The flow-performance relationship in emerging market bond funds

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Abstract

We investigate the relationship between net inflow to mutual bond funds that invest in emerging market economies (EMEs) and the past performance of these funds. Our main finding is that EME bond funds display a *convex* flow-performance relationship. In other words, past performance is a significant factor driving fund inflow when the fund return is positive but its influence vanishes when the return is negative. This convex flow-performance relationship is arguably attributable to practices taken by fund management companies to dampen fund investors' incentives to redeem in reaction to poor performance, bias of media coverage towards outperforming funds, and the relatively high participation costs of EME bond funds. Furthermore, we found that fund performance directly and indirectly affects fund flow. In particular, the performance of a volatile fund is typically less influential on its future fund flow. This can potentially be explained by investors' perception of the volatile return being less informative. We also found that a larger fund would generally record a higher sensitivity in its fund flow in response to a given change of past performance.

Keywords: mutual funds, bond funds, flow-performance relationship, mutual fund flows, convexity

EFM classification: 620

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1 Introduction

Mutual funds investing in emerging market economies (EME) bonds have grown tremendously since the 2007-08 global financial crisis (GFC). According to the EPFR Global, the assets under management (AUM) of actively managed, open-ended EME bond funds totalled US$382.1 billion at the end of 2016, marking a nearly five-fold expansion from US$80.3 billion at the end of 2009. Such an explosive growth is largely driven by the unprecedentedly low interest rate environment in major developed economies, which prompts investors to search for higher yields in EME markets (e.g. Ahmed & Zlate (2014)).[1] The fact that many EMEs are relatively more resilient despite the severe downturn of major developed economies in the aftermath of the GFC also drew the interest of global investors (e.g. Mishra et al. (2014), Ahmed et al. (2017)).[2]

As a result of the spectacular growth of EME bond funds, investors' subscription and redemption activities have increasingly become a crucial factor for the fluctuations of EME bond markets. For the purpose of financial stability surveillance, it is therefore important to understand what drives the behaviour of the investors in EME bond funds for two reasons. First, EME bond markets, in general, are relatively small, with a total size of around one-seventh of developed markets, and therefore lack the depth and liquidity to accommodate any unexpected surge in fund inflows or outflows.[3] Second, an increasing number of EME corporates, such as those in emerging Asia, have tapped the bond market to diversify their funding sources.[4] Therefore, any external disruption to the bond market would bring broader repercussions on the real economy than before.

The past performance of a mutual fund is unquestionably a key factor driving fund flows. According to a survey of the research literature by Christoffersen et al. (2014), it is well established by empirical

[1] Ahmed & Zlate (2014) found empirical evidence that net capital inflows to EMEs are influenced by interest rate differentials between EMEs and advanced economies.

[2] Mishra et al. (2014) found that EME countries with stronger macroeconomic fundamentals, deeper financial markets, and a tighter macro-prudential policy stance experienced smaller currency depreciations and smaller increases in government bond yields during the 2013 tapering episode. Ahmed et al. (2017) also found that the adverse effects of the 2013 tapering episode on financial markets were less severe for those EMEs with sounder economic fundamentals as measured by variables such as current account balance, foreign exchange reserves and government debt.

[3] According to the Bank for International Settlements, at end-2016 the total amount of international debt securities outstanding in EMEs was about US$2.1 trillion, only around one-seventh of that from the developed countries. The contrast in AUM is also stark. According to EPFR, the AUM of EME bond funds was about 8% of developed market bond funds as at the end of 2016.

[4] For the case of Hong Kong, see Leung et al. (2015).

studies that fund flows and fund performance display a positive relationship, which is intuitive. What remains unclear is whether such a relationship is broadly linear or displays some sort of asymmetry. There are two asymmetric cases that should arouse the concerns of policymakers. The first one is that poor performance leads to disproportionately large outflows, but good performance does not lead to similarly large inflows. This is known as a concave relationship. The second case is that good performance leads to disproportionately large inflows, but poor performance does not lead to similarly large outflows, and this is known as a convex relationship. Both cases have unfavourable implications for financial stability. In the first case, the effect of a negative shock would be amplified by elevated fund outflows, potentially leading to a vicious cycle. In extreme cases, this could result in a sudden stop of capital inflow, which is a classic syndrome of financial crisis in many EMEs in the past.[5] In the latter case, the effect of a positive shock would draw massive inflow, therefore heightening the risk of asset bubbles. Furthermore, as shown by Chevalier & Ellison (1997), a convex flow-performance relationship could potentially destabilise financial markets by incentivising excessive risk-taking of fund managers. This is because fund managers would benefit from a substantial inflow if their high-risk strategy works but do not suffer from substantial outflow if such a strategy ends up in adverse performance.

For equity mutual funds, previous studies have generally found a convex relationship between fund flows and fund performance. For example, in their study of US equity mutual funds, Sirri & Tufano (1998) found the best-performing funds in their sample drew disproportionately larger amounts of inflows than an average fund, but the worst-performing funds did not experience significantly larger outflows. However, only a few empirical studies have been conducted for bond funds, and the focus of these studies is on bond funds investing in developed markets. For example, Zhao (2003) found that US bond fund flows tend to be drawn by fund performance but the study did not go further to investigate the convexity of the flow-performance relationship. More recent studies take a look at the shape of this relationship but the results are quite mixed. Chen & Qin (2016) showed that, while US corporate bond fund flows are sensitive to fund performance, there is no evidence of a significant convexity in the flow-performance relationship. Their results are in contrast to Goldstein et al. (2017), which show that the

[5] According to Walutowy (1999), Indonesia, Korea, Malaysia, the Philippines and Thailand recorded a total net private capital outflow of US$22.1 billion during the Asian Financial Crisis in 1997, as compared with a net inflow of US$62.9 billion in the preceding year.

flow-performance relationship of US corporate bond funds exhibits a concave shape, which is primarily due to the lack of market liquidity of the assets held by the funds. In particular, they suggested that as corporate bonds are illiquid assets, funds would have to accept a larger discount in selling these assets when investors redeem their fund units. Since these extra costs would be borne by the remaining investors, the early batch of investors who redeemed their units would have first mover advantage over others. Such first mover advantages will motivate investors to withdraw their capital once market conditions deteriorate, leading to a concave flow-performance curve. Their theory is also supported by Morris et al. (2017), which, in a multi-period setting, found that fund managers of illiquid assets tend to sell the underlying assets by an amount *more* than strictly necessary to meet redemption orders so a cash buffer is built for future redemptions. Such cash hoarding behaviour could potentially amplify fire sales when investors redeem their units.

So far, to the best of our knowledge, no studies have been conducted to analyse the shape of flow-performance curves for EME bond funds.[6] To fill this important gap in the literature, this paper investigates the flow-performance relationship of the EME bond funds by quantifying the fund flow's sensitivity to past returns and exploring their policy implications. Our analysis is conducted at both the fund level and sector level. The fund-level analysis makes use of a panel data model that can better control for the heterogeneities across funds by including fund-specific variables and a cross-section fixed effect. The sector-level analysis investigates how broad market performance affects the aggregate fund flow to EME bond funds as a whole.

To preview our results, we find a convex flow-performance relationship for EME bond funds in fund-level analyses. Similarly, our sector-level analyses show past performance remains a significant factor in explaining aggregate fund inflow when the market return is positive, but its influence nearly vanishes when the return is negative. These results differ from the case of US corporate bond funds as found by Goldstein et al. (2017). Our results suggest that the measures taken by fund management companies (e.g. a large cash buffer, swing pricing) to contain fire sale risks might serve as powerful mechanisms to dampen the incentives of fund investors to redeem their funds in reaction to adverse performance. We

[6]While Morris et al. (2017) compared flow-performance relationship of bond funds with different degrees of liquidity (including EME bond funds) in the supplementary section, the shapes of the curves were left undiscussed.

also discuss other possible explanations for this convex relationship, such as the bias of media coverage towards out-performing funds, and the hurdle to fund investors due to the higher participation costs of EME bond funds.

Another key finding of our study that differs from previous ones lies in the indirect effect of fund performance. Our results suggest that fund performance directly and indirectly affects fund flow, with the indirect effect working through the channels of fund size and return volatility. In other words, fund investors consider fund performance *jointly* with other key attributes of a fund to make their investment decisions. While fund size is a common control variable in previous studies (e.g. Huang et al. (2007), Ferreira et al. (2012)), its effect on fund flow has typically been assumed to be separate from a fund's past performance. Our estimation results of EME bond funds show there is significant interaction between the two variables. In particular, a larger fund would generally record a greater swing in its fund flow in response to a given change of past performance. A possible explanation is that larger funds tend to receive more media coverage and therefore investors are more alert to their performance. This size effect also accounts for the significant higher fund flow sensitivity found in our sector-level analysis compared to the fund-level analysis, as the observations corresponding to huge funds carry larger weights on the sector-level data. We also confirm the importance of return volatility in determining fund flow sensitivity as identified by Huang et al. (2012) in their study on US equity funds. Our results suggest that the performance of a volatile EME bond fund is typically less influential on its future fund flow. This can potentially be explained by investors' perception of the volatile return being less informative about the skill and ability of the fund manager.

The remainder of this paper is organised as follows: Section 2 presents the econometric models used to analyse the flow-performance relationship. Section 3 provides the details of the datasets used. Section 4 discusses the main empirical findings, and Section 5 is the conclusion.

2 Econometric model

We use a fixed effect panel data model to investigate the relationship between the fund flows and fund performance of EME bond funds. In our model, the dependent variable $FF_{i,t}$ is the net fund flow to an EME bond fund i at time t. To facilitate comparability across funds, $FF_{i,t}$ is specified in percentage terms, i.e. the value of the net subscription (defined as subscription minus redemption) to the fund in the period divided by the fund size of the preceding period. In many empirical studies (e.g. Chevalier & Ellison (1997), Sirri & Tufano (1998)), as FF is not readily available in their datasets, it is computed based on the change of a fund's total net assets (TNA) adjusted for a fund's rate of return (RR).[7] The formula is as follows:

$$FF_{i,t} \equiv \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + RR_{i,t})}{TNA_{i,t-1}} \tag{1}$$

To capture the convexity of the flow-performance relationship, we apply a piecewise regression model, which is a commonly used empirical model in previous studies. Specifically, it consists of two linear segments of different slopes, with the turning point set at zero. In a standard specification of piecewise regression, continuity at the breakpoint is ensured by imposing a restriction. We also adapt this specification since in our data abrupt changes in fund flow are not observed when the past return slightly deviates from this breakpoint. Our general model is specified as follows:

$$\begin{aligned} FF_{i,t} = &\alpha_0 + \beta_1 RR_{i,t-1} + \beta_2 D(RR_{i,t-1} \leq 0) RR_{i,t-1} + \beta_3 Ln(TNA_{i,t}) RR_{i,t-1} \\ &+ \beta_4 Vol_{i,t} RR_{i,t-1} + \sum_{k=1}^{n} \gamma_k Z_{k,i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

The key explanatory variable in the model is a fund's performance as measured by its prior-period total return $RR_{i,t-1}$.[8] The convexity of the flow-performance relationship is estimated by an interaction term of $RR_{i,t-1}$ and a dummy variable $D(RR_{i,t-1} \leq 0)$, which is equal to one if the prior-period fund return is less than or equal to zero, and zero if otherwise. Under this specification, a positive (negative) β_2 would indicate that fund flow is more (less) sensitive to a negative return.

Our model differs from typical studies in the literature in two salient features. First, we hypothesise that the sensitivity of fund flow to a fund's past performance is dependent on fund size. The reason is

[7]The Morningstar dataset employed in this study, which will be discussed in more detail in the next section, also generates its net fund flow data similarly. Morningstar's calculation of total return is determined each month by taking the change in price, reinvesting all income and capital gains distributions during that month, and dividing by the starting price. The total return is computed before sales charges (such as front-end loads, deferred loads and redemption fees).

[8]The use of prior-period return can reduce the concern about endogeneity caused by reverse causality, i.e. the possibility that fund flow affects fund returns.

that a larger fund usually attracts more media attention (both positive and negative) and therefore fund investors should be more aware of any movement on its past return, leading to higher flow-performance sensitivity. Such a positive correlation between fund size and media coverage is supported by the empirical evidence found by Sirri & Tufano (1998). In their study, they found that fund size showed a statistically significant influence on the number of stories appearing in LexisNexis, which is a search engine of mainstream newspapers and periodicals, from 1971 to 1990. To the best of our knowledge, all the previous studies assume that fund performance and fund size have separate effects on fund flow. To control for the dynamics between fund size and fund flow sensitivity, we introduce an interaction term by multiplying a fund's past performance with its size, and expect the coefficient β_3 to be positive.

Second, we hypothesise that fund flow sensitivity depends on the volatility of a fund's past returns. The reason, as suggested by Huang et al. (2012), is that if a fund's past performance is highly volatile, this track record of performance is less informative of a fund manager's innate ability or skills. This suggests that investors would respond to a given fund performance less vigorously, leading to a less sensitive flow-performance relationship. We measure the volatility of a fund using the 12-month backward rolling standard deviation of its raw return. If investors indeed rely less on past performances in forming investment decisions in the case of a volatile fund, we would expect the coefficient β_4 to be negative.

In the flow-performance literature, one of the key issues is concerned with the measurement of fund performance. While a variety of indicators (such as total returns, benchmarked returns and excess returns estimated using empirical asset pricing models) have been used, there has been no consensus on which indicator works best under all circumstances.[9] The major reason for choosing total return in our study is that it is the most straightforward performance indicator for investors to compare across funds. Besides, it is a more relevant benchmark for investors to make redemption decisions due to its direct consequence on investors' tax liability after selling the fund (Ivković & Weisbenner (2009)).

For a robustness check, we also use benchmarked return as an alternative measure of fund per-

[9] For example, total return was used by Bergstresser & Poterba (2002), Coval & Stafford (2007), and Ivković & Weisbenner (2009), benchmarked return was used by Chevalier & Ellison (1997), and Karceski (2002), and alpha estimate was used by Khorana (2001), and Goldstein et al. (2017).

formance. Benchmarked return is defined as a fund's total return subtracting the return of the market benchmark index, with both rates of returns in US dollar terms. There has been evidence that the purchasing decision is closely connected to the fund's performance relative to the market (Ivković & Weisbenner (2009)). The reason is that a mutual fund investor can choose either an actively managed EME bond fund or an index fund (or exchange-traded fund) that mechanically tracks an index. The decision to choose a particular EME bond fund would therefore be more dependent on its return relative to the overall market. Another commonly used performance indicator is a fund's alpha, which, in the context of the Capital Asset Pricing Model (CAPM), can be interpreted as the portion of a fund's return that is not attributable to its exposure to overall market risk. As such, it represents the unique capability of the fund manager to add value to the fund. While alpha is also a relevant indicator of fund performance, we do not use it in our robustness check since a reliable estimation of a fund's alpha requires long time series. Given that many EME bond funds have only a short history, the use of alpha will significantly reduce our sample size.

In addition to fund performance, we also include other explanatory variables to control for miscellaneous influences on fund flow, including the age of a fund, the level of market risk aversion and lagged fund flows. The age of a fund is included since it is typical for a newly launched mutual fund to attract substantial fund inflow, which is more likely the result of an intensive marketing campaign and not directly related to a fund's past performance. We include risk aversion level in the model since EME bond funds are often perceived to be riskier than their counterparts from developed markets. A heightened market risk aversion is expected to drive funds out of individual EME bond funds regardless of their past performance. This risk aversion is measured by the CBOE Volatility Index (VIX), which is an indicator of the expected volatility for options on the S&P 500 Index. Finally, given that fund flows are persistent, the lagged fund flows are included in the model to control for the momentum effect, with the lag structure determined by the Akaike Information Criteria. Apart from the above control variables, fund flows could also be influenced significantly by certain unobservable fund-specific factors, such as the general investment philosophy and the framework/ procedures for investment decision-making. As we expect these factors to remain relatively stable over time, cross-section fixed effect is included in our model to take into account these heterogeneities across funds.[10]

When estimating Equation (1), we are aware that different types of bond funds might have different fund flow sensitivities. In particular, Goldstein et al. (2017) found fund flow sensitivities of corporate bond funds and sovereign bond funds deviate from each other significantly, even in the same economy, because the market depth of government bonds is much higher than that of individual corporate bonds. As the same pattern may occur in EME bond funds, we estimate the coefficients separately using (1) full sample, and (2) sample-excluding funds that hold a higher portion of sovereign bonds than corporate bonds (hereafter referred to as Government Bond Funds). Note that, unlike developed market bond funds, those of EMEs typically invest in both sovereign debt and corporate debt. Given the limited market size of individual EME bond markets, it is common for an EME bond fund to invest in multiple countries and regions, and in sovereign and non-sovereign debt.

In addition to fund-level analysis, it is also useful to have a sector-level analysis by looking at the aggregate fund flow to EME bond funds. As part of the fund flows to/ from an individual fund are driven by investors fund switching in the same asset class due to idiosyncratic factors, it should not be a main concern of policymakers. To investigate flow-performance relationship at an aggregate level, Equation (2) is modified as follows:

$$AFF_t = \alpha_0 + \beta_1 EMBI_{t-1} + \beta_2 D(EMBI_{t-1} \leq 0) EMBI_{t-1} + \sum_{k=1}^{n} \gamma_k Z_{k,t} + \varepsilon_t \qquad (3)$$

where AFF is aggregate fund flow in percentage term, and $EMBI$ is the return of the J.P. Morgan Emerging Market Bond Index Global, which is one of the most widely used benchmarks to measure the performance of EME bond funds. Z is a vector of control variables similar to Equation (2), except for the exclusion of fund-specific variables.

[10] As the omitted variable is expected to be correlated with the observed variables (e.g. funds managed by famous fund houses tend to be larger in size), the random effect model is not applicable here. This is also supported by the Hausman specification test performed on our sample.

3 Data

3.1 Sample construction

Subject to data availability, the sample period of this study is January 2000 to December 2016. The sample consists of fund-level and sector-level data. The fund-level dataset retrieved from Morningstar provides information about the net asset value, net fund flows, fund return and other fund-specific details of individual mutual funds.[11] Specifically, it consists of 1784 EME bond funds domiciled around the world under the Morningstar category "Emerging Markets Fixed Income".[12] Since most of these funds invest in more than one EME and across regions, a further breakdown of these funds by country or region is not available. Only open-ended funds are included due to their financial stability concern discussed in Section 1. For closed-end funds, such a concern is less acute since the number of fund units is fixed and massive redemption by fund investors would not prompt a forced fire sale by the fund manager.

Our sector-level dataset of EME bond funds is constructed in two ways. First, we use a bottom-up approach by aggregating the Morningstar fund-level data to obtain the sector-level data. Second, we make use of the EPFR Global dataset, which directly provides sector-level data. Similar to Morningstar, EPFR Global also covers funds domiciled around the world. Note that the EPFR Global dataset covers fund flows generated from funds that exclusively invest in EME bonds and mixed funds that invest in EME bonds and other asset classes. Therefore, the EPFR Global dataset should have a larger coverage. In terms of fund size in 2016, the Morningstar database is roughly 65% of the EPFR Global database. While the comprehensive fund-level data from Morningstar allows us to perform a more in-depth empirical analysis on the underlying mechanism driving investors' behaviour, the wider coverage of the EPFR Global database makes it more representative on sector-level analysis.

The data of market-level explanatory variables is obtained from Bloomberg. In particular, the JP Morgan Emerging Market Bond Index Global is chosen as a proxy indicator for the overall EME bond

[11] More granular data than fund-level data is also available as some funds offer multiple fund classes to cater for different types of investors (e.g. institutional investors, retail investors), and the fund flows of individual classes are also provided by Morningstar. However, for the purpose of this study, it is sufficient to treat the fund itself as the unit of analysis.

[12] In the Morningstar datasets, countries are classified as developed or emerging based on their per capital gross national income as defined by the World Bank. For a full list of the country classification, see: http://corporate.morningstar.com/US/documents/MethodologyDocuments/MethodologyPapers/MorningstarRegions.pdf.

markets since it is the most popular benchmark for actively managed EME bond funds to measure their performance.[13]

The correction of survivorship bias is a crucial issue for the mutual fund data. This is because mutual fund companies tend to liquidate funds with poor performance, particularly if these funds have massive redemptions from investors that make it economically not feasible to continue operating. Therefore, if the survivorship bias is not corrected, the sample would be biased towards funds with good performance. It might also substantially reduce the number of observations in the region of negative returns, thus making the estimation of fund flow sensitivity for that region less reliable. To control for the bias, we include in our sample mutual funds that are in business at the end of the sample period, as well as those liquidated at some point during the sample period.

A final issue is concerned with the pre-processing of fund flow data before quantitative analysis. We note that many extreme outliers in fund flow data are probably attributable to reasons not directly related to a fund's performance or general market condition. For example, restructuring of a mutual fund (e.g. merging with another fund, changes of investment mandate) and a marketing campaign during the launch of a fund would sometimes lead to a surge of inflows or outflows. It is hard to take into account such idiosyncratic factors individually by introducing control variables. Due to the relatively short history of EME bond funds, their fund flows tend to be more volatile and susceptible to the above-mentioned random events. Therefore, to avoid the distortion caused by extreme outliers, the relative fund flows are winsorized at 95%, rather than the standard practice of 99% for many empirical studies dealing with developed markets. A similar situation is also found in the raw data of fund returns. In particular, we note that some funds recorded abnormally high monthly returns (with a return of more than 200% in one case) immediately before their cessations. While the phenomenon could be caused by various reasons, such as an acquisition premium paid to unit holders or processing errors, it appears to be completely random and is not the main focus of our analysis. As such, we have applied a 99% winsorization on the fund returns to stop these outliers distorting our data.

[13] See *BIS Quarterly Review* September 2014, pp28-29.

3.2 Summary statistics

The number of EME bond funds in our sample, together with their aggregate assets under management, for the sample period January 2000 to December 2016 is shown in Chart 1. It is obvious that growth of these funds started to take off around 2005 and further accelerated after the GFC, though the growth momentum showed signs of levelling off from early 2014. By the end of the sample period, the asset size of the sample funds totalled US$285.6 billion, a 62-fold increase over the US$4.6 billion at the start of the sample period. With the proliferation of newly launched EME bond funds after the GFC, the average fund size experienced a drastic decline, from US$323.7 million in early 2010 to US$249.4 million at the end of 2016 (Chart 2). As a result, the market has become less concentrated, with the Herfindahl Index, an index designed to measure the degree of market concentration, posting continued decline.

Table 1 presents the major characteristics of the EME bond funds in our sample. Over the sample period, these funds registered a mean fund flow of 0.12% a month. Despite winsorization, which screens out extreme outliers, the summary statistics still indicate that EME bond fund flow is highly volatile, with a standard deviation at 6.1% and a fairly large range from -10.6% to 20.5%. The high volatility of fund flow, to some extent, reflects the high volatility of the EME bond market. For example, the standard deviation of a monthly fund return is 3.5%, significantly exceeding the mean of 0.19%. Similarly, the standard deviation of a monthly EMBI return is also far higher than its mean.

4 Empirical results

4.1 Shape of the flow-performance curve

Tables 2A and 2B present the estimation results of Equation (2) using total return and benchmarked return respectively. As shown in Column 1 of Table 2A, the findings of the baseline model, which only includes the prior-period fund return, its interaction with the dummy variable $D(RR_{i,t-1} \leq 0)$ and lagged fund flow, suggest that fund flow reacts positively to past return (i.e. β_1 is found to be positive at 0.1247 and significant), which is in line with the findings of previous studies. As the coefficient of the interaction term (β_2) is found to be negative at -0.0407 and significant, the flow-performance relationship is convex.

This convex relationship remains unchanged when other control variables, such as fund age, fund size and the VIX index, are added to the model (Column 2), or when the interaction between fund size and past performance is introduced (Column 3). While the relationship is more complicated in Column 3 due to the interaction term, it remains convex, with the fund flow sensitivity of a mean-sized fund estimated to be 0.1620 and 0.0868 at positive and negative return respectively. The positive sign of β_3 (0.0161)in Column 3 also indicates that a larger fund would typically record a greater change in fund flow for a given past return. Column 4 shows the estimation results of the full model, in which the interaction between fund volatility and fund return is also considered. The coefficient β_4, which captures such interaction, is negative (-0.0171), suggesting that investors put less weight on the past performance of a volatile fund. Columns 5-8 represent the corresponding regression results of Columns 1-4 when Government Bond Funds are excluded from the sample. Their results are similar, with the fund flow sensitivities at positive returns much higher than those at negative returns, again suggesting a convex flow-performance relationship.[14] Table 2B reports the estimation results based on benchmarked returns as an alternative measure of fund performance. As a robustness check, the results are similar to Table 2A in that the flow-performance relationship is found to be convex under all the model specifications.

The single breakpoint model of Equation (2) can be extended to a model with more than one breakpoint. A multiple breakpoint model, though more complicated, has the merit of allowing for a more gradual transition of fund flow sensitivity rather than a sudden jump with respect to positive and negative returns. To model such a gradual change, the original single dummy variable in Equation (2) is replaced with three new ones (D_1, D_2 and D_3). The value of dummy variables assigned to a fund at time t is based on its performance at time t-1. Specifically, D_1, D_2 and D_3 are set to be 1 when the fund's performance at time t-1 is under the following brackets, and 0 otherwise:

D_1 = 1 if $R_{i,t-1} > 25^{th}$ percentile and $R_{i,t-1} \leq 50^{th}$ percentile

D_2 = 1 if $R_{i,t-1} > 50^{th}$ percentile and $R_{i,t-1} \leq 75^{th}$ percentile

D_3 = 1 if $R_{i,t-1} >$ 75th percentile

If the fund's prior-period performance is below or equal to the 25^{th} percentile, all the three dummy

[14] As another robustness check, we have also performed regression analysis on a sample of Government Bond Funds. While the levels of sensitivity deviate slightly from our baseline case, our major finding of the convex relationship between return and fund flow remains valid. Results available upon request.

variables would have the value of 0.

Table 3 presents the results of a multiple breakpoint model and the results are broadly similar to those of the single breakpoint model. In particular, the coefficients for all three interaction terms ($RR_{i,t-1}$ $\times D_1$, $RR_{i,t-1} \times D_2$ and $RR_{i,t-1} \times D_3$) are positive, suggesting that fund flow sensitivity is at its lowest level when past performance is in the bottom quartile. This is consistent with our earlier findings that fund flow is less sensitive toward poor performance of mutual funds. The flow sensitivity, however, does not appear to increase monotonically along with improvement in performance. The coefficient for the interaction term ($RR_{i,t-1} \times D_3$), while still positive, is lower than that of both ($RR_{i,t-1} \times D_1$) and ($RR_{i,t-1} \times D_2$).

4.2 Explaining the convexity of the flow-performance curve

Broadly speaking, there are four sets of explanations to account for a convex flow-performance relationship in EME bond funds. The crux to the first explanation is that EME bond fund managers are well aware of the disruption caused by massive redemptions given that their fund assets are relatively illiquid compared to, say, government bonds of developed markets. As such, they have adapted various practices to pre-empt forced fire sales triggered by massive redemption orders.[15] One of these practices is the precautionary holding of cash. As shown in Chernenko & Sunderam (2016) and Hanouna et al. (2015), a fund having high fund flow volatility and investing in assets with lower liquidity (such as EME bonds) tends to hold a significant cash buffer to meet the redemption orders from their unit holders. This is to avoid the need for selling its underlying illiquid assets at deep discounts when there are outsized redemptions. The sampled EME bond funds in this study display similar features as they had a cash holding ratio of 13.86% in 2016 on average, which is significantly higher than the 9.52% for US bond funds (Table 4A). Note that the level of cash holding is typically reported in the monthly fact sheets of mutual funds and therefore publicly available. As the higher level of cash holding is expected to alleviate investors' concern about fire sales, funds investing in less liquid assets should experience a lower outflow momentum and have a more convex flow-performance curve. To examine if the level

[15] Other mechanisms (e.g. redemption restrictions, credit lines and inter-fund lending programs in lieu of cash) are often used by fund management companies to mitigate the risk of forced fire sale. However, Chernenko & Sunderam (2016) found these mechanisms were less effective for liquidity management.

of cash holding would have any effect on the sensitivity of fund flow, a sub-sample analysis between funds with high cash holding and funds with low cash holding funds is performed (Table 4b). In line with our expectation, the regression result indicates that funds with higher cash holding have lower fund flow sensitivity at negative return than funds with lower cash holding. This finding is also consistent with Goldstein et al. (2017), which shows that the amplification of outflow is reduced when funds hold more cash.

Another common practice to mitigate the fire sale risk of mutual funds holding illiquid assets is the swing pricing mechanism, which is the adjustment of a fund's net asset value to pass on the dilution costs of trading to investors associated with purchasing or redeeming the fund. The mechanism can internalise the transaction costs and liquidation costs incurred by investors who redeem their shares, and neutralise their first-mover advantage from redeeming earlier than others.[16] As a result, fund investors have less incentive to take first-mover advantage by rushing to sell their unit holdings in reaction to adverse fund performance. While swing pricing has long been practised for mutual funds domiciled in many European countries, such as Luxembourg, Ireland and the United Kingdom, mutual funds subject to US regulations are not allowed to adopt the mechanism until November 2018.[17] The effect of swing pricing is also supported by a study by Lewrick & Schanz (2017). In their study, open-ended bond funds in Luxemburg, where swing pricing is allowed, are compared against similar funds in the US and it was found that negative returns prompt larger outflows from US funds than from their Luxemburg counterparts.[18] Note that the EME bond funds in our sample are domiciled around the world, many in jurisdictions that allow swing pricing (eg Luxemburg, Ireland, UK, and Cayman Islands). In terms of total fund size for 2016, about 62% of our sampled funds allow for swing pricing, and US-domiciled funds account for only 19% of our sample. This may explain why a convex flow-performance relationship is identified in our study on EME bond funds, while a concave flow-performance relationship is identified in Goldstein et al. (2017), which focuses on US corporate bond funds.

The second explanation is attributable to the bias of media coverage, notably mutual fund advert-

[16] For details about the working of swing pricing mechanism, see Lewrick & Schanz (2017).

[17] In October 2016, SEC amended Rule 22c-1 of the Investment Company Act 1940 to allow US mutual funds to adopt swing pricing starting from 2018. For details, please refer to: https://www.sec.gov/rules/final/2016/33-10234.pdf.

[18] Lewrick & Schanz (2017) found that swing pricing dampens outflows in reaction to weak fund performance, but has a limited effect during stress episodes such as the taper tantrum in 2013.

isements (Sirri & Tufano (1998)), which tend to focus on outperforming mutual funds and downplay underperforming ones. As found by Jain & Wu (2000), mutual fund advertisements serve as powerful drivers for inflow into the advertised funds.[19] As a result, the attention of fund investors is driven towards the top-performing funds, leading to a convex relationship. This media coverage effect is not only confined to fund advertisements but is also present in news reports that are supposed to be independent of the interest of mutual fund companies. In their empirical study, Kaniel & Parham (2017) found a significant increase of fund flows into mutual funds that were reported in a widely followed "Category Kings" ranking list in the *Wall Street Journal*, compared to those funds that just missed making the list. The list shows the top 10 funds of each category in terms of the previous 12-month returns of the funds. This spotlight effect appears to apply in EME bond funds as the names of the top-performing funds in our sample also show up far more frequently in news media than the worst-performing funds (Table 5). The effect of media coverage depends on the sophistication of fund investors. Investors based in EMEs are probably more susceptible to such influences since, according to an OECD survey on financial literacy competencies, these investors generally have a lower level of financial knowledge.[20] While investors from developed countries also invest in EME bond funds, as they are typically less familiar with foreign markets, they are more likely to be influenced by advertisements and media reporting.

The third explanation is concerned with the participation costs of mutual fund investment (Huang et al. (2007)). In particular, a rational investor would invest in a mutual fund only if its expected return exceeds the participation costs by a threshold, and there is empirical evidence that an investor's expected return of a fund is often based on its past performance (e.g. Goetzmann & Peles (1997)). This explains why investors with higher participation costs are more likely to have a portfolio heavily invested in funds with a track record of outperforming returns. Participation costs can be further divided into two parts, namely information costs and transaction costs. Information costs represent the costs of collecting and analysing information about a mutual fund, while transaction costs are the costs incurred in the buying/ selling of funds. The higher the information costs an investor faces, the fewer funds he would investigate

[19] According to Jain & Wu (2000), 294 mutual funds that advertised in *Barron's* or *Money magazine* grew faster than a control group of funds with similar performance before the advertising period.

[20] The investors' level of financial knowledge of each jurisdiction was determined by respondents' answers to a series of fundamental questions designed to test different aspects of knowledge that are widely considered to be useful to individuals when making financial decisions. For details, see OECD/INFE (2016).

before making an investment decision, resulting in a more concentrated investment portfolio. Similarly, the higher the transaction cost, the higher the expected returns would be required to overcome the hurdle and provide the investor with a positive net return.

While a direct comparison of participation costs across markets could prove difficult due to the unobservable nature of certain components, we may still have a rough estimation on their relative magnitudes by looking at the summary statistics of bond fund net expense ratios in Table 6. We found that the net expense ratios of EME bond funds were significantly higher than funds investing in the US bond market. Together with the higher average transaction costs in emerging markets as identified in previous studies (Chan et al. (2005), Ferreira et al. (2012)), it seems reasonable to conclude that investors in EME bond funds face higher participation costs when making fund investments. The cross-country study on equity mutual funds by Ferreira et al. (2012) also provides a comprehensive comparison to support the effect of participation costs. In their paper, different proxies for participation costs and investor sophistication are found to be highly correlated to the convexity of the flow-performance curve. In particular, a country with a lower level of economic, financial markets and mutual fund industry development (perceivably an emerging market) was found to have a more convex flow-performance curve in general. As these macro environmental factors are not specific to the equity mutual funds sector, their findings should be equally applicable to our study on EME bond funds.

An indirect way to look at the effect of participation costs on fund flow sensitivity is to control for fund family size. The reason is that mutual fund companies typically allow investors to reallocate their investment from one fund to another in the same family at a discount or for no fee. In addition, mutual fund companies usually provide investors with more information about other funds of the same family, and this will reduce the search cost of fund investors. Therefore, investors under a large fund family should face lower participation costs. This conjecture is consistent with Jank & Wedow (2013), who find evidence of significantly higher redemption and purchase rates for funds belonging to a larger fund family. If our hypothesis on the effect of participation cost does hold, mutual funds under large families should have steeper flow-performance curves. To capture this effect, we introduce a dummy variable to represent whether a fund is managed by one of the five largest mutual fund companies.[21] As shown in Table 7, the dummy variable $D(Top5)$ has a positive interaction with the fund's past return in influencing the fund flow, suggesting that investors of funds managed by major fund houses would react more vigorously towards a change in a fund's performance, supporting our participation costs theory.

In addition to the three explanations above, another potential explanation is related to the asymmetric persistence on fund performance, and such asymmetry reflects the employment practice of the fund management industry. In a theoretical study, Heinkel & Stoughton (1994) show fund managers would continue to be employed by an asset management company only if they outperformed the benchmark by a certain amount. As such, fund investors would expect poor performance of individual funds to be non-persistent due to replacement of fund managers, while the good performance would prevail. This explains the asymmetry of investors' reaction towards good and bad performance of funds. A subsequent empirical study by Lynch & Musto (2003) provides evidence supporting a similar theory. They found that strategy/ personnel change was more likely to take place following a bad fund performance, and therefore poor fund performance was unlikely to be persistent. To verify whether this theory is applicable to EME bond funds, we perform a regression analysis on our sample using Equation (4).

$$RR_{i,t} = \alpha_0 + \beta_1 RR_{i,t-1} + \beta_2 RR_{i,t-1} \times D(RR_{i,t-1} \leq 0) + \varepsilon_{i,t} \tag{4}$$

Similar to Equation (2), we introduce a dummy variable to investigate the difference in information content between positive and negative past returns. If bad performance is less informative than the good one, we expect β_2 to be negative. The estimation results of Equation (4) are presented in Table 8. In general, the findings suggest that the third explanation is not applicable for EME bond funds. We found that neither good nor bad performance of individual EME bond funds is persistent. In fact, the total returns of individual funds from our sample show a mean reversion tendency ($\beta_1 = -0.0382$). In other words, funds with good performance from the past are likely to underperform in the following period, and vice versa. This finding clearly contradicts the theory that suggests superior fund performance is

[21] Major fund houses represent the top five mutual fund companies in terms of assets under management (AUM) as at 30 September 2016 (i.e. BlackRock, Vanguard Group, UBS, State Street Global Advisors and Allianz Asset Management). The sum of their AUMs is about 23% of the industry total, based on data extracted from the companies' annual reports and financial statements.

sustainable, but is in line with the findings of Jain & Wu (2000).

4.3 The fund size effect

Previous studies of flow-performance relationship typically focus on the direct effect of fund performance on fund flow and ignore any indirect effects. One of our contributions is to show that fund performance can also affect fund flow indirectly through its interaction with fund size. As shown in Columns 4 and 8 of Table 2A, the coefficient of the interaction term between fund return and fund size is found to be positive and significant, indicating that a larger fund tends to have higher fund flow sensitivity. Chart 3 illustrates the fund size effect. Each line represents the flow-performance relationship of an EME bond fund at the corresponding fund size percentile. While all the four flow-performance curves are in a convex shape, there is a gradual steepening of the lines as fund size increases. This suggests that a larger fund is more responsive to a given change of past performance. As an illustration, an increase of fund size by one standard deviation from its mean would lead to an approximate 21% higher sensitivity to positive returns based on our model. In addition to the interaction term specification, we also perform sub-sample regression analysis and the results also suggest the effect of fund size. As shown in Columns 1 and 2 of Table 9, the flow-performance sensitivity of funds with above-median size is significantly higher than that of funds with below-median size (Columns 1 and 2 of Table 9).

A natural follow-up question is whether the EME bond fund flow has become more sensitive with the rapid expansion of this sector. When taking a closer look at the data, we note that while this could happen to some funds with strong growth in total asset size, the sensitivity for the sector as a whole should not increase rapidly. This is because the EME bond fund sector actually experiences a substantial decline in average fund size due to the rapid increase in the number of new EME bond funds launched in recent years (Charts 1 and 2). With more options available to investors, there is a significant decrease in the Herfindahl Index, an index designed to measure the degree of market concentration. As such, the influence of fund size through media coverage does not necessarily strengthen over time as the spotlight of media is likely to be more dispersed.

4.4 The effect of fund return volatility

Our estimation results suggest that another indirect effect of fund performance on fund flow is through the volatility of a fund's historical returns. As shown in Column 4 of Table 2A, the coefficient of the interaction term between fund return and fund volatility is found to be negative and significant. We also conduct a separate sub-sample analysis and obtain consistent results. Specifically, EME bond funds with below-median volatility have fund flow sensitivity significantly higher than those funds with above-median volatilities (Columns 3 and 4 of Table 9). A possible explanation is the Bayesian learning theory of Huang et al. (2012), which postulates that the higher the historical volatility of a fund's rate of returns, the less informative the fund's past returns would be on the innate ability of the fund manager. As such, the sensitivity of fund flow to past performance is lower. More generally, they propose that only the less sophisticated investors would react purely based on the performance of a fund, while the more experienced investors would take into account other information such as the volatility of returns and the track records of the funds. In their paper, fund age is also a crucial factor as investors' decisions are more likely to be driven more heavily by the latest performance if a fund has a short history. That said, we are unable to identify such a relationship based on our model. In our unreported result, we note that the interaction between fund age and past performance is not statistically significant and the coefficient carries a positive sign, contradicting the negative correlation as suggested in Huang et al. (2012).

4.5 Redemption versus subscription

Net fund flow is widely used in the empirical studies of flow-performance relationship since it can be computed by Equation (1), with the required inputs, namely, a fund's asset size and rate of return, which are readily available in many databases. The use of net flow assumes the investors' behaviours to be symmetric between subscription and redemption of fund units. In reality, subscription and redemption decisions are usually based on different sets of factors (or assigning different weights on identical factors). One of these factors is tax liability. For jurisdictions with capital gains tax, such tax is often imposed only on the realisation of investment gain or loss, and therefore a major consideration for fund redemption is the capital gain of the mutual fund during the holding period. This factor is clearly irrelevant for the subscription of mutual funds. Another key factor is the asymmetry in the search cost between fund subscription and fund redemption. As found by Barber & Odean (2008), individual investors tend to buy stocks that attract their attention (e.g. stocks with extreme returns or abnormally high trading volume), since it is costly to search through thousands of stocks they can potentially buy. The search problem is much less severe for stock selling because investors (except for short sellers) only sell stocks they already own. As the number of mutual funds, though smaller than of stocks, is still very large, search cost cannot be ignored, leading to different investors' behaviour between subscription and redemption of a mutual fund.

To this end, we make use of disaggregate fund flow data to analyse the difference in investors' behaviour between subscripting and redeeming mutual fund units. As disaggregate data is only available in certain funds that file forms N-SAR to the US Securities and Exchange Commission throughout the sample period, our sample is further limited to 68 funds with a total number of observations of 3594. Considering the significant decrease in sample size, we make use of a simplified model to analyse the behavioural difference between fund subscription and redemption.

$$Subscripition_{i,t} = \alpha_{sub,0} + \beta_{1,sub}RR_{i,t-1} + \sum_{k=1}^{m}\gamma_{k,sub}Z_{k,i,t} + \varepsilon_{i,t,sub} \tag{5}$$

$$Redemption_{i,t} = \alpha_{red,0} + \beta_{1,red}RR_{i,t-1} + \sum_{k=1}^{m}\gamma_{k,red}Z_{k,i,t} + \varepsilon_{i,t,red} \tag{6}$$

As shown in Table 10, the estimation results show there is a considerable difference in fund flow sensitivity between subscription and redemption, with the subscription coefficient $\beta_{1,sub}$ around 70% larger than the redemption coefficient $\beta_{1,red}$. A statistical testing based on a seemingly unrelated regression model shows the null hypothesis H_0: $\beta_{1,sub}$= -$\beta_{1,red}$ is strongly rejected with a probability value of 0.0084. These results suggest that redemption decisions of EME bond fund investors are much less affected by past fund performance. In addition, the adjusted R-squared of Equation (6) is found to be 0.23, which is lower than the 0.34 for Equation (5). The significantly lower explanatory power of the model in estimating fund outflow suggests that idiosyncratic factors, such as liquidity needs and tax liability, play a more important role in redemption decisions. This may lessen regulators' concerns about the risk of massive redemption triggered by poor market performance.

Given the lower sensitivity of fund outflow to past performance, investors' redemption may not be the main driver behind the decrease in net flow observed after a poor market performance. Instead, the decrease in investor's subscription may probably play a more important role. As such, imposing restrictions on mutual fund redemption may not be the most appropriate way to forestall a decrease in net flow, as it could further discourage the already low subscription when investors foresee increased difficulty upon future exit, while only having limited effect on the redemption side.

4.6 Sector level analysis

The analysis of fund flow sensitivity at individual fund levels has the merit that fund-specific factors (e.g. fund age, fund size) are taken into account but within-sector fund flows are not netted out. In other words, for an investor switching from one EME bond fund to another, the two transactions are counted separately. However, for the asset class as a whole, there is no change in net fund flow. Therefore, it is useful to conduct an analysis at the sector level, particularly for policymakers more concerned about aggregate fund flow than individual fund flow. In this regard, we estimate Equation (3) using bottom-up sector-level data compiled using Morningstar fund-level data to study how aggregate EME bond fund flow responds to the past performance of the market as a whole. As shown in Column 1 of Table 11, the sector-level relationship between fund flow and market performance as measured by EMBI return (β_1) remains positive and significant, with β_1 estimated to be 0.2898, suggesting that a bullish EME bond market would attract fund inflow to this asset class.[22] Furthermore, consistent with the result of the fund-level analysis, the relationship is found to be convex, with β_2 estimated to be -0.2433 and statistically significant. Column 2 shows the results using EPFR Global sector-level data and they are similar to Column 1.

In the sector-level analysis, fund flow sensitivity at positive returns is found to be significantly higher than that estimated at the fund-level analysis of our baseline model. We consider this to be mainly attributable to higher weights carried by large funds on sector-level data. As discussed earlier, a larger fund typically receives wider media coverage and investors are typically more aware of the changes of its performance over time. This leads to a higher sensitivity of its fund flow to fund performance. As

[22] While the relationship may seem obvious, such a positive relationship was not found in equity mutual funds based on previous studies by Warther (1995) and Goldstein et al. (2017). Their studies found that, after controlling for the persistence in fund flows, past aggregate return of equity funds does not have significant influences on aggregate fund flows in developed markets.

a result of the heavier weights these funds carry in the compilation of sector-level data, the aggregate fund flow sensitivity would be driven up. As such, the influence of past performance on sector-level fund flow would be understated if it is estimated based on the response of an average-sized fund to its past performance. In other words, the risk of an excessive sector-level fund flow may not be detectable based on fund-level analysis. Similar to our fund-level analysis, fund flow sensitivity for a negative return is represented by the sum of β_1 and β_2, which is found to be very close to zero.[23] In addition, a robustness check using EPFR Global data yields a similar result (Table 11 Column 2). These results suggest that, while investors respond to poor performance of individual funds by redeeming their units, most of the withdrawn money is simultaneously reinvested into the same market. As such, the EME bond fund sector appears to be relatively resilient against downward pressure.

Another issue is concerned with the interactions between EME bond fund flow and EME equity fund flow. While bond and equity are two separate asset classes for developed markets due to their distinctive differences in risk profiles, the dividing line is less clear for EMEs since both are subject to significant common shocks, such as changes in global risk appetite, global liquidity condition and country-specific macroeconomic performance. In fact, there is a high positive correlation between EME bond market fund flow and EME equity market fund flow, which is not commonly found for developed markets (Charts 4 and 5). The high correlation raises the possibility that EME bond fund flow could potentially be susceptible to cross-sector spillover. To this end, we perform a regression on EME equity fund flow using EME bond market performance as one of the explanatory variables. Column 3 of Table 11 shows that, after controlling for the equity market performance and lagged fund flow, bond market performance does not exert statistically significant influence on the equity fund flow. Similarly, we run a regression of EME bond fund flow on EME equity market returns and other control variables. The results also suggest that EME equity market returns do not have a significant effect on EME bond fund flow (Columns 1 and 2 of Table 11). As such, the high correlation between fund flows of the two markets is likely to be attributable to common factors affecting both markets rather than cross-market spillover.

[23] The result from Wald test suggests that the null hypothesis: $\beta_1 + \beta_2 = 0$ cannot be rejected.

5 Conclusion

Our estimation results suggests EME bond funds display a convex flow-performance relationship, which suggests that fund flow is more sensitive to good performance than bad performance. This convexity is primarily attributable to the practices (e.g. a large cash buffer, swing pricing) adopted by asset management companies to dampen the incentive of fund investors to take first-mover advantage by rushing to redeem their funds at the first sign of poor performance. Since massive redemption is highly disruptive to a fund with relatively illiquid underlying assets, EME bond fund managers are keen to adopt these practices to contain fire sale risk. Apart from these practices, we also discuss other explanations for the convexity, such as the bias of media coverage towards outperforming funds and the hurdle to investors created by the higher participation cost of EME bond funds. Furthermore, we find evidence that fund performance influences fund flow through multiple channels of fund size and fund return volatility. Specifically, a large fund tends to have high fund flow sensitivity, potentially due to wider media coverage. An increase in return volatility is found to reduce the fund flow sensitivity of a fund, which is consistent with the Bayesian learning theory that investors regard volatile returns as not informative in inferring the skills and innate ability of the fund management team. Finally, in view of the high correlation between EME bond and EME equity fund flows, we examine how the equity fund market may be affected by shocks arising from the bond market. Our results suggest that the spillover from bond market fund sector to equity market fund sector is not significant after equity market performance and lagged fund flows are controlled for.

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Table 1 Summary statistics

This table shows the major characteristics of the 1,784 open-ended emerging market bond funds in our sample from January 2000 to December 2016. These funds, which are domiciled around the world, are corrected for survivorship bias. Fund flow is calculated by Flow$_{i,t}$ / Fund Size$_{i,t-1}$, where Flow$_{i,t}$ is the dollar value of net flow for fund i at time t, winsorized at 95%. Fund return is based on Morningstar's calculation, which is determined each month by taking the change in price, reinvesting all income and capital-gains distributions during that month, and dividing by the starting price. It is winsorized at 99%. EMBI is J.P. Morgan Emerging Market Bond Index Global. Benchmarked fund return is fund return minus EMBI return. Except for EMBI return, the unit of observations is funds months. We exclude index funds, closed-end funds and exchange traded funds in our sample.

	Note	Mean	Median	Max	Min	Std. Dev.	Obs
Fund Flow (%)		0.12	-0.35	20.49	-10.56	6.10	80685
Fund Return (%)	1	0.19	0.45	9.41	-10.47	3.51	80685
EMBI Return (%)		0.67	0.96	7.77	-14.89	2.43	158
Benchmarked Fund Return (%)	1	-0.37	-0.25	6.57	-7.77	2.38	80685
Fund Age (Year)		5.77	4.33	28.02	1.00	4.50	82224
Fund Size (USD mn)		344.1	66.5	15600.0	0.0	864.0	82224

Note:
1. Winsorized at 99% level.

Table 2A Flow-performance relationship based on total return

In column 1 (baseline model), net flow of a fund $FF_{i,t}$ is regressed on its prior-period return $RR_{i,t-1}$, an interactive term $RR_{i,t-1} \times D(RR_{i,t-1} \leq 0)$ to capture convexity of the relationship and lagged flows. Column 2 adds control variables $Ln(TNA)$, $Ln(FundAge)$ and VIX. In column 3, the effect of fund size $Ln(TNA)$ is captured by an interaction term $RR_{i,t-1} \times Ln(TNA_{i,t})$. As for column 4, the effect of fund return volatility is captured by an interaction term $RR_{i,t-1} \times Vol_{i,t}$. Columns 5-8 are robustness checks of columns 1-4 when Government Bond Funds are excluded from the sample.

	EME Bond Fund Flow Dependent Variable : $FF_{i,t}$			
	(1)	(2)	(3)	(4)
Constant	-0.0708***	3.8661***	1.5942	1.5821***
	(0.0297)	(0.4167)	(0.0959)	(0.0965)
RR$_{i,t-1}$	0.1247***	0.1263***	-0.1550***	-0.0536
	(0.0106)	(0.0106)	(0.0413)	(0.0439)
RR$_{i,t-1}$ $\times$ D(RR$_{i,t-1} \leq 0$)	-0.0407**	-0.0719***	-0.0752***	-0.0832***
	(0.0174)	(0.0178)	(0.0177)	(0.0178)
RR$_{i,t-1}$$\times$ Ln(TNA$_{i,t}$)			0.0161**	0.0152***
			(0.0023)	(0.0023)
RR$_{i,t-1}$$\times$ Vol$_{i,t}$				-0.0171***
				(0.0025)
Ln(TNA$_{i,t}$)		-0.1251***		
		(0.0224)		
Ln(Fund Age$_{i,t}$)		-0.8110***	-0.8035***	-0.8054***
		(0.0421)	(0.0421)	(0.0424)
VIX$_t$		-0.0300***	-0.0286***	-0.0282***
		(0.0031)	(0.003)	(0.003)
FF$_{i,t-1}$	0.2880***	0.2832***	0.2818***	0.2815***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
FF$_{i,t-2}$	0.1302***	0.1270***	0.1265***	0.1268***
	(0.0037)	(0.0037)	(0.0037)	(0.0037)
FF$_{i,t-3}$	0.0792***	0.0761***	0.0756***	0.0753***
	(0.0037)	(0.0037)	(0.0036)	(0.0037)
FF$_{i,t-4}$	0.0443***	0.0399***	0.0387***	0.0389***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Fund flow sensitivity at positive return	0.1247***	0.1263***	0.1620***	0.1887***
Fund flow sensitivity at negative return	0.0840***	0.0544***	0.0868***	0.1055***
N	79288	79288	79288	79076
Adjusted-R^2	0.2549	0.2588	0.259	0.26
Durbin-Watson stat	1.9994	1.9999	1.9955	1.9944

Notes:
1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
2. The general formula for computing fund flow sensitivity is as follows: $\beta_1 + \beta_2 D(RR_{i,t-1} \leq 0) + \beta_3 \overline{Ln(TNA)} + \beta_4 \overline{Vol}$

Table 2A Flow-performance relationship based on total return (continued)

	EME Bond Fund Flow ex Govt. Bond Funds Dependent Variable : $FF_{i,t}$			
	(5)	(6)	(7)	(8)
Constant	-0.1672***	5.2552***	1.2016***	1.1797***
	(0.0336)	(0.4988)	(0.1056)	(0.1060)
RR$_{i,t-1}$	0.0844***	0.0842***	-0.0669*	0.0294
	(0.0118)	(0.0118)	(0.0437)	(0.0462)
RR$_{i,t-1}$ $\times$ D(RR$_{i,t-1} \leq 0$)	-0.0207	-0.0420***	-0.0494***	-0.0589***
	(0.0193)	(0.0196)	(0.0196)	(0.0196)
RR$_{i,t-1}$ $\times$ Ln(TNA)$_{i,t}$			0.0090***	0.0088***
			(0.0024)	(0.0024)
RR$_{i,t-1}$ $\times$ Vol$_{i,t}$				-0.0179***
				(0.0028)
Ln(TNA)$_{i,t}$		-0.2251***		
		(0.0271)		
Ln(Fund Age)$_{i,t}$		-0.8050***	-0.7319***	-0.7275***
		(0.0484)	(0.0477)	(0.0479)
VIX$_t$		-0.0251***	-0.0229***	-0.0225***
		(0.0036)	(0.0036)	(0.0036)
FF$_{i,t-1}$	0.3086***	0.3041***	0.3037***	0.3034***
	(0.0041)	(0.0041)	(0.0041)	(0.0042)
FF$_{i,t-2}$	0.1410***	0.1386***	0.1379***	0.1380***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)
FF$_{i,t-3}$	0.0752***	0.0730***	0.0719***	0.0721***
	(0.0043)	(0.0041)	(0.0043)	(0.0043)
FF$_{i,t-4}$	0.0433***	0.0401***	0.0381***	0.0384***
	(0.004)	(0.0041)	(0.004)	(0.0040)
Fund flow sensitivity at positive return	0.0844***	0.0842***	0.1104***	0.1428***
Fund flow sensitivity at negative return	0.0637***	0.0422***	0.0611***	0.0839***
N	58636	58636	58636	58548
Adjusted-R^2	0.2881	0.2919	0.2912	0.2922
Durbin-Watson stat	1.9985	2.0039	1.9962	1.9953

Notes:
1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
2. The general formula for computing fund flow sensitivity is as follows: $\beta_1 + \beta_2 D(RR_{i,t-1} \leq 0) + \beta_3 \overline{Ln(TNA)} + \beta_4 \overline{Vol}$

Table 2B Flow-performance relationship based on benchmarked return

As a robustness check on the findings from Table 2A, we perform regression analysis using benchmarked return as an alternative proxy for fund performance. Columns 1-8 from Table 2B correspond to the same column from Table 2A.

	EME Bond Fund Flow Dependent Variable : $FF_{i,t}$			
	(1)	(2)	(3)	(4)
Constant	0.0025	4.1195***	1.8197***	1.8451***
	(0.0288)	(0.4176)	(0.0952)	(0.0957)
RR$_{i,t-1}$	0.0833***	0.0910***	-0.1189**	-0.0975*
	(0.0169)	(0.0169)	(0.0603)	(0.0632)
RR$_{i,t-1}$ $\times$ D(RR$_{i,t-1}$ ≤ 0)	-0.0288	-0.0727***	-0.0794***	-0.0777***
	(0.0259)	(0.0262)	(0.0262)	(0.0262)
RR$_{i,t-1}$ $\times$ Ln(TNA)$_{i,t}$			0.0123***	0.0122***
			(0.0033)	(0.0033)
RR$_{i,t-1}$ $\times$ Vol$_{i,t}$				-0.0043
				(0.0036)
Ln(TNA)$_{i,t}$		-0.1268***		
		(0.0225)		
Ln(Fund Age)$_{i,t}$		-0.8641***	-0.8579***	-0.8699***
		(0.0420)	(0.0420)	(0.0423)
VIX$_t$		-0.0341***	-0.0325***	-0.0327***
		(0.0003)	(0.0003)	(0.0003)
FF$_{i,t-1}$	0.2919***	0.2861***	0.2857***	0.2860***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
FF$_{i,t-2}$	0.1295***	0.1261***	0.1256***	0.1257***
	(0.0037)	(0.0037)	(0.0037)	(0.0037)
FF$_{i,t-3}$	0.0774***	0.0741***	0.0733***	0.0729***
	(0.0037)	(0.0037)	(0.0037)	(0.0037)
FF$_{i,t-4}$	0.0436***	0.0391***	0.0378***	0.0379***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Fund flow sensitivity at positive return	0.0833***	0.0910***	0.1231***	0.1279***
Fund flow sensitivity at negative return	0.0545***	0.0183	0.0437*	0.0502**
N	79288	79288	79288	79076
Adjusted-R^2	0.2520	0.2565	0.2564	0.2569
Durbin-Watson stat	1.9975	1.9986	1.9946	1.9933

Notes:

1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
2. The general formula for computing fund flow sensitivity is as follows: $\beta_1 + \beta_2 D(RR_{i,t-1} \leq 0) + \beta_3 \overline{Ln(TNA)} + \beta_4 \overline{Vol}$

Table 2B Flow-performance relationship based on benchmarked return (continued)

	EME Bond Fund Flow Dependent Variable : $FF_{i,t}$			
	(5)	(6)	(7)	(8)
Constant	-0.1354***	5.3910***	1.3540***	1.3700***
	(0.0330)	(0.4998)	(0.1048)	(0.1051)
RR$_{i,t-1}$	0.0592***	0.0643***	-0.0528	-0.0246
	(0.0182)	(0.0182)	(0.0627)	(0.0655)
RR$_{i,t-1}$ $\times$ D(RR$_{i,t-1} \leq 0$)	-0.0259	-0.0559**	-0.0700***	-0.0710***
	(0.0279)	(0.0282)	(0.0282)	(0.0282)
RR$_{i,t-1}$ $\times$ Ln(TNA)$_{i,t}$			0.0073**	0.0073**
			(0.0035)	(0.0035)
RR$_{i,t-1}$ $\times$ Vol$_{i,t}$				-0.0057*
				(0.0038)
Ln(TNA)$_{i,t}$		-0.2243***		
		(0.0272)		
Ln(Fund Age)$_{i,t}$		-0.8455***	-0.7756***	-0.7808***
		(0.0482)	(0.0475)	(0.0478)
VIX$_t$		-0.02888***	-0.0265***	-0.0269***
		(0.0036)	(0.0035)	(0.0036)
FF$_{i,t-1}$	0.3104***	0.3053***	0.3054***	0.3055***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)
FF$_{i,t-2}$	0.1408***	0.1382***	0.1375***	0.1374***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)
FF$_{i,t-3}$	0.0741***	0.0718***	0.0705***	0.0705***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)
FF$_{i,t-4}$	0.0429***	0.0396***	0.0376***	0.0378***
	(0.0040)	(0.0041)	(0.0041)	(0.0041)
Fund flow sensitivity at positive return	0.0592***	0.0643***	0.0915***	0.1005***
Fund flow sensitivity at negative return	0.0333**	0.0084	0.0215	0.0296
N	58636	58636	58636	58548
Adjusted-R^2	0.2865	0.2907	0.2899	0.2904
Durbin-Watson stat	1.9972	2.0032	1.9958	1.9945

Notes:

1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
2. The general formula for computing fund flow sensitivity is as follows: $\beta_1 + \beta_2 D(RR_{i,t-1} \leq 0) + \beta_3 \overline{Ln(TNA)} + \beta_4 \overline{Vol}$

Table 3 Flow-performance relationship with multiple breakpoints

This table shows an extension of our model from Column 4 of Table 2A, with the original single dummy variable (D) replaced by three dummy variables (D_1, D_2 and D_3), which allows for a more gradual transition of fund flow sensitivity. These dummy variables divide the sample into four brackets. D_1, D_2 and D_3 are set to be 1 when the fund's return at time t-1 is under the following brackets:

D_1 = 1 if $R_{i,t-1} > 25^{th}$ percentile and $R_{i,t-1} \leq 50^{th}$ percentile
D_2 = 1 if $R_{i,t-1} > 50^{th}$ percentile and $R_{i,t-1} \leq 75^{th}$ percentile
D_3 = 1 if $R_{i,t-1} >$ 75^{th} percentile

	EME bond fund flow Dependent Variable : $FF_{i,t}$
Constant	1.4442***
	(0.0989)
$RR_{i,t-1}$	-0.1759***
	(0.0434)
$RR_{i,t-1} \times D_1$	0.1323***
	(0.056)
$RR_{i,t-1} \times D_2$	0.3920***
	(0.0426)
$RR_{i,t-1} \times D_3$	0.1051***
	(0.0185)
$RR_{i,t-1} \times$ Ln(TNA)$_{i,t}$	0.0150***
	(0.0023)
$RR_{t-1} \times Vol_{i,t}$	-0.0125***
	(0.0026)
Ln(Fund Age)	-0.7955***
	(0.0424)
VIX	-0.0270***
	(0.003)
Lagged fund flow$_{t-1}$	0.2808***
	(0.0036)
Lagged fund flow$_{t-2}$	0.1266***
	(0.0037)
Lagged fund flow$_{t-3}$	0.0753***
	(0.0037)
Lagged fund flow$_{t-4}$	0.0390***
	(0.0035)
Fund flow sensitivity at 1^{st} quartile	0.0575***
Fund flow sensitivity at 2^{nd} quartile	0.1898***
Fund flow sensitivity at 3^{rd} quartile	0.4495***
Fund flow sensitivity at 4^{th} quartile	0.1626***
N	79076
Adjusted-R^2	0.2608
Durbin-Watson stat	1.9951

Notes:
1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
2. The general formula for computing fund flow sensitivity is as follows: $\beta_1 + \beta_2 D(RR_{i,t-1} \leq 0) + \beta_3 \overline{Ln(TNA)} + \beta_4 \overline{Vol}$

Table 4A Cash holding positions of US and EME open-ended funds

This table shows the cash holding positions of 7,075 mutual funds in 2016. Cash holding position is the proportion of fund assets held in cash in per cent. Emerging market bond funds cover funds categorized as "Emerging Markets Fixed Income" (also the same as our sample) according to Morningstar Global Category Classifications (MGCC). US bond funds cover funds under MGCC "US Fixed Income". Emerging market equity funds cover funds under MGCC "Emerging Markets Equity". Finally, US equity funds cover funds under MGCC "US Equity Small Cap", "US Equity Mid Cap" and "US Equity Large Cap Blend".

Cash holding position (2016)	Emerging market bond funds	US bond funds	Emerging market equity funds	US equity funds
Mean (%)	13.86	9.52	6.67	6.25
Median (%)	6.88	5.46	3.59	2.79
SD (%)	10.89	7.91	9.19	9.03
Count	1,251	1,360	1,587	2,877

Source: Morningstar

Note: Morningstar's data providers do not guarantee the accuracy, completeness or timeliness of any information provided by them and shall have no liability for their use.

Table 4B Sub-sample analysis on the effect of cash holding position

This table shows the variation in flow-performance relations of EME bond funds when they are separated into two groups based on their cash holding positions. High cash holding funds represents funds with their cash holding portion (as a % of total net assets) larger than the median and low cash holding funds represents funds with their cash holding portion smaller than or equal to the median.

	EME Bond Fund Flow Dependent Variable : $FF_{i,t}$	
	High cash holding	Low cash holding
Constant	4.3991***	5.0052***
	(0.7336)	(0.5860)
$\text{RR}_{i,t-1}$	0.1712***	0.1065***
	(0.0180)	(0.0149)
$\text{RR}_{i,t-1} \times \text{D}(\text{RR}_{i,t-1} \leq 0)$	-0.1274***	-0.0543**
	(0.0259)	(0.0262)
$\text{Ln(TNA)}_{i,t}$	-0.1405***	-0.1836***
	(0.0395)	(0.0312)
$\text{Ln(Fund Age)}_{i,t}$	-0.8494***	-0.8219
	(0.0706)	(0.060)
VIX_t	-0.0370***	-0.0275***
	(0.0051)	(0.0046)
$\text{FF}_{i,t-1}$	0.3028***	0.2930***
	(0.0058)	(0.0052)
$\text{FF}_{i,t-2}$	0.1221***	0.1277***
	(0.0060)	(0.0054)
$\text{FF}_{i,t-3}$	0.0756***	0.0802***
	(0.0060)	(0.0053)
$\text{FF}_{i,t-4}$	0.0375***	0.0445***
	(0.0057)	(0.0051)
Fund flow sensitivity at positive return	0.1712***	0.1065***
Fund flow sensitivity at negative return	0.0438***	0.0522***
N	29929	36891
Adjusted-R^2	0.2648	0.2708
Durbin-Watson stat	1.9967	1.9998

Notes:
1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
2. The general formula for computing fund flow sensitivity is as follows: $\beta_1 + \beta_2 D(RR_{i,t-1} \leq 0) + \beta_3 \overline{Ln(TNA)} + \beta_4 \overline{Vol}$

Table 5 Coverage of EME bond funds in news media

This table compares the frequencies of appearance in news media of the top and bottom performers among EME bond funds. Performance is measured in terms of five-year average return of the funds according to Morningstar and the news search covers all news articles published from 1 November 2015 to 31 October 2017. Factiva is a global news database of nearly 33,000 worldwide news sources such as newspapers, magazines and influential websites. As for Bloomberg, apart from its original content, the search engine also covers more than 1,000 news sources globally. Some of the major newswires covered by Bloomberg search engine include AP(US), Press Association (UK), DPA (Germany), AFP (France), Ansa (Italy), Interfax (Russia), Xinhua (China), Canadian Press and Press Trust of India.

Ranking by	Search engine	
Five-year return	Bloomberg	Factiva
Top 1^{st} - 5^{th}	11	28
Top 6^{th} - 10^{th}	7	5
Top 11^{th} - 20^{th}	2	2
Worst 1^{st} - 5^{th}	3	3
Worst 6^{th} - 10^{th}	1	0
Worst 11^{th} - 20^{th}	0	0

Sources: Bloomberg, Factiva and Morningstar

Table 6 Net expense ratios of EME and US bond funds

	EME	US
Eightieth Percentile	0.88	0.40
Sixtieth Percentile	1.05	0.58
Fortieth Percentile	1.25	0.78
Twentieth Percentile	1.56	0.97
Count	410	939
Median	1.17	0.66

Source: Morningstar

Table 7 Effect of large fund family size on fund flow sensitivity
This table shows a modified version of our model from Column 2 of Table 2A, with a variable $\text{RR}_{i,t-1} \times$ D(Top 5) added to test the influence of large fund family size on flow sensitivity of EME bond funds.

	EME bond fund flow Dependent Variable : $FF_{i,t}$
Constant	1.5822***
	(0.0965)
$\text{RR}_{i,t-1} \times$ D(Top 5)	0.0684***
	(0.0318)
$\text{RR}_{i,t-1}$	-0.0575*
	(0.0439)
$\text{RR}_{i,t-1} \times$ D($\text{RR}_{i,t-1} \leq 0$)	-0.0826***
	(0.0178)
$\text{RR}_{i,t-1} \times$ Ln(TNA)	0.0153***
	(0.0023)
$\text{RR}_{i,t-1} \times$ Vol	-0.0172***
	(0.0025)
Ln(Fund Age)	-0.8052***
	(0.0424)
VIX	-0.0282***
	(0.003)
$\text{FF}_{i,t-1}$	0.2814***
	(0.0036)
$\text{FF}_{i,t-2}$	0.1269***
	(0.0037)
$\text{FF}_{i,t-3}$	0.0753***
	(0.0037)
$\text{FF}_{i,t-4}$	0.0388***
	(0.0035)
Fund flow sensitivity at positive return	0.1886***
Fund flow sensitivity at negative return	0.1060***
N	79076
Adjusted-R^2	0.2600
Durbin-Watson stat	1.9944

Notes:
1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
2. Fund flow sensitivity is computed based on the assumption that other interaction terms are at their respective sample means.

Table 8 Persistence of EME bond funds' performance

$$RR_{i,t} = \alpha_0 + \beta_1 RR_{i,t-1} + \beta_2 RR_{i,t-1} \times D(RR_{i,t-1} \leq 0) + \varepsilon_{i,t}$$

	Total return Dependent Variable : $RR_{i,t}$
Constant	-0.2458***
	(0.0196)
$RR_{i,t-1}$	-0.0382***
	(0.0019)
$RR_{i,t-1} \times D(RR_{i,t-1} \leq 0)$	0.0324***
	(0.0016)
N	80281
Adjusted-R^2	0.01
Durbin-Watson stat	2.0145

Note:
1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 9 Sub-sample analysis on the effects of fund size and return volatility
This table shows the variation in flow-performance relations of EME bond funds when they are sub-divided into different groups based on fund sizes and return volatilities. Columns 1 and 2 compare the regression results between (i) those samples with their fund sizes smaller than the median ("Small size") and (ii) those with their fund sizes greater than or equal to the median ("Large size"). Columns 3 and 4 compare the regression results between (i) those samples with their return volatilities lower than the median ("Low volatility") and (ii) those with their return volatilities greater than or equal to the median ("High volatility").

	EME Bond Fund Flow Dependent Variable : $FF_{i,t}$			
	Small size (1)	Large size (2)	Low volatility (3)	High volatility (4)
Constant	0.5712***	3.0157***	1.9245***	1.9881***
	(0.1309)	(0.1539)	(0.1507)	(0.1416)
$\text{RR}_{i,t-1}$	0.0888***	0.1612***	0.2255***	0.0917***
	(0.0149)	(0.0151)	(0.0243)	(0.0121)
$\text{RR}_{i,t-1} \times \text{D}(\text{RR}_{i,t-1} \leq 0)$	-0.0519**	-0.0928***	-0.0933***	-0.0535***
	(0.0248)	(0.0254)	(0.0399)	(0.0203)
Ln(Fund Age)$_{i,t}$	-0.4361***	-1.3278***	-0.8064***	-0.9940***
	(0.0630)	(0.0657)	(0.0649)	(0.0620)
VIX_t	-0.0182***	-0.0408***	-0.0435***	-0.0358***
	(0.0046)	(0.0042)	(0.0053)	(0.0041)
$\text{FF}_{i,t-1}$	0.2481***	0.3007***	0.2486***	0.2930***
	(0.0051)	(0.0050)	(0.0051)	(0.0051)
$\text{FF}_{i,t-2}$	0.1159***	0.1260***	0.1111***	0.1307***
	(0.0052)	(0.0052)	(0.0052)	(0.0053)
$\text{FF}_{i,t-3}$	0.0605***	0.0828***	0.0785***	0.0628***
	(0.0052)	(0.0051)	(0.0051)	(0.0052)
$\text{FF}_{i,t-4}$	0.0361***	0.0328***	0.0357***	0.0388***
	(0.0050)	(0.0049)	(0.0049)	(0.0050)
Fund flow sensitivity at positive return	0.0888***	0.1612***	0.2255***	0.0917***
Fund flow sensitivity at negative return	0.0369***	0.0684***	0.1322***	0.0382***
N	39535	39753	39355	39721
Adjusted-R^2	0.2190	0.2900	0.2493	0.2763
Durbin-Watson stat	1.9786	1.9598	2.0197	1.9993

Notes:
1. Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
2. The general formula for computing fund flow sensitivity is as follows: $\beta_1 + \beta_2 D(RR_{i,t-1} \leq 0) + \beta_3 \overline{Ln(TNA)} + \beta_4 \overline{Vol}$

Table 10 Flow-performance relationship on inflow and outflow

$$Subscription_{i,t} = \alpha_{sub,0} + \beta_{1,sub} RR_{i,t-1} + \sum_{k=1}^{m} \gamma_{k,sub} Z_{k,i,t} + \varepsilon_{i,t,sub}$$

$$Redemption_{i,t} = \alpha_{red,0} + \beta_{1,red} RR_{i,t-1} + \sum_{k=1}^{m} \gamma_{k,red} Z_{k,i,t} + \varepsilon_{i,t,red}$$

This table shows the regression results when the dependent variable (net fund flow) is decomposed into fund inflow (subscription) and fund outflow (redemption). The decomposition allows asymmetric investor behavior when making subscription and redemption decisions.

	(1) Net flow	(2) Inflow	(3) Outflow
Constant	2.6330***	3.7161***	2.1926***
	(0.5774)	(0.5365)	(0.3141)
RR$_{t-1}$	0.2730***	0.1784***	-0.1057***
	(0.0318)	(0.0267)	(0.0172)
Ln(Fund Age)	-1.0361***	-1.0442***	-0.2463***
	(0.2408)	(0.2102)	(0.1255)
VIX	-0.0042	0.0193**	0.0198***
	(0.0116)	(0.00099)	(0.0063)
FF$_{i,t-1}$	0.2510***	0.2314***	0.2472***
	(0.0171)	(0.0169)	(0.0171)
FF$_{i,t-2}$	0.1251***	0.1652***	0.0874***
	(0.0173)	(0.0173)	(0.0174)
FF$_{i,t-3}$	0.0875***	0.1038***	0.0626***
	(0.0172)	(0.017)	(0.0174)
FF$_{i,t-4}$	0.0453***	0.0746***	0.0426***
	(0.0165)	(0.0165)	(0.0169)
N	3594	3594	3594
Adjusted-R^2	0.2308	0.3398	0.2527
Durbin-Watson stat	1.9929	1.9961	1.9414

Note: Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

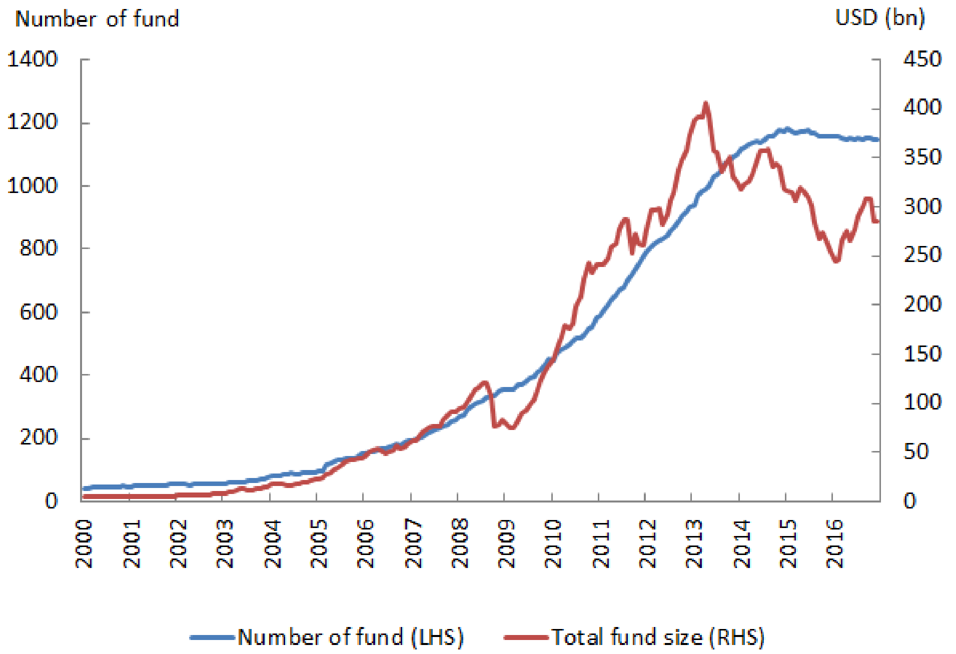
Table 11 Flow-performance relationship on aggregate level

This table shows the results of sector-level regression. The model is largely the same as the fund-level regression model, except for the exclusion of fund-specific variables. AFF is the sector-level fund flow in percentage term, and EMBI is the return of the JP Morgan Emerging Market Bond Index Global.

	(1) Dependent Variable : Bottom-up aggregate EME bond fund flow compiled from Morningstar database	(2) Dependent Variable : Aggregate EME bond fund flow from EPFR database	(3) Dependent Variable : Aggregate EME equity fund flow from EPFR database
Constant	0.0067**	0.0081**	0.0003
	(0.0036)	(0.0037)	(0.0025)
EMBI return$_{t-1}$	0.2898**	0.3827***	0.1452
	(0.1285)	(0.1259)	(0.0883)
EMBI return$_{t-1}$	-0.2443*	-0.4024**	-0.1519
$\times$ D(EMBI return$_{t-1} \leq 0$)	(0.1704)	(0.1744)	(0.1194)
MSCI Emerging Markets	-0.0025	0.0112	0.0507**
Index return$_{t-1}$	(0.0298)	(0.0303)	(0.0271)
Lagged fund flow$_{t-1}$	0.5047***	0.4807***	0.1478*
	(0.0964)	(0.1018)	(0.1081)
Lagged fund flow$_{t-2}$	0.2245***	0.1530**	0.1978***
	(0.0895)	(0.0879)	(0.0826)
VIX	-0.0003*	-0.0006***	0.0000
	(0.0002)	(0.0002)	(0.0001)
N	155	155	155
Adjusted-R^2	0.5559	0.5262	0.2458
Durbin-Watson stat	1.7881	1.8882	2.0355

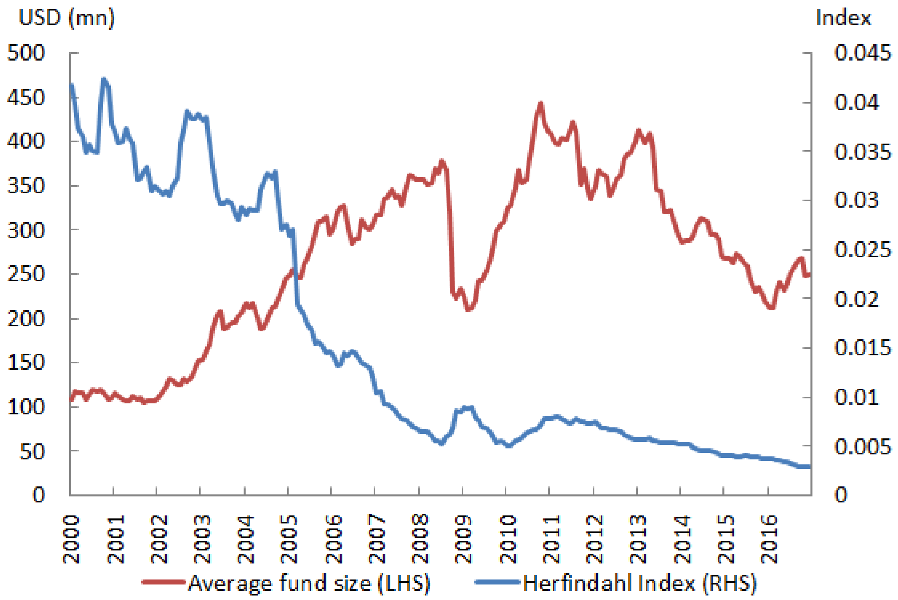
Note: Standard errors in parenthesis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Chart 1 Number of EME bond funds



Source: Morningstar

Chart 2 Average fund size and Herfindahl Index of sampled EME bond funds



Source: Morningstar

Chart 3 Flow-performance relationship of EME bond funds
This chart is to illustrate the effect of fund size on the flow-performance sensitivity based on the estimation by our model. Each line represents the flow-performance relationship of an EME bond fund at the corresponding fund size percentile. While all the four flow-performance curves are in convex shape, there is a gradual steepening of the lines as fund size increases.

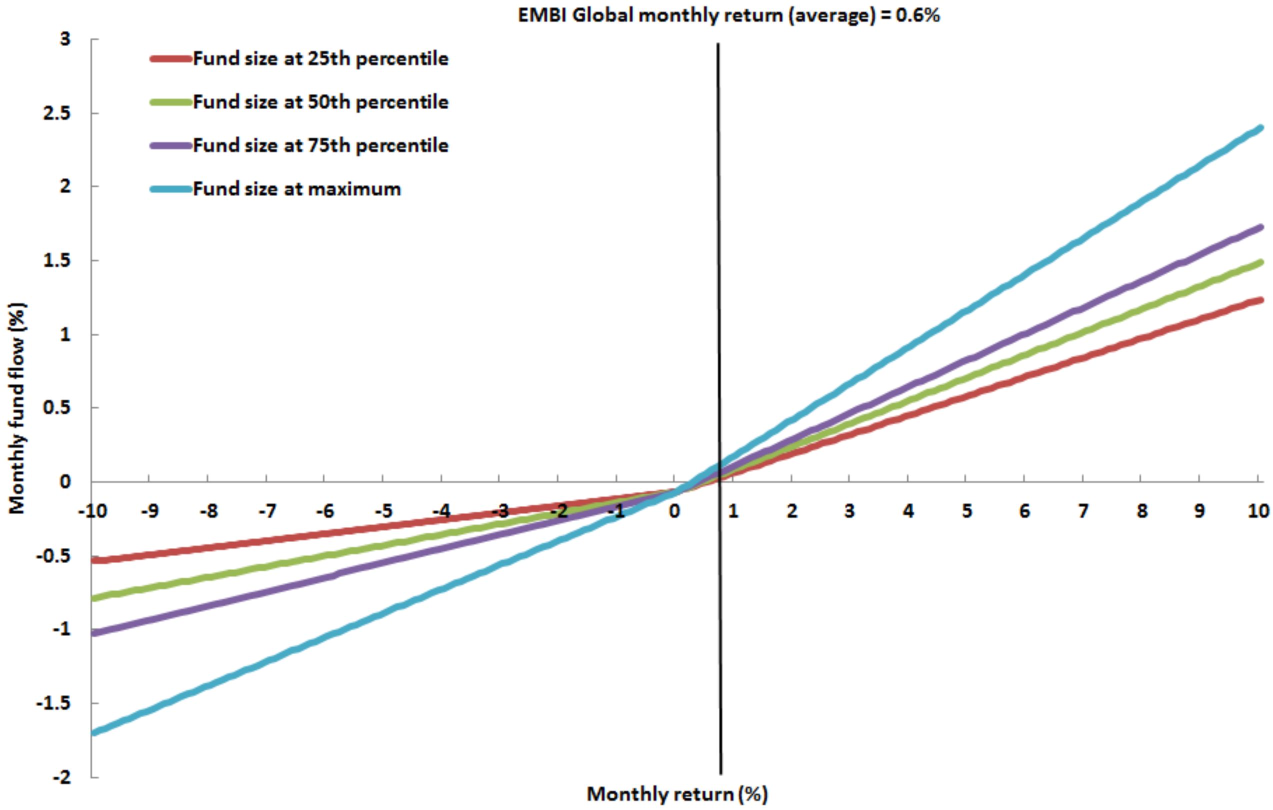


Chart 4 Fund flow correlation in developing markets

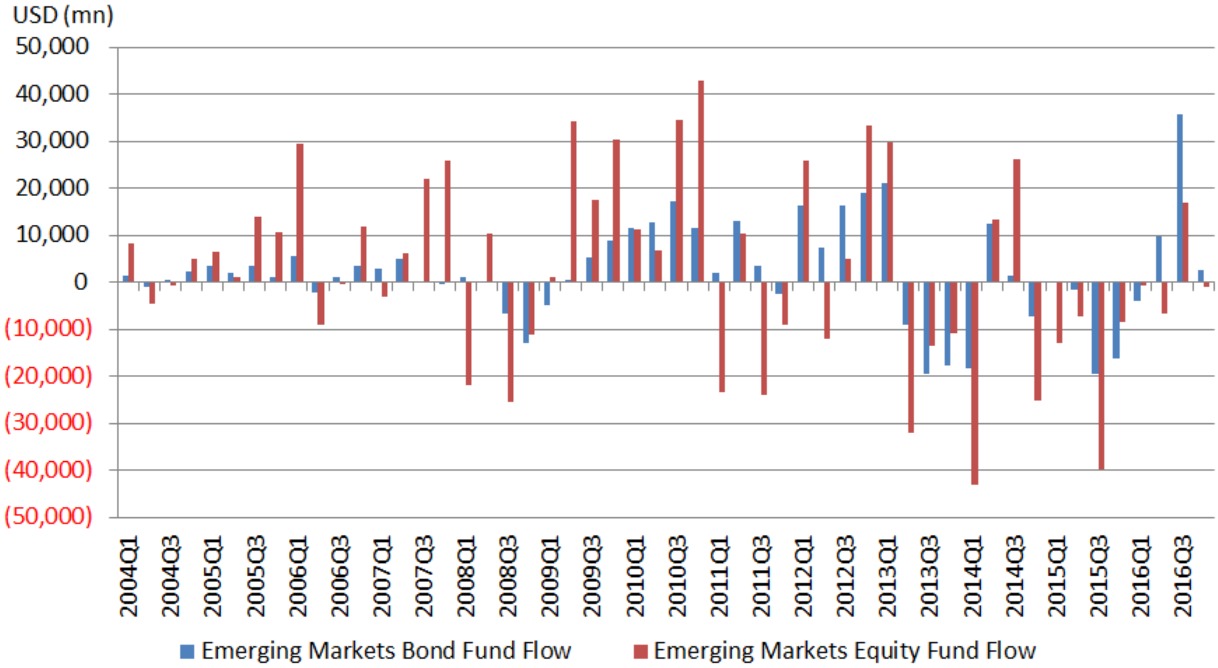


Chart 5 Fund flow correlation in developed markets