Is Trouble Brewing for EMEs?

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Abstract: Financial stability discussions have mainly revolved around the degree of leverage in financial institutions. Yet, some authors have argued that there might be mechanisms associated with unleveraged institutions that could entail financial instability. We aim to shed light on the possible presence of run-like dynamics in the bond fund flows to and from a group of Emerging Market Economies (EMEs). We examine some of the US monetary policy's implications on these dynamics. As argued, e.g., in Feroli et al. (2014), given the type of incentives many funds face, run-like dynamics might take place, although such funds are mostly unleveraged. We find evidence of the presence of run-like dynamics in the bond flows in several EMEs. We also find evidence that changes in US monetary policy affect such dynamics. Evidently, run-like dynamics could potentially take place in the future.
Keywords: Financial leverage, emerging market economies, US monetary policy, unconventional monetary policy.
JEL Classification: F3, F4.

Resumen: Las discusiones sobre estabilidad financiera han girado mayormente en torno al grado de apalancamiento de las instituciones financieras. Empero, algunos autores han argüido que pueden haber mecanismos asociados a instituciones no apalancadas que pudiesen involucrar inestabilidad financiera. Nuestro objetivo es arrojar luz sobre la posible presencia de dinámicas similares a una corrida en los flujos de fondos de bonos hacia y desde un grupo de mercados emergentes (MEs). Examinamos algunas de las implicaciones de la política monetaria de los EE.UU. sobre éstas. Como se argumenta, v.g., en Feroli et al. (2014), dado el tipo de incentivos que muchos fondos enfrentan, dinámicas similares a una corrida pueden ocurrir, aunque mayormente éstos no estén apalancados. Encontramos evidencia de la presencia de dinámicas similares a una corrida en los flujos de bonos en varios MEs y de que cambios en la política monetaria de los EE.UU. las afectan. Evidentemente, este tipo de dinámicas podrían ocurrir en el futuro.
Palabras Clave: Apalancamiento financiero, mercados emergentes, política monetaria de los EE.UU., política monetaria no convencional.

1. Introduction

The unprecedented monetary policy stances in advanced economies (AEs) have had substantial implications on the world economy, and in particular on most emerging market economies (EMEs). Naturally so, EMEs have assessed the extent to which the referred policies have contributed to speed up their economic recovery and, in tandem, the unintended consequences they have brought about. One of the main implications has been the significant capital flows that have entered and exited EMEs, from which bond markets have received a significant share.

As a product of the global financial crisis, a leitmotif in financial stability policy discussions has been the degree of leverage in financial institutions. In effect, financial leverage has been underscored as a central factor leading to 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, i.e., closer to socially optimal, levels of leverage.[1]

Nonetheless, some authors have argued that given the bond flows' magnitude involved, and the incentives faced by many asset management companies, a low degree of leverage in the financial institutions involved will not necessarily assure a stable financial ride through the US policy rate tightening.[2]

Against this backdrop, based on 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 the US monetary policy could have on them. Such dynamics can be rationalized by the presence of delegated investment between the capital owners and fund

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[1] Evidently, leverage in countries recipients of capital flows has also been highlighted as a determining factor for the capacity with which economies will be able to deal with the eventual policy rate tightening in the US, 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 [...]," as we explore in detail for the case of bonds flows in and out of EMEs.

[2] 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, as well as in the economies which are recipients of such flows.

investors, and a concern for relative performance between these investors.[3] Nonetheless, other mechanisms could as well be contributing to this type of dynamics. We emphasize 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, although without taking a specific stance on its relative strength.

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 of the monetary policy framework, we should additionally look at risk premiums in the bond market.

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

Finally, evidently, there is a concern that this type of dynamics may happen again given the current prospects of US monetary policy in the coming quarters. In other words, we

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[3] This one is not the only potential agency conflict. For example, Chevalier and Ellison (1997) document that while the owners of the capital would like to maximize the risk-adjusted fund returns, fund investors would like to maximize its value. In particular, they tend to maximize the funds risk-return profile at the end of the year which, in turn, determines their payments.

hypothesize that up to this point we have only seen a handful of run-like dynamics episodes, but there is a good chance that more will likely follow.

2. Preliminary Analysis: EMEs

To set the stage, we present some of the characteristics EMEs' bond flows and their associated indices have had in recent years. To begin with, note some of the cumulative bond flows' properties based on a simple visual inspection (Figure 1).

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

In addition, the aggregated bond flows pertaining to EMEs and the EMBI spread global have three characteristics (Figure 2). First, they tend to co-move negatively, i.e., bond flows and their prices co-move positively. Second, the EMBI global spread's correlation to changes in bond flows seems to have increased as of 3Q 2011. In other words, variations in the EMBI spread lead to greater changes in bond flows after 3Q 2011. Third, relatedly, the bond flows' variance has increased since around 3Q 2011.

All told, high correlations among bond flows, their negative co-movement with the EMBI global spread, and sharp bond outflows are, jointly, 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 (i.e., a lower price) eventually prompts an upsurge in capital inflows, as some investors jump in to seize the opportunity. In addition, we will see that EMEs' bond flows and EMBI spreads' seem to be affected by monetary policy decisions in the US.

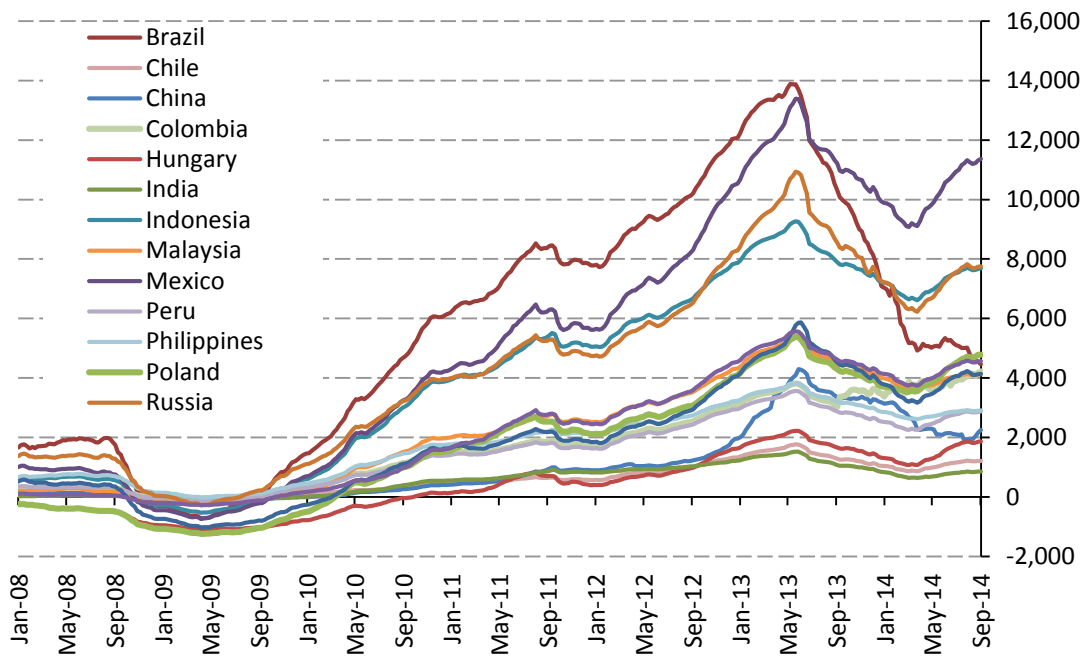**Figure 1. Cumulative Bond Flows in selected EMEs.**
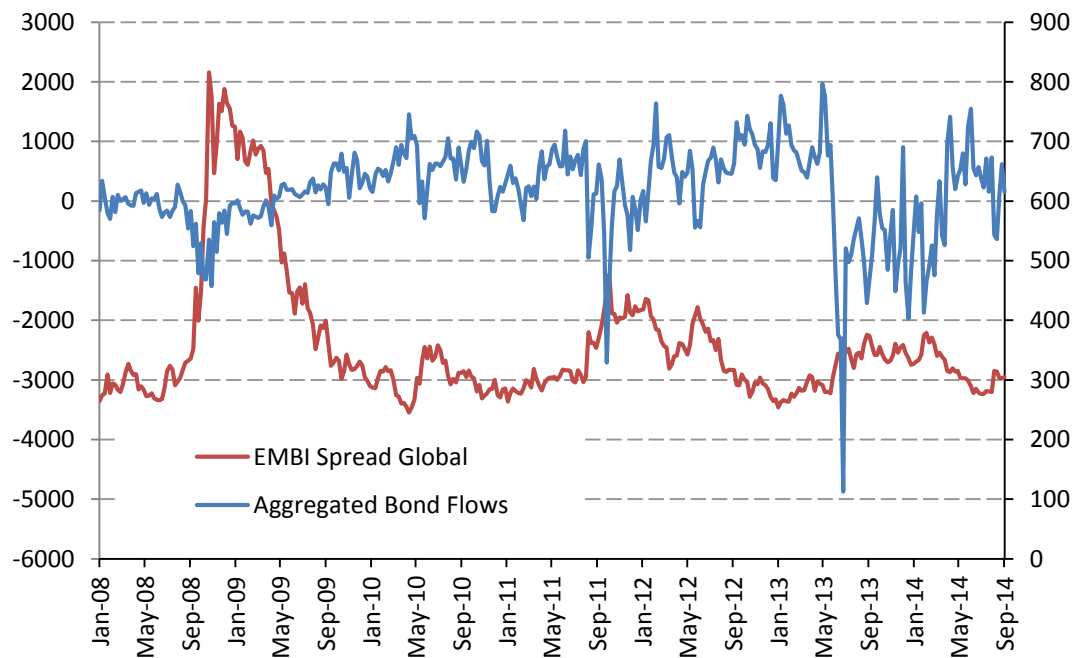(Millions dollar, weekly periodicity).
Source: EPFR.

Figure 2. Aggregated Bond Flows in EMEs and Global EMBI Spread.
(million dollar and index, weekly periodicity)
Source: EPFR and Bloomberg.

3. The Model

We use the model posited in Feroli et al. (2014) as a framework to analyze our data. Feroli et al.'s (2014) model is a simplified version of Morris and Shin's (2014). Accordingly, here we explain some of the most important features of Feroli et al. (2014)'s model. At times, we refer to Banerjee (1992), which puts forward a simple model of herd behavior. Feroli et al.'s (2014) and Banerjee's (1992) will prove useful to analyze our data and organize 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 have documented could be the product of other economic mechanisms behind the run-like dynamics in the bond flows and their indices. Three, although we use one specific model to guide our analysis, just as in Feroli et al. (op. cit.), we do not favor one particularly mechanism over another one. Thus, it could very well be the case that there are other economic mechanisms present that lead 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 investors:

i) *Passive* investors which are risk-averse. Each of them chooses between holding one unit of the risky asset and having her resources in a money market account, which offers a floating rate. This rate is directly associated with the monetary policy rate. Everything else constant, the floating rate is the safest return.

ii) *Active* investors are risk-neutral. Each one also chooses to hold between a risky asset and having her capital in the 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 concern can be rationalized in several ways. Active investors can have a reputation motive or a career concern (e.g., see Scharfstein and Stein, 1990, Hong et al., 2000). A poor relative performance would probably involve a loss of some her clients (Chevalier and Ellison, 1998). The redemption pressure funds face could be considered as another motive.

In their model, each of the active investors keeps a watchful eye on their peers' performance. In practice, this can be achieved by having investors measuring their performance against the same benchmark index. Every active investor knows this. Thus, they play a game in which the effort one exerts will affect the effort of others.[4]

Going further into the model, 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.[5] 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.[6] 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 their relative performance is a concern. In such case, each active investor's demand for one unit 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. Such price is determined by the passive investors' linear demand and by the number of active investors which hold a unit of the risky asset, i.e., $p = V - (\sigma^2/\tau)(S-i)$, where $0 \leq i \leq n$.

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[4] 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 in a series, positioning the initial principal from the last agent farther apart. In this context, relative ranking could be interpreted as an effective monitoring device.

[5] Explicitly, her 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.

[6] 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 ith individual active investor.

If an active investor, say, buys a unit of the risky asset, its price increases by (σ^2/τ). Conversely, if she sells her unit of the risky asset, its 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 $V-(\sigma^2/\tau)(S-(j-1))$. Her return also depends on the order in which she sells it, since, as mentioned, as every time one active investor sells her position in the risky asset, its price drops by (σ^2/τ).

In general, an active investor will seek to have a position in the risky asset first, and once she has such position and suspects that the rest of the active investors will abandon theirs, she will seek to leave her 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.[7]

As mentioned, both investors 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 her 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 $t+m$. Thus, its return depends on the monetary policy's expected path.

The active investor that ranks last faces a penalty fee. That is, on top of her low return relative to her peers, she 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:[8]

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[7] Specifically, assume that at some point all delegated investors buy a unit of the risky asset. Then if such investor sells it in the kth 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 $(\sigma^2/\tau)[n+j-k]/\{V-(\sigma^2/\tau)(S-(j-1))\}$.

[8] The uniform density assumption is motivated by a result in Morris and Shin (2014). In the referred 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 penalized (denoted by x). In their model, x's density is a uniform one.

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

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 decreases. The penalty size's effect is direct: a bigger one will make more active investors turn to the money market account as the threshold declines as the number of active investors decreases.[9]

Note that a larger τ, i.e. less risk-sensitive passive investors, implies smaller differences in returns between investors. Conversely, a smaller τ, i.e. more risk-sensitive passive investors, leads to greater differences in returns between these investors. As an extreme case, suppose that passive investors are near risk-neutral, i.e., 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.[10] Conversely, in the context of Banerjee (1992), greater differences in returns would more probably lead to herd-like behavior.

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, materialized by the penalty taken by the active investor that ranks last. Importantly, the risky asset market's size is sufficiently small so that changes in the active investors' positions affect prices significantly.[11]

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[9] Following the analogy of the musical chairs game, one is more concerned the less players are left. In the referred 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.

[10] 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 is 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 apart, the probability of someone ranking last increases, since distinguishing their relative ranking becomes easier.

[11] This is one of the reasons why we are concerned with EMEs. This is particularly relevant given the size of capital outflows and inflows that some EMEs have faced, in particular, compared to the size of their financial (specially bonds) markets.

Thus, in tandem, their allocation decisions given the changeable money market account's floating rate can lead to a sudden change in active investors' positions, exacerbated by the relative ranking concern. As a few active investors change their portfolio allocation towards the money market account, those active investors who have not done so, 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 estimations, active investors' increments in their positions in the risky assets are captured by the bond inflows; conversely, decrements by the bond outflows. Risky assets' prices are captured by the EMBI spreads. In effect, in the model prices and spreads are directly negatively highly correlated. 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 on the relationship between flows, risk premiums, and the monetary policy rate of the model in Feroli et al. (2014).

i)   As a result of the presence of the two types of investors, and the relative performance concern, there is a positive feedback between bond flows and prices (i.e., a negative feedback between bond flows and risk premium).

ii) Sharp outflows are more likely (than smooth ones), since the relative performance concern is heightened in such cases, increasing the risk premium (i.e., reducing bond prices).

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

After describing the data, we explore these predictions.

4. Data: EMEs

Our database has time series for the following fourteen 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 on these economies as a group, we also consider an aggregated time series.

We use the EMBI spreads as proxies to the risk premiums in the model (Table 1). In theory, the risk premium should be constructed 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 database. This allows us to compare the percentage change in the price of the AUM vs. the variable we use as a measure of the price change, namely, the percentage change in EMBI spread.   Accordingly, we compare the estimated change in the value of AUM for all EME with the change in the EMBI spread (see appendix A). The corresponding series are highly correlated. This lends us confidence to use the EMBI spreads as proxies for the risk premium for each EME.[12]

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

Table 1. EMBI Spreads EMEs.
(Index) **Notes**: Aggregated refers to average of all EMEs'
EMBI spreads. Period: 01/04/2006 to 09/03/2014.
Source: EPFR

Also, the EMBI spread measures the risk premium of EMEs bonds denominated in US dollars which satisfy minimum liquidity requirements. In addition, the index's

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[12] 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) with that of the percentage change of the EMBI spread, question on the EPFR database's representativeness could have been raised.

denomination is appropriate in the sense that the comparison the investors do is against the US policy rate. We use the EPFR bond flows data as a proxy to the changes in the active investors' position in the risky asset in the model (Table 2). As explained in their website, EPFR global tracks both traditional and alternative funds domiciled globally, with $23.5 trillion in total assets. Their aim is to bring a comprehensive view of institutional and individual investor flows driving global markets. What is more, EPFR has the advantage that it covers funds domiciled in the US and Europe (Jotikasthira et al., 2011).

In this context, one might have concerns about the properties of the EPFR bond flows database. First, the extent to which EPFR bond flows are managed by funds that are subject to a delegated investment relationship; second, the proportion of funds in the database which are leveraged. Third, how 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 aims, as we argue next.

First, we claim that the fact that non-delegated investors, which could be included in the data base, do not necessarily care about their relative performance does not hinder 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 the incentives not to ignore their peers under a delegated investment relationship.[13] Crucially, finding evidence favorable to the model using the referred data would bespeak of the delegated investors' significance in the market. Under the assumption that non-delegated investors' behavior is a force against the dynamics of delegated investors' actions, we would then find less evidence favorable 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.

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

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

Table 2. EPFR Bond Flows Statistics (million dollar)
Notes: Weekly frequency. Aggregated refers to the summation of bond flows for all our EMEs. Sample period is from 01/04/2006 to 09/03/2014. **Source:** EPFR

Second, EPFR bond flows capture a relative representative sample of traditional and non-traditional funds. Moreover, the funds considered are typically 90%+ traditional, i.e. un-leveraged.[14] Table 3 presents the specific compositions of the funds' data by classes. Note that potentially leveraged classes are the minority, i.e., hedge funds and the lesser part of ETFs. In addition, note that the majority are open-ended, which could potentially face redemption pressures when underperforming. Moreover, related to this, Borensztein and Gelos (2000) find that in emerging market mutual funds herding among funds is more widespread among open-ended funds than among closed-end ones.

Third, EPFR collects flows data in two frequencies, weekly and monthly. The monthly collections involve a broader fund sample. Yet, when we compared the EMEs time series which are available in weekly and monthly frequencies, we find a high degree of correlation between the respective bond flows.[15] In our exercises, we have obtained a measure of monthly flows simply by summing the weekly flows in each month from the data. This distinction is relevant since, as was mentioned, EPFR collects its data based on

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[14] For example, see Table 3.
[15] 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.

weekly and monthly basis. We only use the weekly based data.[16] In particular, such frequency is relevant to support a causality hypothesis between the series.

More generally, some authors (e.g., Miyajima and Shim, 2014) have argued that EPFR bond flows are not very representative of the entire investment funds universe, as their funds surveys are small in size relative to major custodians.[17,18] Nonetheless, to begin with, the fact that their implicit changes in value are well captured by the EMBI spreads are evidence favorable to 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 one estimating its precise effects. However, by finding that the bonds flows we use clearly have an effect on the corresponding EMBI index, and conversely, underscores the relevance of the mechanisms we are assessing.

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	46,873	90.47%
Hedge funds	72	0.14%
Insurance funds	1,284	2.48%
ETF only	3,580	6.91%
Total	51,809	100.00%

Table 3. EPFR funds data in terms of classes as of August 31, 2014. **Source:** EPFR

In sum, as argued, we do not think that the characteristics of EPFR bond flows database could overturn our main results. However, we certainly reckon that the exact estimated

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[16] This is the case except for the equities data in Appendix E which have a monthly frequency from the source.

[17] To quote Miyajima and Shim (op.cit.): "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."

[18] 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 is more volatile than the EPFR bond flows' series. Thus, their tendencies, in which we are interested in, are strongly correlated.

coefficients could change if we could have access to exact counterparts of the time series in the model.

In addition, reported flows might have some measuring issues for several reasons. As pointed out in Ferioli et al. (2014), funds can merge, be liquidated, and/or be created. To alleviate these issues, for some estimations we have taken a weighted average of bond flows of the past four weeks.[19] We nonetheless underline that our main results do not hinge on this transformation.

What is more, one has to consider the asset gathering capabilities of investment institutions as well. In effect, such institutions have comparative advantages in information gathering, and analysis. Also, operationally, these companies tend to use to same risk management analytical tools, which increase the likelihood of observing similar changes in their portfolio allocation decisions. A handful of investment institutions concentrate the lions' share of the assets under management (Table 4).

As an illustrate example that shows this concentration, consider the assets under management of the top 20 companies as a proportion of those managed by the top 50. This characteristic echoes the importance of asset gathering capabilities among asset management companies. Crucially for our analyses, a change in the capital allocated by one of these institutions could have significant implications in EMEs' financial markets.

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[19] Only for the bivariate VAR in the Bonds Flows and EMBI spread section, which data has a weekly frequency, and the analogous exercises.

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%

Table 4. Asset Under Management (AUM) of the top 20 Asset Management Companies (AMC) relative to the top 50 AMC as of 31/12/13 in USD million. **Source:** www.ipe.com

5. Bond Flows and Risk Premiums: EMEs[20]

We estimate a bivariate VAR having as variables the EPFR bond flows and the EMBI spreads using a weekly frequency (01/07/2009 to 09/03/2014 period). Using a high frequency is favorable to a causality hypothesis, since using time series with a lower frequency would certainly involve other effects.

The identification procedure for the impulse-response functions is based on the Cholesky decomposition of the VAR's variance-covariance matrix. As known, the variables' order is central to such identification technique. On impact, the EMBI spread responds to a shock to EPFR bond flows. Intuitively, such assumption implies that prices move faster than quantities.[21]

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[20] In the appendix, we consider the estimations that add as a control variable the cumulated bond flow in the past month as a third variable.

[21] 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 emphasizing comparison among the EMEs. Note that we always estimate the optimal lag based on the full samples.

Following the order of the models' three main implications, we first present evidence on a possible negative feedback between bond flows and risk premiums. Thus, consider the cumulative responses of bond flows to shocks to the EMBI spreads (Figure 3).
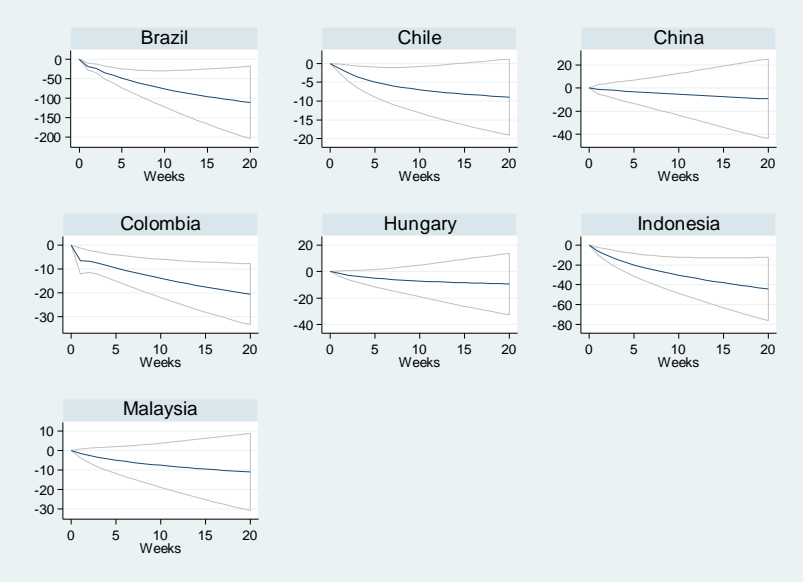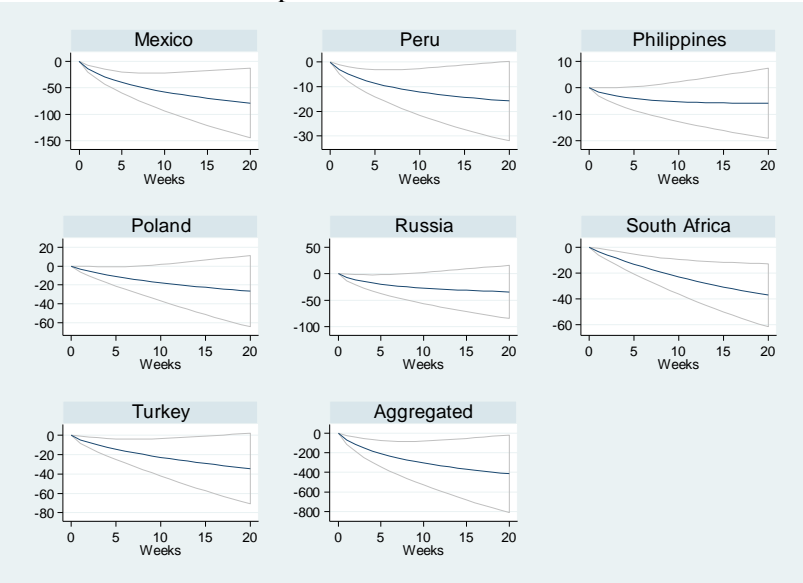

Exhibit A. EMBI Spreads → Bond Flows

Exhibit B. EMBI Spreads → Bond Flows
Figure 3. Cumulative Impulse-Response Functions.
Notes: These functions are estimated based on a bivariate VAR. The aggregated time series are obtained by adding the bond flows, and by taking the average of the EMBI spreads of all EMEs in our database. Confidence level 90%. **Estimation sample:** 01/07/2009 to 09/03/2014.

Only three out of 14 economies in our sample do not present a statistically significant response: China, Hungary, and Malaysia. Philippines and Russia present marginally significant responses.

Importantly, the magnitude of the individual response depends on the EME in question, e.g., while Brazil's response is sizeable, Chile's is in comparison smaller. In terms of its duration, Brazil, Colombia, Indonesia, Mexico, South Africa, and the aggregated time series are notable, all having statistically significant cumulative responses for 20+ weeks after the shock. For the eleven EMEs that have statistically significant responses, their signs are in line with what is predicted by the type of mechanisms that we have considered. In effect, a positive shock to the risk premium (i.e., EMBI spread) reverses the bond flows. Note that the aggregated time series are also in accordance with such 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 significant increment in the EMBI spread will likely make active investors join a possible run, captured by the bond outflows' increase. In particular, note that for many EMEs, the outflow's rate is greater in the initial periods, i.e., the slope of the cumulative response is larger.

On the other hand, consider the cumulative responses of the EMBI spreads to shocks to the bond flows (Figure 4). Only China and Colombia, 2 economies out of 14 in our sample, do not present statistically significant responses. 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 20+ weeks after the shock.
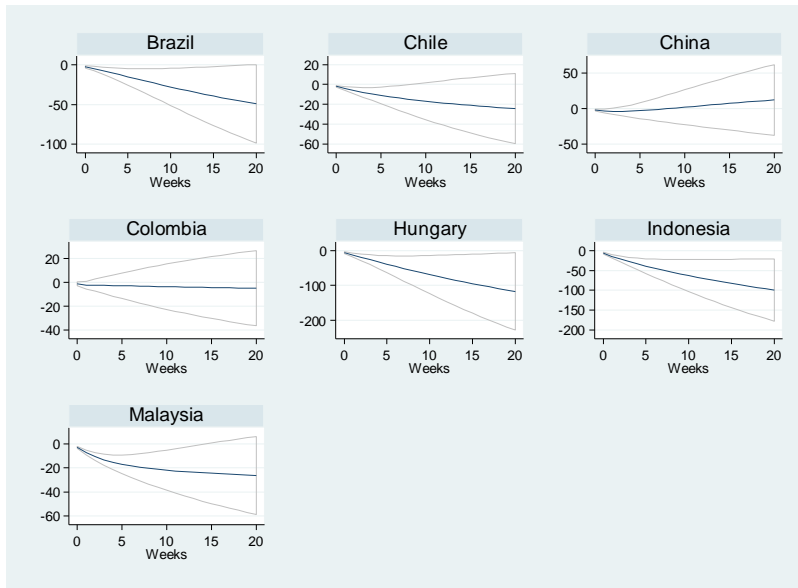
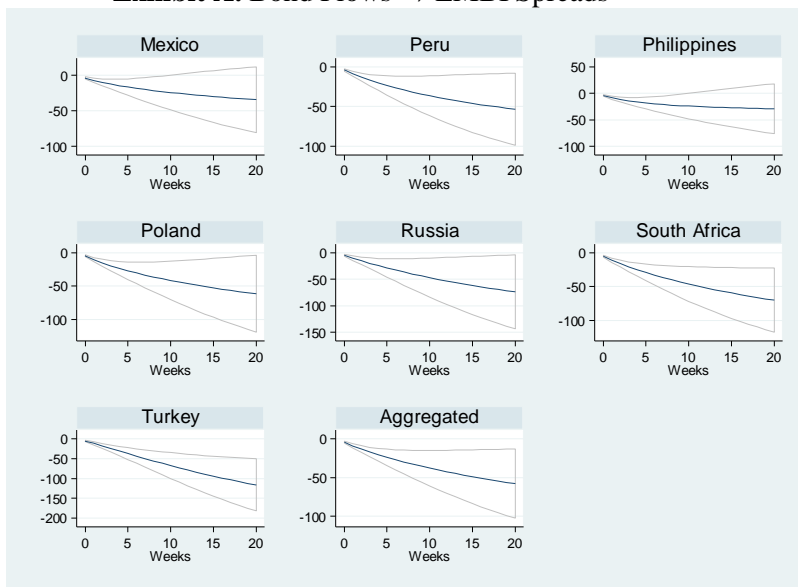**Exhibit A.** Bond Flows → EMBI Spreads

Exhibit B. Bond Flows → EMBI Spreads
Figure 4. Cumulative Impulse-Response Functions. These functions are estimated based on the bivariate VAR. The aggregated time series are obtained by adding the bond flows and taking the average of the EMBI spreads of all EMEs in our database. Confidence level 90%. **Estimation sample:** 01/07/2009 to 09/03/2014.

In all twelve 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 (i.e., in the EMBI spread). This also holds true for the aggregated time series.

In the model, as more active investors take their position in the risky asset (i.e., inflows increase), they 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 (i.e., the price increases) and the threshold level of the former is reached at some point. Given the agency friction at the heart of the model, we should then observe evidence of run-like dynamics.

In sum, we have found some evidence favorable to the first prediction of the model in many of these 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.

6. Bond Flows and Risk Premiums 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 can be set-off. In other words, and as we have observed in the preliminary analysis, bond outflows tend to be acute. Thus, to seek further evidence of such prediction, we introduce a regime-switching model into the variance-covariance matrix of a 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 the regime states tend to coincide with inflows and outflows episodes respectively, based on the model there are at least three relevant implications of the regime-switching model. First, the covariance term when outflows episodes take place should be greater than when inflows episodes occur. Changes in flows due to variations in risk premiums should be more sensitive when outflows take place. Second, the probability of remaining in an inflow episode is greater than the probability of switching to an outflow

regime. Third, the outflows' episodes are less persistent relative to the inflows' episodes. Note that these statements refer to the Markov chain model behind the regime switching.[22] By assumption, there are two regime states in the model. Once we estimate the regime switching VAR, we have that regime state 1 is associated to the greatest negative covariance between the shocks to bonds flows and the shocks to EMBI spreads. Conversely, regime state 2 is the one 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 Figure 5.
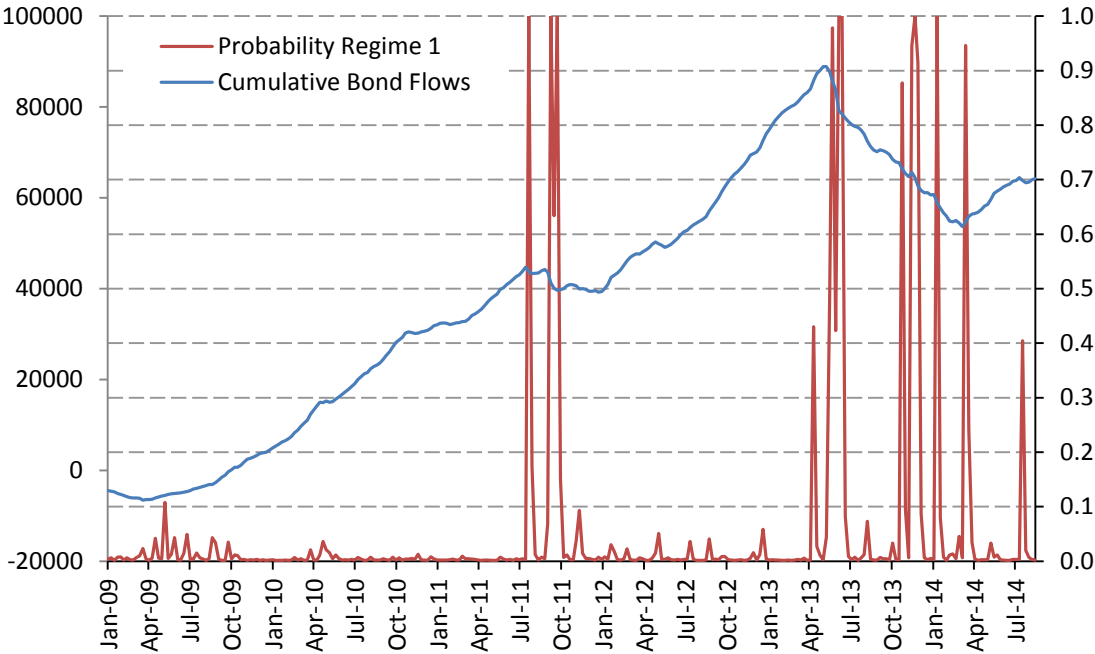
Figure 5. Cumulative Aggregate Bond Flows and Probability of Regime 1. Estimation sample: 01/07/2009 to 09/03/2014.

We observe that regime states in fact do tend to coincide with inflows and the sharpest outflows episodes. *Ex post* such finding may be seen as a foregone conclusion, but it was not necessarily going to be the case as, for example, other mechanisms affect the bond flows and premiums.

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[22] Analytically, the regime switching model has two states: State 1, marked outflow episodes and State 2, 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 implications says that $p_{22} > p_{11}$.

We note that regime 1, the one with the large negative covariance term, is generally associated with the outflows episodes. This can be interpreted as evidence favorable to the first implication listed above. What is more, the estimated probability of staying in regime state 2, the one associated to the inflows episodes, 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 is 0.6, p_{11}, while it is still persistent, it is less so than the probability of remaining in an inflow episode. For the most part, these are broadly in line with the model.

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

7. Preliminary Analysis: AEs

A natural comparison is to estimate the same model but with bond data for Advanced Economies (AEs). In effect, they 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 market perceived maintained a sensible macroeconomic policy framework, e.g., Germany and the U.K. On the other hand, there are those AEs that either have had an unsatisfactory economic performance and where markets perceived maintained a subpar macroeconomic management, e.g., Portugal, Spain, etc. Of course, an economy can fall in between such classifications. Moreover, some of these economies have had the benefit of multilateral institutions readily providing them with financial support. Of course, as emphasized by Jeremy C. Stein in Hodler (2012), markets internalize 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 U.K. Of course, the EMBI spreads are not available for AEs. Instead, we use Credit Default Swaps (CDSs) as a proxy for the risk premium in the model.[23] As for the bond flows, we similarly use EPFR data. The same caveats apply to the EPFR bond flows data for AEs as those mentioned previously for

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[23] It is known that CDSs are closely correlated to EMBI spreads.

EMEs.

Thus, as a preliminary analysis, consider the cumulative bond flows for the AEs in our database (Figure 6). The dynamics are quite different from that of the EMEs'. Except for Germany, Japan, and the UK, the bond flows have lower correlations. In particular, outflows do not seem to be as correlated, nor as sharp, compared to the case of the EMEs. The time series of the average CDSs and the aggregated flows are less suggestive of the presence of run-like dynamics (Figure 7). Indeed, up to this point, there is not much evidence of run-like dynamics in the case of AEs.
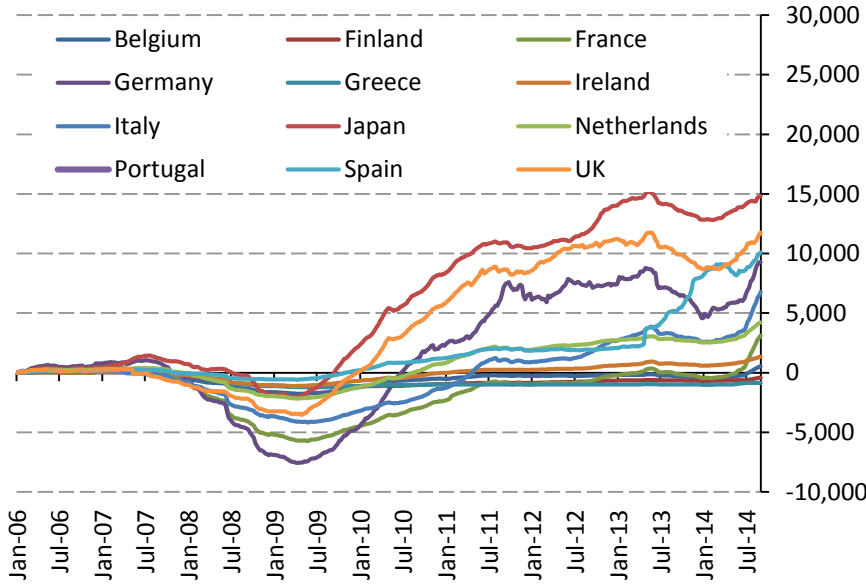
Figure 6. Accumulated Bond Flows in selected AEs.
(million dollar) **Notes:** Weekly Flows. **Source**: EPFR
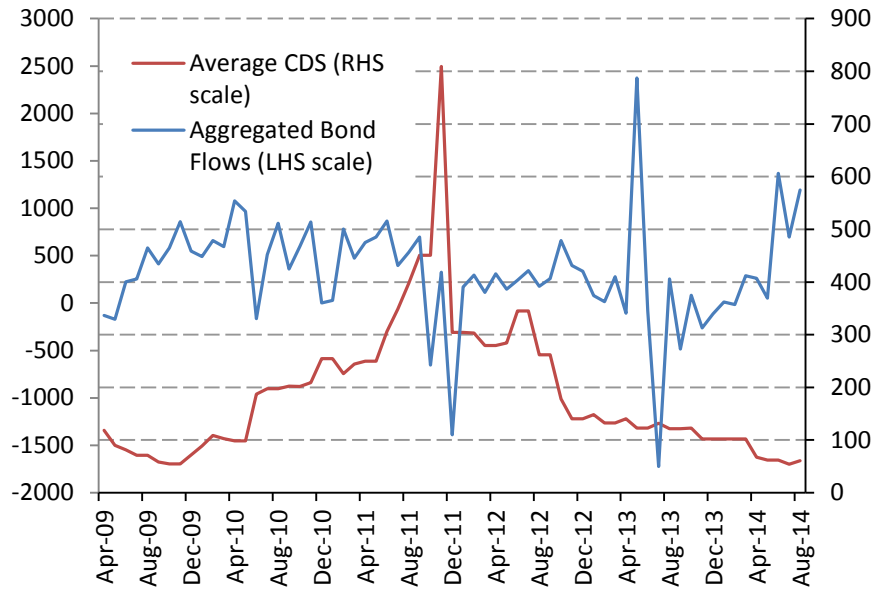
Figure 7. Bond Flows and Average CDS.
Notes: Million Dollars, Monthly Frequency, Index
Sources: EPFR and Bloomberg.

8. Data: AEs

The CDSs' 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, as to be able to seek evidence of run-like behavior in AEs that have had different macroeconomic performance and policies (Table 6).

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

Table 5. CDS Statistics: AEs (Percentage Points)
Estimation sample: 01/04/2006 to 09/03/2014.

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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

Table 6. Bond Flows Statistics AEs (Weekly Million Dollar)
Estimation sample: 01/04/2006 to 09/03/2014.

9. Bond Flows and Risk Premiums: AEs

Here we focus on the bivariate VAR (bond flows and spreads), but for AEs. As explained, we use CDS as proxies for the risk premium in the case of AEs.

As for the responses of bond flows to a CDSs' shock (Figure 8), we note that Belgium, Finland, France, Italy, Japan, the Netherlands, and the U.K. have statistically significant responses. Belgium's, Finland's, France's, Italy's, and the Netherlands', last for 20+ weeks. Note, however, that Japan's and U.K.'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.
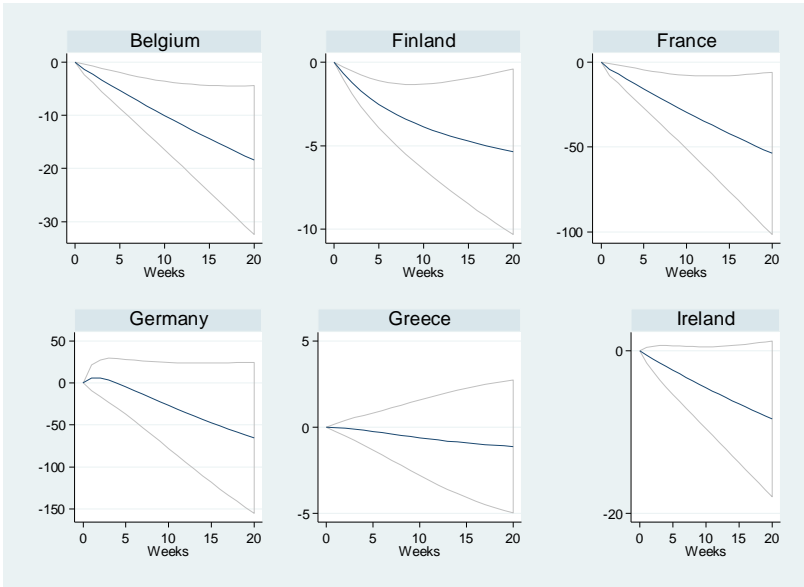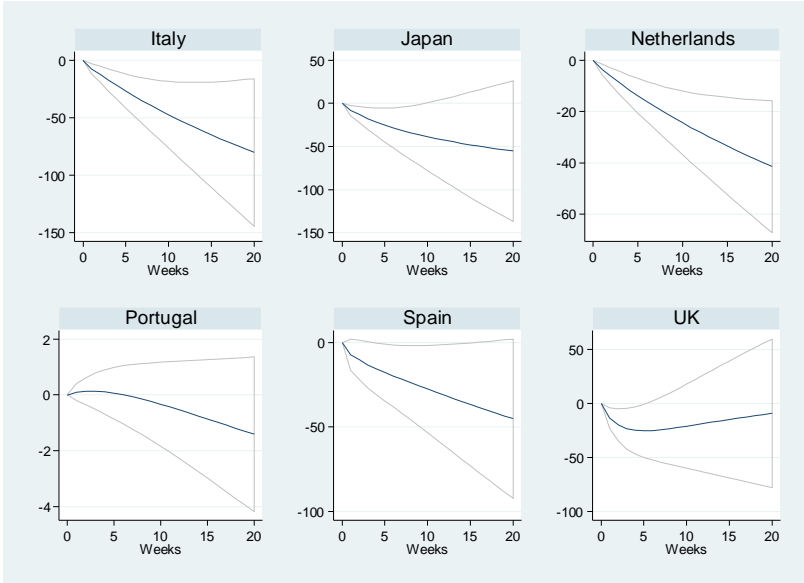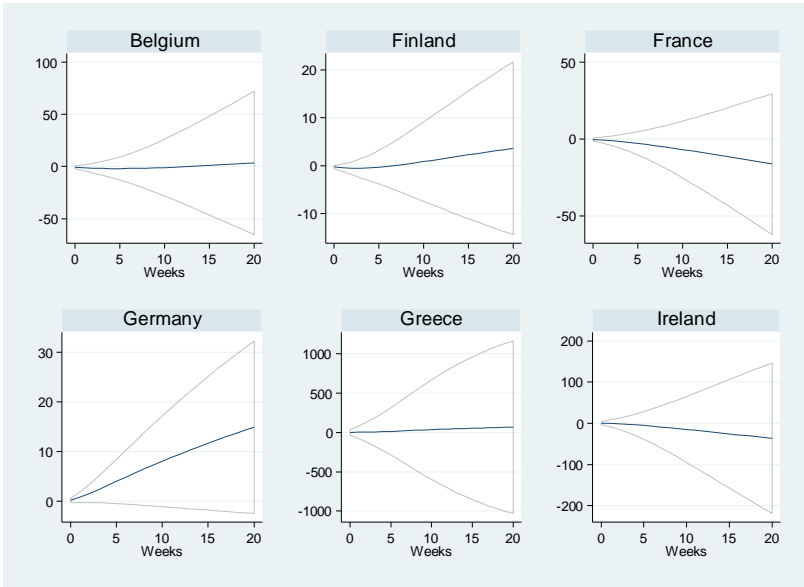

Exhibit A. CDS → Bond Flows

Exhibit B. CDS → Bond Flows
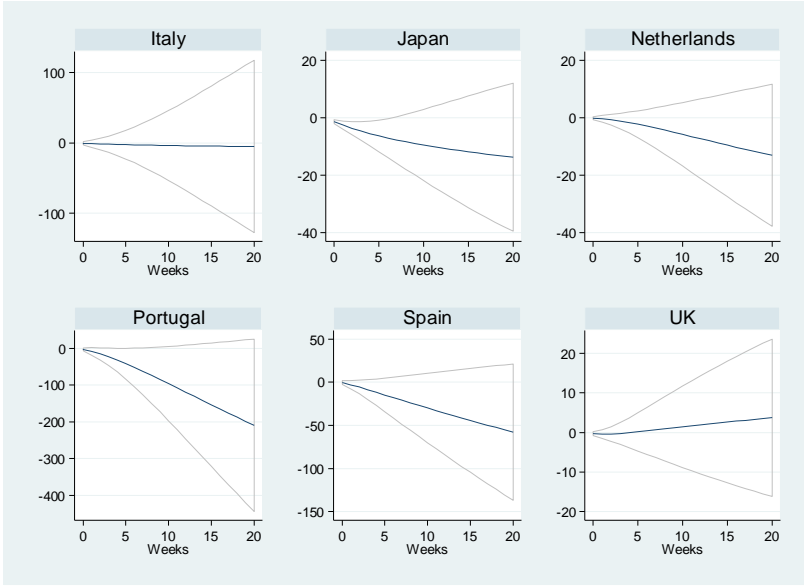**Figure 8. Cumulative Impulse-Response Functions**. Notes: These functions are estimated based on a bivariate VAR. Confidence level 90%. **Estimation sample:** 01/07/2009 to 09/03/2014.

On the other hand, as for the responses of CDS to a bond flows' shock (Figure 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 behavior in the bond flows for our AEs sample.

Exhibit A. Bond Flows → CDS

Exhibit B. Bond Flows → CDS
Figure 9. Cumulative Impulse-Response Functions.
Notes: These functions are estimated based on a bivariate VAR. Confidence level 90%. **Estimation sample:** 01/07/2009 to 09/03/2014.

In sum, we notice that economies like Germany and the U.K., fail to show evidence of run-like dynamics associated with bond flows. In contrast, some economies have statistically significant responses, e.g., Belgium, France, and Italy, among others. As known, these have

had economic difficulties. In effect, Belgium, as well as Italy and France, have had problems with their banking sector 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. Yet, the low and unresponsive bond flows associated with these economies have been plausibly induced by the multilateral aid they have been recipients to, and the expectation of possible future aid and, accordingly, the investors' anticipation that under such aid run-like dynamics are considerably improbable.

In general, these CIRFs are evidence which is less favorable to the presence of run-like dynamics. In effect, essentially in all AEs, shocks to the bond flows do not lead to statistically significant changes in their CDS.

10. Bond Flows, Risk Premiums, 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.[24] 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: 01/2009-08/2014. As explained, such rate attempts to account for the unconventional monetary policy, which is certainly crucial in the present juncture. The time series' frequency is monthly, as that of the Wu and Xia rate.

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

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

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[24] 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 is estimated with a lag of one.[25]

The shock identification is also based on the Cholesky decomposition and, thus, the variables' order is crucial. We assume that the Wu and Xia rate is the slowest moving, followed by the bond flows, and the EMBI spread being the fastest moving. 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, they seek to invest in the safe asset, i.e., 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 (Figure 10).
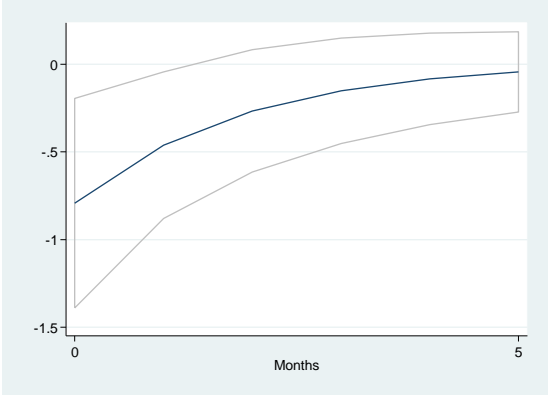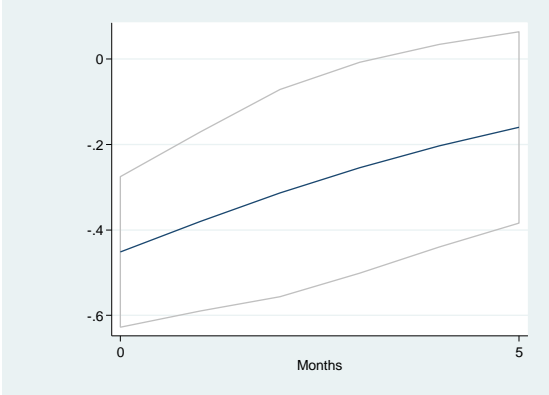

Exhibit A. Wu and Xia Rate→ PC of Bond Flows

Exhibit B. PC of Bond Flows→ PC of EMBI Spreads

Figure 10. Impulse-Response Functions. Notes: These functions are obtained from the tri-variate VAR model. Estimation sample: 01/2009-08/2014.

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 EMBI spreads. In effect, the PC of bond flows' response to a Wu and Xia Rate' shock, and the PC of EMBI spreads' response to a PC of bond flows' shock are both statistically significant. The first

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[25] 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.

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).[26]

Interestingly enough, if we estimate the same VAR model but for the 01/2013-08/2014 period, the PC of bond flows' response to a shock in Wu and Xia rate noticeably increases. Note that the immediate response is around -2.5 (Figure 10), while it is -0.8 when the starting date of the estimation sample is 01/2009 (Figure 11).[27]
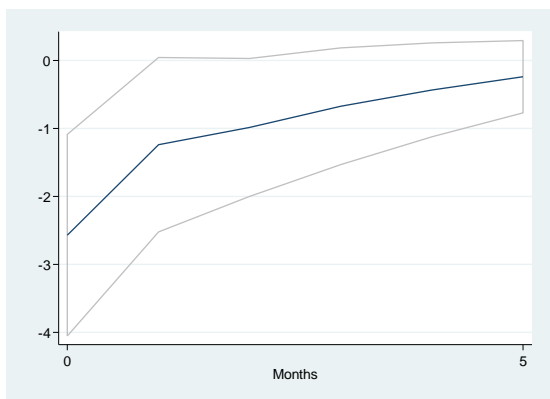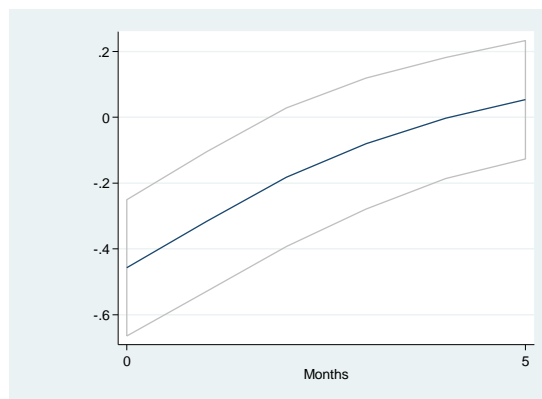

Exhibit A. Wu and Xia Rate$\rightarrow$
PC of Bond Flows

Exhibit B. PC of Bond Flows$\rightarrow$ PC of
EMBI Spreads

Figure 11. Impulse-Response Functions. Notes: These functions are obtained from the tri-variate VAR model. **Estimation sample:** 01/2013-08/2014.

Moreover, this is in line with the dynamics of the estimated probability in the regime switching model in the sense that the regime switches to state 1 became more frequent towards the beginning of 2013, that is, as markets perceive that a change in the direction of monetary policy in the US gets closer.[28] This last set of results suggests that the possible effects of US monetary policy on the run-like dynamics increased around that time.

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[26] As stated in the introduction, evidently, there is a concern that this type of dynamics may happen again given the current prospects of US monetary policy in the coming quarters. Thus, we hypothesize that up to this point we have only seen a handful of this type of episodes. Accordingly, we would not necessarily expect full-fledged economically significant responses.

[27] Another IRF of interest is response of PC of bond flows given a shock to 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.

[28] 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.

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

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

Table 7. General Statistics for the principal components of Bond Flows and EMBI Spreads, and the Wu and Xia Rate.

11. Bond Flows, Risk Premiums, 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 (Figure 12, Exhibit A). We observe that, in contrast to the result for EMEs, it is positive. Also, note that it only lasts for about a month. This result suggests that simply as interest rate in AEs goes up, portfolio shifts take place that imply inflows to those economies as would be expected, or as a group AEs could be acting as a safe heaven, since an increase in the Wu and Xia rate leads to an increase in inflows.

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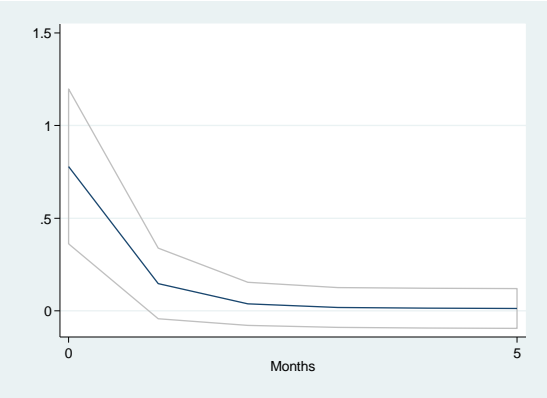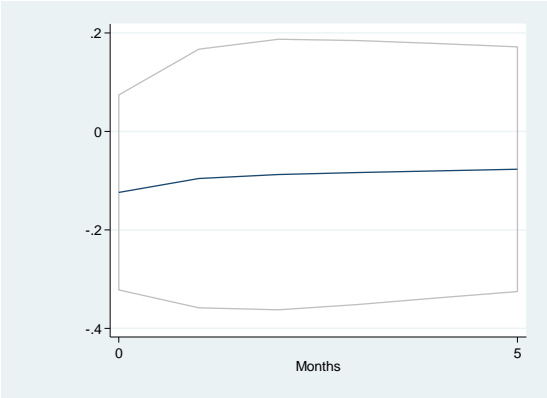

Exhibit A. Wu and Xia Rate → PC of Bond Flows

Exhibit B. PC of Bond Flows → PC of CDS.

Figure 12. Impulse-Response Functions. 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.

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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

Table 8. General Statistics for the PC of Bond Flows, PC of CDS for AE, and the Wu and Xia Rate.

Furthermore, we estimate two versions of the tri-variate VAR. First, we exclude Germany, UK, and Greece from our AEs sample. 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 principal components (PC) of for bond flows and CDS, separately, as we have done so previously.

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.[29] (The Impulse-Response Functions (IRFs) have been estimated but are not presented.)

Second, we use 01/2013-08/2014 as an estimation sample. In such case, the effect of Wu and Xia rate's shock on the PC of bond flows is similar. Moreover, the effect of flows' shock on the PC of CDS is not statistically significant. (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 presented 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 bond flow response given 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 heaven.

In the appendix, we present some important extensions and complementary estimation exercises which test for the robustness of our results. In what follows, we provide a brief description of the exercises therein and of their main implications. First, we compare the

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[29] The magnitude of the immediate response is 10% its standard deviation.

AUM's percentage change in value with the percentage change in the EMBI spreads for EMEs as a group. These time series have 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 bonds flows' representativeness.

Second, we estimate "risk-on" and "risk-off" episodes based on bond flows and compare their behavior to that of the aggregated EMBI spreads.[30] We observe that sharp changes in bond flows are associated to significant changes in aggregated EMBI spreads. In addition, we analyze the correlations between the VIX index with the PC of bond flows and the PC of EMBI spreads. The recent drop in their correlation suggests that the VIX explains less of the observed variability of the referred two variables.

Third, we consider the estimation of the tri-variate VAR but adding a cumulative bond flows variable. Such 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 comment on some robustness checks that control for aspects we believe are relevant as well. These controls are: i) the recent country's economic performance based on the recent changes of their EMBIs; ii) the level of leverage in the banking sector of an economy; and, iii) based on geographical regions. These additional estimations are supportive of the idea that the run-like dynamics we have explored are to an extent independent of economic performance, level of leverage in the banking sector, and geographical region.

Fifth, we present the estimation of the two main VARs we have estimated, but using equities flows instead of bond flows for aggregated EMEs data. Generally, equities 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 favorable to the presence of run-like dynamics.

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[30] As detailed in the appendix, we construct such indicator following Feroli et al. (2014). The risk-on/risk-off indicator is estimated based on the deviations of the average bond flows with respect to its historical standard deviation.

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 return may be seen as one under uncertainty. Thus, this exercise explores an uncertainty element that might be relevant to the mechanism we have explored. Specifically, we observe that an impulse to the uncertainty index leads to a positive response by the PC of bonds 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.

12. Concluding Remarks

The degree of leverage in financial institutions is a characteristic that has brought much attention regarding its implications for financial stability, and justifiably so. Nonetheless, other mechanisms, which are essentially unrelated to the degree of leverage, might play a significant role in determining financial stability. The type of mechanisms we have explored could be associated with the ability EMEs have to deal with the eventual tightening of the US policy rate.

As the data we have analyzed strongly suggests, the possible effects of run-like behavior in the bonds market are latent, albeit they could have distinctive effects on different EMEs. In effect, some economies should be more concerned than others in terms of the implication this channel can have. Moreover, if this channel has gained strength, as we have found some evidence entertaining such possibility, it would add to a plethora of concerns.

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

Stein (2014a) has emphasized that this depends on the level on which the run behavior might take place: at the investors' or fund managers' level. If it is at an investors' level, financial authorities might be able to impose a fee on those investors that decide to withdraw their funds in order to internalize the externality they would impose on those left behind. If, however, it is at a fund managers' level, it is not obvious what financial authorities could do. Of course, in practice, the previous measure could be difficult to implement and could lead to an increase in policy uncertainty.

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More generally, as a result of the last few years of global financial reform efforts, this type of mechanisms would be particularly relevant to the extent to which they are generated by non-banking institutions. Thus, they are essentially exempt from most of the macro-prudential regulations.

Although we have found evidence favorable to the existence of run-like dynamics in bond flows in and out of EMEs, we have not taken a stand on its relative implications. In effect, we have highlighted that this channel is one of several potential ones. We, nonetheless, underscore that a general low level of financial leverage by investors should not be seen as guaranteeing a smooth ride through the eventual US monetary policy rate normalization for EMEs.

Moreover, evidently, there is a concern that this type of dynamics may happen again given the current prospects of US monetary policy in the coming quarters. In other words, we hypothesize that hitherto we have only seen a handful of this type of episodes, although there is a good chance that more will likely follow. This is in the same vein of what Borio (2010) has stated: "What looks like low risk is, in fact, a sign of aggressive risk taking." In fact, in our context, low risk premiums could very well be a prelude to a run.

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Appendices

While the evidence presented in the main text is favorable to the presence of run-like dynamics in EMEs bond markets, one might be concerned about their robustness. Thus, in these appendices we present some additional data and estimations which aim to serve as controls and robustness checks. Their contents and their corresponding conclusions are as follows. (Note that each capitalized letter corresponds to that of each individual appendix).

A. Since we do have access to the Asset Under Management (AUMs) for EPFR's EMEs as a group, we compare the AUM's (minus) percentage change in value against the EME's EMBI spread percentage change. We find a high correlation between these series. Complementarily, we compare the sum of bond flows in our database with the EPFR's EMEs bond flows, to find a very high correlation. Arguably, these results provide support for using the EMBI spreads as proxies to AUMs percentage change for EMEs individually. In addition, they are telling of the EPFR's bond flows database' representativeness.

B. We estimate a risk-on and risk-off indicator based on bond flows, and compare its behavior to the aggregated EMBI spreads, following Feroli et al. (2014). We notice that such indicator is associated with significant changes in the referred spreads, which is in line with the type of mechanisms we have analyzed. In addition, we consider the correlations between the VIX, and the PC of bond flows and PC of EMBI spreads. Centrally, we document their recent drop. This result suggests that the VIX has lately explained less of the observed variability of the referred two variables. This is supportive of the idea that PC of bond flows and PC of EMBI spread have been in recent times explained more by phenomena like herd-like behavior, and less so by economic fundamentals.

C. We consider the estimation of the tri-variate VAR but adding a recent cumulative bond flows variable. This variable attempts to control for the stock of bonds recently accumulated. This control variable is important in terms of the model, as some of its implications depend on the number of active investors already with a position in the risky asset. Our main results are maintained.

D. We implement some exercises that control for aspects that we believe are relevant. Specifically, we estimate the tri-variate VAR but only with a subset of our EMEs based on:

i. The recent country's economic performance measured by the EMBI. Its results suggest that a good recent economic performance does not exclude the possibility of run-like behavior.

ii. The level of leverage in the banking sector of the economy. This emphasizes that the type of mechanisms we have assessed are not necessarily related to the level of leverage. Of course, this is not to say that a high level of leverage will not exacerbate a possible run-like episode.

iii. Their geographic regions. This highlights that a possible run-like episode is also a regional phenomenon.

E. We present the estimations of the two main VARs but using equities flows instead of bond flows, for EMEs and AEs. This serves as a control group in the sense that equity markets are more liquid and, therefore, finding evidence of run-like behavior is less likely. In fact, in a related setup, Chen at al. (2010) argue that strategic complementarities are more prevalent in illiquid funds. They specifically claim that "sensitivity of outflows to bad past performance is stronger in illiquid funds than in liquid funds."

F. We extend the tri-variate VAR model for EMEs adding an economic policy uncertainty index as a fourth variable. This is a simple extension of our main estimations which attempts to capture the role of uncertainty in the model. We find that more uncertainty is associated with an increase in bond flows. This result is reasonable as long as one assumes that a higher economic policy index has been associated with a lower probability for the Federal Reserve to increase its policy rate.

Appendix A: AUM's Value and EMBI Spreads.

In Figure 13, we make two important comparisons. The first shows the (minus) implicit AUM percentage change in value and the EMBI spreads (Exhibit A). The weighted average of the last four weekly observations is taken in both series.
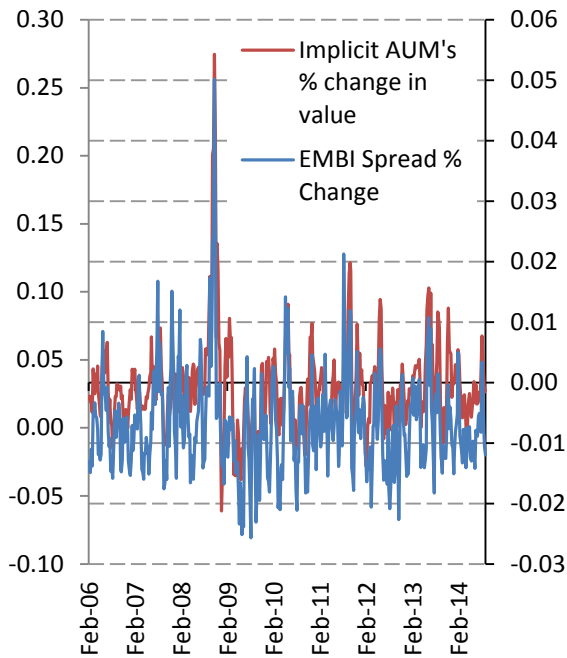
Exhibit A. The (minus) implicit AUM's percentage change in value, and the EMBI spread percentage change. The weighted average of the last four weekly observations is taken in both series. The correlation is 0.74.
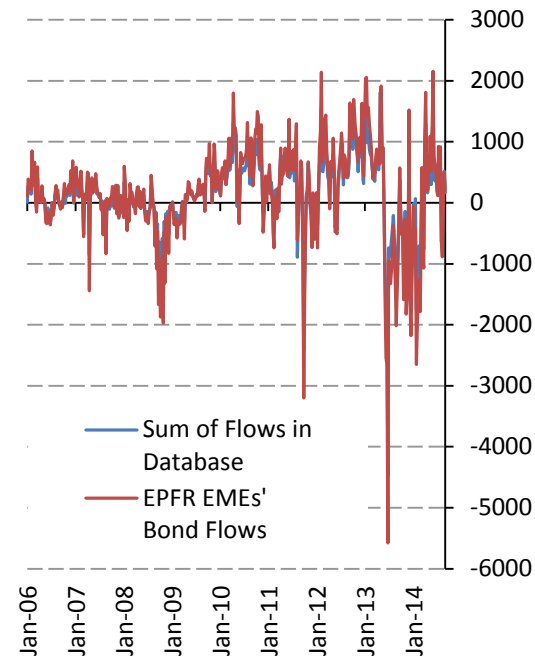
Exhibit B. The sum of flows of the bond flows of the EMEs of our data base. The EPFR EMEs total bond flows. Their correlation is 0.99.

Figure 13. The (minus) implicit AUM's percentage change in value vs. EMBI spread change. Sum of flows in Database vs. EPFR EMEs' Bond Flows.

Their dynamics and correlation provide support for using the EMBI spread as a proxy to the value of AUM. As a corollary, this is supportive of EPFR bond flows' representativeness. In effect, with a biased EPFR bond flows sample, one would hardly obtain a high correlation. Next, we compare the sum of flows in our database with the EPFR EMEs' bond flows (Exhibit B). Their high correlation provides complementary support to our last point.

Appendix B: Risk-on/Risk-off indicator, the VIX, and their relationship to Bond Flows and EMBI Spreads.

We present additional evidence to the predictions of the cited model in the context of EMEs. Thus, we first consider the aggregated EMBI spreads compared to a risk-on/risk-off indicator (Figure 14). We construct such indicator following Feroli et al. (2014).

The risk-on/risk-off indicator is estimated based on the deviations of the average bond flows with respect to its historical standard deviation. By construction, it is positive one if the bond flows are greater than two times its sample standard deviation and negative one if the bond flows are smaller than minus two times its sample standard deviation.

We observe that there is a tendency for the aggregated EMBI spread to decrease in risk-off episodes and, conversely, to increase in the risk-on episodes. There are, however, some exceptions to this behavior, such as the one during the week of February 8, 2012 (Figure 14).

On the whole, these dynamics are supportive of the presence of run-like dynamics in bond flows. This is the case since extreme bond flows episodes are related to fluctuations in the EMBI spread.
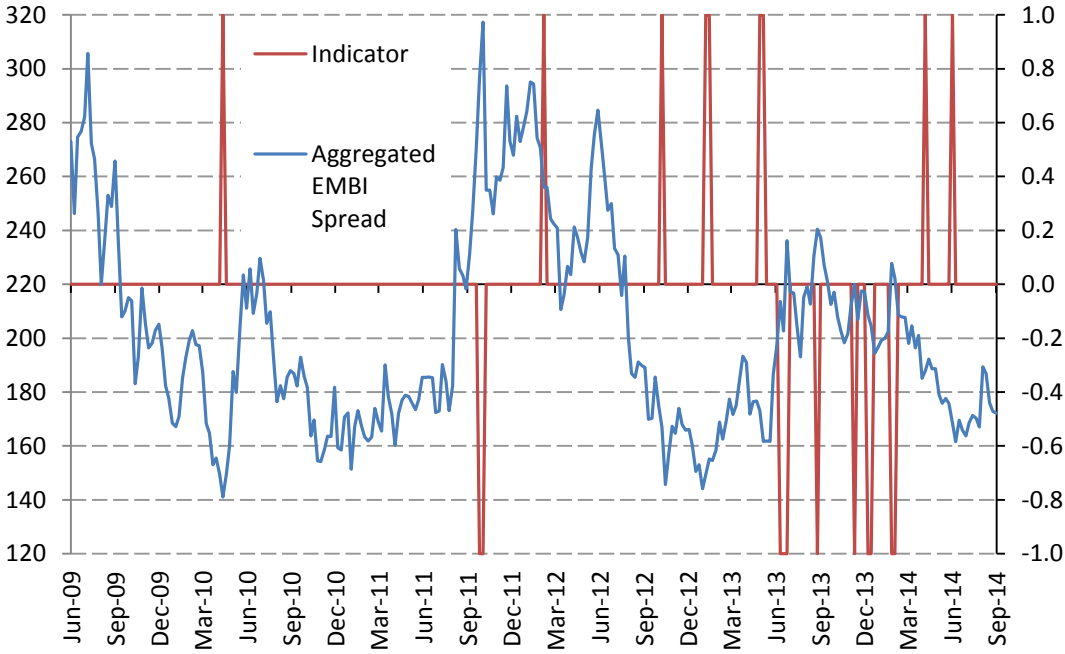
Figure 14. Risk-on Risk-off Indicator and the Aggregated EMBI Spread.
Notes: The risk-on/risk-off indicator is positive one if the bond flows are greater than two times its standard deviation and negative one if the bond flows are smaller than minus two times its standard deviation.

Second, we compare the VIX index with the PC of bond flows and, separately, with the PC of EMBI spreads (Figure 15). Notably, the correlations between the PC of bond flows and the VIX, and the PC of EMBI spreads and the VIX, have markedly dropped. In effect, the correlation of the respective two variables from 2008 to 2010 is -0.64, while this same

statistic in the period 2011 to 2014 (September) dropped to -0.20 (Figure 15, Exhibit A). On the other hand, their correlation based on the 2008 to 2010 period went from 0.92, to a level of 0.57 for the 2011 to September 2014 period (Figure 15, Exhibit B).

The documented drop is favorable to the idea that bond flows and EMBIs spread have not been recently driven as strongly by changes in the VIX, a financial variable which is known to explain changes in investor sentiment and, thus, typically asset prices. This is in line with the possibility that non-fundamental factors such as the presence of the type of mechanisms we have studied might have recently gained prominence in the determination of bond flows and their prices. In effect, we presume that factors such as delegated investment, and redemption pressures, as argued in Feroli et al. (2014), could be some of those mechanisms which have more recently gained relevance.
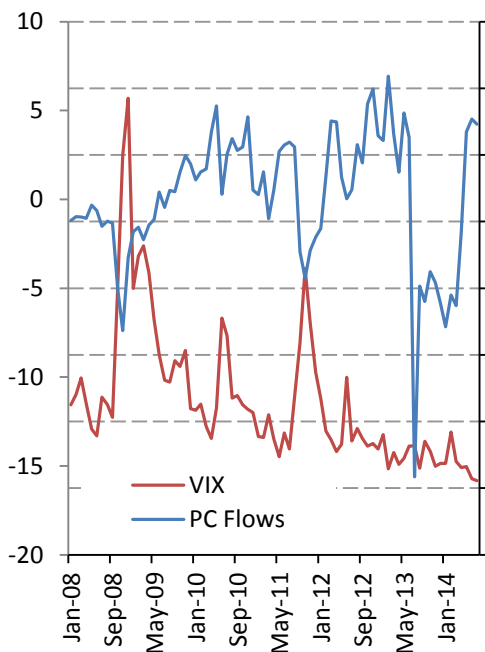
Exhibit A. VIX and PC of Bond Flows
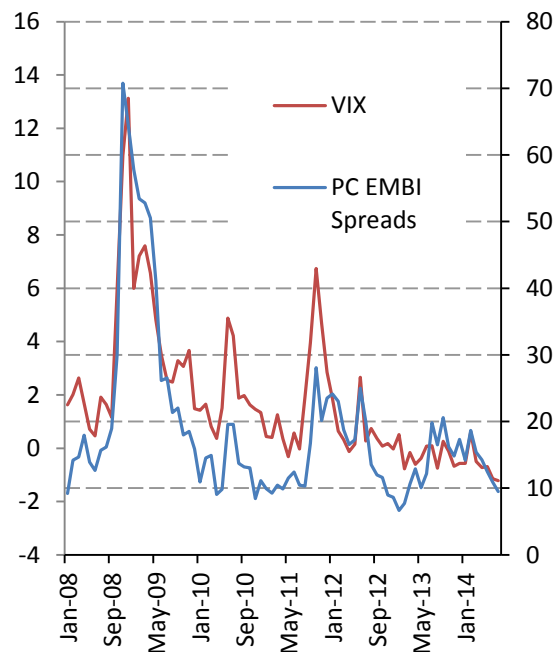
Exhibit B. VIX and PC of EMBI Spreads

Figure 15. VIX vs. PC of Bond Flows, PC of EMBI Spreads. Estimation Sample: 01/2009-08/2014.

Appendix C: Bivariate -VAR and Tri-variate-VAR with cumulative flows as controls

Bond stocks are potentially a relevant variable to control for. Recall that in the model an active investor will care about the number of their peers already with a position in the risky asset (i.e., the cumulative bond flows), as it will impact the return she can possibly obtain.

In this context, we estimate the bivariate VAR and the tri-variate VAR adding proxies for the cumulative bond flows variable. Our aim is to control for the stock of bonds that have accumulated in the immediate past periods. In our case, we consider a month for the bivariate VAR (which has a weekly frequency), and a quarter for the tri-variate VAR (which has a monthly frequency).

Bivariate VAR + Cumulative Bond Flows

As explained, while bond flows are central to the model, the stock's position of the active investors in bonds also potentially matters. Thus, we first construct a proxy by summing the weekly flows in the past month (i.e., $cf_t = f_{t-1} + f_{t-2} + f_{t-3} + f_{t-4}$, where t stands for a week). Then, we add it as a third variable to the bivariate VAR. Last, we estimate it for the 02/01/2009 to 09/03/2014 period.

First, we consider the PC of EMBI spread's response to a shock to PC of bond flows, and the PC of bond flows' response to a shock to PC of EMBI spread. The CIRFs have the expected signs and are statistically significant. Thus, when controlling for cumulative bond flows, the results are maintained.

Tri-variate VAR + Cumulative Bond Flows

Similarly, the same issue arises when one considers the effect of monetary policy in the possible run-like dynamics we have explored. To address such issue, the cumulative bond flows are added as a control variable in the tri-variate VAR. To do so, we sum the monthly's flows in the past quarter (i.e., $cf_t = f_{t-1} + f_{t-2} + f_{t-3}$, where t stands for a month) for the 04/2009-08/2014 period.

Similarly, we examine the PC of EMBI spread's response to a shock to PC of bond flows, and PC of bond flows' response to a shock of PC of EMBI spread. The responses' signs are as expected and their statistical significance is maintained.

Estimating the referred model using the 04/2012-08/2014 period, we find that the signs of the responses are as expected and the statistical significance of the IRFs is maintained. Similarly to the case without the cumulative bonds flows as controls, the response of bond flows to a shock to the Wu and Xia Rate increases, and notably so using the estimation sample 04/2009-08/2014.

In sum, using a proxy to control for the bonds' stock, we conclude that the evidence of run-dynamics is maintained.

Appendix D: The Tri-variate VAR estimated by EMBI performance, by Bank Capital to Assets Ratio, and by Geographical Groups.

One might justifiably ponder whether our results depend on certain characteristics of the economy under consideration. Perhaps, an economy that has performed well recently could respond differently to a run-like episode.

In this context, we run a battery of additional estimations to check on the robustness of our results. For the sake of space, the actual IRFs are not included. First, we consider the recent economic performance of each EMEs. We do so by ranking our EMEs based on their EMBI performance as of January 2009. Specifically, we take each EME EMBI's 01/2009-08/2013 average. Indonesia, Peru, Philippines, and Russia come up at the top.

Assessing the associated IRFs, we observe that an unexpected increase in the Wu and Xia Rate implies a PC of bond flows' response which is statistically significant. On the other hand, a PC of bond flows' surprise leads to a statistically significant change in the PC of EMBI spread, albeit only somewhat economically significant. Both responses have the expected signs. Hence, *it seems that a relative good recent economic performance would not necessarily avoid run-like dynamics.* Making a broad interpretation, this result is in line with the fact that V (i.e., the long run expected value of the risky asset) is independent of the possibility of a run-like dynamics episode.

Second, one should be concerned not only about the leverage in the investment funds, an issue we have dealt with earlier in this paper, but also in the bond flows' recipient economy. To control for this issue, we consider an estimation exercise in which we rank our EMEs based on their Bank Capital to Assets Ratio as a proxy for the level of leverage.[31,32] Under this criteria, Chile, Indonesia, Peru, Philippines, and Russia rank at the top.

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[31] As discussed earlier in the paper, the level of leverage in the funds in the investment funds in our database is minimal and is not a significant concern.

[32] Note that such measure does not account for the non-banking sector. Source: World Bank.

Nonetheless, for this specific exercise, we had to consider the estimation sample as of January 2010, and to exclude Chile from the sample. The change of the initial date hints that the channel did not gain much strength until more recently. The exclusion of Chile suggests that it might be less prone to run-like dynamics. Thus, considering the associates CIRFs, we observe that the effect the Wu and Xia rate has on the PC of bond flows is statistically significant at a 90% level. Moreover, the effect the PC of bond flows has on the PC of EMBI spread is also statistically significant, but somewhat economically significant. Again, both responses have the expected signs.

Accordingly, it seems that a favorable level of leverage will not necessarily avoid the possibility of run-like dynamics in the bond flows and EMBI spreads. This is supportive of our main hypothesis.

Third, we divide the EMEs sample in three geographical regions, and estimate the original tri-variate VAR.

i. For the Latin America group (i.e., Brazil, Chile, Colombia, Mexico, and Peru), the response of PC of bond flows to shocks to the Wu and Xia Rate are statistically significant. Moreover, the PC of EMBI spreads' response to PC of bonds flows' shocks are statistically significant. Both have the expected direction.

ii. For the Asian group (i.e., Indonesia, Malaysia, and Philippines), the response of PC of bond flows to shocks to Wu and Xia Rate are statistically significant. Moreover, the PC of EMBI spreads' response to PC of bonds flows' shocks are statistically significant. Each response has the expected sign.

iii. For the Eastern Europe group (i.e., Hungary, Poland, Russia, and Turkey) we have that the responses of PC of bond flows to shocks to Wu and Xia Rate are statistically significant. What is more, the PC of EMBI spreads' response to PC of bonds flows' shocks are statistically significant as well.

For the three regions, the PC of EMBI spreads' responses to PC of Bonds Flows' impulses are somewhat economically significant.

All in all, while all responses have the expected sign and are statistical significant, some are somewhat economic significant. Nonetheless, we want to bring home the point that these dynamics have not yet fully materialized except for a handful of episodes. Thus, our

concern is about the run-like dynamics *that could potentially take place in the future*. We hypothesize that there is a good change the more will likely follow, as we have underscored in our concluding remarks.

Appendix E: Equities Flows for EMEs and AEs

Generally, equity markets are more liquid than bond markets. Thus, arguably, it is less likely that one could find evidence of run-like dynamics in equity flows. In this appendix, we explore the extent to which this is the case for EMEs' and for AEs' equities markets. We do so mainly as a control exercise.

Here there is also the issue of how to measure the change in the equity spreads. As a proxy we use the percentage change in the respective Morgan Stanley Capital International Index (MSCI) for EMEs and AEs. We denote such statistic by $\Delta\%$MSCI. In sum, as we did in the main text for bond flows, we first estimate the bivariate VARs (for each individual EMEs) and the tri-variate VARs (for EMEs as a group) but considering the data associated with the equity flows. Second, we estimate those same bivariate VARs (for each individual AEs) and the tri-variate VARs (for AEs as a group) using equity flows.

Thus, we estimate the bivariate VAR for each EMEs. The following comments are in order. As for the response of the percentage change in MSCI to a shock in equity flows, we observe that Brazil, Chile, Malaysia and Philippines have statistically significant responses (Figure 16). Nonetheless, all four responses are short-lived. The exception in this exercise is India, which response lasts for 20+ weeks.
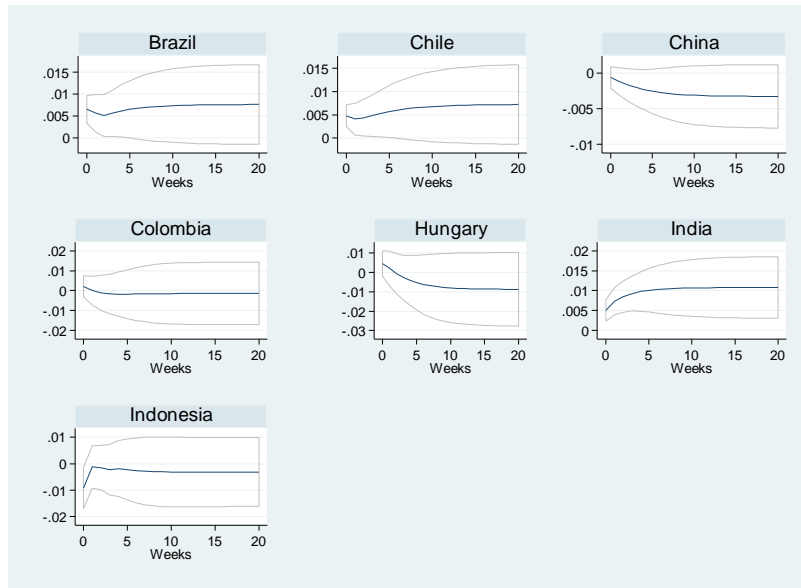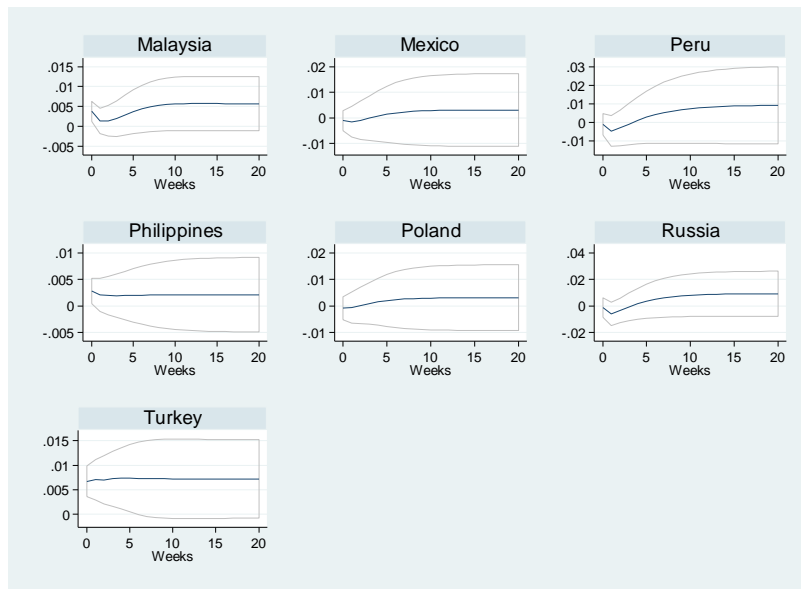
Exhibit A: Equity Flows → Δ%MSCI

Exhibit B: Flows → Δ%MSCI

Figure 16. Cumulative Impulse-Response Functions. These functions are estimated based on a bivariate VAR using the EPFR equity flows and the percentage in MSCI for EMEs. Confidence level 90%.

Estimation sample: 01/07/2009 to 09/03/2014.

On the other hand, as for the responses of equity flows to shocks to the percentage change in MSCI, we have three EMEs with statistically significant responses: Brazil, Chile, and Turkey (Figure 17). All three economies' responses last for 20+ weeks. While the

responses (in Figure 15) for India, and (in Figure 16) for Brazil, Chile, and Turkey are unexpected, we see these economies as the exception rather than the rule. Thus, up to this point, there is little evidence of run-like behavior in equity flows for EMEs.
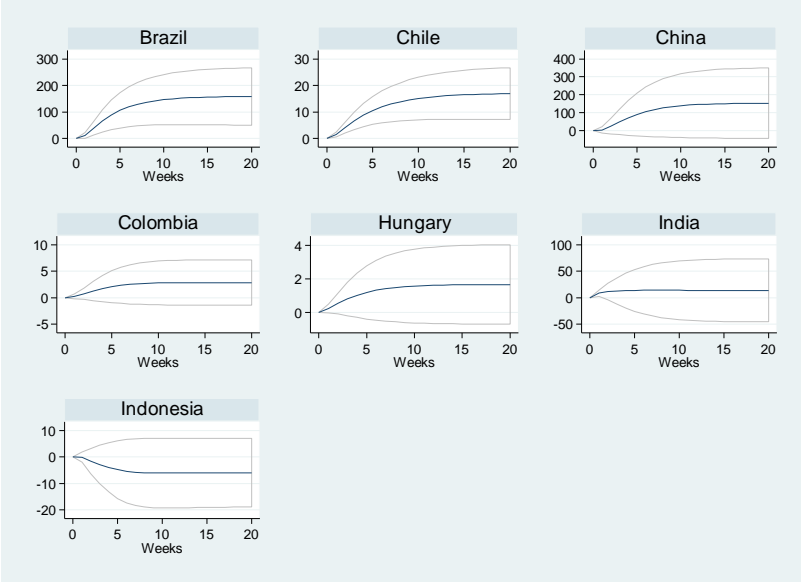
Exhibit A: Δ%MSCI → Flows
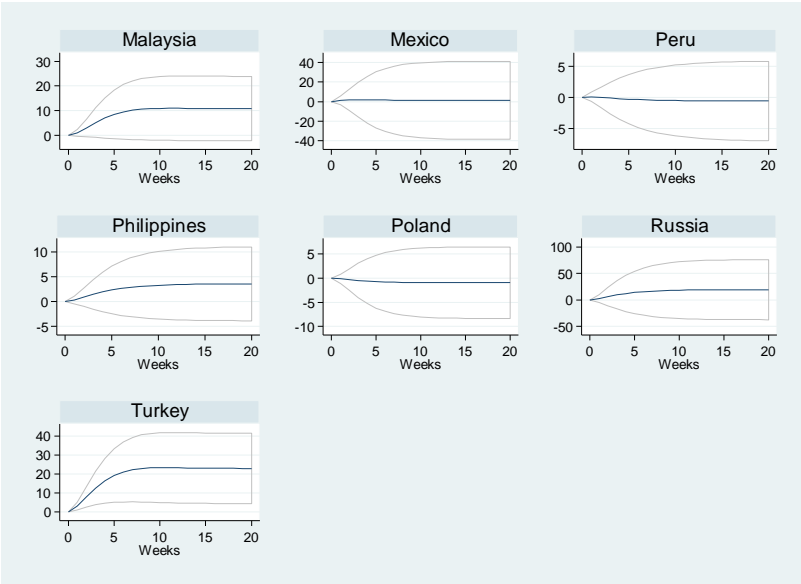
Exhibit B: Δ%MSCI → Equity Flows
Figure 17. Cumulative Impulse-Response Functions. These functions are estimated based on a bivariate VAR using the EPFR equity flows and the percentage change in MSCI for EMEs. Confidence level 90%.
Estimation sample: 01/07/2009 to 09/03/2014.

Next, we consider the tri-variate VAR using equities flows for the EMEs. We have that the PC of equity flows' response to a shock in Wu and Xia Rate is not statistically significant. As a side, note that it has the opposite sign to the one would expect based on the model. As for the response of a percentage change in MSCI to a shock in PC of equity flows, it is statistically significant but short-lived (Figure 18).
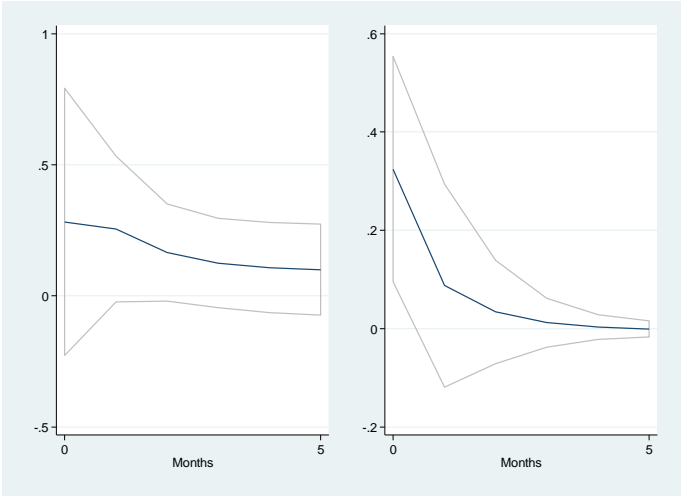

Figure 18. Impulse-Response Functions. The plot in the **left depicts**: Wu and Xia Rate $\rightarrow$ PC of Equity Flows, while the plot in the **right shows**: PC of Equity Flows $\rightarrow$ $\Delta\%$MSCI. **Notes:** These functions are estimated based on a tri-variate VAR using the PC of EPFR EMEs equity flows and the PC of percentage in MSCI for EMEs. Confidence level 90%. **Estimation sample:** 01/07/2009 to 09/03/2014.

In sum, when we consider the equities flows for EMEs, we have found inconclusive evidence for run-like dynamics. For evidence against their presence, we have that, in general, the percentage change in MSCI does not respond to a shock to equity flows. Thus, evidence favorable for the equity flows and prices' feedback predicted by the model is weak. Moreover, in the aggregate, equity flows seem not to respond to an unexpected change in the Wu and Xia Rate. In the setup we are considering, such respond is central evidence as trigger of a run-like episode.

Next, we estimate the bivariate VAR for each AE. With respect to their estimations, we have the following comments. In the case of the percentage change in MSCI' responses to a shock in equity flows, we observe that Spain and the UK have statistically significant ones

(Figure 19). Finland, Germany, and Greece have statistically significant responses; note, however, that they are all short-lived. It is surprising that the UK has such a response, particular so, since it lasts for 20+ weeks.
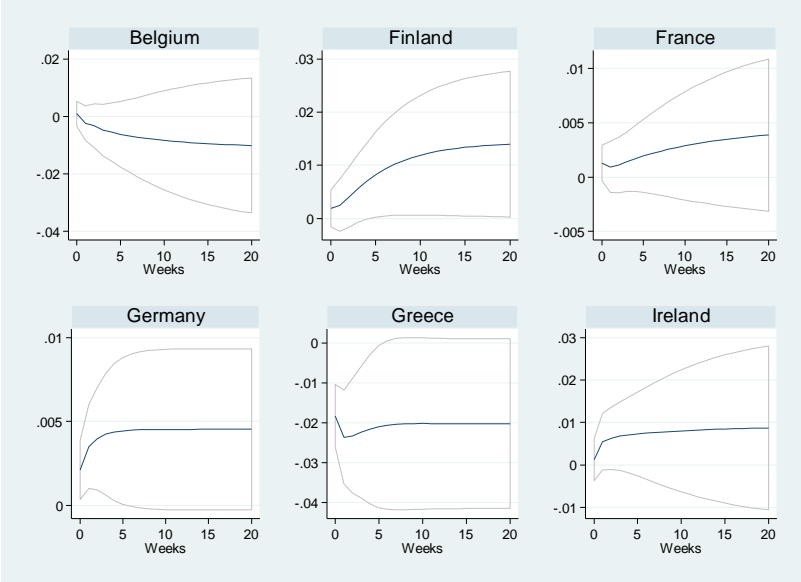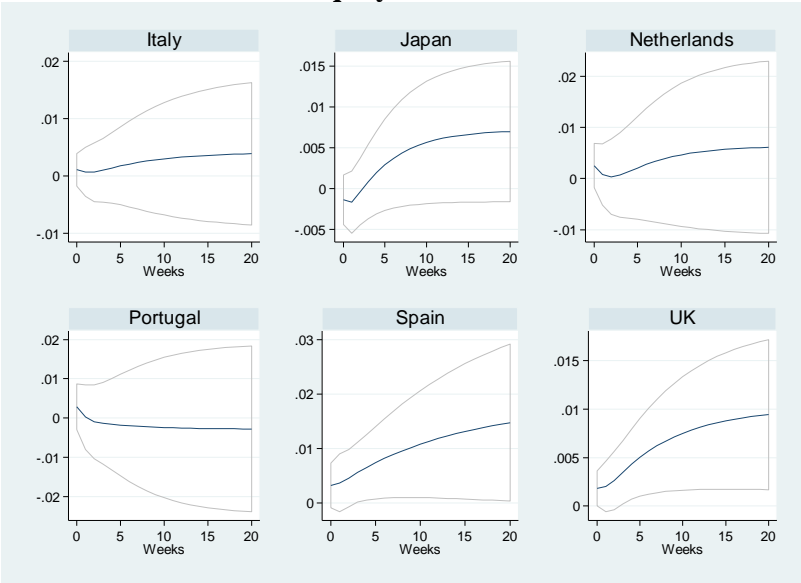

Exhibit A: Equity Flows → Δ%MSCI

Exhibit B: Equity Flows → Δ%MSCI
Figure 19. Cumulative Impulse-Response Functions.
Notes: These functions are estimated based on a bivariate VAR using the EPFR equity flows and the percentage in MSCI for AEs. Confidence level 90%. **Estimation sample:** 01/07/2009 to 09/03/2014.

As for the responses of equity flows to shocks to the percentage change in MSCI, we have one AE with a statistically significant response, namely, Greece (Figure 20). Counterintuitively, it has a negative sign.
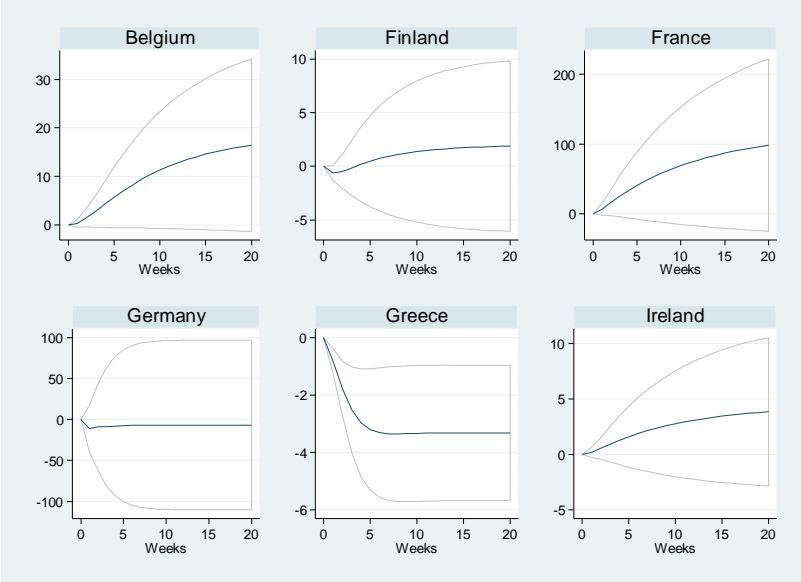

Exhibit A: Δ%MSCI → Equity Flows

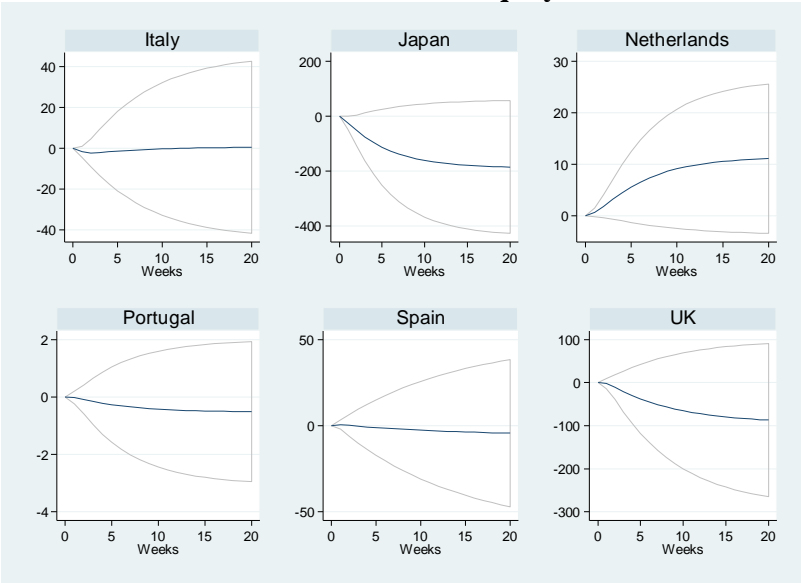**Exhibit B: Δ%MSCI → Equity Flows**
Figure 20. Cumulative Impulse-Response Functions. These functions are estimated based on a bivariate VAR using the EPFR equity flows and the percentage change in MSCI for AEs. Confidence level 90%. **Estimation sample:** 01/07/2009 to 09/03/2014.

In sum, possible evidence to support a feedback mechanism between equity flows and prices is weak. Particularly so given the general statistically insignificant responses of equity flows to a percentage change in the respective MSCI indices.

Finally, when we consider the tri-variate VAR for the AEs, we observe that the PC of equity flows' response to a shock to the Wu and Xia interest rate is statistically significant (Figure 21). Nonetheless, it does not seem to be economically significant. As for the response of a percentage change in MSCI to a shock in PC of equity flows, it is clearly not statistically significant.

Thus, in this case as well we have failed to find evidence favoring run-like behavior in equity flows. In general, prices seem not to respond to unexpected changes in equity flows.

All in all, we believe there is no broad evidence for run-like behavior in the equities flows in both AEs and EMEs. While there might be specific cases where evidence is not as convincing, in general, one or more of the estimation exercises considered is (are) not consistent with the model's implications and, thus, with the type of mechanisms we have in mind.
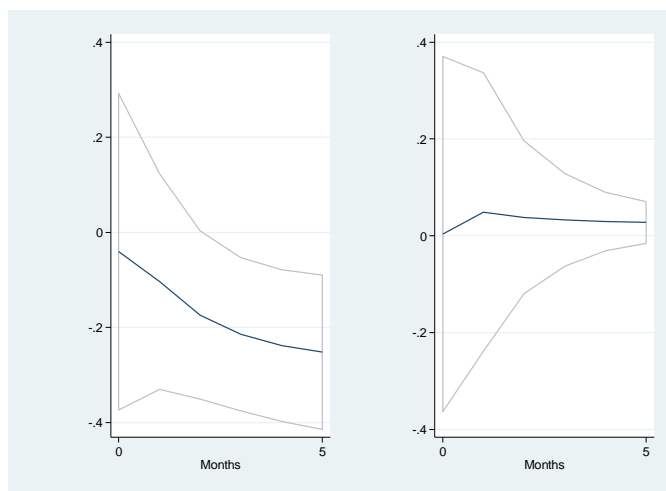

Figure 21. Impulse-Response Functions. The plot on the left shows: Wu and Xia Rate $\rightarrow$ PC of Equity Flows. The plot on the right depicts: PC of Equity Flows $\rightarrow$ $\Delta\%$MSCI**.** These functions are estimated based on a tri-variate VAR using the PC of equity flows, the PC of percentage in MSCI and the Wu and Xia Rate, for AEs. Confidence level 90%. **Estimation sample:** 01/07/2009 to 09/03/2014.

Appendix F: Bond Flows, Risk Premiums, Monetary Policy, and Economic Policy Uncertainty in EMEs

As an aside, it is the possible to explore the role of uncertainty in the type of mechanisms we have explored. There are at least two elements in the model pertaining uncertainty. One is related to the expected path of monetary policy. Recall that the floating rate investors obtain in the money market account is determined by $1+r = E_t \sum_{t=k}^{T} (1+i_{t+k})$, where i_{t+k} is the policy rate at time t+k. One can assume that investors observe r with some noise (see Morris and Shin, 2014). Relatedly, there is the uncertainty every active investor confronts regarding the joint response of the rest of the active investors. Similarly, one could postulate that every active investor acts on signals that affect them all.

While we do not propose a specific model, we do bring forward a plausible way of empirically exploring the uncertainty aspects of the model. Specifically, we propose adding an index that measures economic policy uncertainty (Baker et al., 2013) to the VARs. Moreover, we conjecture that the higher the index is the more likely the Federal Reserve Board will not tighten the reference policy rate.

Thus, the lower the expected return r would be, the less probable a run-like episode would be as well, and the more bond inflows we would observe. Its validity hinges upon the fact that the Federal Reserve Board has had sufficient leeway in terms of the expected inflation it has faced, the level of unemployment, among a broader set of other economic variables.

Next, we estimate the initial tri-variate VAR but adding the economic policy uncertainty index as a fourth variable. On this exercise, we observe that the PC of bond flows increase given a surprise in the referred index. Also, the dynamics of the PC of EMBI spreads' response to a shock to bond flows is maintained.[33]

In sum, we find that given an unexpected increase in the uncertainty level, the bonds flows towards EMEs augment. We have as an assumption that an increase in uncertainty as measured by the referred index will signal active investors that the Federal Reserve Board is less likely to increase its policy rate. Moreover, the known response of EMBI spreads to an unexpected change in bond flows is maintained. Finally, as supplementary material, the

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[33] A weighted average of the economic policy uncertainty index has been used to capture its tendency.

basic statistics for the PC of bond flows, PC of EMBI spreads, and the economic policy uncertainty index are presented in Table 9.
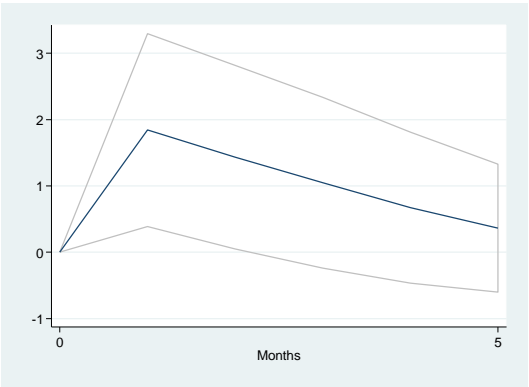

Exhibit A. Economic Policy Uncertainty Index → PC of EMEs Bond Flows
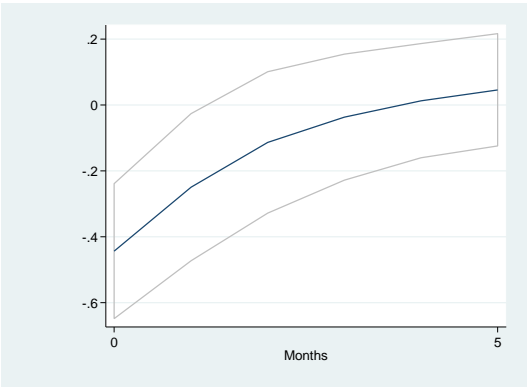
Exhibit B. PC of EMEs Bond Flows → PC of EMEs EMBI Spreads

Figure 22. Impulse-Response Functions. Tri-variate VAR model's variables + the Economic Policy Uncertainty Index. **Estimation sample:** 01/2013-08/2014

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
EUPI	137.68	59.40	312.96	45.73

Table 9. General Statistics for the principal component Bond Flows, PC of EMBI Spreads, and the Economic Policy Uncertainty Index.