets in the equity market, and bond funds hold at least 80% of their assets in the bond market. To construct our sample of bond funds, we exclude exchanged-traded funds, QDII funds, FOFs, and index funds. Hybrid funds are also excluded from our sample as they could have a mixed investment objective.

After deleting observations with missing variables, we have a sample of 61,286 share class-quarter observations. This pertains to 4,462 share classes from 2,812 unique bond funds between Q2 2003 and Q4 2022. Our sample is at the share class-quarter level because Chinese funds report their total net asset value (TNA) on a quarterly basis. Additionally, we collect information on equity funds in order to compare the flow-performance relation. The equity fund sample includes 11,914 share class-quarter observations, which covers 807 share classes from 537 unique equity funds. Finally, we also use data on U.S. bond funds to contrast our main results and use them as counterfactuals. Data on U.S. fund return and fund characteristics are obtained from the Center for Research in Security Prices (CRSP).

The Vanguard Total Bond Market Index Fund return is used as the benchmark return for the aggregate U.S. corporate bond market. Morningstar Direct provides access to this data. We use the CRSP value-weighted stock market return as the benchmark return for the U.S. equity market.

3.2 Variable construction

For each share class i in quarter t, we define the new money growth ($Flow$) as

$$Flow_{i,t} = (\frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}}), \tag{1}$$

where $TNA_{i,t}$ is the total net asset value at the end of quarter t, and $R_{i,t}$ is the return of fund share class i during quarter t. To measure the performance of the bond funds, $\alpha_{i,t}$, we calculate the monthly abnormal return from a two-factor model, where the factor loadings are estimated using a rolling-window time-series regression for each share class over the 12 months before the beginning of the quarter. Then we aggregate the monthly alpha within a quarter to get the quarterly alpha of the fund in percentage (*Alpha*). We follow Goldstein et al. (2017) and use the excess aggregate bond market returns ($R_{bond,t}$) and aggregate stock market returns ($R_{equity,t}$) as the factor returns in the time-series regressions:

$$\alpha_{i,t} = R_{i,t} - \hat{b}_{i,t-1} R_{bond,t} - \hat{e}_{i,t-1} R_{equity,t}. \tag{2}$$

We use the ChinaBond Aggregate Bond Index return (*CBI*)[7] and the A-share value-weighted market return to proxy for aggregate bond and stock market returns, respectively. The risk-free rate of return is the one-year deposit rate. To assess the robustness of our results, we also introduce alternative measures of performance: 1) we use a one-factor model with the excess aggregate bond market return to calculate the bond fund alpha (*AlphaCBI*); 2) instead of using the past 12-month return data, we use the past 24-month and 36-month

[7] https://yield.chinabond.com.cn/cbweb-mn/indices/single_index_query?locale=en_US

returns to compute the fund alpha (*Alpha24*/*Alpha36*); 3) we use the raw excess return to measure the fund performance (*AlphaRaw*); and 4) we use raw return in excess of the cross-sectional average of all bond fund returns to proxy the fund performance (*AlphaBen*).

In addition to measuring flow and performance, our empirical specifications below include a host of control variables. These include the natural logarithm of total net assets in CNY million ($Ln(TNA)$), natural logarithm of fund age in years ($Ln(Age)$), expense ratio that includes management fee, custodian fee and sales fee in percentage terms (*Expense*), an indicator variable that equals one if the fund share charge back-end loads and zero otherwise (*Rear load*), and the flows of the previous period (*Lagged flow*). Using the reported data, we construct two additional variables: the level of institutional ownership of the fund (*Inst.holding),* and the ratio of bank deposit to total assets (*Cash*). These two variables are available only on a semi-annual basis. Finally, to avoid the impact of any extreme values, we winsorize all continuous variables at 5% and 95% levels of the sample distribution.

3.3 Summary statistics

We summarize our bond fund sample in Table 1. Panel A presents the summary statistics of the key variables. The average value of quarterly fund flow is 7.38%, considerably higher than the U.S. rate of 2.5% (compounded from the monthly estimate in Goldstein et al. (2017)). However, the mutual fund industry in China was in its nascent stage in the early 2000s and has undergone exponential growth since then. The unusually high rate of money flow is consistent with this and can also be observed in Figure 1. The quarterly raw return averages 0.85%, and its median value is 0.83, which is comparable to the U.S. corporate bond funds (0.36% monthly return from Choi et al. (2022)). The mean and median values of the quarterly alpha are 0.58% and 0.50%, respectively. The size of the average bond fund in our sample is 160.77 CNY million (23.1 million USD, about half the size of the average U.S. corporate bond fund), and the average age is 4.5 years. The expense ratio is 0.75%, and most funds have back-end load arrangement (92%). In our sample, on average, 51.65%

of the fund shares are owned by institutions, and the funds hold 3.17% of assets in cash. Compared to bond funds, Chinese equity funds have lower institutional ownership (22.75%), and higher bank deposit (8.65%).

Panel B summarizes the sample distribution in various fund styles as classified by the Wind database. The majority of the funds belong to the income style (74.6%) and steady growth style (16.9%), consistent with the general investment purpose of the bond fund.

[Insert Table 1 here]

4 Empirical evidence

In this section, we test our hypothesis outlined before. We first establish the investors' response to fund underperformance in China. Later, we investigate how the change in market liquidity causally affects the investor's response.

4.1 Flow-performance in Chinese market

One of the empirically well established facts in the U.S. is that outflows of corporate bond funds are more sensitive to underperformance than are inflows to outperformance. We begin our empirical analysis by testing if the higher liquidity of the Chinese bond market changes this relation. As a first step, we plot how the money flow varies across the different parts of the fund performance distribution. In each quarter, we rank the funds based on their quarterly performance (alpha) and assign them to a performance decile. A higher decile corresponds to a higher performance rank. We repeat this for each quarter and plot the average (time-series) percentage flow for each decile. The results in Figure 2, show that funds that outperform their peers experience a substantial boost to their asset size. Such return-chasing behavior by mutual fund investors is well documented (see Sirri and Tufano (1998)). Surprisingly, funds that underperform do not experience nearly as much outflow. This preliminary empirical result is novel in the context of bond mutual funds.

We perform a similar exercise using the U.S. bond funds data. The convex relation found in China, however, is not observed in the U.S. data. Outperforming funds attract a lot of new money.[8] But consistent with the concave relation found in Chen and Qin (2017) and Goldstein et al. (2017), underperforming funds seem (visually) to be suffering from significant outflows.

Although the univariate results support Hypothesis 1, there could be many confounding factors. To formally test our hypothesis, we perform a parametric regression that captures the flow-performance relation after controlling for other covariates. In order for the reader(s) to easily compare our results with the seminal paper of Goldstein et al. (2017), we keep our empirical specification exactly identical:

$$\begin{aligned} Flow_{i,t} &= a + \beta_1 Alpha_{i,t-1} + \beta_2 I_{\{Alpha_{i,t-1}<0\}} \\ &+ \beta_3 Alpha_{i,t-1} \times I_{\{Alpha_{i,t-1}<0\}} + \gamma Control_{i,t} + \delta_t + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where $Flow_{i,t}$ is the new money flow in the share class, i, of a corporate bond fund for the quarter ended t. $Alpha_{i,t-1}$ is the alpha of the fund share class estimated as the abnormal return from the 2-factor model described above in E.q. (2). $I_{\{Alpha_{i,t-1}<0\}}$ is an indicator variable equal to one if the fund achieves a negative alpha in the past quarter and zero otherwise. The interaction term captures the nonlinearity, if any, in the flow-performance relation. Earlier defined variables $Ln(TNA)$, $Ln(Age)$, $Expense$, $Rear\,load$, and $Lagged\,flow$ are used as controls in the regression. All the specifications include the quarter fixed effect (δ_t). This helps to control the quarterly variation in the aggregate flows to the fund sector. Additionally, we cluster the standard errors at the fund share class level. This helps improve the statistical inference in case there is time-series dependence in regressions residuals.

[8] In the U.S., the percentage gain of new money is considerably lower than that in China. We attribute this partly to the fact that the average Chinese bond fund is less than half the size of the ones in the U.S. and hence has more room to grow.

Table 2 shows the main results. Results in columns (1) and (2) show that there is no concavity in flow-performance relation in the case of Chinese bond funds. The regression coefficient for *Alpha* is 7.922. The sign is consistent with established studies that argue that investor inflows follow fund outperformance (see Berk and Green (2004)). However, the slope coefficient for the interaction term is negative and highly significant. In fact, the sensitivity of outflows to a negative alpha is 2.307 (7.922 – 5.615), which is more than 70% lower than the sensitivity of inflows to a positive alpha.

For additional robustness, we add the aggregate style flows as a control and re-estimate a model. Results in column (3) remain qualitatively the same. In column (4), we also perform a similar analysis for the equity funds in China. We find the familiar convex relation between flow and performance. The slope coefficient for *Alpha* is 1.002. Although the magnitude of this coefficient is significantly smaller than the comparable number for bond funds, we focus more on the outflows since our emphasis is on investor complementarity and its effect on market fragility.[9] The sensitivity of outflows from equity funds to negative alpha is -0.195 (1.002 – 1.197), which makes the relation convex. Finally, for completeness, we also test the sample of U.S. bond funds. The method of alpha estimation is similar to that described in E.q. (2). However, the Vanguard Total Bond Market Index Fund return and the CRSP value-weighted stock market return are used as the factor returns as they are more appropriate benchmarks for U.S. funds. In column (5), the incremental slope for the funds with negative alpha is positive and statistically significant. This is consistent with the findings of Goldstein et al. (2017) and confirm the concavity of flow-performance relation in the U.S. bond funds.[10]

In Table 3, we test the robustness of our main results. In column (1), we use only the excess returns on the bond index and ignore the stock market factor to compute the fund alpha. In columns (2) and (3), we use the 24-month and 36-month return series to

[9]Variations in investor preferences, access to the market, and market liquidity could lead to differences in flow response. We don't delve into the causal factors as this is beyond the scope of our paper.

[10]We use quarterly data in column (5) of Table 2. In unreported results, we find that the results are qualitatively similar if we use monthly data, as in Goldstein et al. (2017).

compute our alpha and reestimate the specification in Eq. (3). In column (4), we use raw returns as a measure of performance, and in column (5), we use weighted-average peer fund return as the benchmark return to compute the alpha. To allow for the flows to depend on an unobserved time-invariant characteristic, in column (6), we include the share class fixed effect. The results under each of these specifications remain qualitatively similar to the results in Table 2. Money still follows outperforming funds. However, poorly performing funds do not experience a similar outflow.

In column (7) of Table 3, we allow for the regression residuals among the different share classes within a fund to be correlated to each other and cluster the standard errors at the fund level. Since the point estimates are unaffected, the coefficients in column (7) of Table 3 are identical to column (2) in Table 2. As expected, the standard errors of the coefficient increase, and t-statistics decrease. However, the coefficients continue to be highly significant. Although our sample includes only corporate bond funds, these funds often hold other types of assets to diversify and hedge their portfolio risk. In column (8), we look at a subsample of our data with at least 50% of the TNA being invested in corporate bonds.[11] This test alleviates concerns about our earlier results being driven by any differences in asset characteristics. Finally, the level of our analysis, thus far, has been at share class-quarter level. Such a specification accommodates the idea that performance and flows can differ among share classes. In column (9), we change the level of analysis to fund-quarter. All the variables are computed as the average of the share classes within the fund, weighted by their respective TNA. The results are qualitatively similar across the specifications in columns (8) and (9).

4.2 Causal evidence

In this section, we test Hypothesis 2 and aim to establish a causal link between changes in the underlying asset liquidity, which influences investor payoff complementarity, and the

[11] Choi and Kronlund (2018) also use a similar 50% cutoff to build their sample of bond funds. Our results are robust to other choices of cutoffs as well.

investor's redemption decision. We rely on an exogenous event that affects the overall liquidity of corporate bonds in China to help identify this effect. In the recent decade, China made several reforms to open its financial markets to foreign investors. Bond markets were a beneficiary of many of these liberalization policies. The first significant policy change was introduced in March 2012 when certain qualified foreign institutional investors, RQFIIs, were allowed to access the interbank bond market. In March 2013, a new policy mandate allowed a band of new foreign institutional investors, QFIIs, to participate in the same market. Despite these attempts, no significant gains were achieved in terms of foreign investor participation, as there still existed limits on trading volume and the repatriation of the trading gains. Furthermore, we don't use these two events as our identification strategy because the sample of bond funds during this time period was very small (see Fig.1).[12]

Instead, we focus on an event in May 2017 when PBOC and the Hong Kong Monetary Authority (HKMA) jointly announced plans to establish a mutual market access scheme to connect the Mainland China and Hong Kong bond markets. Hong Kong was already an international financial center accessible to a wide variety of foreign investors. With the introduction of the new trading platform called *Bond Connect,* each of these investors could now have direct access to the Chinese bond market.[13] The new trading platform was introduced in July 2017. Trading through *Bond Connect* made it easier for foreign investors to access the bond market as the Overseas Institutional Investors (OIIs) were given quota-free access to the Interbank market, and cumbersome registration requirements were eliminated. Prior to this, it could take upwards of 18 months to finish the registration process and get PBOC approval (see Amstad and He (2022)). Under the new process, no formal registration was required. Instead, the investors only had to make a filing. In addition, repatriation restrictions for currency transactions and holding periods for bonds were also

[12]Although qualified institutional investors got access to the exchange bond market in 2002, it didn't improve the market liquidity as the local institutions weren't participating in it at that time. Besides, the sample of bond funds in 2002 is negligible for us to make any meaningful inference.

[13]*Bond Connect* was the fourth channel for investment into China's bond market. Other official channels include CIBM Direct, QFII Scheme, and RQFII Scheme. The key difference, operationally, was that *Bond Connect* is based offshore in Hong Kong.

removed. Over time, through the increased participation, the launch of *Bond Connect* had a significant impact on the levels of liquidity in the Chinese bond market.[14] Using a difference-in-difference estimator, Mo and Subrahmanyam (2020) show that introducing Bond Connect was the most important policy change of all the regulatory policies that targeted increasing the liquidity of the Chinese interbank bond market.

4.2.1 Effects of Bond Connect

To test the causal effect of liquidity increase on the sensitivity of outflows to low past performance of bond funds we run the following regression.

$$\begin{aligned} Flow_{i,t} = a + \beta_1 Alpha_{i,t-1} + \beta_2 I_{\{Alpha_{i,t-1}<0\}} + \beta_3 Alpha_{i,t-1} \times I_{\{Alpha_{i,t-1}<0\}} \\ + \beta_4 Post \times Alpha_{i,t-1} + \beta_5 Post \times I_{\{Alpha_{i,t-1}<0\}} \\ + \beta_6 Alpha_{i,t-1} \times I_{\{Alpha_{i,t-1}<0\}} \times Post + \gamma Control_{i,t} + \delta_t + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where *Post* is an indicator variable which equal to one for time periods after the introduction of the platform and zero otherwise. In Eq. (4), β_6 is the main coefficient of interest as it measures the incremental effect on flows of underperforming funds (*treated* group) relative to funds having a positive alpha (*control* group). Importantly, β_6 compares the difference among these groups before the liquidity change to the difference after. Our key identification assumption is that absent the reform (*treatment administered*), the change in flows for underperforming funds would not have been different than the change in flows for outperforming funds. In the subsequent analysis, we show evidence supporting our assumption, popularly known as the "parallel trends" assumption.

Controls used in Eq. (4) are the same as those used in Table 2. Note, we do not suffer from

[14] Asset management companies form 88% of the investor base, followed by banks (6%). In terms of jurisdiction, 34% of *Bond Connect* investors come from the U.S., followed by HK, the UK and Singapore with 16%, 15% and 6% of the market shares, respectively.

the "bad control" problem of Angrist and Pischke (2009) as none of the controls themselves are affected by treatment. Every quarter funds are randomly assigned to the treated and control group, as fund performance alone determines this assignment. However, there is some concern that certain factors, like fund size, may correlate with the likelihood of being allocated to the treatment group. This is a concern only if funds with these characteristics are also likely to have a differential trend in flows. Regardless, adding the controls in Eq. (3) mitigates some of these concerns and restores the random assignment to groups; i.e., the probability of being in the treated group (or not) is random after controlling for the observables. All specifications include a quarter fixed-effects. Therefore, we don't include the dummy variable, $Post$, in the specification as it will not be identified due to collinearity.

Although the platform was introduced in July 2017, it took a little while for the participants to understand, adopt, and flourish in the new system. Initially, in 2017, only 139 investors were using this platform. It was not until June 2019 that the number of investors reached 1,000.[15] The increased adoption happened due to a concerted effort by PBOC to improve market access and get China's bonds added in the Bloomberg Barclays Global Aggregate Indices. During the first Bond Connect Anniversary Summit in 2018, Pan Gongsheng, PBOC Deputy Governor, announced seven measures, including full implementation of real-time delivery versus payment (DVP) settlement, cooperation with mainstream international e-trading platforms (such as Bloomberg), tax policy clarification, the launch of trade allocation, reduction of transaction fees, addition of Bond Connect dealers, and permission for repo and derivatives trading. These measures enabled China's bond market to meet all the conditions for inclusion in the Bloomberg Indices, which took effect in April 2019. We highlight these facts to establish the slow-evolving nature of market liquidity and to give us a wider berth for identifying the treatment effects.

Note our design does not suffer from the dynamic treatment effects problem described

[15] More information about the history and milestones achieved by this company can be found here: https://www.chinabondconnect.com/en/About-Us/Milestones.html

in Gormley and Matsa (2011).[16] In our case, the treatment is not applied to the fund; instead, it is macroeconomic in nature. The sample that gets the treatment, controlling for the observables, is randomly assigned to the treatment groups each quarter. We see our data more as repeated cross-sections than as panel data.

We begin by looking at a two-year window around July 2017. The relevant results are presented in Panel A of Table 4. The slope coefficient, β_6, for the three-way interaction of fund performance (alpha), indicator for negative fund performance, and post liberalization dummy is of primary interest to us as it captures the causal effect of liquidity change on investor flow response in poorly performing funds. In the absence of liquidity, every investor's strategy is complementary to the other, which could lead to a run on the fund. The sign and magnitude of the coefficient, β_6, will help us ascertain whether improving bond market liquidity disrupted the complementarity in investor strategy. The results in column (1) confirm that β_6 is negative and statistically significant. We estimate that due to the change in underlying market liquidity in the post-platform regime, when a fund's underperformance is one standard deviation away from the mean, funds are protected against an incremental loss of 23.18 million CNY from their AUM.[17]

For completeness, we also report the results when we use our difference-in-difference estimator within a narrow one-year window. Although the results in column (2) show a similar pattern, the results are, as expected, a little weaker. As we explain above, the impact of *Bond Connect* on market liquidity is not immediate. Market liquidity increased with time as more foreign participants entered the market.

In addition to the introduction of *Bond Connect* in 2017, Chinese regulators, in May

[16] Gormley and Matsa (2011) argue in instances where multiple exogenous events are staggered in time, a conventional difference-in-difference estimator might violate the parallel trends assumption needed for identification. This is particularly true when the treated group for one event becomes the control group for the next event and treatment effects are dynamic. They propose a stacked regression approach to resolve such a problem.

[17] The size of the median fund in our sample is 302 million CNY. One standard deviation decrease in alpha (i.e., 1.01%) will normally lead to an outflow of money. However, due to the increased liquidity of bonds in the post-event period, the outflow among the poor-performing funds is reduced by 23.18 million CNY (1.01% * (-7.6) * 302). This is with respect to the level of outflow of the same poorly performing fund in the pre-event period.

2016, made an effort to liberalize bond market participation. This initiative was specifically targeted to reform the registration process and increase the allocation of trade quota. The scope of this policy was quite small and had marginal impact, if any, on the bond market liquidity (see Mo and Subrahmanyam (2020)). However, we are aware that May 2016 is squarely in the middle of our two-year pre-event period. Therefore, the treatment effect in the pre-treatment period could be affected by the presence of two liquidity regimes, although only marginally. To overcome this concern, in columns (3) and (4) of Table 5, we restrict our pre-event period, without any prejudice to the interpretation of the results, to one year. The results of using a two-year and a three-year post event horizon are reported in columns (3) and (4), respectively. Regardless of the horizon used, the results are materially the same. Improvement in bond market participation and ensuing increase in liquidity has a causal impact on the investor's redemption strategy.

There could be a concern that factors like fund size may influence fund performance, and therefore, assignment to treatment and control groups is not random. To address this problem, we perform a matching exercise using the nearest-neighbor method and generate a matched sample; that is, for each fund in the underperforming group, we find an observationally equivalent fund in the outperforming group. More precisely, we match funds each quarter based on their fund style (exact), fund size, fund age, expense ratio, lagged flow, and rear load. Figure 3 presents the standardized differences between the treated and control groups before and after matching, and our matching process effectively balances the covariates as the two groups become very similar in the observed dimensions. We thus assume that assignment is random conditional on the observables in the matching process described above.

We re-estimate the earlier specification as in Panel A for this matched sample. The results are presented in Panel B of Table 4. As expected, the sample size is smaller than that in Panel A. However, consistent with our expectation, the sign of the three-way interaction coefficient is negative and statistically significant. This matching analysis provides additional convincing evidence about how the improvement in the underlying asset liquidity affects the payoff complementarity of investors.

4.2.2 Supporting the identification

We perform two additional tests to support our identifying strategy. First, we argue that the *Bond Connect* event is irrelevant to the funds in the U.S. and only impacts those in China. Therefore, if we perform a difference-in-difference test on the sample of U.S. funds around July 2017, we should not observe any significant effect. To test this counterfactual, we use the specification in Eq. (4). The results in Panel C of Table 4 clearly indicate that, for the sample of the U.S. funds, the introduction of *Bond Connect* has no impact on the complementarity of investor strategy. The three-way interaction term in all the specifications is statistically indistinguishable from zero.

Additionally, we also perform falsification tests to indirectly verify our identification assumption. The objective of these tests is to ensure that the timing of the observed change in flow coincides with the timing of the exogenous event. In other words, we ensure that there is no pre-trend. To run this test, we assume that the introduction of *Bond Connect* was on a date different than July 2017. For such a date, we run a difference-in-difference specification like in Eq. (4), focusing on a two-year window before and after the hypothetical event. In columns (1) – (5) of Table 5, we assume that the *Bond Connect* happened in July 2012, July 2013, July 2014, July 2015, and July 2016, respectively. Although we report only the point estimate of the three-way interaction variable, all the specifications include the same control variables as in Table 2. As expected, we do not find any statistically significant interaction term in any of the specifications. This test gives us great confidence to confirm that the timing of the observed changes in flows in Table 4 coincides with the identified event.

4.2.3 Other exogenous events

In addition to the above-mentioned market reform, we use two additional exogenous events to test the impact of the changes in market liquidity on investors' flow decisions. Having multiple events at different points in time where treatment is provided to a varied group of funds is very useful for our identification. This setup helps us show that the effect of treatment is similar across the events and is not driven by a particular set of treated funds. Moreover, having multiple events is particularly useful in mitigating concerns about the violation of parallel trends assumption as it is unlikely that the assumption is violated for each unique event.

First, the recent Covid-19 pandemic severely impacted the world economy, and the effects were not distributed uniformly. China, where the first case was found, followed a zero-Covid policy which created a lot of public policy and financial uncertainty. Following the declaration of a pandemic by the World Health Organization (WHO) on March 11, 2020, markets experienced a great deal of panic, triggering a flight to safe and liquid assets. This event severely diminished the market liquidity. The central bank had to intervene to increase the money supply by reducing Loan Prime Rates (LPR) and buying back assets, including corporate bonds. In the wake of these events, we anticipate a differential response among investors to bond fund underperformance.

Second event, involves the debt crisis surrounding Evergrande group. To understand the scale of the problem, note the real estate industry accounts for about 20% of the Chinese economy. Evergrande, the second-largest property developer in China, had access to cheap credit, which it used to invest in various markets, including bottled water and electric cars. In September 2021, Evergrande had about $300 billion in financial obligations. However, the real estate market in China was experiencing weak demand and slowing sales. The inflated house prices were dropping, and the firm's cash flows were affected.[18] This prompted Evergrande to default on its interest commitments to domestic and foreign investors. The

[18]https://www.nytimes.com/2021/10/21/business/china-evergrande-bond-payment.html

credit rating for their debt was downgraded to a Restricted Default status.[19] By the end of September 2021, the stock price had plummeted by over 80% from where it was at the beginning of the year.

The fear was that if the Chinese government did not step in and help with restructuring, this situation could result in a credit crunch for the entire economy as financial institutions would become more risk-averse. A market failure of such proportion could make it harder for other Chinese companies to finance their businesses with foreign investment. Additionally, panic from investors and home buyers could further dampen home prices, affecting household wealth and investor confidence. In the following weeks, Evergrande's financial troubles had already spilled over to other developers. Sunac China Holdings Limited, China Fortune Land Development Limited, and China Properties Group Limited all defaulted on their debts, thereby raising the yield, increasing the spread, and making the bond market more volatile and illiquid.

To test the impact of these events on investor reactions to bond performance, we run the specification in Eq. (4). However, we change the definition of *Post* to fit the event we are studying. In column (1) of Table 6, where we focus on the impact of Covid-19, we identify the quarter beginning April 2020 to the quarter ending September 2021 as our post-event period.[20] PostCovid is a dummy variable that equals one if the sample period is between 2020Q2 and 2021Q3, and zero if the sample period is between 2018Q4 and 2020Q1. Having the post *Bond Connect* period partly overlap with the pre-treatment period of this test is not an issue here. Concerns regarding treatment effects being dynamic are less relevant as a) the treated group is not the same from one period to the other, and b) we expect the effects of the two events to be exactly opposite of each other.

The main effect of performance (alpha) on future flows is still positive. However, this effect is not linear. The coefficient on the interaction between alpha and the indicator of

[19]Restricted Default (RD) is a credit rating which can be given to a company by Fitch if the issuer has defaulted on certain financial obligations but has not entered into insolvency proceedings or deslisting.

[20]The time window for our dummy variable starts in April 2020 based on WHO's declaration of the pandemic in March 2020.

negative alpha for the period before the onset of the pandemic, β_3, is negative, indicating a convex relation between our variables of interest. More importantly, the treatment effect of decreased liquidity is highlighted by the coefficient of the three-way interaction term. The positive sign shows that in the Covid-19 pandemic period, when there was a negative shock to the bond market liquidity, the complementarity in investors' strategy ensured that the poor-performing funds experienced an increased outflow. This result confirms our main hypothesis that market liquidity has a causal impact on the flow-performance relation of underperforming bond funds.

In column (2) of Table 6, for the Evergrande debt crisis, we identify October 2021 to December 2022 as the post-event period. PostEver is a dummy variable that equals one if the sample period is from 2021Q4 to 2022Q4, and zero for the period 2020Q3 – 2021Q3. The results are qualitatively very similar to those in column (1). The effect of increased volatility and decreased liquidity induced by sudden bankruptcy of one of the largest real estate developers in China causally influences investors' decision of how to withdraw their money from poorly performing funds. In the post-event period, the previously observed convexity in flow performance is nonexistent.

Thus far, we have established the impact of both liquidity increase and decrease on the flow decisions of the investors. Even if any one of the results were implausible, the collective results across the different events provide compelling evidence in support of our hypothesis. Overall, the direction and the degree of influence are overwhelmingly consistent with the thesis of strategic complementarity among bond fund investors.

5 Robustness

5.1 Holdings-based evidence

Here we use the variation in portfolio holdings of the bond funds to highlight the role of the underlying market liquidity. Every quarter, bond funds in China disclose certain details regarding the composition of their portfolio holdings in addition to their top 10 holdings. The details include the types of bonds, their trading venues, and the overall composition across these bond categories. Furthermore, the top 10 holdings might only represent a small number of bonds; however, in our sample they represent over 38% of the total portfolio value.

As mentioned above, Chinese bonds trade in two distinct markets—the interbank market, the more liquid of the two markets, and the exchange market. We exploit the difference in their relative liquidity and argue that funds that own a higher fraction of bonds that are listed on the interbank market should be less affected by outflows following a poor performance. In other words, the investors who continue to invest in funds having a greater share of bonds traded on the interbank market are not severely affected by the price impact of the trades made to service the redemption of other investors. To test this hypothesis, we introduce two new indicator variable. First, $No\_Exchange$ is a dummy variable that equals one if the fund holdings have no exchange-traded bonds in a given quarter, and zero otherwise. Second, $No\_Exchange\_top10$ is a dummy variable that equals one if the fund does not hold exchange-traded bonds in its top 10 holdings in a given year, and zero otherwise. Bonds that are cross-listed are not treated as exchange bonds.

The results from using the holdings data are provided in Table 7. In column (1), we use $No\_Exchange$ to tease apart the effects of fund constituents on flow performance relation. In the aggregate sample, the slope coefficient of the two-way interaction between Alpha and No_Exchange is positive and statistically highly significant. This suggests that funds with more liquid assets attract more flows from outperformance. However, importantly, investors in such funds do not display complementarity in their redemption strategy. The point estimate of the three-way interaction between Alpha, $I_{Alpha<0}$, and $No\_Exchange$ is negative and consistent with our priors. In column (2), we use the variable, $No\_Exchange\_top10$, which uses the top 10 disclosed constituents of the portfolio to test our hypothesis. The results are consistent to those in column (1). Overall, when fund liquidity is estimated based on its holdings, we find that the complementarity of the investors' strategy diminishes as liquidity increases.

5.2 Characteristics and flow-performance

In addition to holding liquid bonds, bond funds can also signal their asset liquidity using cash in their portfolio. The global-game model presented in Chen et al. (2010) predicts that funds with liquid assets, where investor complementarities are weaker, exhibit lower sensitivity of outflows to bad past performance than funds with illiquid assets. Therefore, we expect funds with higher cash balances to have lower outflows conditional on underperformance.

Additionally, the same model in Chen et al. (2010) predicts that the presence of large institutional investors in the fund dampens the extent of investor complementarity. The idea is that institutional investors are sophisticated investors typically holding a large fraction of the fund. Given they have access to a larger capital base and the knowledge of the negative externalities imposed by their withdrawals, larger institutions are less likely to redeem immediately after underperformance. Moreover, their inaction also makes the withdrawal by other participants less likely.

We follow Goldstein et al. (2017) and define "cash" as the sum of the fund's cash holdings, repurchase agreements, and short-term debt other than repurchase agreements. We define the variable $Cash\_pct$ as the percentage of fund assets held in cash.[21] $Inst\_holding$ is the three-year moving average of the percentage institutional ownership. We demean these two measures in the regression for easier interpretation. The amount of cash and the level of institutional ownership are both provided by the Wind database. Results from the pooled OLS are provided in Table 8. In column (1), funds with positive alpha attract positive flows. However, the interaction term between $I_{Alpha<0}$ and alpha is negative. This highlights the convexity of flow-performance relation. The three-way interaction term captures how this slope changes between funds with varying levels of cash. Consistent with Chen et al. (2010), we find that funds with above-average cash balances show a lower propensity for

[21]For robustness, we also test our hypothesis using only the cash holdings as a measure of liquidity. Our findings were qualitatively similar (unreported).

outflows following underperformance. The results in column (2) are also in line with our expectations. Funds with higher institutional ownership face less, if any, coordinated outflow. Overall, we find the evidence from Chinese bond funds corroborates the model predictions in Chen et al. (2010). Although the results in Table 8 are coherent with the existence of strategic complementarity, we do not claim any causality. Both cash balance and institutional ownership could be endogenous, as we cannot rule out any reverse causality.

5.3 Subsample Analysis

We next test whether our results regarding convexity of flow-performance relation in the Chinese bond funds hold in different subsamples. Such a test helps us discern if the convex relation is spurious (see Spiegel and Zhang (2013)). Moreover, we perform this test to provide additional support to our earlier findings. The identification in Table 4 relies on the assumption that funds are randomly assigned to treatment (underperforming) and control (outperforming) groups in each quarter. However, we don't rule out the possibility that certain fund characteristics could be correlated with fund alpha. Berk and Green (2004), in their model, assume that there is a diminishing return to the scale when managing mutual funds. Therefore, conditional on everything else, larger funds might be more likely to be assigned to the control group than smaller funds. Having controls in Eq. (4) helps mitigate any bias such a problem might create. An additional way to alleviate such concern is to demonstrate that this "non-random" assignment has no bearing on the outcome variable. In other words, funds, when sorted on observable characteristics, we want to show that there is no significant difference in flow-performance relation across the groups.

We examine whether the convexity in the relation is pervasive across young and old funds, small and large funds, and periods with low and high aggregate fund flows. Young and old funds are defined as funds below– and above– the sample median age, respectively. Similarly, small and large funds are defined as funds with below- and above- the sample median size, respectively. Finally, low and high flows are quarters with below– and above–

median aggregate corporate bond fund flows, respectively. The regression specification used here is the same as in Eq. (3). The relevant results are presented in Table 9.[22] The pattern of evidence is quite consistent across the columns. Outperforming funds attract large sums of money. However, looking at the sign of the interaction coefficient, poor-performing funds do not experience a proportional outflow. This establishes the existence of a convex relation across the different subsamples in China.

5.4 Non-binary performance distribution

In our analysis thus far, we have limited ourselves to two broad areas of performance distribution: above and below zero. Here we test for the convexity of the flow-performance relation by fitting a piecewise linear regression for three different regions of the performance distribution. We follow Sirri and Tufano (1998), and each quarter we order the fund returns, within an investment objective, into ranks. Each fund is assigned a fractional rank ranging from 0 (poorest performance) to 1 (best performance). The performance ranks are divided into three unequal groupings. The bottom performance grouping ($LowPerf$) is the lowest quintile of performance, defined as $Min(Rank_{t-1}, 0.2)$. The middle three performance quintiles are combined into one grouping ($MidPerf$), defined as $Min(0.6, Rank_{t-1} - LowPerf)$, and the highest performance quintile ($HighPerf$) is defined as $Rank_{t-1} - (LowPerf + MidPerf)$.

In Table 10, we run the following regression specification:

$$
\begin{aligned}
Flow_{i,t} = a &+ \beta_1 LowPerf_{i,t-1} + \beta_2 MidPerf_{i,t-1} \\
&+ \beta_3 HighPerf_{i,t-1} + \gamma Control_{i,t} + \delta_t + \epsilon_{i,t},
\end{aligned}
\tag{5}
$$

controls are the same as used in Table 2. Although we don't know whether the investors

[22] Although we used median age to split the data, there are more "old funds" than "young funds." This is because of the tied ranks at the median. Resolving the tie the other way does not materially affect our results. Similarly, the sample of funds varies quarterly, so the number of funds in the "low flows" category is not the same as that in the "high flows" category.

care more about relative performance or absolute returns while making their flow decision, this approach helps us show that our results on convexity in flow-performance relation are robust to either choice. In columns (1) and (2), we show the results for our sample of Chinese bond funds. For top performers—those in the top quintile of funds in their objective category—performance is associated with economically and statistically significant inflows. For funds categorized as $MidPerf$, performance is positively associated with flows, but this relationship is statistically weak. However, importantly, in the lowest quintile (the poorest performers), there is no relationship between historical performance and fund flows.[23] Results in column (3) and (4) are for Chinese equity funds. They exhibit a very similar pattern as well. Overall, our evidence is consistent with Chinese bond funds facing a convex flow-performance relation.

6 Conclusion

Corporate bonds are an important source of financing for firms. However, households do not directly participate in this asset market.[24] Instead, they indirectly invest through financial institutions. Understanding the factors influencing the money flows into and outside of these institutions, i.e., mutual funds, is crucial to the stability of the financial system. Evidence from U.S. financial markets shows that the relationship between flows and performance of corporate bond funds is concave, indicating stronger sensitivity of outflows to poor performance.

In this paper, we show the above finding is due to the presence of payoff complementarities among corporate bond fund investors driven by the illiquidity of the underlying assets. Our evidence is based on the improved liquidity of the Chinese bond market, the second larger corporate bond market in the world. In this market environment, where the investors in

[23] For robustness, we have also tried other breakpoints to define $LowPerf$,$MidPerf$, and $HighPerf$. The results (unreported) based on the alternative definitions are qualitatively similar to those presented here.

[24] According to SIFMA, a trade association for broker-dealers, investment banks, and asset managers, corporate bonds represent only 0.2% of the household's liquid financial assets. See https://www.sifma.org/resources/research/fact-book/.

the fund are less concerned about the liquidity costs imposed by the redemption of other investors, we find that the familiar convex flow performance relation observed in equity funds also holds in corporate bond funds. Importantly, we use many exogenous events to clearly identify the impact of improved liquidity on the investor's redemption strategy. Additionally, our results are consistent with the investor's action predicted by the literature in the presence of higher institutional ownership and holdings of relatively more liquid assets.

Our results will be of interest to the regulators who care about the fragility of the financial market, as there are negative externalities from a fund run to the asset markets. Attempts need to be made to break the feedback loop between unexpected fund redemptions and rapid asset liquidation. Possible solutions include remedial actions to improve bond market liquidity through structural changes and changes to end-of-day NAV pricing (i.e., swing pricing).

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Table 1: Summary of the data

Panel A of this table summarizes the statistics for characteristics of active bond funds in the Chinese market between 2003 and 2022. We report the number of observations (N), mean (Mean), standard deviation (Std.dev), 5th percentile (P5), 10th percentile (P10), etc. The unit of observation is share class-quarter. The sample includes 4,190 unique fund share classes and 2,647 unique funds. We exclude index bond funds and exchange-traded funds from the Wind database. Flow (%) is the percentage of fund flow in a given quarter, and Fund return (%) is the quarterly fund return in percent. Alpha is the abnormal returns of the previous quarter compounded from monthly estimates. The monthly alpha is calculated as the abnormal returns in excess of bond and stock market factor returns, where the factor loadings are computed using the last 12-month data. We use the ChinaBond Aggregate Bond Index return and the A-share value-weighted market return to proxy for aggregate bond and stock market returns. Log(TNA) is the natural log of total net assets (TNA). Log(Age) is the natural log of fund age in years since its inception. Expense (%) is the expense ratio of the fund in percent. Rear load is an indicator variable that equals one if the fund share charges rear loads and zero otherwise. Instl. holding (%) is the average institutional ownership of the fund share in the past three years in percent. Cash (%) is the proportion of fund assets held in cash in percent. Panel B of this table presents the sample distribution across different investment styles.

Panel A: Distribution of the key variables

	N	Mean	Std	P5	P10	P25	P50	P75	P90	P95
Flow (%)	61,286	7.38	52.81	-60.82	-40.59	-13.87	-0.59	1.89	63.32	183.61
Fund return (%)	61,286	0.85	1.31	-1.90	-0.78	0.22	0.83	1.39	2.57	3.89
Alpha (%)	61,286	0.58	1.01	-1.59	-0.61	0.11	0.50	1.00	1.90	2.94
Ln(TNA)	61,286	5.08	2.80	-1.97	0.92	3.70	5.71	7.15	8.16	8.69
Ln(Age)	61,286	1.51	0.52	0.69	0.69	1.10	1.39	1.79	2.20	2.40
Expense (%)	61,286	0.75	0.32	0.40	0.40	0.40	0.78	0.90	1.25	1.30
Rear load	61,286	0.92	0.27	0.00	1.00	1.00	1.00	1.00	1.00	1.00
Instl. holding (%)	46,559	51.65	40.00	0.00	0.00	9.79	49.80	99.39	100	100
Cash (%)	45,459	3.17	4.12	0.06	0.13	0.44	1.46	4.04	9.35	15.54

Panel B: Fund styles as defined by Wind

Style	# of Share classes
Value	166
Appreciation	3,425
Balanced	611
Growth	553
Income	45,719
Active growth	140
Steady appreciation	291
Steady growth	10,381
Total	61,286

Table 2: Flow-performance relation in Corporate Bond funds (I)

This table shows flow-performance relations for active open-ended corporate bond funds and stock funds in China and corporate bond funds in the U.S. from 2003 to 2022. Columns (1)-(3) show the results for Chinese corporate bond funds; column (4) shows the result for Chinese equity funds; and column (5) shows the results for U.S. corporate bond funds. The dependent variable in all the columns is Flow, which is the percentage of fund flow in a given quarter. The variable Alpha is the abnormal returns of the previous quarter compounded from monthly estimates; Lagged Flow is the fund flow lagged by a quarter; Ln(TNA) is the natural log of total net assets; Ln(Age) is the natural log of fund age in years since its inception; Expense is fund expense ratio in percent; Rear load is an indicator variable that equals one if the fund share charges rear loads and zero otherwise; and FlowStyle is the cumulative percentage Flow within the fund style for the quarter. $I_{Alpha<0}$ is an indicator variable that equals one if the alpha of the fund is negative and zero otherwise. The unit of observations is share class-quarter. All the specifications control for a quarter-fixed time effects. The standard errors are cluster by fund share class and the associated t-statistics are provided in parentheses below the point estimates. *, **, and *** indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	Bond Fund China	Bond Fund China	Bond Fund China	Equity Fund China	Bond Fund U.S.
	(1)	(2)	(3)	(4)	(5)
Alpha	8.430***	7.922***	7.946***	1.002***	0.443***
	(20.881)	(20.043)	(20.125)	(8.998)	(5.934)
$I_{Alpha<0}$	1.354	2.494***	2.438***	-3.680***	-0.505***
	(1.497)	(2.671)	(2.610)	(-3.938)	(-5.233)
Alpha$\times I_{Alpha<0}$	-6.202***	-5.615***	-5.736***	-1.197***	0.275**
	(-7.160)	(-6.452)	(-6.582)	(-8.753)	(2.481)
Lagged Flow		0.050***	0.050***	0.152***	0.320***
		(9.273)	(9.270)	(10.435)	(52.339)
Ln(TNA)		1.752***	1.746***	0.821***	0.186***
		(17.205)	(17.204)	(4.365)	(8.246)
Ln(Age)		-2.315***	-2.065***	-2.189***	-2.896***
		(-4.878)	(-4.339)	(-3.204)	(-35.868)
Expense		6.219***	6.207***	7.959***	-1.847***
		(6.603)	(6.593)	(5.348)	(-13.876)
Rear load		0.37	0.231	1.716	-0.449***
		(0.416)	(0.260)	(1.383)	(-3.867)
FlowStyle			0.178***		
			(6.527)		
Constant	1.319***	-9.407***	-11.109***	-16.281***	8.974***
	(3.364)	(-7.107)	(-8.296)	(-4.883)	(40.751)
Observations	61,286	61,286	61,280	10,304	121,419
Adj R-squared	0.046	0.058	0.058	0.085	0.215
Quarter FEs	Yes	Yes	Yes	Yes	Yes

Table 3: Flow-performance relation in Corporate Bond funds (II)

This table shows flow-performance relations for active open-ended corporate bond funds from 2003 to 2022. The dependent variable is Flow, which is the percentage of fund flow in a given quarter. The variable Lagged Flow is the fund flow lagged by a quarter; Ln(TNA) is the natural log of total net assets; Ln(Age) is the natural log of fund age in years since its inception; Expense is fund expense ratio in percent; Rear load is an indicator variable that equals one if the fund share charges rear loads and zero otherwise. Alpha is the abnormal returns of the previous quarter compounded from monthly estimates and $I_{Alpha<0}$ is an indicator variable that equals one if the alpha of the fund is negative and zero otherwise. Columns (1)-(3) differ in the way that alpha is estimated. In column (1), the monthly alpha is computed using only the ChinaBond Aggregate Bond Index return as the factor return (bond factor). Columns (2) and (3) present the results when we use past 24- and 36-months data to calculate the factor loadings, instead of using 12-months. Returns from both bond and stock market factor portfolios were used in this case. In column (4), we use the difference between the raw return of the share class and the risk-free rate of return as alpha. In column (5), the difference between the raw return and the cross-sectional average return of all corporate bond funds is used as alpha. In column (6), we include a share class fixed-effect in our specification. In column (7), we allow regression errors to be clustered at the fund level. In column (8), we restrict our sample to funds with disclosed corporate bond holdings above 50% of their TNA. Finally, in column (9), the share classes are aggregated at the fund level. The unit of observations is share class-quarter in columns (1)-(8), and fund-quarter in column (9). All specifications include quarter-fixed time effects. The standard errors are clustered by share class or by fund, when appropriate. The t-statistics associated with the coefficients are provided in parentheses below the point estimates. Stars denote standard statistical significance (***p<0.01, **p<0.05, *p<0.1, respectively).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Alpha (Bond Idx)	Alpha (24 M)	Alpha (36 M)	Alpha (Raw)	Alpha (Wgt. Avg)	Share FEs	Cluster	Holding (CB 50%)	Fund level
Alpha	5.872***	8.230***	8.322***	7.073***	7.682***	9.204***	7.922***	5.991***	11.708***
	(18.594)	(20.732)	(21.118)	(19.079)	(14.584)	(20.472)	(17.584)	(10.224)	(10.527)
$I_{Alpha<0}$	2.482***	3.043***	2.770***	1.399*	-2.010***	4.061***	2.494**	0.286	3.835**
	(2.591)	(3.444)	(3.200)	(1.692)	(-2.965)	(4.038)	(2.520)	(0.217)	(2.095)
Alpha$\times I_{Alpha<0}$	-3.241***	-5.706***	-6.111***	-5.116***	-8.354***	-9.238***	-5.615***	-6.410***	-11.003***
	(-4.360)	(-6.578)	(-7.140)	(-8.108)	(-11.006)	(-8.885)	(-5.847)	(-4.895)	(-5.855)
Lagged Flow	0.050***	0.050***	0.049***	0.047***	0.047***	-0.066***	0.050***	0.074***	0.060***
	(9.271)	(9.192)	(9.120)	(8.686)	(8.713)	(-10.938)	(8.695)	(8.126)	(7.961)
Ln(TNA)	1.753***	1.744***	1.744***	1.719***	1.753***	11.394***	1.752***	4.326***	4.326***
	(17.112)	(17.109)	(17.112)	(16.916)	(17.225)	(34.503)	(16.426)	(17.477)	(26.322)
Ln(Age)	-2.673***	-2.213***	-2.177***	-2.173***	-2.122***	-0.200	-2.315***	-3.008***	-2.000**
	(-5.616)	(-4.667)	(-4.611)	(-4.602)	(-4.511)	(-0.098)	(-4.371)	(-4.244)	(-2.233)
Expense	5.355***	5.836***	5.793***	5.336***	5.394***	-3.371	6.219***	12.812***	-4.889***
	(5.634)	(6.253)	(6.229)	(5.685)	(5.815)	(-0.543)	(6.384)	(7.318)	(-3.056)
Rear load	0.184	0.257	0.217	0.079	0.462	4.229**	0.370	-1.686	3.424**
	(0.208)	(0.289)	(0.245)	(0.090)	(0.532)	(2.328)	(0.403)	(-1.119)	(2.012)
Constant	-7.142***	-9.269***	-9.288***	-8.001***	-6.010***	-83.689***	-9.407***	-29.791***	-29.161***
	(-5.433)	(-7.016)	(-7.035)	(-6.039)	(-4.400)	(-12.874)	(-6.737)	(-11.528)	(-12.763)
Observations	61,286	61,286	61,286	61,286	61,286	61,286	61,286	20,439	39,813
Adjusted R-squared	0.055	0.058	0.058	0.057	0.057	0.129	0.058	0.0763	0.099
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share FEs	No	No	No	No	No	Yes	No	No	No
Cluster	Share	Share	Share	Share	Share	Share	Fund	Share	Fund

Table 4: Causal flow-performance relation around exogenous liquidity events

This table shows the impact of Bond Connect on the flow-performance relation of bond funds using a difference-in-difference estimator. Panels A present the results for China; Panel B for matched sample of funds in China; and Panel C for funds in the US. The dependent variable in all the columns is Flow, which is the percentage of fund flow in a given quarter. The variable Alpha is the abnormal returns of the previous quarter compounded from monthly estimates. $I_{Alpha<0}$ is an indicator variable that equals one if the alpha of the fund is negative and zero otherwise. Post July 2017 is a dummy variable that equals one if the observation if after July 2017 and zero otherwise. All regressions include untabulated control variables. Lagged Flow is the fund flow lagged by a quarter; Ln(TNA) is the natural log of total net assets; Ln(Age) is the natural log of fund age in years since its inception; Expense is fund expense ratio in percent; and Rear load is an indicator variable that equals one if the fund share charges rear loads and zero otherwise. The unit of observations is share class-quarter. We include quarter-fixed time effects and cluster standard errors by fund share class. The t-statistics associated with the coefficients are provided in parentheses below the point estimates. Stars denote standard statistical significance (***p<0.01, **p<0.05, *p<0.1, respectively).

Panel A: Chinese bond funds (Bond Connect)				
	(1)	(2)	(3)	(4)
	[-2, 2]	[-1, 1]	[-1, 2]	[-1, 3]
Alpha	8.408***	5.216***	5.142***	5.116***
	(8.049)	(4.052)	(4.003)	(3.982)
$I_{Alpha<0}$	11.635***	7.744*	8.177**	8.274**
	(3.587)	(1.944)	(2.055)	(2.079)
Alpha×$I_{Alpha<0}$	-2.057	-2.732	-2.658	-2.497
	(-0.791)	(-0.902)	(-0.880)	(-0.827)
Alpha × Post July 2017	-4.109***	0.215	-1.156	1.511
	(-2.846)	(0.109)	(-0.712)	(0.964)
$I_{Alpha<0}$ × Post July 2017	-14.358***	-10.485**	-11.442**	-11.436***
	(-3.632)	(-2.211)	(-2.511)	(-2.639)
Alpha×$I_{Alpha<0}$ × Post July 2017	-7.600**	-6.699	-6.391*	-9.181**
	(-2.198)	(-1.531)	(-1.681)	(-2.520)
Observations	12,633	6,801	10,134	13,313
Adjusted R-squared	0.103	0.063	0.070	0.080
Controls	Yes	Yes	Yes	Yes

Panel B: Matched Sample (Bond Connect)				
	(1)	(2)	(3)	(4)
	[-2, 2]	[-1, 1]	[-1, 2]	[-1, 3]
Alpha	8.608***	3.758	2.838	2.293
	(3.610)	(1.295)	(1.052)	(0.860)
$I_{Alpha<0}$	13.574***	9.750	7.344	7.208
	(2.926)	(1.591)	(1.286)	(1.274)
Alpha×$I_{Alpha<0}$	-2.456	-1.630	-1.879	-1.130
	(-0.613)	(-0.335)	(-0.424)	(-0.259)
Alpha × Post July 2017	-3.701	5.759	3.042	5.354
	(-1.092)	(1.123)	(0.813)	(1.563)
$I_{Alpha<0}$ × Post July 2017	-19.864***	-10.751	-12.269*	-11.089*
	(-3.294)	(-1.339)	(-1.728)	(-1.682)
Alpha×$I_{Alpha<0}$ × Post July 2017	-12.141**	-11.693	-12.118**	-12.881**
	(-2.224)	(-1.532)	(-2.009)	(-2.315)
Observations	3,400	1,302	2,349	2,996
Adjusted R-squared	0.103	0.0592	0.0800	0.0773
Controls	Yes	Yes	Yes	Yes

Panel C: U.S. bond funds (Bond Connect)				
	(1)	(2)	(3)	(4)
	[-2, 2]	[-1, 1]	[-1, 2]	[-1, 3]
Alpha	0.332*	0.344*	0.361*	0.342*
	(1.856)	(1.798)	(1.879)	(1.781)
$I_{Alpha<0}$	0.423	-0.328	-0.390	-0.436
	(1.615)	(-0.820)	(-0.975)	(-1.088)
Alpha$\times I_{Alpha<0}$	0.404	-0.892	-0.911	-0.900
	(1.522)	(-1.325)	(-1.354)	(-1.336)
Alpha $\times$ Post July 2017	-0.114	0.896*	-0.084	0.086
	(-0.399)	(1.721)	(-0.289)	(0.306)
$I_{Alpha<0}$ $\times$ Post July 2017	-0.959***	0.381	-0.051	0.100
	(-2.700)	(0.730)	(-0.110)	(0.223)
Alpha$\times I_{Alpha<0}$ $\times$ Post July 2017	-0.592	1.073	0.589	0.893
	(-1.572)	(1.258)	(0.835)	(1.274)
Observations	27,425	14,294	20,850	26,889
Adjusted R-squared	0.163	0.190	0.168	0.158
Controls	Yes	Yes	Yes	Yes

Table 5: Placebo test

This table shows the results of placebo tests on the impact of Bond Connect. In columns (1)-(5), we assume that the Bond Connect happened in 2012, 2013, 2014, 2015, and 2016, respectively. The dependent variable in all the columns is Flow, which is the percentage of fund flow in a given quarter. The variable Alpha is the abnormal returns of the previous quarter compounded from monthly estimates. $I_{Alpha<0}$ is an indicator variable that equals one if the alpha of the fund is negative and zero otherwise. All regressions include control variables. Lagged Flow is the fund flow lagged by a quarter; Ln(TNA) is the natural log of total net assets; Ln(Age) is the natural log of fund age in years since its inception; Expense is fund expense ratio in percent; and Rear load is an indicator variable that equals one if the fund share charges rear loads and zero otherwise. Each of the difference-in-difference test focuses on a 4-year window surrounding the hypothetical event date. Two years before, and two years after. We report the coefficients of the interaction terms among Alpha, $I_{Alpha<0}$, and Post dummy. The unit of observations is share class-quarter. We include quarter-fixed time effects and cluster standard errors by fund share class. The t-statistics associated with the coefficients are provided in parentheses below the point estimates. Stars denote standard statistical significance (***p<0.01, **p<0.05, *p<0.1, respectively).

	2012 (1)	2013 (2)	2014 (3)	2015 (4)	2016 (5)
Alpha×$I_{Alpha<0}$ × Post July 2012	7.861 (1.369)				
Alpha×$I_{Alpha<0}$ × Post July 2013		8.350 (1.502)			
Alpha×$I_{Alpha<0}$ × Post July 2014			0.434 (0.082)		
Alpha×$I_{Alpha<0}$ × Post July 2015				-2.763 (-0.595)	
Alpha×$I_{Alpha<0}$ × Post July 2016					-3.225 (-0.841)
Observations	2,508	3,304	5,292	7,871	9,863
Adjusted R-squared	0.095	0.089	0.127	0.128	0.117
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes

Table 6: Additional exogenous events and flow-performance relation

This table shows the estimates from a difference-in-difference procedure and captures how the flow-performance relations for active open-ended corporate bond funds change with the market condition. The dependent variable in all the columns is Flow, which is the percentage of fund flow in a given quarter. PostCovid is a dummy variable that equals one if the sample period is between 2020Q2 and 2021Q3, and zero if the sample period is between 2018Q4 and 2020Q1. PostEver is a dummy variable that equals one if the sample period is from 2021Q4 to 2022Q4, and zero for the period 2020Q3-2021Q3. Alpha is the abnormal returns of the previous quarter compounded from monthly estimates and $I_{Alpha<0}$ is an indicator variable that equals one if the alpha of the fund is negative and zero otherwise. Although the point estimates of other variables are untabulated, all the regressions include Lagged Flow, Ln(TNA), Ln(Age), Expense and Rear load as the control variables. These variables are defined as in Table 2. The unit of observations is share class-quarter. We include quarter-fixed time effects and cluster standard errors by fund share class. The t-statistics associated with the coefficients are provided in parentheses below the point estimates. Stars denote standard statistical significance (***p<0.01, **p<0.05, *p<0.1, respectively).

	(1)	(2)
	COVID	Evergrande
Alpha	10.479***	11.698***
	(9.200)	(9.749)
$I_{Alpha<0}$	-0.094	0.461
	(-0.034)	(0.226)
Alpha$\times I_{Alpha<0}$	-15.415***	-7.047***
	(-5.207)	(-3.290)
Alpha$\times$PostCovid	-3.084**	
	(-2.078)	
$I_{Alpha<0}\times$ PostCovid	-2.128	
	(-0.636)	
Alpha$\times I_{Alpha<0}$ $\times$ PostCovid	9.454***	
	(2.592)	
Alpha$\times$PostEver		-2.818*
		(-1.876)
$I_{Alpha<0}$ $\times$ PostEver		3.815
		(1.306)
Alpha$\times I_{Alpha<0}$ $\times$ PostEver		8.846***
		(2.940)
Observations	17,004	23,947
Adjusted R-squared	0.046	0.054
Controls	Yes	Yes
Quarter FEs	Yes	Yes

Table 7: Bond Holdings and flow-performance relation

This table shows how the flow-performance relations for active open-ended corporate bond funds differ based on bond holding from 2003 to 2022. The dependent variable in all the columns is Flow, which is the percentage of fund flow in a given quarter. Alpha is the abnormal returns of the previous quarter compounded from monthly estimates and $I_{Alpha<0}$ is an indicator variable that equals one if the alpha of the fund is negative and zero otherwise. Although the point estimates of other variables are untabulated, all the regressions include Lagged Flow, Ln(TNA), Ln(Age), Expense and Rear load as the control variables. These variables are defined as in Table 2. The bond holding information in column 1 is aggregated percentage holding of TNA provided by Wind. $No\_Exchange$ is a dummy variable that equals one if the fund does not hold any exchange-traded bonds in a given quarter, and zero otherwise. In column 2, we collect the information on the top 10 bond held by the fund and identify of the trading venues of the bond. $No\_Exchange\_top10$ is a dummy variable that equals one if the fund does not hold exchange-traded bonds in its top 10 holding list in a given year, and zero otherwise. In column 3, we only keep the funds that hold exchange traded bonds and examine how the Bond Connect affects their flow-performance relations. The unit of observations is share class-quarter. We include quarter-fixed time effects and cluster standard errors by fund share class. The t-statistics associated with the coefficients are provided in parentheses below the point estimates. Stars denote standard statistical significance (***p<0.01, **p<0.05, *p<0.1, respectively).

	(1)	(2)
	Full sample Holding	Full sample Holding
Alpha	7.303***	7.209***
	(15.087)	(16.062)
$I_{Alpha<0}$	-1.158	-0.785
	(-0.981)	(-0.753)
Alpha$\times I_{Alpha<0}$	-5.756***	-6.176***
	(-5.906)	(-6.754)
$No\_Exchange$	0.431	
	(0.467)	
Alpha$\times$ $No\_Exchange$	2.216***	
	(2.732)	
$I_{Alpha<0} \times No\_Exchange$	7.003***	
	(3.811)	
Alpha$\times I_{Alpha<0} \times No_Exchange$	-5.099**	
	(-2.547)	
$No\_Exchange\_top10$		2.024**
		(2.373)
Alpha$\times$ $No\_Exchange\_top10$		4.089***
		(4.776)
$I_{Alpha<0} \times No\_Exchange\_top10$		9.198***
		(4.766)
Alpha$\times I_{Alpha<0} \times No_Exchange_top10$		-5.354**
		(-2.352)
Observations	61,286	61,286
Adjusted R-squared	0.059	0.061
Controls	Yes	Yes
Quarter FEs	Yes	Yes

Table 8: Effects of investor and portfolio composition on flow-performance sensitivities.

This table shows the impacts of institutional holdings and cash on the flow-performance relations for active open-ended corporate bond funds from 2003 to 2022. The variables are defined as in Table 2. *Inst_holding* is the average institutional ownership of the fund share in the past 3 years in percent. *Cash_pct* (%) is the proportion of fund assets held in cash in percent. We demean these two measures in the regression for easier interpretation. The unit of observations is share class-quarter. We include quarter fixed effects and cluster standard errors by fund share class. Stars denote standard statistical significance (***p<0.01, **p<0.05, *p<0.1, respectively).

	(1)	(2)
	Cash	Inst. holding
Alpha	8.156***	8.720***
	(17.064)	(18.764)
$I_{Alpha<0}$	2.344**	3.708***
	(2.273)	(3.609)
Alpha$\times I_{Alpha<0}$	-5.093***	-6.211***
	(-5.057)	(-6.312)
$Cash\_pct$	0.920**	
	(2.068)	
Alpha$\times$ $Cash\_pct$	0.180	
	(0.435)	
$I_{Alpha<0} \times Cash\_pct$	-0.644	
	(-0.663)	
Alpha$\times I_{Alpha<0}\times Cash_pct$	-1.870**	
	(-2.006)	
$Inst\_holding$		-8.459***
		(-15.505)
Alpha$\times$ $Inst\_holding$		2.498***
		(5.960)
$I_{Alpha<0}\times Inst\_holding$		7.106***
		(6.797)
Alpha$\times I_{Alpha<0}\times Inst_holding$		-2.099**
		(-2.098)
Observations	45,459	46,559
Adjusted R-squared	0.064	0.071
Controls	Yes	Yes
Quarter FEs	Yes	Yes

Table 9: Subsamples of corporate bond funds

This table shows flow-performance relations for subgroups of active open-ended corporate bond funds from 2003 to 2022. The dependent variable in all the columns is Flow, which is the percentage of fund flow in a given quarter. The variable Alpha is the abnormal returns of the previous quarter compounded from monthly estimates. $I_{Alpha<0}$ is an indicator variable that equals one if the alpha of the fund is negative and zero otherwise. Lagged Flow is the fund flow lagged by a quarter; Ln(TNA) is the natural log of total net assets; Ln(Age) is the natural log of fund age in years since its inception; Expense is fund expense ratio in percent; and Rear load is an indicator variable that equals one if the fund share charges rear loads and zero otherwise. Young and old funds correspond to the funds whose age falls below- and above- the sample median, respectively. Small and Large funds correspond to the funds whose fund size falls below- and above- the sample median, respectively. High and low flows correspond to periods with aggregate corporate bond fund flows above- and below- the sample median, respectively. The unit of observations is share class-quarter. We include quarter-fixed time effects and cluster standard errors by fund share class. The t-statistics associated with the coefficients are provided in parentheses below the point estimates. Stars denote standard statistical significance (***p<0.01, **p<0.05, *p<0.1, respectively).

	(1) Young	(2) Old	(3) Small	(4) Large	(5) Low flows	(6) High flows
Alpha	8.025***	7.744***	5.934***	10.521***	6.444***	9.025***
	(12.187)	(15.444)	(11.399)	(17.314)	(12.354)	(16.016)
$I_{Alpha<0}$	2.929*	2.273**	-0.558	6.188***	2.027*	2.921**
	(1.666)	(2.057)	(-0.474)	(3.937)	(1.652)	(2.100)
Alpha$\times I_{Alpha<0}$	-4.907***	-5.505***	-4.707***	-7.753***	-4.776***	-6.052***
	(-2.836)	(-5.319)	(-4.313)	(-4.654)	(-3.827)	(-4.664)
Lagged Flow	0.048***	0.050***	0.013*	0.075***	0.021***	0.072***
	(6.340)	(6.609)	(1.762)	(9.776)	(2.885)	(10.114)
Ln(TNA)	1.653***	1.887***	1.040***	3.091***	1.274***	2.127***
	(12.395)	(13.130)	(6.785)	(9.193)	(10.098)	(15.322)
Ln(Age)	-2.417	-1.705**	-2.510***	-3.298***	-1.620***	-2.999***
	(-1.529)	(-2.208)	(-3.633)	(-4.787)	(-2.811)	(-4.351)
Expense	8.150***	6.225***	1.190	16.238***	0.545	10.847***
	(4.928)	(5.364)	(0.949)	(10.366)	(0.461)	(8.040)
Rear load	-0.275	1.070	0.527	0.193	-0.166	0.852
	(-0.223)	(0.901)	(0.423)	(0.146)	(-0.149)	(0.627)
Constant	-9.178***	-11.927***	-2.262	-25.096***	-5.965***	-11.852***
	(-3.750)	(-5.914)	(-1.273)	(-8.543)	(-3.429)	(-6.270)
Observations	24,849	36,437	30,637	30,649	28,005	33,281
Adj R-sqr	0.056	0.062	0.040	0.084	0.053	0.056
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Piecewise linear estimation of flow-performance relation

This table shows flow-performance relations for active open-ended corporate bond funds from 2003 to 2022 by applying the performance measure in Sirri and Tufano (1998). The variables are defined in Table 2. The performance ranks are divided into three unequal groupings. The bottom performance grouping (LOWPERF) is the lowest quintile of performance, defined as Min ($RANK_{t-1}$, 0.2). The middle three performance quintiles are combined into one grouping (MIDPERF), defined as Min (0.6, $RANK_{t-1}$ - LOWPERF), and the highest performance quintile (HIGHPERF) is defined as $RANK_{t-1}$ - (LOWPERF + MIDPERF). RANK is defined using the prior quarter's excess return. The unit of observations is share class-quarter. These regressions are run quarter-by-quarter, and the standard errors and t-statistics are calculated from the vector of quarterly results, as in Fama and MacBeth (1970). Stars denote standard statistical significance (***p<0.01, **p<0.05, *p<0.1, respectively).

	Bond Fund		Equity Fund	
	(1)	(2)	(3)	(4)
LOWPERF	11.131	5.601	20.389	35.896
	(0.583)	(0.124)	(1.156)	(1.375)
MIDPERF	16.974***	9.229	-0.704	-1.395
	(3.365)	(1.358)	(-0.149)	(-0.256)
HIGHPERF	41.290**	49.432**	73.085***	51.004***
	(2.267)	(2.629)	(3.581)	(3.073)
Lagged Flow		0.044		0.217
		(0.825)		(1.488)
Ln(TNA)		4.688***		2.277***
		(2.934)		(2.941)
Ln(Age)		-16.521		-3.820
		(-1.425)		(-1.619)
Expense		10.266		-3.880
		(0.664)		(-0.825)
Rear load		2.199		0.420
		(0.202)		(0.258)
Constant	-3.908	-13.337	-3.308	-9.882*
	(-0.950)	(-1.564)	(-0.778)	(-1.907)
Observations	61,286	61,286	10,304	10,304
Adjusted R-squared	0.069	0.133	0.162	0.331

Figure 1: Assets under management by fund type in China

The graph below plots the relative size of the different types of mutual over time.

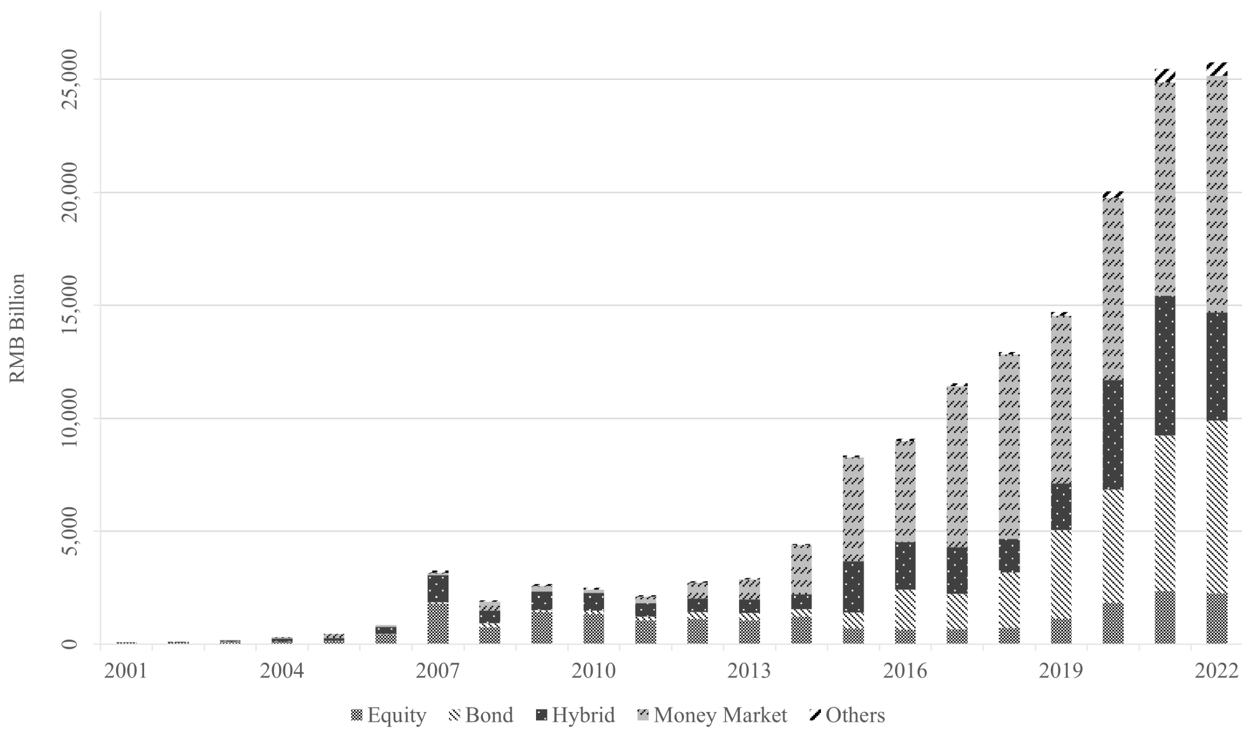
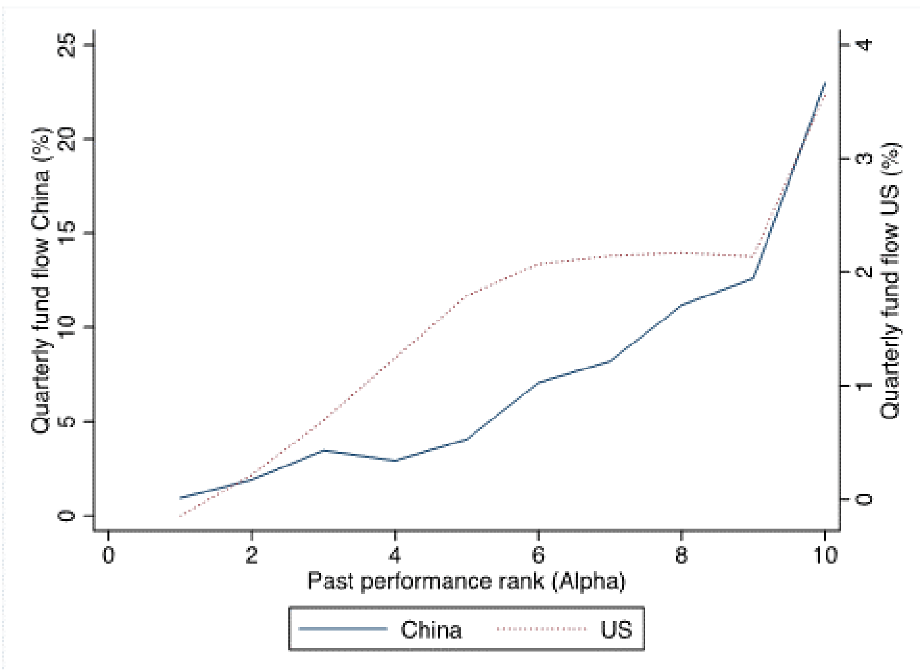


Figure 2: Flow-performance relation by country

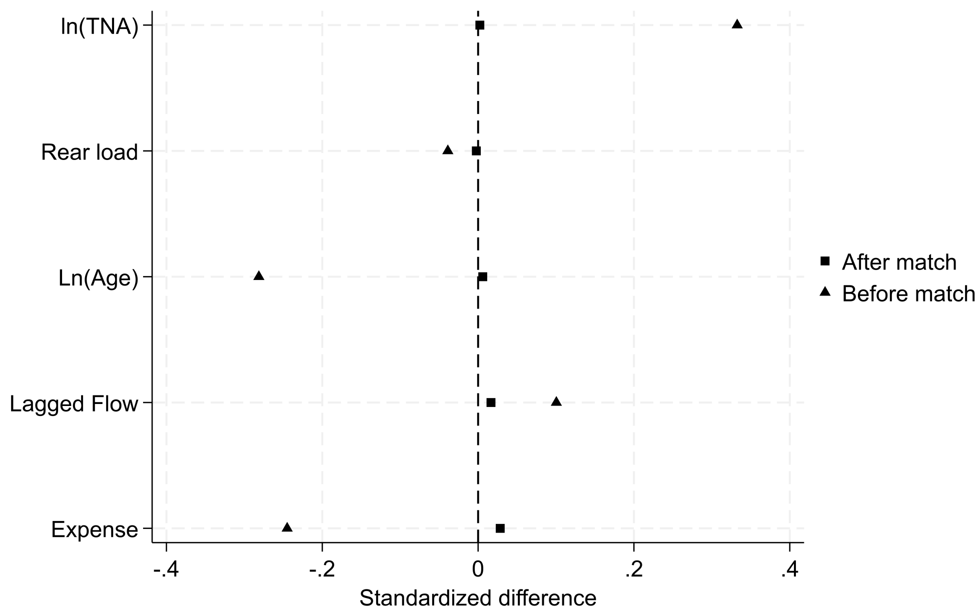
The graph below plots the relative size of the different types of mutual over time.



Flow-performance relation of Chinese and U.S. bond funds

Figure 3: Comparison of matched sample

The graph below plots the standardized differences between the samples before and after matching.



Mean differences across variables before and after matching the samples.