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

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Abstract

We document a considerable increase in foreign financing by the corporate sector in emerging economies (EMEs) since the early 2000s, mainly in the form of bond issuance, and claim that it has opened up an important channel by which external financial factors can drive economic activity in these economies. Such claim is substantiated by a strong negative relationship between economic activity and an external financial indicator that we construct for several EMEs using micro-level data on spreads of bonds issued by EMEs' corporations in foreign capital markets. Three salient features characterize such a negative relationship. First, the financial indicator has considerable predictive power on future economic activity in these economies, even after controlling for other potential drivers of economic activity such as movements in sovereign spreads and global financial risk, among others. Second, on average, an identified adverseshock to the financial indicator generates a large and protracted fall of real output growth in these economies, and up to 14 percent of its forecast error variance is associated to this shock. Lastly, fluctuations in this indicator also respond strongly to shocks in global financial risk emanating from world capital markets thereby implying that changes in corporate spreads also serve as a powerful propagating mechanism to changes in global investors' risk appetite.

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Resumen

Presentamos evidencia de un aumento considerable del financiamiento externo por parte del sector empresarial en las economías emergentes (EME) desde principios de los años 2000, principalmente en la forma de emisión de bonos, y postulamos que éste ha abierto un canal importante por el que factores financieros externos pueden impulsar la actividad económica en estas economías. Esta afirmación se sustenta en una fuerte relación negativa entre la actividad económica y un indicador financiero externo que construimos para varias EME utilizando datos a nivel microeconómico sobre los diferenciales de los bonos emitidos por las empresas de las EME en los mercados de capitales extranjeros. Tres características sobresalen en esta relación tan negativa. En primer lugar, el indicador financiero tiene un poder predictivo importante sobre la actividad económica futura de estas economías, aun después de controlar por otros factores potenciales de la actividad económica, como los movimientos de los diferenciales soberanos y el riesgo financiero mundial. En segundo lugar, en promedio, un choque adverso sobre el indicador financiero genera una caída grande y prolongada del crecimiento del producto real en estas economías, y hasta un 14 por ciento de la varianza del error prevista se asocia a este choque. Por último, las fluctuaciones de este indicador también muestran una respuesta contundente a los choques de riesgo financiero mundial provenientes de los mercados de capitales internacionales, lo que implica que los cambios en los diferenciales de las empresas también son un poderoso mecanismo de propagación de los cambios en el apetito por riesgo de los inversionistas mundiales.

1 Introduction

One of the most important macroeconomic developments in emerging market economies (EMEs) since the turn of the XXI century is a considerable increase in the reliance of foreign debt by their *corporate* sectors. The stock of international debt issued by these economies nearly quadruple in about a little over a decade. For a pool of 18 small EMEs, the outstanding stock of private international debt grew from about 600 billion USD in the early 2000s to 2.4 trillion USD by the end of 2014. Such developments have created an intense debate in both academia and policy circles about their macroeconomic 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 they would otherwise not be able to raise from local sources. However, the crises of the 90s and, more recently, the global financial crisis of 2008, have taught us that greater access to capital markets entails also risks for EMEs; particularly stemming from abrupt changes in the amount and the cost of international capital. This has placed at center stage, yet again, the role of external financial conditions as important drivers of economic activity in EMEs, although with a novel twist relative to previous episodes of surges in external debt that were mostly linked to sovereigns: the role of corporate external debt and its impact on the macroeconomy of EMEs.

This paper aims at shedding new light on the role that external financial factors play when accounting for economic activity in emerging economies, through their effects on debt issued by their corporates in international capital markets. 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 are related to economic activity in these economies. For that purpose we build an external financial indicator for ten 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, how this activity responds to shocks in the indicator, and how such indicator serves also as propagating mechanism for shocks in global capital markets. Our focus is on bond issuance because it is this form of finance that corporates have preferred the most when increasing their reliance on international sources of funding since the mid 2000s.

We find strong evidence that the external financial indicator that we construct contains information on future economic activity in EMEs, after controlling for 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 0.1 percentage points in the following quarter, and up to 0.4 percentage points three quarters ahead. Furthermore, a shock to the external financial indicator, identified within a panel structural vector autoregressive (P-SVAR) model, generates a large and protracted fall in economic activity. On average, a one standard deviation shock in the external financial indicator leads to a fall in real output growth three quarters ahead of more than half of a percentage point, relative to its historic mean, and long run mean growth is reached again 3 years after the shock. Lastly, between 6 and 14 percent of the forecast error variance in real output growth is accounted for by these shocks.

A key challenge of our approach is to properly control for the effects of sovereign spreads on business cycles in EMEs. We follow the literature by using JP Morgan's $EMBI$ as proxy for this spread and find that, in terms of the forecasting information content on economic activity, it does not come out as statistically significant once we control for our measure of corporate spreads, regardless of the forecasting horizon considered. It only does when we deliberately omit our indicator from the forecasting regressions. Furthermore, from the estimated P-SVAR model we find that the variance share of real GDP growth associated to $EMBI$ shocks, when not controlling for shocks to corporate spreads, is already small—between 2 and 4%—and further reduces by about half when one controls for them. In contrast, the variance share associated to shocks to our indicator of corporate spreads remains unchanged after we control for $EMBI$. Overall we view this evidence *not* as pointing that sovereign spreads do not matter when accounting for business cycles in EMEs. Instead, we view it as signaling that researchers ought to take into account *both* corporate and sovereign spreads when accounting for driving forces of aggregate fluctuations in EMEs, as there appears to be some market segmentation between the two debt instruments.

Another finding of interest is the preponderant role of global financial risk, for which we use two alternative proxies, the VIX and the US corporate BAA spread. Both turn out as statistically significant covariates in our forecasting regressions of economic activity. Moreover, identified shocks to both proxies in the estimated P-SVAR models account for a sizeable share of the variance of real economic activity. The important role of shocks to global risk is also prevalent when it comes to accounting for the variance of our measure of corporate spreads. Notably, VIX and $US\ BAA$ shocks account, respectively, for 21 and 24 percent of the variability of our index of corporate spreads, making fluctuations in corporate spreads a propagating mechanism of global financial risk into EMEs. We quantify such propagation force by establishing that the share of real GDP growth variance associated with VIX shocks falls by a half, from 31 to 16 percent, when, the linkages from global risk to corporate spreads are counterfactually turned off. $EMBI$, on the other hand, serves relatively less of a propagating mechanism for these shocks.

This paper is related to and contributes to four different strands of literature. 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 in international capital markets. 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 also relates to a long standing literature that studies the relevance of external financial factors for aggregate fluctuations in EMEs.[1] External financial factors in this literature are typically proxied by U.S. interest rates or spreads of EMEs' *sovereign* debt (see e.g., Canova, 2005; Uribe & Yue, 2006), finding that they explain a sizeable proportion of business cycles.[2] Akinci (2013)

[1]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., Caballero, 2016; Calvo, Leiderman & Reinhart, 1993; Fernández-Arias, 1996; Reinhart & Reinhart, 2009), or because sudden stops in inflows (see e.g., Calvo, 1998; 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.

[2]Several subsequent papers have followed the 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 (2016). 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

further shows that the effect of international financial conditions on EMEs is also largely driven by risk aversion in global financial markets and propagated by its effect on sovereign spreads.[3] We contribute to this literature by paying particular attention to the role of *corporate* debt when quantifying the role of external financial factors.

The kind of empirical work that we undertake when constructing an external financial indicator directly from bond spreads is mostly inspired by the "ground-up"approach of Gilchrist, Yankov & Zakrajsek (2009), who study the predictive ability of bond spreads on business fluctuations in the U.S. in the 1990-2008 period (and subsequently extended to a longer sample by Gilchrist & Zakrajsek, 2012, and to the case of Western Europe by Gilchrist & Mojon, 2018). Our study follows this research agenda on exploring the predictive content of credit spreads—by constructing a country-aggregate bond spread based on micro data—but does not attempt to decompose the spread into the component associated to the idiosyncratic default-risk of firms and a residual (i.e., the excess bond premium, as dubbed by Gilchrist & Zakrajsek, 2012). In this sense, our paper expands the analysis to explore the usefulness of market-based corporate credit spreads as predictors of economic activity for the case of EMEs, but it is silent on whether the information content of corporate spreads comes from the idiosyncratic default risk of bond issuers or from deviations in the pricing of corporate bonds relative to issuers' default risk. Our contribution lies in bringing together this new literature on corporate spreads as predictors of economic activity with the extensive literature on external factors and sovereign spreads as predictors of economic activity in EMEs.

A final strand of literature that our paper is also related to is the one that has developed a new vintage of dynamic and stochastic equilibrium models aimed at accounting for business cycles in EMEs through financial shocks and the amplifying effects of financial frictions (Fernández & Gulan, 2015).[4] Our work contributes to this literature by providing empirical evidence of the

manner, which is what subsequent work shows.

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

[4] This research agenda was started by the contributions of Céspedes, Chang & Velasco (2004), Neumeyer & Perri (2005), and Uribe & Yue (2006). Subsequent works are Gertler, Gilchrist & Natalucci (2007), García-Cicco, Pancrazi & Uribe (2010), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez & Uribe (2011), Chang & Fernández (2013), Fernández, González & Rodríguez (2018). In a recent theoretical contribution, Chang, Fernández & Gulan (2017) study the business cycle effects of the endogenous choice of finance models for emerging economies.

hypotheses derived from these models regarding the links between corporate bond spreads and economic activity, while providing evidence that external financial factors are a key determinant of economic activity in EMEs through their effect on the corporate sector.

The rest of this work is divided into six sections, including this introduction. Section 2 presents the stylized facts on international corporate borrowing in EMEs. Section 3 describes how we construct the external financial indicator and provides descriptive statistics on its business cycle dynamics. Section 4 presents our benchmark forecasting regression and P-SVAR results. Section 5 presents various extensions and robustness checks. Concluding remarks are presented in Section 6. An online appendix gathers further technical material as well as more robustness analysis.

2 External Corporate Borrowing in EMEs: Stylized Facts

This section documents six stylized facts on the access to international capital markets by the corporate sector of EMEs since the turn of the century. The section starts with a description of the data used in this analysis.

2.1 Sample of Countries and Data

When selecting the pool of EMEs studied in this section we use two 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.[5] Second, we discard those countries that have had a history of pervasive high capital controls, as they may have had an impact in the extent to which corporations in EMEs financed themselves abroad.[6] This leaves us with a total of 18 EMEs that can be split into four geographical regions[7]:

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

[5]The academic literature that we use is: Neumeyer & Perri (2005), Uribe & Yue (2006), Aguiar & Gopinath (2007), Fernández & Gulan (2015), and Fernández et al. (2018). The multilateral organizations and rating agencies that we look at are (i) the IMF; (ii) MSCI; and (iii) JPMorgan.

[6]We use the recent index on *de jure* measures of capital controls by Fernández, Klein, Rebucci, Schindler & Uribe (2016) 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 to have had a history of high capital controls if the average index over the whole period is higher than one and a half standard deviations of the median across all 100 countries in the dataset.

[7]Out of a total of 21 EMEs first identified in the first filter, Argentina, China and India were dropped because they surpass the threshold of capital controls (second filter).

(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.

In addition to these four subgroups, we consider two more aggregations based on the data availability of the external financial indicator (EFI) that we build in the next section (see below for further details on its construction and data availability).

(v) **EFI-5**: Brazil, Chile, Mexico, Malaysia, and Philippines. This is the group for which a balanced panel of EFI indexes can be formed for the period 1999 to 2017.

(vi) **EFI-10**: EFI-5 countries, Colombia, Peru, Russia, South Africa, and Turkey. This is the group for which an unbalanced panel of EFIs can be formed for the period 1999 to 2017.

For each of these economies we construct quarterly measures of stocks and flows of corporate debt in international capital markets. For stocks we use the data reported by the Bank of International Settlements (BIS). For flows, we construct a measure of gross bond issuance using information on the universe of bonds reported by Dealogic DCM, a leading data provider that tracks global debt capital markets. The period of analysis goes from 2000 to 2015, which comprises most of the period for which data on bond spreads exist (see next Section).

2.2 Stylized Facts

The total stock of international corporate debt is presented in Figure 1. We disaggregate the stocks of debt between bonds and bank loans. The upper left plot aggregates debt across all 18 EMEs considered while the remaining six plots disaggregate the numbers across the six sub groups defined above. The numbers reported are in current USD Billions. The data are taken from the information on the BIS's website and collected on a nationality basis.[8] The stock of bond debt aggregates non-financial corporates, banks and other financial institutions and excludes sovereign bond issuance. The stock of loan debt includes banks and non-banks.[9]

[8] Shin (2014), among others, suggests that debt on a nationality basis is a more accurate proxy of debt liabilities than a measure based on a residence basis because a non-negligible reliance of corporates in emerging markets of issuing through offshore affiliates. Notwithstanding, the online appendix also presents the figures based on a residence basis.

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

There are two salient stylized facts coming out of Figure 1. One 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 USD 600 billion to 2.4 trillion 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. Such reversal was, however, short-lived and the accumulation of debt continued with a vigorous pace afterwards. The other stylized fact is that the lion's share of this increase in corporate debt comes from bond issuance, particularly in the post-crisis period. Debt from loans also increased but less proportionately than that from bond issuance. These two stylized facts hold across all six sub-groups considered. Evidence on a country-by-country basis, presented in the online appendix, confirms that these stylized facts also hold for each of the countries considered in this analysis.

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 USD, for each of the subgroups 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.[10] 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 the EMEs in the sample 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 and holds across all regions considered.

There are four additional stylized facts related to the issuance of debt securities in EMEs that we summarize in Figure 3, which focuses on EFI-5 countries.[11] First, the top-left subplot of this figure shows that international bond issuance has been a corporate phenomenon, as sovereigns in

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%. 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.

[10] The appendix contains further details about the criteria used when determining if a bond is issued in international 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. The online appendix also documents country-by-country bond issuance.

[11] The online appendix documents how the same patterns are robust across the group of all 18 EMEs considered and EFI-10 countries, separately.

EMEs have instead substituted foreign for domestic financing. Second, the top-right subplot describes how the increase in international bond reliance by the corporate sector has taken place with relatively more strength in non-financial corporations relative to financial corporations. Third, the increase in foreign bond issuance by corporates in EMEs exceeds the recorded growth in economic activity in the post-financial crisis period which has led to increases in the ratios of gross bond issuance to GDP throughout the period studied, as documented in the bottom-left panel of the figure. Fourth, the vast majority of international bond issuance is denominated in foreign currency, most of which is in U.S. dollars (more than 60 percent, on average) or other non-local currency (20 percent), regardless of whether the period is pre- or post-crisis (see bottom-right panel).

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

3.1 Constructing an External Financial Indicator

We now describe the methodology and data sources that we use to construct the external financial indicator (EFI) for emerging economies based on the bonds issued in international markets by their corporate sectors. 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.[12] Formally:

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

[12]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 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^{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 detail on OAS.

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

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

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 data lacks information on bond prices and, in particular, spread measures, we switch to Bloomberg when sourcing the data to compute the external financial indicator. Bloomberg provides 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 life time. We also drop bonds from the sample if information is not available on either date of issuance, bond size, issuer's sector, maturity date, or currency of denomination. Among this pool of bonds, we focus only on USD denominated corporate bonds that have been issued in foreign capital markets.[13,14]

The subset of bonds with spreads in Bloomberg is a representative sample of the universe of bonds in Dealogic DCM. The main stylized fact from Dealogic DCM data presented in the previous Section—the large surge in bond issuance from corporations in the post financial crisis—is also reproduced with the subset of OAS-bonds from Bloomberg. The online appendix documents this with the Bloomberg dataset. In the previous section we presented stylized facts on bond issuance based on Dealogic DCM because it is a more comprehensive database.

After dropping outliers (top and bottom 0.5 percentile of OAS for the entire bond-quarter observations at the country level), we were left with a total of 3476 corporate bonds and 36,078 (unbalanced) bond-quarter observations for the sample period 1999Q2-2017Q1, across ten emerging

[13]Given limitations in Bloomberg to obtain data on governing law and listing place for each bond, we relied on information on ISIN and country of incorporation of the bond issuer to make sure that we kept only international debt securities in our sample. See online appendix for further details on the definition of international debt securities used in our work.

[14]Even though Bloomberg does not allow 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.

economies: Brazil, Chile, Colombia, Mexico, Malaysia, Peru, Philippines, Russia, South Africa, and Turkey. Among the 18 EMEs considered in the previous section, this subgroup of ten countries, labelled EFI-10 in the previous section, was the one with countries for which at least one bond per quarter was observed for every quarter in the sample. Our sample begins in 1999Q2, as this is the earliest quarter when OAS data from Bloomberg are available. Our panel dataset for EFI-10 countries is, nonetheless, unbalanced as some countries do not have their respective EFI as early as 1999Q2. For this reason we also consider a subset of five of these countries, called EFI-5 in the previous section, including Brazil, Chile, Mexico, Malaysia, and Philippines, with which a balanced panel from 1999Q2 can be formed.[15] In the remaining of the analysis we will mostly focus on results coming from the EFI-10 group of countries, and document the robustness for EFI-5 in the online appendix.

The summary statistics of the dataset used to construct the external financial indicators are presented in Table 1 and the online appendix presents results on a country-by-country basis. The average number of bonds per quarter is just over 500, and also differs between countries. Brazil, Turkey, and Mexico exhibit the largest shares of the total number of bonds considered, ranging, respectively, between 1,399, 709, and 501 bonds. In contrast, Malaysia, Philippines, and Russia exhibit fewer bonds with 129, 86, and 9 respectively. In all countries, the number of bond-quarter observations remains stable until 2009 and then steadily increases until the end of the sample period.

The row labelled "size of bond" in Table 1 refers to total proceeds (i.e., the dollar amount raised by the firm by issuing the bond), measured in 2010 U.S. dollars. The average size of bonds is about 300 millions but its 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 represent years left to the maturity at issue date and at observation date, respectively. The mean is between 6 and 7 years for both variables. On average, they are 2 to 3 years shorter than the case of

[15] The initial date for EFI in each of the five countries not included in EFI-5 is (in parenthesis): Colombia (2003.Q1), Peru (1999.Q2), Russia (2003.Q1), South Africa (2005.Q4), and Turkey (1999.Q2). Korea is an additional country for which an EFI can be constructed since 1999.Q2. but that we opted to exclude it from the analysis as data on other crucial control variables are limited: EMBI. For the case of Peru we opted not to include it in the EFI-5 countries as there are several domestic USD bonds and it makes it difficult to separate them from those issued in international capital markets. For the case of Turkey, we drop it because of several missing values for the sample period 2001Q1-2007Q4 and 2008Q4-2009Q1. We will nonetheless include Peru and Turkey in the EFI-10 countries.

U.S. corporate bonds reported in Gilchrist & Zakrajsek, 2012. Arguably, this reflects the ability of U.S. firms to issue bonds at longer maturities than firms in EMEs.[16]

The mean OAS spread is 409 basis points (bp) for the sample period, and it is positively skewed, with a large standard deviation of 511 bp. The same pattern is observed across all countries in the sample, although considerable differences in the average OAS can be seen. South Africa and Russia are the countries with the highest average OAS, 644 and 579 bp, respectively. While Chile (248 bp) and Malaysia (194 bp) exhibit the lowest levels, nearly a third of those in South Africa and Russia.

3.2 Dynamics of the External Financial Indicator

We now document the time series dynamics of EFI, namely its comovement with real economic activity as well as other macro variables. The degree of cyclicality of our measures of EFI is assessed by computing the unconditional serial correlation of leads-lags of EFI with real (contemporaneous) GDP growth, as reported in Figure 4 and Table 2 (first row). Figure 4 reports the median serial correlation across each of the EFI-10 countries. The online appendix presents also country-by-country correlations as well as time series plots of EFI and GDP growth. Results indicate a negative contemporaneous correlation between the two variables. Moreover, they indicate that EFI is a leading indicator of economic activity in these countries (i.e., GDP growth today commoves the most, and in opposite direction, with lagged changes in EFI).

More descriptive statistics on the dynamics of EFI are reported in Table 2. EFI commoves with other known measures of corporate and sovereign spreads at the country level such as JP Morgan's $CEMBI$ and $EMBI$. We note, however, that the correlation is not perfect, signaling that EFI includes different information from these indexes. In subsequent analysis we will explore the marginal information content of EFI relative to these two spreads. Another distinctive property of the EFIs is their strong comovement with two proxies of global risk: the VIX and the US BAA spread. Lastly, the EFI's constructed exhibit a strong comovement: most of the country pair correlations reported are high and statistically significant. The first principal component of the ten EFIs accounts for 80 percent of the sample variance. Likewise, 63 percent of the variance in GDP growth is associated to the first principal component.

[16] It is important to note, however, that the comparison of our dataset to that in Gilchrist & Zakrajsek (2012) is, at best, crude since the sample periods are not identical, nor are their sources.

4 The External Financial Indicator and Economic Activity

Motivated by the strong negative comovement observed between spreads on bonds issued by *corporates* of EMEs in international capital markets and economic activity in these economies, we turn now to a more formal analysis of this interaction. Before that, however, we discuss some of the main theoretical considerations underpinning such analysis.

4.1 A Theoretical Discussion

When modeling the behavior of the (gross) interest rate at which debt with the rest of the world is issued by agents in EMEs, R, be it for investment and/or consumption needs, the literature has always assumed the EME is too small to affect the world interest rate R^*. In the canonical small open economy model of Mendoza (1991), it was simply stated that the two rates were identical and time invariant, $R = R^*$, although an extension considered the case in which R^* varied exogenously as a simple autoregressive process whose shocks aimed at capturing changes in the risk aversion of foreign lenders/investors.

Subsequent contributions aimed at quantifying the role of interest rates in business cycles of emerging economies included the possibility of country-specific spreads playing also a role in shaping aggregate fluctuations in these economies (Neumeyer & Perri, 2005; Uribe & Yue, 2006). Formally, the (gross) interest rate at which debt with the rest of the world is issued by agents in economy j is determined by R^* and a (country-specific) spread S_t^j

$$R_t^j = S_t^j R_t^*$$

Hence, movements in R^j 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^j. 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^j.

An immediate challenge arises in terms of how to model properly the dynamics of spreads, taking into account the empirical regularity documented above in terms of the negative comovement between spreads (as captured by EFI) and economic activity. Which is the causality behind this result? Do spreads drive business cycles or vice versa? Or both? Identification of shocks to spreads is therefore challenging insofar as it needs to disentangle how much fundamentals are affecting spreads, and how are spreads affecting fundamentals.

Three alternatives have been explored in practice to achieve identification. First, using a semi-structural approach, several previous works have postulated a link between spreads and (latent or observed) country fundamentals modeled as exogenous state variables in a structural DSGE model, e.g., future expected productivity or the price of commodities exported by EMEs. Such linkages are then calibrated (or estimated) within the context of the calibration (or estimation) of a dynamic, stochastic, general equilibrium model (Chang & Fernández, 2013; Fernández et al., 2018; Neumeyer & Perri, 2005). Formally, an *ad hoc* equation such as:

$$S_t = \widetilde{\eta}_1 E_t TFP_{t+1} + \widetilde{\eta}_2 E_t P^{co}_{t+1} + \varepsilon^S_t$$

is introduced (omitting the country-specific index j for simplicity), where $E_t TFP_{t+1}$ and $E_t P^{co}_{t+1}$ capture the expectations of future productivity and commodity prices; ε^S_t are exogenous and country-idiosynchratic 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.[17]

A caveat of this semi-structural approach is the fact that microfoundations of spread behavior are absent. For this reason, a second approach in the literature has been characterized by the effort to provide such microfoundations. Mendoza & Yue (2012) do so by embedding an optimal default problem by the government into an equilibrium business cycle model of a small open economy, though they do not model the decisions of the corporate sector. Fernández & Gulan (2015) focus on corporate bankruptcy in an environment where a financial contract is stipulated between (corporate) borrowers in an EME and investors in world capital markets. A financial accelerator endogenously generates a spread process that depends upon financial variables, namely entrepreneurial

[17]If investors are risk averse, shocks ε^S_t could be thought of as a way to capture changes in investors' risk tolerance for risky assets such as bonds issued by EMEs. If investors are assumed to be risk neutral, these shocks are a way to break the natural endogeneity in spreads given that they are an equilibrium outcome of an arbitrage between a risk free bond and a risky bond.

leverage. Hence domestic or external shocks that affect the value of entrepreneurial's net worth will influence spreads.[18]

As in most structural approaches, a rigid structure is imposed on the data. For that reason, the third approach in the literature has been more agnostic and has tried to put as little structure as possible on the data, when trying to identify shocks to spreads. This is the approach that we follow in this work. It postulates modeling a process for spreads jointly with country "fundamentals"(e.g., real output.) and proxies for global financial risk in world capital markets in the context of P-SVAR models. Uribe & Yue (2006) pioneered such approach by using a recursive identification implying that innovations in world interest rates and in sovereign spreads percolate into domestic fundamentals with a lag, and that world interest rates are exogenous to developments in the EMEs considered.Akinci (2013) extended this setup to account for global financial risk and finds that sovereign spreads in EMEs are a powerful propagation mechanism of fluctuations in global financial risk. In the following subsections we will extend this setup to account for EME's corporate spreads. Doing so will imply additional hurdles such as properly disentangling the effect of corporate spreads from that of sovereign's.

With these considerations in the background, the next two subsections will aim at exploring further the documented negative comovement between spreads on bonds issued by *corporates* of EMEs in international capital markets and aggregate economic activity in these economies. The key difference between the two approaches used in both subsections will rest on the varying degree of economic structure imposed on the data. First, we will quantify the information content and predictive ability of credit spreads embedded in EFI on economic activity, without the need to impose any structure on the data in order to identify structural shocks. Next, by imposing enough structure so as to identify exogenous perturbations to these spreads, we will quantify their impact on *future* economic activity.

[18]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.

4.2 Forecasting Information Content of the External Financial Indicator

We now assess the information content of EFI on *future* economic activity in emerging economies by extending Gilchrist & Zakrajsek (2012)'s forecasting specification to a multi-country panel setting tailored to EMEs.[19] Formally, we estimate a dynamic panel regression of future real GDP growth against current changes in EFI:

$$\Delta GDP_{t+h}^{k} = \alpha_k + \sum_{j=0}^{p} \beta_j \Delta GDP_{t-j}^{k} + \gamma \Delta EFI_t^k + \delta \Delta EMBI_t^k + \psi \Delta GR_t + \Gamma \Omega_t^k + \epsilon_{t+h}^k, \quad \text{for } h \geq 1 \quad (3)$$

where index k denotes each of the EMEs considered when building the EFI and $h \geq 1$ is the forecast horizon. We will consider the cases of $h = 1, 2, 3, 4$. Variables ΔEFI and ΔGDP are annual changes in EFI and the (log of) real GDP, respectively.[20] We consider two subsamples of countries: one is the balanced panel of EFI-5 countries for the period 1999.Q2 to 2017.Q1; the other one is the group of EFI-10 countries with an unbalanced panel over the same period. We estimate the dynamic panel regression with country fixed effects (α_k) and lag length equal to twelve ($p = 11$) so as to incorporate enough previous information in terms of economic activity, though we report qualitatively similar results in the online appendix when alternative lag specifications are considered.[21] Lastly, we use the consistent covariance matrix estimation for partially dependent panel dataset developed by Driscoll & Kraay (1998) that yields robust standard error estimates to general forms of spatial and temporal dependence.

We control for several other variables that may influence economic activity in EMEs beyond EFI, of both domestic and global nature. First, we include the country-specific sovereign spread,

[19]As clarified in our introductory remarks, the similarity of our approach with that of Gilchrist & Zakrajsek (2012) lies in exploring the predictive content of market-based credit spreads using a forecasting regression setup, but we do not attempt to decompose the spread into the component associated with the idiosyncratic default-risk of firms and a residual, which the authors call the Excess Bond Premium (EBP) for U.S. corporate bonds. We left the exploration of what component of the corporate spreads is most associated with business fluctuations for future research and focus on documenting the usefulness of corporate credit spreads as predictors of economic activity for the case of EMEs and disentangling this effect from that of sovereign spreads and global financial risk. The online appendix does consider, however, one extension of the forecasting regressions that we present in this section when the (U.S.) EBP variable constructed by these authors is used as an additional explanatory variable. We continue to find that EFI has predictive power.

[20]We will refer to annual real GDP growth and ΔGDP interchangeably form now on.

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

as proxied by JPMorgan's $EMBI$, as a way to account for potential spillovers from sovereign spreads to corporate spreads.[22] Second, following the work by Rey (2013), which identifies a strong effect of a global financial cycle on small open economies, we include a proxy for global financial risk, GR. We use two proxies: the VIX, a measure of uncertainty and risk aversion coming from the implied volatility of S&P 500 index options, as this variable is identified in Rey's work as one that commoves strongly with the global financial cycle in cross border capital flows; and the US BAA $spread$, following Akinci (2013) who finds that shocks to this variable account for a considerable share of movements in aggregate economic activity in a pool of emerging economies. Both variables enter model (3) in annual changes.

Third, we include in vector Ω^k two variables that are common across the countries and that aim at capturing the role of foreign factors beyond those already captured in GR: the (annual) changes in term spreads of 3-month and 10-year US Treasury yields, $\Delta USYield\ Curve$; and the (annual) changes in the US real Federal Funds Rate, ΔRFF_t. As additional country-specific controls in Ω^k, we include the (annual) change in the real monetary policy rate, $\Delta RLocalRate$; and (annual) changes to a country-specific commodity price index that uses as weights the share of the commodities exported by each emerging economy, $\Delta RPcom$.[23]

The estimated coefficients are reported in Tables 3 and 4 which document results using the samples of EFI-5 and EFI-10 countries, respectively. Numbers in parenthesis are t-statistics. Each of the four panels presents results for alternative forecasting horizons (h), from $h = 1$ to 4. The columns in each panel report results according to 5 alternative specifications that vary according to the set of controls used in GR. In the first column, no controls are used for GR. The second and third columns report results where we add, separately, the two proxies for GR that we consider, VIX and US BAA $spread$. The fourth column reports results when both variables are included. The fifth specification in the last column reports results when we deliberately exclude EFI. In all

[22] Of course, the causality may go the other way around too, i.e., from corporate to sovereign spreads. The case of several crises in Asia in the 90s (e.g., Korea) and the more recent experience in Ireland and Spain show how the deterioration of corporate balance sheets may turn into higher sovereign spreads as the public sector absorbs much of the private illiquid debts.

[23] $\Delta RPcom$ 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. (2018) who found 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 about the construction of this variable.

five cases the full set of additional controls (Ω^k) is included, but not reported for the sake of space.

There are three results of interest, looking first at the EFI-5 subsample (Table 3). First, EFI is a statistically significant predictor of economic activity in these countries for any forecasting horizon considered when no controls in GR are considered. Our estimated coefficient for γ increases with h from $\widehat{\gamma} = -0.0017$ for $h = 1$ to $\widehat{\gamma} = -0.0034$ for $h = 3$, and $\widehat{\gamma} = -0.0036$ for $h = 4$. The coefficients are not only of statistical significance, but their size is also of economic relevance. According to the estimated coefficient with $h = 4$, an increase in EFI of 100 basis point in the current quarter is correlated with a reduction of 0.36 percentage points in output's growth rate four quarters ahead. This is a considerable reduction taking into account that such an increase is common in the data, e.g., a one standard deviation in ΔEFI is 250 basis points.

Second, the size and statistical significance of the estimated coefficient of EFI is reduced when the two alternative controls for GR are included. For the particular case of $h = 1$, the coefficient goes from $\widehat{\gamma} = -0.0017$ and a statistical significance of 10% when no GR controls are added (Spec. 1), to $\widehat{\gamma} = -0.0011$ and no statistical significance below that threshold. Importantly, however, this offsetting effect is milder the longer the forecasting horizon considered. Indeed, even when both controls in GR are included (Spec. 4), EFI continues to have statistical power and information on future economic activity for $h \geqslant 2$, and the magnitude of the coefficient increases, although not monotonically. For $h = 2, 3, 4$, the coefficients in Spec. 4 are, respectively, $\widehat{\gamma} = -0.0028, -0.0035$, and -0.0032, and are statistically significant at 10, 5 and 10 percent.

Third, our proxy for sovereign spreads, $EMBI$, does not come out as statistically significant under any of the first four specifications that we try, regardless of the forecasting horizons considered. The only specification where this variable is significant is the fifth one, where we deliberately omit EFI from the forecasting regressions. Thus, sovereign spreads do not possess information that is useful for forecasting future economic activity over and above that already contained in EFI.

Lastly, the results are qualitatively similar to those obtained using the larger (and unbalanced) pool of EFI-10 countries, as reported in Table 4. There is a reduction in the magnitude of the coefficient, though their statistical significance actually improves. For instance, in the case of $h = 3$ and Spec. 4, the coefficient reduces to $\widehat{\gamma} = -0.0018$, about half of that coming from the EFI-5 pool

($\widehat{\gamma} = -0.0035$), and it is now significant at 1%.

4.3 Macroeconomic Effects of Shocks to the External Financial Indicator

4.3.1 A Baseline Structural Model with VIX as Proxy for Global Risk

We now turn to examining the dynamic macroeconomic consequences of shocks to variations in EFI in the EMEs considered in our baseline EFI-10 group of countries.[24] We do so by estimating a quarterly panel structural vector autoregressive (P-SVAR) model with which we identify shocks to ΔEFI, and then assess their effects on GDP growth using variance decomposition and impulse response analysis. Formally, the baseline P-SVAR model that we run is

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

where, k is the country index for the 10 countries in the pool of EFI-10,

$$\mathbf{Y}_t^k = \left[\Delta GDP_t^k; \Delta GR_t; \Delta EFI_t^k\right] \tag{5}$$

$$\varepsilon_t^k = \left[\varepsilon_t^{GDP^k}; \varepsilon_t^{GR}; \varepsilon_t^{EFI^k}\right] \tag{6}$$

and, as before, ΔGDP_t^k is the change in (the log of) real GDP for k and ΔGR is a proxy for global risk which, in our baseline case, is ΔVIX. We identify the shock to ΔEFI^k by imposing two restrictions. First, we assume $\mathbf{A}$ to be lower triangular with unit diagonal elements. Second, we assume that ΔGR is exogenous to economy k.[25] Hence, we identify the shock to ΔEFI^k by assuming that it percolates into domestic real variables (ΔGDP^k) with a one-period lag and that neither ΔEFI^k nor ΔGDP^k influence the dynamics of ΔVIX. At the same time, the identification scheme implies that real domestic shocks ($\varepsilon_t^{GDP^k}$) affect ΔEFI^k contemporaneously. This identification strategy has been used by Gilchrist & Zakrajsek (2012) for the case of the U.S., and in the context of EMEs by Uribe & Yue (2006) and Akinci (2013). It formalizes the idea that financial variables (e.g., spreads) react faster than real variables (e.g., production and investment decisions) due to adjustment costs,

[24] Results for the subset of EFI-5 countries are qualitatively similar and are reported in the online appendix for the sake of space.

[25] Formally, this implies that $\mathbf{A}_{2,1} = \mathbf{A}_{2,3} = \mathbf{B}_{p,2,1} = \mathbf{B}_{p,2,3} = 0$, where element (X,Y) of Matrices $\mathbf{A}$ and $\mathbf{B}_p$ are denoted as $\mathbf{A}_{X,Y}$ and $\mathbf{B}_{p,X,Y}$, respectively.

among other possible reasons. The second identifying assumption is that the k^{th} EME considered is a small player in world capital markets and hence cannot affect measures of global risk. We call this baseline set up "Model A ", which we estimate by pooling quarterly data from our (unbalanced) panel of EFI-10 countries using the least square estimator with country specific dummies ($\mathbf{C}^k$) on the period 1999.Q2 to 2017.Q1.

A potential caveat to Model A is that we are not taking into account the role of sovereign spreads when identifying shocks to ΔEFI^k. Doing so is not trivial, however, as one needs to take a stance in terms of the ordering of this variable in the recursive formulation, and hence on the lag with which corporate and sovereign spreads affect each other. We decided to take an agnostic approach and consider three distinct extensions to account for sovereign spreads. In an expanded setup, labelled "Model B", we extend $\mathbf{Y}_t^k$ to include $\Delta EMBI^k$, our proxy for sovereign spread, ordered last in $\mathbf{Y}_t^k$:

$$\mathbf{Y}_t^k = \left[\Delta GDP_t^k; \Delta GR_t; \Delta EFI_t^k; \Delta EMBI_t^k\right]; \tag{7}$$

$$\varepsilon_t^k = \left[\varepsilon_t^{GDP^k}; \varepsilon_t^{GR}; \varepsilon_t^{EFI^k}; \varepsilon_t^{EMBI^k}\right]; \tag{8}$$

thereby assuming that shocks to ΔEFI^k affect sovereign spreads contemporaneously, but shocks to sovereign spreads only affect ΔEFI^k with a lag.

In the last two extensions, Models C and D, we run the same analysis as in Models A and B, except that $\Delta EMBI^k$ substitutes ΔEFI^k. Formally, Model C postulates that

$$\mathbf{Y}_t^k = \left[\Delta GDP_t^k; \Delta GR_t; \Delta EMBI_t^k\right] \tag{9}$$

$$\varepsilon_t^k = \left[\varepsilon_t^{GDP^k}; \varepsilon_t^{GR}; \varepsilon_t^{EMBI^k}\right] \tag{10}$$

While Model D assumes:

$$\mathbf{Y}_t^k = \left[\Delta GDP_t^k; \Delta GR_t; \Delta EMBI_t^k; \Delta EFI_t^k\right] \tag{11}$$

$$\varepsilon_t^k = \left[\varepsilon_t^{GDP^k}; \varepsilon_t^{GR}; \varepsilon_t^{EMBI^k}; \varepsilon_t^{EFI^k}\right] \tag{12}$$

The set of four models is useful insofar as it allows for various informative comparisons. First, comparing models A and B allows to gauge the extent to which including sovereign spreads diminishes the role of ΔEFI^k shocks when accounting for economic activity in EMEs. Likewise, comparing Models C and D allows to do the same but giving ΔEFI^k the least chance to have an impact as it is ordered last in vector $\mathbf{Y}_t^k$.

Results in terms of variance decomposition and impulse response functions (IRF) are summarized in Table 5 and Figure 5, respectively. Bands in Figure 5 denote 95 percent confidence intervals and are computed using bootstrapping methods.[26] We consider one lag in each of the four models considered ($p = 1$) but later present further robustness analysis using higher lags. The following five results are worth stressing:

1. The share of GDP growth variance associated to ΔEFI^k shocks is 13 percent from Model A, about half that linked to ΔVIX shocks (31 percent). The impulse response function of GDP growth displays a long and protracted slump after a one S.D shock to ΔEFI^k, that achieves its trough three quarters ahead, falling nearly half of a percentage point. Long run mean growth is reached again about 3 years after the shock. The trough of this IRF is about one half that coming from a ΔVIX shock.

2. The share associated to ΔEFI^k shocks when accounting for GDP variance as well as the shape and size of GDP's IRF following this shock remains the same when Model B (with $\Delta EMBI^k$ shocks) is estimated. If anything, the share of ΔEFI^k shocks in the variance of real economic activity increases to 14 percent. Notably, shocks to $\Delta EMBI^k$ do not account for any GDP growth variability, and the IRF of this variable following a shock to $\Delta EMBI^k$ is much milder than that stemming from shocks to ΔEFI^k.

3. The GDP variance share associated to $\Delta EMBI^k$ shocks when not controlling for ΔEFI^k (Model C) is 4 percent. Moreover, when one controls for ΔEFI^k but ordered last in $\mathbf{Y}_t^k$ (Model D), such share reduces by a half, to 2 percent, while that of ΔEFI^k shocks is 12 percent.

4. The role of ΔVIX shocks when accounting for GDP variance is considerable, between 30 to

[26] The length of the simulated data using the estimated structural shocks is four times the original length observed in the data. And the procedure is repeated 300 times.

36 percent across the four Models considered. Moreover, they account for the an important share of ΔEFI^k variability, e.g., between 20-21% in Models A, B and D. They are also of importance when accounting for the dynamics of $\Delta EMBI^k$, between 35 and 40 percent in Models B, C and D.

5. Despite the fact that GDP shocks account for more than half of GDP variability in all four cases considered, they account for a much lower share of the variance of $\Delta EMBI^k$ and ΔEFI^k. In none of the four cases considered this share increases above 4 percent.

To sum up, the results presented across the four cases considered point to a non-trivial role of ΔEFI shocks when accounting for macroeconomic fluctuations in EMEs, even after controlling for the potential spillovers from sovereign spreads. We view this evidence as pointing into the direction of some market segmentation between corporate and sovereign bonds in EMEs, with spreads on corporate bonds incorporating new information of economic activity in these economies over and above the one contained in spreads of sovereign bonds. Lastly, EFI is, to a large extent, also determined by external global risk (GR). For that reason it is of interest to expand the set of variables considered as proxies for GR and to explore how their effects on EMEs operate indirectly through their impact on ΔEFI. We turn to this analysis next.

4.3.2 Global Risk and its Propagation Mechanism

We explore two extensions now. First, we assess how results from Models A-D change when the annual change in $US\ BAA$ spread is taken as alternative proxy for global financial risk, ΔGR. We also explore the propagation mechanism of shocks to (both proxies of) ΔGR, by quantifying the extent to which movements in ΔEFI^k and $\Delta EMBI^k$ triggered by shocks to ΔGR help amplify the role of global financial shocks onto EMEs.

Results of the first extension, in terms of variance decomposition and impulse response functions, are summarized in Table 6 and Figure 6, respectively. Two additional results are worth stressing:

6. Using $\Delta US\ BAA$ as proxy for global risk increases the role of ΔGR shocks when accounting for real economic activity. Indeed, the share of GDP variance that is accounted for by shocks to $\Delta US\ BAA$ spreads is between 50 to 54% across the four Models. In turn, using $\Delta US\ BAA$

as proxy for ΔGR decreases the GDP variance share associated to shocks in both sovereign and corporate spreads, relative to the case where ΔVIX was used. The share of GDP growth accounted for by ΔEFI^k shocks is now 6 percent (Model A), while the one by $\Delta EMBI^k$ shocks is 2 percent (Model C). Both shares remain somewhat similar in the expanded models B and D. The protracted fall in economic activity that follows a one S.D shock to ΔVIX is slightly milder to the one for $\Delta US\ BAA$, while the one following a one S.D shock in $\Delta EMBI^k$ reduces also and, in Model B, is no longer significant.

7. The relevance of shocks to ΔGR further increases when it comes to accounting for the variance of both ΔEFI^k and $\Delta EMBI^k$.

Motivated by these two observations (6. and 7.) we now investigate the extent to which movements in corporate and sovereign spreads in EMEs help propagate ΔGR shocks. This is achieved by means of counterfactual experiments on the P-SVAR estimated coefficients whereby we turn off the effect of ΔGR on our measures of country/corporate spreads.[27] Results are reported in Table 7. The right column contains the counterfactual variance shares for Models A and C and for both proxies of ΔGR, and, for comparison, the left column presents the benchmark results. Likewise, the triangular/green lines in Figures 5 and 6 display the IRF of GDP to a ΔGR shock in our counterfactual experiments. The following additional result emanates from inspecting them:

8. The variance share of real output growth that is accounted for by ΔGR shocks reduces considerably when their spillover onto ΔEFI^k is turned off. When ΔGR is proxied by ΔVIX, the GDP growth variance share of shocks to this variable falls by about a half, from 31 percent to 16 percent in the counterfactual experiment; and, similarly, when using $\Delta US\ BAA$ the fall is by about a fourth, from 50 percent to 36 percent. Interestingly, a similar reduction is observed when the counterfactual experiment is performed with sovereign spreads and the spillover from ΔGR shocks onto $\Delta EMBI^k$ is turned off, but the magnitude of the reduction is relatively smaller. This is echoed in the counterfactual IRFs in Figures 5 and 6 (green/triangles) where the GDP's response after a ΔGR shock reduces against the baseline

[27] In practice, we manually set to zero the coefficients in Matrices A and B in models A and C that relate GR to VIX and $US\ BAA$.

case by more when the effect on ΔEFI^k is turned off, relative to that one gets when the effect in $\Delta EMBI^k$ is turned off. This evidence points to corporate spreads serving relatively more as propagating mechanisms for global risk shocks than sovereign spreads.

5 Extensions and Robustness

5.1 The Role of the World Financial Crisis and Subsequent Recovery

In this subsection we investigate how much the 2008/9 Global Financial Crisis matters for our benchmark results. To do so we reestimate (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), for the four forecasting horizons considered, by adding to the sample one more observation at a time (keeping the starting period fixed at 1999.Q2). For each h's we document the estimated values of γ, the coefficient that links ΔEFI with future states of economic activity and the p-values associated to them. Results are reported in the upper-left and right subplots of Figure 7, respectively. They indicate that, as data of the crisis and the post-recovery are added, the coefficients and their p-values further decrease, particularly during the last three years of the sample (2014-2017). We view this as indicating that the crisis and the post-crisis period account for most of the large information content of EFI in terms of economic activity in emerging economies.

5.2 Removing Financial Corporations' Bonds

Motivated by the large increase in bond issuance by non-financial corporates (NFC), documented in Section 2, we now test how much do the benchmark results hold if we remove the bonds issued by financial corporations in each of the EMEs considered when constructing the EFI. This entails removing roughly half of the total number of bonds considered in the construction of the benchmark EFI. With this modified EFI, labelled $EFI - NFC$, we re-run the P-SVAR model and compare the new impulse responses of output growth to those from the benchmark case following a 1 S.D shock to $\Delta EFI - NFC$. The bottom-left plot of Figure 7 reports the results (solid line), with the green/triangle line depicting the our baseline results with ΔEFI. Results are quite close 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 $\Delta EFI - NFC$, though below the one in the benchmark case.

5.3 Alternative Lag Order

In the benchmark P-SVAR specification we arbitrarily set the number of lags to one, $p = 1$. We now consider alternative lag specifications.[28] Results are reported in the bottom-right plot of Figure 7, with impulse responses of output growth for the alternative lags. They are qualitatively similar to the benchmark case. A S.D shock to ΔEFI leads to a protracted fall in economic activity for all lag specifications considered. The trough continues to lie also between three and four quarters after the shock. Quantitatively, the depth of the trough is about 0.2 percentage points deeper with a higher lag structure, relative to the benchmark case, although the recovery is faster too.

5.4 Alternative Measures of Corporate Spread

An alternative proxy for spreads faced by corporates in EMEs is the Corporate Emerging Market Bond Index ($CEMBI$) produced by JP Morgan which, as documented earlier, commoves with EFI. A valid question is then why don't we use this alternative index instead of EFI. A first reason is that $CEMBI$ is a product that JPMorgan sells via specialized distributors (e.g., Bloomberg) and hence it is not entirely replicable as not all the details for its construction are revealed. One cannot know, for instance, the number of bonds used, their average face value, maturity, etc., as we do/report for EFI (Table 1). Furthermore, $CEMBI$ does not inform the types of sectors that are included in the index, a particularly unattractive property given the nature of our investigation, which postulates the relevance of non-financial corporate's bond issuance. Last, but not least, for the countries considered in the EFI-5 subgroup, EFI has better coverage in the time series dimension. While EFI begins in 1999.Q2, $CEMBI$ does not begin before 2002.Q1. The series of $CEMBI$ are also sparse and irregular. For example, in the case of Peru, $CEMBI$ series begin only in 2005.Q3, unlike ours that begin in 1999.Q1.

With these caveats in mind, we nonetheless compare the performance of the two indicators, EFI and $CEMBI$, in terms of one the metrics that we have analyzed, panel forecasting regressions, across the EFI-5 countries in our baseline case and over the same period of time where we have information from both types of spreads (2002Q1-2017Q1). Results are presented in Table 8. They indicate that EFI outperforms $CEMBI$, which does not turn out to be a significant predictor

[28] The online appendix contains also extensions of the forecasting panel regression (3) with alternative lags.

under any of the forecasting horizons considered.[29]

6 Concluding Remarks

Access to world capital markets by the private sector may be viewed as a necessary condition for emerging economies to achieve sustainable long run growth. However, this also entails the risk that changes in the financial conditions at which the corporations borrow in these markets may carry destabilizing consequences for economic activity. In light of these considerations and the fact that firms in emerging markets have largely increased their reliance on foreign debt, particularly in the form of bonds denominated in USD, quantifying how much changes in these lending conditions impact economic activity is an important question for international macroeconomics.

Motivated by this observation, our work has tried to shed light onto this question. We construct an indicator of external financial conditions for several emerging economies using spreads from bonds issued in foreign capital markets by the corporate sector. 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, even after controlling for other potential drivers of economic activity in these economies, such as movements in sovereign spreads and global financial risk. Fluctuations in this indicator also respond strongly to shocks on world capital markets, implying that changes in such indicator have also served as a powerful propagating mechanism to changes in global investors' risk appetite.

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 faced by corporations in EMEs have on economic activity in these economies. 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 motivate further subsequent work to shed light on this question.

[29] The same criticism that we make to $CEMBI$ could be applied to $EMBI$, which would call for constructing an index using a similar methodology to the one we employ with EFI, but aimed at sovereign bonds. While we think this is a valid concern, we did not opt for this option mainly because the use of $EMBI$ as proxy for sovereign spreads is widespread, both in academic as well as more applied work, making it a more natural benchmark for our work, and facilitating a better assessment of the contribution of EFI. Future work might want to expand our methodology to sovereign bonds.

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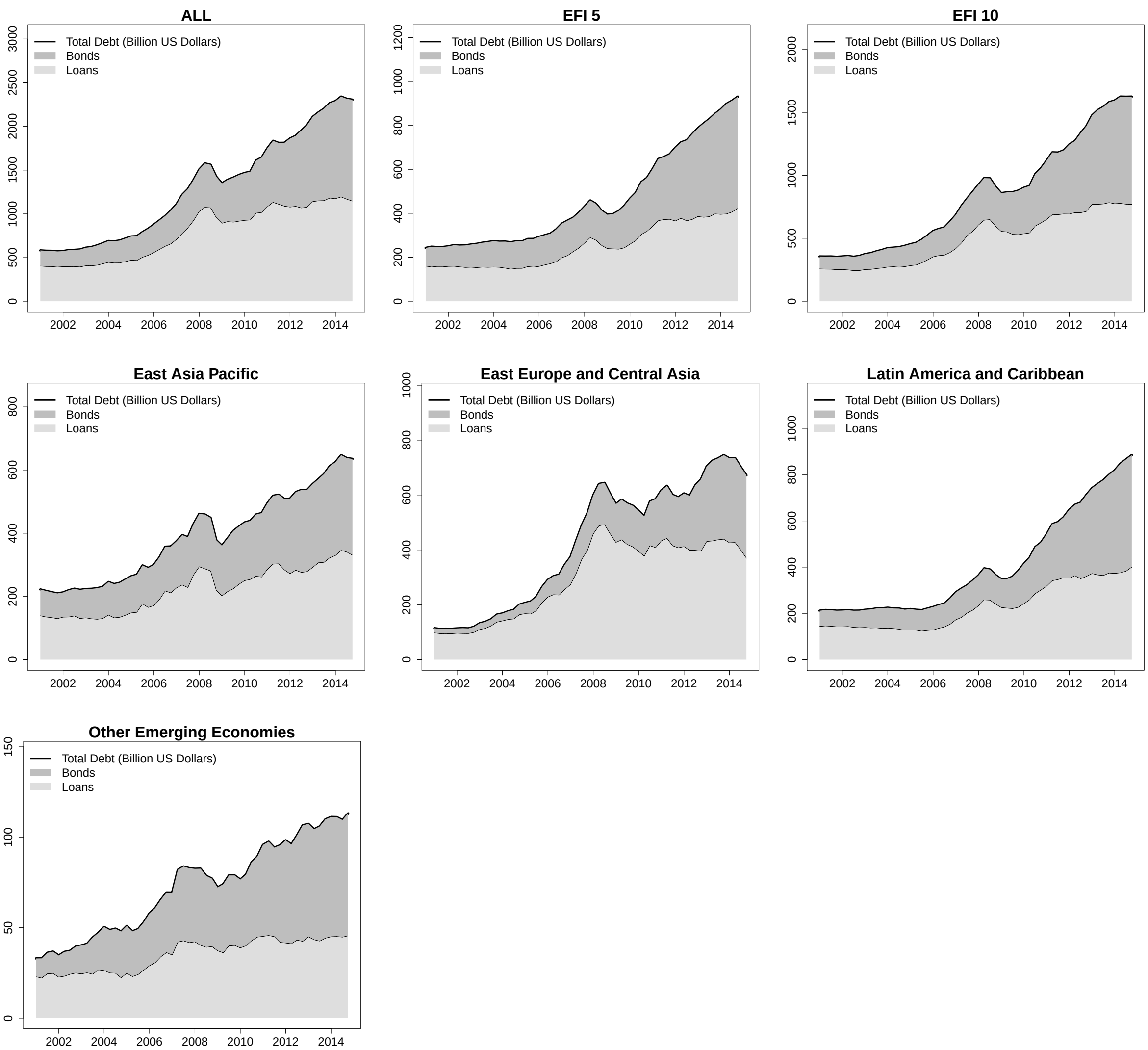
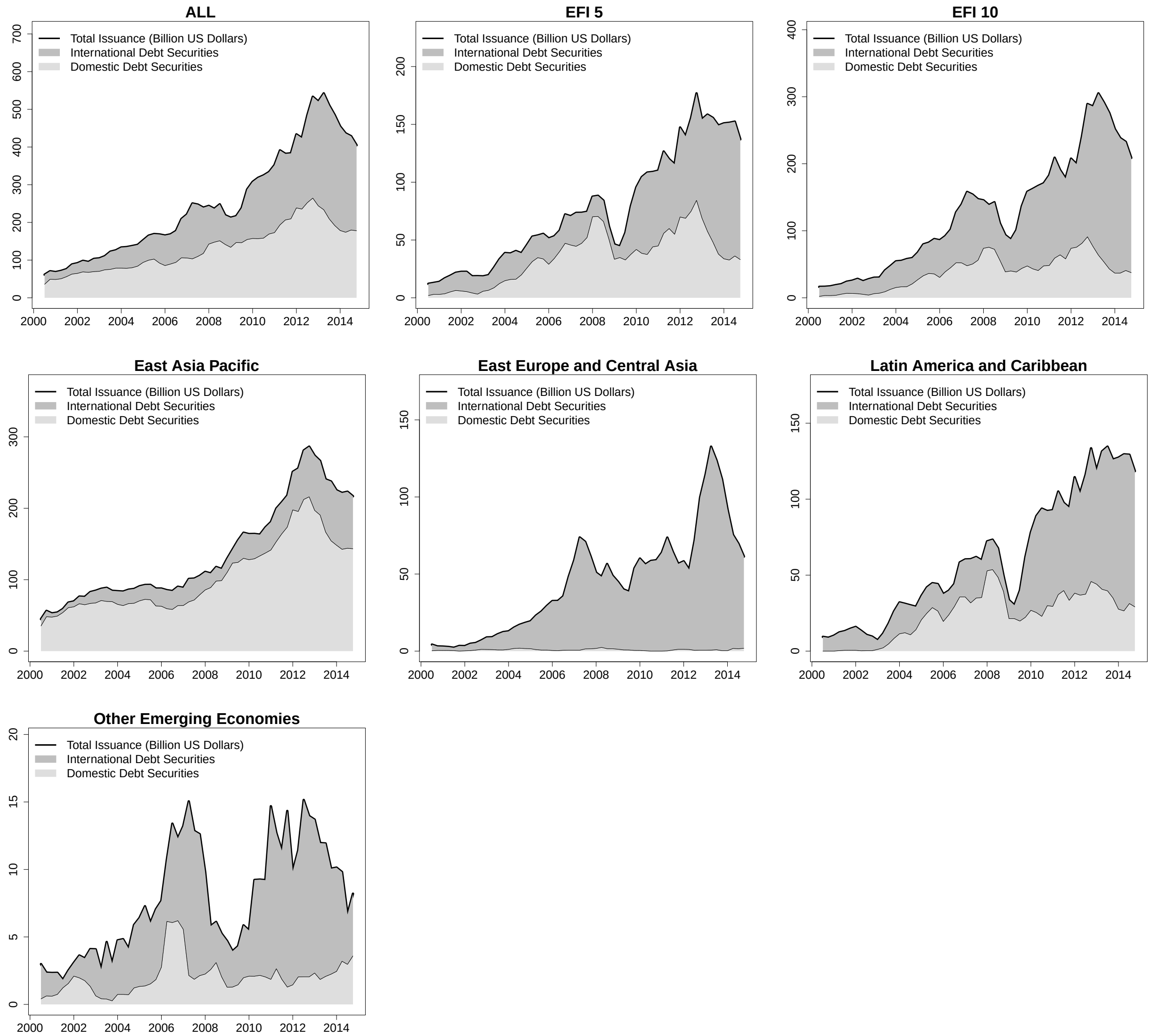
Figures and Tables

Figure 1: Stock of Private Sector International Debt in EMEs (Regional Aggregates, on a Nationality Basis)



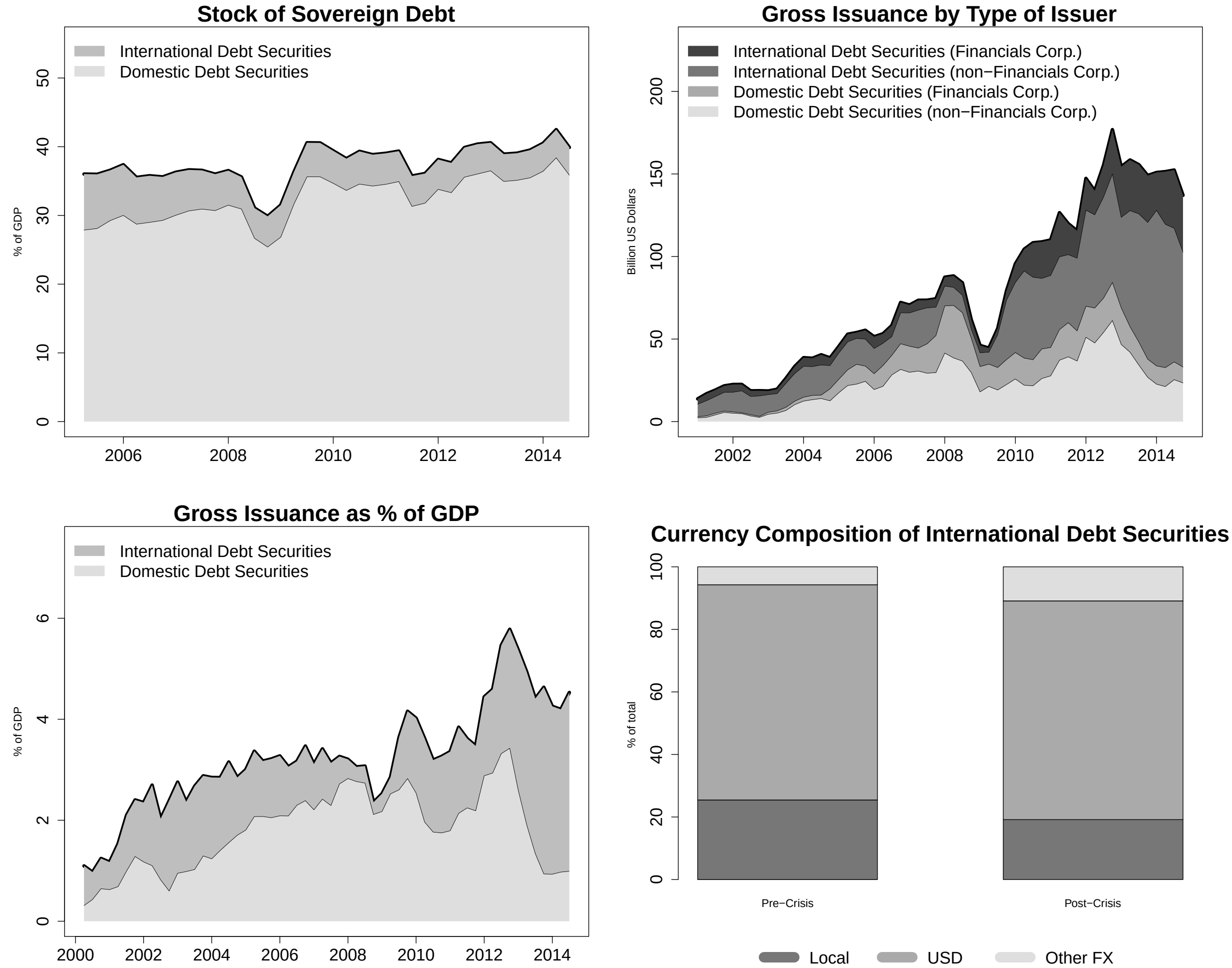
This figure shows the aggregate stock of private sector international debt for 18 emerging economies (EMEs), decomposing the outstanding stock into cross-border bank loans and international debt securities (bonds). The stock of securities is on a nationality basis. The private sector includes all financial institutions and nonfinancial corporations. The figure shows the total stocks over the following regional aggregates: EFI-5: Brazil, Chile, Malaysia, and Philippines. EFI-10: Colombia, Peru, Russia, Turkey, South Africa, and EFI-5 countries. 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, Ecuador, Mexico and Peru. Other Regions: South Africa, and Israel. Geographical aggregation does not net out debt with other EMEs in the aggregate. 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 2: Corporate Gross Bond Issuance in EMEs (Regional Aggregates, on a Nationality Basis)



This figure shows gross issuance of international and domestic debt securities (bonds) by regional aggregates and for EFI-5/EFI-10 countries on a nationality basis. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See the online 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. The figure shows the country total or the total over the regional aggregates detailed in the note to Figure 1.

Figure 3: Other Stylized Facts on International Debt in EMEs



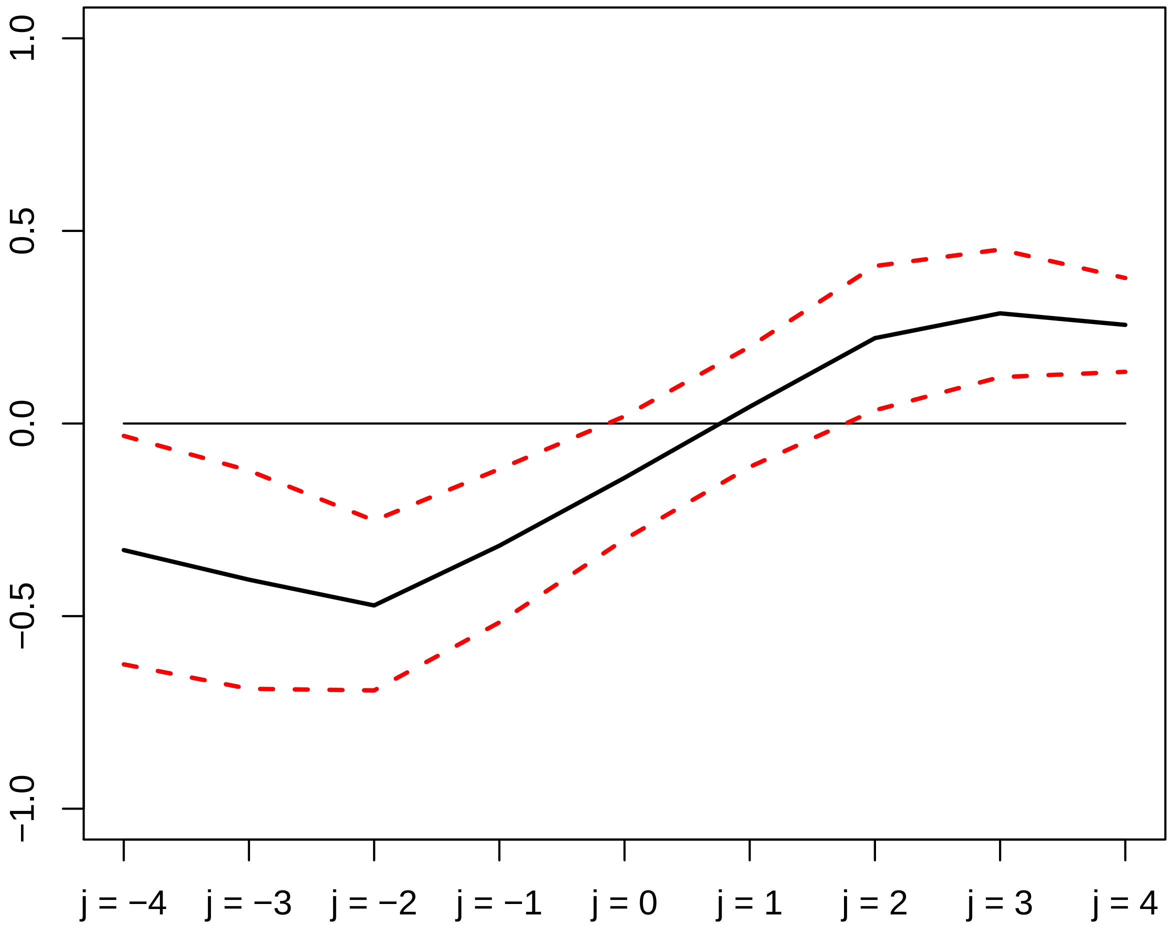
This figure presents four plots with stylized facts on international debt in EMEs, for the aggregate of five emerging economies studied in the paper (EFI-5): Brazil, Chile, Malaysia, Mexico, and Philippines. (i) The plot in the upper left shows the average aggregate stock of sovereign debt, decomposing the outstanding stock of debt into international and domestic debt securities. The average for EFI-5 is obtained after first scaling end-of-year debt stocks by annual GDP at the country level. Data on stocks are from the BIS Securities Statistics database and data on GDP are from the IMF International Financial Statistics Database. (ii) The plot in the upper right shows total gross issuance of international and domestic debt securities by region based on a nationality basis, 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 figure shows the total over all EFI-5 economies. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See the online appendix for a description of how country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities. (iii) The plot in the lower left shows average gross issuance of international and domestic debt securities based on a nationality basis scaled by GDP. The average for EFI-5 is obtained after first scaling annual gross issuance by annual GDP at the country level. Data on gross issuance are sourced from Dealogic's DCM database and data on GDP are from the IMF International Financial Statistics Database. (iv) The plot in the lower right shows the currency composition of total issuances of international debt securities by country based on a nationality basis. The figure shows the total over all EFI-5 economies, decomposing issuance into local currency, U.S. dollars (USD), and other foreign currencies. The pre-crisis period goes from 2003.Q1 to 2008.Q3 while the post-crisis period goes from 2009.Q1 to 2014.Q3. The data are sourced from Dealogic's DCM database.

Table 1: Dataset on Corporate Spreads from Emerging Economies. Summary Statistics

Country	N. of. Bonds	N. of. obs	Variable	Mean	SD	Min	Median	Max
EFI-10 Countries	3476	36078	Number of bonds per quarter	501.08	341.74	168.00	298.00	1433.00
			Size of bond ($ mil)	298.93	416.72	0.10	170.74	4027.38
			Maturity at issue (years)	6.30	7.63	0.08	5.00	100.08
			Term to maturity (years)	6.58	7.47	0.00	5.00	96.25
			OAS spread (basis point)	408.53	511.92	30.45	290.67	16372.01

This table reports summary statistics of the bonds in our dataset of bonds with option-adjusted spreads (OAS). The columns N. of Bonds and N. of obs. report the number of bonds and the number of OAS-quarter observations in the sample aggregated across EFI-10 countries for the entire sample period of 1999Q2-2017Q1. 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 bonds 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).

Figure 4: Median Serial Correlation between Real GDP Growth and the EFI



This figure shows the comovement of financial indicators (EFI) we constructed for each country in our sample with corporate spreads data and the real economic activity. The solid line presents the cross-country median of the correlation between real GDP growth and changes in EFI at different lags $(corr\,(RGDP\,growth_t,\,\Delta EFI_{t+j}))$ for $j = -4, \cdots, 4$. Red dotted lines represent a one-standard deviation confidence interval where the standard deviation is calculated as a cross-country standard deviation of $corr\,(RGDP\,growth_t,\,\Delta EFI_{t+j})$ at a given j. The sample period is 1999Q2-2017Q1 for EFI-10 countries. Data on OAS were sourced from Bloomberg. Data on GDP were sourced from Haver Analytics.

Table 2: Correlation between EFI and Other Variables

Variable	Brazil	Chile	Colombia	Mexico	Malaysia	Peru	Philippines	Russia	Turkey	South Africa
Real GDP growth	-0.26**	-0.50***	-0.12	-0.48***	-0.39***	0.10	-0.55***	-0.21	-0.38**	-0.24***
CEMBI	0.92***	0.94***	0.76***	0.74***	0.94***	0.77***	0.68***	0.85***	0.82***	0.12
EMBI	0.82***	0.87***	0.46***	0.78***	0.87***	-0.23**	0.81***	0.68***	0.32**	0.37**
VIX	0.61***	0.70***	0.48***	0.83***	0.86***	0.61***	0.80***	0.71***	0.61***	0.29*
BAA	0.53***	0.84***	0.38***	0.76***	0.77***	0.72***	0.54***	0.60***	0.07***	0.20
EFI-Brazil	1.00	0.67***	0.47***	0.87***	0.57***	0.07	0.62***	0.60**	0.29*	0.45***
EFI-Chile		1.00	0.31**	0.82***	0.78***	0.46***	0.56***	0.72***	0.07	0.10
EFI-Colombia			1.00	0.41***	0.31**	0.24*	0.61***	0.17	0.24	0.41***
EFI-Mexico				1.00	0.83***	0.36***	0.78***	0.67***	0.48***	0.18
EFI-Malaysia					1.00	0.55***	0.74***	0.77***	0.69***	0.15
EFI-Peru						1.00	0.18	0.53***	0.18	0.29**
EFI-Philippines							1.00	0.64***	0.44***	0.07
EFI-Russia								1.00	0.34	0.37
EFI-Turkey									1.00	0.04
EFI-South Africa										1.00

This table reports the (contemporaneous) correlation between the EFI and other real and financial variables for the sample period 1999Q2-2017Q1 for EFI-10 countries. CEMBI and EMBI refer to Corporate Emerging Market Bond Index and Emerging Market Bond Index respectively. VIX refers to CBOE Volatility Index. "BAA" refers to a spread between the Moody's Seasoned Baa Corporate Bond and the 10-Year constant maturity Treasury Bond. "EFI-country" refers to a country specific EFI. See the main text for more details.

Table 3: Benchmark Forecasting Regressions EFI-5 Countries

One Quarter Ahead Forecasting Horizon ($h = 1$)

	Spec 1	Spec2	Spec 3	Spec 4	w.o EFI
	$RGDP\ growth_{t+1}$	$RGDP\ growth_{t+1}$	$RGDP\ growth_{t+1}$	$RGDP\ growth_{t+1}$	$RGDP\ growth_{t+1}$
$\Delta\, EFI_t$	-0.0017*	-0.0013	-0.0011	-0.0011	
	(-1.93)	(-1.41)	(-1.21)	(-1.19)	
$\Delta EMBI_t$	0.044	0.030	0.022	0.022	-0.091*
	(0.55)	(0.37)	(0.27)	(0.26)	(-1.77)
ΔVIX_t		-0.014		-0.00054	-0.0063
		(-1.20)		(-0.03)	(-0.40)
$\Delta\, US\, Baa - Spread_t$			-0.25	-0.25	-0.30
			(-1.53)	(-1.12)	(-1.37)
R^2	0.824	0.825	0.826	0.826	0.824
Adjusted R^2	0.811	0.812	0.813	0.812	0.811
Observations	334	334	334	334	334

Two Quarter Ahead Forecasting Horizon ($h = 2$)

	Spec 1	Spec2	Spec 3	Spec 4	w.o EFI
	$RGDP\ growth_{t+2}$	$RGDP\ growth_{t+2}$	$RGDP\ growth_{t+2}$	$RGDP\ growth_{t+2}$	$RGDP\ growth_{t+2}$
$\Delta\, EFI_t$	-0.0030**	-0.0033**	-0.0023*	-0.0028*	
	(-2.37)	(-2.05)	(-1.68)	(-1.83)	
$\Delta EMBI_t$	0.050	0.063	0.022	0.041	-0.25***
	(0.35)	(0.42)	(0.15)	(0.27)	(-3.00)
ΔVIX_t		0.012		0.048	0.033
		(0.64)		(1.37)	(0.99)
$\Delta\, US\, Baa - Spread_t$			-0.31	-0.67	-0.80*
			(-1.18)	(-1.45)	(-1.68)
R^2	0.562	0.563	0.565	0.572	0.561
Adjusted R^2	0.530	0.530	0.532	0.538	0.528
Observations	329	329	329	329	329

Three Quarter Ahead Forecasting Horizon ($h = 3$)

	Spec 1	Spec2	Spec 3	Spec 4	w.o EFI
	$RGDP\ growth_{t+3}$	$RGDP\ growth_{t+3}$	$RGDP\ growth_{t+3}$	$RGDP\ growth_{t+3}$	$RGDP\ growth_{t+3}$
$\Delta\, EFI_t$	-0.0034***	-0.0043***	-0.0024*	-0.0035**	
	(-2.94)	(-2.82)	(-1.69)	(-2.31)	
$\Delta EMBI_t$	0.023	0.055	-0.020	0.016	-0.34***
	(0.14)	(0.32)	(-0.12)	(0.09)	(-3.13)
ΔVIX_t		0.030		0.094**	0.075*
		(1.38)		(2.08)	(1.69)
$\Delta\, US\, Baa - Spread_t$			-0.48	-1.19*	-1.35**
			(-1.21)	(-1.79)	(-2.04)
R^2	0.363	0.367	0.371	0.397	0.381
Adjusted R^2	0.316	0.319	0.323	0.349	0.333
Observations	324	324	324	324	324

Four Quarter Ahead Forecasting Horizon ($h = 4$)

	Spec 1	Spec2	Spec 3	Spec 4	w.o EFI
	$RGDP\ growth_{t+4}$	$RGDP\ growth_{t+4}$	$RGDP\ growth_{t+4}$	$RGDP\ growth_{t+4}$	$RGDP\ growth_{t+4}$
$\Delta\, EFI_t$	-0.0036**	-0.0041**	-0.0022	-0.0032*	
	(-2.54)	(-2.37)	(-1.29)	(-1.79)	
$\Delta EMBI_t$	0.028	0.045	-0.032	0.00050	-0.32**
	(0.14)	(0.22)	(-0.16)	(0.00)	(-2.49)
ΔVIX_t		0.015		0.083*	0.067
		(0.46)		(1.97)	(1.61)
$\Delta\, US\, Baa - Spread_t$			-0.65	-1.28	-1.42*
			(-1.08)	(-1.62)	(-1.84)
R^2	0.183	0.185	0.198	0.219	0.206
Adjusted R^2	0.123	0.121	0.136	0.155	0.144
Observations	319	319	319	319	319

This table presents the benchmark results of panel forecasting regressions for different forecasting horizons ($h = 1 \sim 4$) using the Driscoll & Kraay (1998) estimator. The dependent variable is the h-quarter ahead annual real GDP growth at a quarterly frequency. ΔEFI (measured in basis points) refers to annual changes in the external financial indicator. $\Delta EMBI$ refers to annual changes in Emerging Market Bond Index (EMBI) published by JP Morgan (measured in percentage points). ΔVIX refers to annual changes in the CBOE Volatility Index (VIX). $\Delta USBAA - Spread$ refers to annual changes in the spread between BAA corporate bond and 10-year constant maturity Treasury (measured in percentage points). All forecasting regressions include (but not report) the following variables as controls: $\Delta USYield$, ΔRFF, $\Delta R\, Local\, Rate$, $\Delta R\, Pcom$ and 12 lagged dependent variables ($p = 11$). $\Delta USYield$ (measured in percentage points) represents annual changes in the termspreads of 3-month and 10-year US treasuries. ΔRFF (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. core personal consumption expenditure(PCE) 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. (2018) (see the main text for details on the construction of this index). The sample includes 5 emerging economies (EFI-5: Brazil, Chile, Malaysia, Mexico, Philippines) and the period of analysis is 1999Q2-2017Q1. Numbers in parentheses are t-statistics. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

Table 4: Benchmark Forecasting Regressions EFI-10 Countries

One Quarter Ahead Forecasting Horizon ($h = 1$)

	Spec 1	Spec2	Spec 3	Spec 4	w.o EFI
	$RGDP\ growth_{t+1}$	$RGDP\ growth_{t+1}$	$RGDP\ growth_{t+1}$	$RGDP\ growth_{t+1}$	$RGDP\ growth_{t+1}$
$\Delta\, EFI_t$	-0.00097***	-0.00089***	-0.00086***	-0.00086***	
	(-3.41)	(-3.06)	(-3.18)	(-3.06)	
$\Delta EMBI_t$	0.011	0.017	0.018	0.018	-0.049
	(0.20)	(0.35)	(0.36)	(0.37)	(-1.05)
ΔVIX_t		-0.0068		-0.000028	-0.0050
		(-0.95)		(-0.00)	(-0.35)
$\Delta\, US\ Baa - Spread_t$			-0.11	-0.11	-0.15
			(-1.07)	(-0.60)	(-0.76)
R^2	0.843	0.843	0.843	0.843	0.841
Adjusted R^2	0.835	0.835	0.835	0.834	0.832
Observations	550	550	550	550	550

Two Quarter Ahead Forecasting Horizon ($h = 2$)

	Spec 1	Spec2	Spec 3	Spec 4	w.o EFI
	$RGDP\ growth_{t+2}$	$RGDP\ growth_{t+2}$	$RGDP\ growth_{t+2}$	$RGDP\ growth_{t+2}$	$RGDP\ growth_{t+2}$
$\Delta\, EFI_t$	-0.0018***	-0.0019***	-0.0016***	-0.0018***	
	(-3.31)	(-3.34)	(-3.10)	(-3.27)	
$\Delta EMBI_t$	-0.028	-0.038	-0.016	-0.033	-0.17**
	(-0.38)	(-0.47)	(-0.21)	(-0.43)	(-2.21)
ΔVIX_t		0.011		0.044	0.033
		(0.69)		(1.27)	(0.96)
$\Delta\, US\ Baa - Spread_t$			-0.20	-0.56	-0.62
			(-1.16)	(-1.45)	(-1.58)
R^2	0.628	0.628	0.629	0.634	0.623
Adjusted R^2	0.608	0.608	0.609	0.614	0.603
Observations	541	541	541	541	541

Three Quarter Ahead Forecasting Horizon ($h = 3$)

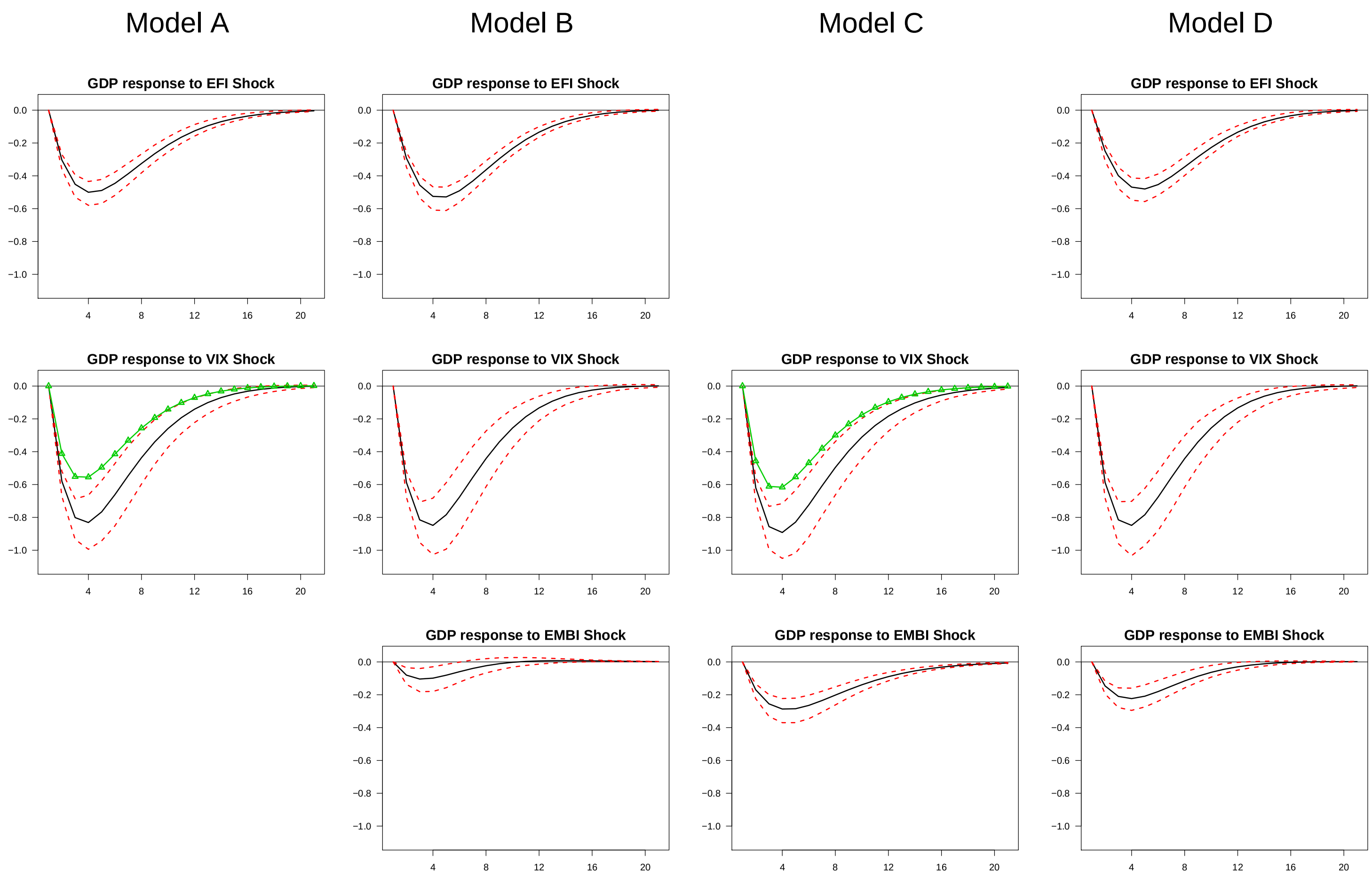
	Spec 1	Spec2	Spec 3	Spec 4	w.o EFI
	$RGDP\ growth_{t+3}$	$RGDP\ growth_{t+3}$	$RGDP\ growth_{t+3}$	$RGDP\ growth_{t+3}$	$RGDP\ growth_{t+3}$
$\Delta\, EFI_t$	-0.0018**	-0.0020***	-0.0015**	-0.0018***	
	(-2.59)	(-2.90)	(-2.21)	(-2.76)	
$\Delta EMBI_t$	-0.11	-0.13	-0.085	-0.12	-0.26***
	(-1.35)	(-1.32)	(-1.12)	(-1.33)	(-2.74)
ΔVIX_t		0.020		0.081	0.069
		(0.95)		(1.55)	(1.34)
$\Delta\, US\ Baa - Spread_t$			-0.36	-1.01*	-1.08*
			(-1.36)	(-1.81)	(-1.91)
R^2	0.438	0.440	0.443	0.460	0.448
Adjusted R^2	0.408	0.409	0.412	0.429	0.418
Observations	532	532	532	532	532

Four Quarter Ahead Forecasting Horizon ($h = 4$)

	Spec 1	Spec2	Spec 3	Spec 4	w.o EFI
	$RGDP\ growth_{t+4}$	$RGDP\ growth_{t+4}$	$RGDP\ growth_{t+4}$	$RGDP\ growth_{t+4}$	$RGDP\ growth_{t+4}$
$\Delta\, EFI_t$	-0.0017*	-0.0018**	-0.0012	-0.0016*	
	(-1.86)	(-2.10)	(-1.53)	(-1.97)	
$\Delta EMBI_t$	-0.12	-0.13	-0.089	-0.12	-0.24**
	(-1.37)	(-1.28)	(-1.17)	(-1.30)	(-2.47)
ΔVIX_t		0.0100		0.075	0.066
		(0.40)		(1.46)	(1.28)
$\Delta\, US\ Baa - Spread_t$			-0.49	-1.10*	-1.16*
			(-1.23)	(-1.69)	(-1.76)
R^2	0.281	0.282	0.291	0.306	0.298
Adjusted R^2	0.242	0.241	0.250	0.265	0.258
Observations	523	523	523	523	523

This table reproduces Table 3 using the sample including 10 emerging countries (EFI-10: Brazil, Chile, Colombia, Malaysia, Mexico, Peru, Philippines, Russia, Turkey, South Africa). All forecasting regressions include an identical set of control variables as in Table 3. The sample period is 1999Q2-2017Q1 for all forecasting regressions. Numbers in parentheses are t-statistics. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

Figure 5: Impulse Response Function of Real GDP Growth



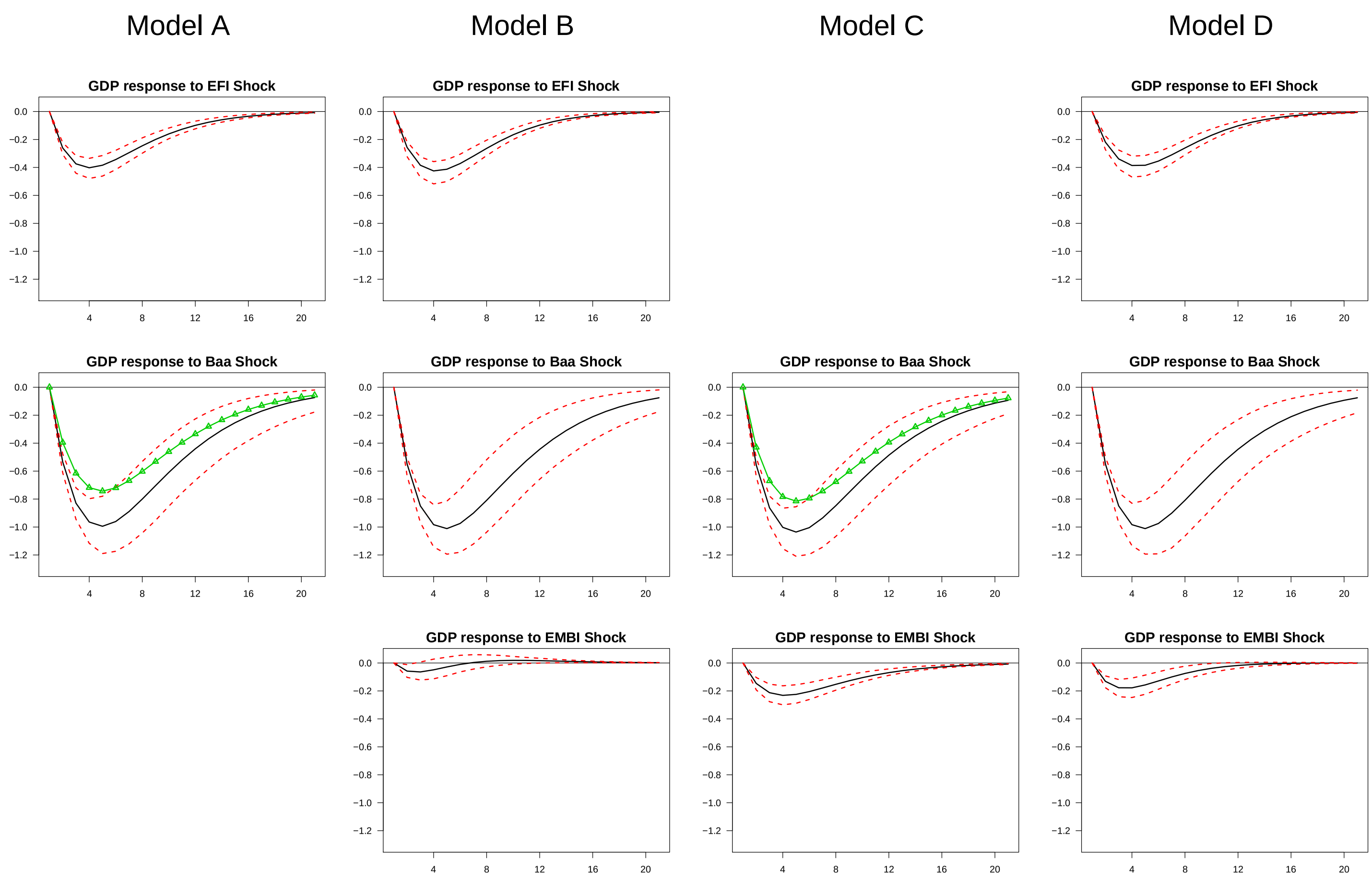
This figure presents the impulse response function of annual real GDP growth from the panel structural VAR. All models are estimated for the sample period 1999Q2-2017Q1 for EFI-10 countries. We impose a recursive ordering assumption to identify structural shocks. In addition, we further assume that the global risk proxied by VIX is exogenous to emerging economies (e.g., it follows a univariate AR process). Model A (baseline) includes three variables: real GDP growth, ΔVIX, and ΔEFI. Model B adds one additional variable, $\Delta EMBI$, into Model A. The ordering of variables in Model A and B is real GDP growth, ΔVIX, ΔEFI, and $\Delta EMBI$. In Model C, we replace ΔEFI with $\Delta EMBI$ from Model A. Model D adds one additional variable, ΔEFI, into Model C. In Model D, we assume that $\Delta EMBI$ is ordered first, before ΔEFI. The first, second, and third row summarizes the impulse response functions to 1 standard deviation shock to ΔEFI, ΔVIX, and $\Delta EMBI$, respectively. Each column represents Model A-D, respectively. Red dotted lines represent bootstrapped 95% confidence intervals. Green-triangular dotted lines present the impulse response of real GDP growth to 1 standard deviation ΔVIX shocks when the feedback from ΔVIX onto ΔEFI or $\Delta EMBI$ is counterfactually turned off. The lag order of the model is one ($p = 1$) for all models.

Table 5: Variance Decomposition of Real GDP Growth

	3-variable SVAR model			4-variable SVAR model			
	Model A			Model B			
	GDP Shock	VIX Shock	EFI Shock	GDP Shock	VIX Shock	EFI Shock	EMBI Shock
Variance Share of GDP	0.57	0.31	0.13	0.55	0.30	0.14	0.00
Variance Share of VIX	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Variance Share of EFI	0.04	0.21	0.75	0.03	0.21	0.76	0.01
Variance Share of EMBI				0.03	0.35	0.28	0.33
	Model C			Model D			
	GDP Shock	VIX Shock	EMBI Shock	GDP Shock	VIX Shock	EMBI Shock	EFI Shock
Variance Share of GDP	0.60	0.36	0.04	0.56	0.31	0.02	0.12
Variance Share of VIX	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Variance Share of EFI				0.04	0.40	0.43	0.13
Variance Share of EMBI	0.02	0.46	0.52	0.03	0.20	0.04	0.73

This table presents a variance decomposition of four different panel structural VAR specifications. Details of the estimated models are identical to those reported in Figure 5. Each row represents the share of forecast error variance of the row variable due to the column variables. All models are estimated for the sample period 1999Q2-2017Q1 for EFI-10 countries.

Figure 6: Impulse Response Function of Real GDP Growth with an Alternative Measure of Global Risk. US BAA Spread



This figure reproduces Figure 5 replacing ΔVIX with an alternative measure of global risk: $\Delta USBAA$. The first, second, and third row summarizes the impulse response functions to 1 standard deviation shock to ΔEFI, $\Delta USBAA$, and $\Delta EMBI$, respectively. Each column represents Model A-D, respectively. Red dotted lines represent bootstrapped 95% confidence intervals. Green-triangular dotted lines present the impulse response of real GDP growth to 1 standard deviation $\Delta USBAA$ shocks when the feedback from $\Delta USBAA$ onto ΔEFI or $\Delta EMBI$ is counterfactually turned off. All models are estimated for the sample period 1999Q2-2017Q1 for EFI-10 countries.

Table 6: Variance Decomposition with an Alternative Measure of Global Risk. US BAA Spread

	3-variable SVAR model			4-variable SVAR model			
	Model A			Model B			
	GDP Shock	VIX Shock	EFI Shock	GDP Shock	VIX Shock	EFI Shock	EMBI Shock
Variance Share of GDP	0.43	0.50	0.06	0.43	0.50	0.07	0.00
Variance Share of VIX	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Variance Share of EFI	0.01	0.24	0.74	0.01	0.23	0.74	0.01
Variance Share of EMBI				0.00	0.39	0.28	0.33
	Model C			Model D			
	GDP Shock	VIX Shock	EMBI Shock	GDP Shock	VIX Shock	EMBI Shock	EFI Shock
Variance Share of GDP	0.44	0.54	0.02	0.43	0.50	0.01	0.06
Variance Share of VIX	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Variance Share of EFI				0.00	0.44	0.45	0.11
Variance Share of EMBI	0.00	0.49	0.51	0.01	0.22	0.06	0.71

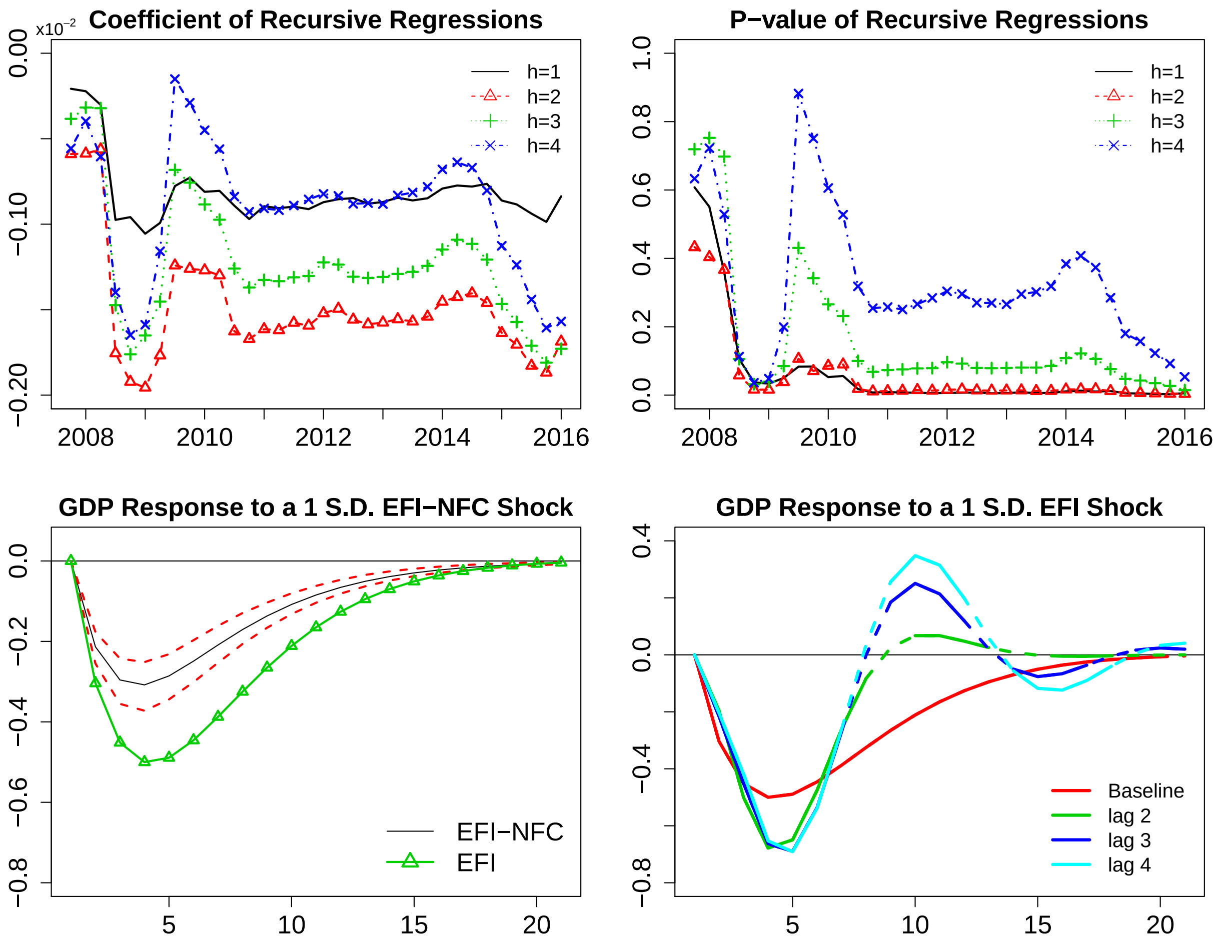
This table reproduces Table 5 replacing ΔVIX with an alternative measure of global risk: $\Delta USBAA$. Each row represents the share of forecast error variance of the row variable due to the column variables. All models are estimated for the sample period 1999Q2-2017Q1 for EFI-10 countries.

Table 7: Transmission of Global Risks. A Counterfactual Analysis

	3-variable SVAR Models			3-variable SVAR Models (Counterfactual)		
	Model A - VIX			Model A - VIX - Counterfactual		
	GDP Shock	VIX Shock	EFI Shock	GDP Shock	VIX Shock	EFI Shock
Variance Share of GDP	0.57	0.31	0.13	0.69	0.16	0.15
Variance Share of VIX	0.00	1.00	0.00	0.00	1.00	0.00
Variance Share of EFI	0.04	0.21	0.75	0.05	0.01	0.93
	Model C - VIX			Model C - VIX - Counterfactual		
	GDP Shock	VIX Shock	EMBI Shock	GDP Shock	VIX Shock	EMBI Shock
Variance Share of GDP	0.60	0.36	0.04	0.75	0.20	0.05
Variance Share of VIX	0.00	1.00	0.00	0.00	1.00	0.00
Variance Share of EMBI	0.02	0.46	0.52	0.04	0.01	0.95
	Model A - BAA			Model A - BAA - Counterfactual		
	GDP Shock	US-BAA Shock	EFI Shock	GDP Shock	US-BAA Shock	EFI Shock
Variance Share of GDP	0.43	0.50	0.06	0.55	0.36	0.08
Variance Share of US-BAA	0.00	1.00	0.00	0.00	1.00	0.00
Variance Share of EFI	0.01	0.24	0.74	0.02	0.01	0.97
	Model C - BAA			Model C - BAA - Counterfactual		
	GDP Shock	US-BAA Shock	EMBI Shock	GDP Shock	US-BAA Shock	EMBI Shock
Variance Share of GDP	0.44	0.54	0.02	0.55	0.42	0.03
Variance Share of US-Baa	0.00	1.00	0.00	0.00	1.00	0.00
Variance Share of EMBI	0.00	0.49	0.51	0.00	0.00	1.00

This table presents a variance decomposition of four different panel structural VAR specifications under normal and counterfactual scenarios. The left half of the table reports variance decompositions of Model A and C (already shown in Tables 5 and 6). The right half of the table reports counterfactual variance decompositions of Model A and C when the feedback from global risks onto ΔEFI or $\Delta EMBI$ is counterfactually turned off. All models are estimated for the sample period 1999Q2-2017Q1 for EFI-10 countries.

Figure 7: Extensions and Robustness Checks



This figure presents different robustness checks to our baseline results. The top-left panel presents the estimated coefficients of ΔEFI (Spec 4 in Table 4) from rolling regression for different forecasting horizons. We extend the sample period sequentially, initially from 1999Q2-2007Q4 to 1999Q2-2017Q1 for the EFI-10 countries. The top-right panel presents corresponding p-values of the ΔEFI for the identical set of forecasting regressions presented in the top-left panel. The bottom-left panel presents the impulse response function of real GDP growth where EFI is calculated after excluding bonds issued by financial corporations (black-solid line), along with the benchmark result (green-triangular line). The impulse is calculated from Model A with VIX. The sample period 1999Q2-2017Q1 for the EFI-10 countries. The bottom-right panel presents impulse response functions of real GDP growth to a 1 standard deviation shock to ΔEFI shocks from Model A with VIX for various lag order specifications. Solid lines represent statistically significant responses at the 95% confidence level. The model is estimated for the sample period 1999Q2-2017Q1 for the EFI-10 countries.

Table 8: Forecasting Regression Results with an Alternative Measure of Corporate Spread

	h=1 $RGDP\,growth_{t+1}$	h=2 $RGDP\,growth_{t+1}$	h=3 $RGDP\,growth_{t+1}$	h=4 $RGDP\,growth_{t+1}$
$\Delta\,EFI_t$	-0.0017**	-0.0035**	-0.0040**	-0.0037*
	(-2.11)	(-2.48)	(-2.65)	(-1.91)
$\Delta CEMBI_t$				
$\Delta EMBI_t$	0.047	0.0058	-0.13	-0.19
	(0.49)	(0.03)	(-0.57)	(-0.73)
ΔVIX_t	0.0055	0.042	0.074*	0.068
	(0.36)	(1.26)	(1.81)	(1.65)
$\Delta\,US\,Baa - Spread_t$	-0.28	-0.55	-0.81	-0.82
	(-1.45)	(-1.32)	(-1.36)	(-1.13)
R^2	0.852	0.649	0.484	0.291
Adjusted R^2	0.838	0.615	0.433	0.220
Observations	279	274	269	264

	h=1 $RGDP\,growth_{t+1}$	h=2 $RGDP\,growth_{t+1}$	h=3 $RGDP\,growth_{t+1}$	h=4 $RGDP\,growth_{t+1}$
$\Delta\,EFI_t$				
$\Delta CEMBI_t$	0.013	0.042	0.10	0.099
	(0.25)	(0.35)	(0.54)	(0.38)
$\Delta EMBI_t$	-0.14	-0.38	-0.64*	-0.67
	(-1.23)	(-1.63)	(-1.92)	(-1.50)
ΔVIX_t	-0.0038	0.023	0.051	0.047
	(-0.27)	(0.73)	(1.25)	(1.17)
$\Delta\,US\,Baa - Spread_t$	-0.35*	-0.70	-1.00*	-1.00
	(-1.84)	(-1.63)	(-1.69)	(-1.40)
R^2	0.849	0.637	0.468	0.278
Adjusted R^2	0.834	0.602	0.416	0.206
Observations	279	274	269	264

This table presents forecasting regression results with an alternative measure of corporate spread: CEMBI. The top panel shows the benchmark forecasting regression results (spec 4) reported in Table 4 for different forecasting horizons ($h = 1 \sim 4$). The bottom panel reports forecasting regression results replacing ΔEFI with $\Delta CEMBI$ for the EFI-5 countries. The sample period is 2002Q1-2017Q1 for both panels. The sample period is chosen so that both ΔEFI and $\Delta CEMBI$ observations are available at a given t. This is to ensure the comparability between the top and the bottom panel. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

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