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DOCUMENTO DE TRABAJO N° 393

Abril de 2026

Citar como:
Fernández, Andrés, Alejandro Vicondoa (2026). Capital Flows to Emerging Markets: Disentangling Quantities from Prices. Documento de trabajo RedNIE N°393.

Capital Flows to Emerging Markets: Disentangling Quantities from Prices[☆]

Andrés Fernández[†] Alejandro Vicondoa[‡]

January 9, 2026

Abstract

We study the joint dynamics in the volume and prices of capital flows to emerging market economies (EMEs). A dynamic factor model augmented with sign and zero restrictions allows us to identify demand/supply shocks of idiosyncratic/common nature. While common credit supply shocks are the main driver of prices, idiosyncratic credit demand and supply shocks account for most of the variation in quantities. A structural multi-country SOE/RBC model is calibrated to EMEs data to further shed light on the main transmission channels. Augmented with correlated productivity and interest rate shocks, the model matches the comovement between prices and quantities as well as business cycle moments. Common credit demand drivers, captured as correlated TFP shocks, account for around half of the observed comovement in quantities but they are not a significant driver of price comovement. Fundamentals matter significantly more for capital flows than for country spreads, which are driven by a sizeable global financial cycle.

Keywords: capital flows, sovereign spread, small open economy, credit supply, credit demand, external factors.

JEL Codes: E31, E32, E43, E52, E58.

[☆]We thank Pablo Cuba-Borda, Sebastian Fanelli, Javier Garcia-Cicco, David Kohn, Juan Pablo Medina, Felipe Saffie, Hernán Seoane, and seminar participants at AAEP 2022, Banco Central de Chile, Banco Central de Uruguay, LACEA-LAMES 2022, Red NIE, Ridge International Macroeconomics Workshop 2022 and 2024, SECHI 2023, SED 2023, SED 2024, Pontificia Universidad Católica de Chile, Universidad Carlos III de Madrid, Universidad de Chile, Universidad Diego Portales, and Universidad de San Andres for useful comments and suggestions. We thank Esteban Espinoza and Andrés Gatty for excellent research assistance. Any errors are our own. Vicondoa acknowledges financial support from ANID Fondecyt Regular 1251053. The views expressed in this paper are those of the authors and do not represent those of the IMF, IMF Management, or its Executive Board.

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1 Introduction

Fickleness in capital flows to and from emerging market economies (EMEs) is often accompanied by large macroeconomic volatility in these countries. The study of the transmission channels behind this well-established fact is a perennial object of research. What drives capital flows to EMEs? Do global factors matter more than domestic drivers? Are credit demand shocks more relevant than credit supply ones? What information does the risk associated to these financial flows have when identifying such drivers?

Our work addresses these questions through a combination of data and theory. On the empirical front, we begin by assembling a dataset of cross-border flows to a sample of EMEs over the past three decades. Crucially, the data includes both volumes of capital flows (quantities) *and* risk associated to such flows (prices).[1] This feature of the dataset together with its cross-country dimension allow us to separately identify credit demand and supply drivers which, in turn, are traced back to being of common or idiosyncratic nature through a combination of sign and zero restrictions within a dynamic factor model (DFM). The empirical setup we use therefore allows us to identify if, for instance, a capital inflow surge to a particular emerging market is driven by common supply forces that impact other EMEs and materializes as increased volumes and lower risk or if, alternatively, it is driven by idiosyncratic demand forces driving residents to build on more debt, increasing the country´s risk profile, among others.

Through variance and historical decomposition analysis, our framework allows us to quantify the drivers behind capital flows unconditionally, as well as during key historical crisis episodes such as the end of the 1990s, the Global Financial Crisis of 2008-09, the Tapper Tantrum in 2013, and COVID. Subsequent extensions to our empirical framework as well as the inclusion of advanced economies in our dataset further allow us to identify global factors from EME-specific ones behind capital flows. They also facilitate the quantification of regional forces within EMEs. Lastly, we extend the empirical analysis by zooming-in on

[1] As will be explained in detail, we proxy risk with various measures of spreads associated to capital flows.

one notable source of capital flow volatility for EMEs: changes in the stance of US monetary policy.

The limited structure imposed on the data when estimating the DFM is useful in that we let the data speak freely without pre-imposing much economic structure. This, however, entails a trade off in that our empirical model is mostly silent about the transmission channels behind the shocks identified and their structural nature. Motivated by this, we complement our empirical analysis with a structural approach grounded on economic theory. We extend the canonical small open economy RBC model to a multi-EME version, and take it to the dataset analyzed in the first part of our work.

The model we build features three types of structural drivers that impact EMs, therefore altering equilibrium dynamics of capital flows. The first is a total factor productivity (TFP) shock that drives the *demand* for capital flows by EMs. Second, perturbations to the international risk-free rate shape the *supply* forces behind capital flows to EMs. Lastly, we allow for shocks to the country spread at which EMs borrow in international markets above the world risk-free rate. While minimalist, we argue that this span of shocks allows us to cover the fundamental drivers behind demand and supply forces that shape capital flows to EMEs. Moreover, because we allow shocks to TFP and spreads to be correlated across EMEs, our structural framework can in principle capture the common forces behind these drivers. The model is calibrated to a subset of the EMEs in our dataset by matching some standard moments while leaving others untargeted, namely those that relate to capital flows and which are the main focus of our work, and upon which the goodness of fit of the structural model is assessed against that of the estimated DFM model. Lastly, we use the calibrated structural model to shed light on the transmission mechanism behind capital flows through impulse responses and counterfactual experiments, allowing us to gauge the relative importance of the various structural drivers in the model.

Our findings from the empirical analysis begin by documenting two robust stylized facts across the sample of EMEs studied: the within-country correlation between spreads and capital flows is negative albeit low, and the degree of cross-country comovement in spreads is much stronger than that of capital flows. Taken together, both facts would suggest that common supply drivers affect prices relatively more than volumes of capital flows. This is further corroborated with the estimated DFM which identifies a common factor in spreads accounting for 64% of their variability, of which the majority (two thirds) can be traced back to supply shocks (41%). In stark contrast, a common factor in capital flow volumes accounts for less than 10% of their volatility, with the lion's share (90%) being driven by idiosyncratic shocks that, in turn, are evenly split between supply and demand origins. Historical decompositions allow us to further document how supply drivers have been crucial in shaping spreads in specific periods like the Asian Crisis of the late 90s, the Global Financial Crisis, and during the Covid outbreak in 2020.

Three extensions to our baseline empirical model allow us to enhance our understanding of the drivers to capital flows to EMEs. First, we re-estimate the DFM with an augmented sample of countries including small advanced economies (AEs). This allows us to differentiate a global factor –impacting all economies– from an EME-specific one –impacting only EMEs– in our estimation. We find that the baseline EME factors are highly correlated with the EME-specific factors that result from our larger sample of countries including AEs. Moreover, global shocks are equally relevant –if not more– than common-EME shocks when accounting for the role of external factors in driving capital flows and spreads. A second extension quantifies regional forces within EMEs, finding two clearly distinct factors for Asia and Latin America, signaling a possible segmentation in the way capital is allocated across these two EM regions. Regional factors are quite relevant for capital flows since their variance share related to common forces nearly quadruples after controlling for regional drivers. The third extension zooms in on the stance of US monetary policy. We provide evidence that shocks to US monetary policy –conventional and unconventional– impact the common factors in spreads and volumes of capital flows to EMEs, thereby making this force an ultimate driver of credit supply forces shaping capital flows to EMEs.

In addition, we subject our baseline empirical results to a battery of robustness tests along several key dimensions. First, we redo the analysis using a wide range of alternative measures of capital flows and sovereign borrowing conditions—including, among others, consistent measures of corporate debt flows and spreads—to ensure that our findings are not driven by our baseline net-flow proxy or by a particular spread measure. Second, we replicate the analysis using gross inflows and outflows instead of net flows to connect more directly with the Global Financial Cycle literature. Third, we zoom in on net portfolio and FDI flows, and we also restrict attention to EMEs with more open financial accounts. Finally, we re-estimate the main results over a pre-COVID sample ending in 2019 to assess the sensitivity of the findings to the pandemic episode.

The findings from the structural model are also novel and insightful. We calibrate a two-EME version of the model to match the business cycle moments of Brazil and Mexico, two representative EMEs in our dataset. TFP processes are set to match the volatility and comovement of the business cycle in both countries, and the processes of the global safe interest rate and spreads are set to match the volatility and comovement in the US TBill three months rate and the spreads of the two EMEs. Overall, the model performs well in matching other non-targeted business cycle moments. A particularly noteworthy aspect of the performance is that the calibrated model can account for the moderate cross-country correlation of net capital flows and the low and negative within-country correlation between spreads and capital flows, the two salient stylized facts first documented in our empirical analysis. To the best of our knowledge, this is the first evidence that an otherwise canonical SOE/RBC framework can reproduce such facts for EMEs.

Counterfactual analyses with the structural model allow us to shed more light on the drivers behind capital flows. Turning off the correlation of TFP shocks across countries bears no impact in the correlation of spreads but reduces that across capital flows to about one fourth the one matched to the data in the baseline calibration. In contrast, turning off the joint shocks to spreads in a separate counterfactual –akin to reducing the presence of a global financial cycle in the model–, does not affect the correlation between capital flows or income significantly, but considerably impacts the synchronization in spreads. Therefore, through the lens of our calibrated structural model, a Global Financial Cycle that materializes through common credit supply shocks is an important source of EME spread fluctuations, while common TFP shocks are key to understand the synchronization in the net volume of capital flows to EMEs. Lastly, we discuss three extensions to our structural framework. We enrich the model with an estimated interest rate process. A second expands the source of shocks in the model by introducing "credit shocks" –i.e. perturbations in the elasticity of the interest rate with respect to debt–, and discusses their ability to bring the model closer to the data, particularly in terms of the volatility of capital flows. A final one assesses the robustness of our analysis to solving the model using non-linear global methods and the implications for the model's performance.

Overall, the key takeaways of our work are as follows. Fluctuations in sovereign spreads across EMEs are largely driven by common credit supply shocks, whereas fluctuations in net capital inflows are predominantly country-specific and can be traced to idiosyncratic credit supply and credit demand drivers in roughly equal measure. Furthermore, allowing for regional components materially increases the share of capital-flow variation attributable to common forces, while the analysis of gross flows indicates that commonality is more apparent in gross measures—particularly gross inflows—than in net financing. Finally, a parsimonious small-open-economy framework with correlated productivity and borrowing-condition shocks rationalizes these patterns jointly in prices and quantities across EMEs.

Literature Review. Our work contributes to several strands of literature. First, a large body of work has emphasized a high degree of comovement in risky asset prices, capital flows and financial aggregates, a phenomenon that Rey (2013) referred to as the Global Financial Cycle. Several others have underscored the role of global variables as key drivers of country spreads (González-Rozada and Yeyati, 2008; Hilscher and Nosbusch, 2010; Longstaff et al., 2011; Csonto and Ivaschenko, 2013; Gilchrist et al., 2022) and capital flows (Calvo et al., 1993; Fernandez-Arias, 1996; Bekaert et al., 2002; Forbes and Warnock, 2012; Cerutti et al., 2019a; Davis et al., 2021). Often, this literature emphasizes the role of "push" factors relative to "pull" factors. Our work complements and sharpens these findings by showing—within a single empirical framework—that the common component is disproportionately reflected in spreads, whereas net capital inflows are largely driven by country-specific forces that can be traced to both credit supply and credit demand drivers. At the same time, allowing for regional components reveals substantial regional synchronization in net flows, helping reconcile limited global comovement in net financing with the presence of meaningful common dynamics at the regional level. We then use a parsimonious structural framework to rationalize these empirical decompositions and to clarify the mechanisms through which global and local shocks transmit to spreads and net financing. To the best our knowledge, our work is the first to quantify the role of credit supply/demand and local/idiosyncratic credit shocks in driving spreads and capital flows.

While country spreads are highly correlated across EMEs, the correlation between capital flows has been documented to be significantly lower (see, for example, Kaminsky, 2019; Cerutti et al., 2019b). More recently, Cerutti and Claessens (2024) have quantified a higher relevance of the Global Financial Cycle when explaining the variability in domestic credit and various local asset prices, relative to that in capital flows. Kaminsky et al. (2020) has also documented a predominant role of regional factors relative to the common factor in explaining capital flows. Our work complements and sharpens these findings by showing—within a single empirical framework—that the common component is disproportionately reflected in spreads, whereas net capital inflows are largely driven by country-specific forces that can be traced to both credit supply and credit demand drivers. At the same time, allowing for regional components reveals substantial regional synchronization in net flows, helping reconcile limited global comovement in net financing with the presence of meaningful common dynamics at the regional level. We then use a parsimonious structural framework to rationalize these empirical decompositions and to clarify the mechanisms through which global

and local shocks transmit to spreads and net financing.

Another important strand of literature has argued that, amid this Global Financial Cycle, the stance of US monetary policy affects global investors' risk perceptions, ultimately driving capital flows in and out of emerging market economies, as documented in Kalemli-Özcan (2019). Several other works have also pointed that U.S monetary policy and fluctuations in global risk are important divers of emerging markets' spreads and their synchronization (see, for example, Arora and Cerisola, 2001, Akinci, 2013; Rey, 2013; Rey, 2015; Vicondoa, 2019; Caballero et al., 2019; Miranda-Agrippino and Rey, 2020; Miranda-Agrippino and Rey, 2022; Gilchrist et al., 2022; Aldasoro et al., 2023). Financial shocks induce a large impact on asset prices contributing to explain the large comovement between sovereign spreads relative to capital flows (see, for example, Bacchetta et al., 2022 and references therein). Relative to this literature, our contribution is to connect U.S. monetary policy shocks to the estimated common component in both spreads and flows within our joint decomposition, and to quantify how strongly that common component loads onto prices versus net financing.

A final strand of literature has analyzed spreads and capital flows in theoretical models. As pointed out recently by Miranda-Agrippino and Rey (2022), it has been a challenge for the finance literature to model quantities and prices jointly within a model of the Global Financial Cycle, and a promising body of work in starting to gain momentum. Some of the these articles are closer to our work. Davis and van Wincoop (2024) offer a framework that can simultaneously produce a fall in gross outflows, inflows, and asset prices following an increase in global risk aversion. Morelli et al. (2022) offer another framework where financial frictions make global financial intermediaries central in driving borrowing costs and consumption fluctuations in EMEs during both debt crises and regular business cycles. Lastly, Bai et al. (2024) develop a neoclassical business cycle model with asset pricing features and default that accounts for the comovements of asset prices across developed and emerging market economies. We complement these works by providing a parsimonious SOE/RBC-based quantitative framework that rationalizes our empirical decompositions of prices and quantities—particularly the differential role of common credit supply forces in spreads versus predominantly idiosyncratic supply and demand drivers in net flows—while remaining transparent about the abstractions required to keep the analysis tractable. In this sense, the model's role is to discipline interpretation of the empirical results rather than to provide a fully-fledged structural model of the Global Financial Cycle.

The remaining of the paper is structured as follows. Section 2 presents a simple theoretical framework to jointly analyze capital flows and country spread in EMEs. Section 3 documents the empirical facts associated with credit markets in EMEs. Section 4 presents the results from the structural model. Section 5 concludes.

2 Drivers of Capital Flows to EMEs: A Simple Analytical Framework

This section builds the simplest theoretical model to analytically characterize the drivers of capital flows to EMEs. The goal is to fix ideas on the propagation channels through which demand and supply factors, of idiosyncratic and common nature, may determine capital flows to these economies. This will pave the road for the empirical analysis in Section 3 and the more realistic DSGE model in Section 4.[2]

Consider a textbook two-period small open economy "i" with access to a one period, non state-contingent bond in international financial markets. The economy receives an endowment each period ($\{y_1^i, y_2^i\}$) that can be either consumed or saved. Assuming that the discount factor by households (β^i) equals the gross interest rate faced by this economy in international financial markets ($1+r^i$), and the economy starts without external debt (i.e. $d_0^i = 0$), the demand for capital flows (i.e. the change in desired net external debt in the first period, d_1) is:

[2]The setup follows the textbook models in Vegh (2013) and Schmitt-Grohé and Uribe (2017). A detailed description and derivation of the model is presented in Appendix C.1.

$$d_1^i = \frac{y_2^i - y_1^i}{2 + r^i} \tag{1}$$

Two distinctive drivers highlighted in (1) that would raise the demand for capital flows in this economy are increases in the endowment over time and decreases of the interest rate.

In turn, this interest rate will be affected by the determinants in the supply of credit from international markets, which we assume takes the form:

$$r^i = r^* + \phi^i \left(\tilde{d}_1^i\right)^2 + \varepsilon^i, \phi^i > 0 \tag{2}$$

where r^* denotes the world interest rate, ϕ^i is a parameter that captures the sensitivity of interest rate to net external debt, and ε^i is a country-specific spread shock.[3] As shown in Appendix C.1, this supply of international credit can be rationalized within an extension of the model with no-commitment to repay the debt and uncertainty on the endowment of period 2, where risk-neutral investors can choose between buying this external bond or a risk-free one.

The equilibrium level of capital flows (d_1^i) will therefore be driven by exogenous variations in the endowment process and in interest rates $\{y_1^i, y_2^i, r^i, r^*, \varepsilon^i\}$ characterized by equations (1) and (2).

In order to illustrate the role of demand and supply drivers in shaping capital flows, consider a first small open economy ("$i = 1$") under two distinct shocks. First, consider an idiosyncratic increase in future endowment $\{y_2^1\}$. As depicted in the left panel of Figure 1a, this induces an outward shift in credit demand (see equation (1)) in order to front load part of the future increase in income and smooth lifetime's consumption path. The increase in the level of equilibrium capital flows ($\Delta d_1^1 > 0$) occurs at a relatively higher country interest rate (r_1^1) associated to the increase in the total debt stock. Second, consider now a shock

[3]As in Schmitt-Grohe and Uribe (2003), households consider only r^i when deciding the demand for external debt, without considering the effects of their decisions on the cross-sectional average stock of debt ($\tilde{d}_1^i$). In equilibrium, it must be the case that $\tilde{d}_1^i = d_1^i$.

that affects the international interest rate (r^*). As depicted in the left panel of Figure 1b, this induces an upward shift in the supply curve of credit (see equation (2)), pushing up to a new higher level the equilibrium country interest rate (r^1) and decreases total capital inflows ($\Delta d_1^1 < 0$).

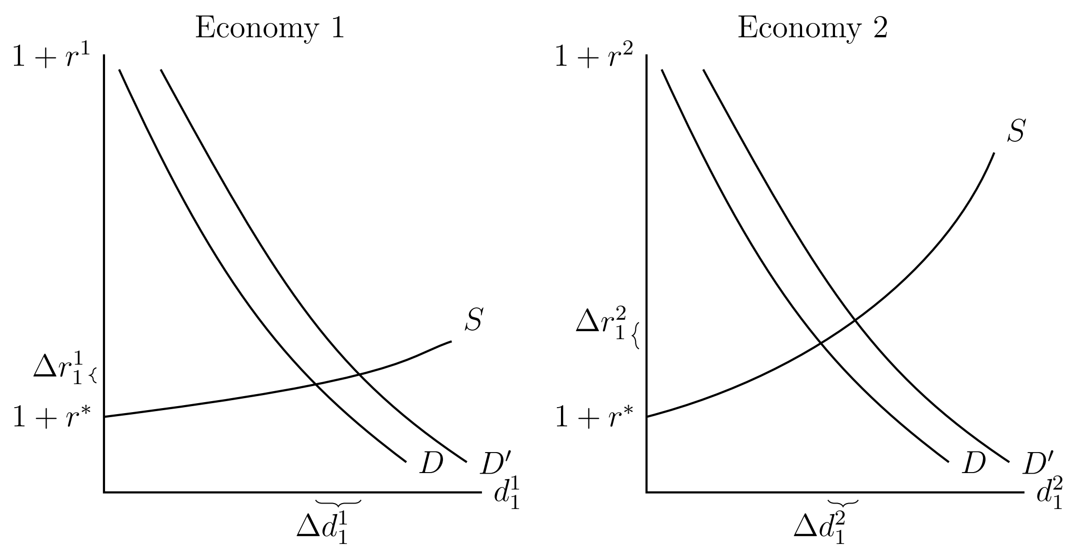
Another crucial distinction to make when identifying drivers of capital flows is their idiosyncratic or common origins. Indeed, changes in capital flows can be traced back to shocks that are specific to a country or common across countries. A textbook example of the latter is movement in world interest rates, as illustrated in the previous example that considered changes in r^*. Furthermore, common shocks can propagate differently across countries and hence have differential impacts on capital flows.

In order to illustrate these additional distinctions, consider now a second small open economy "$i = 2$" that is subject to the same kind of shocks that perturb Economy 1. We assume that the two small open economies differ only in the credit supply they face: they share the same parametrization but Economy 2 faces a less elastic credit supply curve ($\phi^1 < \phi^2$). The latter can come from assuming that investors perceive Economy 2 as having less commitment to repay its debt and/or face higher uncertainty on its endowment (Appendix C.1).

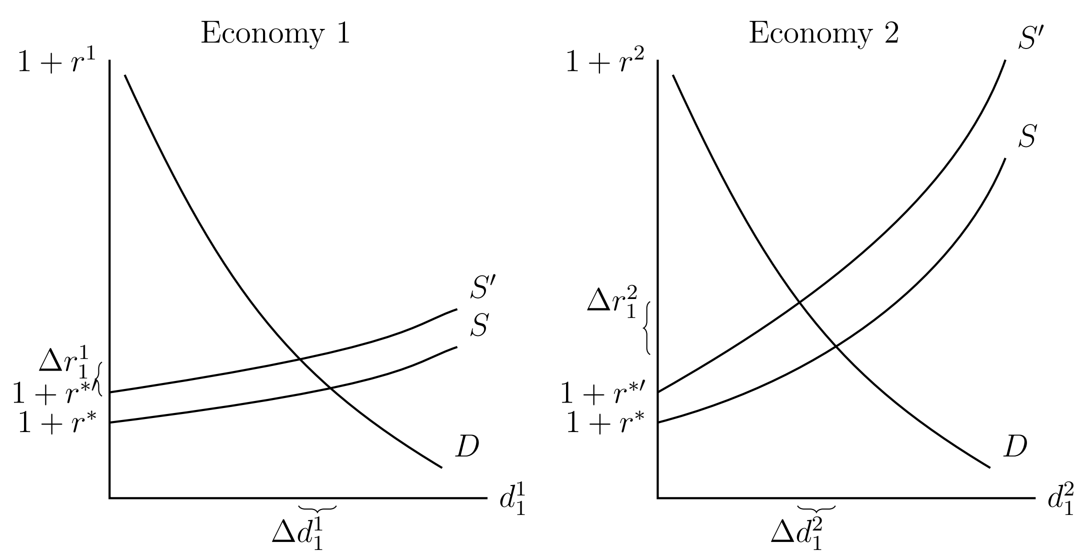
Assume now that the increase in the second period endowment is common across the two economies ($\Delta y_2^1 = \Delta y_2^2$). This can be motivated from e.g. increases in commodity prices across commodity exporters EMEs (see, for example, Fernández et al., 2018). As depicted in the right panel of Figure 1a, similar to what happened to Economy 1, this shock will drive a larger capital inflows together with higher interest rates. However, the shock will not propagate uniformly across the two economies because of the higher debt elasticity in Economy 2, which materializes in a relatively milder increase in capital flows and higher levels of interest rates ($\Delta d_1^1 > \Delta d_1^2; r^1 < r^2$). Similarly, the response to an increase in the world interest rate will have an asymmetric response across economies, as depicted in the right panel in Figure 1b. For illustration purposes, we assume that, in addition to this shock, Economy 2 is impacted by an idiosyncratic shock to the spread ($\varepsilon_1^2 > 0$). The latter can be motivated with world rate increases amid episodes of risk-off in international markets, where some EMEs are viewed as relatively riskier than other. This exerts further upward pressure on domestic rates in Economy 2 and reduces capital inflows to it.

Figure 1 Equilibrium in International Credit Markets

(a) Response to an increase in y_2^1 and y_2^2



(b) Response to an increase in r^* and an increase in ε^2



Note. Example on the effects of a common credit demand shock due to the increase in y_2^1 and y_2^2 (first row) and an increase in the international interest rate r^* plus a country spread shock to economy 2 ε^2 (second row) in two economies that face different credit supplies.

To sum up, we have described the key drivers of capital flows through the lens of the simplest version of the workhorse small open economy model. A key message is that two overlapping dimensions are crucial when studying the forces that shape capital flows to EMEs: the role of demand and supply factors, as well as their idiosyncratic or common origins. Equally relevant is the basic observation that, in order to identify these various drivers, it is crucial to *jointly* observe volumes and prices of capital flows across *various* EMEs. The next section will carry out this task more formally through descriptive statistics and an econometric framework.

3 Capital Flows to Emerging Economies: Stylized Facts

This section presents the empirical analysis of our work. We begin by describing the data of capital flows (volumes) and country spreads (prices) we use in the analysis, together with the sample of countries studied (Subsection 3.1). Next, we take a first look at the data by means of simple correlations between spreads and capital flows both within and across countries (Subsections 3.2 and 3.3). A formal identification of supply-demand and common-idiosyncratic drivers behind these correlations is done next in Subsection 3.4 and contains the main results of the section. Subsection 3.5 extends our framework to account for advanced economies, regional factors, and US monetary policy. Finally, subsection 3.6 presents different robustness exercises.

3.1 Data

To analyze the relationship between capital flows and country spreads accurately, it is paramount to use the highest frequency available. For analysis with low frequency data may blur the identification of credit demand and supply drivers. In practice, however, this can be challenging for capital flows since balance of payments data for emerging markets is typically only available at quarterly or annual frequencies.

To overcome this challenge, and considering that monthly data is available for the trade balance and the stock of foreign reserves across emerging markets, we follow Calvo et al. (2008) in working with a proxy for net capital inflows computed as:

$$KI_t = M_t - X_t + R_t - R_{t-1} \tag{3}$$

where KI_t denotes capital inflows received by the country in period t, X_t denotes exports, M_t denotes imports, and R_t is the stock of international reserves held by the country. The proxy for net capital inflows is thus computed by netting out the trade balance from changes in foreign reserves. While this proxy for net capital inflows does not include net factor income and current transfers, these accounts represent mostly interest payments on long-term debt which should not display substantial variation so as to introduce significant spurious volatility into our capital flows measure (Calvo et al., 2008).[4] Given our focus on external financing pressure and macroeconomic adjustment in EMEs over the business cycle, we use *net* inflows as the baseline object because they map directly into net external financing needs. Moreover, this measure also maps directly into capital flows in the small open economy model used in Section 4. In a later extension, we replicate the analysis using gross flows, which have been central to the Global Financial Cycle literature. Lastly, to remove seasonal movements, we use the cumulative annual flows for each month and then take the first difference of this measure (ΔKI_t).

$$\Delta KI_t = \sum_{k=0}^{11} KI_{t-k} - \sum_{k=0}^{11} KI_{t-k-1} \tag{4}$$

As Calvo et al. (2008), we deflate the measure of capital flows using the U.S. Producer Price Index – All Commodities (PPIACO from FRED) to have a measure of the volume of net capital flows.

We focus on country spreads instead of country interest rates as our main variable for analysis because spreads reflect specific issues of emerging economies as opposed to inter-

[4] Our proxy also abstracts from errors and omissions which could add additional volatility to measures of capital flows.

est rates which also capture characteristics of advanced economies, e.g monetary policy or expected growth.[5] We use the J.P. Morgan Emerging Market Bond Index Global (EMBI Global) for each country.[6] This measure is a good proxy to track the evolution of financial conditions -including those for corporates- in EMEs that has been used extensively by previous works (see, for example, Uribe and Yue, 2006; Akinci, 2013; Fernández et al., 2018; Vicondoa, 2019). In further robustness analysis presented in section 3.6 we use more disaggregated proxies of spreads in EMEs.

The sample of EMEs that we study in the baseline empirical analysis is solely based on data availability. It consists of the largest balanced panel of EMEs we could construct with continuous monthly data on capital flows and country spreads since the mid 1990s. The period analyzed begins in 1997:2 and ends in 2022:7. Our baseline analysis considers the COVID-19 period, though an extension that excludes this period is considered in Section 3.6. The following twelve countries are included in our sample: Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey. This sample accounts for most of capital flows to EMs.[7]

Figure 2 presents the dynamics of the median 12 months cumulative capital inflows (standardized) to EMEs and EMBI spreads (in percentage points) for the countries in our sample.[8] The Asian and Russian crises in the late 90s induced a significant increase in country spreads in EMEs as well as capital outflows. Country spreads declined significantly after that period and into the mid-2000s coupled with capital inflows to EMEs.

The Global Financial Crisis in 2008 induced a sharp yet transitory increase in country

[5] Evidently, our measure of spreads can be indirectly influenced by developments in advanced economies, e.g. episodes of "risk on" or "risk off" triggered by U.S monetary policy. These would be captured as common drivers in the model developed later on.

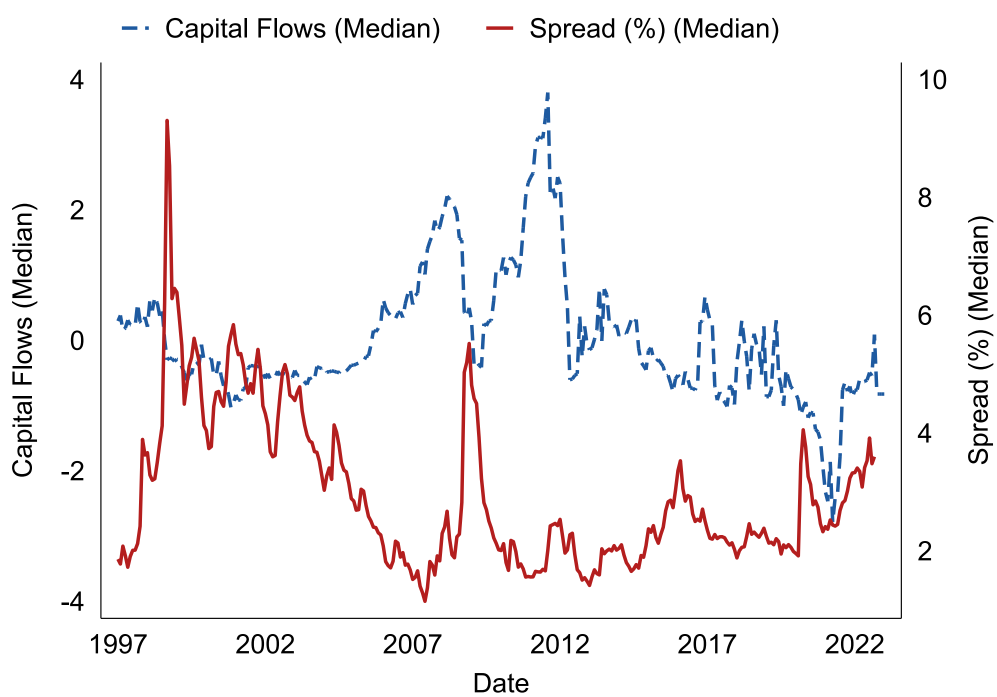
[6] This spread is computed as an arithmetic, market-capitalization weighted average of US-dollar denominated bond spreads issued by sovereign and quasi-sovereign entities over U.S. Treasury bonds of similar duration.

[7] This sample of 12 EMs accounts for 55 percent of median gross inflows to a larger pool of EMs that includes 85 countries, over the years 2017 and 2021.

[8] We employ medians instead of summing over the sample of countries to prevent China from driving most of the dynamics in Figure 2. Figure A.1 presented in the Appendix displays the evolution of capital flows and country spread for each country. Given that the frequency of the capital flows time series is monthly we cannot scale by GDP.

spreads and a fall in net capital flows, which resumed vigorously in 2010. In the last years of the sample we see a decline a capital flows that starts in 2012, which coincides with the peak in commodity prices.[9] The slowdown in capital flows also took place amid volatility in world capital markets, captured by the Taper Tantrum in 2013 and expectations of interest rates increases in the U.S. This decline in capital flows is particularly strong –although brief– in the first part of 2020, associated with the Covid outbreak. While the period analyzed covers until mid 2022 and thus does not capture most of the increase in the US monetary stance, we do not observe any major volatility at the start of this tightening cycle. In the following two Sections we take a closer look at the correlations between spreads and capital flows both within and across EMEs.

Figure 2 Capital Flows and Country Spreads in EMEs



Note. Median net capital flows of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:2-2022:7. Capital flows for each country is defined as the cumulative trade deficit plus the change in international reserves at monthly frequency as defined in equation (4). The aggregate series of capital flows is computed as the monthly median of the capital flow series for all the countries and then standardized. Country spread is expressed in annualized percentage points and computed as the monthly median of the EMBI for the same countries.

[9]For further evidence of the link between commodity prices and capital flows, see also Juvenal and Petrella (2024).

3.2 Correlation between Spreads and Capital Flows within EMEs

In this section we explore the relation between country spreads and capital flows. Table 1 displays the contemporaneous correlation between country spreads and capital flows at the country level.

Table 1 Correlation between Capital Flows and Sovereign Spreads at the Country Level

	ARG	BRZ	CHN	COL	ECU	MEX	MLY	PAN	PHL	POL	SWF	TUR	**Median**
$\rho(s,f)$	0.00	-0.12^{**}	-0.20^{***}	-0.13^{**}	-0.11^{*}	-0.07	-0.03	0.00	-0.10^{*}	-0.15^{**}	-0.15^{***}	-0.16^{***}	-0.11
$\rho(s,f)$ no SS	0.09	-0.09	-0.11^{*}	-0.05	-0.07	-0.02	-0.01	0.00	-0.01	-0.08	-0.06	-0.17^{**}	-0.05

Note. Contemporaneous correlation between capital flows and EMBI of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:1-2022:7. Capital flows is defined as the cumulative trade deficit plus the change in international reserves at monthly frequency (see equation (3)). The first row shows the correlation using the full sample while the second row included the correlation without considering Sudden Stop episodes (see text for details on the definition of a Sudden Stop). Significance level: $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

The correlation between country spreads and capital flows at the country level is negative and relatively low, with a median correlation of -0.11, ranging between -0.20 (China) to 0.00 (Argentina and Panama), and no country in our sample exhibits a strictly positive correlation. This finding is robust to computing the correlation excluding the periods of Sudden Stops, as the table documents in the second row.[10] We also document robustness using different measures for capital flows (see Section 3.6).

Through the lens of the simple theoretical framework presented in Section 2, these results suggest a predominance of credit supply shocks in driving the negative correlation between the two variables for most of the countries in the sample. This will be more formally explored in the next subsections.

[10]We define periods of Sudden Stops following Calvo et al. (2008) as: periods when: i) there is at least one observation where the year-on-year decline in capital flows lies at least two standard deviations below its sample mean; this condition fulfills the 'unpredicted' prerequisite of a sudden stop, ii) the period of sudden stop phase ends when the annual change in capital flows surmounts one standard deviation below its sample mean. This commonly suggests persistence which is a common fact of sudden stops, iii) additionally, in order to ensure symmetry, the onset of a sudden stop phase is ascertained by the first time the annual change in capital flows drops one standard deviation below the mean. Both the first and second moments of the capital flow series are calculated each period using an expanding window with a minimum of 24 (months of) observations and a start date fixed at January 1997, which intends to capture the evolving behavior of the series. Table A.1 included in the Appendix displays the Sudden Stop events of the sample.

3.3 Correlation between Spreads and Capital Flows across EMEs

As illustrated in Section 2, capital flows to EMEs may be impacted by credit shocks of common nature. This section provides a first assessment of the relevance of these common drivers. We do so by analyzing the comovement across country spreads and, separately, capital flows, for the sample of EMEs in our dataset. If the main drivers are common, they would be manifest in the form of high correlations across EMEs.

To determine the degree of comovement between these variables across EMEs, we follow Croux et al. (2001) and compute a cohesion measure, interpreted as the 5-year rolling correlation for each of these variables across countries and at different frequencies. This methodology allows us to complement earlier analysis of the comovement in volumes and prices in the access of EMEs to international capital markets (Rey, 2013; Cerutti et al., 2019c) by documenting changes in this comovement through time and across business cycle frequencies.

Figure 3 displays the cohesion measure for the sample of our analysis and the two variables we investigate: spreads (upper panel) and capital flows (lower panel). Colors denote the magnitude of the correlation at every point in time (x-axis) and frequency considered (y-axis).

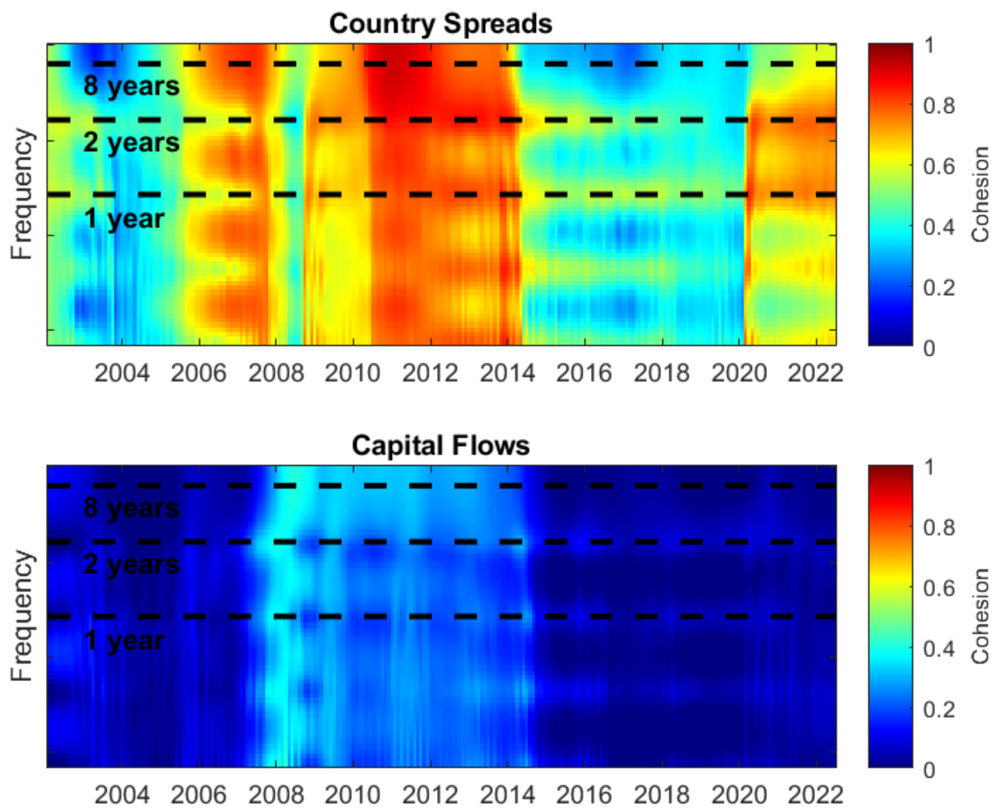
There are three findings from Figure 3 that stand out. First, the stark contrast between the dark colored lower panel and the bright upper panel provides a powerful visual illustration that the degree of comovement in prices is much stronger than that of volumes. This result echoes that of Cerutti et al. (2019c). Indeed, country spreads display a high correlation of 0.6 across EMEs, close to double that of capital flows.[11]

Second, the comovement is time-varying, particularly for spreads, and coincides with times of financial stress in world capital markets. This correlation increased from around

[11] Section B.2 analyzes separately the cohesion for trade balance and foreign reserves, the two components of the proxy for net capital flows. While the change in foreign reserves is slightly more correlated across countries than the trade balance, both components display a significantly lower correlation than country spreads.

0.4 in the early 2000s to above 0.9 during the Global Financial Crisis. A similar increase is observed in 2020 amid the financial stress in world capital markets at the start of the COVID pandemic. This stands in contrast with the comovement in capital flows for which much less significant time variation is observed. Lastly, both correlations are stable across business cycle frequencies, confirming that the kind of relationships that we have uncovered are not only explained by high frequency determinants that are transient.

Figure 3 Dynamic Correlation of Country Spreads and Capital Flows Across EMEs



Note. Cohesion measure (Croux et al., 2001) between Country Spread and Net Capital Flows of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:2-2022:7. Net Capital flows is defined as the cumulative trade deficit plus the change in international reserves at monthly frequency as defined in Equation (4). We use EMBI as a proxy for the country spread. Each point in time denotes the cohesion measure for each frequency computed with 5-year backward rolling window.

Taking stock, the descriptive statistics presented thus far point to an important role of supply shocks in the access of EMEs to world capital markets, with common drivers affecting relatively more spreads than capital flows. We turn next to a more formal econometric approach to disentangle these drivers. In doing so we follow the conceptual framework in

Section 2 by jointly observing volumes and prices of capital flows across the various EMEs in our sample.

3.4 Disentangling the Drivers of Capital Flows to EMEs

This section quantifies the contribution of common vs. idiosyncratic factors, and demand vs. supply shocks in explaining the dynamics of capital flows and country spreads in EMEs. Our methodology involves two steps. We start by pinning down the common and idiosyncratic drivers in these variables. Then we further identify supply and demand disturbances behind the estimated drivers.

Estimating Common Factors

We quantify the contribution of common and idiosyncratic drivers in explaining the dynamics of capital flows and country spreads by estimating a Dynamic Factor Model (DFM) (see, for example, Stock and Watson, 2016). In particular, we recover a common factor for capital flows and one for country spreads with the following model:

$$\begin{aligned} X_t &= \beta F_t + \epsilon_t \qquad (5) \\ F_t &= \gamma F_{t-1} + \eta_t \end{aligned}$$

where X_t is the $(2 \times N) \times 1$ matrix that contains series of capital flows and country spreads for the N countries analyzed, β is the $(2 \times N) \times 2$ matrix with factor loadings, F_t is a 2×1 matrix with two common factors (one for capital flows F_t^k and another one for country spreads F_t^s) which are assumed to follow an AR(1) process, ϵ_t is $(2 \times N) \times 1$ matrix of idiosyncratic shocks to capital flows and country spreads, γ is a 2×2 vector denotes the persistence of each factor, and η_t is a (2×1) vector of disturbances that affect the common factors.[12]

[12] Results are robust to an alternative DFM specification where the idiosyncratic component display persistent effect on country spreads and capital flows (see Section B.3.4 in the Appendix).

We estimate a common factor of capital flows (country spreads) by imposing that the loading of country spreads (capital flows) is 0. In particular, all the series of capital flows are included first in X_t (i.e. from rows 1 to N) and all the spread series are included next (i.e from rows $N+1$ to $2 \times N$). Then, we impose the restriction that $\beta_{N+1:2\times N,1} = 0$ and that $\beta_{1:N,2} = 0$, which implies that the first (second) factor is identified using only series of capital flows (country spreads).

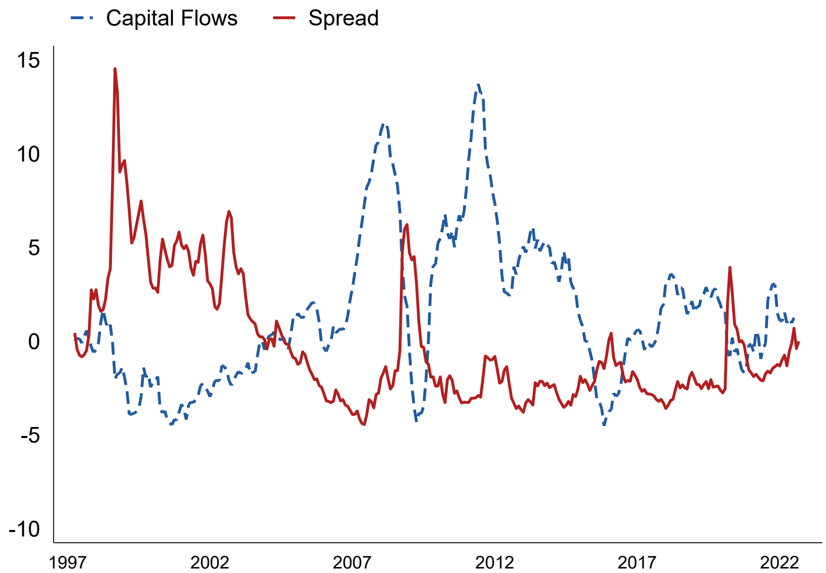
Figure 4 displays the estimated common factors of capital flows (dashed/blue line) and country spreads (solid/red line).[13] The common factor in country spreads displays five clear spikes that overlap with periods of turmoil in world capital markets. It increases significantly during the Russian Crisis of the late 90s and remains high with another spike in late 2001 that coincides with the Argentinian sovereign default, followed afterwards by several years of relatively low levels of the factor. The third spike of this factor coincides with the Global Financial Crisis, which was nonetheless relatively brief and followed by a subsequent decline. A brief and milder spike is observed around 2015, overlapping with the lift off the the FED's Funds Rate from the zero lower bound. Finally, the last spike occurs at the onset of the Covid pandemic in 2020.

The common factor in country spreads is tracked closely by the U.S. CBOE Implied Volatility Index (VIX), which is a proxy of the Global Financial Cycle (see, for example, Rey, 2013). Figure 5 displays both variables. Both series display a strong positive comovement with a contemporaneous correlation of 0.6, that is particularly salient during the periods of global financial turmoil. This comovement reinforces the link between the common factor in spreads and the Global Financial Cycle.

The factor capturing the common movement of capital flows displays a different pattern from that in credit spreads. It initially fell following the crises in the late 90s, until the early

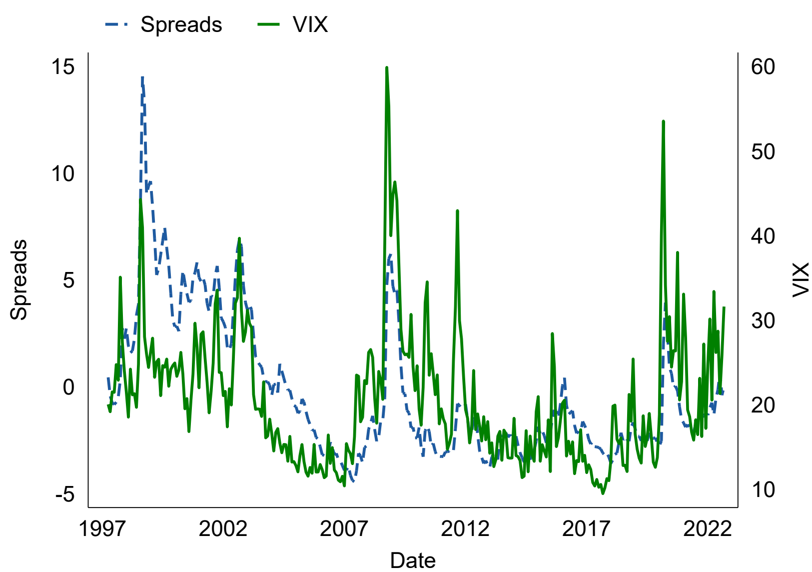
[13] As in Rey (2013), both factors are presented in cumulative terms from the start of the sample, to enhance interpretation. The figure of non-cumulated factors is presented in Appendix B.3. Also, as is standard in the literature, units relate to standard deviations. For spreads, we take the first difference of the monthly average and then standardize it. For capital flows, given that the series are already in first difference, we only standardize them.

Figure 4 Common Factor for Country Spreads and Capital Flows



Note. Cumulated dynamic factors between capital flows and EMBI of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:2-2022:7. Capital flows is defined as the cumulative trade deficit plus the change in international reserves at monthly frequency.

Figure 5 Common Factor of Country Spreads and the VIX



Note. Cumulative dynamic factor between EMBI of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:2-2022:7 and the U.S. CBOE Implied Volatility Index (VIX. Code: VIXCLS in FRED). The correlation between the series is 0.57.

2000s when its downward trend reversed to gradually increase throughout the 2000s. It displays then an increase in its volatility with a clear acceleration in the two years preceding the Global Financial Crisis (GFC), during which it fell abruptly, only to recover vigorously with a spike in 2012. The factor remains high until late 2014, after which it displays a sharp decrease amid the normalization of US monetary policy, until 2016, when it reverts, although at lower levels than in the volatile years after the GFC. Finally, the factor displays a strong decline in 2020, with the Covid outbreak, after which it recovers in 2021.

The common factors on capital flows and country spreads exhibit a strong negative correlation (-0.58). Following the conceptual framework in Section 2, this would suggest that supply forces are preponderant behind the *common* drivers that shape access to world capital markets by EMEs. At the same time, the fact that the correlation is not perfect also suggests that demand forces as well as idiosyncratic shocks may be playing an important role too. In the next subsection we shed more light on the separate role of supply and demand drivers behind idiosyncratic and common factors driving spreads and capital flows to EMs.

The Role of Supply and Demand Drivers

We turn now to a formal approach to disentangle supply from demand forces behind common and idiosyncratic drivers in spreads and capital flows to EMEs. To do so we impose sign and zero restrictions in order to identify structural shocks to the DFM estimated in the previous subsection. Formally, the restrictions we impose are:

- Common supply shocks ($\varepsilon_t^{S,G}$) are identified by assuming that they trigger movements in the factors of spreads (F_t^s) and of capital flows (F_t^k) in opposite directions.
- Common demand shocks ($\varepsilon_t^{D,G}$) are identified by assuming that they trigger movements in F_t^s and F_t^k in the same direction.
- Idiosyncratic supply shocks in country i ($\varepsilon_t^{S,i}$) are identified by assuming that they trigger movements the country i's spreads and capital flows in opposite directions, without affecting F_t^s and F_t^k.
- Idiosyncratic demand shocks in country i ($\varepsilon_t^{D,i}$) are identified by assuming that they

trigger movements in country i's spreads and capital flows in the same direction, without affecting F_t^s and F_t^k.

There are several examples that can serve to illustrate the above identifications restrictions to disentangle supply vs. demand, and common vs. idiosyncratic drivers. A classic example of a global supply force driving capital flows to EMEs is the stance of US monetary policy. By increasing its policy rate, the US Federal Reserve incentivizes investors around the word to redirect flows to the US economy, and away from EMs. Under such "risk off" episode, one would expect that the factors of spreads and capital flows would move in opposite directions. Global forces may also manifest through demand channels via e.g. rising commodity prices. Since many EMEs are commodity exporters, a persistent boom in the price of the commodities they export can fuel aggregate demand simultaneously across several of these economies, further boosting their demand for external borrowing. The increased risk associated with the overborrowing induced by the boom could materialize as movements in the common factors of spreads and flows in the same direction.

Local or country-specific drivers can materialize also through supply and demand channels. Political uncertainty is an example of a force that can reduce the incentives of foreign investors to supply funds to a particular emerging market going through political turmoil, driving spreads and capital flows in opposite directions. Lastly, fiscal policy is an example of a local driver that can boost the demand for capital flows, making spreads rise while capital is flowing in to finance the rise in public expenditure. While mapping the shocks that we identify to their specific origins is clearly beyond the scope of this work, some of the extensions that we explore further below will aim at assessing the relevance of some of these deeper drivers, particularly that associated with US monetary policy.

Since the matrices of idiosyncratic disturbances (ϵ_t) and common disturbances (η_t) in (5) can be rotated to identify the role of demand/supply and common/idiosyncratic credit shocks, we can implement the identifying restrictions above through the following relation between the innovations of system (5) and the underlying four structural shocks:

$$\begin{bmatrix} \eta_t^S \\ \eta_t^K \\ \epsilon_t^S \\ \epsilon_t^K \end{bmatrix} = \begin{bmatrix} + & + & 0 & 0 \\ - & + & 0 & 0 \\ . & . & + & + \\ . & . & - & + \end{bmatrix} \begin{bmatrix} \varepsilon_t^{S,G} \\ \varepsilon_t^{D,G} \\ \varepsilon_t^{S,I} \\ \varepsilon_t^{D,I} \end{bmatrix}$$

where "." denotes that we are leaving the coefficient unrestricted. With the identified structural disturbances, we do a variance decomposition to measure the importance of each shock in accounting for the variance of country spreads and capital flows. Tables 2 and 3 display the fraction of the variance of country spreads and capital flows that is explained by each structural shock, respectively. The upper (lower) panel of each table documents the role of common (idiosyncratic) supply and demand shocks.[14]

Table 2 Share of Variance of Country Spreads Explained by Each Shock

	F_t^s	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	64	6	41	25	48	18	58	42	50	48	35	41	35	41
$\varepsilon_t^{D,G}$	36	3	23	14	27	10	32	23	28	27	19	23	19	23
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	9	64	39	75	28	90	65	78	75	54	64	54	64
$\varepsilon_t^{S,I}$	0	51	18	30	14	37	5	18	11	13	24	18	26	18
$\varepsilon_t^{D,I}$	0	40	18	31	12	36	5	17	11	12	22	19	20	18
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	91	36	61	25	72	10	35	22	25	46	36	46	36

NOTE. One-Year ahead variance decomposition of country-specific and common (Factor) spreads due explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

Two results stand out from a comparison of Tables 2 and 3. First, common drivers are more relevant in accounting for spreads in EMEs, with 64 percent of their median variance traced back to these disturbances. The remaining 36 percent is accounted for idiosyncratic forces. This result echoes the Global Financial Cycle identified in Rey (2013). There is, however, some heterogeneity across countries. Argentina and Ecuador stand out as having

[14] Given our particular interest in business cycle dynamics, we choose to use as metric of analysis the one-year ahead variance decomposition, instead of the R^2 that has been more relied upon in the Global Financial Cycle literature. However, further results below document the estimated R^2 for the baseline as well as extensions (e.g., see table 5).

Table 3 Share of Variance of Net Capital Flows Explained by Each Shock

	F_t^k	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	64	1	33	13	2	2	5	18	1	4	14	5	9	5
$\varepsilon_t^{D,G}$	36	1	18	8	1	1	3	10	1	2	8	2	5	3
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	2	51	21	3	3	8	28	2	6	22	7	14	8
$\varepsilon_t^{S,I}$	0	55	25	39	52	49	44	37	49	48	40	45	48	46
$\varepsilon_t^{D,I}$	0	43	24	40	45	48	48	35	49	46	38	48	38	44
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	98	49	79	97	97	92	72	98	94	78	93	86	90

Note. One-year ahead variance decomposition of country-specific and common (Factor) capital flows due explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

relatively low variance in their spreads associated to global factors, 9 and 28 percent respectively. At the other extreme, countries like Mexico and Colombia have a share of 90 and 75 percent, respectively, of their spread variance that is accounted for by global factors.

The relatively large share of global factors in EM spread dynamics contrasts with the finding that the lion's share of the volatility in capital flows can be traced back to idiosyncratic disturbances. Indeed, the latter account for 90 percent of the median variance in the capital flows data. This also echoes results by Cerutti et al. (2019c) who cast doubts of a Global Financial Cycle in capital flows. Brazil stands as the only exception in our sample where the share of global disturbances that account for net capital flows is slightly larger (51%) than that of idiosyncratic factors (49%). For the remaining countries, the share of capital flow dynamics accounted for by common disturbances is below 28 percent at most.

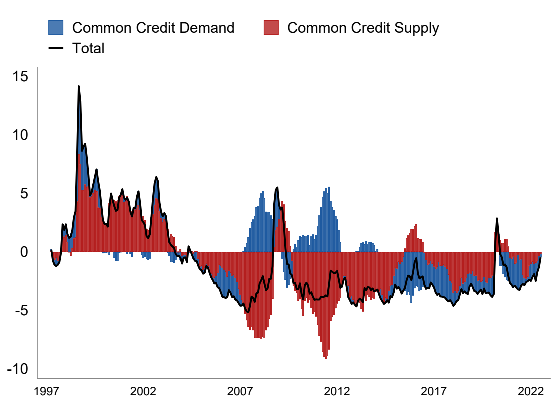
The second noteworthy result from Tables 2 and 3 is that supply shocks are relatively more preponderant. This is more evident when explaining common drivers in spreads, accounting for around 2/3 of the 64 percent median variance in spreads that comes from common shocks. This, in turn, can be traced back to the fact that supply disturbances nearly double in relevance when accounting for the variability in the common factor in spreads (F_t^s), with 64 percent of its variability being traced back to $\varepsilon_t^{S,G}$, while only 36 percent to $\varepsilon_t^{D,G}$. When common and idiosyncratic disturbances are added together, supply forces explain 59 percent of the dynamics in spreads, while demand disturbances the remaining 41 percent.

In contrast, supply and demand disturbances are nearly equal in relevance when explaining dynamics in capital flows to EMEs. While supply shocks continue to drive most of the variability in the estimated common factor in capital flows (F_t^k), the reduced importance of common drivers therefore does not contribute much to making supply disturbances a more relevant force. All in all, when common and idiosyncratic disturbances are added together, supply forces explain a median of 51 percent of the dynamics in capital flows.

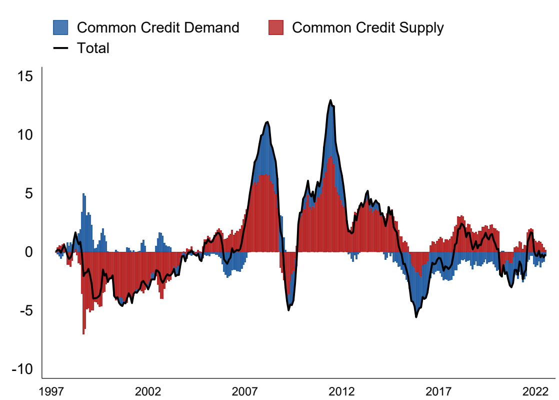
Through a historical decomposition, Figure 6 allows us to further document the relative contribution of supply and demand shocks on the dynamics of common factors in spreads and capital flows. Supply drivers appear as a key force of both factors in periods of global crisis, explaining most of its variability around the Asian Crisis of the late 90s, the years that surrounded the Global Financial Crisis, and during the Covid outbreak in 2020. Demand shocks appear relatively less relevant and grow in importance toward the end of the sample in the mid 2010s as they to contributed to keeping spreads low while capital flows were receding from EMEs.

Figure 6 Historical Decomposition of the Common Factors

(a) Common Factor of Country Spreads



(b) Common Factor of Capital Flows



Note. Evolution of the cumulated common factor of country spreads and capital flows explained by common credit demand and supply shocks. Credit supply and demand shocks are identified using zero and sign restrictions as explained in Section 3.4.

3.5 Extensions

We extend our baseline analysis along three key dimensions that allow us to better illustrate the forces driving the capital flows to EMs. A first extension considers a larger sample of countries by adding advanced economies, thereby allowing us to disentangle a *global* common factor from an EME-specific one. A second extension investigates the role of *regional* EME factors. Lastly, we quantify the extent to which US monetary policy impacts the common factors driving capital flows to EMEs.

Adding Advanced Economies

The common credit demand and supply shocks identified in our baseline estimation may be conflating both global factors linked to the Global Financial Cycle and EME-specific drivers. To disentangle the importance of each of these different drivers, we re-estimate the DFM with an augmented sample of countries that consists of the 12 EMEs in our baseline results plus G7 economies and a representative sample of small open and advanced economies.[15] Our larger sample of advanced and emerging economies accounts now for a median of 70 percent of total gross inflows around the world between the years 2017 through 2021. The advantage of having such a comprehensive coverage is that it allows us to differentiate a global factor –impacting all economies– from an EME-specific one –impacting only EMEs– in our estimation of common factors.

As in our baseline analysis, we construct monthly proxy series of capital flows for these economies following Calvo et al. (2008). For prices, we use the 5-year (5Y) yield of sovereign debt, which we download from Refinitiv. In order to have a comparable measure for EMEs, we compute the 5Y yield as the sum between the 5Y US Treasury yield plus the EMBI. [16]

Figure 7 displays the new estimated common factors of capital flows and interest rate

[15] The G7 economies that we include are Canada, Germany, Italy, Japan, UK, and US. We exclude France which does not have data on interest rates for the full period analyzed. The sample of small open advanced economies is made of Australia, Denmark, Finland, Norway, and Switzerland.

[16] Note that our measure for EMEs therefore excludes currency risk.

yields in the expanded model together with our baseline estimates for comparison. As can be seen from inspecting the figure, the baseline factors are highly correlated with the EME-specific factors as well as the global factors.[17] Thus, the baseline factor contain both a global and an EME-specific component whose importance may differ. It is interesting to see, for instance, how the EME-specific factor comoves strongly with our baseline common factor in spreads, particularly in times of financial turbulence as in the late 90s, the GFC and COVID. In capital flows, on the other hand, the EME-specific factor comoves with our baseline factor only after the GFC. The large volatility in capital flows in the years before is mostly associated with the global factor.

We complement this analysis by further decomposing the shocks impacting the new estimated factors between supply and demand, following the same identification strategy presented in Section 3.4. Table 4 displays the median variance decomposition of capital flows and country yields explained by each shock.[18] Our baseline result that external shocks are more important to explain price (yield) fluctuations, while idiosyncratic shocks are the predominant driver of capital flows, is robust to extending the model with EME-specific and global factors. While global and common-EME supply and demand shocks are equally important in explaining yield dynamics, global shocks are significantly more important than common-EME shocks when accounting for the role of external factors driving capital flows.

Regional EME Factors

The relatively low correlation between capital flows across EMEs may be due to the fact that net capital flows are more correlated at the regional level. This could be due to higher synchronization of business cycles or to geographical segmentation in the way foreign investors allocate their investments.

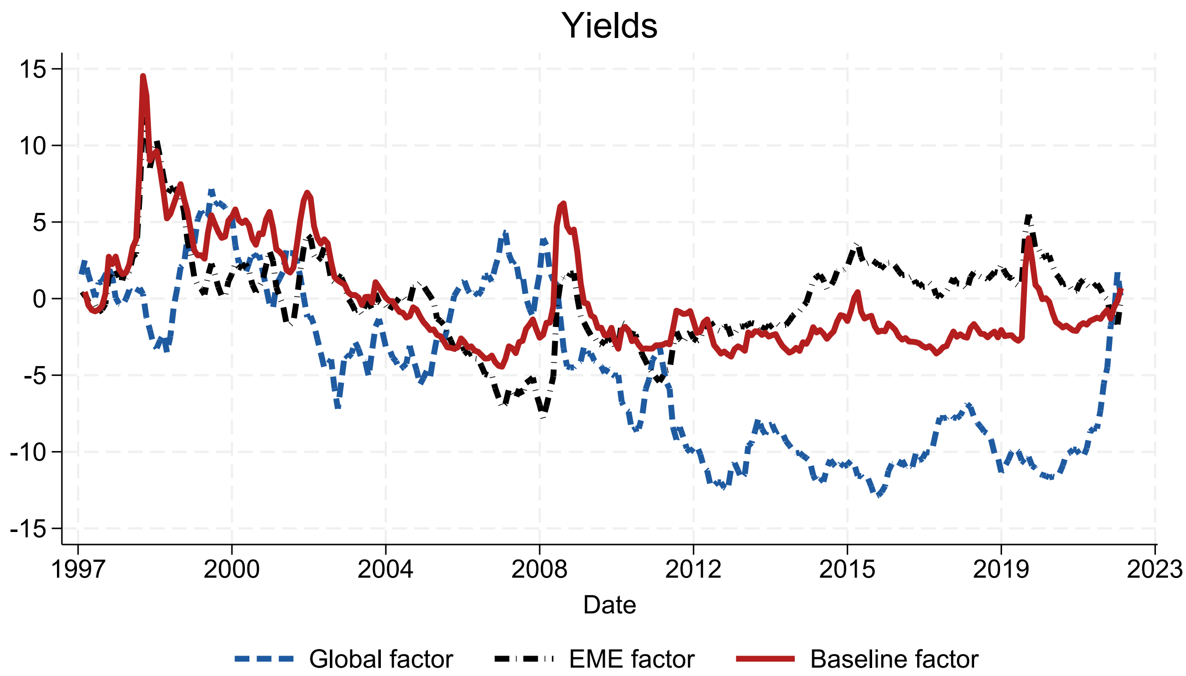
To explore the relevance of regional factors, we extend the baseline DFM presented in (5)

[17]The correlation between the baseline and EME-specific factors is 0.7 for yields/spreads and 0.62 for capital flows. The correlation with the global factors is 0.47 for yields/spreads and 0.77 for capital flows.

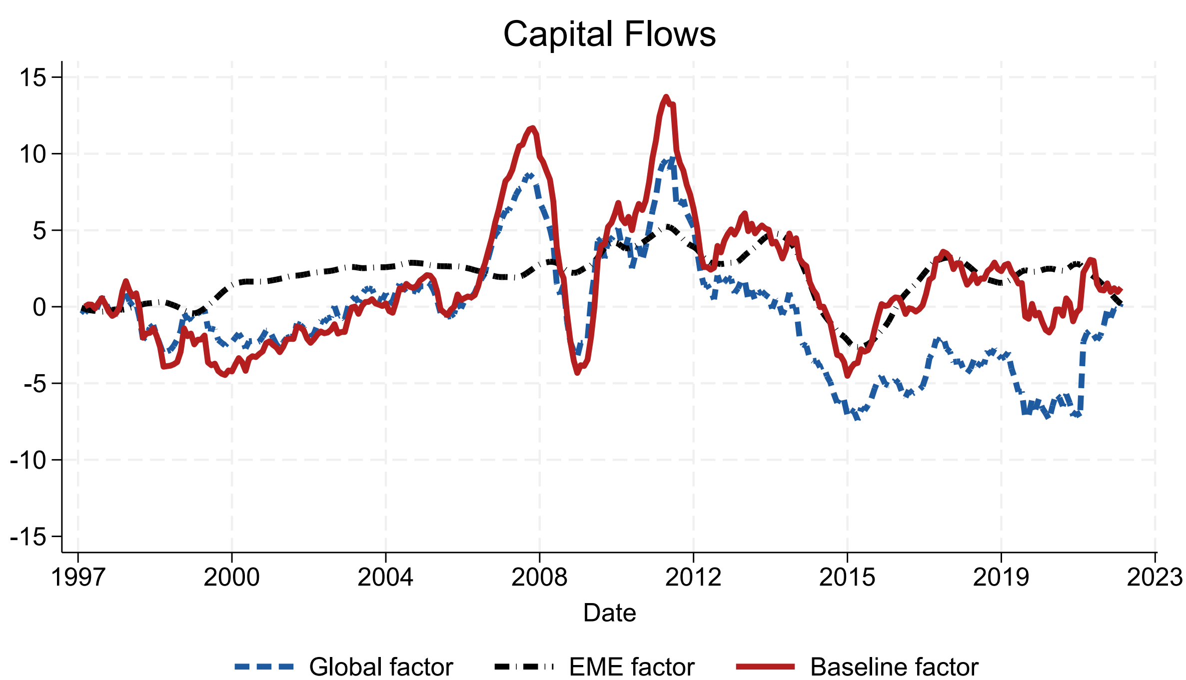
[18]Tables A.5 and A.5 included in the Appendix display the variance decomposition country by country.

Figure 7 Global and EME-Specific Factors

(a) Factors of Yields



(b) Factors of Capital Flows



Note. Cumulated dynamic factor of capital flows and country yield for a sample of 23 economies, including Advanced and EMEs for the period 1997:2-2022:7. Continuous red lines denote the baseline factors of country spreads and capital flows presented in Figure 4. Dashed blue lines denote a common factor that affects all the economies of the sample while dotted-dashed lines denote a common factor that affects all EMEs. Factors are estimated according to the DFM described in Section 3.5.

Table 4 Share of Variance of Country Yields and Capital Flows Explained by Each Shock

	Yields	K Flows
$\varepsilon_t^{S,G}$	20	9
$\varepsilon_t^{D,G}$	17	9
Global	37	18
$\varepsilon_t^{S,EME}$	18	1
$\varepsilon_t^{D,EME}$	15	1
Common EME	33	2
External	70	20
$\varepsilon_t^{S,I}$	15	42
$\varepsilon_t^{D,I}$	15	38
Idiosyncratic	30	80

NOTE. One-year ahead variance decomposition of country-specific yields and capital flows explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, EME credit supply shocks $\varepsilon_t^{S,G}$, EME credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$. We report the median for the 12 EMEs included in our baseline sample.

to extract two region-specific factor: Asian and Latin American.[19] When estimating these two factors we assume that each affects only the countries that belong to each region and have no effect on the remaining ones.

Table 5 documents the role of regional factors.[20] Regional factors are quite relevant for capital flows and, to a lesser extent, for spreads. Indeed, when accounting for additional regional factors, the variance share of capital flows related to common forces nearly quadruples from 11% to 39%. This pattern is consistent with the earlier evidence that net flows exhibit limited global comovement (Rey 2013), but it also shows that allowing for regional components reveals substantial synchronization in net flows at the regional level. It also underscores a central role of regional factors in explaining capital flows, and echoes the work of Kaminsky et al. (2020) who, from a longer historical perspective that us, find that capital flow cycles in the periphery are of a regional pattern.

In terms of spreads, the share accounted for regional factors is also relevant, although

[19]The Latin American factor considers the following countries: Argentina, Brazil, Colombia, Ecuador, Mexico, and Panama. The Asian factor includes: China, Malaysia, Philippines, and Turkey. Poland and South Africa do not belong to any of these regional factors and they are only considered for the common EMEs factors.

[20]In order to compare with the literature the metric used is R^2. Figure A.4 in the Appendix displays the two regional factors for capital flows and country spreads.

their marginal contribution is less than that of capital flows. The sum of common factors –including regional one– is increased from 60% to 70%. All in all, even after accounting for regional factors, our baseline result is robust in that common factors are more important for country spreads than for capital flows.

Table 5 Importance of Common and Regional Factors by Country

	ARG	BRZ	CHN	COL	ECU	MLY	MEX	PAN	PHL	POL	SWF	TUR	Median
Net Flows - Common	0.00	0.39	0.19	0.01	0.16	0.09	0.32	0.08	0.11	0.11	0.03	0.55	0.11
Net Flows - Common + Regional	0.07	0.40	0.75	0.91	0.17	0.09	0.47	0.27	0.37	–	–	0.55	0.39
Spread - Common	0.08	0.72	0.02	0.82	0.41	0.60	0.65	0.89	0.66	0.49	0.34	0.60	0.60
Spread - Common + Regional	0.37	0.99	0.06	0.89	0.45	0.94	0.70	0.89	0.66	–	–	0.69	0.70

NOTE. Share of the country-specific capital flows and country spreads variance explained by the common and regional factors. We report the Adjusted R^2 of the regression of country spread and net capital flows on the common and the common plus regional factors.

Impact of US Monetary Policy

One key finding thus far is the large role played by a common credit supply factor when accounting for capital flows to EMEs. In this extension we aim at zooming in on one likely driver of such factor: the stance of US monetary policy. This is further motivated by the well known finding that US monetary policy is one of the drivers of the Global Financial Cycle (see, for example, Miranda-Agrippino and Rey, 2020). With this purpose in mind, we extend our baseline analysis by quantifying the effects US monetary policy shocks on the two estimated common factors in spreads and capital flows.

A practical challenge that we face comes from the fact that, over most of the sample period that we analyze, conventional US monetary policy was constrained by the zero lower bound, and implementation was mostly carried out through a variety of unconventional instruments, which may induce different effects on both factors. To address this, we use the variety of series of conventional and unconventional US monetary policy shocks computed by Swanson (2021). Concretely, we estimate the effects of surprise changes in: i) the Federal Funds rate; ii) Forward Guidance; and, iii) Large-Scale Asset Purchases (LSAP) –each taken from Swanson (2021)– by estimating the following local projection specification on the period

1997.3 to 2019.6:

$$F^i_{t+h} - F^i_{t-1} = \alpha_h + \alpha^S_h S_t + \alpha^F_h \left(F^i_{t-1} - F^i_{t-2}\right) + \varepsilon_{t+h}, \qquad \forall\ 0 < h < 12$$

where F^i_{t+h} denotes the value of each factor i (spreads or capital flows) h periods ahead and S_t denotes the policy shock (i.e. Federal Funds rate, Forward Guidance or LSAP, respetively). We estimate the effects up to 16 months ahead. Figure 8 displays the IRFs of each factor to a one S.D contractionary shock in each of the three policy variables considered, derived from the estimated local projection specifications.[21]

The three types of monetary policy shocks induce an increase in the common factor of country spreads of about half of a percentage point, and a decrease of the factor of capital flows of roughly the same magnitude. While the effects of a shock to the Fed Funds rate are more immediate, the responses to the change in LSAP are more delayed and sizeable.

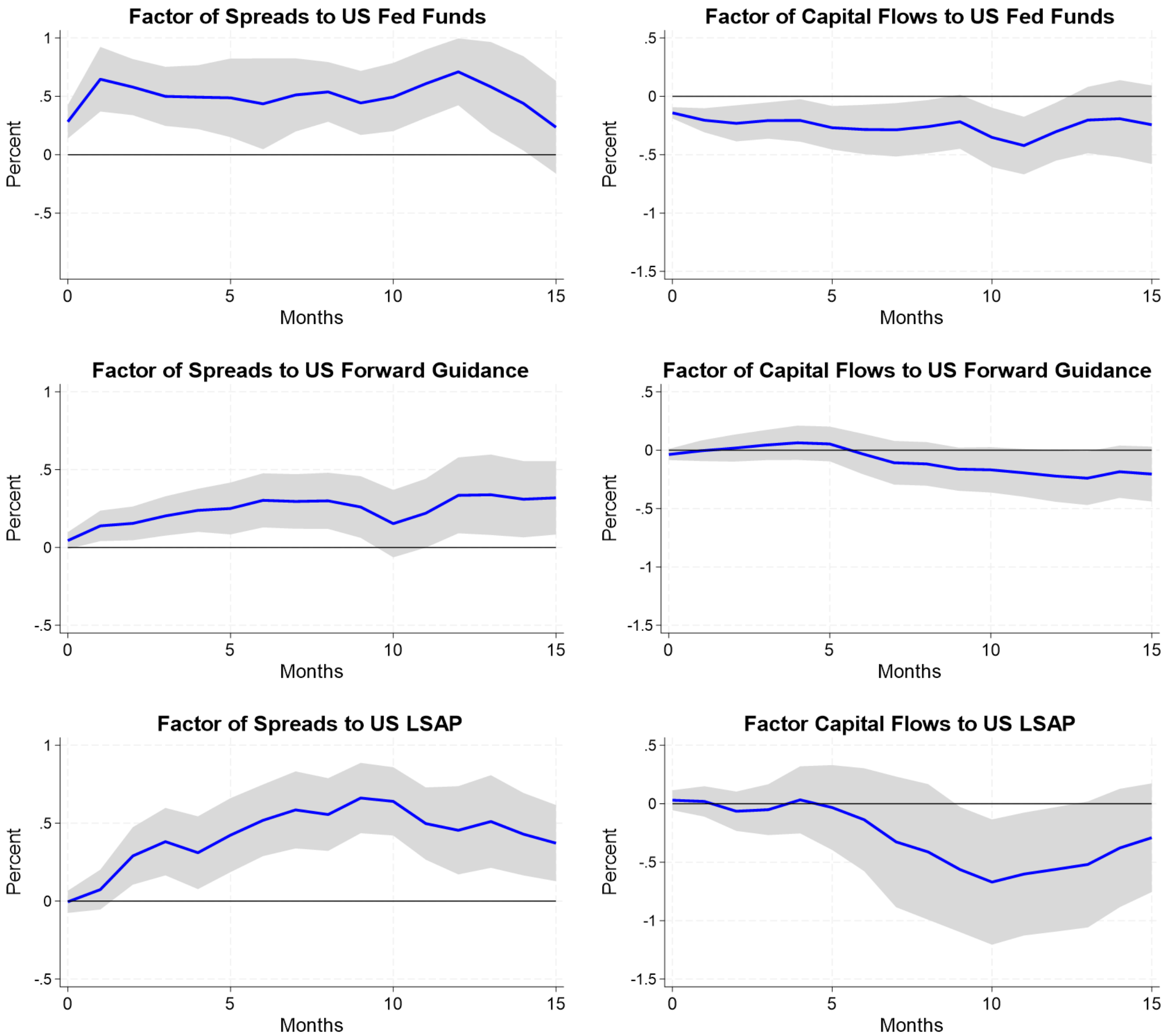
Overall, we see this as evidence that US monetary policy is one important driver behind the global credit supply forces pinned down in our baseline results. This also echoes the findings that US Monetary Policy shocks are an important driver of the Global Financial Cycle.

3.6 Robustness

In this section we assess the robustness of our baseline empirical results across several dimensions. First, we redo our baseline analysis with a wide array of alternative measures of capital flows and country spreads, ranging from the use of official monthly capital flows data available, consistent measures of corporate debt flow volumes and spreads, quarterly IMF BoP data, as well as other proxies of capital flows used in the literature. Second, we redo the baseline analysis with gross capital flows instead of net flows. Third, we zoom in on net foreign direct investment and portfolio inflows, instead of relying on overall net capital

[21] A one standard deviation Fed Funds shock (Forward Guidance) induces an increase of 23 (25) basis points in the 1Y US yield. A one standard deviation LSAP shocks induces an increase of 10 basis points in the 10Y US yield.

Figure 8 IRFs of both Factors to Contractionary US Monetary Policy Shocks



Note. Impulse response functions of the factors of country spreads and capital flows in response to a one standard deviation US Fed Funds rate shock (Fed Funds Factor), Forward Guidance shock (Forward Guidance Factor) and to a Large-Scale Asset Purchases (LSAP Factor) shock. The series of shocks are computed by Swanson (2021). Continuous blue line denotes the median response and shaded areas denote 68% confidence intervals based on Newey-West standard errors. Horizon is in months.

flows. Fourth, we restrict the sample of countries in our baseline analysis to a subsample of EMEs with open financial account. Fifth, we redo the analysis with the sample period until the end of 2019 to assess how much our results are driven by the Covid shock.

Alternative Measures of Capital Flows and Country Spreads

In our baseline analysis, we consider a measure of sovereign spread based on public bonds while our proxy for capital flows includes both public and private flows. Sovereign spreads are highly correlated with corporate spreads in the same economy but they do not coincide (see, for example, Caballero et al., 2019). However, using a more disaggregated proxy for capital flows and country spreads, where both of them are computed based on the same assets, implies loosing country coverage or working with lower frequency data (quarterly), which may blur identification of demand and supply shocks. In this subsection, we show that the previous empirical facts are robust to alternative measures of capital flows and country spreads at monthly and quarterly frequencies. Table A.9 included in the Appendix displays the results for the correlation using these alternative datasets.

First, we consider disaggregated balance of payments monthly data for Brazil (BoP M in Table A.9).[22] Brazil is one of the few countries with balance of payments data available at monthly frequency and the only one in our EME sample. We compute a proxy for capital flows using Portfolio Investment (net incurrence of liabilities) of the balance of payments and sovereign spread (EMBI) as a proxy for country spread. The revised correlation between capital flows and country spread (-0.25) is comparable in sign and magnitude with the one computed our baseline sample (-0.12), with both being statistically significant.

Second, we exploit the quarterly database used by Caballero et al. (2019) (CFP in Table A.9). We define net corporate debt flows as the difference in the stock of corporate debt for some EMEs together with the External Financial Index computed by Caballero et al. (2019). The advantage of this analysis is that the measure of country spread is computed using the same set of bonds used to compute capital flows. Another advantage is that this database covers a representative set of EMEs. The main drawback is that this database is only available at quarterly frequency. The correlation between capital flows and country

[22] This data is available at https://www.bcb.gov.br/content/statistics/specialseriestables/BalPayM.xlsx.

spread is also similar to the one presented in Table 1, with a median correlation between capital flows and country spreads of -0.20, in line with our baseline median correlation, -0.11.

Third, we use issuance of corporate debt and their corresponding yields for Brazil, Colombia, Mexico and Turkey available at quarterly frequency from Thomson Reuters for the period 1994:1-2019:1 (Debt Issuance in Table A.9). In this case, we compute a yield as a weighted average of all the individual bond yields of that country and compute the sum of bond issued for every quarter.[23] The key advantage of this exercise is that we can track the yields associated to each bond when issued in primary markets, for both private and public sectors. The main drawback is that the data only covers total issuance in primary markets and we cannot distinguish between domestic and international bond issuance, which is key for computing capital flows. To partially address this issue, we consider only bond issued in international currency. The main conclusions remain unchanged, with a median correlation between capital flows and country spreads of -0.25.

Fourth, we compute capital flows using balance of payments data published by the IMF (BoP Q in Table A.9). In particular, we consider net capital inflows from the Financial Account. The country spread is the quarterly EMBI average. The key advantage of this database is that is available and comparable for a wide range of countries. The drawback is that it is only available at quarterly frequency and that we do not have a country spread measure based on these capital flows. The main conclusions remain unchanged, with a median correlation between capital flows and country spreads of -0.28.

We also use the series of capital flows at monthly frequency computed by Koepke and Paetzold (2020) together with the EMBI as a proxy for capital flows (KS Total in Table A.9). The advantage of this database is that it contains a comparable measure of capital flows for a wide range of EMEs. The main conclusions remain unchanged, with a median correlation between capital flows and country spreads of -0.27.

Finally, we use the series of net capital flows at quarterly frequency from Balance of

[23]The weights are defined as the share of every bond on the total bond issued by that country in that quarter.

Payments data to compute the role of credit demand/supply idiosyncratic/common shocks in explaining the observed dynamics. In order to have a balanced panel, we have to restrict our baseline sample from 1999Q1:2022Q2 and exclude Poland from the analysis since Balance of Payments data is only available from 2000Q1 for this country. Tables 6 and 7 display the variance decomposition of country spreads and net capital flows explained by each of these shocks. The main conclusions from our baseline sample also hold using quarterly data. First, common credit supply shock are the predominant driver of country spreads. Second, idiosyncratic credit demand and supply shocks are the most important drivers of capital flows. The main difference with respect to baseline results is that the contribution of common shocks is even lower for capital flows, which may be explained by the temporal aggregation.

Table 6 Share of Variance of Country Spread Explained by Each Shock

	F_t^s	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	58	15	26	29	37	28	39	43	43	34	40	29	34
$\varepsilon_t^{D,G}$	42	11	19	21	27	21	28	31	32	25	29	21	25
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	26	45	50	64	49	67	74	75	59	69	50	59
$\varepsilon_t^{S,I}$	0	40	26	26	19	27	18	13	14	20	15	27	20
$\varepsilon_t^{D,I}$	0	34	28	23	17	25	15	13	12	21	16	23	21
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	74	54	49	36	52	33	26	26	41	31	50	41

NOTE. One-year ahead variance decomposition of country-specific and common (Factor) country spreads explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

Table 7 Share of Variance of Net Capital Flows Explained by Each Shock

	F_t^k	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	58	7	20	8	29	5	1	8	14	2	14	12	8
$\varepsilon_t^{D,G}$	42	5	15	6	21	4	1	6	10	2	10	9	6
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	12	35	14	50	9	2	14	24	4	24	21	14
$\varepsilon_t^{S,I}$	0	47	31	45	27	48	53	43	41	47	36	43	43
$\varepsilon_t^{D,I}$	0	40	34	41	23	44	45	43	35	49	40	37	40
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	87	65	86	50	92	98	86	76	96	76	80	83

NOTE. One-year ahead variance decomposition of country-specific and common (Factor) net capital flows explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

Gross Capital Flows

A strand of literature has highlighted the need to study *gross* capital flows instead of working with net flows (see, for example, Broner et al., 2013). This emphasis is also consistent with the Global Financial Cycle evidence documenting strong comovement in gross inflows and outflows across regions, while net flows display no systematic correlation patterns (Rey, 2013 and Kalemli-Özcan, 2019). Motivated by this, in this subsection we redo our baseline analysis using the series of gross capital inflows and outflows for each country, capturing capital flows by residents and non-residents separately. We use balance of payments data available at quarterly frequency for the subset of countries from our baseline sample that have data available for the whole sample. Since only eight countries have data starting from 1997:Q1, we start our analysis from 1999:Q1 to include ten economies in our sample (i.e. the sample period is 1999:Q1-2022:Q2).[24] First, we compute the correlation of these measures of capital flows with country spreads, which are aggregated to the quarterly frequency as the average over the period. Table 8 displays the results. As a reference, the last row also reports the correlation with the series of net capital flows, which is comparable with the one we present in our baseline results.

Table 8 Correlation between Gross Capital Flows and Country Spread

	ARG	BRZ	CHN	COL	ECU	MEX	MLY	PAN	PHL	POL	SWF	TUR	Median
Outflows	-0.15	-0.20^{*}		-0.27^{***}	-0.14	-0.28^{***}	-0.26^{**}	-0.42^{***}	-0.37^{***}		-0.24^{**}	-0.06	-0.25
Inflows	-0.42^{***}	-0.44^{***}		-0.60^{***}	-0.31^{***}	-0.42^{***}	-0.40^{***}	-0.55^{***}	-0.41^{***}		-0.54^{***}	-0.61^{***}	-0.43
Net Flows	-0.37^{***}	-0.43^{***}		-0.67^{***}	-0.23^{**}	-0.23^{**}	-0.28^{***}	-0.28^{**}	-0.14		-0.48^{***}	-0.58^{***}	-0.33

Note. Contemporaneous correlation between real capital inflows/outflows and net capital flows, and EMBI of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the sample period 1999:Q1-2022:Q2. Significance level: $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

The correlation between the country spread and net capital flows is a bit larger than the one at monthly frequency reported in Table 1 (-0.33 at quarterly frequency relative to -0.14 at monthly frequency). Gross capital inflows is the one that displays the more

[24] Gross capital flows data for China and Poland start in 2005:Q1 and 2000:Q1, respectively. Thus, we do not include these countries in our analysis since the DFM is estimated with a balanced panel. Data for Ecuador and Panama is only available from 1998:Q1 and 1999:Q1, respectively. We deflate the series of capital flows using the US Producer Price Index by Commodity: All Commodities (PPIACO from St.Louis FRED).

negative correlation with the country spread. We also compute the common factor using capital inflows or capital outflows instead of net capital flows, using the same DFM described in Eq. 5. Table 9 reports the explanatory power of the capital flows factor for each country.

Table 9 Importance of Common Factors for Gross Capital Flows

	ARG	BRZ	CHN	COL	ECU	MEX	MLY	PAN	PHL	POL	SWF	TUR	Median
Outflows	0.01	0.19		0.11	0.01	0.49	0.18	0.26	0.01		0.01	0.01	0.06
Inflows	0.03	0.79		0.34	0.01	0.32	0.34	0.30	0.03		0.08	0.45	0.31

Note. Share of the country-specific capital inflows and capital outflows variance explained by the common factor. We report the Adjusted R^2 of the regression of capital inflows and outflows on the common factor of capital inflows and outflows, respectively.

A common factor explains more the fluctuations of gross capital inflows than of gross capital outflows. However, the importance of this factor is significantly lower than the one of the common factor in country spreads (see Table 5). The presence of a non-trivial common component in gross inflows echoes the evidence of the Global Financial Cycle that comovement in cross-border flows is more apparent in gross measures than in net flows (Rey, 2013; Kalemli-Özcan, 2019).

Portfolio Investment and FDI

Our baseline results are computed with a proxy of *total* net capital flows. We now assess robustness of the the decomposition between credit demand-supply and idiosyncratic-global drivers using two distinct types of net inflows: foreign direct investment and portfolio. As it is well known, these two types of flows represent a significant fraction of the financial account in EMEs. Due to data availability, our new sample runs from 1999:Q1 till 2022:Q2 and excludes Polonia. Tables A.10, A.11, and A.12 included in the Appendix display the correlation between spreads and capital flows and the variance decomposition of country spreads and capital flows explained by each shock.

The main conclusions from our baseline analysis remain unchanged if we focus on these more disaggregated types of flows. Namely, the correlation between them and spreads is low and negative, and both types of flows are driven mostly by supply and idiosyncratic shocks.

Economies with Open Financial Account

It could be argued that the low correlation between capital flows and country spreads and the low comovement of capital flows relative to country spreads that we observe in the data is explained by economies with closer financial accounts. To address this we consider the subsample of economies with an open financial account as all the economies from the sample that coincide with the ones used by Fernández et al. (2018): Brazil, Colombia, Mexico, Malaysia, Philippines, South Africa, and Turkey.[25] The last row (Open) of Table A.9 displays the correlation between spreads and capital flows only for this subset of countries. The median correlation between capital flows and spreads for this subset of economies is -0.12, very similar to the full sample (-0.11). Thus, the low correlation and negative correlation between spreads and capital flows is not driven by economies with closed financial accounts.

Pre-Covid Sample

The Covid could have changed significantly the dynamics in credit markets, affecting the analysis. In this section we redo the analysis with a shorter sample that ends in 2019:12, excluding the Covid period. Figure A.5 displays the dynamics of the new estimated common factors in capital flows and country spread in the shorter sample. Excluding the Covid period does not affect significantly the estimated factors in the common sample. The correlation between the factors of sovereign spreads and capital flows using the extended and the reduced sample is 0.98 in both cases. Tables A.16 and A.17 display the variance decomposition of country spread and capital flows explained by each shock using the Pre-Covid sample. The results are comparable to those of the baseline sample. All in all, the empirical facts are not affected by Covid.

[25] Fernández et al. (2018) define an economy with an open financial account if it has an average index of de jure measure of capital controls as defined by Fernandez et al. (2016) between 1995 and 2013 higher than one and a half standard deviations of the median across 100 economies in their dataset.

4 Capital Flows and Country Spread Dynamics: A Structural Multi-Country Model

This section extends the simple two-period model in Section 2 to an infinite-horizon, stochastic, general equilibrium setup. The main goal is to *quantify* the shocks and propagation channels through which demand and supply factors –of idiosyncratic and common nature– shape capital flows to the pool of emerging economies studied in the previous section.

Business cycle dynamics derived from the dynamic model are studied, with a particular focus on gaining a better understanding of three key empirical facts documented in the previous Section: the high (low) observed comovement between country spreads (net capital flows) across EMEs, and the negative and low correlation between capital flows and country spreads within EMEs. To the best of our knowledge, these three dimensions have not been jointly analyzed before within a structural general equilibrium dynamic model of EMEs. We consider correlated structural shocks instead of including the estimated equation of the DFM because the baseline DFM is estimated with an extended sample of EMEs instead of the two economies used in this analysis.

The setup we build is a two-EME version of the small open economy RBC model developed by Mendoza (1991) and extended by Schmitt-Grohe and Uribe (2003). It considers only one good, which can be traded in international markets. Each economy faces three shocks to: the international risk-free interest rate, the country spread, and TFP. Guided by the empirical findings on comovement across EMEs documented earlier, we allow for TFP and country spread shocks to be correlated across countries. Correlated TFP shocks allow the model to match the observed business cycle synchronization across economies, capturing common shocks that can give rise to fluctuations in the demand for capital. Correlated country spread shocks account for the additional comovement of spreads, beyond what can be explained by synchronization in the fundamentals of the EMEs.

We choose to use a two-EME model to keep the framework and its calibration simple, tractable, and intuitive. This helps us characterize the determinants of capital flows and country spreads, and the role of key frictions in explaining the results, thereby rationalizing the empirical decompositions presented above (prices vs. quantities; common vs. idiosyncratic; demand vs. supply). The framework can be extended to include additional economies from our empirical sample under the same small-open-economy abstraction.[26]

Our calibration strategy proceeds as follows. We use Brazil and Mexico as two representative EMEs. Accordingly, we model them as two small open economies that borrow and lend with a large rest of the world at an exogenous global rate; and where goods and financial markets clear against the rest of the world.[27] For each of these two economies we calibrate the TFP processes to match output volatilities and comovement across the two economies. We choose to discipline the model in this dimension by forcing it to match the spread dynamics in the data –including the high comovement between country spreads–, while assessing its goodness of fit in terms of matching the untargeted low comovement in net capital flows across EMEs, and the negative and low correlation between capital flows and country spreads. In that sense, our approach is a complement to that of Bai et al. (2024) who, in contrast, endogenize the comovement in spreads in EMEs in the presence of long-run risk, but is silent about capital flows and their comovement with spreads.

We use the model to quantify the role of different country-specific characteristics and frictions in explaining these empirical facts. Our analysis starts by comparing second moments in data and model. Impulse response functions (IRFs) allow us to characterize the propagation of the various shocks considered. Lastly, through counterfactual experiments where we turn off, sequentially, the correlation in TFP and spreads, we can gauge the relative

[26] Such an extension would require judgment regarding the appropriate treatment of bilateral trade and financial linkages across EMEs, which we abstract from in the baseline quantitative framework and which may be less suitable for larger EMEs.

[27] Besides being two quintessential EMEs, Brazil and Mexico are suitable for our calibration because their bilateral trade is relatively low—around 1.5% of their total exports in 2012 (UN Comtrade). This supports our abstraction from direct bilateral trade linkages across the two EMEs, which we adopt for tractability and to keep the focus on common external forces. We also abstract from direct bilateral financial linkages between the two EMEs. These assumptions are consistent with evidence that EM-to-EM financial exposures are limited in aggregate—see the Spring 2024 WEO analytical chapter on EM spillovers, which documents that outward portfolio investment by major EMs remains relatively small.

importance of common credit demand and supply disturbances, respectively.

The calibrated model does a good job along several untargeted business cycle moments. A particularly noteworthy feature is that the model performs reasonably well in replicating the Global Financial Cycle in EMEs, namely the low correlation between capital flows and country spreads and the low correlation of capital flows across countries –both untargeted moments–, while simultaneously matching the processes of spreads. It does, however, underpredict the observed volatility of net capital flows.

Three counterfactual experiments where the cross-country correlations in TFP and interest shocks are separately turned off, and when we set the correlation of country spread shocks equal to that of TFP, further help us shed light onto the propagation mechanism embedded in the model. Business cycle synchronization through correlated TFP is key for explaining capital flows comovement but has no effect on country spread comovement, consistent with the importance of common productivity shocks to explain capital flows dynamics. On the other hand, common shocks to the country spread capturing the Global Financial Cycle do not significantly affect the correlation between capital flows, consistent with flow volumes being determined by idiosyncratic demand shocks relatively more than shifts in international credit supply.Lastly, we consider a variety of extensions to the baseline model as well as alternative solution methods and assess how the baseline results change.

4.1 The Model

We now present the two-EME/RBC model. To simplify notation, we omit the country index and we only use it when common and idiosyncratic variables interact. The full set of equilibrium conditions are presented in Appendix C.

Each small open economy is populated by a large number of identical households with GHH preferences described by the following utility function:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{[c_t - \omega^{-1} h_t^{\omega}]^{1-\gamma} - 1}{1-\gamma} \tag{6}$$

where β is the discount factor, c_t denotes consumption, h_t denotes hours worked, γ is the constant relative risk aversion coefficient, and ω is the inverse of the Frisch labor supply elasticity. These preferences, which have been widely used in international macroeconomic models, do not display an income effect that affects the labor supply decision. The budget constraint is given by:

$$c_t + i_t + \frac{\phi}{2}\left(k_{t+1} - k_t\right)^2 + R_{t-1}d_{t-1} = y_t + d_t - \frac{\psi}{2}(d_t - \overline{d})^2 \tag{7}$$

where i_t denotes investment, ϕ is a parameter that determines the strength of capital adjustment costs, d_t is the net external debt position, R_t the (gross) interest rate on debt –to be defined below–, and ψ is a parameter that determines the strength of the Portfolio Adjustment Costs (PAC). PAC are necessary to induce determinacy in the model (see, for example, Schmitt-Grohe and Uribe, 2003). The representative household is subject to the following no-Ponzi constraint:

$$\lim_{j\to\infty} \mathbb{E}_t \frac{d_{t+j}}{\prod_{s=0}^{j}(1+r_s)} \leq 0 \tag{8}$$

Output is produced by using capital k_t and labor services h_t as inputs according to the following production function:

$$y_t = A_t k_t^{\alpha} h_t^{1-\alpha}; \quad \alpha \in (0,1) \tag{9}$$

where A_t represents the productivity of the economy. The capital stock evolves according to:

$$k_{t+1} = (1-\delta)k_t + i_t \tag{10}$$

where $\delta \in [0,1]$ denotes the rate of capital depreciation.

Capital flows are therefore an object that can be defined within the model. Akin to the treatment in balance of payment statistics, we define kf_t as capital flows in period t in terms of the change in the aggregate debt stock:[28]

$$kf_t = d_t - d_{t-1} \tag{11}$$

An equilibrium is a process for $\{c_t, h_t, y_t, i_t, k_{t+1}, d_t, kf_t\}$ that maximizes the utility function (6) subject to constraints ((7) to (10)), given the exogenous processes of as productivity, as well as domestic and international rates to be specified next.

4.2 Driving Forces

Each economy is affected by shocks to the following variables: the international (gross) interest rate (R_t^*), the domestic interest rate (R_t), and total factor productivity (A_t). While productivity shocks primarily serve as proxies for demand-side drivers of capital flows, shocks to the cost of funds—captured here through movements in international and domestic rates—proxy for supply-side forces by shifting the borrowing conditions faced by EMEs. Furthermore, in order to allow the model to capture cross country comovement in demand and supply drivers –akin to that estimated in our empirical analysis– we allow for correlated shocks in R_t and A_t.[29]

The law of motion of the productivity process is described by:

$$\ln A_t = \rho_A \ln A_{t-1} + \varepsilon_t^A$$

where ρ_A captures the persistence of the productivity process and ε_t^A is the shock to productivity. We assume that productivity shocks for each country are drawn jointly from a

[28]Note that we follow standard balance of payments definitions and include interest payments ($(R_t - 1) * d_t$) in the current account, not in the financial account, and hence are not part of capital flows.

[29]An alternative is to estimate a common factor for the driving forces of the two economies. However, TFP estimates for these countries are not available at quarterly frequency. Modeling the observed correlation as correlated shocks is more direct and helps to keep the model tractable.

Normal distribution with the following variance-covariance matrix:

$$\Sigma^A = \begin{bmatrix} {\sigma_{11}^A}^2 & \sigma_{12}^A \\ \sigma_{21}^A & {\sigma_{22}^A}^2 \end{bmatrix}$$

where ${\sigma_{i,i}^A}^2$ is the variance of country $i = \{1, 2\}$ productivity shock and $\sigma_{i,j}^A$ is the covariance between the productivity shocks where $\sigma_{12}^A = \sigma_{21}^A \neq 0$. This assumption of correlated TFP shocks is a reduced form way of modelling the business cycle synchronization between these economies, which can explain common demand for credit.[30]

We assume that the interest rate faced by each economy in international markets is given by:

$$R_t = R_t^* + \epsilon_t^r$$

where ϵ_t^r denotes the shock to the country interest rate.

We assume that country interest rate shocks are drawn jointly from a Normal distribution with the following variance-covariance matrix:

$$\Sigma^R = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12} \\ \sigma_{21} & \sigma_{22}^2 \end{bmatrix}$$

where $\sigma_{i,i}^2$ is the variance of country $i = \{1, 2\}$ interest rate shock and $\sigma_{i,j}$ is the covariance between the country interest rate shocks where $\sigma_{12} = \sigma_{21} \neq 0$.[31] This is a direct way of modeling the correlation between sovereign spreads that is not driven by business cycle synchronization.

The international interest rate R_t^* dynamics is characterized by the following process:

$$\hat{R}_t^* = \zeta \hat{R}_{t-1}^* + \epsilon_t^*$$

[30]This may also capture in reduced form other common drivers of business cycle synchronization such as comovement in commodity prices, as in Fernandez et.al (2018).

[31]The estimated correlation between country-specific interest rate shocks between these two economies is 0.66.

where $\hat{R}_t^*$ denotes the log-deviation of the international interest rate with respect to the steady state, ζ denotes the persistence of the process, and ϵ_t^* is a shock to the international interest rate drawn from a Normal distribution with variance $\sigma_{R^*}^2$.

Lastly, note that the (gross) spread between domestic and foreign rates, defined as $s_t = R_t/R_t^*$, is entirely exogenous in our baseline setup, and equal to one in steady state. In an extension of the model we will consider a richer specification where spread dynamics can also react to domestic fundamentals as in Uribe and Yue (2006).

4.3 Calibration

The model is calibrated using quarterly data for Brazil and Mexico from 1997:Q1-2019:4. We pick these two countries as representatives of the pool of EMEs studied in the empirical analysis.

A subset of the parameters in the model is calibrated following Schmitt-Grohe and Uribe (2003), adjusted to quarterly frequency. We assume that households in both economies share the same risk aversion coefficient, which equals 2, and the same inverse Frisch elasticity, which equals 1.455. We assume an annual capital depreciation rate of 10% and we calibrate the share of capital in the production function to be equal to 32%.

Another subset of parameters is calibrated to match some long-run ratios in the data. β is calibrated to match the mean international interest rate faced by both economies of 4% annual as in Schmitt-Grohe and Uribe (2003), considering that $\beta R^* = 1$. Parameter $\overline{d}$ is calibrated to match the trade balance-to-output ratio in steady state. Capital and portfolio adjustment costs are calibrated to match the observed investment and trade balance-to-output ratio volatility in each country, respectively.

The standard deviation of the TFP shock is calibrated to match the observed output volatility in each country. The persistence of the TFP process (ρ_A) is set to match the persistence of output in each country. The covariance between TFP shocks ($\sigma_{i,j}^A$) is set to match the observed output correlation between Brazil and Mexico.

The international interest rate process is estimated using quarterly data for the U.S. from 1997:Q1-2019:Q4. Following Uribe and Yue (2006), the real interest rate for the U.S. is proxied by the Real TBILL which is computed as the 3-month gross Treasury bill rate divided by the average gross inflation based on the GDP Deflator over the past four quarters, as a proxy for expected inflation.

Finally, we calibrate the parameters related with the country interest rate spreads to match the volatility and correlation between country spreads. In particular, we calibrate the σ^R_{ii} and σ^R_{ij} to match the standard deviation of country spreads and the correlation between sovereign spreads, respectively. Table 10 displays the calibrated parameters.

Table 10 Calibrated Parameters

Parameter	Description	Target	Brazil	Mexico
γ	CRRA parameter	Schmitt-Grohe and Uribe (2003)	2	
ω	Inverse Frisch elasticity	Schmitt-Grohe and Uribe (2003)	1.455	
δ	Depreciation rate	Schmitt-Grohe and Uribe (2003)	0.025	
α	Capital share	Schmitt-Grohe and Uribe (2003)	0.32	
R^*	Annual Interest rate in SS	Schmitt-Grohe and Uribe (2003)	1.04	
β	Discount factor	$\beta R^* = 1$	0.9901	
ζ	Persistence R^*_t	Estimated	0.92	
σ_{R^*}	Std. Dev. of R^* shock	Estimated	0.00183	
$\bar{d}$	Debt in steady state	Average TBY	0.38	3.9
ϕ	Capital adjustment cost	Investment volatility	0.00386	0.00767
ψ	Portfolio adjustment costs	TBY volatility	0.000000147	0.0000005
ρ_A	Persistence TFP	Output persistence	0.6355	0.765
σ^A_{ii}	Std. Dev. TFP Shock	Output volatility	0.00653	0.00505
σ^A_{ij}	Covariance TFP Shocks	Output correlation	0.3	0.3
σ^R_{ii}	Std. Dev. Spread Shocks	Spread Volatility	0.0083	0.0033
σ^R_{ij}	Covariance Spread Shocks	Spread Correlation	0.707	0.707

4.4 Model Evaluation

Table 11 reports the unconditional theoretical second moments for each economy together with their empirical counterparts.[32] The analysis focuses on standard deviations and correlations of GDP (y), investment (i), the trade balance share (tby), capital flows (kf), world

[32]The model is solved using a first-order approximation. Results solving the model with global methods are presented in an extension and are largely robust.

interest rates (R^*) and country spreads (s). The last three rows of the Table depict cross country correlations of income, spreads and capital flows.

Values in bold denote the three dimensions that our empirical analysis zoomed in: the within correlation between country spreads and capital flows, and the cross-country correlations between spreads and capital flows. It is worth recalling at this stage that our calibration strategy disciplined the model by matching the process of spreads in the two countries while leaving the remaining two moments untargeted. Thus, an important litmus test for the model, considering that it matches the correlation of country spreads across countries and output comovement, is whether it can match the negative and low correlation between capital flows and country spreads and the low correlation of capital flows across countries.

Table 11 Empirical and Theoretical Moments

	Brazil		Mexico	
	Data	Model	Data	Model
std(y_t)	1.73	1.73	1.68	1.68
std(i_t)	5.49	5.46	4.40	4.40
std(tby_t)	2.50	2.50	1.63	1.25
std(kf_t/y_t)	3.16	0.73	1.14	0.60
std(R_t^*)	0.45	0.45	0.45	0.45
std(s_t)	0.83	0.83	0.32	0.32
corr(s_t,kf_t/y_t)	**-0.21**	**-0.10**	**-0.03**	**-0.11**
corr(s_t,y_t)	-0.18	0.00	-0.11	0.00
corr(i_t,y_t)	0.86	0.80	0.77	0.79
corr(y_t,y_{t-1})	0.72	0.72	0.83	0.83
	Data		Model	
corr(y_{BR},y_{MEX})	0.30		0.30	
corr(s_{BR},s_{MEX})	**0.65**		**0.65**	
corr((kf_t/y_t)$_{BR}$,(kf_t/y_t)$_{MEX}$)	**0.35**		**0.34**	

NOTE. . Moments in bold denote the three dimensions studied closely in the empirical analysis: the within correlation between country spreads and capital flows (corr(s_t,kf_t/y_t)), and the cross-country correlations between spreads (corr(s_{BR},s_{MEX})) and capital flow (corr((kf_t/y_t)$_{BR}$,(kf_t/y_t)$_{MEX}$)). When calibrating the model, only one of these is targeted –cross-country correlations between spreads– while the other two are not.

The model matches quite accurately not only the business cycle dynamics across the key macroeconomic aggregates, but also the correlation between net capital flows and country spreads for both countries, and the comovement of capital flows across countries.[33] Thus, the model does a good job in replicating some of the most salient features of the Global Financial Cycle in EMEs, accounting for the high (low) comovement between country spreads (net capital flows). To the best of our knowledge, this is the first evidence that an otherwise canonical SOE/RBC framework can reproduce such facts for EMEs.

The model, however, cannot perfectly match the dynamics of net capital flows, delivering a process that is less volatile and more persistent than in the data. We conjecture that this fact may be explained by the lack of richer portfolio decisions which are not captured by the standard small open economy (see, for example, Devereux and Sutherland, 2011). Indeed, it has been shown that extending the standard model to include portfolio decisions is important to characterize capital flows and asset prices (see, for example, Bacchetta et al., 2022). All in all, the canonical model does a reasonable job in matching some of the key empirical facts that define how the Global Financial Cycle impacts country spreads and capital flows both within and across EMEs. We turn next to the analysis of impulse response function and variance decomposition to further describe the inner workings of the calibrated model.

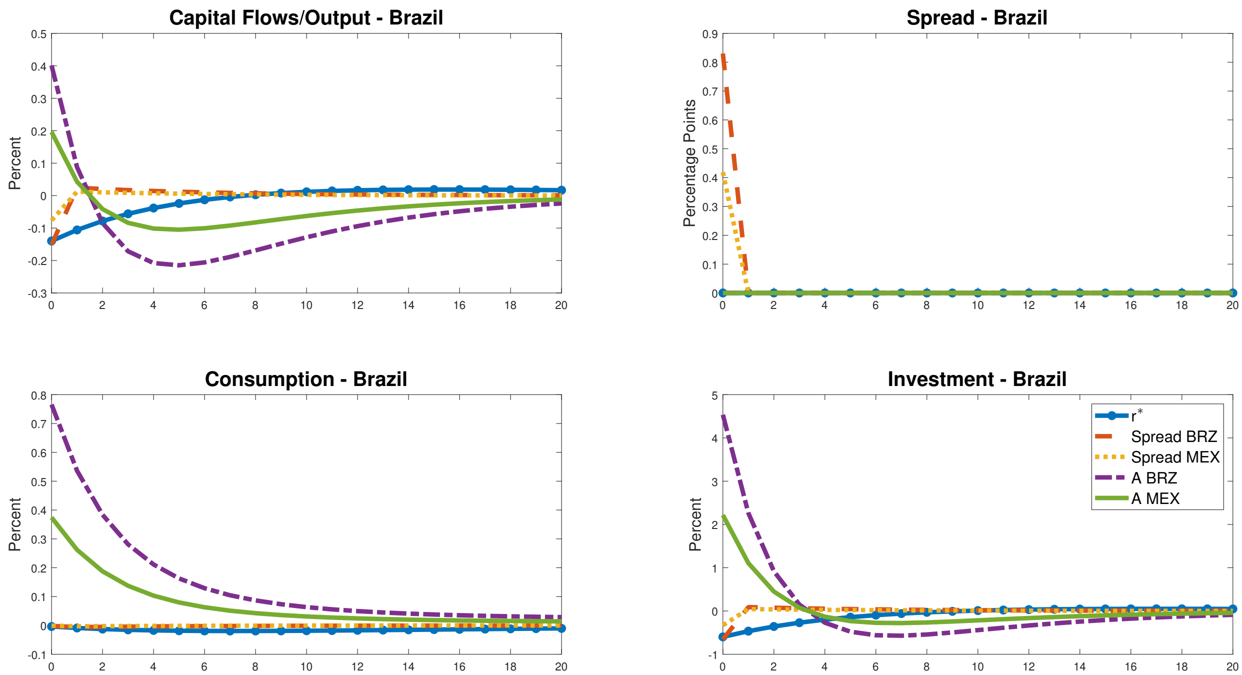
4.5 Impulse Responses

Figure 9 displays the response of capital flows, country spreads, consumption and investment in Brazil to all the shocks considered in the model. Appendix C.2.2 documents the IRFs of additional variables as well as the results for Mexico.

An exogenous one S.D increase in domestic productivity (purple line) induces an immediate increase in capital flows to Brazil, followed by a protracted decrease. These dynamics are explained by the transitory nature of the shock, which induces a shift in the demand for foreign credit in the form of higher consumption and investment to reap the transient benefits of higher productivity. The dynamics of capital flows can be explained by the initial

[33] The absence of a correlation between spreads and income is a mechanical result from assuming an exogenous spread process. This will be addressed in an extension where we endogenize the spread. An expanded set of second moments is presented in the Appendix in Table A.18.

Figure 9 IRFs: The Case of Brazil



NOTE. Response of capital flows-to-output ratio and country spreads in Brazil to a one standard deviation shock in the model. Spread BRZ (Spread MEX) denotes the IRFs to a shock to the interest rate in Brazil (Mexico). A BRZ (A MEX) denotes the IRFs to a TFP shock in Brazil (Mexico). r^* denotes the IRFs to a shock to the international interest rate.

increase in investment due to the observed increase in the marginal productivity of capital, while the subsequent increase in savings allows households to smooth consumption due to the transitory nature of the shock. The spread displays a protracted fall associated to the increase in savings.

An exogenous one S.D increase in the Brazilian spread (red line) increases the country's interest rate, inducing an improvement in the current account associated with capital outflows from the economy. Thus, this shock induces a tightening in the slope of the credit supply curve. The improvement in the current account can be explained both from the fall in investment, due to the increase in the marginal cost of capital.

A one S.D increase in the international interest rate (blue line) induces a shift upwards in the credit supply curve faced by Brazil in international markets, keeping the slope unchanged. In this case, the country spread gradually increases due to the negative effect on business cycle conditions, which then feed into the estimated country spread process. As depicted in the Figure, the shock also induces capital outflows from Brazil due to the increase in the country interest rate which reduce investment.

The IRFs in Figure 9 also reproduce the transmission of shocks to the Mexican economy which, through the comovement in financial assets induced by the Global Financial Cycle, impact the Brazilian economy. Given the matched correlation in spreads in Mexico and Brazil, an increase in the former of one S.D brings about a considerable increase in the Brazilian spread as well as capital outflows from this country. Likewise, the synchronization in business cycles induced by correlated TFP shocks that allows the model to match the business cycle dynamics across Mexico and Brazil, also imply that a transitory improvement in the productivity dynamics of Mexico will be characterized by a similar –though smaller– rise in Brazilian TFP, with the subsequent real effects described before.

4.6 Assessing the Determinants of Synchronization

A central element in our analysis is the role of common credit supply and demand shocks as drivers of the synchronization in prices and quantities that characterize the access of EMEs to global capital markets. In this section we quantify the importance of these drivers through counterfactual experiments performed with the calibrated structural model.

In particular, we simulate the model under three different counterfactuals and, for each case, compute three key moments associated with synchronization: the cross-country correlation of income, spreads and capital flows. The first counterfactual experiment turns off the correlation of TFP shocks across countries (Exp. 1). This allows us to gauge the importance of common credit demand drivers as determinants of the synchronization observed in the data. The second experiment sets the correlation of country spread shocks to zero (Exp. 2). In this case, we eliminate the main source of common credit shocks, allowing us to quantify the extent to which spreads are correlated solely due to business cycle synchronization. The third experiment strikes a balance between the previous two by setting the correlation of country spread shocks equal to the one of TFPs (Exp. 3). In all the experiments we only adjust the corresponding parameter in the variance covariance matrix of perturbations, keeping the remaining parameters unchanged relative to the baseline calibration (see Table 10). Table 12 documents the findings from each experiment. For comparison, the first two columns reproduce the second moments from the data and the baseline calibrated model, respectively. The last three columns gather results from each of the three counterfactual experiments.

Table 12 Unconditional Moments - Baseline and Counterfactual Experiments

	Data	Baseline	Exp. 1	Exp. 2	Exp. 3
corr(y_{BR},y_{Mex})	0.30	0.30	0.00	0.30	0.30
corr(s_{BR},s_{MEX})	0.65	0.65	0.65	0.00	0.30
corr(kf_{BR},kf_{MEX})	0.35	0.34	0.08	0.28	0.33

Note. Unconditional moments computed using simulated data from the theoretical two-EME model presented in this section. Variables y, s, and kf denote income, spreads and capital flows, respectively. Baseline denotes the moments computed the baseline calibration described in Section 4.3. Exp. 1 denotes the moments computed using the baseline calibration but assumes that $\sigma^{A}_{i,j} = 0$ (i.e., no correlation between productivity shocks). Exp. 2 denotes the moments computed using the baseline calibration but assuming $\sigma^{R}_{i,j} = 0$ (i.e. no correlation between country interest rate shocks). Exp. 3 denotes the moments computed using the baseline calibration but assuming the correlation between sovereign spreads equals the one of output $\sigma^{R}_{i,j} = \sigma^{A}_{i,j}$.

A few novel results emerge from Table 12. As the findings from the first experiment illustrate, business cycle synchronization through correlated fundamentals (i.e TFP) is key for explaining capital flows comovement. When the TFP correlation across countries is turned off, business cycle synchronization fades away completely and the correlation between GDP across the two economies is zero.[34] This, however, bears no impact in the correlation of spreads which remains as high as in the baseline case and the data (0.65) due to the exogenous spread process assumed as baseline. This underscores how the Global Financial Cycle manifests in a strong comovement across asset returns that is largely disconnected from fundamentals in EMEs. In contrast, the correlation across capital flows reduces to about one fourth that of the baseline, from 0.34 to 0.08. This finding is consistent with the importance of common productivity shocks when accounting for the synchronization in capital flows across EMEs, as documented also in Table A.20.

[34]Note that this is not a mechanical result, because the correlation of GDP across countries could still be positive, linked to the world interest rate that acts as additional common driving force. In practice, however, this driving force produces no common movement in income across the two countries.

Another relevant result is revealed when turning off the common perturbations in spreads across the two EMEs (Exp.2.) capturing the Global Financial Cycle in the model. Doing so does not affect the correlation between capital flows or income significantly, but considerably impacts the synchronization in spreads. Indeed the correlation across income remains unchanged (0.30) and that of capital flows diminishes only slightly from 0.34 to 0.28. [35] Thus, capital flows seem to be determined by demand shocks more than shifts in international credit supply, in line with the findings presented in Table A.19.

Finally, when we set the common perturbations in spreads across the two EMEs –capturing the Global Financial Cycle– equal to the correlation of TFPs (Exp.3), the correlation across income remains unchanged (0.30) and that of capital flows diminishes only marginally from 0.34 to 0.33. This further corroborates that the correlation of spreads over that of business cycle synchronization does not appear to affect quantitatively the synchronization of capital flows.

In sum, the differences in synchronization in spreads and capital flows –the high correlation between country spreads and the relatively low correlation between capital flows– can be traced back to the different nature of the shocks driving them. While common credit supply shocks –which capture the Global Financial Cycle— are an important source of country spread fluctuations, common TFP shocks are key to understand the synchronization of net capital flows to EMEs.

4.7 Extensions of the Theoretical Model

In this section we assess the robustness of our results after considering different extensions and alternative solution methods to the baseline model presented above. A first extension considers a richer process of the domestic interest rate. The second extension considers "credit risk shocks" by allowing the elasticity of the interest rate with respect to external

[35] The lack of impact on the correlation of incomes across countries is linked to the fact that we assume an exogenous process for spreads and no working capital constraints. We will relax this in the extensions considered below.

to be stochastic, thereby inducing shifts in the slope of the credit supply curve. Lastly, we use global methods to solve our baseline model to assess the role that linearization methods used in our baseline results might be reducing the volatility of some of the key variables that we study, namely capital flows.

Estimated Interest Rate Processes

The baseline model assumes that the sovereign spread does not depend on domestic macroeconomic conditions. However, SOE-RBC models, akin to the one we employ, cannot properly account for spread dynamics unless enriched with a minimal setup of default in equilibrium. Following the specification of Uribe and Yue (2006), we extend the model by estimating an interest rate process for each of these economies, allowing for correlated sovereign spread shocks across the two economies. This extension is important to link credit conditions to the business cycle. In particular, the interest rate faced by each economy in international financial markets evolves according to:

$$\begin{aligned}\hat{R}_t &= \rho_R \hat{R}_{t-1} + \rho_{R^*} \hat{R}^*_t + \rho_{R1^*} \hat{R}^*_{t-1} + \rho_y \hat{y}_t \\ &+ \rho_{y1} \hat{y}_{t-1} + \rho_i \hat{\imath}_t + \rho_{i1} \hat{\imath}_{t-1} + \rho_{tby} tby_t \\ &+ \rho_{tby1} tby_{t-1} + \epsilon^r_t\end{aligned}$$

where variables with $\hat{x}$ denote log-deviations with respect to the steady state, $tby_{i,t}$ is the trade balance-to-output ratio, and ϵ^r_t denotes the shock to the country interest rate. The estimated interest rate for each country are consistent with the estimation of Uribe and Yue (2006) (see Table A.21 included in the Appendix). The spread between domestic and foreign rates is defined as $s_t = R_t/R^*_t$. The calibration remains unchanged relative to the one presented in Table 10 and the theoretical moments remain almost unchanged. Results are presented in Appendix C.3.1. We redo the decomposition of the role of the different frictions in explaining the synchronization of capital flows across economies as explained in

Section 4.6. Table 13 displays the results.

Table 13 Unconditional Moments - Estimated Interest Rate - Baseline and Counterfactual Experiments

	Data	Baseline	Exp. 1	Exp. 2	Exp. 3
corr(y_{BR},y_{Mex})	0.30	0.30	0.00	0.30	0.30
corr(s_{BR},s_{MEX})	0.65	0.65	0.64	0.24	0.30
corr(kf_{BR},kf_{MEX})	0.35	0.39	0.18	0.37	0.37

NOTE. Unconditional moments computed using simulated data from the theoretical two-EME model augmented with the estimated interest rate process. Variables y, s, and kf denote income, spreads and capital flows, respectively. Baseline denotes the moments computed the baseline calibration described in Section 4.3. Exp. 1 denotes the moments computed using the baseline calibration but assumes that $\sigma^A_{i,j} = 0$ (i.e., no correlation between productivity shocks). Exp. 2 denotes the moments computed using the baseline calibration but assuming $\sigma^R_{i,j} = 0$ (i.e. no correlation between country interest rate shocks). Exp. 3 denotes the moments computed using the baseline calibration but assuming the correlation between sovereign spreads equals the one of output $\sigma^R_{i,j} = \sigma^A_{i,j}$.

The main findings of the baseline model hold. First, business cycle synchronization accounts for more than half of capital flows comovement. Second, correlated spread shocks explain little of capital flows comovement across these two economies. The main difference in this specification is that spreads comove even if there are no correlated spread shocks due to the estimated interest rate processes, where the interest rate responds to business cycle conditions. Capital flows are moslty explained by credit demand shocks.

Credit Risk Shocks

While the baseline model is successful in replicating the observed cross-country correlation in capital flows and the within-country correlation between capital flows and country spreads, it underpredicts the volatility of capital flows. In this section we document how three modifications of the baseline setup allow the model to improve its performance in this particular dimension.

First, we shift from Portfolio Adjustment Costs to the Internal Debt Elastic Interest rate as closing device (see Schmitt-Grohe and Uribe, 2003). In this specification, the interest rate that the country faces in international credit markets depends on the stock of external debt. Second, we assume that households internalize that their debt decisions affect the interest rate when they decide how much to consume and save, thereby impacting capital flows. Third, we allow the elasticity of the interest rate with respect to external debt to be stochastic. In particular, the country interest rate process in this version of the model is described by the following equations:

$$\begin{aligned} R_t &= R_t^* + \psi_t \left((d_t - \bar{d}) - 1 \right) + \epsilon_t^r \\ \psi_t &= \psi + \epsilon_t^\psi \end{aligned}$$

where ψ is the steady state value of ψ_t and ϵ_t^ψ denotes a "credit risk shock" to the elasticity of the interest rate with respect to the level of debt.[36][37]

Unlike shifts in the international interest rate and the country spread –which shift the credit supply curve in parallel (see the left panel of Figure 1b)–, a credit risk shock induces a shift in the *slope* of the credit supply (see the right panel of Figure 1b), further amplifying the impact on flows. Moreover, the fact that households internalize the level of debt in their optimal decisions induces additional variability in capital flows.

The rest of the equations in the model, including the process for the international interest rate are left unchanged. We calibrate the correlation between ϵ_t^ψ across countries such that the model matches the comovement of capital flows.[38] We calibrate ψ in steady state to match the trade balance-to-output ratio in steady state and the variance of ϵ_t^ψ to match the volatility of capital flows to output. The rest of the parameters remain unchanged with respect to the baseline calibration. The comovement between interest rates is generated by the correlated spread shock ϵ_t^r as in the baseline model. Table A.25 included in the Appendix displays the moments from this model. The model can now match the volatility of capital

[36] Seoane (2016) considers a similar setup, although within a different motivation than ours.

[37] The introduction of noise traders is another device that has been used to induce more volatility in small open economy models, particularly when matching the observed volatility of exchange rates (Gabaix and Maggiori, 2015; Itskhoki and Mukhin, 2021). It should be noted, however, that such device would not remedy the relatively lower volatility in capital flows in our setup. For this modeling device assumes that noise traders follow a zero-capital strategy by taking a long position in foreign debt (or currency) and shortening an equal value in home debt (or currency). Hence, while noise trading shocks may alter the relative price of flows (the equilibrium exchange rate), they do not alter the net volume of flows.

[38] If we set the comovement equal to 0, the comovement of capital flows across these two economies is 0.03.

flows. However, the changes now induce an excess volatility in investment, associated with capital flows.[39] While the correlation between capital flows and country spreads at the country level is similar to the baseline model, the comovement between capital flows across countries drops from 0.35 to 0.03. Overall, while adding these new features to our baseline framework may improve the model's ability to match capital flows' volatility, they do entail a considerable trade off in terms of its performance along other dimensions.

Solving the Model with Global Methods

The baseline model is solved using first-order Perturbation methods, which is popular in the international macroeconomic models (see, for example, Schmitt-Grohe and Uribe, 2003). de Groot et al. (2019) compare the moments of small open economy models with incomplete markets computed with perturbation methods relative to those computed with fixed-point-iteration global solutions. They show that, under certain parametrizations, these two methods may deliver very different results, specially for the Net Foreign Asset position that is key for our analysis.

Motivated by these observations, in this section we solve our baseline model using fixed-point-iteration global solutions to assess if the previous analysis is affected by the specific solution method used. In particular, we use the Fixed-Point Iteration Algorithm (FiPIt) developed by Mendoza and Villalvazo (2020). This method is based on fixed-point iteration on Euler equations instead of time iteration and endogenous grid algorithms. First, we solve the baseline model presented before, including the Portfolio Adjustment Costs to avoid the unit root in the NFA. Second, we set $\beta(1+r^*) < 1$ and we drop the Portfolio Adjustment Costs, since they are not necessary in this case. In both cases we keep the parametrization as close as possible to the original one and we only recalibrate some parameters following the same calibration strategy described in Section 4.3.

[39] We decided in this exploration to keep constant the parameter governing the strength of capital adjustment costs (ϕ) in order to illustrate the large increase in the volatility of real variables that this modification entails.

Appendix C.3.1 displays the value of the calibrated parameters, some additional details of the simulation, and the theoretical moments. The main takeaway is that the performance of the model in some of the moments that we study does indeed improve with this solution method, particularly along the dimension that previously the model was largely underperforming: the volatility of capital flows. Indeed, we find that the capital flow volatility in Brazil doubles compared to our baseline results, reducing the gap considerably with that in the data. Likewise, for Mexico, the model's implied volatility of capital flows also doubles and now matches that in the data. This comes from the fact that the baseline linearized model displays values of the Portfolio Adjustment Costs that are close to zero, thereby imposing a natural limit to the volatility of capital flows tolerated without displaying a unit root process in the debt process. Instead, the model solved with global methods does not suffer from such constraint and can thus better account for the volatility in capital flows. However, it should be noted that this comes at a cost, since the cross-country correlation in capital flows increases to 0.63, above that in the data (0.35).

5 Conclusions

Access to world capital markets by EMEs has historically been volatile. We have investigated the origins of this volatility by pinning down the demand and supply shocks driving it which, in turn, we map to global vs. idiosyncratic sources. We find that the price of this access to capital markets –the country spreads that EMEs face relative to the world interest rates– is predominantly determined by global supply forces, which can in turn be traced back to US monetary policy. Furthermore, at those prices, idiosyncratic factors play an important role in explaining fluctuations in capital flows.

We show that a calibrated structural model calibrated to multiple EMEs and augmented with correlated productivity and country interest rate shocks matches well some of these dynamics. The correlation between productivity shocks explains around half of capital flows comovement while it does not affect the correlation of sovereign spreads. The correlation between interest rate shocks explains around two thirds of fluctuations in spreads while they do not affect significantly the observed correlation of net capital flows.

Our work has been silent about policy implications. A fruitful area for subsequent work is to explore the extent to which the decomposition of the drivers in capital flows and prices that we do can contribute to further enhance the understanding of the interaction between capital flow volatility and policy responses (Forbes and Warnock, 2012; Ghosh et al., 2018; IMF, 2012). Arguably, a better understanding of these drivers is a promising way to further devise policy tools to mitigate the real effect that fickle capital flows entail.

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A Data Appendix

A.1 Empirical Analysis

Capital flows series are computed using equation (3). The variables are obtained from:

- X: exports in current USD FOB at monthly frequency. Source: International Financial Statistics, IMF.
- M: imports in current USD CIF at monthly frequency. Source: International Financial Statistics, IMF.
- R: stock of foreign reserves in current usd at monthly frequency: Source: International Financial Statistics, IMF.

The series of capital flows is expressed in real terms using the series of U.S. Producer Price Index by Commodity: All Commodities (PPIACO) available at FRED.

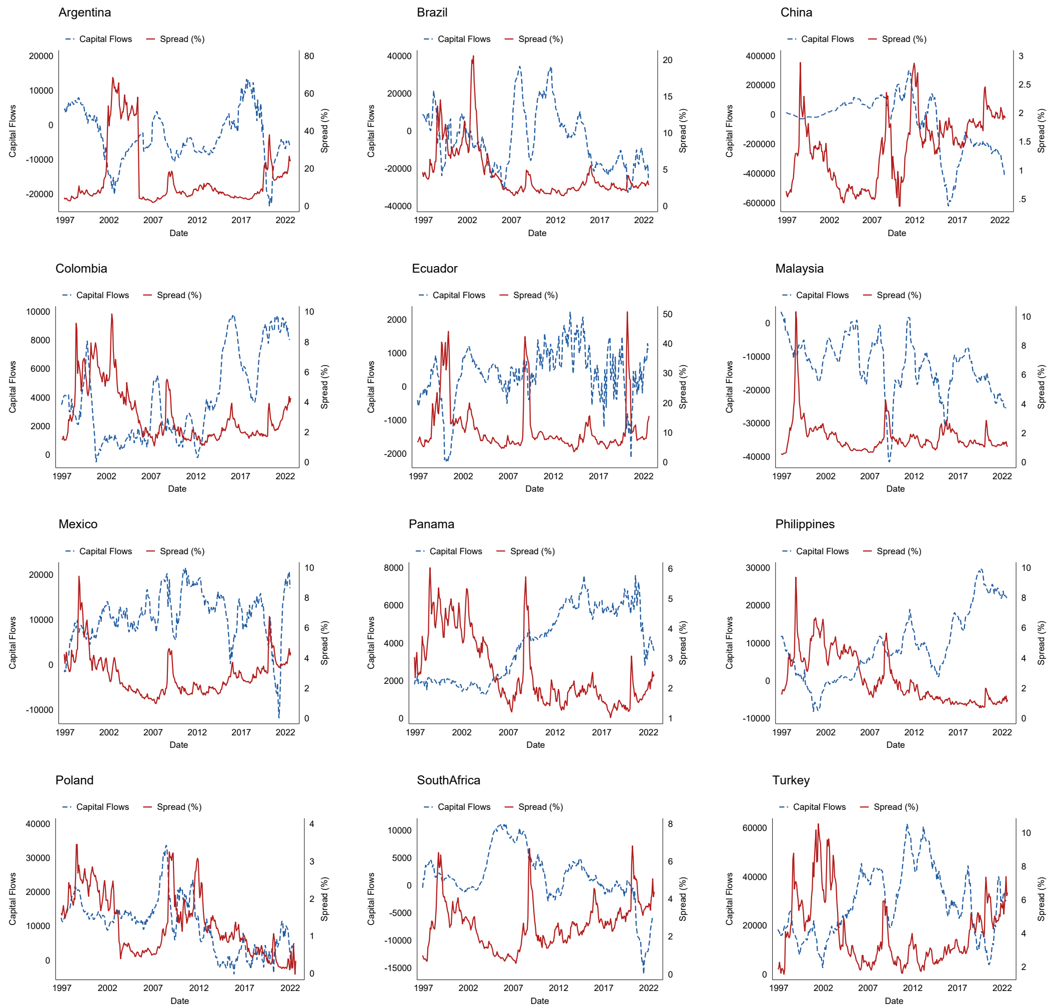
Country spreads are proxied by the monthly average of the JP Morgan Emerging Market Bond Index Global (Stripped Spread).

Figure A.1 displays the evolution of capital flows and sovereign spread by country.

A.2 Structural Multi-Country Model

We compute moments for Brazil and Mexico to calibrate the two-EME model and to estimate the interest rate equation. The data comes from the International Financial Statistics (IFS) database compiled by the IMF. We use national sources of information from national accounts for cases where IFS database did not contain information. Output and investment were downloaded in domestic currency and nominal terms, and the trade balance was downloaded in domestic currency real terms. We deflate output and investment using the GDP deflator. We compute the trade balance-to-output ratio as the trade balance expressed in real terms divided by output expressed in real terms. In order to extract the cyclical components, we

Figure A.1 Capital Flows and Country Spreads by Country



Note. Series of capital flows and country spreads used in the Empirical Analysis.

apply the Hodrick-Prescott filter with $\lambda = 1600$ to the series of real output, real investment, and trade balance-to-output expressed in logs. To estimate the interest rate processes, we follow Uribe and Yue (2006) and extract a log quadratic trend from the series of real output and real investment before estimating the process.

B Additional Empirical Results

B.1 Correlation between Capital Flows and Country Spreads within EMEs

Table 1 displays the correlation between net capital flows and country spread at the country level, using all the sample and excluding periods of Sudden Stops. As explained in the draft, we define periods of Sudden Stops following Calvo et al. (2008) as periods when: i) there is at least one observation where the year-on-year decline in capital flows lies at least two standard deviations below its sample mean; this condition fulfills the 'unpredicted' prerequisite of a sudden stop, ii) the period of sudden stop phase ends when the annual change in capital flows surmounts one standard deviation below its sample mean. This commonly suggests persistence which is a common fact of sudden stops, iii) additionally, in order to ensure symmetry, the onset of a sudden stop phase is ascertained by the first time the annual change in capital flows drops one standard deviation below the mean. Both the first and second moments of the capital flow series are calculated each period using an expanding window with a minimum of 24 (months of) observations and a start date fixed at January 1997, which intends to capture the evolving behavior of the series. Table A.1 displays the periods of Sudden Stops identified in our baseline sample according to this definition.

Table A.2 displays the serial correlation between country spreads and capital flows for each country. The negative and low correlation observed contemporaneously also holds using lags and leads.

B.2 Correlation between Capital Flows across EMEs

Figure 3 shows that there is a low correlation of net capital flows across EMEs. Net capital flows are defined as the sum of the change in foreign reserves plus the difference between imports and exports (see equations 3 and 4). In this section we compute the cohesion for each component of the series of net capital flows separately (i.e. for the change in foreign

Table A.1 List of Systemic Sudden Stop Episodes (1997m1 to 2022m7)

Country	Begins	Ends
Argentina	2000m11	2002m10
Argentina	2018m9	2020m8
Brazil	1999m1	1999m8
Brazil	2008m7	2009m7
China	2005m12	2007m1
China	2008m10	2009m8
China	2011m12	2013m3
China	2014m9	2016m5
Colombia	1997m12	1999m3
Colombia	2000m6	2001m7
Ecuador	1999m7	2000m9
Ecuador	2016m3	2016m7
Ecuador	2017m9	2017m12
Ecuador	2020m3	2020m11
Malaysia	2005m11	2006m10
Malaysia	2008m9	2009m8
Mexico	2009m3	2009m12
Mexico	2015m6	2016m3
Mexico	2019m11	2021m7
Panama	1998m2	1998m5
Panama	1999m6	1999m10
Panama	2001m7	2002m8
Panama	2003m12	2004m10
Panama	2015m9	2016m8
Panama	2020m7	2020m7
Panama	2021m4	2022m6
Phillippines	1997m6	1999m7
Phillippines	2000m3	2001m4
Phillippines	2012m3	2013m2
Poland	1997m1	1997m7
Poland	1999m3	2000m9
Poland	2008m11	2009m9
Poland	2012m2	2012m8
South Africa	1997m1	1997m2
South Africa	2008m8	2009m9
South Africa	2010m8	2011m9
South Africa	2020m9	2021m10
Turkey	1998m10	1999m9
Turkey	2001m6	2002m3
Turkey	2008m10	2009m12
Turkey	2012m4	2012m9
Turkey	2014m3	2016m4
Turkey	2018m10	2019m8

NOTE. Episodes of Systemic Sudden Stops in our baseline sample. These episodes are defined following the definition of Calvo et al. (2008).

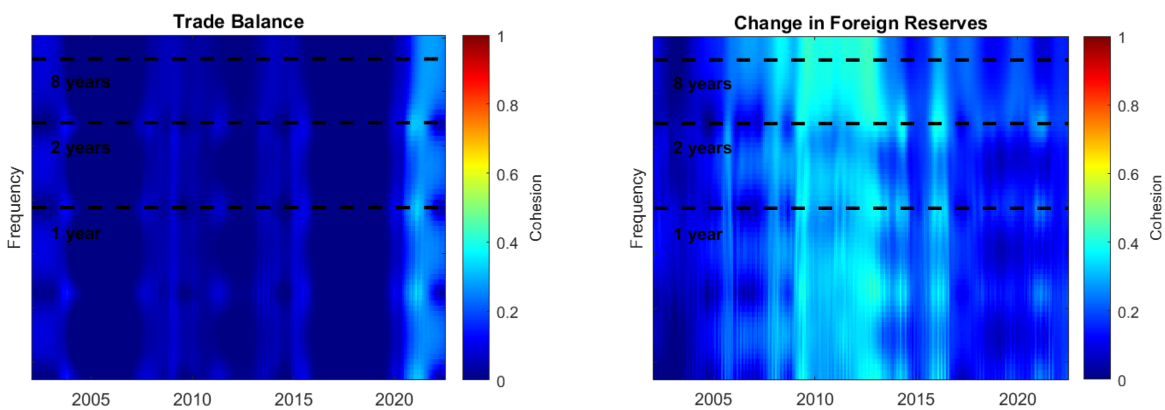
reserves and the difference between imports and exports). Figure A.2 displays the cohesion measure for each component.

Table A.2 Intertemporal Correlation between Capital Flows and Sovereign Spreads at the Country Level

	ARG	BRZ	CHN	COL	ECU	MEX	MLY	PAN	PHL	POL	SWF	TUR	**Median**
$\rho(s,f)L6$	0.12^{**}	0.01	-0.08	-0.09	0.07	0.12^{**}	-0.03	-0.04	0	0	-0.13^{**}	0	0
$\rho(s,f)L5$	0.12^{**}	-0.01	-0.11^{*}	-0.08	0.01	0.09	-0.04	0	-0.01	-0.04	-0.16^{***}	-0.02	-0.01
$\rho(s,f)L4$	0.10^{*}	-0.02	-0.14^{**}	-0.06	-0.03	0.06	-0.06	0	-0.03	-0.05	-0.17^{***}	-0.05	-0.04
$\rho(s,f)L3$	0.07	-0.04	-0.16^{***}	-0.08	-0.04	0.03	-0.09	-0.02	-0.04	-0.09	-0.17^{***}	-0.08	-0.06
$\rho(s,f)L2$	0.06	-0.05	-0.16^{***}	-0.09	-0.07	-0.02	-0.05	-0.02	-0.07	-0.09	-0.16^{***}	-0.10^{*}	-0.07
$\rho(s,f)L1$	0.03	-0.08	-0.18^{***}	-0.10^{*}	-0.10^{*}	-0.03	-0.02	0	-0.08	-0.10^{*}	-0.14^{**}	-0.11^{**}	-0.09
$\rho(s,f)F0$	0	-0.12^{**}	-0.20^{***}	-0.13^{**}	-0.11^{*}	-0.07	-0.03	0	-0.10^{*}	-0.15^{**}	-0.15^{***}	-0.16^{***}	-0.11
$\rho(s,f)F1$	-0.02	-0.12^{**}	-0.22^{***}	-0.15^{***}	-0.11^{*}	-0.11^{*}	-0.03	0	-0.12^{**}	-0.17^{***}	-0.17^{***}	-0.18^{***}	-0.12
$\rho(s,f)F2$	-0.02	-0.11^{**}	-0.22^{***}	-0.15^{***}	-0.10^{*}	-0.11^{*}	-0.01	0	-0.13^{**}	-0.18^{***}	-0.16^{***}	-0.14^{**}	-0.12
$\rho(s,f)F3$	-0.04	-0.10^{*}	-0.19^{***}	-0.14^{**}	-0.10^{*}	-0.11^{**}	0	-0.03	-0.14^{**}	-0.15^{***}	-0.15^{***}	-0.10^{*}	-0.11
$\rho(s,f)F4$	-0.04	-0.11^{*}	-0.17^{***}	-0.14^{**}	-0.11^{*}	-0.11^{*}	-0.02	-0.02	-0.15^{**}	-0.11^{**}	-0.17^{***}	-0.07	-0.11
$\rho(s,f)F5$	-0.06	-0.1^{*}	-0.14^{**}	-0.14^{**}	-0.13^{**}	-0.09^{*}	-0.02	-0.02	-0.14^{**}	-0.10^{*}	-0.17^{***}	-0.05	-0.10
$\rho(s,f)F6$	-0.07	-0.10^{*}	-0.14^{**}	-0.11^{*}	-0.10^{*}	-0.11^{*}	-0.02	-0.02	-0.15^{***}	-0.08	-0.14^{**}	-0.01	-0.10

Note. Intertemporal correlation between capital flows $()andEMBI()$ of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:1-2022:7. Capital flows is defined as the cumulative trade deficit plus the change in international reserves at monthly frequency (see equation (3)). Significance level: $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Figure A.2 Cohesion of Each Component of Net Capital Flows



Note. Cohesion measure (Croux, Forni and Reichlin, 2006) between EMBI and net Capital Flows of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:2-2022:7. Net Capital flows is defined as the cumulative trade deficit and as the change in international reserves at monthly frequency.

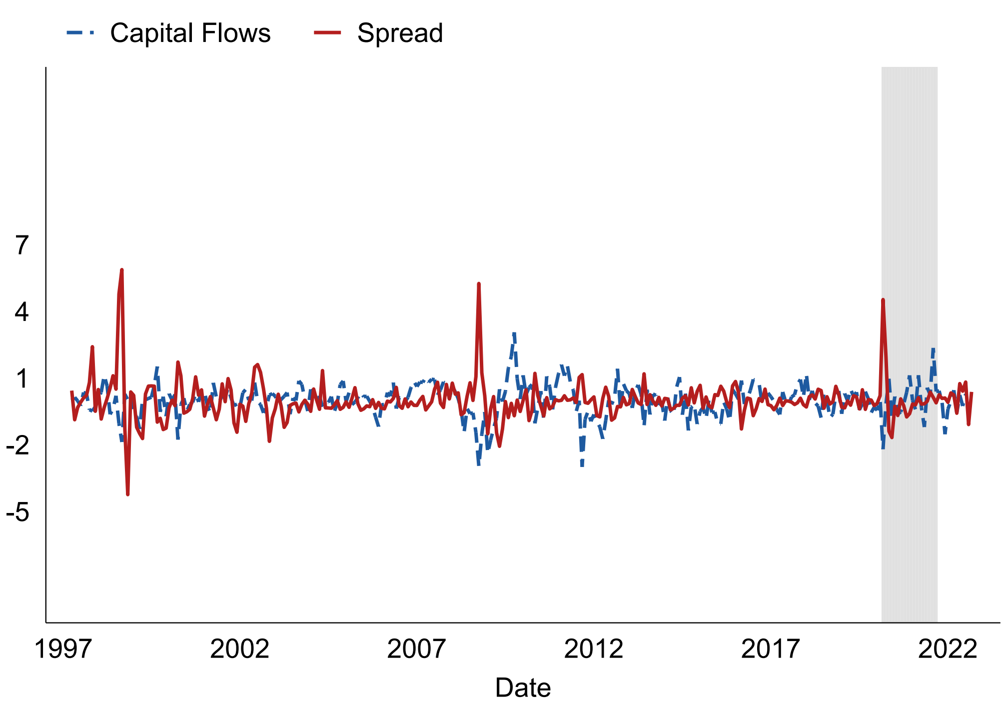
The change in foreign reserves is more correlated across EMEs than the one related with the trade balance. However, the maximum correlation is around 0.4, which is significantly lower than the corresponding number for country spreads (see Figure 3). Thus, both components of the proxy for net capital flows are important for understanding the relatively lower correlation of capital flows across EMEs.

B.3 Dynamic Factors

B.3.1 Non-Cumulated Factors

Figure 4 included in Section 3.3 displays both factors cumulated to enhance the analysis, following previous works (see, for example, Rey, 2013). Figure A.3 displays the dynamic factors of country spreads and capital flows without cumulating them.

Figure A.3 Common Factor for Country Spreads and Capital Flows



Note. Dynamic factors between capital flows and EMBI of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:2-2022:7 in levels (without cumulating). Capital flows is defined as the cumulative trade deficit plus the change in international reserves at monthly frequency.

B.3.2 Alternative Variance Decomposition

Tables 6 and 7 display the one-year ahead variance decomposition using the baseline DFM (Eq. 5) identified with sign restrictions. We use this measure to capture the dynamic contribution of each shock. However, previous works have used the R^2 as a measure to quantify the contribution of the Global Financial Cycle in driving asset prices and capital flows (see, for example, Rey, 2013; Miranda-Agrippino et al., 2020; Cerutti et al., 2019c;

among others). In this section we compute the variance decomposition on impact, which is the closer measure to compare relative to previous works. Tables A.3 and A.4 display the variance decomposition of country spreads and net capital flows driven by the four credit market shocks, respectively. The results are very similar to the baseline ones. The main conclusions regarding the importance of external vs idiosyncratic shocks remains unchanged. While Global and common EME shocks are equally important in accounting for fluctuation in country spreads, Global credit shocks are relatively more important than common EME credit shocks in explaining capital flows fluctuations.

Table A.3 Share of Variance of Country Spreads Explained by Each Shock - On Impact

	F_t^s	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	64	6	41	25	48	18	58	42	50	48	35	41	35	41
$\varepsilon_t^{D,G}$	36	3	23	14	27	10	32	23	28	27	19	23	19	23
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	9	64	39	75	28	90	65	78	75	54	64	54	64
$\varepsilon_t^{S,I}$	0	51	18	30	14	37	5	18	11	13	24	18	26	18
$\varepsilon_t^{D,I}$	0	40	18	31	12	36	5	17	11	12	22	19	20	18
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	91	36	61	25	72	10	35	22	25	46	36	46	36

NOTE. Variance decomposition on impact of country-specific and common (Factor) spreads due explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

Table A.4 Share of Variance of Net Capital Flows Explained by Each Shock - On Impact

	F_t^k	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	64	1	33	13	2	2	5	18	1	4	14	5	9	5
$\varepsilon_t^{D,G}$	36	1	18	8	1	1	3	10	1	2	8	2	5	3
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	2	51	21	3	3	8	28	2	6	22	7	14	8
$\varepsilon_t^{S,I}$	0	55	25	39	52	49	44	37	49	48	40	45	48	46
$\varepsilon_t^{D,I}$	0	43	24	40	45	48	48	35	49	46	38	48	38	44
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	98	49	79	97	97	92	72	98	94	78	93	86	90

NOTE. Variance decomposition on impact of country-specific and common (Factor) capital flows due explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

B.3.3 Extensions of the Baseline DFM

The baseline DFM model only consider emerging economies. In this section we present the results from an extended version of the DFM that considers advanced economies. In particular, we include Australia, Canada, Denmark, Finland, Germany, Italy, Japan, Norway, UK, US and Switzerland. This extension allows to identify global credit shocks, which affect all the economies; common EME credit shock, which affect all EMEs; and idiosyncratic credit shocks. Tables A.5 and A.6 display the variance decomposition of country spreads and capital flows explained by each of the six shocks, respectively.

Table A.5 Share of Variance of Country Spreads Explained by Each Shock - Extended Sample

	$F_t^{s,G}$	$F_t^{s,EME}$	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	51	0	3	9	33	18	3	20	23	26	20	29	20	13	20
$\varepsilon_t^{D,G}$	49	0	2	8	29	16	3	18	20	22	17	27	18	11	17
$\varepsilon_t^{S,EME}$	0	54	3	31	2	27	13	19	28	18	23	6	17	18	18
$\varepsilon_t^{D,EME}$	0	46	3	26	1	22	11	15	23	14	18	5	14	15	15
Total External	100	100	11	74	65	83	30	72	94	80	78	67	69	57	70
$\varepsilon_t^{S,I}$	0	0	50	13	18	9	36	15	3	10	12	17	15	24	15
$\varepsilon_t^{D,I}$	0	0	39	13	17	8	34	13	3	10	10	16	16	19	15
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	0	89	26	35	17	70	28	6	20	22	33	31	43	30

NOTE. One-year ahead variance decomposition of country-specific and common (Factors) country spreads explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, EME credit supply shocks $\varepsilon_t^{S,EME}$, EME credit demand shocks $\varepsilon_t^{D,EME}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$. The shares are computed using the DFM model with 23 economies, including G7 and small open advanced economies as described in Section.

Table A.6 Share of Variance of Capital Flows Explained by Each Shock - Extended Sample

	$F_t^{k,G}$	$F_t^{k,EME}$	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	51	0	1	14	21	4	2	14	9	0	6	15	12	9	9
$\varepsilon_t^{D,G}$	49	0	0	13	21	4	2	14	9	0	5	14	12	9	9
$\varepsilon_t^{S,EME}$	0	54	0	0	8	4	0	0	0	0	0	0	1	0	1
$\varepsilon_t^{D,EME}$	0	46	0	0	9	3	0	1	0	0	0	0	0	1	1
Total External	100	100	1	27	59	15	4	29	18	0	11	29	25	19	20
$\varepsilon_t^{S,I}$	0	0	56	36	20	46	49	36	38	50	46	36	38	46	42
$\varepsilon_t^{D,I}$	0	0	43	37	21	39	47	35	44	50	43	35	37	35	38
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	0	99	73	41	85	96	71	82	100	89	71	75	81	80

NOTE. One-year ahead variance decomposition of country-specific and common (Factors) capital flows explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, EME credit supply shocks $\varepsilon_t^{S,EME}$, EME credit demand shocks $\varepsilon_t^{D,EME}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$. The shares are computed using the DFM model with 23 economies, including G7 and small open advanced economies as described in Section.

B.3.4 Alternative DFM Specification

In the baseline DFM model presented in equation (5) only the factor displays persistence, something that may be affecting the estimation. Thus, we extend the DFM to account for persistence in the idiosyncratic innovations:

$$
\begin{aligned}
X_t &= \beta F_t + \epsilon_t + \alpha \epsilon_{t-1} \\
F_t &= \gamma F_{t-1} + \eta_t
\end{aligned} \tag{12}
$$

where the variables denote the same as in the baseline spefication. Tables A.7 and A.8 display the one-year ahead forecast error variance of country spreads and capital flows due to each type of shock. The estimated contributions remain almost unchanged relative to the baseline results presented in Tables 2 and 3.

Table A.7 Share of Variance of Country Spreads Explained by Each Shock - Alternative DFM

	F_t^s	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	63	6	35	24	48	15	56	38	49	48	35	39	34	36
$\varepsilon_t^{D,G}$	37	4	21	14	28	9	34	23	29	28	21	23	20	22
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	10	56	38	76	24	90	61	78	76	56	62	54	58
$\varepsilon_t^{S,I}$	0	45	22	31	12	38	5	19	11	12	22	19	23	21
$\varepsilon_t^{D,I}$	0	45	22	31	12	38	5	20	11	12	22	19	23	21
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	90	44	62	24	76	10	39	22	24	44	38	46	42

NOTE. One-year ahead variance decomposition of country-specific and common (Factor) country spreads explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$. The shares are computed using the estimated DFM model presented in equation (12).

Table A.8 Share of Variance of Net Capital Flows Explained by Each Shock - Alternative DFM

	F_t^k	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	63	1	12	14	4	2	7	9	1	3	16	8	10	7
$\varepsilon_t^{D,G}$	37	1	7	8	2	1	4	5	1	1	9	5	6	5
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	2	19	22	6	3	11	14	2	4	25	13	16	12
$\varepsilon_t^{S,I}$	0	49	40	39	47	48	44	43	49	48	37	44	42	44
$\varepsilon_t^{D,I}$	0	49	41	39	47	49	45	43	49	48	38	43	42	44
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	98	81	78	94	97	89	86	98	96	75	87	84	88

NOTE. One-year ahead variance decomposition of country-specific and common (Factor) net capital flows explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$. The shares are computed using the estimated DFM model presented in equation (12).

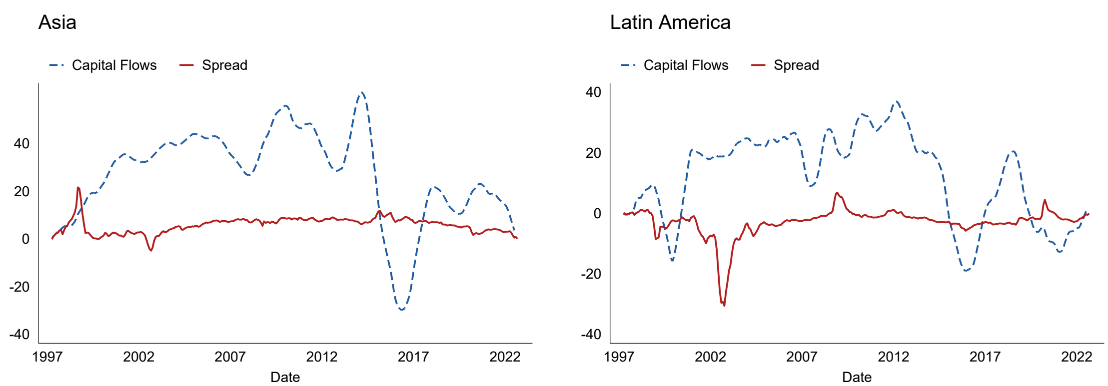
B.3.5 Regional Factors

To quantify the role of regional factors, we estimate the following modified DFM:

$$X_t = \beta F_t + \beta_R F_{R,t} + \epsilon_t \tag{13}$$
$$F_t = \gamma F_{t-1} + \eta_t$$

where $F_{R,t}$ denotes the regional factors of country spreads and capital flows which affect all the countries that belong to that region. The Latin American factor considers the following countries from the baseline sample: Argentina, Brazil, Colombia, Ecuador, Mexico, and Panama. The Asian factor includes: China, Malaysia, Philippines, and Turkey. Poland and South Africa do not belong to any of these regional factors and they are only considered for the common EMEs factors. Figure A.4 displays the estimated regional factors of capital flows and country spreads for Asian and Latin American countries.

Figure A.4 Regional Factors of Country Spreads and Capital Flows



NOTE. Series of cumulated regional factors of capital flows and country spreads estimated with a DFM that includes a global and regional factors for spreads and capital flows. The DFM is specified as in equation (13).

The cumulated factors reflect comovement of capital flows and country spreads at the regional level related with some important events. For example, the factor of country spreads in Asia spiked in 1997, related with the Asian crisis. This comovement in spread amplifies the comovement of country spreads that is observed in the common EMEs factor (see Figure 4).

B.4 Alternative Empirical Specifications

This Section displays the results of the empirical analysis performed using alternative datasets. These exercises are described in Section 3.6.

B.4.1 Alternative Datasets

Table A.9 displays the correlations between capital flows and country spreads for each EME using different datasets for capital flows and country spreads. The main conclusion that the correlation between these variables is negative and low is robust using different datasets.

Table A.9 Correlation between Alternative Measures of Capital Flows and Country Spread

	ARG	BRZ	CHN	COL	ECU	MEX	MLY	PAN	PHL	POL	SWF	TUR	Median
Baseline	0.00	-0.12^{**}	-0.19^{***}	-0.13^{**}	-0.10^{*}	-0.07	-0.02	0.00	-0.09^{*}	-0.14^{**}	-0.15^{***}	-0.16^{***}	-0.11
BoP M		-0.25^{***}											-0.25
CFP		-0.60^{*}		-0.23^{***}		-0.26^{**}	0.15		-0.10		0.04	-0.20	-0.20
D Issuance		-0.13		-0.54^{*}		-0.05						-0.37^{*}	-0.25
BoP Q	-0.37^{***}	-0.43^{***}	0.07	-0.67^{***}	-0.23^{**}	-0.23^{**}	-0.28^{***}	-0.27^{**}	-0.14	0.09	-0.48^{***}	-0.58^{***}	-0.27
KS Total		-0.27^{***}	0.11			-0.39^{**}			0.01	0.17^{**}	-0.32	-0.31^{***}	-0.27
KS Debt		-0.22^{***}	0.00			-0.26^{***}	-0.14		0.01	0.16^{**}	-0.17^{***}	-0.29^{***}	-0.16
Open		-0.12^{**}		-0.13^{**}		-0.07	-0.02		-0.09^{*}		-0.15^{***}	-0.16^{***}	-0.12

NOTE. Our baseline sample of countries for computing the contemporaneous correlation between capital flows (f) and EMBI (s) is made of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey. Baseline results are reported in first row and the remaining rows present robustness using alternative definitions of both variables. "BoP M" uses monthly official BoP data from Brazil. CFP refer to the definition of net capital flows and spread as defined by Caballero et al. (2019). "D Issuance" refers to the definition of capital flows and spreads using the issuance of corporate bonds in foreign currency. "BoP Q" refers to the case where capital flows are computed using quarterly balance of payments data. "KS" refers to the database of capital flows as computed by Koepke and Paetzold (2020). "Open" selects economies with an open financial account using de jure measures of capital controls as defined by Fernandez et al. (2016) (see text for details). Significance level: $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

B.4.2 Net FDI and Portfolio Flows

Table A.10 displays the correlation between country spreads and net FDI and Portfolio flows. The main conclusions from the baseline sample remain unchanged.

Table A.10 Correlation between Net FDI and Portfolio Inflows and Country Spread

	ARG	BRZ	CHN	COL	ECU	MEX	MLY	PAN	PHL	POL	SWF	TUR	Median
FDI	-0.20^{**}	-0.25^{**}	0.19^{*}	-0.47^{***}	0.03	0.11	0.06	-0.46^{***}	-0.26^{**}	-0.25^{**}	0.11	-0.48^{***}	-0.23
Portfolio	-0.36^{***}	-0.29^{***}	0.03	-0.17^{*}	-0.27^{***}	-0.20^{**}	-0.19^{*}	-0.05	0.11	0.25^{**}	-0.33^{***}	-0.44^{***}	-0.20

NOTE. Contemporaneous correlation between Net FDI and Portfolio Inflows and EMBI of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the sample period 1999:Q1-2022:Q2. Significance level: $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Tables A.11 and A.12 display the one-year ahead variance decomposition of country spreads and net FDI flows explained by each shock. The estimations are based on estimating equation 5 and using sign restrictions described in section 3.4 but replacing net capital flows with net FDI capital flows. FDI capital flows are almost entirely explained by idiosyncratic shocks.

Table A.11 Share of Variance of Country Spread Explained by Each Shock

	F_t^s	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	51	13	24		33		33	37	39	30		34	26	33
$\varepsilon_t^{D,G}$	49	13	23		33		32	36	38	29		33	25	32
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	26	47		66		65	73	77	59		67	51	65
$\varepsilon_t^{S,I}$	0	36	26		17		18	14	11	20		16	25	18
$\varepsilon_t^{D,I}$	0	38	27		17		17	14	12	20		17	25	17
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	74	53		34		35	28	23	40		33	50	35

NOTE. One-year ahead variance decomposition of country-specific and common (Factor) country spreads explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

Table A.12 Share of Variance of Net FDI Inflows Explained by Each Shock

	F_t^k	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	58	0	10		10		4	2	11	1		2	9	4
$\varepsilon_t^{D,G}$	42	0	6		7		3	2	12	1		2	4	3
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	0	16		17		7	4	23	2		4	13	7
$\varepsilon_t^{S,I}$	0	48	42		39		48	49	39	49		47	43	47
$\varepsilon_t^{D,I}$	0	51	42		44		46	47	38	50		48	44	46
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	99	84		83		94	96	77	99		95	87	93

NOTE. One-year ahead variance decomposition of country-specific and common (Factor) FDI inflows explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

Finally, Tables A.12 and A.14 display the variance decomposition of country spreads and net Portfolio Flows explained by the different shocks. The estimations are based on estimating equation 5 and using sign restrictions described in section 3.4 but replacing net capital flows with net FDI capital flows. In this case, the contribution of each shock is similar to the one computed using net capital flows.

B.4.3 Pre-Covid Sample

In this section we redo the analysis using Pre-Covid sample. Table A.15 displays the correlation between country spreads and capital flows using this shorter sample. The correlations

Table A.13 Share of Variance of Country Spread Explained by Each Shock

	F_t^s	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	62	16	28		40		40	44	47	36		41	31	40
$\varepsilon_t^{D,G}$	38	10	18		25		25	28	29	23		26	19	25
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	26	46		65		65	72	76	59		67	50	65
$\varepsilon_t^{S,I}$	0	39	27		18		18	14	12	21		17	28	18
$\varepsilon_t^{D,I}$	0	36	27		17		17	14	11	20		17	22	17
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	75	54		35		35	28	23	41		34	50	35

Note. One-year ahead variance decomposition of country-specific and common (Factor) country spreads explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

Table A.14 Share of Variance of Net Portfolio Inflows Explained by Each Shock

	F_t^k	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	61	13	27		13		20	27	0	16		23	32	20
$\varepsilon_t^{D,G}$	39	9	17		8		13	17	0	10		15	20	13
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	22	44		21		33	44	0	26		38	52	33
$\varepsilon_t^{S,I}$	0	41	27		40		35	29	52	37		31	26	35
$\varepsilon_t^{D,I}$	0	38	28		38		33	28	48	36		31	21	33
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	79	55		78		68	57	100	73		62	47	68

Note. One-year ahead variance decomposition of country-specific and common (Factor) Portfolio inflows explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$.

remain almost unchanged relative to those presented in Table 1.

Table A.15 Correlation between Capital Flows and Sovereign Spreads at the Country Level

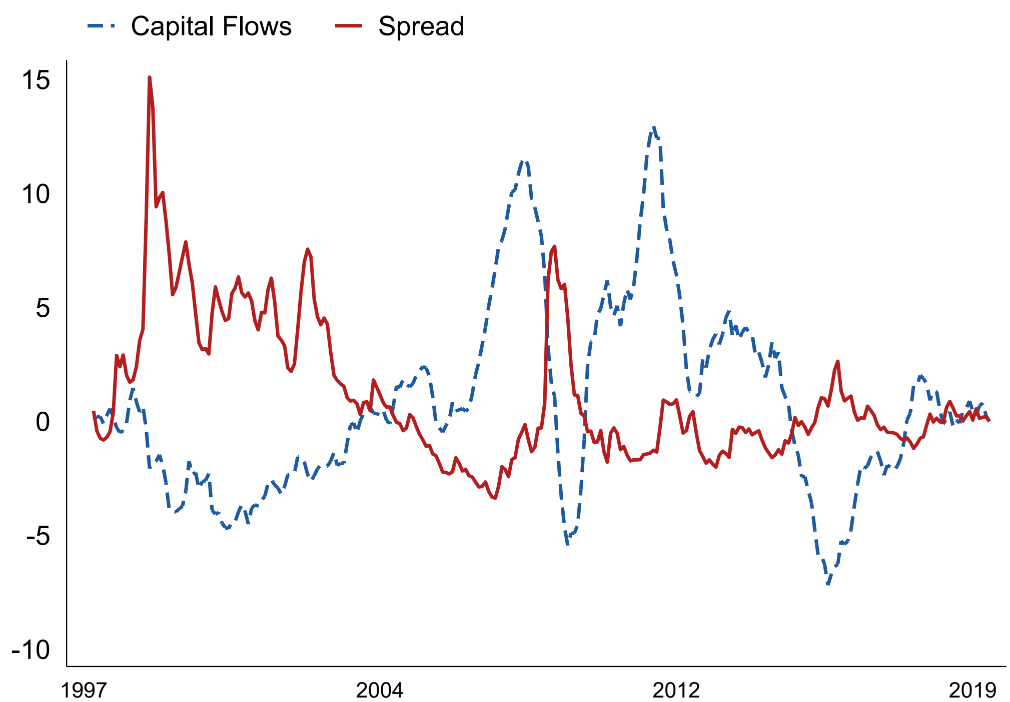
	ARG	BRZ	CHN	COL	ECU	MEX	MLY	PAN	PHL	POL	SWF	TUR	**Median**
$\rho(s, f)$	0.01	-0.13^{**}	-0.19^{***}	-0.15^{**}	-0.11^{*}	-0.08	-0.05	-0.06	-0.14^{**}	-0.17^{***}	-0.15^{**}	-0.18^{***}	-0.13
$\rho(s, f)$ no SS	0.09	-0.10	-0.02	-0.06	-0.07	-0.03	-0.04	-0.03	-0.06	-0.09	-0.10	-0.18^{**}	-0.06

Note. Contemporaneous correlation between capital flows (f) and EMBI (s) of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:1-2022:7. Capital flows is defined as the cumulative trade deficit plus the change in international reserves at monthly frequency (see equation (3)). The first row shows the correlation using the full sample while the second row included the correlation without considering Sudden Stop episodes (see text for details on the definition of a Sudden Stop). Significance level: $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Figure A.5 displays the estimated common factors of country spreads and capital flows using the pre-covid sample. The factors remain almost unchanged relative to the ones presented in Figure A.5. The correlation between the factors estimated including and excluding the covid period over the common sample is 0.98. Thus, the covid sample does not affect the estimation of the factors.

Tables A.16 and A.17 display the variance decomposition of country spreads and capital flows, respectively, using this shorter sample. The main conclusions regarding the importance

Figure A.5 Common Factor for Country Spreads and Capital Flows Excluding Covid



NOTE. Cumulated dynamic factors between capital flows and EMBI of Argentina, Brazil, China, Colombia, Ecuador, Malaysia, Mexico, Panama, Philippines, Poland, South Africa and Turkey for the period 1997:2-2019:12. Capital flows is defined as the cumulative trade deficit plus the change in international reserves at monthly frequency.

of each shock also remains unchanged.

Table A.16 Share of Variance of Country Spreads Explained by Each Shock Excluding Covid

	F_t^s	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	64	3	42	23	48	13	58	41	49	50	37	37	32	39
$\varepsilon_t^{D,G}$	36	2	23	13	27	8	32	23	27	28	21	21	18	22
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	5	65	36	75	21	90	64	76	78	58	58	50	61
$\varepsilon_t^{S,I}$	0	53	18	32	14	41	5	18	12	11	23	22	27	20
$\varepsilon_t^{D,I}$	0	42	17	32	11	38	5	18	12	11	19	20	23	18
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	95	35	64	25	79	10	36	24	22	42	42	50	38

NOTE. 1-year ahead variance decomposition of country-specific and common (Factor) spreads due explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$. The variance decomposition is computed with the sample 1997:2-2019:12.

Table A.17 Share of Variance of Net Capital Flows Explained by Each Shock Excluding Covid

	F_t^k	ARG	BRZ	CHN	COL	ECU	MEX	MSY	PAN	PHL	POL	SWF	TUR	Median
$\varepsilon_t^{S,G}$	64	1	31	17	1	1	5	22	1	4	15	5	8	5
$\varepsilon_t^{D,G}$	36	1	18	10	1	1	3	13	1	2	8	3	4	3
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	100	2	49	27	2	2	8	35	2	6	23	8	12	8
$\varepsilon_t^{S,I}$	0	54	27	36	53	51	46	33	51	49	42	48	48	48
$\varepsilon_t^{D,I}$	0	44	24	37	45	47	46	32	47	45	35	44	40	44
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	0	98	51	73	98	98	92	65	98	94	77	92	88	92

NOTE. 1-year ahead variance decomposition of country-specific and common (Factor) capital flows due explained by common credit supply shocks $\varepsilon_t^{S,G}$, common credit demand shocks $\varepsilon_t^{D,G}$, country-specific credit supply shocks $\varepsilon_t^{S,I}$, and country-specific credit demand shocks $\varepsilon_t^{D,I}$. The variance decomposition is computed with the sample 1997:2-2019:12.

C Theoretical Model

C.1 Simple Two-Period Analytical Model

In this section we present the model presented in Section 2, which follows closely the model presented by Vegh (2013) (see Chapter 2).

C.1.1 Demand for Credit without Uncertainty

The representative household of economy i receives an endowment every period $\{y_1^i, y_2^i\}$ which can be either consumed or traded internationally. The economy has access to international financial markets. The representative household solves the following problem:

$$\text{Max}_{\{c_1^i, c_2^i\}} U(c_1^i) + \beta^i U(c_2^i)$$

subject to

$$c_1^i + \frac{c_2^i}{1+r_1^i} = (1+r_0^i)b_0^i + y_1^i + \frac{y_2^i}{1+r_1^i}$$

where c_t^i denotes the consumption every period, b_0^i is the net international asset position of the economy, and r_t^i is the interest rate that the country faces in international financial markets. The Euler equation is:

$$U'(c_1^i) = \beta^i \left(1 + r^i\right) U'(c_2^i)$$

Let's assume that $b_0^i = 0$, $r_1^i = r^i$ and that $\beta^i (1 + r^i) = 1$. In this case, $c_1^i = c_2^i = \overline{c}^i$. Thus, using the budget constraint, the consumption every period equals:

$$\overline{c}^i = \left[y_1^i + \frac{y_2^i}{1 + r^i}\right] \frac{1 + r^i}{2 + r^i}$$

The associated demand for net international debt is:

$$d_1^i = \frac{y_2^i - y_1^i}{2 + r^i}$$

C.1.2 Equilibrium in Credit Markets with Uncertainty

Let's assume that output is distributed following a Uniform distribution between 0 and $\overline{y_2^i}$ ($y_2^i \sim U[0, \overline{y_2^i}]$). If the country defaults in period 2, it does not pay its debt but it suffers an output loss of ϕy_2^i. Thus, the country decides to default in the second period if $c_2^{D,i}$, the consumption level with default, is larger than $c_2^{N,i}$, the consumption value without default, since these levels determine directly the level of utility. Thus, if the country pays its debt, consumption equals: $c_2^{N,i} = y_2^i + (1 + r^i)\, b_1^i$. If the country does not pay its debt, consumption equals: $c_2^{D,i} = (1 - \phi)\, y_2^i$. The country decides to default if: $d_1^i > \frac{\phi y_2^i}{1+r^i}$. This condition can be expressed as a function of y_2^i as follows: $y_2^i < \frac{d_1^i \left(1+r^i\right)}{\phi}$. Then, the probability of default (π^i) is given by:

$$P(y_2^i < \frac{d_1^i \left(1 + r^i\right)}{\phi}) \tag{14}$$

$$\pi^i = \frac{d_1^i \left(1 + r^i\right)}{\phi} \frac{1}{\overline{y_2^i}} \tag{15}$$

We assume that the international creditors are risk neutral and can either invest in a safe bond with a return r^* or in the domestic bond. Thus, the expected value of both investment have to equalize in equilibrium:

$$\begin{aligned}\left(1-\pi^i\right)\left(1+r^i\right) &= \left(1+r^*\right)\\ \left(1+r^i\right) &= \frac{1+r^*}{1-\pi^i}\end{aligned}$$

Replacing π^i with the value obtained in equation 14 yields:

$$1+r^i=\frac{1+r^*}{1-\frac{d_1^i\left(1+r^i\right)}{\phi\overline{y_2^i}}}$$

Thus, the equilibrium value of $1+r^i$ is given by:

$$\begin{aligned}1+r^i &= \frac{\left(1+r^*\right)\phi\overline{y_2^i}}{\phi\overline{y_2}^i-d_1^i\left(1+r^i\right)}\\ 0 &= d_1^i\left(1+r^i\right)^2-\phi\overline{y_2}^i\left(1+r^i\right)+\left(1+r^*\right)\phi\overline{y_2}^i\end{aligned}$$

The solution to the last equation is given by:

$$r=\begin{cases} r^* & si\, d_1^i\leq 0\\ \frac{2(1+r^*)d_1^{i,\max}}{d_1^i}\left(1-\sqrt{1-\frac{d_1^i}{d_1^{i,\max}}}\right)-1 & si\, 0<d_1^i\leq d_1^{i,\max}\end{cases}$$

where $d_1^{i,\max}=\frac{\phi\overline{y_2}^i}{4(1+r^*)}$. The supply of credit has a positive slope given by:

$$\frac{\partial r^i}{\partial d_1^i}=\frac{(1+r^*)d_1^{i,\max}}{{d_1^i}^2\sqrt{1-\frac{d_1^i}{d_1^{i,\max}}}}\left(2-\frac{d_1^i}{d_1^{i,\max}}-2\sqrt{1-\frac{d_1^i}{d_1^{i,\max}}}\right)>0 \qquad 0<d_1^i<d_1^{i,\max}$$

The credit supply also has the property that if $d_1^i=0$, then $r=r^*$ since there is no default risk in this case. Thus, this credit supply for a country i can be approximated by the following expression that we use in section 2:

$$r^i = r^* + \phi \left(\tilde{d}_1^i\right)^2 + \varepsilon^i, \phi > 0$$

where ε^i is a random variable that captures credit supply shocks.

C.2 Two-EME Model

C.2.1 Equilibrium Conditions

A competitive equilibrium of the model presented in Section 4 is a set of processes $\{d_t, c_t, h_t, y_t, i_t, k_{t+1}, r_t, \lambda_t\}_{t=0}^{\infty}$ that satisfies:

$$
\begin{aligned}
y_t &= A_t k_t^{\alpha} h_t^{1-\alpha} \\
k_{t+1} &= i_t + (1-\delta) k_t \\
\lim_{j\to\infty} E_t \frac{d_{t+j}}{\prod_{s=1}^{j}(1+r_s)} &\leq 0 \\
d_t &= (1+r_{t-1}) d_{t-1} - y_t + c_t + i_t + \frac{\Phi}{2}(k_{t+1}-k_t)^2 + \frac{\psi_3}{2}\left(d_t - \bar{d}\right)^2 \\
\lambda_t &= \beta(1+r_t)\mathbb{E}_t \lambda_{t+1} \\
\left[c_t - \omega^{-1} h_t^{\omega}\right]^{-\gamma} &= \lambda_t \\
\left[c_t - \omega^{-1} h_t^{\omega}\right]^{-\gamma} h_t^{\omega-1} &= \lambda_t A_t (1-\alpha)\left(\frac{k_t}{h_t}\right)^{\alpha} \\
\lambda_t\left[1+\Phi(k_{t+1}-k_t)\right] &= \beta \mathbb{E}_t \lambda_{t+1}\left[A_{t+1}\alpha\left(\frac{h_{t+1}}{k_{t+1}}\right)^{1-\alpha} + 1 - \delta + \Phi(k_{t+2}-k_{t+1})\right] \\
\lambda_t\left[1-\psi_3\left(d_t-\bar{d}\right)\right] &= \beta(1+r_t)\mathbb{E}_t\lambda_{t+1} \\
\hat{R}_{i,t} &= \rho_R \hat{R}_{i,t-1} + \rho_{R^*}\hat{R}_t^* + \rho_{R1^*}\hat{R}_{t-1}^* + \rho_y \hat{y}_{i,t} + \rho_{y1}\hat{y}_{i,t-1} + \rho_i \hat{\imath}_{i,t} + \rho_{i1}\hat{\imath}_{i,t-1} + \rho_{tby} tby_{i,t} \\
&+ \rho_{tby1} tby_{i,t-1} + \gamma_{i,i}\epsilon_{i,t}^r + \gamma_{i,j}\epsilon_{j,t}^r \\
\hat{R}_t^* &= \zeta \hat{R}_{t-1}^* + \gamma_t^* \epsilon_t^* \\
\ln A_t &= \rho_A A_t + \eta \varepsilon_t^A
\end{aligned}
$$

C.2.2 Additional Results from the Theoretical Model

Table A.18 displays the moments of the theoretical model together with the empirical ones, extended to additional variables relative to Table 11.

Figure A.6 displays the IRFs of capital flows and country spreads in Mexico to all the

Table A.18 Empirical and Theoretical Moments

	Brazil		Mexico	
	Data	Model	Data	Model
std(y_t)	1.73	1.73	1.68	1.68
std (c_t)	1.50	3.31	1.46	2.34
std(i_t)	5.49	5.49	4.40	4.40
std(tby_t)	2.50	2.50	1.63	1.25
std(kf_t/y_t)	3.16	0.75	1.14	0.60
std(R_t^*)	0.45	0.45	0.45	0.45
std(s_t)	0.83	0.83	0.32	0.32
corr(s_t,kf_t/y_t)	**-0.21**	**-0.20**	**-0.03**	**-0.11**
corr(s_t,y_t)	-0.18	0.00	-0.11	0.00
corr($\frac{tb_t}{y_t}$,y_t)	-0.32	-0.06	-0.29	-0.01
corr(c_t,y_t)	0.64	0.35	0.80	0.50
corr(i_t,y_t)	0.86	0.79	0.77	0.79
corr(y_t,y_{t-1})	0.72	0.72	0.83	0.83
	Data		Model	
corr(y_{BR},y_{MEX})	0.30		0.30	
corr(s_{BR},s_{MEX})	**0.65**		**0.65**	
corr((kf_t/y_t)$_{BR}$,(kf_t/y_t)$_{MEX}$)	**0.35**		**0.34**	

NOTE. . Moments in bold denote the three dimensions studied closely in the empirical analysis: the within correlation between country spreads and capital flows (corr(s_t,kf_t/y_t)), and the cross-country correlations between spreads (corr(s_{BR},s_{MEX})) and capital flow (corr((kf_t/y_t)$_{BR}$,(kf_t/y_t)$_{MEX}$)). When calibrating the model, only one of these is targeted –cross-country correlations between spreads– while the other two are not.

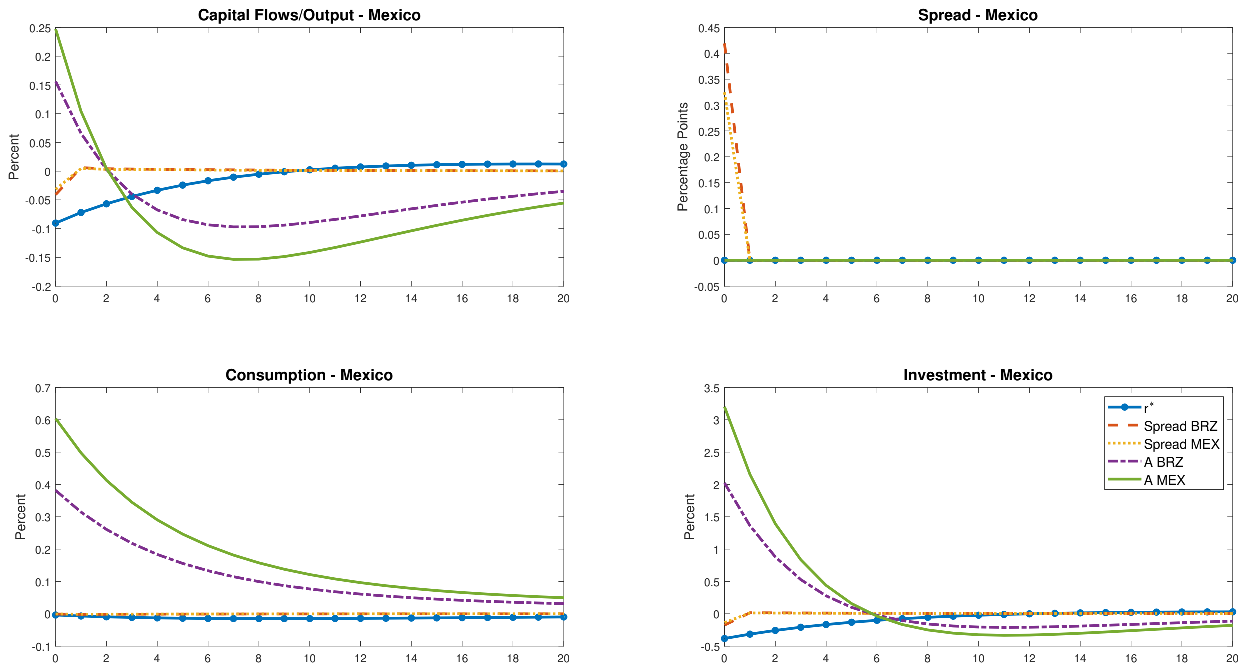
shocks considered in the model.

Tables A.19 and A.20 further complement the study of the model by displaying the one-year ahead variance decomposition of capital flows-to-output ratio and country spreads in each country.

Credit supply shocks are the only driver of credit spreads. This further illustrates the role of a Global Financial Cycle in driving credit supply drivers that account for the high observed comovement between country spreads in EMEs.

Credit demand shocks, in contrast, are an important force behind capital flow dynamics, as depicted in Table A.20. They explain up to 78% and 83% of the variability in capital flows in in Brazil and Mexico, respectively. In turn, idiosyncratic credit demand shocks, due to productivity shocks, account for most of this share in Brazil and Mexico, explaining 63% and 59% of capital flows fluctuations.

Figure A.6 IRFs in Mexico



Note. Response of capital flows-to-output ratio, country spreads, consumption and investment in Mexico to a one standard deviation shock in the model. Spread BRZ (Spread MEX) denotes the IRFs to a shock to the interest rate in Brazil (Mexico). A BRZ (A MEX) denotes the IRFs to a TFP shock in Brazil (Mexico). r^* denotes the IRFs to a shock to the international interest rate.

Table A.19 One-Year Ahead Variance Decomposition of Sovereign Spread

	Brazil		Mexico	
	Data	Model	Data	Model
$\varepsilon_t^{S,G}$	41	34	58	55
$\varepsilon_t^{D,G}$	23	0	32	0
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	64	34	90	55
$\varepsilon_t^{S,I}$	18	66	5	45
$\varepsilon_t^{D,I}$	18	0	5	0
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	36	66	10	45

Note. Percentage of the One-Year ahead variance of country spreads in Brazil and Mexico explained by common credit supply shocks ($\varepsilon_t^{S,G}$), which includes the sum of international interest rate shocks R^* plus common shocks to the interest rate of both economies; common credit supply shocks ($\varepsilon_t^{D,G}$), which considers common TFP shocks to both economies; idiosyncratic credit supply shocks ($\varepsilon_t^{S,I}$), which includes country-specific shocks to the interest rate; and idiosyncratic credit demand shocks ($\varepsilon_t^{D,I}$), which includes country-specific TFP shocks. The results are based on simulations from the theoretical model presented in this Section.

In short, while country spread dynamics are explained by credit supply shocks, credit demand shocks are key to explain capital flow dynamics. This difference in the source of fluctuations drives the high comovement of country spreads coupled with a low comovement of capital flows observed in the empirical analysis. In the next subsection we assess the

Table A.20 One-Year Ahead Variance Decomposition of Capital Flows

	Brazil		Mexico	
	Data	Model	Data	Model
$\varepsilon_t^{S,G}$	33	14	5	15
$\varepsilon_t^{D,G}$	18	16	3	24
$\varepsilon_t^{S,G} + \varepsilon_t^{D,G}$	51	30	8	39
$\varepsilon_t^{S,I}$	25	2	44	1
$\varepsilon_t^{D,I}$	24	68	48	60
$\varepsilon_t^{S,I} + \varepsilon_t^{D,I}$	49	70	97	61

NOTE. Percentage of the One-Year ahead variance of capital flows-to-output ratio in Brazil and Mexico explained by common credit supply shocks ($\varepsilon_t^{S,G}$), which includes the sum of international interest rate shocks R^* plus common shocks to the interest rate of both economies; common credit supply shocks ($\varepsilon_t^{D,G}$), which considers common TFP shocks to both economies; idiosyncratic credit supply shocks ($\varepsilon_t^{S,I}$), which includes country-specific shocks to the interest rate; and idiosyncratic credit demand shocks ($\varepsilon_t^{D,I}$), which includes country-specific TFP shocks. The results are based on simulations from the theoretical model presented in this Section.

contribution of each feature in explaining these dynamics.

C.3 Extensions of the Theoretical Model

C.3.1 Estimated Interest Rate Processes

The country interest rate for Brazil and Mexico is defined as the gross real interest rate for the U.S. times the gross country spread, proxied with the EMBIG. The first column in Table A.21 reports the estimated values from Uribe and Yue (2006) as a reference.

The estimated coefficients are consistent with the original estimations of Uribe and Yue (2006) but less precise since our sample uses only one country instead of a panel. While the coefficients associated with output are lower and less statistically significant, the ones associated with trade balance-to-output ratio are larger for Brazil.

We calibrate the model following the calibration strategy defined in Section 4.3. Table A.22 displays the calibrated coefficients for Brazil and Mexico. Table A.23 displays the theoretical moments using the estimated interest rate process. The moments are comparable to those presented in Table 11. While adding the estimated interest rate process improves the correlation between output and country spread, it does not affect the other main moments related with EMEs credit markets.

Table A.21 Estimated Interest Rate Processes

	UY (2006)	Brazil	Mexico
r_{t-1}	0.63***	0.75***	0.77***
	[0.146]	[0.067]	[0.077]
y_t	−0.79***	−0.22	−0.28***
	[0.212]	[0.153]	[0.097]
y_{t-1}	0.62***	−0.14	0.26***
	[0.213]	[0.163]	[0.089]
i_t	0.11*	0.11*	0.09***
	[0.065]	[0.058]	[0.029]
i_{t-1}	−0.12*	0.03	−0.08**
	[0.071]	[0.060]	[0.031]
tby_t	0.29*	0.80***	0.10
	[0.155]	[0.236]	[0.072]
tby_{t-1}	-0.19	−0.72***	0.01
	[0.148]	[0.230]	[0.075]
R_t^*	0.50	0.71*	0.73***
	[0.323]	[0.409]	[0.171]
R_{t-1}^*	0.36	-0.21	−0.41**
	[0.487]	[0.416]	[0.194]
Obs	160	90	90
R^2	0.62	0.92	0.97

Note. Estimated interest rate processes. The first column presents the original estimates from Uribe and Yue (2006) using a panel of EMEs. Second and third columns present the estimated interest rate processes for Brazil and Mexico, respectively, using data from 1997:1-2019:4. The processes were estimated using instrumental variables, where r_{t-1} was instrumented with r_{t-2}. Standard errors are presented in brackets. ***, **, and * denote 1%, 5% and 10% confidence level.

Table A.22 Calibrated Parameters

Parameter	Description	Target	Brazil	Mexico
γ	CRRA parameter	Schmitt-Grohe and Uribe (2003)	2	
ω	Inverse Frisch elasticity	Schmitt-Grohe and Uribe (2003)	1.455	
δ	Depreciation rate	Schmitt-Grohe and Uribe (2003)	0.025	
α	Capital share	Schmitt-Grohe and Uribe (2003)	0.32	
β	Discount factor	$\beta R^* = 1$	0.9901	
ζ	Persistence R_t^*	Estimated	0.97	
σ_{R^*}	Std. Dev. of R^* shock	Estimated	0.00183	
$\overline{d}$	Debt in steady state	Average TBY	0.38	3.9
ϕ	Capital adjustment cost	Investment volatility	0.00398	0.00781
ψ	Portfolio adjustment costs	TBY volatility	0.00000001	0.00000001
ρ_A	Persistence TFP	Output persistence	0.6355	0.765
σ_{ii}^A	Std. Dev. TFP Shock	Output volatility	0.00641	0.00505
σ_{ij}^A	Covariance TFP Shocks	Output correlation	0.3	0.3
σ_{ii}^R	Std. Dev. Spread Shocks	Spread Volatility	0.00485	0.0014
σ_{ij}^R	Covariance Spread Shocks	Spread Correlation	0.707	0.707

Table A.23 Empirical and Theoretical Moments

	Brazil		Mexico	
	Data	Model	Data	Model
std(y_t)	1.73	1.73	1.68	1.68
std(i_t)	5.49	5.50	4.40	4.40
std(tby_t)	2.50	1.26	1.63	1.25
std(kf_t/y_t)	3.16	0.74	1.14	0.60
std(R_t*)	0.45	0.45	0.45	0.45
std(s_t)	0.83	0.83	0.32	0.32
corr(s_t,kf_t/y_t)	**-0.21**	**-0.10**	**-0.03**	**-0.11**
corr(s_t,y_t)	-0.18	-0.12	-0.11	-0.08
corr(y_t,y_{t-1})	0.72	0.72	0.83	0.83
	Data		Model	
corr(y_{BR},y_{MEX})	0.30		0.30	
corr(s_{BR},s_{MEX})	**0.65**		**0.65**	
corr((kf_t/y_t)$_{BR}$,(kf_t/y_t)$_{MEX}$)	**0.35**		**0.39**	

C.3.2 Credit Risk Shocks

The baseline version of the model only contains shocks to the international interest rate and to the country spread which shifts the credit supply that the economy faces. In the two-period model that we present in Section 2, we consider shocks that change the slope of the credit supply curve depending on the stock of debt. Thus, we extend the baseline model presented in Section 4 to allow for this shock also in the model. Section C.3.2 describes this extension in detail. We calibrate the model following the same strategy as for the baseline version and we set the value of the variance of the credit risk shocks to match the observed variability of the capital flows to output in each economy. Table A.24 displays the calibrated parameters while Table A.25 presents the theoretical moments from this version of the model. The model significantly improves the match of credit market moments while keeping the match of the comovement in capital flows to output.

C.3.3 Solution with Global Methods

In this section we present the results from the model using global methods. We use the Fixed-Point Iteration Algorithm (FiPit) developed by Mendoza and Villalvazo (2020). The

Table A.24 Calibrated Parameters

Parameter	Description	Target	Brazil	Mexico
γ	CRRA parameter	Schmitt-Grohe and Uribe (2003)	2	
ω	Inverse Frisch elasticity	Schmitt-Grohe and Uribe (2003)	1.455	
δ	Depreciation rate	Schmitt-Grohe and Uribe (2003)	0.025	
α	Capital share	Schmitt-Grohe and Uribe (2003)	0.32	
β	Discount factor	$\beta R^* = 1$	0.9901	
ζ	Persistence R_t^*	Estimated	0.92	
σ_{R^*}	Std. Dev. of R^* shock	Estimated	0.00183	
$\overline{d}$	Debt in steady state	Average TBY	0.38	3.9
ϕ	Capital adjustment cost	Investment volatility	0.00386	0.00767
ψ	Portfolio adjustment costs	TBY volatility	0.000000147	0.0000005
ρ_A	Persistence TFP	Output persistence	0.6355	0.765
σ_{ii}^A	Std. Dev. TFP Shock	Output volatility	0.00653	0.00505
σ_{ij}^A	Covariance TFP Shocks	Output correlation	0.3	0.3
σ_{ii}^R	Std. Dev. Spread Shocks	Spread Volatility	0.0083	0.0033
σ_{ij}^R	Covariance Spread Shocks	Spread Correlation	0.707	0.707
σ_{ii}^ψ	Std. Dev. Credit Risk Shock	Capital Flows Volatility	0.00432	0.00036
σ_{ij}^ψ	Covariance Credit Risk Shock	Capital Flows Correlation	0.3524	0.3524

Table A.25 Empirical and Theoretical Moments

	Brazil		Mexico	
	Data	Model	Data	Model
std(y_t)	1.73	1.78	1.68	1.71
std(i_t)	5.49	14.30	4.40	5.87
std(tby_t)	2.50	3.18	1.63	1.16
std(kf_t/y_t)	3.16	3.16	1.14	1.14
std(R_t*)	0.45	0.45	0.45	0.45
std(s_t)	0.83	0.83	0.32	0.32
corr(s_t,kf_t/y_t)	**-0.21**	**-0.05**	**-0.03**	**-0.02**
corr(s_t,y_t)	-0.18	0	-0.11	0
corr(y_t,y_{t-1})	0.72	0.72	0.83	0.83
	Data		Model	
corr(y_{BR},y_{MEX})	0.30		0.30	
corr(s_{BR},s_{MEX})	**0.65**		**0.65**	
corr($(kf_t/y_t)_{BR}$,$(kf_t/y_t)_{MEX}$)	**0.35**		**0.35**	

equilibrium is characterized by the same equations presented in Section C.2.1. We define a grid 350 points for external assets and 60 for capital for each economy. We consider two realizations for each of the shocks (risk free rate, productivity and country spreads). First we focus on the same case as in our baseline model, where $\beta R^* = 1$ and we have portfolio adjustment costs to induce stationarity, and the second one we use $\beta R^* < 1$ without any financial friction. Results are consistent in both specifications. Most of the moments remain unchanged with respect to the baseline results presented in the paper. Using global methods equalizes the variance of capital flows to output relative to trade balance to output. However, the model still underpredicts the volatility of net capital flows to output for Brazil. The second main difference is that the model now yields a higher correlation of capital flows to output between these two economies, closer to the one of sovereign spreads.

C.3.3.1 Version 1: Portfolio Adjustment Costs

Table A.27 presents the theoretical moments. Table A.27 displays the unconditional moments.

Table A.26 Calibrated Parameters

Parameter	Description	Target	Brazil	Mexico
γ	CRRA parameter	Schmitt-Grohe and Uribe (2003)	2	
ω	Inverse Frisch elasticity	Schmitt-Grohe and Uribe (2003)	1.455	
δ	Depreciation rate	Schmitt-Grohe and Uribe (2003)	0.025	
α	Capital share	Schmitt-Grohe and Uribe (2003)	0.32	
β	Discount factor	$\beta R^* = 1$	0.9901	
ζ	Persistence R_t^*	Estimated	0.97	
σ_{R^*}	Std. Dev. of R^* shock	Estimated	0.00183	
$\bar{d}$	Debt in steady state	Average TBY	0.38	3.9
ϕ	Capital adjustment cost	Investment volatility	0.125	0.085
ψ	Portfolio adjustment costs	TBY volatility	0.00000001	0.00000001
ρ_A	Persistence TFP	Output persistence	0.6355	0.765
σ_{ii}^A	Std. Dev. TFP Shock	Output volatility	0.00641	0.00505
σ_{ij}^A	Covariance TFP Shocks	Output correlation	0.3	0.3
σ_{ii}^R	Std. Dev. Spread Shocks	Spread Volatility	0.00485	0.0014
σ_{ij}^R	Covariance Spread Shocks	Spread Correlation	0.707	0.707

C.3.3.2 Version 2: $\beta(1+r) < 1$

Table A.29 presents the theoretical moments. Table A.29 displays the unconditional moments.

Table A.27 Empirical and Theoretical Moments

	Brazil		Mexico	
	Data	Model	Data	Model
std(y_t)	1.73	1.80	1.68	1.63
std(i_t)	5.49	5.64	4.40	4.66
std(tby_t)	2.50	1.69	1.63	1.22
std(kf_t/y_t)	3.16	1.49	1.14	1.16
std(R_t*)	0.45	0.45	0.45	0.45
std(s_t)	0.83	0.81	0.32	0.32
corr(s_t,kf_t/y_t)	**-0.21**	**-0.45**	**-0.03**	**-0.26**
corr(s_t,y_t)	-0.18	-0.05	-0.11	-0.03
corr(y_t,y_{t-1})	0.72	0.67	0.83	0.72

	Data	Model
corr(y_{BR},y_{MEX})	0.30	0.34
corr(s_{BR},s_{MEX})	**0.65**	**0.62**
corr($(kf_t/y_t)_{BR}$,$(kf_t/y_t)_{MEX}$)	**0.35**	**0.63**

Table A.28 Calibrated Parameters

Parameter	Description	Target	Brazil	Mexico
γ	CRRA parameter	Schmitt-Grohe and Uribe (2003)	2	
ω	Inverse Frisch elasticity	Schmitt-Grohe and Uribe (2003)	1.455	
δ	Depreciation rate	Schmitt-Grohe and Uribe (2003)	0.025	
α	Capital share	Schmitt-Grohe and Uribe (2003)	0.32	
β	Discount factor	$\beta R^* = 1$	0.9901	
ζ	Persistence R_t^*	Estimated	0.97	
σ_{R^*}	Std. Dev. of R^* shock	Estimated	0.00183	
$\overline{d}$	Debt in steady state	Average TBY	0.38	3.9
ϕ	Capital adjustment cost	Investment volatility	0.125	0.085
ψ	Portfolio adjustment costs	TBY volatility	0.00000001	0.00000001
ρ_A	Persistence TFP	Output persistence	0.6355	0.765
σ_{ii}^A	Std. Dev. TFP Shock	Output volatility	0.00641	0.00505
σ_{ij}^A	Covariance TFP Shocks	Output correlation	0.3	0.3
σ_{ii}^R	Std. Dev. Spread Shocks	Spread Volatility	0.00485	0.0014
σ_{ij}^R	Covariance Spread Shocks	Spread Correlation	0.707	0.707

Table A.29 Empirical and Theoretical Moments

	Brazil		Mexico	
	Data	Model	Data	Model
std(y_t)	1.73	1.73	1.68	1.66
std(i_t)	5.49	5.87	4.40	4.58
std(tby_t)	2.50	1.61	1.63	1.23
std(kf_t/y_t)	3.16	1.27	1.14	1.06
std(R_t*)	0.45	0.45	0.45	0.45
std(s_t)	0.83	0.81	0.32	0.32
corr(s_t,kf_t/y_t)	**-0.21**	**-0.41**	**-0.03**	**-0.23**
corr(s_t,y_t)	-0.18	-0.05	-0.11	-0.03
corr(y_t,y_{t-1})	0.72	0.68	0.83	0.72

	Data	Model
corr(y_{BR},y_{MEX})	0.30	0.31
corr(s_{BR},s_{MEX})	**0.65**	**0.66**
corr((kf_t/y_t)$_{BR}$,(kf_t/y_t)$_{MEX}$)	**0.35**	**0.58**