# On Corporate Borrowing, Credit Spreads and Economic Activity in Emerging Economies: An Empirical Investigation*

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**Abstract**

We study the influence of external financial factors on economic activity in emerging economies (EMEs) motivated by a considerable increase in foreign financing by the *corporate* sector in EMEs since the early 2000s, mainly in the form of bond issuance. We build a quarterly external financial indicator for several EMEs using bond-level data on spreads of corporate bonds issued in foreign capital markets, and examine its relationship with economic activity. Results show that the indicator has considerable predictive power on future economic activity. Furthermore, an identified adverse shock to the financial indicator generates a large and protracted fall of real output growth, and about a third of its forecast error variance is associated with this shock. These findings are robust to controlling for possible spillovers from sovereign to corporate risk, among other considerations.

Keywords: Foreign corporate bond issuance; options adjusted spread; economic activity; emerging economies
JEL Classification: E32, E37, F34, F37, G15

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## 1 Introduction

One of the most important development in the macroeconomics of emerging market economies (EMEs) since the beginning of the twenty-first century is a major increase in their *corporate* sectors' reliance on foreign debt. This has made the stock of international debt issued by these economies quadruple in a little over a decade, from an outstanding stock of debt of about 600 billion USD in the early 2000s to 2.4 trillion USD by the end of 2014;[1] and has created an intense debate about its macro implications and desirability. A benign view posits that for EMEs, often portrayed as credit-constrained small open economies, access to international capital markets by the corporate sector is essential for sustaining long-run economic growth, as it can provide domestic entrepreneurs with needed funds to finance new investment projects that would otherwise not be available from local sources. However, the costly crises of the 1990s and, more recently, the global financial crisis of 2008/2009, have taught us that greater access to capital markets also entails risks for EMEs, particularly stemming from abrupt changes in the amount and the cost of international capital available. This has placed at center stage the role of external financial conditions as important drivers of economic activity in EMEs.

This paper seeks to shed new light on the role that external financial factors play when accounting for economic activity in emerging economies. Our particular interest is to quantify the extent to which changes in the lending conditions faced by the *corporate* sector of EMEs in world capital markets affect economic activity in these economies. For that purpose we build an external financial indicator for several EMEs using individual bond-level data on spreads from corporate bonds issued in foreign capital markets and traded in secondary markets. We then quantify how much information this indicator contains in terms of future fluctuations in economic activity in these economies, and how this activity responds to shocks in the indicator. Our focus is on bond issuance because, as we document in detail for 17 EMEs, it is this form of finance the one that corporates have preferred the most in recent years when increasing their reliance on international sources of funding.

We find strong evidence that the external financial indicator that we construct contains infor-

[1] This stylized fact is further documented in Section 3 as well as the 17 EMEs that we consider when computing the stock of international debt.

mation on future economic activity in EMEs, even after controlling for other domestic and external factors that may also drive aggregate fluctuations in these economies. Results from panel forecasting regressions indicate that, on average, an increase of $100$ basis points in the external financial indicator is correlated with a decrease in real output growth of $0.22$ percentage points in the following quarter, and up to $0.34$ points three quarter ahead. Furthermore, using a panel structural vector autoregressive (SVAR) model, we find that an identified (positive) shock to the external financial indicator generates a large and protracted fall in economic activity. A one standard deviation shock in the external financial indicator, equivalent to an increase of $150$ basis points, leads to a fall in real output growth of up to $0.75$ percent four quarters ahead, and long-run mean growth is reached again only three years after the shock. Furthermore, $35$ percent of the forecast error variance in real output growth is accounted by these shocks. This number is between two and three times those obtained in previous studies that quantified the role of risk premia shocks for emerging economies' business cycles, but that relied solely on sovereign risk and did not account for the effect of corporate spreads. When looking at other macroeconomic variables, namely aggregate consumption and investment, we find that both react vigorously to shocks to the external financial indicator, but the former appears to be the one that is relatively most affected.

These findings are robust to several extensions. First, our benchmark results are virtually unchanged after we control for possible spillovers from sovereign to corporate risk. This is consistent with the fact, also documented, that in recent times new international lending in EMEs has mainly been channeled to the corporate sector, while governments have substituted foreign sources of finance for domestic ones. Second, we show that, while considerably reduced, the information content that our external financial indicator possesses continues to be significant once we control for the VIX, a measure of uncertainty and risk aversion in global capital markets. Third, we find that the predictive power of the external financial indicator considerably increased during the world financial crisis and, more importantly, the post-recovery years. Moreover, its predictive ability continues to hold when we consider bonds issued only by non-financial corporations. Both results are consistent with the fact that, in the post-crisis period, the bulk of the surge in international bond financing by the corporate sector has been done by non-financial corporations. Lastly, we validate our results when using alternative schemes for identification of shocks to our measure of external financial indicator, alternative measures of economic activity, and alternative specifications of the panel SVAR.

This paper is related to and contributes to four different literatures. The stylized facts that we document in terms of the patterns in external financing by EMEs contribute to the work by Shin (2014), Turner (2014) and Powell (2014), among others, on how corporations from emerging economies have stepped up their financing through international capital markets (rather than traditional bank lending). Our work complements this literature by providing a systematic analysis of the external financing patterns exhibited by several EMEs, particularly the large increase by non-financial corporations (NFCs) in international bond issuance.

Our work, showing that fluctuations in spreads of international bonds issued by NFCs in EMEs contain information on future economic activity, contributes to a long-standing literature that studies the relevance of external financial factors when accounting for aggregate fluctuations in these economies.[2] External financial factors in this literature are typically proxied by U.S. interest rates or spreads of EMEs' *sovereign* debt. The papers in this literature usually estimate VAR models that identify the dynamic effects on EMEs' business cycle from exogenous shocks to U.S. interest rates or EMEs' *sovereign* spreads (see, e.g., the seminal papers by Canova, 2005 and Uribe & Yue, 2006).[3] This literature finds that external financial factors explain a sizeable proportion of business cycles in emerging economies. A recent paper by Akinci (2013), however, shows that the effect of international financial conditions on EME economic activity is driven not by fluctuations in U.S. interest rates, but by risk aversion in global financial markets—as proxied by the volatility of U.S. stock prices—and their effect on sovereign spreads.[4] We contribute to this literature by paying

[2]At least since Díaz-Alejandro (1985) the literature has explored how international financial conditions affect EMEs. A strand of the literature focuses on the role of capital flows in driving economic conditions or the incidence of crises, either because of surges in inflows (see, e.g., Calvo, Leiderman & Reinhart, 1993; Fernández-Arias, 1996; Reinhart & Reinhart, 2009, and Caballero, 2016) or because of sudden stops in inflows (see, e.g., Calvo, 1998 and Calvo, Izquierdo & Mejía, 2008). Another strand of the literature studies the effects of international interest rates and global risk aversion on EMEs' business cycles (see references in main text). Our paper contributes to the latter literature.

[3]Several subsequent papers have followed the seminal works of Canova and Uribe and Yue, including the papers by Mackowiak (2007), Agénor, Aizenman & Hoffmaister (2008), and Österholm & Zettelmeyer (2008). Izquierdo, Romero-Aguilar & Talvi (2008) take a different modelling approach, estimating a Vector Error Correction Model (VECM). Recently, a new vintage of papers using a GVAR approach have studied the global spillovers from U.S. monetary policy, including Chudik & Fratzscher (2011), Chen, Filardo, He & Zhu (2012), Feldkircher & Huber (2016), and Georgiadis (2015). Despite the use of different samples, identifying assumptions and estimation techniques, they all find that external factors explain a sizeable proportion of business cycles in EMEs, ranging from 20 to 60 percent of the variability of economic activity. Neumeyer & Perri (2005) is an early paper showing that sovereign spreads in EMEs behave in a countercyclical manner, which is what subsequent work shows.

[4]The effect of global risk aversion on EMEs' economic fluctuations have also been highlighted by Matsumoto (2011)

particular attention to the role of *corporate* external borrowing, instead of sovereign borrowing, motivated by the aforementioned shift in the composition of borrowers in foreign capital markets from sovereigns to corporates in EMEs.

The empirical work we undertake in this paper in terms of constructing an external financial indicator directly from bond spreads is mostly inspired by Gilchrist, Yankov & Zakrajsek (2009) and Gilchrist & Zakrajsek (2012) on the effects of credit market shocks and economic fluctuations in the United States (subsequently extended to Western Europe by Gilchrist & Mojon, 2014 and Bleaney, Mizen & Veleanu, 2016). Our work expands their analysis to the case of EMEs, while simultaneously providing an analysis of the patterns of foreign finance in these economies, which in turn justifies our focus on the international bond issuance by the corporate sector.

The paper is also related to a new vintage of dynamic, stochastic equilibrium models motivated by much of the empirical findings just highlighted. These models aim at accounting for business cycles in EMEs through financial shocks and the amplifying effects of financial frictions for the decisions of private agents (see, most recently, Fernández & Gulan, 2015).[5] Our work contributes to this literature by providing empirical evidence of the hypotheses derived from these models regarding the links between corporate bond spreads and economic activity. Our results offer strong support to the key hypotheses in this literature insofar as external financial factors are a key determinant for economic activity in EMEs through their effect on the corporate sector.

The paper is divided into seven sections, including this introduction. Section 2 summarizes the theoretical framework used to think about the links between international borrowing, credit spreads and economic activity in EMEs. Section 3 presents the stylized facts on international corporate borrowing in these economies. Section 4 describes how we construct the external financial indicator and studies its time series dynamics. Section 5 presents our benchmark results in terms of the forecasting information content of the external financial indicator, and the macro dynamics

and Carrière-Swallow & Céspedes (2013); although, these papers are silent on its effect on country spreads. On the effects of global factors on EMEs' sovereign spreads, Arora & Cerisola (2001), González-Rozada & Levy-Yeyati (2008), and Ciarlone, Piselli & Trebeschi (2009) show that EMEs' sovereign spreads depend negatively on global financial conditions, such as U.S. interest rates, U.S. high-yield corporate spreads, and the volatility of U.S. stock prices, respectively.

[5]This research agenda was initiated by the contributions of Neumeyer & Perri (2005), and Uribe & Yue (2006). Subsequent works are García-Cicco, Pancrazi & Uribe (2010), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez & Uribe (2011), Chang & Fernández (2013), Fernández, González & Rodríguez (2015). In a recent theoretical contribution, Chang, Fernández & Gulan (2016) study the business cycle effects of the endogenous choice of finance modes for emerging economies.

following a shock to it. Section 6 presents various extensions and robustness checks. Concluding remarks are presented in Section 7. An online Appendix includes further technical material as well as further robustness analysis.

## 2 External Corporate Borrowing, Credit Spreads and Economic Activity in EMEs: A Theoretical Framework

Considerable progress has been made in recent years in building microfounded small open economy models that account for the linkages among external financial factors, foreign corporate debt issuance and economic activity in small EMEs. Two clear hypotheses emerge from these works:

1. Spreads on bonds issued by *corporates* of EMEs in international capital markets contain information on aggregate economic activity. Thus, proxies of economic activity in these economies ought to be correlated with these spreads over the business cycle.

2. Exogenous perturbations to these spreads will have an impact on *future* economic activity, mainly via their effect on aggregate investment and consumption.

For the remainder of this section we provide a brief summary of the main insights from the theoretical frameworks developed in recent times that have established a link between external financial factors, foreign corporate debt and economic activity in these economies. The goal is not to provide a comprehensive literature review. Instead, we intend to lay out the main insights from these studies that give rise to the type of empirical tests undertaken in the rest of our work.

The literature has postulated two reasons why agents in EMEs may borrow funds from world capital markets. One is associated with factors that affect the level of aggregate investment. The other relates to factors affecting aggregate consumption. Each one, in turn, articulates a channel through which changes in the financial conditions of such borrowing may have real effects on economic activity.

The first reason, linked to investment, relates to corporates in EMEs facing borrowing needs. Early works in this literature modeled this by assuming that firms borrow in international markets to finance working-capital needs (Neumeyer & Perri, 2005; Uribe & Yue, 2006). This assumption requires firms to hold an amount of non-interest-bearing assets to finance a share of resources devoted to remunerating inputs of production, namely capital and labor.[6] In practice, this assump-

[6]Formally, this is often modeled with the restriction that $\kappa_t \geq \eta \left( w_t h_t + r_t^k k_t \right), \ \eta \geq 0$, where $\kappa$ are non-interest-

tion drives a wedge between inputs' marginal products and marginal costs. That wedge captures the financial cost associated with the share of resources paid with funds borrowed at interest rate $R$. Hence, changes to external financial conditions that affect $R$ will be correlated with economic activity in these economies to the extent that financial costs associated with the use of inputs in total production change, driving firms in EMEs to optimally alter their production and investment levels.[7]

The second reason postulated in the literature as to why agents in EMEs may borrow funds from world capital markets relates to their desire to smooth consumption. It is often assumed that this is accomplished within an environment of market incompleteness where agents in these economies have only the possibility of issuing one-period, non-state-contingent debt in international markets at an interest rate $R$. Hence, an upward movement in $R$ triggered by changes in foreign financial conditions will be related to a slowdown in economic activity amid a fall in aggregate consumption.[8]

When thinking about $R$, the (gross) interest rate at which debt with the rest of the world is issued by agents in EMEs, whether for investment and/or consumption needs, the literature has unanimously embraced the small open economy assumption whereby the EME is too small to affect the world interest rate $R^*$, but a (country-specific) spread, $S$, may exist over this rate: $R_t = S_t R_t^*$. Hence, movements in $R$ can be traced back to movements in spreads and/or fluctuations in world interest rates. The implicit assumption often used is that there is a large mass of foreign investors willing to lend to the emerging economy any amount at rate $R_t$. Loans to the EME are risky assets because there can be default on payments to foreigners. Time variation in this risk is captured by fluctuations in $S_t$. Variation in $R_t^*$ account for changes in the risk aversion of foreign

bearing assets, $\eta$ is the fraction of resources devoted to remunerate inputs of production, $wh$ is the wage bill and $r^k k$ is the amount of resources devoted to renting capital.

[7] An alternative way to establish a connection between movements in $R$ and investment decisions is to assume that firms' internal resources may not be enough to achieve the optimal level of capital, in which case they need to resort to issuing debt in international markets (Fernández & Gulan, 2015). In this setup, the resource constraint faced by the average entrepreneur is $q_t k_{t+1} = n_{t+1} + d^f_{t+1}$where $k$ is the stock of capital purchased at price $q$; her net worth is $n$; and $d^f$ is the stock of debt issued in international markets at an interest rate $R$. Hence, changes to external financial conditions that lead to upward movements of $R$ will be correlated with a slowdown in economic activity amid an investment slump, as entrepreneurs purchase less capital to produce final goods.

[8] This can be modeled by assuming a sequential budget constraint of a typical consumer as $c_t = d^h_t - R_{t-1} d^h_{t-1} + w_t h_t$, where $d^h_t$ is the stock of (one period, non-state-contingent) debt issued in period $t$ and due in the next period, and $c$ is the amount of consumption. The negative correlation between changes in $R$ and $c$ could also be seen through the intertemporal Euler condition for consumption, which relates present and future consumption, and interest rates.

lenders/investors or movements in global monetary/fiscal policies. This does not preclude the possibility that $R^*$ and $S$ are correlated. In fact, it can be the case that global events that affect the former (i.e., monetary or fiscal policy announcements in the United States) percolate into the risk appetite of foreign investors for emerging market bonds, thereby affecting their spreads, as has been empirically quantified (see Uribe & Yue, 2006).

When modeling the behavior of spreads ($S$) several alternatives have been considered in the literature. The most agnostic and reduced-form approach has been to estimate a process for spreads by simply regressing them to (lagged) country "fundamentals" such as output, investment, the trade balance and white noise perturbations, in the context of SVAR models (Uribe & Yue, 2006; Akinci, 2013). An alternative semi-structural approach has been to directly postulate a link between spreads and (latent or observed) country fundamentals included in the structural model such as future expected productivity or the price of commodities exported by the EME and then calibrate (or estimate) such linkages within the context of the calibration (or estimation) of the full-blown dynamic general equilibrium model (Neumeyer & Perri, 2005; Chang & Fernández, 2013; Fernández et al., 2015). This captures the idea that productivity and/or commodity prices contain information on the creditworthiness of the borrower EME to the extent that they are a determinant of its repayment capacity.[9] Lastly, other studies have resorted to a full structural approach where $S$ is endogenous to the financial contract stipulated between domestic borrowers and external investors (Fernández & Gulan, 2015). Under this approach, a financial accelerator endogenously generates a spread process that depends upon financial variables, namely entrepreneurial leverage. Hence domestic or external shocks that affect the value of entrepreneurs' net worth will influence spreads.[10]

Summing up, spreads on corporate bonds issued by firms in emerging market on international

[9]Formally, what has often been done is to postulate some *ad hoc* reduced-form equation within the structural model whereby spreads react to other variables inside the model, e.g., $S_t = \widetilde{\eta}_1 E_t TFP_{t+1} + \widetilde{\eta}_2 E_t P^{co}_{t+1} + \varepsilon_t$, where $TFP_{t+1}$ and $P^{co}_{t+1}$ capture future productivity and commodity prices; $\varepsilon_t$ are exogenous and country-idiosyncratic perturbations to spreads; and the $\widetilde{\eta}$'s are reduced-form parameters that capture the elasticity of spreads to these variables and are either estimated or calibrated to match some empirical regularities. Default decisions are not directly modeled in this approach. The implicit and simplistic assumption made is that, as in Kehoe & Perri (2004), private domestic borrowers always pay their obligations in full but that in each period there is a probability that the local government will confiscate all interest payments going from local borrowers to the foreign lenders. Fluctuations in the confiscation probability in a particular economy are captured by the above equation, albeit in a reduced form.

[10]Formally, this is obtained by deriving the function $S(\bullet)$ which maps the value of net worth to spreads, e.g., $S_t = S(q_t k_{t+1}/n_{t+1})$, where $qk$ is the market value of assets held by entrepreneurs in EME and $n$ is their equity. It is derived that $S'(\bullet) > 0$, which then implies that, highly leveraged entrepreneurs, when faced with a positive windfall (e.g., a boost in productivity), will de-leverage on the margin, hence driving interest rate down and generating countercyclical interest rates.

capital markets ought to contain information on future economic activity in these economies. Thus one would expect economic activity in EMEs to be correlated with spreads over the business cycle. Moreover, perturbations to these spreads that are orthogonal to current economic activity ought to have an impact on *future* activity, mainly via their effect on aggregate investment and consumption.

In what follows we will formally explore the empirical validity of these hypotheses, first by constructing an external financial indicator that serves as proxy for the behavior of $S$ in several EMEs, using micro level data on international bond issuance by the corporate sector in these economies. We will then quantify the degree of comovement between this index and economic activity. Finally, we will measure the extent to which identified shocks to this indicator generate macroeconomic fluctuations in these economies. Before doing this, however, in the next section we begin by documenting recent trends in the access to international capital markets by the corporate sector in EMEs.

## 3 External Corporate Borrowing in EMEs: Stylized Facts

The relevance of international financial factors for economic activity in emerging markets hinges, to a large extent, on the reliance of foreign debt by the corporate sector in these economies. This section documents the considerable increase in access to international capital markets, in particular through bond market, by the corporate sector of 17 EMEs since the turn of the century.[11]

### 3.1 Sample of Countries and Data

When selecting the pool of EMEs studied we use three filters. First, we select all economies that have been included in the most recent peer-reviewed studies of EMEs' business cycles, or that have been classified as emerging economies by multilateral organizations or rating agencies. [12] Second, we remove from this list those countries where there was at least one episode of sovereign default since the year 2000, as these may have caused important disruptions in the access to foreign capital markets by the corporate sector. Third, we discard those countries that have had a history of high

[11] The stylized facts that we document in terms of the patterns in external financing by EMEs complement work by Shin (2014), Turner (2014) and Powell (2014) on how corporations from emerging economies have stepped up their financing through international capital markets. A recent paper by Gozzi, Levine, Martínez-Peria & Schmukler (2015) documents key characteristics of corporate bonds markets in EMEs.

[12] The academic literature that we use is: Neumeyer & Perri (2005), Uribe & Yue (2006), Aguiar & Gopinath (2007), Fernández & Gulan (2015), and Fernández et al., 2015. The multilateral organizations and rating agencies that we look at are i) the IMF; ii) MSCI; and iii) JPMorgan.

pervasive capital controls.[13] This process leaves us with a total of 17 EMEs that can be split into four geographical regions:[14]

(i) Latin America: Brazil, Chile, Colombia, Mexico and Peru.

(ii) East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand.

(iii) Eastern Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey.

(iv) Other Regions: South Africa and Israel.

For each of these economies we construct quarterly measures of corporate debt in international capital markets. We use data on stocks and flows of corporate debt. For stocks we use the data reported by the Bank of International Settlements (BIS). For flows, or gross issuance, we construct a measure of new bond issuance using information on the universe of bonds reported by Dealogic DCM, a leading data provider that tracks global debt capital markets. We choose the period 2000-2014 for our analysis to be consistent with the period where available data on corporate bonds spreads exists, and that we later analyze.

### 3.2 Stylized Facts

The total stock of international corporate debt is presented in Figure 1. We disaggregate the stocks between debt coming from international bond issuance and that associated with cross-border bank loans. The upper plot aggregates debt across all 17 EMEs considered, while the remaining four plots disaggregate the numbers across the four geographical regions mentioned above. The numbers reported are in current USD Billions. The data are taken from the information on the BIS' website and is collected on a nationality basis.[15] The stock of bond debt aggregates non-financial corporates, banks and other financial institutions and excludes, by construction, sovereign bond issuance. The stock of loan debt includes banks and non-banks.[16]

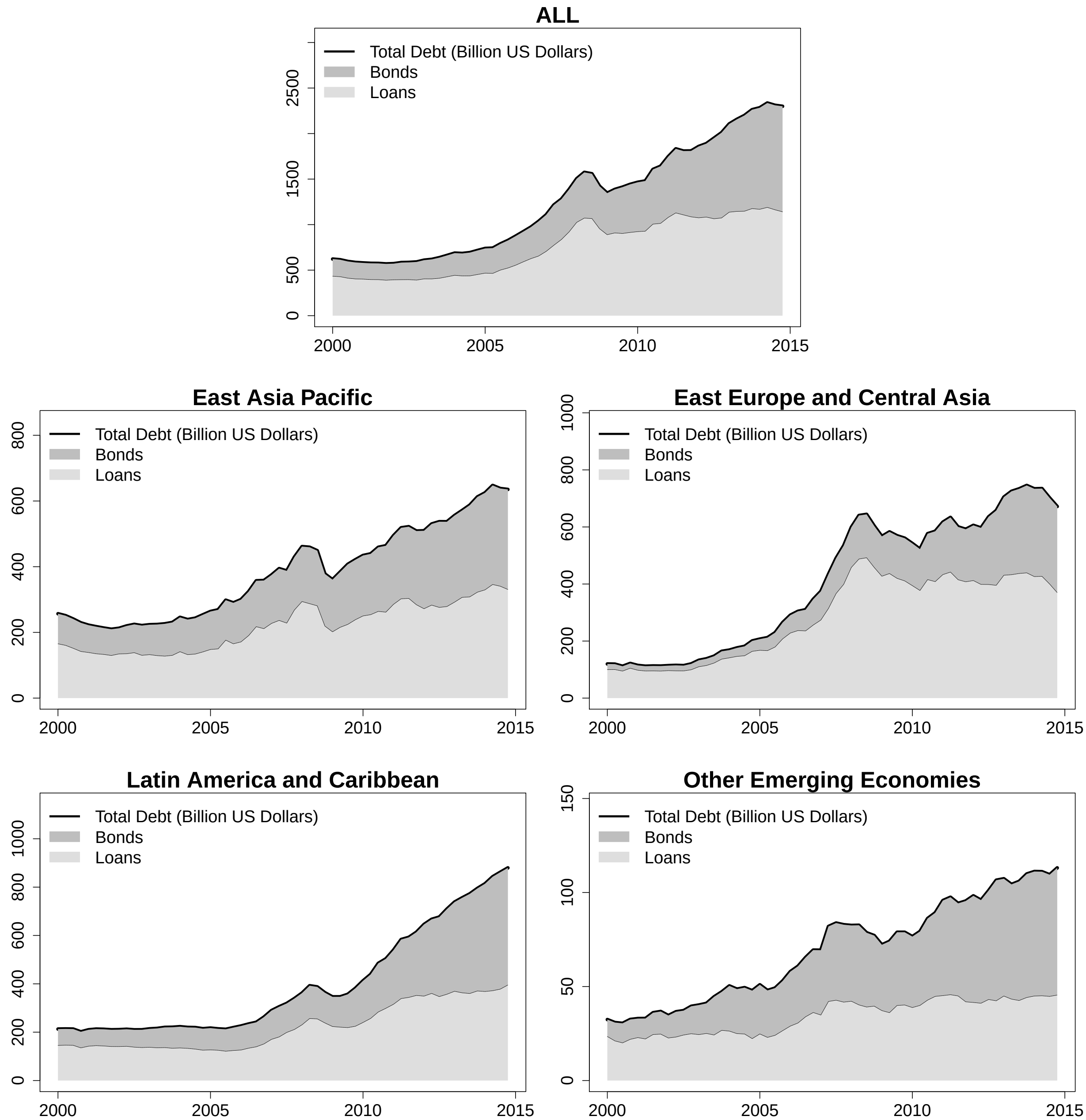
[13] We use the recent index on *de jure* measures of capital controls by Fernández, Klein, Rebucci, Schindler & Uribe (2015), which provides a quantitative measure of the existence of capital controls in both inflows and outflows separately, across various asset categories, for 100 economies between 1995 and 2013. The index is defined between zero (absence of controls in all asset categories) and one (controls in all categories). We define a country as having had a history of high capital controls if the average index over the 19 years is higher than one and a half standard deviations of the median across countries.

[14] Out of a total of 21 EMEs first identified in the first filter, Argentina and Ecuador were removed from the initial pool of economies as they experienced episodes of sovereign default within the period analyzed (second filter). China and India were not considered because they surpass the threshold of capital controls defined earlier (third filter).

[15] Shin (2014) and Turner (2014), among others, suggests debt on a nationality basis is more accurate than on a residence basis due to the increase of debt issues by offshore affiliates of corporates in emerging market.

[16] Although BIS data on cross-border bank loans do not decompose the stock of loans into private sector and government, we assume in Figure 1 that cross-border bank loans to sovereigns of EMEs are negligible. We double-checked

**Figure 1: Stock of Private Sector International Debt in EMEs by Region**




This figure shows the aggregate stock of private sector international debt for 17 emerging economies (EMEs), decomposing the outstanding stock into cross-border bank loans and international debt securities (bonds). The stock of securities is on a nationality basis. The private sector includes all financial institutions and non-financial corporations. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa, and Israel. The data are presented in billions of current U.S. dollars and sourced from the BIS Locational Banking Statistics and BIS Securities Statistics databases.

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this assumption based on data collected from national sources for the largest five Latin American economies and found that for the period 2006-2014 the mean ratio of cross-border loans made to governments to total cross-border loans was less than 1% (see Appendix). In countries with higher levels of development of local bond markets, such as Chile and Mexico, this figure is 0%. We feel it is safe to assume that this pattern is also found in other emerging economies. Lastly, geographical aggregation of debt does not net out debt with other EMEs in the sample.

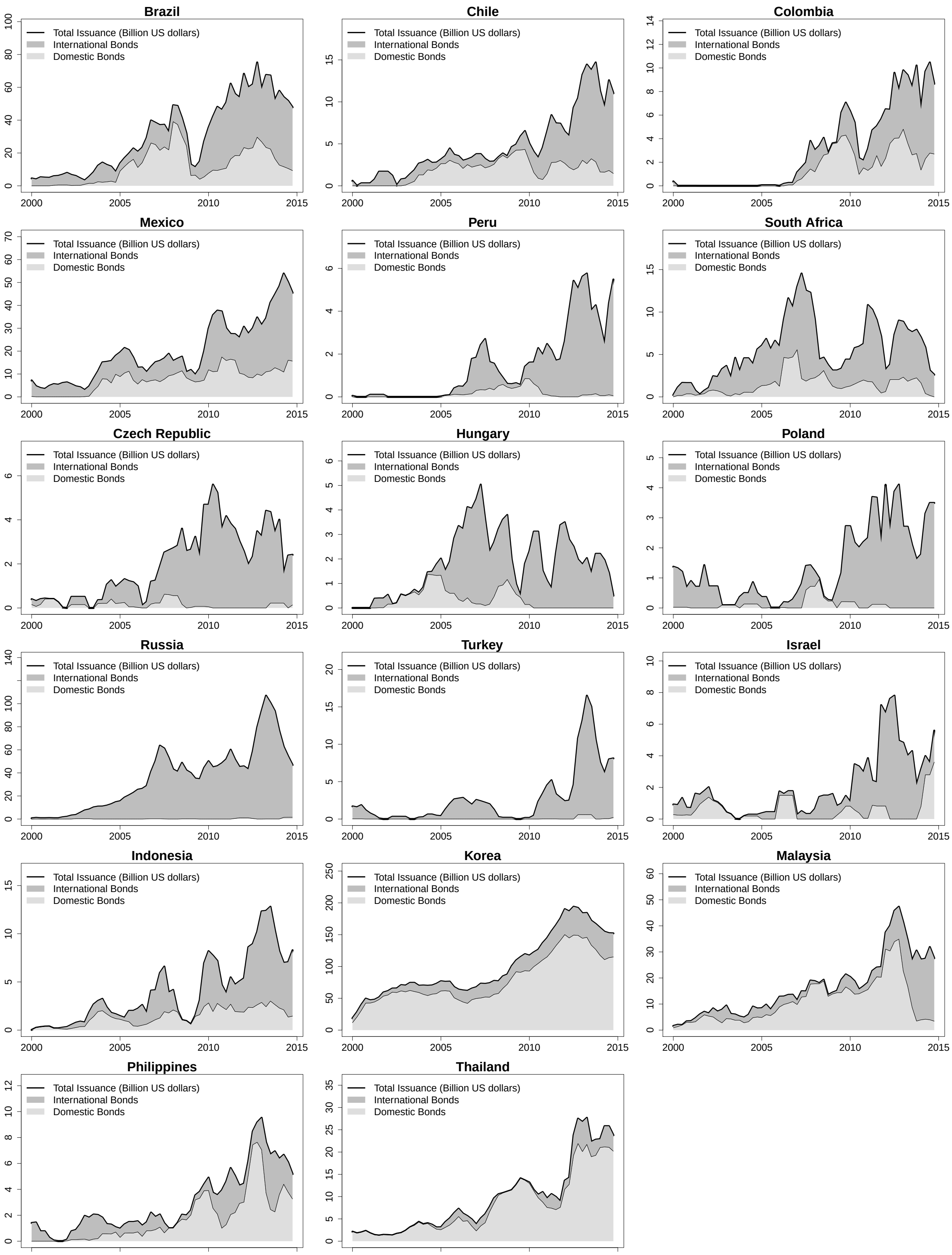
The most salient stylized fact from Figure 1 is the considerable increase in the stock of corporate debt by EMEs' corporations since the early 2000s, which quadrupled from an initial level of about 600 billion USD to 2.4 trillion USD by the end of 2014. The sharpest increase started in the mid-2000s and suffered a reversal during the onset of the Global Financial Crisis in 2008. That reversal was short-lived, however, and the accumulation of debt continued with a vigorous pace afterwards. The other remarkable stylized fact that emerges from Figure 1 is that the lion's share of this increase in corporate debt comes from bond issuance. Debt from loans also increased, but less proportionately than that from new bond issuance. Finally, it is also remarkable that these two stylized facts hold across all four geographical regions considered.

Given the relative importance of bonds in the accumulation of debt in EMEs, we turn to a closer look at bond issuance in Figure 2. It documents the value of total corporate bond issuance for the period considered, in current U.S. dollars, and for each of the 17 EMEs considered. The figure divides gross bond issuance on a nationality basis into domestic and international issuance. Aggregation is done using transaction-level data for all bonds available.[17] Again, the most salient stylized fact that comes out of Figure 2 is that corporate bond issuance has increased considerably since the early 2000s across all EMEs considered and, importantly, the lion's share of this increase comes from bonds issued in international markets. Even though this trend started before the onset of the global financial crisis, most of the expansion occurred afterwards.

In all Latin American countries there is a tendency for both domestic and international bond issuance to increase since the early 2000s, but the trend post-crisis accelerates most vigorously in the latter. In turn, the dominance of international issuance is much more marked for Eastern and Central European countries, where issuance of domestic debt is virtually non-existent in most of the countries. This contrasts with the case of most East Asian countries in our sample, where the share of domestic issuance accounts for the largest share. Nonetheless, for all countries in this region we also observe a tendency for international issuance to increase its share, particularly in the post-financial crisis period.

[17]The Appendix contains further details on the criteria used when determining if a bond is issued in foreign capital markets, and other details of the dataset. It also documents how the stylized facts are, to a large degree, robust to measuring international bond issuance on a residence basis.

## Figure 2: Corporate Gross Bond Issuance in EMEs by Country




This figure shows gross issuance of international and domestic debt securities (bonds) by country on a nationality basis. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See the Appendix for a description of how the country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities.

There are four additional stylized facts related to the issuance of debt securities in EMEs that we summarize here but further document in the Appendix for the sake of space. First, by and large, international bond issuance has been a corporate phenomenon, as sovereigns in EMEs have instead substituted foreign for domestic financing.[18] Second, the increase in international bond reliance by the corporate sector has taken place with roughly the same strength in both financial and non-financial corporations.[19] Third, the vast majority of international bond issuance is denominated in foreign currency, most of which is denominated in U.S. dollars (more than 60 percent, on average) or other non-local currency (20 percent). Fourth, the increase in foreign bond issuance by corporates in EMEs exceeds the recorded growth in economic activity in the post-financial crisis period observed in these economies. The ratios of gross bond issuance to GDP increased in most countries considered, particularly since the onset of the global financial crisis.[20]

Summing up, the systematic analysis of a pool of 17 EMEs reveals that bond issuance by corporations in these economies grew at a fast pace after the turn of the century, mostly driven by issuance in foreign capital markets. This trend accelerated after the Global Financial Crisis, and it was concentrated in bonds denominated in foreign currency, mainly USD, and outperformed other external sources of finance such as direct bank loans. This has led to the stock of debt by corporates in these EMEs to quadruple in little over a decade. Sovereigns, unlike corporates, have moved away from issuing bonds in international markets and have relied more on domestic markets.

## 4 An External Financial Indicator of Credit Spreads on Corporate Bonds in Emerging Economies

### 4.1 Constructing an External Financial Indicator

We now describe the methodology and data sources that we use to construct an external financial indicator for emerging economies based on the bonds issued by their corporate sectors in interna-

[18] A proper analysis of sovereign debt is beyond the scope of this paper. However, it ought to be noted that this trend in sovereign bond issuance should not be taken as evidence that sovereigns are more insulated from external financial shocks since, in some countries, international investors are the majority holders of this locally-issued, locally-denominated debt.

[19] This is in line with the recent work of Cortina-Lorente, Didier & Schmukler (2016), who document that 50 percent of bond issuance in developing countries is done by financial firms.

[20] Latin America, for example, had similar shares of gross bond issuance in both domestic and international securities by 2008, in the order of 1 percentage point of GDP. By the end of our sample, in 2014, this had tripled for the case of international bonds, while it remained constant for domestic ones.

tional markets. We focus on these bonds since our goal is to capture international financial forces that affect economic activity in these economies.

We construct the external financial indicator for the emerging economy $k$ at quarter $t$ ($EFI_t^k$) by taking a weighted average of option-adjusted spreads (OAS) across a sample of bonds issued by the corporate sector of economy $k$. The concept of OAS is suitable for our purpose because it provides a way to homogenize spreads across a variety of bonds of different characteristics.[21] Formally:

$$EFI_t^k = \sum_i w_{it}^k s_{it}^k \tag{1}$$

where $s_{it}^k$ is the OAS for bond $i$ at time $t$ and $w_{it}^k$ its relative weight. The latter is computed as

$$w_{it}^k = \frac{Bond\,Size_i^k}{\sum_{j=1}^{NB_t^k} Bond\,Size_j^k} \tag{2}$$

where $NB_t^k$ denotes the number of bonds issued by the corporate sector in economy $k$ whose OAS is available at time $t$, and $Bond\,Size_i^k$ refers to the size of bond $i$ measured in constant USD.

Because Dealogic, our data source for bond issuance presented in the previous section, lacks information on OAS, we switch to Bloomberg when computing the external financial indicator. This data provider contains OAS for a large pool of bonds issued by corporates in emerging market economies since the late 1990s. When choosing the sample of bonds to compute the external financial indicator we follow a set of criteria. Among the universe of corporate bonds available in Bloomberg, we choose only those with at least one corresponding OAS value at a quarterly frequency for their lifetime. We also drop bonds from the sample if information is not available on either date of issuance, bond size, industry that issuer belongs to, maturity date, or currency of

[21] The terminology "option" originally refers to the callability or puttability of the bond. The concept of OAS is introduced to account for a potential stop of cash flow as a result of call and put options being exercised. It also takes into account default risk since all possible future states of cash flow are considered in calculating OAS. Formally, let $r_t$ and $r_t^{i,k}$ denote, respectively, the (time varying) yield curves of the safe asset and the bond $i$ in economy $k$, so that $s_{it}^k = r_t^{i,k} - r_t$. An OAS, $s_{it}^k$, is computed after deriving $r_t^{i,k}$ as a solution to the following equation (omitting the $k$ index for simplicity)

$$p_t^i = \sum_{n=1}^{N} \prod(n) \sum_{\tau=t}^{M} \frac{C_\tau^i(n)}{(1 + r_\tau + r_t^i)}$$

where $p_t^i$ is the bid price of the risky bond $i$; $\prod(n)$ denotes the probability of $n^{\text{th}}$ path of the economy being realized; $M$ stands for maturity; and $C_\tau^i(n)$ denotes the cash flow in the path $n$. See O'Kane & Sen (2005) and Gabaix, Krishnamurthy & Vigneron (2007) for further explanations on the OAS.

denomination. Among this pool of bonds, we focus only on USD-denominated corporate bonds that have been issued in foreign capital markets.[22,23]

After dropping outliers (top and bottom 0.5 percentiles of OAS for the entire sample of bond-quarter observations by country), we were left with a total of 2,339 bonds and 23,791 (unbalanced) bond-quarter observations for the period 1999.Q2-2013.Q2 and across seven emerging economies: Brazil, Chile, Korea, Mexico, Malaysia, Peru and Philippines. Among the countries considered in the previous section, these were the ones for which at least one bond per quarter was observed for every quarter in the sample (we assigned countries based on issuer's country of incorporation).

The summary statistics of the dataset used to construct the external financial indicators are presented in Table 1. The average number of bonds per quarter is just under 400, and differs between countries. Brazil, Mexico, Korea and Chile exhibit the largest shares of the bonds considered, ranging between 185 to 1,061 bonds. In contrast, Malaysia, Peru and Philippines, exhibit less than a hundred different bonds. In all countries, the number of bond-quarter observations remains stable until 2009 and then increases until the end of the sample (not reported).[24]

The size of bond in Table 1 refers to total proceeds (i.e., the dollar amount raised by the firm by issuing the bond). The average size is 329 million but the size distribution is highly (positively) skewed, akin to that documented in Gilchrist & Zakrajsek (2012) for U.S. corporate bonds. Maturity at issue and terms to maturity respectively represent years left to the maturity at issue date and at observation date. The mean is close to seven years for both variables. On average, they are two to three years shorter than the case for the U.S. reported in Gilchrist & Zakrajsek (2012). Arguably, this reflects the ability of U.S. firms to issue bonds at longer maturities than firms in EMEs, and it also echoes the findings of Broner, Lorenzoni & Schmukler (2013) who document that EMEs tend to borrow short term.

[22] Due to lack of information on governing law and listing place for each bond in our Bloomberg terminal, we used information on ISIN and issuer's country of incorporation to make sure that we kept only international debt securities in our sample. See the technical appendix for details on the definition of international debt securities we use.

[23] Even though Bloomberg does not allow us to download data on the specific treasury used for the OAS computation, we manually checked the Bloomberg screen for a selected number of bonds and found that in all cases with available data it is a U.S. Treasury. We manually checked bonds for all possible combinations of issuer's country of incorporation, country where the bond ISIN was assigned, and type of exchange where the bond is listed (unlisted or international, the latter defined as an exchange different from the issuer's country of incorporation). We checked a total of 54 different bonds, which is the total number of combinations in our data. In all cases with available data the specific treasury used for the OAS calculation was a U.S. Treasury (seven bonds did not have information available).

[24] The online appendix presents evidence that the subsample of bonds with OAS data is representative of the universe of bonds studied in Section 3.

**Table 1: Dataset on Corporate Bond Spreads from Emerging Economics: Summary Statistics**

| Country | N. Bonds | N. Obs. | Statistics | Mean | SD | Min | Median | Max |
|---|---|---|---|---|---|---|---|---|
| All Countries | 2339 | 23791 | Number of bonds per quarter | 394.96 | 201.92 | 176.00 | 324.00 | 1153.00 |
| | | | Size of bond ($ mil) | 329.30 | 375.58 | 0.10 | 236.12 | 3037.77 |
| | | | Maturity at issue (years) | 6.94 | 7.54 | 0.08 | 5.50 | 100.08 |
| | | | Term to maturity (years) | 6.48 | 8.19 | 0.00 | 4.50 | 96.25 |
| | | | OAS spread (basis point) | 370.52 | 420.93 | 27.24 | 254.94 | 5685.23 |
| Brazil | 1061 | 6666 | Number of bonds per quarter | 116.95 | 72.11 | 57.00 | 92.00 | 509.00 |
| | | | Size of bond ($ mil) | 183.18 | 291.15 | 0.10 | 68.71 | 1814.23 |
| | | | Maturity at issue (years) | 3.93 | 4.07 | 0.08 | 2.00 | 30.00 |
| | | | Term to maturity (years) | 3.84 | 3.54 | 0.00 | 2.75 | 30.25 |
| | | | OAS spread (basis point) | 471.29 | 510.36 | 33.50 | 342.90 | 5685.23 |
| Chile | 185 | 3186 | Number of bonds per quarter | 55.89 | 30.84 | 14.00 | 51.00 | 132.00 |
| | | | Size of bond ($ mil) | 416.61 | 218.31 | 4.71 | 406.82 | 1185.77 |
| | | | Maturity at issue (years) | 11.68 | 11.13 | 1.00 | 10.00 | 100.08 |
| | | | Term to maturity (years) | 8.65 | 10.35 | 0.00 | 6.50 | 96.25 |
| | | | OAS spread (basis point) | 249.33 | 143.52 | 27.24 | 229.28 | 1497.09 |
| Korea | 390 | 5170 | Number of bonds per quarter | 90.70 | 52.60 | 35.00 | 78.00 | 221.00 |
| | | | Size of bond ($ mil) | 395.44 | 309.93 | 4.20 | 347.65 | 2053.47 |
| | | | Maturity at issue (years) | 6.74 | 6.93 | 0.50 | 5.00 | 100.00 |
| | | | Term to maturity (years) | 5.57 | 8.08 | 0.00 | 3.75 | 93.25 |
| | | | OAS spread (basis point) | 209.78 | 130.03 | 36.18 | 186.43 | 1017.10 |
| Malaysia | 79 | 1704 | Number of bonds per quarter | 29.89 | 7.16 | 9.00 | 31.00 | 41.00 |
| | | | Size of bond ($ mil) | 704.04 | 580.43 | 59.76 | 524.15 | 3037.77 |
| | | | Maturity at issue (years) | 13.45 | 15.64 | 2.00 | 10.00 | 100.00 |
| | | | Term to maturity (years) | 10.75 | 14.98 | 0.00 | 6.50 | 95.25 |
| | | | OAS spread (basis point) | 211.67 | 203.68 | 37.64 | 177.09 | 2495.75 |
| Mexico | 485 | 5477 | Number of bonds per quarter | 96.09 | 43.67 | 51.00 | 77.00 | 211.00 |
| | | | Size of bond ($ mil) | 493.93 | 477.60 | 0.19 | 333.77 | 2963.59 |
| | | | Maturity at issue (years) | 10.00 | 6.56 | 0.75 | 9.50 | 32.00 |
| | | | Term to maturity (years) | 7.71 | 6.59 | 0.00 | 6.25 | 32.00 |
| | | | OAS spread (basis point) | 507.95 | 569.53 | 27.90 | 333.59 | 5415.02 |
| Peru | 60 | 310 | Number of bonds per quarter | 5.44 | 10.10 | 1.00 | 1.00 | 52.00 |
| | | | Size of bond ($ mil) | 380.66 | 198.62 | 70.44 | 307.34 | 800.44 |
| | | | Maturity at issue (years) | 9.12 | 3.35 | 3.50 | 10.00 | 25.00 |
| | | | Term to maturity (years) | 7.36 | 3.42 | 0.75 | 7.38 | 25.00 |
| | | | OAS spread (basis point) | 430.75 | 256.92 | 84.28 | 347.20 | 1496.38 |
| Philippines | 79 | 1278 | Number of bonds per quarter | 22.42 | 4.57 | 14.00 | 22.00 | 31.00 |
| | | | Size of bond ($ mil) | 336.25 | 243.70 | 113.35 | 274.86 | 1184.59 |
| | | | Maturity at issue (years) | 10.38 | 11.58 | 2.00 | 8.50 | 100.00 |
| | | | Term to maturity (years) | 7.32 | 8.95 | 0.00 | 5.00 | 88.50 |
| | | | OAS spread (basis point) | 405.47 | 219.87 | 55.16 | 356.61 | 1998.70 |

This table reports summary statistics of the bonds in our dataset. The columns N. of Bonds and N. of Obs. report the number of bonds and the number of OAS-quarter observations in the sample for each country for the entire sample period of 1999.Q2-2013.Q2, respectively. Number of bonds per quarter refers to the number of bonds with an OAS observation at a given quarter. Size of bond is measured in real U.S. dollars (2010.Q3 = 100). OAS spread is the option-adjusted spread of a bond in basis points at a given quarter. Maturity at issue refers to the remaining years of a bond from its issuance date to its maturity date. Terms to maturity refers to the remaining years of the bond from a given quarter to its maturity date. We exclude from the sample OAS observations that are below (above) the country-specific $0.5^{th}$ ($99.5^{th}$) percentiles of OAS-quarter observations of all USD denominated bonds available in Bloomberg for the country (including sovereign bonds).

The mean OAS spread is 370 basis points (bp) for the sample period, and it is positively skewed, with a large standard deviation of 420 bp. The same pattern is observed across all seven countries in the sample, although considerable differences in the average OAS can be seen. Mexico and Brazil are the countries with the highest average OAS, 508 bp and 471 bp, respectively, while Chile (249 bp) and Korea (210 bp) exhibit the lowest levels, nearly half of those in Brazil and Mexico.

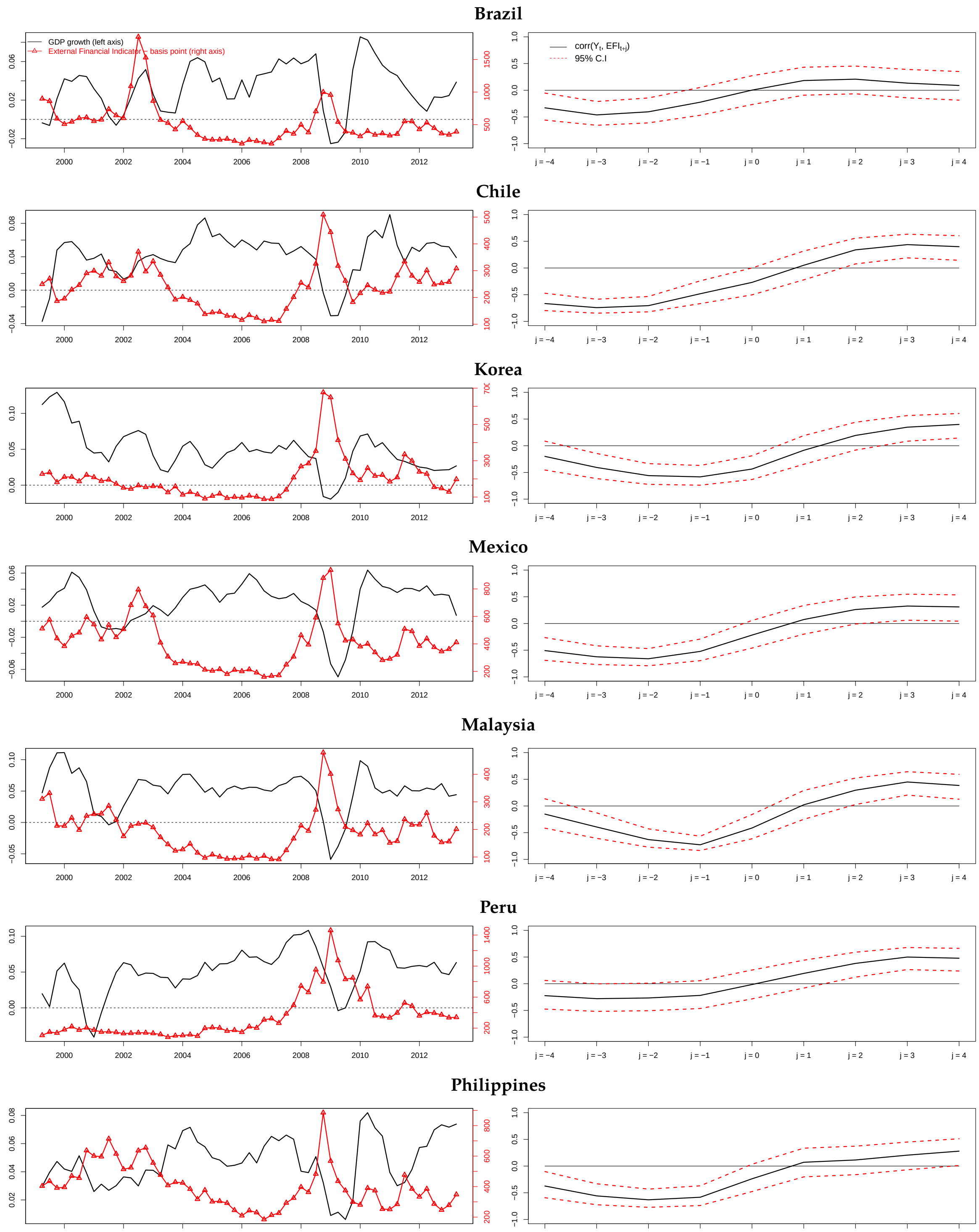
### 4.2 Dynamics of the External Financial Indicator

We now document the time series dynamics of the external financial indicators constructed, paying close attention to its comovement with real economic activity. The left column in Figure 3 plots, for each of the seven countries considered, the time series of $EFI$ together with real annual GDP growth, during the sample period 1999.Q2-2013.Q2. The two variables exhibit negative comovement. This pattern is most evident during the fall in economic activity around the global financial crisis of 2008/9 and the subsequent recovery. The crisis period was characterized by spikes in all the $EFI$s. It is also noteworthy that our series of $EFI$ fell to near pre-crisis levels as the EMEs in the sample recovered from the crisis. The negative comovement is also observed before the crisis in most countries, when these economies experienced sustained economic growth for several years while simultaneously our measure of $EFI$ displayed long and protracted reductions.[25]

The degree of cyclicality of our measures of $EFI$ is further assessed by computing their unconditional serial correlation with real GDP growth: $corr\left(\Delta GDP_t^k, \Delta EFI_{t+j}^k\right)$ for $j = -4, -3, ..., 4$; where $\Delta GDP_t^k$ is real annual GDP growth in economy $k$ and $\Delta EFI_{t+j}^k$ is the (annual) first difference in $EFI^k$. The results of this exercise are reported in the right column of Figure 3. They indicate that $EFI$ is a leading indicator of economic activity, as the correlation exhibits its trough when $j < 0$,, i.e., economic activity today co-moves the most, and in opposite direction, with lagged changes in $EFI$.

[25] Peru is a notable exception, though. This country's $EFI$ remained flat for most of the episode prior to the crisis of 2008/9. This could partly reflect the lack of a well-established market of foreign bonds in this country during this period, as was documented in the previous section.

## Figure 3: Real GDP and the External Financial Indicator




These figures show the time series dynamics of the external financial indicators (EFI) we constructed for each country in our sample with corporate spreads data and their comovement with real economic activity. The left column presents the times series of EFI in levels (diamond/red) and of annual real GDP growth rate (solid/black), both at a quarterly frequency. The right column presents the correlation between real GDP growth and changes in EFI at different lags $(corr\,(\Delta GDP_t,\, \Delta EFI_{t+j}))$ for $j = -4, \cdots, 4$. Red dotted lines represent a 95% confidence interval. The sample period is 1999.Q2-2013.Q2.

Lastly, it is worth noting that the $EFI$s constructed exhibit a strong comovement between them. In fact, the first principal component of the seven indicators accounts for 73 percent of the sample variance. Likewise, growth in the emerging markets considered also exhibits strong comovement: 65 percent of the sample variance is associated with the first principal component. We interpret this as evidence that $EFI$ captures global financial forces that affect real economic activity in emerging economies. Later we will formally test this interpretation.

## 5 The External Financial Indicator and Economic Activity

The evidence presented so far is consistent with the hypothesis that spreads on bonds issued by *corporates* of EMEs in international capital markets have information on aggregate economic activity which would explain the negative comovement observed between the two variables over the business cycle. We turn now to a more formal analysis of this hypothesis by quantifying the information content and predictive ability of credit spreads of these bonds on economic activity. We will also evaluate the hypothesis that exogenous perturbations to these spreads have an impact on *future* economic activity.

### 5.1 Forecasting Information Content of the External Financial Indicator

When assessing the information content and predictive ability from credit spreads of corporate bonds issued in international markets on economic activity in emerging economies, we extend Gilchrist & Zakrajsek's (2012) forecasting specification to a multi-country panel setting. Formally, we estimate a dynamic balanced panel regression of real GDP growth against changes in $EFI$:

$$\Delta GDP^k_{t+h} = \alpha_k + \sum_{j=0}^{p} \beta_j \Delta GDP^k_{t-j} + \gamma \Delta EFI^k_t + \Gamma \Omega_t + \widetilde{\Gamma}\widetilde{\Omega}^k_t + \epsilon_{k,t+h}, \text{ for } h \geq 1 \qquad (3)$$

where $k$ denotes each of the seven emerging economies considered, $k = 1, ..., 7$; and $h \geq 1$ is the forecast horizon. In our benchmark specification we fix $h = 1$, but later consider alternative values. Variables $\Delta EFI$ and $\Delta GDP$ are annual changes in $EFI$ and the (log of) real GDP, respectively.[26] We set the lag length equal to one ($p = 0$), although we later explore a richer lag specification structure as robustness. The estimated period starts in 1999.Q2, when our $EFI$ series begin, and covers until 2013.Q2.

[26]We will refer to annual real GDP growth and $\Delta GDP$ interchangeably form now on.

We estimate the dynamic panel regression with country fixed effects ($\alpha_k$) and use a set of controls that are country-specific ($\widetilde{\Omega}^k$) and of global nature ($\Omega$). The choice of controls is motivated by the literature on drivers of economic activity in emerging economies (see the Introduction). In particular, guided by previous studies on the role of global factors when accounting for economic activity in EMEs, we include in $\Omega$ two variables that are common across the seven countries and that aim at capturing the role of foreign factors beyond those already captured in changes of $EFI$: (annual) changes in term spreads of 3-month and 10-year U.S. Treasury yields, $\Delta USYield\,Curve$, and (annual) changes in the real U.S. Federal Funds Rate, $\Delta RFF_t$. These two were included in Gilchrist & Zakrajsek's (2012) original specification for the U.S. economy as domestic controls. In terms of the country-specific controls, we include in $\widetilde{\Omega}^k$ a measure of the domestic monetary policy stance by including the (annual) change in the policy rate in real terms, $\Delta RLocalRate$, and (annual) changes to a country-specific commodity price index that uses as weights the share of the commodities exported by each emerging economy relative to total exports, deflated by the U.S. CPI, $\Delta RPcom$.[27] Thus, our framework examines the marginal information content of credit spreads, as proxied by $EFI$, conditional on the stance of external and domestic monetary policies as well as real shocks coming from commodity exports.[28]

We estimate the model using the Least Square Dummy Variable estimator (LSDV). The estimated coefficients are reported in Table 2. Numbers in parenthesis are *t*-statistics adjusted for standard errors clustered by country. The columns report results according to 5 alternative specifications that vary according to the set of controls used. In the first column, no controls are used. The second column reports results where we add the two global controls, $\Omega_t = [\Delta USYield\ Curve_t; \Delta RFF_t]$. The third and fourth specifications are reported in the next two columns where we sequentially include the two domestic controls without global controls, $\widetilde{\Omega}^k_t = [\Delta RLocalRate_{k,t}]$ and $\widetilde{\Omega}^k_t = [\Delta RPcom_{k,t}]$, respectively. The final specification reported in the last column reports results when all controls are included.

[27] $\Delta RPcom$ is computed by weighting the international prices of 44 distinct commodities goods in international markets by their country-specific (constant) weights computed as their share in total commodity exports. The source (and motivation) for using $\Delta RPcom$ comes from Fernández et al. (2015) who, among others, argue that exogenous fluctuations in the price of commodities that emerging economies export are an important driver of their business cycles. See this work for further details on the construction of this variable.

[28] It may be argued that more variables could be added to model 3 in order to enhance the forecasting ability of our specification (e.g., industrial production). Such task, however, is not the aim of this investigation. Instead, our goal is to assess the information that the external financial indicator contains over and above a set of standard macro variables.

**Table 2: Panel Forecasting Regression**

| | *Spec 1* | *Spec 2* | *Spec 3* | *Spec 4* | *Spec 5* |
|---|---|---|---|---|---|
| $\Delta GDP_t$ | 0.75*** | 0.82*** | 0.74*** | 0.69*** | 0.75*** |
| | (28.32) | (22.59) | (28.70) | (14.34) | (21.42) |
| $\Delta\, EFI_t$ | -0.000029** | -0.000027** | -0.000028** | -0.000025** | -0.000022** |
| | (-3.30) | (-3.35) | (-3.66) | (-2.72) | (-2.97) |
| $\Delta US\, Yield\, Curve_t$ | | 0.0025* | | | 0.0032** |
| | | (2.27) | | | (2.66) |
| $\Delta RFF_t$ | | 0.0024** | | | 0.0026** |
| | | (2.70) | | | (2.67) |
| $\Delta R\ Local\ Rate_t$ | | | 0.00078 | | 0.00046 |
| | | | (1.43) | | (0.86) |
| $\Delta R\ Pcom_t$ | | | | 0.012 | 0.015* |
| | | | | (1.38) | (2.44) |
| Adjusted $R^2$ | 0.681 | 0.704 | 0.686 | 0.688 | 0.718 |
| Observations | 371 | 371 | 371 | 371 | 371 |

This table presents the benchmark results of country fixed-effect panel regressions. The dependent variable is the one-quarter ahead annual real GDP growth rate at a quarterly frequency ($\Delta GDP_{t+1}$). $\Delta EFI$ (measured in basis points) refers to annual changes in the external financial indicator. $\Delta US\, Yield$ (measured in percentage points) represents annual changes in the term spreads of 3-month and 10-year US treasuries. $\Delta RFF$ (measured in percentage points) is the annual changes in the real Federal Funds rate, which is the effective nominal Federal Funds Rate minus U.S. CPI inflation. $\Delta R\ Local\ Rate$ (measured in percentage points) is the annual changes in the domestic real monetary policy rate (which is computed as the domestic nominal policy rate minus the domestic inflation rate). We use as a proxy for the policy rate the money market rate or the monetary-policy-related interest rate. $\Delta R\ Pcom$ refers to annual changes in the composite commodity index of Fernández et al. (2015) (see Footnote 27 in the text for details on the construction of this index). The sample includes 7 emerging economies (Brazil, Chile, Korea, Malaysia, Mexico, Peru, Philippines) and the period of analysis is 1999.Q2-2013.Q2. Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

Our proxy for global financial conditions for emerging economies, $\Delta EFI$, is a statistically significant predictor of economic activity in these countries. The coefficient associated to this variable is estimated to be negative and statistically significant at $5$ percent significance level in all five specifications considered. Moreover, the magnitude of the estimated coefficient implies a strong and negative relationship between contemporaneous values of changes in $EFI$ and future real output growth. According to the estimated coefficient from the last specification considered, $\widehat{\gamma} = -0.000022$, an increase in $EFI$ of $100$ basis points in the current quarter is correlated with a reduction of $0.22$ percentage points in the output growth rate in the next quarter. This is a considerable reduction considering that such an increase is common in the data (e.g., a one standard deviation in $\Delta EFI$ is $195$ basis points).

The two external controls, $\Delta USYield\,Curve_t$ and $\Delta RFF_t$, are significant when added alone in Spec. 2 and when added jointly with the two country-specific controls in Spec. 5. Moreover, both have positive coefficients, which we interpret as coming from the fact that monetary policy in the U.S. is countercyclical (i.e., interest rates increase to smooth stronger economic activity), which has positive spillovers for emerging economies. Neither of the country-specific controls is significant when added separately in Specs. 3 and 4. Only $\Delta RPcom_{k,t}$ is significant when estimated with all other controls in Spec. 5, in which case it has a positive coefficient indicating that periods of high commodity prices are correlated with increases in macroeconomic activity.

### 5.2 Macroeconomic Effects of Shocks to the External Financial Indicator

We turn now to examining the dynamic macroeconomic consequences of shocks to $EFI$ in the EMEs considered. We do so by running a simple bivariate panel structural vector autoregressive model (see Love & Zicchino, 2006 and Abrigo & Love, 2016) of output growth and changes in $EFI$. Formally, the SVAR model is

$$\mathbf{A}\mathbf{Y}_t = \mathbf{C} + \mathbf{B}_1\mathbf{Y}_{t-1} + ... + \mathbf{B}_p\mathbf{Y}_{t-p} + \Phi_t \tag{4}$$

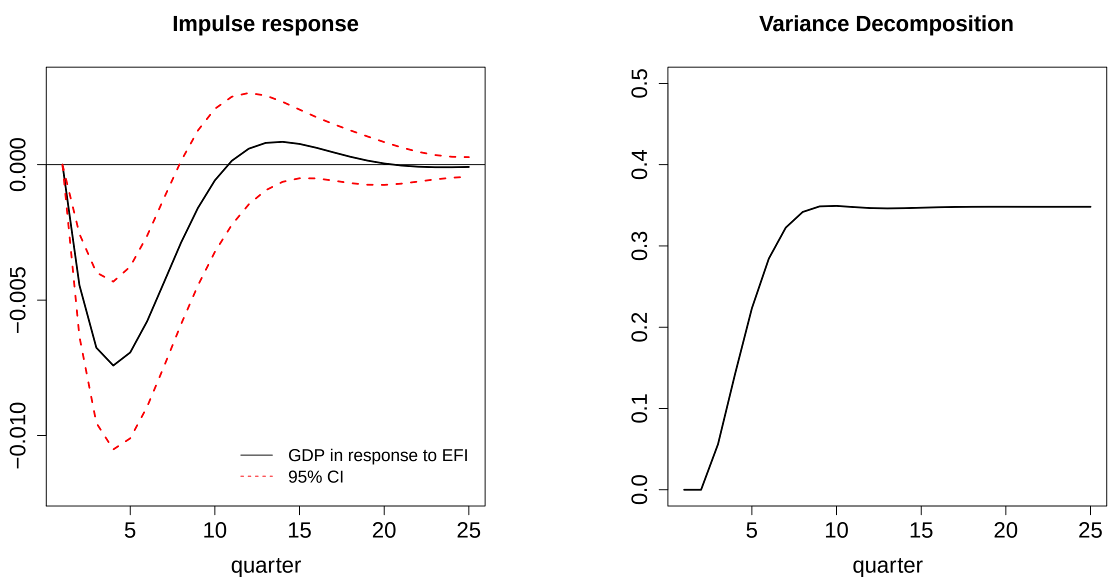
where $\mathbf{Y}_t$ is a $2K$x$1$ vector that collects all pairs of real output growth ($\Delta GDP$) and changes in $EFI$ ($\Delta EFI$) across the $K$ emerging economies; $\mathbf{C}$ is a vector of constants with country fixed effects; $\Phi_t$ is a vector of $i.i.d.$ errors with mean zero and variance-covariance $\Theta$, and matrix $\mathbf{A}$ captures the contemporaneous linkages across the variables, which we construct in a way that allows us to identify the shocks to $\Delta EFI$. In particular, we assume that shocks to $\Delta EFI$ will affect output growth only with a lag, while shocks to this variable may impact $\Delta EFI$ contemporaneously. This identification strategy has been used by Gilchrist & Zakrajsek (2012) for the case of the United States, and in the context of EMEs by Uribe & Yue (2006).[29] This implies that the main diagonal of $\mathbf{A}$ is a sequence of 2x2 lower triangular matrices. Finally, we set the lag length $p$ to one. A robustness section will later consider alternative timing identification assumptions as well as different lag specifications.[30]

[29]This identification strategy is rooted in the realistic assumption that financial variables (e.g., asset prices) react faster than real variables (e.g., production and investment decisions) due to various adjustment costs. Using this identifying assumption also allows our results to be compared more easily with previous studies.

[30]A potential concern emanating from the type of fixed effect panel VAR that we use here is the inconsistency of the

The left panel in Figure 4 depicts the impulse response function of output growth to an orthogonalized shock in $\Delta EFI_t$ derived from the estimated panel SVAR. An unanticipated increase of one standard deviation in the orthogonal component of this variable, roughly 150 basis points, causes a protracted fall of output growth. Indeed, the macroeconomic consequences of this adverse financial shock are substantial: output growth falls as much as 0.75 percentage points one year after the shock when it reaches its trough. After that, growth gradually recovers and returns to its long-run mean six quarters ahead.

**Figure 4: Panel VAR Impulse Response and Variance Decomposition of Real GDP Growth Rate**




This figure presents the impulse response function and the forecast error variance decomposition of the bivariate panel VAR model. The left panel presents the impulse response function of annual real GDP growth rate to a 1 standard deviation shock in $\Delta EFI$. Red dotted lines represent a 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The right panel shows the forecast error decomposition of real GDP growth rate associated with shocks to $\Delta EFI$.

Another result that we derive from the estimated SVAR model is the forecast error variance decomposition (FEVD) for real output growth, depicted in the right panel of Figure 4. The share of the FEVD of output accounted by shocks to $\Delta EFI$ converges to 35 percent as the time horizon increases beyond one and a half years. This number is considerably higher than those from previ-

least squares parameter estimates. Such bias, however, has been shown to decrease as the time dimension gets large (Judson & Owen, 1999), as in our empirical exercise. Still, we tested how robust our panel forecasting estimates are using the Anderson-Hsiao estimator. The results are reported in the Appendix and are qualitatively similar to those found in our benchmark case.

ous studies that quantified the role of risk premia shocks for emerging economies' business cycles that ranged between 12 and 15 percent (Uribe & Yue, 2006; Akinci, 2013). A key difference between these previous studies and ours is that they rely on measures of sovereign risk, unlike ours, which focuses on corporate risk.[31]

Summing up, the two methodologies employed so far, forecasting panel regressions and panel SVAR, have provided evidence that supports the hypotheses that spreads on bonds issued by *corporates* of EMEs in international capital markets have information on aggregate economic activity in these economies, and that exogenous perturbations to these spreads do have an impact on *future* economic activity. These results, we conjecture, are related to the considerable increase in foreign bond issuance by the private sector of EMEs, which we documented in the previous section. We next consider extensions of our empirical explorations as well as various robustness tests.

## 6 Extensions and Robustness Checks

### 6.1 Aggregate Consumption and Investment

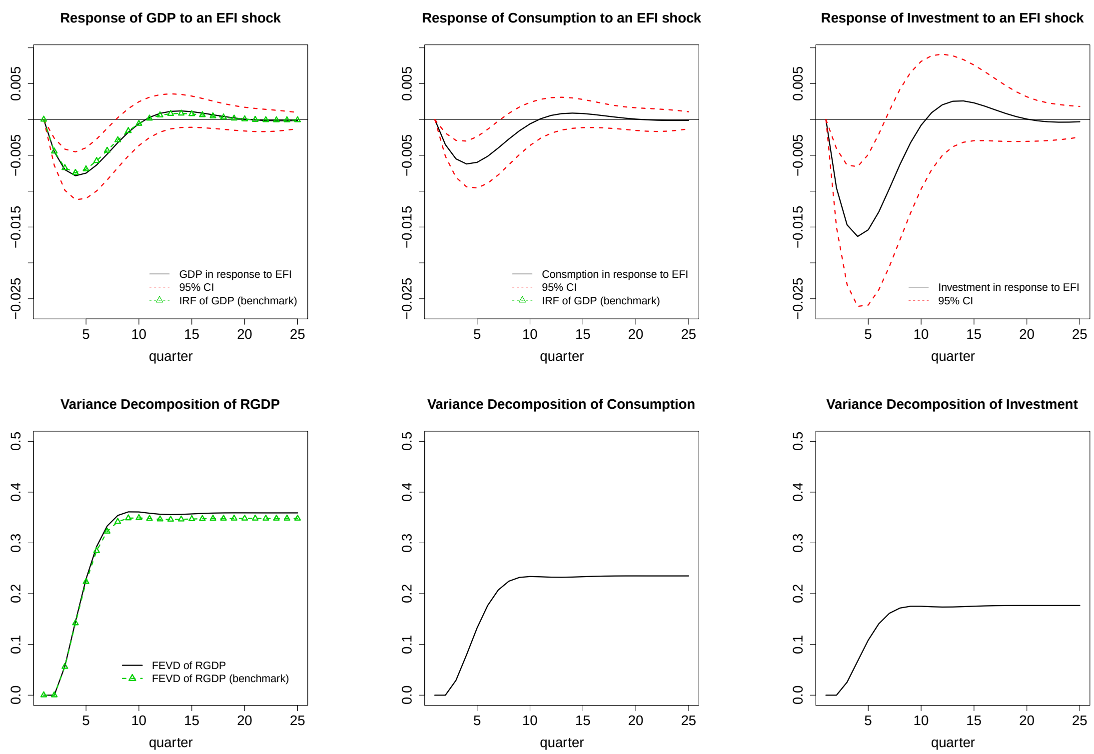
As was described in Section 2, the literature has postulated two reasons why agents in EMEs may borrow funds from world capital markets. One is associated to factors that affect the level of aggregate investment while the other relates to forces that shape aggregate consumption. Hence the response of these two macroeconomic variables represent two channels, mutually non-exclusive, through which international financial shocks can affect aggregate economic activity in EMEs. In this section we extend our analysis by quantifying the degree of responsiveness of consumption and investment following shocks to $\Delta EFI$. We do so by including these two variables in the SVAR specification (4) and deriving the impulse response functions in the expanded model. Our identification scheme remains the same in that we assume that shocks to $\Delta EFI$ affect real variables with a lag.

Results of this extension are reported in Figure 5. The upper panels of the figure display the impulse response functions for real growth in output, consumption and investment following a one S.D. shock in $\Delta EFI$. The lower panels report the variance decomposition for each of these

[31] The SVAR in Uribe & Yue (2006) includes a larger vector of variables than the two that we analyze here (particularly investment, the trade balance and the foreign interest rate). The Appendix presents the results when this larger model is run. They are quite similar to those found for the simpler bivariate VAR. The work by Akinci (2013) includes, in addition to the variables in Uribe & Yue (2006), the VIX. We will also examine this case in one of the extensions below.

variables. There is evidence that both consumption and investment react to a positive shock to $\Delta EFI$ by falling below their average mean growth. In terms of the variance decomposition for consumption, 23 percent of it is accounted for by perturbation in $EFI$, above that of investment, 18 percent. Lastly, the share of variance in real output growth remains around 35 percent, as was found in the benchmark case.

**Figure 5: Impulse Responses from Expanded Panel SVAR**




This figure summarizes impulse response functions and forecast error variance decompositions of the expanded panel VAR model including $\{\Delta GDP_{i,t}, \Delta CONS_{i,t}, \Delta INV_{i,t}, \Delta EFI_{i,t}\}$. The top row presents an impulse response function of annual real GDP, consumption and investment growth rate to a 1 standard deviation shock to $\Delta EFI$. Red dotted lines represent a 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row presents forecast error decompositions of real GDP, consumption and investment growth rates associated with shocks to $\Delta EFI$. The green-triangle dotted lines represent bivariate panel VAR results from Figure 4. Malaysian sample starts in 2005.Q1 due to data availability on investment.

### 6.2 Sovereign Risk

A potentially valid critique of our approach is that the real effects of external financial factors that we associate with corporate credit spreads in EMEs may be influenced by sovereign risk. As argued before, our focus on corporate risk in these economies comes from the stylized fact, presented in Section 3, that the large expansion of international bond issuance in EMEs since the early 2000s has mainly been concentrated in the corporate sector, not in the public sector. Still, it could be argued that the longstanding history of serial default by some EMEs may continue to make international investors wary of potential spillovers from sovereign risk to corporate risk. Such spillovers can arise if, for example, sovereign risk increases due to a rising public deficit, which then increases the probability that governments increase tax rates on the corporate sector or even expropriate private assets, raising their cost of borrowing in foreign markets.[32] Recently, Akinci (2013) found that shocks to the sovereign risk premia, proxied by JP Morgan's Emerging Markets Bond Index ($EMBI$), explained about 15 percent of business cycles in emerging economies, in line with earlier estimates from Uribe & Yue (2006) of about 12 percent.

To address this critique, in this subsection we assess how robust our benchmark results are when we include the country $EMBI$ in the forecasting panel regressions and panel SVARs. The results of the new panel regression are reported in the upper panel of Table 3, where we reproduce the same five specifications of Table 2. The results are virtually identical to the benchmark case. The coefficient associated with the change in $EFI$ continues to be negative, large in absolute value, and statistically significant at 5 percent. That of $EMBI$ is positive but *not* significant at $5$ percent significance level in any of the five specifications considered. In an alternative specification when $EFI$ is turned off (last column in Table 3, upper panel) and only $EMBI$ remains, its coefficient changes sign but continues not to be significant.

The new panel SVAR that we run now includes $\Delta EMBI$ in addition to $\Delta GDP$ and $\Delta EFI$. We assume that shocks to $EMBI$ can contemporaneously affect $EFI$ but not vice versa. The impulse response of output growth from an identified one S.D. shock to $\Delta EFI$ in this expanded panel SVAR is reported in the top left panel of Figure 6. For the sake of comparison the figure also plots the response in the benchmark specification. The results continue to point to the same direction as those in the benchmark: an identified shock to $\Delta EFI$ generates a large and protracted fall in economic activity. Output growth falls as much as $0.6$ percentage points three quarters after the

[32] This is just one of the many channels that may deliver a connection between sovereign and corporate risk. Another channel has been recently analyzed formally by D'Erasmo, Durdu & Boz (2013), where increases in sovereign risk constrain banks' ability to extend credit to firms because their balance sheet weakens as they hold sovereign bonds as part of their assets. Of course, the causality may go the other way around as well (i.e., from corporate to sovereign risk). The case of several crises in Asia in the 1990s (e.g., Korea) and the more recent experience in Ireland or Spain show how the deterioration of corporate balance sheets may turn into higher sovereign risk as the public sector absorbs much of the private illiquid debts. Our robustness check ought to be seen just as a crude first approximation to disentangling the links between corporate and sovereign risk.

shock when it reaches its trough. After that, growth gradually recovers and returns to its long-run mean approximately $8$ quarters later. The dynamics track closely those in the benchmark impulse response. The bottom left panel in Figure 6 also presents the results in terms of FEVD for real output growth. The share of the FEVD of output accounted by shocks to $\Delta EFI$ converges to $20$ percent as the time horizon increases beyond one and a half years. This is close to half the share obtained in the benchmark case.[33]

Overall, the results are pretty robust once one accounts for the possible role that sovereign risk may be playing in driving the dynamics of the external financial indicator. The macroeconomic effects are pervasive although marginally smaller. We interpret this as complementary evidence to that presented in previous studies that argue for a large role of sovereign risk when accounting for economic activity in emerging economies. Our results point to the relevance of shocks to the *corporate* risk premia as an *additional* source of fluctuations in real economic activity.

### 6.3 The VIX and Foreign Investors' Risk Aversion

In an influential work, Rey (2013) identified the $VIX$–a measure of uncertainty and risk aversion coming from the implied volatility of S&P 500 index options–as a variable that co-moves strongly with a global financial cycle in cross border capital flows. Moreover, Akinci (2013) finds that shocks to the $VIX$ account for about 20 percent of movements in aggregate economic activity in a pool of emerging economies. Motivated by these works, in this section we explore to what extent movements in $EFI$ are capturing changes in foreign investors' risk appetite that previous works have proxied by the $VIX$ when quantifying the effects of these changes in emerging economies. We address this question by including the $VIX$ in the panel forecasting regressions and panel SVARs (already controlling for $EMBI$, as we do in the previous section).

The results of the new panel regression are reported in the lower panel of Table 3 where, again, we reproduce the same five specifications that we originally considered in Table 2. The coefficient associated with $\Delta EFI$ in Spec. 5, $\widehat{\gamma} = -0.000018$, falls relative to the benchmark ($-0.000022$) but remains statistically significant (to 1 percent confidence level), and so is the (negative) one associated with the $VIX$.[34] In an additional experiment that we run, in the last column of that

[33] The Appendix presents the results when an alternative ordering is used such that shocks to $EFI$ can affect, contemporaneously, $EMBI$ but not vice versa. For that case the results are even more similar to our benchmark results.

[34] The standard deviation of the change in the $VIX$ is 10.3.

table, we remove $EFI$ from the set of regressors. For that case, the coefficient associated with the $VIX$ increases in absolute terms by nearly $40$ percent.

The new panel SVAR that we run now includes $\Delta VIX_t$ as an exogenous variable in addition to $\Delta GDP$, $\Delta EMBI$ and $\Delta EFI$. The impulse response of output growth from an identified one S.D. shock to $\Delta EFI$ in this expanded panel SVAR is reported in the top right panel of Figure 6. Again, for the sake of comparison, the figure also plots the response in the benchmark specification. The results continue to point to the same direction as those in the benchmark: an identified shock to $\Delta EFI$ generates a fall in economic activity. Output growth falls but the magnitude of the fall is considerably reduced vis-à-vis the benchmark case. Output growth falls as much as $0.25$ percentage points two quarters after the shock when it reaches its trough. Hence the trough is about $1/3$ that of the benchmark specification.

The results of the variance decomposition for output growth go in the same direction (bottom right panel in Figure 6). The share of the FEVD of output growth accounted by shocks to $\Delta EFI$ converges to about $8$ percent, about a fourth of that in the benchmark case.

Overall, the results point to a crucial role of global risk appetite shifts in driving the macroeconomic effects of changes in $EFI$, which we view as complementary to Rey (2013) and Akinci (2013). This is mostly manifested in the dynamic responses of economic activity to shocks in this variable when controlling for endogenous responses to $VIX$ fluctuations. Likewise, shocks to $EFI$, once $VIX$ is taken into account, account for a much more reduced variance share of output growth. Still, it is noteworthy that a non-trivial dynamic response of output growth continues to come from independent fluctuations in $EFI$. We view this as evidence that our measure of external financial index does indeed capture external forces that affect economic activity in EMEs that are intrinsic to these economies, above and beyond global changes in investors' risk appetite.[35]

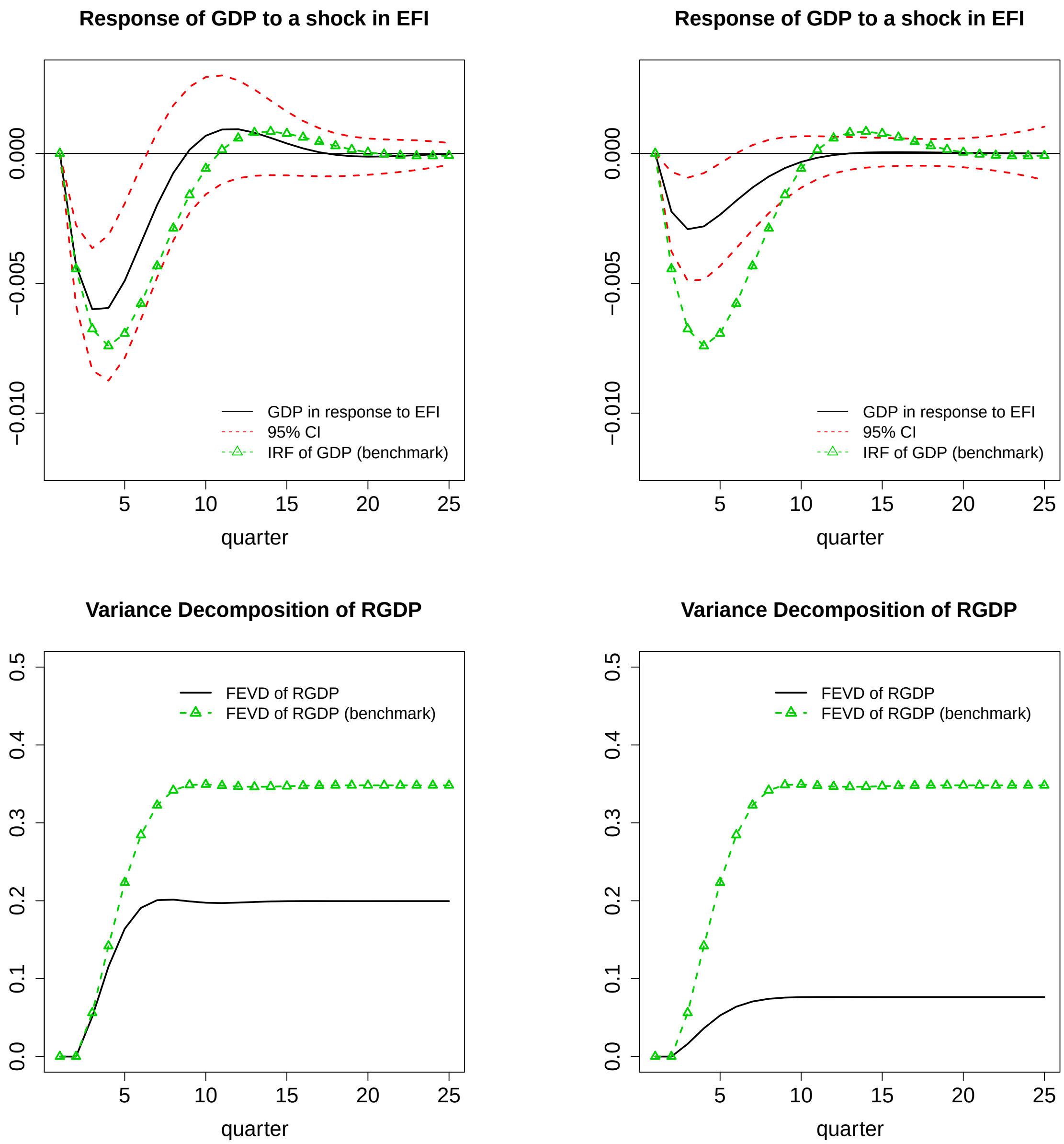
[35]The Appendix contains further experiments where we include other observed external forces that may proxy for the global financial cycle, namely U.S. GDP growth. We find this variable not to have any explanatory value beyond that of the other controls. We also experimented by adding quarter-time fixed effects, which renders $EFI$ no longer significant (although only for $h = 1$). We view this as additional evidence that $EFI$ is capturing, although imperfectly, a financial common factor that is absorbed by the time fixed effect and materializes in a strong comovement across the $EFI$s.

**Table 3: Panel Results Controlling for Sovereign Risk and Foreign Investors' Risk Aversion**

| | *Spec 1* | *Spec 2* | *Spec 3* | *Spec 4* | *Spec 5* | *w.o EFI* |
|---|---|---|---|---|---|---|
| *Panel A. Controlling for sovereign risk* | | | | | | |
| $\Delta GDP_t$ | 0.76*** | 0.83*** | 0.75*** | 0.66*** | 0.73*** | 0.72*** |
| | (27.71) | (21.82) | (29.48) | (11.61) | (16.93) | (18.17) |
| $\Delta\, EFI_t$ | -0.000035** | -0.000035*** | -0.000034** | -0.000028** | -0.000027** | |
| | (-3.29) | (-4.36) | (-3.06) | (-3.08) | (-4.01) | |
| $\Delta EMBI_t$ | 0.000010 | 0.000012 | 0.0000094 | 0.0000097 | 0.000012 | -0.000012 |
| | (0.56) | (0.82) | (0.51) | (0.61) | (0.88) | (-1.31) |
| $\Delta US\, Yield\, Curve_t$ | | 0.0023 | | | 0.0028* | 0.0027* |
| | | (1.78) | | | (2.17) | (2.04) |
| $\Delta RFF_t$ | | 0.0023* | | | 0.0022* | 0.0023* |
| | | (2.20) | | | (2.34) | (2.18) |
| $\Delta R\, Local\ Rate_t$ | | | 0.00072 | | 0.00040 | 0.00043 |
| | | | (1.18) | | (0.66) | (0.67) |
| $\Delta R\, Pcom_t$ | | | | 0.019** | 0.020*** | 0.024*** |
| | | | | (3.33) | (4.05) | (4.24) |
| Adjusted $R^2$ | 0.685 | 0.704 | 0.690 | 0.704 | 0.726 | 0.707 |
| Observations | 317 | 317 | 317 | 317 | 317 | 317 |
| *Panel B. Controlling for foreign investors' risk aversion* | | | | | | |
| $\Delta GDP_t$ | 0.72*** | 0.79*** | 0.72*** | 0.66*** | 0.73*** | 0.72*** |
| | (15.40) | (17.44) | (16.27) | (10.09) | (13.69) | (13.93) |
| $\Delta\, EFI_t$ | -0.000019*** | -0.000020*** | -0.000019*** | -0.000017*** | -0.000018*** | |
| | (-5.98) | (-8.94) | (-5.64) | (-5.29) | (-7.07) | |
| $\Delta EMBI_t$ | 0.0000099 | 0.000012* | 0.0000094 | 0.0000096 | 0.000011 | -0.0000014 |
| | (1.22) | (2.07) | (1.03) | (1.11) | (1.67) | (-0.30) |
| $\Delta VIX_t$ | -0.00053** | -0.00050*** | -0.00050** | -0.00042** | -0.00036** | -0.00049** |
| | (-3.83) | (-4.37) | (-3.66) | (-2.73) | (-2.70) | (-3.76) |
| $\Delta US\, Yield\, Curve_t$ | | 0.0023 | | | 0.0027* | 0.0026* |
| | | (1.90) | | | (2.11) | (2.06) |
| $\Delta RFF_t$ | | 0.0021* | | | 0.0021* | 0.0021* |
| | | (2.39) | | | (2.43) | (2.38) |
| $\Delta R\, Local\ Rate_t$ | | | 0.00048 | | 0.00027 | 0.00024 |
| | | | (0.84) | | (0.45) | (0.38) |
| $\Delta R\, Pcom_t$ | | | | 0.013** | 0.015** | 0.016** |
| | | | | (2.75) | (3.50) | (3.92) |
| Adjusted $R^2$ | 0.709 | 0.725 | 0.710 | 0.717 | 0.735 | 0.729 |
| Observations | 317 | 317 | 317 | 317 | 317 | 317 |

This table shows results of country-fixed effect panel regression controlling for sovereign risk and foreign investors' risk aversion. Panel A reproduces the results of the five specifications in Table 2 adding $\Delta EMBI_t$ as an additional control variable for sovereign risk. Panel B reproduces the results in Table 2 adding both $\Delta EMBI_t$ and $\Delta VIX_t$, the latter as a control for foreign investors' risk appetite. In both panels the last column drops the covariate for $\Delta EFI$. In both panels the dependent variable is the annual real GDP growth rate at a quarterly frequency ($\Delta GDP_{t+1}$). $\Delta EFI$ refers to annual changes in the external financial indicator. $\Delta US\, Yield$ represents annual changes in the term spreads of 3-month and 10-year US treasuries. $\Delta RFF$ is the annual changes in the real Federal Funds rate, which is the effective nominal Federal Funds Rate minus U.S. CPI inflation. $\Delta R\, Local\ Rate$ is the annual changes in the domestic real monetary policy rate. $\Delta R\, Pcom$ refers to annual changes in the composite commodity index of Fernández et al. (2015). The baseline sample includes 7 emerging economies (Brazil, Chile, Korea, Malaysia, Mexico, Peru, Philippines) and the period 1999.Q2-2013.Q2, but in these tables the 1999.Q2 observation for Chile and all observations for Korea are dropped because of lack of EMBI data. Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

## Figure 6: Impulse Response Controlling for Sovereign Risk and Foreign Investors' Risk Aversion




This figure summarizes impulse response functions and forecast error variance decompositions of the panel VAR models after controlling for sovereign and external risks. The first column shows results from a trivariate panel VAR model including $\{\Delta GDP_{i,t}, \Delta EMBI_{i,t}, \Delta EFI_{i,t}\}$ as endogenous variables. The second column shows results from a trivariate panel VAR model including $\{\Delta GDP_{i,t}, \Delta EMBI_{i,t}, \Delta EFI_{i,t}\}$ as endogenous variables, and $\{\Delta VIX_t\}$ as an exogenous variable. The top row presents the impulse response function of annual real GDP growth to a 1 standard deviation shock to $\Delta EFI$. Red dotted lines represent a 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row presents the forecast error decomposition of real GDP associated with shocks to $\Delta EFI$. Green-triangle dotted lines represent results from Figure 4. Korea is excluded due to data availability on sovereign risk (EMBI). 1999.Q2 EMBI observation for Chile is dropped due to EMBI data availability.

### 6.4 Alternative Filtering

Our benchmark results are computed using variables that are expressed in growth rates (or annual differences for spreads and interest rates). This is reasonable to the extent that it is a simple and tractable measure of changes in economic activity and foreign financial conditions. Yet, strictly speaking, this is not a transformation that allows to distinguish between trend and cyclical components of the variables considered, the latter being often the main object of analysis when thinking about changes in economic activity in the literature (see Introduction). We now assess the robustness of the benchmark results when variables are detrended. For this purpose we use the Hodrick-Prescott filter, a commonly used detrending procedure in business cycle analysis.[36]

The upper panel of Table 4 reports the panel regression results with this alternative filter. All variables have been detrended using a smoothing parameter equal to $1,600$. The table reproduces the same columns reported in our benchmark case (Table 2). The results are both qualitatively and quantitatively robust. The estimated coefficient for $EFI$ is now $\widehat{\gamma} = -0.000019$ for Specification 5, very close to the benchmark, and statistically significant at $10$ percent. The Appendix contains the impulse responses which closely track those in the benchmark specification.

### 6.5 Alternative Forecasting Horizons

In our benchmark analysis we arbitrarily fixed the forecasting horizon to be one quarter, $h = 1$, in (3). We now extend our analysis by considering alternative forecasting horizons. In particular, we consider the cases of $h = 0, 2, 3, 4$. The case of $h = 0$ is one of "nowcasting" and can be thought as one where, because of reporting lags, economists typically do not observe current output growth, while financial asset prices that are used to construct $EFI$ may be readily available.

The results of these alternative forecasting horizons are presented in the lower panel of Table 4. For comparison, the first column reports the results in our benchmark case where $h = 1$ and the other columns present, respectively, the cases of $h = 2, 3, 4$, and $0$. In all cases, the specification presented is the one with all controls active (Spec. 5 from Table 2).

[36] A potential shortcoming that this detrending measure poses is the fact that it is a two-sided filter and thus may display less accuracy when extracting the trend component in the end points of any time series. This may be particularly inconvenient in this case, given that our objective is to study the information content within a forecasting regression framework. We try to minimize this problem by using out-of-sample observations on the variables used for the period 2013.Q3-2014.Q4.

## Table 4: Alternative Filtering Method and Forecasting Horizons

| | *Spec 1* | *Spec 2* | *Spec 3* | *Spec 4* | *Spec 5* |
|---|---|---|---|---|---|
| *Panel A. Alternative filter* | | | | | |
| $\Delta GDP_t^c$ | 0.74*** | 0.77*** | 0.73*** | 0.66*** | 0.70*** |
| | (24.94) | (25.86) | (26.07) | (13.63) | (15.66) |
| $EFI_t^c$ | -0.000027** | -0.000025** | -0.000026** | -0.000021* | -0.000019* |
| | (-2.93) | (-2.84) | (-3.11) | (-2.27) | (-2.29) |
| $US\,Yield\,Curve_t^c$ | | 0.0010 | | | 0.0018* |
| | | (1.23) | | | (1.99) |
| $RFF_t^c$ | | 0.0019** | | | 0.0022** |
| | | (2.73) | | | (2.76) |
| $R\,Local\,Rate_t^c$ | | | 0.00048 | | 0.000091 |
| | | | (1.14) | | (0.21) |
| $R\,Pcom_t^c$ | | | | 0.015 | 0.017* |
| | | | | (1.74) | (2.27) |
| Adjusted $R^2$ | 0.675 | 0.688 | 0.677 | 0.686 | 0.701 |
| Observations | 399 | 399 | 399 | 399 | 399 |

| *Panel B. Alternative forecasting horizon* | | | | | |
|---|---|---|---|---|---|
| | *h=1* | *h=2* | *h=3* | *h=4* | *h=0* |
| $\Delta GDP_{t-1}$ | | | | | 0.70*** |
| | | | | | (13.39) |
| $\Delta GDP_t$ | 0.75*** | 0.40*** | 0.063 | -0.24** | |
| | (21.42) | (7.18) | (0.81) | (-2.68) | |
| $\Delta\, EFI_t$ | -0.000022** | -0.000032*** | -0.000034*** | -0.000024** | -0.000013 |
| | (-2.97) | (-3.88) | (-4.24) | (-2.74) | (-1.60) |
| $\Delta US\,Yield\,Curve_t$ | 0.0032** | 0.0042* | 0.0027 | -0.00054 | 0.0011 |
| | (2.66) | (2.41) | (1.48) | (-0.29) | (0.88) |
| $\Delta RFF_t$ | 0.0026** | 0.0048*** | 0.0057*** | 0.0046*** | -0.00024 |
| | (2.67) | (3.76) | (5.71) | (5.57) | (-0.41) |
| $\Delta R\,Local\,Rate_t$ | 0.00046 | 0.00100 | 0.00092* | 0.00056 | 0.00041 |
| | (0.86) | (1.54) | (2.19) | (0.95) | (0.79) |
| $\Delta R\,Pcom_t$ | 0.015* | 0.020* | 0.014 | 0.012 | 0.028** |
| | (2.44) | (2.29) | (1.66) | (1.29) | (3.46) |
| Adjusted $R^2$ | 0.718 | 0.449 | 0.360 | 0.328 | 0.721 |
| Observations | 371 | 371 | 371 | 371 | 371 |

This table shows two robustness checks. Panel A reproduces results in Table 2 using an alternative filter (Hodrick-Prescott filter with smoothing parameter $\lambda = 1600$; a superscript $c$ represents the cyclical component of the filtered series). Panel B reproduces Spec. 5 in Table 2 for different forecasting horizons where the dependent variables are $\Delta GDP_{t+h}$ and $h$ is a forecasting horizon. In Panel B, all variables are identically defined as in Table 2. Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

The coefficient associated with $\Delta EFI$ increases in size (and statistical significance) as $h$ increases above $1$, although not monotonically. The highest value, in absolute terms, is found for $h = 3$, in which case $\widehat{\gamma} = -0.000034$, a 55 percent increase relative to the one found in our benchmark case. And its statistical significance increases to 1 percent. The opposite occurs for the nowcast specification, where the coefficient reduces roughly to half of that in the benchmark specification, and is no longer significant at 10 percent. These results highlight the *forecasting* information content of $EFI$ for economic activity in emerging economies. They are also in line with the serial correlations presented in Figure 3, which showed the strongest comovement between contemporaneous economic activity and lagged values of $EFI$ in all the EMEs considered.[37]

### 6.6 Alternative Lag Order

In the benchmark SVAR specification (4) we arbitrarily set the number of lags to be one, $p = 1$. We now consider alternative lag specifications.[38] The upper left plot in Figure 7 reports the impulse responses of output growth for the alternative cases when $p = 2, 3$. For comparison, we also report those in the benchmark case. Solid lines represent impulses that are statistically significant at 95 percent confidence level.

The results are qualitatively identical to the benchmark case. An orthogonal one S.D. shock to $\Delta EFI$ leads to a protracted fall in economic activity for all lag specifications considered. The trough also continues to lie one year after the shock. Quantitatively, the depth of the trough is $0.55$ percent, slightly below that in the benchmark case where the trough is around $0.75$ percent.[39]

### 6.7 Alternative Identification Scheme

As argued before, the identification assumption used in the SVAR model—that shocks to $\Delta EFI$ affect output growth only with a lag while shocks to this variable may impact $\Delta EFI$ contemporaneously—has been common in the literature on both developed economies and EMEs. Nonetheless, we test

[37]In terms of the controls, the U.S. yield curve reduces its significance, unlike the real FED's fund rate which continues to be significant for $h \geq 1$, but not at $h = 0$. It also increases in magnitude until $h = 3$. The coefficient on the real local rate appears to be significant only at 10 percent when $h = 3$ and with a positive sign, which would signal that domestic monetary policy behaves in a countercyclical and forward-looking way. Finally, the coefficient on real commodity prices is strongest and statistically significant when $h = 0$ and then decreases in magnitude and statistical significance as the forecast horizon increases.

[38]The Appendix contains also extensions of the forecasting panel regression (3) with additional lags.

[39]Because the specification changes in these two alternatives, the size of the S.D. of the shock to $\Delta EFI$ also varies slightly. The shock has a magnitude of $147$ and $142$ basis points for the cases where $p =$ 2,3, respectively.

the robustness of our results to an opposite timing/identification assumption where shocks to $\Delta EFI$ can affect output growth contemporaneously, but not vice-versa.

The results of this alternative identifying assumption are reported in the upper right plot of Figure 7. The plot reports the point estimates of the impulse response of output growth from a one S.D. shock to $\Delta EFI$ under the new identification scheme, along with its 95 percent confidence bands. For comparison, we also include the point estimate of the impulse responses in the benchmark case. The results are robust. On impact, there is a small drop in output growth of about $0.1$ percentage point, although not statistically different from zero. The fall, however, continues until it bottoms after a year when output growth falls by $0.8$ percentage points. The persistence of the shock on real economic activity is also similar, as output growth returns to its long-run mean around three years after the initial shock.

### 6.8 The Role of the World Financial Crisis and Subsequent Recovery

The stylized facts presented in Section 3 showed that, while the increasing trend of international debt securities started since the early 2000s, the trend accelerated most vigorously during the post-crisis recovery that began in mid-2009. Moreover, the time series of economic activity and $EFI$ presented in Section 4 show that the negative comovement between the two is most evident during the world financial crisis of 2008/9 and the subsequent recovery years. In this subsection we investigate how much the post-2008 period matters for our benchmark results. To do so we re-estimate (3) from the beginning of our sample, 1999.Q2, until 2007.Q4, three quarters prior to the collapse of Lehman Brothers. We then sequentially reestimate (3) by adding to the sample one more observation at a time while keeping the starting period fixed at 1999.Q2. For each case we document the estimated values and *p*-values of $\gamma$, the coefficient that links $\Delta EFI$ with future states of economic activity.

Results of this experiment are reported in the left and right middle panels of Figure 7. The left plot reports the recursive *p*-value statistics for each of the five specifications considered in Table 2. Four of the five coefficients considered are statistically significant in the first period considered up to 2007.Q4, and all five exhibit a decreasing trend in the *p*-values as new observations are added. Likewise, the right plot with the estimated coefficients for $\gamma$ shows that, as data of the crisis and the post-recovery are added, the negative coefficient increases in absolute terms.[40] We view this as indicating that the crisis and, more importantly, the post-recovery period account for most of the large information content of $EFI$ in terms of economic activity in emerging economies, although there is evidence that some of the predictive power predates the crisis. We posit that this result is a consequence of the large expansion in corporate bond issuance that began before the financial crisis, but accelerated afterwards, as documented in Section 3.

### 6.9 Removing Financial Corporations' Bonds

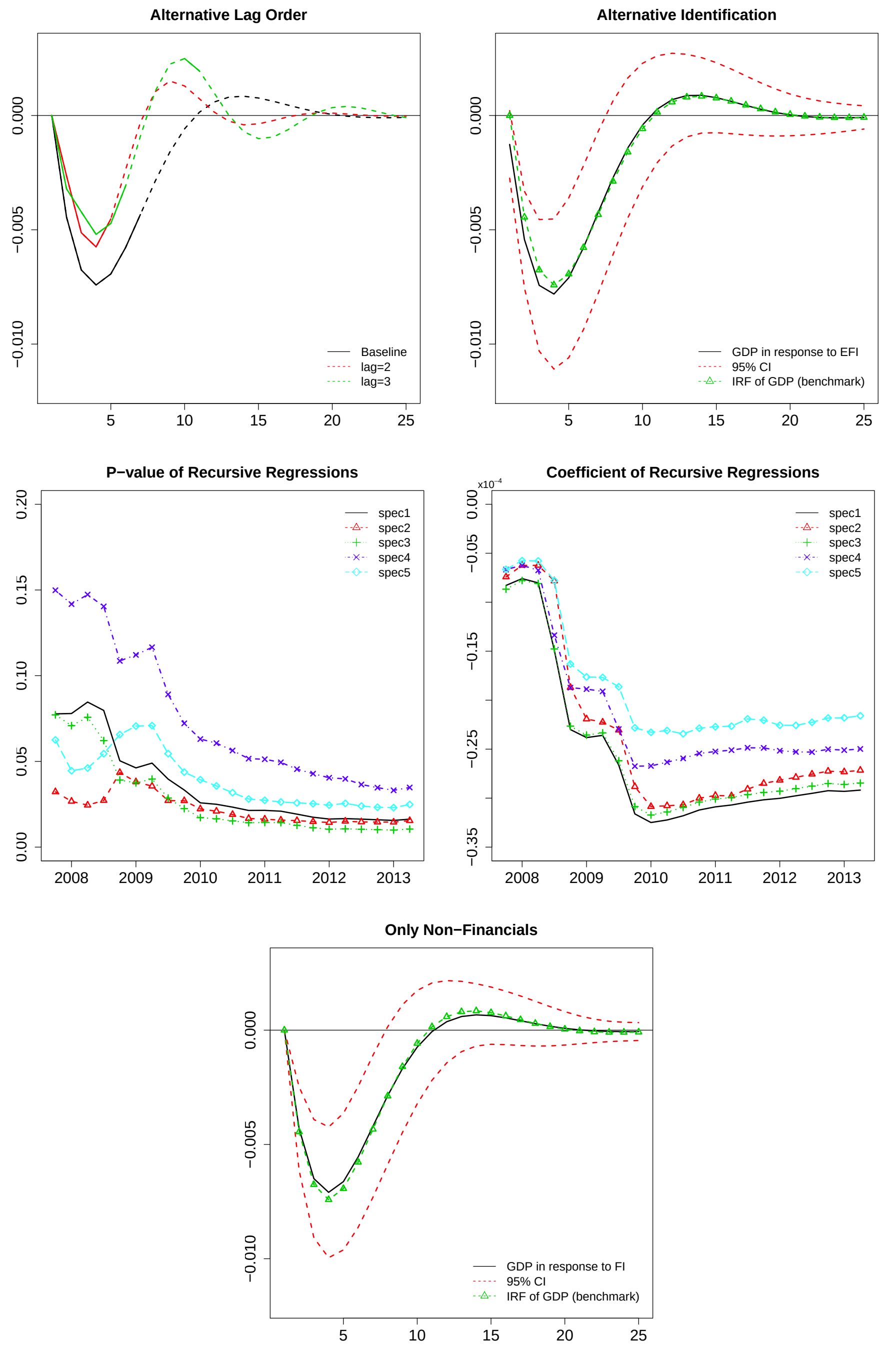
We now assess the extent to which the high information content in $EFI$ comes from bonds issued by non-financial corporates in EMEs. For that purpose we test how much do our result hold if we remove from the construction of the $EFI$ the bonds issued by financial corporations in each of the seven EMEs considered, using the methodology described in (1) and (2). This entails removing roughly half of the total number of bonds considered in the construction of the benchmark $EFI$.[41] With this modified $EFI$ we re-run the panel SVAR model (4) and compare the new impulse responses of output growth to those from the benchmark case.

Results are reported in the lower plot in Figure 7. They are virtually identical to those coming from the benchmark case. There continues to be a large and protracted fall in economic activity following an orthogonal one S.D. shock to changes in the modified $EFI$. We view this as complementary to the evidence discussed in Section 3 that a considerable part of the rise in external bond issuance in emerging economies has been channeled via the corporate non-financial sector.

[40] The decrease in the $p$-values is, however, not monotonic for Specs. 2 and 5, which control for U.S. interest rates and monetary policy stance. In particular, the $p$-values increase between 2008.Q3 and 2009.Q3. One also observes that, for this period, the decrease in the estimated coefficients of $\gamma$ slows down. This coincides with the most turbulent times of the financial crisis and the active use of monetary policy. The results seem to point that, for these two quarters, $EFI'$s information content decreased in favor of the information already embedded in the U.S. interest rates.

[41] Among the total of 2,339 bonds considered in the benchmark case, 1,206 are bonds issued by banks or other financial institutions. The Appendix plots the evolution in time of the size of the financial bonds that we remove for this experiment.

## Figure 7: Various Robustness Checks




This figure presents different robustness checks to our baseline results. The top left panel presents impulse response functions of annual real GDP growth rate to a 1 standard deviation shock to $\Delta EFI$ for two different lag order specifications ($p = 2$ and $p = 3$). Solid lines represent statistically significant responses at the 95% confidence level. The top right panel presents the impulse response function of the bivariate panel VAR with $\Delta EFI$ and $\Delta GDP$ with an alternative ordering in the Cholesky decomposition so that $\Delta EFI$ affects $\Delta GDP$ contemporaneously but not vice-versa. The middle left panel presents the *p*-value of the coefficients corresponding to $\Delta EFI$ from rolling panel regressions for the five specifications in Table 2 (starting in 1999.Q2 through 2007.Q4 and adding one quarter at a time). The middle right panel presents the estimated coefficients of $\Delta EFI$ from these rolling regressions. The lower panel presents the impulse response function of the benchmark bivariate panel VAR with $\Delta GDP$ and $\Delta EFI$, where $EFI$ is calculated after excluding bonds issued by financial firms.

### 6.10 Excluding Countries

How much are the benchmark results driven by one of the EMEs considered? We assess this by redoing the panel forecasting regression (3) excluding each of the seven countries considered, one at a time.

The results are presented in Table 5 which reports the coefficients from Specification 5 in Table 2 sequentially, excluding each of the seven EMEs considered one at a time. Qualitatively, the results are robust for each of the seven cases/columns considered. In all of them the estimated coefficient of $\gamma$ continues to be statistically significant and of similar magnitude to the one estimated in our benchmark case. Our results are therefore not driven by an outlier country in the sample.[42]

**Table 5: Panel Regression Results Excluding Countries One at a Time**

| | *w.o Brazil* | *w.o Chile* | *w.o Korea* | *w.o Mexico* | *w.o Malaysia* | *w.o Peru* | *w.o Philippines* |
|---|---|---|---|---|---|---|---|
| $\Delta GDP_t$ | 0.74*** | 0.76*** | 0.73*** | 0.76*** | 0.76*** | 0.72*** | 0.76*** |
| | (17.34) | (24.05) | (17.11) | (23.31) | (21.14) | (16.02) | (21.41) |
| $\Delta\, EFI_t$ | -0.000033*** | -0.000022** | -0.000020** | -0.000020** | -0.000020** | -0.000021* | -0.000020** |
| | (-4.69) | (-2.92) | (-2.81) | (-2.87) | (-2.88) | (-2.20) | (-2.91) |
| $\Delta US\,Yield\,Curve_t$ | 0.0024 | 0.0038** | 0.0028* | 0.0034** | 0.0030* | 0.0029 | 0.0040** |
| | (1.92) | (3.05) | (2.07) | (2.67) | (2.21) | (1.87) | (3.63) |
| $\Delta RFF_t$ | 0.0017** | 0.0027* | 0.0022* | 0.0027* | 0.0024* | 0.0029* | 0.0031** |
| | (2.59) | (2.38) | (2.23) | (2.37) | (2.30) | (2.54) | (3.34) |
| $\Delta R\,Local\ Rate_t$ | 0.00068 | 0.00067 | 0.00043 | 0.00048 | 0.000095 | 0.00021 | 0.00066 |
| | (1.10) | (1.12) | (0.74) | (0.78) | (0.23) | (0.40) | (0.91) |
| $\Delta R\,Pcom_t$ | 0.0098 | 0.014 | 0.020** | 0.013* | 0.014* | 0.017* | 0.018** |
| | (1.80) | (1.92) | (3.63) | (2.10) | (2.08) | (2.23) | (2.80) |
| Adjusted $R^2$ | 0.734 | 0.721 | 0.724 | 0.694 | 0.725 | 0.713 | 0.728 |
| Observations | 318 | 318 | 318 | 318 | 318 | 318 | 318 |

This table reproduces Spec (5) in Table 2 dropping one country at a time from the pool of EMEs considered in the benchmark estimation (the dropped country is reported in the top of each column). All variables are identically defined as in Table 2. Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

## 7 Conclusions

Access to world capital markets by the corporate sector may be viewed as a necessary condition for emerging economies to achieve sustainable long-run growth. But it can also entail the risk that changes in the financial conditions under which the private sector borrows in these markets may

[42]The Appendix also reports the results for cases where the SVAR and forecasting regressions are estimated for each country independently.

carry destabilizing consequences for real economic activity. These considerations are more pressing now than ever because the corporate sectors of many emerging markets have largely increased their reliance on foreign debt.

Motivated by this observation, we have provided a comprehensive analysis that sheds light on the extent to which changes in the international financing conditions by the corporate sector in emerging economies are related to macroeconomic fluctuations. We do so first by providing a summary of the theoretical literature that postulates the channels through which such economic effects may occur. We then provide empirical evidence of the increased access using information for a pool of 17 emerging economies, particularly in the form of larger corporate bond issuance denominated in USD. We relied on this stylized fact to construct an indicator of external financial conditions for several of these economies using option-adjusted spreads from bonds issued in foreign capital markets by the corporate sector that are traded in secondary markets. We show that changes in this indicator are strongly correlated with future economic activity in EMEs and that identified shocks to the indicator entail large and protracted falls in economic activity.

While we have been silent about the policy implications of our analysis, the results we have presented do warrant a more normative analysis of the extent to which policy actions can (or should try to) mitigate the effects that changes in foreign financing conditions of the corporate sector may have on economic activity in EMEs. The large increase in the stock of foreign debt in the balance sheet of EMEs' corporates will certainly keep this question at the forefront of international macroeconomics for the years to come. Hopefully the results in this paper will motivate further work to shed light on this question.

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## Technical Appendix: Data Sources and Definitions

### A.1 Description of Bonds from Dealogic's DCM Database and Definition of International and Domestic Debt Securities

The bond issuance data used in this paper are sourced from Dealogic DCM database. The figures show country aggregations of transaction-level data. The database includes a total of 625,074 bond tranches (479,678 unique bond deals). The totals shown in Figures A2-A5 and A6-A7 of the Appendix are aggregations for all non-government bonds for the 17 countries in the sample (a total of 13,287 bond tranches). The figures include issuance of government-owned companies (such as utilities, oil companies, universities, and transport systems).

The definition of an international debt security (IDS) used in the paper follows the new methodology implemented by the Bank for International Settlements to define international debt securities. This methodology compares the location where the bond is issued with the residence of the issuer. Following the BIS' practice, the place of residence of a firm is considered to be the jurisdiction where it is incorporated. To identify the place where the bond is issued we use information on the country where the security (or securities as a bond may be composed of multiple individual securities) is listed, the ISIN number (or numbers) assigned to the security (or securities), and the governing law.

A bond is classified as an IDS if it is listed in multiple countries, or if it is listed with an international central depository, or if it includes securities that have been issued ISIN numbers in multiple countries. A security is also considered an IDS if the residence of the issuer is different from the country where the security is issued an ISIN, or if it is different from the security's governing law. Bonds with incomplete information on listing place, ISIN number, and governing laws are classified as international securities if the data provider classifies the bond as foreign by market type.

Similar rules are applied to classify a security as domestic for cases in which the residence of the issuer is the same the governing law, or the same as the ISIN nationality, or the same as the listing place, or all three conditions apply at once (and given no contradiction with classification as international security, and a unique listing place and/or unique ISIN nationality). Given lack of information on ISIN number, listing place, and governing law, the bond is classified as domestic if the vendor designated by Dealogic is domestic by market type.

Applying these rules, we are able to correctly classify all bonds in our sample of 17 EMs.

### A.2 OAS data

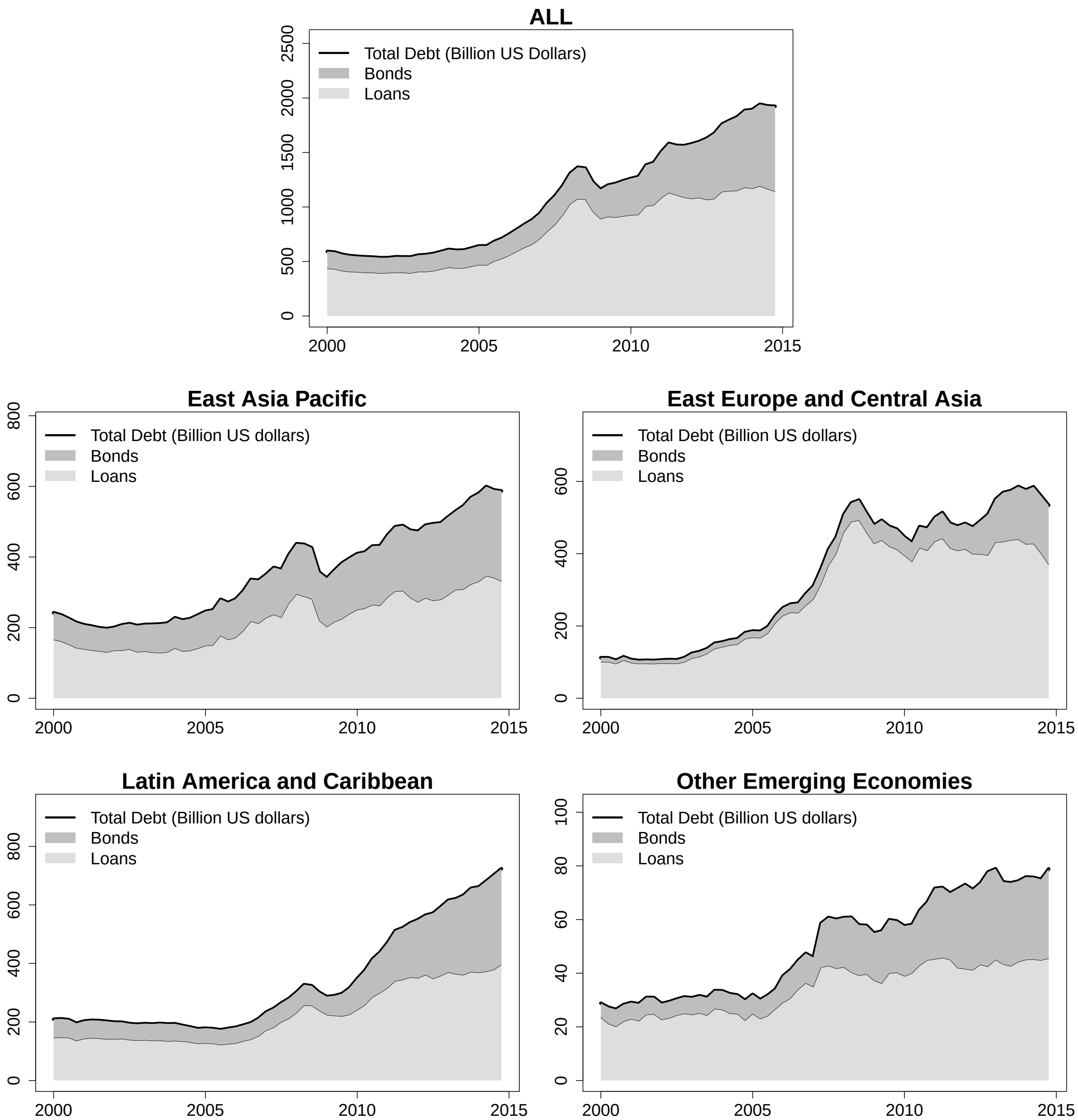
We use data on option-adjusted spreads from Bloomberg. We specifically used the mnemonic `OAS_SPREAD_BID` to retrieve quarterly spreads for all corporate bonds with available OAS data in Bloomberg for the seven countries in our sample. The Bloomberg tickers of the bonds in our sample are available upon request.

### A.3 Other data

We use data on outstanding stocks of international and domestic debt securities from the BIS' Securities Database. We also employ data on cross-border loans from the BIS' Locational Banking Statistics database. For GDP data we collected data from the IMF's International Financial Statistics database. We also used data on sovereign debt held by private banks for five Latin American countries, sourced from the Inter-American Development Bank (IDB) LAC Debt Group database. Data used in the panel regressions and SVAR models are from Fernández et al. (2015) (domestic GDP, consumption and investment; U.S. yields, interest rates, and GDP growth; and commodity prices; see that paper for more details).

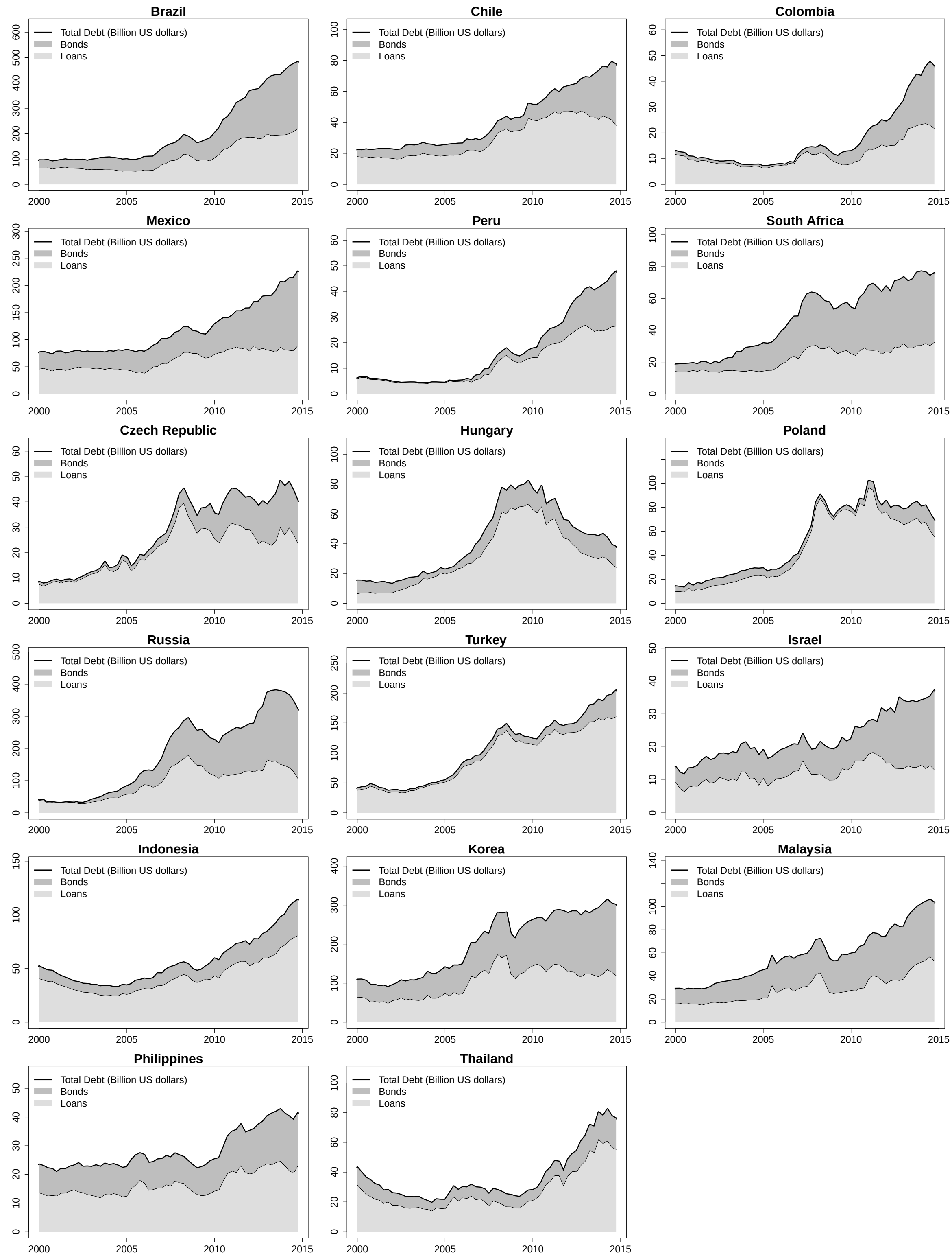
## Online Appendix: Additional Figures and Tables

**Figure A1: Stock of Private Sector International Debt in EMEs (on a Residence Basis)**



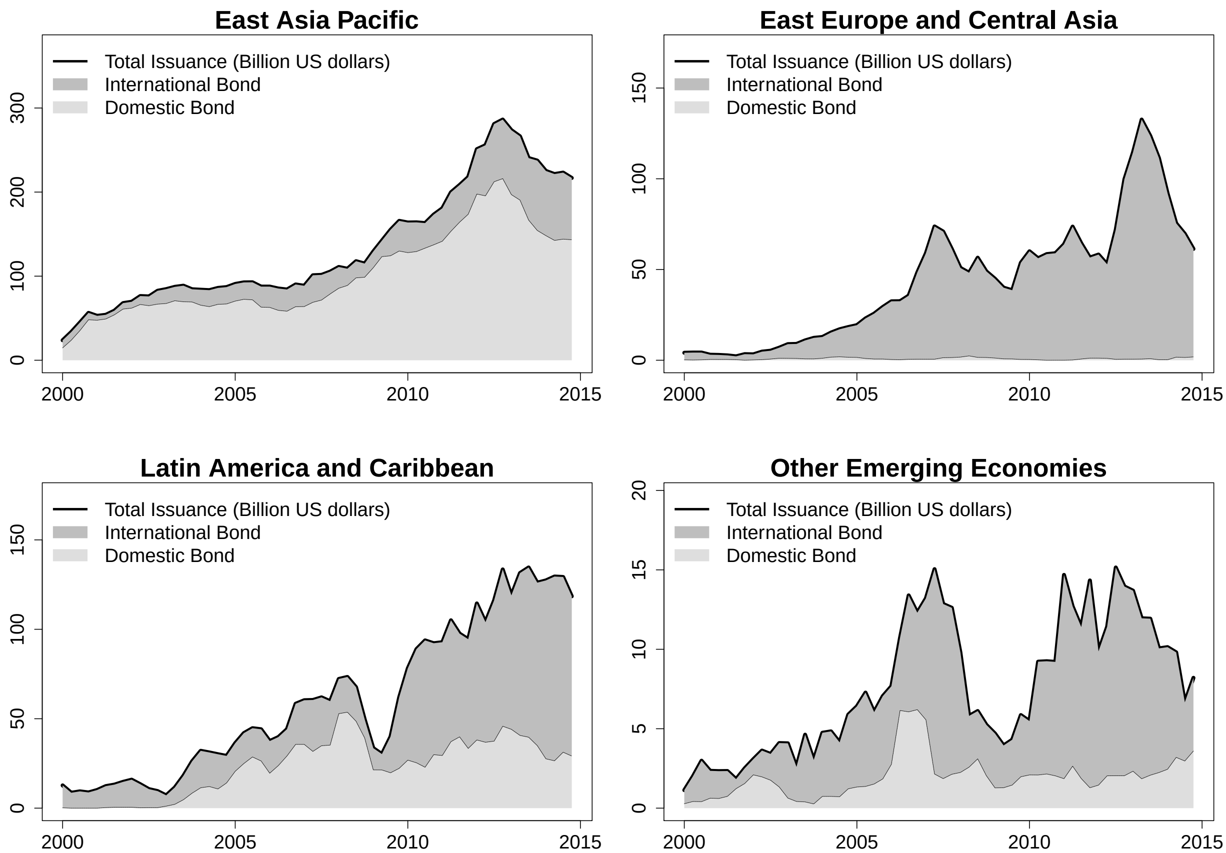

This figure is a replication of Figure 1 measuring the stock of securities on a residence basis, rather than on a nationality basis. As in Figure 1, the figure shows the aggregate stock of private sector international debt for 17 emerging economies, decomposing the outstanding stock into cross-border bank loans and international debt securities. The private sector includes all financial institutions and non-financial corporations. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa, and Israel. The data are presented in billions of current U.S. dollars and sourced from the BIS Locational Banking Statistics and BIS Securities Statistics databases.

# Figure A2: Stock of Private Sector International Debt in EMEs by Country



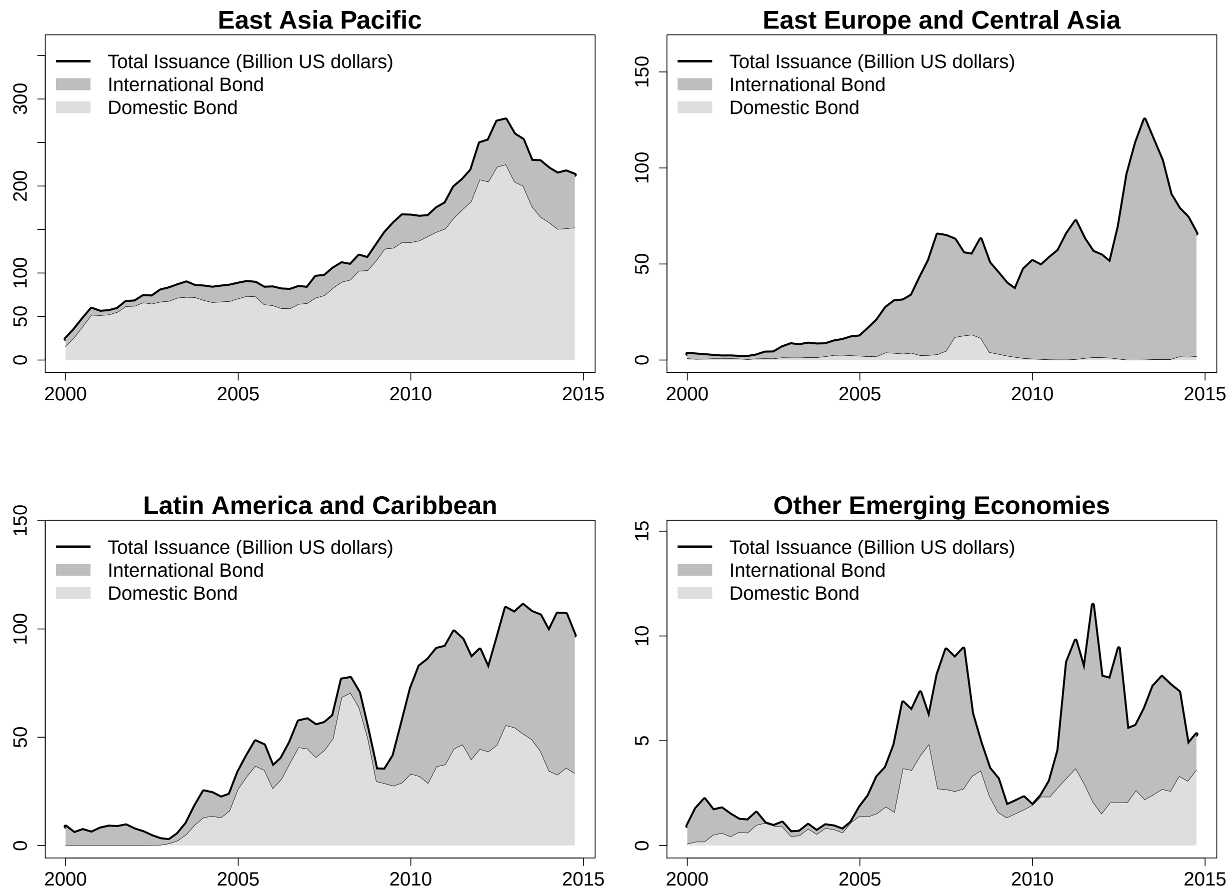

This figure presents country dissaggregations of the stocks of international debt shown by region in Figure 1. As in Figure 1, this figure shows the aggregate stock of private sector international debt for 17 emerging economies, decomposing the outstanding stock into cross-border bank loans and international debt securities. The stock of securities is on a nationality basis. The private sector includes all financial institutions and non-financial corporations. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa and Israel. The data are presented in billions of current U.S. dollars and sourced from the BIS Locational Banking Statistics and BIS Securities Statistics databases.

**Figure A3: Corporate Gross Bond Issuance in EMEs by Region**



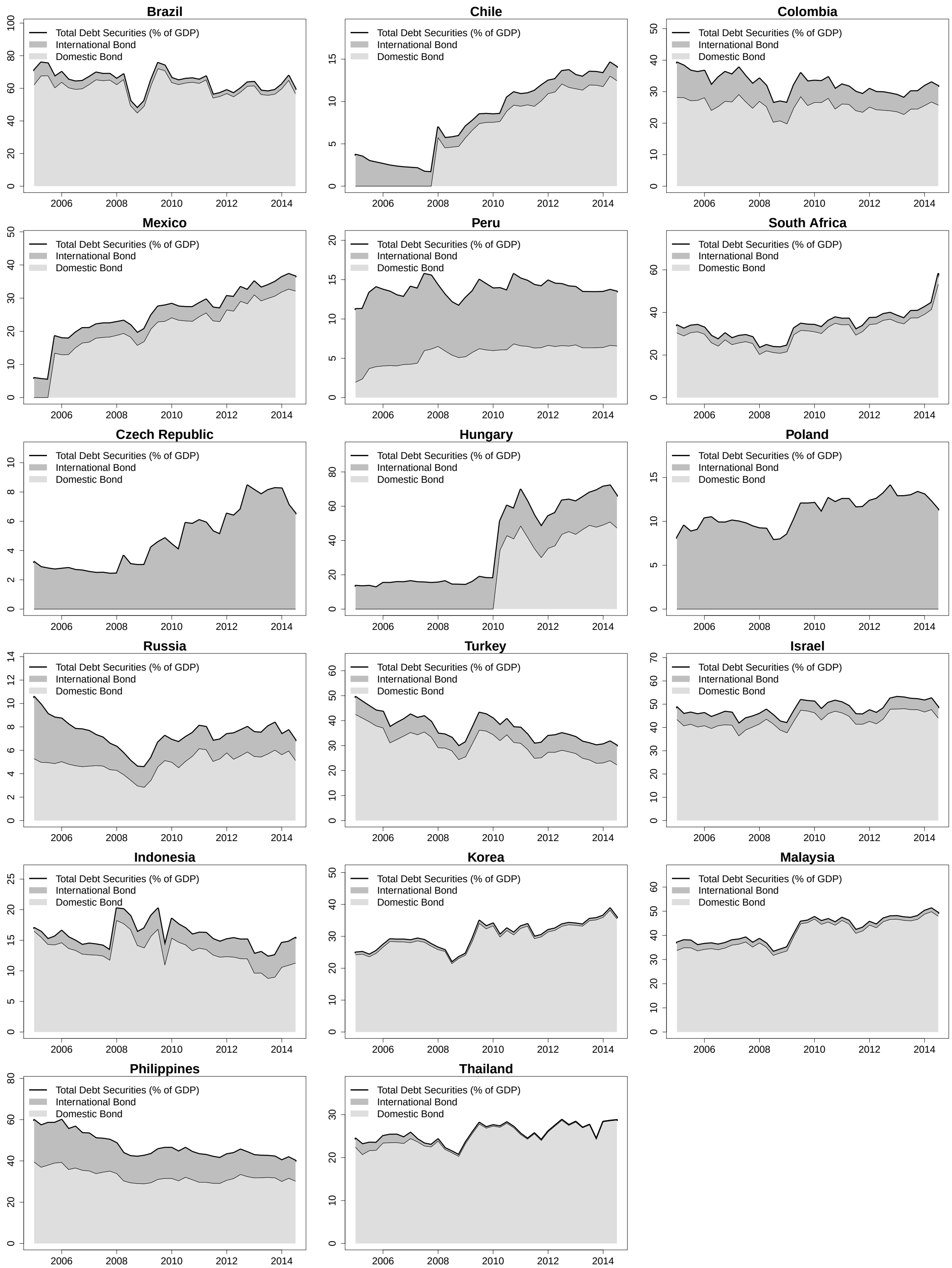

This figure presents regional aggregates of country-by-country gross issuance shown in Figure 2. As in Figure 2, this figure shows gross issuance of international and domestic debt securities based on a nationality basis. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa and Israel. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See the Appendix for a description of how country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities.

**Figure A4: Gross Corporate Bond Issuance by Region (on a Residence Basis)**



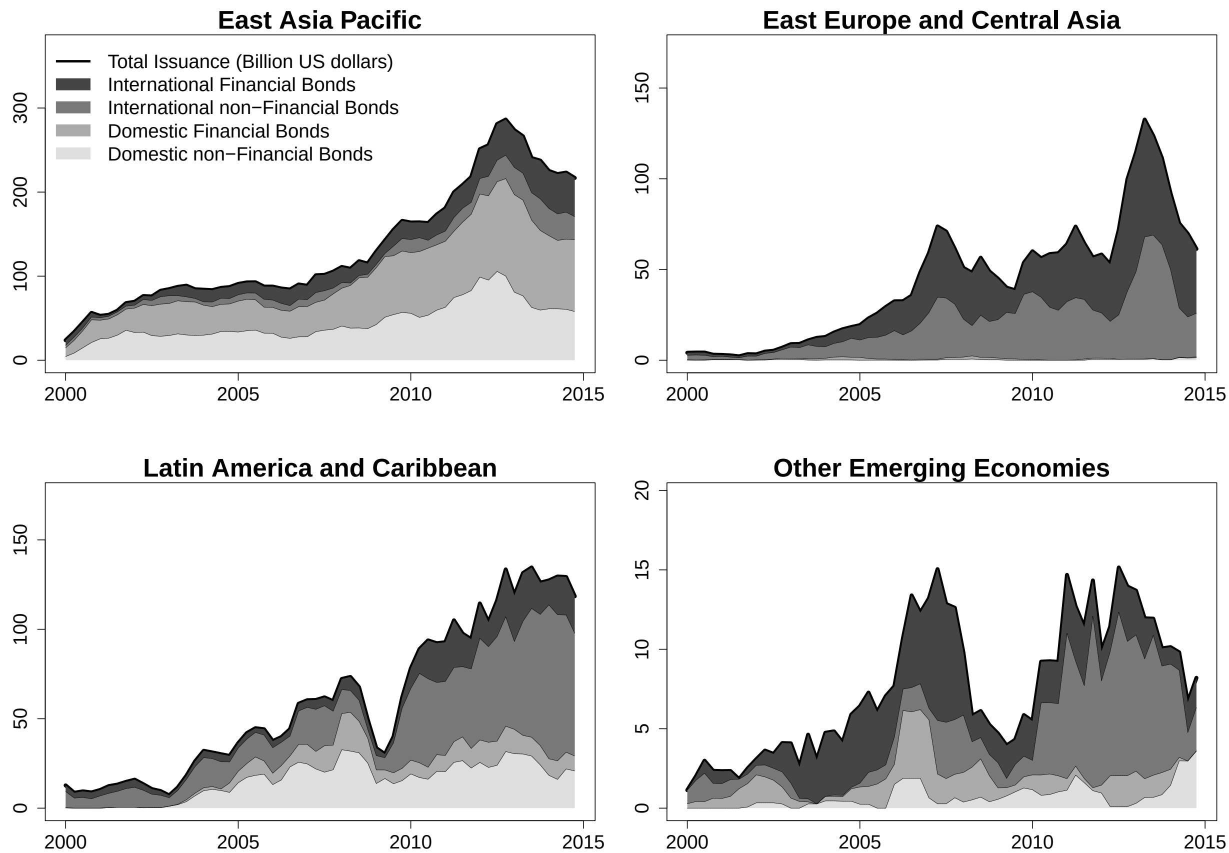

This figure reproduces regional aggregates of gross issuance shown in Figure A3, but on a residence basis. As in Figure A3, the regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa and Israel. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See the Appendix for a description of how country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities.

# Figure A5: Stocks of Sovereign Debt by Country (scaled by GDP)



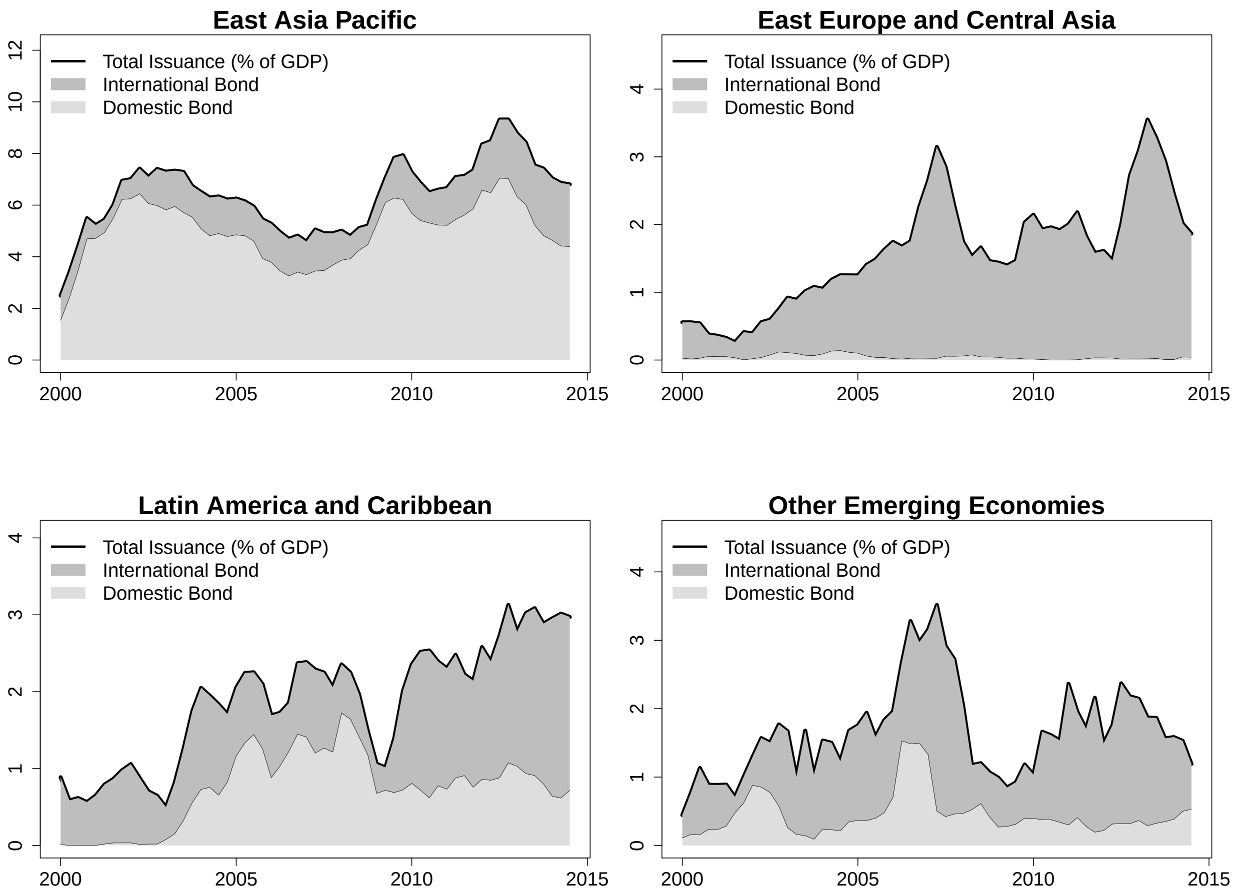

This figure shows the aggregate stock of sovereign debt in 17 emerging economies, decomposing the outstanding stock into international and domestic debt securities. The quarterly stocks are scaled by annual GDP (i.e., the sum of last 4 quarters). Data on stocks are from the BIS Securities Statistics database and data on GDP are from the IMF International Financial Statistics Database.

**Figure A6: Corporate Gross Bond Issuance by Type of Issuer**



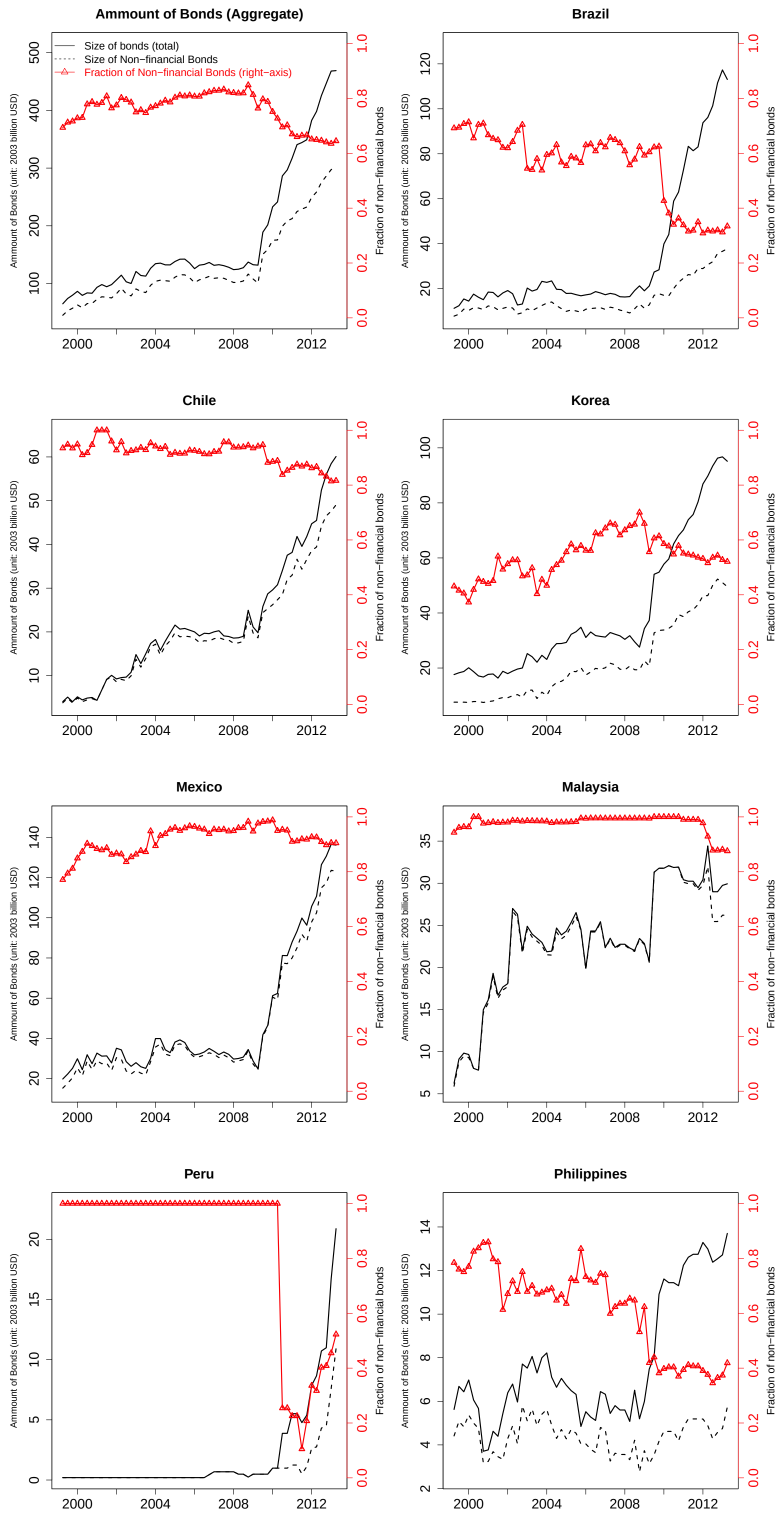

This figure shows gross issuance of international and domestic debt securities by region based on a nationality basis, as in Figure A3, further decomposing issuance by issuer into non-financial and financial corporations. Financial corporations include issuance by any firm classified by the data vendor as operating in the "Finance" and "Insurance" sectors, and issuance by Closed End funds and Holding Companies. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa, and Israel. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See the Appendix for a description of how country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities.

**Figure A7: Corporate Gross Bond Issuance by Region (Scaled by GDP)**



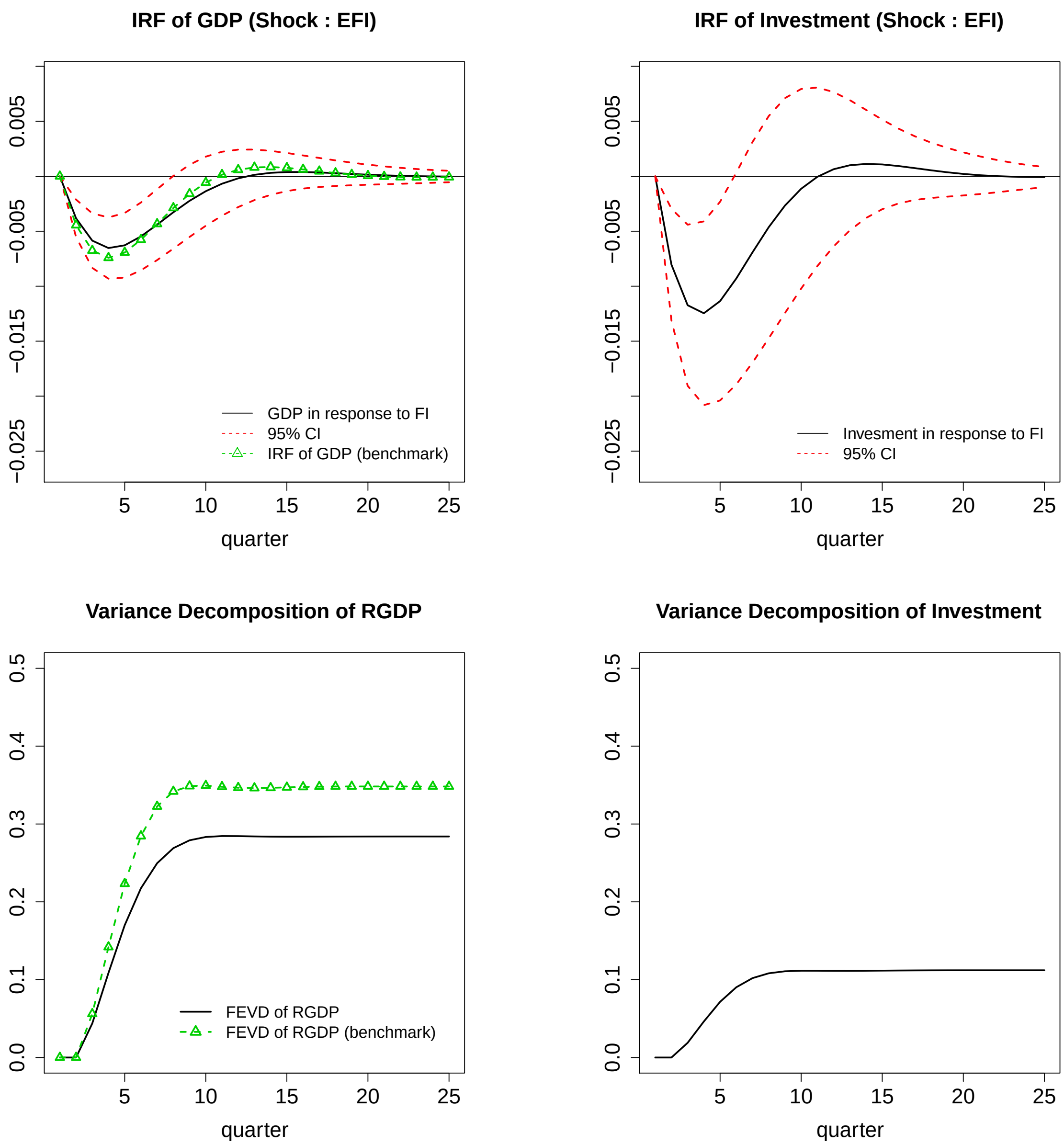

This figure shows gross issuance of international and domestic debt securities by country based on a nationality basis, as in Figure A3, but scaling it by GDP. Data on quarterly gross issuance are scaled by annual GDP (i.e., the sum of last 4 quarters). Data on gross issuance are soured from Dealotic's DCM database and data on GDP are from the IMF International Financial Statistics Database. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa, and Israel.

# Figure A8: The Size of Non-financial and Financial Bonds



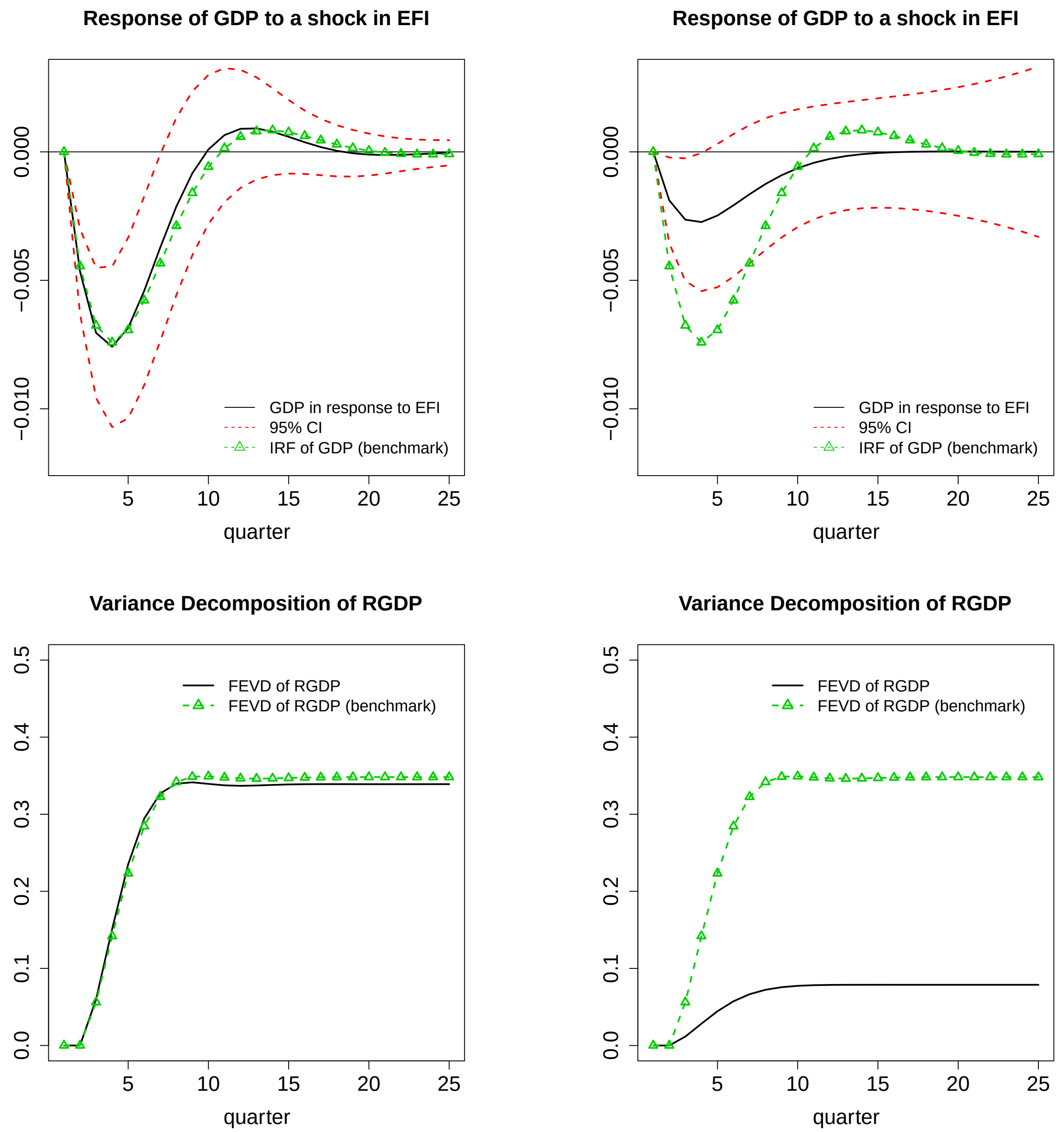

This figure shows the sum of the size of sample bonds (in 2003 Billion USD) used in constructing $EFI$, at a given quarter. The black solid line represents sum of both financial and non-financial bonds. The black dotted line only includes non-financial bonds (left-axis). The red solid line with triangles represents the fraction (right-axis) of non-financial bonds to total bonds. The top left panel represents aggregated statistics across countries, and other panels represents country-by-country statistics. As noted in Footnote 24, these figures show that the subsample of bonds with OAS data used in the paper is representative of the universe of bonds studied in Section 3 insofar as they depict a large increase in issuance after the 2008/2009 crisis.

**Figure A9: IRF and FEVD from the Uribe-Yue panel VAR**



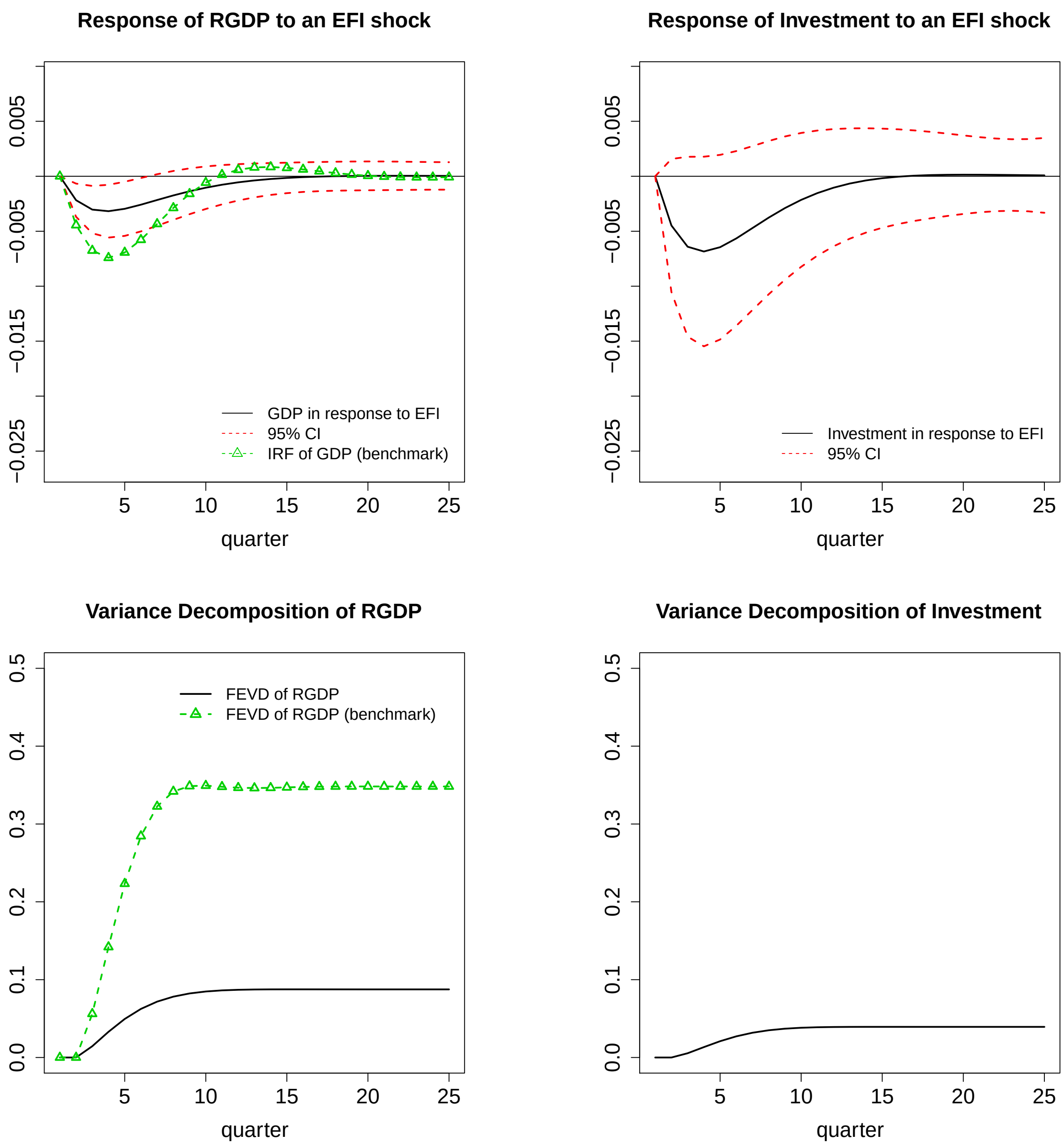

This figure summarizes impulse response functions and forecast error variance decompositions of a panel VAR model as in Uribe & Yue (2006). This model includes $\{\Delta GDP_{i,t}, \Delta Inv_{i,t}, \Delta Trade\,Balance_{i,t}, \Delta EFI_{i,t}\}$ as endogenous variables, and $\{\Delta RFF_t\}$ as an exogenous variable. The top row presents an impulse response function of year-on-year real GDP, and investment growth rate to a 1 standard deviation shock in $\Delta EFI$. Red dotted lines represent 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row summarizes forecast error decompositions of real GDP and investment growth rates. Green-triangle dotted lines represent results from Figure 4. Data for Malaysia starts in 2005.Q1 due to lack of investment data.

**Figure A10: Impulse Response Controlling for Sovereign and External Risk (Alternative Identifying Assumption)**



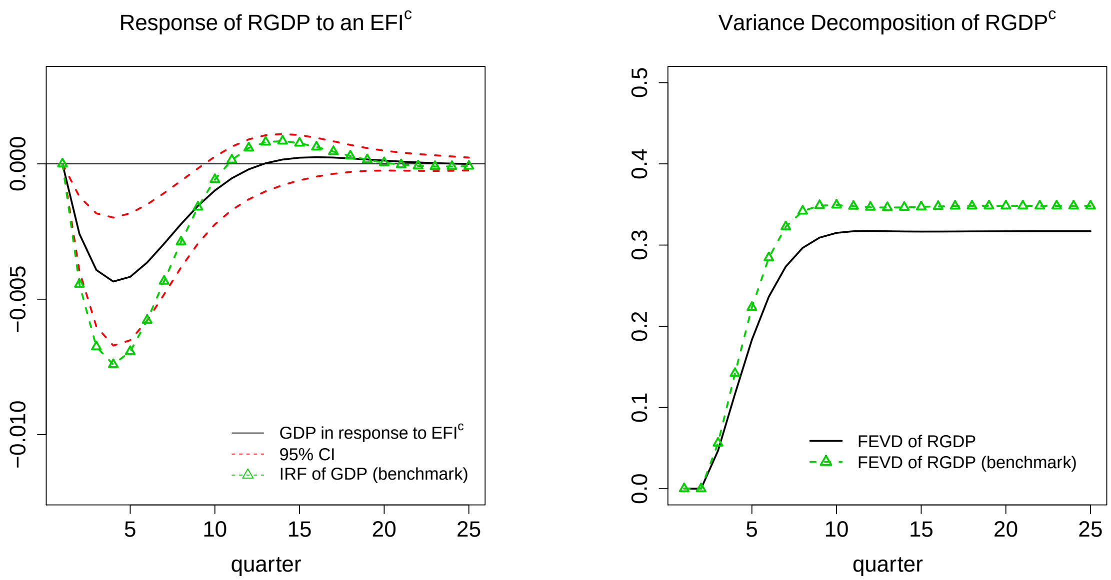

This figure reproduces results in Figure 6 with an alternative ordering in the Cholesky decomposition; $\Delta EMBI$ responds to $\Delta EFI$ only in lags. The first column shows results from a trivariate panel VAR model which includes $\{\Delta GDP_{i,t}, \Delta EFI_{i,t}, \Delta EMBI_{i,t}\}$ as endogenous variables. The second column shows results from a trivariate panel VAR model which includes $\{\Delta GDP_{i,t}, \Delta EFI_{i,t}, \Delta EMBI_{i,t}\}$ as endogenous variables, and $\{\Delta VIX_t\}$ as an exogenous variable. The top row presents an impulse response function of year-on-year real GDP to a 1 standard deviation shock in $\Delta EFI$. Red dotted lines represent 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row presents forecast error decomposition of real GDP associated with $\Delta EFI$ shocks. Green-triangle dotted lines represent results from Figure 4. Korea is excluded due to EMBI data availability. 1999.Q2 EMBI observation for Chile is dropped due to EMBI data availability.

## Figure A11: Alternative Panel VAR



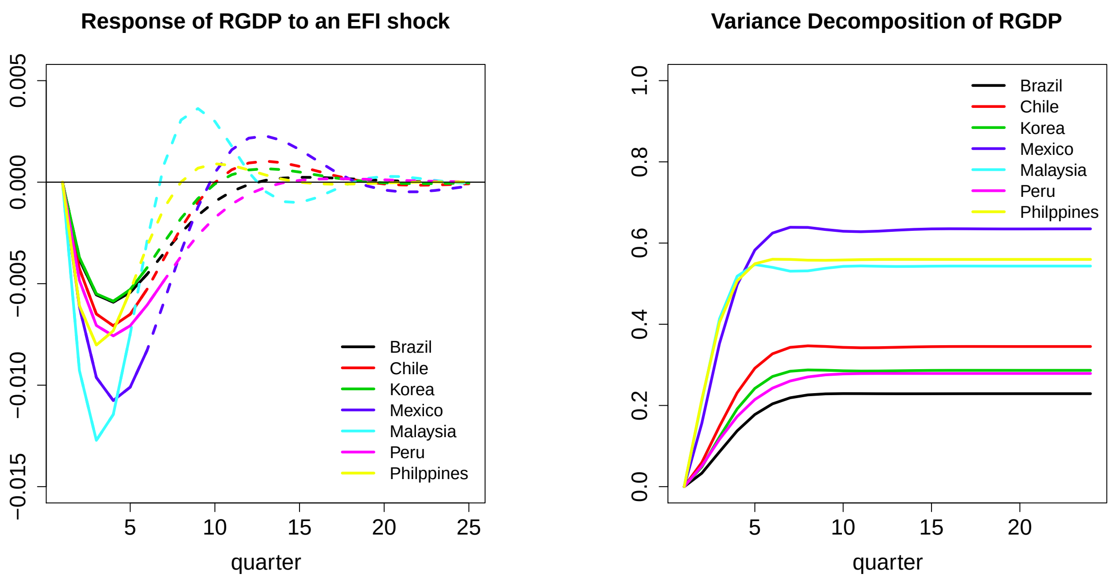

This figure summarizes impulse response functions and forecast error variance decomposition of the following panel VAR model which includes $\{\Delta GDP_{i,t}, \Delta INV_{i,t}, \Delta TB_{i,t}, \Delta EMBI_{i,t}, \Delta EFI_{i,t}\}$ as endogenous variables, and $\{\Delta RFF_t, \Delta VIX_t\}$ as exogenous variables. The top row presents an impulse response function of year-on-year real GDP, and investment growth rate to a 1 standard deviation shock in $\Delta EFI$. Red dotted lines represent 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row presents forecast error decomposition of real GDP and investment growth rates. Malaysian sample starts in 2005.Q1 due to investment data availability. Korea is excluded due to EMBI data availability. Green-triangle dotted lines represent results from Figure 4. 1999.Q2 EMBI observation for Chile is dropped due to EMBI data availability.

## Figure A12: IRF and FEVD with Benchmark Bi-variate Panel VAR with HP-filtered Variables




The two panels reproduce results from Figure 4 replacing $\Delta EFI$ and $GDP\,growth\,rate$ with $EFI^c$ and $\Delta GDP^c$ respectively. The superscript $c$ refers to variables filtered using the Hodrick-Prescott filter with a smoothing parameter of 1600. The left panel presents impulse response functions of $RGDP^c$ to a 1 standard deviation shock in $EFI^c$. The right panel presents a forecast error variance decomposition of real GDP growth rate. Green-triangle dotted lines represent results from Figure 4.

## Figure A13: Country-Specific Forecasting Regressions and SVAR




This figure summarizes impulse response functions and forecast error variance decompositions of the benchmark bivariate model estimated country by country. The plot on the left presents impulse response functions of year-on-year real GDP growth rate to a 1 standard deviation shock in $\Delta EFI$. Solid lines represent the portion of the IRF that is significant portion at the 95% confidence level. The plot on the right panel row presents the fraction of forecast error variance of real GDP growth rate due to $\Delta EFI$.

**Table A1: Share of International Loans to Sovereigns in Total International Bank Loans to EMEs**

| Year | Brazil | Chile | Colombia | Mexico | Peru |
|---|---|---|---|---|---|
| 2006 | 5.21 | 0.00 | 1.74 | 0.00 | 0.01 |
| 2007 | 3.04 | 0.00 | 0.69 | 0.00 | 0.01 |
| 2008 | 2.77 | 0.00 | 1.49 | 0.00 | 0.44 |
| 2009 | 2.85 | 0.00 | 2.24 | 0.00 | 0.41 |
| 2010 | 1.61 | 0.00 | 0.00 | 0.00 | 0.24 |
| 2011 | 1.35 | 0.00 | 0.00 | 0.00 | 0.16 |
| 2012 | 1.53 | 0.00 | 0.13 | 0.00 | 0.11 |
| 2013 | 1.37 | 0.00 | 0.13 | 0.00 | 0.10 |
| 2014 | 1.06 | 0.00 | 0.55 | 0.00 | 0.08 |

This table shows the share of international loans to governments as percentage of all cross-border bank loans to the country for five emerging countries. Data on international bank loans to sovereigns are sourced from the LAC Debt Group Standardized Public Debt Database of the IDB and refer to the stock of outstanding bank loans under external legislation. Data on all cross-border bank loans are from the BIS Locational Banking Statistics and refer to stock of outstanding bank loans in a given country.

**Table A2: Currency Composition of International Debt Securities (on a nationality basis; as percentage of total)**

| | | Local Currency | | USD | | ROW | |
|---|---|---|---|---|---|---|---|
| | | 2003-2008 | 2009-2014 | 2003-2008 | 2009-2014 | 2003-2008 | 2009-2014 |
| EAP | Indonesia | 5.39 | 13.42 | 92.38 | 83.89 | 2.23 | 2.70 |
| | Korea | 4.34 | 14.42 | 60.81 | 54.32 | 34.85 | 31.27 |
| | Malaysia | 24.63 | 66.10 | 71.86 | 23.56 | 3.50 | 10.34 |
| | Philippines | 4.90 | 18.81 | 95.10 | 81.19 | 0.00 | 0.00 |
| | Thailand | 2.23 | 6.57 | 91.88 | 91.03 | 5.90 | 2.40 |
| ECA | Czech Rep. | 13.59 | 15.02 | 22.63 | 13.84 | 63.78 | 71.14 |
| | Hungary | 2.94 | 5.75 | 0.00 | 16.27 | 97.06 | 77.98 |
| | Poland | 35.91 | 16.17 | 5.72 | 13.77 | 58.38 | 70.06 |
| | Russia | 39.92 | 56.28 | 49.73 | 34.68 | 10.36 | 9.05 |
| | Turkey | 7.03 | 7.32 | 81.11 | 84.33 | 11.86 | 8.35 |
| LAC | Brazil | 11.44 | 9.77 | 86.78 | 82.41 | 1.78 | 7.81 |
| | Chile | 4.53 | 5.46 | 93.41 | 83.61 | 2.06 | 10.93 |
| | Colombia | 4.19 | 9.87 | 95.81 | 90.13 | 0.00 | 0.00 |
| | Mexico | 47.05 | 13.87 | 40.85 | 68.86 | 12.09 | 17.27 |
| | Peru | 4.87 | 6.21 | 95.13 | 92.15 | 0.00 | 1.64 |
| Other EM | Israel | 23.00 | 44.06 | 70.29 | 53.14 | 6.71 | 2.80 |
| | South Africa | 54.56 | 28.72 | 16.18 | 54.95 | 29.25 | 16.34 |
| Average | | 17.09 | 19.87 | 62.92 | 60.12 | 19.99 | 20.00 |

This table shows the currency composition of issuances of international debt securities by country based on a nationality basis. The data are sourced from Dealogic's DCM database. See the Appendix for a description of how the country aggregates are obtained from transaction-level data and for a definition of international debt securities.

**Table A3: Anderson-Hsiao Estimator**

| | (1)<br>*Spec 1* | (2)<br>*Spec 2* | (3)<br>*Spec 3* | (4)<br>*Spec 4* | (5)<br>*Spec 5* |
|---|---|---|---|---|---|
| $\Delta GDP_t$ | 0.20***<br>(4.02) | 0.22**<br>(2.04) | 0.21***<br>(3.66) | 0.00046<br>(0.00) | 0.10<br>(0.98) |
| $\Delta\, EFI_t$ | -0.000026***<br>(-2.66) | -0.000025**<br>(-2.53) | -0.000026***<br>(-2.62) | -0.000017*<br>(-1.84) | -0.000016*<br>(-1.81) |
| $\Delta US\,Yield\,Curve_t$ | | 0.00098<br>(0.63) | | | 0.0015<br>(0.95) |
| $\Delta RFF_t$ | | 0.000081<br>(0.07) | | | 0.0011<br>(1.13) |
| $\Delta R\,Local\ Rate_t$ | | | 0.00022<br>(0.34) | | 0.000025<br>(0.03) |
| $\Delta R\,Pcom_t$ | | | | 0.037***<br>(2.61) | 0.036***<br>(2.73) |
| Adjusted $R^2$ | 0.168 | 0.169 | 0.167 | 0.189 | 0.223 |
| Observations | 357 | 357 | 357 | 357 | 357 |

This table reproduces the baseline results of Table 2 using the Anderson-Hsiao estimator to address potential inconsistency of a LSDV estimator in a dynamic panel with fixed effects. Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

## Table A4: Country-Specific Forecasting Regressions

| | *Brazil* | *Chile* | *Korea* | *Mexico* | *Malaysia* | *Peru* | *Philippines* |
|---|---|---|---|---|---|---|---|
| $\Delta GDP_t$ | 0.76*** | 0.53*** | 0.73*** | 0.55*** | 0.45*** | 0.76*** | 0.64*** |
| | (5.83) | (4.50) | (7.59) | (5.89) | (4.21) | (9.86) | (7.40) |
| $\Delta\, EFI_t$ | -0.0000082 | -0.000042 | -0.000038*** | -0.000027*** | -0.00011*** | -0.000017* | -0.000051*** |
| | (-1.48) | (-1.64) | (-2.83) | (-3.37) | (-3.95) | (-1.87) | (-4.78) |
| $\Delta US\, Yield\, Curve_t$ | 0.0064*** | -0.00059 | 0.0043** | -0.0028 | -0.00039 | 0.0054** | -0.0014 |
| | (3.47) | (-0.27) | (2.07) | (-1.16) | (-0.18) | (2.67) | (-1.02) |
| $\Delta RFF_t$ | 0.0052*** | 0.0015 | 0.0032** | -0.000078 | 0.00019 | 0.00028 | -0.00091 |
| | (4.06) | (1.17) | (2.26) | (-0.07) | (0.12) | (0.23) | (-1.01) |
| $\Delta R\, Local\ Rate_t$ | -0.00054 | -0.0012 | 0.00066 | -0.0013 | 0.0029** | 0.0023** | 0.000092 |
| | (-0.74) | (-1.05) | (0.43) | (-1.24) | (2.29) | (2.47) | (0.20) |
| $\Delta R\, Pcom_t$ | 0.030* | 0.021** | -0.0043 | 0.031*** | 0.031** | 0.019* | -0.0033 |
| | (1.98) | (2.30) | (-0.35) | (3.49) | (2.53) | (1.88) | (-0.47) |
| Adjusted $R^2$ | 0.711 | 0.720 | 0.732 | 0.865 | 0.798 | 0.764 | 0.718 |
| Observations | 53 | 53 | 53 | 53 | 53 | 53 | 53 |

This table reproduces Spec (5) in Table 2 estimating the regression on a country by country basis, as indicated at the top of each column. All variables are identically defined as in Table 2. Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

**Table A5: Panel Regression Results with Varying Number of Lagged Dependent Variables**

| | *p=0* | *p=1* | *p=2* | *p=3* |
|---|---|---|---|---|
| $\Delta GDP_t$ | 0.75*** | 1.02*** | 0.97*** | 0.96*** |
| | (21.42) | (17.51) | (17.31) | (15.41) |
| $\Delta GDP_{t-1}$ | | -0.34*** | -0.20*** | -0.24*** |
| | | (-7.63) | (-4.34) | (-4.67) |
| $\Delta GDP_{t-2}$ | | | -0.12*** | -0.0081 |
| | | | (-7.89) | (-0.13) |
| $\Delta GDP_{t-3}$ | | | | -0.10 |
| | | | | (-1.82) |
| $\Delta\, EFI_t$ | -0.000022** | -0.000014** | -0.000013** | -0.000013** |
| | (-2.97) | (-2.86) | (-2.92) | (-3.09) |
| $\Delta US\,Yield\,Curve_t$ | 0.0032** | 0.0016 | 0.0013 | 0.0013 |
| | (2.66) | (1.57) | (1.32) | (1.35) |
| $\Delta RFF_t$ | 0.0026** | 0.0019** | 0.0019** | 0.0020** |
| | (2.67) | (2.82) | (3.10) | (3.13) |
| $\Delta R\, Local\ Rate_t$ | 0.00046 | 0.00029 | 0.00024 | 0.00028 |
| | (0.86) | (0.77) | (0.65) | (0.73) |
| $\Delta R\, Pcom_t$ | 0.015* | 0.012** | 0.011** | 0.011** |
| | (2.44) | (2.66) | (2.65) | (2.78) |
| Adjusted $R^2$ | 0.718 | 0.754 | 0.758 | 0.761 |
| Observations | 371 | 371 | 371 | 371 |

This table reproduces Spec (5) in Table 2 for alternatives values of $p$ (the number of lags of $\Delta GDP$). Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

## Table A6: Panel Regression Results with Time Fixed Effect and Crisis Dummy Variable

| | *Spec 5* | *Spec 6* | *Spec 7* | *Spec 8* | *Spec 9* | *Spec 10* |
|---|---|---|---|---|---|---|
| $\Delta GDP_t$ | 0.75*** | 0.74*** | 0.74*** | 0.82*** | 0.74*** | 0.74*** |
| | (21.42) | (17.27) | (18.08) | (17.08) | (16.17) | (16.89) |
| $\Delta\, EFI_t$ | -0.000022** | -0.000021** | -0.000018** | -0.0000062 | -0.0000062 | -0.0000061 |
| | (-2.97) | (-2.82) | (-2.77) | (-1.24) | (-1.18) | (-1.01) |
| $\Delta US\, Yield\, Curve_t$ | 0.0032** | 0.0037** | 0.0038** | | | |
| | (2.66) | (2.73) | (2.85) | | | |
| $\Delta RFF_t$ | 0.0026** | 0.0027** | 0.0026** | | | |
| | (2.67) | (2.62) | (2.62) | | | |
| $\Delta R\, Local\ Rate_t$ | 0.00046 | 0.00048 | 0.00044 | | | -0.000023 |
| | (0.86) | (0.89) | (0.86) | | | (-0.04) |
| $\Delta R\, Pcom_t$ | 0.015* | 0.014* | 0.012* | | | -0.00017 |
| | (2.44) | (2.20) | (2.18) | | | (-0.02) |
| $US\, \Delta GDP_t$ | | 0.076 | 0.031 | | | |
| | | (1.31) | (0.53) | | | |
| Adjusted $R^2$ | 0.718 | 0.719 | 0.736 | 0.820 | 0.804 | 0.803 |
| Observations | 371 | 371 | 371 | 371 | 371 | 371 |
| Country fixed effect | Yes | Yes | Yes | No | Yes | Yes |
| Crisis dummy | No | No | Yes | - | - | - |
| Time fixed effect | No | No | No | Yes | Yes | Yes |

This table reports panel forecasting regression results with time fixed effect or a crisis dummy variable (1 if 2008.Q4, and 0 otherwise). The first column reports a baseline result (last column of Table 2). Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

## Table A7: Panel Regression Results with Time Fixed Effect and Crisis Dummy Variable and Alternative Forecasting Horizons

| | *h=1* $\Delta GDP_{t+1}$ | *h=2* $\Delta GDP_{t+2}$ | *h=3* $\Delta GDP_{t+3}$ | *h=4* $\Delta GDP_{t+4}$ | *h=0* $\Delta GDP_t$ |
|---|---|---|---|---|---|
| $\Delta GDP_{t-1}$ | | | | | 0.73*** |
| | | | | | (14.57) |
| $\Delta GDP_t$ | 0.74*** | 0.45*** | 0.19* | -0.018 | |
| | (16.89) | (6.84) | (2.42) | (-0.19) | |
| $\Delta\, EFI_t$ | -0.0000061 | -0.0000098* | -0.000013*** | -0.000011 | 0.0000023 |
| | (-1.01) | (-2.35) | (-4.22) | (-1.58) | (0.55) |
| $\Delta R\, Local\ Rate_t$ | -0.000023 | 0.000065 | 0.0000088 | -0.000027 | -0.000040 |
| | (-0.04) | (0.10) | (0.02) | (-0.08) | (-0.08) |
| $\Delta R\, Pcom_t$ | -0.00017 | 0.011 | 0.026 | 0.029* | -0.0083 |
| | (-0.02) | (0.85) | (1.69) | (1.98) | (-1.22) |
| Adjusted $R^2$ | 0.803 | 0.654 | 0.612 | 0.607 | 0.801 |
| Observations | 371 | 371 | 371 | 371 | 371 |
| Country fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |

This table reproduces the bottom panel of Table 4 (panel forecasting regression for different forecasting horizons $h$) including both time and country fixed effects. Numbers in parentheses are $t$-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.