Swept by the tide? The international comovement of capital flows

Luis F. Lafuerza and Luis Servén *

January 27, 2019

Abstract

This paper assesses the international comovement of gross capital flows in a setting simultaneously encompassing aggregate inflows and outflows. It uses as empirical framework a multilevel latent-factor model, implemented on flow data for a large sample of countries over more than three decades. On average, common shocks account for over forty percent of the variance of both inflows and outflows, although with major differences between advanced countries and the rest. Among the former countries, common shocks dominate the pattern of flows, and the same shocks drive both gross inflows and outflows. Among the latter countries, idiosyncratic shocks tend to play the leading role, and gross inflows exhibit less commonality with outflows. The latent factors summarizing common shocks configure an international financial cycle that closely reflects the trends in a handful of global 'push' variables. Recursive estimation of the factor model reveals that the exposure of countries' flows to the international cycle rose sharply prior to the global financial crisis, particularly for advanced countries, and declined slightly afterwards. Exposure to the cycle is robustly related to countries' external financial openness and the (lack of) flexibility of their exchange rate regime.

Keywords: Capital flows, common factors, global financial cycle
JEL codes: F32, F36, G15

*The World Bank. E-mail addresses: lflafuerza@gmail.com, lserven@worldbank.org

1 Introduction

In a world of increasingly open capital accounts, cross-border financial flows offer a major channel for the international propagation of financial turbulence. Thus, an important question for policy makers concerned with macroeconomic and financial stability is to what extent capital inflows and outflows are driven by global forces beyond their control, and how the answer to that question may be affected by domestic policy choices.

These issues are the focus of this paper. It assesses the contribution of common shocks to the observed patterns of gross capital flows across a large sample of countries, and characterizes the structural and policy features that determine countries' exposure to the common shocks. The analysis is conducted in the framework of a multilevel factor model encompassing both gross inflows and gross outflows, and allowing for latent factors that affect all flows to all countries, along with latent factors that affect only flows to/from specific groups of countries and/or going in a single direction. Our focus is on the aggregate flows of advanced and emerging countries, but the main conclusions need little change if developing countries are also included in the analysis.

Our results indicate that capital flows exhibit a considerable deal of commonality. Information criteria show that the patterns of commonality of gross inflows and outflows worldwide are adequately captured by a two-level model featuring a single global factor, along with an advanced-country factor, and a third factor embedded in emerging-country gross inflows – but not outflows. The latter result reflects the fact that, outside advanced countries, gross inflows do not comove closely with gross outflows. [1]

On average, common shocks – as captured by the latent factors – account for over 40 percent of the variance of both gross inflows and outflows. There is a marked contrast between advanced and emerging countries, however. Among the former, common shocks account for 60 percent of the variance of gross flows; among the latter, they contribute just around one-third. These figures show little change if major financial centers are excluded owing to their disproportionate role for global flows.

[1] These conclusions do not change if developing countries are added to the sample. In that case, the third common factor pertains to the gross inflows (but not outflows) of both emerging and developing countries.

We also show that the international financial cycle, as summarized by the latent common factors, can be viewed as reflecting the action of a handful of variables characterizing world financial and real conditions: market perceptions of risk, the U.S. real exchange rate and the term premium, worldwide financial openness, and world commodity prices. Dynamic regressions of the factors on these variables – most of which have featured prominently in the "push vs pull" empirical literature on capital flows – account for over 90 percent of the variance of the global factor, and over 80 percent of that of the group factors.

Countries' exposure to the international financial cycle – as measured by the portion of the standard deviation of flows attributable to the common factors – is robustly related to two key features of their macrofinancial policy framework: the degree of financial openness, and the flexibility of the exchange rate regime. Increased openness raises exposure, while increased exchange rate flexibility has the opposite effect. The latter result suggests that the choice of exchange rate regime continues to matter for the international propagation of shocks, notwithstanding the global reach of the financial cycle.

Our setting also allows us to assess the trends in financial globalization over time, as measured by countries' changing exposure to common shocks driving their capital flows. Recursive estimation of the factor model over 20-year samples reveals a cycle of increasing financial globalization prior to the global financial crisis, and partial reversal in its aftermath. The cycle is especially pronounced among advanced countries. Moreover, in these countries group-specific shocks play a significantly bigger role after the crisis, partly at the expense of global shocks.

Our paper relates to several strands of literature. First, it adds to a long-standing empirical research concerned with the respective roles of common and country-specific factors for the cross-country patterns of capital inflows. Earlier contributions, going back to Calvo et al. (1996), cast the distinction in terms of 'push' and 'pull' factors. In these papers, common / push factors are represented by a handful of variables capturing financial conditions and risk perceptions in world financial markets (Forbes and Warnock (2012), Bruno and Shin (2015a), Bruno and Shin (2015b), Cerutti et al. (2017b)). More recent contributions feature a latent common factor(s) summarizing the international financial cycle (Rey (2013), Miranda-Agrippino and Rey (2015), Barrot and Serven (2018)). The quantitative relevance of the latter has been recently challenged by Cerutti et al. (2017c), who argue that the global cycle accounts only for a modest fraction of the variation of capital flows.

We extend this literature by analyzing jointly gross inflows and outflows in an encompassing empirical framework. To our knowledge, this is the first paper confronting such task.[2] While most previous literature has been concerned with the cross-country comovement of specific types of flows, we take an aggregate perspective, which is the more relevant one for assessing countries' overall vulnerability to common shocks. We show that this choice matters for an accurate quantitative assessment of the reach of the international financial cycle, which is understated by a disaggregated analysis. Our setup also allows us to distinguish between exposure to shocks affecting all countries, and to those affecting specific country groups – advanced, emerging or developing – as well as between the responses of gross inflows and gross outflows. Finally, we also clarify how the 'push vs pull' and latent factor approaches relate to each other, by showing that the common factors embedded in capital flows can be very well explained by a handful of 'push' variables.

The paper also speaks to the debate on the determinants of countries' exposure to international financial shocks. Among the different mechanisms highlighted in the literature[3], special attention has been paid to the role of the exchange rate regime. In theory, the extent to which external shocks ultimately result in actual changes in capital flows should depend on how much of the pressure is absorbed by exchange rate and interest rate changes (e.g., Goldberg and Krogstrup (2018)). Thus, capital flows should respond less to global factors under floating regimes than under pegged regimes. However, in influential contributions Rey (2013) and Miranda-Agrippino and Rey (2015) argue that, with the trend towards more open capital accounts, the choice of exchange rate regime has ceased to matter for countries' exposure to the global financial cycle. This view is consistent with evidence reported by Passari and Rey (2015) and Cerutti et al. (2017c), who find no robust effect of the exchange rate regime on the sensitivity of credit and capital flows, respectively, to external variables

[2] Barrot and Serven (2018) and Cerutti et al. (2017c) also consider both inflows and outflows, at the aggregate and disaggregated levels, respectively, but in both cases sequentially rather than jointly.

[3] For example, Bruno and Shin (2015b) stress the degree of capital account openness and financial depth. In turn, Raddatz and Schmukler (2012), Raddatz et al. (2017) and Cerutti et al. (2017a) focus on the behavior of international investors.

summarizing the global financial cycle. In contrast, Obstfeld et al. (2018) find that, among emerging markets, credit is less sensitive to the global cycle under more flexible regimes. We add to this literature by analyzing how the exposure of aggregate capital inflows and outflows to common shocks is affected by the choice of exchange rate regime, as well as by other key aspects of countries' policy and structural framework. Departing from earlier literature, we use a natural measure of exposure derived from estimation of the factor model, namely the standard deviation of capital flows attributable to the common factors, which summarizes the ability of common shocks to account for the observed variation of cross-border flows. Further, our setting allows us to test for possible differences between inflows and outflows regarding how their exposure to common factors reacts to these determinants.

The paper also relates to a literature concerned with the the trends in financial globalization following the the global financial crisis. The sharp and persistent decline of international capital flows in its aftermath has been interpreted by some observers as proof of financial 'deglobalization', reflected in particular in a generalized contraction of cross-border bank lending in response to regulatory and other policy changes (Forbes (2014), Rose and Wieladek (2014), Van Rijckeghem and Weder di Mauro (2014), Forbes et al. (2017)). However, other papers argue that such view is not supported by more appropriate measures of banking globalization, such as the interconnectedness of the banking network (Cerutti and Zhou (2017)), or nationality-based (as opposed to location-based) measures of cross-border banking activity (McCauley et al. (2017)). Our factor model framework allows us to shed light on this debate, as it yields a natural measure of the overall degree of financial globalization, given by the exposure of cross-border flows to common shocks. Further, the model also permits drawing a distinction between the changing reach of truly global shocks, and that of shocks confined to particular groups of countries.

Finally, from the methodological perspective, a few papers have applied latent factor models to cross-border financial flows, usually focusing on particular types of gross inflows and/or outflows – e.g., Byrne and Fiess (2016), Sarno et al. (2016), Cerutti et al. (2017a), Cerutti et al. (2017c) – and employing Bayesian estimation techniques.[4] We extend this litera-

[4]A number of recent papers likewise employ latent factor models to analyze the international comovement of the prices of risky assets; see Miranda-Agrippino and Rey

ture in two directions. First, we model both gross inflows and outflows simultaneously in a multilevel factor model, whose precise structure is determined by the data. Second, we estimate the model using a recently-developed extension of the standard principal components approach that is computationally much simpler than the Bayesian approach of most earlier work, and also avoids imposing unnecessary restrictions on the factors.

The rest of the paper is organized as follows. Section 2 lays out the multilevel factor model that provides the analytical framework, and describes the paper's approach to estimation and model selection. Section 3 describes the data, and section 4 reports the empirical results. Section 5 concludes. Appendix A contains additional tables and figures. Appendix B summarizes the empirical results obtained using an enlarged country sample including developing countries. Lastly, Appendix C compares our results regarding the quantitative role of common shocks with those reported by Cerutti et al. (2017c).

2 Methodological framework

In principle, the observed patterns of gross capital flows around the world may reflect a variety of common shocks. At one end, some common shocks might affect both inflows and outflows to / from all countries. At the other end, other shocks might influence only inflows or only outflows to a particular group of countries. Intermediate combinations are also possible – e.g., shocks that affect all countries' inflows or outflows (but not both), or shocks that affect both inflows and outflows of a particular set of countries (but not all).

To identify the respective roles of each of these different kinds of common shocks, as well as that of idiosyncratic shocks, our starting point is the four-level latent factor model:

$$y_{m,i,d,t} = (\Gamma_{m,i,d})' G_t + (\Lambda^R_{m,i,d})' F^R_{m,t} + (\Lambda^D_{m,i,d})' F^D_{d,t} + (\Lambda^{RD}_{m,i,d})' F^{RD}_{m,d,t} + u_{m,i,d,t}, \quad (1)$$

where y denotes gross capital inflow or outflow, $m = 1, \ldots, M$ refers to the country group, $i = 1, \ldots, N_m$ to the i-th country within the m-th group,

(2015), Xu (2017) and Abate and Serven (2018) for equity prices, or Longstaff et al. (2011) for sovereign debt.

$d \in \{-1, 1\}$ to the flow direction (inflow or outflow), and $t = 1, \ldots, T$ to time. G_t denotes a $r^G \times 1$ vector of (unobserved) global factors, $F^R_{m,t}$ denotes a $r^R_m \times 1$ vector of factors of group (or region) m (affecting both inflows and outflows), $F^D_{d,t}$ denotes a $r^D_d \times 1$ vector of factors affecting flows in direction d, and $F^{RD}_{m,d,t}$ denotes a $r^{RD}_{m,d} \times 1$ vector of group and flow-direction specific factors; $\Gamma_{m,i,d}$, $\Lambda^R_{m,i,d}$, $\Lambda^D_{m,i,d}$ and $\Lambda^{RD}_{m,i,d}$ denote the corresponding (unobserved) loadings. Finally, $u_{m,i,d,t}$ captures the idiosyncratic factors specific to the flows of country i from group m in direction d at time t.

Vertically stacking observations on the flows of all the countries in group m in direction d at time t, model (1) can be re-written as:

$$Y_{m,d,t} = \Gamma_{m,d} G_t + \Lambda^R_{m,d} F^R_{m,t} + \Lambda^D_{m,d} F^D_{d,t} + \Lambda^{RD}_{m,d} F^{RD}_{m,d,t} + u_{m,d,t}, \tag{2}$$

and we can define the following matrices of factors: $G = (G_1, \ldots, G_T)'$, $F^R_m = (F^R_{m,1}, \ldots, F^R_{m,T})'$, $F^D_d = (F^D_{d,1}, \ldots, F^D_{d,T})'$, and $F^{RD}_{m,d} = (F^{RD}_{m,d,1}, \ldots, F^{RD}_{m,d,T})'$. By horizontally stacking factors other than the global ones into a $T \times \left(\sum_{m=1}^{M} r^R_m + \sum_{d\in\{-1,1\}} r^D_d + \sum_{m=1}^{M} \sum_{d\in\{-1,1\}} r^{RD}_{m,d}\right)$ matrix F (similarly for loadings into Λ), and arranging Y as a $T \times 2N$ (with $N = \sum_{m=1}^{M} N_m$) matrix, we can arrive to the more compact notation:

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

with Γ of dimension $2N \times r^G$, and Λ of $2N \times \Big(\sum_{m=1}^{M} r^R_m + \sum_{d\in\{-1,1\}} r^D_d + \sum_{m=1}^{M} \sum_{d\in\{-1,1\}} r^{RD}_{m,d}\Big)$.

As written, this is a static factor model, 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 their lags as additional static factors (within the same level of the model).

As is typical in factor models, the factors and loadings in (3) are not separately identified – e.g., for any non-singular $r^G \times r^G$ matrix M, G, Γ are observationally equivalent to $\tilde{G} \equiv GM$, $\tilde{\Gamma} \equiv \Gamma M'^{-1}$. To overcome this issue, we impose the following normalization: (i) $G'G/T = I_{r^G}$, ${F^{R}}'_m F^R_m/T = I_{r^R_m}$, ${F^{D}}'_d F^D_d/T = I_{r^D_d}$, ${F^{RD}}'_{m,d} F^{RD}_{m,d}/T = I_{r^{RD}_{m,d}}$ (with I_n the $n \times n$ identity matrix); (ii) $\Gamma'\Gamma$, ${\Lambda^R_{m,d}}'\Lambda^R_{m,d}$, ${\Lambda^D_{m,d}}'\Lambda^D_{m,d}$ and ${\Lambda^{RD}_{m,d}}'\Lambda^{RD}_{m,d}$ are all diagonal matrices; in addition, (iii) if group A is nested in group B, factors of A and B are orthogonal to each other; this implies ${F^R_m}'G = {F^D_d}'G = {F^{RD}_{m,d}}'G = 0$,

$F_{m,d}^{RD\prime} F_m^R = F_{m,d}^{RD\prime} F_d^D = 0$. This still leaves one free sign for each factor-loadings set, which we normalize imposing that the mean (over countries) of the loadings of each factor be non negative.

Importantly, there is no need to impose orthogonality between the group factors of different groups within a given level, in contrast with what is often done in Bayesian analyses of multilevel factor models.[5] Such restriction, which leads to an overidentified model, may or may not hold in the data.

Relative to conventional factor models, estimation of the multilevel model (3) poses two challenges. The first one is the fact that the matrix of group factor loadings Λ contains zero restrictions. This prevents a standard principal-components estimation approach. Most previous literature has confronted this issue employing Bayesian techniques (e.g., Kose et al. (2003)). However, suitable extensions of the principal component approach to the multilevel setting have been recently developed by Breitung and Eickmeier (2016) and Choi et al. (2018). Compared with Bayesian estimation, these methods are computationally much simpler, as they just involve a sequence of iterated OLS regressions over the (preliminary) factors to obtain the (preliminary) loadings, and then over the (preliminary) loadings to obtain the (next-iteration) factors. The sequence is repeated until convergence. The sequential OLS procedure allows us to easily implement the zero restrictions on the loadings implied by the multilevel structure. This approach is equivalent to an EM algorithm using a Gaussian pseudo-likelihood. The 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

[5] It is important to note that correlation between the group factors of different groups at a given level is not equivalent to the presence of a higher-level factor common to those groups. Consider for example a two-level model with global and group-specific factors and two country groups of size N_1 and N_2. Nonzero correlation between a factor of the first group and a factor of the second group does not amount to a global factor common to both groups. While the two correlated factors can always be expressed as a global factor common to both groups plus a group factor specific to one of the groups (say group 1), such reparameterization would involve $2N_1 + N_2$ loadings, rather than just $N_1 + N_2$, thus using up additional degrees of freedom.

above.

The second challenge arises from the fact that the idiosyncratic error terms $u_{i,m,d,t}$ may show heteroskedasticity, and (weak) cross-sectional and/or time-series correlation. While the principal component estimator remains consistent under such conditions, more efficient estimates may be available.

In our case, contemporaneous within-country correlation of the errors is especially likely to be an issue, because the inflows and outflows of a given country should be subject to similar idiosyncratic shocks. Indeed, preliminary experiments showed that the estimated residuals of inflows and outflows exhibited substantial contemporaneous within-country correlation. Thus, for our empirical exercises we implement the feasible generalized principal components estimator (FGPCE) of Choi (2012), adapted to the multilevel setting. It is obtained from minimization of

$$tr\left[\hat{\Omega}^{-1}\left(Y - G\Gamma' + F\Lambda'\right)'\left(Y - G\Gamma' + F\Lambda'\right)\right] \tag{4}$$

where we use a consistent estimate $\hat{\Omega}$ of the residual covariance matrix, obtained from a first-round estimation of the model. Since heteroskedasticity and within-country inflow-outflow correlation are the main concerns here,[6] we assume that the only non-diagonal entries of Ω correspond to the covariance between same-country inflows and outflows, and therefore we construct $\hat{\Omega}$ as:

$$\hat{\Omega}_{m,i,d;m',i',d'} = \begin{cases} \frac{1}{T}\sum_{t=1}^{T} \hat{u}_{m,i,d,t}\hat{u}_{m',i',d',t} & \text{if } m = m', i = i', \\ 0 & \text{otherwise,} \end{cases} \tag{5}$$

where $\hat{u}_{m,i,d,t}$ denotes the residuals from first-round estimation.[7]

The number of factors of each group at each level is not known a priori, and to determine it we use information criteria. In particular, we use the IC_{p2} criterion of Bai and Ng (2002), and the Hannan-Quinn (HQ) cri-

[6] As discussed below, the residuals showed only very modest time-series and cross-country correlation.

[7] One might wonder if iteration over $\hat{\Omega}$ would deliver additional efficiency gains. A residual bootstrap-based analysis using data with properties similar to those of our sample showed that, beyond the first iteration, further iterations re-estimating $\hat{\Omega}$ based on the newly-obtained residuals did not yield any efficiency improvement.

terion as adapted to factor models by Choi and Jeong (2018) [8]. In both cases we adapt the criteria to the multilevel case. This requires appropriately modifying the penalty for the number of parameters, which can be written as $r^G(2N+T)+\sum_{m=1}^{M} r_m^R(2N_m+T)+\sum_{d\in\{-1,1\}} r_d^D(N+T)+\sum_{m=1}^{M}\sum_{d\in\{-1,1\}} r_{m,d}^{RD}(N_m+T)$, where N is total number of countries (so $2N$ is the overall cross-sectional dimension of the inflow-outflow data) and N_m the number of countries in group m. This yields the expressions:

$$
\begin{aligned}
IC_{p2} &= T\ln(V_{NT})+\frac{\ln(\min(2N,T))}{2NT}P, && (6)\\
HQ_c &= T\sum_{m,i,d}\ln(\sigma^2_{m,i,d})+c\ln\left[\ln(2NT)\right](2N+P), && (7)
\end{aligned}
$$

with

$$
\begin{aligned}
V_{NT} &= \frac{1}{2NT}\sum_{m,i,d,t}\hat{u}^2_{m,i,d,t}, \qquad \sigma^2_{m,i,d}=\frac{1}{T}\sum_{t=1}^{T}\hat{u}^2_{m,i,d,t}, && (8)\\
P &= r^G(2N+T)+\sum_{m=1}^{M} r_m^R(2N_m+T)+\sum_{d\in\{-1,1\}} r_d^D(N+T)+\\
&\quad \sum_{m=1}^{M}\sum_{d\in\{-1,1\}} r_{m,d}^{RD}(N_m+T),
\end{aligned}
$$

and $\hat{u}_{i,t}$ is the estimated residual from the factor model with r^G global factors and $r_m^R, r_d^D, r_{m,d}^{RD}$ group, direction, and group-direction factors. The parameter c in the HQ criterion was set to 2, based on the criterion's performance in residual bootstrap-based experiments.

[8] A residual bootstrap-based analysis showed that these criteria were the ones with best performance in multilevel factor models in artificial samples with properties similar to ours. Working on a single-level setting, Choi and Jeong (2018) show that HQ_2 and IC_{p2} are among the better performing criteria (together with eigenvalue-based criteria that do not generalize well to multi-level settings); they also recommend considering several criteria simultaneously.

3 Data

We assemble a balanced panel dataset on annual gross inflows and outflows, drawing from the International Monetary Fund's Balance of Payments Statistics (BoP). The panel comprises 85 countries [9] and spans the years 1979-2015. We further group the sample countries into three categories: 19 advanced countries, 28 emerging countries, and 38 developing countries, as shown in Table A.1.

Gross capital flows are measured by the flows of assets and liabilities of the reporting country's residents vis-a-vis non-residents. Thus, gross inflows are given by the sum of direct investment into the country, plus portfolio investment and other investment liabilities. Gross outflows equal the sum of direct investment abroad, portfolio investment assets, other investment assets, and reserve assets.[10] Figure 1 shows that advanced countries account for the bulk of both inflows and outflows. However, the relative role of emerging countries has been on the rise: over the last decade, their flows represented as much as 30 percent of the total of all countries considered. In contrast, developing countries play a minimal role throughout the sample – taken together, they accounted for less than 2 percent of both inflows and outflows, without any discernible trend in their share.

In absolute terms, advanced and emerging-country capital flows show a rising trend over much of the sample – especially among the former countries, whose flows peak at the onset of the global crisis in 2008. Thus, for the empirical analysis we opt for scaling flows by trend GDP, as done by Broner et al. (2013) and Barrot and Serven (2018). [11]

Figure 2 provides a first look at the cross-country comovement of gross

[9] We start by constructing a balanced panel comprising all the countries with complete data from 1979 to 2015. This yields a total of 98 countries. We exclude from this sample 13 very small countries with population fewer than 500,000 in 2005.

[10] In reality, these concepts are *net* rather *gross*, and can have either sign. Thus, a positive (negative) gross inflow, as just defined, indicates a net increase (decrease) in foreigners' holdings of domestic assets. Likewise, a positive (negative) gross outflow denotes a net increase (decrease) in the holdings of foreign assets by domestic agents. Nevertheless, following convention we refer to these flows as "gross".

[11] In our setting, the use of trend GDP rather than actual GDP helps prevent short-term business cycle fluctuations correlated across countries from distorting the estimates of the model's common factors and common components. Trend GDP is constructed applying the Hodrick-Prescott filter with a parameter of 100 to the series of nominal GDP in US dollars.

capital flows, relative to trend GDP. The figure shows histograms of pairwise correlations of inflows or outflows across countries within the same group (top two rows), across countries in different groups (third and fourth rows), and the within-country inflow-outflow correlations (bottom row).

Three facts stand out in the figure. First, the distributions are skewed to the right, indicating that flows of different countries and/or in different directions tend to rise and fall together. Second, the distribution of the within-group correlations in the top two rows is particularly skewed to the right in the case of advanced countries, likely reflecting their higher degree of financial integration. This feature is less pronounced among emerging countries and, especially, developing countries. Third, the bottom row shows that the within-country correlation of gross inflows and gross outflows varies considerably across country groups. It is generally very high among advanced countries, and quite sizable among emerging countries, but much lower among developing countries. [12]

4 Results

The evidence just summarized shows that gross capital flows exhibit significant cross-sectional dependence, highest among advanced countries and lowest among developing countries. Still, a latent common factor model such as (3) may provide a suitable characterization of the underlying data only if the dependence is strong (or pervasive) – i.e., it reflects common shocks affecting many countries. If dependence is weak instead – e.g., it arises from localized linkages between countries, such as those due to bilateral trade – attempting to capture it through a latent factor model may yield misleading results.[13]. In such conditions, other empirical approaches, such as spatial modeling, are likely to be preferable.[14]

The exponent of cross-sectional dependence of Bailey et al. (2016b) provides a metric to assess the nature of the dependence found in the data. It

[12] Avdjiev et al. (2017b) show that the positive correlation between advanced-country inflows and outflows is primarily due to banks. The inflows and outflows of corporates and government also show positive (but smaller) correlation.

[13] See Onatski (2012).

[14] Strong and weak cross-sectional dependence can be 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, see e.g., Bailey et al. (2016a).

can be viewed as a measure of the rate at which factor loadings (fail to) die off as cross-sectional sample size grows. It ranges between zero and one, with a value of 1 indicating the presence of strong dependence.

Table A.2 reports the computed values for the different country groups, along with their 95 percent confidence bands. For both advanced and emerging countries, the exponent of cross-sectional dependence exceeds 0.90, and the 95 percent confidence region includes 1. In contrast, for developing countries the exponent is just 0.77, and the 95 percent confidence region does not reach up to 0.90. These results agree with the evidence shown in Table 2 that developing countries' flows exhibit less commonality than do the flows of the other country groups. Further, Table A.2 also shows that in a sample combining advanced and emerging countries the exponent of cross-sectional dependence equals 0.94, and its 95 percent confidence region includes 1, while in a sample adding also developing countries the point estimate is under 0.89 and the 95 percent confidence band excludes 1.

Overall, the evidence is clearly supportive of strong dependence among advanced and emerging countries, but less so for developing countries. This casts doubt on the suitability of a factor model to capture the patterns of capital flows of the latter countries. Given also their modest role in worldwide total inflows and outflows as shown earlier, the analysis below will focus primarily on the sample of advanced and emerging countries. We consider an extended sample with developing countries in an appendix.

4.1 Model selection

We turn to the selection of the factor model using the two information criteria introduced earlier. In line with the specification of equation (1) for the case of two country groups (i.e., $M = 2$), we use the notation $(r^G; r_1^R, r_2^R; r_1^D, r_{-1}^D; r_{1,1}^{RD}, r_{1,-1}^{RD}, r_{2,1}^{RD}, r_{2,-1}^{RD})$ to refer to a model with r^G global factors; r_1^R and r_2^R factors for advanced and emerging countries, respectively; r_1^D and r_{-1}^D factors for inflows and outflows, respectively; and $r_{1,1}^{RD}$, $r_{1,-1}^{RD}$, $r_{2,1}^{RD}$ and $r_{2,-1}^{RD}$ factors for advanced-country inflows, advanced-country outflows, emerging-country inflows and emerging-country outflows, respectively.

We considered a wide range of model specifications containing from a minimum of zero factors to a maximum of three at the global, country group and flow direction levels, and two at the country group-flow direction level – a total of 82944 specifications. Overall, models with global and group-specific factors achieved higher scores than models with only global factors. However, specific model rankings vary across the two criteria considered.[15] For this reason, we computed a synthetic standardized score by first dividing each score by the maximum score of the corresponding criterion, and then averaging the two standardized scores computed in this way. Thus, the standardized score is given by $(IC_{p2}/IC_{p2,max} + HQ2/HQ2_{max})/2$, where the max subscript refers to the highest score obtained under each criterion.

Table 1 shows that the highest standardized score corresponds to model specification (1; 1,0; 0,0; 0,0,1,0), featuring one global factor, one advanced-country factor, and one emerging-country inflow factor.[16]It outperforms models with only global factors (shown in the middle block of the table), as well as a variety of more 'symmetric' models that might seem more intuitive at first glance, featuring inflow and outflow factors and/or factors for each country group-flow direction combination (shown in the bottom panel of the table). For example, a model with one global factor plus one factor for each of the two country groups ranked in 6th place, while a model with one global factor plus another factor for each group-flow direction combination ranked in 261st place.

Still, several models shown in the top panel of Table 1 exhibit very similar standardized scores. In order to assess how the choice of specific model affects the estimated factors and loadings, Table 2 reports the correlation between the estimated factors and loadings of the top-ranked model in Table 1 and those of the other most highly-ranked models. It is clear that the estimated global and advanced-country factors are virtually the same regardless of the particular model considered – the correlations with the

[15]Choi and Jeong (2018) show that in single-level factor models the IC_{p2} and HQ_2 criteria (as well as the Eigenvalue Distribution criterion, which does not generalize well to multilevel models) are the ones that perform best when some cross-sectional units have much larger variance than others. They also note that different criteria often yield different rankings of alternative models, and recommend the use of multiple criteria for model selection.

[16]When including also developing countries in the sample, we use a very similar specification, featuring one global factor, one advanced-country factor, and one factor for inflows to emerging and developing countries. Table B.1 shows that such specification ranks second according to the synthetic score, and first under the IC_{p2} criterion.

factors of the top-ranked model exceed 0.94 in all cases. For the emerging countries, factor correlations are again very high, with the exception of the model containing no global factors (0; 1,1; 0,0; 0,0,0,0) [17].

In turn, the estimated loadings are also very highly correlated across models, again with the only exception of the loadings on the emerging-country inflow factor of model (0; 1,1; 0,0; 0,0,0,0). On the basis of these findings, we conclude that the factor and loading estimates do not depend crucially on the particular model selected.

4.2 Factor model estimates

The top-ranked model in Table 1, on which we shall focus, features a single global factor, affecting both gross inflows and outflows of all countries, an advanced-country factor affecting the inflows and outflows of countries in that group, and an additional factor affecting the gross inflows (but not the outflows) of emerging countries.

This specification echoes that reported by Barrot and Serven (2018). Working with gross inflows and outflows separately, they find in each case a global factor plus an advanced-country and an emerging-country factor. However, the global and advanced-country inflow factors are very highly correlated with the corresponding outflow factors (the correlation coefficient equals 0.95 for the global factors and 0.82 for the advanced-country factors). In contrast, the correlation between the inflow and outflow factors is much lower for emerging countries (0.34); moreover, the latter factor (which we fail to identify here) plays a quantitatively marginal role.[18]

In influential contributions, Rey (2013) and Miranda-Agrippino and Rey (2015) find a global factor behind risky asset prices around the world, which they interpret as evidence of a global financial cycle. Our estimates confirm that a similar result applies to cross-border financial flows. Moreover, our estimates also indicate that, together with a global financial cycle, there are also group-specific cycles affecting particular sets of

[17]Because the group factors of model (0; 1,1; 0,0; 0,0,0,0) are not mutually orthogonal, they may be viewed as implicitly embedding a 'global' factor. To compare the estimates of this model with the rest, we redefine its group factors as the residuals of projecting the estimated group factors over the global factor of the top-ranked model (1; 1,0; 0,0; 0,0,1,0).

[18]Indeed, the factor is found to account for only 12.2% of the variance of emerging-country outflows, the smallest contribution of all the common factors considered in that paper (see Barrot and Serven (2018), Table 5).

countries. In the case of advanced countries, the group cycle drives both inflows and outflows. However, among emerging countries we find evidence of a cycle driving inflows only.[19] This finding is reminiscent of the literature on emerging-market sudden stops, which distinguishes between inflow- and outflow-driven stops (Cowan et al. (2008); Rothenberg and Warnock (2011); Calderón and Kubota (2013)), concluding that inflow-driven sudden stops are more bunched over time than outflow-driven sudden stops[20]. The finding of an inflow-specific factor for emerging-countries is consistent with that evidence.

Figure 3 plots the estimated factors, together with 95% confidence bands obtained from a residual block bootstrap [21]. The global factor shows a rising pattern starting in the mid 1990s that becomes sharply steeper in the early 2000s, followed by a collapse at the onset of the global crisis in 2008 and a slight downward trend thereafter. In turn, the advanced-country factor is roughly constant until 1995. It then follows an upward trend until 2000, roughly coinciding with the dot-com bubble. The upward trend resumes subsequently, but gives way to an abrupt fall at time of the global crisis in 2008, consistent with the post-crisis de-leveraging and unwinding of international positions in advanced economies. Lastly, the emerging-country inflow factor displays large swings around the times of major emerging-market crises – most notably, the 1982 Latin America debt crisis and the 1997-98 East Asian crisis.

The confidence bands indicate that the factors are estimated quite precisely. They are fairly persistent – the first order autocorrelation coefficients are 0.90, 0.73 and 0.78 for the global, advanced and emerging in-

[19] As Table 1 shows, this is not exclusive of the top-ranked model. Three out of the six models with highest score likewise feature a factor particular to either emerging market inflows, or inflows in general.

[20] For example, Rothenberg and Warnock (2011), working with a sample of (mainly) emerging countries from 1989 to 2005, conclude that the evidence is "suggestive of a world in which true sudden stops have an important common component–and that perhaps for them contagion is an apt descriptor—-whereas sudden flight episodes are more likely driven by local conditions" (p. 516).

[21] Throughout the paper, we use the residual block bootstrap (e.g., Breitung and Eickmeier (2016)) to compute standard errors for the estimated factors, loadings, and variance contributions. The re-sampling of residuals is done by country, combining inflows and outflows, with the (time) size of the block selected following the analysis of Politis and White (2004) for the circular bootstrap (see also the correction in Patton et al. (2009))

flows factor, respectively – but stationary.[22] On the other hand, the two group factors are only weakly correlated – the correlation coefficient is -0.17, with an approximate standard error of 0.16. [23]

The sensitivity of each country's gross inflows and outflows to the different common factors is given by their respective factor loadings $\Gamma_{m,i,d}$, $\Lambda^R_{m,i,d}$, $\Lambda^D_{m,i,d}$ and $\lambda^{RG}_{m,i,d}$ in (1). The estimated loadings are shown in Figure 4, and summarized in Table 3.

Overall, the loadings are estimated somewhat less precisely than the factors. The vast majority of the global factor loadings – 33 (out of 47) for inflows and 42 for outflows – are positive and significant at the 95% level, and none is significantly negative. The insignificant estimates all belong to emerging markets, with the only exception of New Zealand's. Outflow loadings tend to be larger than inflow loadings. For both gross inflows and outflows, the largest global factor loading corresponds to the Netherlands.

Likewise, most of the loadings on the advanced-country factor are positive and significant: 15 (out of 19) for gross inflows, and 14 for gross outflows. The insignificant estimates are those of Canada, Australia, Japan and Finland, plus New Zealand in the case of outflows. The largest loadings correspond to the U.K. for both inflows and outflows, possibly reflecting its role as a financial center. Lastly, 15 out 28 loadings on the emerging-country inflow factor are significantly positive, while the other 13 are insignificant. The Philippines and Brazil possess the largest loadings.

On the whole, the loadings on both the global and the group factors exhibit considerable variation across countries. Table 3 also shows that they tend to be larger for advanced countries than for emerging countries. The difference is particularly big in the case of gross inflows. Still, some emerging countries do exhibit fairly large loadings – e.g., India in the case of the global factor.

In addition, Table 4 shows that the factor loadings of inflows and outflows are positively correlated. Thus, the responsiveness to common shocks of countries' gross inflows comes hand-in-hand with the responsiveness of their gross outflows. This is especially the case among advanced countries: the correlation between their inflow and outflow loadings equals 0.73 for

[22] An ADF test with two lags rejects the null of a unit root for the emerging-country inflows factor; for the other factors, Zivot-Andrews tests allowing for constant and trend breaks reject the null of a unit root at the 1% level, with the break year endogenously selected as 2006 for the global factor and 2008 for the advanced-country factor.

[23] Recall that, by construction, group factors are orthogonal to the global factor.

the global factor and 0.88 for the group-specific factor. Among emerging countries, the correlation between the global factor inflow and outflow loadings is much smaller (0.27). However, given the absence of a group factor for the outflows of emerging countries, perhaps a more meaningful statistic is the correlation between the sum of the global and group factor loadings of their inflows, on the one hand, and the global factor loadings of their outflows, on the other. That statistic equals a more respectable 0.47.

On the other hand, the loadings on the global and group factors are negatively correlated, which suggests that, to some extent, they play interchangeable roles in capturing countries' exposure to common shocks – although the negative correlation is larger in the case of emerging-country inflows (for which the correlation equals -0.64) than for advanced-country inflows (-0.16) or outflows (-0.34).

Overall, the estimated model does a good job at capturing the comovement of gross capital flows. Figure A.1 in appendix A shows that the estimation residuals appear virtually uncorrelated across countries, while the within-country correlation of inflow and outflow residuals is consderably reduced relative to that in the original data. Further, the model succeeds at removing the strong dependence found in the data, as shown by the exponents of cross-sectional dependence of the residuals reported in Table A.3, which lie well below unity both for the full sample and the two country groups.[24]

4.3 The variance contribution of the common factors

The fact that the group and global factors are mutually orthogonal by construction allows a straightforward decomposition of the variance of gross capital flows into the shares attributable to their global, group, and idiosyncratic components. This helps assess the quantitative role of common shocks for the observed patterns of capital flows.

Table 5 offers a summary view of the fraction of the variance explained by global and group factors (additional details are given in A.5). On aver-

[24] Additionally, panel unit root and stationarity tests reported in Table A.4 in appendix A provide strong indication that the residuals are stationary: for each country group and flow direction, an Im-Pesaran-Shin test clearly rejects the null that all residual series contain a unit root, while a Hadri test fails to reject the null that all residual series are stationary. These results lend support to the validity of the factor model estimates.

age, the common factors taken together account for a considerable portion of the variance of gross flows – 45 percent for gross inflows and 42 percent for gross outflows. However, there is a sharp contrast between advanced and emerging countries. Among the former, common factors account for 58 and 62 percent of the variance of inflows and outflows, respectively. Among the latter, the figures are 36 and 28 percent. Thus, common factors dominate the capital flows of advanced countries, while idiosyncratic factors dominate the capital flows of emerging countries. Further, the respective roles of global and group factors are quantitatively similar in the case of gross inflows, while the global factor dominates gross outflows – trivially so in the case of emerging countries, given the absence of a group factor affecting their outflows.

One might worry that these results overstate the role of common factors because the advanced-country group includes the world's leading financial centers, which could be artificially inflating the role of commonality. However, the lower panel of table (5) shows that excluding the U.S., U.K., Switzerland, Germany, and Japan from the calculations has very little effect on the variance decomposition figures.

These results concerning the quantitative role of common factors might appear to be in contrast with those that Cerutti et al. (2017c) reach using quarterly data on capital flows disaggregated by flow type (FDI, portfolio debt, portfolio equity, bank credit). They find a very modest role for global factors[25]. In Appendix C we show that a large part of the discrepancy disappears when the data used by Cerutti et al. (2017c) is analyzed at the annual frequency and aggregating across flow types.[26] Unsurprisingly, high-frequency flow-specific idiosyncratic shocks are dampened by

[25]When disaggregating by flow type, they find that two factors, one estimated from 6 non-central advanced countries, and another one estimated from 15 emerging market economies (those with weight in the MSCI index above 1%) yield an average (across countries and flow types) adjusted R^2 of 0.05 (figure A7 of Cerutti et al. (2017c). In turn, Cerutti et al. (2017a) likewise find that an emerging-market inflow group factor, specific to the inflow type, accounts on average for just 12 percent of the variance of portfolio equity and bond as well as bank inflows to 33 emerging markets, using quarterly data over 2001-2015. In contrast, Sarno et al. (2016) find that common factors account for 80 percent of the variation of bond and equity flows from the U.S. to 55 other countries.

[26]The mean adjusted R^2 increases from 0.05 to 0.22 in their sample of non-large (mainly emerging) countries, and from 0.07 to 0.44 in their sample of advanced countries, with the rest of the discrepancy attributable to differences in country and time sample coverage as well as estimation methodology.

aggregation across flows and/or over time, thus raising the relative role of common shocks.

Figure 5 depicts the variance contribution of the global and group factors across individual countries, along with the 2-standard error bands (computed through a residual block bootstrap) of their combined total. There is considerable heterogeneity in the quantitative role of the common factors, even across countries within the same group. Their role is biggest in the Netherlands, where almost 90 percent of the variance of both gross inflows and outflows is driven by common shocks. The same country exhibits the largest variance contribution of global shocks – over 70 percent for both inflows and outflows. The latter figures are very similar to India's, which is the emerging market exhibiting the biggest relative contribution of common shocks. At the other end, New Zealand shows the smallest contribution among advanced economies, while among emerging markets that role corresponds to Pakistan. On the basis of the computed standard errors, common shocks represent a statistically significant force in the vast majority of advanced countries (the only exception is New Zealand in the case of gross outflows, plus Japan and Finland in the case of inflows), but in less than half of the emerging countries shown. Still, the largest emerging economies in the sample – Brazil, India, China – do exhibit significant effects of common shocks, both statistically and quantitatively.

The preceding results refer to the fraction of the variance of capital flows attributable to the common factors. From the macroeconomic perspective, however, a more relevant measure of countries' vulnerability to common shocks is the absolute (rather than relative) exposure their financial flows, expressed as percent of their respective GDP. In this vein, Table 6 shows the standard deviation of gross inflows and outflows explained by the factor model.[27]

The cross-country mean and standard deviation of this measure of exposure respectively are 6.02% and 9.45% of GDP for inflows, and 6.37% and 9.74% for outflows. Ireland (with a value of almost 60% of GDP) is a clear outlier, over 5 standard deviations from the overall mean (6.29 for inflows and 5.82 for outflows). Excluding Ireland, the overall mean and standard deviation fall to 4.86% and 5.15% for inflows, and 5.23% and 5.91% for outflows.

[27] This is simply computed as the square root of the product of the variance of the flow under consideration and the percentage of the variance explained by the factors.

4.4 Common factors and "push" variables

The above results show that common shocks, as summarized by a set of latent factors, account for a good deal of the variation of gross capital inflows and outflows around the world. The latent factor approach been used by a few recent papers concerned with the global determinants of capital flows, usually focusing on particular types of flows (e.g., Byrne and Fiess (2016), Sarno et al. (2016), Cerutti et al. (2017b), Barrot and Serven (2018)). However, a longstanding literature, going back to Calvo et al. (1996), takes a different approach. It focuses on the response of capital flows to a handful of "push" variables capturing global real and financial conditions and risk perceptions in international markets. In addition to risk proxies such as the VIX, recent literature has stressed global interest rates, as well as the U.S. real exchange rate, owing to the dominant role of the U.S. dollar in financial transactions worldwide, and global commodity prices (e.g., Forbes and Warnock (2012), Bruno and Shin (2015a)), Bruno and Shin (2015b), Reinhart et al. (2016), Avdjiev et al. (2017a), Cerutti et al. (2017b)).

How do these two approaches relate to each other? To answer this question, we proceed in two steps. First, we examine the association between the estimated common factors and measures of market risk. Recent literature finds that the common factor latent in risky asset prices across the world shows a strong negative correlation with risk proxies (Miranda-Agrippino and Rey (2015), Xu (2017), Abate and Serven (2018), Longstaff et al. (2011). Table 7 reports univariate regressions of the common factors on different measures of risk: the VIX, Moody's U.S. corporate BAA spread, the Gilchrist-Zakrajšek Gilchrist and Zakrajšek (2012) corporate bond spread index, and the uncertainty and risk aversion measures constructed by Xu (2017). For several of these measures, data availability falls short of our sample coverage. Nevertheless, over the available sample they all exhibit negative correlation with the estimated common factors, significant at the 10 percent level (or higher) in all cases except for the correlation between the BAA spread and the emerging-market inflow factor – probably reflecting the limited ability of such variable at capturing the riskiness of emerging-market assets.

Next, we run multivariate regressions of the common factors adding to the risk measure a set of standard "push" variables along the lines mentioned earlier. We also add the degree of openness of capital accounts around the world, which contributes to determine the extent to which shocks should be viewed as common or specific to particular countries or groups; see, e.g., Albuquerque et al. (2005).

Table 8 reports the results of estimating a vector autoregression with the common factors as dependent variables, including the forcing variables just listed as exogenous inputs. In reality, they are likely to be jointly determined with the factors, however, and this implies that the estimates should be seen as characterizing the correlations in the data rather than identifying causal relationships.

Preliminary exercises using the Schwartz information criterion showed that one single lag of the dependent variables suffices to capture the dynamics. The lagged dependent variable is significant in almost all the regressions, which also exhibit some evidence of lagged cross-factor effects. Inspection of the characteristic roots of the VAR's transition matrix confirms that the system possesses stable dynamics.

Columns 1 to 3 of Table 8 report the baseline VAR estimates; columns 4 to 6 present additional estimates using more disaggregated measures of commodity prices. In turn, Figures A.2-A.5 in Appendix A depict the cumulative response of the common factors to a (permanent) one-standard deviation increase in each of the regressors, based on the fitted models in the table.

The BAA spread, taken as risk measure for the regressions owing to its longer sample coverage, follows the same pattern as in the preceding table: its effects are uniformly negative on all three factors, but they are more precisely estimated for the global and advanced-country factors than for the emerging-market inflow factor. In turn, the U.S. real effective exchange rate (defined such that an increase represents a real appreciation) is positively correlated with the global and the advanced-country factors (although for the latter the correlation loses significance over time), but negatively with the emerging-country inflow factor, in line with the arguments of Bruno and Shin (2015a). Next, the measure of worldwide financial openness, which is entered as a two-year moving average to allow for the delayed effects of regulatory changes, has a positive impact on all three factors, particularly large for the global factor. This suggests that rising capital account openness across the world is a key force behind the upward trend observed in cross-border financial flows.

In contrast, the slope of the U.S. yield curve, given by the difference between long and short interest rates, has a strong negative effect on the group factors, but a more muted (and insignificant) effect on the global factor.[28] Lastly, the non-energy commodity price index shows a positive association with the global and emerging-country inflow factors (although only the former is statistically significant), in line with the analysis of Reinhart et al. (2017). However, it is also significantly negatively associated with the advanced-country factor. This sign pattern is consistent with the fact that emerging economies are more intensive in commodities than advanced economies, as measured by net commodity exports relative to GDP.

Since the non-energy commodity price index combines metals and minerals along with agricultural commodities, we can gain further insight on the reasons for these contrasting signs by considering separately the two components. This is done in columns 3-6 of Table 8. The results show that the positive effect on the global factor is attributable to the price of metals and minerals, which has no significant effect on the group factors. In contrast, the agricultural commodities price index shows a significant negative association with the advanced-countries group factor. The coefficients of the other variables show little change relative to those in columns 1-3.

The fit of the estimated models is quite satisfactory, although the sample is admittedly short. The R-squared range between 0.81 and 0.94, with the global factor showing the best fit and the emerging-market inflow factor the worst. The implication is that the common factor and "push vs pull" approaches are essentially equivalent. A small set of global variables can account for the bulk of the common shocks underlying capital flows worldwide, and thereby – in light of the variance decomposition results in Table 5 above – for a substantial portion of the variation in gross inflows and outflows around the world.

In light of the regression results, two variables appear to drive the differing behavior of the advanced-country and emerging-country group factors: the real exchange rate of the U.S. dollar, whose appreciation encourages flows among advanced economies but discourages them among emerging economies – in line with the arguments provided by Bruno and Shin (2015b) – and non-energy commodity prices, which affect negatively the advanced-country factor but not the emerging-country inflow factor.

[28] Adding also the U.S. short-term real interest rate to the regressions did not yield any significant estimates.

4.5 Explaining the impact of common shocks

Many countries have undergone large capital flow shifts at times of global turmoil, such as the 2007-2008 financial crisis or the 2013 'Taper tantrum'. Identifying the policies and structural features that determine the vulnerability of external financing flows to global shocks is a question of primary interest from the policy viewpoint.

Section 4.3 analyzed the variance of gross inflows and outflows attributable to the common factors, and showed that it exhibits considerable variation across countries. Some earlier attempts at identifying the forces behind such heterogeneity have focused on assessing the covariates of the factor loadings, because under conventional normalization assumptions they map into the variance shares of the factors.[29] Thus, Cerutti et al. (2017a) follow this approach in their analysis of bond and equity inflows to emerging markets, while Barrot and Serven (2018) do the same with total inflows and outflows for a sample of advanced and emerging markets.

As argued above, however, the absolute – rather than relative – contribution of the common factors to the variation of flows, shown in table 6, likely provides a more relevant measure of countries' exposure to common shocks. But what ingredients are responsible for the large exposure disparities across countries shown in the figure?

To answer this question, we resort to regressions of the chosen measure of exposure, measured as described, on a set of explanatory variables summarizing countries' key structural and policy features.

We use both financial and real variables. Among the former, we include financial openness – for which we use both de jure and de facto measures, respectively given by the Chinn-Ito index and the sum of foreign assets and liabilities as a ratio to GDP; financial depth (the ratio of credit to GDP); and the degree of flexibility of the exchange rate regime, as derived from the regime classification of Ghosh et al. (2015). To the extent that the common factors capture external financial shocks, we would expect financial openness to raise countries' exposure to them. Indeed, Barrot et al. (2018) find that financial openness increases the vulnerability of emerging markets' GDP growth to external monetary shocks. Financial

[29] With flows and factors standardized to unit variance, the variance share of each factor is just given by the square of its loading. Standardization of the dependent variable is common in the estimation of factor models to prevent high-variance countries from having a disproportionate weight in the analysis.

depth might play a more ambiguous role – facilitating the propagation of external financial shocks but possibly also helping cushion them. Lastly, exchange rate flexibility should help dampen the response of capital flows to common shocks, to the extent that a more flexible exchange rate is able to absorb a larger part of the impact (e.g., Goldberg and Krogstrup (2018)), although the influential work of Rey (2013) and Miranda-Agrippino and Rey (2015) sheds doubt on such presumption.

In turn, the real variables include overall market size, as measured by the log of real GDP; macroeconomic volatility (the standard deviation of real GDP growth); trade openness, proxied by imports plus exports as percent of GDP; and commodity specialization, measured by the ratio of net exports of commodities to GDP.

A larger market size should raise overall exposure, to the extent that international investors tend to be more active in bigger markets offering easier rebalancing opportunities (Eichengreen and Gupta (2015)).[30] Macroeconomic volatility likely has negative effects, if higher volatility results at the margin from greater domestic shocks and hence entails a smaller relative (although not necessarily absolute) role for common shocks; larger volatility might also discourage foreign investors. Openness to trade offers another avenue for the propagation of external disturbances, and thus in principle it should have a positive effect on exposure. Lastly, the effect of commodity specialization is more uncertain, although to the extent that global capital flow fluctuations are partly driven by commodity prices (as argued by Reinhart et al. (2017), countries more highly specialized in the production of commodities should be expected to be also more exposed to common capital flow cycles. In a similar vein, Barrot et al. (2018) find that commodity specialization raises the vulnerability of emerging-market growth to global monetary shocks.

We use as regressors the averages of these variables over the entire sample period employed in the estimation of the factor model. Hence, these cross-sectional results should be taken with some caution, as the explanatory variables have likely undergone significant changes over that time span. The regression results are reported in Table 9. We drop Ireland from the country sample because of the extreme values of the dependent

[30]This is certainly the case in larger, and especially more liquid, financial markets. Unfortunately, no suitable measures of size or liquidity of financial markets are available for the sample under consideration, and therefore we resort to using GDP as an alternative, as done by Eichengreen and Gupta (2015).

variable shown in Table 6 (results including Ireland, shown in Table A.7 in appendix A, are broadly similar but less precise).

Column 1 of Table 9 shows the results of univariate regressions; hence the coefficient estimates capture simple correlations. As conjectured, exposure to common shocks is significantly positively correlated with both de jure and de facto financial openness, as well as financial depth and trade openness. However, it is negatively correlated with the degree of commodity specialization.

The specifications in columns 2-8 use de jure financial openness, while those in columns 9-10 employ de facto financial openness. Both are robustly positive and significant. Column 2 adds exchange rate flexibility. Its parameter estimate is negative and significant at the 10 percent level. Barrot and Serven (2018) likewise find that exchange rate flexibility significantly reduces the impact of global shocks on gross capital inflows (although not outflows). Column 3 adds financial depth to the specification. It carries a positive and significant coefficient; in turn, the parameter on exchange rate flexibility becomes larger in absolute value and more prcisely estimated.

Columns 4 and 5 respectively introduce market size and aggregate volatility in the specification. Neither is significant, and the other coefficients exhibit minimal changes. Column 6 adds trade openness, which carries a positive and significant coefficient. Financial depth becomes insignificant, and the coefficients of financial openness and exchange rate flexibility decline in absolute value. The specification accounts for over half the variation of the dependent variable. Commodity specialization is added in column 7. Its coefficient estimate is well short of statistical significance, and the overall precision of the regression declines. Finally, column 8 re-estimates the specification in column 7 using a procedure robust to influential observations. All the explanatory variables, except for financial depth and commodity specialization, carry significant coefficients – including market size and macroeconomic volatility, whose parameter estimates are positive and negative, respectively.

Columns 9-10 repeat the estimations shown in columns 7-8, replacing de jure with de facto financial openness. Qualitatively, the estimates are broadly similar. The main difference is that trade openness now carries a very small coefficient, well short of statistical significance. Further, in column 9 the explanatory power of the specification rises considerably, to account for over 80 percent of the variation of the dependent variable.

Lastly, in column 10, whose estimates are computed using a procedure robust to influential observations, the degree of commodity specialization becomes marginally significant with a positive sign.

What can we conclude from these empirical exercises? Financial openness – whether de jure or de facto – and the degree of flexibility of the exchange rate regime appear to emerge as robust determinants of exposure to common shocks. Openness raises exposure, while exchange rate flexibility reduces it. For the other regressors considered, results are more fragile across specifications, and therefore no firm conclusions can be drawn.

4.6 Trends in globalization

Following the global crisis of 2007-2008, the fall of international capital flows – especially marked in the case of cross-border bank lending – has raised the question of whether financial globalization is undergoing a reversal (e.g, Forbes (2014)), although what should be the proper measure of financial globalization in this context has been subject of debate (Cerutti and Zhou (2017)), McCauley et al. (2017)).

Our factor model framework allows us to shed light on this issue, as it yields a natural measure of the overall degree of financial globalization, given by the exposure of countries' cross-border flows to common shocks.

To do this, we reestimate the factor model over rolling 20-year windows and recalculate at each step the variance decomposition.[31] Figure A.6 in appendix A shows that the window-specific estimates of the common factors obtained in this way track fairly closely their full-sample counterparts.

Figure 6 depicts the cross-country average of variance share explained by the factors over the different windows, with the latter denoted by their respective end-year. The graphs show separately the percentage contribution of the global and group factors, along with 95-percent confidence bands derived from a bootstrap procedure.

The top graphs show that the estimated variance share of the common factors rose steadily until the onset of the global crisis in 2007, and declined afterwards to levels close to those observed at the beginning of the sample.

[31] Goldberg and Krogstrup (2018) also use rolling windows to assess changes over time in the correlation of their index of capital flow pressure with a global risk factor, summarized by the VIX.

The cycle of rise and fall primarily reflects the changing variance share due to the global factor. At its peak in the window ending in 2007, it was some 15-20 percentage points higher than at the initial window.

The middle graphs of Figure 6 reveal that most of the action came from advanced-country inflows and outflows. Prior to the crisis, the fraction of their variance due to common factors rose by over 20 percentage points – from 40 percent to over 60 percent for inflows, and from 50 percent to 70 percent for outflows. The increase was exclusively attributable to the global factor; indeed, the percentage contribution of the advanced-country group factor declined over this period. Further, the 95-percent confidence bands indicate that these changes are statistically significant. After 2007, however, the process went in reverse: the fraction of the variance attributable to the common factors fell steadily, and the decline was entirely due to the shrinking role of the global factor. In contrast, the percentage contribution of the advanced-country group factor grew without interruption. In the final window, the variance share due to the common factors is somewhat larger than in the initial one, but there is a contrast between the global and the group factor: the latter has increased its contribution, while the former has not.

In turn, emerging-market inflows and outflows, shown in the bottom graphs, exhibit a less-pronounced cycle. The timing is similar to that found among advanced countries, with the contribution of common factors peaking in the 2007 window and declining subsequently, driven by the changing quantitative role of the global factor (trivially so in the case of gross outflows, for which there is no emerging-country group factor). But, unlike among advanced economies, in the case of gross inflows there is virtually no change in the proportion of the variance attributable to the group factor, while in the case of outflows the global factor accounts for a larger fraction (by over 10 percentage points) of the variance in the final window than it did in the initial window, in spite of the globalization reversal.

These results pertain to the variance share of common shocks.[32] To obtain a measure of countries' changing exposure to them, taking also into account the magnitude of flows relative to the size of the economy, we examine the trends in the fraction of the standard deviation of flows, relative

[32] Appendix B shows that the results are little changed if developing countries are added to the analysis.

to trend GDP, attributable to the common factors. In our setting, this is a natural measure of countries' financial globalization.

Figure 7, analogous to Figure 6, summarizes the trends in cross-country average exposure to common shocks. For the sample as a whole, shown in the top graphs, average exposure rose steadily from some 3 percent of trend GDP in the initial window to over 7 percent at the peak, and declined subsequently. In the final window, exposure remained above 6 percent of trend GDP, pointing to a substantial (and statistically significant, according to the 95 percent confidence bands) rise in financial globalization over the period of analysis.

The middle graphs show that the rise was especially marked among advanced countries – from just under 4 percent of trend GDP initially, to over 10 percent in the final window – after peaking at close to 12 percent in the run-up to the crisis.

The rise was also noticeable, albeit smaller, among emerging countries (bottom graphs) – from 2-3 percent of trend GDP to just under 5 percent at the peak. After the post-crisis decline, the estimated exposure of flows to common shocks in the final window remains above the initial-window level, but the poor precision of the estimates does not allow firm conclusions on whether the globalization reversal has been partial or full.

Overall, these results do suggest a cycle of financial globalization ascent and partial reversal, especially pronounced among advanced countries, with the global financial crisis separating the two phases. Advanced countries also exhibit an increased degree of within-group integration post-crisis, reflected in the growing variance share attributable to group-specific common shocks.

5 Conclusions

Recent episodes of worldwide financial turmoil have raised new concerns among policymakers regarding the vulnerability of their economies to shifts in international financial flows driven by global disturbances, prompting renewed interest in the policy measures that might help mitigate their exposure to shocks originating beyond their national borders.

This paper has attempted to shed some light on these questions using a latent factor model to analyze jointly the gross inflows and outflows of a large number of countries. Estimation of the model takes advantage of recent methodological advances in the principal-component approach to factor models.

Overall, the paper finds that capital flows exhibit a substantial degree of commonality. The implication is that the international financial cycle is quantitatively quite significant, contrary to the conclusions of some recent literature. The discrepancy is primarily due to the fact that previous studies have focused on individual types of flows at quarterly frequency, while we focus on aggregate flows – likely more relevant from the macroeconomic perspective – at annual frequency.

Still, there are major contrasts across country groups, along two dimensions: first, the role of common shocks – both global and group-specific – is considerably bigger for advanced countries than for the rest. Second, among the former countries inflows and outflows reflect essentially the same common shocks, but this is not the case among other countries. In addition, there have been marked changes over time as well. The exposure of capital flows to the international financial cycle, which had risen steadily prior to the global crisis – especially among advanced countries – has declined slightly in its aftermath. However, exposure remains at present well above its levels at the beginning of the sample period analyzed in the paper.

In the policy dimension, the paper finds that the degree of openness of the capital account and the flexibility of the exchange rate regime matter for the exposure of capital flows to the international financial cycle: exposure is significantly higher in countries more financially open and with less flexible regimes. This suggests that, in spite of the global trend towards more open capital accounts, the Mundellian Trilemma governing the choice of exchange rate regime, capital account openness, and monetary independence has not been reduced (yet?) to a dilemma in which the exchange rate regime has ceased to matter.

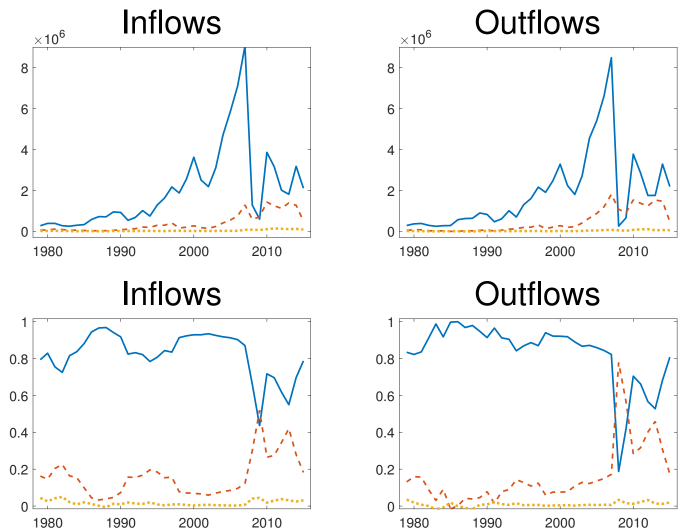


Figure 1: Gross capital flows, by country group: total flows (USD million, upper panels) and percentage shares (lower panels). Advanced (solid), emerging (dashed) and developing countries (dotted).

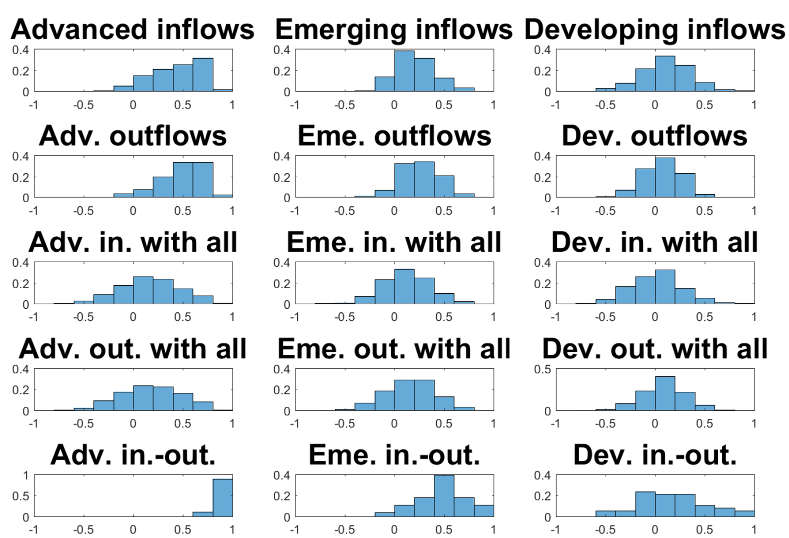


Figure 2: Histograms of the correlation coefficients of gross inflows and outflows (as percent of trend GDP).

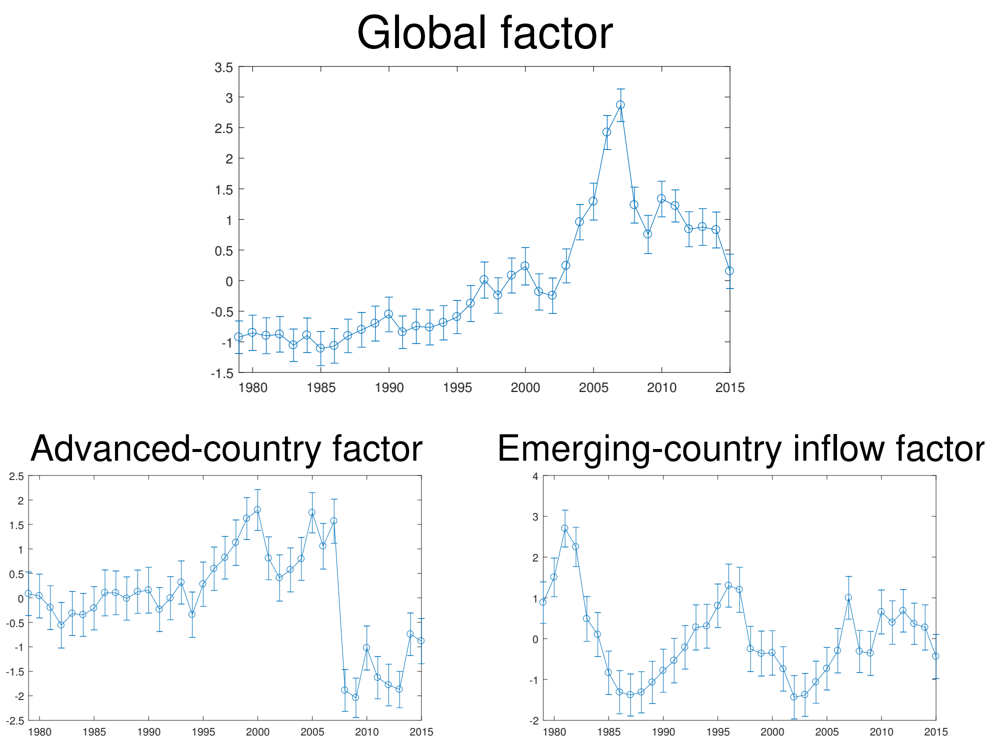
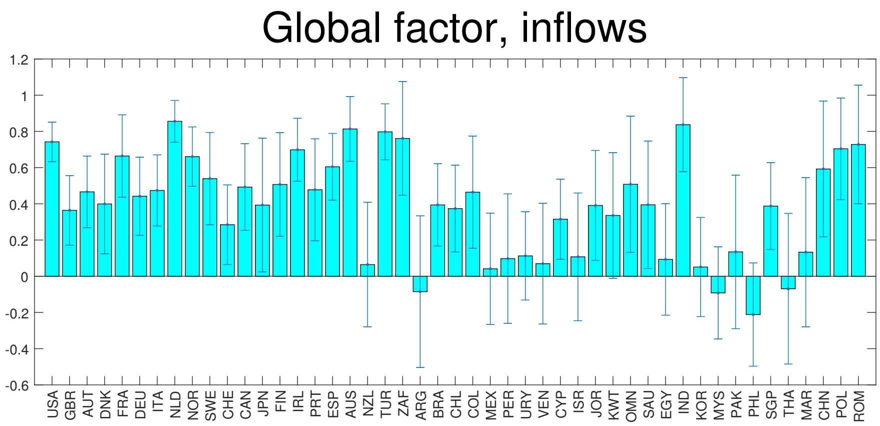
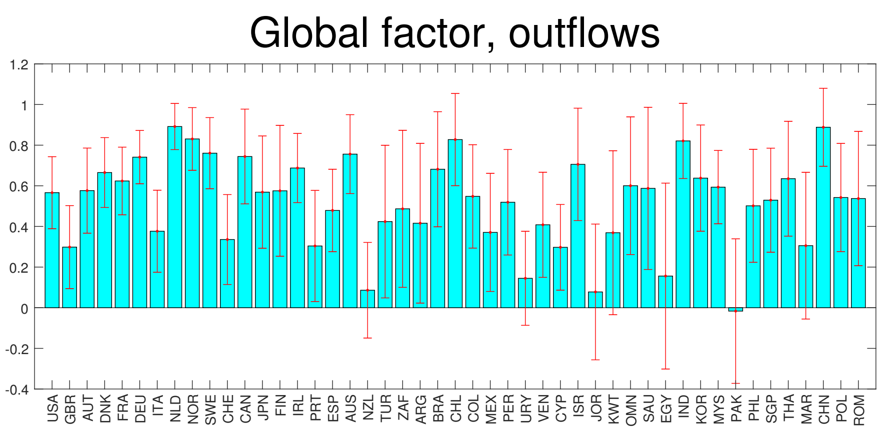


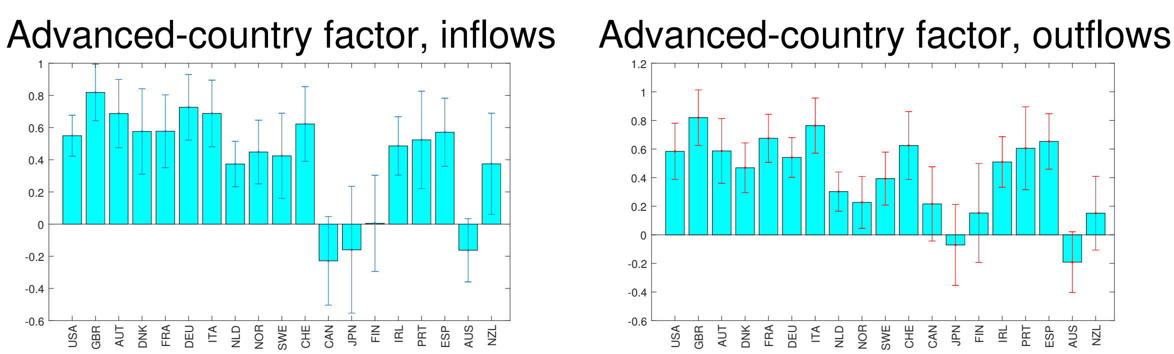
Figure 3: Estimated factors. Two-standard deviation error bars obtained through country block bootstrap with 10000 replications.



(a)

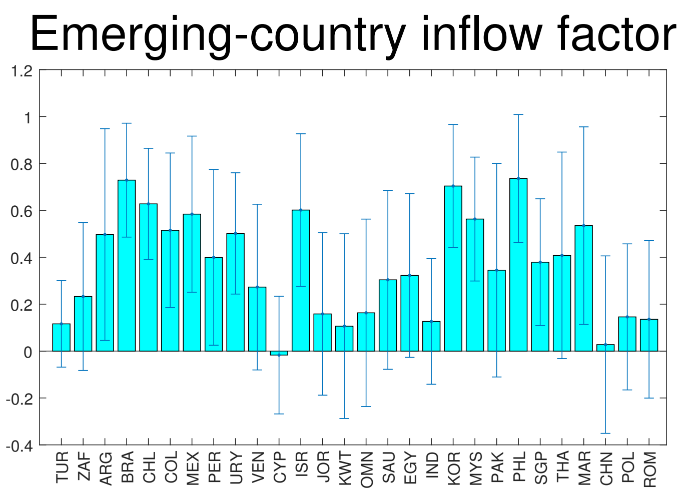


(b)



(c)

Figure 4: Estimated loadings. Two-standard deviation error bars obtained through country block bootstrap with 10000 replications.



(d)

Figure 4: Estimated loadings. Two-standard deviation error bars obtained through country block bootstrap with 10000 replications.

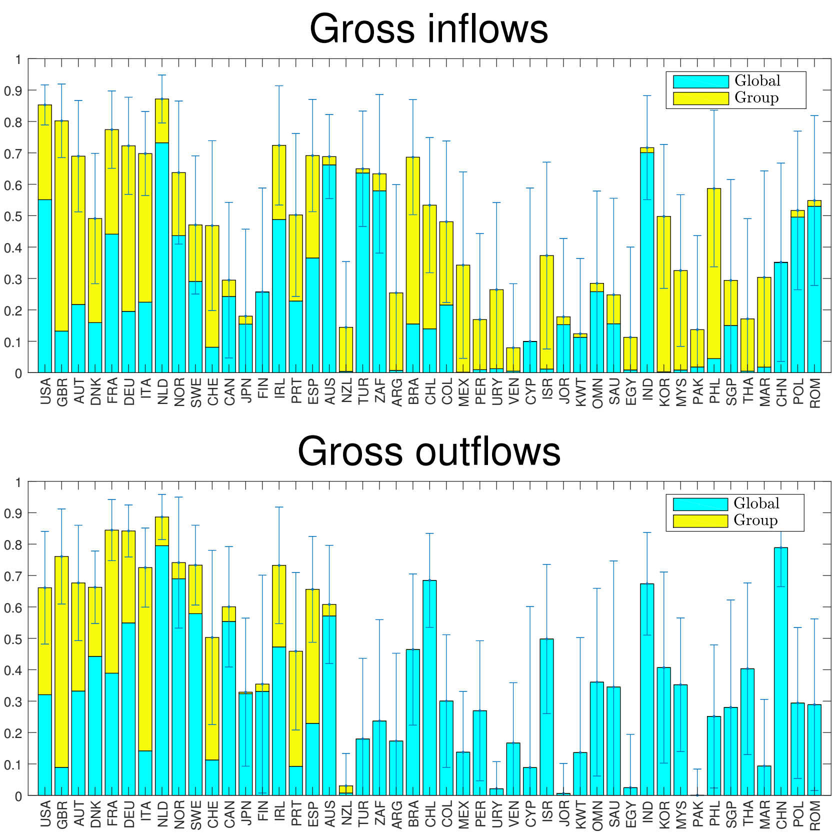


Figure 5: Fraction of variance of gross capital flows explained by the estimated factors. Two-standard deviation error bars obtained through country block bootstrap with 10000 replications.

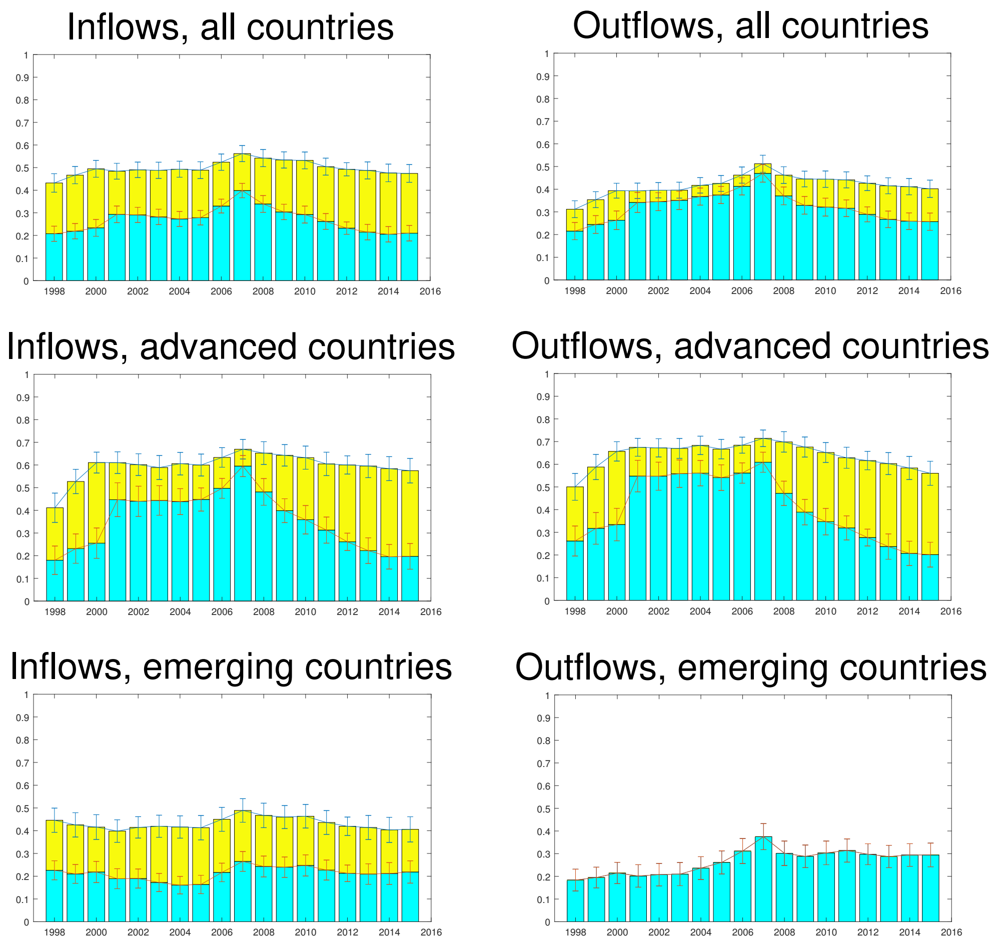


Figure 6: Average over the indicated set of countries of the fraction of the variance of gross capital inflows and outflows explained by the global (blue) and group (yellow) factors, estimated on 20 year overlapping windows ending in the year indicated in the x-axis. Two-standard deviation error bars obtained through country block bootstrap with 10000 replications.

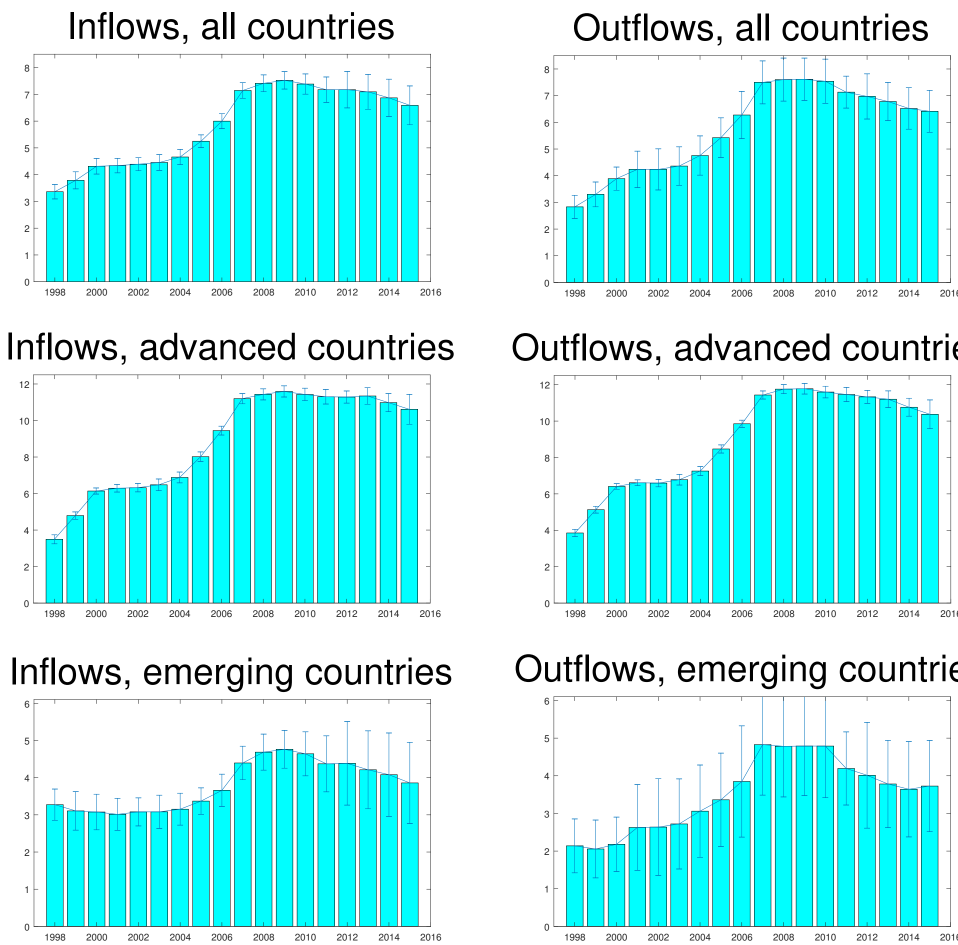


Figure 7: Average over the indicated set of countries of the standard deviation of capital flows, as percent of trend GDP, explained by the factors, estimated over 20-year overlapping windows ending in the year indicated in the x-axis. Two-standard deviation error bars obtained through country block bootstrap with 10000 replications.

Model	IC_{p2}	HQ_2	Stand. score	Rank
(1; 1,0; 0,0; 0,0,1,0)	-0.312	-954.0	0.980	1
(1; 1,0; 0,0; 0,0,0,0)	-0.296	-980.6	0.966	2
(1; 1,0; 1,0; 0,0,0,0)	-0.303	-929.1	0.952	3
(0; 1,1; 0,0; 0,0,0,0)	-0.298	-940.1	0.950	4
(1; 2,0; 0,0; 0,0,1,0)	-0.293	-957.4	0.950	5
(1; 1,1; 0,0; 0,0,0,0)	-0.302	-914.0	0.943	6
(2; 0,0; 0,0; 0,0,0,0)	-0.300	-900.2	0.933	10
(3; 0,0; 0,0; 0,0,0,0)	-0.287	-817.5	0.871	48
(1; 0,0; 0,0; 0,0,0,0)	-0.274	-803.5	0.843	100
(1; 0,0; 0,0; 1,1,1,1)	-0.270	-735.6	0.801	261
(1; 1,1; 1,1; 0,0,0,0)	-0.261	-706.3	0.773	465
(1; 0,0; 1,1; 0,0,0,0)	-0.249	-597.4	0.699	1638
(0; 0,0; 1,1; 1,1,1,1)	-0.236	-634.2	0.697	1679
(0; 0,0; 1,1; 0,0,0,0)	-0.230	-544.6	0.642	3502

Table 1: Information criteria scores. The numbers in the "model" column correspond to the number of factors in each group ($r^G; r_1^R, r_2^R; r_1^D, r_{-1}^D; r_{1,1}^{RD}, r_{1,-1}^{RD}, r_{2,1}^{RD}, r_{2,-1}^{RD}$). The standardized score is computed as (IC$_{p2}$/IC$_{p2,max}$+HQ2/HQ2$_{max}$)/2. The rank is based on the standardized score. The maximum number of factors considered was (3; 3,3; 3,3; 2,2,2,2).

	Factors			Loadings		
Model	Global	Adv	Eme In	Global	Adv	Eme In
(1;1,0;00;0000)	0.996	0.989	—	0.996	0.994	—
(1;1,0;10;0000)	0.997	0.985	0.979	0.999	0.990	0.984
(0;1,1;00;0000)	—	0.982	0.720	—	0.995	0.794
(1;2,0;00;0010)	0.999	0.948	1.000	0.999	0.960	1.000
(1;1,1;00;0000)	0.979	0.977	0.935	0.978	0.993	0.891

Table 2: Correlations of factors and loadings of the the different models with those of the (1;10;00;0010) model (the one with highest score). For model (0;1,1;00;000) the part of the factors orthogonal to the global factor or the main model are considered; the loadings are obtain by regressing the data over these obtained factors and the global factor of the main model (respecting the zero restrictions implied by the (1; 10;00;0010) multilevel structure).

	Global				**Advanced**		**Eme. In**
	Adv		Eme		In	Out	
	In	Out	In	Out			
Significant & positive	18/19	18/19	14/28	22/28	15/19	14/19	13/28
Significant & negative	0/19	0/19	0/28	0/28	0/19	0/19	0/28
Median	0.49	0.58	0.33	0.52	0.52	0.51	0.36
Median t-stat.	4.2	6.3	2.1	3.4	5.1	5.2	1.9

Table 3: Summary statistics for the estimated loadings of the different factors. Significance refers to the 95% confidence level, based in 10000 block bootstrap replications.

Inflows-Outflows			Inflows-Inflows		Outflows-Outflows
Global		Advanced	Global-Advanced	Global-Emerging	Global-Advanced
Adv	Eme				
0.73	0.27 (0.47)	0.88	-0.16	-0.64	-0.34

Table 4: Correlations of the loadings of the different factors. In the number between brackets in the second column, the loadings of the emerging inflows factor are added of those of the global factor over emerging inflows, before computing the correlation with the loadings of the global factor over emerging outflows.

	All factors		Global factor		Group factor	
	Inflows	Outflows	Inflows	Outflows	Inflows	Outflows
All countries						
Median	0.47 (0.07)	0.36 (0.09)	0.16 (0.06)	0.30 (0.07)	0.18 (0.07)	0.00 (0.00)
Mean	0.45 (0.03)	0.42 (0.03)	0.23 (0.03)	0.32 (0.04)	0.22 (0.03)	0.10 (0.02)
Advanced						
Median	0.69 (0.08)	0.66 (0.06)	0.24 (0.09)	0.33 (0.10)	0.27 (0.09)	0.26 (0.10)
Mean	0.58 (0.05)	0.62 (0.04)	0.31 (0.05)	0.37 (0.05)	0.27 (0.05)	0.25 (0.05)
Emerging						
Median	0.31 (0.09)	0.27 (0.08)	0.11 (0.06)	0.27 (0.08)	0.13 (0.08)	0.00 (0.00)
Mean	0.36 (0.05)	0.28 (0.05)	0.17 (0.04)	0.28 (0.05)	0.18 (0.04)	0.00 (0.00)
No financial centers						
All countries						
Median	0.42 (0.07)	0.35 (0.09)	0.16 (0.06)	0.30 (0.07)	0.18 (0.06)	0.00 (0.00)
Mean	0.43 (0.04)	0.40 (0.04)	0.23 (0.03)	0.32 (0.04)	0.20 (0.03)	0.07 (0.02)
Advanced						
Median	0.66 (0.08)	0.67 (0.07)	0.27 (0.10)	0.42 (0.10)	0.22 (0.09)	0.19 (0.09)
Mean	0.57 (0.05)	0.62 (0.05)	0.34 (0.06)	0.40 (0.06)	0.23 (0.06)	0.22 (0.05)

Table 5: Fraction of the variance explained by the estimated factors, median and over the indicated groups. Two standard deviations are shown between brackets . The lower 4 rows show results excluding the main international financial centers (US, UK, Switzerland, Germany and Japan)

	Inflows		Outflows	
	Total	Explained	Total	Explained
All countries				
Median	4.47	2.88(0.30)	4.51	2.69(0.56)
Mean	9.13	6.02(0.57)	10.18	6.37(0.73)
Advanced				
Median	7.74	5.77(0.81)	7.73	6.62(1.01)
Mean	12.13	9.72(0.50)	12.24	10.05(0.48)
Emerging				
Median	4.12	2.52(0.33)	3.97	1.74(0.29)
Mean	7.08	3.52(0.90)	8.78	3.87(1.19)
USA	3.64	3.37(0.13)	2.63	2.14(0.29)
GBR	19.15	17.15(1.23)	19.73	17.21(1.67)
AUT	11.75	9.76(1.27)	11.95	9.83(1.34)
DNK	8.23	5.77(1.20))	8.14	6.62(0.57)
FRA	7.51	6.61(0.52)	7.73	7.11(0.41)
DEU	5.88	4.99(0.53)	5.79	5.31(0.26)
ITA	4.01	3.35(0.32)	3.93	3.35(0.28)
NLD	26.35	24.60(1.08)	26.87	25.30(1.03)
NOR	9.70	7.75(1.37)	13.08	11.26(1.58)
SWE	7.32	5.02(1.15)	8.47	7.25(0.62)
CHE	17.32	11.85(3.33)	19.49	13.82(3.72)
CAN	2.64	1.43(0.59)	3.00	2.33(0.37)
JPN	2.49	1.06(0.76)	2.65	1.52(0.53)
FIN	10.22	5.18(2.98)	11.34	6.75(3.12)
IRL	69.83	59.41(7.59)	68.58	58.68(7.24)
PRT	9.48	6.72(1.69)	7.00	4.74(1.28)
ESP	7.74	6.43(0.82)	6.08	4.92(0.62)
AUS	3.33	2.76(0.27)	2.76	2.15(0.33)
NZL	3.94	1.50(1.00)	3.32	0.58(0.70)
TUR	3.40	2.74(0.38)	1.47	0.62(0.46)
ZAF	4.18	3.33(0.66)	2.45	1.19(0.82)
ARG	3.15	1.59(1.02)	2.68	1.11(0.90)
BRA	2.75	2.28(0.30)	2.34	1.60(0.42)
CHL	5.39	3.94(0.79)	5.42	4.48(0.49)
COL	2.90	2.01(0.54)	2.05	1.12(0.40)
MEX	3.17	1.85(0.79)	2.04	0.76(0.53)

	Inflows		Outflows	
	Total	Explained	Total	Explained
PER	3.56	1.46(1.06)	3.56	1.85(0.74)
URY	5.39	2.77(1.33)	6.28	0.91(1.28)
VEN	3.32	0.94(0.93)	5.68	2.32(1.33)
CYP	51.3	16.2(22.3)	49.6	14.8(23.3)
ISR	4.47	2.73(1.05)	4.51	3.18(0.77)
JOR	8.36	3.52(2.23)	7.89	0.61(1.76)
KWT	7.84	2.76(2.24)	45.51	16.79(19.15)
OMN	4.17	2.22(1.12)	9.48	5.69(2.46)
SAU	2.86	1.42(0.83)	15.18	8.91(5.33)
EGY	5.72	1.92(1.87)	4.47	0.70(1.36)
IND	2.07	1.76(0.20)	1.99	1.63(0.20)
KOR	4.08	2.88(0.66)	3.32	2.12(0.80)
MYS	6.21	3.54(1.29)	7.58	4.49(1.33)
PAK	2.20	0.82(0.73)	1.81	0.03(0.39)
PHL	4.26	3.27(0.69)	3.71	1.86(0.84)
SGP	35.77	19.39(9.90)	40.69	21.53(12.57)
THA	5.85	2.42(1.98)	4.24	2.69(0.92)
MAR	3.29	1.81(0.95)	2.52	0.77(0.81)
CHN	2.55	1.51(0.66)	4.40	3.91(0.30)
POL	3.64	2.62(0.62)	2.38	1.29(0.53)
ROM	6.51	4.82(1.20)	2.63	1.41(0.69)

Table 6: Standard deviation of flows, as percentage of GDP, and fraction explained by the factors. Two standard errors are shown between brackets.

	(1) Fg	(2) Fadv	(3) FemeIn
VIX_s	-0.278**	-0.554**	-0.322***
	(0.107)	(0.217)	(0.0635)
N	25	25	25
R^2	0.271	0.385	0.268
BAA10YM_s	-0.287***	-0.463**	-0.209
	(0.104)	(0.209)	(0.133)
N	36	36	36
R^2	0.412	0.384	0.097
GZ_s	-0.285***	-0.473***	-0.236***
	(0.0642)	(0.169)	(0.0845)
N	36	36	36
R^2	0.406	0.400	0.123
UncD_s	-0.319***	-0.519**	-0.316***
	(0.0648)	(0.219)	(0.0726)
N	29	29	29
R^2	0.415	0.394	0.298
RiskavD_s	-0.295**	-0.564***	-0.332***
	(0.109)	(0.186)	(0.0582)
N	29	29	29
R^2	0.354	0.465	0.329
UncD_s	-0.221***	-0.268	-0.176*
	(0.0480)	(0.177)	(0.0911)
RiskavD_s	-0.154*	-0.393**	-0.220***
	(0.0839)	(0.152)	(0.0592)
N	29	29	29
R^2	0.472	0.527	0.383

HAC estandard errors, Newey-West 4 lags, in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regressions of the factors over different measures of risk aversion (plus a constant, not shown) in first differences. BAA10YM corresponds to Moody's U.S. corporate BAA spread, GZ corresponds to the Gilchrist and Zakrajšek (2012) corporate bond spread index, and UncD and RiskavD correspond to the uncertainty and risk aversion measures constructed by Xu (2017). All the measures have been rescaled to have unit standard deviation, so that the coeficients are comparable.

	(1)	(2)	(3)	(4)	(5)	(6)
		Factor			Factor	
	Global	Advanced	Emerging	Global	Advanced	Emerging
			inflows			inflows
Lagged global factor	0.615***	-0.0916	-0.339*	0.379***	-0.217	-0.217
	(0.126)	(0.161)	(0.200)	(0.134)	(0.191)	(0.239)
Lagged advanced factor	-0.0348	0.216**	-0.0495	-0.0463	0.209**	-0.0516
	(0.0768)	(0.0979)	(0.122)	(0.0687)	(0.0982)	(0.123)
Lagged emerging inflows factor	-0.195***	-0.0961	0.663***	-0.0321	-0.0328	0.610***
	(0.0561)	(0.0715)	(0.0888)	(0.0698)	(0.0999)	(0.125)
BAA spread	-0.253***	-0.470***	-0.129	-0.196***	-0.444***	-0.153
	(0.0631)	(0.0805)	(0.0999)	(0.0585)	(0.0838)	(0.105)
US exchange rate (log)	0.163**	0.190**	-0.195*	0.174***	0.191**	-0.201*
	(0.0652)	(0.0831)	(0.103)	(0.0581)	(0.0831)	(0.104)
Chinn-Ito average	4.442***	2.499*	3.370**	4.490***	2.600*	3.165*
	(1.082)	(1.379)	(1.713)	(0.953)	(1.363)	(1.706)
Yield curve slope	-0.0602	-0.353***	-0.260**	-0.0302	-0.342***	-0.274**
	(0.0667)	(0.0850)	(0.106)	(0.0598)	(0.0856)	(0.107)
Commodity price (non-energy, log)	0.245**	-0.381***	0.257			
	(0.109)	(0.140)	(0.173)			
Agriculture price (log)				-0.210	-0.437**	0.317
				(0.139)	(0.198)	(0.248)
Metals&minerals price (log)				0.470***	0.0258	-0.0607
				(0.123)	(0.177)	(0.221)
_cons	-2.688***	-1.537*	-2.076**	-2.737***	-1.608*	-1.942*
	(0.668)	(0.851)	(1.057)	(0.588)	(0.841)	(1.053)
N	36	36	36	36	36	36
hqic	3.500	3.500	3.500	3.295	3.295	3.295
sbic	4.273	4.273	4.273	4.154	4.154	4.154
R^2	0.926	0.883	0.815	0.942	0.885	0.816

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: VARX (in levels) with one lag and exogenous variables. Both models are stable. The Chinn-Ito capital market openness index is introduced as the mean of the contemporaneous value and lagged by one and two years, averaged over advanced and emerging countries. For both models, an LM test fails to reject absence of auto-correlation in the residuals (for the first five lags, p-values are 0.030, 0.047, 0.675, 0.934, 0.640 (none significant at 5% if a Bonferroni-Holm correction for multiple testing is applied) for the first, simpler, model and 0.111, 0.383, 0.683, 0.856, 0.704 for the second). In both models the Bayesian information criterion selects 1 lag, and the final prection error and the Hannan-Quinn criteria slect 2 lags; the Akaike criterion selects 3 lags in the simpler model and 4 in the more complex. A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Chinn-Ito	8.446***	8.593***	5.817***	6.000***	6.036***	4.160***	4.134***	2.374**		
	(1.859)	(1.821)	(1.792)	(1.716)	(1.740)	(1.494)	(1.496)	(0.906)		
	0.202									
Exchange rate flexibility	-1.932	-2.132*	-2.952**	-2.684**	-2.702**	-2.015*	-1.881	-1.451***	-1.907***	-1.483***
	(1.366)	(1.231)	(1.201)	(1.236)	(1.300)	(1.120)	(1.351)	(0.505)	(0.514)	(0.343)
	0.022									
Domestic credit (over GDP, log)	3.693***		3.016***	3.338***	3.290***	1.428	1.427	-0.280	-0.296	-0.341
	(0.781)		(0.778)	(0.800)	(0.915)	(0.958)	(0.948)	(0.524)	(0.568)	(0.362)
	0.162									
Real GDP (log)	-0.0166			-0.518	-0.533	0.299	0.262	0.492**	0.465**	0.278**
	(0.390)			(0.414)	(0.403)	(0.375)	(0.412)	(0.208)	(0.195)	(0.138)
	-0.011									
GDP growth volatility	-0.254				-0.0402	-0.256	-0.272	-0.471***	-0.00467	-0.427***
	(0.404)				(0.417)	(0.446)	(0.427)	(0.160)	(0.376)	(0.122)
	-0.004									
trade openness	0.0629***					0.0524***	0.0518***	0.0539***	-0.00757	0.00496
	(0.00853)					(0.00672)	(0.00763)	(0.00560)	(0.00687)	(0.00478)
	0.348									
Non-fuel commodity net exports/GDP	-20.63**						-4.896	3.190	6.634	7.174*
	(9.737)						(11.65)	(5.359)	(5.149)	(3.704)
	0.020									
De facto financial openness	2.335***								2.535***	2.030***
	(0.181)								(0.197)	(0.116)
	0.820									
_cons		4.011	-4.956	6.752	7.486	-9.967	-9.121	-8.625	-7.310	-1.898
		(2.441)	(3.096)	(9.847)	(10.83)	(9.503)	(9.797)	(5.547)	(5.303)	(3.693)
N		92	92	92	92	92	92	92	92	91
R^2		0.250	0.335	0.351	0.351	0.507	0.508		0.858	
adj. R^2		0.234	0.313	0.321	0.313	0.472	0.467		0.847	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Regressions of the square root of the variance of each country-flow-direction explained by the factors, excluding Ireland. Values in column (1) correspond to single-variables regressions; the values below the standard errors are the adjusted R^2. Columns (8) and (10) implement robust regression, excluding data with Cook's D >1, applying Hubert's weights until convergence and then bi-weights until convergence.

A Additional tables and figures

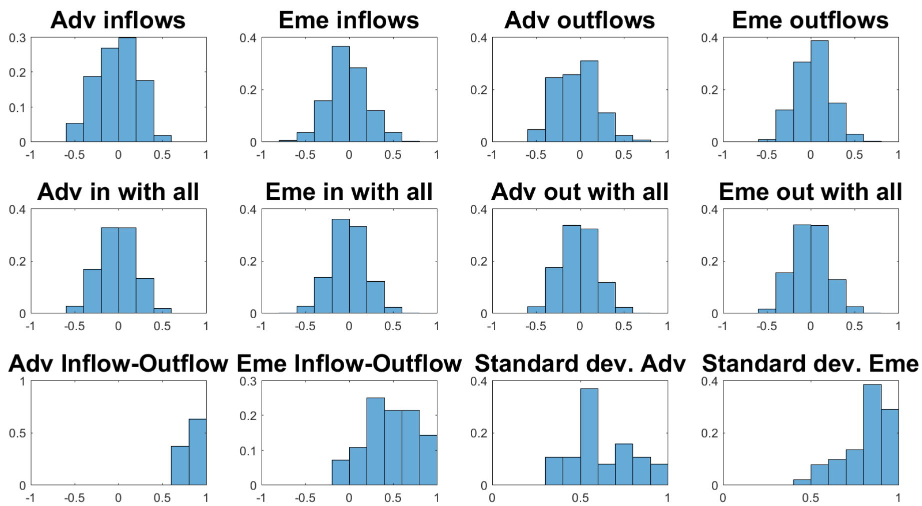


Figure A.1: Histograms of the correlation coefficients of the residuals of the estimated model, and standard deviation of the residuals. Note that the correlations corresponding to different countries are around zero, while inflow-outflow correlations within countries (left two panels of the bottom line) are large and positive. There is also evidence of heteroskedasticity (right two panels of the bottom line).

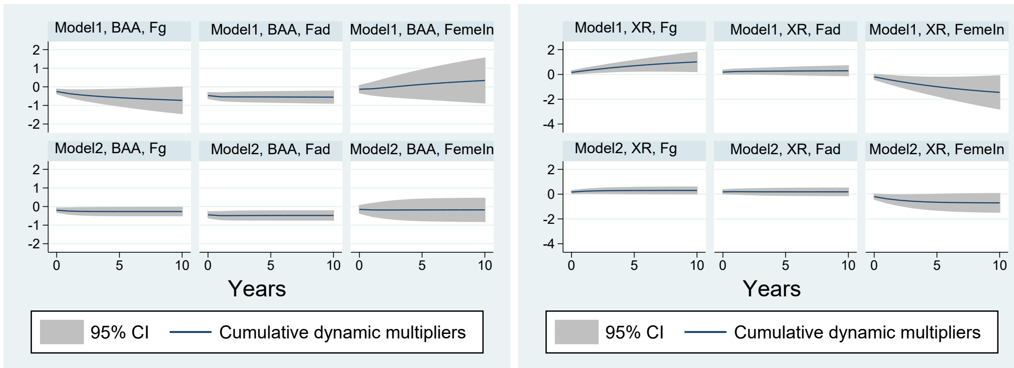


Figure A.2: Cumulative effect of a permanent one standard deviation increase in the bond spread measure (left panel) and the log of the real US trade-weighted exchange rate (right panel), over the estimated factors, based on the simpler model (top graphs) and the more complicated one (lower graphs).

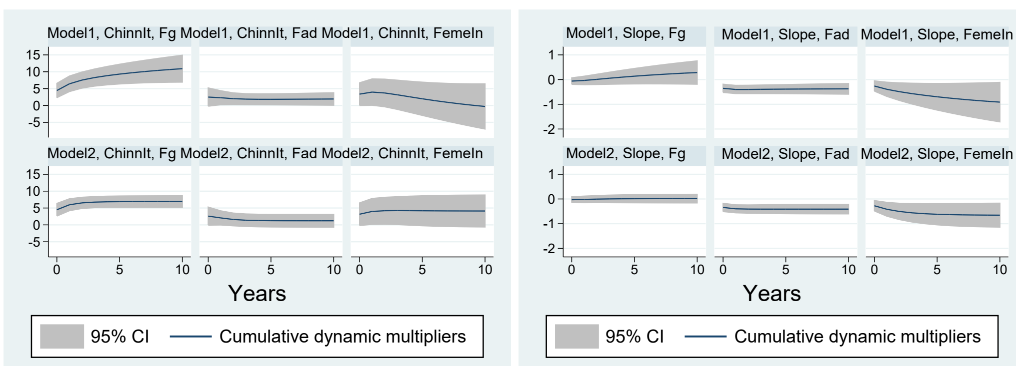


Figure A.3: Cumulative effect of a permanent one standard deviation increase in the average over advanced and emerging countries of the Chinn-Ito capital account openness measure (average of the contemporary value and that lagged by 1 and 2 years, left panel) and the slope of the yield curve (10-year US treasury constant maturity minus federal funds rate, right panel), over the estimated factors. Top (bottom) graphs are based on the simpler (complex) model.

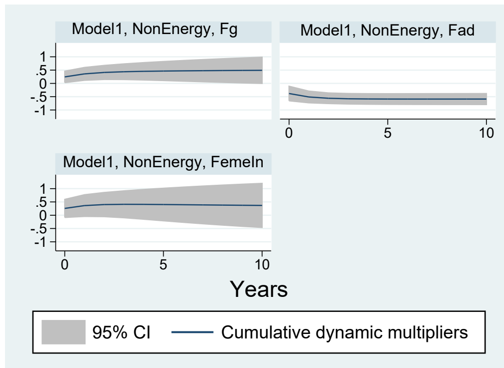
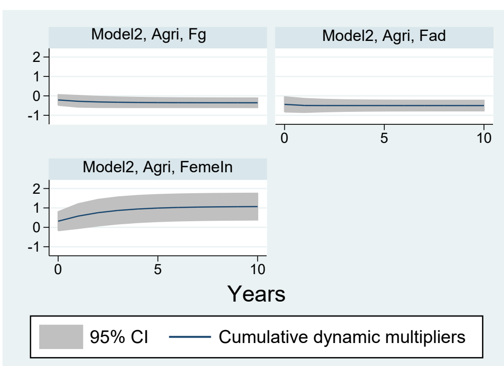


Figure A.4: Cumulative effect of a permanent one standard deviation increase in the log of the non-energy commodity price index, based on the simppler model.



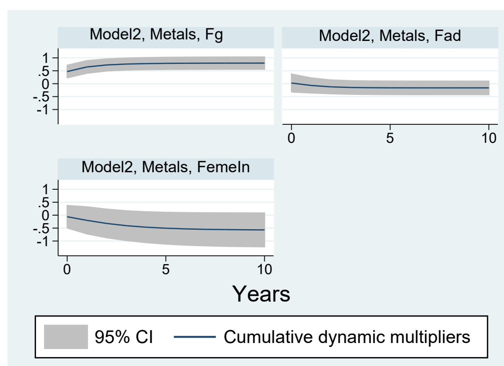


Figure A.5: Cumulative effect of a permanent one standard deviation increase in the log of the agricultural commodity index (left panel) and the log of the metals and minerals commodity price index (right panel), over the estimated factors, based on the more complicated model.

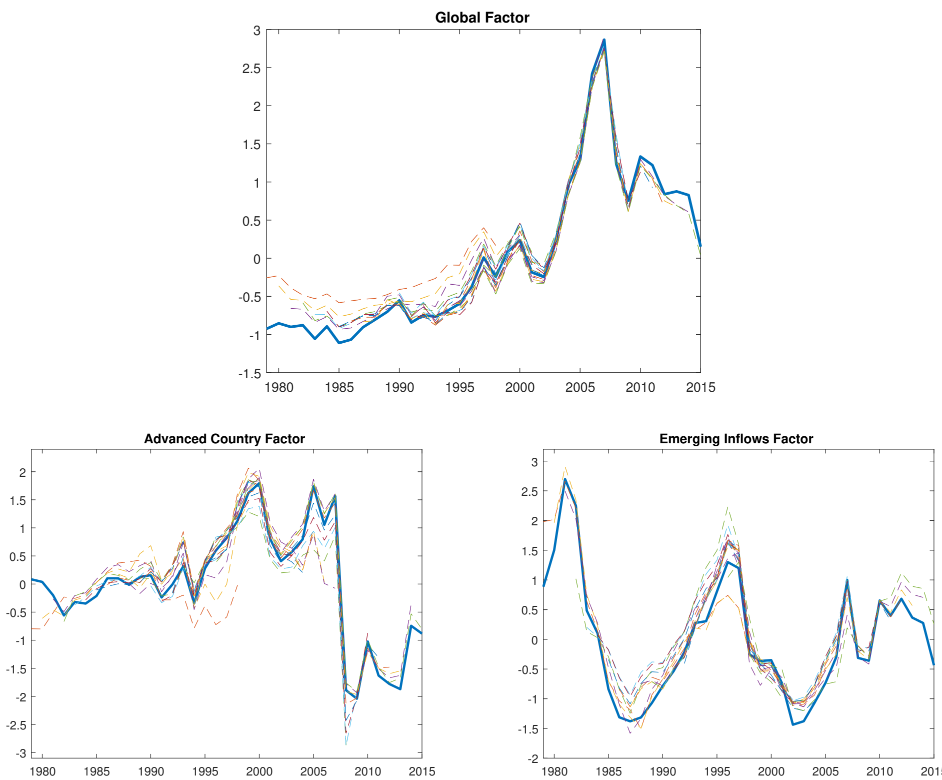


Figure A.6: The thick solid line corresponds to the factor estimated using the complete sample (F_0^α). Dashed lines correspond to the factor estimated using the corresponding 20-year window, re-scaled to have the same variance than F_0^α over the corresponding 20-year widow.

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

Table A.1: List of countries

Adv	Eme	Dev	All	Adv&Eme
0.98 ± 0.12	0.92 ± 0.10	0.77 ± 0.06	0.89 ± 0.08	$0.94 \pm .010$

Table A.2: Exponent of cross-sectional dependence (α), from Bailey et al. (2016b). Errors correspond to two standard deviations. *Errors in α, based in Bailey et al. (2016b) , tend to be underestimated when $\alpha \precsim 0.7$ and overestimated when $\alpha \precsim 1$.*

	Adv	Eme	All
Inflows	0.35 ± 0.06	0.39 ± 0.05	40 ± 0.05
Outflows	0.45 ± 0.17	0.69 ± 0.07	45 ± 0.08
Both	0.29 ± 0.04	0.60 ± 0.07	0.60 ± 0.06

Table A.3: Exponent of cross-sectional dependence (α), from Bailey et al. (2016b) for the residuals of the estimated model. Errors correspond to two standard deviations. *Errors in α, based in Bailey et al. (2016b) , tend to be underestimated when $\alpha \precsim 0.7$ and overestimated when $\alpha \precsim 1$.*

Model		AllIn	AllOut	AdvIn	AdvOut	EmeIn	EmeOut	DevIn	DevOut
(1; 10; 0010)NoDev	IPS	0.	0.	0.	0.	0.	0.		
	Hadri	.81	.88	.86	.70	.63	.81		
(1; 10; 0010)EmeDev	IPS	0.	0.	0.	0.	0.	0.	0.	0.
	Hadri	.73	.37	.76	.56	0.58	.73	.06	.53

Table A.4: Residuals of the estimated models. p-values for Im-Pesaran-Shin (IPS) test of all time-series having a unit root, implemented with 2 lags, and Hadri test for no series having a unit root, implemented with a Bartlett kernel and 2 lags. In "EmeDev" model the EmeIn (EmeOut) column includes emerging and developing inflows (outflows).

	All factors				Global factor				Group factor			
	Inflows		Outflows		Inflows		Outflows		Inflows		Outflows	
Country	value	2S.E.	value	2S.E.	value	2S.E.	value	2S.E.	value	2S.E.	value	2S.E.
All countries												
Median	0.47	0.07	0.36	0.09	0.16	0.06	0.30	0.07	0.18	0.07	0.00	0.00
Mean	0.45	0.03	0.42	0.03	0.23	0.03	0.32	0.04	0.22	0.03	0.10	0.02
Adv.												
Median	0.69	0.08	0.66	0.06	0.24	0.09	0.33	0.10	0.27	0.09	0.26	0.10
Mean	0.58	0.05	0.62	0.04	0.31	0.05	0.37	0.05	0.27	0.05	0.25	0.05
Eme.												
Median	0.31	0.09	0.27	0.08	0.11	0.06	0.27	0.08	0.13	0.08	0.00	0.00
Mean	0.36	0.05	0.28	0.05	0.17	0.04	0.28	0.05	0.18	0.04	0.00	0.00
USA	0.85	0.06	0.66	0.18	0.55	0.12	0.32	0.17	0.30	0.12	0.34	0.19
GBR	0.80	0.12	0.76	0.15	0.13	0.12	0.09	0.11	0.67	0.16	0.67	0.18
AUT	0.69	0.18	0.68	0.19	0.22	0.17	0.33	0.21	0.47	0.22	0.34	0.23
DNK	0.49	0.21	0.66	0.11	0.16	0.20	0.44	0.16	0.33	0.24	0.22	0.15
FRA	0.77	0.12	0.84	0.10	0.44	0.23	0.39	0.18	0.33	0.23	0.46	0.18
DEU	0.72	0.15	0.84	0.08	0.20	0.17	0.55	0.14	0.53	0.21	0.29	0.14
ITA	0.70	0.14	0.73	0.13	0.22	0.16	0.14	0.14	0.47	0.19	0.58	0.18
NLD	0.87	0.08	0.89	0.07	0.73	0.12	0.79	0.10	0.14	0.10	0.09	0.08
NOR	0.64	0.22	0.74	0.21	0.44	0.20	0.69	0.21	0.20	0.17	0.05	0.09
SWE	0.47	0.22	0.73	0.13	0.29	0.22	0.58	0.17	0.18	0.20	0.15	0.14
CHE	0.47	0.27	0.50	0.28	0.08	0.12	0.11	0.14	0.39	0.26	0.39	0.26
CAN	0.29	0.25	0.60	0.19	0.24	0.22	0.55	0.22	0.05	0.13	0.05	0.12
JPN	0.18	0.28	0.33	0.24	0.15	0.25	0.32	0.24	0.03	0.14	0.00	0.07
FIN	0.26	0.33	0.35	0.34	0.26	0.32	0.33	0.33	0.00	0.06	0.02	0.12
IRL	0.72	0.19	0.73	0.18	0.49	0.20	0.47	0.19	0.24	0.16	0.26	0.16
PRT	0.50	0.26	0.46	0.25	0.23	0.24	0.09	0.16	0.27	0.27	0.37	0.27
ESP	0.69	0.18	0.66	0.17	0.37	0.20	0.23	0.18	0.33	0.21	0.43	0.21
AUS	0.69	0.14	0.61	0.19	0.66	0.14	0.57	0.18	0.03	0.07	0.04	0.08
NZL	0.14	0.21	0.03	0.10	0.00	0.08	0.01	0.05	0.14	0.21	0.02	0.08
TUR	0.65	0.18	0.18	0.26	0.64	0.18	0.18	0.26	0.01	0.05	0.00	0.00
ZAF	0.63	0.25	0.24	0.32	0.58	0.28	0.24	0.32	0.05	0.18	0.00	0.00
ARG	0.25	0.35	0.17	0.28	0.01	0.13	0.17	0.28	0.25	0.35	0.00	0.00
BRA	0.69	0.18	0.46	0.24	0.16	0.17	0.46	0.24	0.53	0.23	0.00	0.00
CHL	0.53	0.21	0.68	0.15	0.14	0.16	0.68	0.15	0.39	0.22	0.00	0.00

	All factors				Global factor				Group factor			
	Inflows		Outflows		Inflows		Outflows		Inflows		Outflows	
Country	value	2S.E.	value	2S.E.	value	2S.E.	value	2S.E.	value	2S.E.	value	2S.E.
COL	0.48	0.25	0.30	0.21	0.22	0.24	0.30	0.21	0.27	0.29	0.00	0.00
MEX	0.34	0.30	0.14	0.20	0.00	0.07	0.14	0.20	0.34	0.30	0.00	0.00
PER	0.17	0.27	0.27	0.22	0.01	0.11	0.27	0.22	0.16	0.27	0.00	0.00
URY	0.26	0.28	0.02	0.09	0.01	0.07	0.02	0.09	0.25	0.27	0.00	0.00
VEN	0.08	0.21	0.17	0.19	0.00	0.09	0.17	0.19	0.07	0.19	0.00	0.00
CYP	0.10	0.49	0.09	0.52	0.10	0.50	0.09	0.52	0.00	0.05	0.00	0.00
ISR	0.37	0.29	0.50	0.24	0.01	0.12	0.50	0.24	0.36	0.29	0.00	0.00
JOR	0.18	0.25	0.01	0.10	0.15	0.23	0.01	0.10	0.03	0.12	0.00	0.00
KWT	0.12	0.24	0.14	0.37	0.11	0.22	0.14	0.37	0.01	0.12	0.00	0.00
OMN	0.28	0.29	0.36	0.30	0.26	0.29	0.36	0.30	0.03	0.15	0.00	0.00
SAU	0.25	0.31	0.34	0.40	0.16	0.25	0.34	0.40	0.09	0.24	0.00	0.00
EGY	0.11	0.29	0.02	0.17	0.01	0.10	0.02	0.17	0.10	0.28	0.00	0.00
IND	0.72	0.17	0.67	0.17	0.70	0.19	0.67	0.17	0.02	0.09	0.00	0.00
KOR	0.50	0.23	0.41	0.30	0.00	0.06	0.41	0.30	0.50	0.23	0.00	0.00
MYS	0.33	0.24	0.35	0.21	0.01	0.06	0.35	0.21	0.32	0.25	0.00	0.00
PAK	0.14	0.30	0.00	0.08	0.02	0.15	0.00	0.08	0.12	0.29	0.00	0.00
PHL	0.59	0.25	0.25	0.22	0.04	0.12	0.25	0.22	0.54	0.26	0.00	0.00
SGP	0.29	0.32	0.28	0.34	0.15	0.22	0.28	0.34	0.14	0.23	0.00	0.00
THA	0.17	0.32	0.40	0.28	0.00	0.13	0.40	0.28	0.17	0.31	0.00	0.00
MAR	0.30	0.34	0.09	0.21	0.02	0.15	0.09	0.21	0.29	0.35	0.00	0.00
CHN	0.35	0.31	0.79	0.12	0.35	0.32	0.79	0.12	0.00	0.11	0.00	0.00
POL	0.52	0.25	0.29	0.24	0.50	0.26	0.29	0.24	0.02	0.10	0.00	0.00
ROM	0.55	0.27	0.29	0.27	0.53	0.28	0.29	0.27	0.02	0.11	0.00	0.00

Table A.5: Fraction of the variance explained by the different factors for the different countries and groups.

	(1)	(2)	(3)	(4)	(5)	(6)
		Factor			Factor	
	Global	Advanced	Emerging inflows	Global	Advanced	Emerging inflows
BAA spread	-0.259*	-0.493**	-0.183	-0.201*	-0.444**	0.0431
	(0.103)	(0.152)	(0.129)	(0.0796)	(0.132)	(0.0971)
US exchange rate (log)	-0.0498	-0.133	-0.176	-0.0368	-0.122	-0.169
	(0.0678)	(0.0667)	(0.147)	(0.0642)	(0.0667)	(0.155)
Chinn-Ito (average)	4.424	2.518	17.17*	3.963	1.918	6.241
	(3.540)	(7.053)	(7.258)	(3.312)	(6.989)	(5.689)
Yield curve slope	-0.0625	-0.220*	-0.121	-0.0306	-0.184*	-0.198*
	(0.0716)	(0.0883)	(0.112)	(0.0533)	(0.0740)	(0.0866)
Commodity price (non-energy, log)	0.0189	-0.371*	-0.0898			
	(0.111)	(0.141)	(0.161)			
Agriculture price (log)				-0.166	-0.397**	0.218
				(0.0859)	(0.139)	(0.119)
Metals&minerals price (log)				0.234*	0.0428	-0.259
				(0.102)	(0.135)	(0.130)
cons	-0.00393	-0.0461	-0.168	-0.000412	-0.0415	-0.0867
	(0.0626)	(0.0940)	(0.128)	(0.0592)	(0.0912)	(0.106)
N	36	36	36	36	36	36
R^2	0.482	0.593	0.311	0.603	0.624	0.303

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: Regressions in first differences, with the same regressors used in the VARX of table (8). Standard errors robust to heteroskesdasticity. The p-values for absence of autocorrelation in the residuals in a Breusch–Godfrey test are 0.987, 0.017, 0.849 for Fg, Fad, FemeIn in the first, simpler, model and 0.962, 0.004, 0.607 in the second model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Chinn-Ito	10.34***	10.54***	6.913***	7.239***	6.673***	4.071**	4.188**	2.397**		
	(2.251)	(2.229)	(2.043)	(2.012)	(1.943)	(1.685)	(1.788)	(0.926)		
	0.094									
Exchange rate flexibility	-3.627**	-3.818**	-4.851***	-4.322***	-4.016**	-3.011**	-3.589**	-1.400***	-2.290***	-2.014***
		(1.695)	(1.757)	(1.639)	(1.559)	(1.272)	(1.628)	(0.513)	(0.617)	(0.406)
	0.028									
Domestic credit (over GDP, log)	4.478***		3.906***	4.496***	5.200***	2.556*	2.534*	-0.250	-1.252	-0.646
	(0.980)		(1.048)	(1.143)	(1.633)	(1.313)	(1.341)	(0.535)	(0.802)	(0.415)
	0.073									
Real GDP (log)	-0.426			-0.969*	-0.740	0.410	0.572	0.472**	0.548	0.432**
	(0.480)			(0.534)	(0.465)	(0.456)	(0.520)	(0.212)	(0.342)	(0.164)
	-0.007									
GDP growth volatility	0.307				0.603	0.277	0.339	-0.475***	0.224	-0.449***
	(0.523)				(0.626)	(0.546)	(0.564)	(0.162)	(0.371)	(0.127)
	-0.007									
Trade openness	0.0899***					0.0718***	0.0740***	0.0537***	-0.0339***	-0.00146
	(0.0267)					(0.0242)	(0.0252)	(0.00568)	(0.0126)	(0.00522)
	0.239									
Non-fuel commodity net exports/GDP	-4.142						21.85	2.581	18.76**	11.35***
	(15.31)						(22.05)	(5.401)	(8.238)	(4.253)
	-0.010									
De facto financial openness	3.212***								3.767***	2.378***
	(0.417)								(0.416)	(0.0952)
	0.846									
cons		7.280**	-4.391	17.48	6.295	-17.57	-21.17	-8.296	-6.365	-3.762
		(3.379)	(3.468)	(13.28)	(12.75)	(12.84)	(14.45)	(5.656)	(8.058)	(4.364)
N		94	94	94	94	94	94	94	94	94
R^2		0.146	0.192	0.210	0.219	0.316	0.326	0.671	0.897	0.934
adj. R^2		0.127	0.166	0.175	0.175	0.269	0.271	0.644	0.888	0.928

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Regressions of the square root of the variance of each country-flow-direction explained by the factors, including Ireland (equivalent to figure 9). Values in column (1) correspond to single-variables regressions; the values below the standard errors are the adjusted R^2. Columns (8) and (10) implement robust regression, excluding data with Cook's D >1, applying Hubert's weights until convergence and then bi-weights until convergence.

B Results including developing countries

In this section we report results considering the sample that includes developing countries. Table (B.1) shows the results of the model selection via the information criteria. Here we consider two groupings, one featuring 3 groups (advanced, emerging, and developing countries) and another one featuring 2 groups (advanced, and emerging plus developing countries); in addition, we also consider models with a single group. Table (B.1) shows that models with a multilevel structure obtain larger scores than those with a single level. Model (1; 1,0,0; 2,0; 0,0,0,0,1,0) (composed of 1 global factor, 1 for advanced countries, 2 for inflows and 1 for developing inflows) is the one achieving highest score, closely followed by model (1; 1,0; 0,0; 0,0,1,0) (including 1 global factor, 1 for advanced countries and 1 for emerging and developing inflows). The two inflows factors in model (1; 1,0,0; 2,0; 0,0,0,0,1,0) are not orthogonal to the advanced factor (correlation coefficients -0.56 and 0.31), and the three of them affect advanced inflows, which complicates the interpretation of the factors. For this reason, and given the small difference is standardized score, we will select model (1; 1,0; 0,0; 0,0,1,0).

Table (B.2) shows the correlations between factors and loadings of the selected model with those of the other models with the highest scores. The correlations are rather large (always over 0.93), except for the Emerging and Developing inflows factor and loadings with the inflows factor and loadings of models (1; 10; 10; 0010) and (1; 10; 20; 0010); in these two cases, however, the set of all the factors (loadings) affecting inflows and emerging and developing inflows, spans almost perfectly the emerging and developing inflows (loadings) of the selected model (the correlation between the factor -loading- of the selected model and its projection over the factors -loadings- of the other models is larger than 0.99).

Figure B.1 plots the estimated factors in the sample including developing countries. They are very similar to those found in the main text. The global and advanced countries factors are almost identical across samples (correlation coefficients larger than 0.99), and the emerging (and developing) inflows factor are qualitatively similar (correlation 0.83), the main difference being that the peak around 1997 is less sharp in the sample including developing countries.

The loadings and the fraction of the variance explained for advanced and emerging countries is also very similar across samples (compare Tables B.3-B.5 and Figures B.2-B.3 with Tables 3-5 and Figures 4-5 of the main text). Table B.3 shows that the loadings of developing countries over the global factor tend to be lower and sometimes significantly negative, while those over the emerging and developing inflows factor tend to be somewhat larger than those of emerging countries. This indicates that in this sample the estimated emerging and developing inflows factor is more related to developing countries (still, as mentioned earlier, the correlation between the factors in the two samples is 0.83).

Figure B.4 explores the evolution across time of the fraction of the variance explained by the estimated factors. The results for advanced and emerging countries are very similar to those obtained in the previous sample (Figure 6 of the main text). The results for developing outflows are consistent with a globalization phase until 2007 and a de-globalization phase after that, while the results for developing inflows show a more irregular evolution.

Table B.6 shows the results of estimating a VARX model to the obtained factors. The results are quite similar to those obtained in the main text, but the factor for emerging and developing inflows shows a dependence on some covariates different to those of the emerging inflows factor obtained in the main text. In particular, the new factor shows a weaker response to the spread measure (BAA) and the average of the Chinn-Ito capital market openness index, while showing a stronger dependence on the agricultural, and metals and minerals price indexes. These results are consistent with the fact that the new factor affects also developing countries, which are more dependent on agricultural exports and metals and minerals imports, and have a less consistent capital account management.

B.1 Regressions of factors in first differences

Table B.7 shows the results of regressing the estimated factors over the regressors considered in the VARX models, but this time for each factor separately and in first differences. It is equivalent to table A.6, which uses the sample excluding developing countries. The results are similar across the samples, with some differences mainly in the emerging (and developing) inflows factor, similar to those found in the VARX model described earlier.

B.2 Impulse-response functions

Figures B.6-B.9 depict the impulse-response functions based on the estimated VARX models for the different covariates in the sample including developing countries (equivalent to figures A.2-A.5, which use the sample excluding developing countries) . The results, described in the main text, are very similar across both samples.

Overall, the results are rather similar across the two samples, which lends support to the robustness of the findings.

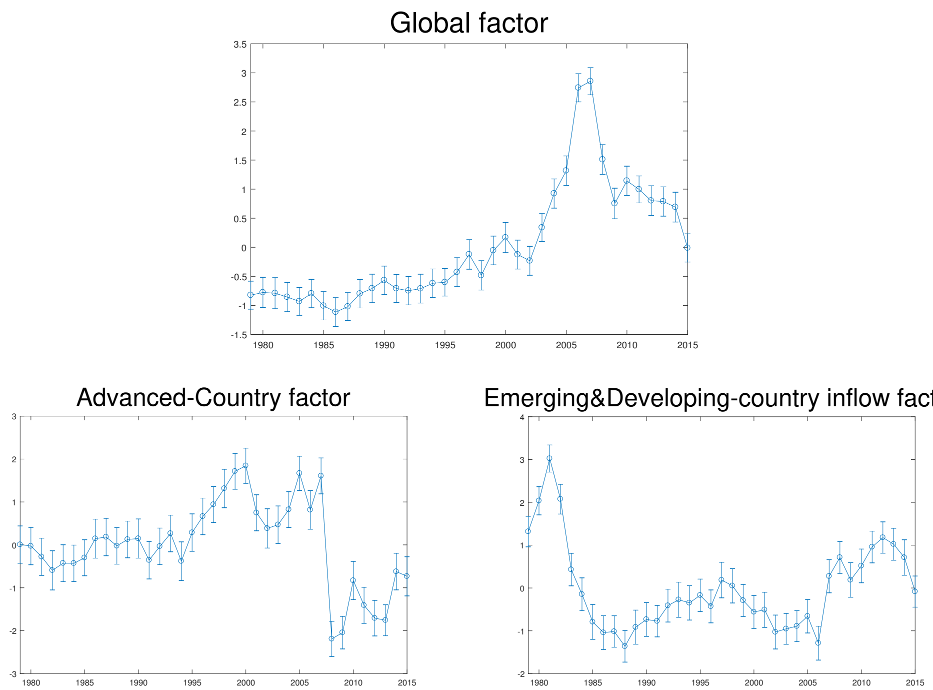
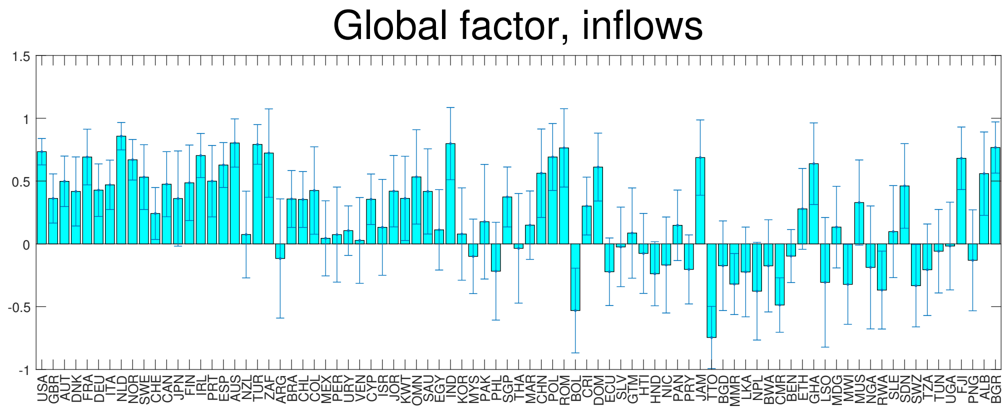
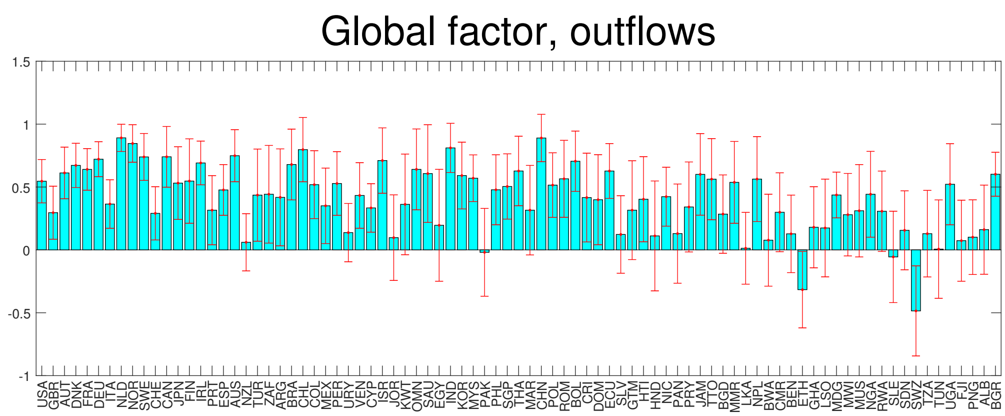


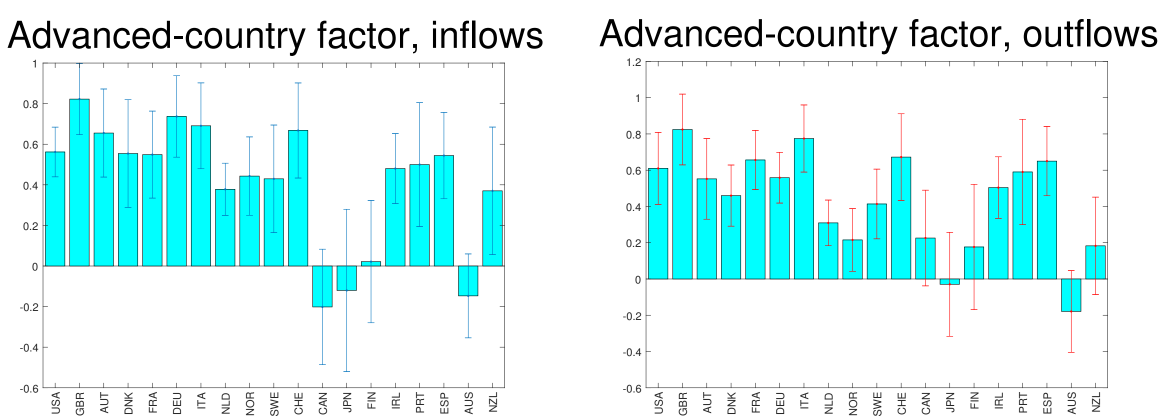
Figure B.1: Estimated factors in the sample including developing countries. Error-bars were obtained through country (inflows and outflows together) block bootstrap with 10000 replications.



(a)

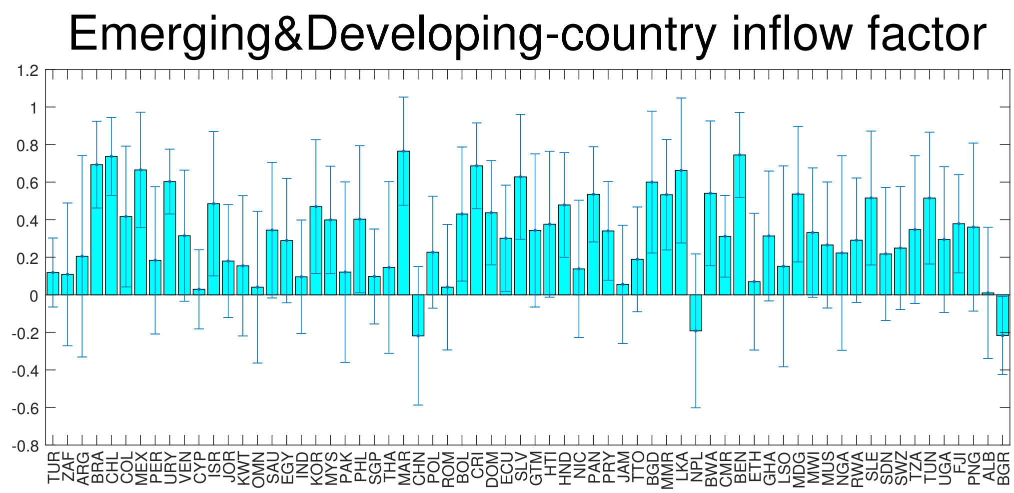


(b)



(c)

Figure B.2: Sample including developing countries. Estimated loadings. Two-standard deviation error bars obtained through country block bootstrap with 10000 replications.



(d)

Figure B.2: Sample including developing countries. Estimated loadings. Two-standard deviation error bars obtained through country block bootstrap with 10000 replications.

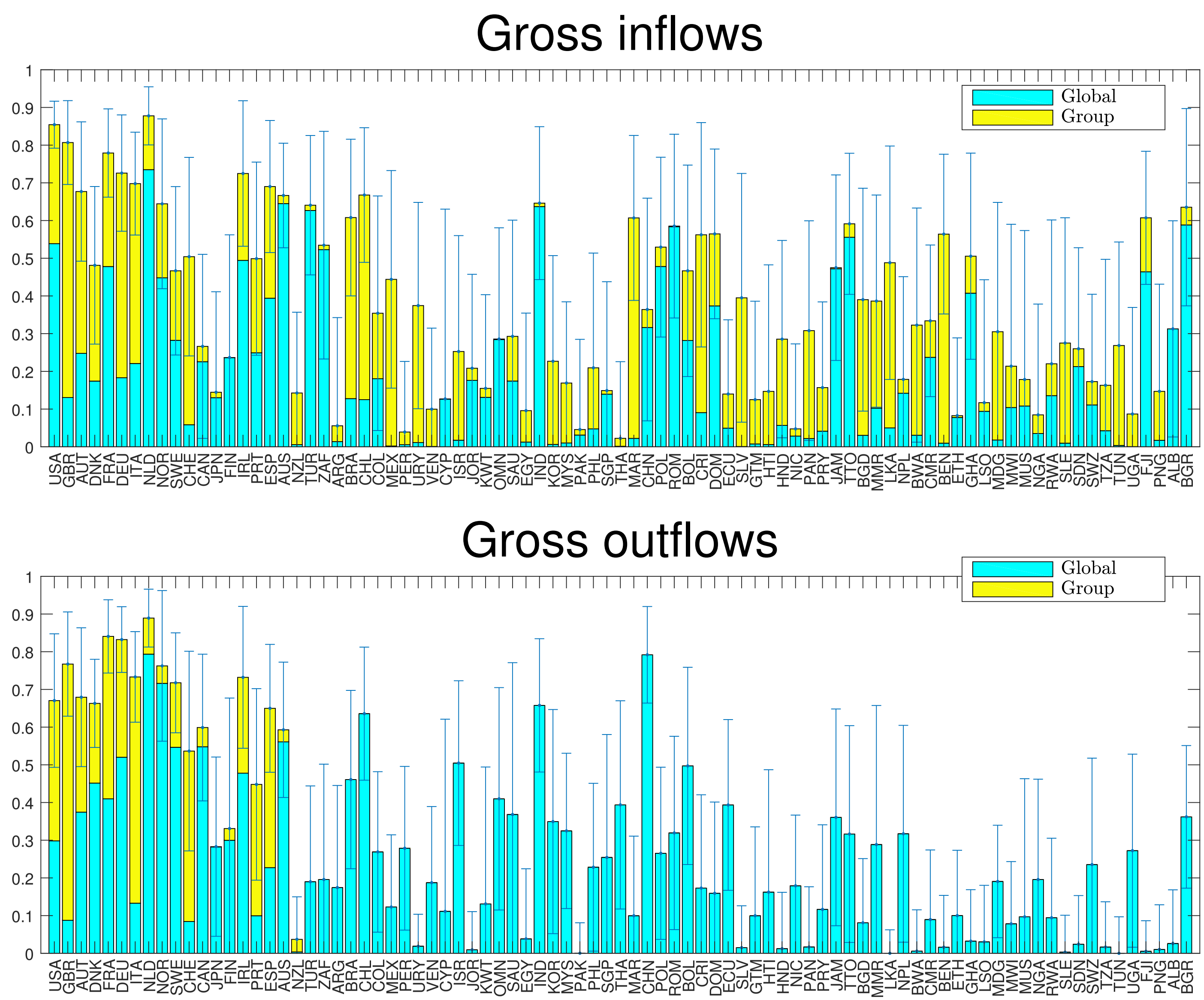


Figure B.3: Sample including developing countries. Fraction of variance explained by factors.

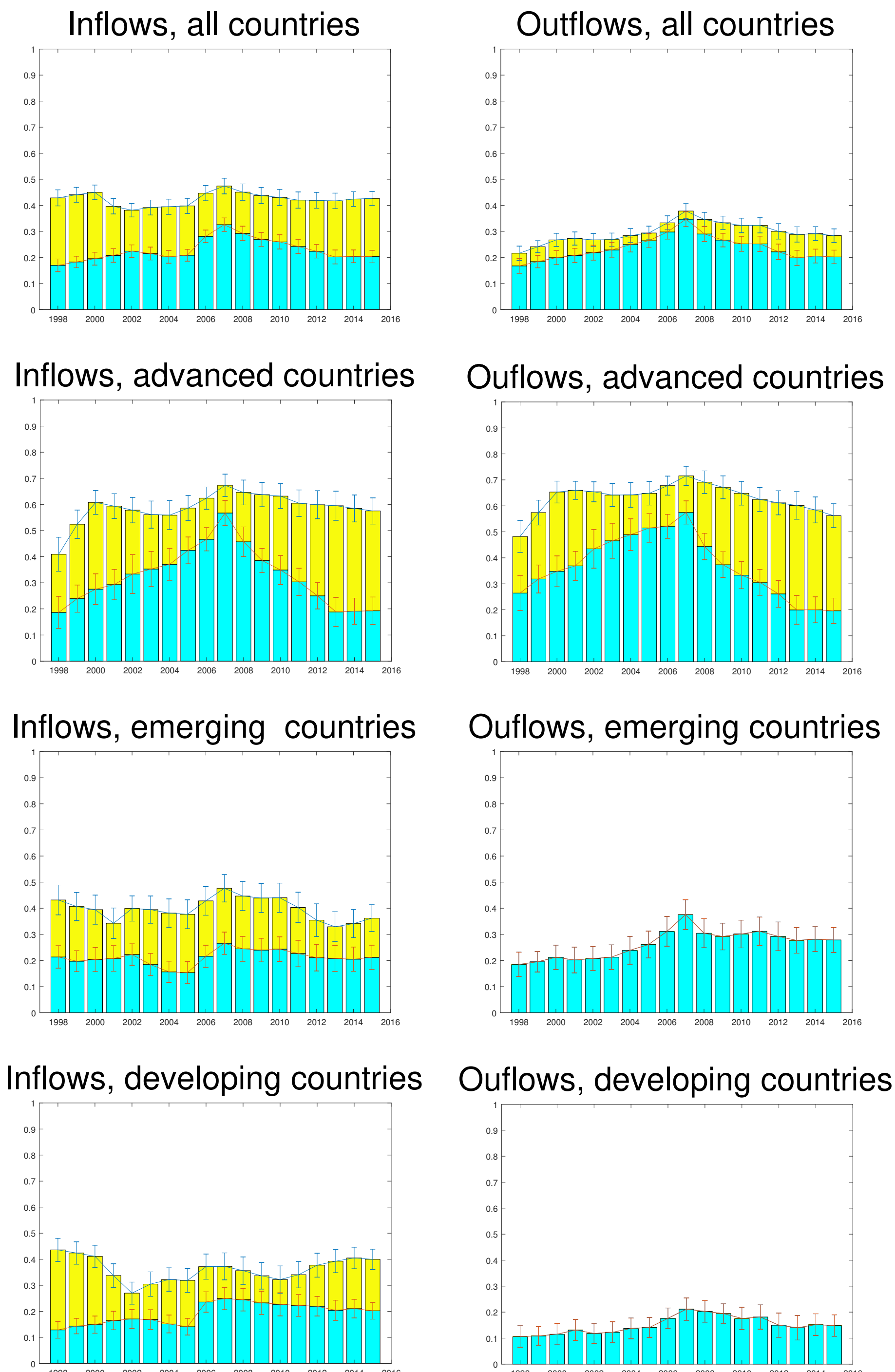


Figure B.4: Sample including developing countries. Average over the indicated set of countries of the fraction of the variance of capital inflows and outflows explained by the global (blue) and group (yellow) factors, estimated on 20 year overlapping windows ending in the year indicated in the x-axis. The error bars correspond to two standard deviations of the total explained fraction, calculated by block bootstrap, based on 10000 replications.

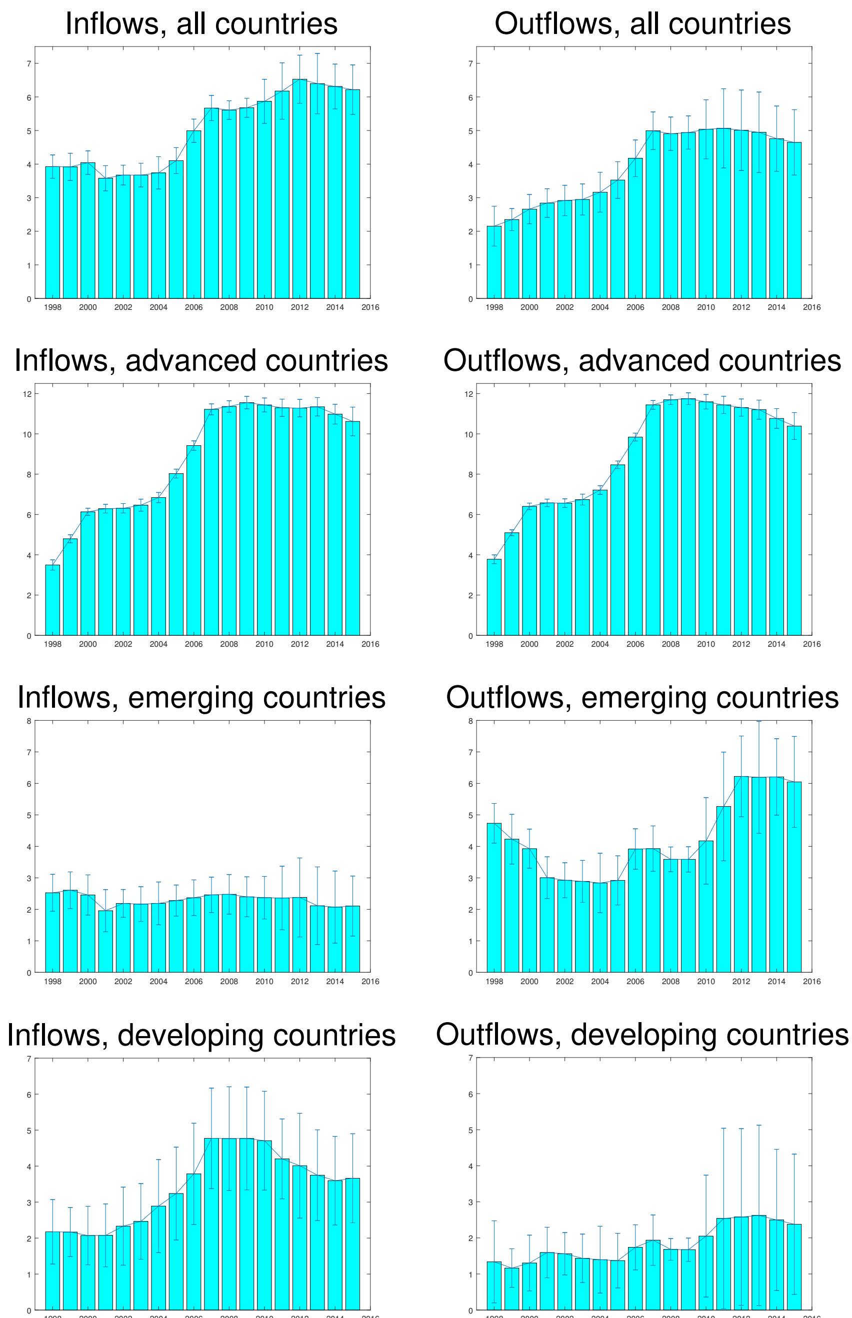


Figure B.5: Sample including developing countries. Average over the indicated set of countries of the standard deviation of the capital flows explained by the factors (as percentage of GDP). Estimations performed over 20 year overlapping windows ending in the year indicated in the x-axis. The error bars correspond to two standard deviations of the total explained fraction, calculated by block bootstrap, based on 10000 replications.

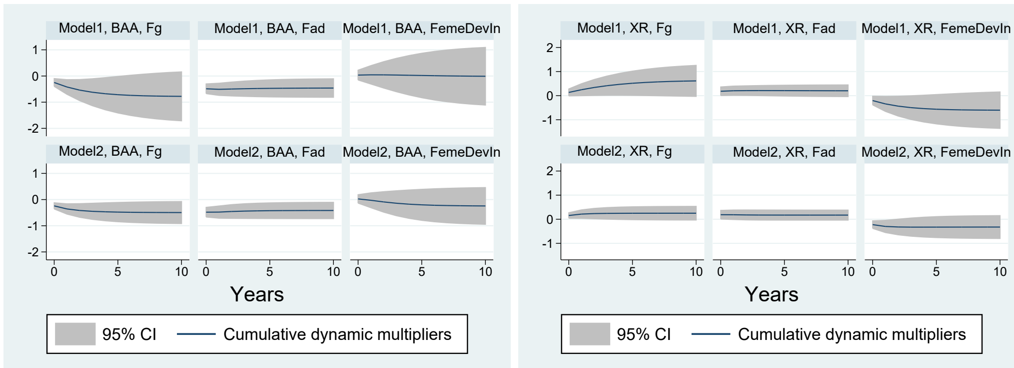


Figure B.6: Sample including developing countries. Cumulative effect of a permanent one standard deviation increase in the bond spread measure (left panel) and the log of the real US trade-weighted exchange rate (right panel), over the estimated factors, based on the simpler model (top graphs) and the more complicated one (lower graphs).

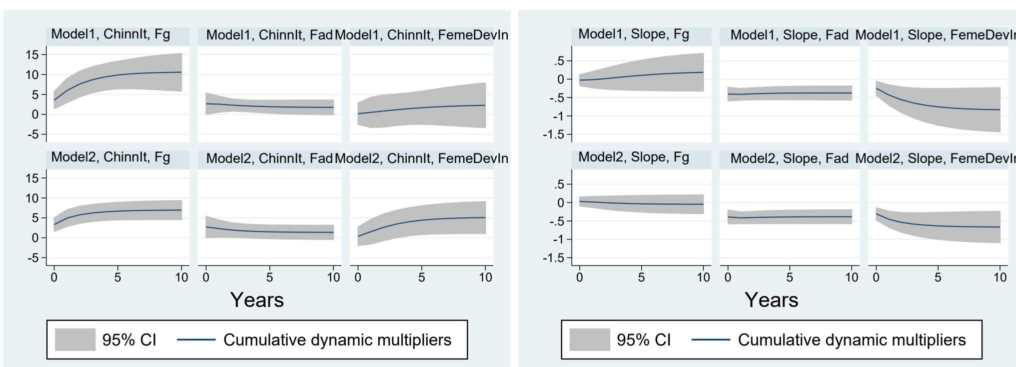


Figure B.7: Sample including developing countries. Cumulative effect of a permanent one standard deviation increase in the emerging and developing countries average Chinn-Ito capital market openness index (average of contemporaneous and 1 and 2 previous years, left panel) and the slope of the yield curve (10-year US treasury constant maturity minus federal funds rate, right panel), over the estimated factors. The top graphs are based on the simpler model and the lower graphs on the more complicated one.

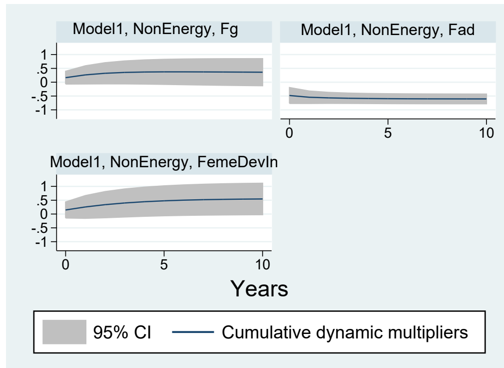
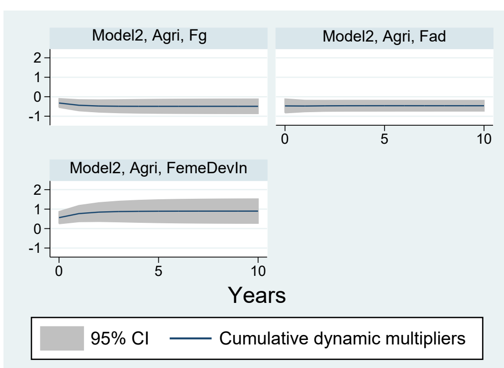


Figure B.8: Sample including developing countries. Cumulative effect of a permanent one standard deviation increase in the log of the non-energy commodities price index, based on the simpler model.



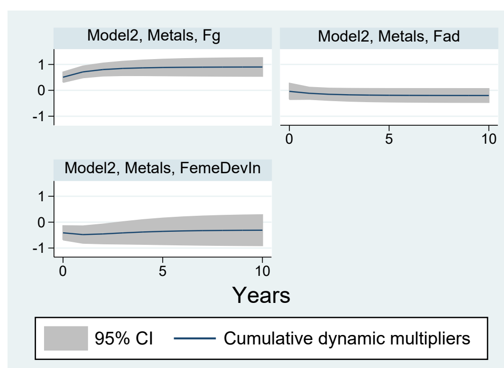


Figure B.9: Sample including developing countries. Cumulative effect of a permanent one standard deviation increase in the log of the metals and minerals price index (left panel) and in the log of the agricultural commodities price index (right panel), over the estimated factors, based on the more complicated model.

Grouping	Model	IC_{p2}	HQ_2	Standardized score	Rank
Adv, Eme,Dev	(1; 1,0,0; 2,0; 0,0,0,0,1,0)	-0.193	-922	0.969	1
Adv, Eme+Dev	(1; 1,0; 0,0; 0,0,1,0)	-0.205	-859	0.962	2
Adv, Eme,Dev	(1; 1,0,0; 1,0; 0,0,0,0,1,0)	-0.196	-878	0.951	3
Adv, Eme+Dev	(1; 1,0; 1,0; 0,0,1,0)	-0.202	-838	0.944	4
Adv, Eme+Dev	(1; 1,0; 2,0; 0,0,1,0)	-0.195	-862	0.941	5
Single	(2; 0,0; 0,0,0,0)	-0.188	-628	0.797	>50
Single	(1; 0,0; 0,0,0,0)	-0.169	-556	0.711	>50

Table B.1: Information criteria scores in the sample including developing countries. The numbers in the "model" column correspond to the number of factors in each group ($r^G; r^R_1, r^R_2, r^R_3; r^D_1, r^D_{-1}; r^{RD}_{1,1}, r^{RD}_{1,-1}, r^{RD}_{2,1}, r^{RD}_{2,-1}, r^{RD}_{3,1}, r^{RD}_{3,-1}$). The standardized score is computed as (IC$_{p2}$/IC$_{p2,max}$+HQ2/HQ2$_{max}$)/2. The rank is based on the standardized score. The maximum number of factors considered was (2; 2,2,2; 2,2; 1,1,1,1,1,1) in the Adv, Eme, Dev grouping and (3; 3,3; 2,2; 1,1,1,1) in the Adv, Eme+Dev grouping.

Grouping	Model	Factors			Loadings		
		Glob	Adv	Eme&Dev In	Glob	Adv	Eme&Dev In
(Adv, Eme, Dev)	(1;1,0,0; 20; 000010)	0.993	0.985	0.984	0.993	0.964	0.981
(Adv, Eme, Dev)	(1;1,0,0; 10; 000010)	0.992	0.95	0.973	0.992	0.93	0.964
(Adv, Eme+Dev)	(1;1,0; 10; 0010)	0.993	0.969	0.919 (0.990)	0.993	0.956	0.853 (0.991)
(Adv, Eme+Dev)	(1;1,0; 20; 0010)	0.992	0.983	0.678 (0.993)	0.992	0.949	0.606 (0.995)

Table B.2: Correlations of factors and loadings of the the different models with those of the (1;10;00;0010) model (the selected one), in the sample including developing countries. The emerging inflows factor is compared with the inflows factor of the other models. Between brackets is the correlation between the emerging and developing inflows factor (loadings) of the selected model and its projection over the (2 or 3) factors (loadings) of the corresponding model affecting only inflows (the correlation of the loadings is computed over emerging and developing countries only).

	Global						Advanced		Eme. Dev. In.	
	Adv		Eme		Dev		In	Out	Eme	Dev
	In	Out	In	Out	In	Out				
Significant & positive	17/19	18/19	15/28	22/28	8/38	14/38	15/19	14/19	10/28	17/38
Significant & negative	0/19	0/19	0/28	0/28	7/38	2/38	0/19	0/19	0/28	1/38
Median	0.5	0.61	0.35	0.51	-0.11	0.29	0.5	0.5	0.22	0.34
Median t-stat	4.1	6.1	2.3	3.6	-0.71	1.7	5.1	5.0	1.4	1.9

Table B.3: Sample including developing countries. Summary statistics for the estimated loadings of the different factors. Significance refers to the 95% confidence level, based in 10000 block bootstrap replications.

Inflows-Outflows				Inflows-Inflows			Outflows-Outflows
Global			Advanced	Glob.-Adv.	Glob.-Eme.	Glob.-Dev.	Glob.-Adv.
Adv	Eme	Dev					
0.73	0.26	-0.06	0.88	-0.13	-0.44	-0.19	-0.33

Table B.4: Sample including developing countries. Correlations of the loadings of the different factors.

All		Adv		Eme		Dev	
In	Out	In	Out	In	Out	In	Out
0.31	0.23	0.67	0.67	0.27	0.26	0.28	.10

Table B.5: Sample including developing countries. Fraction of the variance explained by the estimated factors, median over the indicated groups.

	(1) Global factor	(2) Advanced factor	(3) Eme&Dev inflows factor	(4) Global factor	(5) Advanced factor	(6) Eme&Dev inflows factor
Lagged global factor	0.689***	-0.0813	0.0480	0.468***	-0.177	0.295*
	(0.131)	(0.163)	(0.165)	(0.112)	(0.176)	(0.153)
Lagged advanced factor	-0.00608	0.0769	0.00726	0.0148	0.0797	-0.0118
	(0.0823)	(0.103)	(0.103)	(0.0654)	(0.103)	(0.0898)
Lagged eme&dev inflows factor	-0.107	-0.0887	0.714***	0.0753	-0.0449	0.530***
	(0.0776)	(0.0965)	(0.0974)	(0.0714)	(0.113)	(0.0980)
BAA spread	-0.248***	-0.488***	0.0353	-0.240***	-0.482***	0.0252
	(0.0759)	(0.0945)	(0.0954)	(0.0596)	(0.0940)	(0.0819)
US exchange rate (log)	0.134*	0.183**	-0.204**	0.155***	0.188**	-0.224***
	(0.0731)	(0.0910)	(0.0918)	(0.0580)	(0.0915)	(0.0797)
Chinn-Ito (average)	3.555***	2.661*	0.177	3.310***	2.700**	0.377
	(1.101)	(1.371)	(1.383)	(0.861)	(1.359)	(1.183)
Yield curve slope	-0.0260	-0.406***	-0.248***	0.0311	-0.391***	-0.305***
	(0.0761)	(0.0948)	(0.0956)	(0.0612)	(0.0966)	(0.0841)
Commodity price (non-energy, log)	0.164	-0.481***	0.147			
	(0.117)	(0.146)	(0.147)			
Agriculture price (log)				-0.322***	-0.471***	0.562***
				(0.114)	(0.181)	(0.157)
Metals&minerals price (log)				0.507***	-0.0397	-0.412***
				(0.100)	(0.158)	(0.138)
cons	-1.746***	-1.328*	-0.102	-1.641***	-1.353**	-0.184
	(0.553)	(0.688)	(0.695)	(0.432)	(0.682)	(0.594)
N	36	36	36	36	36	36
hqic	3.931	3.931	3.931	3.340	3.340	3.340
sbic	4.705	4.705	4.705	4.199	4.199	4.199
R^2	0.910	0.863	0.854	0.944	0.864	0.892

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: VARX (in levels) with one lag and exogenous variables, for the sample including developing countries. The Chinn-Ito capital market openness index is introduced as the mean of the contemporaneous value and lagged by one and two years, averaged over advanced, emerging and developing countries. Both models are stable. For both models, an LM test fails to reject absence of autocorrelation in the residuals at the 5% level (for the first 5 lags, the p-values are 0.311, 0.055, 0.872, 0.556, and 0.403 for the first, simpler, model and 0.08 , 0.284, 0.329, 0.942, and 0.231 for the second). For both models all the information criteria (final predictor error, Akaike, Hannan-Quinn and Bayesian) select a single lag . A Dickey-Fuller test on the residuals yield p-values smaller than 0.0003 for both models. Standardized variables.

	(1)	(2)	(3)	(4)	(5)	(6)
		Factor			Factor	
	Global	Advanced	Eme&Dev inflows	Global	Advanced	Eme&Dev inflows
BAA Spread	-0.217*	-0.537**	0.119	-0.154*	-0.492**	0.0499
	(0.0912)	(0.173)	(0.0942)	(0.0724)	(0.153)	(0.100)
Us Exchange rate (log)	-0.00440	-0.158*	-0.135	0.00710	-0.146	-0.158
	(0.0729)	(0.0769)	(0.161)	(0.0703)	(0.0799)	(0.161)
Chinn-Ito (average)	4.094	0.572	2.428	3.721	0.0623	3.029
	(3.942)	(7.020)	(4.937)	(3.504)	(6.904)	(4.989)
Yield curve slope	-0.0648	-0.223*	-0.164	-0.0314	-0.188*	-0.202*
	(0.0690)	(0.104)	(0.100)	(0.0493)	(0.0908)	(0.0905)
Commodity price (non-energy, log)	0.0752	-0.416*	0.0362			
	(0.119)	(0.157)	(0.168)			
Agricultural price (log)				-0.148*	-0.414*	0.220
				(0.0696)	(0.163)	(0.118)
Metals&minerals price (log)				0.276*	0.0116	-0.252
				(0.119)	(0.154)	(0.131)
cons	-0.00390	-0.0242	-0.0546	-0.00149	-0.0209	-0.0585
	(0.0611)	(0.109)	(0.115)	(0.0544)	(0.106)	(0.110)
N	36	36	36	36	36	36
R^2	0.442	0.575	0.190	0.586	0.593	0.287

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.7: Sample including developing countries. Regressions in first differences, with the same regressors used in the VARX of table (B.6). Standard errors robust to heteroskesdasticity. The p-values for absence of autocorrelation in the residuals in a Breusch–Godfrey test are 0.926, 0.0077, 0.8677 for Fg, Fad, FemeDevIn in the first, simpler, model and 0.906, 0.0074 0.638 in the second model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Chinn-Ito	9.128***	9.415***	6.475***	6.860***	6.732***	5.362***	5.758***	2.947***		
	(1.757)	(1.801)	(1.956)	(1.905)	(1.878)	(1.766)	(1.800)	(0.711)		
	0.146									
Exchange rate flexibility	-0.913	-1.497	-1.811*	-0.950	-0.937	-0.486	-0.181	-0.952***	-1.824***	-0.732***
	(1.172)	(1.084)	(1.068)	(1.198)	(1.200)	(1.143)	(1.272)	(0.338)	(0.678)	(0.280)
	-0.001									
Domestic credit (over GDP, log)	2.900***		1.747***	3.205***	3.364***	2.062**	2.057**	0.144	0.511	0.0820
	(0.518)		(0.532)	(1.015)	(1.012)	(1.006)	(1.006)	(0.327)	(0.524)	(0.260)
	0.120									
Real GDP (log)	0.123			-1.055**	-1.030**	-0.453	-0.595	0.197	-0.0457	0.0789
	(0.270)			(0.502)	(0.506)	(0.502)	(0.553)	(0.129)	(0.195)	(0.103)
	-0.005									
GDP growth volatility	-0.247				0.160	0.0894	0.0192	0.0390	0.0999	-0.0428
	(0.216)				(0.199)	(0.198)	(0.206)	(0.0924)	(0.172)	(0.0751)
	-0.001									
trade openness	0.0656***					0.0400***	0.0371***	0.0196***	-0.0187*	-0.00498
	(0.0148)					(0.00984)	(0.0100)	(0.00451)	(0.0106)	(0.00395)
	0.185									
Non-fuel commodity net exports/GDP	-15.32**						-11.34	-0.974	2.853	0.326
	(6.056)						(8.495)	(3.443)	(3.711)	(2.834)
	0.006									
De facto financial openness	2.586***								2.744***	2.259***
	(0.224)								(0.233)	(0.0699)
	0.782									
_cons		2.459	-1.733	17.53**	15.79*	3.391	6.825	-3.804	2.695	-0.884
		(1.659)	(2.245)	(8.735)	(9.043)	(8.997)	(10.15)	(2.840)	(4.348)	(2.227)
N		168	168	168	168	168	166	166	166	166
R^2		0.163	0.192	0.246	0.247	0.290	0.295		0.803	
adj. R^2		0.153	0.177	0.227	0.224	0.263	0.264		0.795	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Sample including developing countries. Regressions of the square root of the variance of each country-flow-direction explained by the factors. Values in column (1) correspond to single-variables regressions; the values below the standard errors are the adjusted R^2. Columns (8) and (10) implement robust regression, excluding data with Cook's D >1, applying Hubert's weights until convergence and then bi-weights until convergence.

C Analyzing Cerutti, Classens and Rose: frequency, aggregation, estimation

As noted in the main text, our results regarding the variance contribution of the estimated factors stand in contrast with those of Cerutti et al. (2017c), who report much smaller figures. From this they conclude that the 'global financial cycle' (or, more broadly, common shocks) is a relatively minor force behind capital flows.

There are five main differences between our analysis and that of Cerutti et al. (2017c): frequency of the data (yearly versus quarterly), level of aggregation of capital flows (total flows versus inflows disaggregated into FDI, portfolio debt, portfolio equity and bank credit), estimation method (principal component versus Bayesian), normalization of the flows (by trend GDP[33] versus current GDP), and empirical sample, both regarding country coverage as well as time frame (1979-2015 versus 1990Q1-2015Q4). In Table C.1 we show that the first four differences – and especially the first two – explain the bulk of the discrepancy.

Using the data of Cerutti et al. (2017c)[34] we reestimate the two factors they consider (one derived from advanced non-central countries, the other from major emerging markets)[35] using the standard principal components approach, which estimates the factors as the eigenvalues of the sample covariance matrix. Since the data is not a balanced panel, we deal with missing values[36] by estimating the sample covariance matrix as:

$$Cov_{t,t'} = \sum_{i \in D_{t,t'}} \frac{Y_{t,i} Y_{t',i}}{N_{t,t'}}, \tag{C.1}$$

[33] Trend GDP is calculated using an HP filter with parameter 100 (with data at yearly frequency).

[34] Downloaded from http://faculty.haas.berkeley.edu/arose/RecRes.htm#Reverse

[35] As detailed in table A1 of Cerutti et al. (2017c), the advanced non-central countries are Australia, Canada, Iceland, New Zealand, Norway, Sweden (large and safe-heaven economies are excluded); the emerging countries are Brazil, Chile, China, Indonesia, Korea, Mexico, Philippines, Poland, Russia, South Africa, Thailand and Turkey (MSCI members with weight larger than 1%). We note that estimating a factor with data from only 6 or 12 countries can be imprecise, potentially leading to factors with smaller explanatory power.

[36] In the data file supplied by Cerutti et al. (2017c) there are, aside from missing values, a number of flows taking the value of exactly zero; we treat those as missing values.

where $Y_{t,i}$ is a particular flow type of country i at time t, $D_{t,t'}$ is the set of countries with data for flow Y for time periods t and t' and $N_{t,t'}$ is the number of such countries. As done in the main text, the flow data is standardized by subtracting the mean and dividing by the standard deviation of the respective time series (before computing the covariance matrix (C.1)).

Comparing the first two rows of Table C.1 we see that using the simple principal component estimator yields an increase of the average adjusted R^2 ($\overline{R^2}$) from 0.054 (corresponding to the 0.05 average shown in their appendix figure A7), to 0.075 when analyzing disaggregated flow data at quarterly frequency. Considering instead total inflows and outflows (obtained by summing all flow types, in the fourth line of the table) leads to an even larger increase in $\overline{R^2}$. In, turn, the same happens when we consider the disaggregated data at yearly, rather than quarterly, frequency (lines 6-7 of Table C.1). With any of these two changes we obtain $\overline{R^2}$ around 0.125. We note that when considering flows at the yearly level, the factor estimation method seems to make less of a difference. Normalizing by trend instead of nominal GDP leads to a modes increase in $\overline{R^2}$. If flow aggregation and yearly frequency are combined, the $\overline{R^2}$ rises above 0.2, almost four times the initial 0.054 value.

Unlike ours, the framework of Cerutti et al. (2017c) includes only two group factors and no global factors. One way to assess how this affects their results is to add to their setup one more factor per group, as a crude way of capturing the contribution of the global factor to the variance of inflows in each of their country groups. These extra factors are computed as the second principal components of the non-central advanced and emerging-country inflows, respectively. Doing this raises the $\overline{R^2}$ to 0.274. The 63 non-large countries considered are mainly emerging (Australia, Canada, Denmark, Norway, New Zealand, Sweden, Switzerland, Iceland and Hong Kong are also included); the number we obtain with our data for emerging countries is 0.290 (this is the adjusted R^2, while the slightly larger values in Table 5 correspond to the conventional R^2). Taking all countries in our sample, but excluding US, UK, GER, CHE and JAP, we obtain 0.376; if we further exclude EMU countries, we obtain 0.315.

If we examine the explanatory power of the estimated factors for the flows of advanced countries (those with "ad"=1 or "nonlarge"=0 in Cerutti et al. (2017c)'s data), we obtain the results shown in the middle section of the table. The $\overline{R^2}$ equals 0.07 with disaggregated flows at the quarterly frequency and raises to 0.18 when considering yearly frequency. Aggregating over flow types, the $\overline{R^2}$ increases up to 0.41 and further to 0.47 if two additional factors are used (these numbers are 0.21, 0.44 and 0.45 if flows are normalized by trend GDP). Normalizing by trend GDP rather than current GDP also tends to increase the explanatory power of the factors, but only by modest amounts – i.e., by 2.1 percentage points on average, and never by more than 3.5. With our data we obtain an average $\overline{R^2}$ over advanced countries of 0.575; the difference can be ascribed to the different time sample (1990-2015 versus 1979-2015) and particular countries considered.

Table C.2 shows how these results change when we add, as in Cerutti et al. (2017c), 8 US financial and real variables[37]. Again considering yearly data and total flows leads to a large increase in $\overline{R^2}$ (from 0.12 to 0.45 for small countries and from 0.18 to 0.61 for advanced countries). In this setting, normalizing by trend GDP also leads to small increases in $\overline{R^2}$.

The conclusion from this analysis is that the global financial cycle is a much stronger force at the yearly frequency and for total capital flows than at the quarterly frequency and for disaggregated capital flows. The likely reason is that particular types of flows at high frequencies might be significantly affected by flow-country-specific factors that cancel out when aggregating across flows and/or over time.

[37] The first line of Table C.2 corresponds to figure 5 of Cerutti et al. (2017c). When reproducing the results we find a small discrepancy in FDI outflows (0.17 versus 0.14), equity outflows (0.13 versus 0.14, not shown) and total outflows (0.11 versus 0.10).

Factors	Flow type	Freq.	Scaling GDP	Sample	All types			FDI		Portf. Eq.		Portf. Debt		Credit	
					Both	In	Out	In	Out	In	Out	In	Out	In	Out
CCR	Disaggr.	Quart.	Nom.	Small	.054	.055	.054	.104	.122	.015	.047	.041	.053	.067	.013
PC	Disaggr.	Quart.	Nom.	Small	.075	.085	.064	.093	.102	.064	.060	.083	.051	.091	.054
PC	Disaggr.	Quart.	Trend	Small	.085	.094	.075	.104	.114	.069	.063	.089	.051	.099	.053
PC	Aggr.	Quart.	Nom.	Small	.125	.159	.087								
PC	Aggr.	Quart.	Trend	Small	.133	.173	.089								
CCR	Disaggr.	Year.′	Nom.	Small	.121	.128	.113	.176	.244	.065	.084	.094	.089	.190	.065
PC	Disaggr.	Year.′	Trend	Small	.127	.138	.117	.205	.217	.096	.100	.102	.087	.178	.085
PC	Disaggr.	Year.	Nom.	Small	.130	.140	.119	.210	.225	.096	.103	.109	.089	.176	.087
PC	Disaggr.	Year.	Trend	Small	.164	.178	.150	.264	.250	.111	.116	.119	.083	.187	.100
PC	Aggr.	Year.	Nom.	Small	.201	.258	.139								
PC	Aggr.	Year.	Trend	Small	.215	.279	.146								
PC 2	Aggr.	Year.	Nom.	Small	.274	.323	.220								
CCR	Disaggr.	Quart.	Nom.	Adv	.073	.071	.075	.065	.143	.025	.040	.111	.059	.054	.067
PC	Disaggr.	Year.	Nom.	Adv	.183	.191	.175	.228	.250	.154	.115	.206	.133	.195	.246
PC	Disaggr.	Year.	Trend	Adv	.213	.211	.214	.261	.291	.176	.156	.180	.132	.211	.274
PC	Aggr.	Year.	Nom.	Adv	.408	.463	.348								
PC	Aggr.	Year.	Trend	Adv	.435	.473	.393								
PC 2	Aggr.	Year.	Nom.	Adv	.471	.498	.441								
PC 2	Aggr.	Year.	Trend	Adv	.448	.460	.436								
PC	Aggr.	Year.	Trend	All	.281	.339	.218								
PC	Aggr.	Year.	Nom	All	.265	.323	.201								
PC2	Aggr.	Year.	Trend	All	.319	.361	.273								
PC2	Aggr.	Year.	Nom	All	.324	.370	.274								

Table C.1: Average, over the sample indicated in the column "Sample" ("Adv." corresponds to advanced countries -characterized by nonbig=0 or ad=1 in Cerutti et al. (2017c) data-, while "Small" correspond to 63 non-large countries -characterized by nonbig=1 in Cerutti et al. (2017c)-), of adjusted R^2 when the flows indicated are regressed over a factor estimated from 6 non-central advanced countries and another factor estimated from 12 emerging countries. CCR uses the factors provided in Cerutti et al. (2017c); PC stands for Principal components estimator; "Aggr." indicates that all flow types are summed; Yearly′ indicates that the the quarterly factors are aggregated yearly (rather than being estimated with the yearly data); "Trend" indicates that flows are normalized by trend (as opposed to nominal) GDP (HP filter with parameter 100 at yearly frequency); 2 indicates that 2 factors from advanced and 2 factors from emerging countries are used. Regressions with less than 10 degrees of freedom are excluded. Values in the first row correspond to those in figure A7 of Cerutti et al. (2017c). Following Cerutti et al. (2017c), columns "All" and "All types" with disaggregated data average the adjusted R^2 over FDI, portfolio equity, portfolio debt, bank credit and total portfolio (portfolio debt plus portfolio equity).

Factors	Flow type	Freq.	Scaling GDP	Sample	All types			FDI		Portf. Eq.		Portf. Debt		Credit	
					Both	In	Out	In	Out	In	Out	In	Out	In	Out
CCR	Disaggr.	Quart.	Nom.	Small	.122	.137	.106	.252	.166	.120	.127	.088	.097	.130	.019
PC	Disaggr.	Quart.	Nom.	Small	.148	.163	.132	.250	.187	.158	.151	.121	.120	.145	.058
PC	Disaggr.	Quart.	Trend	Small	.154	.171	.138	.259	.199	.160	.154	.130	.124	.156	.060
PC	Aggr.	Quart.	Nom.	Small	.187	.233	.138								
CCR	Disaggr.	Yearly′	Nom.	Small	.293	.307	.278	.438	.426	.255	.350	.215	.213	.356	.171
PC	Disaggr.	Yearly′	Nom.	Small	.284	.296	.271	.429	.415	.227	.318	.211	.205	.332	.164
PC	Disaggr.	Yearly	Nom.	Small	.289	.297	.280	.423	.416	.228	.317	.220	.245	.330	.167
PC	Disaggr.	Yearly	Trend	Small	.301	.311	.289	.450	.459	.217	.330	.248	.236	.344	.171
PC	Aggr.	Yearly	Nom.	Small	.426	.453	.388								
PC	Aggr.	Yearly	Trend	Small	.453	.486	.406								
PC 2	Aggr.	Yearly	Nom.	Small	.479	.522	.420								
CCR	Disaggr.	Quart.	Nom.	Adv.	.175	.161	.189	.136	.204	.128	.217	.184	.157	.171	.136
PC	Disaggr.	Yearly	Nom.	Adv.	.355	.364	.345	.384	.464	.211	.372	.404	.196	.452	.331
PC	Disaggr.	Yearly	Trend	Adv.	.359	.373	.345	.427	.516	.223	.395	.393	.207	.478	.353
PC	Aggr.	Yearly	Nom.	Adv.	.576	.637	.506								
PC	Aggr.	Yearly	Trend	Adv.	.610	.654	.559								
PC 2	Aggr.	Yearly	Nom.	Adv.	.630	.667	.582								
PC 2	Aggr.	Yearly	Trend	Adv.	.653	.670	.362								
PC	Aggr.	Yearly	Nom.	All.	.477	.519	.422								
PC	Aggr.	Yearly	Trend	All	.533	.575	.480								
PC2	Aggr.	Yearly	Nom.	All.	.524	.568	.462								
PC2	Aggr.	Yearly	Trend	All	.540	.583	.479								

Table C.2: Average, over the sample indicated in the column "Sample" ("Small" correspond to 63 non-large countries -characterized by nonbig=1 in Cerutti et al. (2017c)-, "Adv." corresponds to advanced countries -characterized by nonbig=0 or ad=1 in Cerutti et al. (2017c) data-), of adjusted R^2 when the flows indicated are regressed over a factor estimated from 6 non-central advanced countries and another factor estimated from 12 emerging countries, plus 8 US variables (VIX, nominal and real funds rate, TED spread, yield curve slope, GDP growth, growth in real effective exchange rate and M2 growth). CCR uses the factors provided in Cerutti et al. (2017c); PC stands for Principal components estimator; "Aggr." indicates that all flow types are summed; Yearly′ indicates that the the quarterly factors are aggregated yearly (rather than being estimated with the yearly data); "Trend" indicates that flows are normalized by trend (as opposed to nominal) GDP (HP filter with parameter 100 at yearly frequency); 2 indicates that 2 factors from advanced and 2 factors from emerging countries are used. Regressions with less than 10 degrees of freedom are excluded. Values in the first row correspond to those in figure 5 of Cerutti et al. (2017c). Following Cerutti et al. (2017c), columns "All types" with disaggregated data average the adjusted R^2 over FDI, portfolio equity, portfolio debt, bank credit and total portfolio (portfolio debt plus portfolio equity).

References

Abate, Girum Dagnachew, and Luis Serven. 2018. "Assessing the international comovement of equity returns." Policy Research Working Paper Series WPS 8516, The World Bank.

Albuquerque, Rui, Norman Loayza, and Luis Servén. 2005. "World market integration through the lens of foreign direct investors." *Journal of International Economics*, 66(2): 267 – 295.

Avdjiev, Stefan, Leonardo Gambacorta, Linda S Goldberg, and Stefano Schiaffi. 2017a. "The Shifting Drivers of Global Liquidity." Working Paper 23565, National Bureau of Economic Research.

Avdjiev, Stefan, Bryan Hardy, Sebnem Kalemli-Ozcan, and Luis Servén. 2017b. "Gross Capital Flows by Banks, Corporates and Sovereigns." Working Paper 23116, National Bureau of Economic Research.

Bai, Jushan, and Serena Ng. 2002. "Determining the Number of Factors in Approximate Factor Models." *Econometrica*, 70(1): 191–221.

Bailey, Natalia, Sean Holly, and M. Hashem Pesaran. 2016a. "A Two-Stage Approach to Spatio-Temporal Analysis with Strong and Weak Cross-Sectional Dependence." *Journal of Applied Econometrics*, 31(1): 249–280.

Bailey, Natalia, George Kapetanios, and M. Hashem Pesaran. 2016b. "Exponent of Cross-Sectional Dependence: Estimation and Inference." *Journal of Applied Econometrics*, 31(6): 929–960.

Barrot, Luis-Diego, César Calderón, and Luis Servén. 2018. "Openness, specialization, and the external vulnerability of developing countries." *Journal of Development Economics*, 134 310 – 328.

Barrot, Luis-Diego, and Luis Serven. 2018. "Gross capital flows, common factors, and the global financial cycle." Policy Research Working Paper Series WPS 354, The World Bank.

Breitung, Jörg, and Sandra Eickmeier. 2016. "Analyzing International Business and Financial Cycles using Multi-Level Factor Models: A Comparison of Alternative Approaches." In *Dynamic Factor Models (Advances in Econometrics, Volume 35)*. Chap. 5 177–214.

Broner, Fernando, Tatiana Didier, Aitor Erce, and Sergio L. Schmukler. 2013. "Gross Capital Flows: Dynamics and Crises." *Journal of Monetary Economics*, 60(1): 113–133.

Bruno, Valentina, and Hyun Song Shin. 2015a. "Capital flows and the risk-taking channel of monetary policy." *Journal of Monetary Economics*, 71 119 – 132.

Bruno, Valentina, and Hyun Song Shin. 2015b. "Cross-Border Banking and Global Liquidity." *The Review of Economic Studies*, 82(2): 535–564.

Byrne, Joseph P., and Norbert Fiess. 2016. "International capital flows to emerging markets: National and global determinants." *Journal of International Money and Finance*, 61 82 – 100.

Calderón, César, and Megumi Kubota. 2013. "Sudden stops: Are global and local investors alike?" *Journal of International Economics*, 89(1): 122 – 142.

Calvo, Guillermo A., Leonardo Leiderman, and Carmen M. Reinhart. 1996. "Inflows of Capital to Developing Countries in the 1990s." *Journal of Economic Perspectives*, 10(2): 123–139.

Cerutti, Eugenio, Stijn Claessens, and Damien Puy. 2017a. "Push factors and capital flows to emerging markets: why knowing your lender matters more than fundamentals." *Unpublished manuscript*.

Cerutti, Eugenio, Stijn Claessens, and Lev Ratnovski. 2017b. "Global liquidity and cross-border bank flows." *Economic Policy*, 32(89): 81–125.

Cerutti, Eugenio, Stijn Claessens, and Andrew K. Rose. 2017c. "How Important is the Global Financial Cycle? Evidence from Capital Flows." *NBER Working Paper*.

Cerutti, Eugenio, and Haonan Zhou. 2017. "The Global Banking Network in the Aftermath of the Crisis: Is There Evidence of De-globalization?" IMF Working Paper No. 17/232 .

Choi, In. 2012. "Efficient Estimation of Factor Models." *Econometric Theory*, 28(2): 274–308.

Choi, In, and Hanbat Jeong. 2018. "Model selection for factor analysis: Some new criteria and performance comparisons." *Econometric Reviews*, 0(0): 1–20.

Choi, In, Dukpa Kim, Yun Jung Kim, and Noh-Sun Kwark. 2018. "A multilevel factor model: Identification, asymptotic theory and applications." *Journal of Applied Econometrics*, 33(3): 355–377.

Cowan, Kevin, José De Gregorio, Alejandro Micco, and Christopher Neilson. 2008. "Financial diversification, sudden stops and sudden starts." In *Current Account and External Finance*. eds. by Kevin Cowan, Sebastian Edwards, and Rodrigo Valdés, Chap. 5 159–194.

Eichengreen, Barry, and Poonam Gupta. 2015. "Tapering talk: The impact of expectations of reduced Federal Reserve security purchases on emerging markets." *Emerging Markets Review*, 25 1 – 15.

Forbes, Kristin. 2014. "Financial deglobalization?: Capital flows, banks and the Beatles." 11, Speech given at Queen Mary University.

Forbes, Kristin J., and Francis E. Warnock. 2012. "Capital flow waves: Surges, stops, flight, and retrenchment." *Journal of International Economics*, 88(2): 235 – 251.

Forbes, Kristin, Dennis Reinhardt, and Tomasz Wieladek. 2017. "The spillovers, interactions, and (un)intended consequences of monetary and regulatory policies." *Journal of Monetary Economics*, 85 1 – 22.

Ghosh, Atish R, Jonathan D Ostry, and Mahvash S Qureshi. 2015. "Exchange Rate Management and Crisis Susceptibility: A Reassessment." *IMF Economic Review*, 63(1): 238–276.

Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review*, 102(4): 1692–1720.

Goldberg, Linda S, and Signe Krogstrup. 2018. "International Capital Flow Pressures." Working Paper 24286, National Bureau of Economic Research.

Kose, M. Ayhan, Christopher Otrok, and Charles H. Whiteman. 2003. "International Business Cycles: World, Region, and Country-Specific Factors." *American Economic Review*, 93(4): 1216–1239.

Longstaff, Francis A., Jun Pan, Lasse H. Pedersen, and Kenneth J. Singleton. 2011. "How Sovereign Is Sovereign Credit Risk?" *American Economic Journal: Macroeconomics*, 3(2): 75–103.

McCauley, Robert N., Agustín Bénétrix, Patrick M. McGuire, and Goetz von Peter. 2017. "Financial Deglobalisation in Banking?" BIS Working Paper No. 650.

Miranda-Agrippino, Silvia, and Hélène Rey. 2015. "US Monetary Policy and the Global Financial Cycle." Working Paper 21722, National Bureau of Economic Research.

Obstfeld, Maurice, Jonathan D. Ostry, and Mahvash S. Qureshi. 2018. "Global Financial Cycles and the Exchange Rate Regime: A Perspective from Emerging Markets." *AEA Papers and Proceedings*, 108 499–504.

Onatski, Alexei. 2012. "Asymptotics of the principal components estimator of large factor models with weakly influential factors." *Journal of Econometrics*, 168(2): 244 – 258.

Passari, Evgenia, and Hélène Rey. 2015. "Financial Flows and the International Monetary System." *The Economic Journal*, 125(584): 675–698.

Patton, Andrew, Dimitris N. Politis, and Halbert White. 2009. "Correction to "Automatic Block-Length Selection for the Dependent Bootstrap" by D. Politis and H. White." *Econometric Reviews*, 28(4): 372–375.

Politis, Dimitris N., and Halbert White. 2004. "Automatic Block-Length Selection for the Dependent Bootstrap." *Econometric Reviews*, 23(1): 53–70.

Raddatz, Claudio, and Sergio L. Schmukler. 2012. "On the international transmission of shocks: Micro-evidence from mutual fund portfolios." *Journal of International Economics*, 88(2): 357 – 374.

Raddatz, Claudio, Sergio L. Schmukler, and Tomás Williams. 2017. "International asset allocations and capital flows: The benchmark effect." *Journal of International Economics*, 108 413 – 430.

Reinhart, Carmen M., Vincent R. Reinhart, and Christoph Trebesch. 2017. "Capital Flow Cycles: A Long, Global View." unpublished manuscript.

Reinhart, Carmen M., Vincent Reinhart, and Christoph Trebesch. 2016. "Global Cycles: Capital Flows, Commodities, and Sovereign Defaults, 1815-2015." *American Economic Review*, 106(5): 574–80.

Rey, Helene. 2013. "Dilemma not trilemma: the global cycle and monetary policy independence." *Proceedings - Economic Policy Symposium - Jackson Hole* 285–333.

Rose, Andrew K., and Tomasz Wieladek. 2014. "Financial Protectionism? First Evidence." *The Journal of Finance*, 69(5): 2127–2149.

Rothenberg, Alexander D., and Francis E. Warnock. 2011. "Sudden Flight and True Sudden Stops." *Review of International Economics*, 19(3): 509–524.

Sarno, Lucio, Ilias Tsiakas, and Barbara Ulloa. 2016. "What drives international portfolio flows?" *Journal of International Money and Finance*, 60 53 – 72.

Van Rijckeghem, Caroline, and Beatrice Weder di Mauro. 2014. "Deglobalization of Banking: The World is Getting Smaller." CEPR discussion paper no. DP10139.

Xu, Nancy. 2017. "Global Risk Aversion and International Return Comovements." unpublished manuscript.