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Redemption risk and cash hoarding by asset managers*

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Abstract

Open-end mutual funds face redemptions by investors, but the sale of the underlying assets depends on the portfolio decision of asset managers. If asset managers use their cash holding as a buffer to meet redemptions, they can mitigate fire sales of the underlying asset. If they hoard cash in anticipation of redemptions, they will amplify fire sales. We present a global game model of investor runs and identify conditions under which asset managers hoard cash. In an empirical investigation of global bond mutual funds, we find that cash hoarding is the rule rather than the exception, and that less liquid bond funds display a greater tendency toward cash hoarding.

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1 Introduction

Our understanding of crisis propagation is heavily influenced by the experience of the 2008 crisis. Banks have been the focus of attention, and the watchwords have been leverage, maturity mismatch, complexity and insolvency.

Discussions of financial stability have also revolved around market liquidity, and actions of asset managers in the face of redemptions by ultimate investors. The concern has been with evaporating market liquidity and "one-sided markets" in the face of concerted investor redemptions. The recent proposals by the Securities and Exchange Commission (SEC) and the Financial Stability Board (FSB) on the asset management sector have addressed the possible financial stability implications of market disruption.[1]

While banks are financed with debt claims, mutual funds have shares, so that the problem of insolvency is less prominent in discussions of the financial stability consequences of asset managers. Instead, two mechanisms involving strategic complementarities have been flagged as potential sources of financial instability. One is the possibility that collective investment vehicles such as open-end bond mutual funds may be vulnerable to concerted redemption flows by investors in "run-like" episodes (Goldstein, Jiang and Ng, 2016; Chen, Goldstein and Jiang, 2010). This mechanism has figured prominently in the policy debates (see FSB, 2015 and 2016). The second mechanism discussed in the literature is concerned with the interactions *across* asset managers arising from competition for fund flows. When decision horizons are shortened due to short-term performance evaluation, strategic elements may enter into portfolio decisions (see Feroli et al., 2014; and Morris and Shin, 2016).

Our paper is concerned with a third dimension to the debate, to do with liquidity management by asset managers in their interactions with ultimate investors. If asset managers use their cash holdings as a buffer to meet investor redemptions, they can deal with redemptions without resorting to the sale of the underlying assets. Such behaviour would be consistent with a "pecking order" choice of actions where asset managers draw on cash first, and only start to sell the underlying assets if the cash runs out. The pecking order mode of liquidity management implies that cash holdings of asset managers decrease in the face of investor redemptions, and serve to stabilise price fluctuations associated with concerted redemptions by investors.

However, if asset managers *increase* their cash holdings in the face of investor redemptions, they will need to sell more of the underlying assets than is strictly necessary to meet investor redemptions. We label this type of liquidity management as "cash hoarding". In contrast to the pecking order mode of liquidity management, cash hoarding implies a positive association between cash and investor redemptions. Cash hoarding may potentially

[1] See FSB (2015, 2016) and the SEC report "Open-End Fund Liquidity Risk Management Programs; Swing Pricing; Re-Opening of Comment Period for Investment Company Reporting Modernization Release", http://www.sec.gov/rules/proposed/2015/33-9922.pdf.

reinforce the impact of investor redemptions by amplifying the sale of the underlying assets.

Our paper asks whether cash hoarding or the pecking order mode of liquidity management is the norm. We combine a theoretical investigation with an empirical analysis. We first gain insights from a global game analysis of investor runs to set the stage for our empirical investigation. In the global game analysis, we identify conditions under which cash hoarding by the asset manager takes place.

As a transition to our empirical analysis, we lay out a methodology for classifying purchases and sales of the underlying assets of an open-end mutual fund into those driven by investor flows and those that are discretionary. Using our methodology for the classification of discretionary sales, we examine a large dataset of global bond mutual funds to ascertain whether the portfolio decision of the asset managers conforms to the pecking order model where cash holdings are used as a buffer to smooth shocks coming from redemptions, or whether the asset managers engage in cash hoarding so as to amplify the fire sale of assets that results from redemptions.

In our empirical investigation, we find that cash hoarding is the rule, rather than the exception. Discretionary sales of the underlying asset tend to reinforce investor redemption-driven sales. As a rule of thumb, for every 100 dollars' worth of sales due to investor redemptions, there is an additional 10 dollars' worth of discretionary sales. A corollary is that mutual fund holding of cash is actually *increasing* in the incidence of investor redemptions. We find that mutual funds that hold more illiquid bonds – such as emerging market economy (EME) local currency sovereign bonds and EME corporate bonds – tend to have more pronounced cash hoarding. Cash hoarding is also a feature of advanced economy bond funds, but the magnitudes are much smaller – around 3 dollars' worth of discretionary sales for every 100 dollars' worth of investor-driven sales.

We find that the more liquid are the underlying bonds, the smaller is the incidence of cash hoarding. These findings are consistent with the results reported in Jiang, Li and Wang (2016) and Chernenko and Sunderam (2016) who examine mutual funds investing in US corporate bonds – bonds which are more liquid than non-US bonds and especially so compared to EME bonds.[2]

Finally, we find evidence of asymmetry between discretionary purchases and discretionary sales. The positive relationship between investor-driven sales and discretionary sales is stronger than the corresponding relationship between investor-driven purchases and discretionary purchases. Similarly, Girardi, Stahel and Wu (2016) show that during crisis or market stress periods, US corporate bond funds tend to hoard cash, but that they do not hoard cash during normal times.

[2] In addition, the average credit rating of US corporate bonds (A−) is higher than the average credit ratings of the four key benchmark indexes (AA−, BBB−, BBB+ and BBB) for the four types of bond fund considered in our paper.

Our results on cash hoarding provide a benchmark in evaluations of the financial stability consequences of open-end funds. However, the overall impact of cash hoarding on market disruptions needs to take account of the endogeneity of the redemption decisions by investors. If investors are less prone to run-like behaviour when the fund holds large cash balances, there is an intertemporal dimension to liquidity management, as developed in Zeng (2016). To the extent that investors are less likely to pull out when faced with higher cash balances, the fund manager may curtail future redemptions by increasing the cash holding today. Nevertheless, the fund manager may face a delicate balancing act between selling too much into an illiquid market, thereby reducing net asset value, and securing enough cash to meet future redemption pressures and defusing the run-like incentives. Our global game model highlights the countervailing effects.

Overall assessments of the financial stability consequences of cash hoarding are subject to a number of caveats. First, the scope of our paper is limited to the sales and purchases associated with a single fund. The strategic interactions take place between the fund manager and the ultimate investors. In practice, the strategic incentives *between* fund managers are also likely to play a role in determining the market outcome. Such interactions across funds may inject additional spillover effects in which when other asset managers sell and market prices come under pressure, an individual asset manager may be tempted to join the selling spree.

Another important caveat is that open-end mutual funds constitute only a fraction of the overall asset management sector, and any conclusions on market functioning will be difficult to draw in the absence of a better understanding of the workings of the entire ecosystem of market participants. As many of the market participants in the asset management sector fall outside the group of firms subject to regulatory oversight, data limitations are an impediment to drawing conclusions on the financial stability consequences of asset managers. These caveats should be borne in mind when considering the policy implications of our findings.

2 Measuring cash hoarding

Our approach to distinguishing investor-driven sales and discretionary sales is based on comparing changes in cash holdings with the inflows and outflows of investors' money as developed in Shek, Shim and Shin (2015). At its simplest, consider a hypothetical passive mutual fund that holds no cash and is fully invested in bonds at all times. Then, investor redemptions result in sales of the same amount. In this case, we define all sales to be driven by investor flows, and there are no discretionary sales by the fund managers.

But now consider an alternative scenario with the same amount of investor redemptions. Suppose that the fund starts with no cash holding at the beginning of the period, but ends the period with a positive holding of cash, in spite of the investor redemptions.

Then the positive cash holding at the end of the period can be regarded as the additional, discretionary sales undertaken by the fund, as the fund has ended up selling more than was strictly necessary to meet investor redemptions. This simple logic can be extended to funds that start the period with positive cash holdings. We can define discretionary sales to be the amount of the increase in cash holdings during the period. This is a conservative definition of discretionary sales that allows funds to hold some cash, but only deems sales to be discretionary if the cash holdings increase in spite of investor redemptions.

To be precise, define F to be the net investor flows over some interval of time, and denote by ΔC the increased cash holding of the fund over the same interval. There are six possible combinations, depending on whether investor flows are positive or negative, and how the change in cash position compares with net flows. By comparing net flows and cash holding changes, we can define for each fund and each month, investor flow-driven purchases and discretionary purchases. The six cases are depicted in Figure 1.

Cases 1 to 3 show investor outflows, as F is negative. In Case 1, cash holdings fall by more than investor outflows. The fund manager buys additional bonds, in spite of investor redemptions, thus playing a stabilising role in the market. Case 2 has investor outflows, and outflows are met partly by reducing cash and partly by selling bonds, and bond sales are entirely driven by investor redemptions. Case 3 represents cash hoarding by fund managers. Redemptions result in net outflows, but cash holding actually increases. The fund manager sells more bonds than is necessary to meet redemptions.

Cases 4 to 6 complete possibilities by considering positive investor inflows. In particular, Case 4 represents the mirror image of cash hoarding. As well as utilising new inflows to purchase the underlying assets, the asset manager taps into cash balances to finance further purchases. In this way, investor inflows are associated with declining cash balances. Case 5 has investor inflows, and inflows are used partly to increase cash and partly to buy bonds, and bond purchases are entirely driven by investor inflows. Finally, in Case 6, cash holdings increase more than positive inflows due to discretionary bond sales. Destabilising or procyclical behaviour by fund managers is given by Cases 3 and 4, whereas Cases 1 and 6 represent stabilising or countercyclical trading behaviour.

Figure 2 plots the frequency of each case in our data on 42 global bond funds over 42 months from January 2013 to June 2016, the details of which will be described in section 4. We find that destabilising behaviour by the fund manager is much more common than stabilising behaviour, and that in all instances but one, destabilising behaviour is the most common. We find that Case 3 (discretionary sales in the middle of investor redemptions) is the most common of all cases for each group of funds.

Our findings raise questions about the way that asset sales interact with the strategic incentives underlying investor redemptions. Although the net asset value of mutual funds adjusts to changes in underlying market values, there are time lags in the adjustment. In addition, redemptions by one group of investors may exert negative spillovers on remaining investors through the shifts in the composition of remaining assets from liquid to illiquid ones, as well as the marked-to-market changes in the value of remaining assets. As argued in Goldstein, Jiang and Ng (2016), the less liquid the underlying assets are, the greater are the spillover effects of investor redemptions to remaining investors, thereby exacerbating the selling pressures in a run-like episode.

A fund manager may then *anticipate* further redemptions and try to secure enough cash to meet such redemptions. In turn, greater cash holdings will mitigate investors' incentive to run. Foreseeing these effects, greater discretionary sales by asset managers would then be a prudent response to anticipated redemptions. For this reason, the overall impact on market prices associated with cash hoarding may go either way. Nevertheless, the fund manager faces a delicate balancing act between selling too much into an illiquid market, thereby reducing net asset value, and securing enough cash to meet future redemption pressures and defusing the run-like incentives. Our global game model brings out the tradeoffs.[3]

To be precise, define F_t to be the net investor flows over some interval of time t, and denote by ΔC_{t-1} the increased cash holding of the fund due to discretionary sales over the previous time interval $t-1$. We can again define six possible cases adapted to this context, depending on whether investor flows in period t are positive or negative, and whether the fund manager sells or buys bonds out of discretion in period $t-1$, which is equivalent to increase or decrease cash holdings. Among the six cases, Case 3 now represents the situation where an increase in cash holdings by fund managers' discretionary sales in $t-1$ is followed by investor redemptions in t. In this case, the fund manager may sell bonds in advance to better meet redemptions in the next period. Case 4 now represents the situation where a decrease in cash holdings by fund managers' bond purchases in $t-1$ is followed by investor net inflows in t. In this case, the fund manager may buy bonds in anticipation of investor inflows in the next period. Also, Case 6 now represents the situation where fund managers' discretionary sale in $t-1$ is followed by investor net inflows in t. We can define the other cases in a similar way.

To the extent that fund managers sell or buy bonds to increase or decrease cash in $t-1$ in anticipation of investor redemptions or net inflows in t, Cases 3 and 4 represent destabilising behaviour of fund managers. Similarly, Cases 1 and 6 represent stabilising

[3] Cash hoarding may also occur when both investors' outflows and the fund manager' bond sales are driven by an underlying negative shock to the demand for the assets held by the fund. Suppose that the asset price has already decreased due to an exogenous negative demand shock. When fund investors react to this negative price shock and sell assets, the asset price will fall further. Now observing the fall in the bond price, the fund manager may want to sell before fund investors sell so that he can secure enough cash to meet redemptions. Then, we can still have the cash hoarding mechanism of the paper. It should be noted that the fund manager has no incentive to sell bonds if the bond price has already fallen, unless he needs to meet redemption requests or it has career concerns such as the aversion to be the worst performer. By contrast, if the fund manager thinks that the bond price has fallen too much below the fundamentals due to fund investor sales, it can be optimal for him to buy bonds at the below-fundamental price.

behaviour since fund managers buy or sell bonds in $t-1$ in anticipation of investor redemptions or net inflows in t, respectively.

Figure 3 plots the frequency of each of the new six cases in our data. We find that Case 3 (cash hoarding in month $t-1$ in anticipation of investor redemptions in month t) is the most frequent case in all groups but one, and that destabilising Case 3 (or Case 4) is always more frequent than stabilising Case 1 (or Case 6).

These factors suggest that we need to understand better the joint determination of investor redemptions and fund managers' discretionary sales. Indeed, how investors and fund managers will interact depends crucially on how liquid the market for the underlying assets is. Understanding the joint determination of investor redemptions and fund managers' portfolio adjustment is one aim of our paper.

3 Theory of fund manager discretionary sales

We hone our insights by using a global game model of redemptions, and then examine the fund manager's decision to secure cash by selling risky assets in anticipation of the redemptions by investors.

The fund manager faces competing objectives when deciding how much of the underlying assets to sell in order to secure cash. Other things being equal, having more cash on hand allows the fund manager to meet redemptions more easily, thereby defusing investors' incentive to run. However, other things are not equal. If the cash has to be secured by selling risky assets at fire sale discounts, future returns to staying invested are reduced, making redemptions more attractive. The fund manager's cash holding decision reflects the tradeoff between securing enough cash to meet redemptions comfortably, but not selling so much that eventual fund returns are reduced.

3.1 Global game model of investor runs

The origin of investor runs in our model will be that redemptions require asset sales which generate fire sale losses for remaining investors. This is captured by assuming a linear cost associated with sales. Our model can be seen as a reduced from version of the theoretical model of investment funds of Chen, Goldstein and Jiang (2010). We add the ingredient of fund managers who make a cash adjustment decision.

We follow Zeng (2016) in modelling the interaction of the liquidity management decisions of fund managers with investor runs. In contrast to Zeng (2016), fund manager sales occur in anticipation of redemptions, and thus sales may exceed redemptions because of uncertainty about the level of redemptions.

We will first describe a general model and identify the equilibrium conditions. The model is not amenable to a closed form solution, and we consider a special case to make further progress on the key questions.

Suppose there is a unit mass of investors, indexed by $i \in [0,1]$. Each investor has one dollar invested in an open-end mutual fund. There are three dates, indexed by $t \in \{0,1,2\}$. The mutual fund has access to a risky asset and cash, but starts date 0 holding the risky asset only. The return on the risky asset between date 0 and date 1 is R_1, and the realisation of R_1 is common knowledge at date 1. The return between date 1 and date 2 is given by a uniformly distributed random variable r.

Assume that r is independent of the first period return R_1. Our results do not depend on this independence assumption, but it helps to focus attention on the key mechanism in the paper, which goes through the decision by the fund manager to secure cash in anticipation of investor redemptions.

The realised return on the mutual fund varies systematically from the return on the risky asset. This is because the fund manager actively manages the composition of the portfolio in response to potential redemptions, and sale of the risky asset is subject to a fire sale discount.

At date 1, the true value of r is not known. The fund manager receives a noisy signal of r at date 1. In particular, his signal ρ_A of the return r is given by

$$\rho_A = r + \eta, \tag{1}$$

where η is distributed according to density $g(\cdot)$. The fund manager faces the decision in date 1 of deciding how much cash he will secure in the face of possible redemptions by the investors. The decision is made conditional on the realisation of the first period return R_1 and the fund manager's own signal ρ_A. The fund manager decides how much of the risky asset to liquidate. We write Y for the amount of liquidation, ie, the cash value obtained from sales.

At date 2, the investors will observe their own signals ρ_i of the return r given by

$$\rho_i = r + \varepsilon_i, \tag{2}$$

where ε_i is also distributed according to density $f(\cdot)$.

The investors fall into two groups. First, there are passive investors who stay invested in the fund. Second, there is a group of *active investors* who decide whether to stay invested or sell. Denote by A the mass of active investors, where $0 < A < 1$.

We leave open the possibility that A is a function of the first period return R_1. We will see, in particular, that when A is a decreasing function of R_1, the fire-sale externalities for the fund investors are magnified.

A *strategy* for an active investor is a mapping:

$$\rho_i \longmapsto \{\text{Hold, Sell}\}. \tag{3}$$

Payoffs are now determined as follows. Denote by X the mass of investors who sell at date 2, which can be written as $X = xA$, where x is the proportion of active investors who sell, and A is the mass of active investors. If the fund manager liquidates at date 1, he faces a fire-sale haircut of δ; if he liquidates afterwards (ex-post liquidation), he faces an additional fire-sale haircut of μ. Thus, when the fund manager sells Y units before redemptions and the realised amount of redemptions are X units, losses to the fund are

$$L(X, Y) = \delta Y + \mu [X - Y]_+ ,$$

where the amount of (additional) liquidation of assets after redemptions is

$$[X - Y]_+ = \begin{cases} X - Y, \text{ if } X \geq Y \\ 0, \text{ otherwise.} \end{cases}$$

Now the return of the investor who stays invested when mass X of investors sell is

$$\frac{(1 - \delta Y) - xA - \mu [xA - Y]_+}{1 - xA} \cdot r. \tag{4}$$

This payoff reflects the fact that the fund loses money from fire sales and these costs are born by those investors who stay invested in the fund.

An equilibrium will now consist of an ex-ante liquidation of the fund manager Y and a collection of switching strategies of the investors of form:

$$\begin{cases} \text{Sell} & \text{if } \rho < \rho^* \\ \text{Hold} & \text{if } \rho \geq \rho^* \end{cases} \tag{5}$$

for some threshold value ρ^*. The investor is indifferent between staying in the fund and selling if the expected value of (4) is equal to 1, which is the expected return of redeeming his share at the unit NAV and investing at the risk-free rate, which is assumed to be zero. In the expression for the expected payoff, the realisation of the random variable r is uncertain, as is x. We are assuming that the investors have observed the fund manager's choice of Y.

To make progress, we invoke the Laplacian principle for beliefs in global games. The Laplacian principle states that, if all players use the switching strategy around the same switching point, then the uncertainty over x can be characterised by the uniform distribution over $[0, 1]$ (see Morris and Shin, 2003 (section 2); and Morris, Shin and Yildiz, 2016). For completeness of the exposition, we give a proof of the Laplacian principle here for the special case where the distribution of investors' noise ε is uniform on $[-\delta, \delta]$ for constant $\delta > 0$. In this case, the uniform density over x will not depend on the value of δ. Morris and Shin (2003) show that the uniform density that characterises strategic uncertainty is a general result whenever the density $f(\cdot)$ of the noise becomes concentrated around 0.

3.1.1 Laplacian principle for beliefs

Recall that investor i observes signal ρ_i of the random variable r given by

$$\rho_i = r + \varepsilon_i, \tag{6}$$

where we now assume that the ε_i is a uniformly distributed noise term, with realisation in $[-\delta, \delta]$ for constant $\delta > 0$. The noise terms $\{\varepsilon_i\}$ are independent across individuals. The ex-ante distribution of r is uniform.

Lemma 1 *Suppose that investors follow the switching strategy around ρ^*. Then, the density of x conditional on ρ^* is uniform over the unit interval $[0, 1]$.*

We prove Lemma 1 as follows. The distribution of x conditional on ρ^* can be derived from the answer to the following question:

"My signal is ρ^*. What is the probability that x is less than z?" (Q)

The answer to question (Q) gives the cumulative distribution function of x evaluated at z, which we denote by $G(z|\rho^*)$. The density over x is then obtained by differentiating $G(z|\rho^*)$. The steps to answering question (Q) are illustrated in Figure 4.

When the true interest rate is r, the signals $\{\rho_i\}$ are distributed uniformly over the interval $[r - \delta, r + \delta]$. Investors with signals $\rho_i > \rho^*$ are those who sell. Hence,

$$x = \frac{r + \delta - \rho^*}{2\delta}. \tag{7}$$

When do we have $x < z$? This happens when r is low enough, so that the area under the density to the right of ρ^* is squeezed. There is a value of r at which x is precisely z. This is when $r = r_0$, where

$$\frac{r_0 + \delta - \rho^*}{2\delta} = z \tag{8}$$

or

$$r_0 = \rho^* - \delta + 2\delta z. \tag{9}$$

See the top panel of Figure 4. We have $x < z$ if and only if $r < r_0$. We need the probability of $r < r_0$ conditional on ρ^*.

For this, we must turn to investor i's posterior density over r conditional on ρ^*. This posterior density is uniform over the interval $[\rho^* - \delta, \rho^* + \delta]$, as in the lower panel of Figure 4. This is because the ex-ante distribution over r is uniform and the noise is uniformly distributed around r. The probability that $r < r_0$ is then the area under the density to the left of r_0, which is

$$
\begin{aligned}
& \frac{r_0 - (\rho^* - \delta)}{2\delta} \\
= & \frac{(\rho^* - \delta + 2\delta z) - (\rho^* - \delta)}{2\delta} \\
= & z, \qquad (10)
\end{aligned}
$$

where the second line follows from substituting in (9). Thus, the probability that $x < z$ conditional on ρ^* is exactly z. The conditional c.d.f. $G(z|\rho^*)$ is the identity function:

$$G(z|\rho^*) = z. \tag{11}$$

The density over x is thus uniform, which proves Lemma 1.

3.1.2 Equilibrium conditions

Using the Laplacian principle derived above, we solve for the investors' redemption decisions, leaving the fund manager's ex-ante liquidation decision Y as given. From (4), the expected payoff to staying invested in the fund is

$$\int_0^1 \frac{(1-\delta Y) - xA - \mu [xA - Y]_+}{1 - xA} dx \cdot r. \tag{12}$$

Since ρ_i is the conditional expectation of r at date 1, the critical value ρ^* of the signal at which the investor is indifferent between selling and staying invested is given by the solution to

$$\int_0^1 \frac{(1-\delta Y) - xA - \mu [xA - Y]_+}{1 - xA} dx \cdot \rho^* = 1. \tag{13}$$

Equation (13) gives the expression for the threshold value ρ^* of the investor's signal at which the investor redeems his share of the mutual fund. Note that the left-hand side of (13) is decreasing in the haircut parameters δ and μ. Thus, as δ and μ increase and the market becomes less liquid, the threshold value of the signal ρ^* is increasing. In other words, the investor switches to running on the fund for a higher level of fundamentals. This result is anticipated in the bank run model of Goldstein and Pauzner (2005), and has been applied in the mutual fund context by Chen, Goldstein and Jiang (2010).

A second condition for equilibrium will be that the fund manager's choice of Y is optimal given investors' equilibrium strategies. The fund manager anticipates the equilibrium strategies of the investors, and thus knows that if he liquidates Y units of the asset, the critical signal will be

$$\rho^*(Y) = \frac{1}{\int_0^1 \frac{(1-\delta Y) - xA - \mu[xA-Y]_+}{1-xA} dx}.$$

Now suppose that the fund manager decides to liquidate $Y = yA$ units of the asset. His expected cost of liquidating will now be

$$A \int_{\eta=-\infty}^{\infty} \delta y + \mu \left[1 - F\left(\rho^*(y) - \rho_A + \eta\right) - y\right]_+ g\left(\eta\right) d\eta.$$

Thus, our second equilibrium condition is

$$y\left(\rho_A\right) = \underset{y}{\operatorname{argmin}} A \int_{\eta=-\infty}^{\infty} \delta y + \mu \left[1 - F\left(\rho^*(y) - \rho_A + \eta\right) - y\right]_+ g\left(\eta\right) d\eta. \tag{14}$$

This equilibrium has the feature that there is feedback between liquidation and redemption. Increased anticipated redemptions give rise to higher ex-ante liquidation. However, higher liquidation has an ambiguous effect on redemptions: on the one hand, fire sale costs are guaranteed, giving a larger incentive to redeem, but the fire sale premium μ for late sales is avoided. In this way, the endogeneity of the investor redemption decision necessitates weighing the cash hoarding decision of the fund manager against the reduced incentive to run on the part of the investor.

The equilibrium described above cannot be solved in closed form. Characterising this equilibrium would be complex, because we have a large player and continuum of small players interacting (as in Corsetti et al., 2004) and the large player taking a continuous action (as in Frankel, Morris and Pauzner, 2003), and we would have to develop new methods to characterise solutions to such global games, which is beyond the scope of the current paper. Instead, we can make progress in analysing the key channel mapping uncertainty about redemptions into early liquidation by fixing the distribution of redemptions. We turn now to this question.

3.2 Fund manager's cash hoarding decision

Concretely, we consider the case where the total redemptions follow a uniform density. Denote by X the total redemptions by investors. We solve for the fund manager's optimal cash holding for the case where X is uniformly distributed in the interval $\left[\overline{X} - \frac{1}{2}\sigma, \overline{X} + \frac{1}{2}\sigma\right]$. Based on these beliefs, the fund manager liquidates Y units of the risky asset before observing the realised redemptions. The expected losses will be

$$\begin{aligned} \frac{1}{\sigma} \int_{X=\overline{X}-\frac{1}{2}\sigma}^{\overline{X}+\frac{1}{2}\sigma} \left(\delta Y + \mu \left[X - Y\right]_+\right) dX &= \delta Y + \frac{\mu}{\sigma} \int_{X=Y}^{\overline{X}+\frac{1}{2}\sigma} \left[X - Y\right] dX \\ &= \delta Y + \frac{\mu}{2\sigma} \left(\overline{X} + \frac{1}{2}\sigma - Y\right)^2. \end{aligned} \tag{15}$$

The first order condition is

$$\delta - \frac{\mu}{\sigma}\left(\overline{X} + \frac{1}{2}\sigma - Y\right) = 0.$$

Solving for Y, we have

$$\begin{aligned} \overline{X} + \frac{1}{2}\sigma - Y &= \frac{\sigma\delta}{\mu} \\ Y &= \overline{X} + \left(\frac{1}{2} - \frac{\delta}{\mu}\right)\sigma. \end{aligned}$$

Thus, the optimal amount of liquidation before redemptions (optimal ex-ante liquidation) will be

$$Y^* = \begin{cases} \overline{X} - \frac{1}{2}\sigma, \text{ if } \mu \leq \delta \\ \overline{X} + \left(\frac{1}{2} - \frac{\delta}{\mu}\right)\sigma, \text{ if } \mu \geq \delta. \end{cases} \tag{16}$$

The optimal ex-ante liquidation will exceed the expected value of redemptions if

$$\begin{aligned} \frac{1}{2} - \frac{\delta}{\mu} &> 0 \\ \frac{\mu}{\delta} &> 2. \end{aligned}$$

Thus, the extra cost of ex-post redemption (ie, $\mu - \delta$) determines if ex-ante liquidation exceeds the expected value of redemptions. In the case of uniformly distributed beliefs over redemptions, we have a very clean condition for cash hoarding in the sense that the fund manager will sell more than the expected redemptions. Cash hoarding occurs when $\mu > 2\delta$, meaning that the fire-sale haircut that applies to late sales is more than twice the liquidity discount that applies to pre-emptive liquidation. Thus, it is the *relative* discounts that matter for cash hoarding, rather than the absolute levels of the discounts.

In contrast, the solution to the global game threshold ρ^* shows that for the threshold value of the global game, it is the absolute values of the discount parameters that matter for the incidence of investor runs. One lesson from the discussion so far is that we must distinguish between the return on the underlying assets held in the mutual fund and the return on the mutual fund itself. This is so because the mutual fund holds cash as well as the risky asset, and the cash holding varies systematically with the fire-sale risk faced by the fund.

4 Empirical investigation

Informed by the theoretical discussion, we proceed to an empirical investigation. Our primary focus is on determining the direction of fund manager cash holding, in particular whether the cash holding serves as a buffer against redemptions or whether the fund manager engages in cash hoarding. As trailed already, we find that cash hoarding is the rule rather than the exception.

We then ask whether there are systematic variations across funds in the incidence of cash hoarding, depending on the liquidity of the underlying assets. We find that the incidence of cash hoarding is more severe for those mutual funds that hold more illiquid underlying assets. We also examine the evidence on whether fund managers are able to anticipate redemptions well in advance, by examining the discretionary sales and purchases in the month previous to when the redemptions take place. We find generally weak evidence of such anticipated sales, at least in our monthly data. Thus, the bulk of the correlation between investor-driven sales and discretionary sales happens within the same month.

We can use our data to address broader issues to do with the spillover across funds. We examine how strong is the clustering in investor flows across bond funds in each asset class. If the underlying assets across funds co-move according to common factors underlying their returns, we would expect to see greater clustering of redemptions across funds. We indeed observe that groups of less liquid funds display a greater degree of clustering. The clustering is especially clear to see when we measure the clustering in terms of dollar amounts rather than the number of funds.

4.1 Data

Our sample consists of bond mutual funds[4] investing globally. In particular, we focus on the following four types of bond fund: (1) bond funds investing globally in both developed market bonds and EME bonds using global bond indexes as benchmarks, which we call global DM bond funds since these bond funds invest predominantly in developed market sovereign bonds; (2) bond funds mainly investing globally in EME sovereign bonds denominated in foreign currency such as the US dollar, euro and Japanese yen, which we call global EME international government bond funds; (3) bond funds mainly investing globally in EME sovereign bonds denominated in their local currencies, which we call global EME local currency government bond funds; and (4) bond funds investing predominantly in corporate bonds issued by non-sovereign entities in all major EMEs and denominated in foreign currency such as the US dollar, euro and Japanese yen, which we call global EME corporate bond funds.

The goal of this paper is to calculate the relationship of cash hoarding by the fund manager and redemptions by investors as well as that of redemption-driven bond sales and discretionary bond sales. To do this, we need to construct a balanced-panel sample of bond funds with complete information on investor flows, asset allocation weights in

[4]In the analysis on investor flow clustering across funds, we also consider bond exchange-traded funds (ETFs) in addition to bond mutual funds.

every month with relatively large cross-sectional and time dimensions.

We obtained data on these four types of bond fund from EPFR Global. The EPFR database contains around 1400 global DM bond funds and 640 global/regional EME bond funds as of the end of June 2016. Among these funds, when we retrieved data from the EPFR database in July and August 2016, the following number of funds had data on investor flows every month from January 2013 to June 2016: 478 global DM bond funds, 104 global/regional EME international government bond funds, 105 global/regional EME local currency government bond funds, and 37 global/regional EME corporate bond funds.

Among them, a smaller set of funds (less than 100) have complete data on monthly investor flows and monthly country allocation weights (including cash holdings[5]) in all months from January 2013 to June 2016 (42 months). Among them, we also choose funds that have information on their investment benchmarks. In addition, since we need to calculate the local/foreign currency bond returns for each fund without knowing their actual bond holding information every month, we use JPMorgan Chase' data on benchmark returns as a proxy for these funds's local/foreign currency bond returns. Those funds that use benchmarks from JPMorgan Chase and Barclay's Capital are included from the sample. Finally, to avoid any bias coming from including more than one fund from the same asset management firm, we include only one fund for each asset management firm in each asset category and exclude exchange-traded funds (ETFs) and closed-end funds. That is, our sample includes only open-end mutual funds. Our final sample consists of 42 funds: 8 global DM bond funds, 13 global EME international government bond funds, 15 global EME local currency government bond funds, and 6 global EME corporate bond funds. The list of 42 funds is provided in Table 1. The number of economies in which these funds invested a positive amount during the sample period as well as of those in the specific benchmarks used to approximate the country-level bond return is summarised in Table 2.

The theoretical model shows the condition for cash hoarding to occur (μ/δ>2) and that as μ/δ increases, the size of cash hoarding increases. In order to see if their levels of liquidity satisfies the model's predictions in both the cross-sectional and time dimensions, we measure the level of liquidity of the underlying bonds of the four types of bond fund using the following three measures: (1) the turnover ratio; (2) bid-ask spread; and (3) return volatility. In terms of the turnover ratio, which is defined as the ratio of the total trading volume to the total amount of bonds outstanding, JPMorgan Chase (2014) shows that the turnover ratio in 2003 and 2008 for EME international currency government bonds was the highest, the ratio for EME local currency bonds was the second highest,

[5]In the EPFR database, cash allocation values are reported numbers from individual funds. The cash category includes cash, collateralised borrowing and lending obligations, money market securities, options, swaps, repos, receivables and payables.

and the ratio for EME international currency corporate bonds was the lowest. As of Q2 2014, the turnover ratio for EME international currency government bonds remained the highest, while the ratio for EME international currency corporate bonds was slightly greater than that for EME local currency government bonds. Figure 5 presents the second and third measures of liquidity for the four most popular benchmark indexes for the four types of bond fund we consider over the sample period of January 2013 to June 2016. In terms of the time dimension, Figure 5 shows that both the bid-ask spread and return volatility of the four benchmark indexes remained relatively low during normal periods (such as investor inflow periods), but sharply increased during market stress periods (such as investor outflow periods) or market turmoil periods (such as the taper tantrum period). In terms of the cross-sectional dimension, the upper panel shows that the bid-ask spread of DM bonds is smallest, while that of EME corporate bonds is largest. The lower panel shows that the return volatility of EME local currency government bonds was largest. Overall, we find that EME bonds, especially EME corporate bonds and EME local currency government bonds, are less liquid than DM bonds at a point in time and that each type of bond exhibit higher levels of liquidity during normal times and much lower levels of liquidity during stress times for all four types of bond.[6]

4.2 Main empirical results

Using the definition of investor-driven sales and discretionary sales, we first examine the incidence of cash hoarding by running panel regressions where the dependent variable is discretionary purchases in month t and we include investor-driven purchases in the same month t as an explanatory variable (contemporaneous cash hoarding). In another specification, we run panel regressions where the dependent variable is discretionary purchases in month t and the explanatory variable is the investor-driven purchases in the following month $t + 1$ (lagged cash hoarding).

As control variables, we include the log of the VIX index to take account of periods of financial market turbulence. In addition, we include a "kink" variable $\max\{0, FP_t\}$, where FP_t is the investor flow-driven purchases in month t. The kink variable is included so as to detect any asymmetry in the degree of co-movement in the discretionary sales and investor-driven sales between sales and purchases.

Table 3 shows the regression results under various specifications for global DM bond funds, global EME international government bond funds, global EME local currency

[6]In addition to liquidity, another possibly important difference is the average credit rating of the bonds included in the bond portfolio. As of Q2 2016, the average Standard and Poor's credit ratings of JPMorgan GBI Global index (most popular index for global DM bond funds), JPMorgan EMBI Global Diversified index (most popular index for global EME international government bond funds), JPMorgan GBI-EM Global Diversified index (most popular index for global EME local currency government bond funds) and JPMorgan CEMBI Broad Diversified index (most popular index for global EME corporate bond funds) were AA−, BBB−, BBB+ and BBB, respectively.

government bond funds and global EME corporate bond funds. Table 4 provides a summary of the main findings across the four groups of funds.

We then calculate the following four correlations for each fund in the four groups of funds and calculate the average correlation within each group:

- Correlation between investor flows at t and discretionary purchase at t (contemporaneous)
- Correlation between investor flows at t and discretionary purchase at $t-1$ (lagged)
- Correlation between investor flows-driven purchase at t and discretionary purchase at t (contemporaneous)
- Correlation between investor flows-driven purchase at t and discretionary purchase at $t-1$ (lagged)

Table 5 shows that the average correlations (both contemporaneous and lagged) are lowest for global DM bond funds and highest for global EME local currency government bond funds or global EME corporate bond funds, while global EME international government bond funds fall in between. This finding is evidence of cross-sectional variation in terms of the liquidity of the underlying assets of various bond funds affecting the cash hoarding incentive of fund managers.

The results consistently point to cash hoarding as being the rule rather than the exception. However, there are differences in the incidence of cash hoarding.

Table 3 shows that for global DM bond funds, there is roughly 3 dollars' worth of discretionary sales for every 100 dollars of investor-driven sales. In columns (3) and (4) that include the kink term, we see that the coefficient increases in absolute value to around 9 dollars per 100 dollars of investor-driven sales. However, we see from columns (3) and (4) that the kink term is not statistically significant, although the sign is negative, indicating some asymmetry where the coefficient on discretionary sales are larger than that on discretionary purchases.

In Table 3, we also see the results for global EME international government bond funds. Columns (1) and (2) show that the coefficient jumps to around 0.07, indicating that there are 7 dollars' worth of discretionary sales for each 100 dollars of investor-driven sales. The VIX is not significant, and the kink term is close to zero.

In contrast to the findings for bond markets that are relatively liquid, Table 3 also shows the results for EME local currency bond funds and EME corporate bond funds. Both of these categories of funds can be considered less liquid than global DM bond funds and EME international currency government bond funds.

Table 3 shows that for global EME local currency government bond funds, the kink variable begins to kick in. Columns (3) and (4) indicate that the coefficient on the investor flow-driven purchases variable jumps to 0.13, indicating that there are 13 dollars of discretionary sales for every 100 dollars of investor flow-driven sales. However, we see that the coefficient on the kink term is around -0.11, so that the 13 dollar number only holds for sales. For discretionary purchases, the figure is close to the 2 dollar mark, as for the global DM bond funds.

The results for the EME corporate bond funds are similar, but the kink term is no longer significant. Columns (1) and (2) of Table 3 show that the coefficient on investor flow-driven sales is again around 0.10, so that 10 dollars of discretionary sales are associated with 100 dollars' worth of investor flow-driven sales. Arguably, the EME corporate bonds are the most illiquid of the bond categories, and it is of note that the kink term is insignificant. The findings suggest that the procyclical impact of cash management is equally strong "on the way up" as it is "on the way down".

Our results for the four classes of bond funds are summarised in the upper half of Table 4. Taken together, we find that the coefficients on contemporaneous investor-driven purchases or investor flows are always positive and overall statistically significant.

The lower half of Table 4 also summarises results obtained when we use investor flow-driven purchases from the following month. The full results are given in Table 6. Compared to the contemporaneous effects, we see that the results are less strong when we consider the previous month's discretionary purchases. We find that the coefficients on the next month's investor-driven purchases are positive and statistically significant only for global EME corporate bond funds, mainly driven by flow-driven net purchases. For global EME corporate bond funds, we also find some asymmetry between flow-driven purchases and sales. In particular, the coefficients on bond sales are significantly smaller than those on bond purchases. Regarding investor flows, we find that the coefficients on the next month's investor flows are positive and statistically significant only for global EME corporate bond funds, and that the coefficients are positive but statistically insignificant for all the other three types of fund.[7]

We have also conducted some robustness checks by using subsamples excluding funds using leverage and derivatives (ie negative cash positions) and by dividing the sample into fund-month observations with positive investor flows and those with negative investor flows (ie existence of asymmetry). We find that the main findings of the paper hold for the subsamples and that cash hoarding is stronger during investor redemptions than during investor inflows. The detailed results are provided in the appendix.

[7] We show empirical evidence of cash hoarding *in anticipation of* future redemptions. However, as Shek, Shim and Shin (2015) observed, it is possible that the fund manager sells bonds out of discretion and increases cash holdings in the next month *in response to* redemptions in the current month. However, the fund manager sells bonds and increases cash holdings precisely because he thinks investors will continue to redeem shares from the fund in the current and coming months. If, by contrast, the fund manager expects that in the current and next months, he will have net investor inflows, then he will not want to increase cash holdings.

5 Other findings

In addition to cash hoarding, we report some other findings of note in this section. In particular, we consider the flow-performance relationship and clustering in investor flows across different funds investing in the same asset classes.

5.1 Flow-performance relationship

In this subsection, we investigate the flow-performance relationship for the four classes of bond fund in our sample. In particular, we run regressions of investor flows in month t on fund returns in month t or in month $t-1$ and other controls. Table 7 provides a summary of the main findings across the four groups of funds, while Table 8 provides the full regression results.

For all four groups of bond funds, we find that the previous month's fund returns increase the current month's investor flows with significant asymmetry for DM bond funds. An interesting finding is that for the global DM bond funds, the VIX in the previous month and investor flows in the current month are positively correlated. By contrast, for the global EME local currency government bond funds, the VIX in the previous month is negatively correlated with investor flows in the current month. This is another evidence of cross-sectional difference across funds investing in bonds with different degree of liquidity in the context of the flow-performance relationship.

5.2 Investor clustering

Investor clustering (ie, directional co-movement of investor flows across funds) is to be expected when the returns of the bond funds are affected by common components. For any given profile of global game run thresholds, we would expect clustering in the investor redemptions across funds where the extent of clustering will depend on the underlying characteristics of the bonds. We conducted investor clustering analyses for the four types of bond fund for which we have complete investor flows data from January 2013 to June 2016. The degree of investor clustering in each month can be measured by the following three indicators:

- The share of the number of funds facing investor net inflows, funds facing zero net inflows and funds facing investor net outflows;
- The dollar amount of the sum of investor net inflows (positive value) over the funds facing net inflows and the dollar amount of the sum of investor net outflows (negative value) over the fund facing net outflows; and
- The share of the sum of investor net inflows over the funds facing net inflows and the sum of investor net outflows (absolute value) over the funds facing net outflows.

Figure 6 shows that investors in these four groups of bond funds exhibit strong directional co-movement in their choice of investment into or redemptions from funds, and that investors in global EME bond funds, especially those in global EME local currency government bond funds and global EME corporate bond funds, simultaneously commit or redeem funds more often than those in global DM bond funds.

Figure 6 also shows that (i) the degree of investor clustering (ie one-sidedness) across funds in each group is higher when we look at the dollar amount than when we look at the number of funds; (ii) investors tend to abruptly switch from inflow-side clustering to outflow-side clustering, and often continue to redeem heavily for a few or several consecutive months before they switch to relatively more inflows than outflows; and (iii) the more illiquid the underlying assets of funds are, the greater degree of investor clustering at a point in time. In particular, on the last point we find that US bond funds are subject to less investor clustering than global ex-US bond funds[8] and that global DM bond funds experience less investor clustering than global EM bond funds.

Such evidence supports the model's prediction that mutual fund investors tend to alternate between two states: in one state, all investors commit new funds; and in the other state, they all redeem. Also, the clustering analysis shows that the more illiquid the underlying bonds are, the more likely to see stronger clustering of investor flows across funds investing in the same asset class. Given that μ and δ capture the level of liquidity of the underlying bonds, the data on the liquidity measures we provide support that μ and δ for global bond funds are indeed the smallest, while μ and δ for EME local currency government bond funds or EME corporate bond funds are the largest. This corresponds to the theoretical model's prediction that, as μ and δ increase, the market becomes less liquid and the threshold value of the signal is increasing. In other words, the investor switches to running on the fund for a higher level of fundamentals, resulting in higher likelihood of investor clustering.

6 Concluding remarks

We have found that cash hoarding is the rule rather than the exception for global bond mutual funds. Just as the procyclical leverage decision of banks tends to amplify the credit cycle, the cash hoarding by bond fund managers may amplify fire sales associated with investor redemptions.

We have further found that the incidence of cash hoarding is more severe for those funds that hold more illiquid classes of bond. This finding highlights the potential interaction of investor redemptions and market liquidity in the context of global bond funds.

There is ongoing discussion of the scope for improving liquidity risk management

[8] The figures showing this result are available from the authors upon request.

practices of the asset management sector. One area of discussion has been on the usefulness of system-wide stress testing that incorporates the impact of collective selling by funds on the resilience of financial markets (see FSB, 2015 and 2016). For both firm-level and system-wide stress testing exercises, our results suggest that a stress scenario would ideally include the possibility of cash hoarding.

Finally, global EME bond funds are an important intermediary in some EMEs where such funds constitute a significant fraction of total portfolio bond inflows. The findings of our paper shed light on potential financial stability implications for these economies stemming from the reversal of bond portfolio flows.

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Appendix: Robustness checks

Negative cash positions

When bond funds use derivatives or leverage, they are recorded as negative cash positions. In our sample of 42 funds, three funds have negative cash positions in more than 50% of the sample period and another three funds have negative cash positions in more than 20% of the sample period, which likely show that these funds use derivatives and leverage frequently. We then consider a subsample of 39 funds (excluding the three funds with negative cash in more than 50% of months from the 42 funds) and call it Subsample 1. We also consider a subsample of 36 funds (excluding the six funds with negative cash in more than 20% of months from the 42 funds) and call it Subsample 2.

For Subsample 1 and Subsample 2, we calculated the histograms reported in Figures 2 and 3 of the paper. We found that the results for the contemporaneous histograms basically do not change at all when we use Subsample 1 and Subsample 2, and that the results for the lagged histograms change only marginally when we use the two subsamples. The main regression results on cash hoarding and the flow-performance relationship do not change in general, when we use these subsamples instead of the full sample. The detailed regression results are available upon request.

Asymmetry between inflows versus outflows

It is possible that the impact of investor inflows and outflows (ie redemptions) on the real economy is asymmetric, with bond sales (ie cash hoarding) associated with investor inflows having a larger impact than bond purchases (ie cash de-stocking) associated with investor outflows. In order to see if there exists significant asymmetry between the effect of outflows and the effect of inflows in the data, we divided the sample into two parts: a subsample for investor inflows and the other subsample for investor outflows. Table A1 shows the regression results for the fund-months when investor flows are positive, while Table A2 shows the results when investor flows are negative. They show that for three types of funds (Global DM bond, Global EME local currency government bond and Global EME corporate bond), the positive correlation between flow-driven purchases and discretionary purchases is stronger when investor flows are negative than when investor flows are positive.

Another way to consider asymmetry in our set-up is to compare return volatility during market upturns and downturns. In particular, we can compare the average volatility during months of positive returns with the average volatility during months of negative returns on each of the four benchmark indexes. Table A3 shows that for all four indexes, the volatility is higher during market downturns (ie negative monthly returns) than during upturns (ie positive monthly returns).

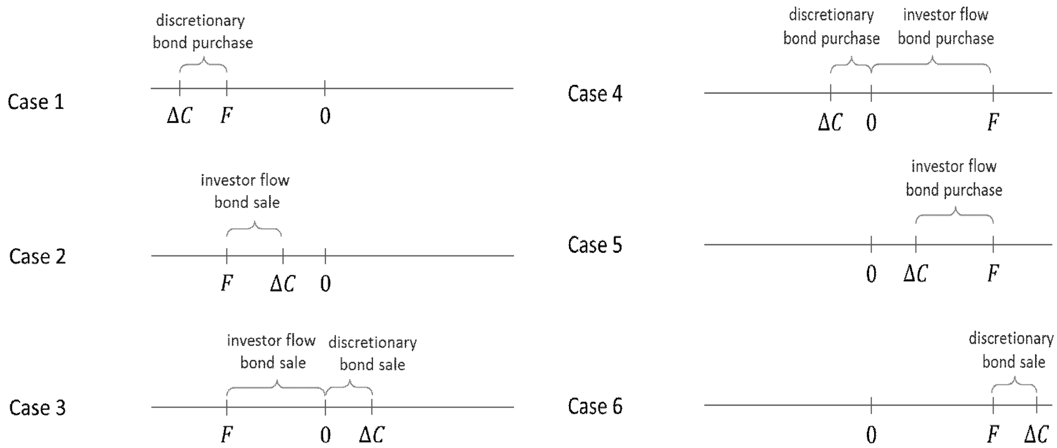


Figure 1. Identifying cash hoarding by bond mutual fund managers. F is net investor flows over some interval of time, and ΔC is the increased cash holding of the fund over the same interval. Discretionary bond sales in Case 3 correspond to cash hoarding, while discretionary bond purchases in Case 4 correspond to cash de-stocking. Source: Shek, Shim and Shin (2015).

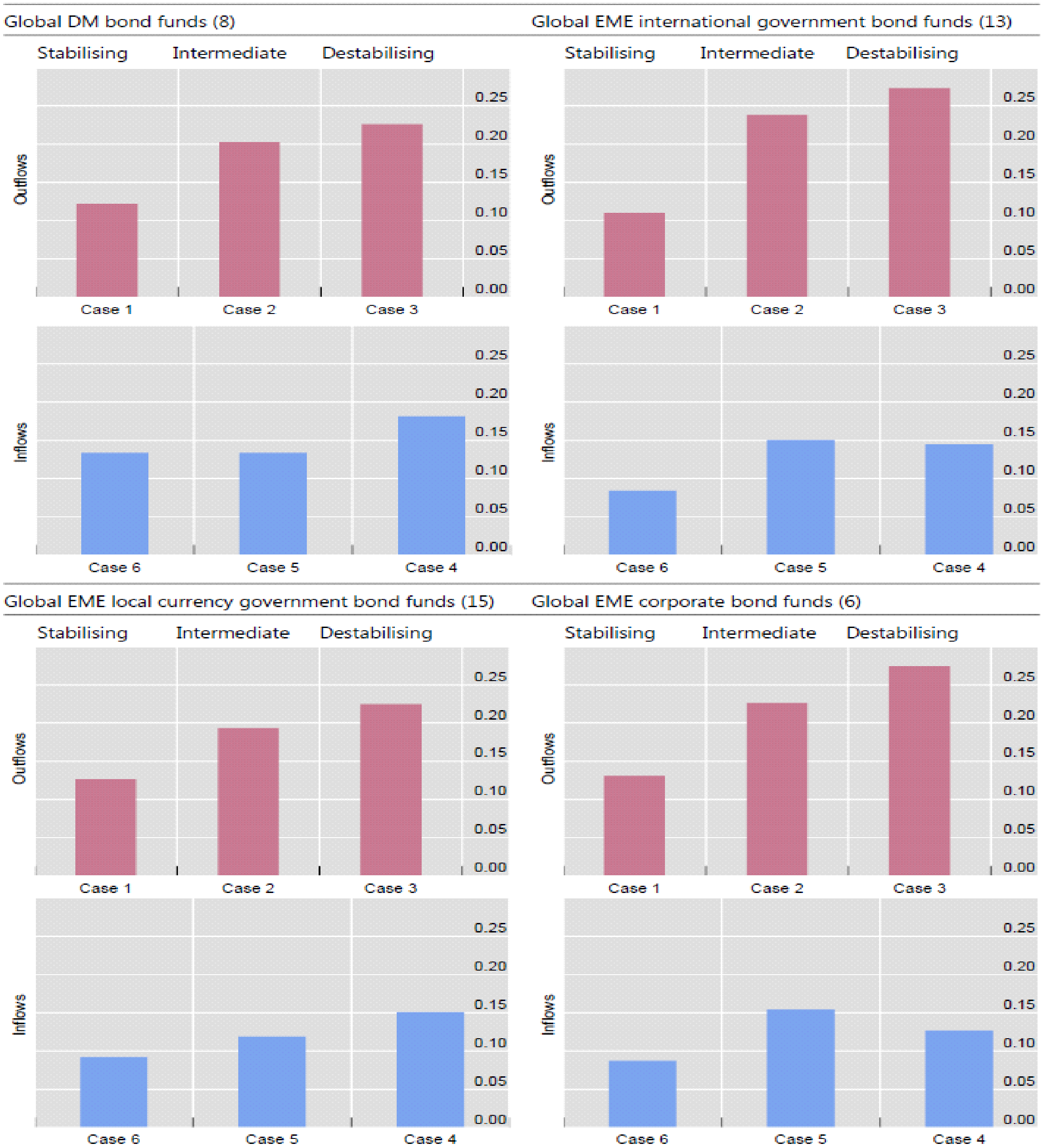


Figure 2. Frequency of stabilising/destabilising sales for four groups of bond funds. Sources: EPFR; authors' calculations.

Figure 3. Frequency of stabilising/destabilising discretionary purchases/sales in month $t-1$ for investor inflows/outflows in month t. Sources: EPFR; authors' calculations.

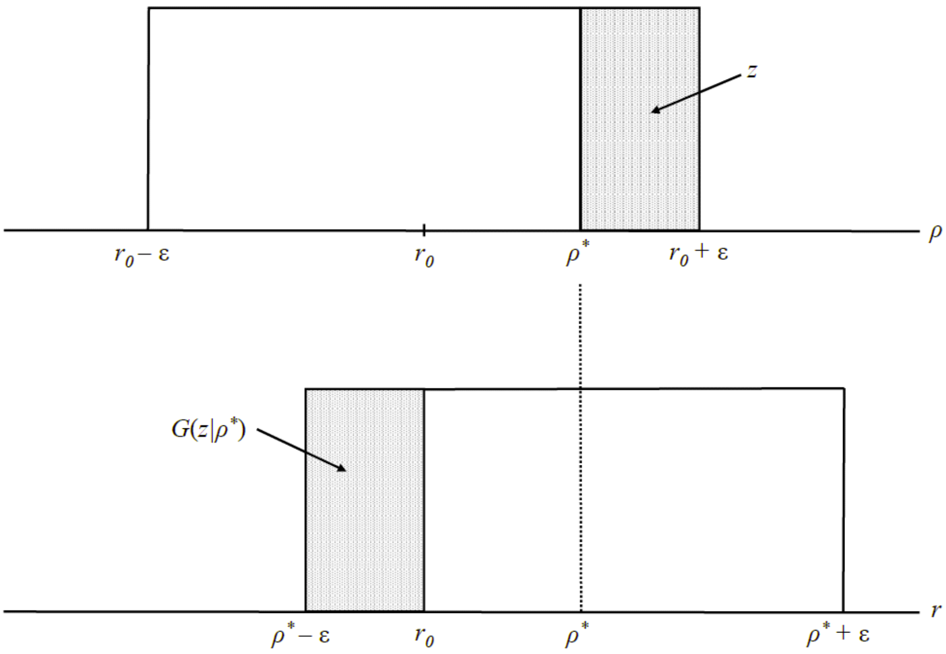


Figure 4. Deriving the subjective distribution over x at switching point ρ^*.

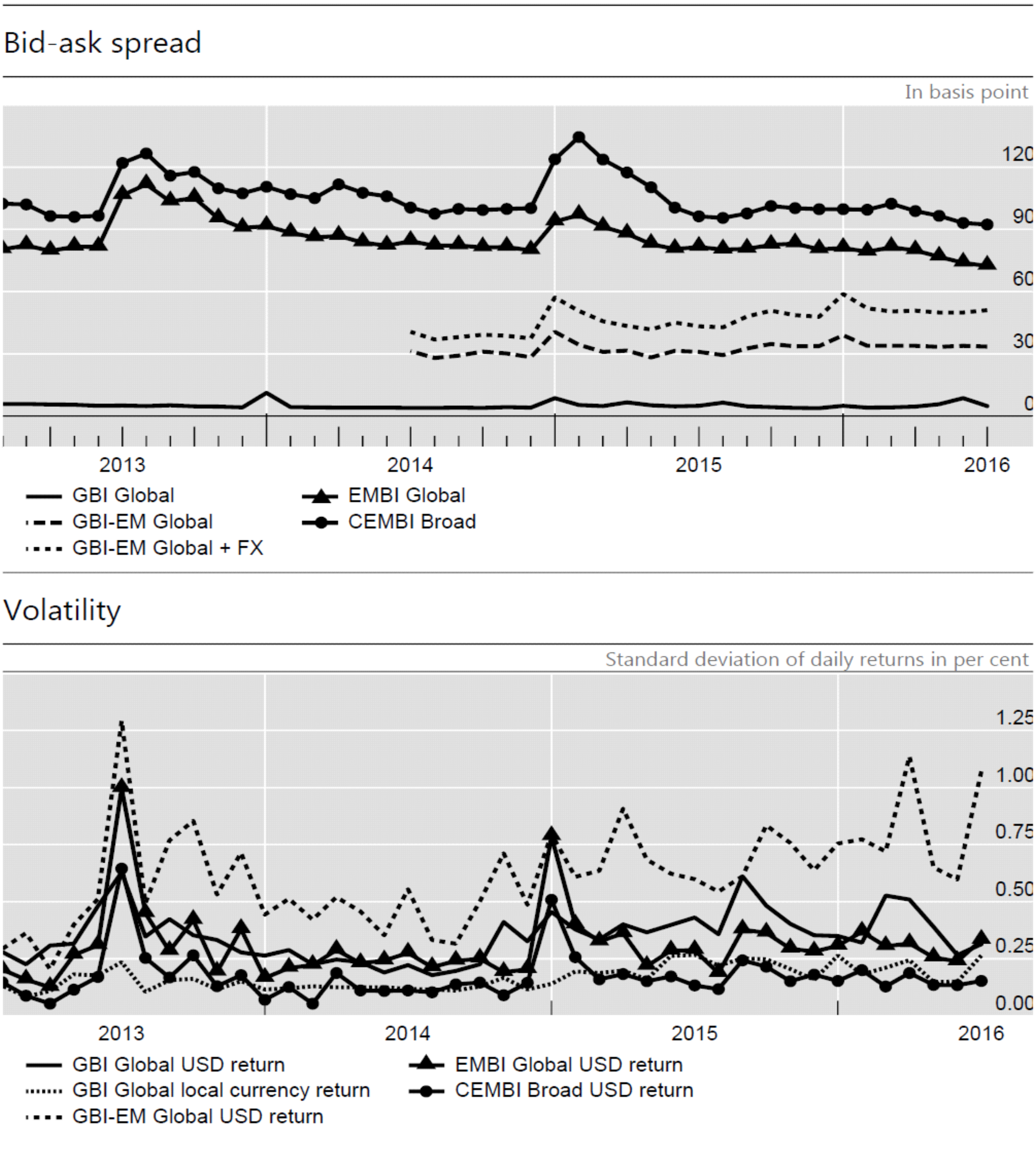
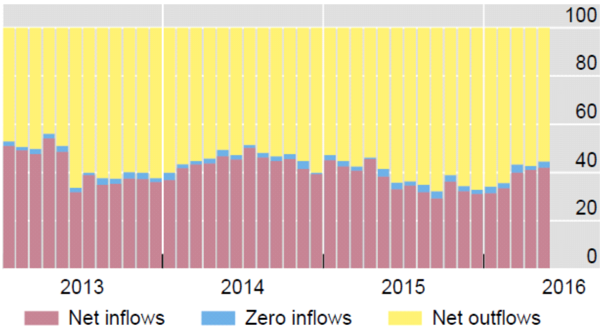


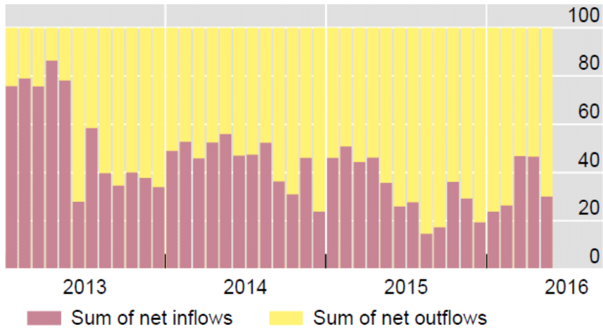
Figure 5. Liquidity indicators for benchmark indexes. The upper panel shows the weighted average of the bid-ask spread of the bonds consisting of each JPMorgan index. FX spread for JPMorgan GBI-EM Global index is the weighted average bid-ask spread of emerging market currencies whose countries are included in the index. The lower panel shows the volatility of daily total returns on each index within a month. JPMorgan GBI Global US dollar return is calculated as the product of the local currency (ie denomination currency) return on bonds in the index and the FX return on the index (ie the weighted average of the appreciation/depreciation of each currency against the US dollar). Sources: Bloomberg; JPMorgan Chase.

Global DM bond funds (478)

Share of the number of funds facing net inflows and the number of funds facing net outflows

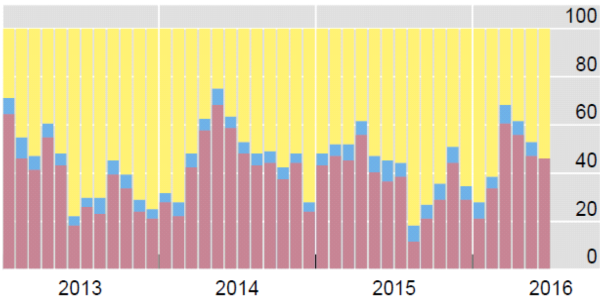


Share of sum of inflows for funds facing net inflows and the sum of outflows for funds facing net outflows

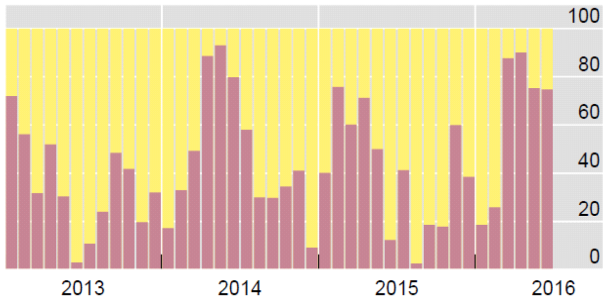


Global EME international government bond funds (104)

Share of the number of funds facing net inflows and the number of funds facing net outflows

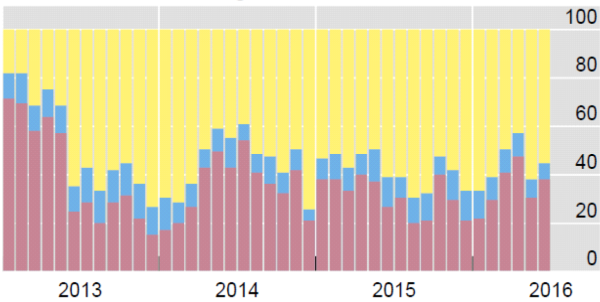


Share of sum of inflows for funds facing net inflows and the sum of outflows for funds facing net outflows

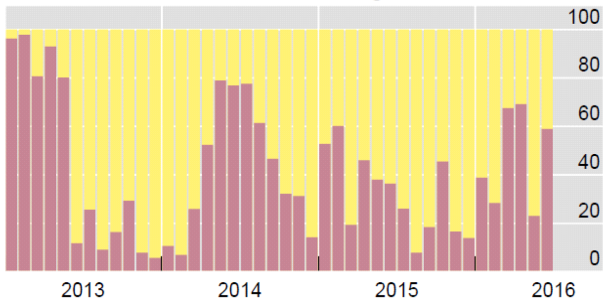


Global EME local currency government bond funds (105)

Share of the number of funds facing net inflows and the number of funds facing net outflows

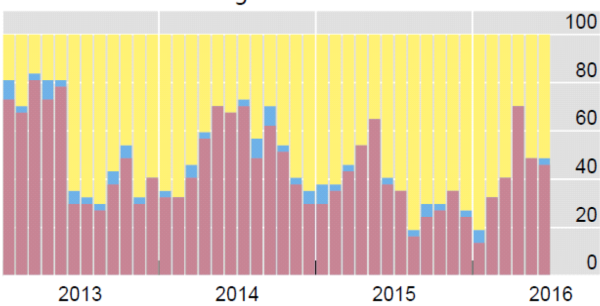


Share of sum of inflows for funds facing net inflows and the sum of outflows for funds facing net outflows



Global EME corporate bond funds (37)

Share of the number of funds facing net inflows and the number of funds facing net outflows



Share of sum of inflows for funds facing net inflows and the sum of outflows for funds facing net outflows

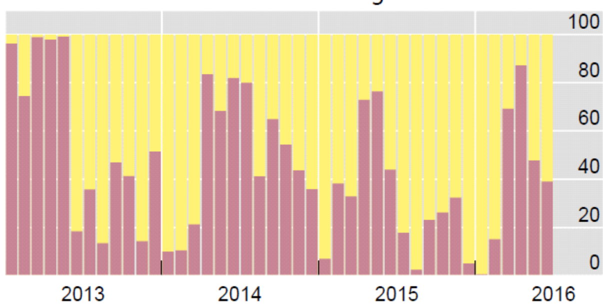


Figure 6. Investor clustering. The figures in parentheses represent the number of bond funds in each category. Source: EPFR.

Table 1: List of 42 funds. Source: EPFR.

Fund name	Benchmark	Geographical focus and type
Global DM bond funds (8)		
Invesco Global Bond Fund	JPMorgan Global Government Bond	Global Gov't
ISI International Bonds Fund	JPMorgan Global Government Bond	Global Gov't
JPMorgan Funds - Global Government Bond Fund	JPMorgan Government Bond Index Global	Global Gov't
Morgan Stanley Investment Funds - Global Bond	Barclays Global Aggregate Bond	Global all
Schroder ISF Global Bond	Barclays Global Aggregate Bond	Global all
Threadneedle Global Bond Fund	JPMorgan Global Bond	Global all
Federated International Bond Fund	JPMorgan Global (ex-US) Government	Global ex-US Gov't
Schroder ISF Global Corporate Bond	Barclays Global Aggregate Credit Component USD	Global Corporate
Global EME international government bond funds (13)		
Aberdeen Global - Select Emerging Markets Bond Fund	JPM EMBI Global Diversified	Global EM Hard Currency Gov't
Aviva Investors - Emerging Markets Bond Fund	JPM EMBI Global	Global EM Hard Currency Gov't
Berenberg Emerging Markets Bond Selection	JPM EMBI+	Global EM Hard Currency Gov't
BlackRock Global Funds Emerging Markets Bond Fund	JPM EMBI Global Diversified	Global EM Hard Currency Gov't
DoubleLine Emerging Markets Fixed Income Fund	JPM EMBI Global Diversified	Global EM Hard Currency Gov't
Invesco Emerging Markets Bond Fund	JPM EMBI Global Diversified	Global EM Hard Currency Gov't
ISI Emerging Market Bonds Fund	JPM EMBI Global Diversified	Global EM Hard Currency Gov't
JPMorgan Funds - Emerging Markets Bond Fund	JPM EMBI Global Diversified	Global EM Hard Currency Gov't
PIMCO Emerging Markets Bond Fund	JPM EMBI Global	Global EM Hard Currency Gov't
Pioneer Funds - Emerging Markets Bond	JPM EMBI Global Diversified	Global EM Hard Currency Gov't
TCW Emerging Markets Income Fund	JPM EMBI Global Diversified	Global EM Hard Currency Gov't
Threadneedle Emerging Market Bond Fund	JPM EMBI Global	Global EM Hard Currency Gov't
Universal Inst Fds Emerging Markets Debt Portfolio	JPM EMBI Global	Global EM Hard Currency Gov't

Table 1 (Continued). List of 42 funds. The fund with * invests mostly in euro-denominated corporates and non-government entities. Source: EPFR.

Fund name	Benchmark	Geographical focus and type
Global EME local currency government bond funds (15)		
Aberdeen Emerging Markets Debt Local Currency Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
Aviva Investors - Emerging Markets Local Currency Bond Fund	JPM GBI-EM Broad Diversified	Global EM Local Currency Gov't
Baillie Gifford Emerging Markets Bond Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
Baring IF Emerging Markets Debt Local Currency Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
BlackRock Global Funds Emerging Markets Local Currency Bond Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
Goldman Sachs Local Emerging Markets Debt Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
Invesco Emerging Local Currencies Debt Fund	JPM GBI-EM Global Diversified Composite	Global EM Local Currency Gov't
Investec GSF Emerging Markets Local Currency Debt Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
ISI Emerging Market Local Currency Bonds Fund	JPM GBI-EM Broad Diversified	Global EM Local Currency Gov't
JPMorgan Funds - Emerging Markets Local Currency Debt Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
Morgan Stanley Investment Funds - Emerging Markets Domestic Debt	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
Pictet - Latin American Local Currency Debt	JPM GBI-EM Global Latin America	Latin America Local Currency Gov't
PIMCO GIS Emerging Local Bond Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
TCW Emerging Markets Local Currency Income Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
WisdomTree Emerging Markets Local Debt Fund	JPM GBI-EM Global Diversified	Global EM Local Currency Gov't
Global EME corporate bond funds (6)		
Invesco Emerging Market Corporate Bond Fund	JPM CEMBI Broad Diversified	Global EM Hard Currency Corporate
Investec GSF Latin American Corporate Debt Fund	JPM CEMBI Broad Diversified Latin America	Latin America Hard Currency Corporate
JPMorgan Funds - Emerging Markets Corporate Bond Fund	JPM CEMBI Broad Diversified	Global EM Hard Currency Corporate
Morgan Stanley Investment Funds - Emerging Markets Debt*	JPM EMBI Global	Global EM Hard Currency Corporate
Schroder ISF Emerging Market Corporate Bond	JPM CEMBI Broad Diversified	Global EM Hard Currency Corporate
WisdomTree Emerging Markets Corporate Bond Fund	JPM CEMBI Broad Diversified	Global EM Hard Currency Corporate

Table 2. Number of economies global bond funds invest in. * CZ, HK, HU, IL, KR, MX, PL, SG and ZA are EMs, according to BIS classifications. ** The Other Bond category includes some of the smaller countries that are not classified separately in the EPFR database. *** JPMorgan EMBI Global index has positive weights for 67 countries between December 2012 and June 2016. However, the 8 global DM bond funds invested a positive amount in only 38 countries' bonds, and 13 global EM international bond funds invested a positive amount in 63 countries. Sources: EPFR, JPMorgan Chase.

Fund type	Number of economies with positive holdings by funds	Number of economies in the benchmarks
8 global DM bond funds	76 individual countries, 3 other regional groups, and the other bond category**	JPMorgan GBI-Broad (27 individual countries including 19 DMs and 9 EMEs*) JPMorgan EMBI Global*** (additional 38 individual EMEs and 3 other regional groups)
13 global EME international bond funds	96 individual countries, 4 other regional groups, and the other bond category	JPMorgan EMBI Global*** (63 individual countries and 4 other regional groups)
15 global EME local currency bond funds	62 individual countries, 4 other regional groups, and the other bond category	JPMorgan GBI-EM Global (19 individual countries and 4 other regional groups) JPMorgan GBI-EM Broad (additional 11 individual countries)
6 global EME corporate bond funds	79 individual countries, 4 other regional groups, and the other bond category	JPMorgan CEMBI Broad: 52 individual countries and 4 other regional groups)

Table 3. Panel regressions of discretionary purchases on investor-driven purchases (or investor flows) in the current month. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent and explanatory variables are normalised by the NAV of each fund at the beginning of the month, except the VIX variable. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

Dependent variable: discretionary purchases in month t						
Global DM bond funds						
	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.030**	0.030**	0.087*	0.087*		
(FP_t)	(3.09)	(3.33)	(1.94)	(2.02)		
Max{0, FP_t}			−0.071	−0.070		
			(−1.44)	(−1.47)		
Total investor flows in month t					0.014**	0.047
(TF_t)					(2.56)	(1.38)
Max{0, TF_t}						−0.042
						(−0.96)
$\Delta\log(VIX_t)$		−0.113		−0.063	−0.159	−0.139
		(−0.17)		(−0.10)	(−0.24)	(−0.22)
N	8	8	8	8	8	8
N x T	336	336	336	336	336	336
R^2	0.015	0.015	0.020	0.020	0.009	0.011
Global EME international government bond funds						
	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.074***	0.074***	0.074*	0.074*		
(FP_t)	(3.18)	(3.31)	(1.99)	(2.04)		
Max{0, FP_t}			0.000	0.001		
			(0.00)	(0.01)		
Total investor flows in month t					0.025	0.032
(TF_t)					(1.48)	(1.03)
Max{0, TF_t}						−0.017
						(−0.36)
$\Delta\log(VIX_t)$		0.074		0.074	−0.088	−0.090
		(0.10)		(0.10)	(−0.12)	(−0.12)
N	13	13	13	13	13	13
N x T	546	546	546	546	546	546
R^2	0.059	0.059	0.059	0.059	0.036	0.036

Table 3 (Continued). Panel regressions of discretionary purchases on investor-driven purchases (or investor flows) in the current month. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent and explanatory variables are normalised by the NAV of each fund at the beginning of the month, except the VIX variable. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

Dependent variable: discretionary purchases in month t						
Global EME local currency government bond funds						
	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.062	0.059	0.132**	0.132**		
(FP_t)	(1.69)	(1.65)	(2.47)	(2.52)		
Max{0, FP_t}			−0.106*	−0.110*		
			(−1.98)	(−2.03)		
Total investor flows in month t					0.040	0.082**
(TF_t)					(1.73)	(2.31)
Max{0, TF_t}						−0.066
						(−1.69)
$\Delta\log(VIX_t)$		−1.147*		−1.224*	−1.192*	−1.236*
		(−1.99)		(−2.06)	(−2.01)	(−2.04)
N	15	15	15	15	15	15
N x T	630	630	630	630	630	630
R^2	0.039	0.047	0.054	0.064	0.034	0.041
Global EME corporate bond funds						
	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.095**	0.097**	0.106*	0.113*		
(FP_t)	(2.68)	(2.63)	(2.21)	(2.23)		
Max{0, FP_t}			−0.017	−0.023		
			(−0.35)	(−0.46)		
Total investor flows					0.062**	0.031
(TF_t)					(2.71)	(1.42)
Max{0, TF_t}						0.046
						(0.79)
$\Delta\log(VIX_t)$		0.425		0.446	0.321	0.283
		(1.18)		(1.26)	(0.95)	(0.92)
N	6	6	6	6	6	6
N x T	252	252	252	252	252	252
R^2	0.060	0.062	0.060	0.063	0.037	0.039

Table 4. Panel regressions of discretionary purchases on investor-driven purchases or investor flows. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent and explanatory variables are normalised by the NAV of each fund at the beginning of the month, except the VIX variable. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

	Global DM bond funds		Global EME international government bond funds		Global EME local currency government bond funds		Global EME corporate bond funds	
Dependent variable: discretionary purchases in the same month								
Exp. variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Flow-driven	0.087*		0.074*		0.132**		0.113*	
purchases (FP_t)	(2.02)		(2.04)		(2.52)		(2.23)	
Max{0, FP_t}	−0.070		0.001		−0.110*		−0.023	
	(−1.47)		(0.01)		(−2.03)		(−0.46)	
Total investor		0.014**		0.025		0.040		0.062**
flows in month t		(2.56)		(1.48)		(1.73)		(2.71)
$\Delta\log(VIX_t)$	−0.063	−0.159	0.074	−0.088	−1.224*	−1.192*	0.446	0.321
	(−0.10)	(−0.24)	(0.10)	(−0.12)	(−2.06)	(−2.01)	(1.26)	(0.95)
N	8	8	13	13	15	15	6	6
N x T	336	336	546	546	630	630	252	252
R^2	0.020	0.009	0.059	0.036	0.064	0.034	0.063	0.037
Dependent variable: discretionary purchases in the previous month								
Exp. variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Flow-driven	−0.010		0.004		0.028		−0.007	
purchases (FP_t)	(−0.32)		(0.17)		(0.79)		(−0.46)	
Max{0, FP_t}	0.015		−0.009		−0.038		0.069**	
	(0.49)		(−0.25)		(−1.00)		(3.01)	
Total investor		0.016		0.017		0.022		0.060**
flows in month t		(1.81)		(1.28)		(0.92)		(3.31)
$\Delta\log(VIX_{t-1})$	−0.258	−0.291	−0.238	−0.214	−1.265**	−1.202*	0.245	0.300
	(−0.40)	(−0.45)	(−0.31)	(−0.28)	(−2.25)	(−2.14)	(1.01)	(1.07)
N	8	8	13	13	15	15	6	6
N x T	328	328	533	533	615	615	246	246
R^2	0.013	0.015	0.033	0.035	0.022	0.024	0.019	0.030

Table 5. Correlations between investor flows and discretionary purchases. Source: EPFR.

Fund type	Average correlation between total investor flows in t and		Average correlation between flow-driven purchases in t and	
	discretionary purchases in t	discretionary purchases in $t-1$	discretionary purchases in t	discretionary purchases in $t-1$
Global DM bond funds	0.076	-0.005	0.168	-0.073
Global EME international government bond funds	0.179	0.112	0.303	0.028
Global EME local currency government bond funds	0.214	0.149	0.297	0.084
Global EME corporate bond funds	0.175	0.168	0.254	0.112
All funds	0.171	0.111	0.268	0.041

Table 6. Panel regressions of discretionary purchases on investor-driven purchases (or investor flows) in the previous month. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent and explanatory variables are normalised by the NAV of each fund at the beginning of the month, except the VIX variable. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

Dependent variable: discretionary purchases in month $t-1$						
Global DM bond funds						
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.003	0.003	–0.011	–0.010		
(FP_t)	(0.22)	(0.27)	(–0.34)	(–0.32)		
Max{0, FP_t}			0.016	0.015		
			(0.51)	(0.49)		
Total investor flows in month t					0.016	0.030
(TF_t)					(1.81)	(0.90)
Max{0, TF_t}						–0.016
						(–0.54)
$\Delta\log(VIX_{t-1})$		–0.265		–0.258	–0.291	–0.298
		(–0.41)		(–0.40)	(–0.45)	(–0.47)
N	8	8	8	8	8	8
N x T	328	328	328	328	328	328
R^2	0.012	0.013	0.013	0.013	0.015	0.016
Global EME international government bond funds						
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.001	0.001	0.005	0.004		
(FP_t)	(0.11)	(0.07)	(0.21)	(0.17)		
Max{0, FP_t}			–0.010	–0.009		
			(–0.28)	(–0.25)		
Total investor flows					0.017	0.020
(TF_t)					(1.28)	(0.89)
Max{0, TF_t}						–0.008
						(–0.24)
$\Delta\log(VIX_{t-1})$		–0.242		–0.238	–0.214	–0.212
		(–0.32)		(–0.31)	(–0.28)	(–0.28)
N	13	13	13	13	13	13
N x T	533	533	533	533	533	533
R^2	0.033	0.033	0.033	0.033	0.035	0.035

Table 6 (Continued). Panel regressions of discretionary purchases on investor-driven purchases (or investor flows) in the previous month. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent and explanatory variables are normalised by the NAV of each fund at the beginning of the month, except the VIX variable. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

Dependent variable: discretionary purchases in month $t-1$						
Global EME local currency government bond funds						
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.007	0.003	0.035	0.028		
(FP_t)	(0.49)	(0.21)	(0.95)	(0.79)		
Max$\{0,\ FP_t\}$			−0.043	−0.038		
			(−1.10)	(−1.00)		
Total investor flows in month t					0.022	0.085
(TF_t)					(0.92)	(1.43)
Max$\{0,\ TF_t\}$						−0.099
						(−1.53)
$\Delta\log(VIX_{t-1})$		−1.296**		−1.265**	−1.202*	−1.116*
		(−2.25)		(−2.25)	(−2.14)	(−2.02)
N	15	15	15	15	15	15
N x T	615	615	615	615	615	615
R^2	0.008	0.020	0.011	0.022	0.024	0.040
Global EME corporate bond funds						
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.035*	0.036*	−0.007	−0.007		
(FP_t)	(2.19)	(2.27)	(−0.47)	(−0.46)		
Max$\{0,\ FP_t\}$			0.068**	0.069**		
			(2.88)	(3.01)		
Total investor flows					0.060**	0.055
(TF_t)					(3.31)	(1.16)
Max$\{0,\ TF_t\}$						0.008
						(0.14)
$\Delta\log(VIX_{t-1})$		0.228		0.245	0.300	0.301
		(0.89)		(1.01)	(1.07)	(1.10)
N	6	6	6	6	6	6
N x T	246	246	246	246	246	246
R^2	0.015	0.016	0.019	0.019	0.030	0.030

Table 7. Summary table of panel regressions for the flow-performance relationship. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent variable is normalised by the NAV of each fund at the beginning of the month. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

	Global DM bond funds		Global EME international government bond funds		Global EME local currency government bond funds		Global EME corporate bond funds	
Dependent variable: investor flows in month t								
Exp. variable	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
FR_t	−0.084		0.404		0.493***		0.981**	
	(−0.18)		(0.77)		(4.37)		(3.28)	
Max{0, FR_t}	0.060		0.112		−0.512***		−0.859	
	(0.13)		(0.16)		(−5.17)		(−1.25)	
$\Delta\log(VIX_t)$	−2.216		−2.964		−0.816		0.224	
	(−1.32)		(−1.61)		(−0.51)		(0.21)	
FR_{t-1}		0.653**		0.622		0.361**		0.396**
		(2.56)		(1.57)		(2.46)		(3.09)
Max{0, FR_{t-1}}		−0.657**		−0.304		−0.223		0.538
		(−2.64)		(−0.65)		(−0.84)		(1.86)
$\Delta\log(VIX_{t-1})$		2.471**		0.323		−2.900*		0.830
		(2.67)		(0.26)		(−1.91)		(1.09)
N	8	8	13	13	15	15	6	6
N x T	336	328	546	533	630	615	252	246
R^2	0.032	0.043	0.118	0.097	0.060	0.074	0.125	0.145

Table 8. Panel regressions for the flow-performance relationship. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent variable is normalised by the NAV of each fund at the beginning of the month. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

Dependent variable: investor flows in month t								
Global DM bond funds								
Exp. variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fund return	-0.009	0.030	-0.034	-0.084				
(FR_t)	(-0.10)	(0.07)	(-0.36)	(-0.18)				
Max$\{0,FR_t\}$		-0.046		0.060				
		(-0.10)		(0.13)				
$\Delta\log(VIX_t)$			-2.185	-2.216				
			(-1.32)	(-1.32)				
FR_{t-1}					0.077	0.522*	0.103	0.653**
					(1.09)	(2.17)	(1.36)	(2.56)
Max$\{0,FR_{t-1}\}$						-0.536*		-0.657**
						(-2.36)		(-2.64)
$\Delta\log(VIX_{t-1})$							2.127*	2.471**
							(2.09)	(2.67)
N	8	8	8	8	8	8	8	8
N x T	336	336	336	336	328	328	328	328
R^2	0.029	0.029	0.032	0.032	0.037	0.039	0.040	0.043
Global EME international government bond funds								
Exp. variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FR_t	0.589***	0.540	0.462**	0.404				
	(3.75)	(1.14)	(2.56)	(0.77)				
Max$\{0,FR_t\}$		0.096		0.112				
		(0.13)		(0.16)				
$\Delta\log(VIX_t)$			-2.958	-2.964				
			(-1.64)	(-1.61)				
FR_{t-1}					0.455*	0.608	0.469	0.622
					(2.06)	(1.70)	(1.75)	(1.57)
Max$\{0,FR_{t-1}\}$						-0.304		-0.304
						(-0.65)		(-0.65)
$\Delta\log(VIX_{t-1})$							0.323	0.323
							(0.26)	(0.26)
N	13	13	13	13	13	13	13	13
N x T	546	546	546	546	533	533	533	533
R^2	0.110	0.110	0.118	0.118	0.096	0.097	0.096	0.097

Table 8 (Continued). Panel regressions for the flow-performance relationship. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent variable is normalised by the NAV of each fund at the beginning of the month. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

Dependent variable: investor flows in month t								
Global EME local currency government bond funds								
Exp. variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FR_t	0.184	0.536***	0.144	0.493***				
	(1.29)	(3.88)	(1.02)	(4.37)				
Max{0,FR_t}		–0.550***		–0.512***				
		(–4.12)		(–5.17)				
Δlog(VIX_t)			–1.707	–0.816				
			(–0.99)	(–0.51)				
FR_{t-1}					0.293**	0.516***	0.210	0.361**
					(2.15)	(4.50)	(1.62)	(2.46)
Max{0,FR_{t-1}}						–0.352		–0.223
						(–1.32)		(–0.84)
Δlog(VIX_{t-1})							–3.285**	–2.900*
							(–2.23)	(–1.91)
N	15	15	15	15	15	15	15	15
N x T	630	630	630	630	615	615	615	615
R^2	0.054	0.060	0.055	0.060	0.067	0.070	0.073	0.074
Global EME corporate bond funds								
Exp. variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FR_t	0.516**	0.967**	0.526**	0.981**				
	(3.22)	(3.31)	(2.71)	(3.28)				
Max{0,FR_t}		–0.858		–0.859				
		(–1.25)		(–1.25)				
Δlog(VIX_t)			0.172	0.224				
			(0.16)	(0.21)				
FR_{t-1}					0.627***	0.343**	0.678***	0.396**
					(4.05)	(2.76)	(4.20)	(3.09)
Max{0,FR_{t-1}}						0.542		0.538
						(1.91)		(1.86)
Δlog(VIX_{t-1})							0.853	0.830
							(1.13)	(1.09)
N	6	6	6	6	6	6	6	6
N x T	252	252	252	252	246	246	246	246
R^2	0.118	0.125	0.118	0.125	0.141	0.144	0.142	0.145

Table A1. Panel regressions of discretionary purchases on flow-driven purchases or investor flows when investor flows are positive. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent and explanatory variables are normalised by the NAV of each fund at the beginning of the month, except the VIX variable. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

	Global DM bond funds		Global EME international government bond funds		Global EME local currency government bond funds		Global EME corporate bond funds	
Dependent variable: discretionary purchases in month t								
Exp. variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Flow-driven purchases in t	0.021		0.112		0.025		0.089***	
	(1.76)		(1.76)		(1.38)		(6.42)	
Total investor flows in t		0.008		0.011		0.012		0.060***
		(0.50)		(0.36)		(1.44)		(8.31)
$\Delta\log(VIX_t)$	-1.044	-1.086	-0.588	-0.795	-0.594	-0.713	0.947*	0.834
	(-1.18)	(-1.23)	(-0.56)	(-0.75)	(-0.92)	(-1.10)	(2.18)	(1.90)
N	8	8	13	13	15	15	6	6
N x T	151	151	205	205	228	228	90	90
R^2	0.050	0.045	0.059	0.039	0.119	0.110	0.112	0.078

Table A2. Panel regressions of discretionary purchases on investor-driven purchases or investor flows when investor flows are negative. Coefficients on each of the explanatory variables from panel regressions with fund fixed effect. Dependent and explanatory variables are normalised by the NAV of each fund at the beginning of the month, except the VIX variable. t-statistics in brackets are calculated from standard errors clustered at the fund level. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively. Source: EPFR.

	Global DM bond funds		Global EME international government bond funds		Global EME local currency government bond funds		Global EME corporate bond funds	
Dependent variable: discretionary purchases in month t								
Exp. variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Flow-driven purchases in t	0.126***		0.071		0.119**		0.116**	
	(3.51)		(1.74)		(2.26)		(2.74)	
Total investor flows in t		0.081**		0.019		0.060		0.006
		(3.17)		(0.65)		(1.70)		(0.11)
$\Delta\log(VIX_t)$	0.788	0.651	0.247	0.178	-1.405*	-1.377*	0.270	0.041
	(0.83)	(0.66)	(0.31)	(0.23)	(-1.82)	(-1.78)	(0.56)	(0.08)
N	8	8	13	13	15	15	6	6
N x T	185	185	339	339	402	402	159	159
R^2	0.052	0.033	0.120	0.097	0.079	0.055	0.070	0.050

Table A3. Average monthly volatility of representative benchmark indexes. The average value of monthly volatility calculated by daily total returns within the month. Source: JPMorgan Chase.

	GBI Global local currency	GBI Global USD	EMBI Global USD	GBI-EM Global USD	CEMBI Broad USD
Positive returns	0.158	0.348	0.278	0.640	0.146
Negative returns	0.193	0.352	0.345	0.616	0.210

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