Institutional Investors Allocation to Emerging Markets: a Panel Approach to Asset Demand

Bonizzi, Bruno

SOAS, University of London

2 February 2015

Institutional Investors Allocation to Emerging Markets: a Panel Approach to Asset Demand

Bruno Bonizzi*

1st February 2015

Abstract

This paper presents empirical evidence on the increasing allocation of institutional investors to emerging markets economies. It seeks to understand which factors are driving this increase, and how this relates to portfolio flows to such economies. By making use of the Emerging Portfolio Fund Research database, it estimates asset demand equations for emerging markets equities and bonds by institutional investors from advanced countries. These are estimated using recent advances in the panel autoregressive distributed lags models literature. Two key results emerge: balance sheet conditions of institutional investors and foreign exchange reserves in emerging markets affect asset allocation; secondly, quarterly returns matter for long-run asset allocations and the portfolio adjustment process is quick. These findings suggest that portfolio flows by institutional investors could still be procylical despit their more long-term horizon, and that additional variables should be monitored to ensure financial stability.

Keywords: Capital flows, emerging markets, institutional investors, Panel ARDL

JEL Codes: F30, G23, G11, G15

1 Introduction

It is a known stylised fact that capital flows to emerging markets (EMs) follow cyclical patterns of booms and busts. The latest of these cycles started with the surge of capital flows during the mid 2000's and

*Department of Economics, SOAS, University of london. b_bonizzi@soas.ac.uk, (+447837303649). I wish to acknowledge the financial support given to me by Investment & Pensions Europe, and Mr. Fennel Betson in particular.

ended with their sharp contraction, during the 2008 financial crisis. Since then flows to EM have quickly recovered in a new surge, which, while yet to come to an end, has experienced several slowdowns, most notably in the summer of 2013 as a result of the possible announcements of the "tapering" of Quantative Easing policies by the Fed. Their magnitude and instability have pushed capital flows back to the fore as a crucial concern for international financial stability.

In these respects, a key theme is the nature of the underlying determinants of capital flows. As a research topic, its origins can be traced back to Calvo *et al.* (1993), who firstly pointed out the key role of external "push" factors, such as US interest rates, in explaining the contemporaneous surge of capital flows to EMs, as opposed to country-specific "pull" factors. The empirical investigation into the relative importance of "push" and "pull" factors has produced a vast literature in the 90's[1], which overall confirmed the importance of global factors, but also found some role of for domestic fundamentals in driving capital flows to EMs.

Aside from "push" and "pull" factors, several other themes and concepts have enriched the discussion about capital flows drivers. A literature focused on some peculiar aspects that characterise the behaviour of portfolio investors towards EMs: there is considerably evidence that investors, and mutual fund institutional investors in particular, rely on return-chasing/momentum trading strategies (Froot and Tjornhom Donohue, 2002; Jinjarak and Zheng, 2010; Hsieh *et al.*, 2011), and that herding behaviour and contagion effects are widespread, especially in times of turbulence (Kaminsky *et al.*, 2004; Broner *et al.*, 2006; Hsieh *et al.*, 2011; Jinjarak and Zheng, 2010). These findings contribute to explain the pro-cyclicality of portfolio flows to EMs, as well as the scope for of informational asymmetries as theoretical explanations for such phenomena.

In the aftermath of the financial crisis, new factors have been highlighted on the basis of a different different understanding of the nature of capital flows. Many authors have argued the importance of focusing on gross rather than net capital flows, as these more closely relate to purely financial cross-border transactions and their financial stability implications, which are increasingly important an ever-more financially integrated world[2]. A novel element emerging from the the empirical analysis of the gross capital flows, is the role of global risk-appetite as a driver of cross-border flows, which ties them to the

[1]See for example Chuhan *et al.* (1998); Fernández-Arias (1996); Taylor and Sarno (1997)

[2]See for example Borio and Disyatat (2011); Obstfeld (2012) for a detailed discussion of theoretical importance the gross vs net flows issue.

cyclical nature of financial cycles (Ananchotikul and Zhang, 2014; Ahmed and Zlate, 2013; Bruno and Shin, 2013a,b; Rey, 2013).

The paper aims to contribute to this analysis by assessing the role of two additional drivers. The first is the level of foreign exchange reserves (FXR). It is a known empirical fact that financial integration of EM in the past decade came with substantial accumulation of FXR by these countries [3]. As argued by Dooley *et al.* (2007, 2014), FXR can be regarded as a country's stock of collateral, which in turn attracts FDI flows. However, as Qian and Steiner (2014) argue, FXR accumulation, by lowering the probability and the magnitude of a currency crash, substantially reduces the risk of EMs 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 as opposed to FDI. This paper follows the same line and assesses whether FXR are associated with higher demand for EM assets by foreign institutional investors.

The second element is the balance sheet of foreign institutional investors. The importance of balance sheet considerations is a key theme emerging from the mentioned literature on global cycles and risk-aversion. Most of the focus has however been on banks. On the other hand, as argued by international institutions such as the IMF (2014) and the BIS (Miyajima and Shim, 2014), institutional investors are increasingly important as drivers of the flow of funds going into EM. The importance of institutional investors liabilities for asset allocation and its macroeconomic implications has also been been the subject of recent work by the Bank of England(BoE, 2014). This thus relates to all these strands of the literature, by assessing whether advanced countries institutional investors' balance sheet conditions are a factor in determining their allocation to EM assets.

The approach used in this paper is that of asset-demand equations. Rather than capital flows, the paper estimates demand for EM assets by advanced countries' institutional investors. As an empirical modeling strategy, this applies new estimators proposed in dynamic panel literature, which take into account the possibility of cross-sectionally dependent errors. A panel ARDL approach is chosen as modeling framework for the estimation of short and long run determinants of asset demands.

The rest of the paper is structured as follows. Section 2 describes the asset demand approach, starting from its origins in the Tobinesque tradition and the more recent Almost-Ideal asset demand approach, and its application to the issue of international portfolio investment to EMs. Section 3 deals with the

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

general features of the econometric framework. Section 4 describes the data and the variables. Section 5 perform some tests and describes the model specification. Section 6 discusses the estimation results and perform some robustness checks. Section 7 gives an interpretation of the results and some of their possible implications. Section 8 concludes.

2 The asset demand equations approach

In a well known paper, Brainard and Tobin (1968) proposed a new method to estimate the demand for financial assets. This method emphasised the importance of taking into account interdependencies across financial markets, and the resulting financial accounting constraints. Demand for assets in their paper is modeled as a function of wealth, and rates of return on own assets and on all the other assets:

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

The desired share of a^* of asset i to wealth w depends linearly on the returns on q different assets plus a constant b_0. This formulation lly implies that households allocate assets as to keep a fixed proportion b_0 of their wealth to each one of them, but this is allowed to vary according to the returns of different assets. Positive/negative returns on one asset will increase/decrease the desired allocation to that asset, while at the same time higher/lower returns on other assets will decrease/increase such a proportion. Finally the allocation is sometimes considered to be also proportional on current income (e.g. Brainard and Tobin, 1968, p. 107), which represents the transaction motive of asset demand. The wealth constraints are essential to the model, in that they determine a constraint on the value of the parameters. Since clearly the sum of desired holdings equals total wealth (i.e. $\sum_i a_i^* = w$) it must be that:

$$\sum_{i=1}^{n} \frac{a_i^*}{w} = 1 \tag{2}$$

$$with \sum_i b_{i0} = 1 \;\; \sum_i b_{ij} = 0$$

This paper gave rise to a vast literature estimating asset demand equations, using data from flow-of-funds accounts[4]. Despite its popularity, the empirical estimation of asset demands faced problems. The most important related to the serious multicollinearity that arose as a result the high correlation between returns taken from aggregate time-series data. Often the models presented incorrectly signed or insignificant parameters. Researchers have tried to overcome these problems by estimating parameters combining the data with some a priori information according to Bayesian principles [5], but were in the end not wholly successful (Buiter, 2003).

It is perhaps also due to this relatively unsuccessful performance, that the development of an alternative methodology emerged at the beginning of the 1980's and establish itself as the most commonly adopted way to estimate demand equations. This 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 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 obtain the following expression Blake (2004, p. 613)[6]:

$$s_{it} = a_i + +b_i \ln(W_t(1 + r_{Wt})) + \sum_j^n c_{ij} \ln(1 + r_j) + \sum_j^m h_{ij} Z_{jt} \tag{3}$$

The portfolio shares depend on the logs of wealth plus the return of the total portfolio, the log of returns on n assets, and m additional variables Z. The model is similar to the original "pitfalls" specifications, but adds wealth effects on portfolio shares, and the possibility to include other additional variables. For example, a typical variable which is often added is current income or expenditure (Barr and Cuthbertson, 1992; Adam, 1999), which, as Blake (2004, p. 614) argues, can be thought of as a liquidity constraint.

The AIDS model has been employed in several studies, although its application to portfolio choice has been much less common than in consumption studies. A line of inquiry in the literature has focused on specific asset or sector, of which the clearest examples are the papers by Barr and Cuthbertson (1991, 1994). For example, Barr and Cuthbertson (1994) applies the methodology to the UK holdings by the

[4]See for example (Hendershott, 1971; Backus *et al.*, 1980)

[5]See Backus *et al.* (1980) for an application.

[6]The procedure, described in the original paper by Deaton and Muellbauer (1980) and then applied to the context of portfolio choice by Barr and Cuthbertson (1991), involves the application of a specific logarithmic functional form, and then, using Shepherd's Lemma, its logarithmic differentiation with respect to price to obtain portfolio shares, and then inverting the resulting "Hicksian" demand function to a standard Marshallian demand function.

overseas sector, and Dinenis and Scott (1993) focus on UK pension funds asset allocation[7].

Another line of studies based on the AIDS system focuses on a complete set of assets held by households, in the spirit of the flow-of-funds models, but extends the set to non-financial assets. An important example of this is Blake (2004), who estimates portfolio choice between financial, housing and durables, pension wealth (private and public) and human capital in the UK. Interestingly, similar studies were conducted in the context of developing and EMs: Adam (1999); Moore *et al.* (2005); Al-Zu'bi and Murinde (2011) have conducted studies respectively for Kenya, India and three middle eastern countries. All this studies also take into account liabilities, typically netting them out from financial assets.

Despite these examples, the contemporary literature on asset demand equations is not particularly vast, although there are signs of renewed interest after the global financial crisis (Ramb and Scharnagl, 2011; Duca and Muellbauer, 2013). This paper will adopt this approach, as it provides a clear link between investors' portfolio choice and capital flows to EM. Portfolio investments to EM are in these sense analysed as an issue of asset allocation, thus trying to uncover the direct link between the financial behaviour of investors and the resulting cross-border asset positions. The basic structure of the asset demand approach relating asset shares with returns and net wealth, understood as the funding level of institutional investors, will be used. However, as done by Blake (2004), additional variables may have an impact in determining portfolio allocation and can be introduced in the model.

In lines with the considerations made in the introduction, two additional factors are going to be proposed: the level of FXR by EM and the funding level of advanced countries pension funds. The former will be used as an indicator of protection against currency risk, whereby accumulating FXR expands the possibility for EM central banks to intervene in the foreign exchange market and stabilise the exchange rate. Higher reserves would therefore encourage increased allocation to EM assets.

The latter is used as a proxy for balance sheet conditions of institutional investors of advanced countries: funding represents the total asset over liability ratio, i.e. the net worth of a pension fund. Since liabilities

[7] Interestingly for the purpose of this paper, they do initially consider to give a role to wealth over liabilities (the surplus or funding status of the pension fund) in determining portfolio allocation. They however drop such a variables in the empirical implementation of their model, following the successful testing for homotheticity of the demand functions, which leads to the parameter measuring the impact of the fund surplus to be restricted to zero(Dinenis and Scott, 1993, p. 302)

are long-term discounted pensions, a negative funding ratio does not necessarily imply insolvency but signifies that current assets would not be enough to cover future payments. For this reason underfunded pension funds have to either reduce the level of their liabilities or increase the return on their assets[8]. The latter mechanism implies that a higher funding level reduces the allocation to riskier investments(BoE, 2014). This would include EM assets, thus establishing a negative relationship between asset allocation to EM and funding levels.

3 Econometric methodology

Most of the works in the "pitfalls" tradition estimated separated long-run to interest rates in the form of 1 and separate short-run responses, for example through partial-adjustment models (Backus *et al.*, 1980). Estimation techniques implicitly or explicitly use of a system of equations approach to estimate the asset shares with either restrictions or mixed-bayesian estimators. However, beside the described issues with multicollinearity, the literature does not deal with other potential sources of bias in the estimation process. In particular, there are no references to the potentially serious issues of non-stationarity in the variables. Returns and especially asset prices and portfolio shares could however be non-stationary which could create issues, since it is well known that this may lead to "spurious" inference, unless there is cointegration between the variables(Phillips, 1986).

The AIDS literature does on the other hand tackle these issues explicitly. The methodology followed is to estimate long-run parameters by pre-testing for cointegration between the variables for each equation, and then estimate the model as a system of equations using the seemingly-unrelated-regression (SUR) method (Moore *et al.*, 2005; Al-Zu'bi and Murinde, 2011), or three-stages least squares to correct for endogeneity especially when estimating short-run dynamic equations (Barr and Cuthbertson, 1991, 1994; Adam, 1999; Blake, 2004).

None of the studies of asset demand equations have utilised a panel-data regression approach[9]. It is a contention of this paper that such an approach is well suited to estimate demand for EM assets by institutional investors from advanced countries. EM countries' assets are analysed together by pooling or

[8] This is the mechanism typical of the UK and US where traditional defined benefits fund are still widespread. In other countries different regulations may have different impacts.

[9] A partial exception is Al-Zu'bi and Murinde (2011), who seeks to apply panel cointegration techniques but reverts to SUR methods following unsuccessful statistical tests.

grouping the observations for individual countries, to obtain parameters for the EM assets as whole. In this sense EM assets are understood to constitute an asset class.

The paper is going to estimate equations for EM equity and bond portfolio shares as single equations. Restrictions of parameters, typical of AIDS approaches, is therefore ruled out. This is a consequence of the specific question tackled by this paper, which focuses exclusively on EM assets. A possible alternative would be to follow Barr and Cuthbertson (1994), in considering EMs assets holdings as total wealth, and analyse the distribution of assets between bonds and equities, or across countries. But this would not allow to tackle the international dimension of portfolio allocation, including the push-pull factors.

The paper is also going to explicitly tackle the issues emerging from the growing literature in panel-time series econometric. With macro-panels, where both the time-series and cross-sectional dimension are "large", several issues can emerge. First, as the time-series dimension grows, the possibility of non-stationarity arises, which led to the formulation of unit roots tests [10]. The issue of non-stationarity naturally leads to the possibility for panel cointegration, which can be likewise tested[11].

In addition to these issues, which are common to time-series econometrics, panel data presents two further complications. Firstly, as the time dimension grows and it becomes possible to individually estimate N time-series regressions, the possibility of obtaining heterogenous slope parameters. 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 individual N slope parameter, are consistent estimators (Pesaran and Smith, 1995)

The second set of issues relates to cross-sectional dependence (CSD), that 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: estimation can be biased, and tests holding under the assumption of cross-sectional independence can provide unreliable results (Banerjee *et al.*, 2004). To address this issue, researchers have a typically assumed factor error structure (Pesaran, 2006, p. 971):

$$y_{it} = a_i d_t + \beta_i x_{it} + e_{it} \tag{4}$$

[10]E.g. Im *et al.* (2003)
[11]E.g. Pedroni (1999); Westerlund (2007)

$$e_{it} = \gamma_i f_t + u_{it} \tag{5}$$

equation (5) shows how the error term of a panel equation can be decomposed in a common unobserved factor f_t plus an idiosyncratic individual specific error term u_{it}. Cross section dependence is therefore driven by a common factor, which can be modeled as a stationary or non-stationary variable. Since however the factor is unobserved, a method must be implemented to estimate it. Three main routes have been suggested by the literature. The first one 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 cross-sectional averages of the dependent variable and the individual specific regressors, which are then added as variables to the model specification. As shown by Pesaran (2006), these cross-sectional averages are a consistent approximation of the unknown factors. Furthermore these correlated-common-effect (CCE) estimators are consistent under a very general set of conditions: in the presence of any number of weak or strong factors in the error structure (Chudik *et al.*, 2011), regardless of their order of integration or that of the regressors (Kapetanios *et al.*, 2011), in the presence of spatial correlation Pesaran and Tosetti (2011), in the case of dynamic panels with lagged dependent or other weakly exogenous regressors (Chudik and Pesaran, 2013). A third method was recently proposed by Eberhardt and Bond (2009). The authors propose a three steps estimator, which they call the augmented-mean group (AMG): in the first step the a first-difference OLS regression with time dummies is estimated; the coefficients of the time dummies are then entered in N level regressions as "common dynamic factors"; finally the cross-sectional specific parameters are averaged as in the mean group (MG) estimators. Using one of these methodologies, it is possible to construct tests and estimators that are consistent with cross-sectional dependent panels.

All these issues, as it will be shown, are relevant to this paper.

4 Data and variables

Variables expressed in monetary terms are denominated in US dollars. All data are measured or converted to quarterly frequency. The period considered is from the first quarter of 2003 for equities and the first quarter of 2004 for bonds until the first quarter of 2013, although the panels may be unbalanced as some countries' series may be shorter. The cross-sectional dimension is 19 countries for equities and 17 countries for bonds. The following is a list of the variables with the expected sign between the brackets.

- *lem_alloc* and *lbem_alloc* are the portfolio shares of EM equities and bonds by institutional investors from advanced countries. This is calculated as the ratio between asset holdings by institutional investors, drawn from the Emerging Portfolio Research Fund (EPFR) country flows database, and their total wealth, coming from national statistical source. These variables have some limitations as indicators of asset shares. Firstly, the EPFR database collects data from mutual funds flows and allocation. Therefore these variables more precisely describe the holdings of EMs held by institutional investors through mutual funds rather than the total allocation. Secondly, while the advanced countries considered to construct the variables constitute the biggest share of the of the global institutional investor sector, some of the holdings captured in the EPFR database may still be held by other institutional investors. Finally, the data lly average out portfolio shares over countries and sectors, since they are based on the sum of total holdings over total wealth, while important differences may exist among investors both across countries and within countries. Despite these limitations, as detailed data on institutional investors portfolio geographical breakdown is not available, the data are the best possible approximation to a macro-level portfolio weight to EMs by foreign institutional investors.

- *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 as an indicator of currency riskiness. (+)

- *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 index 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, rather than the EMBI, which tracks hard currency bonds, is used due to its ability to capture return the effect of appreciation and depreciation of the nominal exchange rate, which are likely to be an important source of the returns as much as they are for equities. Four periods averages of the returns are used, in order to avoid excessive return volatility and further reduce the problem of endogeneity. (+)

- *lwbret* is the logarithmic returns of the JP Morgan GBI global index. The index tracks sovereign bonds from the world advanced countries and is used as an indicator for global "safe" returns. This is different from what is commonly used as a "push" factor, i.e. the US interest-rate [12]. This is to have a more general indicator of low-risk assets, in which while US dollar denominated assets represent the safest alternative, all advanced countries sovereign liabilities represent a qualitatively different type of asset, compared to EMs assets. This is consistent with the evidence that institutional investors typically use advanced countries government bonds being as liability matching securities rather than return-seeking assets (BoE, 2014). Therefore, despite being a simplification, this variable allows for a greater degree of generality than commonly done. (-)

- lfg is the pensions "funding gap". This is the weighted average of the difference from full funding - when assets equal liabilities - of defined benefits pension funds in Japan, the UK and the US. These are collected respectively from the Bank of Japan flow of funds accounts, the Pension Protection Fund 7800 index, and the Milliman Pension Funding Index. As discussed, this variable serves as an indicator of institutional investors balance sheet fragility. (+)

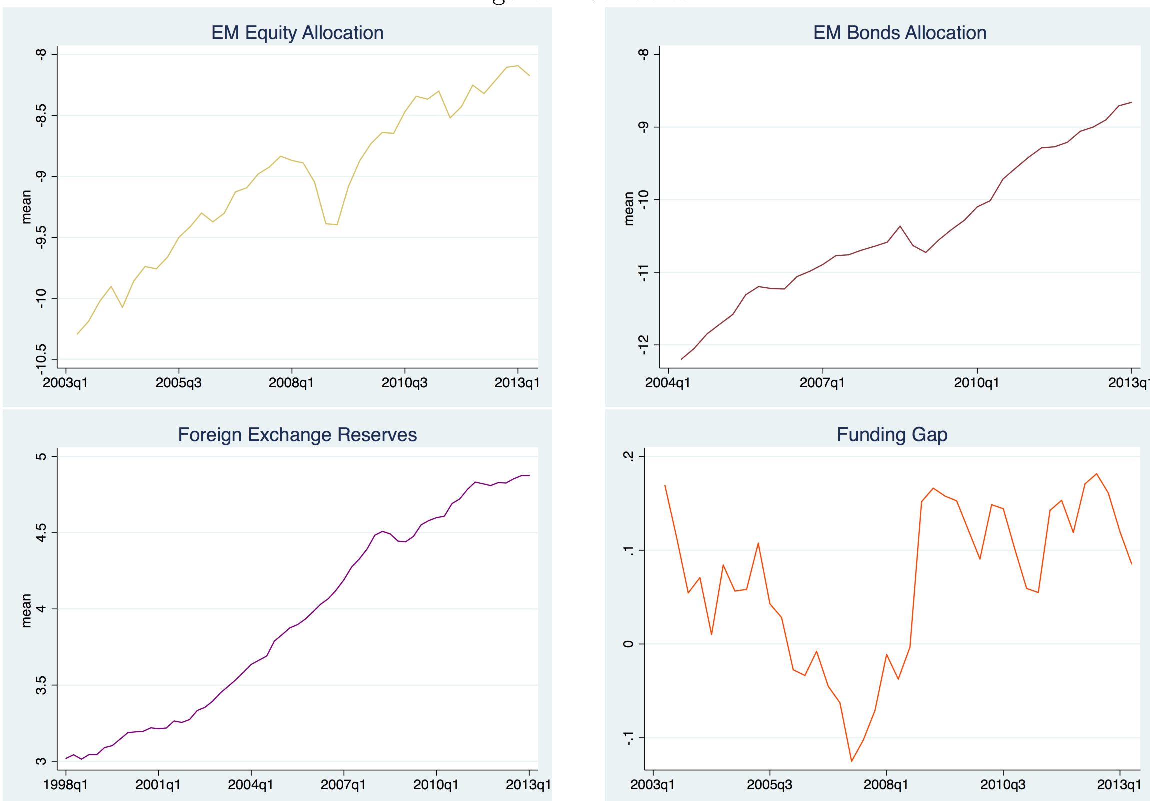
- *vix* is the VIX index, calculated by the Chicago Board Options, which measures the volatility of the Standard and Poor index. Recently, this variable has been widely used as a proxy for global risk perception, particularly in the context of global financial flows (e.g. (Ahmed and Zlate, 2013; Rey, 2013; Ananchotikul and Zhang, 2014)) (-).

The most notable exclusion from this list is GDP growth. This variable is however omitted for a number of reasons. Firstly, it does not fit very well the asset demand approach: the approach is based on 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[13]. Secondly, the rationale for the link is that higher GDP growth will yield higher long-run returns, but since returns already enter the equation specification this would potentially result in double counting the same variable, possibly resulting in multicollinearity issues, in a framework that is already known to suffer from this problem. Finally, if anything, the variable should be expected rather than current GDP

[12]see Ahmed and Zlate (2013) for a recent example.

[13]This is different from measuring the link between capital flows and GDP growth, since the link is in this case may be provided by economic theory.

Figure 1: Variables



growth, but long-run expectations data about any variables do not exist, and are subject to considerably heterogeneity across investors.

5 Tests and specification

Before testing for unit root and cointegration, a look at the CSD of the unit specific variables can give an idea of the extent of its importance in the estimation and testing. Although the presence of some cross-sectionally invariant common variables (lfg vix $lwbret$) should itself work as common factor and reduce CSD, the presence cannot be ruled out a priori. In fact as table 1 shows, the cross-sections of all the variables are highly correlated, all failing to reject the null of no CSD, according the Pesaran (2004) test. This provides a good reason to perform testing and estimation by taking CSD into account.

Table 1: Cross-sectional dependence test

Average correlation coefficients & Pesaran (2004) CD test				
Variable	CD-test	p-value	corr	abs(corr)
lem_alloc	72.05	0.000	0.840	0.840
lbem_alloc	60.63	0.000	0.903	0.903
lem_ret	57.38	0.000	0.662	0.662
lbem_ret	21.44	0.000	0.322	0.414
lem_fx	58.83	0.000	0.877	0.877

Notes: Under the null hypothesis of cross-section independence CD ~ N(0,1)
These are the results of the xtcd Stata routine (Eberhardt, 2011b).

A quick look at the data in figure 1 hints that non-stationarity may be an issue for some of the variables. For the panel cross-sectional specific variables, the unit root tests by Pesaran (2007), which allow for the presence of CSD, is chosen. The test is based on an augmented version of the Im *et al.* (2003) test, which is essentially a panel version of an ADF equation. With p-lags this is:

$$\triangle Y_{i,t} = a_i + b_i Y_{i,t-1} + c_i \overline{Y}_{t-1} + \sum_{j=1}^{p} \delta_{ij} \triangle Y_{t-j} + \sum_{j=0}^{p} d_{ij} \triangle \overline{Y}_{t-j} + \delta_i t + u_{it} \tag{6}$$

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, vix and $lwbret$ standard time-series ADF tests are used.

As shown intable 3, the asset shares, FXR and the indexes do not reject the null of unit root and are treated as non-stationary, while returns variables strongly reject the null of a unit root, and are therefore treated as I(0).

The evidence for the common variables is less clear-cut. As 3 shows, global returns are stationary. However, both vix and lfg reject the null at the 10% level in the case of no deterministic variables, but do not when constant and trends are added. In the literature one can finds examples where the VIX index is regressed with stationary variables in levels (Ahmed and Zlate, 2013; Ananchotikul and Zhang, 2014). In fact, when the test is done considering a longer time-series, the tests seem to reject the null of unit root[14].

[14] Specifically the null is rejected at the 5% and 10% level respectively for the model with a constant and a constant and

For these reasons the variable is considered stationary.

The funding-gap on the other hand should ideally fluctuate around 0, i.e. the fully-funded position, which could make the ADF specification without deterministic component relevant. In practice however, as it 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 2: Time-series Unit Root Test

Augmented Dickey-Fuller Test			
Variable	No constant	Constant	Constant and trend
lfg	0.0531*	0.206	0.1689
vix	0.20	0.09*	0.21
lwbret	0.000***	0.000***	0.000***

Note: Null hypothesis is the presence of a unit root. The time-series length is chosen in line with the length of the estimated equations, and the sample therefore only considers values from the first quarter of 2003.
*,** and *** denote rejection at 1%, 5% and 10% level.

a trend.

Table 3: Panel Unit Root Test

Pesaran (2007) Panel Unit Root test (CIPS)								
Variable	lags	Zt-bar	p-value		Variable	lags	Zt-bar	p-value
lbem_alloc	0	0.415	0.661		lem_alloc	0	0.591	0.723
lbem_alloc	1	1.384	0.917		lem_alloc	1	0.824	0.795
lbem_alloc	2	1.966	0.975		lem_alloc	2	1.260	0.896
lbem_alloc	3	3.613	1.000		lem_alloc	3	1.550	0.939
lbem_ret	0	-14.849	0.000***		lem_ret	0	-19.731	0.000***
lbem_ret	1	-10.374	0.000***		lem_ret	1	-15.729	0.000***
lbem_ret	2	-5.284	0.000***		lem_ret	2	-8.115	0.000***
lbem_ret	3	-2.697	0.003***		lem_ret	3	-6.747	0.000***
lem_fx	0	0.584	0.720					
lem_fx	1	0.335	0.631					
lem_fx	2	0.598	0.725					
lem_fx	3	-0.044	0.483					

Notes: Null hypothesis is the presence of a unit root. The table shows the results for the Pesaran (2007) unit root test, for the specification without a time trend. The results with a unit root test do not show any particular difference. Up to three lags are shown. The multipurt Stata routine was used (Eberhardt, 2011a).
*,** and *** denote rejection at 1%, 5% and 10% level.

The findings of the unit root tests present a challenge. As the literature review on asset demand equations showed, economic theory suggest a relationship between the levels of return and the asset shares. In the cointegration framework, long-run relationships can however only exist between I(1) variables. As returns are stationary, this would imply that no long-run relationship could exist between returns and asset shares. However, as Pesaran (1997) argues, this way of investigating long-run relationship is not the only possible one. He suggests that economic theory should provide the background as to whether a long-run relationship exist, rather than just statistical properties of the data. Econometrically such relationships can be represented with an autoregressive-distributed-lags (ARDL) model. In the panel case, with p and q lags respectively for the regressors and the dependent variable, this is expressed as:

$$Y_{i,t} = \sum_{j=0}^{p} \delta_{ij} \mathbf{X_{i,t-j}} + \sum_{j=1}^{q} \lambda_{i,j} Y_{i,t-j} + \mu_{i,t} + u_{i,t}$$

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

$$\triangle Y_{i,t} \quad = \quad \phi_i Y_{i,t-1} + \beta_i \mathbf{X_{i,t}} + \sum_{j=1}^{p-1} \lambda^*_{i,j} \triangle Y_{i,t-j} + \sum_{j=0}^{p-1} \delta^*_{i,j} \triangle \mathbf{X}_{i,t-j}$$

$$\phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{i,j}\right), \; \beta_i = \sum_{j=0}^{p} \delta_{i,j}, \; \lambda^*_{i,k} = -\sum_{m=j+1}^{p} \lambda_{i,m}, \; \delta^*_{i,j} = -\sum_{m=j+1}^{p} \delta_{i,m}$$

As shown by Pesaran (1997); Pesaran *et al.* (1999), these models can be estimated with the variables being I(0) and I(1), provided that some assumptions, which will be 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. The error-correction reparametrisation, as discussed in section 3, is also convenient, since it allows for a testing of both short-run and long-run impacts.

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

In order for the ARDL models, including the PMG estimator, to be consistent, some assumptions must be met. The first one 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 one 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 to pre-test the existence of a 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 those, a long-run relationship exists (table 4). Two tests were used, both accounting for the possibility of CSD: the first one is based on the significance of the error-correction term Gengenbach *et al.* (2008) [15], the second is based on the stationarity of the residuals (Holly *et al.*, 2010)[16]. 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 (CCEMG) regression between the variables, in the spirit of Cavalcanti *et al.* (2011b), was conducted, yielding the results of stationary residuals for up to five lags. Finally, the negative sign and significance of the error-correction parameters are going to be 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 relax this assumption. Panel ARDL models augmented with cross-sectional averages have been recently proposed (Cavalcanti *et al.*, 2011b; Chudik and Pesaran, 2013; Chudik *et al.*, 2013). In particular, the a CCE version of the PMG (CCE-PMG) estimator has been used recently by Cavalcanti *et al.* (2011a) and Albuquerque *et al.* (2014). The AMG estimator has also been also used in the context of ARDL models (Albuquerque *et al.*, 2014; Sadorsky, 2013; Elliott *et al.*, 2014)], which can be of particular interest to this paper, considering that it does not estimate the unknown source of CSD by cross-sectional averages, which in this paper would be less numerous than the number of variables, since many of them are not cross-sectional specific. This paper is going to use both methodologies to estimate the asset demand equations.

Despite all their merits, as discussed by Chudik *et al.* (2013) in a recent paper, a drawback of ARDL models, is their sensibility to the lag augmentation choice. At the same time, sufficient lag augmentation

[15] 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 to augment the model specification with cross-sectional averages, as in the CCE estimators, to account for the factors.

[16] After estimating a relationship with the CCE pooled estimators, the residuals $u_{it} = Y_{it} - \widehat{\beta}_{CCEP} X_{it} - \hat{\alpha}_i$ are collected and then tested for stationarity with the test of Pesaran (2007)

is needed to correct for serial correlation and endogeneity. For this reason some robustness checks, using different estimators will be conducted.

Table 4: Panel cointegration tests

	Error-correction test (Gengenbach *et al.*, 2008)		CCE Residuals-based test (Holly *et al.*, 2010)	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 (0 lags, 1 lag)	CIPS statistic (0 lags, 1 lag)
Equities	-2.793** -2.745**	-3.037* -3.003*	-2.122*, -2.078	-10.839***, -10.673***
Bonds	-3.017***, -2.8**	-2.936, -2.732	-2.407***, -2.150*	-12.925***, -11.226***

Notes: The first two columns show the Panel t-test statistic specification of the (Gengenbach *et al.*, 2008) test. This test was computed in Stata with the routine described by prof. Markus Eberhardt on his website (https://sites.google.com/site/medevecon/home).
The third column shows the result CIPS test statistic, resulting from the residuals-based testing procedure used by Holly *et al.* (2010).
The fourth column shows the residuals 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 1%, 5% and 10% level.

6 Estimation results and implications

6.1 Estimation

The CCE-PMG specification of the equation is:

$$\begin{aligned} \triangle Y_{i,t} &= \phi_i(Y_{i,t-1} - \boldsymbol{\beta}'\mathbf{X}_{i,t} - \boldsymbol{\gamma}'\mathbf{W}_t) + \sum_{j=1}^{p-1} \boldsymbol{\lambda}^{*'}_{i,j} \triangle Y_{i,t-j} + \sum_{j=0}^{p-1} \boldsymbol{\delta}^{*'}_{i,j} \triangle \mathbf{X}_{i,t-j} + \sum_{j=0}^{p-1} \boldsymbol{\theta}^{'}_{i,j} \triangle \mathbf{W}_j \\ &\quad + a_i \bar{Y}_t + \mathbf{b}_i \bar{\mathbf{X}}_t + \sum_{j=0}^{p-1} \mathbf{c}^{'}{}_{i,j} \triangle \bar{\mathbf{X}}_{t-j} + \sum_{j=0}^{p-1} d_{i,j} \triangle \bar{Y}_{t-j} + \mu_i + u_{i,t} \end{aligned} \tag{7}$$

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

With $\mathbf{X}$ being the vector of cross-sectional specific variables and $\mathbf{W}$ that of common variables, and $\bar{\mathbf{X}}$ and $\bar{Y}$ being the cross-sectional averages of the variables. As discussed above, since the VIX is treated as a measure of short-run risk-aversion/appetite, it only enters the short-run specification of the equation in first-differences. The AMG specification is the same, with the only difference being that $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ have heterogeneous slopes $(\boldsymbol{\beta}_i, \boldsymbol{\gamma}_i)$, and that instead of cross-sectional averages, it enters dynamic common factor estimated as discussed.

In order to cope with the issues related to the lag augmentation, three different model specification are estimated. The first two model specifications apply the same lag augmentation to all variables, respectively one lag for model (1) and two lags for model (2). Model (3) allows the lag length to be selected according to information criteria, up to 3 lags[17]. This results in adding 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. The cross-sectional averages lag length for the CCE was chosen to be the same as that of the variables. Given the relative short time dimension of the panels, longer lags specifications are unfeasible. Model (4) is the same as model (3) with addition of the vix variable.

The results of the estimation are shown in table 5 and table 6. In all models the error-correction terms in the dynamically stable range, since they are strongly significant, negative, and within 0 and 1. As said above, this constitutes this confirms the existence of a long-run relationship between the variables. Also, there does not seem to be major differences between the speed of convergence between bonds and equities.

As expected returns and asset allocation are positively related. For EM equities a 1% return increase implies a more than double response in terms of asset allocation, whereas for bonds the response is even higher, ranging from more than 3.6% to above 4.8%. While these may seem implausibly big parameters, it has to be remembered that asset allocations to EMs are still small, which implies that relative changes may in fact still imply a relatively small absolute change. The short-run parameters for equities are also all positive and significant. The results of global returns are less decisive. Most of the parameters are negative, but only for equities in models (3) and (4) they are statistically significant.

The parameters of FXR are always positive, and significant in all but one model. The value of the parameters seems to be slightly smaller for equities, but there doesn't seem to be a major difference

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

Table 5: Estimation results-Equities

ARDL model, dep. variable: $\triangle$lem_alloc						
Model	AMG (1)	AMG (2)	AMG (3)	AMG (4)	CCE-PMG (3)	CCE-PMG (4)
Long Run						
lem_fx	0.577*	0.683	0.807**	0.713*	0.688***	0.937***
lem_ret	2.792***	2.199***	2.181***	2.636***	2.193***	2.026***
lwbret	-0.566	-0.44	-0.627	-0.924**	-0.628*	-0.77***
lfg	0.661***	0.583*	0.593***	0.461**	0.05	0.319**
Short run						
ec	-0.535***	-0.681***	-0.556***	-0.595***	-0.372***	-0.393***
$\triangle$lem_ret	0.827***	0.878***	0.829***	0.938***	1.615***	1.543***
vix				-0.014***		-0.0005
$\triangle$lwbret	0.166	0.181	0.127	0.248**	-0.008	0.056
$\triangle$lem_alloc(-1)						
CDP	0.845***	0.873***	0.85***	0.933***		
Hausman test					3.98 (0.409)	5.29 (0.259

	CS-DL (1 lag)	CS-DL (SBC lags)	GMM	LSDVC
lem_fx	0.73***	0.87**	0.2***	0.15**
lem_ret	2.093***	2.2***	0.672***	0.768***
lwbret	-0.062	-0.123	0.068	0.223
lfg	0.035	0.193	0.484***	0.558***
vix		0.0003	-0.006***	-0.005***

Notes: Models (1) (2) and (3) refers to the different lags augmentation described in the paper. CDP is to the common dynamic process estimated by the augmented mean group, ec is the error correction term. The Hausman test reports the p-value in brackets: non-rejection allows long-run pooling. All models contain individual constants and time trends. Long-run standard errors for the AMG model were computed with the delta method.
The following Stata routines were used: xtpmg (Blackburne and Frank, 2007), xtmg (Eberhardt, 2013), nlcom, xtdpdsys, xtlsdvc.

between the two assets. The funding gap parameters also seem to conform to the expectations. The parameters are positive and significant. The impact on bonds allocation seems to be particularly high, being considerably higher than 1% for each percentage point of underfunding, while the impact on equities is smaller ranging between roughly 0.5% and 0.6%.

Adding the VIX. The variable is negative in equities specification, denoting a decrease in allocation to EMs when risk-aversion is high. However it is positive in the bonds equation, a rather strange finding that is hard to explain.

The common dynamic process in the AMG models is always positive and statistically significant and

Table 6: Estimation results - Bonds

ARDL model, dep. variable: $\triangle$lbem_alloc						
	AMG (1)	AMG (2)	AMG (3)	AMG (4)	CCE-MG (3)	CCE-MG (2)
Long Run						
lem_fx	0.697*	0.897**	0.892***	0.408	0.543	0.596
lbem_ret	4.837**	3.623**	4.565***	3.649***	2.174	3.612
lwbret	-0.868	0.917	0.577	-1.348	-1.246	-2.37
lfg	1.395**	1.528***	1.317**	1.2*	0.388	1.16*
Short run						
ec	-0.551***	-0.724***	-0.591***	-0.669***	-0.717***	-0.741***
$\triangle$lbem_ret	0.03	-0.024	0.098	0.234	0.271	0.488*
vix				0.031**		
$\triangle$lwbret	0.213	-0.13	0.161	0.576	0.075	0.591
CDP	0.678***	0.777***	0.703***	0.729***		
Hausman test					7.11 (0.13)	

	CS-DL (1 lag)	CS-DL (2 lags)	GMM	LSDVC
lem_fx	0.491**	0.596	0.261**	0.219****
lbem_ret	2.091	3.612	0.824***	0.633
lwbret	-0.444	-0.385	-0.151	-0.204
lfg	0.405	0.59	0.563***	0.547**
vix	-0.005	-0.002	-0.009***	-0.009

Notes: Models (1) (2) and (3) refers to the different lags augmentation described in the paper. CDP is to the common dynamic process estimated by the augmented mean group, ec is the error correction term. The Hausman test reports the p-value in brackets: non-rejection allows long-run pooling. All models contrain individual constants and time trends, except in the CCE models due to estimation failures when time trends are added. Long-run standard errors for the AMG model were computed with the delta method.
The following Stata routines were used: xtpmg (Blackburne and Frank, 2007), xtmg (Eberhardt, 2013), nlcom, xtdpdsys, xtlsdvc.

of a very similar range across all models. As Eberhardt and Bond (2009) discuss, the estimator is designed to explicitly account for and interpret the estimated common factor[18]. In this scenario, it is hard to guess what the process is in fact capturing. Its positive sign suggests it is capturing some unobserved factor positively affecting the growth of EMs holdings. This could be, for example, higher expectations about GDP expectations, or the decrease in risk-aversion towards the asset class as a whole.

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

6.2 Some robustness checks

As discussed above, the ARDL model augmented with cross-sectional averages is consistent under a very general set of assumptions. However, as shown by Chudik *et al.* (2013), panel ARDL models may perform poorly when the considered sample is small. Moreover, while increasing the lag augmentation reduces sizably the issues of serial correlation and endogeneity, one cannot entirely rule out their presence, since the maximum lag chosen was 2.

Chudik *et al.* (2013) propose another estimator, which they name cross-sectionally augmented distributed lags (CS-DL) As the name implies, this is based on a (non-autoregressive) distributed lag model, once again augmented with cross-sectional averages. This estimator has a number of good properties, being robust in the presence of unit roots in factors and/or regressors, serial correlation, breaks in error process and multiple factors. The authors also documents its better overall small sample performance compared to the ARDL approach. However, as the model is not autoregressive, unlike the ARDL approach, the CS-DL estimator may suffer from the endogeneity bias. This is likely a serious issue in this paper, since causality between asset demand and returns or foreign exchange, could run both ways. For this reason, the ARDL approach was preferred.

Standard dynamic panel techniques are generally not affected by the problem of endogeneity and/or serial correlation. The system generalised method of moments (GMM) estimator by 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), perform well in the presence of (even second-order) serial correlation, and endogeneity. While the GMM estimator remain consistent also in the presence of weak CSD, such as spatial dependence (Sarafidis, 2009), these estimators do not in general take into account CSD. Moreover the GMM techniques are typically designed for large N small T panels, clearly not the case of this paper.

The results, are shown in table 5 and table 6, do not substantially differ from the the ARDL results presented in the previous subsection.

7 Interpretation and implications

These results provides evidence for the hypothesised asset demand equations figure 2. Institutional investors investors seem to broadly conform to the asset demand specifications proposed. Several observations can be made in terms of the interpretation and implications of this finding.

Figure 2: Fitted vs actual

Graphs are averages of both the fitted and actual values of *lem_alloc* and *lbem_alloc*.

First of all, the size of the error correction, is above 50% in the majority of the equations. This implies that investors do not instantaneously achieve their wanted portfolio shares, but are able to adjust to their desired portfolio shares relatively quickly, correcting half of the gap in one period. This is in contrast to most of the AIDS literature, which generally finds slow adjustment processes, even for institutional investors (Blake, 2004; Dinenis and Scott, 1993). This finding suggest that frictions, such as transaction costs, may not be a major obstacle for foreign institutional investors to reach their desired EMs asset allocations.

Secondly, FXR positively affect asset allocation to EMs. This is in line with the ideas discussed in the introduction: FXR can be interpreted as collateral provided by EMs, which reduces the overall riskiness of their assets, thereby increasing demand by foreign institutional investors.

Thirdly, the balance sheet of investors also matters. The finding that the funding gap matters for demand for EM assets is perhaps the most relevant finding of this paper. Institutional investors demand for EM assets is increased when they are need of higher returns to reinforce their balance sheets. In policy terms, this may add on 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 bonds flows to EMs really exploded after the 2008 crisis. A recover of institutional investors balance sheet may have important adverse consequences on these patterns.

Returns on safe asset do not seem to be a major determinant of EM assets. This could show that the allocation to EMs is not necessarily "pushed" by low interest rates in advanced countries. Two caveats are in order. Firstly, the findings can reflect a problem of the variable itself. It is hard to find a single variable for advanced markets "safe" returns. In practice portfolio choice is not a binary selection between safe advanced countries government bonds and risky EMs assets. Secondly, it is important to point out that while global safe returns may not have direct influence on portfolio allocation, they still matter indirectly through the balance sheet conditions. As the funding gap is influenced by the size of the pension liabilities, which in turn depend on a discount factor, usually linked to the value of bond yields. In particular, ceteris paribus, an increase in interest rates decreases liabilities, thereby reducing the funding gap. Therefore indirectly, an increase in advanced countries bond yields may generate still generate a decrease in allocation to EMs.

Overall, these findings combined indicate a long-term approach to demand for one EMs by institutional investors, as they are not concerned about immediate returns and sudden shifts in risk-appetite. This does not preclude however medium/long-run responses to changes in their balance sheet level and long-run returns, which may have sizable impact on capital flows. It is also important to remember that this paper uses quarterly data, implying a relatively "short" long-run. Furthermore, the positive impact of reserves accumulation of EMs and the quick adjustment to the desired long-run allocations suggest that pro-cyclicality of portfolio flows to EMs remains a potentially serious issue.

Finally, from a methodological point of view, it shows the usefulness of the asset demand equation approach to the analysis of international portfolio choice. It allows to clearly draw the links between the macroeconomic phenomenon of international portfolio investment, and their direct driver, i.e. the behaviour of foreign investors. Capital flows and portfolio choice are thereby directly related, giving the phenomena of financial globalisation a more structural and deliberate character: EMs assets are being purchased by foreign investors, because they explicitly seek to increase their allocation to these countries. This also permits to broaden the scope of asset demand equations, from being the estimation of a complete picture of the flows of funds within an economy, to providing insights to other empirically important issues.

8 Conclusion

This paper has provided evidence on the demand for EMs assets by advanced countries institutional investors. It has estimated asset demand equations in the spirit of and the Almost-Ideal-Demand system applied to portfolio choice. The paper has used a panel data approach, taking into account features emerging from the recent panel-time series literature, in particular heterogeneity and cross-sectional dependence. An innovative panel ARDL modeling framework was eventually chosen, to account for both long-run and short-run dynamics of EMs asset shares.

The findings of the paper seem to confirm the hypothesised relationships. Institutional investors do care about long-run returns. However in making their decision they take into account at least two additional factors: the amount of FXR that EMs hold, which indicate, and the conditions of their balance sheet, proxied by the funding ratio of advanced countries' pensions funds.

These findings contribute to the understanding of international portfolio investments. Institutional investors are not immediately affected by short-term factors, such as short-term returns increases and shifts in risk-apettite. However, quarterly returns affect their long-run allocation, and overall their behaviour remains driven by factors that are sensitive to the economic cycle, such as balance sheets conditions and accumulation of FXR. Coupled with the quick adjustment process to long-run allocations, the findings show that overall institutional portfolio flows fluctuations are still a potential danger., despite the long-term nature of institutional investors.

References

Adam, C.S. (1999). 'Asset Portfolios and Credit Rationing: Evidence from Kenya.' *Economica*, **66** (261): pp. 97–117.

Ahmed, S. and Zlate, A. (2013). 'Capital flows to emerging market economies: a brave new world?' International Finance Discussion Paper 1081, Board of Governors of the Federal Reserve System (U.S.).

Al-Zu'bi, B. and Murinde, V. (2011). 'Household portfolio behaviour: evidence from Middle East economies.' *Applied Financial Economics*, **21** (17): pp. 1281–1289.

Albuquerque, B., Baumann, U. and Krustev, G. (2014). 'Has US household deleveraging ended? a model-based estimate of equilibrium debt.' Working Paper Series 1643, European Central Bank.

Ananchotikul, N. and Zhang, L. (2014). 'Portfolio Flows, Global Risk Aversion and Asset Prices in Emerging Markets.' IMF Working Paper 14/156, International Monetary Fund.

Backus, D., Brainard, W.C., Smith, G. and Tobin, J. (1980). 'A Model of U.S. Financial and Nonfinancial Economic Behavior.' *Journal of Money, Credit and Banking*, **12** (2): pp. 259–293.

Bai, J. and Ng, S. (2004). 'A PANIC Attack on Unit Roots and Cointegration.' *Econometrica*, **72** (4): pp. 1127–1177.

Banerjee, A., Marcellino, M. and Osbat, C. (2004). 'Some cautions on the use of panel methods for integrated series of macroeconomic data.' *Econometrics Journal*, **7** (2): pp. 322–340.

Barr, D.G. and Cuthbertson, K. (1991). 'Neoclassical Consumer Demand Theory and the Demand for Money.' *The Economic Journal*, **101** (407): pp. 855–876.

—— (1992). 'Company Sector Liquid Asset Holdings: A Systems Approach.' *Journal of Money, Credit and Banking*, **24** (1): pp. 83–97.

—— (1994). 'The Demand for Financial Assets Held in the U.k. by the Overseas Sector: An Application of Two-Stage Budgeting*.' *The Manchester School*, **62** (1): pp. 1–20.

Blackburne, E.F.I. and Frank, M.W. (2007). 'XTPMG: Stata module for estimation of nonstationary heterogeneous panels.'

Blake, D. (2004). 'Modelling the composition of personal sector wealth in the UK.' *Applied Financial Economics*, **14** (9): pp. 611–630.

Blundell, R. and Bond, S. (1998). 'Initial conditions and moment restrictions in dynamic panel data models.' *Journal of Econometrics*, **87** (1): pp. 115–143.

BoE (2014). 'Procyclicality and structural trends in investment allocation by insurance companies and pension funds.' Discussion paper, Bank of England.

Borio, C. and Disyatat, P. (2011). 'Global imbalances and the financial crisis: Link or no link?' BIS Working Paper 346, Bank for International Settlements.

Brainard, W.C. and Tobin, J. (1968). 'Pitfalls in Financial Model Building.' *The American Economic Review*, **58** (2): pp. 99–122.

Broner, F.A., Gaston Gelos, R. and Reinhart, C.M. (2006). 'When in peril, retrench: Testing the portfolio channel of contagion.' *Journal of International Economics*, **69** (1): pp. 203–230.

Bruno, G.S.F. (2005). 'Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models.' *Economics Letters*, **87** (3): pp. 361–366.

Bruno, V. and Shin, H.S. (2013a). 'Capital Flows and the Risk-Taking Channel of Monetary Policy.' Working Paper 18942, National Bureau of Economic Research.

—— (2013b). 'Capital Flows, Cross-Border Banking and Global Liquidity.' Working Paper 19038, National Bureau of Economic Research.

Buiter, W.H. (2003). 'James Tobin: An Appreciation of his Contribution to Economics.' Working Paper 9753, National Bureau of Economic Research.

Calvo, G.A., Leiderman, L. and Reinhart, C.M. (1993). 'Capital Inflows and Real Exchange Rate Appreciation in Latin America: The Role of External Factors.' *Staff Papers - International Monetary Fund*, **40** (1): pp. 108–151.

Cavalcanti, T.V.d.V., Mohaddes, K. and Raissi, M. (2011a). 'Commodity Price Volatility and the Sources of Growth.' Cambridge Working Papers in Economics 1112, Faculty of Economics, University of Cambridge.

—— (2011b). 'Growth, development and natural resources: New evidence using a heterogeneous panel analysis.' *The Quarterly Review of Economics and Finance*, **51** (4): pp. 305–318.

Chudik, A., Mohaddes, K., Pesaran, M.H. and Raissi, M. (2013). 'Debt, Inflation and Growth - Robust Estimation of Long-Run Effects in Dynamic Panel Data Models.' CESifo Working Paper Series 4508, CESifo Group Munich.

Chudik, A. and Pesaran, M.H. (2013). 'Common Correlated Effects Estimation of Heterogeneous Dynamic Panel Data Models with Weakly Exogenous Regressors.' CESifo Working Paper Series 4232, CESifo Group Munich.

Chudik, A., Pesaran, M.H. and Tosetti, E. (2011). 'Weak and strong cross-section dependence and estimation of large panels.' *The Econometrics Journal*, **14** (1): pp. C45–C90.

Chuhan, P., Claessens, S. and Mamingi, N. (1998). 'Equity and bond flows to Latin America and Asia: the role of global and country factors.' *Journal of Development Economics*, **55** (2): pp. 439–463.

Deaton, A. and Muellbauer, J. (1980). 'An Almost Ideal Demand System.' *The American Economic Review*, **70** (3): pp. 312–326.

Dinenis, E. and Scott, A. (1993). 'What Determines Institutional Investment? An Examination of UK Pension Funds in the 1980s.' *Oxford Economic Papers*, **45** (2): pp. 292–310.

Dooley, M.P., Folkerts-Landau, D. and Garber, P.M. (2014). 'The Revived Bretton Woods System's First Decade.' Working Paper 20454, National Bureau of Economic Research.

Dooley, M.P., Garber, P.M. and Folkerts-Landau, D. (2007). 'The Two Crises of International Economics.' Working Paper 13197, National Bureau of Economic Research.

Duca, J.V. and Muellbauer, J. (2013). 'Tobin LIVES: Integrating evolving credit market architecture into flow of funds based macro-models.' Working Paper Series 1581, European Central Bank.

Eberhardt, M. (2011a). 'MULTIPURT: Stata module to run 1st and 2nd generation panel unit root tests for multiple variables and lags.'

—— (2011b). 'XTCD: Stata module to investigate Variable/Residual Cross-Section Dependence.'

—— (2013). 'XTMG: Stata module to estimate panel time series models with heterogeneous slopes.'

Eberhardt, M. and Bond, S. (2009). 'Cross-section dependence in nonstationary panel models: a novel estimator.' MPRA Paper 17692, University Library of Munich, Germany.

Elliott, R.J.R., Sun, P. and Zhu, T. (2014). 'Urbanization and Energy Intensity: A Province-level Study for China.' Discussion Paper 14-05, Department of Economics, University of Birmingham.

Fernández-Arias, E. (1996). 'The new wave of private capital inflows: Push or pull?' *Journal of Development Economics*, **48** (2): pp. 389–418.

Flannery, M.J. and Hankins, K.W. (2013). 'Estimating dynamic panel models in corporate finance.' *Journal of Corporate Finance*, **19**: pp. 1–19.

Froot, K.A. and Tjornhom Donohue, J. (2002). 'The Persistence of Emerging Market Equity Flows.' Working Paper 9241, National Bureau of Economic Research.

Gengenbach, C., Urbain, J.P. and Westerlund, J. (2008). 'Panel Error Correction Testing with Global Stochastic Trends.' Research Memorandum 051, Maastricht University, Maastricht Research School of Economics of Technology and Organization (METEOR).

Hendershott, P.H. (1971). 'A Flow-of-Funds Model: Estimates for the Nonbank Finance Sector.' *Journal of Money, Credit and Banking*, **3** (4): pp. 815–832.

Holly, S., Pesaran, M.H. and Yamagata, T. (2010). 'A spatio-temporal model of house prices in the USA.' *Journal of Econometrics*, **158** (1): pp. 160–173.

Hsieh, M.F., Yang, T.Y., Yang, Y.T. and Lee, J.S. (2011). 'Evidence of herding and positive feedback trading for mutual funds in emerging Asian countries.' *Quantitative Finance*, **11** (3): pp. 423–435.

Im, K.S., Pesaran, M.H. and Shin, Y. (2003). 'Testing for unit roots in heterogeneous panels.' *Journal of Econometrics*, **115** (1): pp. 53–74.

IMF (2014). 'How do changes in the investor base and financial deepening affect emerging market economies?' In: IMF (Ed.), *Global financial stability report, April*, pp. 67–99. International Monetary Fund.

Jinjarak, Y. and Zheng, H. (2010). 'Financial panic and emerging market funds.' *Applied Financial Economics*, **20** (23): pp. 1793–1805.

Kaminsky, G., Lyons, R.K. and Schmukler, S.L. (2004). 'Managers, investors, and crises: mutual fund strategies in emerging markets.' *Journal of International Economics*, **64** (1): pp. 113–134.

Kapetanios, G., Pesaran, M.H. and Yamagata, T. (2011). 'Panels with non-stationary multifactor error structures.' *Journal of Econometrics*, **160** (2): pp. 326–348.

Lane, P.R. and Milesi-Ferretti, G.M. (2007). 'The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970-2004.' *Journal of International Economics*, **73** (2): pp. 223–250.

Miyajima, K. and Shim, I. (2014). 'Asset managers in emerging market economies.' *BIS Quarterly Review*.

Moore, T., Green, C.J. and Murinde, V. (2005). 'Portfolio Behaviour in a Flow of Funds Model for the Household Sector in India.' *Journal of Development Studies*, **41** (4): pp. 675–702.

Obstfeld, M. (2012). 'Financial flows, financial crises, and global imbalances.' *Journal of International Money and Finance*, **31** (3): pp. 469–480.

Pedroni, P. (1999). 'Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors.' *Oxford Bulletin of Economics and Statistics*, **61** (S1): pp. 653–670.

Pesaran, M.H. (1997). 'The Role of Economic Theory in Modelling the Long Run.' *The Economic Journal*, **107** (440): pp. 178–191.

—— (2004). 'General Diagnostic Tests for Cross Section Dependence in Panels.' IZA Discussion Paper 1240, Institute for the Study of Labor (IZA).

—— (2006). 'Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure.' *Econometrica*, **74** (4): pp. 967–1012.

—— (2007). 'A simple panel unit root test in the presence of cross-section dependence.' *Journal of Applied Econometrics*, **22** (2): pp. 265–312.

Pesaran, M.H., Shin, Y. and Smith, R.P. (1999). 'Pooled Mean Group Estimation of Dynamic Heterogeneous Panels.' *Journal of the American Statistical Association*, **94** (446): p. 621.

Pesaran, M.H. and Smith, R. (1995). 'Estimating long-run relationships from dynamic heterogeneous panels.' *Journal of Econometrics*, **68** (1): pp. 79–113.

Pesaran, M.H. and Tosetti, E. (2011). 'Large panels with common factors and spatial correlation.' *Journal of Econometrics*, **161** (2): pp. 182–202.

Phillips, P.C.B. (1986). 'Understanding spurious regressions in econometrics.' *Journal of Econometrics*, **33** (3): pp. 311–340.

Qian, X. and Steiner, A. (2014). 'International Reserves and the Composition of Foreign Equity Investment.' *Review of International Economics*, **22** (2): pp. 379–409.

Ramb, F. and Scharnagl, M. (2011). 'Household's portfolio structure in Germany - analysis of financial accounts data 1959-2009.' Working Paper Series 1355, European Central Bank.

Rey, H. (2013). 'Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence.' Tech. Rep. Presented at 2013 Economic Policy Symposium, Federal Reserve Bank of Kansas City, Jackson Hole.

Sadorsky, P. (2013). 'Do urbanization and industrialization affect energy intensity in developing countries?' *Energy Economics*, **37**: pp. 52–59.

Sarafidis, V. (2009). 'GMM Estimation of Short Dynamic Panel Data Models With Error Cross-Sectional Dependence.' MPRA Paper 25176, University Library of Munich, Germany.

Taylor, M.P. and Sarno, L. (1997). 'Capital Flows to Developing Countries: Long- and Short-Term Determinants.' *World Bank Economic Review*, **11** (3): pp. 451–470.

Westerlund, J. (2007). 'Testing for Error Correction in Panel Data.' *Oxford Bulletin of Economics and Statistics*, **69** (6): pp. 709–748.