Redemption risk and procyclical 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 response to 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 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.

JEL codes. E52, EG11, G15, G23.

Keywords. asset manager, bond market liquidity, cash hoarding, global game, investor redemption, strategic complementarity.

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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 liquidity regulation of the asset management sector have focused discussions on 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 related issues have come to the fore in discussions of open-end mutual funds and their role in episodes 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) and Chen, Goldstein and Jiang (2010)). Financial Stability Board (2016) recently identified liquidity mismatch between fund investments and redemption terms and conditions for open-end fund units as one of the main structural vulnerabilities associated with asset management activities that pose potential financial stability risks.

The second, related, issue is the possibility of fire sales of assets that may interact with the redemption pressures arising from investor runs.[2] Here, the portfolio decision of the asset managers themselves is key. If asset managers use their cash holding as a buffer to meet investor redemptions, they can mitigate fire sales of the underlying assets (Chernenko and Sunderam (2016)). 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.

However, if the asset managers attempt to anticipate the redemptions of the investors and attempt to *increase* their cash holdings in the face of investor redemptions, they will

[1] See 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.

[2] Financial Stability Board (2015) points out asset liquidation / market channel as a potential source of systemic risk stemming from investment funds. This channel describes the impact of distress or liquidation of an investment fund on other market participants through asset sales that negatively impact market prices and, in turn, the market value of other participants' financial positions.

need to sell more of the underlying assets than is necessary to meet investor redemption demands. Their actions will tend to amplify the fire sale of the underlying assets, and exacerbate market disruptions arising from investor redemptions.

Our paper addresses this question of the cash holding decision of asset managers. We first present a global game analysis of investor runs to set the stage for our empirical investigation. We identify conditions under which cash serves the role of a buffer in the global game, and thereby stabilise the market, and identify the conditions under which cash hoarding takes place, thereby amplifying fire sales.

We proceed to 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 bond mutual funds to ascertain whether the portfolio decision of the asset managers conform 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 result 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 amplify the 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. One tell-tale sign of such behaviour 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.

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 positive association between investor-driven purchases and discretionary purchases.

Our results shed light on the financial stability implications of fire sales associated with open-end mutual funds. Although asset managers typically do not employ much leverage, if at all, asset fire sales and cash hoarding inject an important element of procyclicality, akin to the procyclicality that is associated with leverage.

The focus of our paper is on the sales and purchases associated with a single fund with a large number of small investors. If there are strategic incentives *between* funds, the procyclicality associated with asset managers can be seen to be that much greater. Feroli et al (2014) and Morris and Shin (2016) examine models of “market runs” where the short horizon behaviour of asset managers may inject an additional element of fire sale externalities in that, when other asset managers sell and market prices come under pressure, an individual asset manager may be tempted to join the selling spree. We do not examine this dimension of fire sales in this paper, but this added dimension will be relevant if the decision horizon of asset managers is shortened due to short-term assessment of performance.

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 so that the fund has undertaken discretionary sales by 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 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.

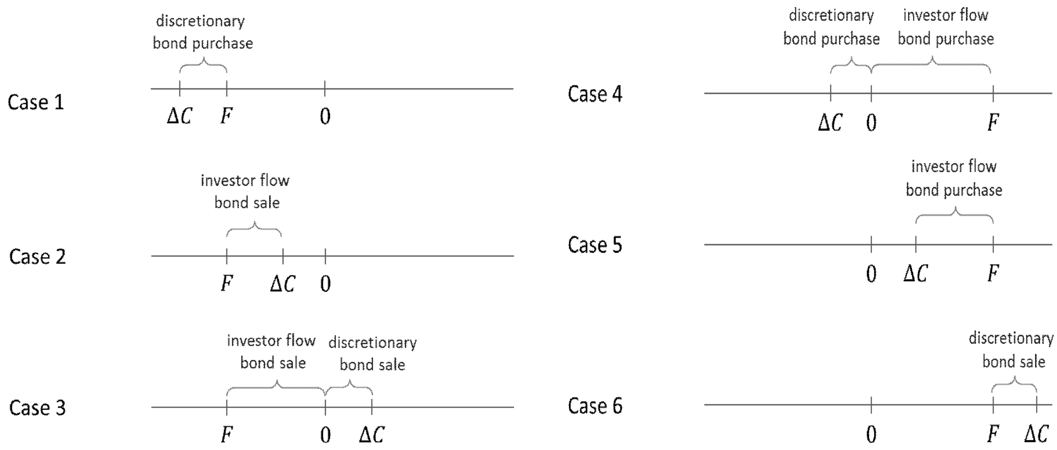

Figure 1. Identifying cash hoarding by bond mutual fund managers

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, where 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 cash de-stocking by fund managers. Using all new inflows, the fund manager buys bonds. In addition, the fund manager buys more bonds than he purchases from new inflows and decreases cash holdings. Case 5 has investor inflows, and inflows are used partly to increase cash and partly to buy bonds, where 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 also find that Case 3 (discretionary sales in the middle of investor redemptions) is the most common of all cases for each group of funds.

When we implement our definitions, one practical complication arises from the fact

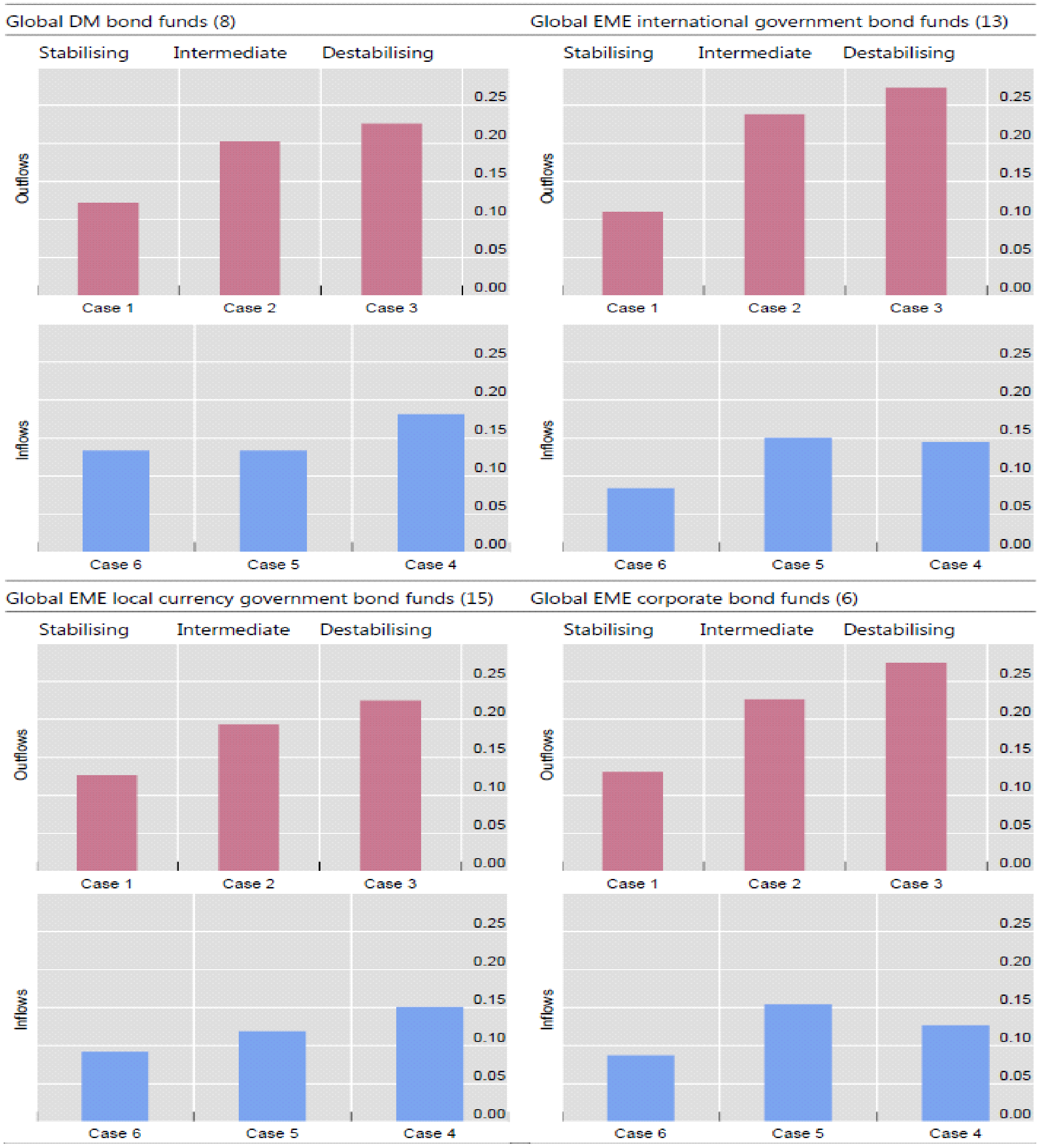

Figure 2. Frequency of stabilising/destabilising sales for four groups of bond funds. Sources: EPFR; authors' calculations.

that we observe snapshots of our variables only at the end of each time interval, whereas investor flows happen continuously throughout the time interval. Similarly, the fund could sell or buy at any time during the interval of time, but we would only observe snapshots of portfolio holdings at the end of the time interval. This mismatch between observations in the data series and the underlying decisions becomes worse in practice, because the portfolio information we need is available only at the monthly frequency.

To overcome these data limitations, we proceed in two steps. First, we consider a benchmark case where all purchases and sales of bonds happen at the end of the month in frictionless competitive markets at prices reported at the end of the month. Any payments to investors of the proceeds of sales are also made at the end of the month following the sales. Meanwhile, any inflows from investors during the month are kept as cash balances until the end of the month when the investors' purchase orders are executed at the end-of-month prices.

We then take note of the net asset value (NAV) of the fund under this benchmark scenario. In practice, the observed NAV will deviate from this hypothetical NAV of the benchmark scenario due to departures from the assumptions of the benchmark scenario. For instance, investor flows will lead to purchases or sales during the month at prices other than the prices ruling at the end of the month. There may also be fire sale discounts when large quantities are sold in distressed episodes in the market.

The second step in our procedure is to take note of the discrepancy between the hypothetical NAV that comes from the benchmark scenario and the observed NAV, and define a residual term that reconciles the hypothetical numbers with the observed numbers. We then keep track of the residual term, which holds interest in its own right, as it gives us a measure of the market liquidity frictions.

Under this decomposition, one gauge of the degree or procyclicality of the bond fund managers is *how much* discretionary sales take place, as a proportion of investor-driven sales. Figure 3 plots a bar chart showing six components of the change in total net assets (TNA) of 15 global EME local currency government bond funds. It shows that in most months during the sample period, redemption-driven sales and discretionary sales reinforce each other, that currency return against the US dollar and local currency bond returns mostly move in the same direction, that two types of sales, currency returns and local currency bond returns are often all in the same direction, and that the total amount of bond sales and the residual (potentially capturing valuation gains or fire sale losses) often go hand in hand. The appendix shows three bar charts for 8 global bond funds (mainly investing in developed market (DM) bonds), 13 global EME international

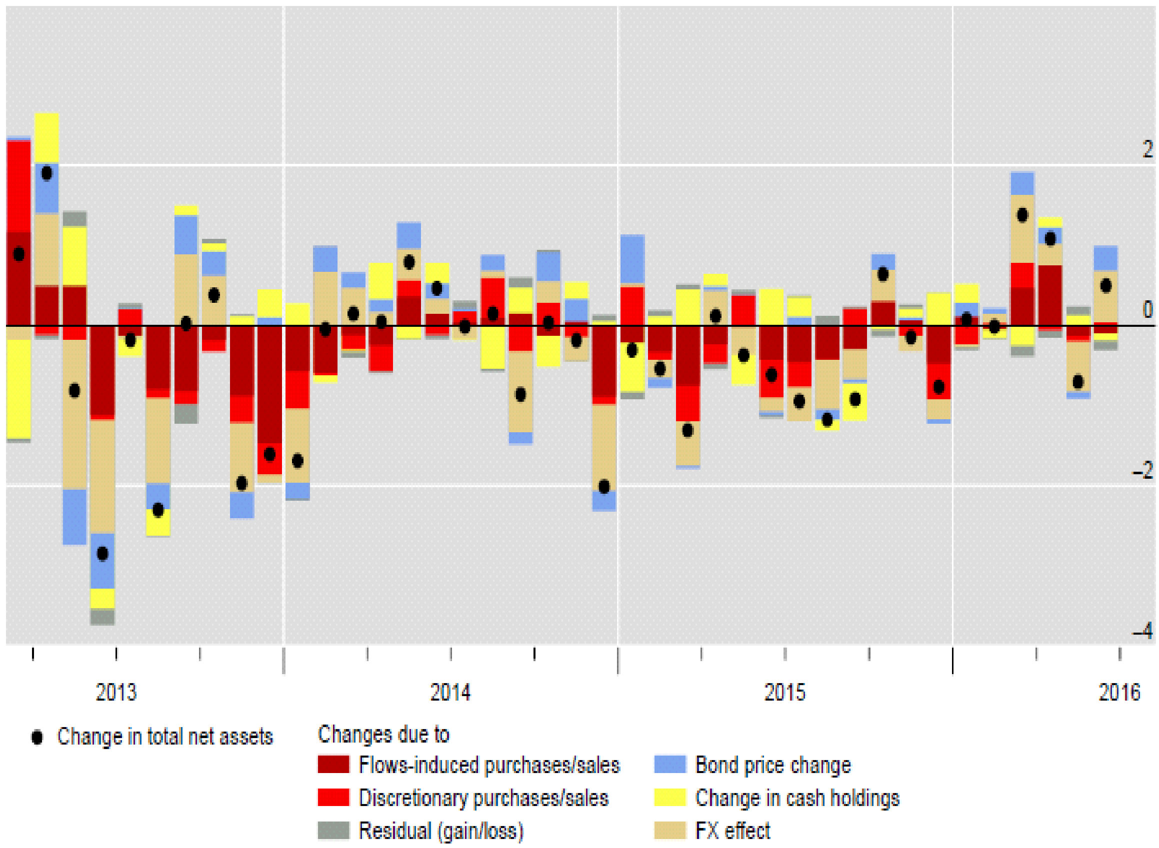

Figure 3. Breakdown of monthly changes in total net assets for 15 global EME local currency bond funds (in billions of US dollars). Sources: EPFR; authors' calculations.

government bond funds and 6 global EME corporate bond funds, respectively. They also show similar relationships among two kinds of sales, bond returns and the residual.

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. Indeed, 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 (Goldstein, Jiang and Ng (2016)).

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. The fund manager will foresee these effects, and greater discretionary sales would then be a prudent response to anticipated redemptions. 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.[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 but in a slightly different way, 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 increases or decreases in cash holdings, respectively. Among the new 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 behaviour since fund managers buy or sell bonds in $t-1$ in anticipation of investor redemptions or net inflows in t, respectively.

Figure 4 plots the frequency of each of the new six cases. 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 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 are. Understanding the joint determination of investor redemptions and fund managers' portfolio adjustment is one aim of our paper. Financial Stability Board (2015) states that investors of open-end funds could have an incentive to redeem before other investors to avoid sharing the costs associated with other investors' redemptions, particularly for funds investing in less liquid asset classes.

[3] We can also consider strategic incentives among fund managers underlying fund manager sales and cash hoarding.

Figure 4. Frequency of stabilising/destabilising discretionary purchases/sales in month $t-1$ for investor inflows/outflows in month t. Sources: EPFR; authors' calculations.

3 Theory of fund manager discretionary sales

We hone our insights by using a global game model of redemptions, and then examine separately 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 is 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-form version of the theoretical model of investment funds in Chen, Goldstein and Jiang (2010). We add the ingredient of asset managers who make a cash hoarding decision in anticipation of redemptions. We follow Zeng (2016) in modelling the interaction of the liquidity management decisions of asset managers with investor runs. In contrast to Zeng (2016), our model is set in a simplified static context, to allow for closed-form expressions.

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. However, all investors receive a noisy signal of r at date 1. Investor i observes signal ρ_i of the return r given by

$$\rho_i = r + s_i \tag{1}$$

where s_i is a uniformly distributed noise term, with realisation in $[-\varepsilon, \varepsilon]$ for constant $\varepsilon > 0$. The noise terms $\{s_i\}$ are independent across individuals.

The investors fall under 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:

$$\rho_i \longmapsto \{\text{Hold, Sell}\} \tag{2}$$

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_i. If the fund manager liquidates before redemptions (ex-ante liquidation), he faces a fire sale haircut of δ; if he liquidates afterwards (ex-post liquidation), he faces a fire sale haircut of μ. Thus, when the 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

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

The fund manager and investors choose their actions simultaneously. For the investors, a collection of strategies (one for each investor) is an *equilibrium* if the action prescribed by i's strategy maximises i's expected payoff at every realisation of signal ρ_i given the others' strategies. We solve for an equilibrium in switching strategies of the form:

$$\begin{cases} \text{Sell} & \text{if } \rho > \rho^* \\ \text{Hold} & \text{if } \rho \leq \rho^* \end{cases} \tag{3}$$

for some threshold value ρ^*.

Denote by X the mass of investors who sell at date 1, 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 secures cash of Y through ex-ante liquidation, then the additional ex-post liquidation costs resulting from redemptions of X are given by $\mu [X - Y]_+$. Thus, the return of the investor who stays invested when mass X of investors sell is

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

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 are x and 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.

3.1.1 Laplacian principle for beliefs

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

$$\rho_i = r + s_i \tag{5}$$

where s_i is a uniformly distributed noise term, with realisation in $[-\varepsilon, \varepsilon]$ for constant $\varepsilon > 0$. The noise terms $\{s_i\}$ are independent across individual investors. 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 5.

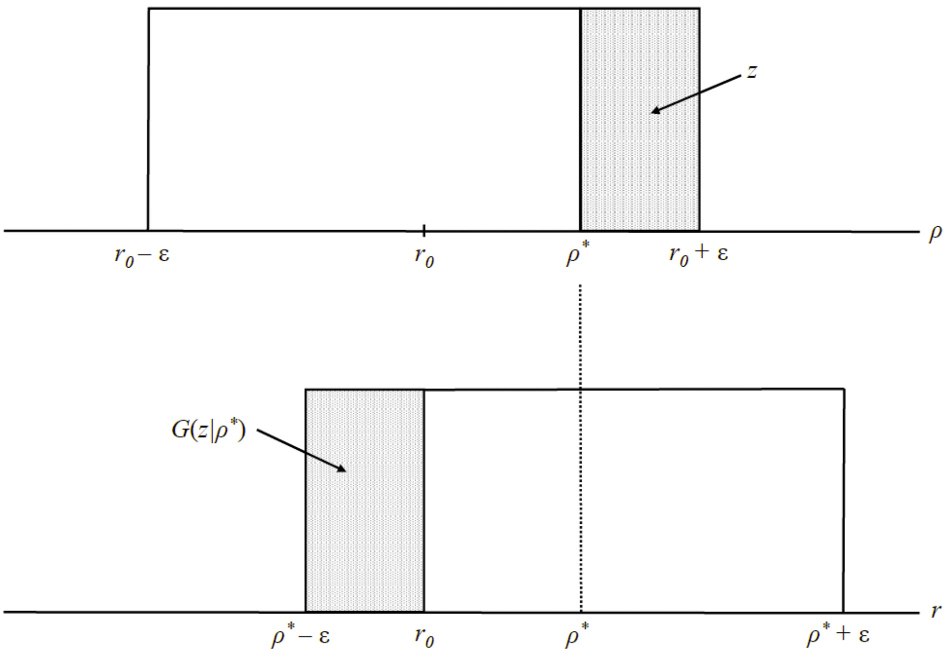

Figure 5. Deriving the subjective distribution over x at switching point ρ^*

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

$$x = \frac{r + \varepsilon - \rho^*}{2\varepsilon}. \tag{6}$$

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

$$\frac{r_0 + \varepsilon - \rho^*}{2\varepsilon} = z \tag{7}$$

or

$$r_0 = \rho^* - \varepsilon + 2\varepsilon z. \tag{8}$$

See the top panel of Figure 5. 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 player i's posterior density over r conditional on ρ^*. This posterior density is uniform over the interval $[\rho^* - \varepsilon, \rho^* + \varepsilon]$, as in the lower panel of Figure 5. 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

$$\begin{aligned}
& \frac{r_0 - (\rho^* - \varepsilon)}{2\varepsilon} \\
= & \frac{(\rho^* - \varepsilon + 2\varepsilon z) - (\rho^* - \varepsilon)}{2\varepsilon} \\
= & z \qquad (9)
\end{aligned}$$

where the second line follows from substituting in (8). Thus, the probability that $x < z$ conditional on ρ^* is exactly z. The conditional c.d.f. $G(z|\rho^*)$ is the identity function:

$$G(z|\rho^*) = z. \qquad (10)$$

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

Note also that the uniform density over x does not depend on the value of ε, and this is also true in the limit as $\varepsilon \to 0$. However, we do not invoke this limiting result in our game, and we make essential use of the uncertainty faced by investors and the fund manager in the game about the underlying fundamentals.

3.1.2 Threshold for investor runs

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

$$\int_0^1 \frac{(1-\delta Y) - (1+\mu)[xA - Y]_+}{1 - xA} dx \cdot r \qquad (11)$$

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

$$\int_0^1 \frac{(1-\delta Y) - (1+\mu)[xA - Y]_+}{1 - xA} dx \cdot \rho^* = 1. \qquad (12)$$

Equation (12) 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 (12) 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 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).

3.2 Fund manager's cash hoarding decision

We now turn to the fund manager's cash holding decision, and solve separately for the optimal pre-emptive selling of assets when the distribution of investor redemptions is exogenous.

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 in this case will be

$$\begin{aligned} \frac{1}{\sigma} \int_{X=\overline{X}-\frac{1}{2}\sigma}^{\overline{X}+\frac{1}{2}\sigma} \left(\delta Y + \mu \left[X - Y\right]_+\right) dX &= \delta Y + \frac{\mu}{\sigma} \int_{X=Y}^{\overline{X}+\frac{1}{2}\sigma} \left[X - Y\right] dX \\ &= \delta Y + \frac{\mu}{2\sigma} \left(\overline{X} + \frac{1}{2}\sigma - Y\right)^2 . \end{aligned} \tag{13}$$

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

$$Y^* = \begin{cases} \overline{X} - \frac{1}{2}\sigma, \text{ if } \mu < \delta \\ \overline{X} + \left(\frac{1}{2} - \frac{\delta}{\mu}\right)\sigma, \text{ if } \mu \geq \delta. \end{cases} \tag{14}$$

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 asset manager cash holding, in particular whether the cash holding serves as a buffer against redemptions or whether the asset 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 asset 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 mostly 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.

- Bond funds investing globally in both developed market bonds and EME bonds using global bond indexes as benchmarks. Since these bond funds invest predominantly in developed market sovereign bonds, we call them global DM bond funds.
- 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.
- Bond funds mainly investing globally in EME sovereign bonds denominated in their local currencies. We call them global EME local currency government bond funds.
- 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. We call them global EME corporate bond funds.

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

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

[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.

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 Tables 10 and 11 in the appendix. The number of economies in which these funds invested a positive amount during the sample period as well as those in the specific benchmarks used to approximate the country-level bond return are summarised in Table 12 in the appendix.

4.2 Decomposing changes in net asset value

We first calculate the six components of the monthly change in total net assets by using the decomposition described in Section 2.

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 1 shows the results for global DM bond funds and global EME international government bond funds, while Table 2 shows the results for global EME local currency government bond funds and global EME corporate bond funds. Table 3 provides a summary of the main findings across the four groups of funds.

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

Table 1. **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 10, 5 and 1 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
Adjusted R^2	−0.009	−0.012	−0.007	−0.010	−0.018	−0.019
Global EME international government bond funds						
	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.074***	0.076***	0.074*	0.075*		
(FP_t)	(3.18)	(3.35)	(1.99)	(2.05)		
Max{0, FP_t}			0.000	0.001		
			(0.00)	(0.02)		
Total investor flows in month t					0.026	0.033
(TF_t)					(1.25)	(0.96)
Max{0, TF_t}						−0.016
						(−0.36)
$\Delta\log(VIX_t)$		−0.026		−0.026	−0.008	−0.008
		(−0.47)		(−0.47)	(−0.13)	(−0.13)
N	13	13	13	13	13	13
N x T	546	546	546	546	546	546
Adjusted R^2	0.036	0.034	0.034	0.032	0.011	0.009

Table 2. **Panel regressions of discretionary purchases on investor-driven purchases (or investor flows) in the current month (continued).** 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 10, 5 and 1 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	0.060	0.132**	0.130**		
(FP_t)	(1.69)	(1.68)	(2.47)	(2.50)		
Max{0, FP_t}			−0.106*	−0.105*		
			(−1.98)	(−1.99)		
Total investor flows in month t					0.041*	0.080**
(TF_t)					(1.77)	(2.29)
Max{0, TF_t}						−0.062
						(−1.64)
$\Delta\log(VIX_t)$		0.034		0.032	0.037	0.035
		(1.37)		(1.40)	(1.38)	(1.41)
N	15	15	15	15	15	15
N x T	630	630	630	630	630	630
Adjusted R^2	0.015	0.034	0.034	0.032	0.011	0.009
Global EME corporate bond funds						
	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.095**	0.092**	0.106*	0.101*		
(FP_t)	(2.68)	(2.73)	(2.21)	(2.08)		
Max{0, FP_t}			−0.017	−0.013		
			(−0.35)	(−0.25)		
Total investor flows					0.058**	0.020
(TF_t)					(2.68)	(0.66)
Max{0, TF_t}						0.055
						(0.86)
$\Delta\log(VIX_t)$		0.040		0.039	0.049	0.055
		(0.40)		(0.38)	(0.46)	(0.52)
N	6	6	6	6	6	6
N x T	252	252	252	252	252	252
Adjusted R^2	0.036	0.034	0.034	0.032	0.011	0.009

Table 3. **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 10, 5 and 1 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								
Explanatory variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Flow-driven purchases in month t	0.030**		0.076***		0.060		0.092**	
	(3.33)		(3.35)		(1.68)		(2.73)	
Total investor flows in month t		0.014**		0.026		0.041*		0.058**
		(2.56)		(1.25)		(1.77)		(2.68)
$\Delta\log(VIX_t)$	−0.113	−0.159	−0.026	−0.008	0.034	0.037	0.040	0.049
	(−0.17)	(−0.24)	(−0.47)	(−0.13)	(1.37)	(1.38)	(0.40)	(0.46)
N	8	8	13	13	15	15	6	6
N x T	336	336	546	546	630	630	252	252
Adjusted R^2	−0.012	−0.018	0.034	0.011	0.034	0.011	0.034	0.011
Dependent variable: discretionary purchases in the previous month								
Explanatory variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Flow-driven purchases in month t	0.003		0.001		0.004		0.029	
	(0.21)		(0.09)		(0.35)		(1.56)	
Total investor flows in month t		0.016		0.018		0.024		0.055**
		(1.63)		(1.38)		(0.98)		(3.64)
$\Delta\log(VIX_{t-1})$	0.021	0.020	0.005	−0.003	0.046	0.040	0.061	0.043
	(0.75)	(0.72)	(0.08)	(−0.04)	(1.42)	(1.31)	(0.56)	(0.40)
N	8	8	13	13	15	15	6	6
N x T	328	328	533	533	615	615	246	246
Adjusted R^2	−0.015	−0.013	0.006	0.008	−0.014	−0.009	−0.011	0.002

Table 4. **Correlations between investor flows and discretionary purchases.** Source: EPFR.

Fund type	Average correlation between total investor flows in t and discretionary purchases in t	Average correlation between total investor flows in t and discretionary purchases in $t-1$	Average correlation between flow-driven purchases in t and discretionary purchases in t	Average correlation between flow-driven purchases in t and 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

- 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 4 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 1 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 discretionary sales are larger than the discretionary purchases.

In Table 1, we also see the results for global EME international government bond funds. Columns (1) and (2) show that the coefficient jumps to around 0.08, indicating that there are 8 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 2 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 those examined in Table 1.

Table 2 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 -0.1, so that the 13 dollar number only holds for sales. For discretionary purchases, the figure is close to the 3 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 2 show that the coefficient on investor flow-driven sales is again around 0.1, 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 into one table in Table 3. Taken together, we find that the coefficients on contemporaneous investor-driven purchases or investor flows are always positive and overall statistically significant.

Table 3 also summarises results obtained when we use investor flow-driven purchases from the following month. The full tables are given in the Appendix. 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 or investor flows are positive and statistically significant for global EME corporate bond funds, and that the coefficients on the next month's investor flows are positive for all the other three types of fund but statistically insignificant.

Table 3 also shows similar results: the coefficient on the current month' or the next month's investor-driven purchases or investor flows is smallest for global DM bond funds and global EME international bond funds, largest for EME local currency bond funds, and in between for EME corporate bond funds. Appendix Tables 8 and 9 show full regression results from the regression of discretionary purchases in month $t-1$ on flow-driven purchases in month t or investor flows in month t. They show that less liquid funds have larger coefficients on investor flows than more liquid ones such as global DM bond funds, although only the coefficient on investor flows for EM corporate bond funds is significant. For global EME corporate bond funds, we also find some asymmetry between flow-driven purchase and sales. In particular, the coefficients on bond sales are significantly smaller than those on bond purchases.

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 funds 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 5 shows the results for global DM bond funds and EME international government bond funds, while Table 6 shows the results for EME local currency bond funds and EME corporate bond funds. Table 7 provides a summary of the main findings across the four groups of funds.

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 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 funds for which we have complete investor flows data from January 2013 to June 2016. The degree of investor clustering (that is,

Table 5. **Panel regressions for the flow-performance relationship.** 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 10, 5 and 1 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
Adjusted R^2	0.005	0.002	0.005	0.002	0.013	0.012	0.013	0.013
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
Adjusted R^2	0.088	0.087	0.095	0.094	0.073	0.073	0.072	0.071

Table 6. **Panel regressions for the flow-performance relationship (continued).** 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 10, 5 and 1 percent level, respectively. Source: EPFR.

Dependent variable: Investor flows in month t								
Global EME local currency 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)				
$\Delta\log(VIX_t)$			−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)
$\Delta\log(VIX_{t-1})$							−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
Adjusted R^2	0.031	0.036	0.031	0.034	0.044	0.045	0.049	0.048
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)				
$\Delta\log(VIX_t)$			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)
$\Delta\log(VIX_{t-1})$							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
Adjusted R^2	0.096	0.100	0.092	0.096	0.119	0.119	0.117	0.116

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 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 10, 5 and 1 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
Adjusted R^2	0.002	0.013	0.094	0.071	0.034	0.048	0.096	0.116

directional co-movement of investor flows across funds) in each month can be measured by the following three indicators:[6]

- The share 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 fund 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. 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.

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 and that global DM bond funds experience less investor clustering than global EM bond funds.

6 Concluding remarks

We have found that cash hoarding is the rule rather than the exception for bond mutual funds. Just as the procyclical leverage decision of banks tends to amplify the credit cycle,

[6] Other possible methods to measure the cross-sectional co-movement of investor flows across funds include using the first principal component over the fund-level flows or calculating the average of pairwise correlations across funds. The three measures described here focuses on the directional movement (that is, inflow vs outflow).

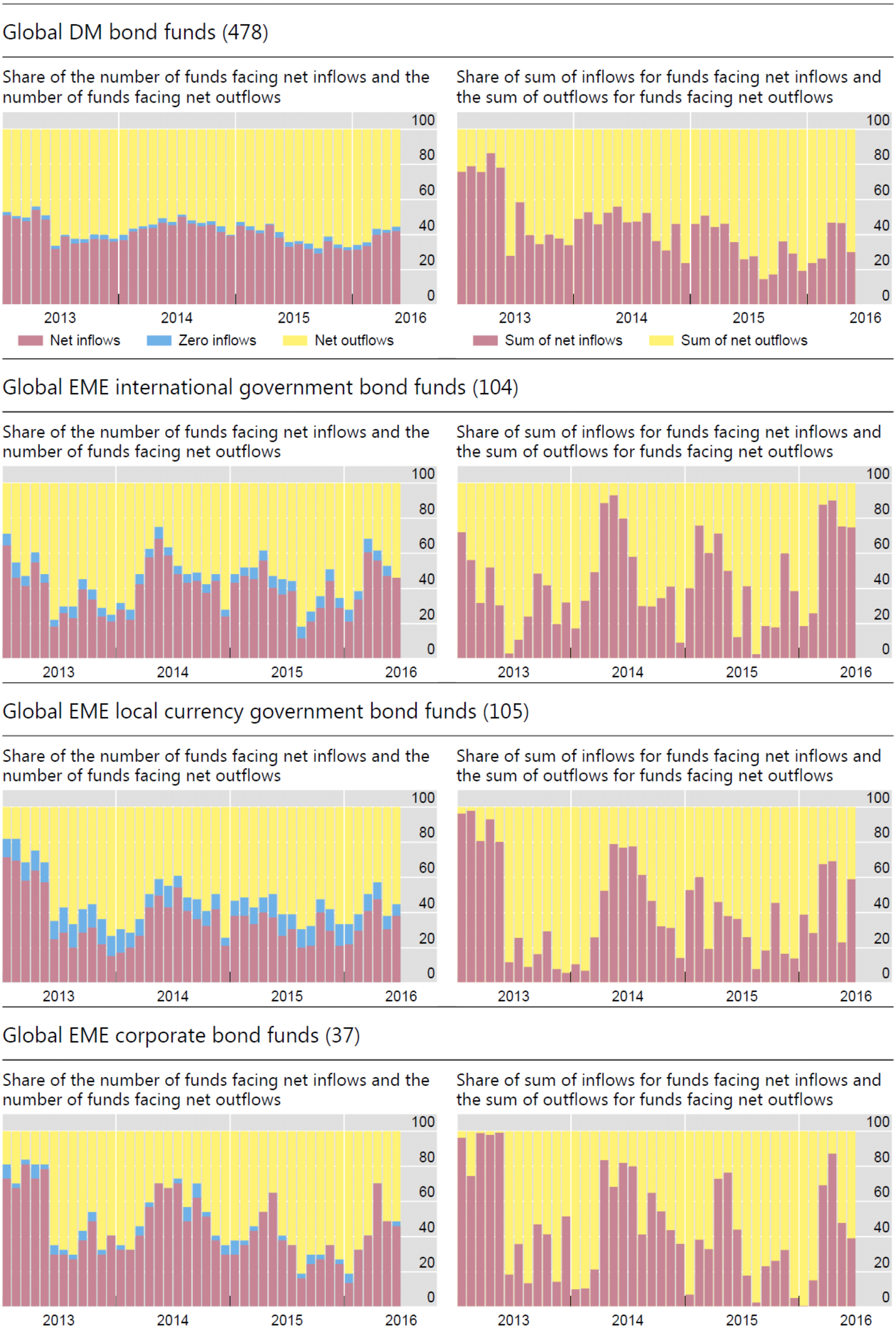

Figure 6. Investor clustering. The figures in parentheses represent the number of bond funds in each category. Source: EPFR.

the procyclical cash hoarding choices of bond fund managers have the potential to amplify fire sales associated with investor redemptions. We have seen in our global game model of investor runs that fund managers' actions to anticipate investor runs by pre-emptively liquidating assets can serve to amplify the market movement further.

We have further found that the incidence of cash hoarding is more severe for those funds that hold more illiquid classes of bonds.

There is ongoing discussion of the welfare effects of liquidity rules on the asset management sector, such as the ones proposed by the SEC and Financial Stability Board. Financial Stability Board (2016) recommends that when authorities require or provide guidance on funds' liquidity risk management, they should take into account the expected liquidity of the assets and investor behaviour during normal and stressed market conditions. It also recommends that authorities should require and/or provide guidance on stress testing at the level of individual open-end funds to support liquidity risk management to mitigate financial stability risk. In the context of market liquidity, Financial Stability Board (2016) also recommend authorities to consider system-wide stress testing capturing the effects of collective selling by funds and other institutional investors on the resilience of financial markets and the financial system more generally. In both firm-level and system-wide stress testing exercises, the stress scenario would need to include the possibility of cash hoarding behaviour and procyclical bond sales by fund managers. Our findings are relevant for this ongoing discussion.

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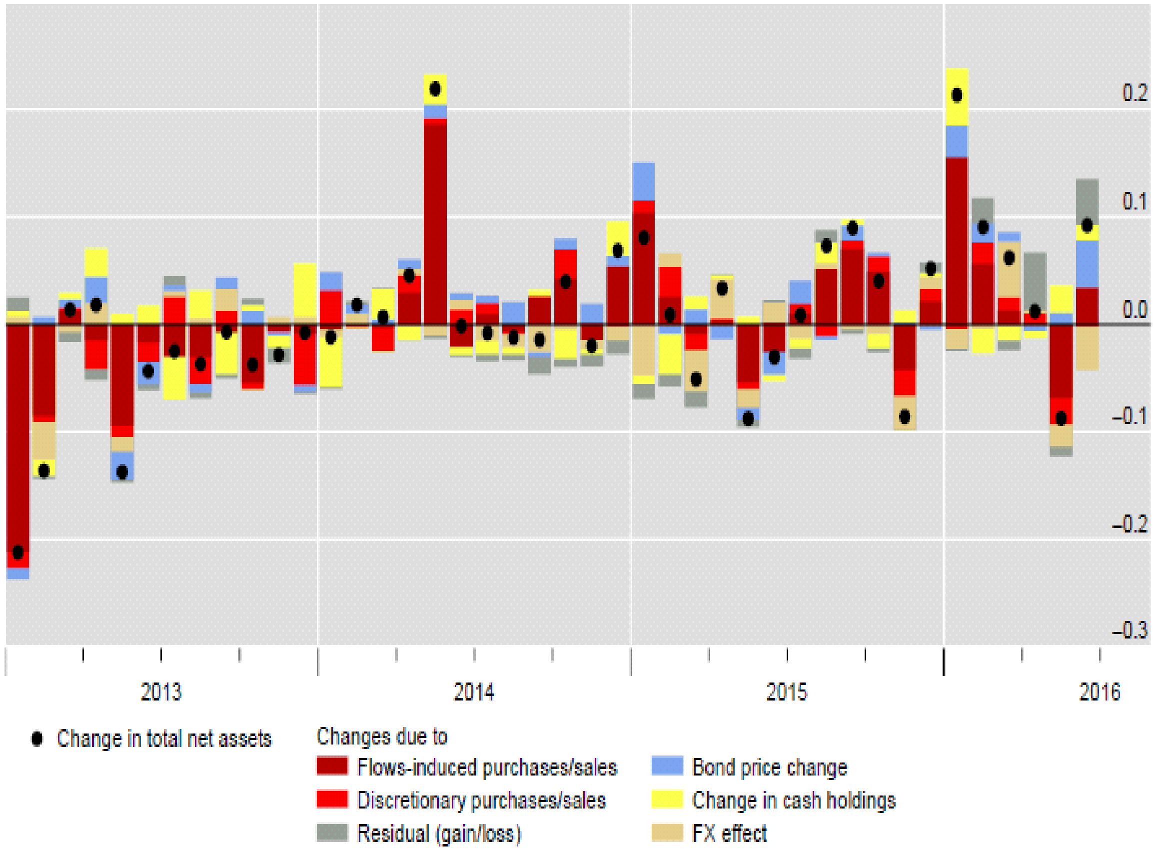
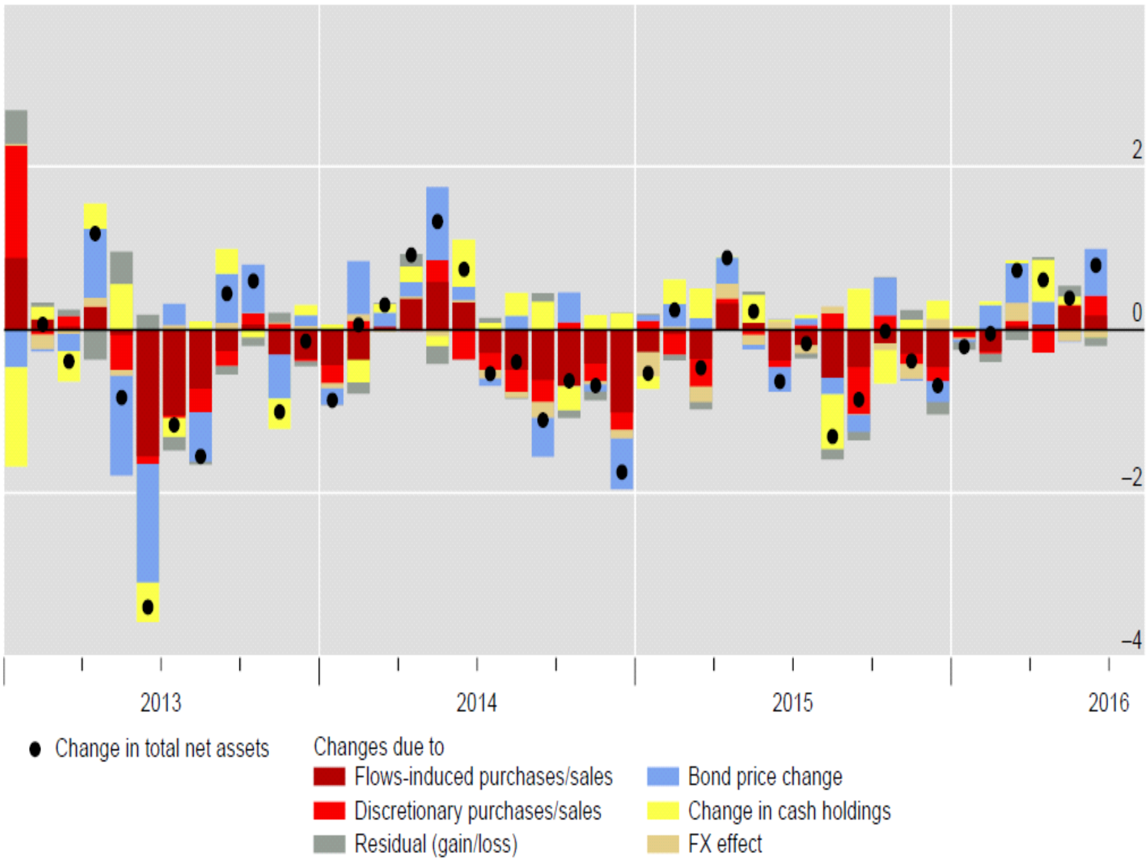
Appendix



Appendix Graph 1. Breakdown of monthly changes in total net assets for six global DM bond funds (in billions of US dollars).

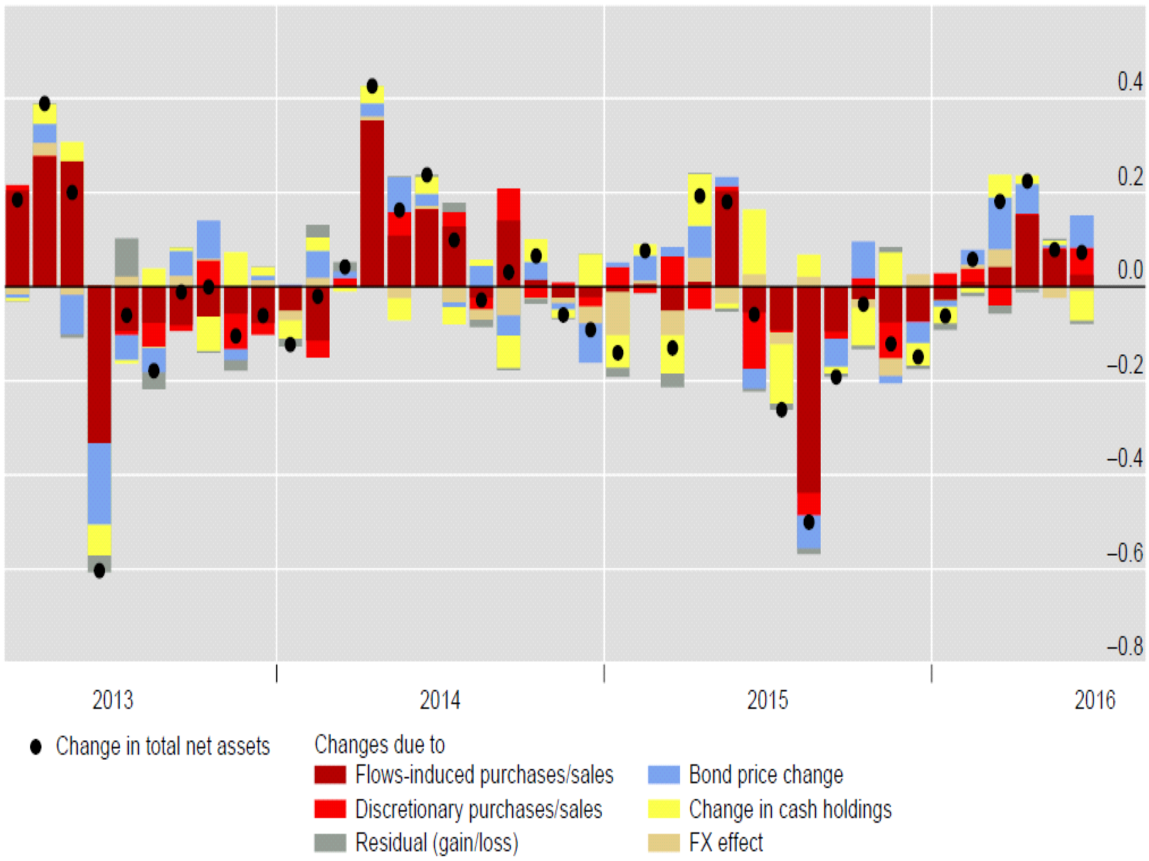
Among the eight global DM bond funds, this graph does not include two Schroder global bond funds which experienced a large one-off institutional inflows in May 2014.

Sources: EPFR; authors' calculations.



Appendix Graph 2. Breakdown of monthly changes in total net assets for 13 global EME international government bond funds (in billions of US dollars).

Sources: EPFR; authors' calculations.



Appendix Graph 3. Breakdown of monthly changes in total net assets for six global EME corporate bond funds (in billions of US dollars).

Sources: EPFR; authors' calculations.

Table 8. **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 10, 5 and 1 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)	(0.21)	(−0.34)	(−0.32)		
Max{0, FP_t}			0.016	0.015		
			(0.51)	(0.48)		
Total investor flows in month t					0.016	0.029
(TF_t)					(1.63)	(0.84)
Max{0, TF_t}						−0.016
						(−0.52)
$\Delta\log(VIX_{t-1})$		0.021		0.020	0.020	0.020
		(0.75)		(0.71)	(0.72)	(0.77)
N	8	8	8	8	8	8
N x T	328	328	328	328	328	328
Adjusted R^2	−0.012	−0.015	−0.015	−0.018	−0.013	−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	0.005		
(FP_t)	(0.11)	(0.09)	(0.21)	(0.19)		
Max{0, FP_t}			−0.010	−0.010		
			(−0.28)	(−0.26)		
Total investor flows					0.018	0.021
(TF_t)					(1.38)	(0.93)
Max{0, TF_t}						−0.008
						(−0.26)
$\Delta\log(VIX_{t-1})$		0.005		0.004	−0.003	−0.003
		(0.08)		(0.06)	(−0.04)	(−0.05)
N	13	13	13	13	13	13
N x T	533	533	533	533	533	533
Adjusted R^2	0.008	0.006	0.006	0.005	0.008	0.007

Table 9. **Panel regressions of discretionary purchases on investor-driven purchases (or investor flows) in the previous month (continued).** 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 10, 5 and 1 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	0.004	0.035	0.031		
(FP_t)	(0.49)	(0.35)	(0.95)	(0.90)		
Max{0, FP_t}			−0.043	−0.040		
			(−1.10)	(−1.08)		
Total investor flows in month t					0.024	0.088
(TF_t)					(0.98)	(1.47)
Max{0, TF_t}						−0.101
						(−1.55)
$\Delta\log(VIX_{t-1})$		0.046		0.043	0.040	0.035
		(1.42)		(1.44)	(1.31)	(1.25)
N	15	15	15	15	15	15
N x T	615	615	615	615	615	615
Adjusted R^2	−0.016	−0.014	−0.015	−0.014	−0.009	0.006
Global EME corporate bond funds						
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Flow-driven purchases in month t	0.035*	0.029	−0.007	−0.016		
(FP_t)	(2.19)	(1.56)	(−0.47)	(−0.61)		
Max{0, FP_t}			0.068**	0.071**		
			(2.88)	(2.65)		
Total investor flows					0.055**	0.049
(TF_t)					(3.64)	(1.02)
Max{0, TF_t}						0.009
						(0.15)
$\Delta\log(VIX_{t-1})$		0.061		0.064	0.043	0.043
		(0.56)		(0.59)	(0.40)	(0.40)
N	6	6	6	6	6	6
N x T	246	246	246	246	246	246
Adjusted R^2	−0.009	−0.011	−0.010	−0.011	0.002	−0.002

Table 10. **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 11. **List of 42 funds (continued).** 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 12. **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 EM 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 EM 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 EM 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)