Understanding the evolution of global capital flows *

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Abstract

We propose a factor stochastic volatility model to analyze the relationship between global macroeconomic factors and country-specific capital flow dynamics. Studying a global sample of 35 countries from 1994 until 2014, we detect a pronounced time-varying pattern of capital flows, mirroring in several instances well-known crisis episodes. We are able to show that global co-movement of macroeconomic, financial and capital flow variables is able to explain a major share of country-specific capital flow volatility and this impact has become more important after the 2008–2009 global financial crisis. It turns out that global financial factors explain by far the largest share of capital flow volatility, followed by global and regional capital flow factors and global macroeconomic factors. Our results thus suggest that country-specific changes in capital flows are strongly affected by fluctuations in global financial cycles.

Keywords: Volatility of capital flows, factor stochastic volatility model, global co-movement, emerging markets

JEL Codes: C30, F32, F41.

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1 Introduction

The sudden stop and reversals of capital flows have important implications for the macro-financial stability of a country, as they are often accompanied by severe economic downturns, currency depreciation and inflationary episodes. Several countries featured episodes of sharp increases in the volatility of capital flows, leading to increased economic uncertainty, ultimately hampering investment and economic activity. From a policy point of view, the question on what drives the volatility of capital flows and to what extent do country-specific capital movements relate to global business and financial cycles proves to be of prime importance for efficient policy design.

There is already a plethora of literature analyzing the determinants of capital flows in both advanced and emerging economies, stressing among others the retrenchment of capital flows in the course of the global financial crisis (GFC) 2008–2009 (e.g. Milesi-Ferretti and Tille, 2011). In a recent study, Alberola, Erce, and Serena (2016) show that countries equipped with more reserve assets are less subject to a slump in capital inflows during stress periods (but not linearly). Exploiting a global panel data set featuring information on bilateral gross cross-border equity flows, Portes and Rey (2005) use a gravity model to investigate the driving forces of cross-border equity flows. Within a similar framework, Portes, Rey, and Oh (2001) show that international transactions in financial assets are well explained by a simple gravity model. Another common observation in the literature is that capital flows display strong common movements around the world (Passari and Rey, 2015). Förster, Jorra, and Tillmann (2014) exploit this feature of the data and 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, while the global capital factor explains only a small share of the overall variation.

However, several research questions have not been sufficiently addressed so far. For instance, does co-movement in the data indicate the existence of a global or regional capital flow cycle? Which types of capital flows are more volatile over time? To which extent can the volatility of capital flows be explained by supranational factors? How important are different types of supranational factors, like global macroeconomic versus global financial factors? Does the explanatory power of supranational factors differ across regions and over time? To answer at least some of these questions, we offer in this paper an analytic approach that allows for addressing, in a single attempt, both the time-varying nature of capital flow changes and the impact of supranational factors.

Dynamic factor models have gained popularity in recent years. As an important contribution, Kose, Otrok, and Whiteman (2003) were among the first ones to use a a Bayesian dynamic latent factor model to estimate common components in macroeconomic aggregates (output, consumption, and investment) in a global sample. Their results indicate that a common global factor is an important source of volatility for aggregates in most countries, providing evidence for a world business cycle.

Studying a sample of 35 worldwide countries from 1994 until 2014, we detect a pronounced time-varying pattern of capital flows, mirroring in several instances well-known crisis episodes and showing some differences across various country groups. We thus opt to use a framework that is capable of exploiting large data sets and accounting for shifts in the volatility of the time series involved. Our approach, closely related to the factor stochastic volatility framework of Pitt and Shephard (1999) and Aguilar and West (2000), provides new insights on the relative importance of different fundamental factors across time and space. Since the sensitivity of capital flows with respect to global fundamental factors are subject to structural breaks in the parameters, we assume that the factor loadings are time-varying.

From our data set 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 (direct, portfolio and other investment flows). For each capital flow variable we extract also a regional factor, which captures 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 global financial factors explain a large fraction of capital flow volatility, closely followed by global and regional capital flow factors. Compared to the study of Förster, Jorra, and Tillmann (2014), our findings indicate that global financial and macroeconomic factors are very important for explaining variation in capital flows (and these types of factors were not included by Förster, Jorra, and Tillmann (2014)). Moreover, we find significant time variation, indicating that the importance of global factors to explain capital flow movements increases in times of economic crises. Especially in the recent GFC, the importance of all global factors increases markedly. This suggests that in the presence of global financial shocks, global variables prove to be important determinants of capital flow volatility.

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 Stylized facts and recent developments

We distinguish between following groups of countries: on the one hand advanced economies consisting of "advanced Europe" (i.e. Western European EU member states plus Norway) and "advanced non-Europe" (among others including the U.S. and Japan) and on the other hand emerging economy regions consisting of Central, Eastern and Southeastern Europe (CESEE), Latin America and Asia.

Advanced Europe (12):	AT, DE, DK, ES, FI, FR, GB, IT, NL, NO, PT, SE
Advanced non-Europe (6):	AU, CA, JP, NZ, US, ZA
Central, Eastern and Southeastern Europe (CESEE, 8):	BG, CZ, HU, RO, RU, SI, SK, TR
Latin America (5):	AR, BR, CL, MX, PE
Asia (4):	ID, KR, PH, TH

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

Figures 1 to 2 show – in line with IMF (2009) – for the five defined regional groups and for three types of capital flows (direct, portfolio and other investment) the evolution of net flows as well as the underlying (net) changes in financial liabilities (as percentage of GDP, cumulative moving annual values). An aggregate view on the three types of 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[1]. Net borrowing was particularly sizable in CESEE before the 2008–2009 crisis or in Asia before the 1997-1998 Asia crisis (mounting to 8-9 % of GDP) 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 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 donator over time.

[Fig. 1 about here.]

[Fig. 2 about here.]

In our econometric analysis (see section 5) we focus primarily on the net incurrence of financial liabilities, given that it is the best available empirical proxy for capital *in*flows[2]. Recall that our main analytic interest lies in getting a better understanding of the driving forces of volatile capital inflows – in line with the observation that during a situation of elevated global macro-financial risk, foreign investors are likely downsizing their investment in markets which are perceived to be particularly risky (IMF, 2013).

We can see in Fig. 2 that (net) changes in financial liabilities are subject to a marked volatility pattern over time, which is more pronounced than that for the overall balance and correlates again with crisis episodes. The 2008–2009 global financial crisis is clearly visible across all the regions and was associated with significant reversals, especially in the case of portfolio investment and other investment inflows. For instance, in the CESEE region new direct, portfolio and other investment by foreign residents in domestic assets (less repayments) had risen on average to more than 16 % of GDP before 2008, consisting to a major part of other investment, which had steadily grown

[1]Negative net capital flows indicate a net borrowing situation vis-à-vis the rest of the world, i.e. net incurrence of financial liabilities outweighs net acquisition of financial assets.

[2]Note that we cannot 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 redemption of bonds issued.

since the early 2000s. However, the GFC brought an immediate and strong slump in other investment inflows, while FDI inflows have remained relatively stable. During the 2010 to 2012 period, capital flows into emerging markets resumed again somewhat and consisted to a large degree of new portfolio investment inflows, associated with a shift of capital from low yields in advanced economies to higher returns in emerging markets.

3 A formal 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). 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

Let us assume that a $N = ML$ dimensional vector X_t of country-wise (M) macroeconomic and financial time-series (L) can be described by a set of K lower dimensional latent factors F_t (with $N \gg K$) that represent the driving forces of the global economy. The corresponding factor model is then given by

$$X_t = \Lambda_t F_t + e_t, \tag{3.1}$$

with Λ_t being a $N \times K$ dimensional matrix of time-varying factor loadings and e_t denotes an N-dimensional vector of idiosyncratic shocks, distributed as $e_t \sim \mathcal{N}(0, \Omega_t)$. The law of motion of Λ_t is

$$\text{vec}(\Lambda_t) = \text{vec}(\Lambda_{t-1}) + u_t, \tag{3.2}$$

with $u_t \sim \mathcal{N}(0, Q)$ being a normally distributed error with variance-covariance Q. Furthermore, we assume that $\Omega_t = \text{diag}(e^{\omega_{1t}}, \ldots, e^{\omega_{Nt}})$ is 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 Ω_t is diagonal implies that the co-movement between the elements of X_t stems exclusively from movements in F_t. This is a typical identification assumption employed in dynamic factor analysis.

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 errors are smoothly 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 to the factors in F_t.

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

$$F_t = \Phi F_{t-1} + v_t. \tag{3.4}$$

Here, $\Phi = \text{diag}(\phi_1, \ldots, \phi_K)$ with $\phi_j \in (-1, 1)$ for $j = 1, \ldots, K$ being a matrix of autoregressive coefficients and $v_t \sim \mathcal{N}(0, \Sigma_t)$ is a vector white noise error term with $H_t = \text{diag}(e^{h_{1t}}, \ldots, e^{h_{Kt}})$. 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.

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. More specifically we can compute the variance of the ith element of Y_t as

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

Equation (3.6) allows us to compute the relative contributions of the jth factor F_{jt} to the variance of Y_{it} for a given point in time.

3.2 Prior elicitation

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).

For the initial state of the factor loadings Λ_0 we use a multivariate Gaussian prior with the prior mean centered on zero and a rather high value for the prior variance,

$$\text{vec}(\Lambda_0) \sim \mathcal{N}(0, \underline{V}_\Lambda), \tag{3.7}$$

with $\underline{V}_\Lambda$ being a prior variance matrix and the prior mean is set equal to zero. We assume that $\underline{V}_\Lambda = \underline{a} \times I_{NK}$. In our empirical application we set $\underline{a} \in \mathbb{R}$ to a rather high value, effectively rendering the prior uninformative and thus minimizing the impact on our final estimates.

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

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

with prior scale matrix $\underline{Q}$ 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 Q lead to similar results.[3]

For the K autoregressive coefficients in Φ we impose a normally distributed prior,

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

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.

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

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

Here, $\underline{V}_i = 10^2$ denotes the prior variance set such that the prior is non-influential.

We follow Kastner and Frühwirth-Schnatter (2014) and impose a Beta prior on the persistence parameter of the log-volatility process,

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

Here, a_0 and a_1 are hyperparamaters 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.

3.3 Estimation

We apply a rather standard Markov chain Monte Carlo (MCMC) algorithm. We simulate the full history of factor loadings with the well-known forward-filtering backward-sampling (FFBS) algorithm proposed in Carter and Kohn (1994) and Frühwirth-Schnatter

[3] The specific results are available on request.

(1994). Conditional on the loadings, the corresponding state equation is a simple linear regression model, implying that we can simulate Q from a well-known conditional posterior of inverted Wishart form. The diagonal elements of 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 fact that X_t contains over 350 time series, rendering an additional FFBS step infeasible.

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.

3.4 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 Λ_t to identify the shocks as being global and variable-specific. To this end, we specify Λ_t to be block-diagonal, implying that only real output variables load on the output factor, prices on the price factor and so on.[4] Finally, we solve the rotational indeterminacy problem (Bernanke, Boivin, and Eliasz, 2005) by imposing $C'C/T$, with C being the space spanned by the factors and the corresponding blocks of X_t.

In addition to global macroeconomic and financial factors we also include a regional capital flow factor. This 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 belongs to region j, then we include a factor extracted from all capital flow series associated with countries located within region j.

4 Data preparation for estimation

We use quarterly data from 1994q1 until 2014q4 for $M = 35$ worldwide economies and include for each country $L = 10$ macroeconomic and financial time series, consisting of three groups. First, we include one series for a particular capital flow category, calculated in moving annual cumulative terms and as 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. Third, the group of financial sector variables consists of a short-term interest rate (typically 3-months-market rates, per annum), a long-term interest rate (typically government bond yields, rates per annum), changes in equity prices, and credit to as well as deposits of

[4] We thus simply extract the principal components from the corresponding subsets of X_t.

the domestic private sector. Data are taken from the IMF (IFS database), OECD, ECB, Eurostat, and Thomson Reuters.[5]

Nominal stock variables have been deflated by using the CPI index. All variables (except for the interest rates) have been seasonally adjusted by using the difference from moving average. All index variables enter as logarithms. Capital flow data were only available in USD and were transformed into national currency by using the average quarterly rate of the local currency per USD. In case 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 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

As already stressed in section 2, 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 inflows[6]. More specifically, we show in the subsequent figures the variance decomposition results based on Eq. (3.6), whereby the net incurrence of various types of financial liabilities (incurrence less repayment) is labeled for convenience as "inflow" of the respective capital flow series[7] (Fig. 3 to Fig. 6). Results for net lending/net borrowing of totaled direct, portfolio and other investment (assets less liabilities) – labeled for convenience as "financial account balance" – are shown in the appendix (Fig. A.1). Moreover, the appendix also contains detailed tables with a breakdown of the variance decompositions per capital flow category for each country in our sample (Table A.1 to Table A.5).

The volatility of the respective capital flow series, according to Eq. (3.6), is depicted as a red line (right-hand side scale) in each figure. We can see that global or regional economic and financial crises have become manifest in an increasing volatility of capital flows, e.g. very clearly the 2008–2009 global financial crisis (GFC) in all the country groups but also the dot-com collapse in 2000 (advanced non-Europe panel); the Argentine economic crisis 1998–2002 (Latin America panel) or the 1997–1998 Asia crisis. More recently, the start of tapering by the U.S. Fed in early 2013 has been associated with a rather strong hike in capital flow volatility across all the country groups, reaching for instance in the case of other investment inflows levels comparable to those during the run-up to the GFC.

[5]The discussion thus suggests that we follow the literature and transform our data to be approximately stationary.

[6]Across all the various types of capital flows, the variance decomposition results for the net acquisition of financial assets as well as for the corresponding net lending/net borrowing positions(assets minus liabilities) are qualitatively in line with those for the net incurrence of financial liabilities and are available from the authors upon request.

[7]Recall that these are not pure gross inflows given that the incurrence of new financial liabilities is netted out against redemption.

Turning to the relative variance contribution of the extracted factors, we can see very consistently across different types of capital flows and across different regions that the global factors (these are, in line with the number of included variables, four global macroeconomic factors, five global financial factors and one global capital factor) together with one regional capital factor explain the lion's share and their importance has steadily widened over time[8]. For instance, in the case of totaled direct, portfolio and other investment inflows (Fig. 3), labeled as "capital inflows", the four supranational factors explain on average across the regions 75 % of the variance in the period 1994–2008; after the GFC this share has increased to more than 80 %. The related numbers for the three components are not that different; e.g., the variance share explained by the four supranational factors is somewhat less pronounced in the case of portfolio investment inflows (a bit more than 70 % until 2008 and nearly 80 % more recently) and somewhat more pronounced in the case of FDI inflows (reaching nearly 80 % already before 2009 and increasing recently to about 86 %).

[Fig. 3 about here.]

[Fig. 4 about here.]

[Fig. 5 about here.]

[Fig. 6 about here.]

Consistent with the observation that capital flow volatility peaks are often associated with global economic crises (take the GFC), it is no surprise that in such a situation the variance share explained by the supranational factors shoots up remarkably. 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. On the other hand, the 1997–1998 Asia crisis was also associated with a volatility peak, but due to its primarily regional impact on Asian economies the variance share explained by idiosyncratic factors, rather than that of the other factors, ticked up. This regionally concentrated shock provides some evidence for the presence of regional macro and financial factors, in addition to global factors.

Having a closer look on the relative importance of different supranational factors, it becomes evident that global financial factors have the strongest explanatory power. For instance, in the case of totaled direct, portfolio and other investment inflows (Fig. 3), global financial factors explain on average about 45 % of the variance in the period 2009–2014, compared to about 38 % before 2009. The figures indicate that this share did markedly rise during the GFC and after the tapering announcement by the U.S. Fed in May 2013. Across the various types of capital flows there are no considerable differences.

[8] 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.

Global macroeconomic factors, on the other hand, explain on average about 20 % of the variance of capital inflows, whereby this share has remained rather stable over time and across regions. The strongest explanatory power of global macroeconomic factors in the post-2008 period can be found for CESEE economies in the case of portfolio and other investment inflows (nearly 25 %).

Finally, the two extracted capital flow factors (global and regional) explain together on average about 20 % of the variance of capital inflows in the period 2009–2014, a share which has slightly risen compared to the period before 2009 (with an average of 16 %). It should be noted that Asian economies differ considerably from other regions in the sample. In Asia the explanatory power of the two capital flow factors is a way stronger than in other regions (with an explained variance share of on average 33 % for total capital inflows or even 40 % in the case of direct investment or other investment inflows in the post-2008 period). In turn, the variance share explained by global financial factors is in Asia a bit lower than in other regions. Another noteworthy observation across most of the cases 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.

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 macro 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 capital inflows. No matter which types of capital inflows or which economic regions are considered, the extracted supranational factors – capturing common global (or regional) macro-financial dynamics – are able to explain a major share of capital flow volatility.

It is striking that after the 2008–2009 global financial crisis (GFC) supranational 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 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 financial and macro factors.

Given that supranational factors are decisive in explaining a major proportion of capital flow volatility and given that this explanatory power has increased over time, more intensified international policy coordination should be helpful in smoothing capital flow fluctuations. Depending on the relevance of different types of supranational factors, different policy areas are in demand. For instance, given that global financial factors turn out to explain a lion's share of capital flow volatility, international coordination of financial market policies seems to be very important.

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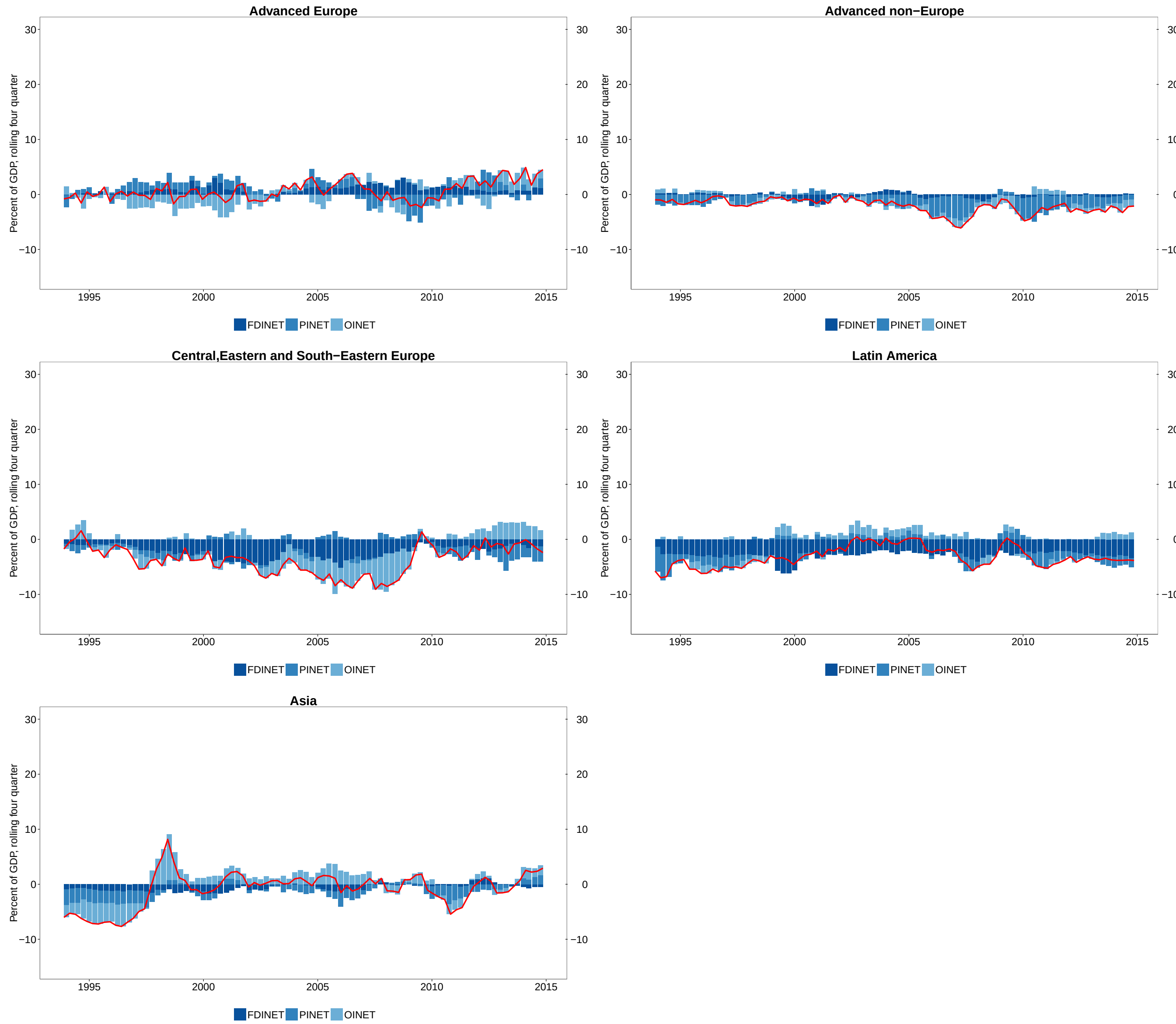
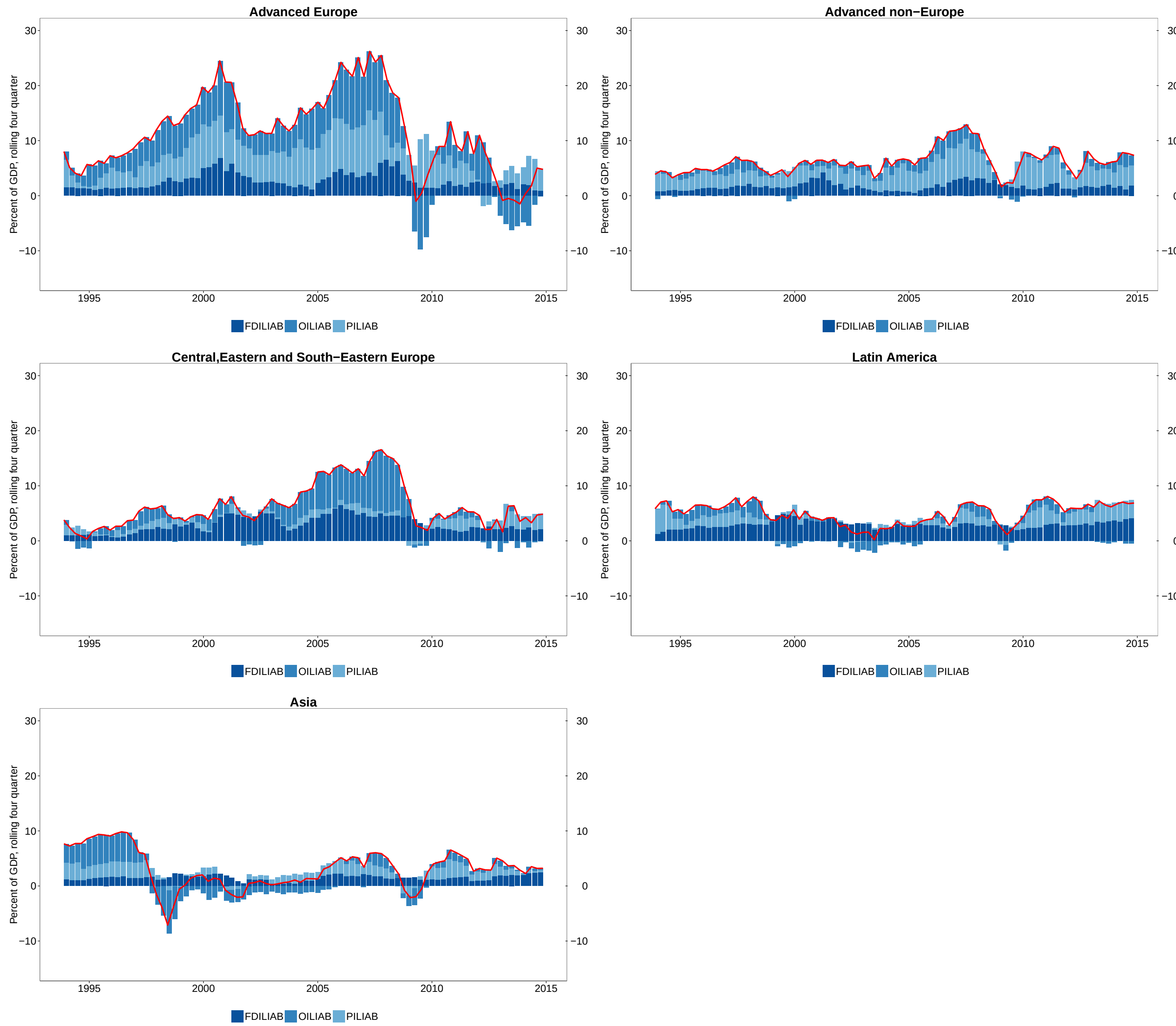


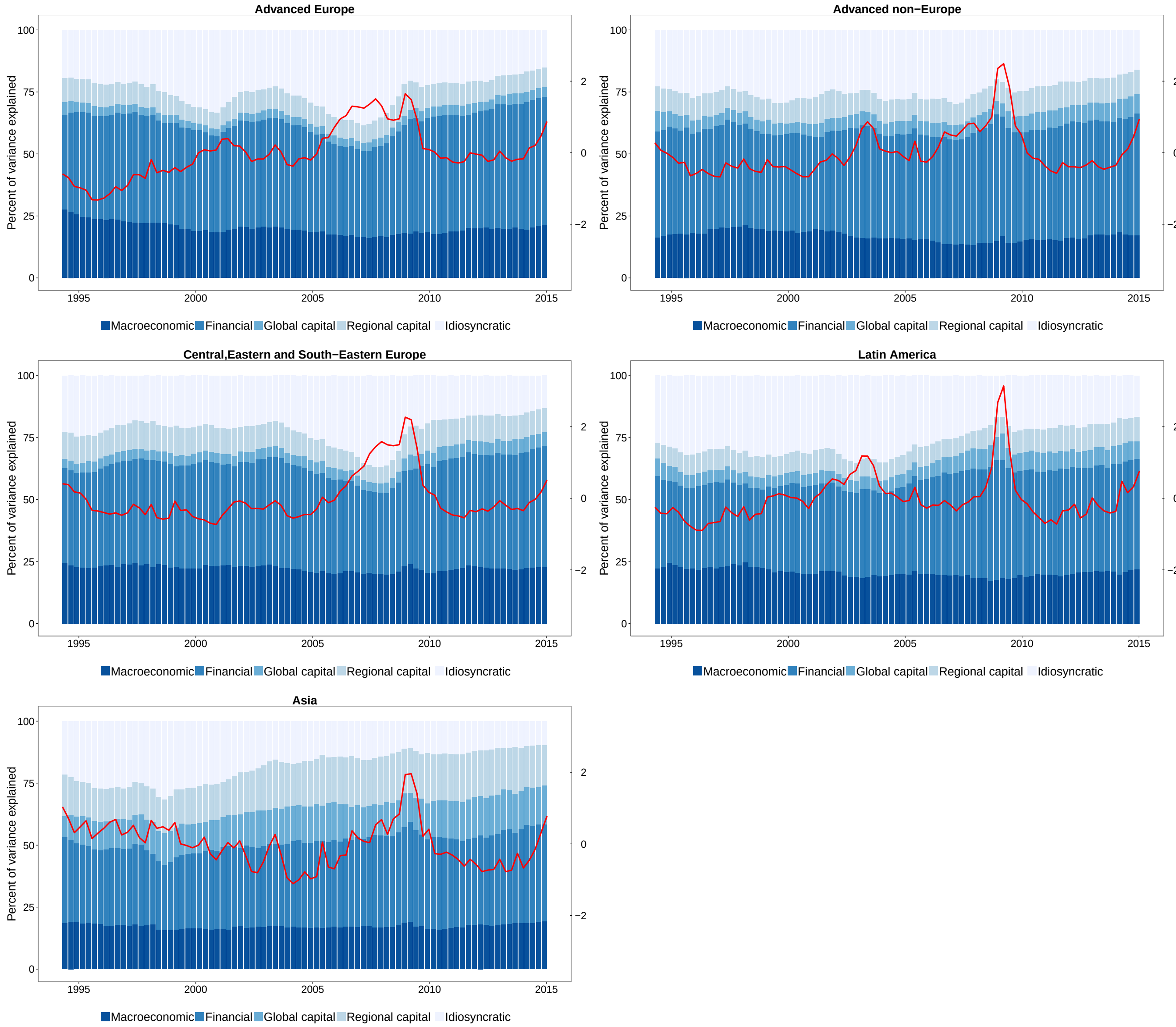
Notes: FDINET: net direct investment, PINET: net portfolio investment, OINET: net other investment.

Fig. 1: Net lending (+) or net borrowing (–) of direct, portfolio and other investment (net acquisition of financial assets less net incurrence of financial liabilities)



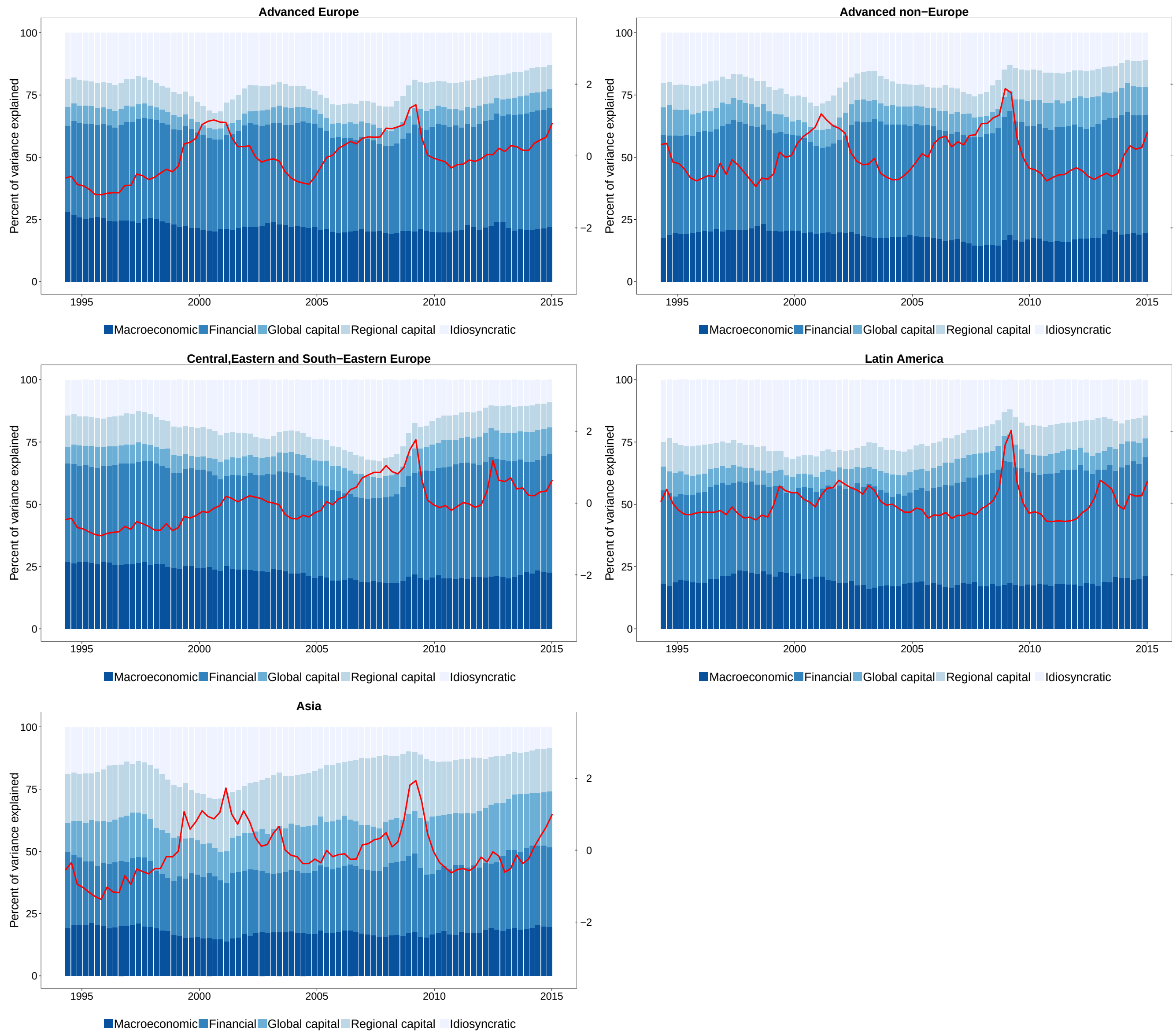
Notes: FDILIAB: direct investment liabilities, PILIAB: portfolio investment liabilities, OILIAB: other investment liabilities.

Fig. 2: Net incurrence of direct, portfolio and other investment liabilities
(incurrence less repayment, investment by foreign residents in domestic assets)



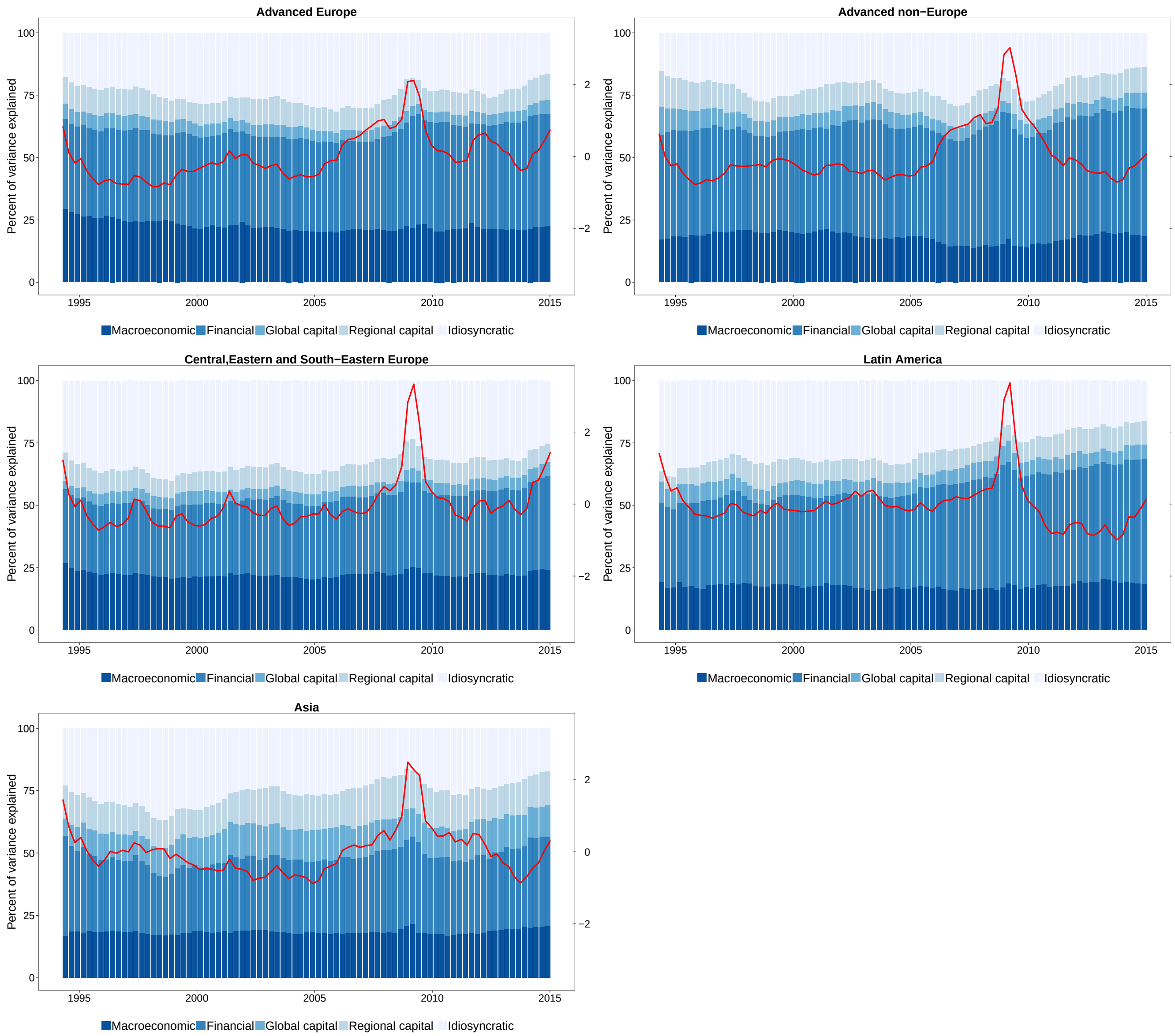
Notes: Capital inflows refer to the totaled net incurrence of direct, portfolio and other investment liabilities (incurrence less repayment).

Fig. 3: Variance decomposition of **total capital inflows (FDI+PI+OI)** over time. Standardized volatility in red on the right-hand scale.



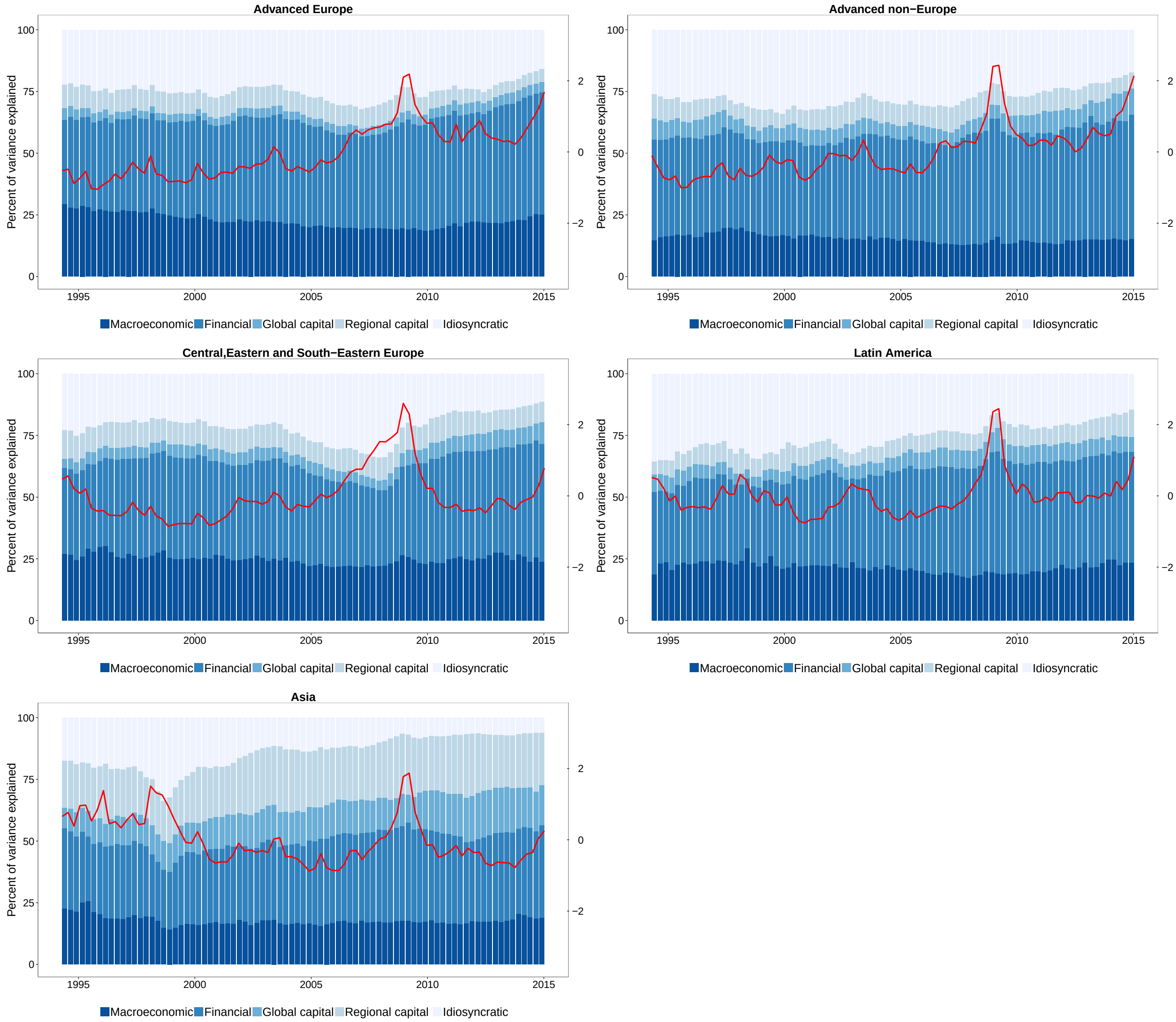
Notes: FDI inflows refer to the net incurrence of direct investment liabilities (incurrence less repayment).

Fig. 4: Variance decomposition of **FDI inflows** over time. Standardized volatility in red on the right-hand scale.



Notes: Portfolio investment inflows refer to the net incurrence of portfolio investment liabilities (incurrence less repayment).

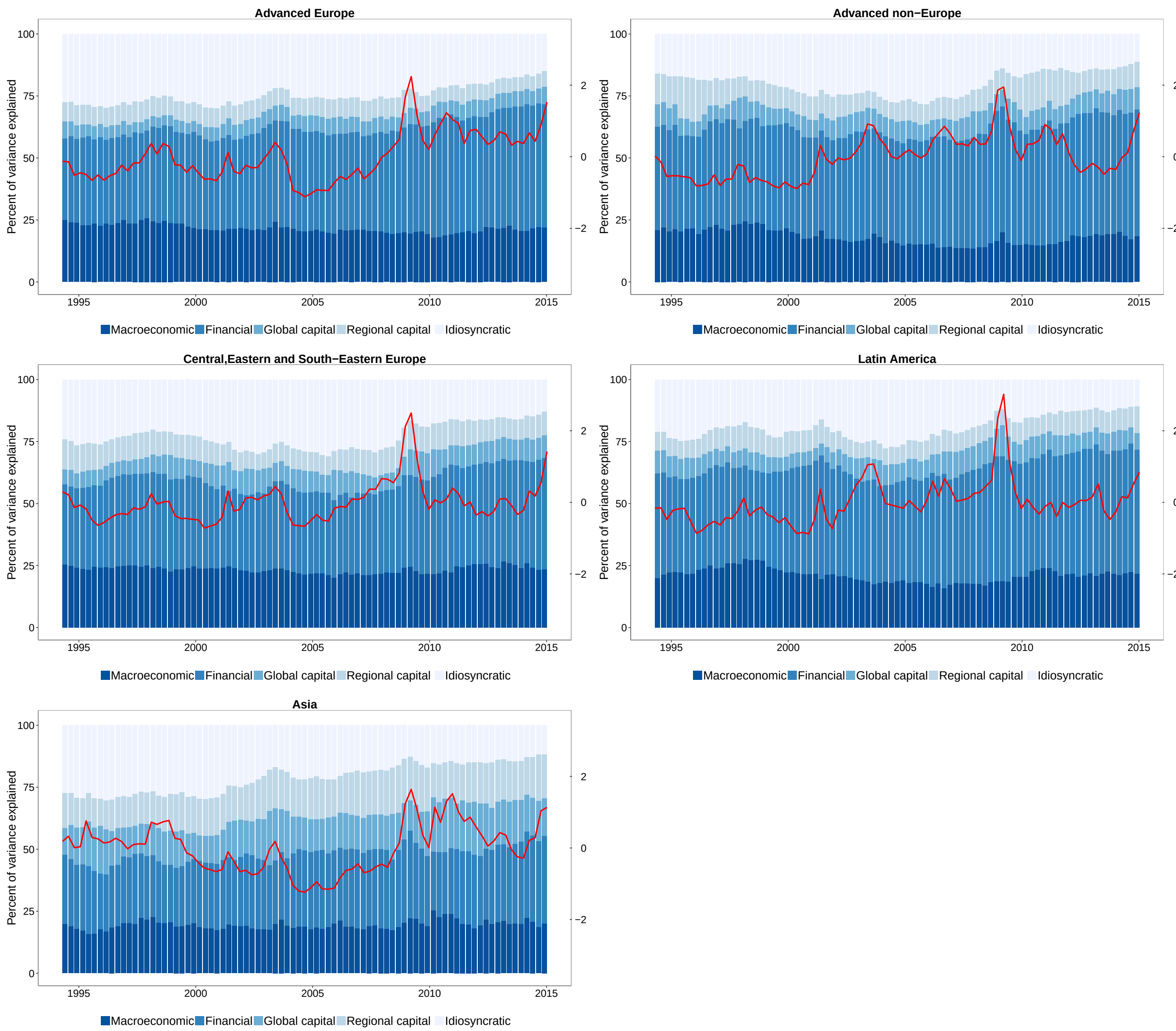
Fig. 5: Variance decomposition of **portfolio investment inflows** over time. Standardized volatility in red on the right-hand scale.



Notes: Other investment inflows refer to the net incurrence of other investment liabilities (incurrence less repayment).

Fig. 6: Variance decomposition of **other investment inflows** over time. Standardized volatility in red on the right-hand scale.

Appendix A Additional results



Notes: Financial account balance refers to the totaled net flows of direct, portfolio and other investment (assets less liabilities).

Fig. A.1: Variance decomposition of **financial account balance** over time. Standardized volatility in red on the right-hand scale.

Table A.1: Variance decomposition of **financial account balance** by country

	1994 - 2000				2001 - 2008				2009 - 2014			
	M	F	C	R	M	F	C	R	M	F	C	R
AT	0.26	0.35	0.07	0.03	0.29	0.39	0.12	0.03	0.24	0.43	0.18	0.02
DE	0.17	0.26	0.03	0.05	0.24	0.37	0.06	0.07	0.21	0.55	0.05	0.04
DK	0.15	0.23	0.09	0.16	0.10	0.33	0.13	0.12	0.12	0.35	0.11	0.15
ES	0.21	0.50	0.02	0.08	0.16	0.46	0.02	0.06	0.11	0.68	0.01	0.04
FI	0.20	0.52	0.02	0.07	0.15	0.58	0.03	0.06	0.13	0.67	0.02	0.04
FR	0.27	0.35	0.03	0.17	0.19	0.45	0.02	0.17	0.26	0.41	0.01	0.14
GB	0.31	0.25	0.06	0.04	0.24	0.33	0.08	0.03	0.31	0.32	0.08	0.01
IT	0.32	0.30	0.06	0.10	0.28	0.24	0.08	0.09	0.26	0.30	0.06	0.08
NL	0.15	0.39	0.03	0.04	0.13	0.40	0.03	0.06	0.13	0.52	0.02	0.07
NO	0.23	0.46	0.02	0.07	0.23	0.49	0.03	0.08	0.20	0.59	0.03	0.05
PT	0.20	0.39	0.09	0.04	0.19	0.40	0.06	0.04	0.16	0.47	0.10	0.04
SE	0.34	0.31	0.08	0.09	0.33	0.30	0.10	0.10	0.33	0.37	0.08	0.07
Adv Europe	0.23	0.36	0.05	0.08	0.21	0.39	0.06	0.07	0.21	0.47	0.06	0.06
AU	0.30	0.28	0.08	0.19	0.22	0.30	0.10	0.15	0.24	0.34	0.11	0.16
CA	0.15	0.42	0.14	0.04	0.16	0.38	0.09	0.03	0.21	0.48	0.15	0.04
JP	0.23	0.45	0.06	0.04	0.16	0.51	0.07	0.04	0.23	0.48	0.06	0.04
NZ	0.23	0.54	0.02	0.07	0.16	0.58	0.03	0.05	0.12	0.69	0.02	0.05
US	0.19	0.35	0.11	0.18	0.10	0.37	0.16	0.05	0.10	0.39	0.13	0.24
ZA	0.19	0.43	0.03	0.16	0.16	0.41	0.03	0.17	0.14	0.54	0.02	0.15
Adv non-Europe	0.21	0.41	0.07	0.11	0.16	0.43	0.08	0.08	0.17	0.49	0.08	0.11
BG	0.38	0.41	0.08	0.03	0.29	0.31	0.19	0.04	0.31	0.43	0.13	0.07
CZ	0.29	0.31	0.03	0.05	0.32	0.31	0.05	0.03	0.32	0.46	0.05	0.03
HU	0.16	0.33	0.09	0.05	0.17	0.35	0.06	0.05	0.21	0.41	0.09	0.04
RO	0.29	0.45	0.09	0.10	0.21	0.34	0.07	0.05	0.23	0.53	0.11	0.08
RU	0.27	0.29	0.11	0.14	0.24	0.33	0.12	0.06	0.26	0.33	0.11	0.12
SI	0.12	0.30	0.08	0.07	0.15	0.30	0.07	0.06	0.20	0.29	0.12	0.07
SK	0.16	0.33	0.02	0.32	0.13	0.28	0.04	0.35	0.14	0.35	0.06	0.33
TR	0.27	0.41	0.06	0.04	0.28	0.38	0.08	0.03	0.26	0.48	0.07	0.04
CESEE	0.24	0.35	0.07	0.10	0.22	0.33	0.09	0.08	0.24	0.41	0.09	0.10
AR	0.21	0.46	0.11	0.08	0.22	0.44	0.07	0.10	0.21	0.53	0.12	0.10
BR	0.22	0.39	0.05	0.13	0.15	0.40	0.06	0.13	0.22	0.46	0.05	0.12
CL	0.20	0.42	0.03	0.12	0.20	0.46	0.06	0.07	0.18	0.47	0.07	0.11
MX	0.19	0.35	0.12	0.07	0.11	0.41	0.20	0.04	0.13	0.56	0.14	0.05
PE	0.36	0.35	0.04	0.04	0.25	0.44	0.02	0.04	0.34	0.42	0.01	0.05
LatAm	0.24	0.39	0.07	0.09	0.19	0.43	0.08	0.08	0.22	0.49	0.08	0.09
ID	0.20	0.26	0.23	0.04	0.18	0.31	0.24	0.04	0.17	0.36	0.32	0.05
KR	0.10	0.25	0.14	0.16	0.13	0.28	0.12	0.11	0.13	0.24	0.19	0.18
PH	0.20	0.21	0.09	0.18	0.19	0.30	0.13	0.27	0.31	0.24	0.12	0.24
TH	0.26	0.29	0.08	0.15	0.25	0.29	0.11	0.22	0.23	0.37	0.09	0.19
Asia	0.19	0.26	0.14	0.13	0.19	0.30	0.15	0.16	0.21	0.30	0.18	0.16

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 share explained by global macro factors, global financial factors, global capital factors and regional capital factors, respectively.

Table A.2: Variance decomposition of **total capital inflows (FDI+PI+OI)** by country

	1994 - 2000				2001 - 2008				2009 - 2014			
	M	F	C	R	M	F	C	R	M	F	C	R
AT	0.22	0.42	0.03	0.04	0.16	0.34	0.03	0.03	0.21	0.61	0.04	0.03
DE	0.25	0.29	0.03	0.12	0.22	0.27	0.03	0.15	0.25	0.29	0.03	0.17
DK	0.16	0.33	0.07	0.12	0.11	0.37	0.08	0.12	0.12	0.47	0.10	0.12
ES	0.22	0.45	0.01	0.06	0.16	0.41	0.01	0.05	0.17	0.57	0.02	0.06
FI	0.17	0.44	0.01	0.06	0.13	0.47	0.02	0.07	0.11	0.47	0.02	0.08
FR	0.28	0.38	0.02	0.18	0.22	0.33	0.01	0.17	0.27	0.43	0.01	0.14
GB	0.25	0.43	0.05	0.08	0.20	0.44	0.05	0.04	0.22	0.49	0.07	0.03
IT	0.30	0.37	0.02	0.09	0.29	0.35	0.03	0.10	0.28	0.41	0.03	0.11
NL	0.14	0.57	0.04	0.04	0.10	0.50	0.02	0.06	0.11	0.56	0.02	0.09
NO	0.23	0.55	0.02	0.07	0.19	0.49	0.02	0.06	0.17	0.57	0.02	0.06
PT	0.16	0.46	0.07	0.02	0.15	0.48	0.08	0.02	0.14	0.54	0.08	0.02
SE	0.30	0.29	0.03	0.13	0.30	0.31	0.03	0.12	0.29	0.38	0.04	0.11
Adv Europe	0.22	0.41	0.03	0.08	0.19	0.40	0.03	0.08	0.19	0.48	0.04	0.09
AU	0.25	0.35	0.03	0.17	0.23	0.29	0.04	0.22	0.21	0.36	0.05	0.21
CA	0.12	0.41	0.07	0.06	0.14	0.39	0.07	0.06	0.19	0.37	0.12	0.08
JP	0.18	0.29	0.06	0.02	0.16	0.40	0.08	0.02	0.18	0.40	0.09	0.02
NZ	0.19	0.47	0.01	0.15	0.13	0.52	0.02	0.14	0.12	0.55	0.02	0.15
US	0.25	0.43	0.10	0.08	0.16	0.44	0.09	0.05	0.15	0.51	0.11	0.07
ZA	0.15	0.49	0.03	0.06	0.13	0.51	0.03	0.07	0.12	0.56	0.03	0.07
Adv non-Europe	0.19	0.41	0.05	0.09	0.16	0.42	0.06	0.09	0.16	0.46	0.07	0.10
BG	0.35	0.44	0.03	0.05	0.29	0.40	0.03	0.08	0.27	0.47	0.03	0.12
CZ	0.27	0.27	0.02	0.05	0.32	0.34	0.03	0.03	0.32	0.41	0.04	0.04
HU	0.17	0.52	0.07	0.11	0.15	0.49	0.06	0.10	0.13	0.53	0.07	0.11
RO	0.21	0.50	0.03	0.18	0.16	0.36	0.02	0.12	0.18	0.57	0.03	0.16
RU	0.23	0.36	0.04	0.18	0.21	0.34	0.04	0.14	0.21	0.38	0.05	0.16
SI	0.15	0.49	0.07	0.10	0.14	0.46	0.06	0.07	0.18	0.46	0.08	0.06
SK	0.20	0.33	0.02	0.18	0.20	0.37	0.04	0.15	0.19	0.38	0.06	0.15
TR	0.28	0.38	0.04	0.03	0.26	0.39	0.05	0.03	0.30	0.41	0.07	0.03
CESEE	0.23	0.41	0.04	0.11	0.22	0.39	0.04	0.09	0.22	0.45	0.05	0.11
AR	0.16	0.45	0.06	0.09	0.16	0.46	0.07	0.10	0.17	0.57	0.10	0.12
BR	0.21	0.31	0.05	0.05	0.17	0.35	0.06	0.05	0.19	0.41	0.08	0.06
CL	0.21	0.37	0.02	0.14	0.19	0.36	0.04	0.14	0.18	0.37	0.07	0.17
MX	0.17	0.28	0.09	0.08	0.14	0.37	0.11	0.05	0.13	0.43	0.12	0.07
PE	0.36	0.29	0.03	0.04	0.32	0.33	0.01	0.04	0.33	0.38	0.01	0.05
LatAm	0.22	0.34	0.05	0.08	0.20	0.37	0.06	0.08	0.20	0.43	0.07	0.10
ID	0.17	0.33	0.10	0.05	0.17	0.37	0.11	0.06	0.18	0.49	0.14	0.07
KR	0.11	0.31	0.17	0.18	0.13	0.29	0.20	0.22	0.15	0.25	0.21	0.24
PH	0.16	0.27	0.11	0.20	0.15	0.38	0.14	0.27	0.15	0.36	0.16	0.26
TH	0.25	0.32	0.09	0.12	0.24	0.34	0.10	0.17	0.23	0.37	0.11	0.15
Asia	0.17	0.31	0.12	0.14	0.17	0.34	0.14	0.18	0.18	0.37	0.15	0.18

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 share explained by global macro factors, global financial factors, global capital factors and regional capital factors, respectively.

Table A.3: Variance decomposition of **FDI inflows** by country

	1994 - 2000				2001 - 2008				2009 - 2014			
	M	F	C	R	M	F	C	R	M	F	C	R
AT	0.28	0.47	0.12	0.04	0.22	0.41	0.10	0.03	0.24	0.49	0.12	0.04
DE	0.23	0.43	0.04	0.12	0.24	0.42	0.05	0.11	0.25	0.45	0.06	0.09
DK	0.20	0.25	0.12	0.24	0.15	0.31	0.14	0.23	0.14	0.38	0.14	0.26
ES	0.24	0.49	0.02	0.07	0.21	0.46	0.02	0.05	0.19	0.57	0.03	0.06
FI	0.15	0.47	0.02	0.06	0.12	0.49	0.02	0.05	0.12	0.55	0.03	0.07
FR	0.20	0.23	0.02	0.16	0.16	0.23	0.01	0.15	0.20	0.31	0.01	0.21
GB	0.32	0.29	0.06	0.13	0.27	0.29	0.07	0.07	0.30	0.35	0.10	0.07
IT	0.34	0.36	0.05	0.10	0.31	0.34	0.06	0.10	0.35	0.32	0.07	0.11
NL	0.16	0.48	0.06	0.04	0.13	0.52	0.04	0.07	0.11	0.54	0.03	0.10
NO	0.24	0.44	0.02	0.08	0.23	0.44	0.02	0.09	0.18	0.43	0.03	0.11
PT	0.19	0.40	0.09	0.02	0.17	0.43	0.11	0.02	0.16	0.47	0.14	0.02
SE	0.32	0.31	0.07	0.09	0.33	0.35	0.07	0.08	0.31	0.38	0.10	0.10
Adv Europe	0.24	0.39	0.06	0.10	0.21	0.39	0.06	0.09	0.21	0.44	0.07	0.10
AU	0.25	0.23	0.10	0.19	0.22	0.23	0.08	0.26	0.23	0.28	0.13	0.26
CA	0.14	0.45	0.15	0.05	0.16	0.39	0.15	0.05	0.19	0.36	0.23	0.07
JP	0.27	0.45	0.06	0.03	0.24	0.49	0.05	0.03	0.23	0.51	0.07	0.04
NZ	0.20	0.48	0.02	0.07	0.17	0.58	0.02	0.06	0.16	0.62	0.03	0.06
US	0.18	0.30	0.12	0.15	0.15	0.37	0.14	0.12	0.14	0.42	0.15	0.12
ZA	0.17	0.49	0.06	0.11	0.14	0.53	0.03	0.08	0.12	0.59	0.03	0.12
Adv non-Europe	0.20	0.40	0.08	0.10	0.18	0.43	0.08	0.10	0.18	0.46	0.11	0.11
BG	0.39	0.46	0.05	0.05	0.31	0.36	0.05	0.04	0.31	0.44	0.08	0.11
CZ	0.33	0.33	0.05	0.07	0.27	0.36	0.05	0.03	0.31	0.47	0.07	0.02
HU	0.21	0.45	0.10	0.12	0.17	0.50	0.11	0.08	0.15	0.51	0.10	0.11
RO	0.23	0.44	0.09	0.14	0.18	0.39	0.08	0.07	0.19	0.56	0.09	0.09
RU	0.26	0.28	0.05	0.21	0.23	0.27	0.08	0.18	0.22	0.29	0.06	0.22
SI	0.14	0.35	0.15	0.08	0.14	0.34	0.21	0.07	0.15	0.26	0.32	0.05
SK	0.21	0.41	0.02	0.25	0.14	0.32	0.05	0.14	0.16	0.45	0.10	0.17
TR	0.29	0.43	0.04	0.04	0.27	0.42	0.05	0.04	0.20	0.64	0.04	0.03
CESEE	0.26	0.39	0.07	0.12	0.21	0.37	0.08	0.08	0.21	0.45	0.11	0.10
AR	0.17	0.46	0.10	0.09	0.17	0.51	0.15	0.08	0.16	0.59	0.14	0.07
BR	0.19	0.40	0.07	0.04	0.18	0.49	0.06	0.04	0.20	0.50	0.06	0.05
CL	0.15	0.29	0.02	0.25	0.13	0.31	0.04	0.24	0.11	0.30	0.06	0.33
MX	0.22	0.28	0.11	0.07	0.15	0.30	0.13	0.07	0.13	0.41	0.14	0.08
PE	0.30	0.35	0.05	0.03	0.28	0.35	0.02	0.04	0.32	0.50	0.01	0.03
LatAm	0.21	0.36	0.07	0.10	0.18	0.39	0.08	0.09	0.19	0.46	0.08	0.11
ID	0.17	0.30	0.21	0.05	0.16	0.32	0.17	0.05	0.17	0.39	0.29	0.07
KR	0.10	0.26	0.23	0.23	0.10	0.21	0.31	0.24	0.12	0.18	0.33	0.28
PH	0.23	0.19	0.12	0.30	0.20	0.20	0.13	0.31	0.19	0.22	0.15	0.28
TH	0.23	0.26	0.07	0.24	0.21	0.29	0.09	0.29	0.24	0.36	0.09	0.17
Asia	0.18	0.25	0.16	0.21	0.17	0.26	0.17	0.22	0.18	0.29	0.22	0.20

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 share explained by global macro factors, global financial factors, global capital factors and regional capital factors, respectively.

Table A.4: Variance decomposition of **portfolio investment inflows** by country

	1994 - 2000				2001 - 2008				2009 - 2014			
	M	F	C	R	M	F	C	R	M	F	C	R
AT	0.21	0.38	0.05	0.04	0.16	0.34	0.04	0.03	0.24	0.56	0.05	0.03
DE	0.31	0.28	0.05	0.10	0.25	0.23	0.04	0.07	0.35	0.35	0.06	0.09
DK	0.16	0.31	0.15	0.07	0.13	0.38	0.13	0.08	0.12	0.43	0.11	0.09
ES	0.29	0.44	0.02	0.09	0.22	0.45	0.02	0.09	0.21	0.49	0.02	0.08
FI	0.21	0.40	0.02	0.09	0.18	0.47	0.02	0.08	0.17	0.54	0.02	0.05
FR	0.24	0.26	0.04	0.26	0.21	0.26	0.01	0.32	0.21	0.33	0.01	0.26
GB	0.20	0.34	0.09	0.12	0.20	0.39	0.08	0.07	0.20	0.42	0.08	0.05
IT	0.34	0.29	0.05	0.11	0.32	0.29	0.05	0.11	0.27	0.28	0.05	0.12
NL	0.19	0.42	0.05	0.07	0.13	0.32	0.02	0.08	0.16	0.51	0.02	0.12
NO	0.26	0.44	0.03	0.06	0.23	0.47	0.03	0.05	0.22	0.52	0.03	0.05
PT	0.21	0.47	0.06	0.05	0.19	0.49	0.06	0.06	0.17	0.41	0.05	0.05
SE	0.35	0.28	0.05	0.10	0.33	0.29	0.05	0.10	0.28	0.31	0.06	0.09
Adv Europe	0.25	0.36	0.06	0.10	0.21	0.36	0.05	0.10	0.22	0.43	0.04	0.09
AU	0.26	0.35	0.04	0.25	0.21	0.30	0.04	0.23	0.22	0.37	0.04	0.20
CA	0.19	0.44	0.07	0.04	0.20	0.43	0.06	0.04	0.23	0.38	0.06	0.05
JP	0.16	0.45	0.07	0.05	0.14	0.55	0.05	0.04	0.15	0.52	0.06	0.05
NZ	0.20	0.43	0.02	0.10	0.18	0.51	0.03	0.07	0.14	0.52	0.02	0.11
US	0.19	0.42	0.17	0.07	0.13	0.45	0.14	0.06	0.12	0.56	0.12	0.06
ZA	0.19	0.38	0.05	0.10	0.20	0.42	0.03	0.11	0.19	0.50	0.02	0.11
Adv non-Europe	0.20	0.41	0.07	0.10	0.17	0.44	0.06	0.09	0.18	0.48	0.06	0.10
BG	0.26	0.21	0.04	0.04	0.24	0.21	0.04	0.07	0.24	0.25	0.04	0.08
CZ	0.28	0.26	0.04	0.06	0.28	0.29	0.04	0.04	0.26	0.34	0.04	0.02
HU	0.17	0.37	0.06	0.06	0.16	0.40	0.04	0.06	0.18	0.42	0.05	0.07
RO	0.17	0.30	0.04	0.12	0.17	0.34	0.04	0.10	0.18	0.38	0.04	0.11
RU	0.24	0.31	0.05	0.10	0.25	0.34	0.05	0.10	0.26	0.40	0.05	0.07
SI	0.14	0.30	0.05	0.07	0.15	0.29	0.04	0.07	0.20	0.28	0.06	0.07
SK	0.18	0.27	0.03	0.19	0.16	0.27	0.03	0.22	0.16	0.33	0.05	0.20
TR	0.33	0.27	0.07	0.03	0.34	0.28	0.07	0.03	0.34	0.31	0.07	0.03
CESEE	0.22	0.29	0.05	0.08	0.22	0.30	0.04	0.09	0.23	0.34	0.05	0.08
AR	0.17	0.41	0.05	0.14	0.16	0.40	0.05	0.16	0.20	0.50	0.06	0.16
BR	0.17	0.50	0.07	0.09	0.16	0.57	0.06	0.08	0.20	0.56	0.07	0.09
CL	0.19	0.28	0.03	0.05	0.16	0.29	0.04	0.05	0.17	0.39	0.06	0.06
MX	0.14	0.28	0.13	0.10	0.12	0.34	0.13	0.07	0.11	0.46	0.11	0.08
PE	0.23	0.25	0.04	0.03	0.24	0.35	0.02	0.04	0.24	0.41	0.01	0.05
LatAm	0.18	0.34	0.06	0.08	0.17	0.39	0.06	0.08	0.19	0.47	0.06	0.09
ID	0.19	0.35	0.10	0.05	0.19	0.39	0.14	0.07	0.20	0.46	0.14	0.07
KR	0.15	0.32	0.12	0.12	0.16	0.31	0.13	0.13	0.19	0.27	0.13	0.13
PH	0.13	0.24	0.12	0.22	0.13	0.25	0.14	0.27	0.13	0.28	0.15	0.25
TH	0.26	0.23	0.09	0.08	0.25	0.24	0.10	0.11	0.23	0.27	0.10	0.11
Asia	0.18	0.28	0.11	0.12	0.18	0.30	0.13	0.14	0.19	0.32	0.13	0.14

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 share explained by global macro factors, global financial factors, global capital factors and regional capital factors, respectively.

Table A.5: Variance decomposition of **other investment inflows** by country

	1994 - 2000				2001 - 2008				2009 - 2014			
	M	F	C	R	M	F	C	R	M	F	C	R
AT	0.35	0.35	0.02	0.04	0.23	0.39	0.02	0.04	0.24	0.51	0.06	0.02
DE	0.25	0.34	0.03	0.13	0.26	0.32	0.03	0.15	0.25	0.35	0.04	0.12
DK	0.15	0.34	0.09	0.11	0.11	0.38	0.10	0.09	0.10	0.48	0.10	0.07
ES	0.26	0.34	0.01	0.07	0.23	0.36	0.02	0.07	0.19	0.45	0.02	0.06
FI	0.15	0.51	0.01	0.08	0.13	0.55	0.02	0.07	0.10	0.55	0.02	0.05
FR	0.28	0.34	0.03	0.21	0.23	0.38	0.01	0.17	0.27	0.43	0.01	0.09
GB	0.30	0.40	0.06	0.07	0.24	0.43	0.06	0.04	0.28	0.43	0.09	0.02
IT	0.30	0.29	0.02	0.13	0.27	0.28	0.03	0.13	0.27	0.30	0.03	0.12
NL	0.13	0.54	0.03	0.04	0.11	0.56	0.02	0.06	0.14	0.59	0.02	0.06
NO	0.39	0.39	0.02	0.06	0.24	0.44	0.02	0.06	0.20	0.57	0.02	0.03
PT	0.21	0.35	0.05	0.03	0.17	0.40	0.06	0.03	0.22	0.43	0.06	0.02
SE	0.35	0.33	0.03	0.09	0.30	0.36	0.03	0.10	0.32	0.39	0.04	0.05
Adv Europe	0.26	0.38	0.03	0.09	0.21	0.40	0.03	0.08	0.21	0.46	0.04	0.06
AU	0.22	0.29	0.11	0.15	0.20	0.31	0.08	0.18	0.18	0.32	0.18	0.13
CA	0.11	0.44	0.07	0.05	0.15	0.39	0.07	0.07	0.16	0.39	0.10	0.06
JP	0.21	0.29	0.05	0.02	0.18	0.38	0.05	0.02	0.20	0.43	0.05	0.03
NZ	0.17	0.59	0.02	0.06	0.12	0.55	0.02	0.07	0.11	0.71	0.02	0.06
US	0.22	0.42	0.13	0.03	0.15	0.46	0.13	0.04	0.12	0.53	0.13	0.05
ZA	0.10	0.31	0.02	0.12	0.09	0.35	0.01	0.16	0.10	0.39	0.02	0.14
Adv non-Europe	0.17	0.39	0.07	0.07	0.15	0.41	0.06	0.09	0.14	0.46	0.08	0.08
BG	0.36	0.42	0.03	0.04	0.31	0.39	0.03	0.06	0.31	0.44	0.04	0.09
CZ	0.36	0.30	0.04	0.04	0.45	0.37	0.04	0.02	0.38	0.43	0.05	0.02
HU	0.24	0.47	0.07	0.07	0.16	0.43	0.06	0.06	0.22	0.49	0.08	0.07
RO	0.36	0.37	0.02	0.09	0.20	0.31	0.02	0.06	0.28	0.49	0.05	0.08
RU	0.23	0.35	0.09	0.16	0.20	0.34	0.08	0.12	0.21	0.40	0.12	0.11
SI	0.11	0.46	0.06	0.06	0.12	0.38	0.06	0.04	0.17	0.44	0.09	0.05
SK	0.17	0.28	0.02	0.31	0.15	0.28	0.03	0.33	0.14	0.32	0.06	0.30
TR	0.29	0.45	0.04	0.03	0.29	0.41	0.05	0.03	0.29	0.47	0.06	0.03
CESEE	0.26	0.39	0.05	0.10	0.23	0.37	0.05	0.09	0.25	0.43	0.07	0.09
AR	0.28	0.40	0.06	0.09	0.21	0.43	0.06	0.11	0.26	0.49	0.09	0.11
BR	0.23	0.33	0.05	0.04	0.21	0.47	0.06	0.04	0.23	0.54	0.07	0.05
CL	0.17	0.26	0.02	0.14	0.18	0.31	0.04	0.09	0.17	0.33	0.06	0.13
MX	0.17	0.35	0.10	0.06	0.12	0.41	0.13	0.05	0.11	0.47	0.13	0.07
PE	0.31	0.30	0.03	0.05	0.31	0.36	0.02	0.05	0.29	0.39	0.01	0.05
LatAm	0.23	0.33	0.05	0.08	0.21	0.40	0.06	0.07	0.21	0.44	0.07	0.08
ID	0.28	0.32	0.07	0.05	0.20	0.41	0.09	0.06	0.20	0.50	0.19	0.06
KR	0.10	0.38	0.18	0.17	0.12	0.33	0.21	0.20	0.14	0.32	0.22	0.20
PH	0.17	0.24	0.13	0.23	0.15	0.34	0.15	0.31	0.18	0.31	0.17	0.29
TH	0.20	0.20	0.06	0.34	0.21	0.26	0.09	0.36	0.19	0.31	0.09	0.35
Asia	0.19	0.28	0.11	0.20	0.17	0.33	0.13	0.23	0.18	0.36	0.17	0.23

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 share explained by global macro factors, global financial factors, global capital factors and regional capital factors, respectively.