Is trouble brewing for EMEs?[1]

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Abstract

Discussions regarding financial stability have revolved mainly around the degree of leverage in financial institutions. However, some authors have argued that mechanisms associated with unleveraged institutions could entail financial instability. With this in mind, we aim to shed light on the possible presence of run-like dynamics in the in- and outflows emanating from bond funds vis-à-vis a group of emerging market economies (EMEs). In addition, we examine some of the implications of US monetary policy on these dynamics. As argued by some authors (see Feroli et al (2014)), although bond funds are mostly unleveraged, the type of incentives they face might generate run-like dynamics. Such dynamics could prove unfavourable for financial stability. Indeed, we find evidence of the presence of run-like dynamics in the bond flows of several EMEs, although some economies seem to be more vulnerable than others. We also find evidence that changes in US monetary policy affect such dynamics, and that the strength of those dynamics could have increased since the beginning of 2013. Our main concern in this paper relates to run-like dynamics that could potentially take place in the near future. In other words, we hypothesise that hitherto we have seen only a handful of episodes with run-like dynamics, although we believe that there is a good chance that more such episodes could follow.

Key words: Financial leverage, emerging market economies, US monetary policy, unconventional monetary policy

JEL codes: F3, F4

[1] The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Bank of Mexico. Comments are welcome. We would like to thank the Financial Stability Directorate, the Central Bank Operations Directorate, and the Economic Research Directorate at the Bank of Mexico for providing us with some of the data. Conversations with Fabrizio López Gallo, Andrés Jaime, Claudia Tapia Rangel, and Ariadna Valle Carmona have been useful.

Introduction

The unprecedented easy monetary policy stances implemented in advanced economies (AEs) have had substantial implications for the world economy, and, in particular, for most EMEs. For their part, EMEs have assessed how far such policies have contributed to speeding up their economic recovery and they have considered the possible unintended consequences. One of the main implications has been the significant capital flows into and out of EMEs, of which bond markets have contributed to a significant share.

Since the global financial crisis, a leitmotiv in financial stability policy discussions has been the degree of leverage in financial institutions. In effect, leverage has been identified as a central factor behind the recent global financial crisis. Accordingly, many financial sector reforms have been designed with the goal, among others, of providing better incentives for financial institutions to attain sustainable (ie closer to socially optimal) levels of leverage.[2]

Nonetheless, some authors have argued that given the magnitude of bond-related flows, and the incentives faced by many asset management companies, a low degree of leverage in the financial institutions involved will not necessarily ensure a stable financial ride through the tightening of the US policy rate.[3]

Against this backdrop, following the work of Feroli et al (2014), we seek evidence of the existence of run-like dynamics in bond flows in a set of EMEs. We also explore some of the possible implications of US monetary policy for such dynamics. Run-like dynamics can be rationalised by the presence of delegated investment decisions between the ultimate owners of the invested capital and the managers of the funds, and a concern for the relative performance of these actors.[4] Nonetheless, other mechanisms could also be contributing to such dynamics. We emphasise some of the aspects that are relevant to EMEs.

Of course, this is not to say that the degree of leverage is either more or less important. Its relative importance is indeed a very pertinent question, but one that will not be addressed here. In other words, we seek evidence of a specific channel among other possible ones, but without taking a specific stance on its relative strength.

2 Leverage in countries receiving capital flows has also been highlighted as a determining factor of the capacity with which economies will be able to deal with the eventual tightening of the US policy rate, particularly so in EMEs (Rajan (2013)). To quote Rajan (2013): "As leverage in the receiving country builds up, vulnerabilities mount and these are quickly exposed when markets sense an end to the unconventional policies and reverse the flows." What is more, Rajan (2014) has argued that "Leverage need not be the sole reason why exit may be volatile after prolonged unconventional policy. Investment managers may fear underperforming relative to others […]". We explore this in detail for the case of bonds flows in and out of EMEs.

3 As is made clear in the previous footnote, we believe that the level of financial leverage is relevant in both the investment institutions that originate the flows and the economies that are the recipients of such flows.

4 This is not the only potential agency conflict. For example, Chevalier and Ellison (1997) document that, while the owners of the invested capital would like to maximise the risk-adjusted returns of their funds, fund managers would like to maximise the value of those funds. In particular, fund managers tend to maximise the funds' risk-return profile at the end of the year which, in turn, determines their compensation.

The study of the relationship between asset prices and financial stability is, of course, not new. For example, Borio and Lowe (2003) argue that "sustained rapid credit growth combined with large increases in asset prices appears to increase the probability of an episode of financial instability." While credit is not a component of the models we use here, significant increases in bond prices are indicative of potential financial stability problems, as we will be exploring in more detail.

Relatedly, Stein (2014b) underlines, in the context of financial stability and monetary policy, that instead of mainly focusing on a measure of financial leverage as an input into the monetary policy framework, we should additionally look at risk premia in the bond market.

It goes without saying that the monetary authorities of the AEs are pursuing their own interests. In effect, they are following their legal mandates. Nonetheless, given their monetary policy stances – in terms of the magnitude of those stances, the time they have been in place, and the degree of uncertainty involving their implementation and exit – one has to recognise that the implications of such monetary policies are less well understood. In short, we are keenly interested in understanding the economic implications that these policies entail for EMEs.

Finally, our general concern is about the run-like dynamics that could potentially take place in the near future. In other words, we hypothesise that up to this point we have only seen a handful of episodes of run-like dynamics, but there is a good chance that more will follow.

Preliminary analysis: EMEs

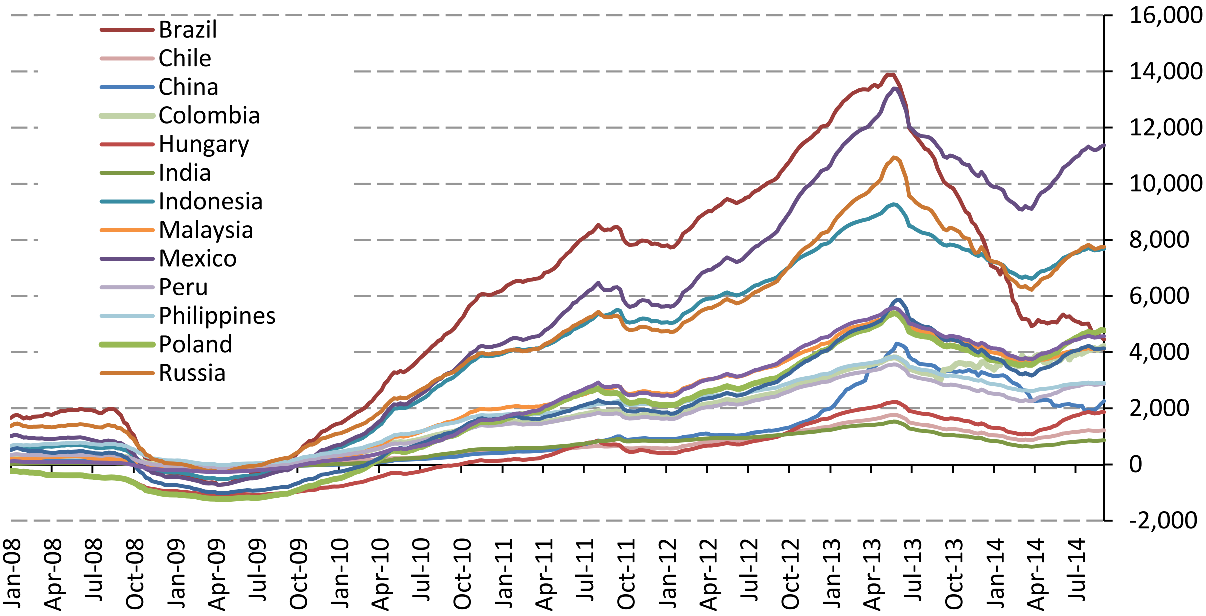
To set the stage, we present some evidence relating to the recent evolution of bond flows to and from EMEs, and to the returns associated with well-known EMEs' bond market indices. To begin with, based on a simple visual inspection (Graph 1), we note some of the properties of cumulative bond flows.

First, such flows are highly correlated. Second, in general, the longer inflows have been accruing to an economy, the greater their fall once an outflow episode takes place. Relatedly, the pace of the inflows tends to be slower than that of the outflows. This was seen most clearly in September 2011. Third, some of the most significant changes in the direction of flows are associated with US monetary policy announcements, most notably during the so-called taper tantrum of May 2013.

In addition, the aggregated bond flows pertaining to EMEs and the spread on the universe of securities covered by the EMBI Global Index display three features (Graph 2). First, they tend to co-move negatively (ie bond flows and related bond prices co-move positively). Second, the correlation between the spread on the EMBI Global Index and changes in bond flows seems to have increased as of Q3 2011. In other words, variations in the EMBI spread lead to greater changes in bond flows after Q3 2011. Third, the bond flows' variance has increased since around Q3 2011.

Cumulative bond flows in selected EMEs

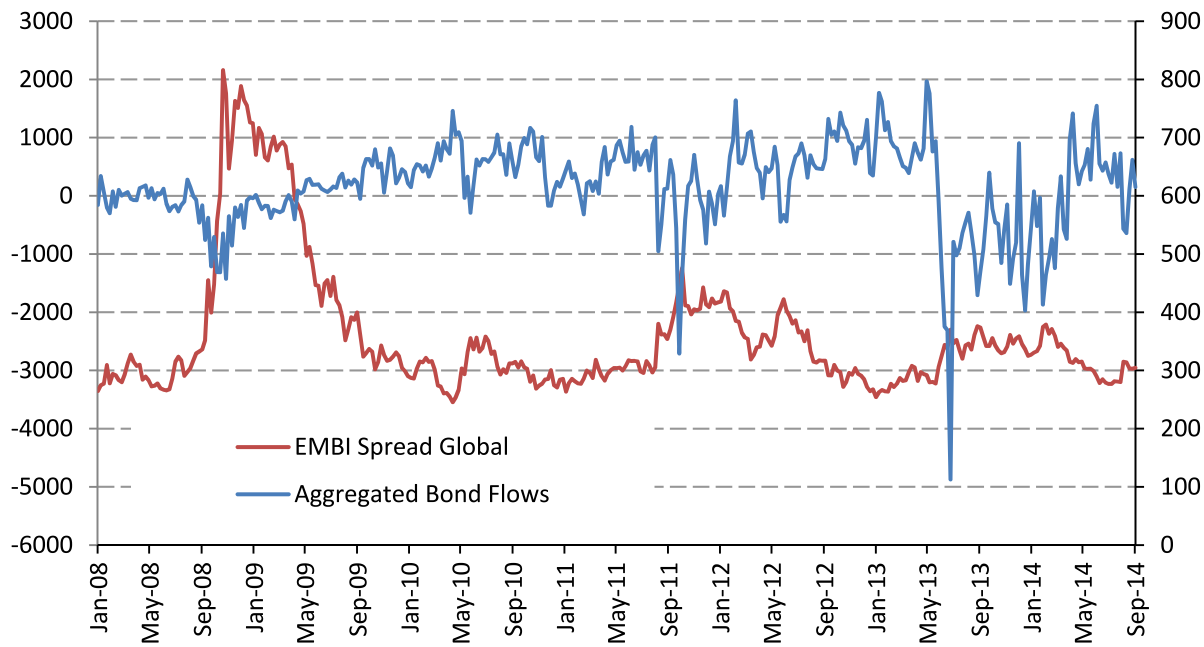
US dollars millions, weekly periodicity | Graph 1



Source: EPFR

Aggregated bond flows in EMEs and spread of Global EMBI Index

US dollars millions, and index, weekly periodicity | Graph 2



Source: EPFR and Bloomberg

All told, high correlations among bond flows, their negative co-movement with the spreads on the EMBI Global Index, and sharp bond outflows provide joint evidence pointing to the presence of run-like dynamics, as we will explore in detail in the rest of the paper. This situation contrasts with the classic case in which an increase in the risk premium (ie a lower price) eventually prompts an upsurge in capital inflows, as some investors seize the opportunity to invest. In addition, we will see that EME-related bond flows and the EMBI spread seem to be affected by monetary policy decisions in the United States.

1. The model

In this section, we use the model posited by Feroli et al (2014), which is a simplified version of the model developed by Morris and Shin (2014), as a framework for the analysis of our data. At times, we also refer to Banerjee (1992), who put forward a simple model of herd behaviour. Those models will prove useful in organising part of our discussion.

Next, we make three important clarifications. First, we do not intend to calibrate or estimate an economic model. Instead, our analysis is mostly based on the estimation of a set of vector auto-regressions (VARs). Second, the facts we document could be the product of other economic mechanisms behind the run-like dynamics of the bond flows and the relevant bond market indices. Three, although we use one specific model to guide our analysis, just as in Feroli et al (2014), we do not favour one mechanism over another. Thus, there could well be other economic mechanisms leading to the type of dynamics that we seek to document.

A brief description of the model posited in Feroli et al (2014) is as follows. There are two types of investor:

(i) *Passive* investors who are risk-averse. Each such investor chooses between holding one unit of the risky asset and investing the equivalent of that unit in a money market account, offering a floating rate that is directly associated with the policy rate. Everything else constant, the floating rate is the safest return.

(ii) *Active* investors who are risk-neutral. Each one also chooses either to hold a risky asset or having her/his capital in a money market account. However, they are *delegated* investors. Thus, although they care about long term fundamentals, they are also concerned about their *relative performance* vis-à-vis their peers. Such a concern can be rationalised in several ways. Active investors can have a reputation motive or a career concern (see Scharfstein and Stein (1990) and Hong et al (2000)). A poor relative performance would probably involve a loss of some their clients (Chevalier and Ellison (1998)). The redemption pressure funds face could be considered as another motive.

In their model, each active investor keeps a watchful eye on the performance of its peers. In practice, this can be achieved by having investors measuring their performance against the same benchmark index. Every active investor knows this. Thus, active investors play a game in which the effort that one exerts will affect the efforts of the others.[5]

[5] As pointed out by Feroli et al (2014), the delegated relationship is typically a sizeable chain of relationships. Thus, although conceptually one can think of a principal and an agent, in practice it would probably involve several principal-agent relationships, positioning the initial principal from

Exploring the model further, there is a fixed supply of risky securities denoted by S. All investors care about the fundamental expected value V of the risky security at some terminal date T. Passive investors have a quadratic utility function.[6] The aggregation of their first-order conditions implies a linear demand of the form: $p = V - (\sigma^2/\tau)\, q$, where p and q are, respectively, the price and quantity demanded of the risky asset by the passive investors. Also, σ^2 can be interpreted as the variance of the risky asset, and τ is a risk-sensitive coefficient.[7] The lower the value of the coefficient, the more risk-averse the passive investors are.

There are n active investors, where $n<S$. As active investors are risk-neutral, they will demand the risky asset at price V (or at a smaller value) as long as they do not think that their relative performance is a concern. In such a case, each active investor's demand for one unit of asset is totally elastic. Thus, if all active investors have a position in the risky asset, in the aggregate they will demand n such assets.

Passive investors will not pay V for the risky asset since they are risk-averse. Instead, they will demand the remaining S-i risky assets, where i is the number of active investors which hold a unit of the risky asset, at an equilibrium market price p. This price is determined by the passive investors' linear demand and by the number of active investors which hold a unit of the risky asset, ie $p = V-(\sigma^2/\tau)(S-i)$, where $0 \leq i \leq n$.

If an active investor, say, buys a unit of the risky asset, its price increases by (σ^2/τ). Conversely, if that investor sells its unit of the risky asset, the asset's price decreases by (σ^2/τ). Moreover, if all active investors sell their positions in the risky asset, its price falls by $(\sigma^2/\tau)n$, to reach a price of $V-(\sigma^2/\tau)S$, its minimum bound.

Suppose then that there are no active investors with a position in the risky security. The first active investor would buy it at $V-(\sigma^2/\tau)S$, and the jth active investor would do so at a price $V-(\sigma^2/\tau)(S-(j-1))$. The investor's return also depends on the order in which the asset has been sold, as mentioned, as every time an active investor sells its position in the risky asset, the asset's price drops by (σ^2/τ).

In general, an active investor will seek to have a position in the risky asset first. Once the investor has such a position and suspects that the rest of the active investors will abandon theirs, that investor will seek to leave its position as soon as possible. In short, buying before the rest of the active investors, and selling ahead of the run, yields the greatest return.[8]

As mentioned, both types of investor have access to a money market account which pays a floating rate closely associated with the policy rate. More specifically, an investor that rolls over its investments in the money market account obtains a gross return of: $1+r = \mathbf{E_t}\, \Sigma^{T}_{m=1} (1+i_{t+m})$, where i_{t+m} is the policy rate at time t+m.

the last agent farther apart. In this context, a relative ranking could be interpreted as an effective monitoring device.

6 Explicitly, the investor's utility function is: $Vy - (1/2\tau)y^2\sigma^2 + (W-py)$, where y is the position in the risky-asset, σ^2 its variance, and W the investor's wealth.

7 Morris and Shin (2014) derive the aggregate demand, noting that $\tau=(\tau_1+\tau_2+...+\tau_K)$, where τ_i is the risk coefficient of the i^{th} individual active investor.

8 Specifically, assume that at some point all delegated investors buy a unit of the risky asset. Then if such investor sells it in the k^{th} place, she will sell at a price of $V-(\sigma^2/\tau)((S-n)+(k-1))$. Thus, under such scenario, buying at j and selling at j yields $(\sigma^2/\tau)[n+j-k]/\{V-(\sigma^2/\tau)(S-(j-1))\}$.

Thus, the return on the money market account depends on the expected path of monetary policy.

The active investor that ranks last faces a penalty fee. That is, on top of the investor's low return relative to that of its peers, it loses C. Thus, in the model, active investors play a global game, which is a simplified version of the model in Morris and Shin (2014). Specifically, assuming a uniform density of beliefs over the other active investors' decisions to sell their position in the risky asset, it can be shown that investors will prefer the risky asset if r is less than a threshold:[9]

$$r \leq (V-p)/p - C/n. \quad (1)$$

The intuition is straightforward: adjusted for the penalty and the number of active investors, the investment opportunity with the higher premium (ie (V-p)/p) is preferred. Thus, as C augments or as n decreases, the threshold declines. The effect of the penalty's size is direct: a bigger one will make more active investors turn to the money market account as the threshold declines when the number of active investors decreases.[10]

Note that a larger τ, ie less risk-sensitive passive investors, implies smaller differences in returns between investors. Conversely, a smaller τ, ie more risk-sensitive passive investors, leads to greater differences in returns between these investors. As an extreme case, suppose that passive investors are nearly risk-neutral, ie, τ is very large. Thus, based on their demand curve, $p = V-(\sigma^2/\tau)(S-i)$, changes in their position in the risky asset would lead to negligible changes in its price, leading to undistinguishable rankings between passive investors.[11] Conversely, in the context of Banerjee (1992), greater differences in returns would more probably lead to herd-like behaviour.

At this point, it is useful to elaborate on the model's intuition. Active investors care about the risky asset's fundamental long-run value. Yet, they have a relative ranking concern in the short-run, which is realised in the penalty taken by the active investor that ranks last. Importantly, the risky asset market's size is sufficiently small that changes in the active investors' positions affect prices significantly.[12]

9 The uniform density assumption is motivated by a result in Morris and Shin (2014). In that paper, the penalty fee is endogenously determined as a function of the proportion of active investors having a portfolio value above the investor's portfolio value which is penalised (denoted by x). In their model, x's density is a uniform one.

10 Following the analogy of the musical chairs game, one gets more concerned the fewer players are left. In this game, assuming a uniform density for getting a chair, given n participants, one fails to get one with probability 1/n. Thus, if n is big, the probability is low. On the other hand, as n decreases, the probability grows until it reaches 1/2.

11 A direct way of seeing this is considering two extreme cases in the model. On the one hand, as τ tends to infinity, p tends to V and all returns in the risky asset tend to 0. Thus, as all investors get the same return, the probability of ranking last approaches 0. Price dynamics are, following the analogy, as if in the game of musical chairs there was one chair for every player. On the other hand, as τ diminishes, p becomes more sensitive to changes in the passive investors' position in the risky asset. Thus, as differences in returns grow wider, the probability of someone ranking last increases, since distinguishing their relative ranking becomes easier.

12 This is one of the reasons we are concerned with EMEs, particularly given the size of capital outflows and inflows that some such countries have faced relative to the size of their financial (especially bond) markets.

Thus, in tandem, the allocation decisions of active investors, given the changeable money market account's floating rate, and exacerbated by relative ranking concerns, can lead to a sudden change in active investors' positions. As a few active investors change their portfolio allocation towards the money market account, those active investors who do not, based on their short-run concern of ranking last, sell their positions in the risky assets, giving place to the run-like dynamics.

In our estimation work, active investors' increments in risky assets are captured by bond inflows; conversely, decrements result in bond outflows. Risky assets' prices are captured by the EMBI spreads. In effect, in the model prices and spreads show a direct and negative correlation. In addition, the policy rate is measured by the Wu and Xi rate, which tries to capture non-conventional monetary policy; that is, it tries to measure through a negative policy rate further monetary accommodation at the zero lower bound.

All in all, we test for three main predictions of the relationship between flows, risk premia, and the policy rate of the model in Feroli et al (2014).

(i) As a result of the presence of the two types of investor, and the relative performance concern, there is a positive feedback effect between bond flows and prices (ie a negative feedback between bond flows and risk premia).

(ii) Sharp outflows are more likely than smooth ones, since the relative performance concern is heightened when there are sharp movements, increasing the risk premium (ie reducing bond prices).

(iii) A rise in the policy rate is likely to set off episodes of outflows, as r rises, and the probability of it surpassing the threshold level in (1) increases. In short, such a change in the policy rate leads to a fall in active investors' demand for risky assets. As its price falls, its risk premium increases.

After describing the data, we explore these predictions.

2. Data: EMEs

Our database has time series for the following 14 EMEs: Brazil, Chile, China, Colombia, Hungary, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa and Turkey. In order to assess possible run-like dynamics in these economies as a group, we also consider an aggregated time series. We use the EMBI spreads as proxies to the risk premia in the model (Table 1). In theory, the risk premium should be based on the actual prices of the bonds under management by the funds. Yet, we do not have access to the data at a country level and at a high frequency.

We do, however, have access to the assets under management (AUM) at an aggregate level for EMEs from the EPFR Global database. This allows us to compare the percentage change in the price of the AUM with the percentage change in the EMBI spread. Accordingly, we compare the estimated change in the value of the AUM for all EMEs with the change in the EMBI spread (see the appendix). The corresponding series are highly correlated. This gives us confidence in using the EMBI spread as proxy for the risk premium for each EME.[13]

Moreover, the EMBI spread measures the risk premium of EME bonds denominated in US dollars (satisfying minimum liquidity requirements). In addition, the index's denomination is appropriate in the sense that the comparison investors make is against the US policy rate.

EMBI spreads for EMEs

Index

Table 1

Country	Mean	Std. Dev.	Max	Min
Aggregated	206.02	84.06	580.36	97.29
Brazil	226.28	71.12	670.00	134.00
Chile	147.20	62.52	409.00	67.00
China	135.22	64.30	328.00	26.00
Colombia	202.91	92.48	699.00	96.00
Hungary	271.04	159.21	758.00	56.00
Indonesia	283.70	153.87	1099.00	137.00
Malaysia	142.84	68.85	481.00	66.00
Mexico	194.31	75.96	596.00	93.00
Peru	193.10	82.06	612.00	94.00
Philippines	219.58	91.18	678.00	101.00
Poland	145.68	75.15	370.00	45.00
Russia	245.89	143.93	892.00	89.00
South Africa	204.63	108.76	752.00	51.00
Turkey	271.85	93.78	733.00	145.00

Notes: Aggregated refers to the average of all EME EMBI spreads. Period: 01/04/2006 to 09/03/2014

Source: EPFR

We use the EPFR bond flows data as a proxy to the changes in active investors' positions in the risky asset in the model (Table 2). As explained on their website, EPFR tracks both traditional and alternative funds domiciled globally, with $23.5 trillion in total assets. Their aim is to provide a comprehensive view of how institutional and individual investor flows drive global markets. What is more, the EPFR data have the advantage of covering funds domiciled in the United States and Europe (Jotikasthira et al (2011)).

In this context, one might have concerns about the properties of the EPFR bond flows database. First, there is an issue relating to the extent to which the flows covered by the database are managed by funds that are subject to a delegated investment relationship. Second, there are questions concerning the proportion of funds in the database which are leveraged. Third, there is the issue of how

[13] As a corollary, this result is consistent with the representativeness of the EPFR bond flows data. Had we not observed a high correlation between the percentage change in the value of the assets under management (at an aggregate level for EMEs from the EPFR database) and the percentage change of the EMBI spread, questions on the EPFR database's representativeness could have been raised.

representative the EPFR data are of investors' bond flows in global markets. We believe that none of these should be a significant concern for our analysis, as we argue next.

First, the fact that non-delegated investors, which could be included in the database, do not necessarily care about their relative performance should not affect our results. Consider, on the one hand, that run-like dynamics could still persist to the extent that delegated investors are responsible for a significant portion of the AUM. Thus, non-delegated investors would have an incentive not to ignore their peers under a delegated investment relationship.[14] Crucially, finding evidence favourable to the model using the data referred to would illustrate the significance of delegated investors in the market. Under the assumption that non-delegated investors' behaviour is a force against the dynamics of delegated investors' actions, we would then find less evidence favourable to such dynamics.

Note the significant differences between the EMBIs spreads' characteristics, and the bond flows among EMEs (Tables 1 and 2). This reflects some of the differences of the EMEs in our sample.

EPFR bond flows statistics

US dollars millions

Table 2

Country	Mean	Std. Dev.	Max	Min
Aggregated	141.72	604.41	1810.82	-4472.85
Brazil	9.83	116.26	317.26	-789.98
Chile	2.68	14.00	44.25	-123.08
China	4.98	43.42	366.55	-290.18
Colombia	9.31	47.66	376.59	-295.38
Hungary	4.11	25.91	93.06	-143.25
Indonesia	16.96	53.63	163.52	-319.31
Malaysia	9.11	32.21	114.54	-201.04
Mexico	25.10	87.37	318.79	-589.22
Peru	6.34	24.37	78.84	-172.65
Philippines	6.42	24.15	76.02	-143.17
Poland	10.55	41.70	147.78	-281.09
Russia	17.12	81.14	327.00	-644.13
South Africa	10.08	35.66	103.64	-218.71
Turkey	9.12	50.98	190.85	-372.91

Notes: Weekly frequency. Aggregated refers to the summation of bond flows for all our EMEs. Period: 01/04/2006 to 09/03/2014
Source: EPFR

Second, EPFR bond flows capture a relatively representative sample of traditional and non-traditional funds. Moreover, more than 90% of the funds considered are typically traditional (ie unleveraged).[15] Table 3 presents the specific

[14] In effect, their response can be interpreted as being part of a rational speculative bubble.

[15] For example, see Table 3.

composition of the funds' data by classes. Note that potentially leveraged classes are in the minority (hedge funds and the lesser part of ETFs). In addition, note that the majority are open-ended and could therefore potentially face redemption pressures when underperforming. Moreover, related to this, Borensztein and Gelos (2000) find that in EME mutual funds herding behaviour is more widespread among open-ended funds than among closed-end ones.

Third, EPFR collect flows data in two frequencies: weekly and monthly. The monthly collections involve a broader sample of funds. Yet, when we compare the EME time series that are available in weekly and monthly frequencies, we find a high degree of correlation between the respective bond flows.[16] In our exercises, we obtained a measure of monthly flows simply by summing up the weekly flows in each month. This distinction is relevant since, as was mentioned earlier, EPFR collect their data on a weekly and monthly basis. We only use the weekly data because data at such frequency are better suited to supporting a causality hypothesis between the series.[17]

More generally, some authors (eg Miyajima and Shim (2014)) have argued that EPFR bond flows are not very representative of the entire universe of investment funds, as the funds surveyed are small in size relative to major custodians.[18,19] Nonetheless, to begin with, the fact that the implicit change in their values is well captured by the EMBI spreads provides favourable evidence for their representativeness. Furthermore, even under some degree of "under-representativeness", our focus is neither on predicting the time when an outflow episode might occur nor on estimating its precise effects. Moreover, by finding that the bonds flows we use clearly have an effect on the corresponding EMBI index (and conversely), we underscore the relevance of the mechanisms we are assessing.

16 The correlation for the aggregated bond flows' series on a weekly basis with the series on a monthly basis is 0.86 for the January 2005–August 2013 estimation sample. Once a quarterly average is taken in both series, such correlation goes to 0.92 for the same estimation sample.

17 This is the case except for the equities data which have a monthly frequency from the source (see Appendix).

18 To quote Miyajima and Shim (2014): "the individual institutional investors represented by the EPFR data are believed to be relatively small in size compared with those that use the major global custodians. Therefore, the EPFR institutional flows may not be a very good proxy for the entire universe of institutional investment flows."

19 In the particular case of Mexico, when comparing the EPFR bond flows to the change in positions for Cetes, Bonos and TIIE swaps, which are reported to the Central Securities Depository (Institución para el Depósito de Valores, Indeval), one obtains a correlation of around .80% for such time series during 2013. To estimate the correlation, a simple moving average for the change in positions is taken, since such series are more volatile than the EPFR bond flows' series. Thus, their movements, which is what we are interested in, are strongly correlated.

EPFR Global - number of mutual funds that report on a weekly basis

as of October 1, 2014 Table 3

Type	No. of classes	% of total
Open-end	51,315	99.05%
Closed-end funds	494	0.95%
Total	51,809	100.00%

Open-end funds sub-sets	No. of classes	% of total
Traditional	46,397	90.42%
Hedge funds	72	0.14%
Insurance funds	1,284	2.50%
ETF only	3,562	6.94%
Total	51,315	100.00%

Source: EPFR bond flows statistics

In sum, as argued, we do not think that the characteristics of the EPFR bond flows database could overturn our main results. However, we acknowledge that the exact estimated coefficients could potentially change if we had access to the exact counterparts of the time series in the model.

In addition, there might be a number of measurement issues regarding reported flows. As pointed out in Feroli et al (2014), funds can merge, be liquidated, and/or be created. To alleviate these issues, we took a weighted average of bond flows of the past four weeks for some estimations.[20] We nonetheless underline that our main results do not hinge on such a transformation.

What is more, one has to consider the asset-gathering capabilities of investment institutions as well. Such institutions have a comparative advantage in information gathering and analysis. Moreover, they tend to use similar risk management tools, which increase the likelihood of observing similar changes in their portfolio allocation decisions.

The lion’s share of assets under management is concentrated in a handful of investment institutions (Table 4). As an illustration of this concentration, consider the assets under management of the top 20 companies as a proportion of those managed by the top 50 companies (see table below). The concentration observed echoes the importance of asset-gathering capabilities among asset management companies. Crucially for our analysis, a change in the capital allocated by any one of these institutions could have significant implications for EME financial markets.

20 Only for the bivariate VAR in the bonds flows and EMBI spread section, for which data have a weekly frequency, and the analogous exercises.

Assets under management (AUM) of the top 20 asset management companies (AMC) relative to the top 50 AMC

as of 31/12/13 in US dollars millions Table 4

Name	Country	AUM	AUM % of Top 50 Total	AUM Cumulative
BlackRock	US/UK	4,329,162	10.5%	10.5%
Vanguard Asset Management	US/UK	2,753,926	6.7%	17.1%
State Street Global Advisors	US/UK	2,345,556	5.7%	22.8%
Fidelity Investments	US/UK	1,945,267	4.7%	27.5%
BNY Mellon Investment Management	US/UK	1,584,992	3.8%	31.3%
J.P. Morgan Asset Management	US/UK	1,557,391	3.8%	35.1%
PIMCO	US/Germany/UK	1,539,651	3.7%	38.8%
Deutsche Asset & Wealth Management	Germany/US	1,283,290	3.1%	41.9%
Capital Group	US	1,251,462	3.0%	44.9%
Pramerica Investment Management	US	1,109,072	2.7%	47.6%
Amundi	France	1,071,170	2.6%	50.2%
Northern Trust Asset Management	UK/US	884,770	2.1%	52.3%
Franklin Templeton Investments	US/UK	880,992	2.1%	54.5%
Natixis Global Asset Management	France/US	867,289	2.1%	56.6%
Wellington Management Company	US	834,671	2.0%	58.6%
Goldman Sachs Asset Management Int.	US/UK	807,889	2.0%	60.5%
Invesco	US/Belgium/UK	779,186	1.9%	62.4%
AXA Investment Managers	France	753,574	1.8%	64.2%
Legal & General Investment Management	UK	744,802	1.8%	66.0%
T.Rowe Price	US/UK	692,627	1.7%	67.7%

Source: www.ipe.com

Bond flows and risk premia: EMEs[21]

We estimate a bivariate VAR having as variables the EPFR bond flows and the EMBI spreads, at a weekly frequency from 1 July 2009 to 9 March 2014. Whereas the use of a higher frequency is more likely to demonstrate a hypothesis of causality, the use of lower frequency data would involve other “contaminating” effects.

The identification procedure for the impulse-response functions is based on the Cholesky decomposition of the VAR’s variance-covariance matrix. As is well-known, the variables’ order is central to such an identification technique. On impact, the EMBI spreads respond to a shock to EPFR bond flows. Intuitively, this implies that prices move faster than quantities.[22]

21 In other additional exercises (not reported), we consider estimations that add as a control variable the cumulated bond flows in the past month as a third variable (see Appendix).

22 Also, a lag of two periods is used in the VAR, broadly in line with the four tests used to determine an optimal lag (FPE, AIC, HQIC and SBIC), and emphasising comparison among EMEs. Note that we always estimate the optimal lag based on the full samples.

Following the order of the model's three main implications, we first present evidence on a possible negative feedback loop between bond flows and risk premia. Thus, consider the cumulative responses of bond flows to shocks to the EMBI spreads (Graph 3). Only three out of 14 economies in our sample do not present a statistically significant response: China, Hungary, and Malaysia. The Philippines and Russia present marginally significant responses.

Cumulative impulse-response functions

as of 31/12/13 in US dollars millions Graph 3

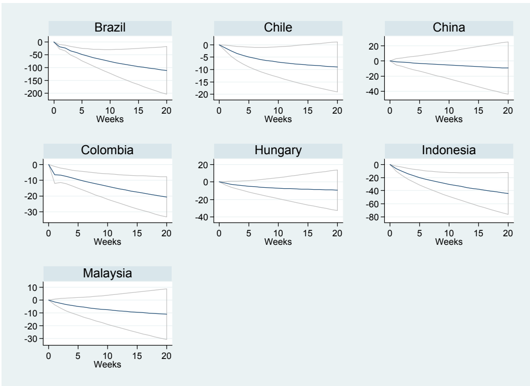


Exhibit A. EMBI spreads -> bond flows

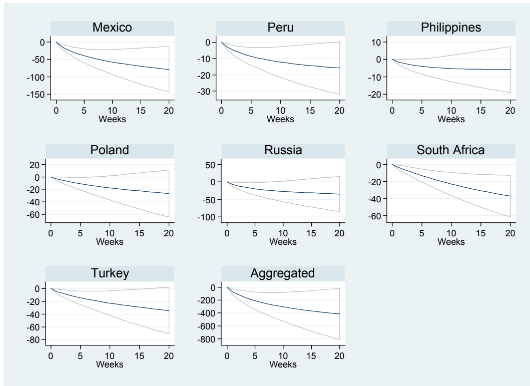


Exhibit B. EMBI spreads -> bond flows

Notes: These functions are estimated on the basis of a bivariate VAR using data from EPFR and Bloomberg. We obtained the aggregated time series by adding the bond flows, and by taking the average of the EMBI spreads of all the EMEs in our database. Confidence level 90%.
Estimation sample: 01/07/2009 to 09/03/2014
Sources: Own estimations with data from EPFR and Bloomberg

It is important to note that the magnitude of the individual response depends on the EME in question. For example, Brazil's response is sizeable, but that of Chile is smaller. In terms of the duration of responses, Brazil, Colombia, Indonesia, Mexico, South Africa, and the aggregated time series, are notable in that all have statistically significant cumulative responses for more than 20 weeks after the shock. For the 11 EMEs that have statistically significant responses, the signs of the responses are in line with what is predicted by the type of mechanism that we considered. In effect, a positive shock to the risk premium (EMBI spread) reverses the bond flows. Note that the aggregated time series are also in accordance with such a prediction.

More specifically, based on the model, an increase in the risk premium is indicative of active investors leaving their position in the risky asset. Thus, an unexpected and significant increment in the EMBI spread will likely induce active investors to join a possible run, captured by the increase in bond outflows. In particular, note that for many EMEs, the rate of outflows is greater in the initial periods (the slope of the cumulative response is larger).

We also consider the cumulative responses of the EMBI spreads to shocks to the bond flows (Graph 4). Only China and Colombia do not present statistically significant responses in our sample of 14 countries. In terms of size, Indonesia and Turkey have notable responses. Moreover, Hungary, Indonesia, Peru, Poland, Russia, South Africa and Turkey all have responses which last for more than 20 weeks after the shock.

Cumulative impulse-response functions

Graph 4

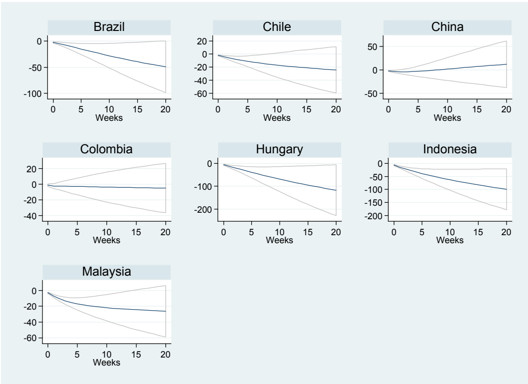


Exhibit A. Bond flows -> EMBI spreads

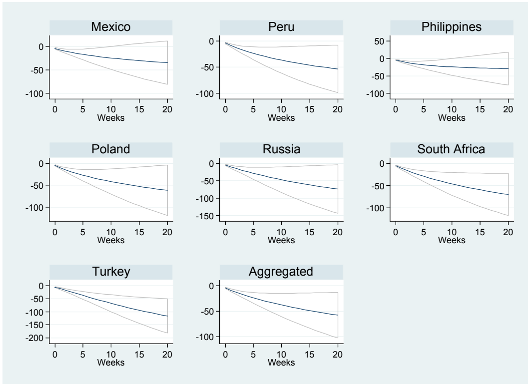


Exhibit B. Bond flows -> EMBI spreads

Notes: These functions are estimated on the basis of a bivariate VAR using data from EPFR and Bloomberg. We obtained the aggregated time series by adding the bond flows and taking the average of the EMBI spreads of all the EMEs in our database. Confidence level 90%.
Estimation sample: 01/07/2009 to 09/03/2014
Sources: Own estimations with data from EPFR and Bloomberg

In all 12 cases in which the responses are statistically significant, we observe that a prediction of the model is satisfied. Namely, a positive shock to bond flows is associated with a reduction in the risk premium (EMBI spread). This also holds true for the aggregated time series.

In the model, as more active investors take a position in the risky asset (inflows increase), such investors do so with the expectation that the risk premium will be greater than the floating rate. In effect, all are attempting to obtain the highest return.

Of course, as the number of delegated investors with a position in the risky asset increases, the risk premium decreases (the price increases) and the threshold level of the former is reached at some point. Given the friction relating to the agency problem at the heart of the model, we should then observe evidence of run-like dynamics.

In sum, we have found some evidence favourable to the first prediction of the model in many EMEs. Naturally so, economies respond differently to each shock. Thus, countries like China seem not to be sensitive to surprises on any of these variables, while economies such as Brazil seem to be quite responsive to them.

Bond flows and risk premia under regime-switching: EMEs

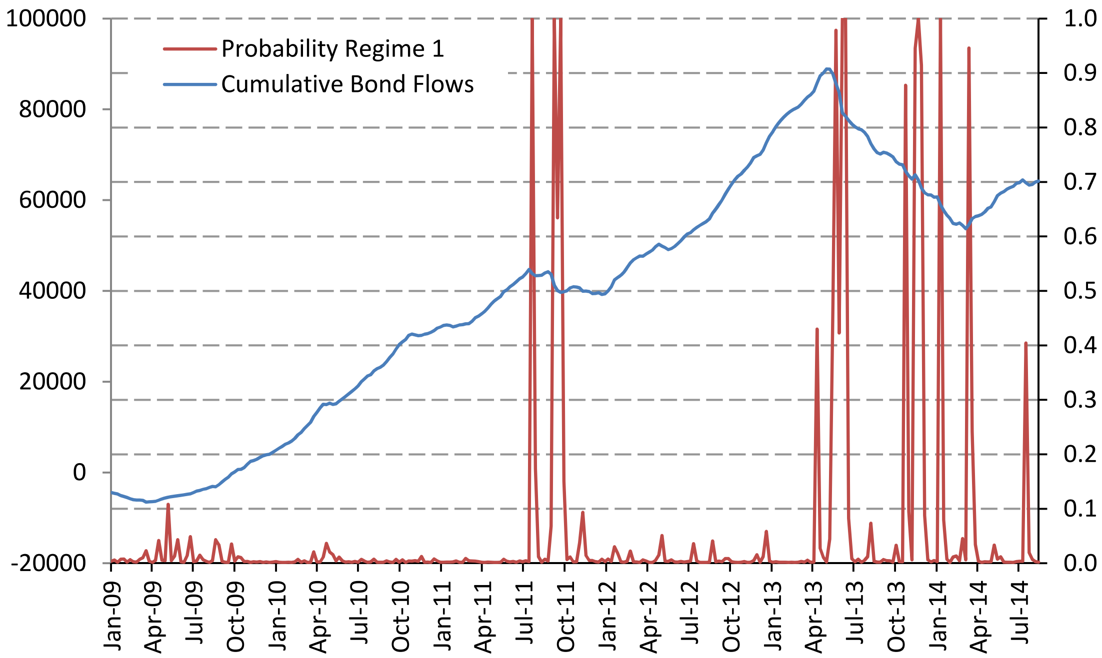
By assumption, in a VAR the response's magnitude to a shock is symmetrical regardless of its direction. However, the model predicts that outflows tend to move at a swifter speed, as the run-like mechanism is set off. In other words, and as we have observed in the preliminary analysis, bond outflows tend to be more acute than inflows. Thus, to seek further evidence of such a prediction, we introduce a regime-switching model into the variance-covariance matrix of the bivariate VAR model with aggregated data (similar to the one just estimated). As is common, the regime-switching is modelled as a Markov chain.

Under the assumption that regime states tend to coincide with inflows and outflows episodes, respectively, there are at least three relevant implications of the regime-switching model. First, the covariance term when episodes of outflows take place should be greater than when episodes of inflows occur. Changes in flows due to variations in risk premia should be more sensitive when outflows take place. Second, the probability of remaining in an episode of inflows is greater than the probability of switching to a regime of outflows. Third, the episodes of outflows are less persistent relative to the episodes of inflows. Note that these statements refer to the Markov chain model behind the regime-switching model.[23]

By assumption, there are two regime states in the model. Once we estimate the regime-switching VAR, we have the result that regime state 1 is associated with the greatest negative covariance between the shocks to bonds flows and the shocks to EMBI spreads. Conversely, regime state 2 is associated with the covariance term nearest to zero. Thus, consider the estimated probability of being in regime state 1, and the cumulative bond flows in our EMEs as shown in Graph 5.

Cumulative aggregate bond flows and probability of regime 1

Graph 5



Note: Estimation sample: 01/07/2009 to 09/03/2014
Source: Own estimations with data from EPFR

We observe that regime states in fact do tend to coincide with inflows and the sharpest episodes of outflows. Ex post, such findings could be seen as a foregone

[23] Analytically, the regime-switching model has two states: state 1, with marked outflow episodes, and state 2, with inflow or tranquil outflow episodes. This model has four transitional probabilities, denoted by $p_{i,j}$, ie the probability of switching to regime j given that the current regime is i in one period. The second implication says that $p_{22}>p_{21}$ or equivalently $p_{22}>0.5$. The third implication is that $p_{22}>p_{11}$.

conclusion. However, it is not necessarily the case as, for example, other mechanisms affect bond flows and risk premia.

We note that regime 1, the one with the large negative covariance term, is generally associated with episodes of outflows. This can be interpreted as evidence favourable to the first implication listed above. What is more, the estimated probability of staying in regime state 2, the one associated with episodes of inflows, is 0.97. Analytically, this object is p_{22}, ie the probability of switching to regime 2 given that the current regime is 2. On the other hand, the probability of staying in regime 1, or $p_{11,}$ is 0.6. While this last probability is still persistent, it is less so than the probability of remaining in an episode of inflows. For the most part, these are broadly in line with the model.

All in all, the introduction of regime-switching in the VAR model provides further evidence that is consistent with the predictions of the model with delegated investment and a relative performance concern in terms of the second prediction.

Preliminary analysis: AEs

A natural comparison is to estimate the same model but with bond data for advanced economies (AEs). In effect, such economies are a natural control group. However, it is important to make a further distinction among AEs. There are those AEs that have had a reasonable economic performance and that markets perceive as having maintained a sensible macroeconomic policy framework (such as Germany and the United Kingdom, for example). On the other hand, there are AEs that have had an unsatisfactory economic performance or whose macroeconomic management is perceived to have been subpar (such as Portugal and Spain). Of course, an economy can fall between such classifications. Moreover, some of these economies have benefited from financial support from multilateral institutions. As emphasised by Stein in Hodler (2012), markets internalise and react to such policies.

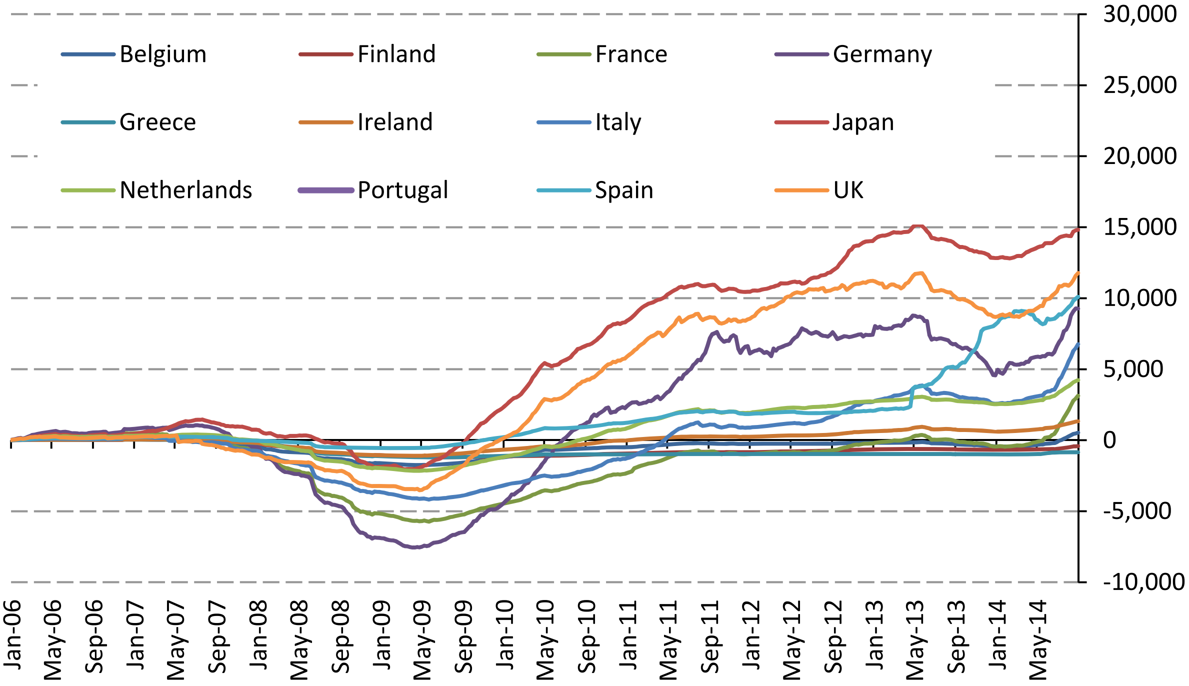
The AEs in our database are Belgium, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, Portugal, Spain and the United Kingdom. Of course, EMBI spreads are not available for AEs. Instead, we use credit default swaps (CDS) spreads as a proxy for risk premia in the model.[24] As for the bond flows, we similarly use the EPFR data. The same caveats apply to the EPFR bond flow data for AEs as those mentioned previously for EMEs.

Thus, as a preliminary analysis, consider the cumulative bond flows for the AEs in our database (Graph 6). The dynamics are quite different from those of the EMEs. Except for Germany, Japan and the United Kingdom, the bond flows have lower correlations. In particular, outflows do not seem to be as correlated, nor as sharp, when compared to those of EMEs. The time series of the average CDS and the aggregated flows are less suggestive of the presence of run-like dynamics (Graph 7). Indeed, up to this point, there is not much evidence of run-like dynamics in the case of AEs.

24 It is known that CDS spreads are closely correlated with EMBI spreads.

Cumulative bond flows in selected AEs

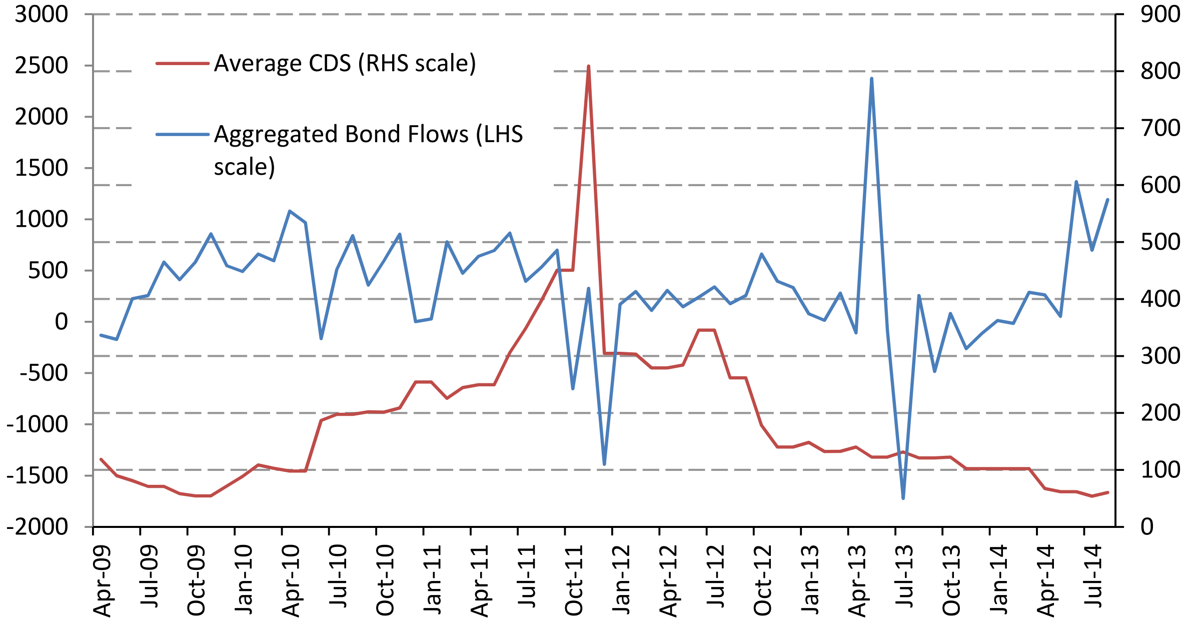
US dollars millions | Graph 6



Note: Weekly flows.
Source: EPFR and Bloomberg

Bond flows and average CDS

Graph 7



Notes: US dollars millions, monthly frequency, index.

Sources: EPFR and Bloomberg

3. Data: AEs

The CDS statistics partly reflect the economic differences among the AEs in our sample (Table 5). Likewise, the bond flows' statistics are partly explained by such differences. Naturally, it is important to have a heterogeneous sample, so as to be able to seek evidence of run-like behaviour in AEs with differing macroeconomic performances and policies (Table 6).

CDS statistics: AEs

Percentage points — Table 5

Country	Mean	Std.Dev.	Max	Min
Belgium	81.46	84.09	381.43	2.05
Finland	27.55	22.26	89.51	4.37
France	59.72	57.89	249.63	1.67
Germany	32.42	27.30	109.93	2.13
Greece	346.59	842.92	6200.00	4.00
Ireland	271.44	253.52	1060.01	5.48
Italy	158.91	145.61	576.82	5.64
Japan	51.93	37.57	157.21	2.17
Netherlands	56.68	28.74	132.99	10.83
Portugal	304.27	348.90	1374.97	4.09
Spain	161.10	151.34	624.50	2.63
UK	60.37	27.35	161.59	16.50

Notes: Estimation sample: 01/04/2006 to 09/03/2014

Bond flows statistics AEs

US dollars millions, weekly — Table 6

Country	Mean	Std.Dev.	Max	Min
Belgium	1.17	22.09	97.47	-165.77
Finland	-0.92	11.91	32.08	-145.03
France	6.92	73.35	372.95	-580.53
Germany	20.45	163.59	644.67	-975.60
Greece	-1.88	12.10	24.92	-172.08
Ireland	2.96	16.29	64.84	-129.19
Italy	14.93	74.33	430.19	-432.51
Japan	32.72	87.63	335.23	-297.21
Netherlands	9.34	37.27	150.16	-258.46
Portugal	1.43	4.40	35.29	-23.75
Spain	22.31	88.33	1242.33	-308.51
UK	26.00	105.58	407.59	-468.41

Notes: Estimation sample: 01/04/2006 to 09/03/2014

Bond flows and risk premia: AEs

In this section, we focus on the bivariate VAR (bond flows and spreads) for AEs. As explained, we use CDS spreads as proxies for the risk premia on AEs.

We note that Belgium, Finland, France, Italy, Japan, the Netherlands and the United Kingdom have statistically significant responses to a shock to CDS spreads (Graph 8). In the case of Belgium, Finland, France, Italy and the Netherlands, the response lasts for more than 20 weeks. Note, however, that Japan's and the United Kingdom's responses are short-lived. Spain has a marginally statistically significant response. Based solely on these cumulative impulse-response functions (CIRFs), there could be potential for run-like dynamics in some AEs.

Cumulative impulse-response functions | Graph 8

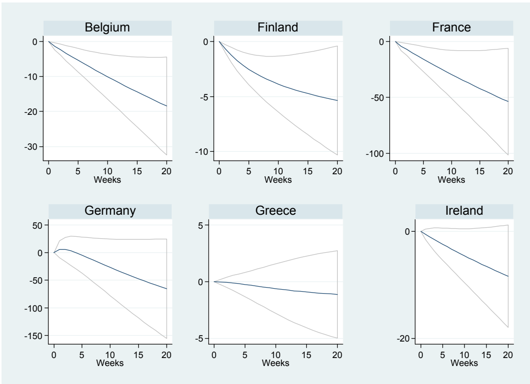


Exhibit A. CDS -> bond flows

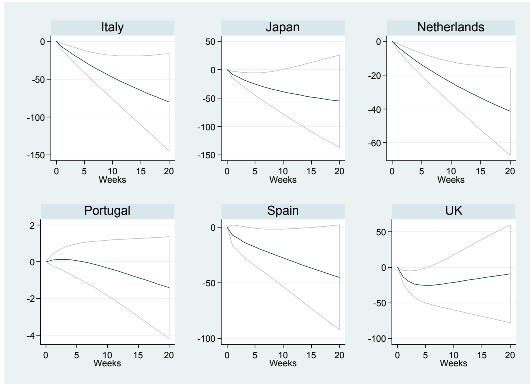


Exhibit B. CDS -> bond flows

Notes: These functions are estimated based on a bivariate VAR. Confidence level 90%.
Estimation sample: 01/07/2009 to 09/03/2014
Sources: Own estimations with data from EPFR and Bloomberg

On the other hand, as for the responses of CDS spreads to a shock to bond flows (Graph 9), we note that only Japan's response is statistically significant, albeit it lasts for no more than five weeks, and it is small relative to its standard deviation (Table 5). Thus, based on these CIRFs, there is little evidence of run-like behaviour in the bond flows for our AEs sample.

In sum, we find that economies such as Germany and the United Kingdom fail to show evidence of run-like dynamics associated with bond flows. In contrast, some economies have statistically significant responses, including Belgium, France and Italy, among others. As is well known, those economies have faced economic difficulties, such as problems with their banking sectors, or have had to make sharp fiscal adjustments, or both. As underlined by Rajan (2014), "even rich recipient countries with strong institutions, [...], have not been immune to capital-flow-induced fragility."

Initially, it might be considered puzzling not to observe significant responses in economies such as Greece and Portugal. This may have been the result of the multilateral aid they received and of expectations by investors of possible future aid. Under such expectations, run-like dynamics are less probable.

Cumulative impulse-response functions

Graph 9

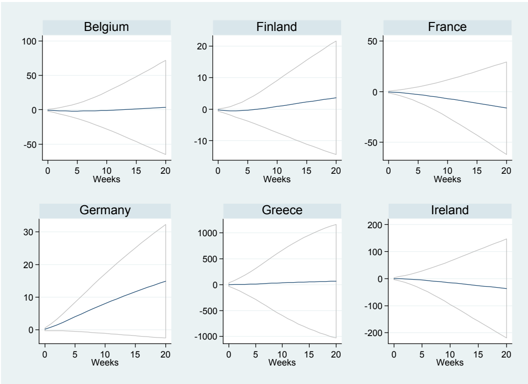


Exhibit A. Bond flows -> CDS

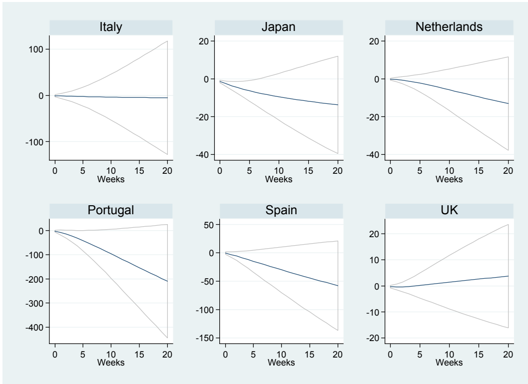


Exhibit B. Bond flows -> CDS

Notes: These functions are estimated based on a bivariate VAR. Confidence level 90%.
Estimation sample: 01/07/2009 to 09/03/2014
Sources: Own estimations with data from EPFR and Bloomberg

In general, the CIRFs obtained present evidence that is less favourable to the existence of run-like dynamics. In effect, shocks to bond flows do not lead to statistically significant changes in the CDS of AEs.

Bond flows, risk premia and US monetary policy: EMEs

In this section, we go back to the case of EMEs to explore the third implication of the model. To this end, we estimate a tri-variate VAR.[25] The variables we include in this model are: the first principal component (PC) of the EPFR bond flows, the first principal component (PC) of EMBI spreads, and the Wu and Xia rate, using as an estimation sample a period ranging from January 2009 to August 2014. As explained earlier, the Wu and Xia rate attempts to account for unconventional monetary policy, which is certainly crucial at the present juncture. The time series frequency is monthly, as is that of the Wu and Xia rate.

Note that we obtain from all the bond flows and, separately, from all the EMBI spreads, a first principal component. We use these time series starting from January 2009 to estimate the VAR model. To estimate the principal components, we use the series from January 2006.

The first principal component of a set of time series captures the most variability possible in such a set within a single time series. In a sense, it summarises the most information possible in the original time series set within one variable.

[25] To make the bivariate VAR using the EPFR data with a weekly frequency and the tri-variate VAR comparable, we transform the EPFR data with a weekly frequency to a monthly frequency in order to estimate the tri-variate VAR.

Based on the results in Section 5, we have excluded China from our data set for this exercise, as it lacks a significant response in its associated CIRF. It is worth mentioning that the VAR model is estimated with a lag of one.[26]

The shock identification is also based on the Cholesky decomposition and thus the ordering of the variables is crucial. On a scale of the slowest to the fastest moving series, we assume that the Wu and Xia rate is the slowest, followed by bond flows and the EMBI spread. In effect, the quantities are faster than the rate, but slower than the prices.

Thus, the main predictions from the model are: (i) a positive shock to the policy rate is associated with an increase in bond outflows. As the active investor's threshold is surpassed, investors seek to invest in the safe asset (the money market account), and (ii) in tandem, a positive shock to the bond flows is associated with a decrease in the risk premium, as more active investors gain a position in the risky asset (Graph 10).

Impulse-response functions | Graph 10

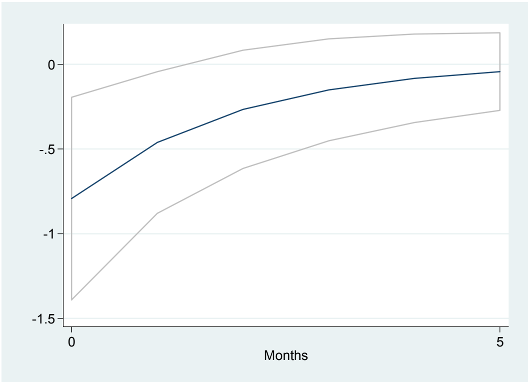


Exhibit A. Wu and Xia Rate→ PC of bond flows

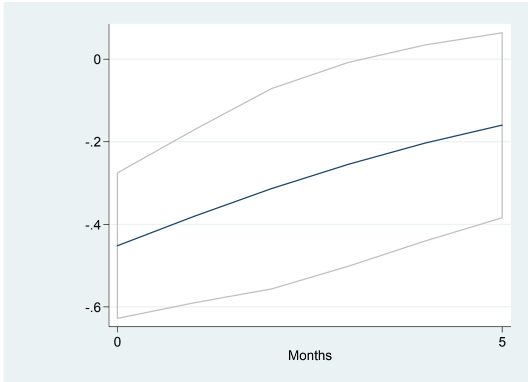


Exhibit B. PC of bond flows→ PC of EMBI spreads

Notes: These functions are obtained from the tri-variate VAR model.
Estimation sample: 01/2009-08/2014
Sources: Own estimations with data from EPFR, Bloomberg and Wu and Xia (2015)

We find that both predictions hold when using the Wu and Xia rate as a measure of the US monetary policy stance, and the PC of bond flows and, separately, of the PC of EMBI spreads. In effect, the PC of the response of bond flows to a shock to the Wu and Xia rate, and the response of the PC of EMBI spreads to a shock to the PC of bond flows are both statistically significant. The first one is significant for about two months, and the second one for about three. Note that the latter is somewhat economically significant (see Table 7).[27]

Interestingly, if we estimate the same VAR model but for the period between January 2013 and August 2014, the PC of bond flows' response to a shock in the Wu

26 This is largely in line with the tests previously cited to determine an optimal lag. In all VARs estimated in this paper, the lag is determined using the full samples.

27 As stated in the introduction, our main concern is about the run-like dynamics that could potentially take place in the future. Thus, we hypothesise that, up to this point, we have only seen a handful of such episodes. Accordingly, we would not necessarily expect fully fledged economically significant responses.

and Xia rate increases noticeably. Note that the immediate response is around –2.5 (Graph 10), while it is –0.8 when the starting date of the estimation sample is 01/2009 (Graph 11).[28]

Impulse-response functions

Graph 11

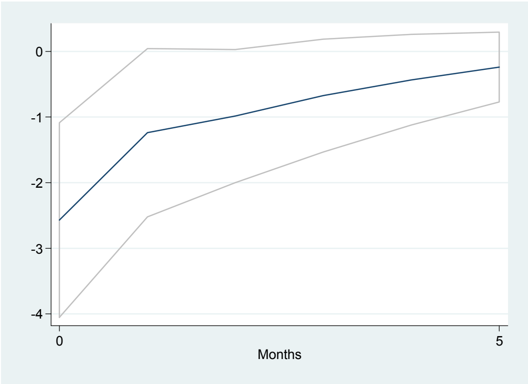


Exhibit A. Wu and Xia Rate→ PC of bond flows

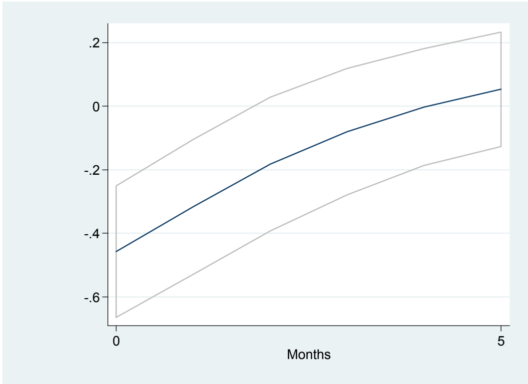


Exhibit B. PC of bond flows→ PC of EMBI spreads

Notes: These functions are obtained from the tri-variate VAR model.
Estimation sample: 01/2013-08/2014
Sources: Own estimations with data from EPFR, Bloomberg and Wu and Xia (2015)

Moreover, this is in line with the dynamics of the estimated probability in the regime-switching model in the sense that regime switches to state 1 became more frequent towards the beginning of 2013, that is, as markets perceived that a change in the direction of monetary policy in the United States was approaching.[29] This last set of results suggests that the possible effects of a change in US monetary policy on run-like dynamics increased at around that time.

In sum, we conclude that there is evidence that (i) as a group, EMEs are vulnerable to changes in the US policy rate through channels akin to the one we are exploring; and (ii) there exist mechanisms which might jeopardise financial stability.

General statistics for the principal components of bond flows and EMBI spreads, and the Wu and Xia rate

Table 7

Variable	Mean	Std. Dev.	Max	Min
PC Flows	0.00	3.41	7.06	-16.11
PC EMBI Spread	0.00	3.29	14.46	-3.98
Wu and Xia Rate	0.62	2.69	5.26	-2.99

Sources: Own estimations with data from EPFR, Bloomberg and Wu and Xia (2015)

28 Another IRF of interest is the response of the PC of bond flows to a shock to the PC of EMBI spreads. We explored such IRF also using principal components, but do not report the results. They are in line with the analogous IRFs obtained at a country level.

29 As described, regime state 1 is the one associated with the greatest (negative) conditional covariance. Conversely, regime state 2 is the one associated with the covariance term nearest zero.

Bond flows, risk premia and US monetary policy: AEs

As a control exercise, we estimate the same tri-variate VAR based on the data of a group of AEs. Specifically, we first consider the PC of bond flows' response to a shock in the Wu and Xia rate (Graph 12, Exhibit A). We observe that, in contrast to the result for EMEs, it is positive. We also note that it only lasts for about a month. This result suggests that as the interest rate in the group of AEs goes up, portfolio shifts take place that imply inflows to those economies, as would be expected. Alternatively, as a group AEs could be acting as a safe haven, since an increase in the Wu and Xia rate leads to a rise in inflows.

Moreover, we also consider the PC of the response of CDS spreads to a shock to the PC of bond flows (Graph 12, Exhibit B). Such a response is clearly not statistically significant. This is not surprising given the results we have seen for the individual bivariate VARs.

Impulse-response functions | Graph 12

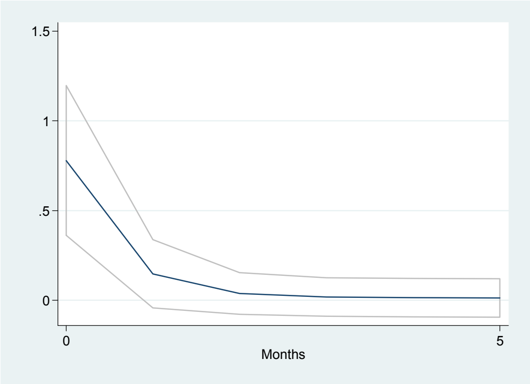


Exhibit A. Wu and Xia rate → PC of bond flows

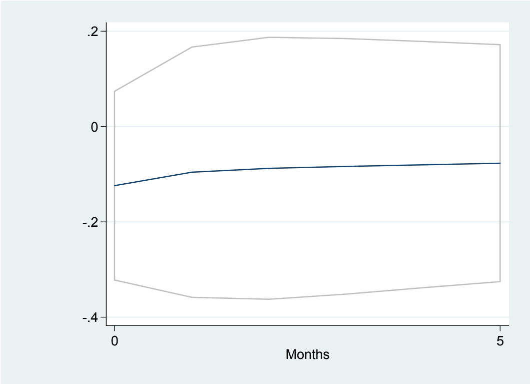


Exhibit B. PC of bond flows → PC of CDS

Notes: These functions are obtained from the tri-variate VAR model. All AEs are included when estimating the tri-variate VAR.
Estimation sample: 01/2009-08/2014
Sources: Own estimations with data from EPFR, Bloomberg and Wu and Xia (2015)

Furthermore, we estimate two versions of the tri-variate VAR. First, we exclude Germany, the United Kingdom and Greece from our sample of AEs. This decision is based on the results of the bivariate VAR, as these economies' bond flows and CDS seem to be the least responsive. We estimate the PC of bond flows and CDS spreads separately as we have done previously.

General statistics for the PC of bond flows, PC of CDS for AEs, and the Wu and Xia rate | Table 8

Variable	Mean	Std. Dev.	Max	Min
PC Flows	0.00	2.79	7.31	-13.12
PC CDS	0.00	2.98	7.11	-3.66
Wu and Xia Rate	0.62	2.69	5.26	-2.99

Sources: Own estimations with data from EPFR, Bloomberg and Wu and Xia (2015)

The response of the PC of bond flows to a shock in the Wu and Xia rate, being positive, does not have the expected sign. The response of PC of CDS to a shock to PC of bond flows is not statistically significant. Nonetheless, it is worth mentioning that the response is small relative to the standard deviation.[30] (The IRFs have been estimated but are not presented.)

Second, we use an estimation sample ranging from January 2013 to August 2014. In such a case, the effect of the Wu and Xia rate's shock on the PC of bond flows is similar. Moreover, the effect of the flows' shock on the PC of CDS spreads is not statistically significant. (Again, the IRFs have been estimated but are not presented.)

All in all, the evidence does not suggest the presence of run-like dynamics in the bond flows in the AEs as a group, although there is some heterogeneity in the case of individual countries. What is more, economies which have faced economic challenges have some significant responses but the evidence for the type of mechanism we are looking for in general breaks down with the positive response of bond flows to a shock to the Wu and Xia rate. It should be in the direction opposite to the one expected based on the type of mechanism we have assessed. In effect, it seems that, as a group, AEs act as safe havens.

Concluding remarks

Much attention has focused on the implications of the degree of leverage of financial institutions for financial stability. Nonetheless, other mechanisms that are essentially unrelated to the degree of leverage might play a significant role in affecting financial stability. The type of mechanism we have explored could be associated with the ability of EMEs to deal with an eventual tightening of the US policy rate.

As the data analysed strongly suggest, the possible effects of run-like behaviour in bond markets are latent. Moreover, they could be distinctive for different EMEs, which means that some economies should be more concerned than others in terms of the implication this channel might have. Moreover, if this channel has gained strength, as some of the evidence suggests it has, it would add to existing concerns.

What is equally relevant from the point of view of policymakers is that there might be little they could do about this, at least in the short and medium term. This is because the current economic policy tools cannot necessarily target run-like dynamics.

Stein (2014a) has emphasised that this depends on the level at which the run behaviour might take place: ie whether it is at the investor or fund manager level. If it is at the investor level, financial authorities might be able to impose a fee on investors who decide to withdraw their funds in order to internalise the externality they would impose on those left behind. If, however, it is at a fund manager level, it is not obvious what the financial authorities could do. Of course, in practice, any

30 The magnitude of the immediate response is 10% of its standard deviation.

measure affecting investors could be difficult to implement and could lead to an increase in policy uncertainty.

More generally, following global financial reform efforts in the last few years, this type of mechanism would be relevant to the extent to which non-banking institutions have assumed greater prominence, particularly given that they are exempt from most macroprudential regulations.

Although we have found evidence favourable to the existence of run-like dynamics in bond flows in and out of EMEs, we have not taken a stand on their implications. In effect, we have highlighted that this channel is one of several potential ones. Nonetheless, we underscore that a generally low level of financial leverage by investors should not be seen as guaranteeing a smooth ride for EMEs as the US monetary policy rate is eventually normalised.

Moreover, our main concern is about the run-like dynamics that could potentially take place in the future. In other words, we hypothesise that hitherto we have only seen a handful of such episodes, although there is a good chance that more will follow. This is in the same vein as Borio (2010), who has stated: "What looks like low risk is, in fact, a sign of aggressive risk-taking." In fact, in our context, low risk premia could very well be the prelude to a run.

Appendix

We performed important extensions and complementary estimation exercises to test the robustness of our results. However, we do not report them in this paper. In what follows, we provide a brief description of these exercises and of their main implications. First, we compare the AUMs' percentage change in value with the percentage change in the EMBI spreads for EMEs as a group. These time series show high correlations. This result provides support for using the EMBI spreads as proxies for individual EME's AUM values. As mentioned, this is also supportive of the EPFR bond flows' representativeness.

Second, we estimate "risk-on" and "risk-off" episodes based on bond flows and compare their behaviour to that of the aggregated EMBI spreads.[31] We observe that sharp changes in bond flows are associated with significant changes in aggregated EMBI spreads. In addition, we analyse the correlations between, on the one hand, the VIX index, and, on the other, the PC of bond flows and the PC of EMBI spreads. We observe recent drops in the correlations, which suggests that the VIX explains less of the observed variability of the two variables.

Third, we estimate a tri-variate VAR but add a cumulative bond flows variable. The variable attempts to control for the stock of bonds accumulated in the past month. This is an important variable in terms of the model, as it proxies the number of active investors already present with a position in the risky asset. In this estimation, the feedback mechanisms between bond flows and indices are essentially maintained.

Fourth, we conduct robustness checks for aspects we believe are relevant as well. These controls are: (i) the country's recent economic performance based on the changes of their EMBIs; (ii) the level of leverage in the banking sector of an economy; and (iii) geographical location. These additional estimations are supportive of the idea that the run-like dynamics we explored are to an extent independent of economic performance, level of leverage in the banking sector and geographical location.

Fifth, we make a re-estimation of the two main VARs previously mentioned, but use aggregated EME data on equity flows instead of bond flows. Generally, equity markets are much more liquid. Thus, it is less likely that one could find evidence of run-like dynamics in equity flows. Confirming our prior, we find little evidence favourable to the presence of run-like dynamics.

Sixth, as an extension to the tri-variate VAR model for EMEs, we add the economic policy uncertainty index as a fourth variable. In the model, the comparison between the risk premium and the floating rate return may be seen as representative of uncertainty. Thus, this exercise explores an uncertainty element that might be relevant to the mechanism we explored. Specifically, we observe that an impulse to the uncertainty index leads to a positive response by the PC of bond

[31] We construct such an indicator following Feroli et al (2014). The risk-on/risk-off indicator is estimated on the basis of the deviations of the average bond flows with respect to their historical standard deviations.

flows. Thus, assuming that the Federal Reserve is less likely to tighten the policy rate under the presence of more economic policy uncertainty, this result is consistent with the type of mechanisms we have explored.

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