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How Important are Global Factors for Understanding the Dynamics of International Capital Flows? *

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Abstract

We propose a dynamic factor model with time-varying parameters and stochastic volatility to analyze the relationship between global factors and country-specific capital flow dynamics. Studying a global sample of 43 countries from 1994 until 2015, we show that global co-movement of macroeconomic, financial and capital flow variables can explain a major share of country-specific capital flow volatility and that the impact of these variables has become even more important since the 2008–2009 global financial crisis. Our results indicate that country-specific changes in capital flows are strongly affected by fluctuations in global financial cycles and - to some extent - by global real business cycles. There is some evidence that countries with higher foreign exchange reserves, flexible exchange rates, lower public indebtedness or more developed domestic stock markets may better shield themselves from the global financial cycle.

Keywords:	Volatility of capital flows, dynamic factor model, stochastic volatility, global co-movement, global real business cycle, global financial cycle
JEL Codes:	C38, F32, F41, F42, F44.

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1 Introduction

Sudden stops and reversals of gross capital inflows have important implications for the macro-financial stability of recipient countries, as they often go hand in hand with sharp recessions, deleveraging pressures, currency depreciation and banking crises. In their work on 800 years of financial crises, Reinhart and Rogoff (2010) found that high levels of international capital flows were strongly correlated with severe financial crises. Agosin and Huaita (2011) found that the best predictor of a "sudden stop" was a previous surge in capital inflows, in particular portfolio inflows and cross-border lending. Sharp halts of capital inflows were usually considered being associated with emerging economies (Reinhart and Calvo, 2000). But the 2008–2009 global financial crisis (GFC) brought about an unprecedented collapse in gross capital inflows for many emerging and advanced economies alike, with countries relying on bank flows being hardest hit (see Milesi-Ferretti and Tille, 2011). The connection between the surge of gross capital inflows and financial boom-bust cycles surrounding the GFC has revived a long-standing debate about the determinants of global capital flows (for a survey see Koepke, 2015). In particular, the question of whether pull or push factors are driving capital flows (e.g. Calvo et al., 1996; Agénor, 1998; Forbes and Warnock, 2012; Fratzscher, 2012) has gained increased attention in the wake of the taper tantrum of 2013 and the subsequently observed large declines in currency values and domestic asset prices in most of the emerging countries (e.g. Ghosh et al., 2016; Chari et al., 2017; Pagliari and Hannan, 2017; Eichengreen et al., 2018). According to this literature, push factors typically refer to fluctuations in global risk aversion or monetary policy in advanced economies that drive capital flows into emerging markets, while pull factors typically reflect domestic fundamental economic conditions that pull capital into a country.

Various attempts have been made to empirically assess the relative importance of global push versus domestic pull factors. In general, the majority of the contributions, which noticeably diverge in terms of methodology, provide evidence for the predominance of common push factors over domestic economic forces. Among the more recent contributions, Sarno et al. (2016) show for a sample of 55 countries that more than 80 % of the volatility in portfolio flows is driven by global push factors – significantly related to US economic variables. Forbes and Warnock (2012) find that episodes of extreme capital flow volatility are mainly driven by global movements in risk, growth and interest rates. Scheubel et al. (2018a) show that variation in their global financial cycle measure has a significant impact on the likelihood of extreme capital flow episodes (surges, sudden stops, flights and currency crises). Rey (2015) and Miranda-Agrippino and Rey (2018) notably maintain that a single global financial factor driven primarily by shifts in international investors' risk aversion as well as monetary policy in center countries account for much of the volatility of capital flows. Bruno and Shin (2015) substantiate this view and stress the crucial role of cross-border flows via global banks that transmit financial conditions from the center across the globe. By applying a two-level factor model, Barrot and Serven (2018) find that common factors including country-group specific factors account for close to half of capital flows variance, while global factors play a much larger role among advanced countries than in emerging economies.

In contrast, other papers found evidence for a high relevance of domestic pull factors, such as Förster et al. (2014), who apply a dynamic factor model to study the co-movement of gross capital inflows. They distinguish between global, regional and country-specific capital flow factors and show that the latter two explain a major fraction of fluctuations in capital inflows, with the global capital factor explaining only a small share of the overall variation. In a similar vein, Cerutti et al. (2017) find that selected global variables including common dynamic factors extracted from actual capital flows rarely explain more than a quarter of the variation in capital flows. Both approaches rely on methods that do not explicitly take into account the changing nature of the volatility of capital flows as well as the relationship between global factors and domestic capital flow dynamics.

Disentangling global push and country-specific pull factors is of utmost importance to policy makers. If push factors are the dominant drivers of capital flows – and negative cross-border spillovers prevail – some have argued that macroprudential policies may or should also include capital flow management measures to shelter the economies from global shocks. A related implication was notably suggested by Rey (2015) and Miranda-Agrippino and Rey (2018): Given the sensitivity of non-center countries to a global financial cycle which can lead to excessive credit growth that is not aligned with a country's economic conditions, Mundell's "trilemma" may have morphed into a "dilemma" where autonomous monetary policy is no longer effective, irrespective of the exchange rate regime. Restricting the capital account would be the only way to retain autonomy in monetary policy. This view has, however, been challenged by Obstfeld and Taylor (2017) and Aizenman et al. (2016), who demonstrate that the exchange rate regime will still affect the country's sensitivity to financial conditions in the center economies. In turn, Aizenman et al. (2016) add a fourth dimension, namely financial stability, to the trilemma's original policy goals. Navigating the ensuing quadrilemma effectively may thus shield open economies from global financial shocks. The high degree of heterogeneity with regard to the sensitivity of emerging market countries to financial conditions of the center found in this literature may in fact reflect different ways of managing this quadrilemma.

In this paper we offer an approach that allows us to address many of the questions raised in the literature cited above in a single attempt, accounting for both, the time-varying nature of capital flow changes and the impact of global and regional-scale factors. In particular, we are interested in the following questions: How important are financial as well as macroeconomic global factors in explaining country-specific volatility of cross capital inflows – across different types of capital flows, across countries and over time? Do particular countries drive the global co-movement of macroeconomic and/or financial variables? Does the way global factors explain the volatility of capital flows depend on country-specific characteristics? To answer these questions, we propose a Bayesian dynamic factor model in the spirit of Pitt and Shephard (1999), Aguilar and West (2000), Kose et al. (2003) and Del Negro and Otrok (2008) to extract the co-movement of various macroeconomic and financial variables across countries from a global sample. This framework allows us to exploit large data sets and take account of shifts in the volatility of the time series involved. Since the sensitivity of capital flows with respect to global fundamental factors is likely subject to structural breaks in the parameters, one additional key feature of our model is that we assume that the factor loadings are time-varying.

Studying a sample of 43 countries from 1994 until 2015, we extract global factors for macroeconomic variables (GDP growth, inflation, exchange rate dynamics, trade balance), financial sector variables (short-term and long-term interest rate, changes in equity prices, private-sector credit and deposits), and the respective capital flow variable under investigation (total, direct, portfolio and other investment flows). For each capital flow variable, we also extract a regional factor, capturing common capital flow dynamics within each defined regional subgroup. The global (and regional) factors are used to provide a parsimonious representation of the data, efficiently capturing the prevailing co-movement in the data set. In addition, the factors are, by construction, orthogonal to each other and thus possess a structural interpretation.

Our findings indicate that the global factors identified by our model approach explain a large share of country-specific capital flow movements. These shares, commonly referred to as commonalities, exhibit a pronounced time-varying pattern, mirroring in several instances well-known crisis episodes. We also observe some differences across country groups. Moreover, we find that the importance of all global factors has increased markedly especially during and after the GFC. This suggests that in the presence of global financial shocks, global variables prove to be important determinants of country-specific capital flow volatility.

These empirical findings are consistent with earlier ones on the role of pull and push factors in determining capital flow movements (Bruno and Shin, 2015; Rey, 2015; Banerjee et al., 2016) and confirm contributions that report an increased role of global factors during/since the GFC (Sahay et al., 2014; Beckmann and Czudaj, 2017). Moreover, since our analysis indicates that US variables (particularly financial variables) are highly correlated with the identified global financial factors, we can relate our findings also to papers that highlight the pronounced impact US monetary policy actions have had on global capital movements in recent years (Bruno and Shin, 2015; Anaya et al., 2017). Regarding the issue whether and how countries can shield themselves from global common dynamics, where the findings in the literature are less from clear, our panel regression results indicate that the economies' sensitivity to global common factors can be alleviated if they follow a flexible exchange rate regime, have higher foreign exchange reserves, higher GDP per capita growth and lower public indebtedness.

The remainder of the paper is structured as follows: section 2 provides a descriptive overview of different types of capital flows across regions, section 3 describes the properties of the chosen econometric framework, section 4 adds details on the investigated database, section 5 delineates our main findings and section 6 concludes and stresses relevant policy implications.

2 Development of capital flows across countries

We distinguish between five groups of countries. On the one hand advanced economies consisting of "advanced Europe" (i.e. Western European EU member states plus Norway and Switzerland) and "advanced non-Europe" (among others including the US and Japan) and on the other hand emerging economy regions consisting of the three groups "Central, Eastern and Southeastern Europe" (CESEE), "Latin America" and "Asia". For convenience the only country from Africa – South Africa – is added to the Latin America group.

Advanced Europe (13):	AT, CH, DE, DK, ES, FI, FR, GB, IT, NL, NO, PT, SE
Advanced non-Europe (5):	AU, CA, JP, NZ, US
Central, Eastern and Southeastern Europe (12):	BG, CZ, EE, HU, LT, LV, PL, RO, RU, SI, SK, TR
Latin America (6):	AR, BR, CL, MX, PE, ZA
Asia (7):	CN, ID, IN, KR, MY, PH, TH

Notes: Abbreviations refer to the two-digit ISO country code.

Figures 1 to 2 show – in line with the IMF (2009) – for all the countries included in our analysis ("Overall", upper-left panel) as well as the five defined regional groups the evolution of net capital flows and gross capital inflows (sums of direct, portfolio and other investment flows) as percent of GDP, 1994–2015. Gross capital outflows are shown in the appendix in Fig. B.1.

An aggregate view of net capital flows (Fig. 1) reveals that emerging market regions (especially CESEE and Latin America) tend to consistently have a net borrowing position vis-à-vis the rest of the world. Net borrowing was particularly sizable in CESEE before the GFC (more than 10 % of GDP) but also in Asia before the 1997–1998 Asia crisis and was followed in both cases by a strong reversal of portfolio investment and other investment flows (note that the latter comprise to a large extent bank flows). Net FDI flows, on the other hand, are apparently more stable over time. Emerging market regions turn out, not surprisingly, to be net FDI receivers (quite sizable in CESEE and Latin America in terms of GDP), while advanced Europe is a consistent FDI donor over time.

[Fig. 1 about here.]

Later on (in section 5) we focus the presentation of our results on the liability side of the financial account to get a better understanding of the driving forces of volatile capital *in*flows, in line with the observation that during a situation of elevated global macro-financial risk, foreign investors are likely downsizing their investment in markets perceived to be particularly risky (IMF, 2013). The best available empirical proxy for gross capital inflows is incurrence less repayment of financial liabilities.[1]

[1] Note that we cannot really resort to pure gross flows, as they are not or only insufficiently delivered in the IMF's IFS database. Instead, we rely on a net recording concept (IMF, 2009), whereby debit entries are netted against credit entries. E.g., in the case of portfolio investment, new bonds issued are netted against the redemption of bonds issued.

We can see in Fig. 2 that changes in gross capital inflows are subject to a marked volatility pattern over time, which is much more pronounced than that for net flows and correlates again with crisis episodes. The GFC is clearly visible across all regions and was associated with significant reversals, especially in the case of gross portfolio investment and other investment inflows. World financial inflows have since risen to less than half of their pre-crisis levels. The composition of global inflows has changed substantially both in terms of flow type and geography (see also Bussière et al., 2018; McQuade and Schmitz, 2017). Bank flows, that used to account for the largest share of the total before the GFC, declined substantially, mainly reflecting deleveraging of large global banks as well as restraining cross-border operations in response to regulatory reform, while FDI flows that in the pre-crisis period were slightly lower than bank flows have fallen much less than bank flows. Moderation of gross capital inflows was considerably strong in advanced as well as emerging Europe while the decline was much less pronounced in advanced non-Europe. Conversely, in the post-crisis period Latin America and Asia have received more inflows than in the years before the GFC. This suggests that uphill flows from poorer to richer countries, after intensifying in the run-up to the GFC, have reversed and tend to flow downhill (Boz et al., 2017).

Advanced Europe stands out as the region that received the largest gross inflows relative to GDP since the mid-1990s, reaching peaks of more than 20 % of annual GDP around the year 2000 and about 25 % before 2008, reflecting a surge in other investment and portfolio flows, and, to a lesser extent, FDI flows. The sharp retrenchment after the Lehman collapse that was most vigorous for bank and portfolio flows was followed by a swift rebound in 2010–2011, but gross inflows in the post-crisis period remained roughly around a third of the size they had reached in the pre-crisis period. This extraordinary surge before the GFC that was similarly observed for gross capital outflows can be essentially explained by large European banks recycling US dollars from US money market funds back to the United States by purchasing mortgage-backed securities that eventually became toxic (Shin, 2012).

Likewise, in the years before 2008, the CESEE region received sizable gross capital inflows that had risen to nearly 20 % of GDP, consisting to a major extent of other investment and FDI inflows which had progressively increased since the early 2000s, while portfolio inflows have played a negligible role. The GFC brought an immediate and strong slump in other investment inflows, while FDI inflows were much less affected. During the 2010 to 2012 period, capital flows into emerging Europe rebounded somewhat, consisting to a considerable degree of portfolio investment inflows, associated with a shift of capital from low yields in advanced economies to higher returns in emerging markets, as well as of FDI inflows. In the post-crisis period capital inflows into the CESEE countries have dropped to almost one quarter of the flows received in the pre-crisis period.

Advanced non-Europe has experienced a less pronounced capital flow cycle where in 2008 gross inflows reached about 10 % of GDP. After a substantial decline, capital inflows recovered quickly on the back of quite resilient portfolio and FDI inflows and remained at levels of around three quarters of the post-crisis period.

Latin America and Asia have both reached capital inflow peaks of up to 8 % of GDP in 2008, far less than the other regions. They are the regions in our sample that have – after the GFC hit – on average received more capital inflows than before the crisis hit. Nonetheless, Asia was particularly affected by the unwinding of monetary policies in the US. From 2012 until the end of our observation period (end-2015), we can observe some reduction of gross capital inflows.

[Fig. 2 about here.]

3 Econometric framework

We investigate the relationship between country-specific capital flows and international macroeconomic, financial and capital factors by means of a dynamic factor model with stochastic volatility and time-varying factor loadings (TVP-DFM-SV). This model is closely related to the framework proposed in Del Negro and Otrok (2008) and differs from recent contributions who apply DFMs to capital flow data (see, e.g., Förster et al., 2014; Sarno et al., 2016; Barrot and Serven, 2018) by assuming that the relationship between the country-specific capital flow series and the common factors as well as the error variances are time-varying. We opt for this flexible econometric specification due to two regularities commonly observed, namely the changing sensitivity of country-specific capital flow dynamics with respect to movements in global macroeconomic and financial driving forces and the strong evidence in favor of heteroscedasticity present in capital flow time series. In the following section, we provide a brief description of the modeling framework employed along with the prior setup used.

3.1 The dynamic factor stochastic volatility model

Our key goal is to efficiently summarize the information contained in an international panel of macroeconomic and financial time series using a dynamic factor model (Stock and Watson, 2002; Kose et al., 2003). For each of the M countries in our panel, we include L country-specific macroeconomic and financial time series that are consequently stacked in an $N = ML$-dimensional vector $\boldsymbol{X}_t$. The main modeling assumption is that the dynamics in $\boldsymbol{X}_t$ may be efficiently summarized by a set of K lower dimensional latent factors $\boldsymbol{F}_t$ (with $N \gg K$) that represent the driving forces of the global economy. The elements in $\boldsymbol{F}_t$ can be interpreted as statistical measures of concepts such as global output, inflation, interest rates, and equity prices.

We assume that the factors in $\boldsymbol{F}_t$ are related to the observed quantities in $\boldsymbol{X}_t$ by the following relationship

$$\boldsymbol{X}_t = \boldsymbol{\Lambda}_t \boldsymbol{F}_t + \boldsymbol{e}_t. \tag{3.1}$$

Hereby, we let $\boldsymbol{\Lambda}_t$ be a $N \times K$ dimensional matrix of time-varying factor loadings with typical element $\lambda_{ij,t}$, and $\boldsymbol{e}_t$ an N-dimensional vector of idiosyncratic factors, distributed as $\boldsymbol{e}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega}_t)$. These idiosyncratic factors are typically labeled measurement errors in standard factor analysis (Kose et al., 2003).

Equation (3.1) constitutes the observation equation that relates the observed macroeconomic quantities with the unobserved factors. We assume that the factor loadings and the volatility of the idiosyncratic shocks are changing over time, effectively accounting for the high volatility commonly observed in financial time series data and allowing for shifts in the sensitivity of individual time series in X_t with respect to the factors in F_t. More specifically, the law of motion of $\boldsymbol{\Lambda}_t$ is

$$\text{vec}(\boldsymbol{\Lambda}_t) = \text{vec}(\boldsymbol{\Lambda}_{t-1}) + \boldsymbol{u}_t, \tag{3.2}$$

with $\boldsymbol{u}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{Q})$ being a normally distributed error vector with variance-covariance matrix $\boldsymbol{Q}$. Furthermore, let $\boldsymbol{\Omega}_t = \text{diag}(e^{\omega_{1t}}, \ldots, e^{\omega_{Nt}})$ be a diagonal time-varying variance-covariance matrix that evolves according to

$$\omega_{jt} = \mu_{\omega j} + \rho_{\omega j}(\omega_{jt-1} - \mu_{\omega j}) + \varepsilon_{jt}, \ j = 1, \ldots, N, \tag{3.3}$$

where $\mu_{\omega j}$ is the level of the log-volatility, $\rho_{\omega j} \in (-1, 1)$ denotes the autoregressive parameter and $\varepsilon_{jt} \sim \mathcal{N}(0, \varsigma_\omega)$ is a white noise error term with variance ς_ω. The assumption that $\boldsymbol{\Omega}_t$ is diagonal implies that the co-movement between the elements of $\boldsymbol{X}_t$ stems exclusively from movements in $\boldsymbol{F}_t$. This is a typical identification assumption employed in dynamic factor analysis.

We assume that the factors follow a set of univariate autoregressions with stochastic volatility,

$$\boldsymbol{F}_t = \boldsymbol{\Phi} \boldsymbol{F}_{t-1} + \boldsymbol{v}_t. \tag{3.4}$$

Here, $\boldsymbol{\Phi} = \text{diag}(\phi_1, \ldots, \phi_K)$ with $\phi_j \in (-1, 1)$ for $j = 1, \ldots, K$ being a matrix of autoregressive coefficients and $\boldsymbol{v}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t)$ is a vector white noise error term with $\boldsymbol{\Sigma}_t = \text{diag}(e^{h_{1t}}, \ldots, e^{h_{Kt}})$. The law of motion for h_j is given by

$$h_{jt} = \mu_{hj} + \rho_{hj}(h_{jt-1} - \mu_{hj}) + \eta_{jt}, \ j = 1, \ldots, K. \tag{3.5}$$

Similar to Eq. (3.3) μ_{hj} denotes the level of the log-volatility, ρ_{hj} denotes the autoregressive parameter and η_{jt} is again a normally distributed error term with zero mean and variance ς_h. The stochastic volatility assumption on the shocks to the latent factors implies that not only measurement errors are subject to smoothly changing error variances but also the factors in $\boldsymbol{F}_t$. This captures, for instance, global increases in volatility commonly observed within crisis episodes. Capturing these movements in error variances has been identified as a crucial ingredient in successful macroeconomic forecasting models (see, e.g, Clark, 2011; Clark and Ravazzolo, 2015).

Equations (3.1) to (3.5) form a state space system. This model allows us to unveil the relative importance of global factors to explain variations in capital flows across the globe and, more importantly, across time. Under the assumption that the factors are orthogonal to each other we can straightforwardly compute a variance decomposition by noting that the variance of the ith element of $\boldsymbol{X}_t$, labeled X_{it}, is

$$\text{Var}(X_{it}) = \sum_{j=1}^{K} \lambda_{ij,t}^2 \text{Var}(F_{jt}) + \exp(\omega_{it}). \tag{3.6}$$

Equation (3.6) enables us to compute the relative contributions of the jth factor F_{jt} to the variance of X_{it} for a given point in time, a feature that allows inferring how the explanatory power of the different factors changes over time.

3.2 Prior elicitation and posterior simulation

We follow a Bayesian route to estimation and inference. This implies that we have to specify a suitable set of prior distributions on the parameters of the model given by Eq. (3.1) - Eq. (3.5). The prior setup adopted is standard in the literature (see, for instance, Del Negro and Otrok, 2008).

For the initial state of the factor loadings $\boldsymbol{\Lambda}_0$ we use a multivariate Gaussian prior with the prior mean centered on zero and a rather high value for the prior variance,

$$\text{vec}(\boldsymbol{\Lambda}_0) \sim \mathcal{N}(\boldsymbol{0}, \underline{\boldsymbol{V}}_\Lambda), \tag{3.7}$$

with $\underline{\boldsymbol{V}}_\Lambda$ being a prior variance matrix, and the prior mean is set equal to zero. We assume that $\underline{\boldsymbol{V}}_\Lambda = \underline{a} \times \boldsymbol{I}_{NK}$. In our empirical application we set $\underline{a} = 10^2$ to a rather high value, effectively rendering the prior uninformative and thus staying fairly agnostic on the initial state of the system.

We impose an inverted Wishart prior on $\boldsymbol{Q}$, the variance-covariance matrix of the state equation associated with the factor loadings,

$$\boldsymbol{Q} \sim \mathcal{IW}(\underline{\boldsymbol{Q}}, \underline{q}) \tag{3.8}$$

with prior scale matrix $\underline{\boldsymbol{Q}}$ and prior degrees of freedom $\underline{q}$. We set $\underline{Q} = \underline{b} \times I_{NK}$, with $\underline{b} = 0.1^2$. Furthermore, to ensure that the prior is proper we set $\underline{q} = NK + 1$. In typical applications, the choice of $\underline{b}$ proves to be quite influential. However, robustness checks with different values for $\underline{b}$ and an uninformative inverted Gamma prior on the elements of $\boldsymbol{Q}$ lead to similar results.[2]

For the K autoregressive coefficients in $\boldsymbol{\Phi}$, we impose a normally distributed prior,

$$\phi_j \sim \mathcal{N}(0, \underline{V}_\phi), \; j = 1, \ldots, K, \tag{3.9}$$

where $\underline{V}_\phi$ is the prior variance related to the (j, j)th element of Φ. Similarly to the loadings we set $\underline{V}_\phi$ to high values, implying that the prior is uninformative.

On the level of the log-volatilities in Eq. (3.3) and Eq. (3.5), we use the same set of priors, i.e.

$$\mu_{ij} \sim \mathcal{N}(0, \underline{V}_i), \; i \in \{\omega, h\} \tag{3.10}$$

[2]The specific results are available on request.

Here, $\underline{V}_i = 10^2$ denotes the prior variance set such that the prior is rendered weakly informative. We follow Kastner and Frühwirth-Schnatter (2014) and impose a Beta prior on the persistence parameter of the log-volatility process,

$$\frac{1+\rho_{ij}}{2} \sim \mathcal{B}(a_0, a_1),\ i \in \{\omega, h\} \tag{3.11}$$

Here, a_0 and a_1 are hyperparameters set such that considerable prior mass is placed on high persistence regions of ρ. The specific values are $a_0 = 25$ and $a_1 = 1.5$, yielding a prior mean of around 0.94 and a prior standard deviation of 0.04. This choice proves to be of great importance in our application, because the data is typically quite uninformative on the persistence of the log-volatility. Thus, the influence of the prior on the posterior of ρ_{ij} is strong. However, the impact of the persistence parameter on the log-volatilities appears to be rather limited, as long as we do not impose too much prior mass on low persistence regions.

Finally, we impose a Gamma prior on the innovation variances of both log-volatility processes,

$$\varsigma_i \sim \mathcal{G}(1/2, 1/(2B_i)),\ i \in \{\omega, h\} \tag{3.12}$$

with $B_i = 1$ being a hyperparameter controlling the tightness of the prior. A value of unity translates into a rather non-informative prior distribution on the variance of the log-volatility. However, if the actual volatility is rather constant this prior provides more shrinkage than other traditional prior distributions like the inverted Gamma prior.

Combining the priors with the likelihood yields the joint posterior distribution of the model. Unfortunately, however, this high dimensional object is not available in closed form and we thus need to resort to simulation based techniques. Our Markov chain Monte Carlo (MCMC) algorithm of choice is a standard Gibbs sampling algorithm that iteratively simulates the parameters and states from well-known conditional distributions.

We simulate the full history of factor loadings with the well-known forward-filtering backward-sampling (FFBS) algorithm proposed in Frühwirth-Schnatter (1994) and Carter and Kohn (1994). Conditional on the loadings, the corresponding state equation is a simple linear regression model, implying that we can simulate $\boldsymbol{Q}$ from a well-known conditional posterior of inverted Wishart form. The diagonal elements of $\boldsymbol{\Phi}$, Φ_j, are sampled from normally distributed posterior distributions where we impose the restriction that the absolute values have to be below unity. All stochastic volatility components (i.e. the parameters of the state equations and the log volatilities) are simulated by means of the algorithm proposed in Kastner and Frühwirth-Schnatter (2014). Finally, we approximate the latent factors with their principal components. This choice is motivated by the large dimension of $\boldsymbol{X}_t$, containing over 430 time series, which renders an additional FFBS step unfeasible.

In what follows we base our inference on 15,000 posterior draws out of a total chain of 30,000 iterations of our MCMC algorithm. Usual convergence diagnostics indicate convergence towards the stationary distribution.

3.3 Identification and specification

The question we want to answer in the empirical application is how global macroeconomic and financial factors influence country-specific capital movements. Thus, we have to impose certain restrictions on the elements of $\mathbf{\Lambda}_t$ to identify the shocks as being global and variable-specific. To this end, we specify $\mathbf{\Lambda}_t$ to be block-diagonal, implying that only real output variables load on the output factor, prices on the price factor and so on.[3]

In addition to global macroeconomic, global financial factors and a global capital factor, we also include a regional capital flow factor. This factor captures the notion that capital movements display strong regional tendencies, effectively flowing in and out of a specific region. This implies that if a given country belongs to region j, we include a factor extracted from the capital flow series for all countries located within region j. Finally, we identify the scale and sign of the latent factors and associated loadings by restricting the first non-zero element of each column of $\mathbf{\Lambda}_t$ to unity for all t (Geweke and Zhou, 1996; Bernanke et al., 2005).

4 Data preparation for estimation

We use quarterly data from 1994q1 until 2015q4 for $M = 43$ worldwide economies and include for each country $L = 10$ macroeconomic and financial time series, consisting of three groups (see Table A.1 for a detailed variable description). First, we include one series for a particular capital flow category, calculated in moving annual cumulative terms and as a percentage of GDP (see section 2). Second, the group of macroeconomic variables consists of the real GDP growth rate, quarter-on-quarter CPI inflation rate, change in the CPI-based real effective exchange rate and the difference between exports and imports of goods and services (trade balance). Third, the group of financial sector variables consists of a short-term interest rate (typically 3-month market rates, per annum), a long-term interest rate (typically government bond yields, rates per annum), changes in equity prices, and growth of bank credit to as well as bank deposits of the domestic private sector. Data are taken from the IMF (IFS database), OECD, ECB, Eurostat, Thomson Reuters and national statistical offices.[4]

This choice of variables closely resembles the typical set of macroeconomic and financial quantities included in the literature on global macroeconometric modeling (see, for instance, Crespo Cuaresma et al., 2016; Feldkircher and Huber, 2016) augmented with a set of additional explanatory variables that were previously identified to be important determinants of capital flows (e.g. Broto et al., 2011; Milesi-Ferretti and Tille, 2011; IMF, 2014; Mishra et al., 2014; Olaberría, 2015; McQuade and Schmitz, 2017). As opposed to the literature on modeling capital flows by means of gravity equations (e.g. Portes et al., 2001; Portes and Rey, 2005), we do not aim to explain

[3] We thus simply extract the principal components from the corresponding subsets of $\boldsymbol{X}_t$.

[4] We follow the literature and transform our data to be approximately stationary (Stock and Watson, 2002; McCracken and Ng, 2016).

bilateral movements in capital flows but focus on explaining the variation of different types of capital inflows by means of global fundamental factors.

Nominal stock variables have been deflated using the CPI index. All variables (except for the interest rate variables) have been seasonally adjusted using the Census X12 method. All index variables enter as logarithms. A few capital flow, trade flow and GDP series were not satisfactorily available at quarterly frequency at the beginning of the sample; we therefore used the corresponding annual figures and the quarterly dynamics of the rest of the sample for data interpolation. Moreover, if the short-term (long-term) interest rate was not available, we used the dynamics of the deposit (lending) rate for data interpolation. In the case of few remaining missing observations at the beginning or the end of the sample, we used the average of the subsequent or previous four quarters to fill these gaps.

5 Empirical findings

In subsection 5.1 we first provide an overview of the characteristics of the latent factors extracted from our dataset and also investigate whether the global co-movement of specific variables is driven by particular countries. In subsection 5.2, we present the variance decompositions for different types of capital flows (above all gross capital inflows) to provide an understanding how important different factors are in explaining capital flow volatility over time and across countries. Finally, subsection 5.3 studies whether the way global factors explain the volatility of capital inflows is related to country-specific characteristics.

5.1 The latent dynamic factors

In line with the grouping of variables outlined in the previous section, we estimate four global macroeconomic factors, five global financial factors, one global capital factor and five regional capital factors, yielding a total of $K = 15$ factors in $\boldsymbol{F}_t$.

To provide additional intuition on the specific shape of the latent factors and to provide a rough gauge on how well our relatively small number of latent factors summarize the dynamics of the time series included in the sample, Fig. 3 depicts the estimated factors (in red) and the actual time series for the different countries in gray for macroeconomic and financial variables. A few interesting findings emerge. Note that for the majority of variables, a single factor tracks the actual developments rather well. Especially for GDP growth and inflation the co-movement across countries is quite pronounced. As a direct consequence of the GFC, output growth dropped markedly across the globe and most countries witnessed deflationary developments.

For equity prices, credit growth, deposit growth and the change in real effective exchange rates we also find that the latent factors closely track most low-frequency movements of the underlying time series. Especially for equity prices, the strong degree of international synchronization suggests that the dynamic behavior of equity price markets may be neatly captured by a single global factor, effectively soaking up the vast majority of equity price movements. Notice that the credit factor successfully summarizes low to medium-frequency developments of the credit growth series in our sample. This rather strong amount of co-movement for credit growth points towards the presence of a global financial cycle that has been emphasized as an important channel for the international transmission of macroeconomic shocks (Rey, 2015; Banerjee et al., 2016).

With respect to nominal interest rates, the latent factor for short-term rates captures the general downward trend across our global sample rather well – at least since the early 2000s and right after the GFC, before gradually increasing again until the end of our sample. Policy rates have evolved in a similar vein and this latent factor could thus also be interpreted as tracking the impact of conventional monetary policy measures (with the qualification that monetary policy transmission has not always perfectly operated during the observation period). On the other hand, the latent factor estimated for long-term interest rates is apparently less capable of tracking the underlying dynamics. While it tracks the general decline in 10-year government bond yields closely at the beginning of the sample, it departs significantly afterwards.

Short- and long-term interest rates appear to be highly correlated, and apparently most of the broader variation is already incorporated in the latent factor for short-term interest rates, as the factors are constructed to be mutually orthogonal. This implies that the factor associated with long-term rates captures only movements of these series that are orthogonal to the dynamics in the short-term rate and thus might be seen as an additional component, e.g. absorbing movements in expectations about the future short-term rate and the risk premium not traced by the short-term rate factor.[5] Especially in times of a financial turmoil, this factor could indicate a flattening yield curve in several economies, when the expected future short-term interest rate and the risk premium decrease to a stronger degree compared to the actual short-term rate. Note, for instance, that the extracted factor for long-term interest rates shows a significant decrease during the 1997–1998 Asia crisis and the 2008–2009 GFC. The high correlation of the term-spread (computed as the difference between short- and long-term interest rates) with the long-term interest rate factor, moreover, endorses this conjecture that the long-term interest rate factor can be interpreted as a hypothetical slope of a global yield curve (see Diebold et al., 2008).

[Fig. 3 about here.]

To provide further evidence on the degree of co-movement of capital flows in our sample, Fig. 4 depicts the estimated latent global and regional capital factors together with the actual data for gross capital inflows. We can see that global and regional capital

[5] The long-term interest rate is commonly decomposed into expectations about the future short-term rate and the risk premium which collects risks such as lack of safety, prepayment, default, illiquidity and duration risks (Krishnamurthy and Vissing-Jorgensen, 2011). According to Krishnamurthy and Vissing-Jorgensen (2011) and Gagnon et al. (2011) the signaling channel mainly drives the expectations of the future short-term rate, whereas the portfolio balance channel accounts for variances in the risk premium.

factors capture low-frequency movements of gross capital inflows rather well. For some regions, we observe a particularly pronounced degree of co-movement of capital inflows across the series (most notably in Asia and Latin America), whereas for other regions the estimated regional capital factor seems to be strongly driven by a single country and thus closely tracks country-specific noise in addition to the overall general trend observed in a given region (e.g. the CESEE region).

[Fig. 4 about here.]

Finally, to give an indication whether particular countries drive the global co-movement of specific variables, we calculate (rolling) cross-correlations between domestic variables and the estimated latent factors. These correlations are computed by extracting the principal components based on an initial sample (or training sample) which is then expanded by successive quarters until the end of the full sample is reached. Table 1 summarizes average cross-correlations for US and Chinese variables since 2001 or 2011, respectively.[6] Both countries show comparatively strong correlations with global factors. While economic developments in China seem to be very important for global price developments, US variables appear to be crucial for global GDP dynamics. Since 2011, the correlation of global factors with US variables has increased further, not only with regard to GDP growth, but notably also in the case of financial variables – likely reflecting that unconventional monetary policy in the US had an important impact on global financial developments during that time. The correlation of Chinese variables with global factors also tends to rise since 2011, especially with regard to global GDP dynamics. At the same time, China's role for global financial factors remains modest in comparison to the US (corroborating Aizenman et al., 2016).[7]

[Table 1 about here.]

5.2 How important are different factors in explaining capital flow volatility?

Figure 5 shows the variance decomposition results for gross capital inflows based on Eq. (3.6). The time-varying, standardized volatility of gross capital inflows is depicted as a red line (right-hand side scale). We can see that global and/or regional economic and financial crises have become manifest in volatility spikes, e.g. very clearly the

[6] We refer here to the US and China as they account for significant shares of global GDP and belong to the most important "core" countries, whose economic impact on "periphery" countries has recently been lively debated (e.g. in Aizenman et al., 2016). Moreover, we show the results for the second subperiod starting with 2011 in order to avoid that fluctuations immediately after the GFC distort the results.

[7] The same exercise for the largest euro area economies – Germany and France – reveals that also European variables are not as strongly related to global financial factors as US variables (except for the short-term interest rate). Moreover, since 2011 the correlation of global factors with European variables has not increased as strongly as with US variables. The results for other countries than the US and China as well as for different subperiods are available on request.

2008–2009 GFC and the crisis following the dot-com collapse in 2000 in all five regions, but also the Argentine economic crisis 1998–2002 (Latin America panel) or the 1997–1998 Asian crisis. At the end of the sample, while gross capital inflows have slightly decreased in several regions (recall section 2), a renewed hike in capital flow volatility can be observed, reaching in some regions similar heights as during the GFC and being especially pronounced for gross portfolio investment inflows (see Fig. B.3). Most likely, this volatility hike is associated with increased global uncertainty alongside geopolitical tensions and turbulence in emerging markets following the Fed's tapering announcement.[8]

Turning to the relative variance contribution of the extracted factors, we can see very consistently across different regions that the global factors (together with the regional capital factor) explain the largest share. Consistent with the observation that capital flow volatility peaks are often associated with global crises (take the GFC), it is no surprise to see in such a situation that the variance share explained by global factors rises markedly. Thus, if a global shock hits the system, the degree of co-movement between capital flow variables increases, strongly pointing towards a factor structure in the data. In general, the importance of global factors has steadily widened over time.[9] For instance, global and regional factors explained on average across all the included countries about 74 % of the variance of gross capital inflows in the period 1994–2008; after the GFC this share increased to more than 80 %.

However, it is remarkable that countries in both advanced and emerging Europe experienced a marked drop in the variance share explained by global factors during the pre-GFC boom period, which was actually not the case in other regions. In both regions this decrease mainly reflected the temporarily declining relevance of global financial factors in explaining capital flow volatility. Apparently, strong gross capital inflows to emerging Europe were so sizable between 2003 and 2008 that global financial factors contributing to this surge in capital inflows like the buildup of global leverage were not as dominant as in other periods, a result that could partly be the outcome of the strategic positioning of banks from advanced in emerging Europe (see Eller et al., 2016).

Having a closer look on the relative importance of different factors (Table 2), it becomes evident that global financial factors, and among them especially the ones describing co-movements in long-term interest rates as well as credit and deposit growth, explain the largest share of the variance of gross capital inflows. The figures indicate that this share did clearly rise in the aftermath of the GFC: In the period 2009–2015 global financial factors explain on average about 44 % of the variance, compared to

[8] McQuade and Schmitz (2017), in contrast, found that capital flow volatility markedly decreased after the GFC and did not rise again until the end of 2015 (despite the tapering tantrum). Since they rely on 8-quarter rolling standard deviations, we conjecture that this observation stems from the backward-looking nature of their volatility measure whereas our flexible state space model allows for swift changes in the shock variances, if necessary.

[9] As a corollary, the variance share explained by idiosyncratic factors has continuously decreased over time. Recall that idiosyncratic factors characterize everything else which cannot be explained by the extracted factors, i.e. country-specific particularities and other global and regional factors we did not explicitly account for.

about 39 % before 2009. Global macroeconomic factors, on the other hand, explain on average about 23 % of the variance of capital inflows. Similar to global financial factors, the explanatory power of global macroeconomic factors has also increased over time. The strongest explanatory power of global macroeconomic factors can be found for Latin American economies (more than 27 %). In addition, the two extracted capital flow factors (global and regional) explain together on average about 13 % of the variance of capital inflows, a share which has remained rather stable over time. It should be noted that in Asia the explanatory power of the two capital flow factors is clearly stronger than in other regions (with an explained variance share of 23 % on average). In turn, the variance share explained by global financial factors is in Asia not as large as in other regions. Another noteworthy observation is the result that the regional capital flow factor shows a somewhat stronger explanatory power than the global one, suggesting that countries in our sample are apparently more strongly linked to a regional capital flow cycle as opposed to a global one.

The respective variance decomposition results for the different subcategories of gross capital inflows (direct, portfolio and other investment inflows) as well as for gross capital outflows and net capital flows are shown in the appendix (Figures B.2 to B.6). It can be seen that the relative contribution of the different factors explaining capital flow volatility for the subcategories are broadly similar to the results discussed for gross capital inflows. If any, it can be pointed out that there was no temporary drop in the explanatory power of global factors in the pre-GFC boom period in both, advanced and emerging Europe in the case of portfolio investment inflows. Moreover, the variance share explained by the global and regional factors is somewhat less pronounced in the case of portfolio investment inflows (below 75 %) and somewhat more pronounced in the case of direct and other investment inflows (reaching more than 75 % already before 2009 and increasing to clearly more than 80 % in post-crisis years).

Finally, to illustrate the cross-country heterogeneity in our sample, we include in the appendix also Table B.1 with a breakdown of the variance decomposition of gross capital inflows by country. Despite the general trend of an increasing role of global factors in explaining the volatility of capital inflows, there are still several countries with a rather large variance share explained by idiosyncratic factors, most notably China, Malaysia, Canada but also a few European countries like Finland, Sweden, Portugal, Russia or Slovakia. Brazil or Indonesia are examples for countries that also faced a large variance share explained by idiosyncratic factors before the GFC; this share, however, has reduced remarkably thereafter.

[Fig. 5 about here.]

[Table 2 about here.]

5.3 Role of country-specific shelters

The findings of the literature that examines the question of what determines economies' sensitivity to global common dynamics, is far from clear. Bruno and Shin (2015) show that global factors have a significantly larger impact than local factors in countries with bigger banking flows and a higher degree of financial openness. They also find that the composition of the foreign investor base matters, rather than institutional fundamentals. Interestingly, studying the immediate impact of the taper tantrum in 2013, Eichengreen and Gupta (2015) note that countries with larger and more liquid markets were more heavily affected. Further, they are skeptical regarding the role of better domestic macroeconomic fundamentals that are found not being capable of shielding countries from global push factors. Likewise, Scheubel et al. (2018b) found that country fundamentals are mostly insignificant in influencing the likelihood of experiencing an extreme capital flow episode. In contrast, studying episodes of net capital surges to emerging market economies, Ghosh et al. (2014) point to the relevance of domestic factors. While global factors act as "gatekeepers" that determine when surges of capital to EMEs will occur, the size of inflows mainly depends on domestic factors such as a country's external financing need, its capital account openness, and its exchange rate regime.

Following this type of literature, we investigate in this subsection to which extent the share of the variance of gross capital inflows explained by common global and regional factors depends on country-specific macrofinancial characteristics. This should shed some light on the sources of cross-country heterogeneity observed in our variance decomposition results. One could argue that more flexible exchange rates, higher foreign exchange reserves, lower public or external debt or deeper financial markets with more capacity to absorb capital inflows reduce the share of variance of capital inflows that is explained by common global factors, as suggested by empirical evidence provided by the IMF (2016) for a large sample of worldwide emerging markets. Or, to put this view differently, the sounder domestic macrofinancial fundamentals, the less susceptible these economies are to fluctuations in global business or global financial cycles.

To address this type of questions, we run a series of simple fixed-effects panel regressions of the following form

$$\text{glob}_{it} = \alpha + \gamma_i + \tau_t + \boldsymbol{\beta} \boldsymbol{z}_{it-1} + \epsilon_{it}, \tag{5.1}$$

where glob_{it} represents the share of the variance of gross capital inflows in country i and year t (quarterly figures have been morphed into yearly ones) explained by all the global (and regional) factors together. Country-specific macrofinancial fundamentals enter with one lag in order to account for potential endogeneity at least to certain extent ($\boldsymbol{z}_{it-1}$). In addition, an overall constant (α), country-fixed effects (γ_i) and a linear time trend (τ_t) are included to control for country-specific particularities which remain constant over time or for time-specific issues which affect all the included countries equally.[10]

When it comes to selecting specific macrofinancial fundamentals to be included in $\boldsymbol{z}_{it-1}$, variables that inform about domestic macroeconomic and financial fundamentals

[10] Instead of a linear time trend, we have also experimented with time-fixed effects. Baseline results remain qualitatively unchanged. But in order to keep the model tractable, e.g. in order to examine advanced and emerging market economies separately, we eventually opted for the trend specification.

or vulnerabilities, respectively, as well as indicators for the international economic and financial exposure of the country are natural candidates. Accordingly, we included following five groups of regressors. First, we include in all the various specifications baseline regressors which proved to be of robust importance in related investigations (log level and growth of GDP per capita, gross government debt and foreign exchange reserves as percentage of GDP, volatility of the REER). Second, we add alternately institutional variables capturing the quality of governance (the World Bank's rule of law indicator), the degree of capital account closeness with respect to inflows or simply the economic relevance of the respective economy (approximated by nominal GDP in USD). The third group of regressors captures financial fundamentals, i.e. private sector credit and stock market capitalization as percentage of GDP as well as the spread between short-term and long-term interest rates. Fourth, we add variables reflecting the general external openness of the respective country, i.e. trade openness (sum of exports and imports over GDP), current account balance and gross external debt as percentage of GDP as well as export in relation to import value indices to account for terms of trade changes.[11] Finally, in a fifth step we add time-varying volatilities for several variables that already entered the factor model studied before. These are based on the posterior mean estimate of a simple univariate stochastic volatility model for each (demeaned) time series in $\boldsymbol{X}_t$,

$$\tilde{X}_{jt} = e^{\omega_{jt}/2} \times \eta_{jt}, \tag{5.2}$$

$$\eta_{jt} \sim \mathcal{N}(0, 1), \tag{5.3}$$

with $\tilde{X}_{jt}$ being the demeaned jth element of $\boldsymbol{X}_t$. The state transition equation is again given by Eq. (3.5).

Table 3 reports the respective panel estimation results. We can see that global factors tend to have a weaker impact on capital flow volatility if countries are characterized by more volatile exchange rates, lower public indebtedness, higher GDP per capita growth or more developed domestic stock markets (robust across different specifications). Higher FX reserves or simply larger economies also provide for the expected dampening effect, though the respective results are only statistically significant if we consider the effect of global macroeconomic factors (instead of all factors together).[12] The counterintuitive results for the current account balance (global factors are weaker if the CA deficit gets larger) or for external debt (global factors are weaker in the case of larger external debt) do not remain robust across different specifications (e.g. if we separate emerging and advanced economies). Interestingly, institutional variables –

[11] Data for the just listed variables are from the IMF (World Economic Outlook database, International Financial Statistics), the World Bank (Governance Indicators, World Development Indicators, Quarterly External Debt Statistics) and Fernández et al. (2015).

[12] We have implemented various robustness checks: tighter dependent variables (e.g. accounting for the explanatory power of global financial factors or global macroeconomic factors only), alternative definitions of regressors, separating the sample into advanced and emerging economies. All the respective results are available upon request.

such as capital account closeness or strength of rule of law – do not show a statistically significant impact on the explanatory power of global factors (though often showing the expected negative sign).

Without digging too much into the details of these estimations – as the dimension of the panel is still somewhat small especially in the case of sample splitting – it should be noted that exchange rate flexibility as a shock absorbing device has frequently been discussed in the literature. Our results seem to back these papers that came to the conclusion that exchange rate flexibility is mitigating a country's exposure to external shocks (e.g. Aizenman, 2018).

[Table 3 about here.]

6 Closing remarks

In this paper we develop a time-varying parameter factor model with stochastic volatility in the observation and the transition equation. Our model incorporates several stylized features commonly observed in the study of macroeconomic and financial data. Our findings indicate that global co-movement of macroeconomic, financial and capital flow variables has a crucial relevance for explaining country-specific fluctuations in gross capital flows. No matter which types of capital flows or which economic regions are considered, the extracted global factors – capturing common global (and to some extent also regional) macro-financial dynamics – are able to explain a major share (on average about 3/4) of country-specific capital flow volatility.

It is striking that after the 2008–2009 global financial crisis, global factors are able to explain a larger share of capital flow volatility than before (although starting already from relatively high levels). This points to a recently stronger reliance of capital flow changes on global-scale developments, which could be explained, among others, by unconventional economic policy measures which have been implemented since 2008 and could have affected the way capital flow volatility is related to global macro-financial factors. At least some respective indication is given by our result that the correlation of the estimated global factors with US variables has increased since 2011.

Given that global factors are decisive in explaining a major proportion of capital flow volatility and given that this explanatory power has increased over time, it is of interest how sizable any negative spillover effects are. If negative externalities were sizable, more intensified international policy coordination could be helpful in smoothing capital flow fluctuations. Depending on the relevance of different types of global factors, different policy areas are in demand. For instance, given that global financial factors turn out to explain a dominant share of capital flow volatility, international coordination of monetary policies and of financial market policies seems to be very important. Nevertheless, experience has shown that it is rather difficult to achieve a satisfactory degree of international policy coordination, except for crisis times (Blanchard et al., 2013). As a consequence, the analytic focus has shifted to the analysis of the effectiveness of domestic policies in shielding countries from globally determined fluctuations in capital flows. We provided in this paper some evidence that global factors have a weaker impact on capital flow volatility if countries are characterized by more volatile exchange rates, lower public indebtedness, higher GDP per capita growth or more developed domestic stock markets.

However, what we did not address in this paper – and we leave that for future research – was the role of macroprudential policy. Given that macroprudential measures have been increasingly implemented in the past few years, it is of interest to study which types of macroprudential measures are effective in shielding countries from globally determined capital flow volatility. Some recent empirical evidence suggests that the structure of the domestic financial system plays an important role in mitigating negative cross-border spillovers (Beirne and Friedrich, 2017). On the other hand, there is also evidence that macroprudential policies are not the only way to prevent the build-up of financial market bubbles, although they are apparently able to reduce the procyclicality of credit and successful in building up buffers (Igan and Tan, 2017). There is certainly demand for more research along these existing lines, in particular with regard to the cross-border impact of domestic economic policies on cyclical capital flow fluctuations.

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Table 1: Correlation of US and Chinese variables with the estimated global factors

	Global factors										
	Correlation of / with	GDP growth	Inflation rate	REER change	Trade balance change	Short-term interest rate	Long-term interest rate	Equity price growth	Credit growth	Deposit growth	Gross capital inflows
US	GDP growth	0.35	0.09	0.21	0.04	0.14	0.14	0.22	0.16	0.07	0.06
	Inflation rate	0.40	0.16	0.16	0.25	0.30	0.20	0.12	0.19	0.06	0.07
	REER change	0.30	0.09	0.61	0.09	0.25	0.03	0.39	0.04	0.05	0.05
	Trade balance change	0.24	0.11	0.03	0.23	0.10	0.12	0.10	0.15	0.08	0.30
	Short-term interest rate	0.18	0.40	0.23	0.07	0.50	0.19	0.12	0.13	0.05	0.18
	Long-term interest rate	0.34	0.67	0.19	0.03	0.35	0.20	0.08	0.11	0.09	0.14
	Equity price growth	0.26	0.13	0.21	0.04	0.07	0.13	0.69	0.08	0.05	0.19
	Credit growth	0.12	0.08	0.08	0.13	0.27	0.08	0.16	0.44	0.06	0.11
	Deposit growth	0.22	0.17	0.04	0.17	0.35	0.15	0.08	0.19	0.06	0.18
	Gross capital inflows	0.28	0.40	0.12	0.03	0.14	0.31	0.13	0.30	0.11	0.16

a.: US since 2001

	Global factors										
	Correlation of / with	GDP growth	Inflation rate	REER change	Trade balance change	Short-term interest rate	Long-term interest rate	Equity price growth	Credit growth	Deposit growth	Gross capital inflows
US	GDP growth	0.66	0.04	0.07	0.04	0.19	0.06	0.27	0.16	0.06	0.01
	Inflation rate	0.52	0.26	0.25	0.26	0.25	0.33	0.19	0.06	0.02	0.06
	REER change	0.33	0.06	0.68	0.09	0.24	0.02	0.28	0.03	0.07	0.05
	Trade balance change	0.42	0.02	0.05	0.29	0.08	0.09	0.10	0.23	0.07	0.33
	Short-term interest rate	0.36	0.43	0.13	0.01	0.66	0.13	0.06	0.14	0.02	0.03
	Long-term interest rate	0.41	0.59	0.10	0.01	0.52	0.24	0.03	0.09	0.04	0.08
	Equity price growth	0.51	0.02	0.02	0.02	0.03	0.08	0.71	0.14	0.01	0.14
	Credit growth	0.03	0.06	0.13	0.14	0.46	0.07	0.12	0.48	0.08	0.14
	Deposit growth	0.30	0.07	0.03	0.06	0.39	0.19	0.01	0.14	0.04	0.17
	Gross capital inflows	0.42	0.17	0.06	0.03	0.05	0.52	0.10	0.48	0.03	0.14

b.: US since 2011

	Global factors										
	Correlation of / with	GDP growth	Inflation rate	REER change	Trade balance change	Short-term interest rate	Long-term interest rate	Equity price growth	Credit growth	Deposit growth	Gross capital inflows
China	GDP growth	0.18	0.16	0.21	0.17	0.29	0.07	0.12	0.06	0.03	0.06
	Inflation rate	0.27	0.79	0.16	0.15	0.51	0.14	0.05	0.03	0.07	0.04
	REER change	0.14	0.12	0.20	0.57	0.15	0.17	0.13	0.13	0.08	0.23
	Trade balance change	0.13	0.29	0.15	0.28	0.16	0.06	0.08	0.15	0.30	0.18
	Short-term interest rate	0.14	0.89	0.05	0.03	0.18	0.18	0.05	0.05	0.09	0.31
	Long-term interest rate	0.12	0.85	0.10	0.03	0.18	0.16	0.06	0.07	0.05	0.39
	Equity price growth	0.15	0.14	0.15	0.20	0.17	0.13	0.29	0.11	0.13	0.26
	Credit growth	0.32	0.33	0.10	0.19	0.32	0.15	0.23	0.16	0.10	0.17
	Deposit growth	0.22	0.25	0.03	0.12	0.36	0.27	0.12	0.10	0.06	0.13
	Gross capital inflows	0.19	0.30	0.09	0.02	0.26	0.36	0.13	0.27	0.07	0.32

c.: China since 2001

	Global factors										
	Correlation of / with	GDP growth	Inflation rate	REER change	Trade balance change	Short-term interest rate	Long-term interest rate	Equity price growth	Credit growth	Deposit growth	Gross capital inflows
China	GDP growth	0.25	0.04	0.22	0.05	0.22	0.11	0.07	0.07	0.02	0.02
	Inflation rate	0.29	0.71	0.14	0.15	0.37	0.24	0.07	0.07	0.11	0.05
	REER change	0.18	0.08	0.26	0.54	0.11	0.01	0.09	0.15	0.10	0.26
	Trade balance change	0.01	0.21	0.18	0.28	0.02	0.01	0.04	0.22	0.27	0.19
	Short-term interest rate	0.15	0.85	0.06	0.06	0.13	0.27	0.07	0.03	0.06	0.24
	Long-term interest rate	0.17	0.83	0.11	0.05	0.19	0.20	0.10	0.06	0.01	0.31
	Equity price growth	0.25	0.19	0.12	0.22	0.17	0.07	0.35	0.07	0.05	0.22
	Credit growth	0.48	0.28	0.02	0.10	0.24	0.10	0.33	0.19	0.13	0.14
	Deposit growth	0.42	0.14	0.03	0.12	0.32	0.21	0.11	0.10	0.01	0.05
	Gross capital inflows	0.30	0.20	0.05	0.02	0.27	0.45	0.11	0.36	0.07	0.37

d.: China since 2011

Source: Authors' estimates. **Notes:** Average absolute correlations of domestic variables in the US and in China with the estimated global factors are shown.

Table 2: Variance shares of **gross capital inflows** explained by different factors

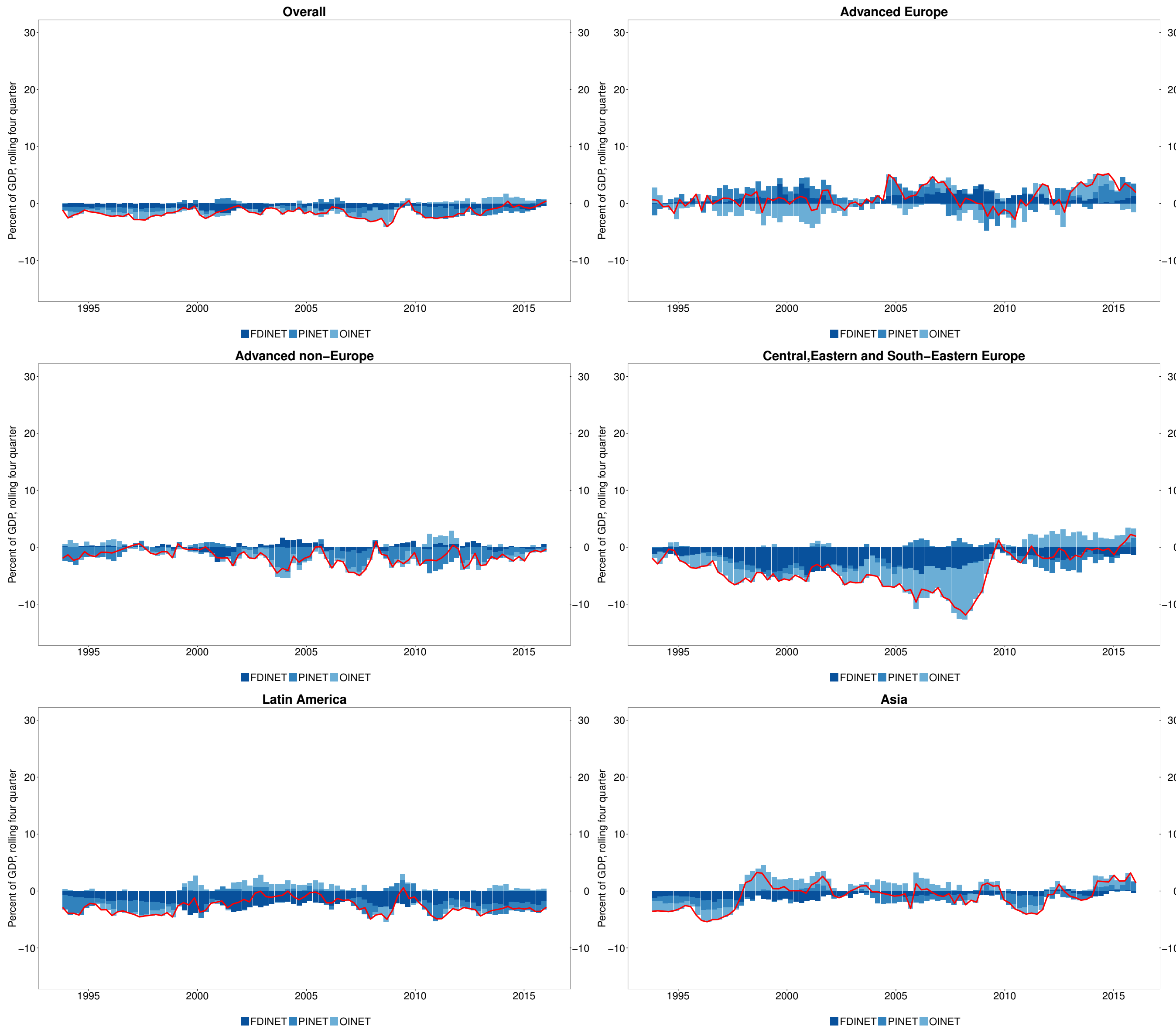
Sample averages	Total sample	Advanced Europe	Advanced non-Europe	CESEE	Latin America	Asia	1994–2000	2001–2008	2009–2015
GDP growth	5.8	7.1	6.1	4.8	5.4	5.2	6.3	5.2	6.0
Inflation rate	4.8	4.8	4.6	4.2	5.6	5.1	4.6	4.9	4.8
REER change	3.4	3.5	4.1	3.7	3.3	2.5	3.7	3.1	3.5
Trade balance change	8.6	7.9	6.3	8.8	13.2	7.4	7.1	8.8	10.0
MACRO	22.6	23.3	21.1	21.6	27.5	20.2	21.7	22.0	24.3
Short-term interest rate	5.0	4.2	5.7	5.6	5.4	4.9	4.8	5.2	5.0
Long-term interest rate	13.5	14.4	15.5	14.6	10.0	11.7	13.0	12.9	14.8
Equity price growth	2.3	2.9	2.0	2.0	2.0	2.3	2.5	2.2	2.4
Credit growth	10.1	11.6	6.7	12.3	9.1	7.0	10.9	8.8	10.9
Deposit growth	9.4	9.2	11.8	9.4	10.7	6.7	8.4	9.1	10.6
FINANCIAL	40.4	42.3	41.8	43.9	37.2	32.6	39.6	38.2	43.7
Global capital	5.5	3.6	2.9	4.3	5.9	12.4	5.3	5.2	5.9
Regional capital									
Advanced Europe	2.0	6.5	0.0	0.0	0.0	0.0	2.1	1.9	2.0
Advanced non-Europe	1.0	0.0	8.2	0.0	0.0	0.0	1.0	0.9	1.0
CESEE	1.8	0.0	0.0	6.5	0.0	0.0	2.1	1.5	1.8
Latin America	1.2	0.0	0.0	0.0	8.6	0.0	1.2	1.2	1.2
Asia	1.8	0.0	0.0	0.0	0.0	11.0	1.7	1.9	1.8
Idiosyncratic	23.8	24.3	26.1	23.8	20.8	23.7	25.3	27.2	18.3

Source: Authors' estimates. **Notes:** This table presents the variance shares of gross capital inflows (incurrence less repayment of totaled direct, portfolio and other investment liabilities) as a share of GDP, explained by different factors for all countries in our sample. Results are based on 15,000 posterior draws. Unweighted cross-country averages are shown for each region.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
VARIABLES	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**	**glob**
GDP p.c.	0.352	-8.705	-6.251	-6.904	-9.023	-9.313	-7.361	-8.708	-8.515	-8.511	-8.557	-9.483*	-8.719	-8.862	-9.621*	-7.369	-17.250***
	[9.155]	[5.394]	[6.359]	[5.884]	[5.556]	[5.753]	[7.036]	[5.392]	[5.232]	[5.379]	[5.300]	[5.504]	[5.417]	[5.536]	[5.701]	[5.163]	[6.197]
GDP p.c. growth	-0.608***	-0.641***	-0.655***	-0.640***	-0.670***	-0.711***	-0.504***	-0.642***	-0.611***	-0.646***	-0.639***	-0.620***	-0.648***	-0.646***	-0.633***	-0.569***	-0.737***
	[0.207]	[0.152]	[0.148]	[0.193]	[0.155]	[0.163]	[0.185]	[0.149]	[0.149]	[0.152]	[0.151]	[0.151]	[0.169]	[0.154]	[0.147]	[0.128]	[0.156]
Gov. debt (% GDP)	0.080	0.116***	0.109**	0.122***	0.116***	0.095**	0.100**	0.116***	0.115***	0.114***	0.113**	0.116***	0.115***	0.115***	0.110**	0.096**	0.128***
	[0.055]	[0.041]	[0.045]	[0.043]	[0.042]	[0.043]	[0.046]	[0.042]	[0.041]	[0.042]	[0.042]	[0.041]	[0.041]	[0.041]	[0.042]	[0.041]	[0.038]
FX reserves (% GDP)	-0.099	-0.027	-0.031	-0.020	-0.026	-0.050	-0.010	-0.027	-0.030	-0.026	-0.027	-0.029	-0.027	-0.027	-0.040	-0.047	-0.115
	[0.101]	[0.080]	[0.080]	[0.096]	[0.079]	[0.083]	[0.088]	[0.080]	[0.080]	[0.079]	[0.080]	[0.080]	[0.080]	[0.080]	[0.080]	[0.078]	[0.082]
Vola. REER	-172.510***	-133.404**	-136.567**	-144.082**	-137.320**	-130.509**	-153.524***	-133.202**	-136.927**	-136.183**	-137.652**	-124.229**	-132.494**	-134.039**	-132.188**	-134.696**	-119.495**
	[47.716]	[51.696]	[52.830]	[55.502]	[53.271]	[50.555]	[42.608]	[52.457]	[51.109]	[54.428]	[54.902]	[52.921]	[51.359]	[51.334]	[52.669]	[52.079]	[50.881]
Economic size	-3.734		-1.705														
	[3.251]		[2.927]														
Cap.acc. closeness	0.311			0.448													
	[2.619]			[2.342]													
Rule of law	0.555				-0.750												
	[3.470]				[2.061]												
Credit (% GDP)	-0.046					-0.046											
	[0.033]					[0.031]											
Stock market capitaliz.	-0.074***						-0.055***										
	[0.021]						[0.017]										
Interest rate spread	0.132							0.010									
	[0.225]							[0.178]									
Vola. GDP	79.855								68.063								
	[74.507]								[56.535]								
Trade openness	-0.010													0.008			
	[0.061]													[0.039]			
Trend	0.742*	0.700**	0.713**	0.621**	0.698**	0.876***	0.620*	0.700**	0.719**	0.699**	0.716**	0.725**	0.697**	0.697**	0.789**	0.618**	1.376***
	[0.381]	[0.285]	[0.287]	[0.296]	[0.295]	[0.315]	[0.350]	[0.285]	[0.282]	[0.283]	[0.288]	[0.283]	[0.284]	[0.290]	[0.300]	[0.266]	[0.335]
Vola. inflation										0.191							
										[0.620]							
Vola. interest rates											0.059						
											[0.142]						
Vola. credit												-33.394*					
												[18.059]					
Vola. equity prices													-2.034				
													[15.535]				
Terms of trade															0.004		
															[0.056]		
Curr.acc. balance																0.408**	
																[0.196]	
Ext. debt (% GDP)																	-0.070***
																	[0.012]
Constant	-1,352.698*	-1,241.537**	-1,268.626**	-1,101.410**	-1,233.673**	-1,581.592***	-1,089.901*	-1,241.416**	-1,282.443**	-1,241.777**	-1,274.423**	-1,283.110**	-1,234.777**	-1,234.609**	-1,409.772**	-1,089.046**	-2,506.236***
	[697.929]	[522.139]	[526.872]	[540.922]	[539.363]	[579.400]	[636.591]	[522.900]	[518.179]	[519.406]	[531.228]	[517.742]	[520.462]	[532.143]	[548.570]	[487.047]	[611.600]
Observations	597	831	831	738	791	831	675	831	831	831	831	831	831	831	814	831	787
R-squared	0.217	0.190	0.191	0.183	0.189	0.200	0.194	0.190	0.193	0.191	0.191	0.196	0.190	0.191	0.200	0.211	0.276
No. of countries	39	43	43	40	43	43	40	43	43	43	43	43	43	43	43	43	43
Between R-Squared	0.00425	0.0394	0.0503	0.0203	0.0512	0.0945	0.0325	0.0393	0.0372	0.0406	0.0445	0.0413	0.0399	0.0411	0.0504	0.0171	0.101
Overall R-squared	0.0478	0.0917	0.110	0.0812	0.0928	0.117	0.0714	0.0917	0.0929	0.0937	0.0951	0.0917	0.0921	0.0925	0.101	0.0995	0.102
F-stat	6.247	11.20	10.16	8.765	8.791	10.85	7.588	9.897	10.12	9.794	9.742	13.27	9.982	10.56	9.719	10.37	17.56

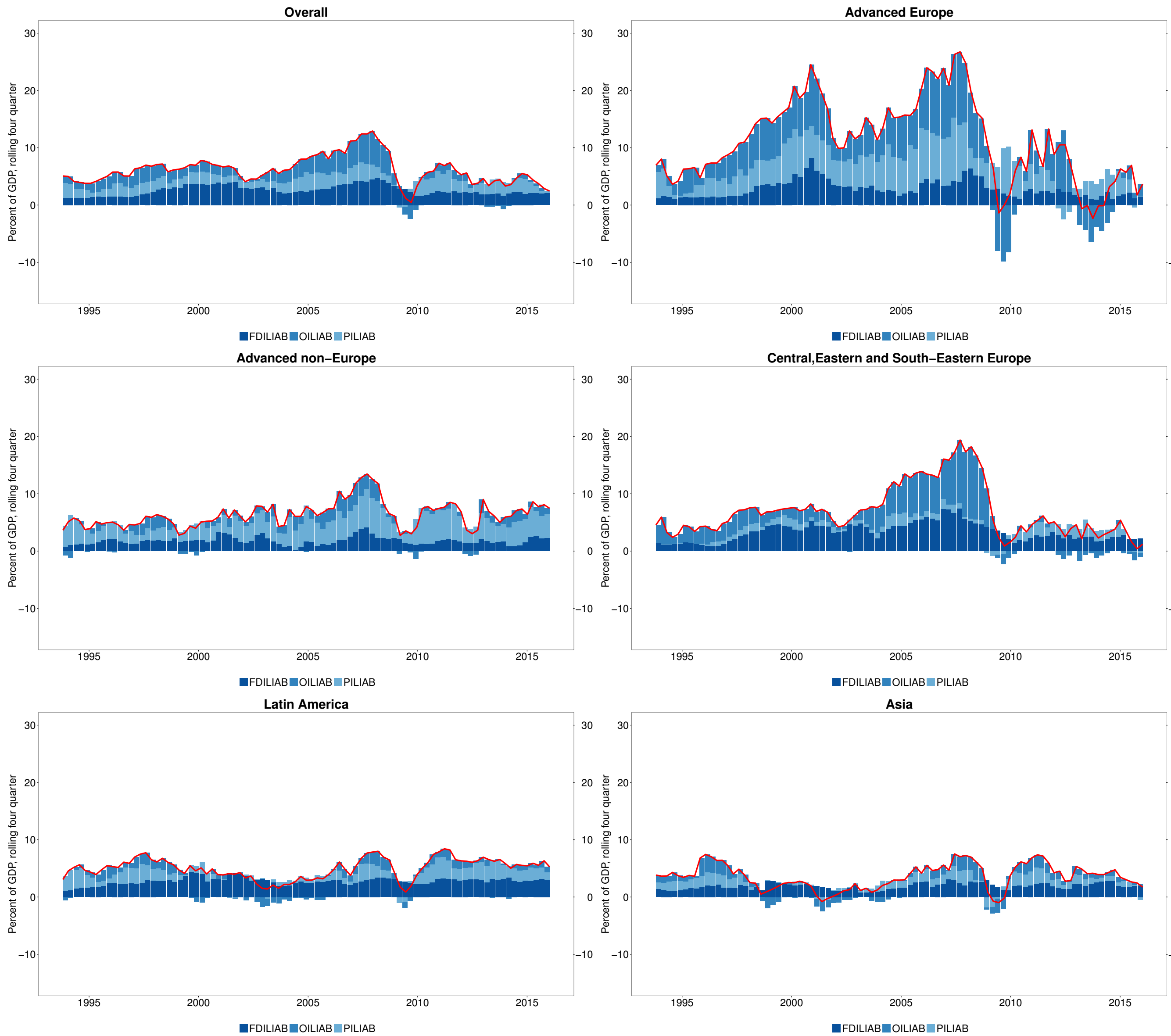
Source: Authors' estimates. **Notes:** Panel regressions with country-fixed effects and linear time trend. All regressors enter with a lag of one quarter.

Table 3: Explanatory power of global factors and role of country-specific characteristics



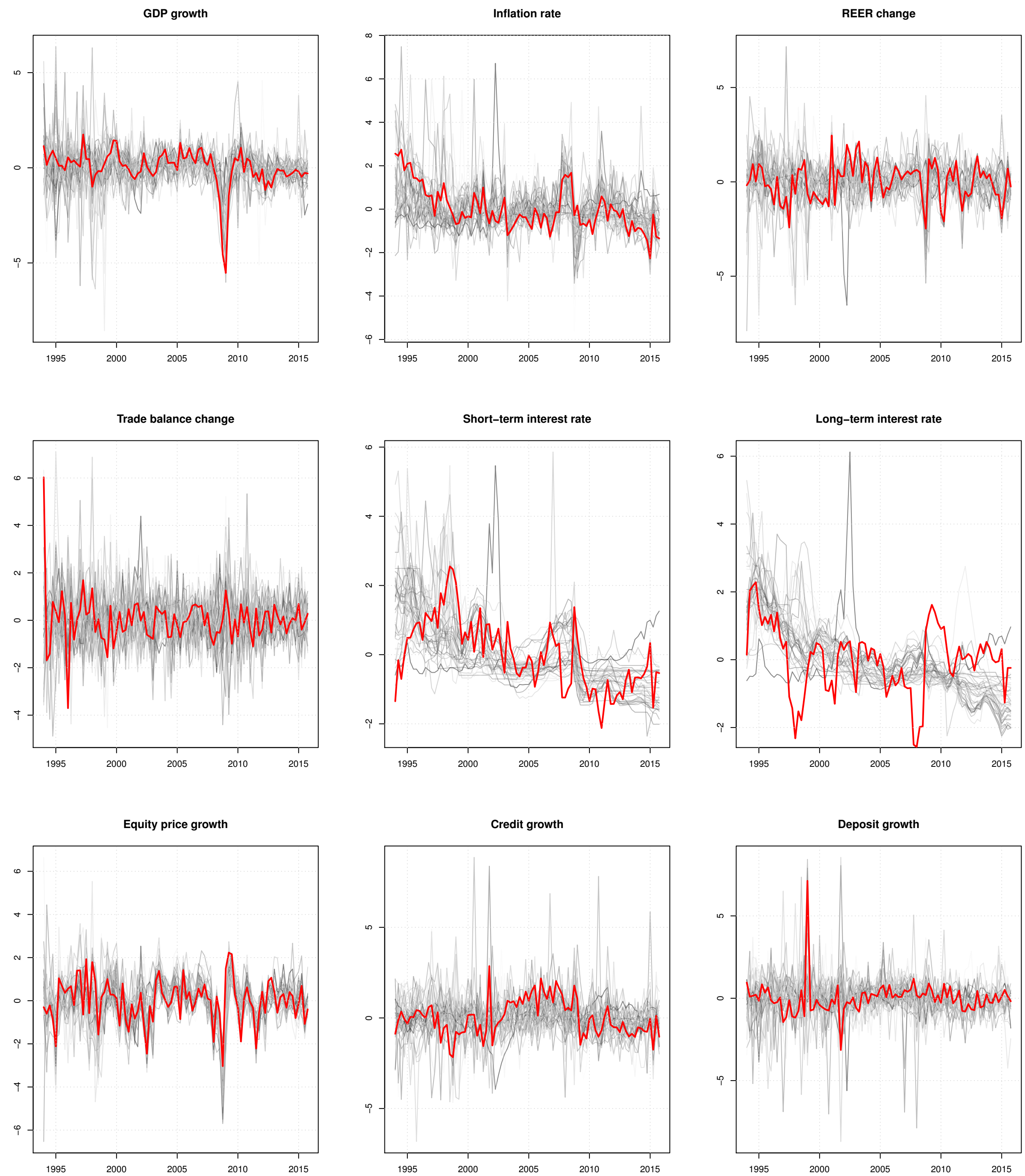
Notes: FDINET: net direct investment, PINET: net portfolio investment, OINET: net other investment; in percent of GDP, cumulative four-quarter moving sums. Unweighted cross-country averages are shown for each region.

Fig. 1: Net capital flows (gross capital outflows less gross capital inflows of totaled direct, portfolio and other investment)



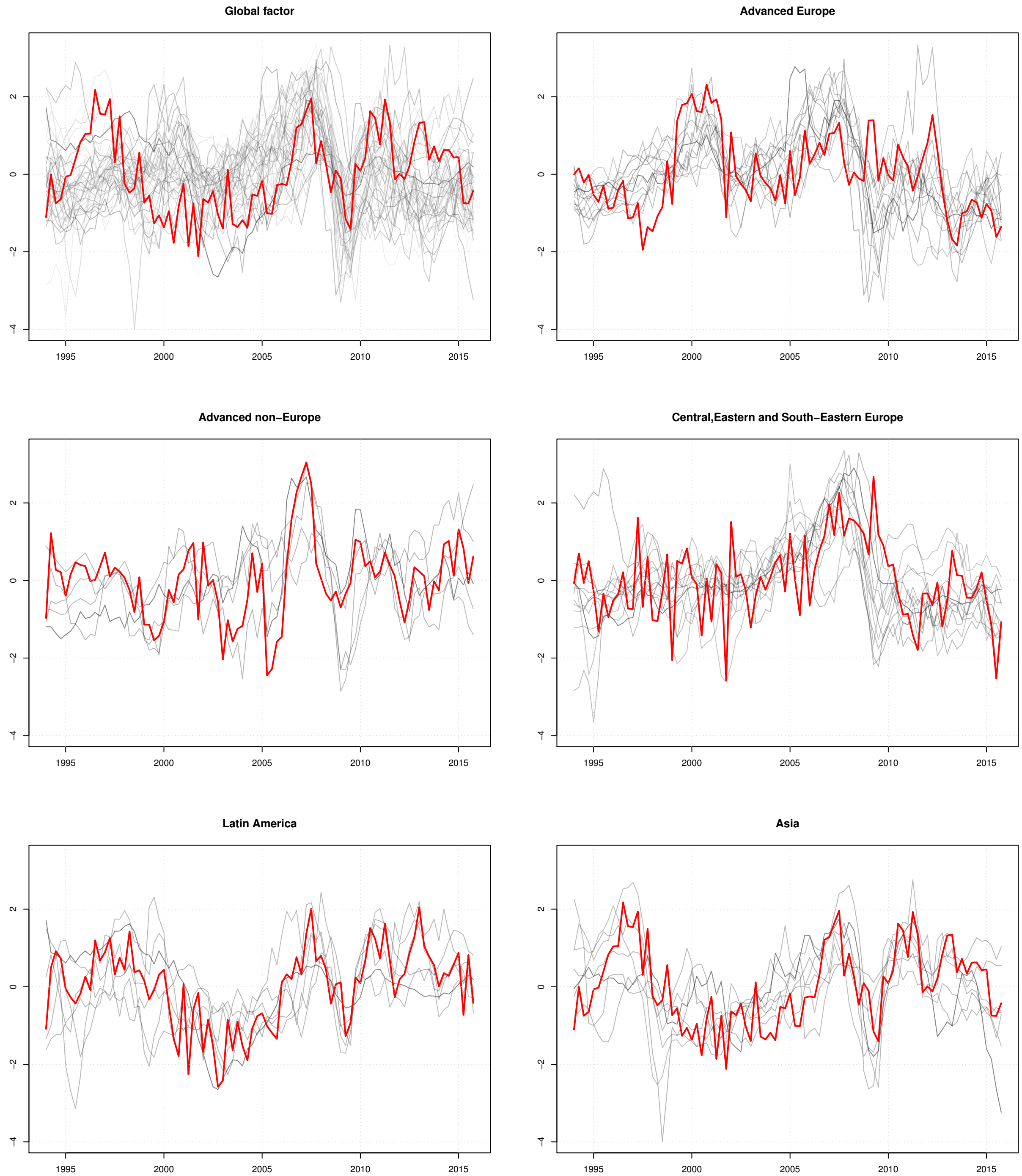
Notes: FDILIAB: gross direct investment inflows, PILIAB: gross portfolio investment inflows, OILIAB: gross other investment inflows; in percent of GDP, cumulative four-quarter moving sums. Unweighted cross-country averages are shown for each region.

Fig. 2: Gross capital inflows (incurrence less repayment of direct, portfolio and other investment liabilities)



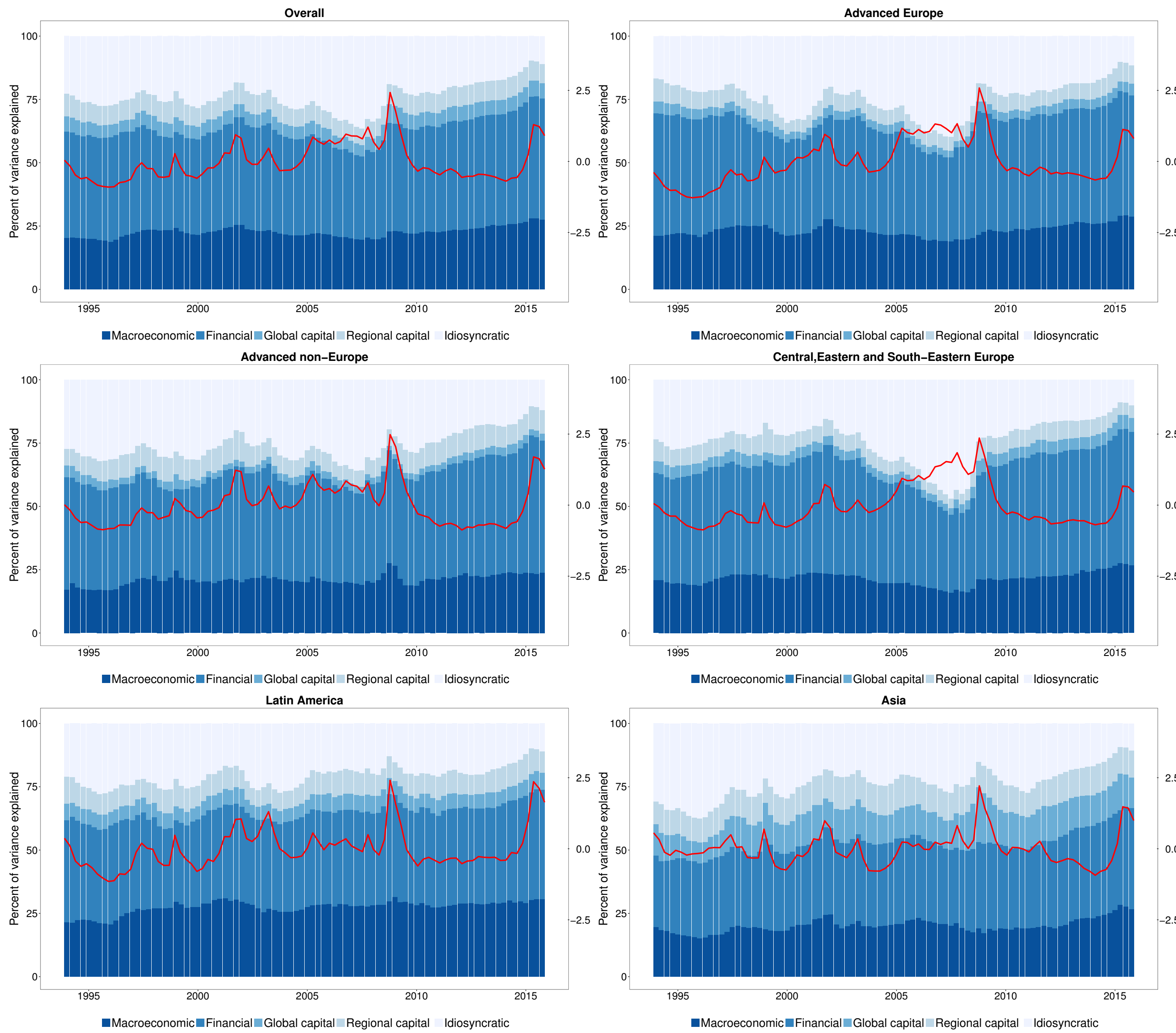
Notes: Estimated latent factors based on principal components in red. Actual data for different countries in gray. All quantities have been standardized by subtracting the mean and dividing through by the standard deviation of the given time series under scrutiny.

Fig. 3: Estimated latent factors and actual data for macroeconomic and financial variables: 1994Q3:2015Q4



Notes: Estimated latent factors based on principal components in red. Actual data for different countries in gray. All quantities have been standardized by subtracting the mean and dividing through by the standard deviation of the given time series under scrutiny.

Fig. 4: Estimated latent global and regional factors and actual data for **gross capital inflows**: 1994Q3:2015Q4



Notes: Variance shares of gross capital inflows (incurrence less repayment of totaled direct, portfolio and other investment liabilities) as a share of GDP, explained by global macroeconomic factors, global financial factors, the global capital factor, the regional capital factor and idiosyncratic factors, respectively. Standardized volatility of gross capital inflows in red on the right-hand scale. The upper-left panel "Overall" shows the results for all the countries included in our sample. Unweighted cross-country averages are shown for each region.

Fig. 5: Variance decomposition of **gross capital inflows** over time

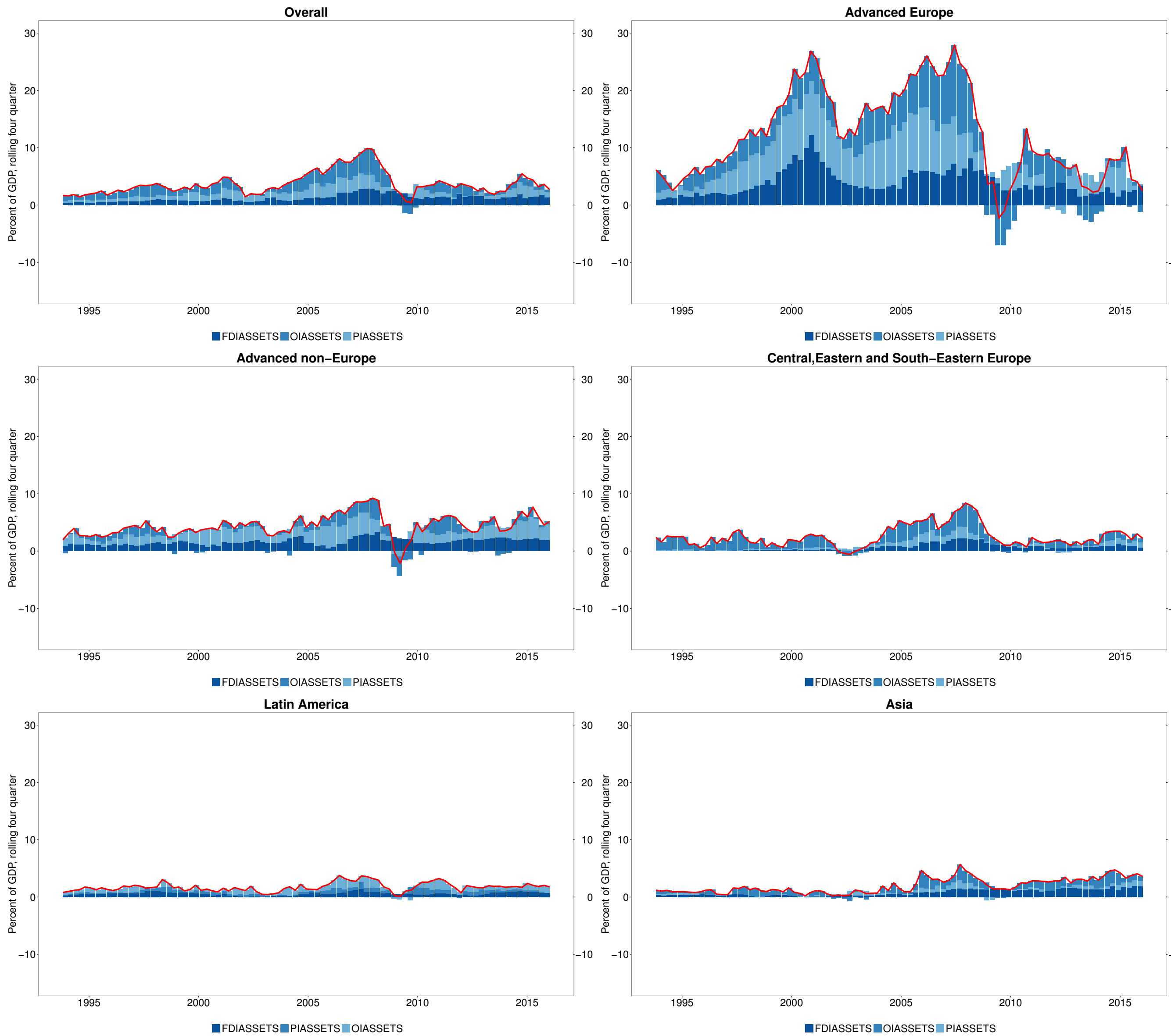
Appendix A Variable description

Table A.1: Variable description

Variable type	Variable	Description
Capital	Capital flows	Cumulative four-quarter moving sums of gross direct investment, portfolio investment and other investment flows (BPM6 definition) as percentage of nominal GDP
Macro	GDP growth	GDP volume, 2010=100, seasonally adjusted, in logarithms, quarter-on-quarter change
Macro	Inflation rate	(Harmonized) consumer price index, 2010=100, seasonally adjusted, quarter-on-quarter change
Macro	REER change	Real effective exchange rate, CPI-based index, seasonally adjusted, in logarithms, quarter-on-quarter change
Macro	Trade balance change	Exports over imports of goods and services, CPI deflated, seasonally adjusted, in logarithms, quarter-on-quarter change
Financial	Short-term interest rate	Typically, three-month money market rate (per annum)
Financial	Long-term interest rate	Typically, yield on ten-year-government bonds (per annum)
Financial	Equity price growth	Equity price index, 2005=100, seasonally adjusted, in logarithms, quarter-on-quarter change
Financial	Credit growth	Claims on domestic private sector, CPI deflated, seasonally adjusted, in logarithms, quarter-on-quarter change
Financial	Deposit growth	Deposits of domestic private sector, CPI deflated, seasonally adjusted, in logarithms, quarter-on-quarter change

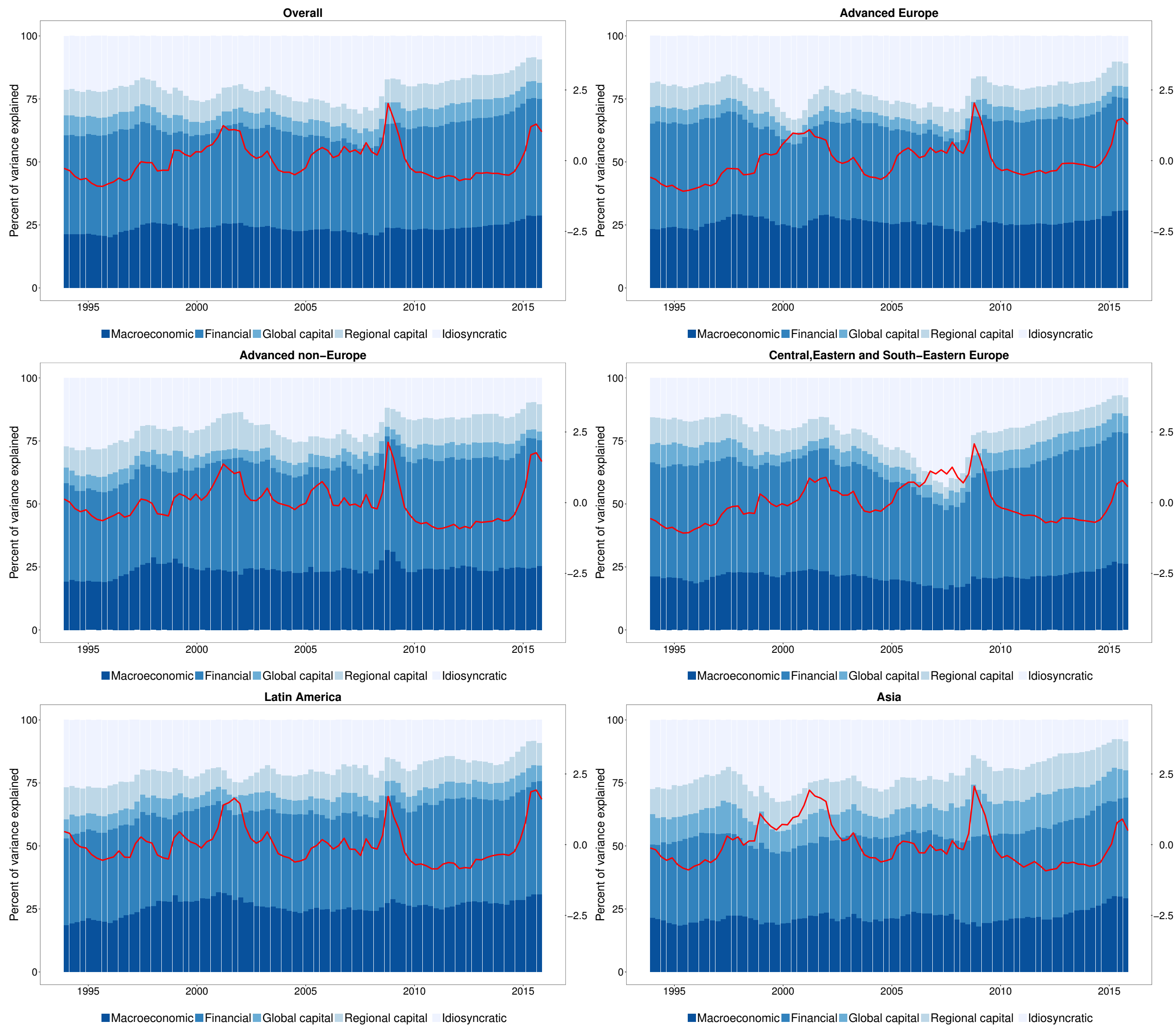
Source: Authors' compilations. Data are taken primarily from the IMF's International Financial Statistics (IFS) database but also from the OECD, ECB, Eurostat, Thomson Reuters and national statistical offices. **Notes:** Seasonal adjustment was conducted using the Census X12 method. A few capital flow, trade flow and GDP series were not satisfactorily available at quarterly frequency at the beginning of the sample; we used the corresponding annual figures and the quarterly dynamics of the rest of the sample for data interpolation. Moreover, if the short-term (long-term) interest rate was not available, we used the dynamics of the deposit (lending) rate for data interpolation. In the case of few remaining missing observations at the beginning or the end of the sample, we used the average of the subsequent or previous four quarters to fill these gaps.

Appendix B Additional results



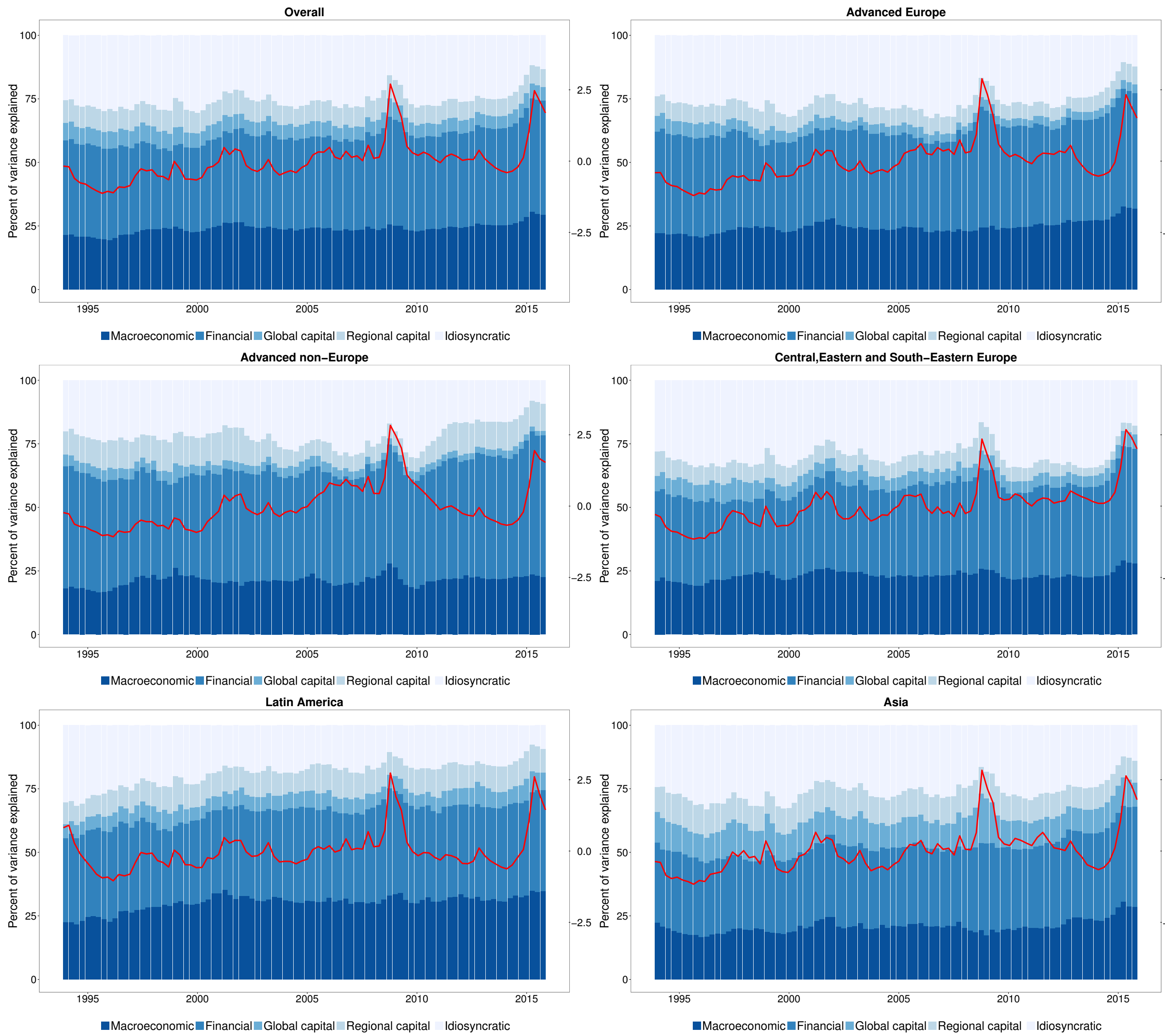
Notes: FDIASSETS: gross direct investment outflows, PIASSETS: gross portfolio investment outflows, OIASSETS: gross other investment outflows; in percent of GDP, cumulative four-quarter moving sums. Unweighted cross-country averages are shown for each region.

Fig. B.1: Gross capital outflows (acquisition less disposal of direct, portfolio and other investment assets)



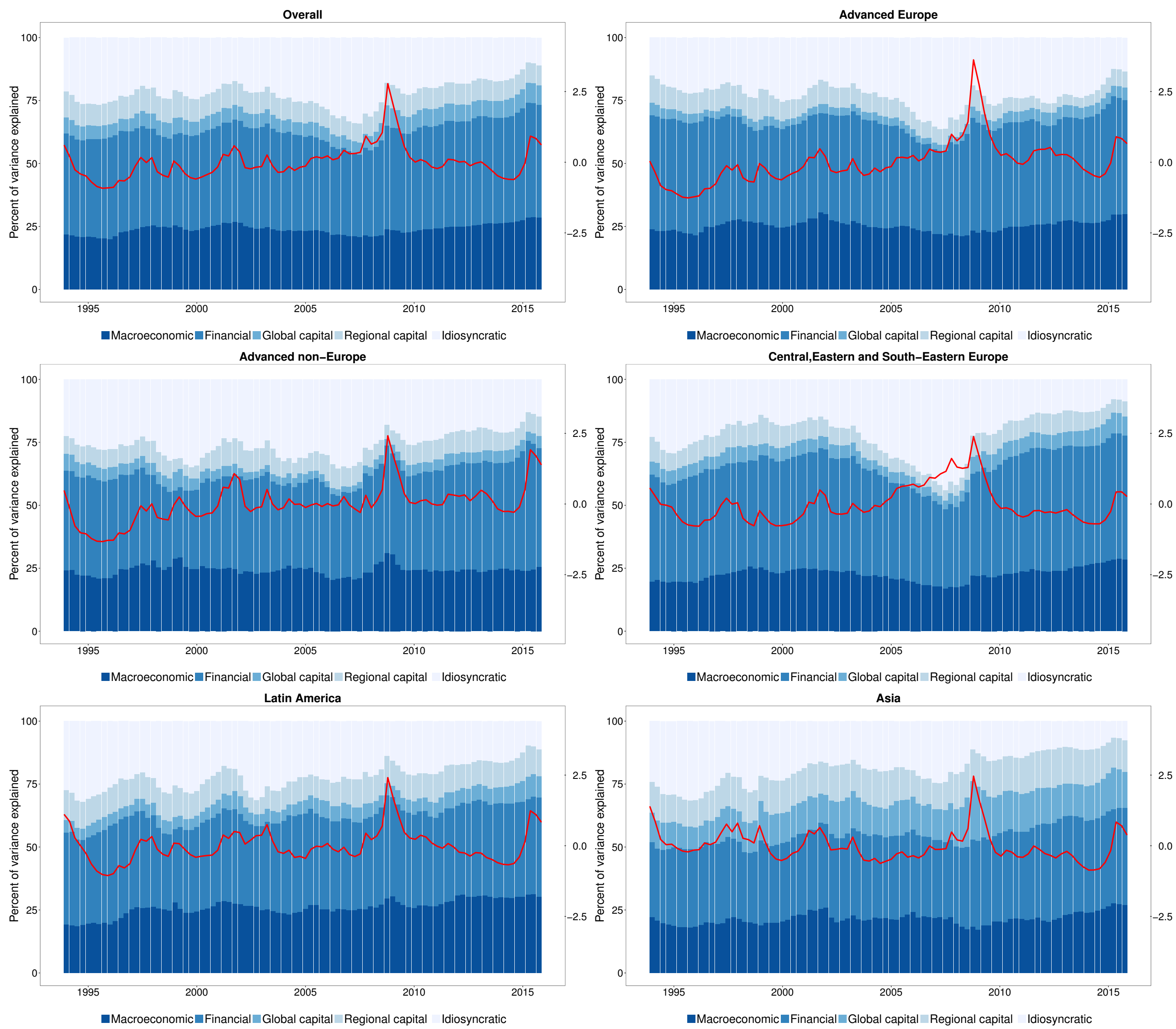
Notes: Variance shares of gross FDI inflows (incurrence less repayment of direct investment liabilities) as a share of GDP, explained by global macroeconomic factors, global financial factors, the global capital factor, the regional capital factor and idiosyncratic factors, respectively. Standardized volatility of gross FDI inflows in red on the right-hand scale. The upper-left panel "Overall" shows the results for all the countries included in our sample. Unweighted cross-country averages are shown for each region.

Fig. B.2: Variance decomposition of **gross direct investment inflows** over time



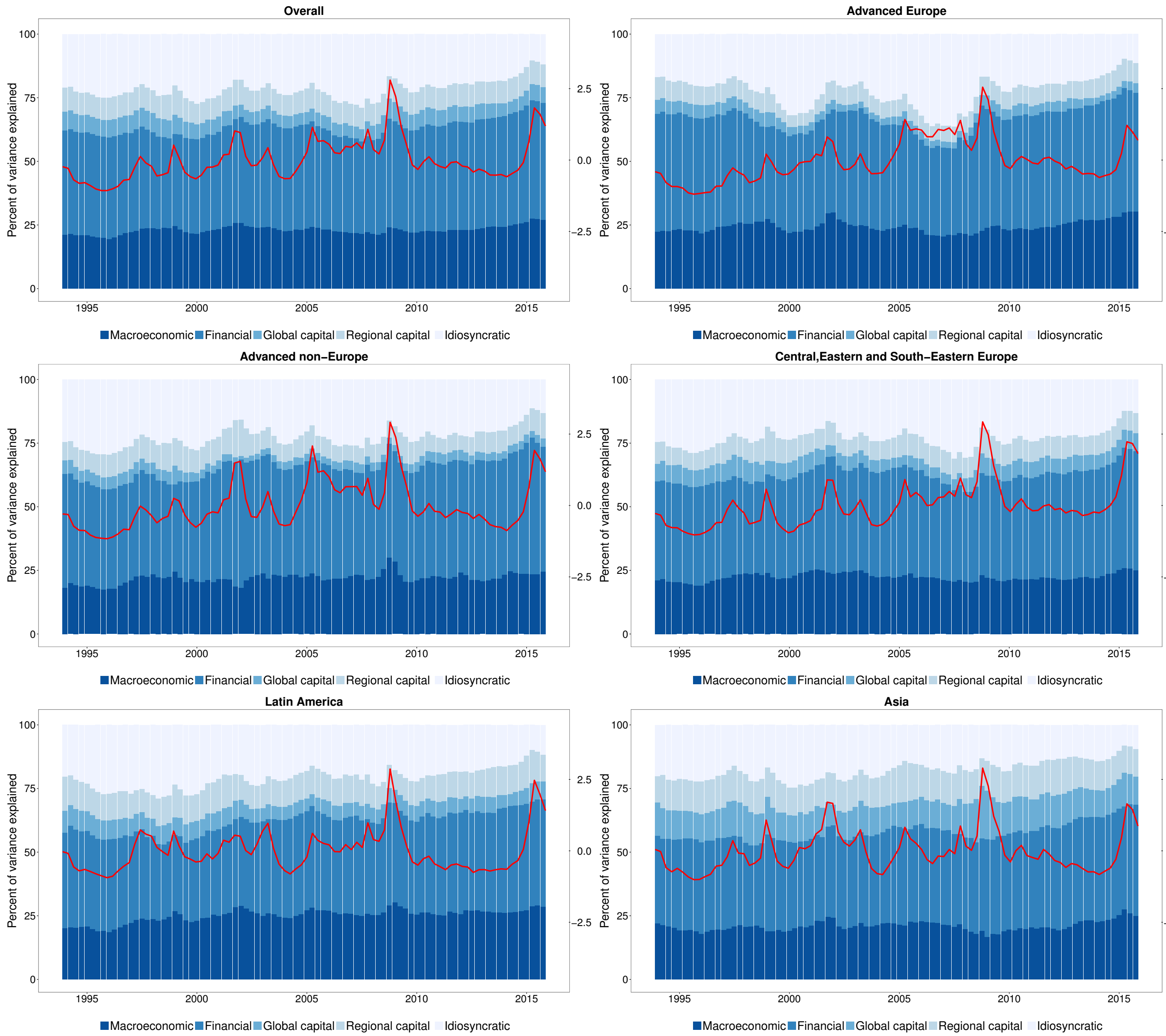
Notes: Variance shares of gross PI inflows (incurrence less repayment of portfolio investment liabilities) as a share of GDP, explained by global macroeconomic factors, global financial factors, the global capital factor, the regional capital factor and idiosyncratic factors, respectively. Standardized volatility of gross PI inflows in red on the right-hand scale. The upper-left panel "Overall" shows the results for all the countries included in our sample. Unweighted cross-country averages are shown for each region.

Fig. B.3: Variance decomposition of **gross portfolio investment inflows** over time



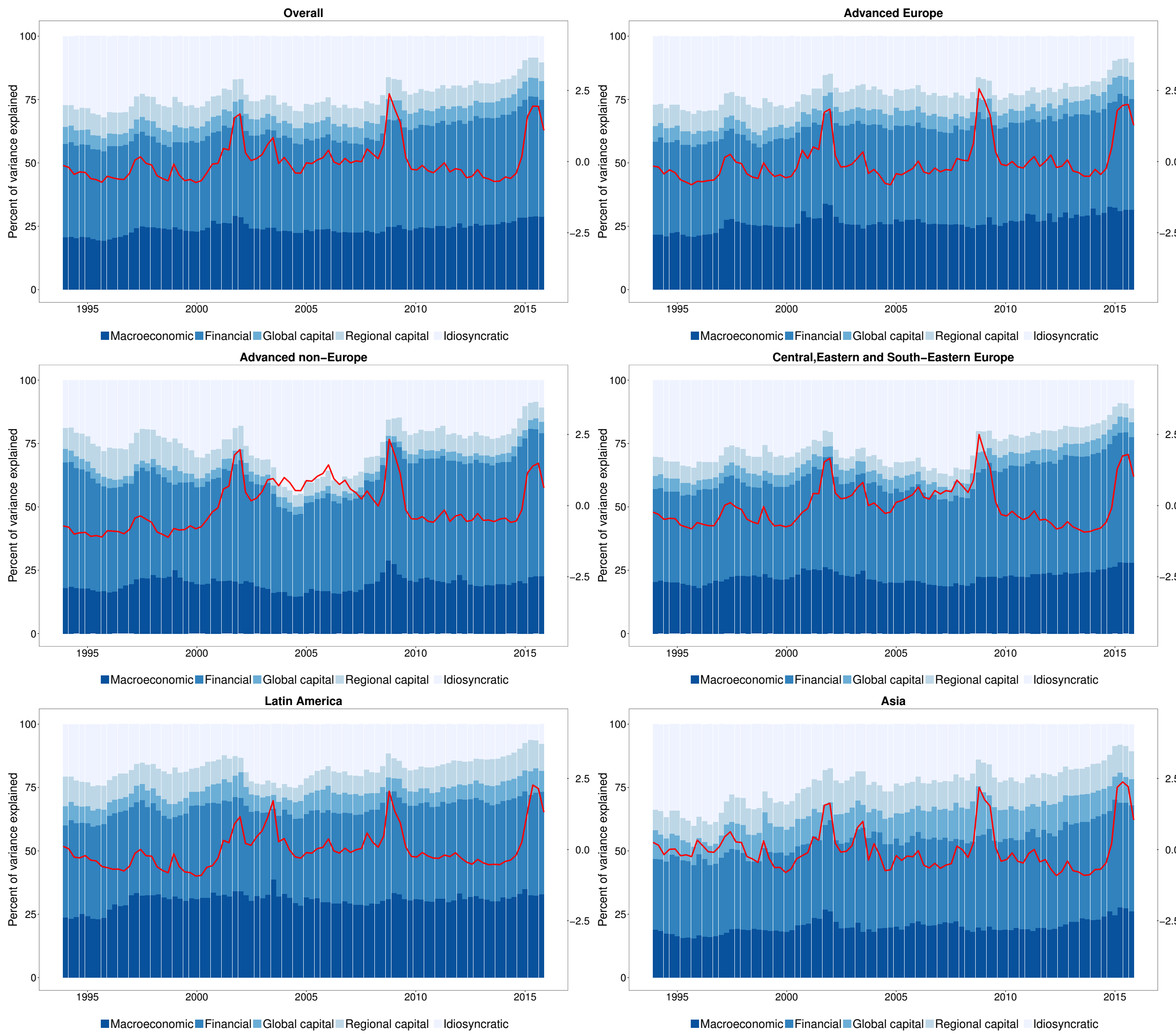
Notes: Variance shares of gross OI inflows (incurrence less repayment of other investment liabilities) as a share of GDP, explained by global macroeconomic factors, global financial factors, the global capital factor, the regional capital factor and idiosyncratic factors, respectively. Standardized volatility of gross OI inflows in red on the right-hand scale. The upper-left panel "Overall" shows the results for all the countries included in our sample. Unweighted cross-country averages are shown for each region.

Fig. B.4: Variance decomposition of **gross other investment inflows** over time



Notes: Variance shares of gross capital outflows (acquisition less disposal of totaled direct, portfolio and other investment assets) as a share of GDP, explained by global macroeconomic factors, global financial factors, the global capital factor, the regional capital factor and idiosyncratic factors, respectively. Standardized volatility of gross capital outflows in red on the right-hand scale. The upper-left panel "Overall" shows the results for all the countries included in our sample. Unweighted cross-country averages are shown for each region.

Fig. B.5: Variance decomposition of **gross capital outflows** over time



Notes: Variance shares of net capital flows (gross capital outflows less gross capital inflows of totaled direct, portfolio and other investment) as a share of GDP, explained by global macroeconomic factors, global financial factors, the global capital factor, the regional capital factor and idiosyncratic factors, respectively. Standardized volatility of net capital flows in red on the right-hand scale. The upper-left panel "Overall" shows the results for all the countries included in our sample. Unweighted cross-country averages are shown for each region.

Fig. B.6: Variance decomposition of **net capital flows** over time

Table B.1: Variance decomposition of **gross capital inflows** by country

	1994 - 2000				2001 - 2008				2009 - 2015			
	M	F	C	R	M	F	C	R	M	F	C	R
AT	25.2	39.5	5.6	4.2	21.1	30.4	4.1	6.1	32.1	49.1	6.7	4.7
CH	32.2	32.4	3.2	12.6	28.9	41.8	0.5	9.2	32.4	36.4	0.6	11.7
DE	24.8	34.5	1.8	4.5	23.3	40.0	2.4	3.5	27.8	45.3	2.1	3.4
DK	12.5	44.4	1.4	10.3	15.6	41.3	0.5	8.7	15.2	52.5	0.6	11.3
ES	24.6	46.3	6.1	3.8	29.8	35.7	6.5	1.6	28.6	41.5	8.0	1.6
FI	19.8	47.9	2.8	10.1	16.3	48.9	5.1	9.1	13.6	45.0	2.5	10.9
FR	26.0	50.1	3.5	8.7	24.9	37.4	2.4	7.4	30.2	48.8	2.8	6.1
GB	25.1	42.8	5.3	3.8	23.6	34.6	4.2	6.1	30.6	47.3	5.8	4.2
IT	18.5	54.3	3.3	3.8	17.1	54.9	3.0	5.1	18.8	58.2	3.3	4.8
NL	24.5	54.3	5.5	3.7	18.5	46.5	3.7	3.8	23.4	53.3	5.1	3.2
NO	24.5	50.0	5.5	3.0	28.2	31.7	4.9	1.1	28.6	42.9	6.0	1.1
PT	19.8	35.9	2.8	7.6	18.6	32.9	3.8	9.0	20.2	41.2	4.0	9.3
SE	20.1	23.4	2.4	12.5	20.3	35.0	0.4	9.7	26.4	28.8	0.5	13.4
Adv Europe	22.9	42.8	3.8	6.8	22.0	39.3	3.2	6.2	25.2	45.4	3.7	6.6
AU	23.6	39.0	5.8	11.7	28.8	34.7	4.6	11.8	27.3	39.0	5.9	13.0
CA	14.8	31.2	2.6	9.0	15.7	36.1	3.0	9.0	17.6	41.3	3.4	10.7
JP	21.4	26.9	3.3	6.3	25.7	44.6	0.7	4.5	31.7	38.5	0.7	6.5
NZ	22.2	48.7	3.0	5.0	17.4	47.5	4.9	5.5	17.3	57.6	3.3	4.8
US	16.6	49.9	1.8	10.0	17.9	39.3	0.6	6.5	17.9	53.0	0.8	8.7
Adv non-Europe	19.7	39.1	3.3	8.4	21.1	40.4	2.8	7.5	22.4	45.9	2.8	8.8
BG	21.2	51.9	2.5	14.2	17.7	44.4	2.8	11.4	20.7	53.9	3.7	14.4
CZ	18.7	35.7	5.7	3.5	21.9	44.8	6.2	4.9	19.6	51.4	8.0	5.3
EE	19.4	42.0	3.9	4.4	17.1	43.7	2.8	0.7	22.1	58.4	4.7	0.9
HU	23.6	44.5	6.2	5.3	26.4	33.9	4.0	1.6	29.6	44.5	6.6	2.4
LT	21.9	55.8	2.3	9.8	18.1	52.3	1.5	6.7	20.6	58.2	1.7	6.1
LV	15.6	44.6	5.5	4.6	11.6	40.3	4.0	4.5	13.3	58.9	6.2	5.4
PL	24.3	38.6	5.6	3.5	31.2	38.6	4.7	1.1	28.7	43.6	6.2	1.1
RO	26.0	37.6	6.1	11.2	21.2	24.1	3.6	7.4	33.0	33.3	6.7	11.4
RU	18.2	54.4	4.3	5.4	13.3	42.4	3.1	6.7	17.7	48.5	4.2	5.2
SI	20.5	39.4	6.0	12.2	17.6	30.2	4.3	9.1	23.6	41.8	6.3	11.6
SK	20.1	39.7	2.0	7.1	20.0	41.6	1.6	5.5	22.3	41.2	1.5	7.9
TR	27.6	40.1	2.9	8.9	25.1	46.6	4.3	5.9	29.3	45.9	3.2	7.7
CESEE	21.4	43.7	4.4	7.5	20.1	40.2	3.6	5.5	23.4	48.3	4.9	6.6
AR	27.0	38.0	3.2	11.3	31.3	33.0	3.4	11.3	34.3	42.6	3.7	11.8
BR	28.8	30.8	7.8	2.5	31.1	28.6	8.7	1.1	37.9	33.1	10.0	1.2
CL	20.3	36.3	10.8	8.4	21.9	34.3	10.9	14.4	22.9	35.2	9.6	9.7
MX	28.3	36.1	2.3	9.0	28.9	43.9	3.7	6.5	27.6	39.7	3.0	8.1
PE	25.3	34.4	5.0	11.0	32.8	34.2	4.9	8.5	28.0	35.5	3.7	11.1
ZA	22.2	41.4	5.0	10.3	22.2	46.7	4.5	8.6	23.7	46.7	5.6	10.1
Latin America	25.3	36.1	5.7	8.7	28.0	36.8	6.0	8.4	29.1	38.8	5.9	8.7
CN	16.8	27.0	3.8	8.6	16.7	32.0	3.8	9.7	19.4	33.1	3.2	9.8
ID	19.0	36.5	7.3	6.6	19.8	35.9	11.8	7.0	25.4	45.3	14.7	7.3
IN	20.8	25.7	17.3	16.6	23.5	26.3	17.5	14.9	25.9	25.8	19.8	17.8
KR	15.9	24.6	13.7	10.9	19.7	25.7	15.0	11.7	20.2	28.1	15.3	12.5
MY	15.7	36.8	5.2	18.2	20.8	36.5	2.2	19.7	15.3	37.5	1.9	18.1
PH	25.1	25.2	12.8	5.0	33.5	33.4	21.7	2.0	32.7	35.0	20.7	1.8
TH	13.1	36.1	16.4	7.2	12.4	37.7	17.8	16.4	11.8	40.3	18.9	9.2
Asia	18.1	30.3	10.9	10.4	20.9	32.5	12.8	11.6	21.5	35.0	13.5	10.9
Overall	21.7	39.6	5.3	8.1	22.0	38.2	5.2	7.3	24.3	43.7	5.9	7.9

Notes: The table presents the posterior mean of the variance decompositions for all countries in our sample averaged across three distinct time periods. Results are based on 15,000 posterior draws. M, F, C, R represent the variance shares of gross capital inflows (incurrence less repayment of totaled direct, portfolio and other investment liabilities) as a share of GDP, explained by global macro factors, global financial factors, the global capital factor and the regional capital factor, respectively. Regional figures refer to unweighted cross-country averages.