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The Dynamics of International Capital Flows: Results from a Dynamic Hierarchical Factor Model

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The present paper examines the degree of comovement of gross capital inflows, which is a highly sensitive issue for policy makers. We estimate a dynamic hierarchical factor model that is able to decompose inflows in a sample of 47 economies into (i) a global factor common to all types of flows and all recipient countries, (ii) a factor specific to a given type of capital inflows, (iii) a regional factor and (iv) a country-specific component. We find that the latter explains by far the largest fraction of fluctuations in capital inflows followed by regional factors, which are particularly important for emerging markets' FDI and portfolio inflows as well as bank lending to emerging Europe. The global factor, however, explains only a small share of overall variation. The exposure to global drivers of capital flows, i.e. the global factor and the factor specific to each type of capital inflows, is particularly pronounced for countries with a more developed financial system. A fixed exchange rate regime does not shield countries from the ebb and flow of global capital flow cycles.

KEYWORDS: Capital flows, dynamic hierarchical factor model, emerging economies, financial crises

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1. Introduction

Over the last two decades, swings in international capital flows have been a salient feature of the world economy. Both mature economies and emerging markets experienced the ebb and flow of foreign investment in domestic financial assets. Some countries, notably emerging market economies, even suffered from boom-bust cycles in capital flows, where a massive inflow is followed by a "sudden stop" and an eventual sharp reversal of cross-border flows.

The recent financial crisis in 2008/09 is only the latest incident in a series of swings in global capital flows. At the peak of the crisis following the Lehman collapse in September 2008, investors in almost all countries repatriated foreign investments. The result was a massive retrenchment of capital flows. In 2009, when many central banks around the globe started to flood financial markets with liquidity, international capital flows quickly resumed.[1]

Swings in capital inflows often appear synchronized across countries, what encouraged many observers to speculate whether global factors rather than conditions in the recipient countries dominate investors' decisions to invest abroad. For example, The Economist (2011) recently argued that flows "may have less to do with [the receiving countries'] long-term prospects than with temporary factors such as unusually loose rich-world monetary policy, over which they have no control."

The discussion of the determinants of capital flows often distinguishes between pull and push factors. If investors carefully discriminate between countries, thus sending funds as a response to the recipient countries' fundamentals such as growth prospects or return differentials with respect to advanced economies, capital is said to be driven by pull factors. If, however, investors treat emerging coun-

[1] See International Monetary Fund (2011b) for a detailed account of these recent episodes and a thorough analysis of international capital flows.

tries similarly irrespective of domestic fundamentals, thus responding mostly to global developments such as abundant liquidity in advanced economies, financial stress or weak growth prospects in mature economies, capital flows are said to be driven by push factors.

The extent to which capital flows to different countries are linked, i.e. the degree of comovement of capital flows, is a key question for policy makers. The reason is that the appropriate policy response to capital inflows depends on the driving forces behind capital flows. Naturally, domestic economic policies may influence pull factors but they have by definition no impact on the nature and the strength of push factors. Therefore, it is important to gauge the extent to which flows are correlated on a global level. Standard static or dynamic factor analysis offers valuable tools to accomplish this end.

Unfortunately, empirically distinguishing between global and local determinants of capital flows does not necessarily lead to a clear-cut categorization of push and pull factors. The reason is that such a decomposition would only identify those push factors that affect all countries simultaneously and in a similar way. A general increase in investors' home bias that causes a synchronized retrenchment of global capital flows might be an event that fits this description. Other push factors, however, are more likely to have a differentiated effect on the current account of specific country groups. The sensitivity of capital flows to interest rates in advanced economies, e.g., implies that a tightening of monetary policy in these countries risks triggering a sharp reversal of capital flows which can have large effects on emerging economies. Hence, we would observe an increased comovement of capital flows at the regional level, i.e. among industrial and emerging economies, but heterogeneous outcomes at the global level. Similarly, contagious crisis in one emerging economy may lead to "sudden stops" of capital inflows or withdrawals in neighboring or even remote countries but are less likely to affect industrialized economies.

In this paper we address this issue and disentangle the determinants behind international capital flows into driving forces attributable to different levels of aggregation. In particular, we estimate a dynamic hierarchical factor model that is able to decompose capital flows in a large panel of countries into (i) a global factor common to all types of inflows and all recipient countries, (ii) a factor specific to a given type of capital inflows, i.e. either foreign direct investment (FDI), portfolio investment or other kinds of investment, (iii) a regional factor driving economies in geographical proximity and (iv) a country-specific component. To our knowledge this paper is the first to shed light on the relative importance of these four determinants for global capital flows. The empirical approach draws on a recently developed dynamic hierarchical factor model (see Moench *et al.* (2011)). With its pyramidal structure, the model allows for the possibility that the global factor affects regional and other subordinated factors but not vice versa.

Based on a quarterly data set of 47 countries and three different types of gross capital inflows, we find that the country-specific component explains by far the largest fraction of fluctuations in capital inflows. This factor alone is responsible for around 80% of the observed volatility. The regional factor explains between 5% and 20% of fluctuations and is particularly important for emerging markets' FDI and portfolio inflows as well as bank lending to emerging Europe. The global factor, however, explains only a small share of overall variation.

We also relate the exposure of the economies in our sample to the global drivers of capital flows, i.e. the global factor and the factor specific to each type of capital inflows, to a set of explanatory variables which are often used to describe a country's openness to trade and financial flows as well as its financial system. It turns out that the exposure to global driving forces is particularly pronounced for countries with a large financial system. A fixed exchange rate regime does not shield countries from the ebb and flow of global capital flow cycles.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and our contribution to this field of research in some detail. The data set we construct for this research project is presented in Section 3. Section 4 introduces our dynamic hierarchical factor model. The core results are discussed in Section 5. In Section 6 we relate the exposure of countries to the global factor and the idiosyncratic factor to structural characteristics of the economies in our sample. Robustness analyses are carried out in Section 7. Section 8 concludes.

2. Related Literature

The present paper is related to three different branches of the literature: First, a number of papers use factor analysis to study the degree of international business cycle synchronization. Kose *et al.* (2003) pioneered this field and estimate a Bayesian dynamic factor model for macroeconomic aggregates from 60 countries. Their results suggest that a common global factor, i.e. a world business cycle, explains a large fraction of variation across countries. Kose *et al.* (2012) decompose output, investment and consumption series of more than 100 countries into a global factor, group-specific factors that drive fluctuations in industrial, emerging and developing economies as well as country-specific factors and idiosyncratic factors. They are interested in whether business cycles became more synchronized during the post-1985 period of increasing globalization. Interestingly, they find a convergence of business cycles within each group, but divergence, i.e. a decoupling of business cycles, between different country groups. Inspired by these contributions, Eickmeier *et al.* (2011), Helbling *et al.* (2011) and others examine how financial shocks originating in the U.S. affect the common component of fluctuations in the G7 economies. All these contributions model macroeconomic aggregates but are silent about capital inflows.

A second branch of the literature studies the comovement of bond spreads across emerging financial markets. McGuire and Schrijvers (2003) and Bunda *et al.* (2010) employ factor models to extract a global factor from bond spreads. González-Rozada and Yeyati (2008) argue that a global factor, which they attribute to investors' risk appetite, global liquidity and contagion, can explain a large fraction of movements in bond spreads. Their results thus stress the role of exogenous determinants driving emerging economies' borrowing costs. Neither of these papers, however, takes account of a regional dimension of comovement that is arguably most relevant for developing and emerging economies susceptible to contagious financial stress in neighboring countries.

A third and most relevant strand addresses the role of global determinants for international capital flows.[2] Here we briefly survey some recent studies, which were all written against the backdrop of the retrenchment and the subsequent rebound of flows observed after 2008. Milesi-Ferretti and Tille (2011) document this unprecedented collapse in international capital flows during the financial crisis. They show that the main driving force has been a risk shock that made investors more cautious about future investment prospects. The size of the capital flow reversal that precedes the current wave of inflows was tightly linked to the extent of international financial integration as well as domestic macroeconomic conditions. A second observation is that the retrenchment was highly heterogeneous across time, across types of flows and across geographic regions.[3] Forbes and Warnock (2012) study the determinants of extreme movements of capital across borders. They identify "waves" of capital flows, i.e. prolonged phases of capital flows re-

[2]Early, and by now classic, contributions include Calvo *et al.* (1996), Chuhan *et al.* (1998) and Fernandez-Arias (1996).

[3]In a study prepared for the World Economic Outlook, the International Monetary Fund (2011b) also addresses the role of global factors. Estimates of time dummies and regional dummies in a simple panel of capital flows suggest that a common factor plays a minor role for capital flows.

ferred to as surge, stop, flight and retrenchment periods.[4] Interestingly, they also focus on gross flows rather than net flows as capital flows initiated by foreigners are likely to be driven by other considerations than flows brought about by domestic investors. Both type of investors could also react differently to political and economic circumstances, and potentially respond by adjusting different types of capital flows. Their findings attribute a crucial role to global factors, a somewhat less important role to contagion and an even less prominent role to domestic pull factors. Among these global factors, global risk has the largest explanatory power. Global growth predicts surges of capital flows and sudden stops while contagion through financial linkages is a significant predictor of stops and retrenchments. In contrast to other studies, Forbes and Warnock (2012) find that liquidity conditions and global interest rates are insignificant explanatory variables. Among the pull factors domestic growth has the strongest impact on surges and stops. Finally, Zalduendo *et al.* (2012) identify "surges" of net capital inflows and assess the role of push and pull factors in causing these surges. They find that global push factors explain the occurrence of a surge in inflows. The size of the surge, once it occurs, is dependent on domestic pull factors.

While most of the existing studies focus on capital flows at a quarterly or even annual frequency, the recent study by Fratzscher (2011) is based on portfolio flow data at daily, weekly and monthly frequency. This is particularly interesting in the current crisis and the subsequent recovery as quarterly data wash out many of the high frequency movements of volatile portfolio inflows. He finds that common factors driving flows across countries have a highly heterogeneous impact on the 50 countries included in the study. This impact is associated with a country's strength of domestic institutions, its country risk assessment and domestic macroeconomic fundamentals. A second finding is related to the current surge in capital inflows.

[4] A similar classification of capital flow surges is presented by Reinhart and Reinhart (2009).

The author shows that idiosyncratic pull factors originating in emerging market economies dominated the driving forces during the recovery from the global crisis.

In this paper we borrow from each of these strands. We use a dynamic hierarchical factor model developed by Moench and Ng (2011) and Moench *et al.* (2011) that is able to decompose a country's capital inflows into three different explanatory factors. Thus, instead of looking at refinancing conditions measured in terms of bond spreads as in González-Rozada and Yeyati (2008), we use actual flow data to study the degree of comovement. Finally, rather than relating capital flows to structural determinants such as shocks to investors' risk aversion, financial conditions in advanced economies or growth prospects in emerging economies, our approach is purely data-driven in the sense that the factors we identify do not lend themselves to a straightforward economic identification. The advantage, however, is that this approach does not require us to restrict capital flows to respond to a prespecified set of explanatory variables only.

3. The Data Set

Following recent research by Forbes and Warnock (2012) and Broner *et al.* (2011), our focus is on gross inflows measured in percent of GDP. Gross capital inflows are more informative for our purpose as capital flows brought about by foreigners are likely to be driven by other considerations than flows initiated by domestic investors. Both types of investors could also be affected differently by policy measures and economic shocks, and potentially respond by adjusting different types of capital flows. We differentiate between portfolio, FDI and "other" flows where the last category contains residual transactions that are predominately related to bank lending activities. To this end, we augment quarterly data from the IMF's *International Financial Statistics* with additional information from a few national sources listed in Appendix A. After excluding major financial centres which could otherwise bias our estimation results we end up with a sample of 47 countries with data from 1994Q1 to 2010Q4. Our sample period thus covers the Asian crisis, the debt crises in Latin America and Russia and the recent global financial crisis.

For each country in our sample, we use data on portfolio, FDI and other capital inflows.[5] These three categories of capital flows constitute distinctive blocks in our hierarchical dynamic factor model. This specification choice allows for, e.g., FDI and portfolio inflows to react differently to changing global macroeconomic and financial conditions. To isolate the effect of regional developments we further arrange the block-specific data into geographical subblocks. Building upon the World Bank's classification we differentiate between four country groups: Asia, emerging Europe, Industrial and Latin America.[6] Appendix B describes our sample and the regional classification.

Prior to estimation, all series are transformed in order to meet the assumptions of the dynamic factor analysis. We seasonally adjust the capital flow series using the Census X12 method. The resulting series are then standardized by the recipient country's GDP to guarantee that large economies do not dominate the estimated global factors simply because of their size.[7] Standard unit root tests clearly reject the hypothesis that the capital flow to GDP series are integrated. Based on these results – summarized in Appendix C – we decide to estimate our factor model in levels. As a last step, all series are normalized to have a mean of zero and a variance of one.

[5] The exceptions are Bolivia and Nicaragua for which data on portfolio inflows are not available. Smaller gaps in two further series have been filled using data from the balance of payments' errors and omissions category. See Appendix A for details.

[6] The World Bank's geographical classification is simplified by merging the "South Asia" and "East Asia & Pacific" block into one block (Asia). Furthermore, Israel and South Africa are allocated to the emerging Europe and Asia block, respectively.

[7] We use annual GDP divided by four for this exercise. Qualitative similar results can be obtained using data on quarterly GDP for reporting countries. These results are available from the authors upon request.

Table 1 contains some descriptive statistics for the original capital flow to GDP series. Several aspects are noteworthy. First, some regions and income groups attract significantly more inflows relative to domestic economic activity than others. Inflows to industrial economies, e.g., averaged to 4.2% of their respective GDP across all types of flows whereas the number is only 1.65% for the typical Latin American country. Second, the geographical groups differ in the type of flow on which their members predominantly depend. While portfolio inflows are the major source of finance for industrial and Asian economies, other inflows and FDI inflows are more important for countries falling into the emerging Europe and Latin America group, respectively. Third, industrialized (5 cases) as well as emerging European economies (1 case) account for all of the most extreme observations in our sample. This mainly reflects their dominant role in the run-up to and the aftermath of the recent global financial crisis. Finally, we also find some support for the notion that FDI is a more resilient source of finance than other types of capital inflows (Stiglitz, 2000). Across all regions, the FDI to GDP series have the smallest standard deviation (5.7%). Somewhat surprisingly, however, those of the portfolio inflows to GDP series are only slightly larger (5.8%).

The descriptive statistics discussed so far are silent about the degree of comovement between international capital flows which is central to our analysis. A first impression of this aspect can be gauged from Table 2 which shows the average group-specific correlation coefficients of our capital flows to GDP series along with Pesaran's CD-statistic (Pesaran, 2004). This statistic – displayed in parenthesis – is based on all estimated individual correlation coefficients and offers a test of the null hypothesis of no cross section dependence.[8] Using these concepts, we find evidence for an economically weak but statistically significant degree of comove-

[8]For balanced panels the CD-statistic is calculated as $CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$, where N and T denote the number of series and time periods, respectively. The $\hat{\rho}_{ij}$ are the estimated correlation coefficients between the series i and j. Under the null hypothesis, CD follows a standard normal distribution.

ment between capital inflows. Contrary to the notion that all capital flows tend to move together, the average correlation coefficient across all types and recipients is just 0.05. A single common factor obtained from a standard dynamic factor model is thus likely to have only limited explanatory power for the individual series of capital inflows. The average correlation coefficients are somewhat larger among specific flow types and country groups. Encouragingly, the degree of comovement is even higher for region-specific FDI, portfolio and other inflows. The average correlation between FDI flows to emerging Europe, e.g., is 0.17 compared to a value of just 0.08 for all FDI inflows. Similar tendencies can be found for other regions and types of capital flows. This observation is consistent with the hypothesis that important developments are common to groups of countries and capital flows but not to all series in our data set. The dynamic hierarchical factor model is thus an ideal tool to disentangle the relative importance of these factors.

4. A Dynamic Hierarchical Factor Model for Gross Capital Flows

The econometric framework we rely on is the dynamic hierarchical factor model as presented in Moench *et al.* (2011). It is a four level model allowing us to split the causes of dynamics in our data into four categories, namely idiosyncratic, regional, flow-specific and global disturbances.[9] The model's hierarchical structure implies that subblock factors, i.e. factors on the most disaggregated level, hinge on superordinated factors. These interdependencies are taken into account during estimation.

[9] In another application, Moench and Ng (2011) use the dynamic hierarchical factor model downsized to three levels to analyze the U.S. housing market after the Bretton-Woods era.

Our four level factor model is build as follows. Let b and s respectively denote the specific block and subblock the observed variable n is assigned to. In our case, block b corresponds to a specific type of capital inflows whereas subblock s classifies a geographical region. Each subblock consists of N_{bs} time series different among subblocks. For the observation Z_{bsnt} in period t, we assume the following relation between the data point and the factors:

$$Z_{bsnt} = \Lambda_{Zbsn} H_{bst} + u_{Zbsnt} \tag{1}$$

$$H_{bst} = \Lambda_{Hbs} G_{bt} + u_{Hbst} \tag{2}$$

$$G_{bt} = \Lambda_{Gb} F_t + u_{Gbt} \tag{3}$$

Here, Λ_{Zbsn}, Λ_{Hbs} and Λ_{Gb} denote the time-invariant factor loadings. The factor H_{bst} captures common movements between all the variables in subblock s of block b. All subblock factors of block b are related to the factor G_{bt} which explains joint fluctuations on the block level. In turn, G_{bt} depends on the global factor F_t collecting the part of the variance that is common to all time t observations. Thus, innovations to one factor will have an effect on all subordinated levels but not the other way round, e.g. global factors are independent of local incidents.

To address the persistence in our data set we make the assumption of autoregressive processes. This is the case for the global factor F_t:

$$F_t = \rho_F F_{t-1} + \epsilon_{Ft} \tag{4}$$

where the matrix ρ_F would contain the autocorrelation parameters. For estimation, we consider only one global factor so that ρ_F is a scalar. Moreover, we assume that:

$$u_{Zbsnt} = \rho_{Zbsn} u_{Zbsn(t-1)} + \epsilon_{Zbsnt} \tag{5}$$

$$u_{Hbst} = \rho_{Hbs} u_{Hbs(t-1)} + \epsilon_{Hbst} \tag{6}$$

$$u_{Gbt} = \rho_{Gb} u_{Gb(t-1)} + \epsilon_{Gbt} \tag{7}$$

with $\epsilon_{jt} \sim N(0, \sigma_j^2)$, $j = Zbsn, Hbs, Gb, F$. All ϵ_{jt} are uncorrelated across j and t.

Since we are interested in only one factor on each stage described by equations (1), (2), (3), restrictions necessary to ensure identification are reduced to a minimum. The first elements of Λ_i, $i = Zbs, Hbs, Gb$, takes a value of unity. Moreover, as in Moench *et al.* (2011), the variances σ^2_{Hbs}, σ^2_{Gb} and σ^2_F are set to 0.1.

Estimation of the dynamic hierarchical factor model requires the consideration of the vertical connection between the factors as constituted in equations (1), (2), and (3). We do so by applying Markov Chain Monte Carlo methods. Iteratively, it first draws each factor given the parameters, the other factors and, for the subblocks, the data. In a second step, parameters are drawn based upon the obtained factors.[10] Overall, we perform 100,000 draws from which we retain every 50th of the last 50,000 draws for our analysis.

The dynamic hierarchical factor model is ideally suited for our analysis of capital inflows. Its level structure allows to separately identify regional and global factors. Furthermore, all factors are influenced by superordinated factors while subordinated effects do not spill over to global factors. A conventional non-hierarchical factor model would not take account of this one-directional relationship. Moreover, with our hierarchical model we are able to investigate how important fluctuations

[10]See Moench *et al.* (2011) for a detailed description of the specific Markov Chain Monte Carlo procedure applied in this setup. We use the MATLAB codes available on Serena Ng's website.

on different stages are for a specific time series, a feature not on hand in a simple factor analysis.

5. Results

The rich set of results of the factor decomposition is presented in two parts. In a first part, we provide a graphical analysis of the evolution of the global, the type-specific and the regional factors separately for each type of flows and for each region. These results can be found in Figures 1 to 3. In a second part, we decompose the variance of each capital inflows series into the shares attributable to either of our three factors and the idiosyncratic component. This variance decomposition is presented in Table 3.

Our estimated global factor extracted from the large set of countries closely reflects the well-known capital flow cycles of the past two decades. While the Mexican crisis of 1994, the Asian crisis of 1997 and the crises hitting Russia, Brazil and Argentina thereafter are indicated by relatively small declines in the global factor, its overall evolution is clearly dominated by the most recent financial crisis in 2008/09. At the peak of the crisis the connection between all factors intensifies suggesting that the pattern of comovement changes substantially during severe global crises.[11]

The flow-specific factors follow a similar pattern, although the similarity with the global factor differs remarkably across types of capital inflows. Whereas the portfolio and other flow factors tracks the global factor quite closely, see Figure 2 and Figure 3, the FDI factor is considerably more independent from the global factor, see Figure 1. Flows to emerging Asia or Latin America, as characterized by their

[11]In a companion paper (Förster *et al.*, 2012) we show that actual capital inflows are also more closely tracked by the global factor during the recent crisis period.

regional factors, in turn, appear only loosely connected to conditions reflected by the global factor. Likewise, the regional factors evolve differently from each other over time and sometimes even exhibit divergent dynamics. In the aftermath of the recent financial crisis, for example, the regional factors for FDI inflows to Asia reflect the regained momentum of FDI flows into this region, while FDI flows to Latin America and emerging Europe remained subdued.

While the graphical analysis of the factors is interesting, it cannot reveal the extent to which capital inflows in a given region or within a given asset class are affected by different factors. To address this issue, the factors have to be discussed together with estimated factor loadings. To facilitate the interpretation, Table 3 reports a decomposition of the variance of capital inflows into the shares attributable to our different factors. This decomposition has been constructed using the mean within each subblock for every draw, from which the median and the 33% as well as the 66% percentiles over all retained draws are reported.

The results show that the idiosyncratic component is by far the most important determinant of capital inflows. It explains about 80% of fluctuations in capital inflows. The regional factor is responsible for between 5% and 36% of overall variation and is more relevant for emerging economies than for capital flows to industrial countries. Flows to Latin America are particularly prone to fluctuations in the regional factor, which accounts for 17% of the variation in FDI inflows to Latin America and 18% of portfolio inflows to this region. For Asia and emerging Europe, the regional factor matters most for FDI inflows and other types of inflows, but less so for portfolio inflows. The regional factor is very important for flows other than FDI or portfolio flows to emerging European economies. This may reflect the strong dependence of those economies on bank lending from advanced European economies.

The flow type-specific factor plays an important role for FDI inflows into industrial economies. For those economies 13% of fluctuations can be traced back to fluctuations in the global FDI factor. Surprisingly, the global portfolio factor plays a small role with a share of about 5% only.

Finally, the global factor, i.e. the factor potentially affecting all countries and all types of capital inflows, has a small impact on portfolio inflows to the Asian and the industrial countries in our sample but almost no impact on FDI inflows or portfolio inflows to Latin America. The global factor seems to matter most for inflows other than FDI and portfolio inflows to industrial economies. This probably again reflects the strong impact of cross-border bank lending among global financial intermediaries in advanced economies as these lending activities might be reduced disproportionally after a global financial shock.

The sum of the variance shares explained by global and flow type-specific factors, respectively, indicates the extent to which a country is affected by forces common to all countries. The results suggest that this measure is substantially larger for portfolio flows to Asia than for FDI flows into this region. This confirms the popular view that portfolio investors are particularly affected by global conditions, whereas FDI investment is not. In Latin America, however, this measure is stronger for FDI than for portfolio flows. Taken together, we do not see a clear-cut pattern as to which type of capital flows is less affected by global forces.[12] However, the global factor explains less than 1% of variations in FDI inflows across all regions, whereas it explains a sizeable fraction of fluctuations in portfolio and other types of inflows.

In sum, our findings are consistent with the view that the bulk of swings in capital inflows is driven by country-specific components followed by the regional fac-

[12]This also implies that, if a high dependency on global forces is considered detrimental to financial stability, it is not straightforward to classify one of these types of capital inflows along the lines of either "good" or "bad" or "cold" or "hot" types of inflows. This supports the results presented by, among others, Claessens *et al.* (1995) and Sarno and Taylor (1999).

tors.[13] Thus, we cannot lend support to the view put forward by the The Economist (2011) arguing that capital inflows are driven by factors beyond the control of domestic policy. However, the results do also illustrate that the recent financial crisis was characterized by an extraordinarily large comovement of capital flows across regions and flow types. We address this issue again in section 7. Prior to this, the next section examines the variables that determine the extent to which a country is exposed to global drivers of capital flows.

6. Explaining the Exposure to Global and Country-Specific Drivers of Capital Flows

According to the results of the previous section, common shocks have rather heterogeneous implications for capital inflows to different economies. Furthermore, some countries seem to be particularly prone to idiosyncratic shocks. In this section we set out to explain why this is the case focusing on the cross-section of countries. We proceed in two steps. In a first step, we quantify the fractions of capital inflow volatility that are due to global or country-specific developments. To this end, we multiply the variance shares attributable to either global or idiosyncratic shocks by the overall variance of the original capital flow series.[14] Larger values for the newly constructed variables thus reflect that shocks at the respective level are more important in absolute terms. In a second step, we relate these measures of exposure to structural features of small open economies in a cross-sectional regression. Here, we follow several prior studies (e.g., Broner and Rigobon (2006), International Monetary Fund (2007), Neumann *et al.* (2009), Broto *et al.* (2011),

[13]Our results are notably different from those presented by Broto *et al.* (2011), who argue that based on a panel of capital flows series up to 2006 global factors became increasingly more important relative to country-specific drivers after 2000.

[14]In this section, the term 'global variance share' refers to the sum of the variance shares accounted for by the global and the flow type-specific factor. See Section 5 for a discussion of this measure.

Hegerty (2011), and Mercado and Park (2011)) that used macroeconomic, political and financial variables to explain the volatility of capital flows. We contribute to the literature by investigating whether the same set of determinants that shields a country from global drivers of capital flow instability also makes it less prone to local shocks.

Six different explanatory variables are taken into account in each regression. The first is an index of capital controls *(Capital Controls)*, for which we use the indicator for financial integration developed in Schindler (2009). A high value of this index indicates tighter controls on capital inflows. The degree of trade openness *(Trade)*, our second explanatory variable, is measured by the sum of exports and imports relative to GDP. The data for this measure comes from the World Bank (2011). As the third variable we use the degree of flexibility of the exchange rate regime *(Exchange Rate Flexibility)*, which we measure using Iltzeki *et al.* (2008) de facto classification of exchange rate regimes ranging from one (completely fix) to six (completely flexible). We use the ratio of liquid liabilities to GDP *(Liquid Liabilities)*, our forth variable, as a measure of financial depth. We take this measure from Beck *et al.* (2009), who constructed it as the interest-bearing liabilities of banks and other financial intermediaries divided by GDP. For each of these four explanatory variables we use the mean over the sample period, i.e. 1994 to 2010. Finally, we also include the mean GDP growth rate and its volatility.[15]

We have no clear prior for most regression coefficients as economic theory often offers conflicting views on the relationship between the variables and capital flow volatility. Capital controls, e.g., might either decrease volatility by preventing capital flight in times of crisis or lead to increased instability as risk sharing is impaired. Similary, the effect of trade openness might be either positive or negative. On the one hand, trade linkages might transmit contagious financial crisis thereby increasing the sensitivity to global forces. On the other hand, trade glo-

[15]See Appendix A for further details on data sources and definitions.

balization might also lead to greater resilience as shown by Martin and Rey (2006). Fixed exchange rates should stabilize financial inflows during normal times by lowering the uncertainty regarding the dollar return of foreign investments. At the same time, the risk of currency crisis rises which, in turn, might trigger a balance of payment crisis. Additionally, a large financial sector could signal a high degree of risk sharing or domestic financial imbalances. Even the effect of the two GDP variables are not clear-cut. A large average growth rate could point to sound macroeconomic policies that should lead to stable capital account positions but may also indicate that the country is an emerging economy which tend to be more crisis-prone. Finally, one would expect to find that countries with unstable growth rates are also more likely to suffer from financial crisis and volatile capital flows. Again, however, the opposite might be true as countries with a more stable macroeconomic environment may attract higher average ratios of capital inflows to GDP. Hence, the effect of a sudden stop, which causes this ratio to drop to zero, would also be larger. Overall, we conclude that economic theory highlights complex relationships between most variables and capital inflow volatility. Whether they relate positively or negatively to our dependent variables is thus ultimately an empirical question.

Table 4 and Table 5 report the results from a simple cross-sectional regression of the exposure measures on all six explanatory variables and a constant. As expected, we find that a higher level of capital account restrictions reduces the exposure to global factors for FDI and portfolio flows. Openness to exports of goods and services has no significant net impact on the exposure to global determinants of capital inflows. Interestingly, fixed exchange rates are associated with a larger FDI exposure to global factors, although the effect is small. For portfolio inflows and other inflows the exchange rate regime seems to be irrelevant. Thus, fixing the exchange rate does not shield the economy from global drivers of capital flows. A positive connection can be seen between the development of the financial system and the exposure to global factors, which is, however, insignificant. The exposure to global determinants also seems to be larger for countries with stable GDP growth.

The results for a country's exposure to idiosyncratic factors are similar. For portfolio and other types of capital inflows the tightness of capital controls plays the largest role. Furthermore, idiosyncratic portfolio flows are negatively affected by the degree of exchange rate flexibility and the standard deviation of GDP growth. Overall, the results are in line with the empirical literature. Most studies found only few determinants of capital flow volatility to be significant. In Broner and Rigobon (2006), e.g., not a single variable enters significantly when all explanatory variables are considered jointly. Our most robust finding that capital controls lower the volatility of inflows is consistent with the results from Mercado and Park (2011) for FDI inflows but stands in contrast to those from the International Monetary Fund (2007). This may reflect differences in sample composition and the fact that one or the other aforementioned theory is more relevant for a specific country at a specific point in time. This interpretation is supported by the country-specific heterogeneity of effects documented in Hegerty (2011). Furthermore, it should be stressed that our cross-sectional regressions should be interpreted as illustrative only as they neglect potentially severe endogeneity problems and rely on long-run averages of both our measures of exposure and the explanatory variables. With an R^2 of more than 20%, however, the explanatory power of these parsimonious regressions is surprisingly high. In most studies that do not differentiate between global and local drivers of capital flow volatility the corresponding values are considerably lower. Allowing for a differentiated reaction thus at least increases the model fit, although many variables still do not enter significantly.

7. Robustness

In this section we check the robustness of our results with respect to changes in the econometric model, the treatment of outliers and the sample period. As a first step, we want to investigate whether our results are dependent on hierarchical modeling approach. So far, we revealed that country-specific properties to a large extent explain variations in capital inflows. One aspect to be considered is that the limited influence of the global factor may hinge on the pyramidal structure of our econometric model. Furthermore, the transmission channel depends on the pass-through of the superordinated factors to the data via subordinated factors.

To examine these concerns, we confront our data set with an alternative factor model. For that purpose we choose the latent dynamic factor approach of Kose *et al.* (2003) and Neely and Rapach (2011).[16] The main difference between these two approaches is the absence of the hierarchical structure in the Neely-Rapach model. Instead, the authors estimate the factors via a set of dummy variables for which no explicit interdependence is assumed.[17] The outcome of this exercise is presented in Table 6.[18] While the idiosyncratic component explains on average 80.2% of the variance of our observables in the hierarchical factor model, Neely and Rapach (2011)'s method yields a value of 79.6% which is only slightly smaller than ours. Remarkably, around half of the estimated individual variance shares are identical, i.e. deviations are smaller than 1 percentage point. Furthermore, within the groups of FDI inflows and other inflows their ranking coincides with our results. Altogether, our outcomes regarding the role of the idiosyncratic components are robust since we observe only minor differences between both methodologies.

[16]We use the MATLAB code accompanying the publication of Neely and Rapach (2011) on the journal's web site for our robustness exercise.

[17]Another, third approach to estimate latent variables on different levels of aggregation is made by Beck *et al.* (2011) in their analysis of sectoral prices in the European Monetary Union.

[18]Since we are interested in whether idiosyncratic effects remain important, we refrain from enhancing the Neely and Rapach (2011) model with a flow-type specific factor.

Returning to our original dynamic hierarchical factor framework, we next analyze whether our results are robust with respect to the treatment of outliers. In principle, extreme values of capital inflows could be the consequence of rare economic events like balance of payments crises that are in turn caused by global, regional or country-specific developments. Hence, our previous approach would be correct and the original data should be used in the econometric analysis. However, extreme observations could also reflect measurement errors in which case an outlier adjustment would be more appropriate. Since it is a priori unclear which interpretation is more accurate, we assess the importance of the outlier treatment by reestimating our model using transformed data. Here we follow the procedure of Stock and Watson (2005) and identify outliers as those observations where the absolute median deviation exceeds the series-specific inter quartile range by a factor larger than six. These values are than replaced by the median value of the preceding five observations.

Table 7 contains the variance decomposition for the estimated dynamic hierarchical factor model with outlier correction. The results are generally close to those obtained for the unadjusted series. Most striking is the absence of any significant change in the variance share of the idiosyncratic factors. Here, one would have expected to find lower values if the eliminated outliers were the consequence of series-specific measurement errors. Using the unadjusted series thus seems to be the appropriate choice.

As a final robustness exercise we investigate whether our results are subject to structural change. Unfortunately, a full-fledged subsample analysis is precluded by our relatively short sample size. However, we are able to isolate the effects of the recent global financial crisis by restricting our sample to the period 1994Q1 to 2008Q2 which ends before the Lehman collapse. Conjecturing that the degree of comovement between capital flows has been exceptionally high during the latest downturn, we expect to find a reduced importance of global factors in this subsample.

A look at Table 8 reveals that our time series are indeed less influenced by global forces during the pre-crisis period. This holds true for all types of capital inflows. Instead, regional determinants seem to be more important for foreign investors. As expected, the comovement among capital inflows has been exceptional large during and after the global financial crises. Thus excluding this period leads to a significant reduction in the variance explained by global forces that is matched by an increased importance of regional aspects. Furthermore, the variance share of the idiosyncratic component falls only slightly by 3% on average and is still by far the most important driving force behind capital inflows accounting for over three quarters of the observed variance.

8. Conclusions

In this paper, we estimated a dynamic hierarchical factor model that is able to decompose capital flows in a large panel of countries into (i) a global factor common to all types of inflows and all recipient countries, (ii) a factor specific to a given type of capital inflows, i.e. either foreign direct investment (FDI), portfolio investment or other kinds of investment, (iii) a regional factor driving economies in geographical proximity and (iv) a country-specific component.

Our results demonstrate that the global factor tracks the overall capital flow cycles well, but leaves a large degree of heterogeneity attributable to either regional or country-specific determinants. In fact, the country-specific determinant explains by far the largest fraction of fluctuations in capital inflows. This component alone accounts for between 60% and 80% of the dynamics of international capital inflows.

The regional factor explains between 5% and 20% of the fluctuations. Finally, only a small share of overall variation can be attributed to the global factor.

This suggests that domestic policy has considerable room to affect capital flows and, if this is deemed appropriate, also to limit the consequences of capital inflows such as asset price booms and a real appreciation of the domestic currency. Policymakers of small open economies are often anxious about waves of global capital flows. Inflows unrelated to country-specific economic fundamentals but instead driven by global driving forces, the argument goes, pose a threat to domestic financial stability. Curbing capital inflows by means of outright capital controls or other measures is often seen as the ultima ratio in a situation in which a country receives massive capital inflows driven by global determinants over which domestic policy has no control (see Ostry *et al.* (2011)). Our results, however, suggest that this is less often the case than previously thought. Thus, the primary responsibility for dealing with large and volatile capital flows remains with domestic policymakers.

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Tables

Table 1: Descriptive Statistics

	Obs	Mean	Std. Dev.	Min	Max
FDI inflows					
Industrial	1156	0.0283	0.0589	-0.3473	0.9552
Asia	612	0.0131	0.0169	-0.0397	0.2228
Emerging Europe	816	0.0434	0.0803	-1.0698	0.9206
Latin America	612	0.0364	0.0333	-0.0863	0.3096
All	3196	0.0308	0.0572	-1.0698	0.9552
Portfolio inflows					
Industrial	1156	0.0530	0.0736	-0.6166	0.5793
Asia	612	0.0143	0.0325	-0.1407	0.1992
Emerging Europe	816	0.0145	0.0459	-0.4151	0.3811
Latin America	476	0.0084	0.0310	-0.1038	0.3019
All	3060	0.0281	0.0579	-0.6166	0.5793
Other inflows					
Industrial	1156	0.0445	0.1286	-1.3225	0.9356
Asia	612	0.0056	0.0426	-0.2816	0.1551
Emerging Europe	816	0.0443	0.0808	-0.2845	0.5132
Latin America	612	0.0030	0.0617	-0.7485	0.3105
All	3196	0.0290	0.0954	-1.3225	0.9356

Table 2: Average Correlation Coefficient and Pesaran CD-statistic

	Industrial	Asia	Emerging Europe	Latin America	All
FDI	0.11	0.06	0.17	0.09	0.08
	(10.96***)	(2.74***)	(11.65***)	(4.23***)	(22.70***)
Portfolio	0.14	0.13	0.05	0.10	0.08
	(12.98***)	(6.24***)	(3.40***)	(3.94***)	(19.56***)
Other	0.16	0.15	0.25	0.03	0.10
	(15.08***)	(7.52***)	(17.04***)	(1.57)	(27.54***)
All	0.08	0.05	0.08	0.04	0.05
	(24.43***)	(7.76**)	(17.10***)	(5.21***)	(39.55***)

Pesaran CD-statistics are shown in parenthesis. ***, **, and * denote significance levels of 1%, 5% , and 10%.

Table 3: Variance Decomposition

	global	flow-specific	regional	idiosyncratic
FDI inflows				
Industrial	0.6	13.3	6.2	79.2
	[0.2, 1.1]	[12.3, 14.6]	[5.7, 6.8]	[77.9, 80.4]
Asia	0.0	0.2	17.6	82.0
	[0.0, 0.0]	[0.1, 0.3]	[16.3, 19.3]	[80.4, 83.2]
Emerging Europe	0.0	0.1	20.9	78.8
	[0.0, 0.0]	[0.1, 0.3]	[19.2, 22.6]	[77.2, 80.4]
Latin America	0.0	1.3	17.2	81.2
	[0.0, 0.1]	[0.7, 2.0]	[16.4, 17.9]	[80.6, 81.8]
Portfolio inflows				
Industrial	5.7	5.0	4.6	84.0
	[4.0, 7.4]	[4.3, 5.9]	[4.1, 5.2]	[82.9, 85.1]
Asia	4.9	4.6	10.6	77.3
	[3.5, 6.4]	[3.4, 6.9]	[8.7, 13.0]	[75.1, 79.1]
Emerging Europe	1.1	1.1	9.4	88.0
	[0.8, 1.6]	[0.7, 1.6]	[8.0, 10.2]	[87.3, 88.7]
Latin America	0.4	0.4	18.4	80.2
	[0.2, 0.8]	[0.2, 0.8]	[17.6, 19.2]	[79.4, 81.0]
Other inflows				
Industrial	12.9	5.5	5.2	76.1
	[11.9, 14.0]	[5.1, 6.0]	[4.9, 5.5]	[74.8, 77.3]
Asia	3.2	1.4	12.6	82.7
	[2.5, 4.1]	[1.1, 1.7]	[11.5, 13.7]	[81.5, 83.4]
Emerging Europe	0.4	0.2	35.5	63.6
	[0.2, 0.9]	[0.1, 0.4]	[33.2, 37.5]	[61.8, 65.3]
Latin America	1.1	0.5	15.7	82.4
	[0.7, 1.7]	[0.3, 0.8]	[14.8, 16.6]	[81.6, 83.1]

Medians, 1/3 and 2/3 percentiles (in brackets) denoted in percentage terms.

Table 4: Explaining the Exposure to Global Factors

dep. variable: global factor variance share $\times$ variance	(1) *FDI*	(2) *Portf.*	(3) *Other*
Capital Controls	-4.99*	-2.86*	-60.42
	(-2.00)	(-1.92)	(-1.34)
Trade	0.06	0.00	0.19
	(1.18)	(0.23)	(0.54)
Exchange Rate Flexibility	-1.91*	-0.03	-0.96
	(-1.93)	(-0.06)	(-0.09)
Liquid Liabilities	1.97	0.47	22.98
	(0.82)	(0.33)	(0.65)
Mean(GDP Growth)	1.51	0.29	11.99
	(1.45)	(0.52)	(1.12)
Std(GDP Growth)	-0.85	-1.04**	-17.18
	(-1.51)	(-2.36)	(-1.05)
Constant	3.40	3.66	30.17
	(0.89)	(1.49)	(0.67)
Obs	40	39	40
R^2	0.32	0.21	0.07

t-statistics are shown in parenthesis. ***, **, and * denote significance levels of 1%, 5%, and 10%.

Table 5: Explaining the Exposure to Idiosyncratic Factors

dep. variable idisyncratic factor variance share × variance	(1) *FDI*	(2) *Portf.*	(3) *Other*
Capital Controls	-4.26	-37.48**	-87.95**
	(-0.14)	(-2.58)	(-2.58)
Trade	1.19	0.26	0.42
	(1.26)	(0.99)	(1.40)
Exchange Rate Flexibility	15.29	-10.86**	-13.95
	(0.66)	(-2.08)	(-1.30)
Liquid Liabilities	-13.47	8.85	7.18
	(-0.61)	(0.56)	(0.27)
Mean(GDP Growth)	-15.99	7.55	8.85
	(-0.68)	(1.32)	(0.99)
Std(GDP Growth)	-9.56	-7.03**	-9.12
	(-1.05)	(-2.11)	(-0.94)
Constant	-53.88	43.81*	79.77
	(-0.66)	(1.89)	(1.66)
Obs	40	39	40
R^2	0.19	0.38	0.24

t-statistics are shown in parenthesis. ***, **, and * denote significance levels of 1%, 5%, and 10%.

Table 6: Variance Decomposition for Alternative Factor Model

	global	specific to flow/region	idiosyncratic
FDI inflows			
Industrial	3.3	14.7	82.0
	[2.9, 3.6]	[14.2, 15.2]	[81.6, 82.4]
Asia	5.2	6.8	87.7
	[4.6, 5.9]	[4.9, 8.9]	[85.6, 89.7]
Emerging Europe	8.4	13.3	78.0
	[7.6, 9.3]	[12.3, 14.4]	[77.1, 79.0]
Latin America	2.0	16.8	81.2
	[1.6, 2.4]	[16.4, 17.2]	[80.6, 81.2]
Portfolio inflows			
Industrial	11.7	12.0	76.2
	[10.9, 12.5]	[11.5, 12.6]	[75.6, 76.9]
Asia	8.7	16.1	75.0
	[7.8, 9.8]	[14.9, 17.2]	[74.3, 75.9]
Emerging Europe	3.5	8.2	88.3
	[3.2, 3.9]	[7.6, 8.7]	[87.7, 88.9]
Latin America	2.8	11.1	86.1
	[2.3, 3.3]	[9.7, 12.3]	[84.8, 87.4]
Other inflows			
Industrial	11.6	14.2	74.3
	[10.7, 12.4]	[13.7, 14.7]	[73.7, 74.9]
Asia	7.8	12.5	79.3
	[7.0, 8.7]	[10.8, 14.0]	[78.2, 80.7]
Emerging Europe	15.4	21.4	63.1
	[14.2, 16.6]	[20.1, 22.7]	[62.7, 63.6]
Latin America	6.3	11.1	82.6
	[6.0, 6.7]	[10.2, 11.8]	[81.8, 83.5]

Medians, 1/3 and 2/3 percentiles (in brackets) denoted in percentage terms.

Table 7: Variance Decomposition with Corrected Outliers

	global	flow-specific	regional	idiosyncratic
FDI inflows				
Industrial	0.5	14.5	4.9	79.5
	[0.2, 0.9]	[13.4, 16.0]	[4.5, 5.3]	[78.0, 80.8]
Asia	0.0	0.2	17.4	82.0
	[0.0, 0.0]	[0.1, 0.5]	[15.9, 19.0]	[80.6, 83.4]
Emerging Europe	0.0	0.2	22.0	77.3
	[0.0, 0.0]	[0.1, 0.5]	[20.1, 23.7]	[75.7, 79.3]
Latin America	0.0	0.2	20.7	78.6
	[0.0, 0.0]	[0.1, 0.5]	[19.2, 22.6]	[77.1, 80.1]
Portfolio inflows				
Industrial	7.5	4.3	4.2	83.9
	[6.1, 8.7]	[3.9, 4.8]	[3.8, 4.7]	[82.7, 84.9]
Asia	5.8	3.5	13.6	76.1
	[4.4, 7.3]	[2.7, 4.5]	[11.9, 15.4]	[74.3, 77.9]
Emerging Europe	1.2	0.7	10.5	87.3
	[0.9, 1.7]	[0.5, 1.0]	[9.8, 11.1]	[86.8, 87.9]
Latin America	0.5	0.3	18.7	80.1
	[0.2, 0.9]	[0.2, 0.6]	[17.8, 19.5]	[79.2, 80.9]
Other inflows				
Industrial	13.6	5.4	5.1	75.7
	[12.5, 14.6]	[5.0, 5.8]	[4.8, 5.5]	[74.4, 76.9]
Asia	3.3	1.3	12.5	82.5
	[2.6, 4.2]	[1.0, 1.7]	[11.6, 13.6]	[81.6, 83.4]
Emerging Europe	0.4	0.2	35.4	63.6
	[0.2, 0.9]	[0.1, 0.4]	[33.0, 37.6]	[61.8, 65.3]
Latin America	1.1	0.5	15.5	82.6
	[0.7, 1.7]	[0.3, 0.7]	[14.7, 16.3]	[81.7, 83.4]

Medians, 1/3 and 2/3 percentiles (in brackets) denoted in percentage terms.

Table 8: Variance Decomposition without Financial Crisis

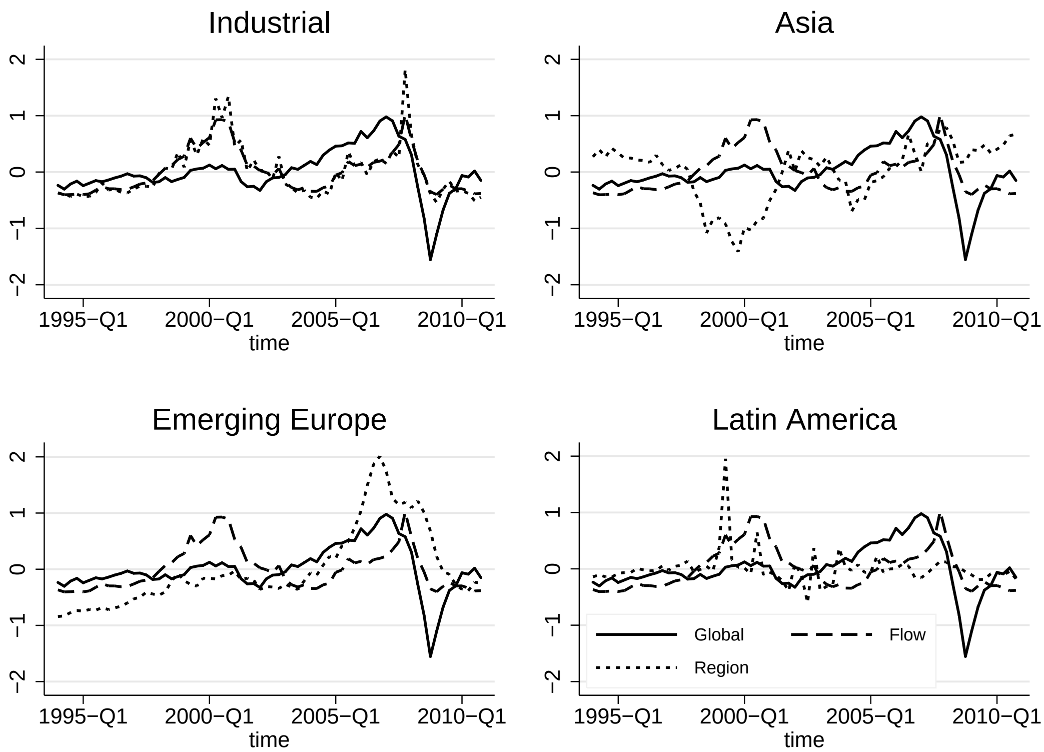
	global	flow-specific	regional	idiosyncratic
FDI inflows				
Industrial	0.2	14.0	8.0	77.2
	[0.1, 0.4]	[13.0, 15.0]	[7.4, 8.8]	[75.9, 78.6]
Asia	0.0	0.0	31.8	68.0
	[0.0, 0.0]	[0.0, 0.1]	[23.9, 41.3]	[58.5, 75.9]
Emerging Europe	0.0	0.1	28.0	71.7
	[0.0, 0.0]	[0.0, 0.2]	[25.2, 31.6]	[68.1, 74.4]
Latin America	0.0	0.7	18.9	80.0
	[0.0, 0.0]	[0.3, 1.4]	[18.1, 19.6]	[79.3, 80.6]
Portfolio inflows				
Industrial	0.1	18.4	3.6	77.7
	[0.0, 0.1]	[16.6, 20.6]	[3.3, 4.0]	[75.5, 79.4]
Asia	0.0	0.2	15.8	83.7
	[0.0, 0.0]	[0.1, 0.5]	[15.0, 16.5]	[82.9, 84.4]
Emerging Europe	0.0	0.4	13.8	85.6
	[0.0, 0.0]	[0.2, 0.7]	[13.0, 14.6]	[84.8, 86.3]
Latin America	0.0	1.1	17.4	81.1
	[0.0, 0.0]	[0.6, 1.8]	[16.5, 18.3]	[80.4, 81.9]
Other inflows				
Industrial	5.4	5.1	5.0	84.3
	[5.1, 5.9]	[4.9, 5.4]	[4.7, 5.3]	[83.4, 85.0]
Asia	0.1	0.1	21.3	78.4
	[0.0, 0.1]	[0.0, 0.1]	[20.2, 22.8]	[76.9, 79.5]
Emerging Europe	0.2	0.2	44.3	55.1
	[0.1, 0.3]	[0.1, 0.3]	[42.2, 46.7]	[52.6, 57.1]
Latin America	0.4	0.4	16.6	82.3
	[0.2, 0.7]	[0.2, 0.7]	[15.6, 17.4]	[81.4, 83.1]

Medians, 1/3 and 2/3 percentiles (in brackets) denoted in percentage terms.

Figures

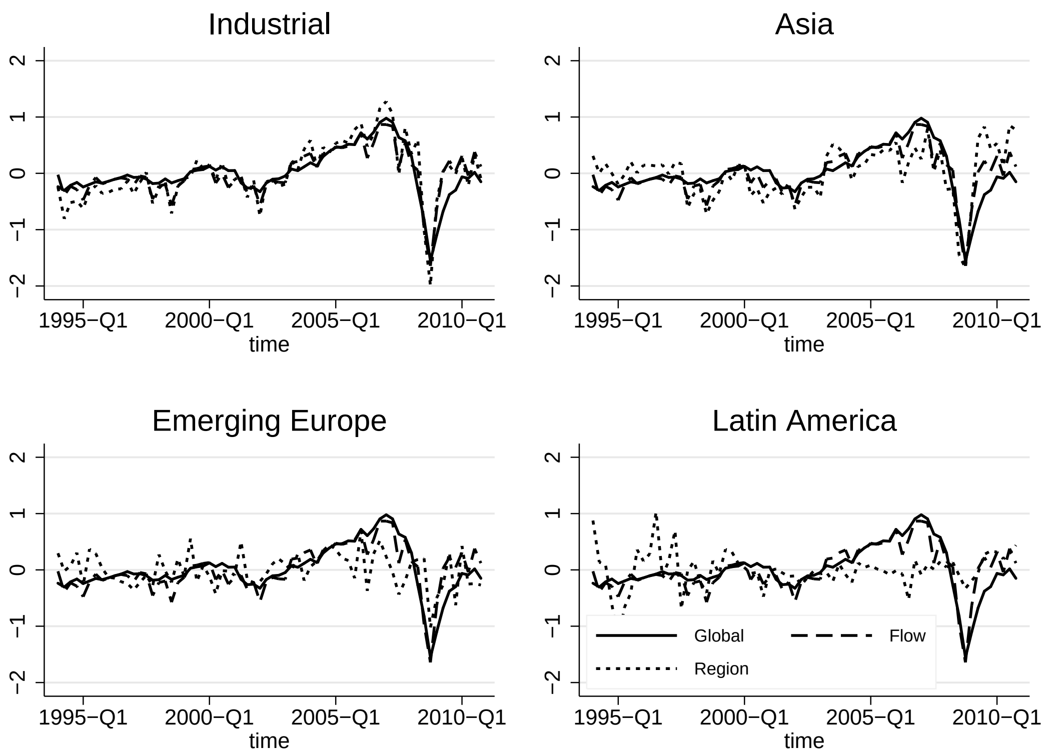
Estimated Factors

Figure 1: Decomposition of FDI Inflows



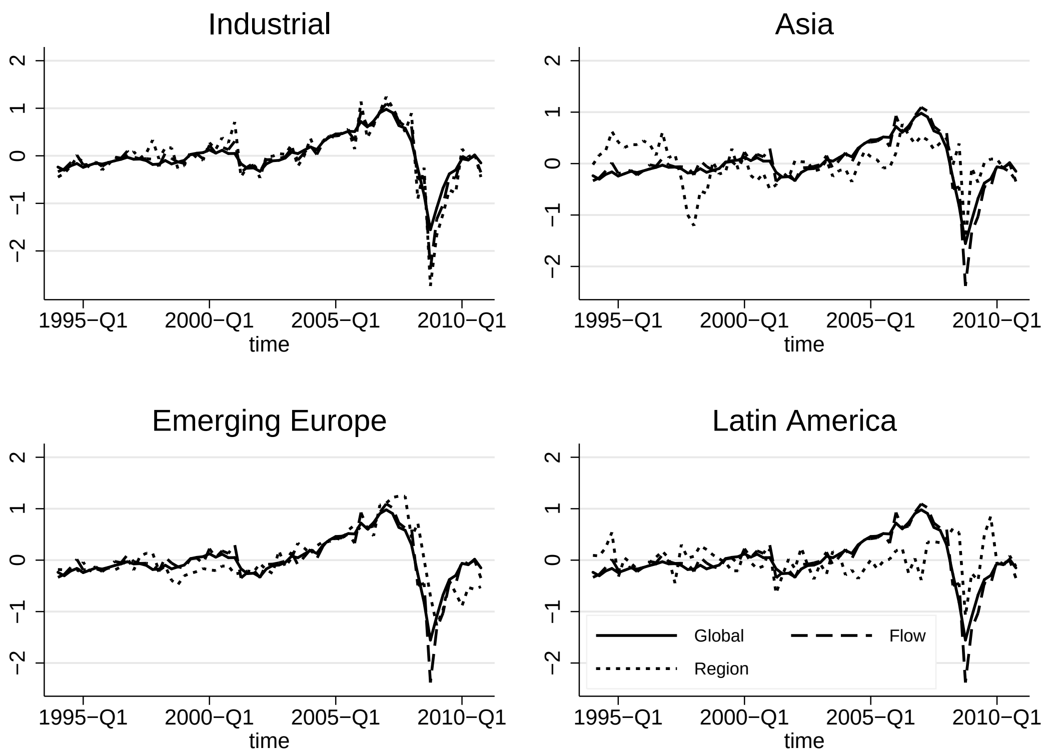
Notes: Depicted are median values of global, flow-specific and regional factors.

Figure 2: Decomposition of Portfolio Inflows



Notes: Depicted are median values of global, flow-specific and regional factors.

Figure 3: Decomposition of Other Inflows



Notes: Depicted are median values of global, flow-specific and regional factors.

Scatter Plots

Figure 4: Variance explained by global factors vs. capital controls

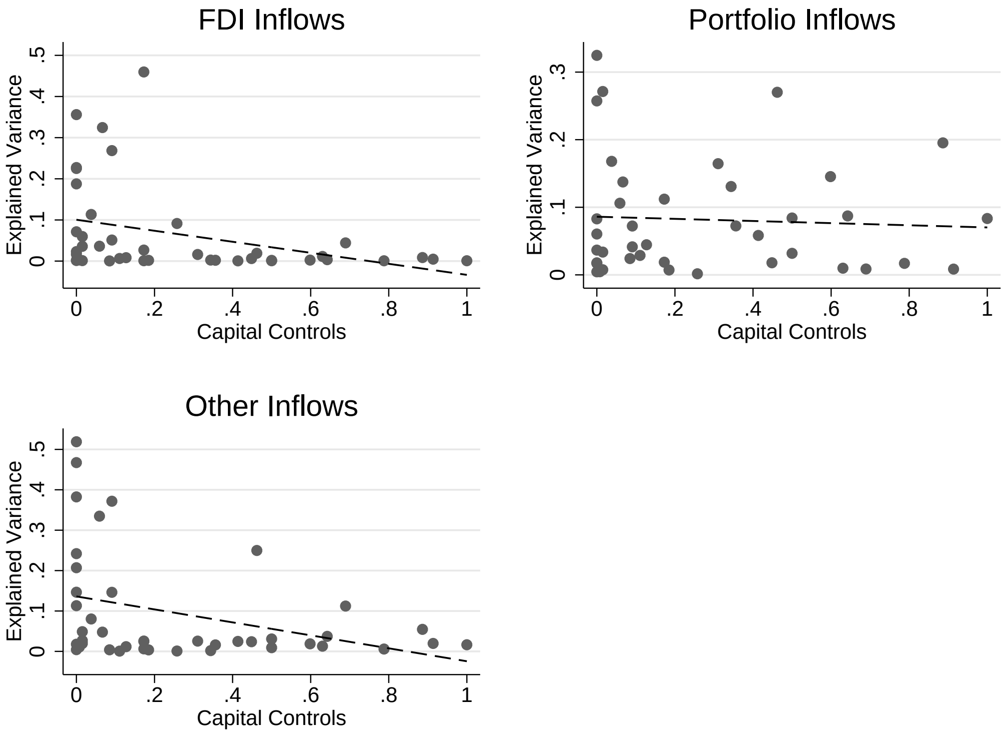


Figure 5: Variance explained by global factors vs. trade openness

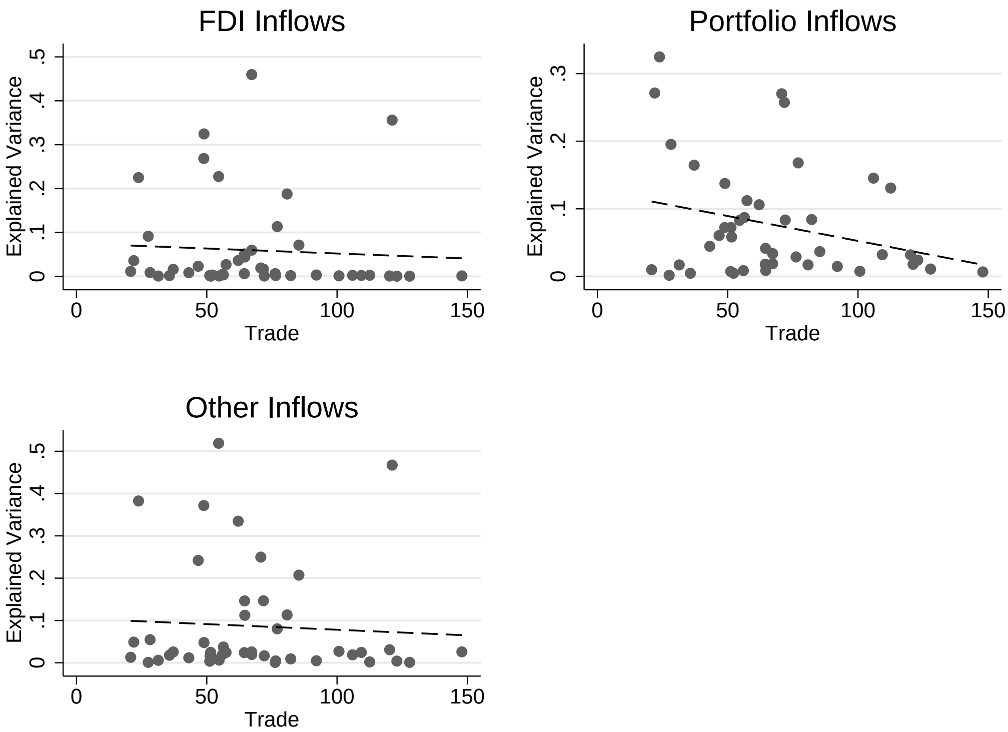


Figure 6: Variance explained by global factors vs. exchange rate flexibility

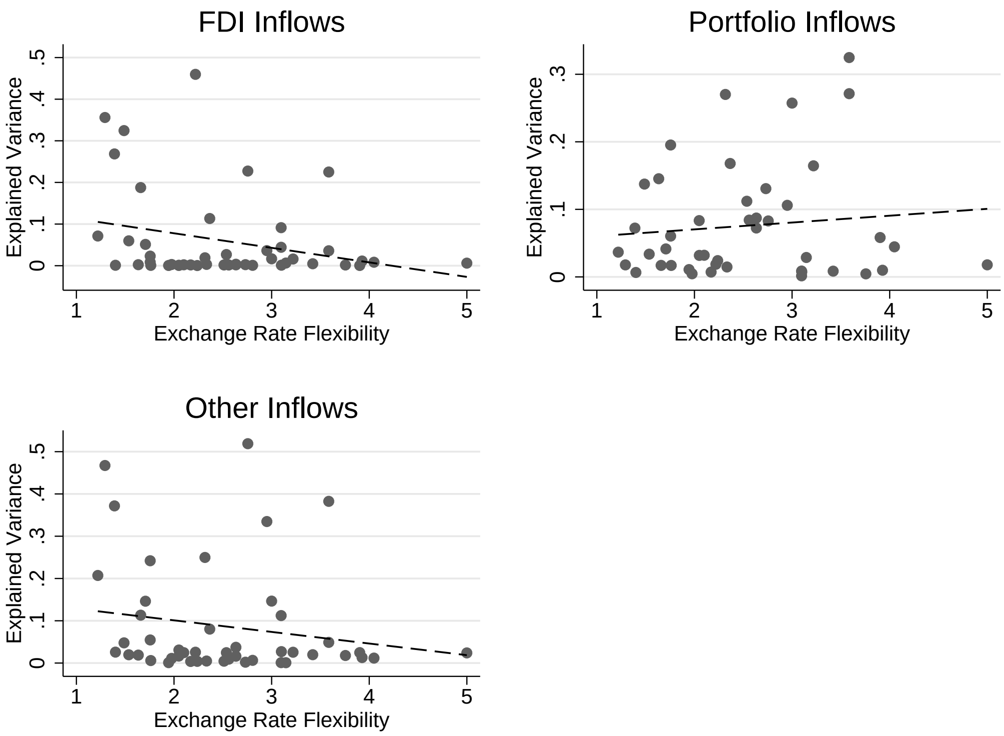
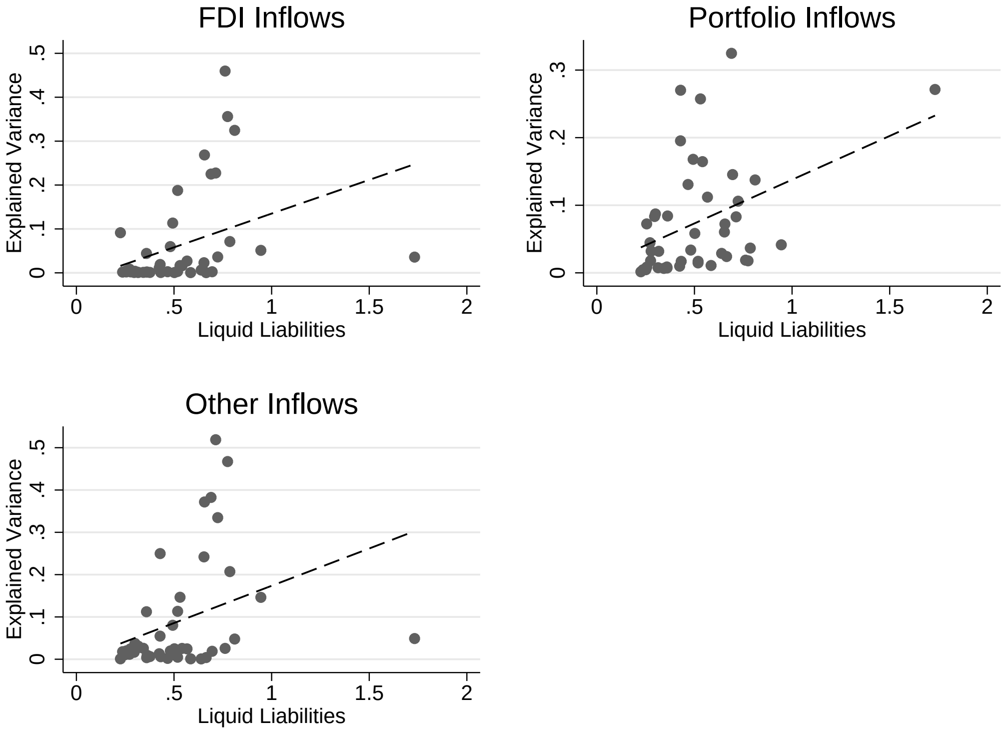


Figure 7: Variance explained by global factors vs. liquid liabilities



Appendix A. Data Sources and Definitions

Construction of the capital flow to GDP series

Data on Capital Flows:

- Primary source: IMF (2011b).
- Data on FDI, portfolio and other capital inflows measured in millions of U.S. dollars.
- Augmented with data from Taiwan (CBS (2011)) and – for 2001q1-2001q4 – from the Slovak Republic (NBS (2011)).
- Gaps in Latvia's portfolio inflows (1994Q1-1994Q4) and Slovenia's other inflows series (1994Q1-1994Q4) have been filled using data from the balance of payments' errors and omissions category as suggested by Forbes and Warnock (2012).

Data on GDP:

- Data on annual GDP expressed in national currency units from IMF (2011b).
- Augmented with data from Taiwan (using information from NSC (2011) for 1994-1996 and CBS (2011) for 1997-2010) and Nicaragua (2010) (from World Bank (2011)).
- Local currency GDP figures are converted into millions of U.S. dollars using information on exchange rates (annual period averages) from the same sources. For Euro zone members, currency conversion further requires data on official Euro conversion rates from ECB (2011).

Control Variables for Cross-sectional Regression

Capital Control Index *(Capital Controls)*:

- Index of restrictions on capital inflows
- Range: 0 (no restrictions) to 1 (fully restricted)
- Source: Schindler (2009)

Trade Openness *(Trade)*:

- Total trade (exports + imports) in percent of GDP
- Source: World Bank (2011)

Index of Exchange Rate Flexibility *(Exchange Rate Flexibility)*:

- Annual coarse classification of exchange rates
- Scale: 1 (completely fix) to 6 (most flexible)
- Source: Iltzeki *et al.* (2008)

Liquid-Liabilities-to-GDP Ratio *(Liquid Liabilities)*:

- Ratio of liquid liabilities to GDP
- Liquid liabilites = currency + demand deposits + interest bearing liabilities of all financial institutions
- Source: Beck *et al.* (2009)

Appendix B. Country Coverage and Regional Classification

Industrial countries (*Industrial*)			
Australia	Austria	Canada	Denmark
Finland	France	Germany	Italy
Japan	Netherlands	New Zealand	Norway
Portugal	Spain	Sweden	United Kingdom
United States			
Asia, Pacific Region & South Africa (*Asia*)			
Bangladesh	India	Indonesia	Korea, Republic of
Philippines	South Africa	Sri Lanka	Taiwan
Thailand			
Eastern Europe & Israel (*Emerging Europe*)			
Croatia	Czech Republic	Estonia	Hungary
Israel	Latvia	Lithuania	Romania
Russia	Slovak Republic	Slovenia	Turkey
Latin America & the Caribbean (*Latin America*)			
Argentina	Bolivia	Brazil	Chile
Guatemala	Mexico	Nicaragua	Peru
Venezuela, Rep. Bol.			

Appendix C. Unit Root Tests

Stationarity of the capital flow to GDP series is assessed using the augmented Dickey-Fuller (*ADF*) and Phillips-Perron (*PP*) unit root tests. Table C.1 shows for each test how often the null hypothesis of instationarity is rejected at the 5 percent and 1 percent level of significance. The augmented Dickey-Fuller tests do not indicate the presence of unit roots in the majority of series irrespective of whether the regressions include only a constant (columns 3-4) or a constant and a time trend (columns 5-6).[19] The results from the Phillips-Perron tests (columns 7-8) point to the same conclusion. We therefore treat all capital flow to GDP series as I(0) and estimate the dynamic factor model in levels.

Table C.1: Unit root tests: number of stationary series

Flow Type	Number of variables	ADF[a]		ADF[a] (trend)		PP[b]	
		(5%)	(1%)	(5%)	(1%)	(5%)	(1%)
FDI	47	45	41	44	40	44	41
Portfolio	45	45	45	45	44	45	45
Other	47	47	45	45	42	45	44
Total	139	137	131	134	126	134	130

Notes: [a,b] ADF and PP denote the augmented Dickey-Fuller and Phillips-Perron tests, respectively.

[19]The augmented Dickey-Fuller tests are based on a specification with only one lag of the dependent variable. The fraction of series for which the null hypothesis is rejected decreases when a lag length of four is considered instead. The depicted specification was selected on the basis of standard information criteria.