Have drivers of portfolio capital flows changed since the Global Financial Crisis?

Boonman, Tjeerd

Monmouth University

30 January 2023

Have drivers of portfolio capital flows changed since the Global Financial Crisis?

Tjeerd M. Boonman*

Leon Hess Business School, Monmouth University, United States

January 30 2023

Abstract

The Global Financial Crisis had a substantial impact on the size and composition of portfolio capital flows, which raises the question whether the factors driving these capital flows have changed. The literature is scarce and shows mixed results, which may be attributable to the time windows used to compare the periods before and especially after the crisis. I identify and compare robust drivers of portfolio capital inflows for 75 countries in two non-overlapping periods (1996–2007 and 2011–19) using the Bayesian Model Averaging method. I find that the drivers have changed since the crisis. Bond investors in advanced and emerging economies have become more prudent, while investors in emerging market equity search for return. After the crisis, the more advanced economies continue to capture more portfolio inflows, which confirms the Lucas paradox, and is driven by institutions rather than capital openness.

Keywords: Portfolio Capital Flows, Bayesian Model Averaging

JEL Code: C11, F32, G15

*400 Cedar Ave, West Long Branch, NJ 07764, United States; email: `tboonman@monmouth.edu`; tel.: 732 402 7018.

1 Introduction

Capital flows can be an important source of funding for the public and private sectors, contributing to economic development. But countries can also be severely harmed by capital-flow disruptions. Capital surges can lead to exchange rate misalignment, credit booms, and vulnerabilities in the financial sector. Sharp reversals of capital flows, known as sudden stops, can threaten borrowers' access to finance and lead to a decline in asset prices and a large currency depreciation, undermining financial stability and GDP growth (Alberola et al., 2016; Calvo, 1998; Sarno et al., 2016; Gelos et al., 2022).

Since the 1990s, a strand of literature has aimed to understand what drives capital flows. Calvo et al. (1996) observe that "global factors affecting foreign investment tend to have an important cyclical component, which has given rise to repeated booms and busts in capital inflows." These global (or push) factors reflect the general condition of the global economy and are beyond the control of the country receiving capital. They explain international synchronization of flows and are associated with the global financial cycle (Rey, 2015). In turn, capital flows are heterogeneous across countries, and this differential pattern can be attributed to country-specific macroeconomic, financial, and institutional conditions, known as pull factors. In the empirical literature, there has been a long-running debate on whether capital flows are influenced by global push or country-specific pull factors.

The theoretical foundation that fits the push-pull story well is the modern portfolio theory following Markowitz (1952) and more specifically the international version as laid out by Grubel (1968). Markowitz states that rational investors should care about two main factors: expected returns and risk. The portfolio share of a particular asset depends on its expected return and risk relative to those of alternative assets. In the international sphere, country-specific pull factors affect the expected return and risk of domestic assets, while global push factors primarily affect the relative attractiveness of alternative assets—that is, the expected return and risk of external assets (Koepke, 2019). The neoclassical model of trade and growth also provides a theoretical framework to explain capital flows. In this model, new investments occur in the country that is less productive because it has a lower level of capital per worker. The law of diminishing returns implies that the marginal product of capital is higher in the less productive (that is, poorer) economy, so all capital should flow to this economy. Although wealthy countries invest some capital in poorer ones, observed capital flows fall short of the flows predicted by the theory (Lucas, 1990). This is known as the Lucas paradox. Theoretical explanations for the paradox include cross-country differences in fundamentals affecting productivity, in institutions, and in capital market imperfections. Lucas (1990) points to differences in human capital or human development, North (1994) and Alfaro et al. (2008) find that institutions are the leading explanation, and Chinn and Ito (2008) and Reinhardt et al. (2013) find that capital openness is the key to explaining the Lucas paradox.

Before getting into the empirical determinants of capital flows, it is necessary to distinguish between gross and net capital flows. Gross capital inflows are nonresidents' purchases of domestic assets minus their sales of such assets, and gross capital outflows are residents' purchases of foreign assets minus their sales of such assets. Net capital flows are defined as gross capital inflows minus gross capital outflows (BIS, 2021). Forbes and Warnock (2012) argue that the previously strong link between gross and net flows has weakened, as inflows and outflows move together more closely than before. As a result, volatility of gross flows has increased, while volatility of net flows has not. The literature that surged after the Global Financial Crisis (GFC) of 2008–09 emphasizes that gross inflows are the dominant driver of overall capital flows to emerging market economies (EMEs) and matter most for financial stability (Broner et al., 2013; Gelos et al., 2022). Capital flows consist of foreign direct investments, portfolio investments, and banking flows. Portfolio capital flows are among the more volatile gross capital inflows (Koepke, 2019) and are therefore potentially more destabilizing than the other two.

The GFC led to an unprecedented collapse in capital flows (Milesi-Ferretti et al., 2011). Since the GFC, global liquidity has increased and investors are faced with an extended period of very low interest rates in advanced economies (AEs). At the same time, macroprudential policies, including capital controls and financial regulations, have surged (Forbes and Warnock, 2021). One of the most salient changes in the post-GFC period is a retrenchment of cross-border bank lending, which has been offset by the growing importance of market-based flows, particularly portfolio inflows to EMEs (BIS, 2021).

This raises the question whether the drivers of portfolio capital inflows have changed in the aftermath of the GFC. And if so, how have they changed? Has the relative importance of push versus pull factors changed? Does the Lucas paradox continue to hold, and through which channels?

Although the influence of the GFC on capital flows has been studied widely, very few have explicitly compared the drivers of portfolio capital flows in the pre-GFC and post-GFC eras. Most studies include the GFC or its immediate aftermath in the studied post-GFC period, which affects the results. I determine and compare the most robust indicators for gross portfolio capital inflows in two separate subperiods: before the GFC (1996–2007) and after the GFC (2011–19). I separate portfolio inflows into bond and equity inflows because, compared to portfolio equity inflows, portfolio debt inflows are more volatile and driven by global factors (Mercado and Park, 2011; Forbes and Warnock, 2012; and Tchorek et al., 2017). I conduct the analysis for 75 countries but separately for AEs and EMEs because substantial evidence suggests that the drivers and effects of capital flows are different for these two groups (Koepke, 2019; Cerutti et al., 2019).

Traditionally, drivers of capital flows have been identified by finding a few optimal regression specifications from a set of preselected, potentially relevant explanatory variables.

However, the selected model may be unstable, as additional data or explanatory variables can ruin its performance. This model uncertainty can be addressed by using data-driven methods, such as Bayesian Model Averaging (BMA). BMA explicitly acknowledges that the true model is not known, and instead of searching for a single best specification, it analyzes every possible model that can be constructed from a set of potential independent variables (Maltritz and Molchanov, 2013). I choose this method because averaging over all the models provides better average predictive ability relative to using a single model (Ca'Zorzi et al., 2012). Additionally, in theoretical works, BMA point estimators and predictions minimize mean squared error, its estimation and prediction intervals are calibrated, and its predictive distributions have optimal performance (Raftery and Zheng, 2003). In simulations and out-of-sample tests, BMA outperforms other methods (Porwal and Raftery, 2022).[1] In the capital flows literature, BMA has been used to identify the determinants of foreign direct investments (Blonigen and Piger, 2014; Eicher et al., 2012), portfolio capital flows (Yupho and Huang, 2014), and foreign direct investment, portfolio and banking flows (Tchorek et al., 2017; Cerutti et al., 2019). Most studies include a panel of countries, except Yupho and Huang (2014), which studies Thailand only. The BMA method has been applied in other fields of economics and finance—see Moral-Benito (2015) for a list of applications.

I preselect a large number of potential drivers, 7 global and 19 country-specific, based on the literature and stylized facts, and I add two and four regional dummies for AEs and EMEs, respectively. Using annual instead of quarterly data enables me to analyze long-run cyclical trends rather than the higher-frequency, more volatile movements of portfolio capital flows, which tend to be very noisy (Davis et al., 2021). Using annual data allows me to include more EMEs and variables in the sample.

[1] BMA outperforms Bayesian model selection and penalized likelihood methods including LASSO, smoothly clipped absolute deviation, minimax concave penalty, and elastic net methods.

This work is closely related to Ahmed and Zlate (2014), which compares the determinants of net private capital inflows to EMEs in the pre-GFC (2002Q1–2008Q2) and post-GFC (2009Q3–2012Q2) periods for a panel of 12 EMEs. The authors find that interest rate differentials gain a more prominent role in the post-GFC period, while risk aversion is a key determinant of portfolio net inflows in both periods. I depart from this work by focusing on gross capital inflows instead of net capital flows. Furthermore, I use a much larger number of preselected potential drivers (26 plus regional dummies versus 5) and a different methodology. Finally, I use a distinct sample, with more countries (75 rather than 12), lower frequency (annual rather than quarterly), and a longer time horizon (1996–2019 rather than 2002–12), and I exclude a longer period to ensure that the studied post-GFC period does not contain dynamics from the GFC (2008–10 rather than 2008Q3–2009Q2).

Another closely related work is Tchorek et al. (2017), which uses BMA to identify the determinants of portfolio capital flows, foreign direct investments, and banking flows for 19 AEs and 33 EMEs. The authors study two periods, 1990–2007 and 1990–2011, where the latter includes the GFC. They find that the robust determinants mostly remain the same for both periods. They study a set of 24 potential candidates for robust determinants. For equity, the robust determinants are stock market capitalization and the S&P 500 stock market–index return for EMEs and stock market capitalization and turnover for AEs. For bonds, the robust drivers are inflation and crises for EMEs and public debt, communications infrastructure, and eurozone membership for AEs. I depart from Tchorek et al. (2017) by explicitly analyzing non-overlapping pre-GFC and post-GFC periods, a larger sample, and a distinct set of preselected potential drivers.

I find that the drivers of portfolio flows have changed almost entirely after the GFC, particularly for AEs. The banking and sovereign debt crises during and after the GFC in several AEs have shifted investors' attention to financial sector risk and institutional quality. The changes in the drivers of bond inflows to both EMEs and to AEs reveal that bond investors have become more prudent in the post-GFC period. In the post-GFC period, equity investors also look for sound institutions in EMEs, but contrary to bond investors, they prefer to invest in less developed economies in search of a higher return. My second finding is that there have not been major shifts in the relative importance of global push and country-specific pull factors. Equity flows to EMEs continue to be driven by country-specific pull factors. This makes investing in equity more appealing for both international investors and receiving countries, as these flows are less influenced by global factors and therefore offer diversification benefits and are less prone to global shocks. Finally, my results indicate that the Lucas paradox still holds, although with shifts in the explanations or channels. In the post-GFC period, institutions are more dominant than development. An exception is portfolio equity inflows to EMEs that increase for poorer countries, confirming the neoclassical model.

The findings can be useful for policy makers in EMEs. In the post-GFC period, portfolio bond inflows have doubled, while portfolio equity inflows have decreased by more than half. More portfolio bond inflows make EMEs more vulnerable to sudden stops of capital flows (Forbes and Warnock, 2014). Lower portfolio equity inflows to EMEs, which are driven primarily by country-specific pull factors, do not help EMEs become more immune to global shocks. To curb these trends, EMEs should stimulate international investors to opt for equity rather than bonds in their portfolio investments. To stimulate equity inflows, policy makers should increase regulatory quality rather than easing capital controls, since the latter stimulates foreign direct investment but reduces portfolio equity inflows. For scholars, my results indicate that the push-pull framework and the Lucas paradox continue to be relevant. The changes in the individual drivers reveal shifts in the dynamics of portfolio capital inflows, such as a shift to more prudence for bond investors and the increased importance of institutions to explain the Lucas paradox.

The main contribution of this paper is the explicit comparison and analysis of pre-GFC and post-GFC drivers of portfolio inflows in separate analyses for a large sample of AEs and EMEs. The few existing comparisons include the GFC or its immediate aftermath in the post-GFC period, which may affect the results. Apart from the aforementioned Ahmed and Zlate (2014) and Tchorek et al. (2017), Avdjiev et al. (2020) analyze drivers of bond flows to EMEs, using time windows that includes the GFC (2001Q1–2008Q4 and 2009Q1–2013Q4). Hannan (2017) identifies key drivers of portfolio inflows to EMEs for the post-GFC period only (2009Q3–2015Q4). The comparison reveals changing dynamics of portfolio inflows after the GFC, and is useful for policymakers. The results also indicate that the push-pull framework and the Lucas paradox remain relevant after the GFC, although with different channels.

The remainder of this paper is structured as follows. I present my methodology in Section 2 and my data in Section 3. Section 4 contains the empirical results, and Section 5 concludes.

2 Methodology

2.1 Model specification

I use the following model with portfolio capital inflows as a percentage of GDP as the dependent variable $Y_{i,t}$ for country i (i= 1, 2, .., N) in year t (t = 1, 2, .., T):

$$\begin{aligned} Y_{i,t} = \beta_0 + \beta_1 X_{1,i,t-1} + \beta_2 X_{2,i,t-1} + ... + \beta_K X_{K,i,t-1} \\ + \gamma_1 Z_{1,t} + \gamma_2 Z_{2,t} + ... + \gamma_M Z_{M,t} + \delta_1 D_1 + ... + \delta_R D_R + \epsilon_t, \quad (1) \end{aligned}$$

with $X_{k,i,t-1}$ ($k = 1, 2, .., K$) the K country-specific variables that are lagged one period, $Z_{m,t}$ ($m = 1, 2, .., M$) the M global variables, and D_r ($r = 1, 2, .., R$) the R regional dummies.

Capital flows and some country-specific variables may be endogenous. For example, large portfolio capital inflows may lead to high stock market returns when demand for stocks increases, while high stock market returns can cause foreign investors to purchase stocks. How to address the endogeneity problem is an open issue in the model-averaging literature. One proposed method is Instrumental Variables (Eicher and Leukert, 2009; Lenkoski et al., 2014). In a two-step approach, potentially endogenous variables are replaced by instruments. This raises two concerns. The first is the uncertainty surrounding the selection of endogenous variables and exogenous variables. The second concern is the selection of the instrumental variables. We need to have as many instruments as endogenous regressors to guarantee identification (Moral-Benito, 2015). With a large number of country-specific variables (19) in my panel setting, the selection of endogenous and instrumental variables complicates the Instrumental Variables approach.

Other suggested methods are the dynamic panel model, as in Moral-Benito (2013), and the global VAR model, as in Chisiridis et al. (2022). These models are also not appropriate for my data sample, because of the short time dimension, particularly in the post-GFC period (2011–19). Therefore, I opt for an approach employed by Benkovskis et al. (2020). By using a lag of one year for the country-specific variables, I remove contemporaneous endogeneity, and I assume that realizations of the regressors one or more years back in time are independent of the capital flows.

Following Barro (1996) and De Santis and Luhrmann (2009), I do not include country-fixed effects. The disadvantage of fixed effects is that time-constant factors cannot be included in $X_{k,i,t-1}$, as they cannot be distinguished from time-constant unobservables. In other words, by filtering out all the cross-country differences in levels, fixed effects take away much of the economically meaningful part of the analysis, as some of the structural determinants of international capital flows mainly vary across countries, not across time (Barro, 1996). I include several structural factors that vary little over time, hence the decision not to include country fixed effects. By running separate regressions for AEs and EMEs and by using regional dummies, I can account for differences in income and geographic region.

2.2 Bayesian Model Averaging

Traditionally, researchers try to find the optimal prediction model specification by searching for the best possible combination of explanatory variables to estimate the dependent variable. This often results in a specification that is sensitive to minor changes in the list of variables, and to addition or exclusion of data observations. Instead of looking for the best possible regression specification, the researcher could explicitly acknowledge that the 'true' model is not known, and account for uncertainty in model specification (Maltritz and Molchanov, 2013). From a theoretical point of view, there is a trade-off in the model selection. Using all the available covariates reduces the approximation bias, but it leads to overfitting and to a larger variance of the estimator. Using parsimonious models may lead to inconsistent estimators because of relevant omitted variables (Lucchetti et al., 2022). Several methods have been developed to identify a set of robust indicators. These methods use information from all possible combinations of the indicators, rather than a single selected model, making the results more informative.

One of the first methods is the Extreme Bounds Analysis (EBA), introduced in economics by Leamer (1985) and McAleer et al. (1985). Here, all possible combinations of the indicators are considered. The more consistent the sign of the coefficient in all possible combinations where the indicator is included in, the more robust the indicator is. In general, the method lacks a statistical framework, which is provided by the Bayesian Model Averaging (BMA) method that has been applied in economics since the late 1990s.

The BMA strategy is to estimate models with all possible combinations of the explanatory variables, but instead of focusing on the sign of the coefficients, it computes the average estimates from a range of different models, using weights that reflect the models' goodness of fit (Lucchetti et al., 2022). In other words, the predictive distribution of a variable of interest is a weighted average of its predictive distributions under the different candidate models, where the weights are equal to the models' posterior probabilities given the data at hand (Porwal and Raftery, 2022).

Using the linear regression model for a stacked panel, we estimate each of the M_j model specifications that can be constructed from the regressors X:

$$y = X\beta + \epsilon, \epsilon \sim N(0, \sigma^2 I_L) \tag{2}$$

where $y = (y_1, \ . \ . \ . \ , y_L \ )'$ is an L x 1 vector of the dependent variable, where L is the total number of country-year observations, so for an unbalanced panel with N countries, $L = \sum_{i=1}^{N} T_i$ (T_i representing the number of periods for country i). X is a L x q matrix of regressors in the model, where q is the number of independent variables. β is the q x 1 vector that contains the parameters to be estimated, and ϵ the L x 1 vector of the random shocks. The total number of models that can be constructed with q indicators is 2^q. Each model M_j ($j = 1, \ . \ . \ . \ , 2^q$) yields parameters β^j.

The posterior model probability $P(M_j|y)$ can be calculated using Bayes' Rule:

$$P(M_j|y) = \frac{f(y|M_j)P(M_j)}{\sum_{i=1}^{2^q} f(y|M_i)P(M_i)}, \tag{3}$$

with $f(y|M_j)$ the marginal likelihood of model specification M_j, and $P(M_j)$ the prior model probability that M_j is the true model.

BMA requires prior distributions for the unknown parameters under the various models M^j for $j = 1, \ ... \ , 2^q$. I use a conditional prior for the j-th model's parameters $(\beta^j|\sigma^2)$

with zero mean and prior covariance given by $g(X_j'X_j)^{-1}$. This prior covariance, originally proposed by Zellner (1986), is proportional to the posterior covariance arising from the sample $(X_j'X_j)^{-1}$, with the scalar g determining the importance attributed to the prior beliefs of the researcher. Many options for choosing parameter prior g and the prior sample space have been proposed in the literature. For the parameter prior g, I employ the widely used Unit Information Prior (g-UIP), proposed by Kass and Wasserman (1995), which corresponds to taking $g = N$, the sample size. For the a priori model space, I assume a uniform distribution. When there is little prior information about the relative plausibility of the models considered, the assumption that all models are equally likely a priori is a reasonable "neutral" choice (Hoeting et al., 1999). Thus, I assign equal prior probabilities to each model; in other words, I assume that the prior model probabilities ($P(M_j)$) follow a uniform model. With these choices I follow Eicher et al. (2012) and Babecky et al. (2013) with the assumptions on the parameter prior g and the a priori model space, as these priors perform well in forecasting exercises.

The expected coefficient for β, the posterior mean, is calculated as the weighted average of the coefficients for β in all equations where the variable is included, with the weights equal to the models' posterior probabilities:

$$E(\beta|y) = \sum_{j=1}^{2^q} P(M_j|y)E(\beta|y, M_j) \tag{4}$$

The posterior variance[2] is calculated as:

$$V(\beta|y) = \sum_{j=1}^{2^q} P(M_j|y)V(\beta|y, M_j) + \sum_{j=1}^{2^q} P(M_j|y)[E(\beta|y, M_j) - E(\beta|y)]^2 \tag{5}$$

[2]For derivation of the post mean and post variance I refer to Moral-Benito (2015).

The robustness of a variable in explaining the dependent variable is captured by the probability that a given variable is included in the regression. This is known as the Posterior Inclusion Probability (PIP), and is computed by:

$$PIP = P(\beta_j \neq 0|y) = \sum_{\beta_j \neq 0} P(M_j|y) \tag{6}$$

The PIP is a useful diagnostic for deciding whether an individual explanatory variable plays an important role (Desbordes et al., 2018). I use the rule of thumb of Kass and Raftery (1995): The evidence of a regressor having an effect is weak, positive, strong, or very strong if the posterior inclusion probabilities lie between 50–75%, 75–95%, 95–99% or are greater than 99%, respectively.

With 28 and 30 possible regressors for AEs and EMEs respectively, the number of models to be estimated is enormous (2^{28} exceeds 250 million models). Therefore I employ the widely used Markov chain Monte Carlo (MCMC) sampling method. The method consists of keeping the models with higher posterior probabilities. The number of times each model is kept is used to approximate the posterior model probability (Benkovskis et al., 2020). To obtain the posterior distributions of the parameters I use 100,000 iterations after discarding the first 5,000 burn-in points. All of the computations are performed using the R-package BMS from Amini and Parmeter (2011).

3 Data

The data set contains 75 countries: 32 AEs and 43 EMEs (see Appendix B). I exclude countries with severe data-availability issues,[3] and small countries with extended periods of zero portfolio inflows. Also excluded are countries whose capital flows are disproportional

[3] Additionally, I exclude years at the beginning and end of the series because of hyperinflation or data-availability issues in certain countries: Bulgaria (1996–98), Latvia (1996–98), Russia (1996–97), Venezuela (2014–19)

for fiscal or regulatory reasons: Cyprus, Hong Kong, Ireland, Luxembourg, Malta, Netherlands, and Singapore (Lane and Milesi-Ferretti, 2017).

I use the World Bank categorization of AEs and EMEs. AEs are high income in at least ten years of the time sample (1996–2019). EMEs are low or high middle income in at least five years (see Appendix B for a list of the countries).

Using annual data, I estimate the model for two separate periods, the pre-GFC period (1996–2007) and the post-GFC period (2011–19). The post-GFC period ends in 2019 to avoid the impact of the COVID-19 pandemic on capital flows in 2020. Annual frequency is useful to analyze long-run cyclical trends, because portfolio capital flows at a higher frequency tend to be very noisy (Davis et al., 2021). A second argument for annual frequency is data availability. Using annual data allows me to include more countries and more variables in the sample. Other studies on portfolio capital flows that use annual frequency are Alfaro et al. (2007), De Santis and Luhrmann (2009), Mercado and Park (2011), and Tchorek et al. (2017).

3.1 Portfolio capital inflows

Portfolio capital inflows are expressed as a percentage of GDP. Stylized facts are presented in two dimensions—(i) AEs and EMEs and (ii) pre-GFC (1996–2007) and post-GFC (2011–19)—for bonds and equity flows in Tables 1 and 2 respectively.

Table 1: Bonds portfolio capital inflows, as percentage of GDP

	AEs		**EMEs**	
	Pre-GFC 1996–2007	**Post-GFC 2011–19**	**Pre-GFC 1996–2007**	**Post-GFC 2011–19**
Mean	2.68	1.31	0.63	1.26
Standard deviation	3.32	3.74	2.16	2.00
Coefficient of variation	1.24	2.85	3.45	1.58
Kurtosis	3.61	8.79	11.16	6.85
Skewness	1.50	-1.53	2.26	1.95
Observations	381	288	371	328

Two observations are in order. First, in the post-GFC period, average portfolio bond inflows as a percentage of GDP have dropped substantially in AEs, while the opposite has taken place in EMEs (Table 1). Capital inflows to AEs remain larger than those to EMEs in the post-GFC period. According to the BIS Committee on the Global Financial System, the GFC marks a turning point in the global trend of gross capital flows to EMEs (BIS, 2021). Bank-intermediated credit have declined, which is mirrored by the growing importance of market-based flows—that is, portfolio capital inflows. The post-GFC decrease in capital flows was especially pronounced for banking flows and for AEs, while EMEs and portfolio flows displayed more resilience and even an increase (Lane and Milesi-Ferretti, 2017). The post-GFC period features excess liquidity in AEs that is in search of attractive returns, and with their relatively high yields, EME bonds attract more capital inflows (Avdjiev et al., 2020). According to Forbes and Warnock (2014), most episodes of extreme global capital flow movements are debt-led. The increase in portfolio bond flows could therefore make EMEs more vulnerable to sudden stops of capital flows.

Second, heterogeneity among AEs has grown, as the standard deviation has increased while the mean has halved. Given the large reduction in the mean, the dispersion between the two periods is best compared by the coefficient of variation—calculated as the ratio of standard deviation to mean—which demonstrates a surge in relative dispersion. For EMEs the heterogeneity or dispersion in portfolio bond inflows shows the opposite trend. The dispersion in the portfolio inflows to AEs is confirmed by the increased kurtosis, while the opposite has occurred in EMEs. Skewness shows that these outliers are not equally distributed over the tails. Portfolio bond flows to AEs have experienced a major change in skewness. This implies that the economies contain more outliers with high portfolio capital inflows before the crisis, while in the post-GFC period, outliers can be found in low (or even negative) capital inflows. For EMEs the skewness decreases slightly but remains clearly biased toward higher capital inflows.

Portfolio equity inflows as a percentage of GDP are smaller than portfolio bond flows, as the comparison of the means in Tables 1 and 2 shows. The average equity inflows have halved since the GFC (see Table 2). In general, AEs and EMEs demonstrate similar trends in terms of equity inflows, unlike bond inflows.

Table 2: Equity portfolio capital inflows, as percentage of GDP

	AEs		**EMEs**	
	pre-GFC 1996–2007	**post-GFC 2011–19**	**pre-GFC 1996–2007**	**post-GFC 2011–19**
Mean	0.80	0.38	0.32	0.13
Standard deviation	1.55	1.22	0.97	0.56
Coefficient of variation	1.94	3.16	2.99	4.33
Kurtosis	11.49	6.68	16.38	7.24
Skewness	0.82	-0.35	2.65	1.14
Observations	381	288	394	319

3.2 Explanatory variables

With the objective that the BMA method identifies the most robust drivers, I select a large number of explanatory variables, based on the literature and stylized facts. I refer the reader to Appendix A for the description, source, literature reference, and expected sign of each explanatory variable. I have revised all variables for pairwise correlations, excluding one indicator for any pair of indicators with an absolute correlation greater than 0.70.

Following the literature, I distinguish between global push factors, described in Section 3.2.1, and country-specific pull factors, described in Section 3.2.2. Country-specific pull indicators outnumber global push indicators because there has been more discussion on the importance and identification of country-specific than global determinants (Cerutti et al., 2019).

3.2.1 Global push factors

For global push factors, the relation depends on which markets (bonds or equities) and which countries (advanced or emerging economies) are considered. For example, higher global risk aversion leads to a reduction in risky assets, including investments in EMEs and equity investments in AEs, while AE bonds serving as safe havens, capture more capital inflows (Li, 2021).

I select seven commonly used indicators for the global push factors. A fall in real rates of return in AEs leads to an increase in capital flows to EMEs, as investors search for higher yields. According to Byrne and Fiess (2016), long-term interest rates appear more connected to global financial developments than short-term rates, hence my choice of the 10-year US Treasury bond yield rather than the three-month T-bill rate. The VIX index is a widely used proxy for global risk aversion (Koepke, 2019). High global risk aversion leads to a withdrawal of investments in risky assets, which include emerging markets and equity. It tends to drive a flight to safety, encouraging investments at home or in countries that are perceived as safe havens (Montiel, 2014; Li, 2021). During a large financial crisis, a liquidity squeeze and a freezing of credit markets can make it difficult for financial and nonfinancial institutions to obtain capital. Following Fratzscher (2012), I use the TED spread to proxy this liquidity risk in the financial system. A higher TED spread implies that as markets dry up, international investors become more reluctant to invest. The time spread is a measure for the slope of the US yield curve. A flatter US yield curve induces investors to seek yields in riskier securities, such as EME bonds and equity. It also implies that EMEs can issue long-term, dollar-denominated bonds for a relatively lower yield, thus accelerating issuance of dollar bonds by borrowers outside the US (McCauley et al., 2015). For AEs, a flat yield curve is a widely used predictor for economic slowdowns (Croushore and Marsten, 2016). In summary, I expect a positive relation for AEs and a negative relation for EMEs. There is some evidence in the literature that global economic growth encourages portfolio capital flows to EMEs (Koepke, 2019). The impact of global commodity prices on capital flows has been studied widely, including the connection between the commodity-price supercycle and the ebbs and flows of financial capital (Reinhart et al., 2016). For commodity-producing countries, price increases lead to higher investments, financed by capital inflows. Last, there is mixed evidence on the impact of global stock market returns on capital flows. On the one hand, higher global stock prices reflect a positive global economic outlook, which also boosts stock prices in the rest of the world (Tchorek et al., 2017). On the other hand, an underperforming US stock market leads to an increase of portfolio capital flows to EMEs, as investors seek a higher return (Sarno et al., 2016).

3.2.2 Country-specific pull factors

I preselect 19 country-specific variables, that I divide in two groups: cyclical and structural factors. The cyclical factors include country-specific time varying factors. The structural factors include slow moving variables that represent specific characteristics of the economy (Hannan, 2018).

The first group contains ten cyclical factors. Larger stocks of international reserves are linked to higher capital inflows (Alberola et al., 2016; Hannan, 2017). International financial integration has made EMEs more vulnerable to shifts in global portfolio weights (Alberola et al., 2016; Lane and Milesi-Ferretti, 2017), and by accumulating foreign exchange reserves, EMEs can reduce this vulnerability. A higher domestic interest rate attracts more portfolio bond inflows, particularly when international investors search for high yields (Sarno et al., 2016). High domestic stock market–index returns attract more portfolio equity inflows in search of a high return (Koepke, 2018). Capital inflows are procyclical in most advanced and developing economies (Kaminsky et al., 2004), so I expect a positive relation between domestic economic growth and gross capital inflows. The fiscal balance and the public debt level can have two opposite effects on capital flows. On the one hand, a higher fiscal deficit and larger public debt leave governments with less room to respond to adverse demand shocks, which reduces creditworthiness and capital inflows (Bems et al., 2016; Koepke, 2019). On the other hand, a higher fiscal deficit and larger public debt imply more financing needs, triggering more capital inflows (Koepke, 2019). A higher credit-to-GDP ratio is expected to result in more portfolio equity inflows, because more credit indicates a more developed financial market and thus less information asymmetry (Tchorek et al., 2017). I expect a negative relation between the current account balance and gross capital inflows. A current account deficit reflects increased financing needs, which are funded by net capital flows or depletion of reserves. Koepke (2019) finds that this effect outweighs the opposing effect of deteriorated creditworthiness when lenders and rating agencies perceive higher risk. Exchange rate volatility can reduce a country's investment attractiveness and thus reduce portfolio capital inflows (Tchorek et al., 2017; Mercado and Park, 2011; Baek, 2006). Foreign investors in EMEs' local-currency-denominated debt and equity are affected directly by a depreciation (appreciation) of the real effective exchange rate because returns in the investors' home currency decrease (increase), which leads to smaller (larger) capital inflows (Koepke, 2019).

The second group consists of nine structural factors. Several of these indicators can be used to provide possible explanations for the Lucas paradox. The Financial Markets Development Index is a relative ranking of countries on the depth, access, and efficiency of financial markets. A more developed financial infrastructure is expected to attract more capital inflows (Hannan, 2017). Countries frequently introduce capital controls on portfolio flows to limit the consequences of capital flight, thereby making domestic financial markets less attractive for foreigners (De Santis and Luhrmann, 2009). However, empirical evidence on the role of capital controls is not decisive, as the impact of capital controls depends on the development of the domestic financial system (Bush, 2019) and the global financial cycle (Bems et al., 2016). Capital openness is proxied by the Chinn-Ito index, a (de jure) index measure, with higher values indicating fewer capital controls. Countries with higher trade openness tend to be more sensitive to global push factors and extreme capital-flow movements (Cerutti et al., 2019). Fixed exchange rate regimes attract larger volumes of capital inflows compared to flexible ones since currency pegs reduce transaction costs, which encourages cross-border investment (Magud et al., 2014). Reliable institutions enhance transparency, and a sound legal and political system offers better protection against fraud (Alderighi et al., 2019). Alfaro et al. (2008) show that low institutional quality is the leading explanation for the Lucas paradox. I use the Regulatory Quality Index as a measure for institutional quality. Polity2 measures the degree of democracy and is also used as a proxy for institutional quality (Lashitew and Werker, 2020). Democratic regimes have more accountability and reduced country risk, with a positive impact on capital inflows (Papaioannou, 2009; Alfaro et al., 2007). Income per capita is a proxy for the development of the economy. According to the neoclassical model of trade and growth, investors allocate capital to economies with higher potential output growth—that is, EMEs with low income per capita, attracted by expectations of higher asset returns (De Santis and Luhrmann, 2009). However, according to Lucas (1990), capital flows to wealthy economies with higher levels of human development. The human development index is highly correlated with the income per capita (Islam, 1995). Exporters of natural resources are expected to save a portion of their export income for intergenerational-equity reasons, thus leading to higher current account balances (Cubeddu et al., 2019). This in turn is associated with lower capital inflows as described before. More uncertainty, proxied by the text-based EIU Uncertainty Index, will ceteris paribus lead to lower capital inflows. Regional dummies are added (two for AEs and four for EMEs) to account for regional differences, following suggestions in the literature (Baek, 2006; Tchorek et al., 2017).

In total, I use 26 explanatory variables, two regional dummies for AEs, and four regional dummies for EMEs. Appendix A provides the full list and data sources.

4 Empirical results

A comparison of the robust determinants of bond portfolio capital inflows is presented in Section 4.1, and a comparison for equity portfolio flows in Section 4.2. I first identify the robust determinants in the pre-GFC period (1996–2007) and in the post-GFC period (2011–19), separately for AEs and EMEs. Second, I compare the determinants in these two periods and analyze the differences.

4.1 Bond portfolio inflows

Portfolio bond inflows to AEs decreased by more than half in the post-GFC period (see Table 1). I analyze whether this change in volume has also affected the drivers of these inflows. The most robust determinants are presented in Table 3, while the complete results can be found in Appendix C, Table 14.

Portfolio bond inflows to AEs in the pre-GFC period are driven by both country-specific pull factors and global push factors. The expected negative sign of the mean coefficient of Current Account to GDP (-0.195) implies that a current account deficit leads to an increase in portfolio bond inflows, which confirms Koepke (2019). The positive sign of the mean coefficient of Fiscal Balance to GDP (0.142) implies that a fiscal surplus (or lower deficit) leads to an increase in portfolio bond inflows. Combining these two results, portfolio bond inflows are directed toward AEs with a larger current account deficit and a more sound fiscal balance. The first implies that the effect of financing needs weighs more than the

Table 3: Robust determinants of bond portfolio capital inflows to AEs, before and after the GFC

Pre-GFC (1996–2007)				**Post-GFC (2011–19)**			
	PIP	**P.Mean**	**P.SD**		**PIP**	**P.Mean**	**P.SD**
Current Acct to GDP	1.000	-0.195	0.034	Regulatory Quality	0.999	2.150	0.541
Trade Openness	1.000	-0.035	0.006	TED Spread	0.861	-8.497	4.314
Dummy Rest of World	1.000	-2.849	0.477	Real GDP Growth	0.774	0.235	0.157
VIX	0.999	-0.134	0.030				
Fin-Market Development	0.990	3.417	1.020				
Fiscal Balance to GDP	0.969	0.142	0.050				
Dummy Non-euro Europe	0.716	-0.703	0.529				
GDP per Capita	0.702	1.050	0.824				
10-Year T-Bond Yield	0.631	-0.310	0.279				

Notes:
PIP: posterior inclusion probability; P.Mean: posterior mean; P.SD: posterior standard deviation.
Determinants are ordered by descending PIP, ranging from 1.00 to 0.50. The evidence the regressor has an effect is very strong, strong, positive, or weak if the posterior inclusion probabilities are greater than 0.99, 0.95–0.99, 0.75-–0.95, or 0.50—0.75, respectively. Regressors with a PIP below 0.50 are not shown.
Dark gray colored: global push factors; light gray colored: country-specific pull factors; no color: regional dummies.

opposing effect of deteriorated creditworthiness, and the latter indicates the opposite. The other robust pull factors reflect structural country features. The negative sign for Trade Openness confirms Hannan (2017), with the novelty that I find this relation for AEs. A possible explanation is that countries with higher trade openness are more sensitive to global push factors and more volatile (Cerutti et al., 2019), which reduces portfolio investments from nonresidents. The positive signs of Financial Market Development and Real GDP per Capita demonstrate that investors prefer to invest in countries that have a more developed economy and financial infrastructure. Two robust push factors, global risk aversion (VIX) and 10-Year US T-Bond Yield, reveal that investors distinguish between AEs. The negative sign of the mean coefficient of VIX (-0.134) implies that not all AEs in the sample are considered safe havens. Similarly, the negative sign of the 10-Year US T-Bond Yield (-0.310) implies that when the T-bond yield increases, investors reduce their bond investments in other AEs. The regional dummies reflect large capital flows to the eurozone in 1996–2007, mainly to finance investments in the periphery of the eurozone, confirming Tchorek et al. (2017).

In the post-GFC period, three indicators—two pull factors and one push factor—are identified as robust, and all have the expected sign. Investors prefer to invest in countries with higher regulatory quality, which may be a consequence of the banking crises in several AEs during the GFC (Laeven and Valencia, 2018). It shows the importance of institutions as an explanation for the Lucas paradox, and confirms Alfaro et al. (2008). Along the same lines, the robustness of the TED spread demonstrates that the GFC led to an increased perception of financial-sector risk. Last, more portfolio bond investments flow to AEs with higher economic growth, which is expected since capital flows are procyclical.

Comparing the robust drivers in the two periods, the drivers change entirely in the post-GFC period. Global risk aversion and sensitivity to global events, proxied by trade openness, are replaced by aversion to financial-institution risk, as proxied by the TED spread. In terms of structural country-specific drivers, the pre-GFC focus on development of financial markets and the economy is replaced by a focus on regulatory quality. The GFC seems to have changed the focus toward financial-sector risk and regulatory quality, which seems to be a natural consequence of the financial crises that hit several AEs during the GFC. Finally, the proportion of push to pull factors remains similar, which implies that the push-pull framework continues to hold.

Portfolio bond inflows to EMEs have surged in the post-GFC period (see Table 1). Therefore, I also expect a change in the set of robust drivers for EMEs, which is confirmed in Table 4. Complete results are shown in Appendix C, Table 15.

In the pre-GFC period, fiscal balance and current account balance are robust indicators with a negative sign, indicating that the effect of financing needs weigh more than the opposing effect of deteriorated creditworthiness. Stated differently, EMEs finance current account and fiscal deficits with bond inflows. Foreign investors reduce bond investments in

Table 4: Robust determinants of bond portfolio capital inflows to EMEs, before and after the GFC

Pre-GFC (1996–2007)				Post-GFC (2011–19)			
	PIP	**P.Mean**	**P.SD**		**PIP**	**P.Mean**	**P.SD**
Fiscal Balance to GDP	0.732	-0.088	0.065	Change Reserves	0.873	0.016	0.008
Current Acct to GDP	0.654	-0.039	0.034	VIX	0.774	-0.071	0.048
VIX	0.616	-0.034	0.032	GDP per Capita	0.687	0.410	0.348
				Polity2	0.640	0.045	0.041
				Current Acct to GDP	0.582	-0.036	0.035

Notes: See Notes Table 3

EMEs when global risk aversion (VIX) increases, which confirms the widely documented evidence that investors consider EME bonds a risky asset class.

In the post-GFC period, current account and VIX remain robust and with the same sign. Three other country-specific drivers are robust in the post-GFC period. Nonresidents prefer to invest in countries with increasing reserves, as these reduce the risk of an exchange rate depreciation and fiscal stress, because authorities have more funds to defend the exchange rate or to pay off foreign currency-denominated debt. Nonresidents invest more in higher-middle-income EMEs rather than in lower-middle-income EMEs, which fits with an explanation of the Lucas paradox, namely that more developed countries attract more capital flows. The positive sign of Polity2 implies that bond inflows are higher for more democratic political regimes, which are associated with accountability and higher institutional quality (Lashitew and Werker, 2020). This fits with another explanation of the Lucas paradox, namely institutional quality (Alfaro et al., 2008). These results do not confirm Avdjiev et al. (2020), which finds that since the GFC, global push drivers have been more important for bond inflows. A possible explanation lies in the authors' sample, as they analyze a period that includes the GFC.

Robust drivers in the post-GFC period coincide partially with the drivers in the pre-GFC period, but the differences reveal a shift toward more prudence on the part of investors. Instead of financing EMEs with a fiscal deficit, in the post-GFC period portfolio investments have flowed to EMEs with higher reserves, which provide more security to investors. The robustness of structural country-specific drivers in the post-GFC period is in line with two possible explanations for the Lucas paradox. Investors prefer to invest in EMEs that are more developed (higher GDP per capita) and have better institutions (more accountability, proxied by Polity2). The proportion of push to pull factors remains similar. Comparing AEs with EMEs, the robust drivers of bond inflows to AEs have changed entirely, while for EMEs two drivers are robust in both periods. In this respect, the GFC has had a larger impact on bond flows to AEs, not only in size but also in dynamics.

4.2 Equity portfolio inflows

The robust drivers for equity portfolio capital inflows to AEs are shown in Table 5, and the complete results in Appendix C, Table 16.

Table 5: Robust determinants of equity portfolio capital inflows to AEs, before and after GFC

Pre-GFC (1996–2007)				**Post-GFC (2011–19)**			
	PIP	**P.Mean**	**P.SD**		**PIP**	**P.Mean**	**P.SD**
World Economic Growth	0.850	0.335	1.000	Time Spread	0.911	0.392	0.167
Trade Openness	0.598	-0.005	0.000	VIX	0.850	-0.067	0.036
Regulatory Quality	0.588	0.308	1.000	Exch Rate Volatil	0.688	0.113	0.093
				Trade Openness	0.571	-0.003	0.003

Notes: See Notes Table 3

In the pre-GFC period, higher world economic growth leads to more equity portfolio flows, but the impact depends on the trade openness of the country. More open AEs are perceived as more vulnerable for global shocks and are thus riskier, resulting in lower portfolio equity inflows. Higher regulatory quality is another robust country-specific structural factor to attract more portfolio equity flows.

In the post-GFC period, most robust indicators relate to risk. Global risk aversion, measured by VIX, is robust and has the expected negative sign, identifying equity as a risky asset class. The expected positive sign of the time spread confirms that a flat yield curve is a predictor of an economic slowdown and leads to lower equity investments.

Exchange rate volatility, a proxy for exchange rate risk, has a positive sign, implying that more volatility in the exchange rate is followed by more capital inflows. The volatility of the euro vis-á-vis the US dollar plays a major role, as 13 out of the 32 AEs in the sample belong to the eurozone.

Robust drivers change completely after the GFC, with the exception of trade openness, which is weakly robust in both periods. The robust drivers in the post-GFC period are associated with risk, possibly because of the banking crises during the GFC and the European sovereign debt crisis. The proportion of push to pull factors remains approximately the same over time. However, a more careful examination shows that all global drivers are positive to strongly robust, while all country-specific drivers are only weakly robust. In other words, equity portfolio inflows to AEs are driven predominantly by global push factors.

The robust drivers for equity portfolio capital inflows to EMEs are shown in Table 6, and the complete results in Appendix C, Table 17. In both periods, portfolio equity flows to EMEs are driven by country-specific pull factors, with the exception of VIX. The change in the robust drivers provides insight into the changing dynamics before and after the GFC.

Table 6: Robust determinants of equity portfolio capital inflows to EMEs, before and after GFC

Pre-GFC (1996–2007)				**Post-GFC (2011–19)**			
	PIP	**P.Mean**	**P.SD**		**PIP**	**P.Mean**	**P.SD**
Credit to GDP	1.000	0.009	0.001	Capital Openness	0.996	-0.142	0.032
Dummy Sub-Sah Africa	1.000	0.747	0.138	Regulatory Quality	0.993	0.491	0.133
Polity2	0.999	0.046	0.011	GDP per Capita	0.935	-0.223	0.087
Capital Openness	0.993	-0.142	0.038	Trade Openness	0.908	-0.003	0.002
VIX	0.983	-0.031	0.009	Dummy Asia	0.734	-0.175	0.130
Change reserves	0.926	0.003	0.001	Natur-Resource Rev	0.513	0.010	0.011
Current Acct to GDP	0.781	-0.019	0.013	VIX	0.500	-0.011	0.013

Notes: See Notes Table 3

In the pre-GFC period, three structural factors drive portfolio equity flows. Credit to GDP has the expected positive sign. Increasing credit indicates a more developed financial market with less information asymmetry (Tchorek et al., 2017), which attracts more foreign capital. The expected positive sign of Polity2 implies that nonresidents invest more in democratic regimes, as these are expected to be more accountable than autocratic regimes. The negative sign of Capital Openness implies that a country that is more open to international capital flows will receive less equity inflows than a more restrictive country. To assess this unexpected outcome, I run additional regressions. I find a statistically significant and positive impact of capital openness on foreign direct investment and no significant relation between capital openness and portfolio bond inflows. This demonstrates that with fewer capital restrictions, nonresident investors opt for foreign direct investment, thus reducing portfolio equity investments. The positive sign of Change in Reserves implies that equity investors prefer countries with increasing reserves, because these countries have more means to stabilize the exchange rate or to pay foreign currency-denominated debt. A current account deficit can be considered beneficial to equity investors, if imports are used to purchase productive assets. The assets lead to more economic growth, which enables the country to repay the foreign capital associated with the current account deficits (Cubeddu et al., 2019). The only robust global push factor is VIX, confirming that equity investments in EMEs are considered a risky asset category.

In the post-GFC period, Capital Openness and VIX continue to be robust and have negative signs. With the exception of VIX, all robust drivers are country-specific and structural. Regulatory quality has the expected positive sign, which points toward equity investors' preference for countries with higher institutional quality. The negative sign of GDP per Capita implies that investors prefer to invest in relatively underdeveloped economies. This result is in line with the neoclassical theory that capital flows to the poorer country in search of higher returns. It contrasts with motivation for bond investments in

EMEs, which prefer more developed EMEs. The negative sign of Trade Openness coincides with Hannan (2017), and reveals that investors prefer exposure in countries with less trade openness, because these countries are less sensitive to global push factors and less volatile. Natural Resource Revenues is weakly robust and has the expected positive sign, as several EMEs list large commodity producers on their stock exchanges, which attract foreign equity investors when the prices are high, as in Latin America in the commodity price boom in the early 2010s. In the subsequent years with lower commodity prices, portfolio equity inflows have lowered for the region (Goncalves et al., 2019). Regional differences matter: countries from sub-Saharan Africa receive substantially more than the base region (Latin America) in the pre-GFC period. In the post-GFC period, Asia has received substantially less than Latin America.

Overall, equity capital flows to EMEs are mainly driven by country-specific pull factors, more specifically structural indicators. When comparing the two periods, all but two indicators change after the GFC. The robustness of the GDP per Capita variable in the post-GFC period stands out, as it is in line with the neoclassical theory of capital. All other structural variables provide evidence for the alternative explanations of the Lucas paradox.

While equity inflows to AEs are driven mainly by global push factors (Table 5), the drivers for EMEs are dominated by country-specific structural indicators (Table 6). Comparing the robust drivers of bond inflows to EMEs (Table 4) and equity inflows to EMEs (Table 6), I observe several insightful similarities and differences. VIX is robust and has a negative sign for both categories and both periods, confirming the widely documented importance of global risk aversion for EMEs. The robustness and sign of GDP per capita in the post-GFC period reveal that bond investors prefer more developed EMEs, as the risk is lower, while equity investors prefer less developed EMEs in search of high returns.

4.3 Robustness checks

4.3.1 Alternative selection methods

The BMA technique is not the only data-driven method to identify a set of robust determinants. For robustness checks, I apply two alternative methods: least absolute shrinkage and selection operator (LASSO) and extreme bounds analysis (EBA).

Unlike BMA, LASSO is based on a penalizing likelihood approach. LASSO is the first and most commonly used penalized likelihood approach (Porwal and Raftery, 2022). LASSO provides an efficient procedure to identify from a large set of predictors those exhibiting the strongest effects. It sets some coefficients to zero, while it shrinks other coefficients. A penalty is imposed to reduce the number of variables and simultaneously shrink other variables (Tibshirani, 1996). I adjust the penalty such that the number of determinants is comparable to the number of robust determinants according to the BMA approach.

EBA has been criticized for its lack of statistical foundations (Eicher et al., 2012), but it has intuitive appeal and is still widely employed. I follow the definition in the seminal paper of Leamer (1985), in which an interval is constructed for each indicator, running from the lowest to the highest value obtained from all the regressions the indicator was included in. If this interval does not contain zero, then the indicator is robust.

The results generated by BMA, LASSO, and EBA are shown in Appendix C, Tables 18 and 19. The selected determinants that are identified with the LASSO method coincide strongly with the results yielded by the BMA approach. The EBA method selects a larger set of robust determinants, but in all cases except one, it includes all robust indicators that BMA identifies. For the robust drivers identified by the BMA method, the signs coincide with the signs generated by LASSO and EBA.

I also perform a panel OLS regression with the robust determinants as identified by the BMA model, and I compare the coefficients with the posterior mean of the BMA model. The coefficients are very close and always exhibit the same sign. The results are reported in Appendix C, Tables 20 and 21.

Lastly, I have checked the panel regression estimators with heterogeneous estimators using the mean group estimation approach, originally proposed by Pesaran and Smith (1995). For each country, the set of robust estimators as identified by the BMA approach is used as the set of explanatory variables. The mean of the coefficient of all countries is then compared to the coefficient in the BMA and panel OLS methods. The results are reasonably close, and are available upon request. Possible explanations for the differences can be found in the data. The mean group estimation method is recommended for datasets with large T (time periods), while my samples contain 12 and 9 periods for pre-GFC and post-GFC periods, respectively. Additionally, institutional variables such as capital openness and political system have low or no variation over time, and regional dummies that are robust in several of the panel regression results cannot be included in the individual country regressions.

4.3.2 Alternatives for global risk measures

I use the VIX as the proxy for global investor risk aversion. As alternatives, I use the Economic Policy Uncertainty (EPU) index and the credit spread of corporate BBB-rated US bonds over US Treasury securities (Koepke, 2019). Although there is some overlap for EMEs, VIX is robust in more subsamples than the other two measures are, which is expected given the body of evidence in the literature that VIX is a key driver of capital flows. I summarize the results in Appendix C, Tables 22 and 23.

4.3.3 Changes in the sample

The sample of 32 AEs includes 10 countries that are considered EMEs for at least for ten years of the sample period (1996–2019): Chile, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Oman, and Slovak Republic. Excluding these countries and thus focusing only on countries that are considered AEs during the entire period (1996–2019) does not change the main findings. For EMEs, the conclusions do not change when using Asia as the base instead of Latin America. Excluding two countries, US and China, from the sample has no impact on the sets of robust indicators. Results are available upon request.

5 Conclusions

The decade following the GFC has seen significant changes in the volume and composition of capital flows (Garcia Lopez and Stracca, 2021). Portfolio investments in EME bonds on the part of nonresidents have surged, while portfolio inflows to AEs and portfolio equity inflows to EMEs have plummeted. It is to be expected that such a high-impact event as the GFC affects the drivers of gross portfolio inflows. Several empirical works have looked at the influence of the GFC on capital flows, including a comparison of the drivers of portfolio capital flows before and after the GFC. However, these studies include the GFC or its immediate aftermath in the post-GFC period, which affects the results. I compare the robust drivers in the pre-GFC period (1996–2007) and the post-GFC period (2011–19). Instead of preselecting determinants, I use a data-driven method to identify robust drivers of gross portfolio inflows from a wide range of potential drivers, both global push factors and country-specific pull factors. I apply the method to different subsamples, distinguishing between income groups (AEs versus EMEs) and between asset classes (bonds versus equity).

I find that robust drivers before and after the GFC have changed significantly, particularly for AEs. This result departs from Tchorek et al. (2017) that find no major changes. The selected time horizon (2011–19 vs 1990–2011) is likely the cause for these different conclusions. A possible explanation is that the banking and European sovereign debt crises that hit several AEs directly, as well as the monetary response in AEs during and after the GFC, have changed the motivations of investors in AEs more than in EMEs. This explanation is confirmed by the robust drivers of AE bonds in the post-GFC period, in particular regulatory quality and the liquidity risk in the international financial system. Drivers of portfolio equity flows to AEs also demonstrate increased attention to risk and vulnerability. Nonresident investments in EME bonds have surged after the GFC, and investors seem to have become more prudent. They prefer to invest in more developed EMEs that accumulate reserves and are more politically accountable. In the language of international portfolio theory, investors prefer investments with lower domestic risk since the GFC. Portfolio equity investments in EMEs are driven by country-specific structural factors. Unlike investors in EME bonds, investors in EME equity prefer less developed economies, with a potentially greater return after the GFC. Not all robust variables change over time. The global risk aversion (VIX) is robust for EME bonds and equity, both before and after the GFC. This result confirms Ahmed and Zlate (2014) and implies that EMEs continue to be considered as risky assets.

My second finding is that the push-pull framework continues to hold. There have been no major shifts in the relative importance of push versus pull factors since the GFC. Both before and after the GFC, drivers of bond flows reflect a similar mix of push and pull factors. Equity flows to EMEs are driven by country-specific, structural factors. These results are in line with Alderighi et al. (2019) and can be observed both before and after the GFC. It makes investing in equity more appealing for international investors, as these flows are less influenced by global factors and therefore fit better in an international investment portfolio. Equity flows to AEs are driven by both country-specific and global factors, however, all country-specific factors are only weakly robust, while global factors are positive to very strong robust, both before and after the GFC.

Finally, for bond portfolio inflows, I find that the Lucas paradox continues to hold after the GFC, but that the explanations or channels have changed. For AE bonds, the focus has shifted from development (real GDP per capita and financial-market development) to institutions (regulatory quality). For EME bonds, the focus in the post-GFC period has been development (real GDP per capita) and institutions (polity2, a proxy for political accountability). For EME equity, institutions are a robust channel before and after the GFC. Additionally, the post-GFC period investors prefer less developed EMEs in search of higher returns. This confirms the neoclassical trade-and-growth theory and contrasts the Lucas paradox.

This study has important policy implications. Equity inflows have dropped severely since the GFC, both for AEs and EMEs, while EMEs have received more bond inflows than before. This is unfortunate according to Forbes and Warnock (2014), which finds that portfolio bond inflows make EMEs more vulnerable to sudden stops of capital flows. My results show that portfolio equity flows to EMEs are primarily driven by country-specific pull factors, which makes the investor and the receiving country less vulnerable to global conditions. For these reasons, EMEs should stimulate international investors to opt for equity rather than bond portfolio investments. My results identify regulatory quality as a better tool than capital openness. I find that more openness lead to a shift in composition: foreign direct investments surge, and portfolio equity inflows decrease. Improving regulatory quality has a stimulating effect on portfolio equity inflows, so it is a more efficient tool for EME policy makers.

Future research can focus on banking flows and foreign direct investment to provide more insight into the capital flow dynamics. Adding indicators of sentiment and expectations (and dispersion) from survey forecasts to the set of potential determinants also merits research.

References

Ahmed, S. and A. Zlate (2014), "Capital flows to emerging market economies: A brave new world?", *Journal of International Money and Finance*, **48**, 221–248.

Alberola, E., A. Erce, and J.M. Serena (2016), "International reserves and gross capital flows dynamics", *Journal of International Money and Finance*, **60**, 151–171.

Alderighi, S., S. Cleary and P. Varanasi (2019), "Do institutional factors influence cross-border portfolio equity flows? New evidence from emerging markets", *Journal of International Money and Finance*, **99**, 102070.

Alfaro, L., S. Kalemli-Ozcan, and V. Volosovych (2007), "Capital flows in a globalized world: The role of policies and institutions", in S. Edwards, editor, *Capital Controls and Capital Flows in Emerging Economies: Policies, Practices and Consequences*, University of Chicago Press, Chicago, IL, 19–71.

Alfaro, L., S. Kalemli-Ozcan, and V. Volosovych (2008), "Why doesn't capital flow from rich to poor countries? An empirical investigation", *The Review of Economics and Statistics*, **90(2)**, 347–368.

Amini, S.M. and C.F. Parmeter (2011), "Bayesian Model Averaging in R", *Journal of Economic and Social Measurement*, **36**, 253–287.

Avdjiev, S., L. Gambacorta, L.S. Goldberg, and S. Schiaffi (2020), "The shifting drivers of global liquidity", *Journal of International Economics*, **125**, 103324.

Babecky, J., T. Havranek, J. Mateju, M. Rusnak, K. Smidkovs, and B. Vasicek (2013), "Leading indicators of crisis incidence: Evidence from developed countries", *Journal of International Money and Finance*, **35**(Supplement C), 1 – 19.

Baek, I.-M. (2006), "Portfolio investment flows to Asia and Latin America: Pull, push or market sentiment?", *Journal of Asian Economics*, **17**, 363–373.

Barro, R.J. (1996), "Democracy and growth", *Journal of Economic Growth*, **1(1)**, 1–27.

Bems, R., L. Catao, Z. Koczan, W. Lian, and M. Poplawski-Ribeiro (2016), "Understanding the slowdown in capital flows to emerging markets", in *World Economic Outlook: Too slow for too long*, International Monetary Fund, Washington DC, 63–99.

Benkovskis, K., B. Bluhm, E. Bobeica, C. Osbat, and S. Zeugner (2020), "What drives export market shares? It depends! An empirical analysis using Bayesian Model Averaging", *Empirical Economics*, **59**, 817–869.

BIS, Committee on the Global Financial System (2021), "Changing patterns of capital flows", *CGFS Papers* 66, Bank for International Settlements, Basel, Switzerland.

Blonigen, B.A. and J. Piger (2014), "Determinants of foreign direct investment", *Canadian Journal of Economics / Revue canadienne d'economique*, **47**(3), 775–812.

Broner, F., T. Didier, A. Erce, and S. Schmukler (2013), "Gross capital flows: dynamics and crises", *Journal of Monetary Economics*, **60**(1), 113–133.

Bush, G. (2019), "Financial development and the effects of capital controls", *Open Economies Review*, **30**, 559–592.

Byrne, J.P. and N. Fiess (2016), "International capital flows to emerging markets: national and global determinants", *Journal of International Money and Finance*, **61**, 82–100.

Calvo, G.A. (1998), "Capital flows and capital-market crises: the simple economics of sudden stops", *Journal of Applied Economics*, **1**, 35–54.

Calvo, G.A., L. Leiderman, and C.M. Reinhart (1996), "Inflows of capital to developing countries in the 1990s", *Journal of Economic Perspectives*, **10(2)**, 123–139.

Ca' Zorzi, M., A. Chudik, and A. Dieppe (2012), "Thousands of models, one story: current account imbalances in the global economy", *Journal of International Money and Finance*, **31**, 1319–1338.

Cerutti, E., S. Claessens, and D. Puy (2019), "Push factors and capital flows to emerging markets: why knowing your lender matters more than fundamentals", *Journal of International Economics*, **119**, 133–149.

Chinn, M.D. and H. Ito (2008), "A new measure of financial openness", *Journal of Comparative Policy Analysis: Research and Practice*, **10**(3), 309–322.

Chisiridis, K, K. Mouratidis, and T. Panagiotidis (2022), "The north-south divide, the euro and the world", *Journal of International Money and Finance*, **121**, 102516.

Croushore, D. and K. Marsten (2016), "Reassessing the relative power of the yield spread in forecasting recessions", *Journal of Applied Econometrics*, **31**, 1183–1191.

Cubeddu, L., S. Krogstrup, G. Adler, P. Rabanal, M.C. Dao, S.A. Hannan, L. Juvenal, N. Li, C. Osorio Buitron, C. Rebillard, D. Garcia-Macia, C. Jones, J. Rodriguez, K.S. Chang, D. Gautam, and Z. Wang (2019), "The External Balance Assessment methodology: 2018 update", *IMF Working Paper* 65, International Monetary Fund, Washington, DC.

Davis, J.S., G. Valente, and E. van Wincoop (2021), "Global drivers of gross and net capital flows", *Journal of International Economics*, **128**, 103397.

De Santis, R.A. and M. Luhrmann (2009), "On the determinants of net international portfolio flows: a global perspective", *Journal of International Money and Finance*, **28**, 880–901.

Desbordes, R., G. Koop, and V. Vicard (2018), "One size does not fit all ... panel data: Bayesian Model Averaging and data poolability", *Economic Modelling*, **75**, 364–376.

Eichengreen, B., P. Gupta, and O. Masetti (2018), "Are capital flows fickle? Increasingly? And does the answer still depend on type?", *Asian Economic Papers*, **17**(1), 22–41.

Eicher, T.S., L. Helfman, and A. Lenkoski (2012), "Robust FDI determinants: Bayesian Model Averaging in the presence of selection bias", *Journal of Macroeconomics*, **34**, 637–651.

Eicher, T.S. and A. Leukert (2009), "Institutions and economic performance: Endogeneity and parameter heterogeneity", *Journal of Money, Credit and Banking*, **41(1)**, 197–219.

Forbes, K.J. and F.E. Warnock (2012), "Capital flow waves: surges, stops, flight, and retrenchment", *Journal of International Economics*, **88**, 235–251.

Forbes, K.J. and F.E. Warnock (2014), "Debt- and equity-led capital flow episodes", in M.D. Fuentes, C.E. Raddatz, and C.A. Reinhart, editors, *Capital Mobility and Monetary Policy*, Central Bank of Chile, Santiago, 291–322.

Forbes, K.J. and F.E. Warnock (2021), "Capital flow waves—or ripples? Extreme capital flow movements since the crisis", *Journal of International Money and Finance*, **116**, 102394.

Fratzscher, M. (2012), "Capital flows, push versus pull factors and the Global Financial Crisis", *Journal of International Economics*, **88(2)**, 341–356.

García Lopez, G. and L. Stracca (2021), "Changing patterns of capital flows", *Committee on the Global Financial System Papers* 66, Bank for International Settlements, Basel, Switzerland.

Gelos, G., L. Gornicka, R. Koepke, R. Sahay, and S. Sgherri (2022), "Capital flows at risk: taming the ebbs and flows", *Journal of International Economics*, **134**, 103555.

Goncalves, C., A. David, and S. Pienknagura (2019), “Capital flows to Latin America in the aftermath of the commodities super-cycle”, in *Regional Economic Outlook: Western Hemisphere*, International Monetary Fund.

Grubel, H.G. (1968), “Internationally diversified portfolios: welfare gains and capital flows”, *American Economic Review*, **58**, 1299–1314.

Hannan, S.A. (2017), “The drivers of capital flows in emerging markets post Global Financial Crisis”, *Journal of International Commerce, Economics and Policy*, **8(2)**, 1750009.

Hannan, S.A. (2018), “Revisiting the determinants of capital flows to emerging markets—a survey of the evolving literature”, *IMF Working Papers* 214, IMF, Washington D.C.

Hoeting, J.A., D. Madigan, A.E. Raftery, and C.T. Volinsky (1999), “Bayesian model averaging: a tutorial”, *Statistical Science*, **14(4)**, 382–417.

Islam, S. (1995), “The human development index and per capita GDP”, *Applied Economics Letters*, **2**, 166–167.

Kaminsky, G.L., C.M. Reinhart and C.A. Vegh (2004), “When it rains, it pours: procyclical capital flows and macroeconomic policies”, in M. Gertler and K. Rogoff, editors, *NBER Macroeconomics Annual, Vol. 19*, The University of Chicago Press, Chicago, IL.

Kass, R. and A. Raftery (1995), “Bayes factors”, *Journal of the American Statistical Association*, **90**, 773–795.

Kass, R. and L. Wasserman (1995), “A reference Bayesian test for nested hypothesis with large samples”, *Journal of the American Statistical Association*, **90**, 928–934.

Koepke, R. (2018), “Fed policy expectations and portfolio flows to emerging markets”, *Journal of International Financial Markets, Institutions and Money*, **55**, 170–194.

Koepke, R. (2019), "What drives capital flows to emerging markets? A survey of the empirical literature", *Journal of Economic Surveys*, **33**(2), 516–540.

Laeven, L. and F. Valencia (2018), "Systemic banking crises revisited", *IMF Working Paper* 206, International Monetary Fund, Washington, DC.

Lane, P.R. and G.M. Milesi-Ferretti (2017), "International financial integration in the aftermath of the Global Financial Crisis", *IMF Working Papers* 115, IMF, Washington.

Lashitew, A.A. and E. Werker (2020), "Do natural resources help or hinder development? Resource abundance, dependence, and the role of institutions", *Resource and Energy Economics*, **61**, 101183.

Leamer, E.A. (1985), "Sensitivity analyses would help", *American Economic Review*, **75**(3), 308–313.

Lenkoski, A., T.S. Eicher, and E. Raftery (2014), "Two-Stage Bayesian Model Averaging in endogenous variable models", *Econometric Reviews*, **33(1-4)**, 122–151.

Li, Y. (2021), "Investor sentiment and sovereign bonds", *Journal of International Money and Finance*, **115**, 102388.

Lucas Jr., R.E. (1990), "Why doesn't capital flow from rich to poor countries?", *American Economic Association*, **80**(2), 92–96.

Lucchetti, R., L. Pedini, and C. Pigini (2022), "No such thing as the perfect match: Bayesian Model Averaging for treatment evaluation", *Economic Modelling*, **107**, 105729.

Magud, N.E., C.M. Reinhart, and E.R. Vesperoni (2014), "Capital inflows, exchange rate flexibility and credit booms", *Review of Development Economics*, **18(3)**, 415–430.

Maltritz, D. and A. Molchanov (2013), "Analyzing determinants of bond yield spreads with Bayesian Model Averaging", *Journal of Banking & Finance*, **37**, 5275–5284.

Markowitz, H. (1952), "Portfolio selection", *The Journal of Finance*, **7**(1), 77–91.

McAleer, M., A.R. Pagan, and P.A. Volker (1985), "What will take the con out of econometrics?", *American Economic Review*, **75**(3), 293–307.

McCauley, R.N., P. McGuire, and V. Sushko (2015), "Global dollar credit: links to US monetary policy and leverage", *Economic Policy*, **30**(82), 187–229.

Mercado, R. and C.-Y. Park (2011), "What drives different types of capital flows and their volatilities in Developing Asia?", *International Economic Journal*, **25**(4), 655–680.

Miao, Y. and M. Pant (2012), "Coincident indicators of capital flows", *IMF Working Paper* 55, International Monetary Fund, Washington, DC.

Milesi-Ferretti, G.M., C. Tille, G.I.P. Ottaviano, and M.O. Ravn (2011), "The great retrenchment: International capital flows during the Global Financial Crisis", *Economic Policy*, **26**(66), 285–342.

Montiel, P.J. (2014), "Capital flows: Issues and policies", *Open Economies Review*, **25**, 595–633.

Moral-Benito, E. (2013), "Likelihood-based estimation of dynamic panels with predetermined regressors", *Journal of Business & Economic Statistics*, **31**(4), 451–472.

Moral-Benito, E. (2015), "Model Averaging in economics: An overview", *Journal of Economic Surveys*, **29**(1), 46–75.

North, D.C. (1994), "Economic performance through time", *American Economic Review*, **84(3)**, 359–368.

Papaioannou, E. (2009), "What drives international financial flows? Politics, institutions and other determinants", *Journal of Development Economics*, **88**, 269–281.

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

Porwal, A. and A.E. Raftery (2022), “Comparing methods for statistical inference with model uncertainty”, *PNAS*, **119(16)**, 1–8.

Raftery, A.E. and Y. Zheng (2003), “Discussion: Performance of Bayesian Model Averaging”, *Journal of the American Statistical Association*, **98**(464), 931–938.

Reinhardt, D., L.A. Ricci, and T. Tressel (2013), “International capital flows and development: Financial openness matters”, *Journal of International Economics*, **91**(2), 235–251.

Reinhart, C.M., V. Reinhart and C. Trebesch (2016), “Global cycles: Capital flows, commodities, and sovereign defaults, 1815–2015”, *American Economic Review*, **106**(5), 574–580.

Rey, H. (2015), “Dilemma not Trilemma: The Global Financial Cycle and monetary policy independence”, *NBER Working Paper* 21162, National Bureau of Economic Research, Cambridge, MA.

Sarno, L., I. Tsiakas and B. Ulloa (2016), “What drives international portfolio flows?”, *Journal of International Money and Finance*, **60**, 53–72.

Tchorek, G, M. Brzozowski, and P. Sliwinski (2017), “Determinants of capital flows to emerging and advanced economies between 1990 and 2011”, *Portuguese Economics Journal*, **6**, 17–48.

Tibshirani, R. (1996), “Regression shrinkage and selection via the Lasso”, *Journal of the Royal Statistical Society. Series B (Methodological)*, **58(1)**, 267–288.

Yupho, S. and X. Huang (2014), “Portfolio capital flows in Thailand: a Bayesian Model Averaging approach”, *Emerging Markets Finance and Trade*, **50**(S2), 89–99.

Zellner, A. (1986), “On assessing prior distributions and bayesian regression analysis with g-prior distributions”, in P.K. Goel and A. Zellner, editors, *Bayesian Inference* *and Decision Techniques: Essays in Honor of Bruno De Finetti (Studies in Bayesian Econometrics Statistics)*, volume 6, Elsevier Science Ltd, North Holland, 233–243.

A Variables: definitions and sources

Table 7: Variables: definitions and data sources

Symbol	Description	Source
Dependent variable: capital inflows		
Portfolio bond inflow	Portfolio bond capital inflows: total, % of GDP	Constructed with data from IFS (IMF)
Portfolio equity inflow	Portfolio equity capital inflows: total, % of GDP	Constructed with data from IFS (IMF)
Global push factors		
T-bond 10 year yield	Yield on 10 years US Treasury Bonds	FRED, St Louis Fed
VIX	CBOE Volatility Index; proxy for global risk aversion	FRED, St Louis Fed
TED spread	Spread between 3-month T-bill and 3-month LIBOR rate; proxy for risk perception of the financial sector	FRED, St Louis Fed
Time spread	Forecast of spread between 10 year T-bond and 3 months T-bill rates	Philadelphia Fed
World economic growth	Real GDP growth of the G7 countries	Constructed with data from OECD
Change commodity prices	Change in commodity price index	FRED, St Louis Fed
S&P 500 return	Annual change in the S&P 500 stock market index	Calculated with data from Bloomberg
BBB credit spread	Credit spread of BBB rated nonfinancial US corporates	FRED, St. Louis Fed
EPU	US Economic Policy Uncertainty, newspaper-based index with higher values representing more uncertainty	Economic Policy Uncertainty
Country-specific pull factors: macroeconomic and financial indicators		
Change reserves	Change in foreign reserves ex. gold (USD)	Calculated with data from IFS (IMF)
Real interest rate	Real interest rate	IFS (IMF), complemented by WDI
Domestic Stock Return	Return on domestic stock market index	GEM, complemented by OECD and Bloomberg
Real GDP growth	Annual change in real GDP in local currency	IFS
Fiscal balance to GDP	Fiscal Balance to GDP	WEO
Public Debt to GDP	General government gross debt to GDP	WEO, complemented by IMF Fiscal Affairs Departmental Data
Credit to GDP	Credit to GDP	WDI

Table 8: Variables: definitions and data sources (cont.)

Symbol	Description	Source
Country-specific pull factors: macroeconomic and financial indicators (cont.)		
Real GDP growth	Real GDP growth	WEO
Current Account to GDP	Current Account Balance to GDP	WEO
Exchange Rate Volatility	Standard deviation of the nominal exchange rate vis-à-vis US dollar, based on past 12 monthly observations	Calculated with data from IFS (IMF)
Change in REER	Real Effective Exchange Rate: a high (low) level represents an overvalued (undervalued) real exchange rate	Calculated with data from IFS (IMF), complemented by calculated Real Exchange Rate vis-à-vis US dollar with IFS data
Country-specific pull factors: structural indicators		
Fin Markets development	Financial Markets Index, with high value representing highly developed-in terms of depth, access and efficiency	IMF Financial Development Index Database
Capital Openness	Chinn-Ito index: capital account openness, with higher values representing more capital openness (fewer constraints on capital flows)	Chinn and Ito
Trade Openness	Trade openness: sum of absolute value of exports and imports to GDP	WDI
Exchange rate regime	De facto Exchange Rate Regime: dummy ranging 1 to 6, where 1 is fixed and 6 fully floating regime	Ilzetzki, Reinhardt and Rogoff (2016)
Regulatory Quality	Regulatory Quality, with high values representing strong governance performance	WGI
GDP per capita	GDP per capita, constant (2011 international dollar) prices	WEO
Natural Resources revenues	Total natural resources rents, as % of GDP	WDI
EIU Uncertainty index	Total count of the word "uncertainty" (or its variant) in the EIU country reports. A higher number means a higher level of uncertainty and vice versa.	WUI
polity2	Polity2 index is a dummy ranging -9 to +9, where -9 is autocratic system, and +9 democratic system	Polity IV

Notes: IFS: International Financial Statistics (IMF); FRED: Federal Reserve Economic Data (St. Louis Fed); OECD: Organisation for Economic Co-operation and Development; WEO: World Economic Outlook (IMF); WDI: World Development Indicators (World Bank); GEM: Global Economic Monitor (World Bank); WGI: Worldwide Governance Indicators (World Bank); WUI: World Uncertainty Index (IMF), based on EIU country reports. Retrieved from: worlduncertaintyindex.com/data; Polity IV: Polity IV project, systemicpeace.org

Table 9: Variables: used by, and motivation and expected sign

Variable	**Used by[4]**	**Sign AEs**	**Sign EMEs**
T-bond 10 year yield[1]	BF-16, DVW-21, H-17, MP-12, STU-16, TBS-17; K-19*	Depends: a higher yield attracts more bond investments, and less equity investments	Negative: relatively less attractive return for both bonds and equity
VIX	BF-16, DVW-21, EGM-18, H-17, K-18, MP-12; K-19*	Depends: a flight to safe havens sees AEs' bond investments increase, while equity investments decrease	Negative: reduce risky investments
TED spread	DVW-21, STU-16	Negative: A higher liquidity risk perception in the US financial system implies that markets dry up, and international investors become more reluctant to invest.	Negative: A higher liquidity risk perception in the US financial system implies that markets dry up, and international investors become more reluctant to invest.
Time spread	DVW-21	Positive: a flattening of the US yield curve predicts economic slowdown and thus less capital inflows	Negative: a lower time spread means a flattening of the US yield curve induces investors to seek yield in riskier securities, and emerging economy governments can issue bonds with lower yields
World economic growth[2]	BF-16, DVW-21, H-17, MP-11, TBS-17, YH-14; K-19*	Positive: high economic growth attracts more capital	Positive: when global growth is high, then investments in EMEs increase
Change commodity prices	BF-16, DVW-21, H-17	N/A	Positive: higher commodity prices attract more investments, both bonds and equity
S&P 500 return[3]	ACV-19, MP-11, MP-12, STU-16, TBS-17, YH-14	Positive: higher returns attract more investments, particularly in equity	Mixed. Negative: investors invest in US stock market, rather than in emerging economies. Positive as higher stock prices reflect positive outlook for the global economy, benefiting EMEs.

Notes:
[1] Also used: short term rate, global yield; [2] Also used: US or global economic growth; [3] Also used: global stock index, e.g. MSCI Global
[4] References: AES-16: Alberola, Erce and Serena (2016); ACV-19: Alderighi, Cleary and Varanasi (2019); AKV-07: Alfaro, Kalemli-Ozcan and Volosovych (2007); BF-16: Byrne and Fiess (2016); CCP-19: Cerutti, Claessens and Puy (2019); DVW-21: Davis, Valente and van Wincoop (2021); DL-09: De Santis and Luhrmann (2009); EGM-18: Eichengreen, Gupta and Masetti (2018); H-17: Hannan (2017); K-18: Koepke (2018); MP-11: Mercado and Park (2011); MP-12: Miao and Pant (2012); STU-16: Sarno, Tsiakas and Ulloa (2016); TBS-17: Tchorek, Brzozowski and Śliwiński (2017); YH-14: Yupho and Huang (2014); K-19*: survey of 34 empirical studies by Koepke (2019)

Table 10: Variables: used by, and motivation and expected sign (cont.)

Variable	**Used by**[4]	**Expected sign**
Change reserves	CCP-19, DVW-21, H-17, YH-14	Positive: higher reserves indicate the ability to prevent a sudden stop of private capital inflows or the difficulty of sovereign borrowing
Real interest rate	BF-16, H-17, STU-16, YH-14	Depends. For equity negative: when real interest rates increase, then equity investments decrease, as investors switch from equity to bonds. For bonds positive: higher interest rate attracts more investors in search for high return
Domestic Stock Return	ACV-19, K-18, STU-16, YH-14; K-19*	Positive: a higher return attracts more portfolio inflows in equity
Real GDP growth	BF-16, CCP-19, DL-09, EGM-18, H-17, TBS-17, YH-14; K-19*	Positive: higher GDP growth attracts more foreign capital - both because there is more need for capital and because foreign capital is attracted to higher economic growth
Fiscal balance to GDP	DVW-21, YH-14	Opposite effects. Negative, because the financing needs decrease if lower deficit. Positive, because creditworthiness improves if lower deficit.
Public Debt to GDP	TBS-17	Negative: higher levels of public debt generate lower portfolio inflows, because governments have less room to respond to adverse shocks
Credit to GDP	CCP-19, DVW-21, TBS-17	Positive, because countries with high credit have deep financial markets, including equity markets.
Current Account to GDP	AES-16, MP-12; K-19*	Negative: current account deficit is financed with capital inflows, which outweighs the deteriorated creditworthiness
Exchange Rate Volatility	MP-11, TBS-17	Negative, because a higher exchange rate volatility can reduce a country's investment attractiveness, and thus reduce portfolio capital inflows
Change in REER	DL-09	Positive. An appreciation of the domestic currency is associated with a loss in competitiveness and thus a deterioration of the current account balance, which is associated with a higher capital account balance.

Table 11: Variables: used by, and motivation and expected sign (cont.)

Variable	Used by[4]	Expected sign
Fin Markets development	DVW-21, H-17	Positive: countries with more developed financial markets attract more foreign investors
Capital Openness	AKV-07, BF-16, DVW-21, DL-09, EGM-18, H-17, MP-11, STU-16	Positive: more openness in the capital account, more attractive for foreign investors
Trade Openness	AKV-07, CCP-19, H-17, MP-11, YH-14	Inconclusive. Negative: more openness implies more vulnerable for global shocks. Positive: more openness attracts more capital
Exchange rate regime	AES-16, CCP-19, DVW-21, H-17, MP-11, TBC-17	Negative: Economies with less flexible exchange rate regimes attract more capital inflows than economies with more flexible regimes. However, little support from empirical research
Regulatory Quality	ACV-19, AKV-07, BF-16, MP-11	Positive: higher institutional (or regulatory) quality attracts more capital inflows
GDP per capita	AKV-07, DL-09, H-17, TBS-17	Depends. Negative: a poor country has a higher potential output growth ("stage of development" theory). Positive: a richer country is more resilient for adverse events
Natural Resources rev	-	Negative: higher export revenues lead to higher current account balance and thus lower capital flows
EIU Uncertainty index	-	Negative: more uncertainty implies lower capital inflows, particularly in times when global risk aversion is high
polity2	AKV-07	Positive: democratic political systems tend to have more accountability, and attract more capital inflows
Regional dummies	DVW-21, MP-11, TBS-17	N/A

B Countries

Based on GNI per capita in US$ (Atlas methodology).

Source: World Bank Analytical Classifications (presented in World Development Indicators).

Categories (sample size):

- AEs (32 countries): High income
- EMEs (43 countries): Lower middle income & Upper middle income

Table 12: AEs

Euro zone	**Non-euro Europe**	**Rest of the world**
Belgium	Croatia*	Australia
Estonia*	Czech Republic*	Canada
Finland	Denmark	Chile*
France	Hungary*	Israel
Germany	Norway	Japan
Greece	Poland*	Korea, Rep.
Italy	Sweden	Kuwait
Latvia*	Switzerland	New Zealand
Lithuania*	United Kingdom	Oman*
Portugal		United States
Slovak Republic*		
Slovenia		
Spain		

* These countries have moved from an EME to an AE during the period 1996-2019.

Table 13: EMEs

LAC	Asia	SSA	MENA	CEE-CIS
Argentina	Bangladesh	Botswana**	Egypt	Bulgaria
Belize*	China	Ghana*	Jordan	Georgia
Brazil	India	Kenya	Lebanon	Kyrgyz Republic*
Colombia	Indonesia	Namibia	Morocco	Moldova
Costa Rica	Malaysia	Nigeria	Tunisia**	Romania
Dominican Republic*	Pakistan	South Africa	Turkey	Russian Federation
Guatemala*	Philippines	Uganda		Ukraine
Guyana*	Sri Lanka	Zambia		
Jamaica	Thailand			
Mexico				
Panama*				
Peru				
Venezuela				

LAC: Latin America and Caribbean
SSA: Sub-Saharan Africa
MENA: Middle East and North Africa
CEE-CIS: Central & Eastern Europe, Commonwealth of Independent States
*: portfolio debt inflows only
**: portfolio equity inflows only

C Results

Complete results (Tables 14 to 17) and robustness checks (Tables 18 to 23).

Table 14: Bond portfolio capital inflows; AEs

	Pre-GFC (1996-2007)			Post-GFC (2011-2019)		
Variable	**PIP**	**P.Mean**	**CP.Sign**	**PIP**	**P.Mean**	**CP.Sign**
T-bond 10 year yield	0.631	-0.3102	0.000	0.084	0.0512	0.975
VIX	0.999	-0.1335	0.000	0.126	-0.0112	0.003
TED spread	0.086	0.0254	0.728	0.861	-8.4970	0.000
Change commodity prices	0.174	0.0027	1.000	0.072	0.0001	0.739
S&P 500 return	0.134	-0.0017	0.000	0.218	0.0107	0.988
Time spread	0.102	0.0216	0.981	0.075	-0.0087	0.207
World economic growth	0.081	-0.0168	0.162	0.063	0.0158	0.942
Change reserves	0.155	-0.0014	0.000	0.072	-0.0005	0.000
Real interest rate	0.047	-0.0002	0.434	0.076	-0.0085	0.001
Domestic Stock Return	0.069	-0.0003	0.041	0.313	0.0114	1.000
Real GDP growth	0.309	-0.0417	0.000	0.774	0.2351	1.000
Fiscal balance to GDP	0.969	0.1421	1.000	0.069	0.0021	0.959
Public Debt to GDP	0.111	0.0008	0.968	0.073	-0.0001	0.325
Current Account to GDP	1.000	-0.1955	0.000	0.064	-0.0012	0.087
Exchange Rate Volatility	0.076	0.0038	0.915	0.107	-0.0189	0.000
REER	0.054	-0.0001	0.230	0.069	-0.0007	0.189
Credit to GDP	0.118	0.0007	1.000	0.091	-0.0004	0.007
GDP per capita	0.702	1.0495	1.000	0.076	0.0408	0.962
Trade Openness	1.000	-0.0350	0.000	0.072	0.0002	0.930
Exchange rate regime	0.143	-0.0435	0.000	0.072	0.0101	0.976
Fin Markets development	0.990	3.4170	1.000	0.060	-0.0309	0.032
Regulatory Quality	0.054	0.0014	0.409	0.999	2.1504	1.000
Natural Resources rev	0.132	0.0054	0.997	0.070	0.0013	0.962
Capital Openness	0.069	-0.0055	0.219	0.300	-0.2592	0.000
polity2	0.075	-0.0030	0.090	0.111	-0.0082	0.005
EIU Uncertainty index	0.049	-0.0002	0.328	0.056	0.0004	0.866
Dummy non-euro Europe	0.716	-0.7028	0.000	0.063	-0.0152	0.009
Dummy Rest of world	1.000	-2.8491	0.000	0.081	0.0292	0.964

Notes:
PIP: Posterior Inclusion Probability; Indicators with a posterior inclusion probability between 0.500 and 0.750 (weak) are marked in light gray, and greater than 0.750 (positive to very strong) are marked in dark gray.
P.Mean: Posterior Mean; the average value of the coefficient, includes the sign.
CP.Sign: Conditional Positive Sign. A conditional positive sign of 1.000 (0.000) means that the coefficient has a positive (negative) sign in *each* regression specification in which it is included.

Table 15: Bond portfolio capital inflows; EMEs

	Pre-GFC (1996-2007)			Post-GFC (2010-2019)		
Variable	**PIP**	**P.Mean**	**CP.Sign**	**PIP**	**P.Mean**	**CP.Sign**
T-bond 10 year yield	0.069	-0.0065	0.109	0.226	-0.1575	0.000
VIX	0.616	-0.0344	0.000	0.774	-0.0713	0.000
TED spread	0.087	0.0468	0.999	0.137	-0.2642	0.073
Change commodity prices	0.108	0.0011	0.997	0.070	-0.0002	0.124
S&P 500 return	0.062	0.0002	0.859	0.102	0.0010	0.805
Time spread	0.068	-0.0004	0.452	0.338	0.0990	1.000
World economic growth	0.071	-0.0127	0.021	0.088	0.0243	0.990
Change reserves	0.071	0.0001	0.999	0.873	0.0155	1.000
Real interest rate	0.050	0.0001	0.557	0.086	0.0017	0.958
Domestic Stock Return	0.069	-0.0001	0.161	0.058	0.0001	0.798
Real GDP growth	0.256	0.0157	1.000	0.096	0.0044	0.974
Fiscal balance to GDP	0.732	-0.0876	0.000	0.062	-0.0002	0.484
Public Debt to GDP	0.057	0.0000	0.641	0.197	0.0017	0.997
Current Account to GDP	0.654	-0.0395	0.000	0.582	-0.0357	0.000
Exchange Rate Volatility	0.428	-0.0127	0.000	0.070	-0.0002	0.000
REER	0.098	0.0006	1.000	0.063	0.0001	0.605
Credit to GDP	0.072	-0.0001	0.195	0.140	0.0000	0.475
GDP per capita	0.095	0.0237	0.966	0.687	0.4100	1.000
Trade Openness	0.060	0.0001	0.906	0.098	0.0004	0.988
Exchange rate regime	0.199	-0.0382	0.000	0.069	0.0031	0.737
Fin Markets development	0.077	-0.0474	0.017	0.162	-0.2010	0.075
Regulatory Quality	0.069	0.0153	0.904	0.117	0.0383	0.978
Natural Resources rev	0.058	-0.0004	0.295	0.081	0.0010	0.712
Capital Openness	0.079	0.0042	0.813	0.056	0.0000	0.569
polity2	0.305	0.0154	1.000	0.640	0.0447	1.000
EIU Uncertainty index	0.054	0.0001	0.716	0.235	-0.0052	0.000
Dummy Asia	0.067	-0.0114	0.191	0.358	-0.2507	0.001
Dummy CEE and CIS	0.394	-0.2855	0.000	0.147	-0.0801	0.000
Dummy MENA	0.276	-0.2199	0.000	0.111	0.0409	0.745
Dummy S Sahara Africa	0.059	-0.0096	0.167	0.167	0.1005	0.935

Notes: See Table 14

Table 16: Equity portfolio capital inflows; AEs

	Pre-GFC (1996-2007)			Post-GFC (2010-2019)		
Variable	**PIP**	**P.Mean**	**CP.Sign**	**PIP**	**P.Mean**	**CP.Sign**
T-bond 10 year yield	0.071	0.0068	0.885	0.075	-0.0032	0.437
VIX	0.164	0.0041	1.000	0.848	-0.0653	0.000
TED spread	0.073	0.0166	0.590	0.275	-0.6547	0.001
Change commodity prices	0.049	-0.0001	0.092	0.139	-0.0011	0.000
S&P 500 return	0.049	0.0001	0.909	0.090	0.0005	0.848
Time spread	0.104	0.0078	0.733	0.907	0.3868	1.000
World economic growth	0.850	0.3351	1.000	0.072	-0.0008	0.345
Change reserves	0.064	-0.0002	0.001	0.059	0.0000	0.873
Real interest rate	0.061	-0.0009	0.077	0.102	0.0055	0.972
Domestic Stock Return	0.096	0.0004	1.000	0.117	0.0008	0.987
Real GDP growth	0.050	0.0002	0.678	0.060	-0.0002	0.455
Fiscal balance to GDP	0.069	-0.0005	0.329	0.083	0.0005	0.732
Public Debt to GDP	0.134	0.0005	1.000	0.074	0.0000	0.380
Current Account to GDP	0.145	0.0026	1.000	0.104	-0.0015	0.023
Exchange Rate Volatility	0.084	0.0028	0.984	0.639	0.1029	1.000
REER	0.085	0.0004	0.902	0.285	-0.0062	0.000
Credit to GDP	0.063	0.0000	0.321	0.096	0.0001	0.888
GDP per capita	0.069	0.0062	0.779	0.130	0.0427	0.908
Trade Openness	0.598	-0.0049	0.000	0.579	-0.0029	0.000
Exchange rate regime	0.311	-0.0581	0.000	0.158	-0.0211	0.068
Fin Markets development	0.229	0.1778	1.000	0.140	0.0658	0.962
Regulatory Quality	0.588	0.3085	1.000	0.160	0.0445	0.999
Natural Resources rev	0.069	-0.0002	0.448	0.164	0.0024	0.999
Capital Openness	0.311	0.0533	1.000	0.089	0.0096	0.980
polity2	0.083	-0.0012	0.343	0.145	-0.0037	0.108
EIU Uncertainty index	0.069	-0.0008	0.002	0.139	-0.0019	0.007
Dummy non-euro Europe	0.119	-0.0311	0.000	0.267	-0.0869	0.001
Dummy Rest of world	0.081	-0.0147	0.176	0.180	0.0663	0.984

Notes: See Table 14

Table 17: Equity portfolio capital inflows; EMEs

	Pre-GFC (1996-2007)			Post-GFC (2011-2019)		
Variable	**PIP**	**P.Mean**	**CP.Sign**	**PIP**	**P.Mean**	**CP.Sign**
T-bond 10 year yield	0.099	0.0068	0.993	0.092	-0.0083	0.080
VIX	0.983	-0.0313	0.000	0.500	-0.0109	0.000
TED spread	0.173	0.0495	0.997	0.443	-0.4261	0.000
Change commodity prices	0.054	0.0000	0.376	0.079	0.0002	0.796
S&P 500 return	0.061	0.0001	1.000	0.138	0.0005	0.910
Time spread	0.125	-0.0081	0.020	0.311	0.0268	1.000
World economic growth	0.072	0.0001	0.646	0.076	-0.0047	0.015
Change reserves	0.926	0.0030	1.000	0.097	0.0002	1.000
Real interest rate	0.196	-0.0013	0.000	0.389	-0.0059	0.000
Domestic Stock Return	0.058	0.0000	0.152	0.089	0.0001	0.971
Real GDP growth	0.046	0.0001	0.826	0.075	-0.0005	0.244
Fiscal balance to GDP	0.074	0.0007	0.948	0.092	-0.0012	0.003
Public Debt to GDP	0.086	-0.0001	0.029	0.227	0.0005	0.998
Current Account to GDP	0.781	-0.0190	0.000	0.150	0.0015	0.902
Exchange Rate Volatility	0.176	-0.0015	0.000	0.074	0.0000	0.995
REER	0.071	0.0001	0.970	0.069	-0.0001	0.087
Credit to GDP	1.000	0.0095	1.000	0.072	0.0000	0.799
GDP per capita	0.427	0.0795	1.000	0.935	-0.2229	0.000
Trade Openness	0.447	-0.0013	0.000	0.908	-0.0034	0.000
Exchange rate regime	0.099	0.0048	1.000	0.078	-0.0007	0.361
Fin Markets development	0.145	0.0725	1.000	0.085	0.0182	0.875
Regulatory Quality	0.100	0.0108	0.830	0.993	0.4914	1.000
Natural Resources rev	0.074	0.0006	0.890	0.513	0.0097	1.000
Capital Openness	0.993	-0.1416	0.000	0.996	-0.1418	0.000
polity2	0.999	0.0457	1.000	0.060	0.0003	0.990
EIU Uncertainty index	0.106	-0.0009	0.000	0.115	0.0004	0.996
Dummy Asia	0.099	-0.0119	0.193	0.734	-0.1748	0.000
Dummy CEE and CIS	0.076	0.0066	0.670	0.092	-0.0085	0.079
Dummy MENA	0.107	0.0209	0.999	0.071	-0.0029	0.319
Dummy S Sahara Africa	1.000	0.7468	1.000	0.236	0.0453	0.999

Notes: See Table 14

Table 18: Robustness: BMA, LASSO and EBA methods—AEs

	Bond portfolio inflows						**Equity portfolio inflows**					
	pre-GFC			**post-GFC**			**pre-GFC**			**post-GFC**		
Variable	**B**	**L**	**E**	**B**	**L**	**E**	**B**	**L**	**E**	**B**	**L**	**E**
T-bond 10 year yield	x	x	x									
VIX	x	x	x						x	x	x	x
TED spread				x	x	x					x	
Change commodity prices		x	x									
S&P 500 return			x									
Time spread										x	x	x
World economic growth							x	x	x			
Change reserves		x	x			x			x			
Real interest rate						x						
Domestic Stock Return						x			x			
Real GDP growth			x	x	x	x						
Fiscal balance to GDP	x		x									
Public Debt to GDP												
Current Account to GDP	x	x	x						x			
Exchange Rate Volatility						x				x		x
REER												x
Credit to GDP												
GDP per capita	x	x	x									
Trade Openness	x	x	x				x	x	x	x	x	x
Exchange rate regime		x	x						x			
Fin Markets development	x	x	x						x			
Regulatory Quality				x	x	x	x		x			
Natural Resources rev			x									
Capital Openness		x				x			x			
polity2												
EIU Uncertainty index												
Dummy non-euro Europe	x		x						x			
Dummy Rest of world	x	x	x									
# variables	9	11	15	3	3	8	3	2	11	4	4	5
# coinciding BMA-LASSO		7			3			2			3	
# coinciding BMA-EBA			9			3			3			4

Notes: B: Bayesian Model Averaging (BMA), L: Least Absolute Shrinkage and Selection Operator (LASSO), E: Extreme Bounds Analysis (EBA).
x marks a robust determinant according to the method employed. Cells are marked gray when the result according to LASSO, EBA or both coincide with the BMA method.

Table 19: Robustness: BMA, LASSO and EBA methods—EMEs

	Bond portfolio inflows						**Equity portfolio inflows**					
	pre-GFC			**post-GFC**			**pre-GFC**			**post-GFC**		
Variable	**B**	**L**	**E**	**B**	**L**	**E**	**B**	**L**	**E**	**B**	**L**	**E**
T-bond 10 year yield						x						
VIX	x	x	x	x	x	x	x	x	x	x		x
TED spread											x	x
Change commodity prices												
S&P 500 return									x			
Time spread						x					x	x
World economic growth												
Change reserves				x	x	x	x	x	x			x
Real interest rate									x			x
Domestic Stock Return												
Real GDP growth			x									
Fiscal balance to GDP	x	x	x									
Public Debt to GDP												
Current Account to GDP	x	x	x	x	x		x	x	x			
Exchange Rate Volatility			x			x			x			
REER												
Credit to GDP							x	x	x			
GDP per capita				x		x				x	x	x
Trade Openness									x	x	x	x
Exchange rate regime			x									
Fin Markets development									x			
Regulatory Quality										x		x
Natural Resources rev										x		
Capital Openness							x	x	x	x	x	x
polity2				x	x	x	x	x	x			
EIU Uncertainty index						x			x		x	
Dummy Asia					x					x		x
Dummy CEE and CIS			x			x						
Dummy MENA												
Dummy S Sahara Africa							x	x	x		x	
# variables	3	3	7	5	5	9	7	7	13	7	7	10
# coinciding BMA-LASSO		3			4			7			3	
# coinciding BMA-EBA			3			4			7			6

Notes: See Notes in Table 18.

Table 20: Robustness: Comparison of BMA-generated coefficients and coefficients of the OLS regression using the robust determinants — AEs

Pre-GFC (1996-2007)				Post-GFC (2011-2019)			
	Coefficient		**signifi-**		**Coefficient**		**signifi-**
Determinant	**BMA**	**OLS**	**cance**	**Determinant**	**BMA**	**OLS**	**cance**
Bond capital flows							
Current Account to GDP	-0.212	-0.192	***	Regulatory Quality	2.141	1.985	***
Trade Openness	-0.032	-0.036	***	TED spread	-8.575	-10.387	***
Dummy Rest of world	-2.846	-3.012	***	Real GDP growth	0.220	0.333	***
VIX	-0.135	-0.125	***				
Fin Markets development	3.680	2.978	***				
Fiscal balance to GDP	0.149	0.127	***				
Dummy non-euro Europe	-0.773	-0.988	***				
GDP per capita	0.948	1.553	***				
T-bond 10 year yield	-0.268	-0.501	***				
Adjusted R^2		0.403		Adjusted R^2		0.150	
Equity capital flows							
World economic growth	0.326	0.344	***	Time Spread	0.392	0.456	***
Trade Openness	-0.005	-0.008	***	VIX	-0.067	-0.081	***
				Exch Rate Volatility	0.113	0.130	**
				Trade Openness	-0.003	-0.005	***
Adjusted R^2		0.049		Adjusted R^2		0.110	

Notes: OLS regression with the robust determinants as identified by the BMA method.

Table 21: Robustness: Comparison of BMA-generated coefficients and coefficients of the OLS regression using the robust determinants — EMEs

Pre-GFC (1996-2007)				**Post-GFC (2011-2019)**			
	Coefficient		**signifi-**		**Coefficient**		**signifi-**
Determinant	**BMA**	**OLS**	**cance**	**Determinant**	**BMA**	**OLS**	**cance**
Bond capital flows							
VIX	-0.034	-0.060	***	VIX	-0.071	-0.085	***
Fiscal balance to GDP	-0.088	-0.088	**	Change reserves	0.016	0.018	***
Current Acct to GDP	-0.039	-0.059	***	Curr Acct to GDP	-0.036	-0.065	***
				GDP per capita	0.410	0.471	***
				polity2	0.045	0.062	***
Adjusted R^2		0.071		Adjusted R^2		0.113	
Equity capital flows							
VIX	-0.031	-0.033	***	VIX	-0.011	-0.020	***
Change reserves	0.003	0.003	***	Capital openness	-0.142	-0.166	***
Current Account to GDP	-0.019	-0.021	***	Regulatory quality	0.491	0.542	***
Credit to GDP	0.009	0.009	***	GDP per capita	-0.223	-0.242	***
Capital openness	-0.142	-0.144	***	Trade openness	-0.003	-0.004	***
polity2	0.046	0.047	***	Natur resources rev	0.010	0.021	***
Dummy Sub Sah Africa	0.747	0.697	***	Dummy Asia	-0.175	-0.222	***
Adjusted R^2		0.278		Adjusted R^2		0.146	

Notes: OLS regression with the robust determinants as identified by the BMA method.

Table 22: Robustness: comparison Posterior Inclusion Probability for alternative risk aversion measures (VIX, BBB spread and EPU) –AEs

Type	**Period**	**VIX**	**EPU**	**BBB**
bonds	pre-GFC	0.999	0.169	0.076
bonds	post-GFC	0.126	0.056	0.196
equity	pre-GFC	0.164	0.076	0.062
equity	post-GFC	0.848	0.388	0.312

Notes:
PIP: Posterior Inclusion Probability; Indicators with a posterior inclusion probability between 0.500 and 0.750 (weak) are marked in light gray, and greater than 0.750 (positive to very strong) are marked in dark gray.
VIX: CBOE Volatility Index, EPU: Economic Policy Uncertainty, BBB: credit spread of BBB rated nonfinancial US corporates.

Table 23: Robustness: comparison Posterior Inclusion Probability for alternative risk aversion measures (VIX, BBB spread and EPU) –EMEs

Type	**Period**	**VIX**	**EPU**	**BBB**
bonds	pre-GFC	0.616	0.222	0.101
bonds	post-GFC	0.774	0.225	0.128
equity	pre-GFC	0.983	0.191	0.893
equity	post-GFC	0.500	0.101	0.077

Notes: See Table 22