Policy Research Working Paper 8354

Gross Capital Flows, Common Factors, and the Global Financial Cycle

Luis-Diego Barrot
Luis Serven

WORLD BANK GROUP
Development Research Group
Macroeconomics and Growth Team
February 2018

Policy Research Working Paper 8354

Abstract

This paper assesses the international comovement of gross capital inflows and outflows using a two-level factor model. Among advanced and emerging countries, capital flows exhibit strong commonality: common (global and country group-specific) factors account, on average, for close to half of their variance. There is a contrast across groups: common factors dominate advanced-country capital flows, while idiosyncratic factors dominate emerging-country flows and, especially, developing-country flows. The reason is the much larger role of global factors among advanced countries. Importantly, these findings apply to both inflows and outflows: their respective common factors are very similar—although global factors play a bigger role for outflows than for inflows. The commonality of flows reflects a global cycle, summarized by a small set of variables (the VIX, the U.S. real interest rate and real exchange rate, U.S. GDP growth, and world commodity prices) that explain much of the variance of the estimated factors—especially the global factors. Over time, the quantitative role of the common factors exhibits a "globalization" stage up to 2007, during which they acquire growing importance, followed by a phase of "deglobalization" post-crisis. Greater financial openness, deeper financial systems, and more rigid exchange rate regimes amplify countries' exposure to the global financial cycle.

This paper is a product of the Macroeconomics and Growth Team, Development Research Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at lserven@worldbank.org.

Gross Capital Flows, Common Factors, and the Global Financial Cycle*

Luis-Diego Barrot and Luis Servén†

JEL: F32, F36, G15

Keywords: Capital Flows, Comovement, Common Factors, Global Financial Cycle

*We thank Eugenio Cerutti, In Choi, Sebnem Kalemli-Ozcan, Andy Rose and Sergio Schmukler for useful comments. We are also grateful to Jorg Breitung and Sandra Eickmeier, and In Choi and Yun Jung Kim, for kindly sharing their computer code. Any remaining errors are ours only. The views expressed here do not necessarily reflect those of the World Bank, its Executive Directors, or the countries they represent.

†The World Bank. email addresses: lbarrotaraya@worldbank.org, lserven@worldbank.org

1 Introduction

There is wide consensus that capital flows can have major consequences for macroeconomic and financial stability in both source and destination countries. Understanding better their determinants is therefore a first-order priority for both academics and policy makers. Following the global crisis, increasing attention has focused on the global factors that may drive inflows and outflows across the world, and on the implications of the international comovement of capital flows for the ability of national policy makers to shelter their economies from global financial shocks.

These questions had been first addressed in the context of capital flows to emerging markets by an empirical literature that drew a distinction between what have come to be termed 'push' factors, affecting capital flows across many countries, and 'pull' factors driving country-specific flows (e.g., Calvo, Leiderman and Reinhart 1996). The distinction has been revived in a more recent literature stressing the high degree of synchronization of financial conditions across the world. Along these lines, Forbes and Warnock (2012) find that extreme capital flows episodes are driven by a small set of global variables – notably global risk aversion, as captured by the VIX index, along with global GDP growth and global interest rates. In turn, influential contributions by Rey (2013) and Miranda-Agrippino and Rey (2015) conclude that one latent global factor accounts for much of the variance of capital flows and risky asset returns around the world. They interpret this result as evidence of a global financial cycle, driven by investors' time-varying risk aversion – although they do not offer an explicit assessment of its quantitative importance. A closely-related view (Bruno and Shin 2015b) stresses the role for capital flows of 'global liquidity', which involves the transmission of credit conditions in global financial centers to the rest of the world through cross-border flows reflecting changes in global banks' leverage, itself largely driven by changing risk perceptions summarized by the VIX. More recently, Cerutti, Claessens and Rose (2017) find that panel and individual-country regressions of different types of capital flows on selected global variables – including latent global factors specific to the flow type – rarely account for more than a quarter of the variation in the dependent variable.

The literature has also examined the trends over time in the role of common factors driving international financial conditions. Over the long term, the degree of international comovement of asset prices (Jordá et al 2017) as well as capital inflows (Reinhart, Reinhart and Trebesch 2017) appears to have been on the rise. Particular attention has been paid to the question whether the role of global factors changed with the global financial crisis and the ensuing 'deglobalization', as termed by some observers. Fratzscher (2012) argues that common factors played the leading role in the fluctuations of net capital flows during the

2007–08 financial crisis, but domestic factors became dominant in the post-crisis. In turn, Avdjiev et al (2017a) find significant changes in the sensitivity of international bank and bond flows to particular global variables: after the crisis, the impact of US monetary policy changes on both types of flows increased, while the responsiveness of cross-border loan flows to global risk conditions declined.

Several papers address the question of what determines the extent to which a country's capital flows reflect world financial conditions – and thereby the country's exposure to global financial shocks. Financial openness has been singled out as a likely contributing factor, as has financial depth. For example, Bruno and Shin (2015b) find that global factors have a larger impact on cross-border bank flows in more financially open countries with bigger banking flows. The composition of investors and/or flows may also matter, because some may be more sensitive than others to common factors. Thus, Raddatz and Schmukler (2012) stress the role of mutual funds in propagating shocks across countries. Cerutti, Claessens and Puy (2017) argue that the foreign investor base – as reflected by the relative importance of global banks and international mutual funds – matters for the sensitivity of emerging-market portfolio and bank inflows to global variables.

The literature has paid particular attention to the role of the exchange rate regime. Rey (2013) and Miranda-Agrippino and Rey (2015) argue that the worldwide reach of the global financial cycle renders the Mundellian Trilemma – governing the choice among exchange rate regime, monetary independence, and capital account openness – just a dilemma, so that with an open capital account the exchange rate regime ceases to matter for the international transmission of global financial conditions. Cerutti, Claessens and Rose (2017) find that the (limited) explanatory power of global factors and push variables in capital flow regressions is not sensitive to the exchange rate regime, while Cerutti, Claessens and Puy (2017) conclude that more flexible regimes augment, rather than reducing, the effects of global conditions on emerging-market capital inflows. In contrast, Obstfeld, Ostry and Qureshi (2017) conclude that, among emerging markets, the response of gross capital inflows (specifically, portfolio and other investment inflows) to global risk, as measured by the VXO index, is significantly greater under fixed exchange rate regimes than under more flexible regimes.[1]

In this paper we investigate the contribution of common shocks to the observed patterns of gross capital flows around the world, using a large cross-country annual data set spanning nearly four decades. In contrast with most of the recent literature, which focuses on flows disaggregated by type,[2] our focus is on aggregate gross flows. This allows us to assess the

[1]Bekaert and Mehl (2017) also find that countries with more rigid exchange rate regimes tend to exhibit significantly higher degrees of interest rate pass-through than countries with more flexible regimes.

[2]Recent examples include Byrne and Fiess (2016); Eichengreen, Gupta and Masetti (2017); Cerutti, Claessens and Puy (2017); and Cerutti, Claessens and Rose (2017).

overall sensitivity of countries' cross-border flows to common shocks, and thus the quantitative relevance of the global financial cycle for total capital flows – a first-order question from the macroeconomic perspective. Also, while most previous literature has focused on gross inflows, we consider both aggregate inflows and outflows. This allows us to examine their commonality, as well as the differences in the extent to which they reflect the global cycle.

The analysis is conducted in the framework of a two-level latent factor model that combines global factors affecting all countries with factors affecting specific groups of countries – advanced, emerging and developing. The two-level factor model setting permits disentangling the common shocks with global reach from those affecting only particular country groups. The variance decompositions obtained from the factor model provide a direct assessment of the quantitative importance of the global cycle for capital flows across the world as well as across particular country groups.

The model is estimated using a recently-developed extension of the standard principal-component approach to the multi-level setting. This approach avoids unnecessary parameter restrictions often imposed in earlier literature, and offers the key advantage of its computational simplicity. Recursive estimation of the factor model over moving time samples allows us to assess changes over time in the overall contribution of common shocks – rather than just that of particular variables, as considered by the existing literature.

To determine the observable counterparts of the latent factors, we analyze the relation between the estimated factors and global variables stressed in the 'push vs pull' literature. Likewise, we explore the determinants of countries' exposure to the global cycle by relating the estimated factor loadings to variables describing countries' structural and policy framework, including in particular the exchange rate regime.

We find that capital flows exhibit a considerable degree of commonality among advanced and emerging countries. For both inflows and outflows, information criteria indicate the presence of one global factor plus one group factor for each of the two groups.[3] On average, the estimated common factors account for just under half of the observed variation of gross capital flows of advanced and emerging countries. However, there are clear differences across

[3] Cerutti, Claessens and Puy (2017) also employ a two-level latent factor model to examine disaggregated flows to advanced and emerging countries. Like us, they find a common factor driving gross inflows to emerging countries but, in contrast with our results, they do not find a common factor behind inflows to advanced economies, nor a global factor affecting inflows to both groups of countries. One possible reason for the discrepancy ia that we use a different dataset (aggregate annual data rather than their quarterly disaggregated data) and estimation method. Still, in our sample inflows to advanced countries display stronger commonality (as reflected by cross-country correlations) than those to emerging or developing countries. Using quarterly data, Advjiev et al (2017b) likewise find that aggregate debt inflows to advanced countries react more strongly to global shocks than do inflows to emerging countries. Further, as discussed below, measures of cross-sectional dependence computed on our data strongly indicate the presence of common factors in advanced-country inflows (as well as outflows).

countries, as well as country groups. Across countries, common factors are virtually irrelevant for, e.g., New Zealand or Pakistan, but account for the bulk of the variance in, e.g., Norway or India. Across groups, common factors dominate advanced-country capital flows – on average they contribute close to two-thirds of the variance – while local (idiosyncratic) factors dominate emerging-country capital flows and, especially, developing-country flows. The difference is primarily due to the action of the global factors: their average variance contribution is over twice as large among advanced countries as among the rest.[4]

Importantly, these results apply to both gross inflows and gross outflows. In most cases, their respective latent factors show a large positive correlation. This is particularly the case for the global factors, and also for the advanced-country group factors. Developing countries represent the exception to this rule. However, across all country groups we also find that outflows reflect more strongly than inflows the action of global factors, while group factors affect gross inflows more strongly than gross outflows. These results suggest that a significant part of the variation of gross capital flows over the cycle may reflect outflows from a relatively large number of countries into a relatively smaller number of countries – e.g., safe havens during global busts, and high-return risky destinations during global booms.

The estimated common factors (global and group-specific, for inflows as well as outflows) are robustly negatively correlated with the VIX and similar risk proxies. Much of their variation (70 to 80 percent in the case of the global factors, and around 50 percent in the case of the group factors) can be explained by a small set of global variables – the VIX, U.S. interest rates, the U.S. real exchange rate, U.S. GDP growth, and world commodity prices. Thus, through the common factors, these fundamental variables indirectly account for close to half the variance of advanced-country inflows and outflows, and around one-quarter of the variance of emerging-country inflows and outflows.

Over the available time sample, the quantitative role of common factors – as measured by their variance contribution – displays a cyclical pattern, especially marked among advanced countries. During an initial 'globalization' stage up to the 2008 crisis, common factors gain growing importance. In particular, global factors become increasingly dominant, partly at

[4]Our results appear to stand in contrast with those of Cerutti, Claessens and Rose (2017), in that we find a quantitatively larger role of common factors. However, their analysis differs from ours in important respects. First, they focus on flows disaggregated by flow type, while we focus on aggregate gross flows. Second, they consider only global factors affecting all countres, while we also consider group factors specific to advanced, emerging and developing countries. And third, country coverage is also different. Our focus is primarily on advanced and emerging countries, while theirs is esentially on emerging and developing countries. Additionally, country samples differ, primarily in that theirs includes some 20 former socialist economies whose annual time series are shorter than required for our analysis (they use quarterly data), while ours includes six emerging markets and twenty-four developing countries (mainly in Africa) omitted from theirs.

the expense of group factors. After the crisis, the trend goes in reverse and 'deglobalization' takes place: the role of common factors and, in particular, global factors, experiences a decline.

Lastly, we find that countries' exposure to global cycles, as captured by the estimated loadings on the global factors, is significantly related to their structural and policy framework. Financial openness and financial depth amplify the impact of global cycles on both the inflow and the outflow sides of capital flows. Additionally, a less-flexible exchange rate regime has the same effect on the gross inflow side. The latter result implies that exchange rate pegs reduce, to an economically significant extent, countries' ability to insulate their financial conditions from changes in global financial centers – suggesting that, in spite of the global financial cycle, the Mundellian Trilemma continues to characterize the trade-offs in the choice of exchange rate regime, capital account openness, and monetary policy autonomy.

The rest of the paper is organized as follows. Section 2 describes the two-level latent factor model employed in the estimation. Section 3 turns to the data. Empirical results are presented in Section 4. We first report the factor model estimates, and then discuss how the factors relate to global 'push' variables. Next, we consider how commonality changes over time, and investigate the determinants of countries' exposure to global conditions. Lastly, we extend the empirical setting to encompass developing countries. Finally, Section 5 concludes.

2 Analytical framework

Our primary objective is to analyze the comovement of gross capital flows across countries, and assess the respective roles of global, group and idiosyncratic factors. For this purpose, we study the behavior of capital inflows and outflows in a large panel dataset. To capture the cross-sectional dependence of capital flows, we use a latent factor model. Specifically, we consider a simple two-level factor model:

$$y_{m,it} = \left(\gamma_{m,i}\right)' G_t + \left(\lambda_{m,i}\right)' F_{m,t} + u_{m,it} \quad i = 1, ...N_m;\; m = 1, ..., M;\; t = 1, ...T. \tag{1}$$

Here $y_{m,it}$ denotes the chosen measure of gross capital inflows or outflows for the i-th country of group (or region) m over period t; G_t is a set of r_G unobserved common (world) factors, and $F_{m,t}$ is a set of r_m unobserved factors specific to group m. In turn, $\gamma_{m,i}$ and $\lambda_{m,i}$ are the respective factor loadings, and $u_{m,it}$ is an idiosyncratic component that may be heteroskedastic and serially and/or cross-sectionally (weakly) correlated. Stacking all the observations for group m at time t, we can write

$$Y_{mt} = \Gamma_m G_t + \Lambda_m F_{mt} + u_{mt} \tag{2}$$

and combining capital flows for all groups into a $T \times N$ matrix Y (where $N = \sum N_m$) the model can be compactly written

$$Y = G\Gamma^{'} + F\Lambda^{'} + U \tag{3}$$

where G and F respectively are $(T \times r_G)$ and $(T \times \sum r_m)$ matrices of factors, and Γ and Λ are $(N \times r_G)$ and $(N \times \sum r_m)$ matrices of global and group factor loadings respectively. In particular, Λ is block-diagonal, with the m-th block containing the loadings of the N_m countries in the m-th group on their r_m group factors.

The model as written is static, with factors affecting the dependent variable only contemporaneously. However, it can be reinterpreted as a dynamic factor model with lagged effects of the factors, by expressing the lags as additional static factors.

As the factors and their loadings are unobserved, both need to be estimated from the data. With the model as written, they cannot be identified without imposing additional restrictions. A set of restrictions that yields exact identification is the following: (i) $\frac{G'G}{T} = I_{r_G}$ and $\frac{F_m' F_m}{T} = I_{r_m}$ for all m; (ii) $\Gamma^{'}\Gamma$ and $\Lambda_m^{'}\Lambda_m$, $m = 1, ..., M$, are diagonal matrices, and (iii) $F_m' G = 0$ for all m. Restrictions (i) impose a normalization of the factors, in particular forcing the global factors to be mutually orthogonal, and similarly for the group factors of any given group. In turn, (ii) uniquely determines the rotation of the factors; (i) and (ii) are commonly imposed in single-level factor models. Lastly, (iii) imposes orthogonality between global and group factors.

These restrictions suffice to uniquely identify the factors and loadings, up to a sign change. In the empirical estimation we determine the sign of each factor by requiring that the loading of the respective group's largest country be positive.[5] Importantly, there is no need to impose orthogonality between the group factors of different groups to identify the model, in contrast with what is often done in Bayesian analyses of multi-level factor models. Such restriction may or may not hold in practice, and imposing it leads to an overidentified model. Indeed, imposing the restriction when it does not hold would result in inconsistent estimates. We find below that group factors are not mutually orthogonal in our data, although the magnitude of their correlation is fairly modest.

In contrast with single-level factor models, which can be estimated by straightforward application of principal component analysis, estimation of the multilevel model (3) faces

[5] An alternative is to set the sign of each factor so that the majority of its loadings are positive. In our case, this rule leads to exactly the same sign choices as the one in the text.

the difficulty that the matrix of group factor loadings Λ contains zero restrictions. This prevents a standard principal-components approach, which cannot separately identify G and F. Most previous literature has confronted this issue employing Bayesian techniques (e.g., Kose et al 2003). A recently-developed alternative, which we shall follow below, builds on an extension of the principal component approach to multi-level models; see e.g., Wang (2014), Breitung and Eickmeier (2016) and Choi et al (2017). Compared with Bayesian estimation, these methods are computationally much simpler, as they just involve a sequence of OLS regressions. Their objective is to minimize the sum of squared residuals

$$SSR(G, F, \Gamma, \Lambda) = tr\left[\left(Y - G\Gamma' + F\Lambda'\right)'\left(Y - G\Gamma' + F\Lambda'\right)\right]$$

with respect to G, F, Γ and Λ, subject to the identifying restrictions listed above.

Estimation proceeds in iterative fashion: starting from an initial estimate of the global factors, estimates of the group factors are computed for each country group. With these, an updated estimate of the global factors can be obtained, and the process is repeated until convergence. Below we follow the sequential least squares approach of Breitung and Eickmeier (2016) and Choi et al (2017), with the initial estimate chosen through canonical correlation analysis.[6]

When N and T are both large, principal components estimators are consistent under general forms of heteroskedasticity and (weak) serial and cross-sectional correlation of the idiosyncratic components. Further, their small-sample performance in the multi-level factor setting is quite satisfactory (Choi et al 2017).[7] However, if the idiosyncratic components are not *iid*, a more efficient estimator may be available. Specifically, letting $\Omega = E(u_t u_t')$, where $u_t = (u_{(1,1),t}, ..., u_{(M,N_M),t})'$, Choi's generalized principal component estimator (GPCE) is obtained by minimizing

$$tr\left[\Omega^{-1}\left(Y - G\Gamma' + F\Lambda'\right)'\left(Y - G\Gamma' + F\Lambda'\right)\right]$$

with respect to G, F, Γ and Λ (Choi 2012). If Ω is not known, a feasible estimator (FGPCE) can be computed using a consistent estimate $\hat{\Omega}$. The FGPCE may allow significant efficiency gains regarding the estimated factors and common components. This is relevant in our case because we consider a large sample of countries that display a good deal of heterogeneity in

[6] In essence, the initial estimate of the global factors is constructed through linear combination of 'candidate' group factors. The linear combinations are chosen so as to maximize the correlation with the candidate group factors across all groups.

[7] Performance is particularly robust for the estimates of the global factors, regardless of sample sizes in either dimension, and irrespective of the properties of the idiosyncratic components. In turn, the performance of the estimates of the regional factors is significantly affected by N_m, the size of the groups. As N_m grows, performance improves significantly, especially if the idiosyncratic components are not *iid*.

terms of the volume and variability of capital flows, so that cross-sectional heteroskedasticity in particular is a concern. Below we use the HAC covariance estimator of Andrews and Monahan (1992) to estimate $\hat{\Omega}$ from the residuals of a first-round estimation.

The above discussion assumes that the numbers of global and group factors are known a priori, which in practice is rarely the case. Following Choi and Jeong (2017), we determine the appropriate number of factors using the IC_{p_2}, BIC, and HQ criteria, as adapted to the multi-level setting by Choi et al (2017).[8]

3 Data

To study the global and group patterns of capital flows, we assemble a large cross-country dataset drawing from the International Monetary Fund's Balance of Payments Statistics (BoP). After dropping countries with incomplete data and very small economies, we end up with a balanced panel of 85 countries covering the years 1979-2015, with a total of 3,145 observations.[9] We classify the countries into three groups: advanced (19 countries), emerging (28) and developing (38). The list of countries and their grouping are given in Table A1 in the appendix.

Following Broner et al (2013), we construct two measures of capital flows from the BoP data:

i. Capital inflows by foreign agents (CIF): the sum of direct investment in the reporting economy, portfolio investment liabilities, and other investment liabilities.

ii. Capital outflows by domestic agents (COD): the sum of direct investment abroad, portfolio investment assets, other investment assets, and international reserve assets.

These measures of flows relate to the assets and liabilities of the reporting country's residents vis-a-vis non-residents. CIF is recorded as capital inflows to the reporting economy by foreign agents, with a positive entry indicating an increase in foreigners' holdings of domestic assets. Similarly, COD records flows from the reporting economy, with a positive value denoting an increase in the holdings of foreign assets by domestic agents. Hence a positive COD represents a capital outflow by domestic agents, while a negative COD means capital repatriation.

[8] We standardize the data prior to estimation subtracting the country-specific mean and dividing by the country-specific standard deviation, as recommended by Choi and Jeong (2017).

[9] Specifically, we download capital flows data from 1945 to 2015 for 196 countries. The data is heavily unbalanced, with some countries possessing very few observations. We construct a balanced panel comprising 98 countries with complete data from 1979 to 2015. We exclude from this sample 13 countries with population fewer than 500,000 in 2005. In addition to dropping very small countries, this also has the effect of removing from the dataset several offshore financial centers and tax havens that display an extremely high volume of financial flows. We are left with 85 countries.

Importantly, both CIF and COD are *net* concepts. They do not represent *gross* purchases of domestic assets by foreign residents, or *gross* purchases of foreign assets by domestic residents. However, in keeping with common usage, we shall refer to them somewhat loosely as "gross inflows" and "gross outflows", respectively.

Like Broner et al (2013), we scale capital flows by trend GDP.[10] We use trend rather than actual GDP to prevent the short-term cross-country comovement of GDP found in the data from distorting the estimates of the common factors and common components of capital flows.

To study the covariates of the global and group factors, below we use a set of variables commonly employed to capture world real and financial conditions. Specifically: (i) global risk, as measured by the CBOE Volatility Index (VIX) and similar measures; (ii) the global short-term interest rate, given by the FED effective federal funds rate minus the U.S. GDP inflation rate; (iii) global growth, as measured by the real GDP growth rate of the U.S. (although we experiment also with G7 and world GDP growth); (iv) the real effective exchange rate of the U.S. dollar; and (v) an index of real commodity prices – specifically, the UNCTAD index for metals and minerals, deflated by the U.S. GDP deflator.

Likewise, to assess the covariates of the factor loadings, we use a set of variables capturing countries' structural and policy framework. These include: (i) financial openness, as measured by the Chinn-Ito index; (ii) trade openness, given by total exports plus imports as a percentage of GDP, and expressed in log terms; (iii) financial depth, measured by domestic credit to the private sector as a percentage of GDP; and (iv) the exchange rate regime, summarized by the index of de facto exchange rate arrangements of Ghosh, Ostry and Qureshi (2015). Table A2 in the appendix gives the details on the data sources.

Figure 1 shows the time path of aggregate flows, for the full country sample as well as each of the three country groups, expressed as percent of the respective group's trend GDP. The full-sample flows reveal two facts. First, inflows and outflows exhibit a high degree of comovement. Second, both inflows and outflows display pronounced cycles. Inspection of the figures corresponding the three country groups shows that the comovement between inflows and outflows is particularly noticeable among advanced countries. Also, the exact timing of the capital flow cycles varies across country groups. Advanced-country flows show an upward trend starting in the mid-1990s. They peak at around 25 percent of trend GDP just before the global crisis of 2007-2008, and collapse thereafter. In turn, emerging-market flows exhibit wide swings, with sharp drops at the time of the 1981 debt crisis and the East Asia crisis of the late 1990s. They subsequently peak in 2006, and fall sharply afterwards. Finally,

[10] Trend GDP is calculated applying the Hodrick-Prescott filter, using a parameter of 100, to the series of nominal GDP in U.S. dollars.

developing countries' inflows and outflows experience a steep fall in the 1980s, and recover thereafter. They peak in 2011, after the global financial crisis, and decline subsequently.

Table 1 reports descriptive statistics. The figures in the table are group averages of the underlying country data. Like with the aggregates in Figure 1, advanced countries exhibit by far the largest gross flows as percent of trend GDP. Moreover, as noted by Broner et al (2013), their inflows and outflows are highly synchronized – their average contemporaneous correlation exceeds 0.90.[11] The correlation between CIF and COD is smaller for emerging and, especially, developing countries. The individual-country data, shown in Table A3 in the appendix, reveal that all of the 19 advanced-country inflow-outflow correlations are significantly positive.[12] This is also the case for 22 out of 28 emerging countries, but only for 10 out of 30 developing countries. On the other hand, advanced countries show the smallest degree of capital flow variability, as measured by the coefficient of variation, while developing countries show the largest, for both inflows and outflows.

4 Empirical results

To check the suitability of a latent factor model for characterizing the patterns of capital flows, we first assess their degree of international comovement. Table 2 reports cross-country correlations of gross capital flows. The numbers shown in the top panel of the table are averages of individual-country figures. In each block, the diagonal entries correspond to within-group correlations (i.e., the average of all the intra-group pairwise cross-country correlations), while the off-diagonal entries are average between-group correlations.[13] In turn, the bottom panel of the table indicates what fraction of the total number of individual correlations underlying each of the averages in the top panel are significantly different from zero.

All but one of the average within-group correlations are positive, with the negative entry corresponding to the developing country group's inflow-outflow correlation. For both inflows and outflows, the highest average within-group correlation corresponds to advanced countries – they are the countries whose flows co-move most strongly. The figures shown in the

[11] The correlation is similarly high (0.86) if flows are expressed in first differences rather than ratios to trend GDP. In a disaggregated analysis of capital flows by economic sector, Avdjiev et al (2017b) show that the positive correlation between inflows and outflows, especially in advanced countries, is primarily due to banks, although the inflows and outflows of corporates and government also show positive (but smaller) correlation. On this issue see also Davis and van Wincoop (2017).

[12] The standard error of a correlation r is approximated as $\sqrt{\frac{1-r^2}{T-1}}$.

[13] The average inflow-outflow correlations in the table exclude the within-country correlation. On the other hand, all the qualitative conclusions in the text continue to hold if flows are expressed as first differences rather than ratios to trend GDP.

bottom panel of the table confirm this view – between 80 and 90 percent of all the pairwise advanced-country correlations are significant, a much higher percentage than for the other groups. Moreover, the large value of the advanced-country inflow-outflow cross-country correlation (.43) suggests that among advanced countries gross inflows (outflows) frequently come from (go to) other advanced countries. At the other extreme, the smallest within-group correlations (including the one negative entry) correspond to developing countries, who also tend to exhibit the smallest percentages of significant correlations in the bottom panel of the table.

Finally, the data also suggest that gross outflows exhibit stronger commonality than gross inflows, as shown by the fact that, in both panels of the table, all but one of the entries in the southeast block exceed the corresponding entries in the northwest block.

As for the average between-group correlations also shown in the top panel of the table, in all three blocks the largest one corresponds to the advanced country-emerging country pair, suggesting that the capital flows of these two groups are the most likely to share common factors. In contrast, the smallest values correspond to developing countries, which also account for the three negative off-diagonal entries in the table.

Overall, the information in Table 2 suggests that gross capital flows exhibit a good deal of commonality among advanced and emerging markets – and especially in the former. In contrast, developing countries' capital flows show less commonality with the flows of other countries – whether developing, emerging, or advanced.

These results indicate the presence of cross-sectional dependence in capital flows, especially among advanced and emerging countries, but do not tell us if the dependence is strong or weak. Strong dependence arises from pervasive common factors, i.e., factors that affect many countries. Weak dependence reflects localized interactions, e.g., bilateral financial linkages. The distinction is important, because standard factor models provide a suitable characterization of the former but not the latter form of dependence.[14]

To assess if dependence is strong or weak, we turn to the exponent of cross-sectional dependence (Bailey et al 2015). It can be viewed as a measure of the rate at which factor loadings (fail to) die off as cross-sectional sample size grows. The exponent ranges between zero and one, with a value of 1 indicating the presence of strong dependence. Table 3 reports the computed values for the three country groups, along with the 95 percent confidence bands. For both advanced and emerging countries, and for both inflows and outflows, the exponents

[14] Strong and weak cross-sectional dependence are defined in terms of the rate at which the largest eigenvalue of the covariance matrix of the cross-section units rises with the number of the cross-section units. In the cross-sectional dependence literature, strong dependence is typically modeled with factor models, while weak dependence is modeled with spatial models. Estimation of standard factor models on weakly cross-sectionally dependent data is likely to yield inconsistent estimates; see, e.g., Onatski (2012).

of cross-sectional dependence exceed 0.95, and the confidence regions include 1. This confirms the presence of strong cross-section dependence in the gross inflows and outflows of these two country groups.[15]

In contrast, for developing countries the evidence is less supportive of strong dependence. The estimated exponent of cross-sectional dependence is just above 0.8 for both CIF and COD, and the 95 percent confidence region does not reach up to 0.90 in either case. This result is in line with the weaker commonality found in Table 2 for developing countries' capital flows. It also raises doubts on the suitability of a factor model to describe the patterns of capital flows of this country group. In light of this evidence, the analysis below focuses primarily on advanced and emerging countries. Developing countries are considered in a subsequent extension.

4.1 Factor model estimates

We turn to estimation of the global and group factors. To that end, we estimate the model (1) for gross inflows and gross outflows. In each case, we compute the three information criteria mentioned earlier (IC_{p_2}, BIC and HQ) for specifications ranging from 1 to 3 global factors and 1 to 3 group factors per group. All three criteria select one global and one group factor per country group (see Table A4 in the Appendix). As noted, we determine the sign of each factor so that the largest economy in the respective group carries a positive loading. For advanced and emerging countries, respectively, the largest economies are the U.S. and China. For the global factors, we set the sign using again the U.S. loading. By construction, the estimated factors have zero mean and unit variance.

Figure 2 plots the estimated global factors for gross inflows and outflows. Both display a steep rise since the mid-1990s until the inception of the global crisis, and a sharp decline afterwards. This pattern roughly matches the one shown in Figure 1(a) for aggregate flows.

Figure 3 reports the group factors. The advanced-country factors (panel (a)) exhibit a gradual rise since the mid- to late 1980s, with a hump in the late 1990s, and an abrupt collapse in 2007, especially marked in the case of outflows. In turn, the emerging-country factors (panel (b)) display wide swings coinciding with the debt crisis of the 1980s and the Asia-Russia crises of the 1990s. Those fluctuations are as wide (wider, in the case of inflows) as the fluctuations seen at the time of the global crisis.

The common factors exhibit considerable persistence, more so in the case of the global than the group factors. The first-order autocorrelation coefficient of the global factors is .79 for CIF and .83 for COD. For the group factors, the values range from .67 and .68 for

[15] This conclusion is in contrast with that of Cerutti et al (2016), who fail to find common factors in advanced countries' capital flows.

the advanced- and emerging-country CIF factors respectively, to .28 and .21 for the COD factors. Standard ADF tests reject at the 5 percent confidence level the null of a unit root for the emerging-country group factors, as well as the advanced-country COD factor. For the remaining factors (global CIF and COD, and advanced-country CIF), both ADF and KPSS tests fail to reject their nulls of non- and stationarity, respectively. However, unit root tests allowing for a break in constant and trend in the run up to the global crisis do reject the null of a unit root at the 5 percent level in all three cases.[16] We conclude that all the common factors are stationary.[17]

It is also apparent from Figure 2 that the global CIF and COD factors follow very similar patterns. Their correlation coefficient equals 0.95. Table 4, which reports the correlation pattern of the group factors, shows that the advanced-country CIF and COD factors are also highly correlated – their correlation equals 0.82. Overall, this implies that advanced-country inflows and outflows are driven essentially by the same common shocks. In turn, the emerging-country group factors are also positively correlated, but to a more limited extent – their correlation is just 0.34. The table also shows that the group factors are not significantly correlated across groups. This applies to both inflow factors and outflow factors, as well as the cross-group inflow-outflow correlation.

The estimated factor model provides a satisfactory account of the observed cross-country comovement of capital flows. The exponents of cross-sectional dependence of the CIF and COD residuals from the estimation equal 0.40 and 0.33, respectively, and their 95 percent confidence regions reach up to 0.50 and 0.37, far below 1. Thus, once the common factors have been removed, the residuals show no traces of strong cross-sectional dependence. Also, panel unit root and stationarity tests indicate that the residuals are stationary (see Table A5 in the Appendix).

The sensitivity of each country's gross flows to global and group-specific common factors is given by its factor loadings ($\gamma_{m,i}$ and $\lambda_{m,i}$ in equation (1)). Figures 4 and 5 show the estimated global and group factor loadings, respectively. The dots denote the 95-percent confidence bands. For advanced countries, Figure 4 shows that the global factor loading estimates, for both inflows and outflows, are positive in every case, except for the COD global factor loading in the case of New Zealand. Further, all the loadings, except New Zealand's (for both CIF and COD) are significant at the 5 percent level.[18] For emerging markets,

[16] When the test procedure endogenously selects the date of the break, it is placed at some point in the 2005-2007 interval, depending on the exact specification of the test and the common factor under consideration.

[17] It is important to note that, even if the factors were I(1), estimates of the factor model in levels (as computed here) should perform better than estimates of the model in first differences, as long as the idiosyncratic components are I(0); see Choi (2017) and Ergeman and Rodriguez-Caballero (2016). Such condition holds in our case, as noted later in the text.

[18] Inference on the loadings is based on Choi (2012). His analysis applies to single-level factor models.

twenty-one of the estimated loadings on the global CIF factor are positive, and fourteen of them are statistically significant. The remaining seven are negative, although only one of them (which corresponds to the Philippines) is statistically significant. In turn, all but two of the emerging-country COD global factor loading estimates are positive and significant. The exceptions are Uruguay and Pakistan, whose loadings are small and insignificant.

In general, the largest global factor loadings are found among the advanced countries (there are some exceptions, such as India). In other words, advanced countries are more exposed than emerging countries to the global factors. For inflows, the median global factor loading is .53 for advanced countries, and .25 for emerging countries. For outflows, the median estimates are .54 and .48, respectively. Further, countries with large loadings on the CIF global factor also tend to exhibit large loadings on the COD global factor: the correlation between both sets of loadings is 0.62, although it is larger for advanced countries (.72) than for emerging countries (.45).

Figure 5 presents similar information for the group factor loadings. Sixteen advanced countries exhibit positive loadings on the CIF group factor, of which all except New Zealand's are significant. The remaining three loadings (corresponding to Canada, Japan and Australia) are significantly negative. The same three countries, plus Norway and Finland, exhibit negative loadings on the COD group factor, although only Australia's is significantly negative. The other fourteen loadings on the COD group factor are all positive, and all significant except for that of the Netherlands. Interestingly, the largest loading for both CIF and COD belongs to the U.K., perhaps reflecting its role as financial center.

In turn, all of the emerging-market CIF group factor loadings are positive, and twenty-one of them are statistically significant. As for the COD group factor loading estimates, twenty-tree are positive, of which fifteen significantly so. The remaining five are negative, although none is significant. Interestingly, for both CIF and COD the smallest (or negative) group factor loading estimates tend to be found among Middle Eastern countries, while the largest ones are found among East Asian and Latin American emerging markets.

Unlike with the global factor loadings, emerging countries exhibit group factor loadings roughly as large or even larger than those of advanced countries. The median loading on the group CIF factor is .39 for advanced countries and .40 for emerging countries. For COD, the corresponding figures are .31 and .24. In fact, the largest group factor loading corresponds to the Philippines in the case of CIF, and to Thailand in the case of COD. Across countries, CIF and COD group factor loadings show a strong positive correlation, more so for advanced countries (the correlation equals .83) than for emerging countries (.73) – the

However, Wang's (2014) results suggest it should apply also to the multi-level setting, although a formal proof is not available at present.

same patterns found for the global factor loadings. The clear conclusion is that countries' exposure to the international drivers of gross inflows goes hand-in-hand with their exposure to the international drivers of gross outflows.

4.2 The variance contribution of common factors

The orthogonality conditions imposed to identify the factor model allow a straightforward decomposition of the variance of each country's capital flows into three orthogonal components: a global component, a group component, and a country (or idiosyncratic) component.[19] Table 5 summarizes the results for both inflows and outflows.[20] The figures shown are averages of the individual-country results.

Four facts stand out. First, the global and group-specific common factors account, on average, for close to half the variance of gross capital flows. Second, global factors play a bigger role than group factors. This is particularly the case for gross outflows; in contrast, gross inflows are more strongly affected than gross outflows by group factors. Together, the latter two observations suggest that a major part of the variation of gross capital flows over the cycle may reflect outflows from a relatively large number of countries and into a relatively small number of countries – possibly following a 'risk-on / risk-off' pattern according to which capital flows into safe havens as investors run for cover during global busts, and into high-return destinations as international investors engage in search for yield during global booms.

Third, there is a major difference between advanced and emerging countries. Common factors contribute a much bigger share of the variance among the former countries (averaging almost 60 percent for inflows and 64 percent for outflows) than among the latter (35 and 37 percent, respectively). Put differently, local factors dominate emerging-country capital flows, while common factors dominate advanced-country flows. Fourth, the difference is primarily due to the global factors: their contribution to the overall variance of flows is much larger for advanced economies than for emerging countries. This applies to both inflows and outflows: among advanced countries, global factors account for 38 percent of the variance of inflows and 47 percent of the variance of outflows, while the corresponding figures for emerging countries are just 15 percent and 25 percent, respectively. In contrast, the role of group

[19] Because group factors are not mutually orthogonal in our setting, the variance contribution of each group factor can be in principle further decomposed into the portion attributable to the factor's component uncorrelated with other groups' factors, and that attributable to the component correlated with the factors of other groups However, the cross-group correlation between group factors is sufficiently low that the latter contribution is virtually negligible, and therefore we do not report such additional decomposition.

[20] Cerutti, Claessens and Puy (2016) carry out a similar decomposition for different types of gross inflows to a set of emerging markets.

factors is, on average, not very different across the two sets of countries. As a result, the variance contribution of global factors far outweighs that of group factors among advanced countries, but not among emerging countries – in fact, the opposite happens in the case of emerging-country gross inflows. Importantly, these results are not due to the fact that the advanced-country group includes the leading global financial centers (the U.S., U.K., Germany and/or Japan). Table A6 in the Appendix shows that excluding them has little effect on the average variance contributions shown in Table 5.

Figure 6 reports the individual-country variance decomposition results underlying Table 5. The respective roles of common and idiosyncratic factors exhibit considerable variation across countries, even within the same country group. Among advanced countries, common factors contribute the bulk of the variance of both gross inflows and outflows in the Netherlands and Norway, but play only a modest role in New Zealand, Japan and Finland, where idiosyncratic factors dominate. Overall, common factors account for at least one-fourth of the variance of both inflows and outflows in all countries except New Zealand.

The contribution of the global factors in particular also shows substantial variation across countries. They play virtually no role in New Zealand, but account for over 80 percent of the variance in the Netherlands, for inflows as well as outflows in both cases. Further, their role is not disproportionately larger in the four center countries mentioned above: in three of them, the contribution of the global factors is below the group average. The exceptions are the U.S., in the case of inflows, and Germany, in the case of outflows. In turn, group factors are virtually irrelevant in Finland, but play a dominant role in the U.K., again for both inflows and outflows.

Emerging markets also display considerable heterogeneity along these dimensions. In some countries (e.g., Egypt, Pakistan), neither global nor group factors play any significant role for inflows or outflows. In contrast, in several major emerging markets they account for half the variance or more (e.g., Korea, India). The global factor contributes less than 10 percent of the variance of gross inflows in over half the countries in the group. At the other extreme, it accounts for two-thirds of the variance of Turkey's inflows and China's outflows. Interestingly, among Middle Eastern economies – Egypt, Jordan, Kuwait, Oman, Saudi Arabia – as well as Cyprus and Turkey, the contribution of group factors tends to be quite small, suggesting that, once global forces are taken into account, their capital flows do not have much in common with those of other emerging markets.

4.3 Common factors and the global financial cycle

The variance share of common factors shown in Table 5 can be interpreted as the contribution of the international cycle to the variation of capital inflows and outflows. A separate question is what drives that cycle, and how it is reflected in observable variables. The 'push vs pull' literature, going back to Calvo, Leiderman and Reinhart (1996), as well as the more recent literature on the global financial cycle (starting with Rey 2013), have stressed the role of a few global (or financial-center) variables capturing financial conditions worldwide as key drivers of the commonality of capital flows. Global risk, as summarized by the VIX and similar measures, is often taken as a sort of summary statistic of the 'global financial cycle' (Rey 2013, Miranda-Agrippino and Rey 2015), and typically found to be negatively related to capital flows, especially inflows to emerging markets.[21] However, other global financial variables capturing advanced-country monetary policy (such as the U.S. short-term interest rate and/or the term premium), as well as global growth, are often found to affect capital flows to multiple countries, even after controlling for the VIX or other risk proxies (e.g., Avdjiev et al 2017a; Cerutti, Claesens and Ratnovsky 2017). Bruno and Shin (2015b) argue that the same should apply to the U.S. real exchange rate: because of the dominant role of the dollar as currency of denomination of financial contracts worldwide, dollar appreciation constitutes a tightening of global financial conditions.

To explore the fundamental covariates of the global financial cycle, Table 6 reports regressions of the estimated common factors on selected global variables (or U.S. variables, as they pertain to the world's leading financial center).[22] The top block of the table reports univariate regressions of the factors on the VIX and other risk proxies. Because the VIX is not available prior to 1990, we also use its predecessor the VXO, which is available since 1986, as well as the BAA 10-year corporate spread, which represents a commonly-used measure of market risk premia. Consistent with earlier literature, all the factors exhibit a significant negative correlation with the three measures of risk. This applies to the global factors as well as the advanced-country and emerging-country group factors, and to both inflows and outflows. The largest coefficient estimates are found in the regression with the advanced-country COD factor as dependent variable, suggesting that risk particularly discourages outflows from these countries, over and above its effects on other flows.

[21] See Forbes and Warnock (2012), Broner et al (2013), Bruno and Shin (2015a,b), Cerutti, Claessens and Ratnovsky (2017), Avdjiev et al (2017a,b), Eichengreen, Gupta and Masetti (2017), and Obstfeld, Ostry and Qureshi (2017).

[22] Because of the high persistence of the factors, to avoid spurious inferences the exercises are run with the variables expressed in first differences. This tends to weaken the explanatory power of the regressions, so they offer a conservative view on the strength of the relations under consideration. At the same time, the samples are short enough that the results should be taken with caution.

The bottom block of Table 6 reports regressions of the factors on the VIX plus other global variables. The main purpose of the regressions is to assess their ability to account for the variation of the common factors, rather than to establish the sign or magnitude of particular coefficients. The additional explanatory variables are the main ones used in the recent literature, and intend to provide a minimalist representation of the global financial cycle: the real short-term U.S. interest rate, the U.S. real exchange rate, and the U.S. real growth rate.[23] We also include global commodity prices (measured by the world price of metals and minerals in real terms), whose links with global capital flows have been stressed by Reinhart, Reinhart and Trebesch (2017).[24]

The results in Table 6 show that the estimated coefficient on the VIX remains negative and significant in all six columns. Moreover, the magnitude of its coefficient is not much affected by the presence of the additional variables. In turn, the real interest rate carries in most cases a positive coefficient, but it is significant only in the advanced-country CIF factor regression. The signs of the coefficients of the other regressors are more heterogeneous. The U.S. real exchange rate carries a significant positive sign in the global CIF factor regression, and significant negative coefficients in the group CIF factor regressions. Growth has a positive and significant effect on the global CIF and COD factors, as well as the advanced-country CIF factor, but a negative one on the emerging-country COD factor. Lastly, the commodity price index carries significant coefficients in all regressions except for that of the emerging-country CIF factor. The coefficients are positive in the global factor regressions, and negative in the rest.

Overall, the R^2 of these augmented regressions indicate that a small set of variables capturing real and financial conditions worldwide can account for the bulk of the variation of the global factors – over 70 percent for the CIF factor, and over 80 percent for the COD factor. They also account for a respectable portion of the variation of the group factors – ranging from 45 percent for the emerging-market factors, to 55 percent for the advanced-country COD factor. Combining these results with the variance decomposition in Table 5, we can infer the extent to which this handful of fundamental variables can explain the variation in capital flows across the world through the global and group factors combined. Simple calculations show that they account for about 50 percent of the variance of advanced-country outflows, and about 40 percent of the variance of advanced-country inflows. For emerging-country flows, the figures are smaller – around 25 and 20 percent for COD and CIF, respectively. However, we should keep in mind that these are conservative estimates,

[23] The results are very similar if the growth rate U.S. GDP is replaced with that of G7 GDP or world GDP.

[24] Augmenting these regressions with other variables summarizing global financial conditions, such as the U.S. term spread or the TED spread, yields very small increases in explanatory power, along with insignificant parameter estimates for the additional regressors.

given that the regressions in Table 6 are run in differences, which likely tends to understate their explanatory power.

4.4 Has there been a 'deglobalization' post-crisis?

It seems plausible that the global trend towards financial integration witnessed over the last quarter-century should be reflected in a growing effect of common factors on capital flows.[25] However, it has been argued that the rising trend was interrupted by the global crisis, and followed by what has been termed 'financial deglobalization' – attributed to regulatory and other policy measures discouraging, in particular, cross-border bank lending (Rose and Wieladek 2014; Forbes, Reinhart and Wieladek 2017).

Our setting allows a straightforward assessment of changes in the reach of common factors over time, by examining the time pattern of their variance contribution. To do this, we re-estimate the factor model over rolling time samples. Specifically, we use 20-year windows, starting with 1979-98, shifting them forward one year at a time, so that the final estimation is done over the 1996-2015 sample. This yields eighteen different estimates of the factor model. For each one of them, we compute the variance decomposition as done above. Because the time samples underlying these estimates are short, the results need to be taken with some caution.

Figure 7 plots the time path of the respective variance contributions of global, group and local factors that results from these rolling estimates. The decomposition pertaining to each estimation window is denoted by the window's final year. Like in Table 5, for each window the figure reports group averages for advanced and emerging countries.

Among advanced countries, for both CIF and COD the role of common factors grows markedly over the first ten windows. For CIF, the average variance contribution of common factors rises from 45 percent to just over 70 percent; for COD, from 55 percent also to just over 70 percent. Most of this increase is concentrated in the first few years, and is attributable to the rising importance of the global factors, whose contribution grows partly at the expense of that of the group factors. For both inflows and outflows, the variance share of global factors peaks at over 60 percent in the window ending at the onset of the global crisis (2007). At its peak, the combined variance contribution of common factors reaches 72 percent for both CIF and COD. Thereafter, as the subsequent estimation windows start including post-crisis years, the share of the common factors – especially the global factors – in the variance of both CIF and COD enters a period of gradual decline. In the context of the factor model, this literally is a 'deglobalization'. In the final window of the sample

[25] This was the case for FDI over the 1990s: Albuquerque, Loayza and Servén (2006) find that external financial liberalization was reflected in a rising contribution of global factors to the variation of FDI.

(1996-2015), common factors account for 60 percent of the variance of CIF and COD, with global factors contributing close to two-thirds of that total.[26]

Emerging countries exhibit similar fluctuations, but on a reduced scale. In their case, the variance contribution of common factors remains consistently smaller than in advanced countries, for both CIF and COD. Their variance share remains relatively flat until the mid-2000s, and then rises until the global crisis – especially in the case of outflows – reflecting an increasing role of global factors. At the peak, common factors account for just under 50 percent of the overall variance of both inflows and outflows. Like in advanced countries, the contribution of the common factors declines post-crisis – although in this case there is no noticeable change in the relative shares of global and group factors. In the final window of the sample, the global and group factors combined account for some 40 percent of the overall variance of both CIF and COD. Unlike in advanced countries, where global factors play by far the biggest role for both inflows and outflows, among emerging countries the relative roles of global and group factors vary depending on the direction of the flows. The former factors outweigh the latter for outflows, but the opposite happens with inflows.

4.5 What shapes the role of the global factors?

The global crisis has prompted renewed interest in the factors that shape countries' exposure to common shocks through their capital flows. As Figures 5 and 6 show, exposure varies a lot across countries. This raises the question of what drives such heterogeneity. In this regard, structural and policy features such as capital account openness and financial development have received considerable attention. In addition, the ability of flexible exchange rates to provide insulation from the global financial cycle has attracted an active debate following Rey's (2013) influential work.

As a first illustration of these issues, we present variance decompositions of capital flows over time, analogous to those shown in Figure 7, but grouping countries according to particular features of their structural and policy framework. Figure 8 does this distinguishing between countries exhibiting high and low degrees of financial openness. For each estimation window, countries are allocated to either group depending on whether their average financial openness (as measured by the Chinn-Ito index) over the window in question is above or below the overall sample median. The pattern of rise and subsequent fall of the variance contribution of common factors found in Figure 7 is apparent in the group of more financially

[26] The rise and fall in the contribution of common factors before and after the global crisis are consistent with the changing composition of flows. The reason is that the pre-crisis capital flow boom, as well as the post-crisis collapse, were led by portfolio and, especially, bank flows, which are commonly found to be the flow type most responsive to global variables.

open countries, but not in the group of less financially open countries. Further, the common factors play a larger role in the former countries than in the latter. This applies to both inflows and outflows, and it is primarily due to the variance contribution of the respective global factors, which is consistently bigger among the former group than among the latter.

In turn, Figure 9 highlights the role of the exchange rate regime using the de facto classification compiled by Ghosh, Ostry and Qureshi (2015), which distinguishes between fixed, intermediate, and floating regimes. For the purposes of the figure, we consolidate the three-way classification into two groups, again depending on how each country's average degree of flexibility over each window compares to the full-sample median; this yields two groups of countries that, in a slight abuse of language, we label 'pegs' and 'floats'. The graphs show that the inflows and outflows of countries on pegged regimes consistently reflect the action of common factors to a greater extent than do the inflows and outflows of countries on floating regimes. This is particularly the case for the global factors, whose variance contribution is up to twice as big in the former group than in the latter. The difference between the two groups along this dimension is especially large in the case of gross outflows. Moreover, while the trend of rise and fall of the quantitative role of the common factors around the global crisis affects both country groups, it is much more pronounced among countries with pegs than among those with floating regimes.

Finally, Figure 10 turns to financial depth, classifying the countries into high and low financial depth groups following the same procedure as in the preceding figures. Greater financial depth is associated with a bigger role of common factors, for both inflows and outflows, which again is primarily due to the larger variance contribution of the global factors – although the difference between both country groups along this dimension seems to have narrowed after the global crisis.

These figures highlight some ingredients that shape the effect of common factors across countries. However, since they consider one ingredient at a time, they may not convey an accurate picture of the respective role of each one of them. An alternative way to do this is by regressing the estimated factor loadings, which capture the impact of the factors on capital flows, on suitable measures of countries' policy and structural features.[27]

In principle, we could run cross-sectional regressions using as dependent variable the full-sample estimates of the loadings. However, these pertain to the full 37-year sample, a time span over which any candidate explanatory variables have surely undergone major changes, which would then obscure their relationship with the loadings in a pure cross-section. To remedy this, we opt instead for using the estimates of the loadings obtained from the moving-

[27] Cerutti, Claessens and Puy (2016) report a similar exercise for portfolio and banking inflows to emerging markets.

window estimation. This offers two advantages: first, the windows cover a shorter time span (20 years), which partly mitigates (although it certainly does not eliminate) the concern with the variation of the explanatory variables over time. Second, it allows us to build a panel combining the factor loading estimates from the different windows, so that the estimation can exploit, at least to some extent, the time variation of the regressors across windows.

Table 8 reports the estimation results, for both the CIF and COD global factor loadings.[28] In addition to financial openness, financial depth and the exchange rate regime, we also examine the role of trade openness, which might offer another channel for the propagation of global financial conditions. The explanatory variables are averaged over the corresponding 20-year window. In particular, we compute GLS estimates, using an AR(1) specification to take into account the likely persistence arising from the fact that consecutive windows share a good deal of information.

The first five columns of Table 8 correspond to the regressions with the CIF global factor loadings as dependent variable. The results indicate that countries' exposure to the global forces behind capital inflows rises significantly with their degree of financial openness (column 1), as well as trade openness (column 2) and financial depth (column 3). A higher degree of exchange rate rigidity (i.e., a decline in the value of the exchange rate regime index) has the same effect (column 4). These results are highly significant, and survive when all four variables are jointly considered (column 5), except for the effect of trade openness, which becomes insignificant.

The last five columns of Table 8 report the results using the COD global factor loadings as dependent variable. For the most part, the estimates are not very different from those obtained with the CIF factor loadings. This is unsurprising given that, as shown earlier, the loadings on both global factors show large positive correlation. The main difference is that the coefficient estimate on the exchange rate regime in column 4 of the outflow loadings regressions is only half as large as that in column 4 of the inflow loadings regressions. Finally, when all four regressors are jointly considered, the exchange rate regime becomes insignificant, and only financial openness and financial depth remain statistically significant. The conclusion is that, once these two variables are taken into account, the degree of exchange rate rigidity still matters for countries' sensitivity to the global forces driving capital inflows, but not for their sensitivity to the global forces driving capital outflows.[29]

[28] We focus on the global factor loadings, because – as Figures 4 and 5 showed – they vary markedly between advanced and emerging countries, much more so than do the group factor loadings. They also display more variation over time than do the group factor loadings, as can be inferred from the cyclical patterns shown in Figures 8-10.

[29] For emerging markets, Obstfeld, Ostry and Qureshi (2017) likewise find a significant dampening effect of exchange rate flexibility on the responsiveness of gross inflows to global risk, as measured by the VXO index, but not on the response of gross outflows. In contrast, Cerutti, Claessens and Puy (2017) find the

What is the economic significance of the estimates shown in Table 8? To assess this question, consider the effects of raising in turn each of the explanatory variables considered (except for trade openness, which is not significant in the multivariate regressions) from its 25th to its 75th sample percentile. Start with financial openness. Simple calculations show that such a change in the capital account openness index would raise the loading on the global factor by 0.08 for inflows and 0.12 for outflows. With the inflow and outflow global factors unchanged, this in turn would increase the variance share of the global factor by 7 percentage points in the case of inflows and 14 percentage points in the case of outflows.[30]

Similar calculations show that raising financial depth from the 25th to the 75th percentile would increase the variance share of the global factor by 16 and 13 percentage points for inflows and outflows, respectively.

Finally, because of the definition of the exchange rate regime index, raising its value from the 25th to the 75th percentile amounts to moving from a peg to a floating regime. The same calculations as with the other variables reveal that this would reduce the variance share of the global inflow factor by 12 percentage points.

A look at the average variance contribution of the global factors, shown in the first column of Table 5, helps put these calculations in perspective. Each of the experiments considered would change the variance share of global factors by as much as half of its sample average in the case of inflows, and at least one-third in the case of outflows. The overall conclusion is that financial openness, financial depth, and the degree of rigidity of the exchange rate regime all augment countries' exposure to the global drivers of capital flows to an economically-significant extent.

4.6 Adding developing countries

So far we have focused on advanced and emerging countries, leaving aside developing countries due to the lack of evidence that their capital flow patterns reflect the action of (strong) common factors. We next extend the analysis to include the thirty-eight developing countries in Table A1 as another country group. Thus, we re-estimate the factor models for CIF and COD allowing in each case for a developing-country group factor.[31] As already noted, the estimates have to be taken with extra caution, because the principal-component method un-

opposite result: exchange rate flexibility augments the effect of common factors on emerging-country bond and bank inflows.

[30] To compute the change in the inflow and outflow loadings, we use the estimates in the last column of the respective block of Table 5. Because of the normalization imposed, the variance contribution of the factor is just given by the square of its loading. The change in the variance share of the global factor is evaluated at its median value.

[31] To save space, we only provide here a brief summary of the main findings; detailed results are available upon request.

derlying our estimation approach is poorly suited to situations in which the common factors are just weakly (rather than strongly) influential.

The estimated global factors, as well as the group factors for emerging and advanced countries, show little change relative to those obtained when estimating the model on the sample without developing countries. The correlation of the newly-estimated factors (whether global or group-specific) with their respective counterparts in the two-group model exceeds .90 in all cases. In other words, they are virtually indistinguishable from those depicted in Figures 2 and 3 above, and to save space we do not show them here. Likewise, the advanced- and emerging-country loadings on the global and group factors remain virtually unchanged relative to those obtained from the sample without developing countries: the correlation of the loadings from the two samples exceeds 0.97 for the global factor loadings and 0.95 for the group factor loadings. The only discernible difference relative to the earlier results is the fact that advanced countries' group factor loadings rise slightly, at the expense of their global factor loadings. The likely reason is that the addition of developing countries weakens the role of advanced countries in shaping the global factors. The latter must now also reflect the patterns of developing-country gross flows, which – as shown in Table 2 – are less correlated than emerging-country gross flows with the CIF and COD of advanced countries.

Figure 11 depicts the developing-country group factors. We set their sign so that the loading of the largest country (Nigeria) is positive. The CIF factor displays a peak at the onset of the debt crisis in 1981, followed by a sharp decline and a subsequent steady rising trend, interrupted by an abrupt fall in 2006. The factor's first-order autocorrelation coefficient equals 0.54. The COD factor appears somewhat less persistent (its first-order autocorrelation is 0.43). It also shows a deep fall following the global crisis. In both cases, standard ADF unit root tests are able to reject at the 5 percent level the null of a unit root.

On the other hand, the developing-country factors exhibit some distinct features. The pattern of their correlations with other factors replicates that of the between-group correlation of gross flows found in Table 2. In particular, the correlation between the developing-country inflow and outflow factors equals -0.25, in sharp contrast with the positive correlations between the inflow and outflow factors of the other country groups. Also, the CIF factor is negatively correlated with that of advanced countries, and positively correlated with that of emerging countries. In turn, the COD factor is positively correlated with both the COD and the CIF factors of advanced countries.

Empirical exercises similar to those reported in Table 6 show that neither the CIF nor the COD factors of the developing-country group are significantly correlated with the VIX or with the other risk proxies considered before. The same conclusion obtains from regressions similar to those in the bottom block of Table 6, adding as explanatory variables the short-term U.S. real interest rate, the real exchange rate, the U.S. GDP growth rate and the relative price of commodities. The explanatory power of such regressions is very poor, with R^2 under 0.1 in all but one case.[32] In other words, standard 'push' variables do not seem to play a major role as drivers of developing-country capital flows.

The estimated factor loadings of developing countries also merit comment. Overall, the loadings are smaller – especially in the case of the global factors – and their signs are more heterogeneous than among advanced and emerging countries.[33] Moreover, the loadings on the COD and CIF factors are virtually uncorrelated, in contrast with the large positive correlation found in the other country groups. This applies to the loadings on both the global and developing-country group factors.

The conclusion is that developing-country capital flows are less reflective of common external forces than are the flows of the other country groups. This just corroborates the descriptive evidence reported earlier on the limited extent of cross-sectional dependence in the developing-country data. Indeed, Table 7 confirms this presumption. Like Table 5, it shows the decomposition of the variance of capital inflows and outflows, now for the three-group country sample. On average, developing countries exhibit the smallest variance contribution of the common factors, for both CIF and COD, with the difference vis-a-vis the other country groups particularly noteworthy in the case of the latter. The average variance share of the idiosyncratic factors is close to 70 percent for inflows, and close to 80 percent for outflows. Both global and group factors – whose respective contributions are of roughly similar magnitude – play a smaller role in developing-country capital flows than they do in the flows of the other country groups.

Finally, comparing Tables 5 and 7 also reveals that adding developing countries to the analysis causes some changes in the variance decomposition of the capital flows of both advanced and emerging-country groups. For the latter, the changes are minimal, for both inflows and outflows. For the former, the respective roles of idiosyncratic and common factors also exhibit very modest changes. However, although the total contribution of the common factors is roughly unchanged, the respective shares of global and group factors in the total variance of advanced-country inflows and outflows do change: for both inflows and outflows, the share of the group factors rises at the expense of the share of the global factors.[34]

[32] To save space, the results are omitted here but are available from the authors.

[33] For inflows, the majority of the global factor loadings (22 out of 38) are negative, thirteen of them significantly so. Nine are significantly positive. In contrast, all but two of the loadings on the developing-country CIF factor are positive, and 19 of them are significant. In turn, all but four developing countries exhibit positive loadings on the global COD factor, and twenty-two of them are significantly positive at the 5 percent level (two are negative). The signs of the loadings on the developing-country COD factor are more evenly distributed: twenty-seven are positive (of which ten significant) and eleven are negative (of which four significant).

[34] Like with Table 5 above, the advanced-country variance decomposition results in Table 7 are not mate-

5 Concluding remarks

The extent to which countries' financial flows are driven by global forces beyond their control remains a subject of interest for both academics and policy makers. This paper offers a quantitative assessment of the role of common factors for the observed patterns of gross capital flows across a large number of countries. To do this, the paper implements a two-level latent factor model using a novel estimation method based on an extension of the standard principal-component approach. Unlike most of the previous literature, the analysis considers both inflows and outflows.

Our results speak to the ongoing debate on the quantitative importance of the global financial cycle for the observed patterns of capital flows around the world. They can be summarized in four points. First, among advanced and emerging countries, capital flows exhibit a considerable degree of commonality. Common factors – specifically, a global factor, plus an advanced-country factor and an emerging-country factor for each of inflows and outflows – account, on average, for just under half of the observed variation in gross capital flows. Second, commonality is particularly strong among advanced countries, where common factors are responsible for the majority (around 60 percent) of the variation. Among emerging countries, just over one-third of the observed variation in capital flows is attributable to common factors. In other words, common factors dominate advanced-country capital flows, while local (idiosyncratic) factors dominate emerging-country capital flows. Third, the difference between advanced and emerging countries regarding the contribution of common factors is primarily due to the global factor. Its variance contribution is, on average, over twice as large among the former countries than among the latter. In contrast, the contribution of the group-specific factor is roughly similar across the two groups of countries. Fourth, all of the preceding observations apply to both inflows and outflows. In fact, the latent factors for inflows and outflows show a large positive correlation. This is particularly true for the global factors and the advanced-country inflow and outflow group factors. The emerging-country inflow and outflow group factors also show positive, but weaker, correlation. Still, across all country groups, gross outflows are more strongly affected than gross inflows by global factors.

In conclusion, international cycles, as summarized by the estimated common factors, are responsible for much of the observed variation of capital flows, especially among advanced countries. Going one level deeper to explore the forces behind those cycles, we find that a good deal of the variation of the factors themselves can be explained by a handful of variables summarizing real and financial conditions across the world. In particular, all the

rially affected if leading financial centers are omitted from the calculation of the averages.

factors (global and group-specific, for inflows as well as outflows) are robustly negatively correlated with the VIX and similar indices of investor risk aversion. The VIX, along with U.S. interest rates, the U.S. real exchange rate, U.S. real GDP growth, and world commodity prices, account for a substantial share of the variance of the factors – as much as 70 to 80 percent in the case of the global factors, and between 40 and 50 percent in the case of the group factors. This means that, through the common factors, a small set of global variables drives up to half of the variance of advanced-country inflows and outflows, and around one-quarter of the variance of emerging-country inflows and outflows.

Our results shed light on the trends in globalization – as measured by the common component of capital flows – before and after the global crisis. We find a cyclical pattern, with an initial stage ('globalization') in which the common factors gain growing importance up to the crisis, with global factors becoming increasingly dominant, especially in advanced countries – and partly at the expense of group factors. After the crisis, the trend goes in reverse: the role of common factors and, in particular, global factors enters a stage of decline – a 'deglobalization' phase follows.

Exposure to the global cycle varies greatly across countries, and the paper also sheds light on the underlying reasons. Empirical tests find a significant role of the structural and policy framework: countries exhibiting a higher degree of financial openness and/or greater financial depth tend to be impacted more strongly by global cycles – on both the inflow and the outflow side of capital flows. In addition, the exchange rate regime also matters: pegged exchange rates raise, to an economically significant extent, the sensitivity of gross capital inflows to global cycles. Thus, in spite of the wide reach of the global financial cycle, the Trilemma still remains an accurate characterization of countries' choice of exchange rate regime, capital account openness, and monetary autonomy.

References

[1] Adrian, T., D. Stackmand and E. Vogt (2017): "Global price of risk and stabilization policies", unpublished manuscript.

[2] Albuquerque, R., N. Loayza and L. Servén (2006): "World market integration through the lens of foreign direct investors", *Journal of International Economics* 66, 267-295.

[3] Avdjiev, S., L. Gambacorta, L. Goldberg and S. Schiaffi (2017a): "The shifting drivers of global liquidity", BIS Working Paper 644.

[4] Avdjiev, S., B. Hardy, S. Kalemli-Ozcan and L. Servén (2017b): "Capital inflows to banks, corporates, and sovereigns", NBER Working Paper 23116.

[5] Andrews, D. and J. Monahan (1992): "An Improved Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator", *Econometrica* 60, 953-966.

[6] Bai, J. (2003): "Inferential theory for factor models of large dimensions", *Econometrica* 71, 135-71.

[7] Bailey, N., G. Kapetanios and H. Pesaran (2015): "Exponent of cross-sectional dependence: estimation and inference", *Journal of Applied Econometrics*

[8] Bekaert, G., and A. Mehl (2017): "On the global financial integration 'Swoosh' and the Trilemma", unpublished manuscript.

[9] Bluedorn, J., R. Duttagupta, J. Guajardo and P. Topalova (2013): "Capital flows are fickle: anytime, anywhere", IMF Working Paper 13/183.

[10] Breitung, J. and S. Eickmeier (2016): "Analyzing International Business and Financial Cycles using Multi-Level Factor Models: A Comparison of Alternative Approaches", in E. Hillebrand and S.Koopman (eds.), *Advances in Econometrics* vol 33.

[11] Broner, F., T. Didier, A. Erce, and S. Schmuker (2013): "Gross capital flows: dynamics and crises", *Journal of Monetary Economics* 60, 113-133.

[12] Bruno, V. and H. Shin (2015a): "Capital flows and the risk-taking channel of monetary policy", *Journal of Monetary Economics* 71, 119-132.

[13] Bruno, V. and H. Shin (2015b): "Cross-border banking and global liquidity", *Review of Economic Studies* 82, 535-564.

[14] Byrne, J. and N. Fiess (2011): "International Capital Flows to Emerging and Developing Countries: National and Global Determinants, " *Journal of International Money and Finance* 61, 82-100.

[15] Calvo, G., L. Leiderman and C. Reinhart (1996): "Inflows of capital to developing countries in the 1990s", *Journal of Economic Perspectives* 10, 123-139.

[16] Cerutti, E., S. Claessens, and D. Puy (2017): "Push factors and capital flows to emerging markets: why knowing your lender matters more than fundamentals", unpublished manuscript.

[17] Cerutti, E., S. Claessens, and L. Ratnovski (2017): "Global liquidity and cross-border bank flows", *Economic Policy*, 81-125.

[18] Cerutti, E., S. Claessens, and A. Rose (2017): "How important is the global financial cycle? Evidence from capital flows", CEPR Discussion paper 12075.

[19] Choi, I. (2012): "Efficient estimation of factor models", *Econometric Theory* 28, 274-308.

[20] Choi, I. (2017): "Efficient estimation of nonstationary factor models", *Journal of Statistical Planning and Inference* 183, 18-43.

[21] Choi, I. and H. Jeong (2017): " Model Selection for Factor Analysis: Some New Criteria and Performance Comparisons" , *Econometric Reviews*

[22] Choi, I., D. Kim, Y. Kim and N. Kwark (2017): "A multilevel factor model: identification, asymptotic theory and applications", *Journal of Applied Econometrics* (forthcoming).

[23] Davis, J. and E. van Wincoop (2017): "Globalization and the Increasing Correlation between Capital Inflows and Outflows ", NBER Working Paper 23671.

[24] Eichengreen, B., P. Gupta and O. Masetti (2017): "Are capital flows fickle? Increasingly ? and does the answer still depend on type?", World Bank Policy Research Working Paper 7972.

[25] Ergemen, Y. and C. Rodriguez-Caballero (2016): "A dynamic multi-level factor model with long-range dependence", CREATES Research Paper 2016-23.

[26] Forbes, C. and F. Warnock (2012): "Capital flow waves: surges, stops, flight and retrenchment", *Journal of International Economics* 88, 235-251.

[27] Forbes, K., D. Reinhardt and T. Wieladek (2017): "The spillovers, interactions, and (un)intended consequences of monetary and regulatory policies", *Journal of Monetary Economics* 85, 1-22.

[28] Fratzscher, M. (2012): "Capital flows, push versus pull factors, and the global financial crisis", *Journal of International Economics* 88, 341-356.

[29] Ghosh, A., J. Ostry and M. Qureshi (2015): "Exchange Rate Management and Crisis Susceptibility: A Reassessment", *IMF Economic Review* 63, 238-276.

[30] Jorda, O., M. Schularick, A. Taylor and F. Ward (2017): "Global financial cycles and risk premiums", unpublished manuscript.

[31] Kose, A., C. Otrok and C. Whiteman (2003): "International Business Cycles: World, Region, and Country-Specific Factors", *American Economic Review* 93, 1216-1239.

[32] Leamer, E. (1984): *Sources of International Comparative Advantage: Theory and Evidence*, Cambridge, MA: MIT Press.

[33] Leamer, E. (1995): *The Heckscher-Ohlin Model in Theory and Practice*, Princeton Studies in International Finance.

[34] Miranda-Agrippino, S. and H. Rey (2015): "World asset markets and the global financial cycle", NBER Working Paper 21722.

[35] Obstfeld, M., J. Ostry and M. Qureshi (2017): "A Tie That Binds: Revisiting the Trilemma in Emerging Market Economies", IMF Working Paper 17/130.

[36] Onatski, A. (2012): " Asymptotics of the principal components estimator of large factor models with weakly influential factors", *Journal of Econometrics* 168, 244-258.

[37] Raddatz, C. and S. Schmukler (2012): "On the International Transmission of Shocks: Micro-Evidence from Mutual Fund Portfolios," *Journal of International Economics* 88, 357-374.

[38] Reinhart, C., V. Reinhart and C. Trebesch (2017): "Capital flow cycles: a long, global view", unpublished manuscript.

[39] Rey, H. (2013): "Dilemma not Trilemma: the global financial cycle and monetary policy independence", *Proceedings of the Federal Reserve Bank at Kansas City Economic Symposium at Jackson Hole.*

[40] Rose, A. and T. Wieladek (2014): "Financial protectionism: first evidence", *Journal of Finance* 69, 2127–2149.

[41] Wang, P. (2014): "Large dimensional factor models with a multi-level factor structure: identification, estimation and inference", unpublished manuscript.

Table 1
Gross capital flows: descriptive statistics

	CIF			COD			Correlation CIF - COD
	Mean	Std. Deviation	Coef. of Variation	Mean	Std. Deviation	Coef. of Variation	
All countries	7.71	10.03	1.20	6.69	10.09	1.92	0.47
Advanced	11.99	12.15	0.92	12.03	12.24	0.96	0.90
Emerging	6.16	7.25	1.16	6.07	8.97	1.40	0.48
Developing	6.39	11.19	1.42	3.87	9.73	2.99	0.19

Notes: this table reports group averages of the individual-country statistics (shown in Table A3). CIF = gross inflows; COD = gross outflows.

Table 2
Gross capital flows: cross-country comovement
(a) Average cross-country correlation

Flow / Region		CIF			COD		
		Advanced	Emerging	Developing	Advanced	Emerging	Developing
CIF	Advanced	0.435					
	Emerging	0.143	0.209				
	Developing	-0.074	0.085	0.109			
COD	Advanced	0.434	0.142	-0.087	0.488		
	Emerging	0.290	0.155	-0.009	0.315	0.251	
	Developing	0.133	0.089	-0.006	0.151	0.142	0.070

(b) Percentage of significant correlations

Flow / Region		CIF			COD		
		Advanced	Emerging	Developing	Advanced	Emerging	Developing
CIF	Advanced	0.87					
	Emerging	0.55	0.58				
	Developing	0.58	0.53	0.54			
COD	Advanced	0.82	0.53	0.60	0.90		
	Emerging	0.77	0.51	0.51	0.81	0.69	
	Developing	0.54	0.47	0.40	0.59	0.56	0.42

Notes: In panel (a), entry (*i,j*) is the average of the pairwise correlations between the flows of countries in group *i* and those of countries in group *j*. In panel (b), entry (*i,j*) indicates the percentage of all the pairwise correlations underlying the average shown in panel (a) that are statistically significant at the 95 percent level, with the standard error of a correlation *r* approximated by the square root of $(1 - r^2)/(T\text{-}1)$. Diagonal entries in each block of the table correspond to within-group correlations (excluding the own-country correlation), off-diagonal elements correspond to between-group correlations.
CIF = gross inflows; COD = gross outflows.

Table 3

Exponent of cross-sectional dependence

Group	Flow CIF	COD
Advanced	0.97	0.99
	(0.83, 1.10)	(0.88, 1.11)
Emerging	0.96	0.95
	(0.90, 1.02)	(0.84, 1.05)
Developing	0.86	0.82
	(0.82, 0.89)	(0.74, 0.89)

Notes: CIF = gross inflows; COD = gross outflows.
95-percent confidence intervals shown in parentheses.

Table 4
Correlation of common factors

Flow / Region		CIF		COD	
		Advanced	Emerging	Advanced	Emerging
CIF	Advanced	1.000			
	Emerging	-0.016	1.000		
COD	Advanced	0.821	-0.068	1.000	
	Emerging	-0.140	0.343	0.157	1.000

Note: CIF = gross inflows; COD = gross outflows.

Table 5

Variance decomposition by group (percent)

(a) Gross Inflows

	All countries	Advanced countries	Emerging countries
Global share	24.1	37.5	15.0
Group share	21.3	22.3	20.6
Country share	54.6	40.2	64.5

(b) Gross Outflows

	All countries	Advanced countries	Emerging countries
Global share	33.8	46.7	25.1
Group share	14.3	17.2	12.2
Country share	51.9	36.1	62.7

Note: The numbers shown are averages of the individual-country estimates.

Table 6
Covariates of the common factors

Variables	Factors Global CIF	Global COD	Advanced countries CIF	Advanced countries COD	Emerging countries CIF	Emerging countries COD
A. Regressions on risk measures						
VIX (1990-2015)	-0.076 **	-0.057 ***	-0.095 **	-0.154 **	-0.099 ***	-0.123 ***
	(0.033)	(0.021)	(0.042)	(0.068)	(0.012)	(0.027)
R^2	0.222	0.155	0.227	0.274	0.302	0.164
VXO (1986-2015)	-0.050 *	-0.032 *	-0.074 *	-0.134 **	-0.073 ***	-0.105 *
	(0.028)	(0.019)	(0.040)	(0.066)	(0.020)	-(0.054)
R^2	0.147	0.075	0.212	0.312	0.252	0.183
10-year BAA spread (1979-2015)	-0.598 *	-0.509 ***	-0.713 **	-1.032 *	-0.558 ***	-0.812 *
	(0.311)	(0.165)	(0.352)	(0.557)	(0.226)	(0.428)
R^2	0.266	0.237	0.245	0.229	0.155	0.131
B. Multivariate regressions						
VIX	-0.059 ***	-0.036 ***	-0.085 *	-0.159 ***	-0.084 ***	-0.133 ***
	(0.017)	(0.013)	(0.045)	(0.061)	(0.027)	(0.045)
U.S. short-term real interest rate	0.043	-0.026	0.364 *	0.606	0.243	0.583
	(0.089)	(0.077)	(0.217)	(0.380)	(0.195)	(0.399)
Log U.S. real exchange rate	5.413 ***	0.580	-10.943 *	-5.108	-11.156 **	-7.639
	(1.970)	(2.042)	(6.353)	(7.310)	(5.363)	(7.866)
U.S. real GDP growth	13.280 ***	23.275 ***	17.052 **	-3.715	-2.768	-31.188 **
	(3.464)	(3.431)	(8.464)	(12.970)	(6.936)	(12.317)
Log world commodity price index	2.610 ***	1.863 ***	-3.867 ***	-4.435 **	-1.560	-4.051 **
	(0.487)	(0.556)	(1.481)	(1.904)	(1.142)	(1.807)
R^2	0.726	0.833	0.495	0.555	0.441	0.457

Notes: All variables except U.S. real GDP growth are expressed in first differences. HAC standard errors in parentheses.
All regressions include a constant. *** p<0.01, ** p<0.05, * p<0.1

Table 7

Variance decomposition including developing countries (percent)

(a) Gross Inflows

	All countries	Advanced countries	Emerging countries	Developing countries
Global share	19.0	31.9	16.1	14.6
Group share	20.0	26.6	19.6	17.0
Country share	61.0	41.5	64.3	68.3

(b) Gross Outflows

	All countries	Advanced countries	Emerging countries	Developing countries
Global share	23.9	39.7	27.2	13.5
Group share	12.9	23.2	11.4	8.8
Country share	63.3	37.1	61.4	77.7

Note: The numbers shown are averages of the individual-country estimates.

Table 8
Covariates of the global factor loadings

Covariates	CIF					COD				
	1	2	3	4	5	1	2	3	4	5
Financial openness	0.251***				0.139***	0.274***				0.206***
	[0.041]				[0.051]	[0.044]				[0.050]
Trade openness		0.062**			-0.046		0.0824**			0.033
		[0.024]			[0.031]		[0.036]			[0.037]
Domestic credit (% of GDP)			0.001***		0.002***			0.001***		0.001***
			[0.000]		[0.000]			[0.000]		[0.000]
Exchange Rate arrangement				-0.104***	-0.115***				-0.042**	-0.042
				[0.0221]	[0.0244]				[0.0197]	[0.0425]
Observations	846	846	846	846	846	846	846	846	846	846
Prob > Chi2	0.000	0.010	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Panel GLS-AR(1) regressions. The dependent variable is the global factor loadings estimates over moving 20-year windows, and a constant is included. Standard errors in brackets. The explanatory variables are averages over the respective window. Financial openness is the Chinn-Ito index, trade openness is the log of total trade over GDP, the exchange rate arrangement is measured using the De Facto aggregate classification of Ghosh, Ostry and Qureshi (2015), setting Peg = 1, Intermediate = 2, and Float = 3 . *** p<0.01, ** p<0.05, * p<0.1

Table A1
Country List

Advanced countries	Emerging countries	Developing countries	
Australia	Argentina	Albania	Paraguay
Austria	Brazil	Bangladesh	Rwanda
Canada	Chile	Benin	Sierra Leone
Denmark	China	Bolivia	Sri Lanka
Finland	Colombia	Botswana	Sudan
France	Cyprus	Bulgaria	Swaziland
Germany	Egypt	Cameroon	Tanzania
Ireland	India	Costa Rica	Trinidad and Tobago
Italy	Israel	Dominican Rep.	Tunisia
Japan	Jordan	Ecuador	Uganda
Netherlands	Korea	El Salvador	
New Zealand	Kuwait	Ethiopia	
Norway	Malaysia	Fiji	
Portugal	Mexico	Ghana	
Spain	Morocco	Guatemala	
Sweden	Oman	Haiti	
Switzerland	Pakistan	Honduras	
United Kingdom	Peru	Jamaica	
United States	Philippines	Lesotho	
	Poland	Madagascar	
	Romania	Malawi	
	Saudi Arabia	Mauritius	
	Singapore	Myanmar	
	South Africa	Nepal	
	Thailand	Nicaragua	
	Turkey	Nigeria	
	Uruguay	Panama	
	Venezuela	Papua New Guinea	

Table A2
Data Sources

#	Series	Description	Source	Coverage
1	Capital Flows	Gross Asset and Liability Flows	IMF BOP	1970-2015
2	Nominal GDP in U.S. dollars	Nominal GDP in U.S. dollars	UN National Accounts	1960-2015
3	VIX	CBOE Volatility Index	FRED	1990-2015
4	VXO	CBOE S&P 100 Volatility Index	FRED	1986-2015
5	10-year BAA spread	Moody's Baa Corporate rate minus Treasury 10Y rate	FRED	1970-2015
6	U.S. short-term real interest rate	Effective Fed Funds Rate minus GDP inflation	FRED	1970-2015
7	U.S. real GDP growth	Gross Domestic Product in constant US dollars	IMF IFS	1970-2015
8	U.S. real exchange rate	Real Effective Exchange Rate REER	IMF IFS	1979-2015
9	World commodity price index	Commodity Price Index - Metals and Minerals	UNCTAD	1960-2015
10	Financial openness	Chinn-Ito Index of Capital Account Liberalization	Chinn-Ito	1960-2014
11	Trade openness (% of GDP)	Total Exports plus Imports over GDP	UN National Accounts	1960-2015
12	Domestic credit (% of GDP)	Domestic credit to private sector over GDP	WB WDI	1960-2015
13	Exchange Rate regime	De Facto Aggregate ERA	Gosh, Ostry and Qureshi (2015)	1980-2011
14	Commodity intensity	Net Exports of Commodities over GDP (Leamer index)	Comtrade/UNCTAD	1960-2015

Table A3
Descriptive statistics by country

Countries	CIF Mean	CIF Std. Deviation	CIF Coef. of Variation	COD Mean	COD Std. Deviation	COD Coef. of Variation	Correlation CIF & COD
Advanced							
Australia	8.16	3.33	0.41	3.97	2.76	0.69	0.93
Austria	9.23	11.75	1.27	9.34	11.95	1.28	0.98
Canada	7.08	2.64	0.37	5.43	3.00	0.55	0.69
Denmark	7.57	8.23	1.09	8.83	8.14	0.92	0.89
Finland	10.36	10.22	0.99	10.77	11.34	1.05	0.89
France	8.46	7.51	0.89	8.50	7.73	0.91	0.98
Germany	6.54	5.88	0.90	8.45	5.79	0.69	0.88
Ireland	60.23	69.83	1.16	57.47	68.58	1.19	1.00
Italy	5.44	4.01	0.74	4.56	3.93	0.86	0.90
Japan	2.33	2.49	1.07	4.53	2.65	0.59	0.84
Netherlands	23.88	26.35	1.10	27.29	26.87	0.98	0.99
New Zealand	6.06	3.94	0.65	1.76	3.32	1.89	0.69
Norway	8.22	9.70	1.18	13.19	13.08	0.99	0.89
Portugal	10.28	9.48	0.92	6.81	7.00	1.03	0.89
Spain	8.83	7.74	0.88	6.42	6.08	0.95	0.91
Sweden	9.48	7.32	0.77	10.46	8.47	0.81	0.90
Switzerland	12.11	17.32	1.43	20.95	19.49	0.93	0.97
United Kingdom	18.15	19.15	1.06	16.95	19.73	1.16	0.99
United States	5.78	3.64	0.63	3.49	2.63	0.75	0.88
Emerging							
Argentina	3.66	3.15	0.86	1.96	2.68	1.37	0.56
Brazil	4.04	2.75	0.68	1.77	2.34	1.33	0.48
Chile	9.21	5.39	0.59	6.02	5.42	0.90	0.65
China	3.63	2.55	0.70	4.97	4.40	0.88	0.75
Colombia	4.41	2.90	0.66	2.18	2.05	0.94	0.50
Cyprus	21.84	51.33	2.35	17.18	49.63	2.89	1.00
Egypt	3.55	5.72	1.61	2.93	4.47	1.53	-0.09
India	3.15	2.07	0.66	1.77	1.99	1.13	0.80
Israel	5.88	4.47	0.76	5.70	4.51	0.79	0.57
Jordan	9.01	8.36	0.93	6.46	7.89	1.22	0.66
Korea	3.68	4.08	1.11	4.05	3.32	0.82	0.19
Kuwait	1.57	7.84	4.98	20.90	45.51	2.18	0.51
Malaysia	6.21	6.21	1.00	7.33	7.58	1.03	0.20
Mexico	4.59	3.17	0.69	1.81	2.04	1.13	0.37
Morocco	4.43	3.29	0.74	1.74	2.52	1.45	0.06
Oman	3.79	4.17	1.10	6.57	9.48	1.44	0.41
Pakistan	2.84	2.20	0.78	0.75	1.81	2.42	0.04
Peru	6.06	3.56	0.59	2.74	3.56	1.30	0.51
Philippines	4.36	4.26	0.98	2.71	3.71	1.37	0.38

Table A3 (continued)
Descriptive statistics by country

Countries	CIF			COD			Correlation CIF & COD
	Mean	Std. Deviation	Coef. of Variation	Mean	Std. Deviation	Coef. of Variation	
Emerging (continued)							
Poland	4.89	3.64	0.74	2.35	2.38	1.01	0.49
Romania	4.29	6.51	1.52	1.64	2.63	1.60	0.58
Saudi Arabia	2.07	2.86	1.38	5.13	15.18	2.96	0.33
Singapore	32.21	35.77	1.11	43.77	40.69	0.93	0.97
South Africa	3.51	4.18	1.19	2.39	2.45	1.03	0.79
Thailand	5.03	5.85	1.16	3.96	4.24	1.07	0.41
Turkey	3.76	3.40	0.90	1.44	1.47	1.02	0.57
Uruguay	6.19	5.39	0.87	3.76	6.28	1.67	0.70
Venezuela	2.45	3.32	1.35	4.95	5.68	1.15	0.20
Developing							
Albania	6.19	6.66	1.08	3.64	3.78	1.04	0.50
Bangladesh	2.50	1.16	0.46	1.61	1.40	0.87	-0.08
Benin	4.13	6.64	1.61	1.32	4.09	3.09	0.31
Bolivia	7.26	5.86	0.81	3.81	5.19	1.36	-0.14
Botswana	6.75	5.81	0.86	12.77	11.97	0.94	0.06
Bulgaria	7.14	12.12	1.70	3.63	4.96	1.37	0.57
Cameroon	4.07	3.31	0.81	0.92	2.45	2.67	0.26
Costa Rica	7.15	4.77	0.67	3.02	2.38	0.79	0.60
Dominican Rep.	4.75	2.75	0.58	1.10	2.14	1.95	0.27
Ecuador	3.23	3.30	1.02	1.84	2.39	1.30	-0.06
El Salvador	5.29	6.50	1.23	0.95	3.41	3.58	0.26
Ethiopia	3.73	2.02	0.54	-0.67	2.85	-4.25	-0.17
Fiji	4.99	6.86	1.37	0.73	3.87	5.33	0.41
Ghana	5.35	4.17	0.78	0.57	1.92	3.39	0.14
Guatemala	4.60	2.29	0.50	0.78	2.43	3.13	0.66
Haiti	2.41	3.52	1.46	1.06	3.49	3.29	-0.46
Honduras	6.34	3.71	0.58	1.71	2.54	1.49	0.24
Jamaica	10.50	8.26	0.79	3.96	5.51	1.39	0.79
Lesotho	11.80	12.53	1.06	14.18	10.49	0.74	0.05
Madagascar	7.61	5.74	0.75	0.95	2.27	2.40	0.39
Malawi	4.01	9.85	2.46	0.17	2.29	13.62	0.10
Mauritius	40.95	116.95	2.86	39.16	116.12	2.97	1.00
Myanmar	3.78	2.42	0.64	1.31	2.64	2.02	-0.08
Nepal	3.05	1.84	0.60	2.37	4.36	1.84	-0.32
Nicaragua	7.00	19.62	2.80	1.51	3.04	2.02	-0.02
Nigeria	2.38	3.82	1.60	4.16	4.10	0.99	0.09
Panama	10.67	73.39	6.88	6.00	70.96	11.83	1.00
Papua New Guinea	1.23	5.23	4.24	1.39	5.57	4.01	0.07
Paraguay	2.51	3.79	1.51	0.42	3.19	7.60	-0.01

Table A3 (continued)
Descriptive statistics by country

Countries	CIF			COD			Correlation CIF & COD
	Mean	Std. Deviation	Coef. of Variation	Mean	Std. Deviation	Coef. of Variation	
Developing (continued)							
Rwanda	2.66	6.94	2.61	1.07	2.59	2.41	-0.13
Sierra Leone	7.28	10.11	1.39	0.77	2.78	3.63	-0.41
Sri Lanka	5.16	2.58	0.50	1.10	2.37	2.15	0.33
Sudan	5.13	3.16	0.62	1.03	1.49	1.45	0.41
Swaziland	4.88	3.78	0.78	4.03	8.01	1.99	0.07
Tanzania	4.80	4.98	1.04	0.87	1.36	1.56	-0.06
Trinidad and Tobago	-1.18	8.44	-7.14	3.09	7.95	2.57	-0.28
Tunisia	6.34	2.21	0.35	2.59	2.16	0.83	0.30
Uganda	3.54	5.12	1.45	0.99	1.76	1.78	0.18

Table A4

Information criteria for selecting the number of factors

Global factors	Factors by Group	CIF			COD		
		IC_{P2}	BIC	HQ	IC_{P2}	BIC	HQ
1	1	3.8	7.0	7.1	3.7	7.0	7.1
1	2	6.2	7.5	7.6	6.1	7.5	7.6
1	3	8.6	7.9	8.0	8.5	7.8	7.9
2	1	5.4	7.4	7.5	5.3	7.4	7.5
2	2	7.8	7.8	7.9	7.8	7.7	7.8
2	3	10.2	8.1	8.2	10.2	8.0	8.1
3	1	7.1	7.7	7.8	7.0	7.6	7.7
3	2	9.5	8.0	8.1	9.4	7.9	8.0
3	3	11.9	8.2	8.3	11.9	8.2	8.3

Note: CIF = gross inflows; COD = gross outflows.

Table A5

Panel unit root and stationarity tests

Test	Null Hypothesis	CIF P-Val	COD P-Val
Im-Pesaran-Shin	Ho: All panels contain unit roots	0.00	0.00
Hadri LM	Ho: All panels are stationary	0.35	0.61

Notes: the specification includes two lags and no time trend.
CIF = gross inflows; COD = gross outflows.

Table A6

Variance decomposition by group, excluding global financial centers (percent)

(a) Gross Inflows

	All countries	Advanced countries	Emerging countries
Global share	23.1	38.1	15.0
Group share	20.3	19.9	20.6
Country share	56.6	42.0	64.5

(b) Gross Outflows

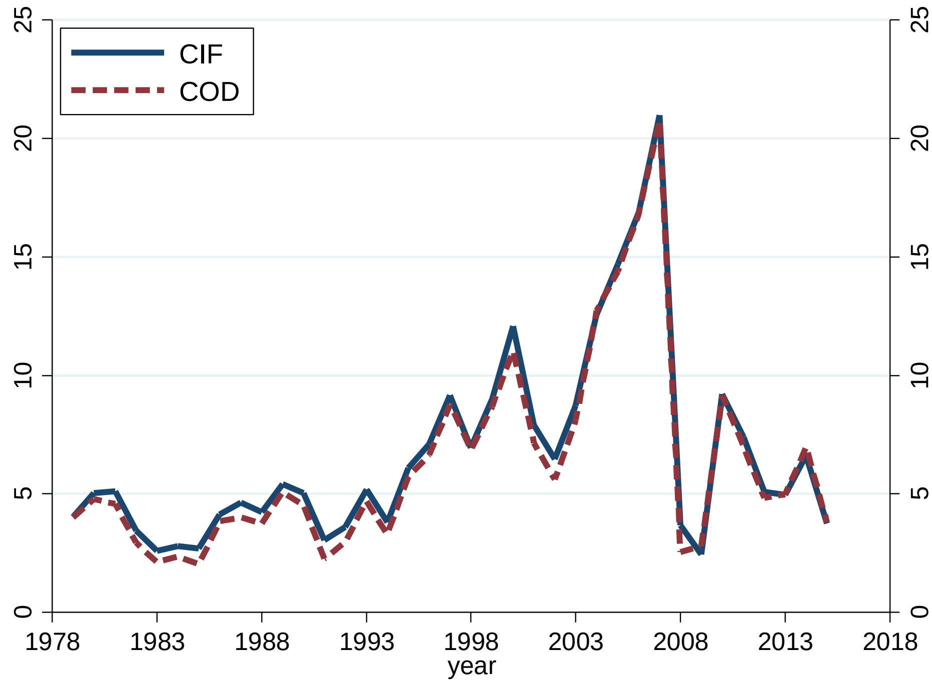
	All countries	Advanced countries	Emerging countries
Global share	33.2	48.5	25.1
Group share	13.3	15.4	12.2
Country share	53.4	36.1	62.7

Note: The numbers shown are averages of the individual-country estimates, computed excluding the U.S., U.K., Germany, and Japan.

Figure 1

Gross capital flows by country group (percent of trend GDP)

(a) All countries



(a) Advanced countries

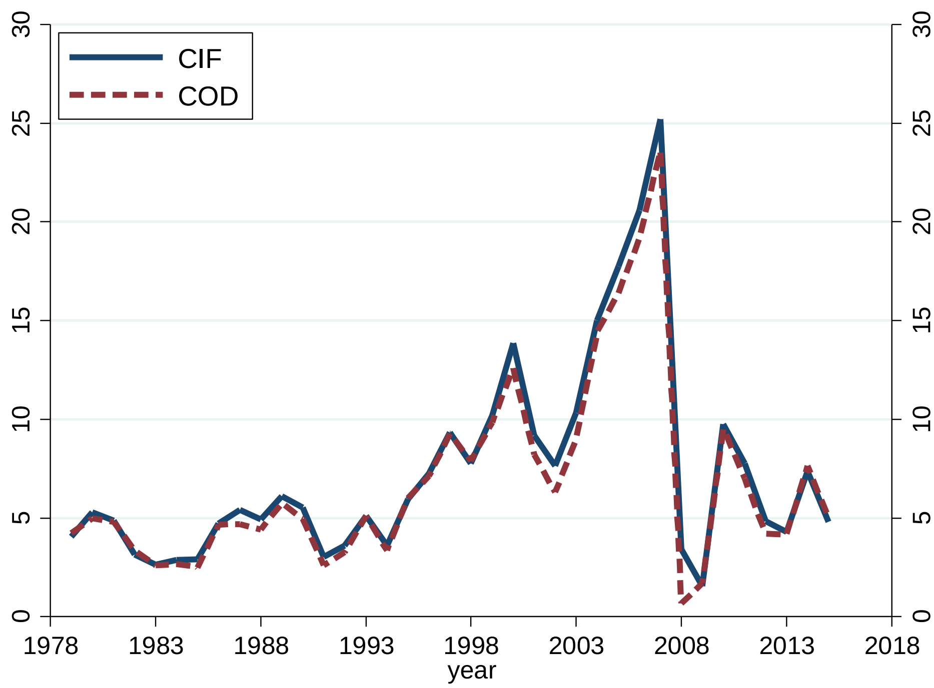
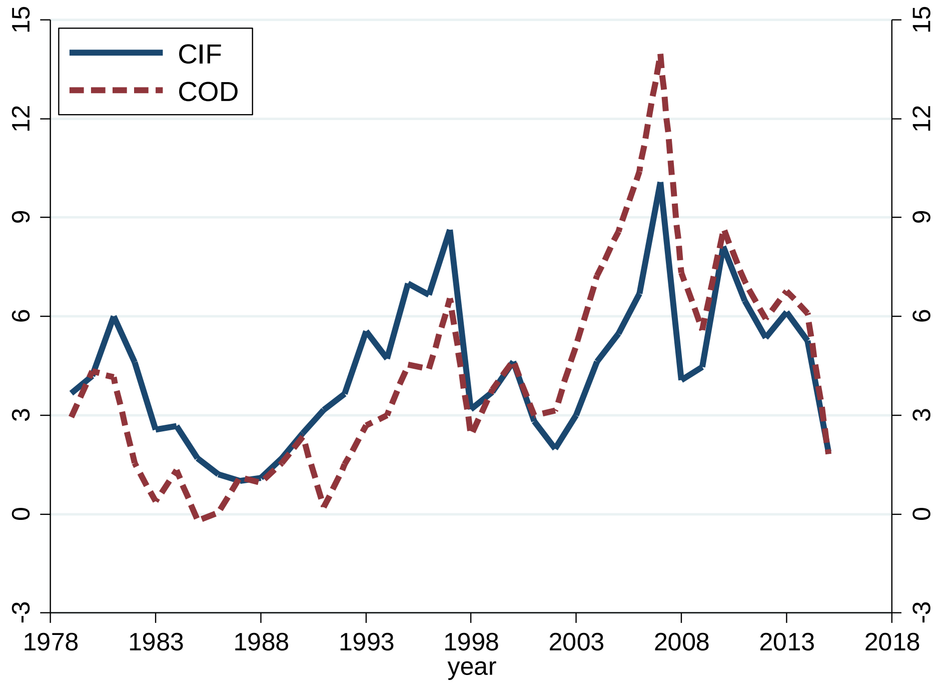


Figure 1 (continued)
Gross capital flows by country group (percent of trend GDP)

(b) Emerging countries



(c) Developing countries

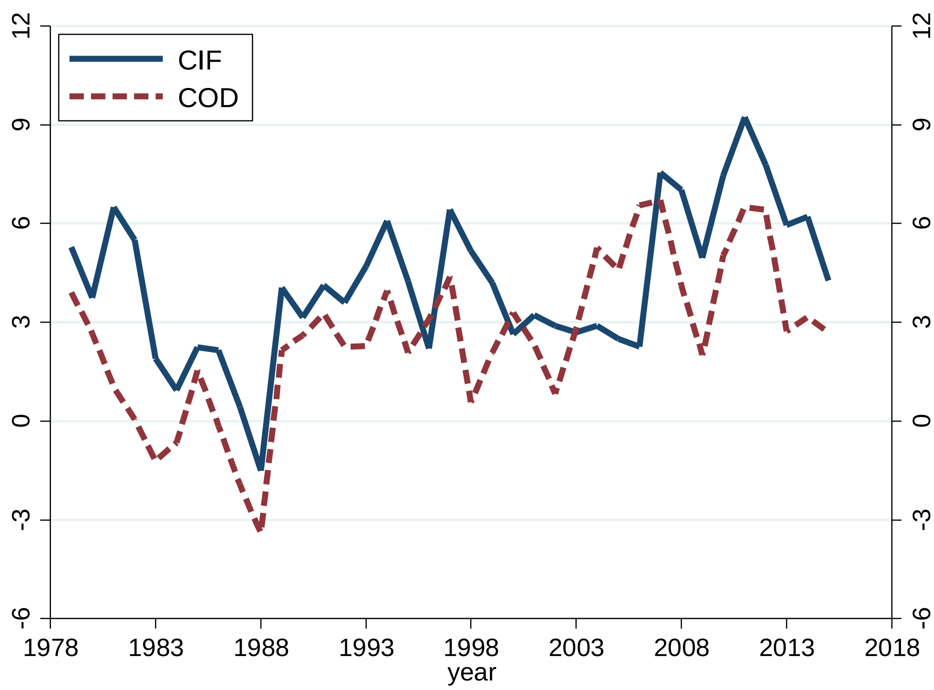


Figure 2
Global factors

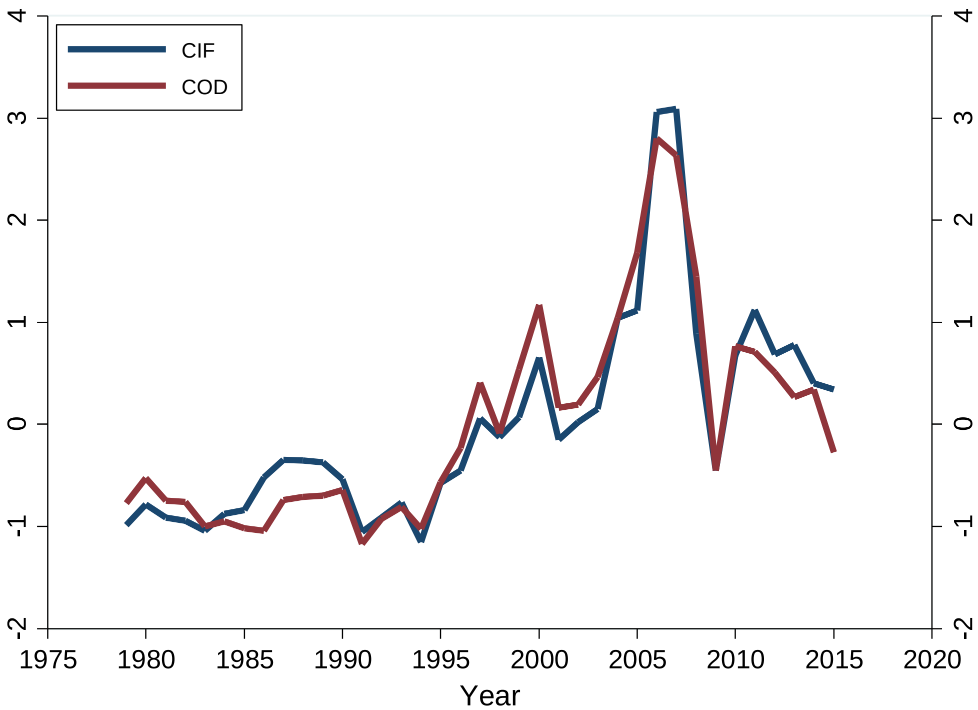
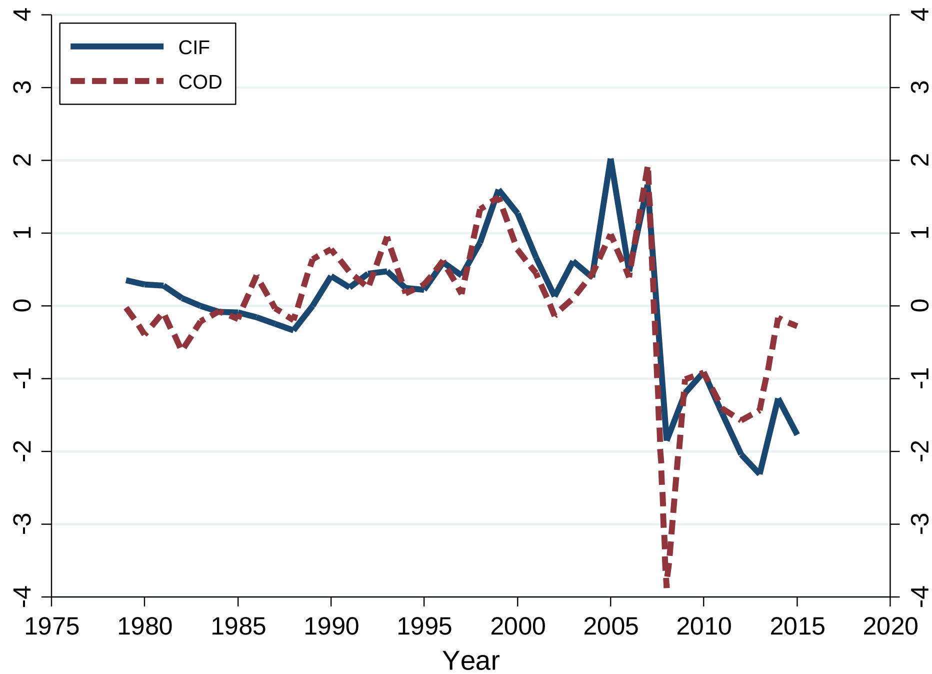


Figure 3
Group factors

(a) Advanced countries



(b) Emerging countries

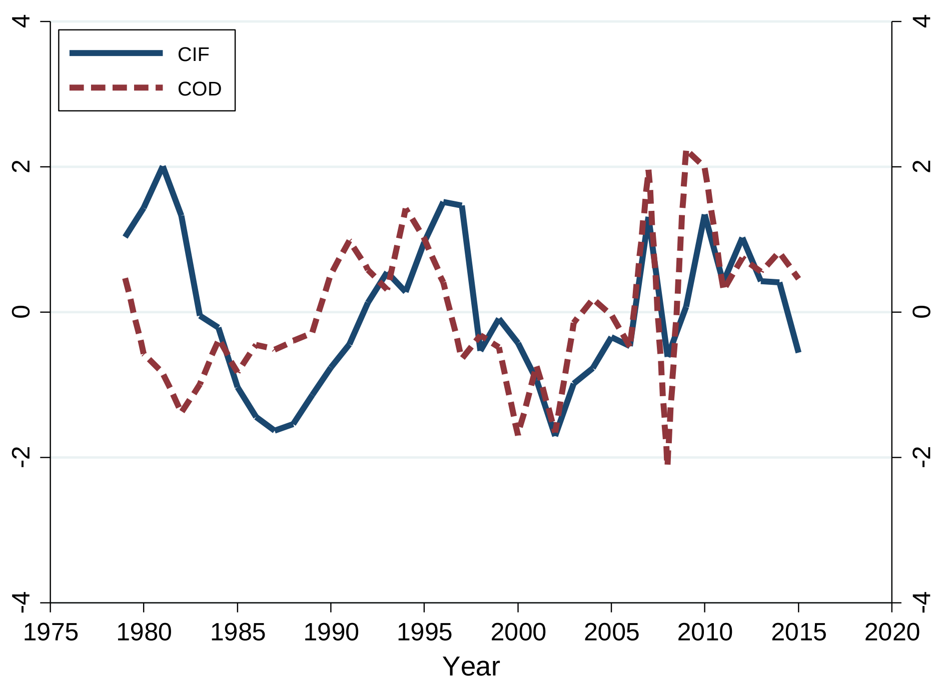
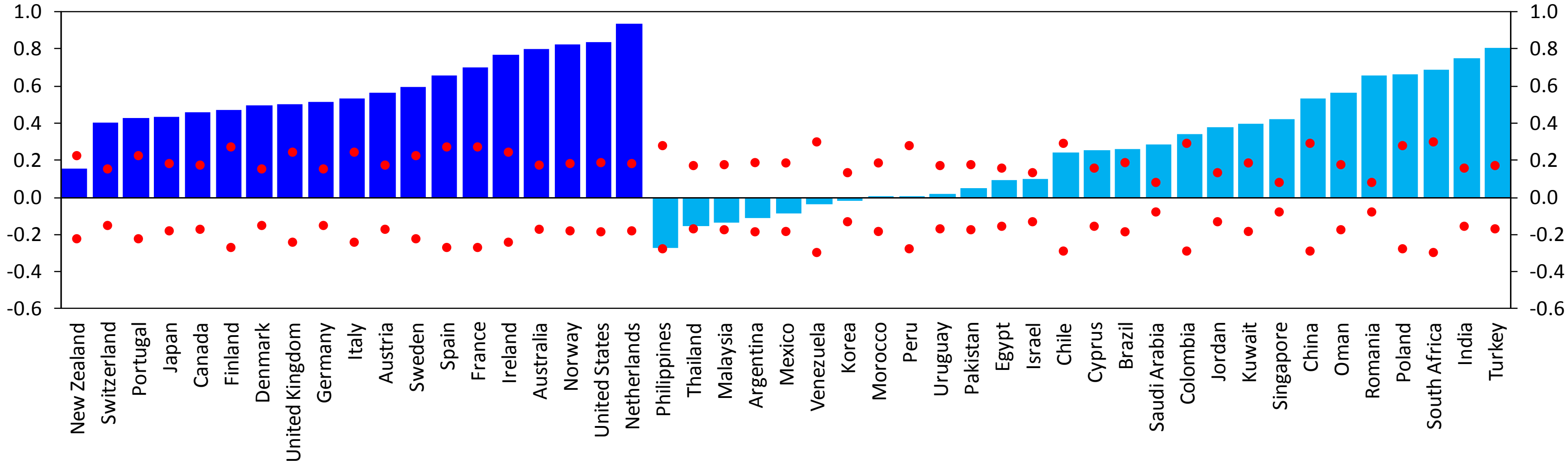


Figure 4
Global factor loadings

(a) Gross Inflows



(b) Gross Outflows

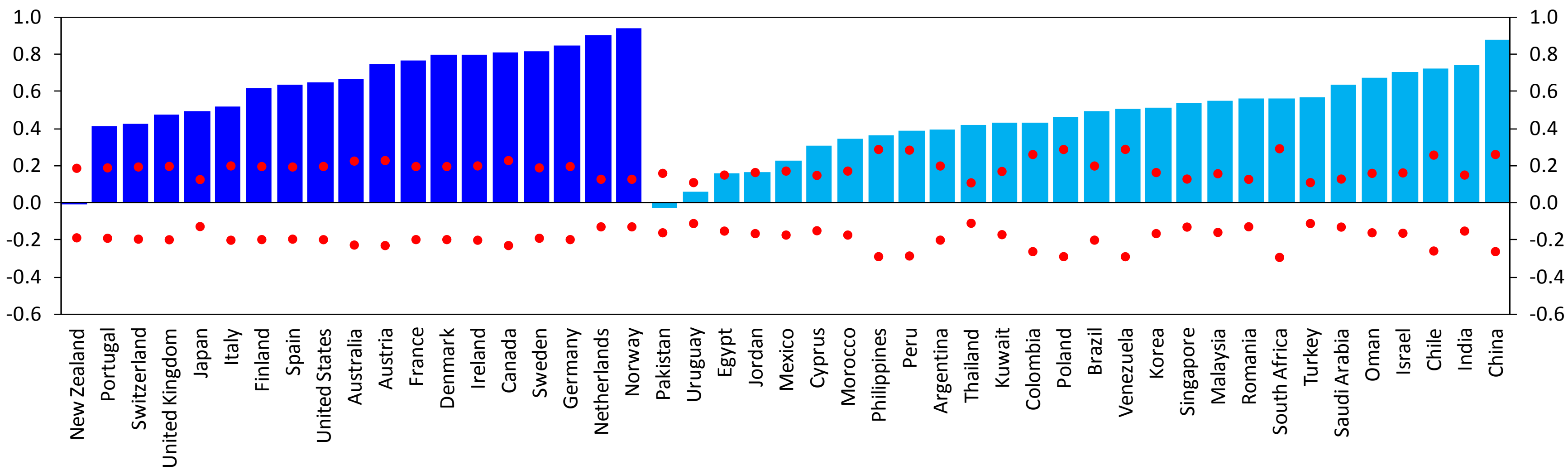
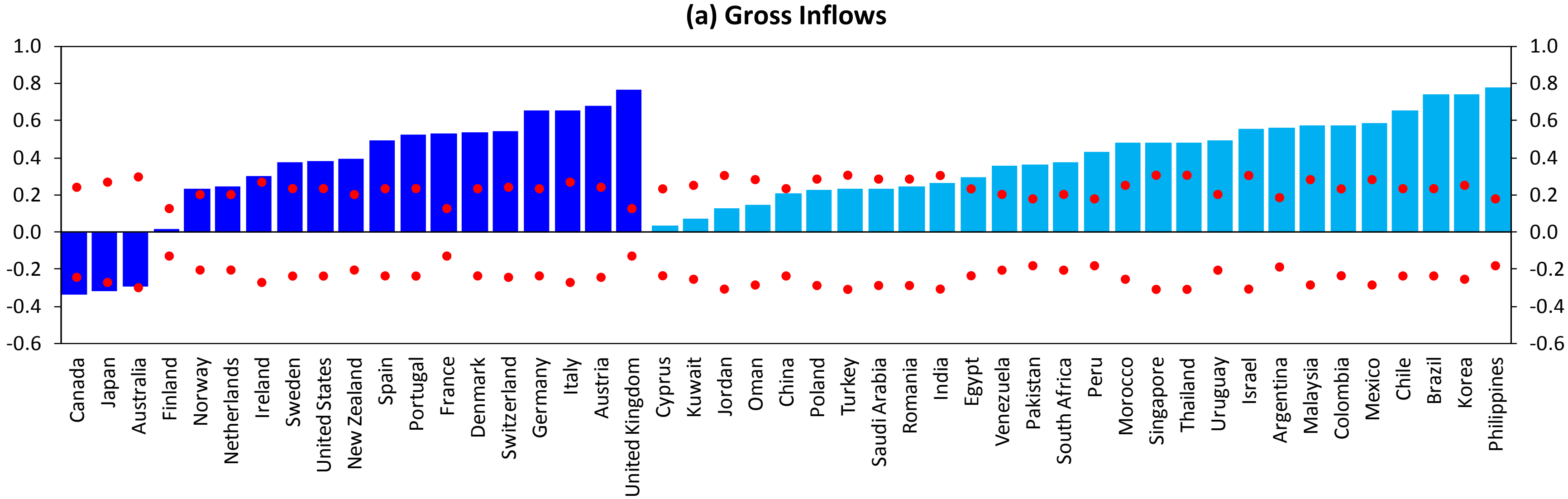


Figure 5
Group factor loadings



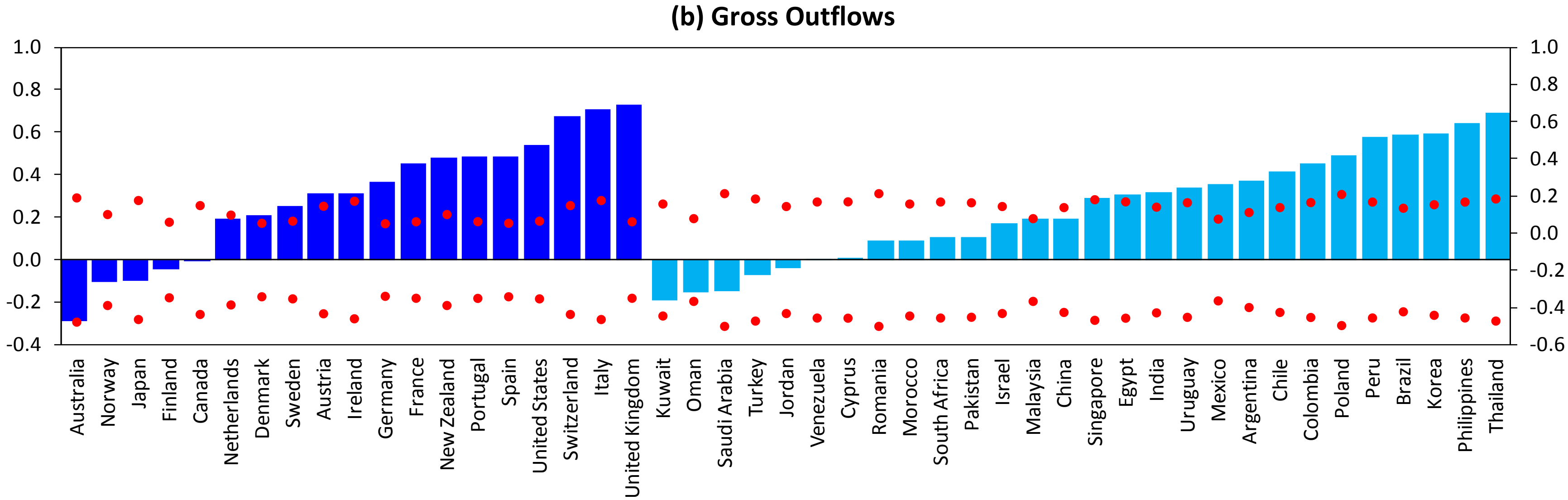


Figure 6
Variance decomposition by country

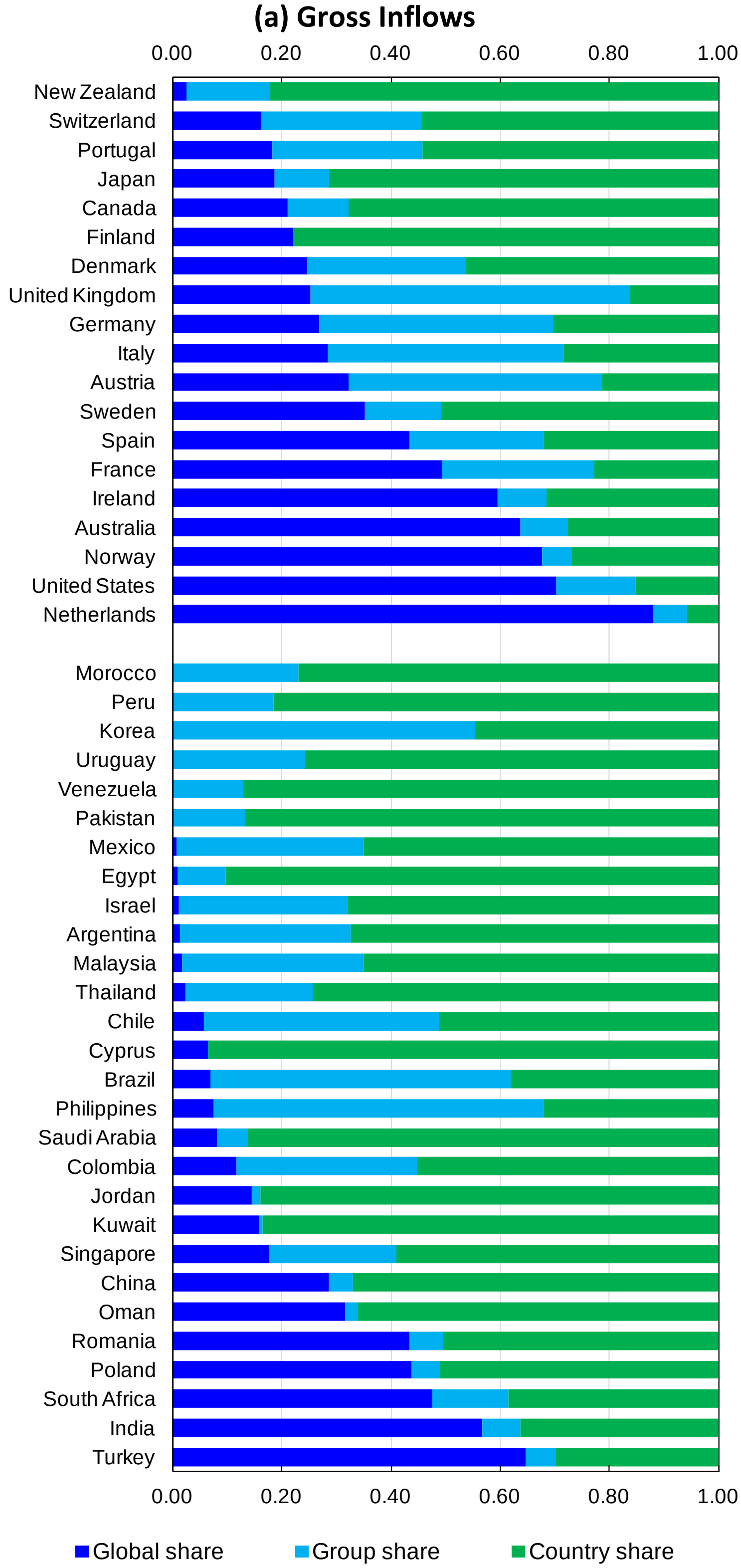


Figure 6 (continued)
Variance decomposition by country

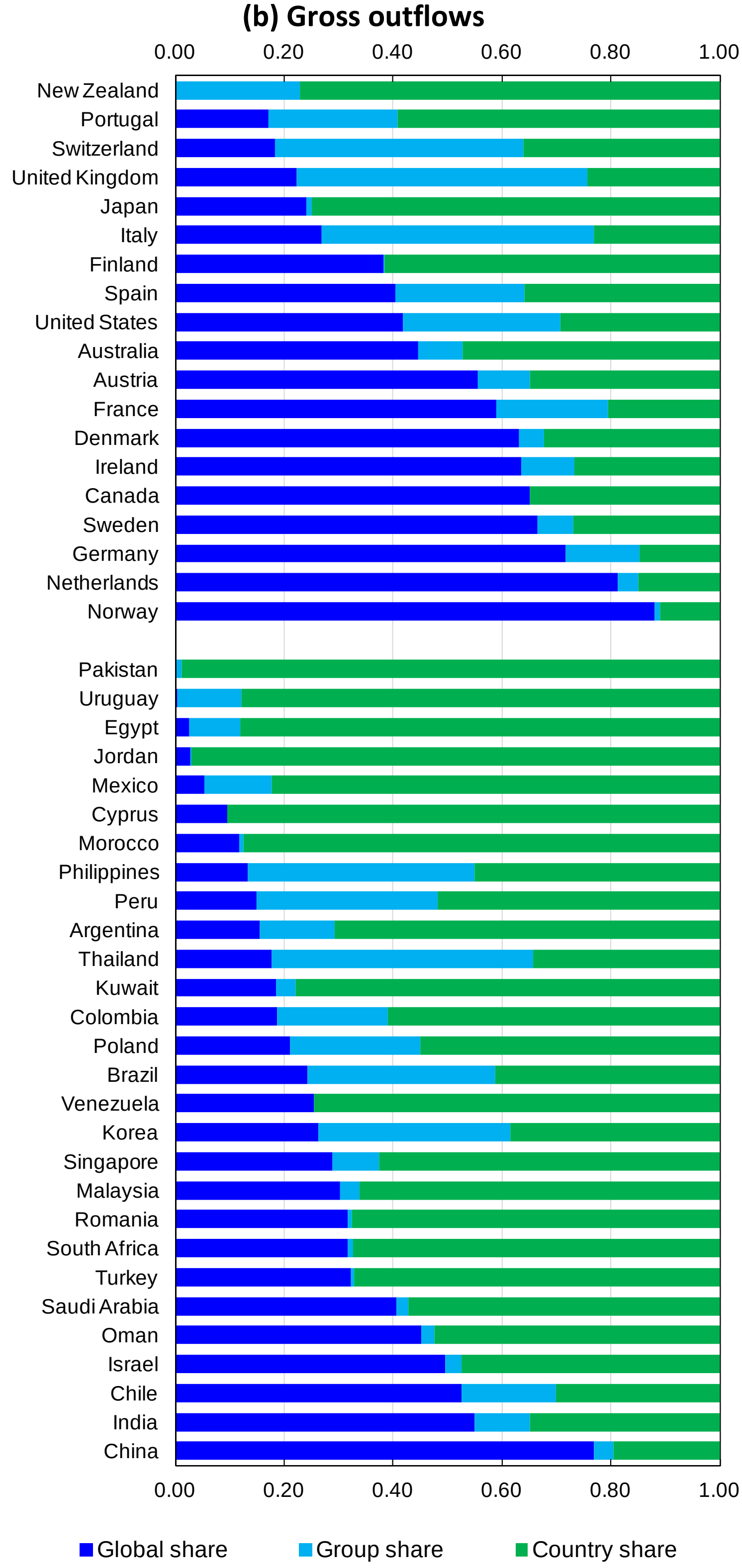
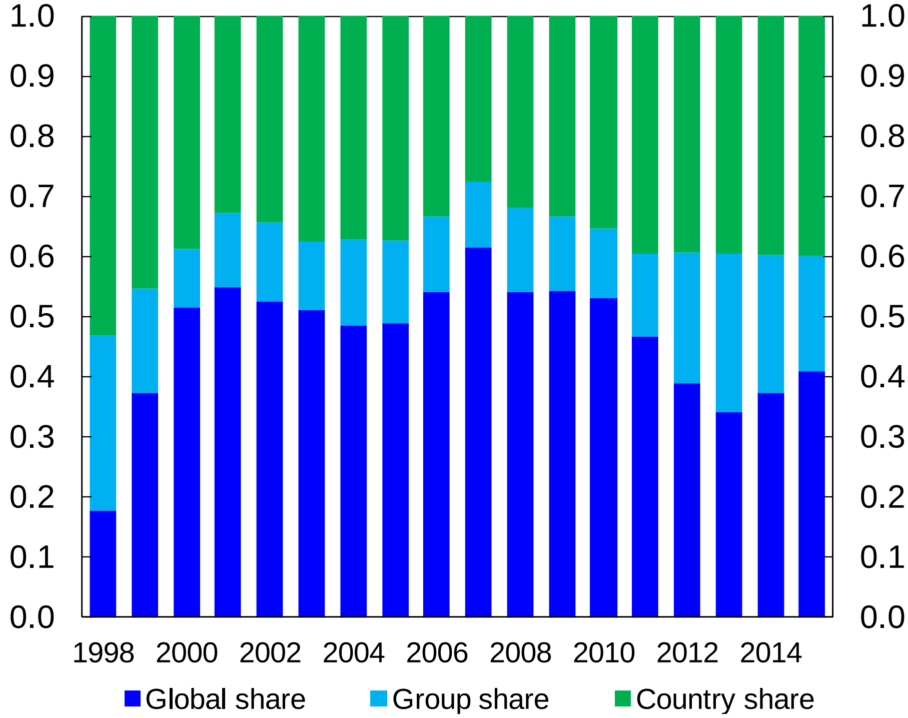


Figure 7

(a) Gross inflows: variance decomposition over time

(i) Advanced countries



(ii) Emerging countries

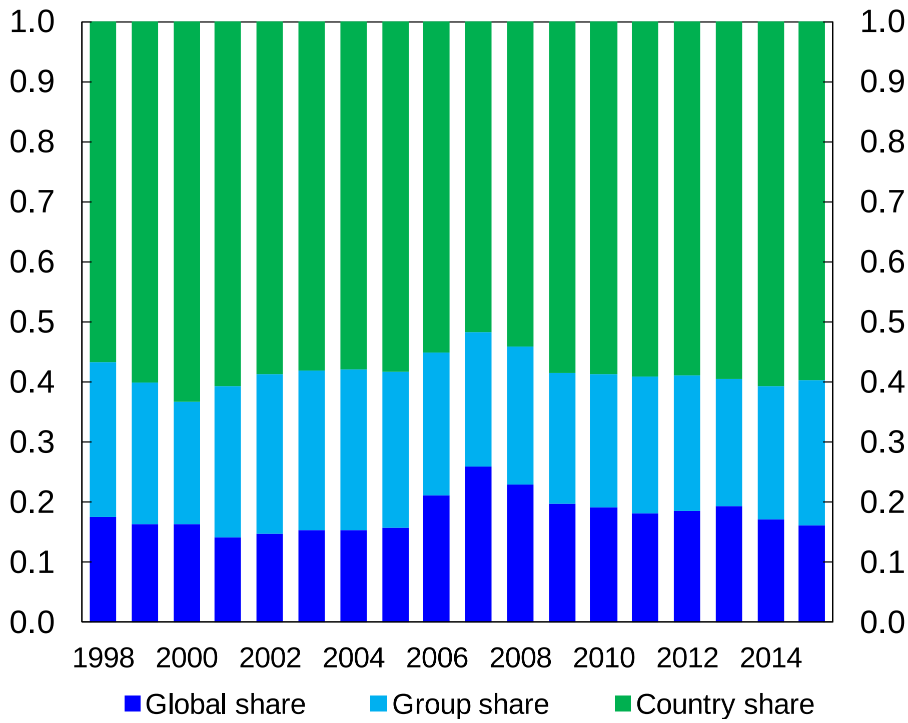
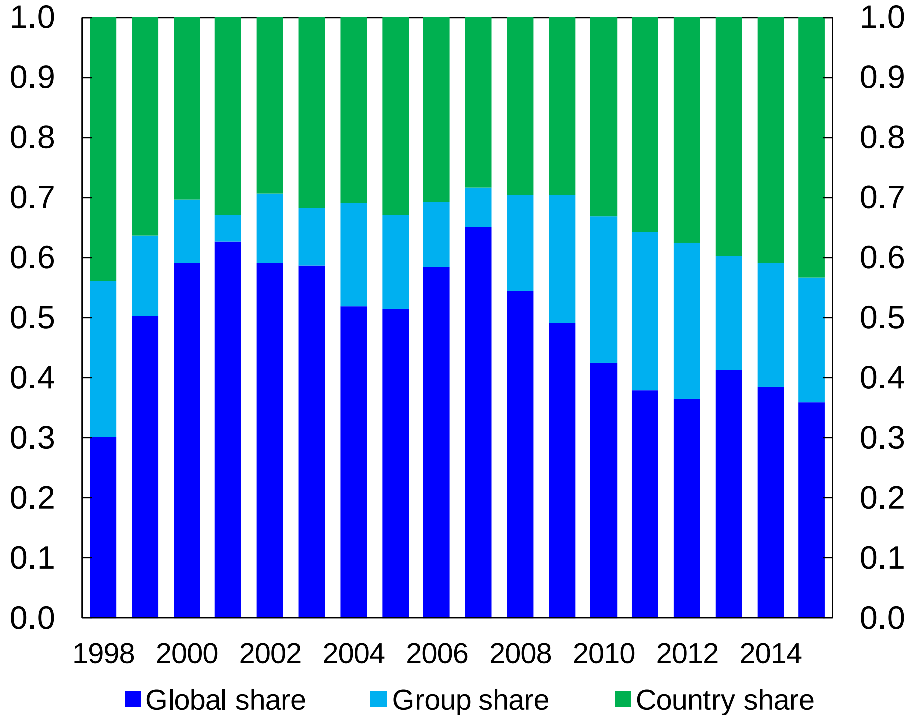


Figure 7 (continued)

(b) Gross outflows: variance decomposition over time

(i) Advanced countries



(ii) Emerging countries

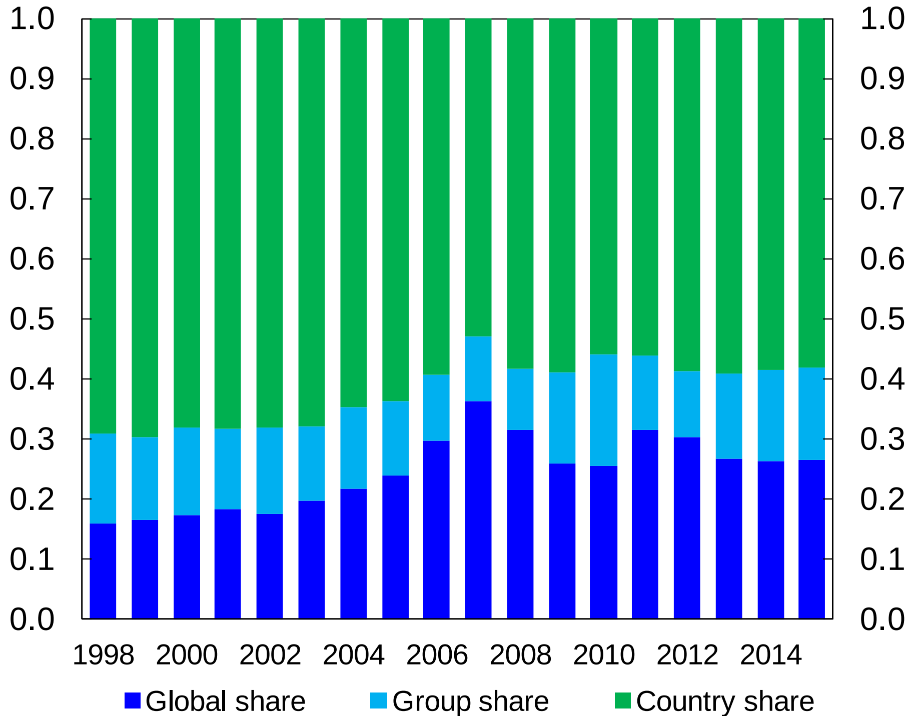
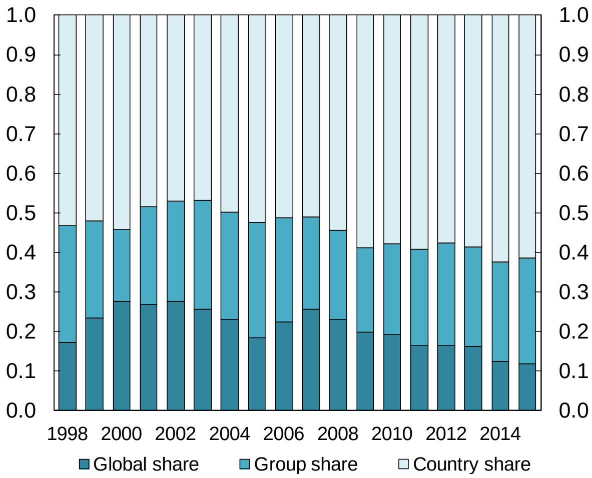


Figure 8

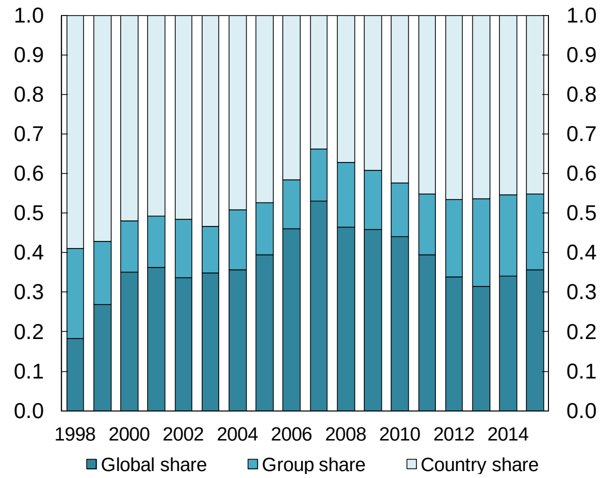
Variance decomposition over time, by degree of financial openness

(a) Gross inflows

Low financial openness

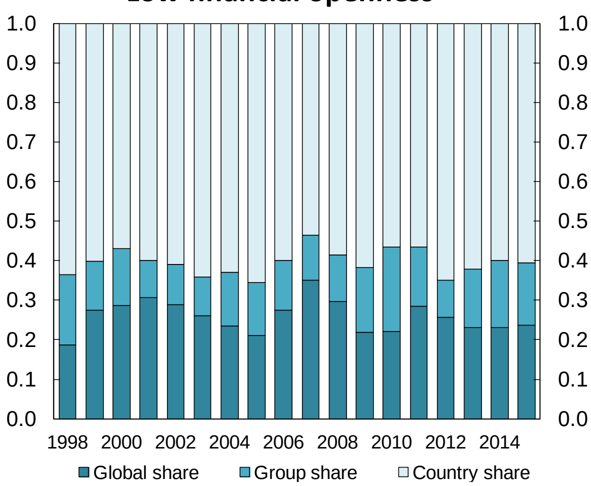


High financial openness



(b) Gross outflows

Low financial openness



High financial openness

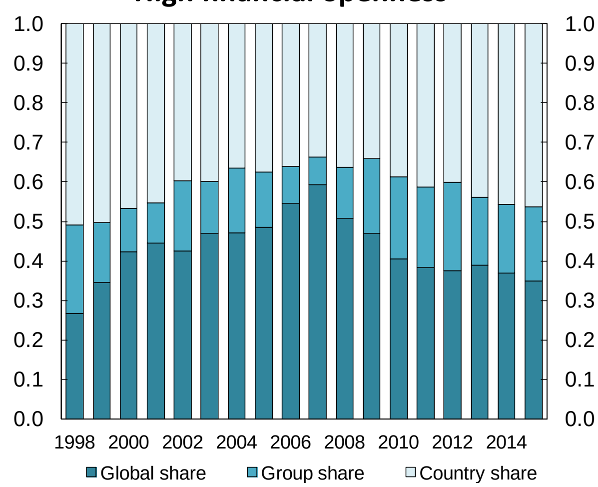
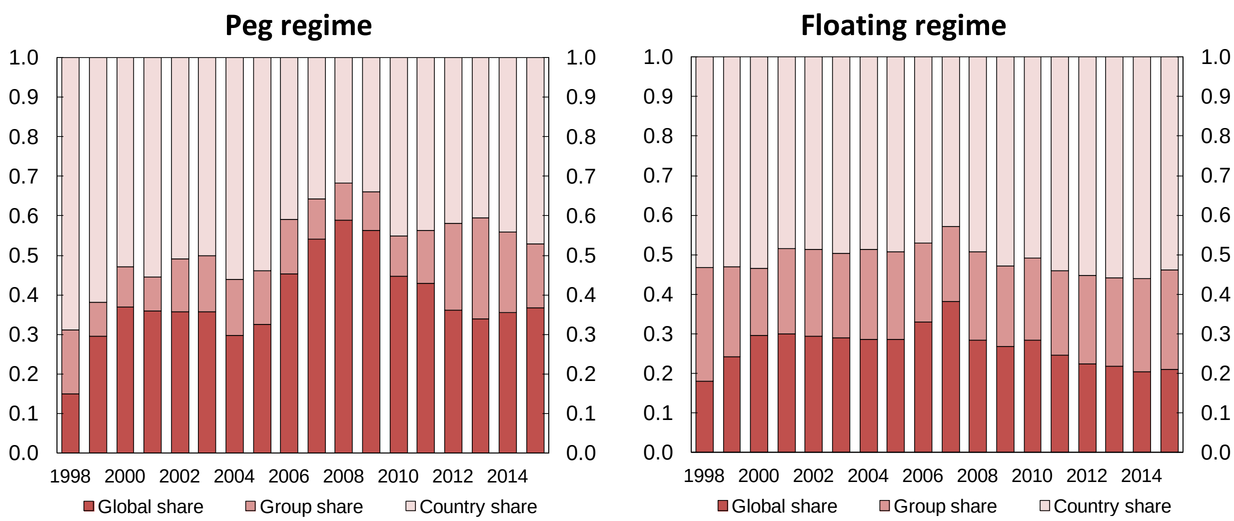


Figure 9

Variance decomposition over time, by exchange rate regime

(a) Gross inflows



(b) Gross outflows

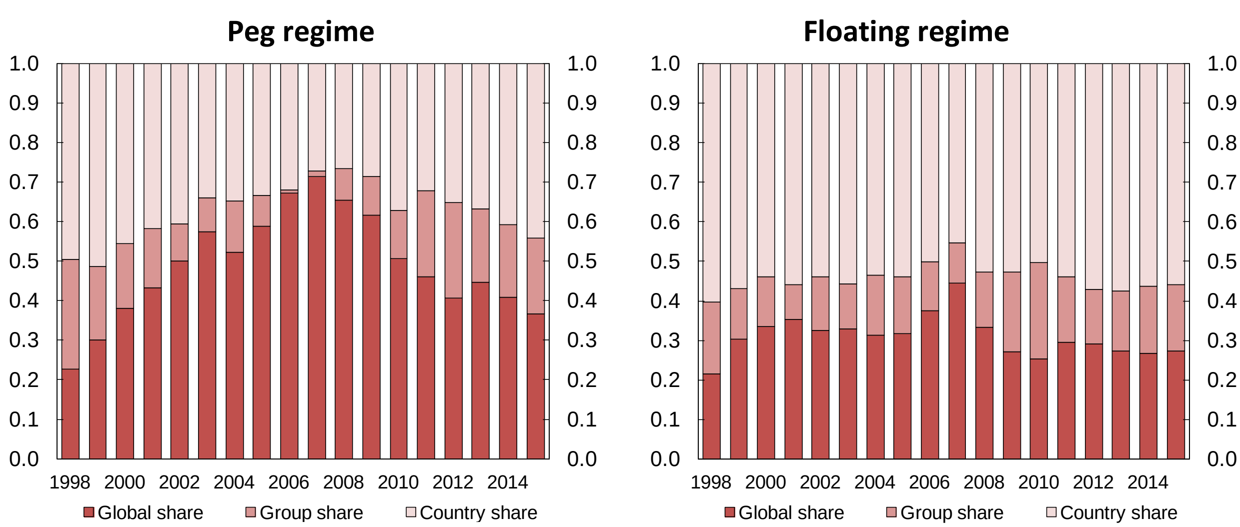
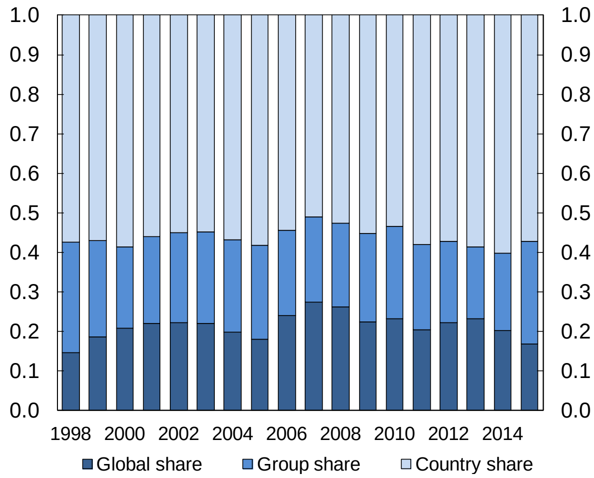


Figure 10

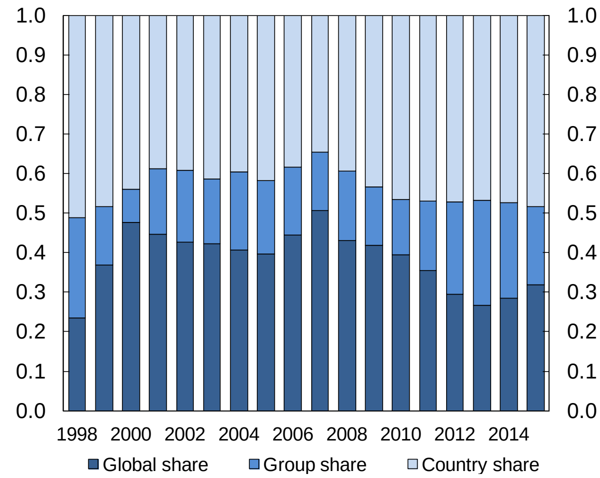
Variance decomposition over time, by degree of financial depth

(a) Gross inflows

(i) Low financial depth

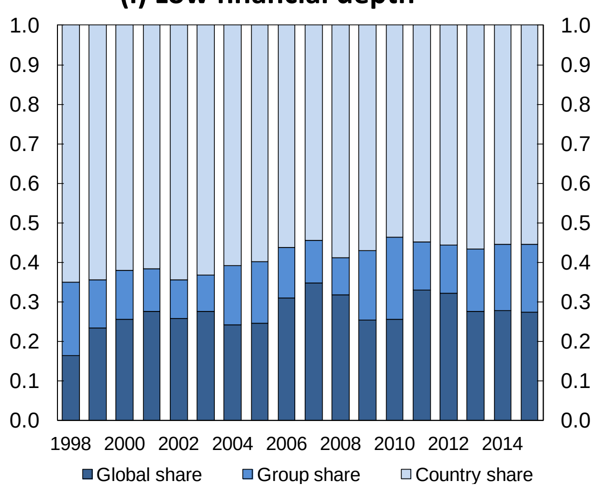


(ii) High financial depth



(b) Gross outflows

(i) Low financial depth



(ii) High financial depth

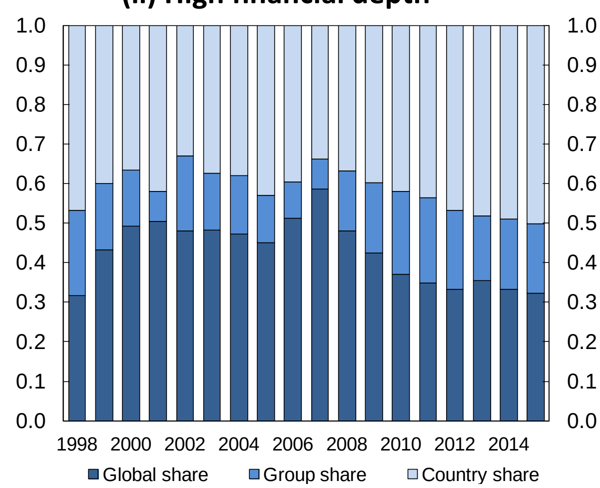


Figure 11
Developing-country group factors