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Time-variation in the effects of push and pull factors on portfolio flows: evidence from a Bayesian dynamic factor model

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Non-technical summary

Research Question

International capital flows can either be triggered by international factors (push factors) or country-specific factors (pull factors). The extent to which push and pull factors affect international capital flows has been widely and controversially debated. However, the role of time-variation in the effects of those factors on high frequency portfolio flow data has not been researched yet.

Contribution

We use a factor model to decompose the underlying data into a common component (i.e. a push factor) and a country-specific component (i.e. pull factors). Unlike previous studies, we do explicitly allow for time-variation in the sensitivity of portfolio flows towards the corresponding common component. This approach enables us to investigate if and when the importance of international and country-specific effects has changed.

Results

Our results suggest that time-variation matters a lot and that there is a substantial amount of heterogeneity in the importance of factors across regions (advanced versus emerging market economies) and asset classes (equity versus bonds). We find that the importance of push factors for flows into advanced economies has on average increased over time, particularly for EU countries. With respect to flows into emerging market economies we find very heterogeneous results between individual countries. We also find that the extracted push factors are closely related to risk measures, US stock market returns, the US real effective exchange rate and the oil price. Pull factors seem to be connected with country-specific stock market returns, in particular.

Nichttechnische Zusammenfassung

Fragestellung

Internationale Kapitalströme lassen sich entweder durch internationale Faktoren (*push*-Faktoren) oder länderspezifische Faktoren (*pull*-Faktoren) erklären. In welchem Ausmaß die internationalen Kapitalströme durch diese Faktoren beeinflusst werden, wurde bereits umfangreich und kontrovers diskutiert. Jedoch wurde die zeitliche Variation der Einflüsse im Zusammenhang mit hochfrequenten Daten zu Portfolioströmen noch nicht untersucht.

Beitrag

Wir verwenden ein Faktor-Modell, welches die zugrundeliegenden Daten in eine gemeinsame Komponente (*push*-Faktor) und länderspezifische Komponente (*pull*-Faktoren) zerlegt. Im Gegensatz zu anderen Ansätzen berücksichtigen wir in unserem Modell explizit zeitliche Variation in der Sensitivität der Portfolioströme hinsichtlich der gemeinsamen Komponente. Dieser Ansatz erlaubt uns zu untersuchen, inwiefern und wann sich die Bedeutung internationaler und länderspezifischer Faktoren verändert hat.

Ergebnisse

Die Analyse legt nahe, dass die zeitliche Variation von besonderer Bedeutung ist und dass ein hohes Maß an Heterogenität hinsichtlich der Bedeutung der Faktoren innerhalb verschiedener Regionen (entwickelte versus sich entwickelnde Volkswirtschaften) und Anlageklassen (Aktien versus Anleihen) vorliegt. So ist die Bedeutung der *push*-Faktoren für Portfolioströme in entwickelten Volkswirtschaften im Zeitverlauf gestiegen – insbesondere in EU-Ländern. Im Hinblick auf Portfolioströme in sich entwickelnde Volkswirtschaften sind die Ergebnisse bezogen auf einzelne Länder sehr unterschiedlich. Zudem deuten die Ergebnisse darauf hin, dass die extrahierten *push*-Faktoren stark mit Risikomaßen, Renditen am US-Aktienmarkt, dem realen effektiven Wechselkurs des US-Dollar sowie dem Ölpreis zusammenhängen. Die *pull*-Faktoren scheinen besonders stark mit den länderspezifischen Renditen an den jeweiligen Aktienmärkten in Verbindung zu stehen.

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Abstract

The extent to which push and pull factors affect international capital flows is widely debated. We contribute to this strand of literature by estimating the relative importance of push and pull factors for portfolio flows over a time span, encompassing the global financial crisis, the European sovereign debt crisis as well as the beginning of the Covid-19 pandemic. To do so, we extract common and country-specific components from fund flow data using Bayesian dynamic factor models with time-varying coefficients and stochastic volatility. Assuming that the common component represents push factors and the country-specific component pull factors, we show that (i) time-variation matters and (ii) there is a substantial amount of heterogeneity in the importance of factors across regions (advanced versus emerging market economies) and asset classes (equity versus bonds). We find that the relative importance of push factors for flows into advanced economies has on average increased over time, particularly for EU countries. With respect to flows into emerging market economies, we find very heterogeneous results between individual countries. Moreover, we identify risk measures, US stock market returns, US real interest rates, the US real effective exchange rate and the oil price as important push factors. Pull factors seem to covary with domestic stock market returns, in particular.

Keywords: portfolio flows, push and pull factors, bayesian dynamic factor model, time-variation

JEL classification: C32, E52, F32.

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1 Introduction

International portfolio flows have important implications for the economy. However, it is controversial to what extent flows are influenced by domestic and global factors. This paper aims to contribute to this debate by providing empirical evidence from a factor model on high frequency data, which explicitly allows for time-variation in the factor loadings and stochastic volatility. This enables us to investigate how the relative importance of domestic and global factors has evolved over time.

Our study proxies portfolio flows with help of data on fund flows and distinguishes between equity flows and bond flows. Both types of flows affect the supply and demand on the forex markets (where applicable) as well as on the asset markets and induce price effects, depending on the elasticities. Both, exchange rate and asset price changes affect the economy in different ways:[1]

On the one hand, exchange rate changes affect the domestic and foreign prices of traded goods, translating into changes in aggregate supply and demand (see Obstfeld and Rogoff (1996)). Heavy exchange rate fluctuations raise hedging costs and potentially disrupt international trade chains. Portfolio flows, on the other hand, are not directly linked to real macroeconomic variables. Unless there is a direct transaction with the issuer (e.g. in an initial public offering), portfolio flows do not provide equity or credit to the issuer of the corresponding asset. However, portfolio flows can have indirect effects on the real economy via financing costs or wealth effects, for instance. Equity flows may affect the stock prices and thus the market capitalisation of the corresponding firms. A high market capitalisation can reduce the financing costs of that specific firm, *et vice versa*. A rise in the market capitalisation also increases the wealth of the shareholders, which may result in higher consumption. The effects of bond flows are more intuitive. Here, the supply and demand for specific bonds controls the effective yield and thus the financing costs.

Especially in times of large inflows (booms) and large outflows (busts), these channels become of particular importance. The 1998/1999 Asian financial crisis is probably one of the most prominent cases where large capital inflows followed by large outflows led to severe distress in a number of countries.

These examples show that portfolio flows are very important variables for policy makers, especially with respect to macroeconomic stabilisation. In order to understand the nature of portfolio flows, we need to understand the drivers of those flows. Here, we distinguish between global (external) forces, pushing capital into economies, and country-specific forces, attracting foreign capital. Therefore, the literature, influenced by Calvo, Leiderman, and Reinhart (1993, 1996), distinguishes between the so-called *push* and *pull* factors.

There is a wide range of different approaches, investigating the relative importance of push and pull factors as well as the nature of the factors themselves. Research dealing with the effects of the Global Financial Cycle (hereafter: GFCy) can be interpreted as a push factor (see Rey (2013)). Similarly, global liquidity can also be regarded as push factor (see Bruno and Shin (2015)). We discuss the literature from a methodological perspective and focus on papers using factor models. For a broader view on the literature of push and pull factors, we refer the reader to Koepke (2018). Importantly, comparing

[1] We acknowledge that the exchange rate can be interpreted as an asset price (see Obstfeld and Rogoff (1996)). The separation, however, simplifies the explanation of different channels.

the results is not straightforward, because most empirical research uses not only different measures of flows, but also different data frequencies. Therefore, the importance of push and pull factors is heavily influenced by the choice of the data frequency.

The factor model approach differs from standard (panel) regression models of capital flows on observable variables in such a way that it is much more agnostic with respect to factors. The basic idea is to decompose the data into common and country-specific components. The common components represent unobservable factors, which are highly correlated with all relating capital flow series. Therefore, it is assumed that this part of the data is influenced by external factors (i.e. push factors). Consequently, the country-specific component is influenced by pull factors. Hence, both components can be interpreted as aggregates, representing push and pull factors, respectively.

This assumption provides both components with an economic interpretation. However, it is still unknown, which economic variables affect the factors. A well established approach to find out what the factors actually represent is regressing the extracted push and pull factors on potential observable variables such as the VIX, interest rates, or output. Consequently, the factor model approach also captures potentially omitted variables and may thus yield a better estimate of data variability, explained by push and pull factors.

Barrot and Serven (2018) estimate a factor model for annual gross capital inflows and outflows of 85 countries between 1979-2015. They normalise the flows using trend GDP, derived from a Hodrick-Prescott filter. Using rolling-window estimates, Barrot and Serven (2018) also provide evidence for time-variation in the importance of common and country-specific components of the data. Their results suggest that the co-movements, introduced by the global factor, are particularly high for advanced economies.

Davis, Valente, and van Wincoop (2021) investigate annual aggregated capital flows (i.e FDI flows, debt flows, equity flows, banking flows and reserve accumulation) for 58 countries between 1996-2015. They estimate two global factors (i.e. GFCy and commodity prices) and find that both factors have significant explanatory power for gross and net capital flows. Both factors taken together explain about 40% of the variation in capital flows.

Using quarterly data for 85 countries during the period 1990Q1 to 2015Q4, Cerutti, Claessens, and Rose (2019) regress capital flows (as % of GDP) on a battery of factors, obtained in 180 ways. Hereby, they distinguish between the direction of flows, the type of flows (i.e. FDI, debt, equity, credit as well as the sum of debt and equity) and the region (i.e. advanced economies, emerging market economies and a mix of both). Their results suggest that the GFCy, approximated by common factors, explains only a small share of capital flow variability.

Sarno, Tsiakas, and Ulloa (2016) provide evidence for a sample of 55 countries, ranging from January 1988 to November 2013, suggesting that push factors explain more than 80% of the variation in bond and equity flows from the US to other economies. Their study differs from others mainly in the sense that they use monthly bilateral portfolio flows from the US TIC data. The flows are defined as the difference between gross purchases by foreigners from US residents and gross sales by foreigners to US residents (in US dollar). Similarly, Fratzscher (2012) finds evidence in his dataset of 50 economies (12 October 2005 to 22 November 2010), suggesting that push factors are important - especially during the global financial crisis (hereafter: GFC). His results are based on weekly fund level data where flows are interpreted as net capital flows to specific countries.

Other papers focus on macro-financial linkages. Potjagailo and Wolters (2019), for example, use a model, which is similar to ours, but limit their analysis of the GFCy to annual macro-financial variables. Similarly, Breitung and Eickmeier (2015) provide evidence of macro-financial cycles using a hierarchical factor model. Both papers do not use capital flow data.

Despite ambiguous results regarding the average importance of the push and pull factors, there seems to be strong evidence, suggesting that there is a high degree of heterogeneity with respect to the importance of the factors across individual countries (see Cerutti, Claessens, and Puy (2019) or Sarno et al. (2016)), determined by the quality of domestic institutions, country-specific risk or domestic macroeconomic fundamentals (see Fratzscher (2012)). Moreover, it seems uncontroversial that the global factor is negatively correlated with a measure of uncertainty such as the VIX (see, for example, Davis et al. (2021)). Other important covariates are exchange rates, growth and commodity prices (see Barrot and Serven (2018)). Important pull factors are industrial production, interest rates and the degree of openness (see Sarno et al. (2016)).

We contribute to this literature in several ways. Our main contribution is the application of a time-varying dynamic factor model on fund flow data for 26 emerging market economies and 21 advanced economies over the period August 2005 to September 2020, which enables us to decompose the data into common and country-specific components (i.e. into push and pull factors). In fact, we estimate four different models: Bond flows into emerging market economies, bond flows into advanced economies, equity flows into emerging market economies and equity flows into advanced economies. The time span encompasses the GFC, the sovereign debt crisis in the euro area as well as the beginning of the Covid-19 pandemic. Hereby, we estimate four different models: bond flows into emerging market economies, bond flows into advanced economies, equity flows into emerging market economies and equity flows into advanced economies. This separation is motivated by the findings of Cerutti et al. (2019) and Koepke (2018), who show that push and pull factors may differ across region and asset class. Unlike Barrot and Serven (2018), who use rolling-window estimates, we do explicitly allow for time-variation in the coefficients and stochastic volatilities. We also provide results from high frequency fund flow data. More specifically, we use monthly data on fund flows in order to proxy portfolio flows. In fact, Fratzscher (2012) uses the same dataset in weekly frequency, which is even higher than our frequency. We, however, draw our factors directly from the data, whereas Fratzscher (2012) derives his factors from other variables. His approach is common in the capital flows literature, because the high volatility of capital flows often leads to poor estimates of the factors.[2] We will show later that we are not subject to this issue when using monthly data. This way, we have a lower data frequency, but we do not need to make any assumptions regarding the common factor (i.e. the push factors). Moreover, we do explicitly allow for time-variation in the coefficients of the model, which Fratzscher (2012) does not. Another paper, using high data frequency is Sarno et al. (2016), who employ monthly bilateral US portfolio flows. The advantage of their dataset is that it is not limited to fund flows. However, their analysis is limited to a US perspective. Hence, our approach complements those papers.

[2]We also estimated factors from weekly data, which led to very poor estimates of the factors (i.e. high uncertainty). Therefore, we decided to use data with a lower frequency.

We find that the time-variation matters a lot. Our estimates show that the relative importance of the push factor has increased significantly for bond and equity fund flows into most of the AEs. With respect to flows into EMEs we find that the results are very heterogeneous. The regression models identify risk measures, US stock market returns, the US real effective exchange rate, the oil price and US real interest rates as important push factors. According to panel regression models, domestic stock market returns are the most important pull factors, followed by inflation rates and reserve accumulation, depending on the asset class and region. Additionally, we show that convergence also happened with respect to the volatility of flows into EMEs over the sample period. For AEs, we observe such a convergence only during the GFC. After the crisis, volatility levels diverged again.

The paper is organised as follows. The next section presents the time-varying factor model together with different priors and settings for robustness analyses. Section 3 describes that fund flow dataset and its peculiarities. Results are presented in sections 4, 5 and 6. Finally, Section 8 concludes.

2 Model

We employ the dynamic factor model with time-varying parameters as proposed by Del Negro and Otrok (2008):

$$y_{i,t} = a_i + b_{i,t} f_t + \epsilon_{i,t} \tag{1}$$

Their approach enables us to model each observable variable $y_{i,t}$ with $i = 1, \dots, n$ and $t = 1, \dots, T$ as the sum of a constant a_i, an unobservable factor f_t, as well as an idiosyncratic component $\epsilon_{i,t}$. Note that the unobserved factor is common to all observable variables. The factor loadings $b_{i,t}$, are variable-specific, independent across i and follow a random walk:

$$b_{i,t} = b_{i,t-t} + \sigma_{\eta_i} \eta_{i,t}, \tag{2}$$

where $\eta_{i,t} \sim \mathcal{N}(0,1)$. The factors and the idiosyncratic innovations follow autoregressive processes of order q and p, respectively:

$$\begin{aligned} f_t &= \phi_{0,1} f_{t-1} + \dots + \phi_{0,q} f_{t-q} + e^{h_{0,t}} u_{0,t} & (3) \\ \epsilon_{i,t} &= \phi_{i,1} \epsilon_{i,t-1} + \dots + \phi_{i,p} \epsilon_{i,t-p} + \sigma_i e^{h_{i,t}} u_{i,t} & (4) \end{aligned}$$

$$h_{i,t} = h_{i,t-1} + \sigma_{\zeta_i} \zeta_{i,t}, \text{ with } i = 0, 1, \dots, n \tag{5}$$

whereby $h_{i,t}$ is the stochastic volatility and $\zeta_{i,t} \sim \mathcal{N}(0,1)$ is independent across i.

2.1 Normalisation and identification

The present model class requires important assumptions regarding the model structure in order to achieve identification and convergence. One essential assumption is the independence of $\eta_{i,t}$ across i. Otherwise, co-movement would not be limited to the factor itself, but appear in the time-varying factor loadings ($b_{i,t}$) as well. Moreover, the model is subject to the problem that the scale of the factor and the loadings is indeterminate. We solve this issue by constraining the scale of the factor ($\sigma_0 = 1$), which is a standard assumption in the literature (see Del Negro and Otrok (2008)). Equivalently, we set the initial conditions of the processes $h_{0,0} = 0$ and $h_{i,0} = 0$ for all i. Another issue of indeterminacy relates to the sign of the loadings ($b_{i,t}$) and the factor (f_t). The sign of one or the other could switch during the Markov chain Monte Carlo (hereafter: MCMC) process. In our case – as in Del Negro and Otrok (2008) – this never happened.[3] Therefore, we did not impose further restrictions on the model structure.

We observed switching signs during the MCMC process in exercises with more than one factor. In that case, the identification of the factors becomes more complex due to the time-variation. In time-invariant models it is common to restrict a significant loading of one object in each factor to be positive. Note that in a time-invariant model, this restriction is – loosely speaking – imposed on the average loading over time. In a setting with time-varying parameters, however, the identification can be problematic, as the restriction has to be imposed on any point in time. Hence, it is much more restrictive when applied to the time-invariant case. If, for example, a factor loading is positive and significant over the first two third of the time periods and zero thereafter (e.g. due to the introduction of capital controls), the restriction could be fulfilled in a time-invariant case, but violated in the time-varying case. A restriction that is at odds with the data could introduce a strong bias into the corresponding factor. Hence, we decided to perform the analysis with a one time-varying factor model.

2.2 Estimation

The estimation follows the same procedure, as outlined in Del Negro and Otrok (2008). In four main blocks, we sample subsets of parameters from distributions conditional on all other parameters. First, we sample from the distributions of the constant term, the autoregressive parameters and the component of σ_i^2, which is not time-varying conditionally on the factors, factor loadings and stochastic volatilities. Second, we bring the obtained values into the state space representation suggested by Carter and Kohn (1994) and draw the factors. Third, we use the initially obtained values as well as the factors to draw the time-varying loadings (see Carter and Kohn (1994)). Finally, the stochastic volatilities can be sampled (see Kim, Sheppard, and Chib (1998)). For details, we refer the reader to Del Negro and Otrok (2008), who provide a technical appendix with derivations of the distributions.

Overall, we made 22,000 MCMC draws and discarded the first 2,000 (burn-in). The starting values for the factors are the corresponding sample means and those of the loadings are zero. In order to check for convergence we also used the first principal components as well as random data from a standard normal distribution with a mean of 0 as starting values for the factors. In each case, the results were qualitatively similar to those, presented below.

[3] As we can see from Figure 4 the narrowness of the bands indicates that the factors are precisely estimated and do not point to possible sign switches.

2.3 Priors

Given the empirical evidence from Del Negro and Otrok (2008) and Ritschl, Sarferaz, and Martin (2015) priors do matter in this model class. We take this into account by estimating models with very different specifications.

The prior distributions for the variances are given by $\sigma_{\zeta_i} \sim IG(\nu_{\zeta_i}, s^2_{\zeta_i})$ and $\sigma_{\eta_i} \sim IG(\nu_{\eta_i}, s^2_{\eta_i})$. Here, ν represents the strength of the believe that the variance equals s^2. Table 1 represents the different prior specifications which are similar to those in Del Negro and Otrok (2008). The benchmark model is specified in such a way that the amount of time-variation in the loadings is higher relative to the volatilities. The prior on the volatilities is substantially tighter ($\nu_{\zeta_i} = T$) than the prior on the loadings ($\nu_{\eta_i} = 0.1 \times T$). We also consider models where our beliefs regarding time-variation in the loadings are tighter (Alternative 1, 2 and 3: $\nu_{\eta_i} = 0.25 \times T, 0.5 \times T$ and T, respectively – $s^2_{\eta_i} = 0.05^2$). At the same time, we relaxed the tightness of the beliefs regarding time-variation in the volatilities ($\nu_{\zeta_i} = 0.5 \times T$). The prior for σ_i is $(IG(\nu_i, s^2_i))$, where $\nu_i = 0.05 \times T$ and $s^2_i = 1$. The constant terms have normally distributed priors with mean 0 and precision 1 (i.e. $N_k(0, 1)$). Our prior for the initial conditions for the loadings is also normally distributed, but with mean 0 and precision 1/10. The prior distributions for the autoregressive coefficients for the factor and the idiosyncratic terms, ϕ_i are normally distributed such that $\phi_i \sim N(\bar{\phi}_i, \bar{V}_i^{-1})$, where $\bar{\phi}_i$ is $0_{q\times1}$ or $0_{p\times1}$, respectively. We set $p = 2$ and $q = 3$ in order to capture sufficient dynamics for push and pull factors. $\bar{V}_0^{-1}$ is the diagonal precision matrix for the factor's autoregressive coefficients with elements proportional to $\frac{1}{0.75^l}$, where l is the corresponding lag length. The precision matrix for the autoregressive coefficients of the idiosyncratic terms is typically looser (see Del Negro and Otrok (2008); Potjagailo and Wolters (2019)). Therefore, we set $\bar{V}_i^{-1} = \bar{V}_0^{-1} \times 0.2$.

Table 1: Prior specification

	ν_{η_i}	$s^2_{\eta_i}$	ν_{ζ_i}	$s^2_{\zeta_i}$
Benchmark	$0.1 \times T$	0.1^2	T	0.025^2
Alternative 1	$0.25 \times T$	0.05^2	$0.5 \times T$	0.025^2
Alternative 2	$0.5 \times T$	0.05^2	$0.5 \times T$	0.025^2
Alternative 3	T	0.05^2	$0.5 \times T$	0.025^2

3 Data

Our dataset consists of flows into 26 emerging markets (hereafter EMEs) and 21 advanced economies (hereafter AEs) and ranges from August 2005 to September 2020. We proxy portfolio flow data using fund flow data from EPFR Global. Emerging market economies and advanced economies are categorised according to the EPFR classification, which is not equivalent to the IMF classification. The sample lengths is $T = 182$. This is capital, flowing from all investment funds, reporting to EPFR Global, into specific countries where this capital is being invested.[4] For example, if a US citizen buys shares of a fund, investing

[4]Note that not all internationally available investment funds report their asset purchases and sales to EPFR Global.

in Brazilian assets, this would be a Brazilian inflow - no matter where the domicile of the fund actually is. Even if it was a Brazilian fund, it would be considered as a Brazilian inflow. The only matter is the domicile of the final investment target. These monthly flows are expressed as a percentage of total net assets at the start of the period. The flows are calculated as the difference between the end of period assets minus the beginning of period assets minus the portfolio performance (including asset and exchange rate changes).[5] This way, valuation effects are eliminated. We measure only capital which enters or leaves the specific fund group within a specific period. In case that an investment fund has the mandate to invest in more than one country, each US dollar entering the fund is automatically allocated to the target countries given their current weight in the fund.

Koepke and Paetzold (2020) provide a detailed comparison between official Balance of Payments (BoP) statistics and EPFR fund flows data. They show that the data in monthly frequency cover about 96 percent of assets under management of the global investment fund industry. Nevertheless, we acknowledge that fund flows are only a sub-category of portfolio flows. Transactions by private investors, pension funds, sovereign wealth funds etc. are not taken into account. Hence, results should be cautiously taken when we extrapolate to more general results on the drivers of portfolio flows.

Note that EPFR data and BoP statistics are not exactly equivalent (see Koepke and Paetzold (2020)). For example, let's assume that a German investor invests capital in an Ireland or Luxembourg based investment fund, which has a mandate to invest in German equity. This example may sound odd, but is common practice. As soon as the fund utilises the capital to purchase German equity, the flows appear in the German BoP statistics as well as in the EPFR data. The German investor, however, could also purchase investment certificates from a Germany based fund. In this case, the transaction would appear in the EPFR statistics, but not in the German BoP statistics. While the EPFR statistics record all fund flows, the BoP statistics measure cross-country transactions, only.

4 Results: Time-variation in the push and pull factors of fund flows

We start with a decomposition of the data in order to get a better understanding of the differences between the common cycles and country-specific cycles. Afterwards, we will analyse the quantitative importance of the components as well as their dynamics with respect to macroeconomic variables.

4.1 Capturing comovements

In order to show that the model successfully decomposes the data into common cycles and country-specific cycles we start with a decomposition of the data. Figures A.1, A.2, A.3 and A.4 show the decompositions for the four models and datasets, respectively. Each top panel displays a plot of the corresponding standardised (i.e., each series was demeaned and divided by its standard deviation) fund flows ($y_{i,t}$). The Figures show that the outflows during the GFC and the Covid-19 pandemic are much more pronounced in the bond flows

[5]Note that the net total assets at the start of the period is not necessarily equal to the total net assets at the end of the previous period, as additional funds could have started reporting to EPFR Global.

series than in the equity flows series. Furthermore, most of the persistence in the data comes from the common cycles (middle panel), derived by multiplying the country-specific time-varying loadings by the common factor ($b_{i,t} f_t$). Moreover, the common cycles of bond flows are more persistent than those relating to equity flows. We also observe that global events such as the 2008/2009 GFC and the Covid-19 pandemic are well captured by the common cycles, implying that the models do actually capture global and common effects in the data. Country-specific cycles ($\epsilon_{i,t}$) show a very low persistence compared with common cycles. We also observe substantial changes in the volatilities over time. Country-specific fluctuations of bond and equity flows into AEs show a relatively high volatility during the GFC and the European debt crisis and a decline in volatility thereafter. The volatility of country-specific fluctuations with respect to bond flows into EMEs decline from the beginning of the sample to about 2011/2012 and increase subsequently. The corresponding volatilities for equity flows into EMEs show a gradual decline in the volatility from the beginning to the end of the sample.

Hence, the results suggest not only that our model actually captures comovements, but also that time-variation and stochastic volatility may play an important role for the analysis of these data.

4.2 Measuring comovements

First, we draw our attention on the cross-correlation in the data. A high degree of cross-correlation in the data would imply that the fund flow series under investigation share a relatively high degree of comovement, implying that common factors (i.e. push factors) are of importance. Hence, changes in the correlation indicate time-variation in the push and pull factors.

Instead of computing rolling-window estimates of pairwise correlation as in Barrot and Serven (2018), we use the factor loadings and stochastic volatilities to derive the average implied pairwise correlation between the flows for all country pairs i and j at any point t in our sample (and for every MCMC draw):

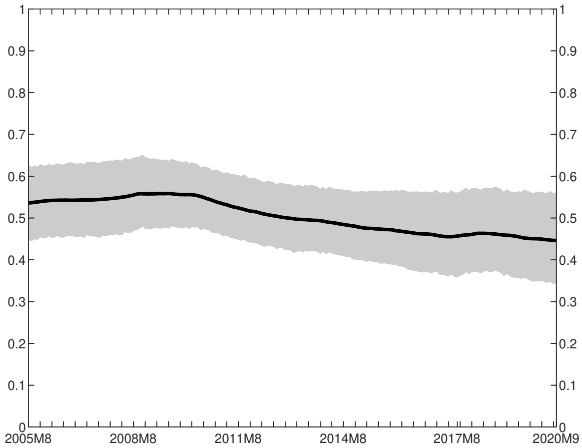
$$\rho_{ij,t} = \frac{\beta_{i,t}\beta_{j,t} Var_t^{factor}}{\sqrt{Var_{i,t}^{total}}\sqrt{Var_{j,t}^{total}}} \tag{6}$$

The advantage of this approach over rolling-windows estimates is that the present correlation measure is time-specific and does not relate to a relatively large window. We can also compute measures for every observation t. In a rolling-window set-up we would loose a number of observations, corresponding to the window-size minus 1. The disadvantage of our approach is that we would understate the pairwise correlation if we had omitted certain common factors. Given that our sample is disaggregated with respect to region and asset classes, this caveat is supposed to be of minor importance.

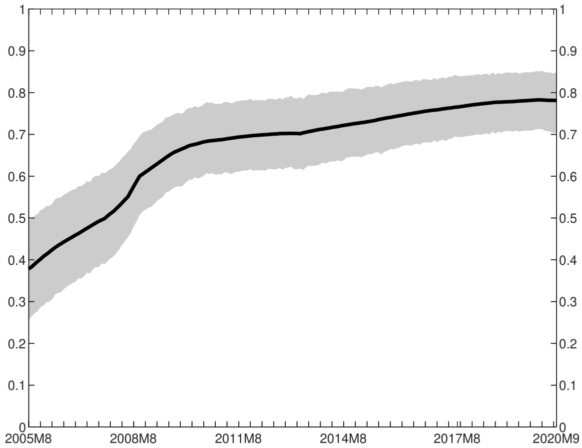
Figure 1 shows the time-specific medians (black lines) as well as the 90% bands (grey area) of the average implied cross-country correlations for each of our estimated models. The figure exhibits an increase in all correlations from the beginning of the sample period until the outbreak of the GFC. However, the increase is less pronounced with respect to flows into bonds, investing in EMEs. Henceforth, the patterns begin to change.

Figures 1a and 1c show that the correlation between flows into funds, having a mandate

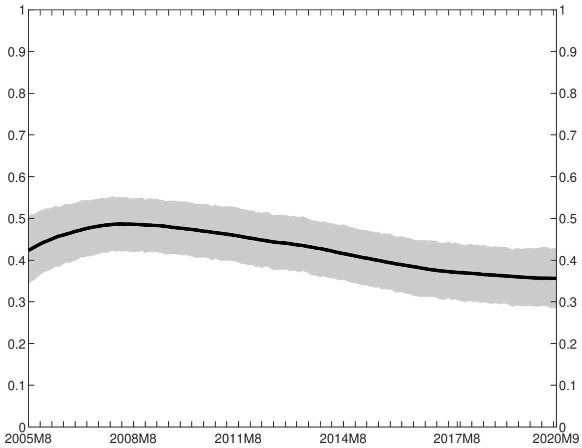
Figure 1: Average pairwise cross-correlations



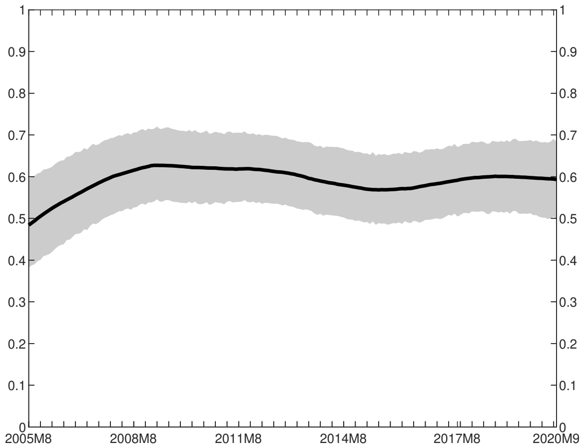
(a) Bonds EME



(b) Bonds AE



(c) Equities EME



(d) Equities AE

Notes: The figure displays the time-specific medians (black lines) and 90% bands (grey areas) of the average implied pairwise cross-correlations derived from each MCMC draw for all estimated models.

to invest in EME bonds decreased after the GFC. Contrary, Figure 1b implies that the average correlation between flows into funds, investing in AEs bonds increased, while the correlation between flows into AE equities remained relatively stable (see Figure 1d). Overall, the model implies that the correlation between flows into AEs has increased or remained stable over time, while the correlation between flows into EMEs has declined. As a consequence, we would expect that the importance of the push factors (i.e. the common component) on average has increased in AEs and declined in EMEs.

An alternative way of measuring effects of common factors is a variance decomposition of the different variables (see, for example, Kose, Otrok, and Whiteman (2003); Karadimitropoulou and León-Ledesma (2013); Karadimitropoulou (2018)). Here, the model- implied variance of a variable (i.e. a country flow) is decomposed into the variance contributed by shocks to the common factor and idiosyncratic shocks. Given that our model allows for time-variation, we can estimate how the relative importance of the common component and the idiosyncratic component evolves over time (see Del Negro and Otrok (2008); Potjagailo and Wolters (2019)). Technically, we multiply the factor loading at time t by the model implied variance of the factor at time t in order to compute the variance, contributed by the factor. Dividing this measure by the model implied variance of variable i yields the relative importance of the factor for variable i in terms of contributed variance.

The figures relating to the relative importance of push and pull factors are displayed in Tables B.1, B.2, B.3, and B.4, respectively. The tables show the relative contributions of the common factors and country-specific effects to the implied variance of flows into country i (in rows). For the purpose of exposition, the corresponding time dimension (in columns) is limited to 6 observations: 2005M8 (beginning of the sample), 2008M8, 2011M8, 2014M8, 2017M8 and 2020M9 (end of the sample). All figures are in percent and figures in parenthesis correspond to the 90% posterior bands. We also account for significance in the changes over time. Speaking in frequentist language, figures are boldfaced (underlined) if a change in the share of explained variance relative to the beginning of the sample (the previous sample) is statistically significant at the 10% level.

Table (B.1) shows significant changes in the relative importance of the common factor or the idiosyncratic component for bond flows into some of the EMEs, but not into all countries. However, even within this group of countries, there is quite some heterogeneity regarding the source of the change. In some countries the common factor became more important over time (e.g. Argentina, Chile, Indonesia, Kasachstan, Mexiko, Panama, Peru, Russia, South Africa and Turkey). In other countries the idiosyncratic component gained importance (e.g. China, Colombia, Czech Republic, India, Korea, Pakistan, Romania and Thailand). In other words, comovements became stronger across some countries, while they weakened across other countries in the sample. Overall, there is no clear pattern, which confirms the results from our average pairwise cross-correlation analysis before (see Figure 1a). Also Cerutti et al. (2019) and Sarno et al. (2016) documented such a heterogeneity. Nevertheless, the results provide statistical evidence that push factors should not be ignored for EMEs. They are important for selected countries.

The figures regarding flows into bond funds, investing in AEs, are not ambiguous at all (see Table B.2). Whenever we observe significant changes in the variance decomposition, it is the relative importance of the common factor that increases – in line with the developments of the average pairwise cross-correlations (see Figure 1b). This applies to Australia, Hong Kong, Japan, Singapore, Austria, Belgium, Denmark, Finland France, Germany, Greece, Ireland, Italy, Netherlands, Norway, United Kingdom, Canada and United States. Within the group of EU member countries, we observe particularly high shares of factor importance and several period-to-period changes in the significance around 2014M8 and 2017M8. Obviously, the common component became an important source in fluctuations of bond fund flows for those country. A reason could be that investors see the European advanced economies as a whole. These figures are somewhat higher than those in Barrot and Serven (2018), who focus on aggregate capital flows, but point in the same direction.

The figures of flows into equity funds, investing in EMEs, are more ambiguous, again (see Table B.3). On the one hand, the relative importance of the factor increased in Argentina, Hungary, Indonesia, Kasachstan, Malaysia, Panama, Pakistan, Philippines and South Africa. On the other hand, the relative importance of the factor weakened in Chile, China, Colombia, Croatia, Israel, Korea, Mexico, Romania and Thailand. As in the case of bond fund flows into EMEs we see a heterogeneous picture. While push factors seem to be less important for some countries, they are of importance for others. These findings also confirm the overall picture presented in Figure 1c.

Lastly, the flows into equity funds, investing in AEs, are also very much in line with the correlation analysis above (see Figure 1d). We observe that the importance of the common factor has increased significantly for several countries until 2008M8 – most likely as a consequence of the GFC. Later, the picture become slightly more heterogeneous. Overall, the relative importance of the factor increased significantly in Belgium, Denmark, Finland, France, Ireland, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and United Kingdom. It weakened in Australia, Hong Kong, Japan, Singapore, Austria and Germany (here only in 2011M8). Although the picture is slightly more heterogeneous than in Table B.2, there is strong evidence regarding the relative importance of the common factor for EU member countries (except Austria and Germany). In Ireland, for example, the factor explains 99% of the fund flow variability in 2017M8 and 2020M9. Asian countries, on the other hand, seem to be less prone to push factors.

We can conclude this section by arguing that the variances of fund flows into EMEs behave similarly across both asset classes. Push factors affect certain countries more than others, whereby the countries may differ across asset classes. The same applies to fund flows into AEs. Especially for flows into AEs, we observe an increase in the relative importance of the push factors. These statistics, however, are more of a descriptive nature and lack economic interpretation. The following sections provide deeper insights into the economic meaning of the identified push and pull factors.

4.3 Time-variation in the loadings of common factors

Having analysed the importance of the common factors using variance decompositions, we also want to shed light on the importance of time-variation in the factor loadings ($b_{i,t}$) as one driver of the relative importance of the factors. Figures 2 and 3 show the loadings for bond flows and equity flows, respectively. For expositional purposes, we limit our analyses to China (the largest emerging market economy) Germany (the largest EMU member), Greece (an economy that was hit by a severe economic crisis) and the US (the largest economy in our sample). Note that the common factors differ between emerging and advanced economies as well as between bond flows and equity flows.

With respect to bond flows we observe no evidence for time-variation in the loadings of flows into China and Germany. However, bond flows into Greece have decoupled from the common factor following the global financial crisis. This result is not surprising given the idiosyncratic economic crisis that took place in Greece, following the GFC. There is only weak evidence suggesting that the United States was effected by the common factor at the beginning of the sample. This, however, has changed significantly over the sample period, as we observe a very strong increase in the loadings over time. Hence, this movement has also supported the relative increase in the importance of the factor documented in the variance decomposition (see Table B.2). Note that the figures presented in this section reflect an increase or decline in the correlation of the country-specific series with the common factor. They are not necessarily in line with the variance decompositions, that is relative changes in the importance of the factors and country-specific components, which could be driven by either changes in the (1) loadings, (2) variance of the factor, and (3) the variance of the country-specific series.

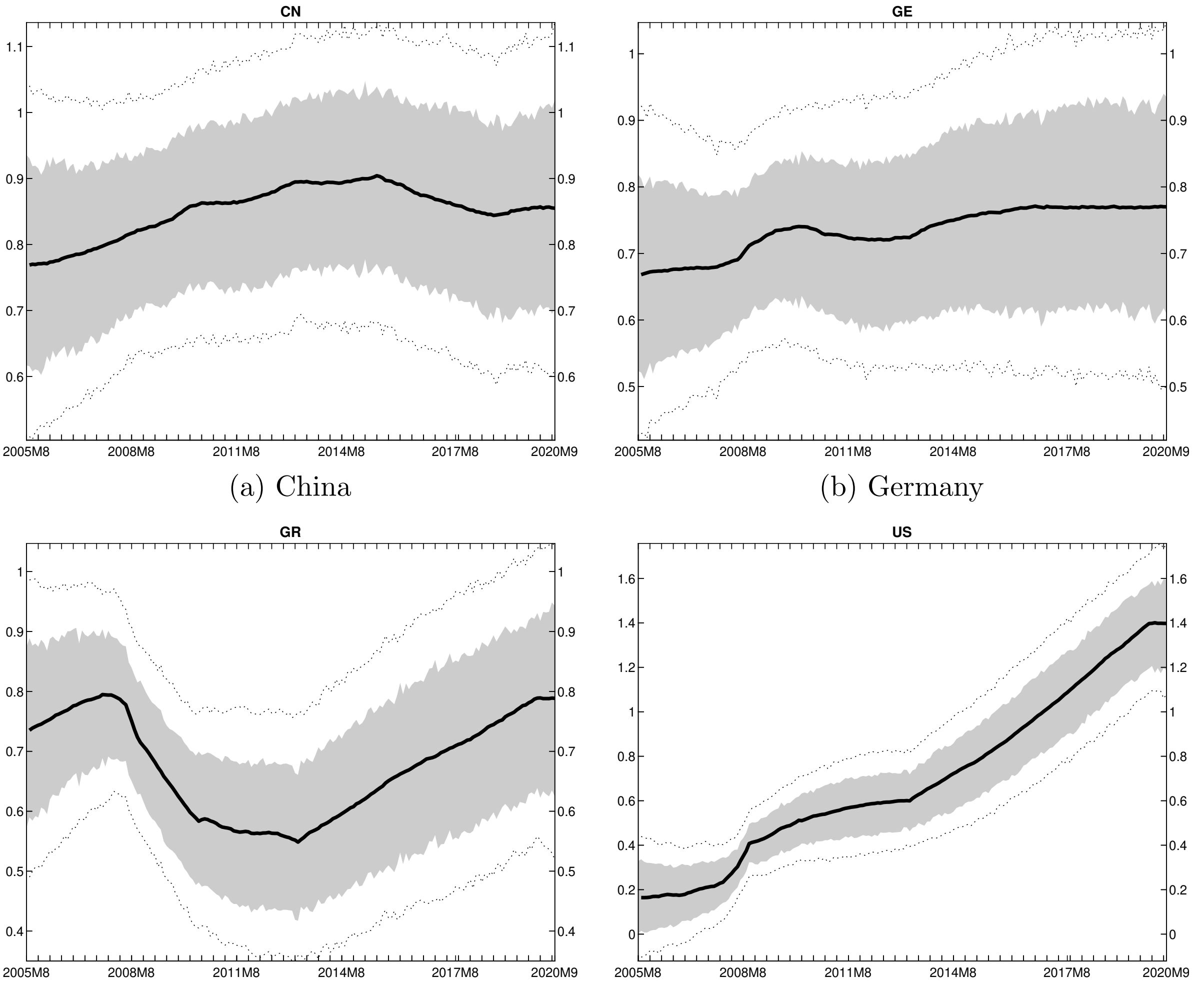
We observe more variation in the factor loadings relating to equity flows. For flows into China, the importance of the global factor began to decline after the beginning of the global financial crisis. This finding is also in line with the variance decomposition (see Table B.3), which suggests that the relative importance of the factor has declined significantly over the sample period. For Germany, we observe a decline in the loadings after the global financial crisis and a recovery around 2013 and 2014. The loadings for Greece and the United States increased until the middle of our sample and dropped thereafter. Both loadings, however, began to increase again around the end of 2014.

These findings suggest that the time-variation, which we have found using the variance decompositions, can at least to some extent be attributed to changes in the factor loadings. Hence, there is evidence, suggesting that a time-varying parameter model helps in estimating the relationships between fund flows and common factors.

5 Push factors

In each model we extract one common factor from the data. The corresponding estimates together with 90% credibility sets are plotted in Figure 4. All four graphs show that the credibility bands are very tight, implying that we obtain relatively precise estimates of the factors. We also observe that flows into bond funds show very pronounced periods of strong outflows and fast recoveries during the GFC and the COVID-19 pandemic (see Figures 4a and 4b). Figures 4c and 4d display outflows and recoveries from equity funds. For the latter asset class, the events are less pronounced. Less obvious is that all factors share some degree of correlation (see Table 2 and Figure C.5). The average pairwise correlation is 0.47, whereby the correlations between flows into funds investing in EMEs and AEs is particularly strong (0.75). The Table also reports a relatively high correlation between flows into equity and bond funds, investing in AEs. The correlations indicate that common factors could represent similar drivers. As a robustness check, we also obtained factors from a Bayesian dynamic factor model with time-invariant loadings. The correlation coefficients representing the relationship between factors from the time-varying model and the corresponding time-invariant model are 0.9970 (bond factor - AEs), 0.9937 (bond factor - EMEs), 0.9960 (equity factor - AEs) and 0.9765 (equity factor - EMEs).

Figure 2: Time-varying loadings of bond flows



(a) China

(b) Germany

(c) Greece

(d) United States

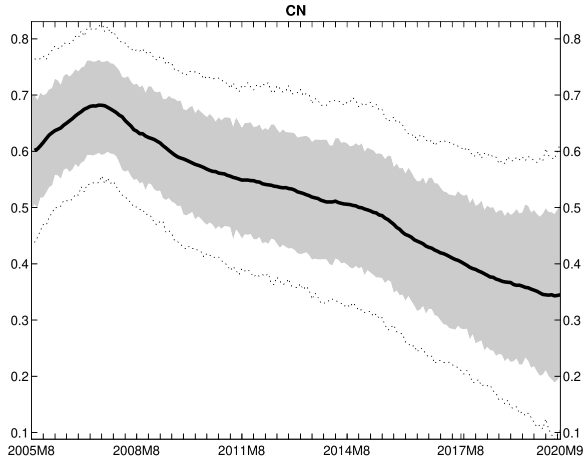
Notes: The figures display the time-specific medians (black lines), 68% bands (grey areas) and 90% bands (dotted lines) of the country-specific factor loadings derived from each MCMC draw for all estimated models.

Table 2: Correlation between common factors

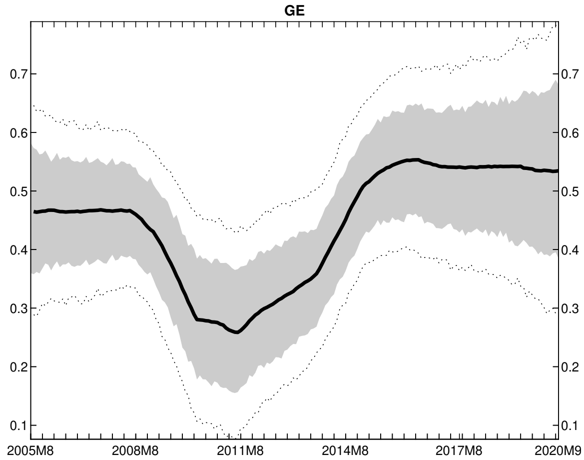
	Bond flows (EME)	Bond flows (AE)	Equity flows (EME)	Equity flows (AE)
Bond flows (EME)	1.00			
	–			
Bond flows (AE)	0.75	1.00		
	(0.00)	–		
Equity flows (EME)	0.33	0.21	1.00	
	(0.00)	(0.00)	–	
Equity flows (AE)	0.50	0.65	0.36	1.00
	(0.00)	(0.00)	(0.00)	–

Notes: This table shows the pairwise correlations between the common factors, obtained from the four different models. p-values in parentheses.

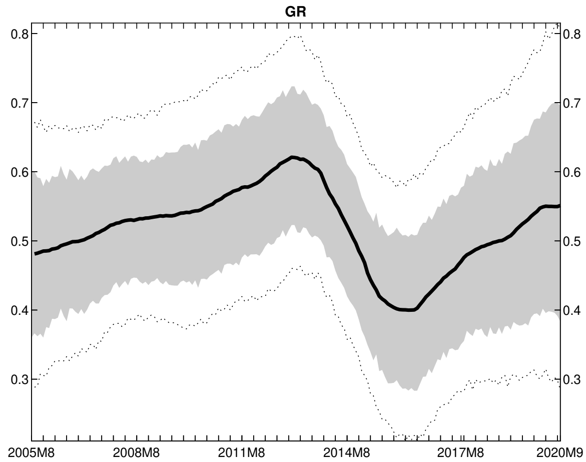
Figure 3: Time-varying loadings of equity flows



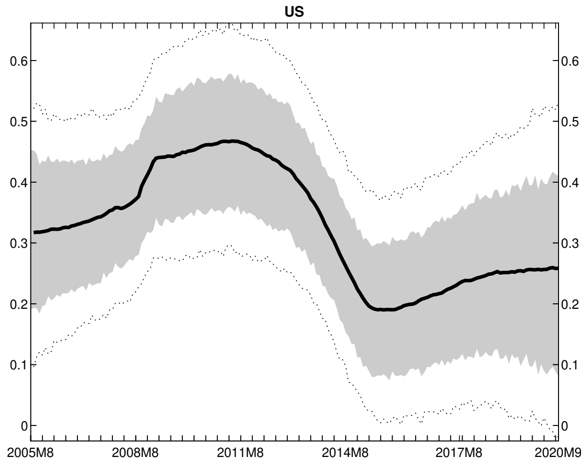
(a) China



(b) Germany



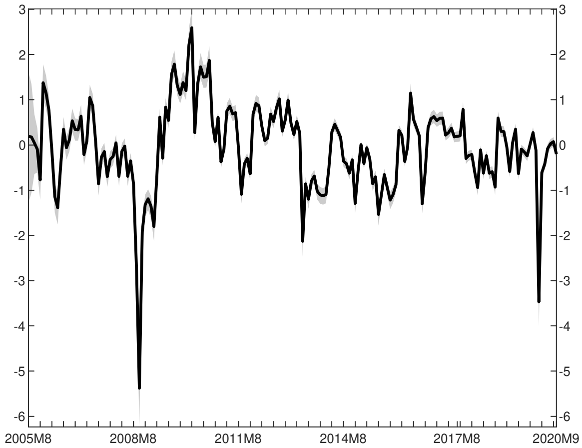
(c) Greece



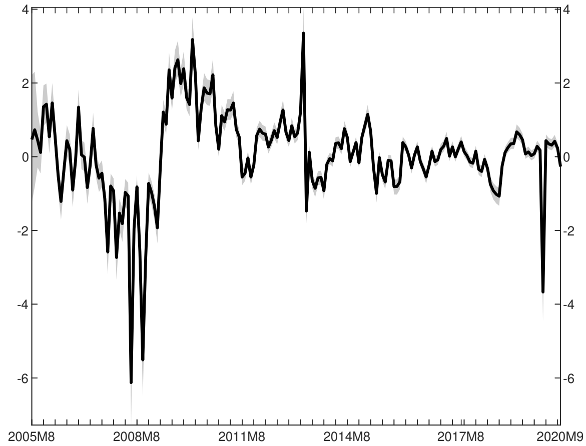
(d) United States

Notes: The figures display the time-specific medians (black lines), 68% bands (grey areas) and 90% bands (dotted lines) of the country-specific factor loadings derived from each MCMC draw for all estimated models.

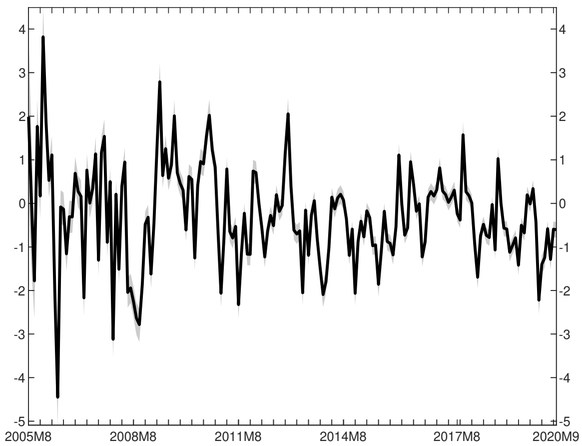
Figure 4: Factors and uncertainty



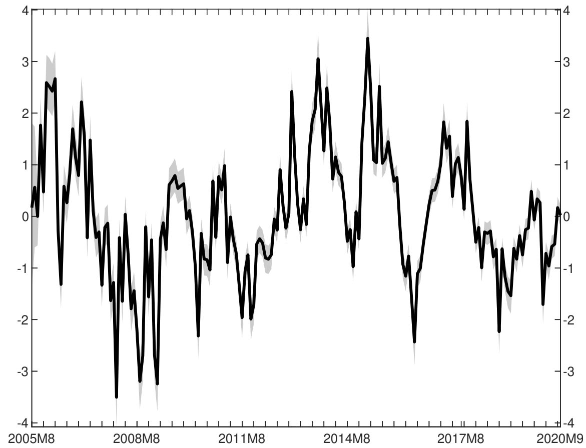
(a) Bonds EME



(b) Bonds AE



(c) Equities EME



(d) Equities AE

Notes: The figure displays the time-specific medians (black lines) and 90% bands (grey areas) of the common factors derived from each MCMC draw for all estimated models.

In order to get a better understanding of the common factors, we regress the medians of the posterior distributions of factors on potential covariates.[6] The literature on common factors in capital flows presents strong evidence, suggesting that global factors are negatively correlated with specific risk measures, representing the risk assessment on international financial markets. Other variables, such as the external value of the US dollar are correlated with factors, common to some countries, but not to all (see, for example, Sarno et al. (2016); Cerutti et al. (2019); Barrot and Serven (2018)). We examine if the findings in the literature are robust with respect to fund flows and factors, derived from a factor model that explicitly allows for time-variation in the loadings and stochastic volatility.

We start with regressions of the factors on specific risk measures (in levels), only (see Table 3). Data for all measures are obtained from the St. Louis Fed FRED database. The sample also ranges from August 2005 to September 2020, such that $T = 182$. The table shows regression coefficients for the specific factors (in columns) and risk measures (in rows). Since fund flows are standardized, we do not interpret the loading itself. We rather focus on the sign and the level of statistical significance. The p-values are given in parenthesis. Our results suggest strong negative relationships between the common factors and various risk measures (estimated in levels) such as the TED spread (spread between 3-month LIBOR based on US dollars and 3-month Treasury Bill rate), the VIX and Moody's Baa-Aaa spread (spread between Baa and Aaa rated US Corporate Bond yields with maturities 20 years and above). Except for the loading of the Baa-Aaa spread on equity fund flows into EMEs, the coefficients are all statistically significant on the 90% level, or above. Especially the VIX is highly significant in all regressions. Overall, the results indicate strong negative links between risk measures and common factors estimated from fund flows, supporting the findings in the empirical literature, mentioned above. An increase in global risk perception thus goes hand in hand with outflows from bond and equity funds. Hence, our factor model with time-variation also finds strong evidence for the link between risk measures and the common factor for monthly fund flow data.

The exercise sheds light on the relationship between specific risk measures and global factors estimated from fund flows. However, it does not account for the high correlation between those risk measures. In order to control for a common risk component across these variables, we also perform multivariate regressions on other traditional push factors of capital flows. The choice of the variables is based on findings in the literature (see, for example, Barrot and Serven (2018); Sarno et al. (2016); Cerutti et al. (2019); Buiter and Rahbari (2012)). We employ the risk measures as well as the percentage change in the US real effective exchange rate (hereafter: REER)[7], monthly US industrial production growth, the US real interest rate (1 month T-Bill rate minus CPI inflation) and the

[6]We acknowledge that this approach ignores the uncertainty provided by the posterior distributions of the factor estimates. However, we follow this common approach as our 90% credibility sets are extremely tight around the median (see Figure 4).

[7]The variable represents the real (CPI based) exchange rate of the US dollar vis-a-vis a basket of all IMF members between October 2005 and September 2020 in quantity quotation. Hence, an increase in the series corresponds to a real appreciation of the US dollar vis-à-vis the basket. In the case that purchasing power parity (PPP) holds, the exchange rate should be modeled in levels and not in percentage changes. However, we believe that the sample is way too short to assume that PPP holds. Moreover, it is reasonable to assume that PPP may not hold, due to Balassa-Samuelson effects in emerging and developing economies. Therefore, we consider percentage changes in the US REER.

Table 3: Risk measures as covariates of common factors

	Bonds EM	Bonds AE	Equity EM	Equity AE
TED spread	-1.100***	-1.732***	-0.525*	-1.249***
	(0.00)	(0.00)	(0.06)	(0.00)
Observations	182	182	182	182
R-squared	0.25	0.38	0.04	0.18
VIX	-0.046***	-0.049***	-0.031***	-0.070***
	(0.00)	(0.00)	(0.01)	(0.00)
Observations	182	182	182	182
R-squared	0.20	0.14	0.06	0.26
Baa-Aaa spread	-0.663***	-0.720*	-0.184	-1.062***
	(0.01)	(0.02)	(0.55)	(0.00)
Observations	182	182	182	182
R-squared	0.11	0.08	0.01	0.15

Notes: This table shows the loadings of risk measures on factors, representing the medians of the posterior distributions of factors, derived from a Bayesian dynamic factor model with time-varying coefficients. The loadings are obtained from single equation OLS regressions. Each regression includes a constant (not reported). p-values (based on HAC standard errors) in parentheses. *** $p < 0.01$, *** $p < 0.05$, * $p < 0.1$.

percentage changes in the S&P 500 as well as the percentage change in the oil price (WTI). Data for the US REER and the S&P 500 are obtained from Haver Analytics – other variables from the St. Louis Fed FRED database.

Table 4: Covariates of common factors

	Bonds EM	Bonds AE	Equity EM	Equity AE
VIX	0.0026	0.0264	-0.0017	-0.0495**
	(0.90)	(0.26)	(0.93)	(0.02)
TED spread	-0.7187***	-1.5694***	-0.1660	-0.8096***
	(0.01)	(0.00)	(0.49)	(0.00)
Baa-Aaa spread	-0.1987	-0.1436	0.1070	0.0485
	(0.50)	(0.64)	(0.68)	(0.87)
US REER	-27.5332***	-9.8261*	-31.0877***	-3.8543
	(0.00)	(0.08)	(0.00)	(0.61)
US industrial prod.	0.0310	0.0497	0.0168	0.0205
	(0.47)	(0.39)	(0.78)	(0.80)
US RIR	0.1075	0.1565	0.1665	0.2615*
	(0.38)	(0.23)	(0.24)	(0.04)
S&P 500	5.8315***	12.7256***	9.4726***	5.1176*
	(0.01)	(0.00)	(0.01)	(0.06)
Oil price (WTI)	-0.2863	-1.1216*	-0.1118	-2.2554**
	(0.53)	(0.08)	(0.89)	(0.02)
Observations	182	182	182	182
R-squared	0.50	0.52	0.37	0.34

Notes: This table shows the loadings of various covariates on factors, representing the medians of the posterior distributions of factors, derived from a Bayesian dynamic factor model with time-varying coefficients. The loadings are obtained from single equation OLS regressions. Each regression includes a constant (not reported). p-values (rounded; based on HAC standard errors) in parentheses. *** $p < 0.01$, *** $p < 0.05$, * $p < 0.1$.

Table 4 presents the results of the multivariate regressions. Once controlling for different risk measures, the TED spread becomes the dominant covariate, which confirms the findings by Fratzscher (2012). This result can be explained by the sample period, which includes the GFC where the TED spread played an important role. It is highly significant in regressions of both bond flows factors and the factor corresponding to equity flows into AEs. In the latter regression, the VIX is also statistically significant. Interestingly, in the regression of the factor based on equity flows into EMEs no risk factor is statistically significant. We assume that this finding is spurious because of a statistically significant negative correlation between risk measures and the S&P 500 returns. When omitting the returns, the VIX becomes statistically significant. Results are available upon request.

Also the S&P 500 returns (positive sign) appear to be of importance. The loadings are statistically significant in all regressions. Additionally, we find statistically significant relationships with respect to the US real effective exchange rate (negative sign) for all factors except for the factor, extracted from equity funds, investing in AEs. The coefficients are highly significant for both EME asset classes. For bond funds, investing in

AEs, the significance is weaker. Also the oil price has statistically significant coefficients (with negative sign) in regressions of factors relating to bond and equity funds, investing in AEs. Therefore, flows into EMEs are less prone to oil price changes. Lastly, the US RIR has a positive and statistically significant sign with respect to the factor extracted from equity funds, investing in AEs.

Overall, the results support findings by Rey (2013); Barrot and Serven (2018); Sarno et al. (2016); Cerutti et al. (2019); Fratzscher (2012) and others. The relevance of risk measures, exchange rates, stock market returns and commodity prices also holds for fund flow data at a high frequency. Also the introduction of time-variation in the factor loadings and stochastic volatility seems to have no effect on the qualitative importance of those variables with respect to the common factor. The following section analyses the pull factors.

6 Pull factors

Apart from the common factors, the idiosyncratic components entail important information, as well. We interpret these idiosyncratic components as pull-factors – i.e. variables which attract or repel capital from a country's perspective. We account for commonly used variables in this context (see, for example, Sarno et al. (2016); Fratzscher (2012)): industrial production, short-term interest rates, inflation, reserve accumulation, exchange rates and the local stock price index. We obtained all variables from Haver Analytics. Due to publication lags, the sample is smaller and ranges from August 2005 to December 2019, such that $T = 173$ (for other datasets $T = 182$). The relationships between the estimated pull factors and the potential explanatory variables are estimated with fixed effects panel regressions:

$$y_{i,t} = \alpha_i + \beta f_t + \gamma x_{i,t} + \epsilon_{i,t} \tag{7}$$

According to the regression equation, we regress the country-specific fund flows (y_{it}) on a country-specific constant (α_i), a common factor (f_t) with common loading (β) and country-specific explanatory variables (x_{it}) with country-specific loading (γ_i). ϵ_{i_t} captures the error term and is IID. Potential control variables such as the exchange rate regime, capital mobility and a crisis dummy do not cause any qualitative change to the results.

The regression design follows Cerutti et al. (2019) and accounts for an important feature of the data. Recall from equation 4.1 that the factor model decomposes each variable into a common component and an idiosyncratic component. Following the philosophy of section 5, one could obtain the pull factors by subtracting the estimated push factors from the data. The next logical step would be regressing the pull factors on the aforementioned covariates. This approach, however, would discard the fact that the country-specific covariates such as industrial production, or the stock price index possess information, common to all variables over the cross-section. In other words, the country-specific covariates are supposed to be correlated with the common factor. In order to control for this correlation, we regress the data on the common factor and the country-specific covariates.

Table 5 reports the results for each panel regression model (in columns). Not surprisingly, the common factors are highly significant in each regression. In addition, the

Table 5: Covariates of pull factors

	Bond EME	Equity EME	Bond AE	Equity AE
Common factor	0.9590***	0.7194***	0.6525***	0.5849***
	(0.00)	(0.00)	(0.00)	(0.00)
Ind. Production	0.2770	0.6125	0.1080	0.2860
	(0.37)	(0.31)	(0.53)	(0.44)
Short-term rate	-0.0067	-0.0053	-0.0035	0.0622
	(0.32)	(0.55)	(0.95)	(0.31)
Inflation	-2.5515*	-0.0441	7.1614**	-3.0201
	(0.07)	(0.98)	(0.03)	(0.15)
Reserves	0.1454*	0.0267	-0.0207**	-0.0232
	(0.10)	(0.84)	(0.01)	(0.22)
Exchange rate	0.2211	0.0108	0.6097	-1.1204
	(0.33)	(0.97)	(0.20)	(0.15)
Stock index	0.2602**	0.8607***	0.5436*	1.6312**
	(0.04)	(0.00)	(0.068)	(0.01)
Groups	26	26	21	21
Obs	173	173	173	173
R squared	0.86	0.70	0.66	0.60

Notes: This table shows the loadings of various covariates on pull facors, representing the medians of the posterior distributions of factors, derived from a Bayesian dynamic factor model with time-varying coefficients. The loadings are obtained from fixed effects regressions. Constants are not reported. p-values (rounded; robust standard errors) in parentheses. *** $p < 0.01$, *** $p < 0.05$, * $p < 0.1$.

local stock price index is also statistically significant in all models – at least at the 10% level. Moreover, we find evidence for the importance of the inflation rate and reserve accumulation for bond flows. Interestingly, the signs change between the regions. For bond flows into EMEs, inflation has a negative sign and reserve accumulation a positive sign. Both signs are intuitive. Low inflation rates make bonds more attractive and reserve accumulation implies higher exchange rate stability (less uncertainty). For equity flows into AEs, however, inflation has a positive sign and reserve accumulation a negative sign.

The positive sign with respect to inflation in AEs seems to be counterintuitive. However, during the sample period inflation levels in most AEs were extraordinary low and bond prices extraordinarily high. The sign of the coefficient might reflect that market participants expectations regarding a reversal increased with declining inflation rates. The negative relationship between inflows and reserve accumulation could imply that reserve accumulation in AEs is interpreted as sign of a misalignment rather than a stabilisation policy.

Our R squared statistics are relatively high, implying that the variables can explain a high share of the fund flow variability. This is actually at odds with findings by Forbes and Warnock (2012), who show that R squared statistics are typically very low in capital flow regressions. The reason for our high values is that we include common factors from the factor model as a control variable. For many countries, this variable entails a large part of the information as we have learned. Therefore, we do not interpret the R squared values, but focus on the significance and the signs of the other explanatory variables.

7 Convergence in the volatility of fund flows across countries

Apart from time-variation in the push and pull factors of capital flows we are able to analyse a further dimension of comovements between the fund flows. Our model framework enables us to test if there has been convergence in volatility of flows across countries over time. Thereby, we can distinguish between volatility convergence due to the push factors or the pull factors. In other words, we analyse if the impact of shocks to push factors became more similar across countries, or if the magnitude of pull factor cycles became more similar.

Technically, we compute the model implied volatilities of the variables, common factors and idiosyncratic components for every MCMC draw and period as described in section 4. Taking the cross-sectional standard deviation for every period yields a time-varying measure of volatility convergence. In order to account for statistical significance we compute the median and 90% credibility sets.

Figures D.6 and D.7 show decompositions of the cross-sectional implied (time-varying) volatility of flows into bond and equity funds, respectively. The total volatility is decomposed into the variance attributed to the idiosyncratic as well as the common component. Both figures are very similar and unveil very different patterns between flows into funds, investing in EMEs and AEs. Flows into EMEs and AEs have in common that convergence is mainly a phenomenon of the 2008 financial crisis, as the dispersions between the idiosyncratic and common components decline significantly in the wake of the crisis. This result is impressive, but not surprising, as volatility increased in all countries during the GFC. Afterwards, the dispersion relating to flows into EMEs remained at the same level for both asset classes. For AEs, however, convergence in the volatility is only a phenomenon relating to the GFC (see Figures D.6d and D.7d). Later, the initial overall convergence has lost significance (see Figures D.6f and D.7f).

8 Conclusion

There is a controversial discussion on how strong capital flows into specific countries are affected by global push factors and domestic pull factors. The results vary widely, depending on the data frequency and the type of capital flow under investigation.

We contribute to this literature by estimating a Bayesian dynamic factor model with time-varying parameters and stochastic volatility for fund flow data as proxy for portfolio flows. The data by EPFR Global are based on fund flows into specific economies and are available in monthly frequency with a very short publication lag. The model enables us to extract common factors from the data, while the sensitivity to the common factor may vary over time – just as the stochastic volatility of the factor and the idiosyncratic component. We disaggregate the dataset into four categories and estimate four models, respectively: bond fund flows into EMEs, bond fund flows into AEs, equity fund flows into EMEs and equity fund flows into AEs. For each dataset we interpret the common factor as an aggregate of different push factors and the idiosyncratic component as an aggregate of country-specific pull factors. Using variance decompositions we estimate changes in the relative importance of push and pull factors over time and regression analysis helps us in identifying economic covariates of both factors.

Our results suggest that the relative importance of push and pull factors for portfolio flows most importantly depends on the region and time. The variance decompositions show that the relative importance of the push factor on average increased significantly for bond and equity fund flows into most of the AEs. In particular, push factors became very important for EU members, while being slightly less important for Asian economies. A reason could be that investors see the European advanced economies as a whole. With respect to flows into EMEs we find that the results are very heterogeneous – within and across asset classes. Important covariates of the common factors are risk measures such as the TED spread and the VIX, US stock markets returns, the US real effective exchange rate, the oil price and US real interest rates. Idiosyncratic components covary with domestic stock market returns, in particular. Inflation rates and reserve accumulation do also play a role, but only for bond fund flows. Moreover we provide evidence, suggesting a significant convergence in volatility of flows into EMEs over the sample period. For AEs, we observe such a convergence only during the GFC. After the crisis, volatility levels diverged again. Overall, we can summarise that there is a substantial degree in heterogeneity with respect to the relative importance of push and pull factors. In order to provide adequate policy measures in times of crisis, we need to monitor changes over time as these changes can be substantial and significant.

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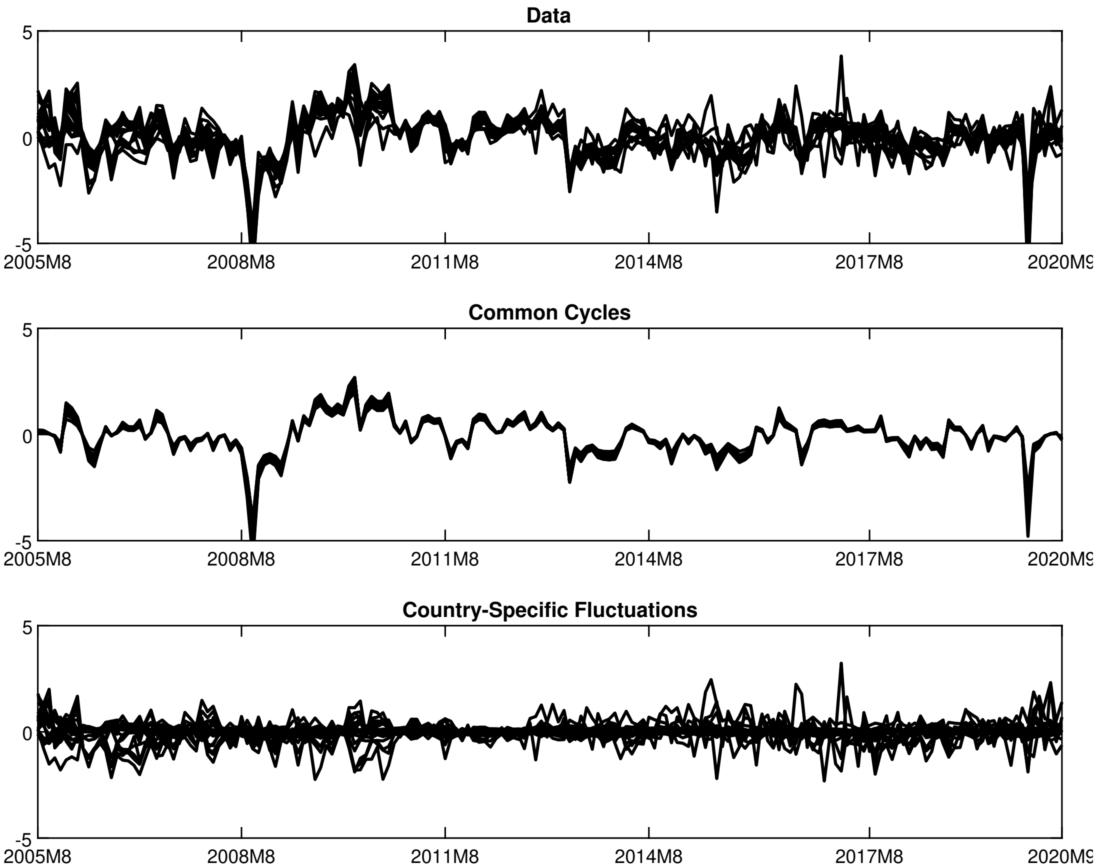
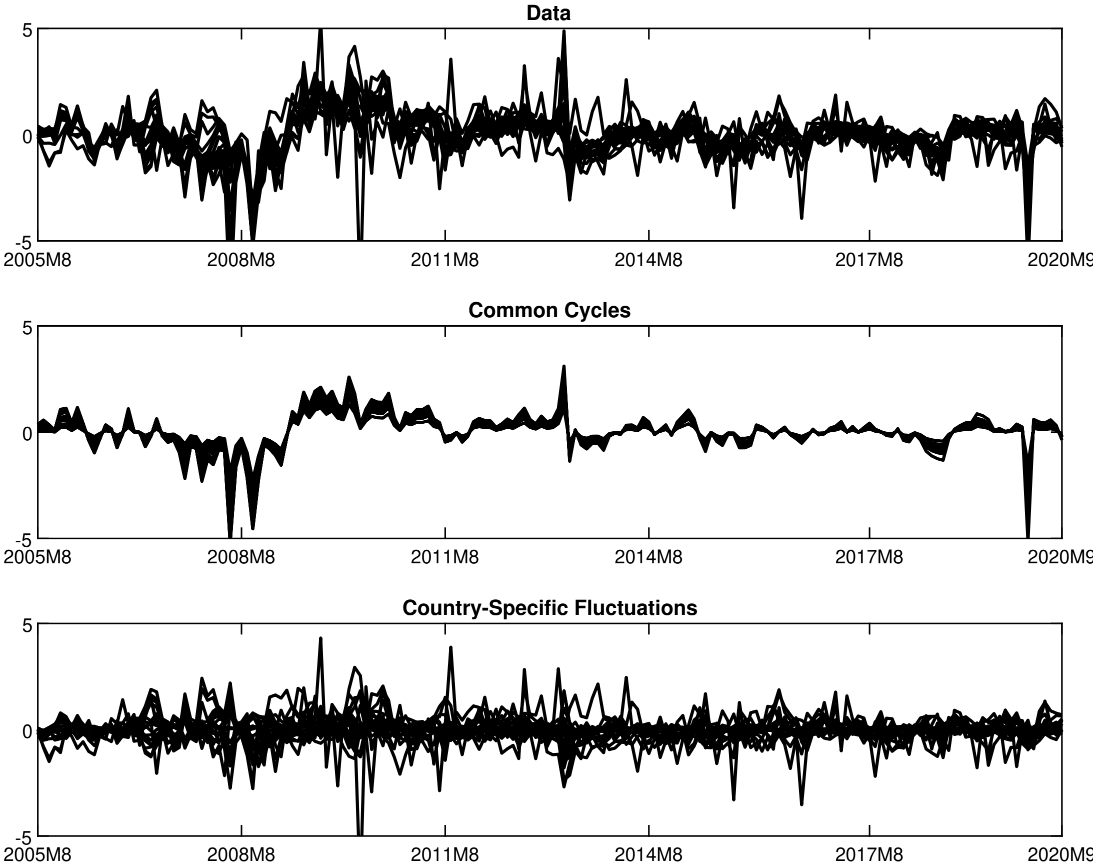
A Decomposition of data

Figure A.1: Decomposition of bond flows into EMEs



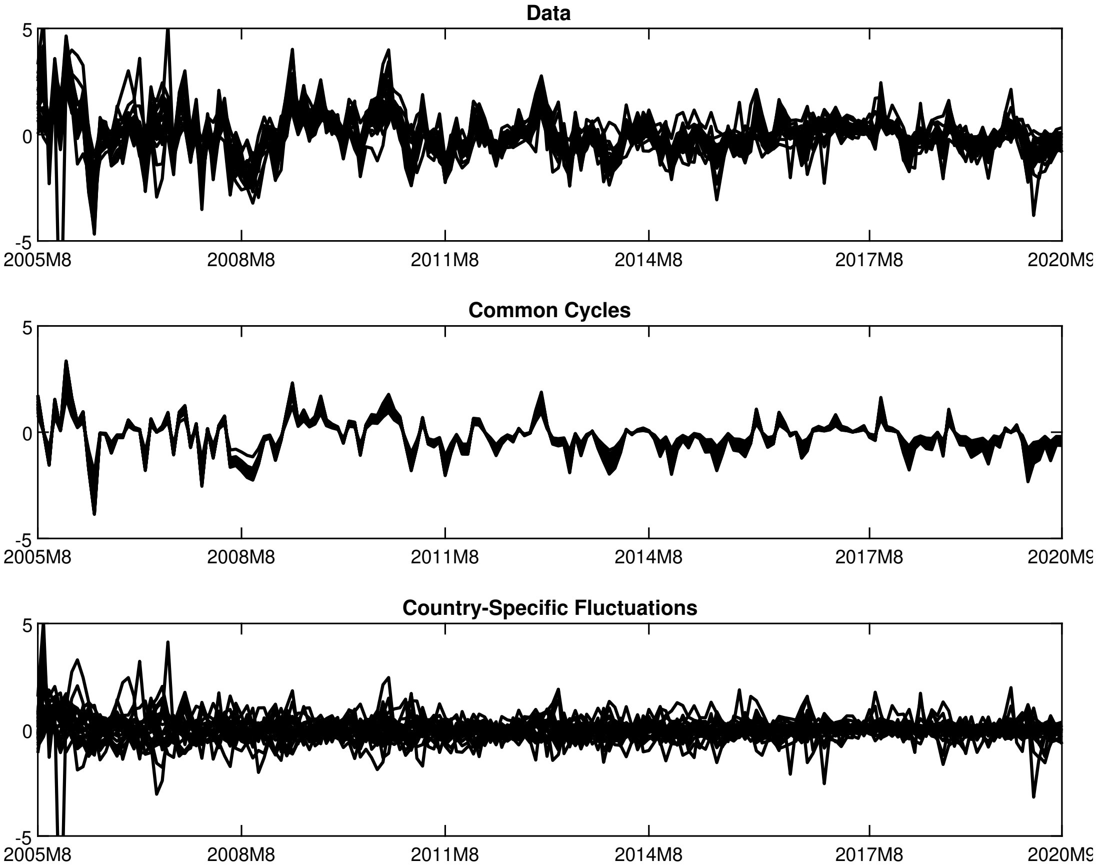
Notes: The figure displays the standardised EPFR Global data (top panel), the medians of the common factors times the medians of the loadings (middle panel) as well as country-specific components (bottom panel) for all countries, derived from each model-specific MCMC draw.

Figure A.2: Decomposition of bond flows into AEs



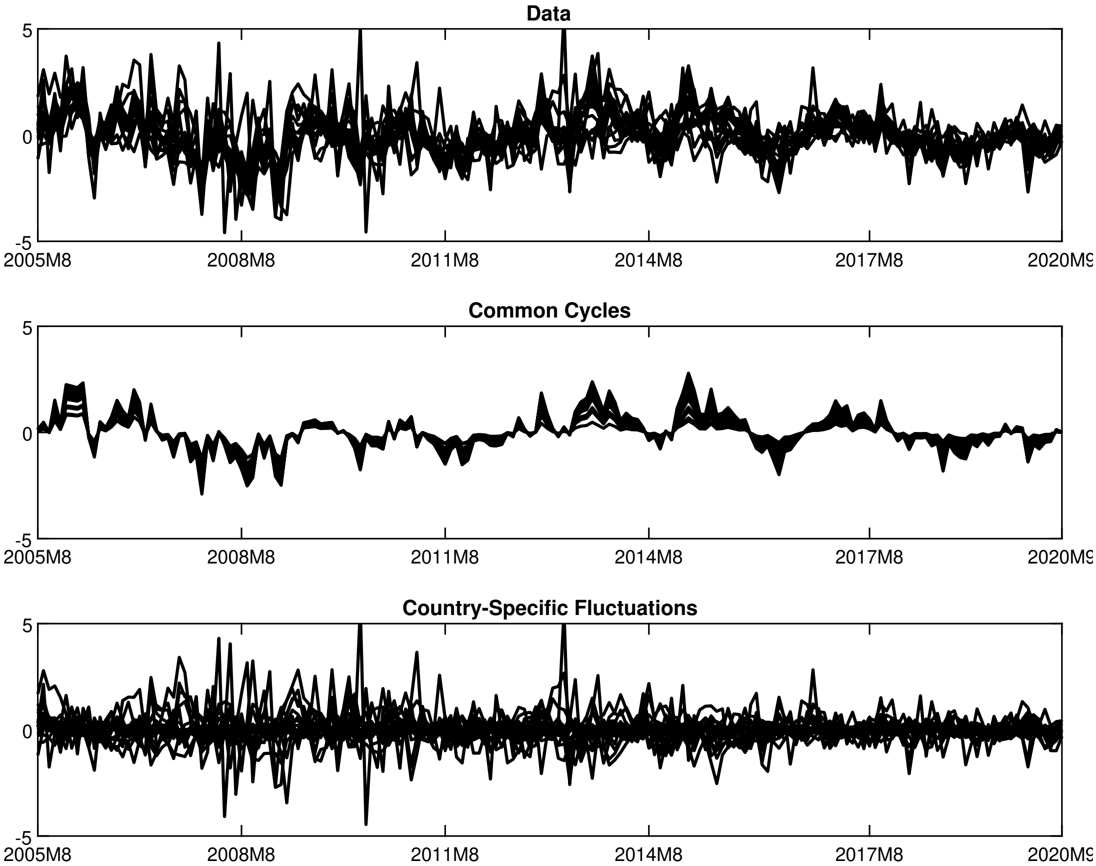
Notes: The figure displays the standardised EPFR Global data (top panel), the medians of the common factors times the medians of the loadings (middle panel) as well as country-specific components (bottom panel) for all countries, derived from each model-specific MCMC draw.

Figure A.3: Decomposition of equity flows into EMEs



Notes: The figure displays the standardised EPFR Global data (top panel), the medians of the common factors times the medians of the loadings (middle panel) as well as country-specific components (bottom panel) for all countries, derived from each model-specific MCMC draw.

Figure A.4: Decomposition of equity flows into AEs



Notes: The figure displays the standardised EPFR Global data (top panel), the medians of the common factors times the medians of the loadings (middle panel) as well as country-specific components (bottom panel) for all countries, derived from each model-specific MCMC draw.

B Variance decomposition

B.1 Flows into bond funds (EMEs)

Dates		2005M8		2008M8		2011M8		2014M8		2017M8		2020M9	
AR	Factor	54	(30,77)	**76**	(54,94)	**83**	(63,97)	**84**	(64,97)	**85**	(67,96)	**84**	(64,97)
	Country	46	(23,70)	**24**	(6,46)	**17**	(3,37)	**16**	(3,36)	**15**	(4,33)	**16**	(3,36)
BR	Factor	55	(35,73)	57	(36,75)	57	(35,76)	54	(32,74)	56	(31,78)	57	(31,81)
	Country	45	(27,65)	43	(25,64)	43	(24,65)	46	(26,68)	44	(22,69)	43	(19,69)
CH	Factor	52	(27,75)	**79**	(53,96)	**88**	(65,98)	**88**	(64,98)	**85**	(58,98)	**83**	(52,98)
	Country	48	(25,73)	**21**	(4,47)	**12**	(2,35)	**12**	(2,36)	**15**	(2,42)	**17**	(2,48)
CN	Factor	54	(34,71)	**33**	(20,48)	**21**	(10,32)	**15**	(6,24)	**11**	(4,19)	**10**	(3,19)
	Country	46	(29,66)	**67**	(52,80)	**79**	(68,90)	**85**	(76,94)	**89**	(81,96)	**90**	(81,97)
CO	Factor	64	(48,79)	**48**	(33,63)	**37**	(23,52)	**29**	(14,43)	**29**	(13,46)	**32**	(15,52)
	Country	36	(21,52)	**52**	(37,67)	**63**	(48,77)	**71**	(57,86)	**71**	(54,87)	**68**	(48,85)
CR	Factor	54	(34,74)	58	(34,79)	60	(36,82)	63	(37,83)	63	(36,87)	62	(33,87)
	Country	46	(26,66)	42	(21,66)	40	(18,64)	37	(17,63)	37	(13,64)	38	(13,67)
CZ	Factor	69	(54,83)	**36**	(22,49)	**15**	(7,24)	**11**	(4,17)	**9**	(4,17)	**10**	(4,18)
	Country	31	(17,46)	**64**	(51,78)	**85**	(76,93)	**89**	(83,96)	**91**	(83,96)	**90**	(82,96)
EG	Factor	61	(41,78)	70	(50,88)	72	(52,89)	71	(48,89)	75	(51,93)	75	(50,94)
	Country	39	(22,59)	30	(12,50)	28	(11,48)	29	(11,52)	25	(7,49)	25	(6,50)
HU	Factor	53	(32,71)	54	(32,75)	55	(33,77)	60	(34,81)	62	(34,86)	61	(33,87)
	Country	47	(29,68)	46	(25,68)	45	(23,67)	40	(19,66)	38	(14,66)	39	(13,67)
IN	Factor	53	(32,73)	**26**	(15,38)	**12**	(6,20)	**5**	(2, 9)	**3**	(1, 7)	**4**	(1, 8)
	Country	47	(27,68)	**74**	(62,85)	**88**	(80,94)	**95**	(91,98)	**97**	(93,99)	**96**	(92,99)
ID	Factor	49	(29,69)	**67**	(46,86)	**74**	(54,91)	**74**	(52,91)	67	(44,89)	65	(37,87)
	Country	51	(31,71)	**33**	(14,54)	**26**	(9,46)	**26**	(9,48)	33	(11,56)	35	(13,63)
IS	Factor	62	(45,79)	65	(46,83)	60	(39,78)	57	(35,77)	52	(28,74)	50	(25,74)
	Country	38	(21,55)	35	(17,54)	40	(22,61)	43	(23,65)	48	(26,72)	50	(26,75)
KA	Factor	57	(33,78)	**78**	(53,95)	**85**	(62,98)	**87**	(63,98)	**85**	(60,98)	**82**	(54,98)
	Country	43	(22,67)	**22**	(5,47)	**15**	(2,38)	**13**	(2,37)	**15**	(2,40)	**18**	(2,46)
KS	Factor	60	(40,78)	**40**	(27,53)	**25**	(14,35)	**14**	(7,23)	**11**	(4,19)	**10**	(3,18)
	Country	40	(22,60)	**60**	(47,73)	**75**	(65,86)	**86**	(77,93)	**89**	(81,96)	**90**	(82,97)
ML	Factor	47	(25,65)	55	(36,74)	62	(42,81)	62	(40,82)	58	(34,79)	56	(30,79)
	Country	53	(35,75)	45	(26,64)	38	(19,58)	38	(18,60)	42	(21,66)	44	(21,70)
ME	Factor	54	(31,74)	**75**	(52,93)	**81**	(59,95)	**82**	(59,96)	**81**	(57,97)	**79**	(51,97)
	Country	46	(26,69)	**25**	(7,48)	**19**	(5,41)	**18**	(4,41)	**19**	(3,43)	**21**	(3,49)
PN	Factor	55	(33,76)	**75**	(53,93)	**83**	(61,96)	**83**	(61,96)	**82**	(57,96)	**78**	(51,96)
	Country	45	(24,67)	**25**	(7,47)	**17**	(4,39)	**17**	(4,39)	**18**	(4,43)	**22**	(4,49)
PA	Factor	64	(48,79)	**49**	(33,64)	**40**	(25,56)	**32**	(17,48)	**24**	(11,40)	**19**	(7,34)
	Country	36	(21,52)	**51**	(36,67)	**60**	(44,75)	**68**	(52,83)	**76**	(60,89)	**81**	(66,93)
PE	Factor	51	(26,73)	**78**	(53,96)	**87**	(64,98)	**88**	(64,98)	**84**	(56,98)	**81**	(51,98)
	Country	49	(27,74)	**22**	(4,47)	**13**	(2,36)	**12**	(2,36)	**16**	(2,44)	**19**	(2,49)
PH	Factor	53	(35,71)	58	(39,74)	59	(39,76)	55	(35,74)	48	(26,69)	46	(23,69)
	Country	47	(29,65)	42	(26,61)	41	(24,61)	45	(26,65)	52	(31,74)	54	(31,77)
PO	Factor	56	(36,73)	55	(35,74)	54	(33,73)	53	(31,72)	53	(31,76)	54	(30,79)
	Country	44	(27,64)	45	(26,65)	46	(27,67)	47	(28,69)	47	(24,69)	46	(21,70)
RO	Factor	53	(35,69)	43	(25,60)	**36**	(20,55)	**35**	(18,55)	**35**	(15,55)	35	(14,58)
	Country	47	(31,65)	57	(40,75)	**64**	(45,80)	**65**	(45,82)	**65**	(45,85)	65	(42,86)
RF	Factor	51	(30,70)	**71**	(49,89)	**77**	(57,92)	**75**	(53,92)	**73**	(48,92)	**72**	(45,91)
	Country	49	(30,70)	**29**	(11,51)	**23**	(8,43)	**25**	(8,47)	**27**	(8,52)	**28**	(9,55)
SF	Factor	56	(36,76)	**73**	(53,90)	**79**	(59,93)	**80**	(58,94)	**77**	(53,94)	71	(46,91)
	Country	44	(24,64)	**27**	(10,47)	**21**	(7,41)	**20**	(6,42)	**23**	(6,47)	29	(9,54)
TH	Factor	43	(12,68)	30	(16,43)	19	(10,31)	**10**	(4,18)	**10**	(4,18)	18	(7,31)
	Country	57	(32,88)	70	(57,84)	81	(69,90)	**90**	(82,96)	**90**	(82,96)	82	(69,93)
TR	Factor	58	(41,76)	**70**	(52,86)	**74**	(56,89)	71	(50,87)	63	(40,85)	48	(24,72)
	Country	42	(24,59)	**30**	(14,48)	**26**	(11,44)	29	(13,50)	37	(15,60)	52	(28,76)

B.2 Flows into bond funds (AEs)

Dates		2005M8		2008M8		2011M8		2014M8		2017M8		2020M9	
AT	Factor	28	(5,51)	31	(13,50)	**49**	(28,71)	**51**	(28,73)	**63**	(41,82)	**68**	(47,85)
	Country	72	(49,95)	69	(50,87)	**51**	(29,72)	**49**	(27,72)	**37**	(18,59)	**32**	(15,53)
HK	Factor	12	(0,32)	30	(13,47)	**45**	(22,65)	**47**	(25,70)	**54**	(32,77)	**58**	(34,78)
	Country	88	(68,100)	70	(53,87)	**55**	(35,78)	**53**	(30,75)	**46**	(23,68)	**42**	(22,66)
JA	Factor	34	(10,56)	**59**	(40,77)	**85**	(73,95)	**91**	(83,97)	**94**	(87,98)	**95**	(89,99)
	Country	66	(44,90)	**41**	(23,60)	**15**	(5,27)	**9**	(3,17)	**6**	(2,13)	**5**	(1,11)
SI	Factor	16	(0,36)	**34**	(15,51)	**53**	(31,74)	**54**	(29,74)	**61**	(38,82)	**66**	(44,83)
	Country	84	(64,100)	**66**	(49,85)	**47**	(26,69)	**46**	(26,71)	**39**	(18,62)	**34**	(17,56)
AU	Factor	55	(34,75)	**81**	(69,92)	**92**	(84,97)	**96**	(92,99)	**97**	(94,99)	**97**	(94,99)
	Country	45	(25,66)	**19**	(8,31)	**8**	(3,16)	**4**	(1, 8)	**3**	(1, 6)	**3**	(1, 6)
BE	Factor	50	(28,72)	**81**	(67,93)	**94**	(88,98)	**97**	(94,99)	**98**	(96,100)	**98**	(96,100)
	Country	50	(28,72)	**19**	(7,33)	**6**	(2,12)	**3**	(1, 6)	**2**	(0, 4)	**2**	(0, 4)
DE	Factor	44	(19,68)	58	(41,74)	**78**	(65,89)	**83**	(71,93)	**87**	(76,95)	**89**	(81,96)
	Country	56	(32,81)	42	(26,59)	**22**	(11,35)	**17**	(7,29)	**13**	(5,24)	**11**	(4,19)
FI	Factor	52	(29,73)	**84**	(70,94)	**93**	(86,98)	**97**	(92,99)	**98**	(94,100)	**98**	(94,100)
	Country	48	(27,71)	**16**	(6,30)	**7**	(2,14)	**3**	(1, 8)	**2**	(0, 6)	**2**	(0, 6)
FR	Factor	53	(27,75)	**90**	(75,98)	**97**	(92,100)	**99**	(97,100)	**99**	(98,100)	**99**	(98,100)
	Country	47	(25,73)	**10**	(2,25)	**3**	(0, 8)	**1**	(0, 3)	**1**	(0, 2)	**1**	(0, 2)
GE	Factor	51	(28,70)	**70**	(56,84)	**81**	(69,92)	**88**	(78,96)	**91**	(83,97)	**92**	(84,98)
	Country	49	(30,72)	**30**	(16,44)	**19**	(8,31)	**12**	(4,22)	**9**	(3,17)	**8**	(2,16)
GR	Factor	66	(48,83)	74	(61,85)	66	(47,83)	72	(54,88)	81	(66,92)	**84**	(71,94)
	Country	34	(17,52)	26	(15,39)	34	(17,53)	28	(12,46)	19	(8,34)	**16**	(6,29)
IR	Factor	54	(30,76)	**87**	(71,97)	**95**	(87,99)	**98**	(94,100)	**99**	(96,100)	**99**	(97,100)
	Country	46	(24,70)	**13**	(3,29)	**5**	(1,13)	**2**	(0, 6)	**1**	(0, 4)	**1**	(0, 3)
IT	Factor	54	(31,76)	**88**	(74,97)	**96**	(89,99)	**98**	(95,100)	**99**	(96,100)	**99**	(96,100)
	Country	46	(24,69)	**12**	(3,26)	**4**	(1,11)	**2**	(0, 5)	**1**	(0, 4)	**1**	(0, 4)
NE	Factor	50	(23,74)	**91**	(75,99)	**98**	(92,100)	**99**	(96,100)	**99**	(98,100)	**99**	(98,100)
	Country	50	(26,77)	**9**	(1,25)	**2**	(0, 8)	**1**	(0, 4)	**1**	(0, 2)	**1**	(0, 2)
NO	Factor	37	(10,61)	43	(26,60)	**57**	(40,75)	54	(33,74)	53	(28,76)	46	(17,71)
	Country	63	(39,90)	57	(40,74)	**43**	(25,60)	46	(26,67)	47	(24,72)	54	(29,83)
SP	Factor	64	(44,82)	73	(62,85)	72	(56,85)	73	(57,87)	77	(62,90)	78	(62,91)
	Country	36	(18,56)	27	(15,38)	28	(15,44)	27	(13,43)	23	(10,38)	22	(9,38)
SW	Factor	45	(21,69)	52	(35,69)	63	(44,79)	57	(34,77)	55	(30,78)	56	(30,79)
	Country	55	(31,79)	48	(31,65)	37	(21,56)	43	(23,66)	45	(22,70)	44	(21,70)
ST	Factor	25	(4,46)	25	(11,41)	22	(4,39)	19	(0,36)	23	(0,42)	25	(0,46)
	Country	75	(54,96)	75	(59,89)	78	(61,96)	81	(64,100)	77	(58,100)	75	(54,100)
UI	Factor	40	(16,63)	**64**	(46,80)	**79**	(64,91)	**85**	(73,95)	**91**	(82,97)	**93**	(86,98)
	Country	60	(37,84)	**36**	(20,54)	**21**	(9,36)	**15**	(5,27)	**9**	(3,18)	**7**	(2,14)
CD	Factor	45	(21,69)	46	(28,66)	60	(41,78)	64	(45,82)	**73**	(55,87)	**77**	(61,90)
	Country	55	(31,79)	54	(34,72)	40	(22,59)	36	(18,55)	**27**	(13,45)	**23**	(10,39)
US	Factor	7	(0,26)	**26**	(9,44)	**51**	(29,74)	**65**	(44,83)	**82**	(68,92)	**88**	(80,95)
	Country	93	(74,100)	**74**	(56,91)	**49**	(26,71)	**35**	(17,56)	**18**	(8,32)	**12**	(5,20)

B.3 Flows into equity funds (EMEs)

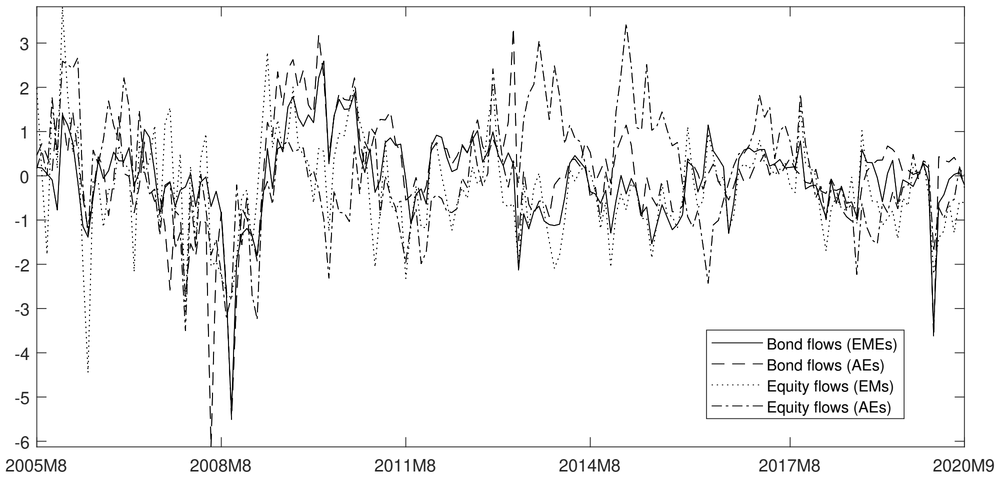
Dates		2005M8		2008M8		2011M8		2014M8		2017M8		2020M9	
AR	Factor	41	(26,57)	**56**	(39,71)	**57**	(40,75)	**59**	(39,76)	**59**	(37,77)	59	(34,81)
	Country	59	(43,74)	**44**	(29,61)	**43**	(25,60)	**41**	(24,61)	**41**	(23,63)	41	(19,66)
BR	Factor	43	(27,59)	52	(36,66)	49	(32,66)	47	(29,65)	42	(24,63)	40	(17,61)
	Country	57	(41,73)	48	(34,64)	51	(34,68)	53	(35,71)	58	(37,76)	60	(39,83)
CH	Factor	26	(6,43)	16	(7,25)	12	(5,20)	**8**	(3,14)	**5**	(1, 9)	**4**	(0, 9)
	Country	74	(57,94)	84	(75,93)	88	(80,95)	**92**	(86,97)	**95**	(91,99)	**96**	(91,100)
CN	Factor	42	(26,57)	35	(23,48)	**20**	(10,32)	**13**	(4,22)	**7**	(1,14)	**5**	(0,11)
	Country	58	(43,74)	65	(52,77)	**80**	(68,90)	**87**	(78,96)	**93**	(86,99)	**95**	(89,100)
CO	Factor	46	(30,62)	44	(30,58)	35	(19,50)	**27**	(12,42)	**16**	(4,30)	**11**	(0,24)
	Country	54	(38,70)	56	(42,70)	65	(50,81)	**73**	(58,88)	**84**	(70,96)	**89**	(76,100)
CR	Factor	55	(40,70)	51	(36,64)	**40**	(25,56)	**32**	(16,48)	**20**	(6,35)	**16**	(0,31)
	Country	45	(30,60)	49	(36,64)	**60**	(44,75)	**68**	(52,84)	**80**	(65,94)	**84**	(69,100)
CZ	Factor	48	(31,64)	**59**	(40,75)	**65**	(46,82)	**69**	(49,86)	**70**	(48,87)	70	(44,89)
	Country	52	(36,69)	**41**	(25,60)	**35**	(18,54)	**31**	(14,51)	**30**	(13,52)	30	(11,56)
EG	Factor	36	(19,52)	40	(25,56)	48	(30,64)	51	(33,68)	**53**	(34,72)	54	(33,75)
	Country	64	(48,81)	60	(44,75)	52	(36,70)	49	(32,67)	**47**	(28,66)	46	(25,67)
HU	Factor	51	(35,67)	**68**	(52,82)	**75**	(59,88)	**78**	(61,90)	**79**	(61,92)	**80**	(60,94)
	Country	49	(33,65)	**32**	(18,48)	**25**	(12,41)	**22**	(10,39)	**21**	(8,39)	**20**	(6,40)
IN	Factor	36	(19,52)	46	(30,61)	40	(23,57)	33	(15,50)	23	(7,42)	22	(3,42)
	Country	64	(48,81)	54	(39,70)	60	(43,77)	67	(50,85)	77	(58,93)	78	(58,97)
ID	Factor	36	(19,51)	**55**	(40,69)	**61**	(46,76)	**64**	(47,79)	**66**	(48,81)	**65**	(47,84)
	Country	64	(49,81)	**45**	(31,60)	**39**	(24,54)	**36**	(21,53)	**34**	(19,52)	**35**	(16,53)
IS	Factor	48	(32,63)	40	(26,53)	**21**	(9,32)	**9**	(1,18)	**7**	(0,15)	**8**	(0,18)
	Country	52	(37,68)	60	(47,74)	**79**	(68,91)	**91**	(82,99)	**93**	(85,100)	**92**	(82,100)
KA	Factor	40	(23,58)	**52**	(35,70)	**58**	(38,76)	**66**	(46,84)	**71**	(50,88)	**73**	(49,90)
	Country	60	(42,77)	**48**	(30,65)	**42**	(24,62)	**34**	(16,54)	**29**	(12,50)	**27**	(10,51)
KS	Factor	40	(22,58)	43	(30,56)	32	(19,45)	**19**	(8,30)	**12**	(3,22)	**12**	(2,23)
	Country	60	(42,78)	57	(44,70)	68	(55,81)	**81**	(70,92)	**88**	(78,97)	**88**	(77,98)
ML	Factor	38	(23,55)	49	(34,64)	**56**	(40,71)	**62**	(45,76)	**64**	(47,80)	**63**	(44,80)
	Country	62	(45,77)	51	(36,66)	**44**	(29,60)	**38**	(24,55)	**36**	(20,53)	**37**	(20,56)
ME	Factor	48	(32,64)	49	(35,62)	43	(28,57)	**33**	(18,48)	**23**	(9,38)	**21**	(5,37)
	Country	52	(36,68)	51	(38,65)	57	(43,72)	**67**	(52,82)	**77**	(62,91)	**79**	(63,95)
PN	Factor	26	(9,42)	**61**	(44,77)	**69**	(53,83)	**71**	(54,85)	**74**	(56,88)	**74**	(55,90)
	Country	74	(58,91)	**39**	(23,56)	**31**	(17,47)	**29**	(15,46)	**26**	(12,44)	**26**	(10,45)
PA	Factor	40	(22,57)	**54**	(40,68)	**55**	(41,70)	55	(40,70)	**57**	(40,72)	56	(38,73)
	Country	60	(43,78)	**46**	(32,60)	**45**	(30,59)	45	(30,60)	**43**	(28,60)	44	(27,62)
PE	Factor	43	(27,59)	51	(35,64)	48	(31,64)	49	(31,66)	48	(29,66)	49	(27,68)
	Country	57	(41,73)	49	(36,65)	52	(36,69)	51	(34,69)	52	(34,71)	51	(32,73)
PH	Factor	32	(16,47)	**47**	(32,62)	**55**	(38,70)	**59**	(42,75)	**60**	(42,77)	**61**	(39,78)
	Country	68	(53,84)	**53**	(38,68)	**45**	(30,62)	**41**	(25,58)	**40**	(23,58)	**39**	(22,61)
PO	Factor	55	(40,69)	57	(41,71)	57	(40,73)	55	(36,73)	52	(30,73)	50	(25,74)
	Country	45	(31,60)	43	(29,59)	43	(27,60)	45	(27,64)	48	(27,70)	50	(26,75)
RO	Factor	69	(56,82)	**49**	(36,62)	**31**	(18,45)	**20**	(9,33)	**15**	(5,26)	**14**	(3,26)
	Country	31	(18,44)	**51**	(38,64)	**69**	(55,82)	**80**	(67,91)	**85**	(74,95)	**86**	(74,97)
RF	Factor	51	(36,65)	51	(37,65)	49	(33,64)	45	(28,62)	44	(25,62)	45	(23,66)
	Country	49	(35,64)	49	(35,63)	51	(36,67)	55	(38,72)	56	(38,75)	55	(34,77)
SF	Factor	39	(21,55)	**63**	(46,78)	**76**	(61,88)	**82**	(69,92)	**84**	(71,94)	**84**	(70,95)
	Country	61	(45,79)	**37**	(22,54)	**24**	(12,39)	**18**	(8,31)	**16**	(6,29)	**16**	(5,30)
TH	Factor	54	(38,69)	56	(44,68)	45	(32,59)	**30**	(17,43)	**16**	(4,27)	**16**	(3,29)
	Country	46	(31,62)	44	(32,56)	55	(41,68)	**70**	(57,83)	**84**	(73,96)	**84**	(71,97)
TR	Factor	53	(37,67)	58	(45,71)	59	(45,73)	52	(36,67)	45	(27,62)	44	(24,64)
	Country	47	(33,63)	42	(29,55)	41	(27,55)	48	(33,64)	55	(38,73)	56	(36,76)

B.4 Flows into equity funds (AEs)

Dates		2005M8		2008M8		2011M8		2014M8		2017M8		2020M9	
AT	Factor	61	(43,78)	63	(48,77)	51	(32,70)	**32**	(10,55)	**34**	(9,58)	**37**	(0,60)
	Country	39	(22,57)	37	(23,52)	49	(30,68)	**68**	(45,90)	**66**	(42,91)	**63**	(40,100)
HK	Factor	62	(44,78)	56	(40,72)	**40**	(19,60)	**24**	(3,44)	**30**	(7,53)	**36**	(6,63)
	Country	38	(22,56)	44	(28,60)	**60**	(40,81)	**76**	(56,97)	**70**	(47,93)	**64**	(37,94)
JA	Factor	35	(11,57)	39	(21,60)	33	(11,54)	24	(3,44)	15	(0,36)	10	(0,35)
	Country	65	(43,89)	61	(40,79)	67	(46,89)	76	(56,97)	85	(64,100)	90	(65,100)
SI	Factor	69	(53,84)	70	(56,84)	**53**	(30,74)	**35**	(6,59)	**39**	(8,66)	**42**	(0,68)
	Country	31	(16,47)	30	(16,44)	**47**	(26,70)	**65**	(41,94)	**61**	(34,92)	**58**	(32,100)
AU	Factor	74	(61,86)	**65**	(50,78)	64	(48,79)	**58**	(41,75)	**58**	(39,76)	**57**	(29,80)
	Country	26	(14,39)	**35**	(22,50)	36	(21,52)	**42**	(25,59)	**42**	(24,61)	**43**	(20,71)
BE	Factor	49	(28,70)	**82**	(68,94)	**94**	(87,98)	**97**	(93,99)	**98**	(95,100)	**98**	(95,100)
	Country	51	(30,72)	**18**	(6,32)	**6**	(2,13)	**3**	(1, 7)	**2**	(0, 5)	**2**	(0, 5)
DE	Factor	53	(32,73)	**74**	(57,88)	**88**	(77,95)	**93**	(87,98)	**95**	(89,98)	**95**	(89,99)
	Country	47	(27,68)	**26**	(12,43)	**12**	(5,23)	**7**	(2,13)	**5**	(2,11)	**5**	(1,11)
FI	Factor	59	(41,77)	**81**	(69,91)	**91**	(84,96)	**94**	(90,98)	**96**	(92,99)	**96**	(92,99)
	Country	41	(23,59)	**19**	(9,31)	**9**	(4,16)	**6**	(2,10)	**4**	(1, 8)	**4**	(1, 8)
FR	Factor	50	(28,71)	**81**	(64,93)	**93**	(84,98)	**97**	(93,99)	**98**	(95,100)	**98**	(95,100)
	Country	50	(29,72)	**19**	(7,36)	**7**	(2,16)	**3**	(1, 7)	**2**	(0, 5)	**2**	(0, 5)
GE	Factor	39	(18,59)	39	(23,56)	**17**	(0,34)	39	(22,57)	48	(29,66)	47	(23,72)
	Country	61	(41,82)	61	(44,77)	**83**	(66,100)	61	(43,78)	52	(34,71)	53	(28,77)
GR	Factor	43	(22,65)	49	(32,65)	54	(36,71)	49	(30,66)	44	(22,64)	52	(27,76)
	Country	57	(35,78)	51	(35,68)	46	(29,64)	51	(34,70)	56	(36,78)	48	(24,73)
IR	Factor	49	(25,71)	**88**	(73,97)	**96**	(90,99)	**98**	(94,100)	**99**	(96,100)	**99**	(96,100)
	Country	51	(29,75)	**12**	(3,27)	**4**	(1,10)	**2**	(0, 6)	**1**	(0, 4)	**1**	(0, 4)
IT	Factor	43	(22,64)	**68**	(51,84)	**82**	(69,92)	**89**	(79,96)	**90**	(81,97)	**91**	(79,98)
	Country	57	(36,78)	**32**	(16,49)	**18**	(8,31)	**11**	(4,21)	**10**	(3,19)	**9**	(2,21)
NE	Factor	54	(33,73)	**82**	(68,92)	**93**	(86,98)	**97**	(93,99)	**98**	(96,100)	**98**	(96,100)
	Country	46	(27,67)	**18**	(8,32)	**7**	(2,14)	**3**	(1, 7)	**2**	(0, 4)	**2**	(0, 4)
NO	Factor	60	(42,77)	**74**	(60,86)	**81**	(70,91)	**84**	(73,93)	**87**	(77,95)	**89**	(77,97)
	Country	40	(23,58)	**26**	(14,40)	**19**	(9,30)	**16**	(7,27)	**13**	(5,23)	**11**	(3,23)
SP	Factor	42	(20,62)	**68**	(50,84)	**84**	(70,93)	**90**	(81,96)	**92**	(83,98)	**93**	(83,98)
	Country	58	(38,80)	**32**	(16,50)	**16**	(7,30)	**10**	(4,19)	**8**	(2,17)	**7**	(2,17)
SW	Factor	70	(56,84)	**79**	(68,88)	**81**	(70,91)	80	(67,91)	**84**	(72,94)	**86**	(72,95)
	Country	30	(16,44)	**21**	(12,32)	**19**	(9,30)	20	(9,33)	**16**	(6,28)	**14**	(5,28)
ST	Factor	63	(47,79)	72	(60,84)	**75**	(62,87)	75	(61,87)	74	(57,88)	76	(55,91)
	Country	37	(21,53)	28	(16,40)	**25**	(13,38)	25	(13,39)	26	(12,43)	24	(9,45)
UI	Factor	58	(38,76)	**75**	(60,87)	**81**	(68,92)	**85**	(73,95)	**87**	(75,96)	**87**	(70,97)
	Country	42	(24,62)	**25**	(13,40)	**19**	(8,32)	**15**	(5,27)	**13**	(4,25)	**13**	(3,30)
CD	Factor	20	(0,38)	24	(7,41)	14	(0,29)	5	(0,17)	11	(0,27)	12	(0,34)
	Country	80	(62,100)	76	(59,93)	86	(71,100)	95	(83,100)	89	(73,100)	88	(66,100)
US	Factor	20	(0,39)	26	(9,43)	35	(16,56)	15	(0,29)	12	(0,29)	14	(0,37)
	Country	80	(61,100)	74	(57,91)	65	(44,84)	85	(71,100)	88	(71,100)	86	(63,100)

C Factors

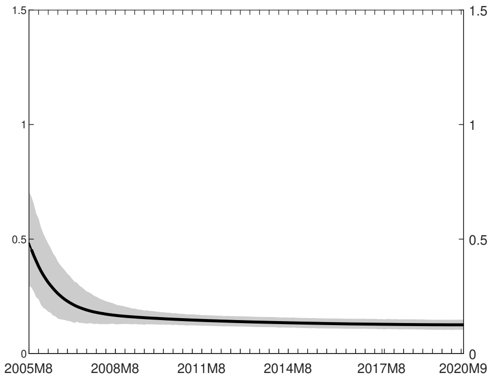
Figure C.5: Comparison of factors



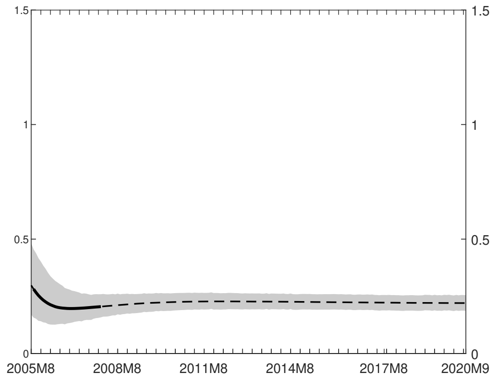
Notes: The figure displays the medians of the common factors, derived from each model-specific MCMC draw for all estimated models.

D Convergence in volatility

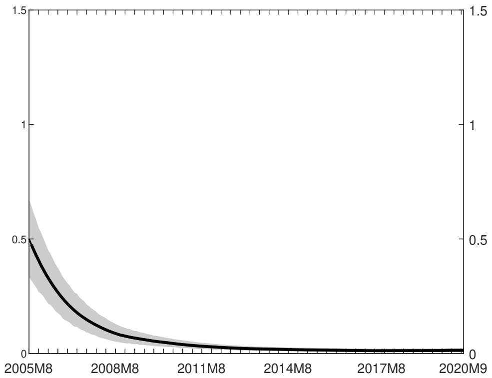
Figure D.6: Cross-sectional dispersion in volatility (Bond funds)



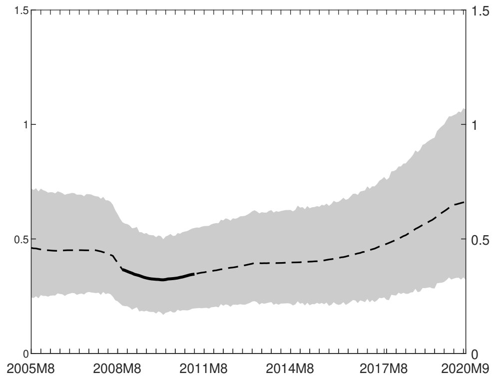
(a) Idiosyncratic component (EMEs)



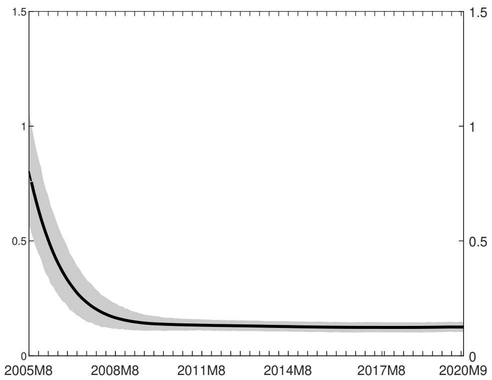
(b) Idiosyncratic component (AEs)



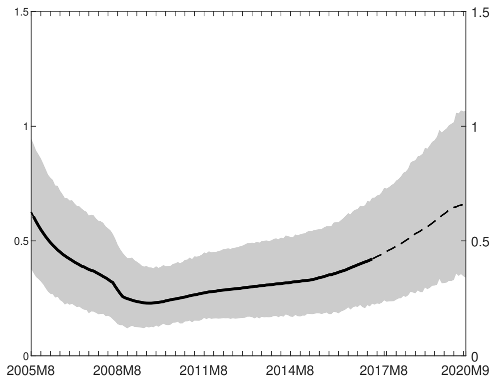
(c) Common component (EMEs)



(d) Common component (AE)



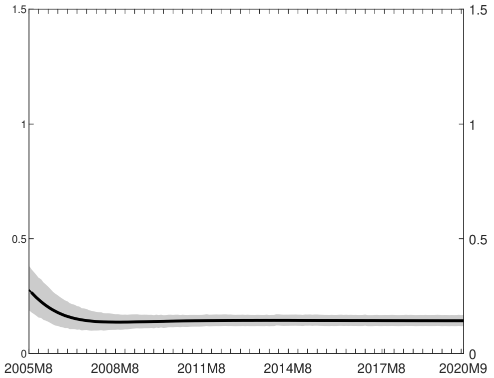
(e) Total (EMEs)



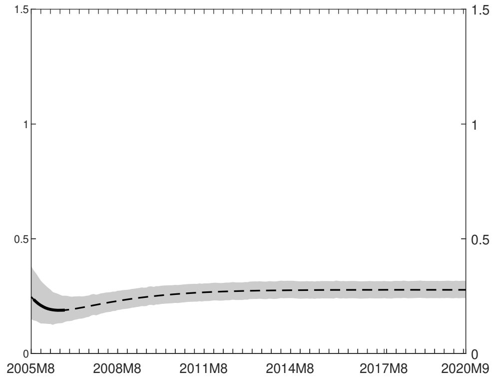
(f) Total (AEs)

Notes: The figure displays the time-specific medians (black lines) and 90% bands (grey areas) of the average implied pairwise cross-correlations derived from each MCMC draw for all estimated models. Lines are solid whenever the cross-sectional standard deviation declined significantly (at the 10% level) relative to the beginning of the sample. Otherwise, the line is dashed.

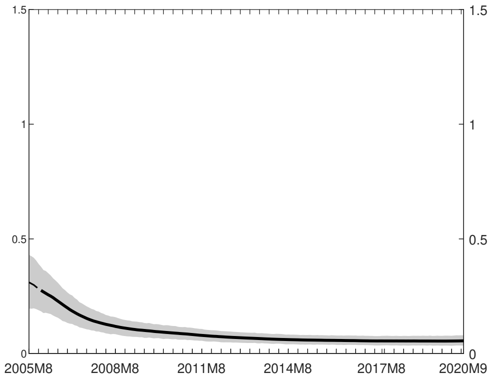
Figure D.7: Cross-sectional dispersion in volatility (Equity funds)



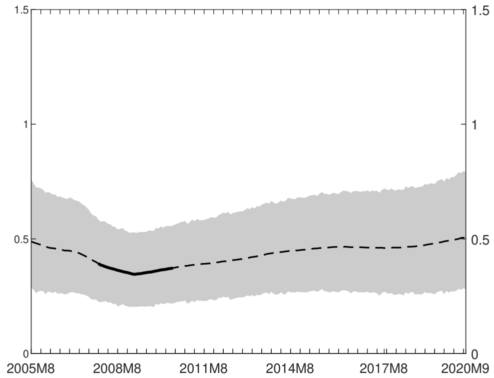
(a) Idiosyncratic component (EMEs)



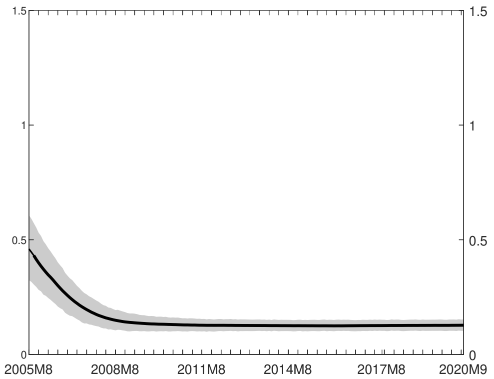
(b) Idiosyncratic component (AEs)



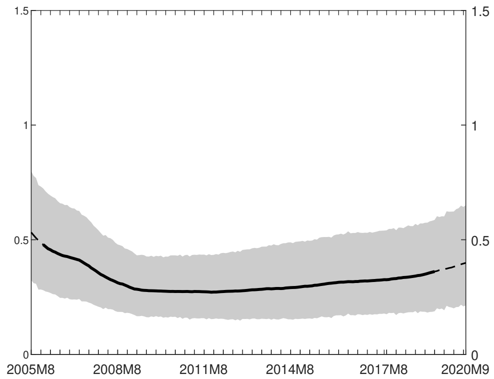
(c) Common component (EMEs)



(d) Common component (AEs)



(e) Total (EMEs)



(f) Total (AEs)

Notes: The figure displays the time-specific medians (black lines) and 90% bands (grey areas) of the average implied pairwise cross-correlations derived from each MCMC draw for all estimated models. Lines are solid whenever the cross-sectional standard deviation declined significantly (at the 10% level) relative to the beginning of the sample. Otherwise, the line is dashed.