Institutional Investors' Allocation to Emerging Markets: A Panel Approach to Asset Demand

Abstract

This study assesses the factors driving insurance companies and pension funds' portfolio allocation to emerging market assets. By making use of the Emerging Portfolio Fund Research database, it estimates asset demand equations for emerging markets' equities and bonds for insurance companies and pension funds from advanced countries. These are estimated by using recent advances in the literature on panel autoregressive distributed lag models. Two key results emerge: firstly, consistent with 'search for yield' investment behaviour, weaker balance sheet conditions, measured by the lower funding level of pension funds, positively affect the asset allocation to emerging markets. Secondly, the accumulation of reserves by emerging markets is a significant attractor of foreign institutional investment.

Keywords: Asset demand, emerging markets, insurance companies, pension funds, institutional investors, panel ARDL, search for yield

JEL Codes: F30, G23, G11, G15

1. Introduction

The determinants of portfolio investment in emerging markets (EMs) have been subject to intense scrutiny. At the macroeconomic level, the origins of this scrutiny can be traced back to Calvo et al. (1993), which was the first study to point out the key role of external 'push' factors such as US interest rates in explaining the contemporaneous surge in capital flows to EMs as opposed to country-specific 'pull' factors. The empirical investigation into the relative importance of push and pull factors produced a vast literature in the 1990s [1], which confirmed the importance of global factors, but also found some role for domestic fundamentals in driving capital flows to EMs.

In the aftermath of the 2008 global financial crisis, much focus was placed on the role of global risk appetite as a driver of cross-border flows. Several studies have found that risk appetite shifts, often driven by liquidity provision and the monetary policy stance of major central banks, explain much of the movement in the asset prices of EMs (González-Rozada and Yeyati, 2008; Özatay et al., 2009; Ciarlone et al., 2009) as well as the capital flows to such countries (Fratzscher, 2012; Rey, 2013; Ahmed and Zlate, 2014). Low

[1] For example, (Fernández-Arias, 1996; Chuhan et al., 1998).

interest rates and ample liquidity have induced investors to display 'search for yield' behaviour by expanding cross-border investment (Shin, 2013).

While the literature is generally concerned with the overall dynamics of financial investments in EMs, this study focuses on insurance companies and pension funds (ICPFs). These institutions are large players in global financial markets that have modified the portfolio composition substantially over the past decade, away from domestic equities towards international and externally managed assets. Furthermore, they have become increasingly important as drivers of flows to EMs, especially following the global financial crisis, as their allocations to EM bonds and equities have risen substantially (Miyajima and Shim, 2014; IMF, 2014, 2016). Understanding their behaviour is therefore crucial for addressing financial stability in EMs.

This study contributes to the analysis of capital flows to EMs by focusing on the role of two additional determinants of ICPFs' asset allocations. The first are their balance sheet conditions, represented by the aggregate funding levels of advanced countries' pension funds. ICPFs' portfolio choices, in addition to standard factors such as returns, may be affected by the conditions of their balance sheets. In fact, there is evidence that ICPFs, in the present conditions of extremely low interest rates, may be 'searching for yield' to achieve sufficient returns to meet their long-term obligations (Boubaker et al., 2015; Tran et al., 2015; OECD, 2015; Becker and Ivashina, 2015; IMF, 2016), a search that may be more pressing when liabilities grow larger than assets (i.e. when funding ratios or solvency requirements deteriorate). This study thus investigates whether lower funding levels are associated with higher allocation to EMs at the macro level, in line with the 'search for yield' explanation.

The second determinant is the level of foreign exchange reserves (FXR). The financial integration of EMs in the past decade has been accompanied by the substantial accumulation of FXR by these countries; according to the World Bank's World Development Indicators report for 2014, EMs[2] collectively hold about USD 6.5 trillion of FXR, with China holding about 60%, Brazil, India, Russia, and South Korea about 5% each, and the remaining 20% split across the other countries. FXR may work as a country's stock of systemic 'collateral' that EMs provide to foreign investors (Dooley et al., 2004, 2014; Qian and Steiner, 2014): foreign lenders can then indirectly 'claim' FXR as EMs' central banks intervene by selling them in FX markets when substantial capital outflows occur. Higher reserves therefore signal a stronger collateral and a higher capability of EMs to intervene in FX markets. This study thus examines the role of FXR as a key pull factor: the higher the level of FXR, the safer EMs are perceived to be and therefore the more attractive they are to foreign investors.

The significance of these two factors is the key contribution of this study. Demand for EM assets by ICPFs is negatively related to funding levels, thus characterising the 'search for yield' behaviour of ICPFs related to

[2]The EMs in this study are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Peru, the Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey.

their balance sheet conditions as well as the ability of EMs to reduce their currency risk by providing FXR as collateral. These findings point out the importance of looking at these additional factors to better understand the patterns of portfolio flows given the crucial importance of ICPFs. A second related contribution of this study is its methodological design, particularly its use of asset demand equations. Rather than capital flows, the study estimates demand for EM assets from advanced countries' ICPFs. This approach is effective at clearly drawing out the links between the macroeconomic phenomenon of international portfolio investment and its micro-level driver, namely the asset allocation of investors. This study also contributes to the existing asset demand equations literature in two ways. Firstly, it adopts a panel approach. In this regard, new estimators are proposed for panel autoregressive distributed lag (ARDL) models that take into account the possibility of cross-sectional dependence (CSD) and parameter heterogeneity. Secondly, it applies this approach to the issue of international portfolio choice specifically and demand for EM assets in particular.

The rest of the paper is structured as follows. Section 2 discusses the evolution of ICPFs' presence in EMs and describes the link between their balance sheet conditions and portfolio allocation. Section 3 describes the asset demand approach and its application to the issue of international portfolio investment in EMs. Section 4 describes the data and variables. Section 5 describes the tests and discusses the model specification. Section 6 presents the estimation results, including some robustness checks. Section 7 interprets these results and offers possible implications. Section 8 concludes.

2. Insurance companies and pension funds' balance sheet and emerging markets

ICPFs are large players in financial markets. As shown in Figure 1, at the end of 2014, they collectively owned about USD 45 trillion, about 60% of global GDP or 30% of total world bonds and stocks outstanding. The figure also shows that ICPFs are highly concentrated across countries: the United States, the United Kingdom, and Japan account for just under 80% of total ICPF assets, a figure that has changed little over the past 15 years.

[Figure 1 about here.]

Over the same period, however, ICPFs have seen important changes in their asset allocations. As shown in Figure 2, they have broadened the geographical scope of their investments by investing a larger proportion of their wealth in foreign assets. Furthermore, their portfolios have become more diversified in terms of asset classes. In OECD countries, on average, ICPFs have reduced their direct allocation to equities in favour of indirect holdings of assets through external funds.

[Figure 2 about here.]

Over the same period, EMs have become increasingly integrated into the global financial system[3]. The trends of internationalisation and increasing allocation to funds of ICPFs are at least partially responsible for these developments. As shown in Figure 3, allocations to EMs' bonds and equities by ICPFs' channelled through funds have grown substantially, from 0.17% at the turn of the century to about 1.85% in the third quarter of 2013[4]. While these allocations may appear small, they translate into sizable numbers: a 1.85% allocation, considering the wealth of ICPFs in the same period (USD 46.531 trillion), results in about USD 860 billion worth of EM asset holdings. This is roughly equal to 21.5% of the total portfolio liabilities of EMs at the end of 2013[5]. Indeed, considerable evidence suggests that foreign ICPFs have become a more sizable presence in EMs (Miyajima and Shim, 2014; IMF, 2014). Understanding their portfolio choices is therefore a crucially relevant macroeconomic issue.

[Figure 3 about here.]

An important development in the portfolio choice mechanism of ICPFs over the past decade has been the adoption of 'liability-driven investment' strategies (BIS, 2011). Under such a framework, the goal of asset allocation is not simply to maximise returns for a given level of risk, but rather ensure that assets adequately provide for the institution's liabilities. In practice, liability-driven investment typically involves splitting assets into two portfolios. The first is a return-seeking portfolio, whose purpose is to generate sufficiently high returns in order to increase the asset size in line with the growth in liabilities. The second is a liability-matching portfolio, whose purpose is to protect existing wealth from volatility by investing in assets that hedge liability risk. Liability-matching portfolios mainly consist of government bonds and, to some extent, derivatives, whereas return-seeking portfolios are typically much more diversified across several asset classes including EMs.

The extent to which liabilities are covered can be seen in pension funds' funding ratios (i.e. the ratio between assets and liabilities). Under a liability-driven investment strategy, low funding ratios imply a need to increase returns by either increasing the size of the return-seeking portfolio or tilting its composition towards assets with higher expected returns.

As Figure 4 shows, funding ratios have worsened substantially since 2008 because of a combination of declines in asset prices, low returns, and low interest rates. The latter are particularly important since they have a double impact on funding ratios: they decrease returns, and therefore the growth of assets, and increase the size of liabilities[6]. As a result, the combination of low interest rates and liability-driven

[3]See, for example, Lane and Milesi-Ferretti (2007).

[4]These figures are calculated from the Emerging Portfolio Research Fund database. More details on this database and its usage in this study are discussed in Section 4.

[5]Source: own calculations from IMF balance of payments statistics.

[6]Liabilities are discounted future obligations and therefore are inversely related to the discount rate, typically based on investment-grade bond yields.

investment strategies creates pressure on pension funds to generate higher returns.

The current environment of low interest rates and returns has affected insurance companies in a way similar to that of pension funds, by lowering returns on assets and inflating the value of liabilities, and thus threatening their solvency in the long-term (Kablau and Weiß, 2014; Berdin et al., 2015; Gibas et al., 2015; IMF, 2016). Cross-country data on insurers' solvency ratios (i.e. the ratio between actual and regulatory capital reserves) are not publicly available for a sufficiently long and frequent time scale. Furthermore, they are traditionally based on book value measures in contrast to pension funding ratios, thus concealing the true impact of market factors such as interest rates and asset prices (Kablau and Weiß, 2014). However, as Figure 5 suggests, when mark-to-market valuations are applied[7], pension funding ratios and insurance companies' solvency margins move together, as they respond to the same market factors, chiefly interest rates and asset prices. For this reason, funding ratios can be taken as a representative indicator of the balance sheet-induced pressure to generate returns for the ICPFs sector as a whole.

The literature has traditionally found an inverse relationship between funding ratios and allocation to risky assets (Rauh, 2009). However, recent evidence suggests that in the post-crisis environment, the converse has been true and that weaker balance sheets combined with low interest rates have been pushing ICPFs towards 'search for yield' behaviour to enhance their returns on assets (Boubaker et al., 2015; Tran et al., 2015; OECD, 2015; Becker and Ivashina, 2015; IMF, 2016). Indeed, the trends described above seem to indicate that this mechanism has been at work; equity allocations, being a poor match for liabilities, have been declining, while allocations to funds, promising higher and more diversified returns, have increased.

[Figure 4 about here.]

[Figure 5 about here.]

This study tests whether such a mechanism affects allocations to EMs at the macro level. The hypothesis put forward is that the declining funding ratios and resulting 'search for yield' behaviour have induced ICPFs to increase their allocations to EMs. This hypothesis is tested in conjunction with other traditional portfolio choice variables, using an asset demand approach, as discussed in the next section.

3. Asset demand equation approach

One way to model empirically ICPFs' portfolio choice is that of asset demand equations. In this method, originally proposed by Brainard and Tobin (1968) demand for any asset is modelled as a function of wealth, and asset returns:

[7] This is the case in the Netherlands, for which annual data on life insurers' solvency margins exist. See also Gibas et al. (2015) for Sweden, where life insurers follow the same regulation and have also been affected in the same way by the current macro-financial environment.

$$\frac{a_i^*}{w} = b_{i0} + \sum_{j=1}^{q} b_{ij} r_j \,. \tag{1}$$

The desired share of a^* of asset i relative to wealth w depends linearly on the returns on the q alternative assets plus a constant b_0. This formulation implies that households allocate assets to keep a fixed proportion b_0 of their wealth in each of them; however, this varies according to the returns on different assets. Positive (negative) returns on one asset increase (decrease) the desired allocation to that asset, while at the same time higher (lower) returns on other assets decrease (increase) such a proportion.

This study gave rise to a vast literature estimating asset demand equations, using data from flow-of-funds accounts[8]. Despite its popularity, however, the empirical estimation of asset demands has faced problems. The most important of these related to the serious multicollinearity that arose as a result of the high correlation between returns taken from aggregate time-series data. The models often presented incorrectly signed or non-significant parameters. Researchers tried to overcome these problems by estimating parameters combining the data with a priori information according to Bayesian principles [9]; however, such attempts were not wholly successful (Buiter, 2003).

In addition, an alternative methodology emerged at the beginning of the 1980s and established itself as the most commonly adopted approach to estimating demand equations. This methodology is based on the Almost-Ideal Demand System (AIDS) approach, developed by Deaton and Muellbauer (1980), which is an empirical implementation of a demand system based on neoclassical consumer theory. In the case of portfolio choice, agents are assumed to maximise the utility given by total assets subject to the inter-temporal wealth constraint. By making use of the associated 'dual' problem of cost minimisation and choosing a PIGLOG cost function, one obtains the following expression (Blake, 2004, p. 613):

$$s_{it} = a_i + b_i \ln(W_t(1 + r_{Wt})) + \sum_{j}^{n} c_{ij} \ln(1 + r_j) + \sum_{j}^{m} h_{ij} Z_{jt} \,. \tag{2}$$

Portfolio shares depend on the logs of wealth plus the return on the total portfolio, the logs of the returns on n assets, and m additional variables Z. The model is then similar to the original specifications, but adds wealth effects on portfolio shares as well as the possibility of including other variables. For example, a typical variable often added is current income or expenditure, which, as Blake (2004, p. 614) argues, can be thought of as a liquidity constraint.

The present study adopts this approach, as it provides a clear link between investors' portfolio choices and capital flows to EMs. Portfolio investments in EMs are, in this sense, analysed as demand for EM assets

[8] See, for example, (Hendershott, 1971; Backus et al., 1980).
[9] See Backus et al. (1980) for an application.

from foreign ICPFs, the aim being to uncover the direct link between the financial behaviour of investors and resulting cross-border asset positions.

In line with the considerations made in the Introduction, two additional factors are also introduced into the basic formulation of the model[10]. The first is the funding ratio of ICPFs, measuring the 'search for yield' mechanism discussed in the previous section. The second is the level of FXR held by EMs. As argued by Dooley et al. (2004, 2014), FXR can be regarded as a country's stock of collateral, which in turn attracts capital flows. Moreover, as Qian and Steiner (2014) argue, FXR accumulation, by lowering the probability and the magnitude of a currency crash, substantially reduces the riskiness of EM assets, thereby increasing their attractiveness to foreign portfolio investors. The authors, in fact, show that FXR are associated with a higher proportion of portfolio equity holdings than foreign direct investment. Since exchange rate risk is a crucial component of foreign ICPFs in EMs (Gadanecz et al., 2014), a country's ability to mitigate such risk by accumulating FXR is likely to be a major attractor of portfolio flows. Cerutti et al. (2015) indeed find that FXR are among the few 'fundamental' factors that matter for bond flows.

In this vein, this study assesses whether FXR are associated with higher demand for EM assets from foreign ICPFs. The accumulation of FXR increases EM central banks' capability to intervene in the FX market and stabilise the exchange rate. Higher FXR would therefore encourage increased allocations to EM assets. FXR are in this sense seen as a crucial fundamental pull factor.

Aside from the additional variables chosen, the application of the asset demand approach in this study is innovative in two ways. Firstly, this is the first study to adopt a panel approach. Demand for EM assets is analysed by pooling or grouping observations for individual countries to obtain parameters for EM assets as a whole. Two separate single equations of asset demand for EM equity and bond portfolios are thus estimated. The restriction of the parameters, typical of AIDS approaches, is therefore ruled out. Secondly, this study applies the approach in the context of international portfolio choice, which is also novel, as the literature typically focuses on a closed-economy, complete set of assets.

4. Data and variables

All data are measured at a quarterly frequency or converted into one when the frequency is higher[11]. The period considered is from the first quarter of 2003 for equities and the first quarter of 2004 for bonds to the second quarter of 2013, although the panels may be unbalanced as some countries' series may be shorter. While this may seem a short time span, longer datasets do not exist for constructing all the variables. The

[10] Robustness checks with additional variables were also conducted.

[11] As this happens only for the Emerging Portfolio Fund Research (EPFR) holdings variable, the end-of-month value is chosen.

cross-sectional dimension is 20 countries for equities and 17 countries for bonds[12].

The dependent variables, *lem_alloc* and *lbem_alloc*, are the logarithms of the portfolio shares of EM equities and bonds held by ICPFs from advanced countries. The allocation variables are constructed as the ratio between the EPFR end-of-period holdings over the total wealth of ICPFs of the Eurozone, Japan, the United Kingdom, the United States, Australia, and Canada, taken respectively from the European Central Bank, the Bank of Japan, the UK Office for National Statistics, the Federal Reserve Economic Data, the Reserve Bank of Australia, and Statcan. These represent the vast majority of ICPFs worldwide. For all these countries, the end-of-quarter total assets figures for ICPFs are used to measure the total wealth of ICPFs. All individual countries' figures are converted into US dollars, using the exchange rate data taken from the IMF Exchange Rate Report, and then aggregated to create the denominator of the portfolio shares variables.

The EPFR dataset, which has already been used in other studies related to portfolio investments in EMs (e.g. Fratzscher, 2012), collects flows and holdings data from a large number of mutual funds and ETFs. This study uses the 'Country Flows' database, which extracts information from each fund and aggregates it by recipient country. The database also distinguishes between institutional and retail underlying investors' clients, and in this study only the former are used. The data used in this study to construct the allocation variables are the estimated end-of-period holdings for each sample country, which are used as the numerator of the ratio between holdings and total wealth, as discussed. Although fund coverage has increased over time, the database has been shown to be a consistent representation of both balance-of-payment and fund-level data for the sample period considered (Pant and Miao, 2012; Jotikasthira et al., 2012; Kroencke et al., 2015).

These variables have some limitations as indicators of asset shares. Firstly, they only capture the EM holdings of ICPFs that are intermediated by funds rather than the total allocation. Secondly, while the advanced countries considered to construct the variables constitute the largest share of the global institutional investor sector, some of the holdings captured in the EPFR database may still be held by other ICPFs. Finally, the variable averages out portfolio shares over countries and sectors, since it is based on the sum of the total holdings over the total wealth of ICPFs, while important differences may exist among investors both across countries and within countries. Despite these limitations, as detailed data on the geographical breakdown of ICPFs' portfolios are not available, the data are the best possible approximation to the macro-level portfolio weights for EMs allocated by foreign ICPFs.

The following is a list of the independent variables with the expected parameter sign given in brackets:

[12]In the bonds equations, owing to data availability and consistency issues, Taiwan, Argentina, and the Philippines are excluded.

- lfg is the pension's 'funding gap'. This is the weighted average of the difference from full funding (i.e. a funding ratio equal to 1) of the aggregate defined benefits pension funds sector in Japan, the United Kingdom, and the United States[13]. These are collected from the Bank of Japan flow of funds accounts, the Pension Protection Fund 7800 index, and the Milliman Pension Funding Index, respectively. As discussed, this variable serves as an indicator of ICPFs' balance sheet fragility, denoting their potential incentive to 'search for yield' by investing in EM assets. (+)

- lem_fx are the FXR officially held by EMs, in billions of US dollars, collected from the Economist Intelligence Unit. As discussed, this variable is used to measure the collateral function of FXR, which lower the possibility of currency crashes. (+)

- lem_ret and $lbem\_ret$ are the logarithmic returns of EMs' equities and bonds. Logarithmic returns can be calculated from an index as $log = (\frac{p_t}{p_{t-1}})$, where p_t is the value of the index at time t. The indexes used are the Morgan Stanley Capital International (MSCI) total return index for equities and the JP Morgan EM-GBI index for bonds. The EM-GBI, which tracks local currency bonds, is used rather than the EMBI, which tracks hard currency bonds, because of its ability to capture the return effects of the appreciation and depreciation of the nominal exchange rate, which are likely to be an important determinant of the returns, much as they are for equities. (+)

- *lwbret* are the logarithmic returns of the JP Morgan GBI global index. The index tracks sovereign bonds from the world's advanced countries and it is used as an indicator of global 'safe' returns. This is different from what is commonly used as a 'push' factor (i.e. the US interest rate). This provides a more general indicator of low-risk assets in that while US dollar-denominated assets represent the safest alternative, all advanced countries' sovereign liabilities represent a qualitatively different type of asset compared with EM assets. This is consistent with the evidence that ICPFs typically use advanced countries' government bonds as liability-matching securities rather than as return-seeking assets. Therefore, despite being a simplification, this variable allows for a greater degree of generality than is commonly achieved. (-)

- *lwret* are the logarithmic returns of the MSCI World Index, which tracks the equity markets of advanced economies. The rationale for including this variable is similar to that of advanced countries' bond returns: advanced countries' equities are an alternative asset class to EMs assets. While they do not represent globally 'risk-free' assets, unlike advanced countries bonds, they still represent a distinct asset class. (-)

[13]Unfortunately, sufficiently long data series on a quarterly basis do not exist for the other countries. Nonetheless, these three countries represent the largest three defined benefits sectors by portfolio size, as shown in Section 2.

The most notable exclusion from this list is GDP growth. Firstly, this does not fit the asset demand approach well: the approach is based on the direct relationship between asset shares and their financial determinants as well as the wealth of the investor. Asset allocation and GDP growth are indirectly related, unlike balance sheet conditions and FXR. Secondly, the rationale for the link is that higher GDP growth yields higher long-run returns, but since returns are already entered into the equation specification, this could lead to double-counting the same variable, possibly resulting in multicollinearity issues, in a framework already known to suffer from this problem. Finally, if anything, the variable should be expected GDP growth rather than current GDP growth; however, long-run expectations data do not exist at high frequencies for all variables and would be subject to considerable heterogeneity across investors. Despite these considerations, as a robustness check, the estimation results with additional variables in the baseline specification, including GDP growth differentials, are provided.

Figure 6 confirms that allocations to EM bonds and equities have increased over the past decade, roughly at an exponential pace, although equity allocations have increased more slowly since the crisis. Funding ratios, as also discussed in Section 2, have worsened since the crisis, oscillating around a 10% gap. FXR also increased over the whole period, although the pace seems to have slowed since 2008. Table 1 shows the basic statistics for the rest of the variables: EM assets returns have been higher, with correspondingly higher volatility.

[Figure 6 about here.]

[Table 1 about here.]

5. Tests and specification

When dealing with macro-panels, where both the time-series and the cross-sectional dimensions are 'large', some additional issues can emerge. First, as the time-series dimension grows, the possibility of non-stationarity arises, which is what led to the formulation of unit root tests [14]. The issue of non-stationarity naturally leads to the possibility of cointegration, which can likewise be tested[15].

In addition to these issues common to time-series econometrics, macro-panel data present two further complications. Firstly, as the time dimension grows and it becomes theoretically possible to individually estimate N time-series regressions, the possibility of obtaining heterogeneous slope parameters arises. In the presence of such heterogeneity, pooled estimators can produce biased results, while mean-group (MG) estimators, which estimate panel parameters as averages of the N individual slope parameters, are consistent (Pesaran and Smith, 1995).

[14] See **?**

[15] See Pedroni (1999); Westerlund (2007).

The second set of issues relates to CSD, which is the correlation between the cross-sectional observations of a panel variable, giving rise to correlation between the cross-sectional errors. CSD creates serious inference problems: estimations can be biased and tests that would hold under the assumption of cross-sectional independence can provide unreliable results (Banerjee et al., 2004). To address this issue, researchers have usually assumed a factor error structure (Pesaran, 2006, p. 971):

$$y_{it} = a_i d_t + \beta_i x_{it} + e_{it} \ , \tag{3}$$

$$e_{it} = \gamma_i f_t + u_{it} \ . \tag{4}$$

Equation (4) shows that the error term of a panel equation can be decomposed into a common unobserved factor f_t as well as an idiosyncratic individual-specific error term u_{it}. CSD is therefore driven by a common factor, which can be modelled as a stationary or non-stationary variable. However, since the factor is unobserved, a method must be implemented to estimate it. Three main routes have been suggested in the literature. The first is to estimate the factor directly as a principal component of the residuals or the variables of a first-stage regression, 'decomposing' them into their idiosyncratic and common components (Bai and Ng, 2004). The second is to approximate the factor by taking the cross-sectional averages of the dependent variable and individual-specific regressors, which are then added to the model specification as variables. As shown by Pesaran (2006), these cross-sectional averages are a good approximation of the unknown factors, and OLS estimation including those approximations – the so-called correlated common effects (CCE) estimators – is consistent. A third method has recently been suggested by Eberhardt and Bond (2009). The authors propose a three-step estimator, which they call the augmented-mean group (AMG): in the first step, a first-difference OLS regression with time dummies is estimated; the coefficients of the time dummies are then entered into N level regressions as 'common dynamic factors'; finally, the cross-sectional-specific parameters are averaged as in the MG estimators.

Before testing for unit roots and cointegration, a look at the CSD of the cross-sectional specific variables can provide an idea of the extent of its importance in the estimation and testing. Although the presence of some cross-sectionally invariant common variables (lfg, $lwbret$, and $lwret$) should itself work as a common factor to reduce CSD, the latter's presence cannot be ruled out a priori. In fact, as Table 2 shows, the variables are highly correlated across countries, all failing to reject the null of no CSD, according to the Pesaran (2004) test. This finding provides a good reason to perform testing and estimation by taking CSD into account.

[Table 2 about here.]

A quick look at the data in Figure 6 hints that non-stationarity may be an issue for some of the variables. For the panel cross-sectional-specific variables, the unit root test proposed by Pesaran (2007), which allow for the presence of CSD, is chosen. This test is based on an augmented version of the Im et al. (2003) test, which is a panel version of an augmented Dickey–Fuller (ADF) equation. With p-lags, this is

$$\triangle Y_{i,t} = a_i + b_i Y_{i,t-1} + c_i \overline{Y}_{t-1} + \sum_{j=1}^{p} \delta_{ij} \triangle Y_{t-j} + \sum_{j=0}^{p} d_{ij} \triangle \overline{Y}_{t-j} + \delta_i t + u_{it} \ . \tag{5}$$

The panel test statistic is based on a truncated average of the OLS t-ratios of b_i. For the non-cross-sectional-specific variables lfg, $lwbret$, and $lwret$, standard time-series ADF tests are used.

As shown in Table 3, the equity asset shares and FXR do not reject the null of the unit root and are treated as non-stationary, while the returns variables strongly reject the null of a unit root and are therefore treated as I(0). The bond asset shares present a less clear-cut result, rejecting the null of non-stationarity for specifications with 0 and 1 lags, but not rejecting it with any further lags. Given the relatively short sample size, the observation of the variable in Figure 6, and the result obtained for equities' allocations, it is thus preferable to consider the variable to be I(1).

[Table 3 about here.]

The evidence for the common variables is mixed. As Table 4 shows, global returns are stationary. However, the test for lfg rejects the null of a unit root at the 10% level in the case of no deterministic variables, but does not when a constant and trends are added. The funding gap should ideally fluctuate around 0 (i.e. the fully funded position), which would make the ADF specification without a deterministic component relevant. In practice, however, as seems to be the case in the period considered, pension funding may significantly and persistently differ from full funding. For these reasons, lfg is treated as non-stationary.

[Table 4 about here.]

The findings of the unit root tests present a challenge. As the literature review on asset demand equations showed, economic theory suggests a relationship between the levels of returns and asset shares. In the cointegration framework, long-run relationships can, however, only exist between the I(1) variables. As returns are stationary, this would imply that no long-run relationship exists between returns and asset shares.

However, as Pesaran and Shin (1998) argue, this is not the only possible way in which to investigate long-run relationships. They suggest that economic theory should provide the background as to whether a long-run relationship exists rather than only the statistical properties of the data. Econometrically, such relationships can be represented by an ARDL model. In the panel case, with p and q lags for the regressors and dependent variable, respectively, this is expressed as

$$Y_{i,t} = \sum_{j=0}^{q} \boldsymbol{\delta}_{ij}^{'} \mathbf{X_{i,t-j}} + \sum_{j=1}^{p} \lambda_{i,j} Y_{i,t-j} + \mu_{i,t} + \epsilon_{i,t} \ , \tag{6}$$

which can be conveniently reparametrised in an error-correction form:

$$\triangle Y_{i,t} \quad = \quad \phi_i Y_{i,t-1} + \boldsymbol{\beta}_i^{'} \mathbf{X}_{i,t} + \sum_{j=1}^{p-1} \lambda_{i,j}^{*} \triangle Y_{i,t-j} + \sum_{j=0}^{p-1} \boldsymbol{\delta}_{i,j}^{*'} \triangle \mathbf{X}_{i,t-j} + \mu_{i,t} + \epsilon_{i,t} \ ,$$

$$\phi_i = -\left(1 - \sum_{j=1}^{q} \lambda_{i,j}\right) , \ \boldsymbol{\beta}_i = \sum_{j=0}^{q} \boldsymbol{\delta}_{i,j}, \ \lambda_{i,j}^{*} = -\sum_{m=j+1}^{p} \lambda_{i,m}, \ \boldsymbol{\delta}_{i,j}^{*} = -\sum_{m=j+1}^{p} \boldsymbol{\delta}_{i,m} \ .$$

As shown by Pesaran et al. (1999), the advantage of ARDL models of this kind is that they can be estimated with I(0) and I(1) variables, provided that some assumptions, discussed below, are met. This seems to be particularly appropriate in the case of asset demand equations, since it would allow for the inclusion of returns variables in the long-run relationship. Moreover, as these models are autoregressive, they do not suffer from endogeneity bias (Chudik and Pesaran, 2013), which would otherwise be a serious issue in this study, since the causality between asset demand and returns or FX could run both ways.

In the panel case, ARDL models can be estimated under different assumptions in terms of heterogeneity: with heterogeneous parameters, utilising the MG estimator (Pesaran and Smith, 1995). An alternative specification could be to assume that the coefficients were homogeneous, so that all coefficients were equal for all the N cross-sections, which could be estimated with standard panel estimators, such as in the fixed effects model. An intermediate technique is the pooled-mean group (PMG) estimator proposed by Pesaran et al. (1999), which imposes homogeneity on the long-run coefficients but allows the short-term dynamics to be heterogeneous.

For the ARDL models, including the PMG estimator, to be consistent, some conditions must be met. The first is the absence of serial correlation in the residuals, which can be achieved by adding further lags to the specifications, so that the regressors become exogenous. The second is the existence of a long-run relationship between the variables of interest, ensuring that the model is dynamically stable, and therefore $\phi_i < 0$.

There is no formal way in which to pre-test the existence of a long-run relationship in the panel case. Therefore, aside from economic theory considerations, the long-run relationship between the variables can be inferred in three ways. Firstly, the cointegration tests show that the non-stationary variables are cointegrated in the traditional sense, suggesting that, at least between them, a long-run relationship exists (Table 5). Two tests are used, both accounting for the possibility of CSD: the first is based on the significance of the error-correction term (Gengenbach et al., 2008) [16], the second on the stationarity of the residuals (Holly et al., 2010; Banerjee and Carrion-i Silvestre, 2011)[17]. Here, the rejection of a unit root indicates the presence of cointegration. Secondly, as the CCE estimators are consistent 'irrespective of the order of integration of the data observed' (Kapetanios et al., 2011, p. 338), a unit root test on the residuals of a CCE mean group regression between the variables, in the spirit of Cavalcanti et al. (2011b), is conducted, yielding the results of stationary residuals for up to five lags. Finally, the negative sign and significance of the error-correction parameters are taken as a further indicator of the existence of a long-run relationship (Cavalcanti et al., 2011a; Albuquerque et al., 2014).

A final condition to be met, in the panel case, is the absence of CSD. As shown above, this assumption is most likely not met. However, suitable modifications to the estimators can be made to estimate the parameters in the presence of CSD. Panel ARDL models augmented with cross-sectional averages have recently been proposed(Cavalcanti et al., 2011b; Chudik and Pesaran, 2013; Chudik et al., 2013). For example, a CCE version of the PMG estimator has been used by Cavalcanti et al. (2011a) and Albuquerque et al. (2014). The estimator used in this study for the baseline specification, however, is the AMG estimator, which has also been used in the context of ARDL models (Albuquerque et al., 2014; Sadorsky, 2013; Elliott et al., 2014). This approach can deal with the unknown source of CSD, which, as discussed, is based on the estimation of a common dynamic process based on time dummies. As some of the variables in this study are not cross-sectional-specific, fewer cross-sectional averages estimate the factor than the independent variables. The AMG approach to CSD, not being subject to this issue, is therefore preferred. The study, however, also uses other estimators, including CCE ones, to check the robustness of the results.

[Table 5 about here.]

6. Estimation results

6.1. Baseline results

The baseline specification of the equation is

[16] As in the test of Westerlund (2007), the test statistic pools the individual t-ratios of the parameters of the lagged dependent variable, with the null of insignificant error correction. The test is based on a factor error structure, and is therefore robust to CSD, even in the presence of non-stationary factors. The authors suggest augmenting the model specification with cross-sectional averages, as in the CCE estimators, to account for the factors.

[17] After estimating a relationship with the CCE pooled estimators, the residuals $u_{it} = Y_{it} - \widehat{\beta}_{CCEP}\mathbf{X}_{it} - \hat{\alpha}_i$ are collected and then tested for stationarity by using the test fromPesaran (2007).

$$\triangle Y_{i,t} = \phi_i(Y_{i,t-1} - \boldsymbol{\beta_i'}\mathbf{X}_{i,t} - \boldsymbol{\gamma_i'}\mathbf{W}_t) + \sum_{j=1}^{p-1} \lambda_{i,j}^{*'} \triangle Y_{i,t-j} + \sum_{j=0}^{p-1} \boldsymbol{\delta}_{i,j}^{*'} \triangle \mathbf{X}_{i,t-j} + \sum_{j=0}^{p-1} \boldsymbol{\theta}_{i,j}^{'} \triangle \mathbf{W}_{t-j}$$
$$+\rho_{i,t} CDP_t + \mu_{i,t} + \epsilon_{i,t} \ , \qquad (7)$$

$$\mathbf{X} = \begin{bmatrix} lem\_fx \\ lem\_ret \\ \end{bmatrix} \text{ and } \mathbf{W} = \begin{bmatrix} lfg \\ lwbret \\ lwret \end{bmatrix} \ ,$$

with $\mathbf{X}$[18] being the vector of the cross-sectional-specific variables and $\mathbf{W}$ that of the common variables. CDP is the common dynamic process of the AMG estimator, calculated as discussed.

To cope with the issues related to the lag augmentation, three model specifications are estimated. The first two apply the same lag augmentation to all variables, namely one lag for model (1) and two lags for model (3). Model (2) allows the lag length to be selected according to the Schwarz information criterion, up to three lags[19]. This results in choosing the following lag structure: one for lfg, two for lem_fx, one for $lwbret$, two for $lbem\_ret$ and lem_ret, and one for the dependent variables. Given the relatively short time dimension of the panels, longer lag specifications are unfeasible.

The results of the estimation are shown in Tables 6 and 7. In all models, the error-correction terms are in the dynamically stable range since they are strongly significant, negative, and between 0 and -1. As stated above, this finding confirms the existence of a long-run relationship between the variables. In addition, there does not seem to be a major difference between the speeds of convergence for bonds and equities, with the former being slightly higher.

[Table 6 about here.]

[Table 7 about here.]

As expected, the returns and asset allocation are positively related. For EMs' bonds, a 1% return increase implies a response of more than double that in terms of asset allocation, whereas for bonds the response is even higher, at about 4.2%. While these may seem implausibly large parameters, it has to be remembered that asset allocations to EMs are still small, which implies that relative changes may in fact still imply relatively small absolute changes in portfolio weights. The short-run parameters for equities are, however, negative and statistically significant. The results for global returns are less decisive. Advanced countries'

[18] for bonds, lem_ret is replaced by $lbem\_ret$.

[19] For the country-specific variable, the information criterion was applied to the individual time series, as done by Pesaran et al. (1999).

bond returns seem to have a negative long-run impact on EMs' asset allocations in all but one model specification for bonds, while global equity returns are not statistically significant in any of the specifications.

The FXR parameters are always positive and significant. Once again, there does not seem to be a major difference between the two asset classes, with the parameters indicating a 1.2% increase in allocation for each percentage point increase in FXR. The funding gap parameters are also positive and significant, thus suggesting higher allocations to EMs in the case of underfunding. The impact on bond allocations seems to be particularly notable, ranging between 1.7% and 1.9% for each percentage point of underfunding, while the impact on equities is smaller, ranging roughly between 0.5% and 0.6%.

The common dynamic process in the AMG models is positive and significant across all models. As Eberhardt and Bond (2009) discuss, the estimator is designed to explicitly account for and interpret the estimated common factor[20]. In this scenario, it is hard to guess what the process is in fact capturing. Its positive sign suggests that it is capturing some unobserved factor positively affecting the growth in EM holdings. This could be, for example, a decrease in risk aversion regarding the asset class as a whole or the growing accessibility of these countries because of their increasing openness and the creation of new EM funds.

6.2. Robustness checks

This section presents the results of the alternative model specifications to verify the robustness of the results.

First, model (2) is estimated by using the cross-sectional averages method to deal with CSD, as proposed by Chudik and Pesaran (2013). The lag length of the cross-sectional averages for these CCE models is chosen to be the same as that of the variables. Hausman tests are used to check whether long-run pooling is feasible; in the case of rejection, the MG approach is chosen over that of the PMG.

Secondly, as shown by Chudik et al. (2013), while consistent under general assumptions, panel ARDL models may not always perform well when the sample considered is small. The long-run relationships are therefore also estimated by using more standard dynamic panel techniques: the system generalised method of moments (GMM) estimator of Blundell and Bond (1998) and the bias-corrected least squares dummy variables (LSDVC) (Bruno, 2005). As shown in the comprehensive simulation exercise of Flannery and Hankins (2013), these estimators perform well in the presence of (even second-order) serial correlation and endogeneity. However, while the GMM estimator remains consistent even in the presence of weak CSD, such as spatial dependence (Sarafidis, 2009), these estimators do not, in general, take CSD into account. Moreover, the GMM techniques are designed for large-N-small-T panels, and the related issues of non-stationarity and cointegration, which is clearly at odds with the data used in this study.

[20]The authors discuss, for example, the estimation of total factor productivity in a neoclassical production function.

Finally, three variables are introduced into the baseline specification[21]. The first is the CBOE volatility index, better known through its ticker VIX. This index measures the implied volatility of the Standard and Poor's 500 index, calculated on the basis of a number of options prices. This variable is added into the short-run specification to check for the impact of short-term risk appetite, which has been found to have a significantly negative impact on capital flows in many recent studies (e.g. Rey, 2013; Ahmed and Zlate, 2014). The second, to check for the standard portfolio theory contention that higher return volatility *ceteris paribus* should reduce an asset's desirability, is the standard deviation of the returns variable[22]. This variable is added into both the long-run and the short-run relationships. The third is GDP growth differential between EMs and advanced countries[23], as it is often the presumption that higher growth in EMs is a major 'pull' factor for foreign investors. These variables are added one at a time and all together into the baseline AMG specification, with the number of lags included being chosen according to the Schwarz information criterion.

The results of all these robustness checks are shown in Tables 8 and 9. The impact of the VIX is negative, as expected, and significant for the equities allocation, denoting a decrease in allocations to EMs when risk aversion is high. On the contrary, it is not significant in the bonds equation. Nevertheless, the values of the parameters are small at little over 0.01%, therefore indicating a small impact of short-run risk-aversion swings on allocations to EMs. These results are not affected by the inclusion of other control variables. Neither growth or standard deviation has a statistically significant impact in any of the equations.

The inclusion of the control variables does not substantially change any of the results. In the equity equations, the impact of the main variables is unchanged, although the long-run funding gap coefficient becomes not statistically significant when growth and the VIX index are added, but remains significant in the short run in all cases. In the bonds equations, the negative impact of global bond returns becomes not statistically significant.

The alternative estimators used do not yield substantially different results either.

[Table 8 about here.]

[Table 9 about here.]

7. Interpretation and implications

These results provide evidence of the hypothesised relationship that ICPFs investors seem to broadly conform to the asset demand specifications proposed. Several observations can be made in terms of the interpretation and implications of the results.

[21] Tests on these variables have also been conducted, but are omitted because of space limitations.
[22] This calculated from daily data as a quarterly rolling standard deviation from the returns data.
[23] Quarterly real GDP growth was used.

Firstly, the size of the error correction is between 30% and 60% in the majority of the equations. This fact implies that investors do not instantaneously achieve their desired portfolio shares, but are able to adjust to them relatively quickly, correcting between roughly one third/half of the gap in one period. This is in contrast to most of the AIDS literature, which often finds slow adjustment processes, even for ICPFs (Blake, 2004). This finding suggests that frictions such as transaction costs may not be a major obstacle to foreign ICPFs reaching their desired EM asset allocations.

Secondly, FXR positively affect asset allocations to EMs. This finding is in line with the ideas discussed in the Introduction: FXR can be interpreted as the collateral provided by EMs, which reduces the overall riskiness of their assets, thereby increasing demand from foreign ICPFs. This finding may, however, have potentially destabilising implications: as EM authorities draw down on reserves when facing capital outflows, investors may be further induced to sell EM assets.

Thirdly, the investor's balance sheet also matters. The finding of the positive impact of the funding gap on allocations to EM assets is perhaps the most relevant of this study. ICPFs' demand for EM assets rises when they are in need of higher returns to reinforce their balance sheets, consistent with 'search for yield' investment behaviour. In policy terms, this may add to the list of important 'push' factors that need to be taken into account when assessing capital flows. The finding that the impact on bonds is higher is particularly relevant, since the rise in the flow of bonds to EMs exploded after the 2008 crisis. A recovery of ICPFs' balance sheets may thus have important adverse consequences on these patterns.

Returns on advanced countries assets – equities in particular, but also bonds when additional variables are controlled for – do not seem to be a major determinant of allocations to EM assets. This finding could show that the allocation to EMs is not necessarily 'pushed' by low returns in advanced countries. Two caveats are in order here. Firstly, the findings could reflect a problem with the variables themselves. In practice, portfolio choice is not a binary selection between 'safe' advanced countries and 'risky' EM assets. Secondly, it is important to point out that while advanced countries' returns per se may not have a direct influence on portfolio allocation, they still matter indirectly through balance sheet conditions. Lower returns in advanced countries increase the pension funding gap, as assets grow more slowly and liabilities are discounted at lower discount rates. In this way, an increase in advanced countries' returns may still generate a decrease in the allocation to EMs.

Finally, ICPFs seem to care about long-run returns. The impact of short-term returns on allocations is negative for equities and not statistically significant for bonds. The finding that the VIX has a small impact further suggests that these investors are not overly concerned with sudden shifts in global market volatility. However, the statistical insignificance of GDP growth differentials seems to indicate that investors, when seeking returns, are not always mindful of the underlying real economic growth in EMs.

Overall, these findings indicate, on the one hand, a long-term approach taken by ICPFs in their demand for EM assets and a lack of concern over immediate returns and sudden shifts in risk appetite. However, these investors respond to changes in their balance sheet conditions and the level of FXR in EMs, over a relatively short – quarterly – 'long' run, with a rather quick adjustment to their desired levels, and this may be unrelated to economic growth in such countries.

This finding suggests that demand for EM assets over a medium-term horizon may decrease should funding levels start to improve. An increase in interest rates implemented by advanced countries' central banks, by improving the funding levels of pension funds, could reduce the pressure to 'search for yield' in riskier assets and thus reduce allocations to EMs. This could also be procyclically reinforced by EMs' decumulation of FXR, thereby potentially generating issues for financial stability.

8. Conclusions

This study provided evidence on demand for EM assets from advanced countries' ICPFs. It applied innovative estimators for ARDL models to the estimation of asset demand. This contributes, on the one hand, to the literature on the determinants of portfolio investment by providing a link between international portfolio investment and the behaviour of investors. On the other hand, it expands the application of the asset demand approach to international portfolio choice and to demand for EM assets in particular.

The findings of the study broadly confirm the hypothesised relationships. While ICPFs do care about long-run returns, their demand for EM assets is affected by two additional factors: the amount of FXR that EMs hold and the conditions of their balance sheets, proxied by the funding ratio of advanced countries' pensions funds. The latter factor is consistent with 'search for yield' investment behaviour, which induces pension funds to invest in assets with higher expected returns such as EM assets when funding levels deteriorate. These results are robust to the inclusion of additional control variables.

As ICPFs become increasingly important in influencing demand for EM assets, looking at the factors that determine their asset allocation will be increasingly important for understanding the patterns and stability of today's international portfolio investments. This study suggests that FXR and the balance sheets of ICPFs are two factors that deserve close attention.

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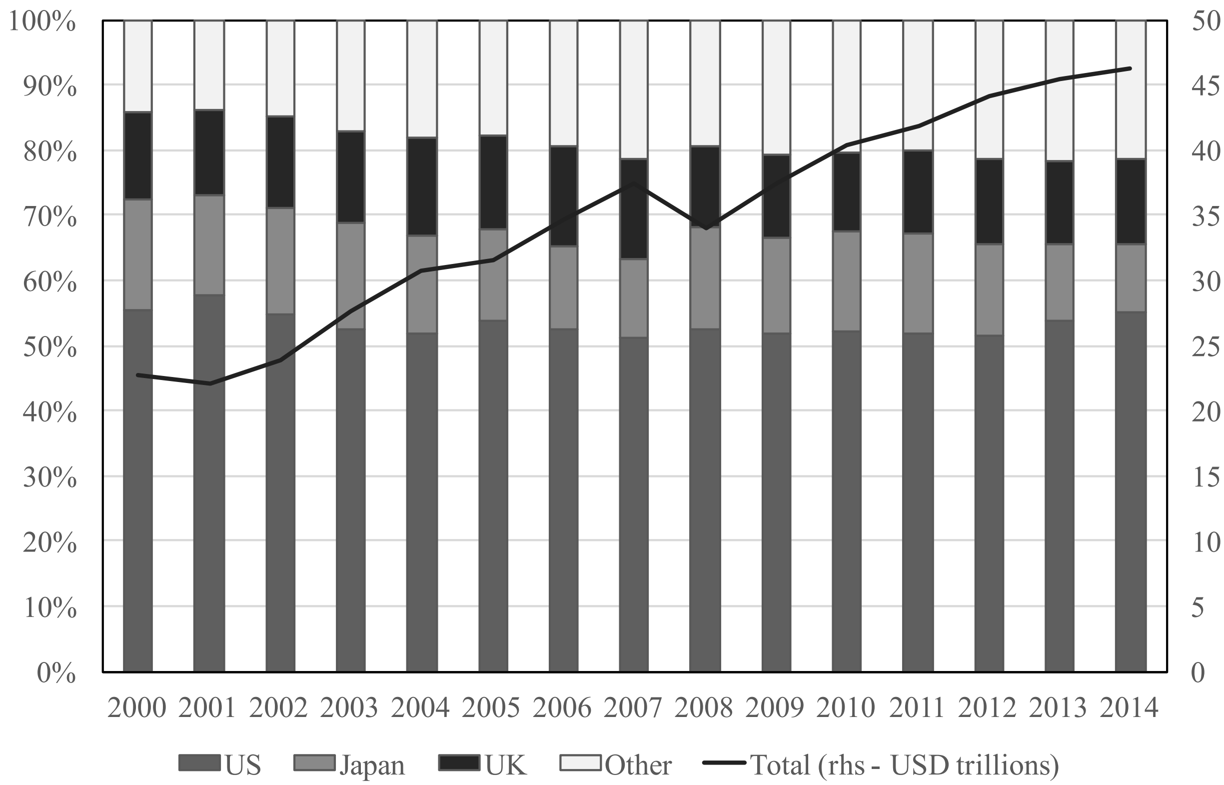
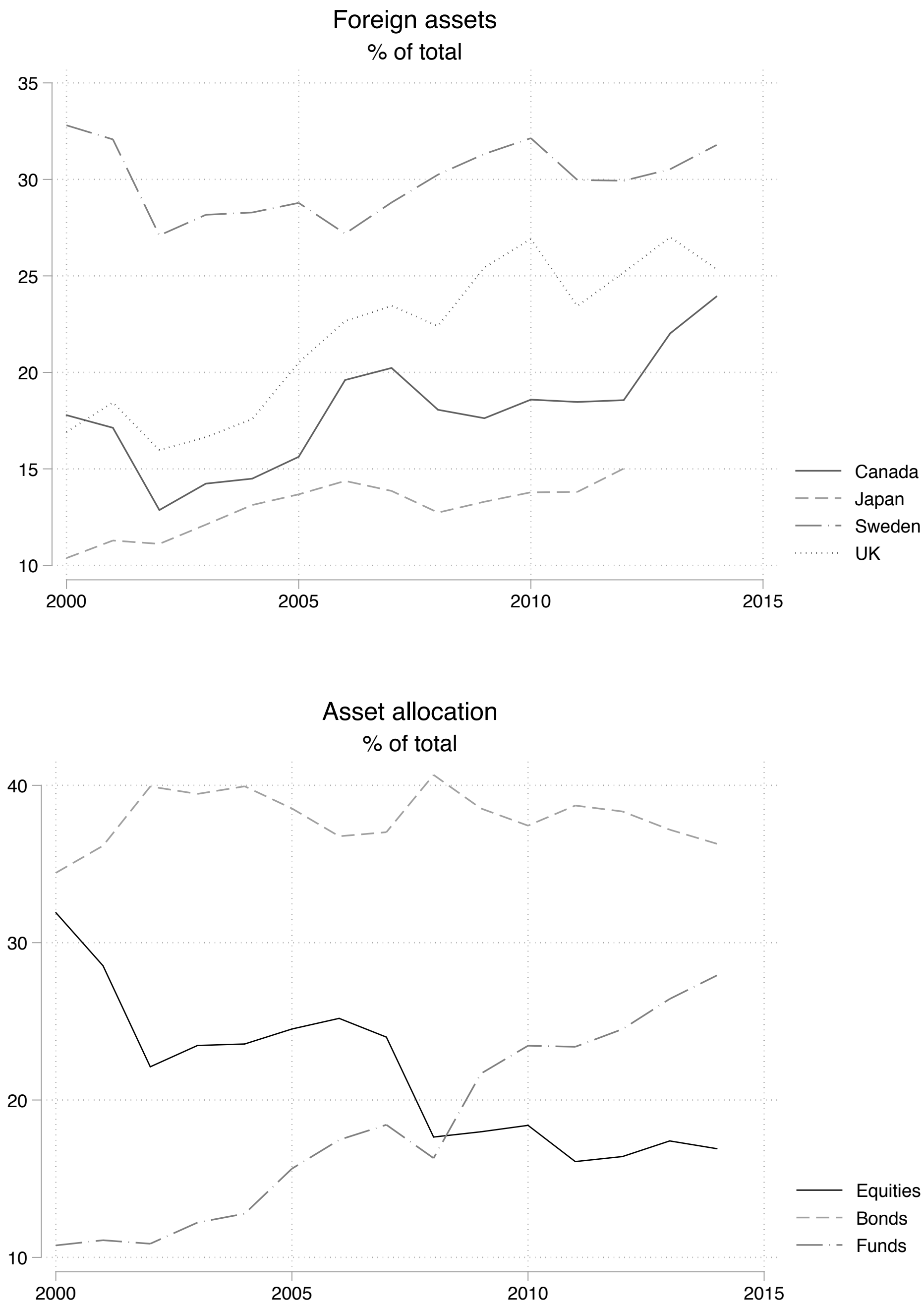
Figure 1: The size of insurance companies and pension funds



Source: OECD institutional investors statistics

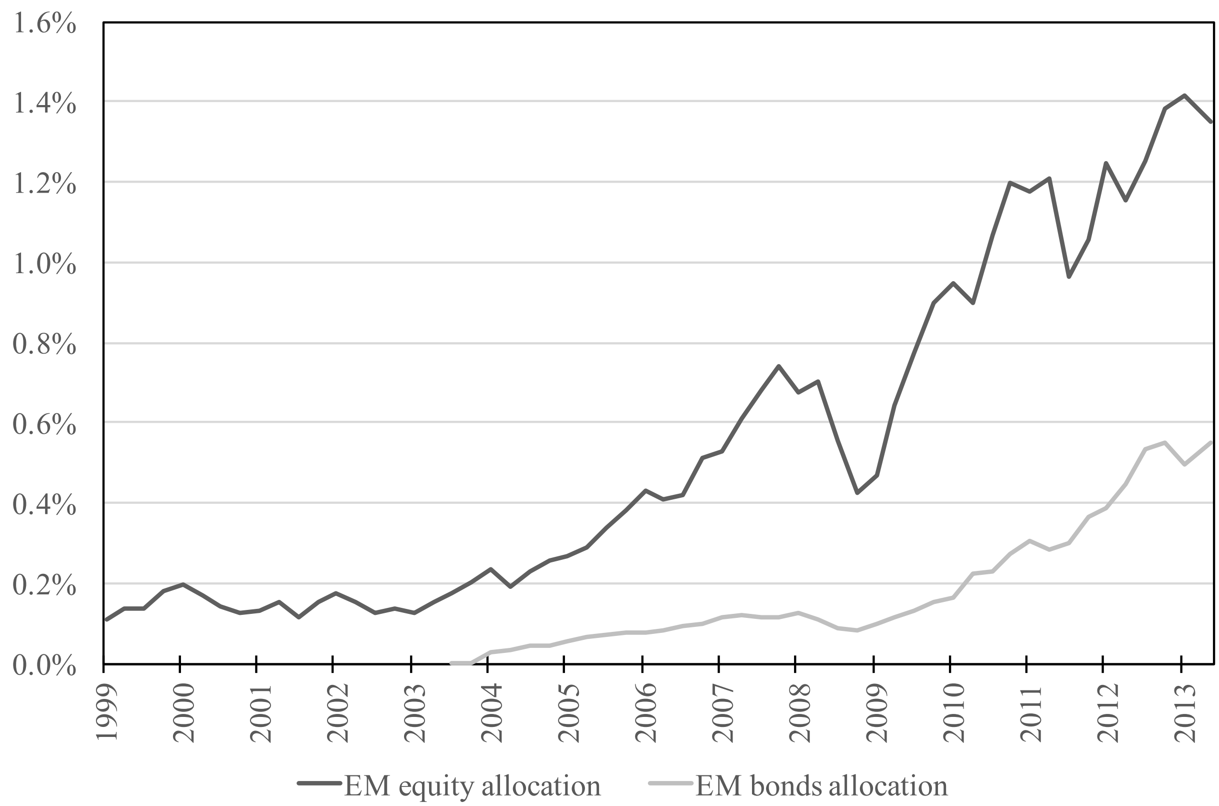
Note: The figure shows total wealth of insurance companies and pension funds. Other includes all countries included in the OECD institutional investors statistics database with data on total asset holdings, except the United Kingdom, the United States, and Japan.

Figure 2: The evolution of insurance companies and pension funds' balance sheets



Source: Author's calculations based on OECD institutional investors statistics.
Note: The top chart shows the allocation to foreign-issued assets to ICPFs' total wealth across selected countries for which these data are available. The bottom chart shows the cross-country average allocation to the three major asset classes. Funds denote investment funds' holdings by ICPFs.

Figure 3: ICPFs' allocation to EMs' assets

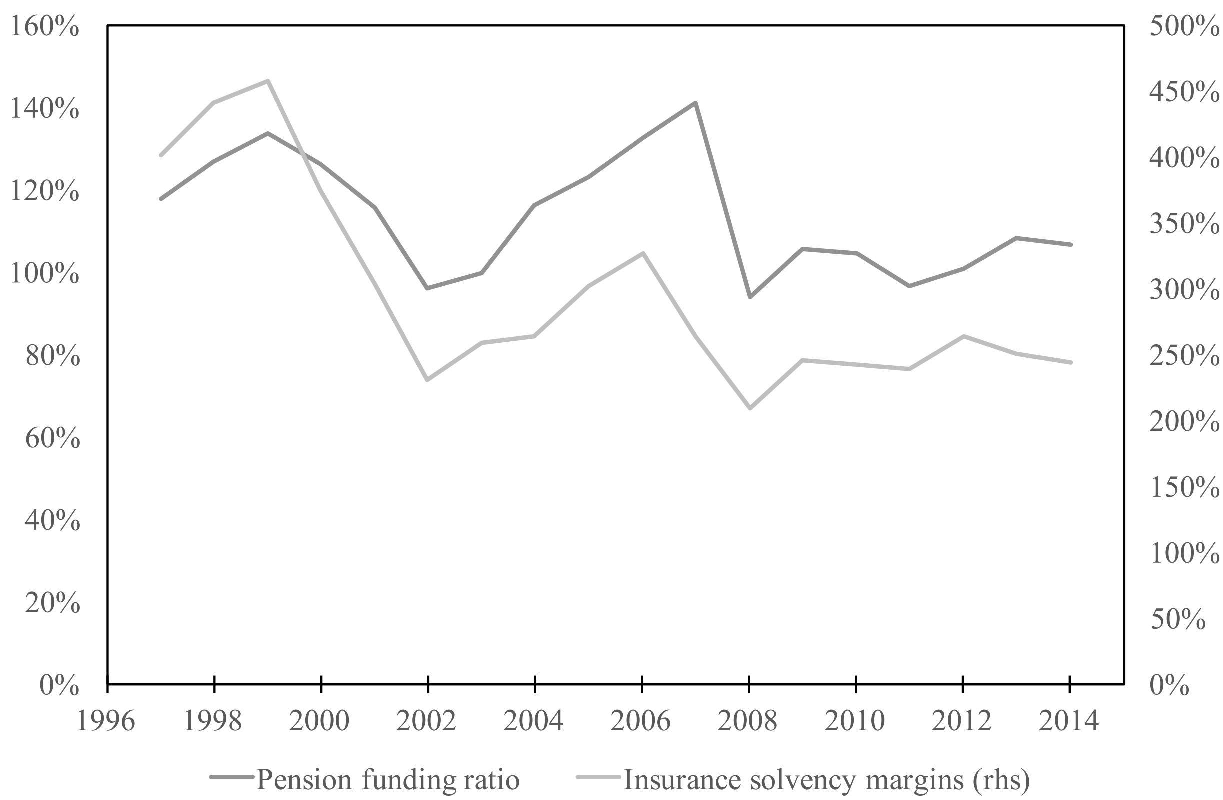


Source: Author's calculations based on Emerging Portfolio Fund Research, national sources (ECB financial accounts, Bank of Japan flow of funds, FED financial accounts of the United States, Canadian socio-economic database financial accounts, Australian National Accounts: Financial Accounts) and IMF exchange rate archives.
Note: The figure shows ICPFs' allocations to EM assets, calculated as the ratio between the end-of-month holdings of EMs' equities and bonds and total wealth of ICPFs.

Figure 4: Funding ratios

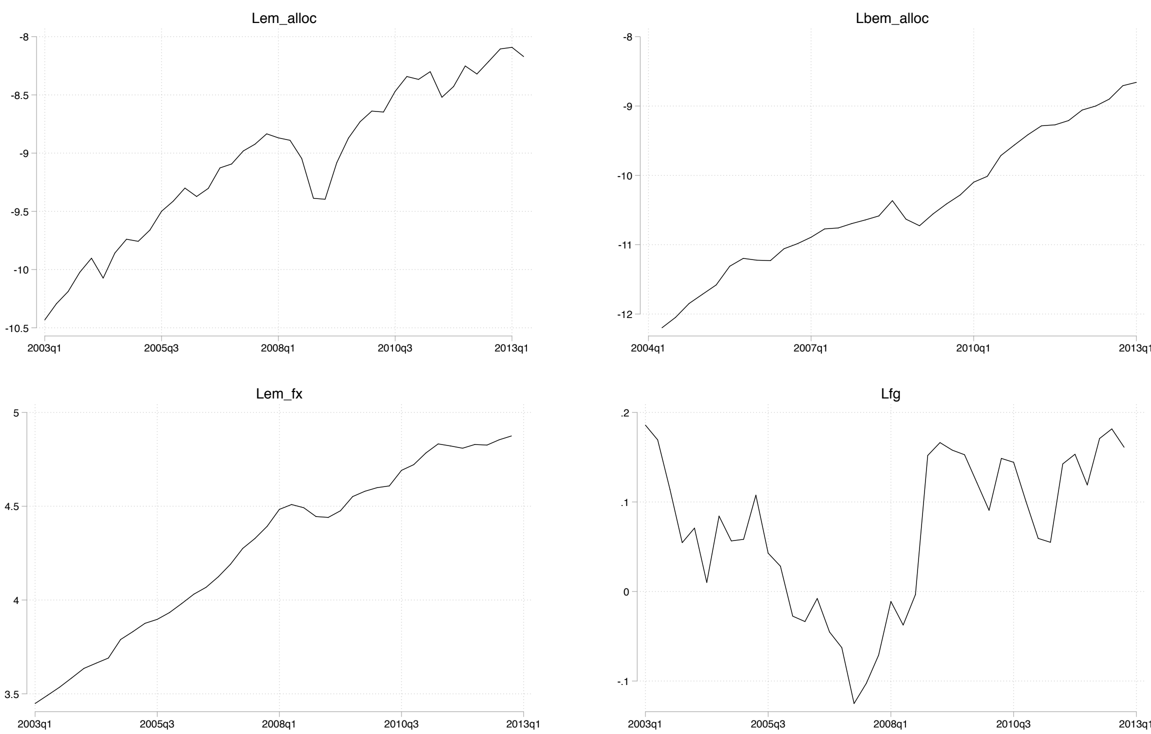
Source: Author's calculation based on the Milliman Pension Funding Index for the United States and the Pension Protection Fund 7800 index for the United Kingdom.
Note: The figure shows the funding ratios of US and UK pension funds. This is calculated as the ratio between the assets and liabilities of the pension fund sector.

Figure 5: Dutch ICPFs



Source: Author's calculations based on DNB (Dutch Central Bank) statistics.
Note: The figure shows the pension funding ratio, calculated as the ratio between the assets and liabilities of Dutch pension funds, and insurers' solvency margins, calculated as the ratio between the actual and regulatory capital reserves of Dutch life insurers.

Figure 6: Asset allocation, FXR, and the funding gap



Note: lem_alloc and $lbem\_alloc$ are the dependent variables, representing allocations to EMs' equities and bonds. lem_fx represents EMs' FXR holdings. lfg represents the funding gap of the pension fund sectors, calculated as the gap to full funding (i.e. an asset liability ratio equal to 1), for a weighted average of the US, UK, and Japanese pension fund sectors. Figures shown for lem_alloc, $lbem\_alloc$ and lem_fx are averages across countries. All figures are on a logarithmic scale.

Table 1: Summary statistics for the returns variables

Variable	Obs	Mean	Std. Dev.	Min	Max
lwbret	840	0.013	0.031	-.049	0.093
lwret	840	0.021	0.092	-0.244	0.191
lem_ret	840	0.039	0.163	-0.719	0.508
lbem_ret	677	0.022	0.071	-0.293	0.304

Note: *lem_ret* and *lbem_ret* are the logarithmic returns of EMs' equities and bonds. *lwbret* and *lwret* are the logarithmic returns of advanced countries' bonds and equities. *lem_ret* and *lbem_ret* are averages across countries. Statistics start from the beginning of the estimation period (first quarter of 2003), except for bond returns.

Table 2: CSD test

Average correlation coefficients and Pesaran's (2004) CSD test			
Variable	CSD-test	p-value	corr
lem_alloc	81.58	0.000***	0.777
$lbem\_alloc$	63.71	0.000***	0.910
lem_ret	64.12	0.000***	0.586
$lbem\_ret$	21.65	0.000***	0.327
lem_fx	98.68	0.000***	0.902

Note: The null hypothesis is cross-sectional independence. lem_alloc and $lbem\_alloc$ are the dependent variables, representing allocations to EMs' equities and bonds. lem_ret and $lbem\_ret$ are the logarithmic returns of EMs' equities and bonds. lem_fx represents EMs' FXR holdings.
These are the results of the xtcd Stata routine (Eberhardt, 2011b). *, **, and *** denote rejection at the 1%, 5%, and 10% levels, respectively.

Table 3: Panel unit root test

Pesaran's (2007) Panel Unit Root test (CIPS)							
Variable	lags	Zt-bar	p-value	Variable	lags	Zt-bar	p-value
lem_alloc	0	-0.489	0.312	*lem_alloc*	0	0.180	0.571
lem_alloc	1	-0.846	0.199	*lem_alloc*	1	0.607	0.728
lem_alloc	2	-0.291	0.386	*lem_alloc*	2	1.582	0.943
lem_ret	0	-19.388	0.000***	*lem_ret*	0	-18.393	0.000***
lem_ret	1	-13.524	0.000***	*lem_ret*	1	-12.418	0.000***
lem_ret	2	-6.564	0.000***	*lem_ret*	2	-4.350	0.000***
lem_fx	0	-0.982	0.163	*lem_fx*	0	1.140	0.873
lem_fx	1	-1.089	0.138	*lem_fx*	1	1.020	0.846
lem_fx	2	-0.524	0.300	*lem_fx*	2	1.469	0.929
lbem_alloc	0	-2.928	0.002***	*lbem_lloc*	0	-2.186	0.014**
lbem_alloc	1	-2.219	0.013**	*lbem_alloc*	1	-1.949	0.026**
lbem_alloc	2	-1.062	0.144	*lbem_alloc*	2	-0.610	0.271
lbem_ret	0	-16.334	0.000***	*lbem_ret*	0	-15.282	0.000***
lbem_ret	1	-12.041	0.000***	*lbem_ret*	1	-10.815	0.000***
lbem_ret	2	-7.419	0.000***	*lbem_ret*	2	-5.951	0.000***

Note: The null hypothesis is the presence of a unit root. The table shows the results for the Pesaran (2007) unit root test. The right half of the table specifies the model with a time trend.
lem_alloc and *lbem_alloc* are the dependent variables, representing allocations to EMs' equities and bonds. *lem_ret* and *lbem_ret* are the logarithmic returns of EMs' equities and bonds. *lem_fx* represents EMs' FXR holdings.
*, **, and *** denote rejection at the 1%, 5%, and 10%. The multipurt Stata routine was used (Eberhardt, 2011a). levels, respectively.

Table 4: Time-series unit root test

ADF Test			
Variable	No constant	Constant	Constant and trend
lfg	0.054*	0.1708	0.1575
$lwbret$	0.000***	0.000***	0.000***
$lwret$	0.000***	0.000***	0.003***

Note: The null hypothesis is the presence of a unit root. The time-series length is chosen in line with the Schwarz information criterion. The sample considers values from the first quarter of 2003, namely the beginning of the estimation period. P-values for the test statistics are reported.
lfg is the pension funding gap. *lwbret* and *lwret* are the logarithmic returns of advanced countries' bonds and equities.
*, **, and *** denote rejection at the 1%, 5%, and 10% levels, respectively.

Table 5: Panel cointegration tests

	Error-correction test (Gengenbach et al., 2008)		CCE Residuals-based test (Banerjee and Carrion-i Silvestre, 2011)	CCE-MG Residuals-based test (Cavalcanti et al., 2011b)
	Panel t-test (0 lags, 1 lag)	Panel t-test trend (0 lags, 1 lag)	CIPS statistic (constant, trend)	CIPS statistic (0 lags, 1 lag)
Equities	-2.775**, -2.589*	-3.076*, -2.705	-1.919, -1.901	-7.654***, -7.187***
Bonds	-2.786***, -2.669**	-2.830, -2.405	-2.689**, 2.980**	-9.818***, -8.644***

Note: In all tests, the null hypothesis is the absence of cointegration.
The first two columns show the panel t-test statistic, with different model specifications, based on the error-correction test of Gengenbach et al. (2008).
The third column shows the CIPS test statistic, a cross-sectionally augmented panel Dickey-Fuller test, resulting from the residuals-based testing procedure of Banerjee and Carrion-i Silvestre (2011).
The fourth column shows the results of a CIPS test on the residuals of a CCE-MG regression with all the variables included in levels, as done by Cavalcanti et al. (2011b). .
*, **, and *** denote rejection at the 1%, 5%, and 10% levels, respectively. The first two tests were computed in Stata by using the routine described by Prof. Markus Eberhardt on his website (https://sites.google.com/site/medevecon/code).

Table 6: Estimation results - Equities

ARDL model, dep. variable: $\triangle lem\_alloc$			
Model	AMG (1)	AMG (2)	AMG (3)
Long Run			
lfg	0.601**	0.477*	0.631*
lem_fx	0.971*	1.300**	1.294**
lem_ret	4.129***	4.179***	4.232***
$lwbret$	-2.173***	-1.977***	-1.552
$lwret$	-0.066	0.451	-0.315
Short run			
ec	-0.285***	-0.310***	-0.339***
$\triangle lfg$	0.540**	0.575***	0.395
$\triangle lem\_fx$	0.123	0.001	-0.074
$\triangle lem\_ret$	-0.126**	-0.229***	-0.373**
$\triangle lwbret$	0.101	0.080	0.095
$\triangle lwret$	-0.011	-0.104	0.108
$\triangle l.lem\_alloc$			-0.035
CDP	0.491***	0.509***	0.563***

Note: Models (1), (2), and (3) refer to the different lag augmentations described in the study. CDP is the common dynamic process estimated by the augmented mean group; ec is the error-correction term. All models contain individual constants and time trends if statistically significant. Long-run standard errors were computed by using the delta method.
The dependent variable is the change in allocations to EM equities. lfg measures pension funds' funding gap, lem_fx measures the logarithms of FXR holdings by EMs, and lem_ret, $lwbret$, and $lwret$ measure the logarithmic returns on EMs' equities, advanced countries' bonds, and advanced countries' equities, respectively. $l.lem\_alloc$ is the lagged value of the dependent variable.
*, **, and *** denote rejection at the 1%, 5%, and 10% Levels, respectively. The following Stata routines were used: xtmg (Eberhardt, 2013) and nlcom.

Table 7: Estimation results - Bonds

ARDL model, dep. variable: $\triangle lbem\_alloc$			
Model	AMG (1)	AMG (2)	AMG (3)
Long Run			
lfg	1.816***	1.707***	1.883***
lem_fx	1.150**	1.253**	1.274**
$lbem\_ret$	2.401***	3.911***	2.596**
$lwbret$	-1.912**	-1.179*	-0.068
$lwret$	0.172	0.627	0.652
Short run			
ec	-0.513***	-0.536***	-0.731***
$\triangle lfg$	-0.246	-0.108	-0.42
$\triangle lem\_fx$	0.522	0.351	0.293
$\triangle lbem\_ret$	-0.268	-0.963	-0.870
$\triangle lwbret$	0.371	-0.192	-0.197
$\triangle lwret$	-0.154	-0.303*	-0.417*
$\triangle l.lbem\_alloc$			0.106
CDP	0.694***	0.656***	0.847***

Note: Models (1), (2), and (3) refer to the different lag augmentations described in the study. CDP is the common dynamic process estimated by the augmented mean group; ec is the error-correction term. All models contain individual constants and time trends if statistically significant. Long-run standard errors were computed by using the delta method.
The dependent variable is the change in allocations to EM bonds. lfg measures pension funds' funding gap, lem_fx measures the logarithms of FXR holdings by EMs, and $lbem\_ret$, $lwbret$, and $lwret$ measure the logarithmic returns on EMs' bonds, advanced countries' bonds, and advanced countries' equities, respectively. $l.lbem\_alloc$ is the lagged value of the dependent variable.
*, **, and *** denote rejection at the 1%, 5%, and 10% Levels, respectively. The following Stata routines were used: xtmg (Eberhardt, 2013) and nlcom.

Table 8: Robustness checks - Equities

Dep. variable: $\triangle lem\_alloc$ for the AMG and CCE models, lem_alloc for GMM and LSDVC							
Long Run							
Model	AMG	AMG	AMG	AMG	CCE	GMM	LSDVC
lfg	0.391	0.533**	-0.041	0.462	0.423*	0.07**	0.098**
lem_fx	1.383**	1.323***	1.361***	1.455***	0.840	0.070***	0.035**
lem_ret	3.840**	4.092***	3.953***	3.592***	4.500	1.120***	1.127***
$lwbret$	-1.987***	-1.820***	-2.082***	-2.141**	-1.970	-0.128	-0.184*
$lwret$	0.478	0.445	0.569	0.536	-1.329	-0.290	-0.326***
$growth\_diff$	0.504			3.388			
lem_sd		0.056		0.332			
Short run							
ec	-0.336***	-0.315***	-0.328***	-0.345***	-0.260***		
$\triangle lfg$	0.682***	0.553***	0.590***	0.656***	0.937***		
$\triangle lem\_fx$	-0.069	-0.042	0.023	0.502	0.109		
$\triangle lem\_ret$	-0.720	-0.242	-0.022**	-0.230***	-0.101		
$\triangle lwbret$	0.125	0.080	0.146	0.221	0.004		
$\triangle lwret$	-0.086	-0.107	-0.172	-0.155	-0.060		
$\triangle growth\_diff$	-0.474			-1.170			
$\triangle lem\_sd$		-0.010		-0.115			
$\triangle lvix$			-0.011***	-0.010***			
CDP	0.529***	0.511***	0.507***	0.544***			
Hausman test					7.96 (0.093)		

Note: Lag structure of the ARDL models chosen according to the Schwarz information criterion. The Hausman test reports the p-value in brackets: non-rejection allows long-run pooling in the CCE model. All AMG models contain individual constants and time trends if statistically significant. Long-run standard errors for the AMG model were computed by using the delta method.
The dependent variable is the change in allocations to EM equities. lem_sd is the standard deviation of the logarithmic returns of EMs' equities, $growth\_diff$ is the difference between the specific EM and an average of OECD countries' quarterly real GDP growth rates, and $lvix$ is the logarithm of the VIX index. For all the other variables refer to Tables 6 and 7.
*, **, and *** denote rejection at the 1%, 5%, and 10% Levels, respectively. The following Stata routines were used: xtpmg (Blackburne and Frank, 2007), xtmg (Eberhardt, 2013), nlcom, xtdpdsys, and xtlsdvc.

Table 9: Robustness Checks - Bonds

Dep. variable: $\triangle lbem\_alloc$ for the AMG and CCE models, $lbem\_alloc$ for GMM and LSDVC							
Long Run							
Model	AMG	AMG	AMG	AMG	CCE	GMM	LSDVC
lfg	1.912***	1.302**	1.561**	0.782*	0.538***	0.107	0.109
lem_fx	1.230**	1.121**	1.264**	0.516	1.185***	0.216**	0.130***
$lbem\_ret$	3.475**	4.067**	3.268***	3.085*	4.126***	0.906***	0.845***
$lwbret$	-0.289	-0.999	-1.429	-1.910	-2.486**	-0.865***	-0.870***
$lwret$	0.874	0.592	0.841	0.805*	-0.783*	0.389***	0.309**
$growth\_diff$	4.231			7.550			
$lbem\_sd$		2.036		2.767			
Short run							
ec	-0.535***	-0.563***	-0.573***	0.584***	0.352***		
$\triangle lfg$	-0.226	-0.036	0.072	0.382	0.293		
$\triangle lem\_fx$	0.218	0.278	0.461	0.322	0.661		
$\triangle lbem\_ret$	-0.675	-1.180	-0.951	-0.514	-0.512**		
$\triangle lwbret$	-0.074	0.192	0.264	0.377	0.148		
$\triangle lwret$	-0.349	-0.363	0.841	-0.056	0.0368		
$\triangle growth\_diff$	-1.036			-1.206			
$\triangle lbem\_sd$		-0.989		-1.297			
$\triangle lvix$			0.056	-0.165			
CDP	0.736***	0.679***	0.678***	0.566***			
Hausman test					0.80(0.977)		

Note: Lag structure of the ARDL models chosen according to the Schwarz information criterion. The Hausman test reports the p-value in brackets: non-rejection allows long-run pooling in the CCE model. All AMG models contain individual constants and time trends if statistically significant. Long-run standard errors for the AMG model were computed by using the delta method.
The dependent variable is the change in allocations to EM bonds. $lbem\_sd$ is the standard deviation of the logarithmic returns of EMs' equities, $growth\_diff$ is the difference between the specific EM and an average of OECD countries' quarterly real GDP growth rates, and $lvix$ is the logarithm of the VIX index. For all the other variables refer to Tables 6 and 7.
*, **, and *** denote rejection at the 1%, 5%, and 10% Levels, respectively. The following Stata routines were used: xtpmg (Blackburne and Frank, 2007), xtmg (Eberhardt, 2013), nlcom, xtdpdsys, and xtlsdvc.