Equity Returns, Bond Spreads, and Economic Activity in Emerging Countries*

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Abstract

While simultaneously accounting for the effects of sovereign and corporate bond spreads, we document that emerging market economy (EME) equity returns have a strong predictive power for future output growth and account for a significant fraction of output fluctuations in these countries. Our results are based on the environment of Caballero, Fernández, and Park (2019), who show that corporate bond spreads are a better driver of EME economic activity than sovereign bond spreads. We find that equity returns, a proxy of domestic and external financial conditions, play a more important role for EME output growth than both types of bond spreads. We attribute this difference to the effectiveness of equity returns in transmitting global financial risk shocks to EMEs and to the role of equity issuance in international capital flows in EMEs.

JEL classification: E32, E37, F34, F37, G15

Keywords: equity returns, bond spreads, economic activity, emerging economies

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1 Introduction

The recent deepening of global financial integration has had a great impact on business cycle fluctuations in emerging market economies (EMEs). A large strand of literature shows that sovereign bond spreads are a central driver of EME business cycles, because of their influence on the interest rate at which countries borrow in international financial markets (see, e.g., Neumeyer and Perri, 2005; Uribe and Yue, 2006; Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe, 2011; Akıncı, 2013; Boz, Durdu, and Li, 2015; Fernández and Gulan, 2015; Epstein, Shapiro, and Gómez, 2019). Caballero, Fernández, and Park (2019)—henceforth, CFP—advance the literature by documenting corporate bond spreads to be a key factor in forecasting future output growth, accounting for output fluctuations, and transmitting global financial risk shocks to EMEs. In this paper, we provide evidence that equity returns play a more important role than corporate and sovereign bond spreads in explaining and predicting EME economic activity. Our mechanism suggests that this is due to equity returns amplifying the propagation of global financial risk shocks to EMEs, as equity flows account for a significant fraction of international capital flows. This is consistent with Asis, Chari, and Haas (2021), who show that the responsiveness of equity returns to changes in global financial conditions can worsen firms' financial distress in EMEs.

We use stock market returns in EMEs as a measure summarizing local and external financial conditions in each country. This is in comparison to CFP's corporate bond spread measure, the external financial indicator (EFI), constructed from a weighted average of option-adjusted spreads on bonds issued in US dollars by corporations in EMEs.[1] It also contrasts with the J.P. Morgan's Emerging Bond Market Index (EMBI), which represents yields on U.S. dollar-denominated Brady bonds, loans, and Eurobonds by EMEs and is commonly used to measure sovereign bond spreads. Our main contribution consists of demonstrating that equity returns embed additional information to corporate and sovereign bond spreads for (i) predicting future economic activity, (ii) explaining fluctuations in output growth, and

[1] See CFP's Footnote 12 for more details on EFI construction.

(iii) propagating global financial risk shocks to EMEs. The results point to a partial segmentation between equity and debt markets, consistent with the works of Duffie (2010); Greenwood, Hanson, and Liao (2018); Pitkäjärvi, Suominen, and Vaittinen (2020). We contribute to the vast theoretical and empirical literature that examines the role of external factors in driving EME business cycles (e.g., Maćkowiak, 2007; Garcia-Cicco, Pancrazi, and Uribe, 2010; Carrière-Swallow and Céspedes, 2013; Charnavoki and Dolado, 2014; Miyamoto and Nguyen, 2017; Cesa-Bianchi, Ferrero, and Rebucci, 2018; Croce, Jahan-Parvar, and Rosen, 2018; Bhattarai, Chatterjee, and Park, 2019; Rothert, 2020).

The rest of the paper proceeds as follows. Section 2 presents forecasting regressions. Section 3 describes a panel structural vector autoregressive model and Section 4 analyzes the transmission of global financial risk shocks to EMEs. Section 5 concludes.

2 Forecasting Regressions

CFP first investigate the relationship between bond spreads and economic activity in EMEs by considering forecasting regressions. This allows the authors to impose little structure on the data while controlling for various global and country-specific factors. We extend the forecasting regressions by including a measure of EME equity returns (*EqR*) and find that equity returns have a stronger predictive power of future GDP growth, especially at longer horizons, than corporate (*EFI*) and sovereign (*EMBI*) bond spreads. Due to data availability and to ease comparison, we use the sample of 10 emerging countries constructed by CFP, EFI-10, to conduct our analysis.[2]

In line with CFP, we estimate the following dynamic forecasting panel regressions of future real GDP growth on current changes in *EFI*, *EMBI*, *EqR*, and several global and

[2]The EFI-10 sample consists of Brazil, Chile, Colombia, Malaysia, Mexico, Peru, Philippines, Russia, South Africa, and Turkey. CFP also consider a sample of five countries, EFI-5, which includes Brazil, Chile, Malaysia, Mexico, and Philippines. We center our discussion on the more representative EFI-10 sample. The results also hold for the EFI-5 sample and can be found in the Online Appendix.

country-specific control variables over the 1999Q2-2017Q2 period:

$$\triangle GDP^k_{t+h} = \alpha_k + \sum_{j=0}^{p} \beta_j \triangle GDP^k_{t-j} + \gamma \triangle EFI^k_t + \delta \triangle EMBI^k_t + \theta EqR^k_t + \psi \triangle GR_t + \Gamma \Omega^k_t + \epsilon^k_{t+h}, \quad (1)$$

where t represents the current period, h captures the forecast horizon that ranges up to five periods, k denotes an EME country, p represents the number of lags set to 11, and α_k is a country fixed effect. Economic activity is measured by $\triangle GDP^k$, which represents percentage annual log changes in real GDP of each EME. $\triangle EFI^k$ denotes annual changes in the external financial indicator, a country-specific proxy for corporate bond spreads built by CFP. $\triangle EMBI^k$ refers to annual changes in the J.P. Morgan's Emerging Market Bond Index (EMBI). Both spreads are measured in percentage points.

EqR^k is our new variable denoting real equity returns expressed in percentages. We construct it using annual log differences of country-specific stock market index prices, which are deflated by the country's consumer price index.[3] We find that equity returns exhibit a high median correlation of 0.42 with output growth across the EFI-10 countries. In addition, a principal component analysis reveals a large comovement of equity returns in EMEs—the first principal component accounts for about 69 percent of the sample variation in EME stock market returns.

The remaining variables in equation (1) include global financial risk ($\triangle GR$) proxied by the VIX index ($\triangle VIX$) capturing the US option-implied volatility of the S&P 500 index, and by the US Baa spread ($\triangle Baa$) representing the difference between the Moody's US Baa corporate and 10-year Treasury rates. Both global risk proxies enter the equation in annual changes. Ω^k consists of an additional set of global and local control variables. The global set includes annual changes in the US real federal funds rate (the difference between the effective nominal federal funds rate and the US core personal consumer expenditure inflation) and annual changes in the US yield spread (difference between the 10-year and 3-month US

[3] We use the following capitalization-weighted stock market indexes sourced from Global Financial Data: IBXD (Brazil), IGPAD (Chile), IGBCD (Colombia), KLSED (Malaysia), MXXD (Mexico), SPBLPGPT (Peru), PSID (Philippines), MCXD (Russia), JALSHD (South Africa), and XU100D (Turkey).

Treasury rates). The local set contains country-specific annual changes in the real monetary policy rate (domestic nominal policy rate less of domestic inflation) and the commodity price index constructed by Fernández, González, and Rodriguez (2018). Equation (1) is estimated with Driscoll and Kraay (1998) robust standard errors.

The estimated coefficients for the variables of interest are reported in Table 1 together with t-statistics in parenthesis. The top panel, Spec.4 (with EqR), presents results from estimating equation (1). The bottom panel, Spec.4 (CFP), excludes *EqR* from the equation, and hence replicates the results in CFP for their most general specification 4.[4] We expand the forecasting horizon to five instead of four quarters, and convert *EFI* from basis to percentage points to ease comparison.

Table 1 reveals three sets of results. First, the forecasting power of *EqR* for future output growth in EMEs is statistically significant at the 1% level for all considered horizons. Moreover, the t-statistics associated with the coefficient for *EqR* ($\hat{\theta}$) are, on average, 2.8 times larger than the ones for $\triangle EFI$. Second, the inclusion of *EqR* reduces the significance of $\triangle EFI$. The estimated coefficient for $\triangle EFI$ ($\hat{\gamma}$) decreases by over a third across the horizons and the corresponding t-statistics decrease by about a fifth. The $\triangle EFI$ coefficient remains statistically significant at the 1% level for the first two horizons ($h = 1, 2$), but its significance decreases to 5% for $h = 3$. $\triangle EFI$ becomes insignificant for $h = 4, 5$. $\triangle EMBI$ remains statistically insignificant after the inclusion of *EqR*. Third, the estimated coefficients for *EqR*, although smaller in magnitude than for $\triangle EFI$, are economically sizeable given the large variability of equity returns. The coefficient for *EqR* ranges from 0.015 to 0.040, while for $\triangle EFI$ from -0.031 to -0.14. However, the sample standard deviation of $\triangle EFI$ and *EqR* is 2.5 and 28.0. For $h = 1$, for example, this implies that a one standard deviation increase in *EqR* is associated with a 0.42 ($= 28.0 \times 0.015$) percentage point increase in the next quarter's GDP growth, whereas for $\triangle EFI$ it translates into a change of only -0.16 ($= 2.5 \times -0.065$) percentage points.

[4]The results hold for other CFP specifications and are available upon request.

Table 1: Forecasting regressions

Spec.4 with EqR	h=1: $\triangle GDP^k_{t+1}$	h=2: $\triangle GDP^k_{t+2}$	h=3: $\triangle GDP^k_{t+3}$	h=4: $\triangle GDP^k_{t+4}$	h=5: $\triangle GDP^k_{t+5}$
$\triangle EFI^k_t$	-0.065***	-0.14***	-0.13**	-0.10	-0.031
	(-2.92)	(-3.28)	(-2.44)	(-1.36)	(-0.37)
$\triangle EMBI^k_t$	0.040	0.0087	-0.062	-0.060	-0.038
	(1.33)	(0.19)	(-1.23)	(-0.98)	(-0.58)
EqR^k_t	0.015***	0.029***	0.038***	0.040***	0.029***
	(5.22)	(5.97)	(7.49)	(7.10)	(3.59)
$\triangle VIX_t$	0.0047	0.053*	0.093**	0.088**	0.045
	(0.37)	(1.85)	(2.15)	(2.08)	(1.07)
$\triangle Baa_t$	-0.084	-0.50	-0.94**	-1.03*	-0.56
	(-0.51)	(-1.57)	(-2.01)	(-1.85)	(-1.14)
R^2	0.853	0.671	0.524	0.378	0.233
Adjusted R^2	0.845	0.652	0.496	0.341	0.187
Observations	550	541	532	523	514
Spec.4 (CFP)	**h=1: $\triangle GDP^k_{t+1}$**	**h=2: $\triangle GDP^k_{t+2}$**	**h=3: $\triangle GDP^k_{t+3}$**	**h=4: $\triangle GDP^k_{t+4}$**	**h=5: $\triangle GDP^k_{t+5}$**
$\triangle EFI^k_t$	-0.086***	-0.18***	-0.18***	-0.16*	-0.076
	(-3.06)	(-3.27)	(-2.76)	(-1.97)	(-0.89)
$\triangle EMBI^k_t$	0.018	-0.033	-0.12	-0.12	-0.078
	(0.37)	(-0.43)	(-1.33)	(-1.30)	(-0.95)
EqR^k_t					
$\triangle VIX_t$	-0.000028	0.044	0.081	0.075	0.035
	(-0.00)	(1.27)	(1.55)	(1.46)	(0.81)
$\triangle Baa_t$	-0.11	-0.56	-1.01*	-1.10*	-0.60
	(-0.60)	(-1.45)	(-1.81)	(-1.69)	(-1.11)
R^2	0.843	0.634	0.460	0.306	0.192
Adjusted R^2	0.834	0.613	0.429	0.265	0.143
Observations	550	541	532	523	514

Notes: The table reports estimated coefficients, and t-statistics in parenthesis, from a dynamic panel regression specified in equation (1) in the main text, with the dependent variable being future annual real GDP growth ($\triangle GDP^k{}_{t+h}$) measured in percentages. The EFI-10 sample is unbalanced over the 1999Q2-2017Q1 period and includes countries Brazil, Chile, Colombia, Malaysia, Mexico, Peru, Philippines, Russia, South Africa, and Turkey. $\triangle EFI$ and $\triangle EMBI$ refer to annual percentage point changes in country-specific corporate and sovereign bond spreads. EqR denotes equity returns measured as annual percent log changes in country-specific stock market prices. $\triangle VIX$ and $\triangle Baa$ stand for annual changes in the US option-implied S&P 500 index volatility and in the difference between the Moody's US Baa Corporate and 10-year Treasury rates, expressed in percentage points. *, **, and *** indicate significance level at 10%, 5%, and 1%. The bottom panel replicates the results of Caballero et al. (2019) for their specification 4. The top panel adds equity returns to the specification.

3 Structural Vector Autoregressive Models

Using panel structural vector autoregressive (PSVAR) models, CFP impose additional structure on the data, which enables them to isolate the impact of exogenous shocks to corporate and sovereign bond spreads on economic activity in EMEs. In this section, we enrich the PSVAR models with our measure of EME equity returns, *EqR*. Our results show equity return shocks to be a more important driver of output fluctuations than corporate and sovereign bond spread shocks.

Following CFP, we use the least-squares dummy variable approach and data for EFI-10 countries over the 1999Q2-2017Q1 period to estimate the following PSVAR model:

$$AY_t^k = C^k + \sum_{j=1}^{p} B_j Y_{t-j}^k + \epsilon_t^k. \tag{2}$$

C^k denotes a country fixed effect, p is the number of lags, A and B denote coefficient matrices, Y^k represents a vector of variables of interest, and ϵ^k represents the corresponding structural shocks.

We consider the 3-variable and 5-variable PSVAR models M1-M7 shown in Table 2. In each model, the Y vector consists of $\triangle GDP^k$ ordered first, $\triangle GR$ ordered second, and some combination of domestic financial variables: $\triangle EFI^k$, $\triangle EMBI^k$, and EqR^k.[5] The 3-variable models (M1-M3) include one domestic financial variable at a time, which allows us to isolate the individual impact of shocks to corporate bond spreads, sovereign bond spreads, and equity returns on economic activity in EMEs. Note that models M1 and M2 correspond to CFP's *Model A* and *Model C*. The 5-variable models (M4-M7) incorporate the three domestic financial variables simultaneously in the Y vector and consider all possible orderings of the three variables.[6] These models allow us to run a horse race among the domestic financial variables while being agnostic about their ordering.

Identification is achieved by imposing two conditions. First, the matrix A is assumed to be lower triangular with ones on the diagonal. Second, given the typically small size of EMEs, global financial risk ($\triangle GR$) is assumed not to respond to changes in the country-specific macroeconomic and financial conditions. The variable ordering in Y implies that domestic

[5] The order of variables shown in the first column of Table 2 represents the actual ordering of variables in the Y vector.

[6] Note that our models M4 and M6 extend CFP's *Model B* and *Model D* with EqR^k ordered last.

Table 2: Variance decomposition of GDP growth

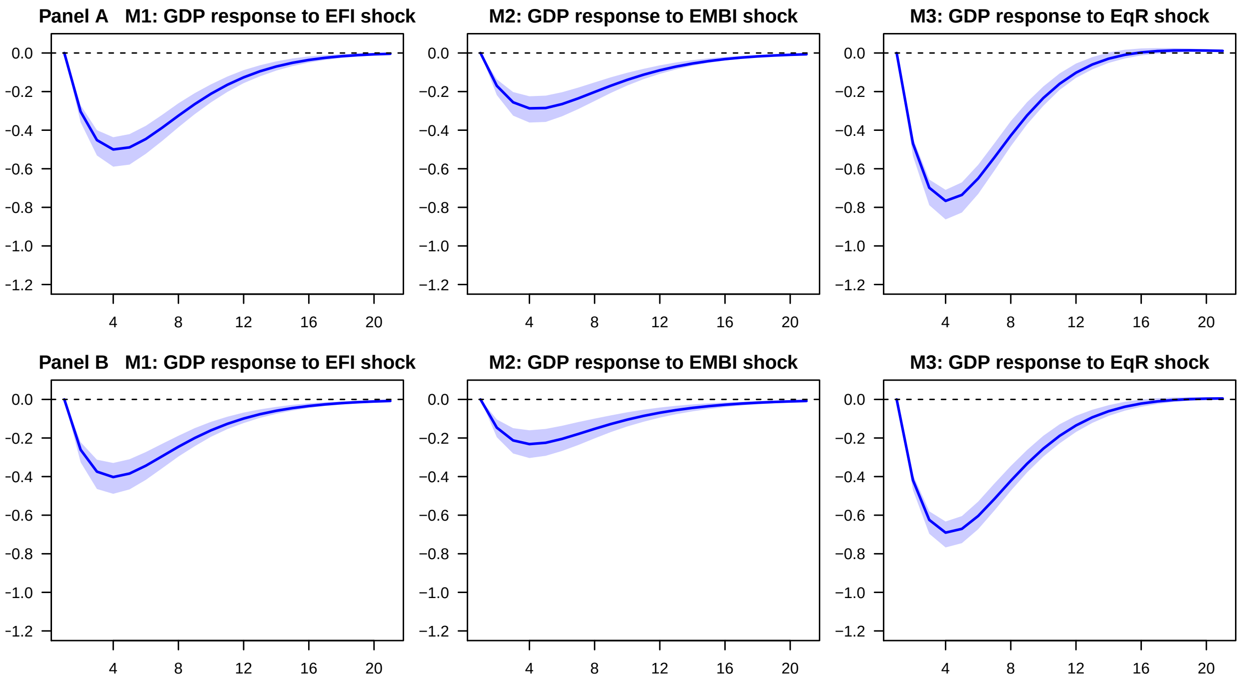
Panel A: Global Risk (GR) is proxied by VIX					
3-variable PSVAR models	GDP shock	VIX shock	EFI shock	EMBI shock	EqR shock
M1(CFP):$[\triangle GDP_t^k, \triangle GR_t, \triangle EFI_t^k]$	0.57	0.31	0.13	-	-
M2(CFP):$[\triangle GDP_t^k, \triangle GR_t, \triangle EMBI_t^k]$	0.60	0.36	-	0.04	-
M3:$[\triangle GDP_t^k, \triangle GR_t, EqR_t^k]$	0.47	0.23	-	-	0.30
5-variable PSVAR models					
M4:$[\triangle GDP_t^k, \triangle GR_t, \triangle EFI_t^k, \triangle EMBI_t^k, EqR_t^k]$	0.44	0.20	0.14	0.00	0.23
M5:$[\triangle GDP_t^k, \triangle GR_t, EqR_t^k, \triangle EFI_t^k, \triangle EMBI_t^k]$	0.44	0.20	0.05	0.00	0.30
M6:$[\triangle GDP_t^k, \triangle GR_t, \triangle EMBI_t^k, \triangle EFI_t^k, EqR_t^k]$	0.43	0.20	0.13	0.01	0.23
M7:$[\triangle GDP_t^k, \triangle GR_t, EqR_t^k, \triangle EMBI_t^k, \triangle EFI_t^k]$	0.44	0.20	0.06	0.00	0.30
Average across M1-M7	0.48	0.24	0.10	0.01	0.27
Panel B: Global Risk (GR) is proxied by US Baa spread					
3-variable PSVAR models	GDP shock	Baa shock	EFI shock	EMBI shock	EqR shock
M1(CFP):$[\triangle GDP_t^k, \triangle GR_t, \triangle EFI_t^k]$	0.43	0.50	0.06	-	-
M2(CFP):$[\triangle GDP_t^k, \triangle GR_t, \triangle EMBI_t^k]$	0.44	0.54	-	0.02	-
M3:$[\triangle GDP_t^k, \triangle GR_t, EqR_t^k]$	0.41	0.38	-	-	0.21
5-variable PSVAR models					
M4:$[\triangle GDP_t^k, \triangle GR_t, \triangle EFI_t^k, \triangle EMBI_t^k, EqR_t^k]$	0.38	0.39	0.07	0.00	0.16
M5:$[\triangle GDP_t^k, \triangle GR_t, EqR_t^k, \triangle EFI_t^k, \triangle EMBI_t^k]$	0.38	0.39	0.02	0.01	0.20
M6:$[\triangle GDP_t^k, \triangle GR_t, \triangle EMBI_t^k, \triangle EFI_t^k, EqR_t^k]$	0.38	0.39	0.07	0.01	0.16
M7:$[\triangle GDP_t^k, \triangle GR_t, EqR_t^k, \triangle EMBI_t^k, \triangle EFI_t^k]$	0.38	0.39	0.03	0.00	0.20
Average across M1-M7	0.40	0.43	0.05	0.01	0.19

Notes: The table shows the forecast error variance decomposition, i.e., the fraction of real GDP growth variance explained by GDP, VIX, Baa, EFI, EMBI, and EqR shocks across 3-variable and 5-variable panel structural VAR models M1-M7. The sample period is 1999Q2-2017Q1 and includes EFI-10 countries. See Table 1 for variable descriptions.

output responds to variations in global risk with a one-period lag, while the domestic financial variables, given their fast-moving nature, are assumed to respond to changes in global risk within the same period. As in CFP, the number of lags (p) is set to one.

Table 2 reports the variance decomposition results for real GDP growth in EMEs and shows that equity return shocks are a more important driver of output fluctuations than shocks to corporate and sovereign bond spreads. Panel A uses the VIX index as a proxy of global risk, and Panel B uses the US baa spread. In line with CFP, we find that $\triangle EMBI$ shocks account for only up to 4 percent, while $\triangle EFI$ shocks account for 2 to 14 percent of output fluctuations. More notably, depending on the global risk proxy, innovations in EqR

Figure 1: Impulse response functions of GDP growth to domestic financial variable shocks



Notes: The figure shows impulse response functions of annual real GDP growth to a one standard deviation $\triangle EFI$, $\triangle EMBI$, and EqR shock. EqR displays a negative shock for comparison. M1, M2, and M3 in given columns denote 3-variable panel structural VAR models 1,2, and 3 shown in Table 2, estimated over the 1999Q2-2017Q2 period for EFI-10 countries. Global risk (GR) is proxied by the VIX index (VIX) in Panel A and by the US Baa corporate spread (Baa) in Panel B. The shaded areas represent 95% confidence bands obtained with bootstrapping.

explain on average 19 (GR proxied by Baa) and 27 percent (GR proxied by VIX) of the variance in output growth. In contrast, $\triangle EFI$ innovations explain on average only 5 and 10 percent of output variance in EMEs.

Table 2 also shows that global risk shocks explain a significant fraction, between 20 and 54 percent, of the fluctuations in EME output growth. We find, however, that their contribution decreases considerably when we consider equity returns in the 3-variable PSVAR models, instead of corporate or sovereign bond spreads. The contribution of global risk shocks to EME output variance decreases from about a third to a fourth when using the VIX index as a proxy of GR, and from roughly a half to two fifths when using the US baa spread.

Additional results can be seen in Figure 1, where each row depicts an impulse response function of real GDP growth to a positive one standard deviation shock to $\triangle EFI$ (M1),

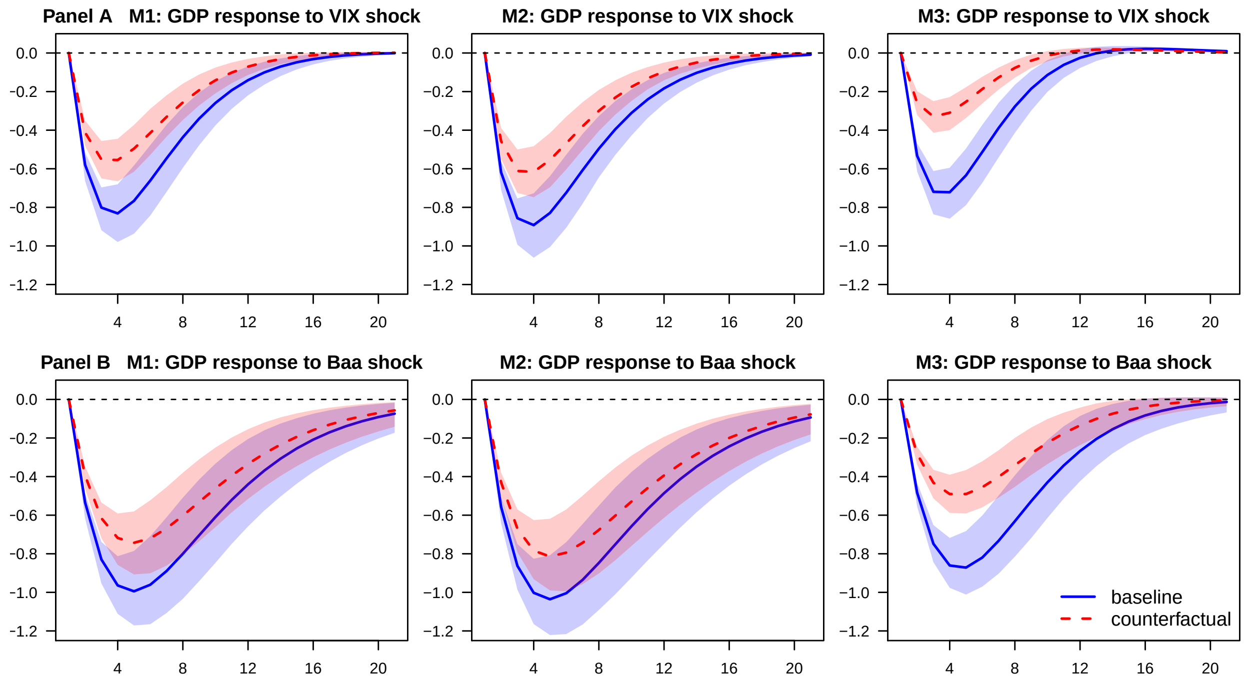
Table 3: Variance decomposition of GDP growth: counterfactual analysis

Panel A: Global Risk (GR) is proxied by VIX					
Model	GDP shock	VIX shock	EFI shock	EMBI shock	EqR shock
M1	0.57	0.31	0.13	-	-
M1 counterfactual	0.69	0.16	0.15	-	-
M2	0.60	0.36	-	0.04	-
M2 counterfactual	0.75	0.20	-	0.05	-
M3	0.47	0.23	-	-	0.30
M3 counterfactual	0.58	0.05	-	-	0.37
Panel B: Global Risk (GR) is proxied by US Baa spread					
Model	GDP shock	Baa shock	EFI shock	EMBI shock	EqR shock
M1	0.43	0.50	0.06	-	-
M1 counterfactual	0.55	0.36	0.08	-	-
M2	0.44	0.54	-	0.02	-
M2 counterfactual	0.55	0.42	-	0.03	-
M3	0.41	0.38	-	-	0.21
M3 counterfactual	0.53	0.17	-	-	0.30

Notes: The table shows the fraction of real GDP growth variance explained by GDP, VIX, EFI, EMBI, and EqR shocks. M1-M3 denote baseline models, which allow feedback from changes in global risk to EFI, EMBI, or EqR. M1 counterfactual - M3 counterfactual denote models when EFI, EMBI, or EqR is assumed not to respond directly to changes in global risk, measured by the VIX index in Panel A and by the US Baa spread in Panel B. The sample period is 1999Q2-2017Q1 and includes EFI-10 countries.

$\triangle EMBI$ (M2), and, for comparison, a negative shock to EqR (M3). The global risk ($\triangle GR$) is proxied by $\triangle VIX$ in the top row (Panel A) and by $\triangle Baa$ in the bottom row (Panel B). Figure 1 shows that (negative) EqR shocks lead to a substantially more pronounced decrease of output than $\triangle EFI$ and $\triangle EMBI$ shocks. Specifically, equity return shocks lower GDP growth in EMEs by over 50 percent more than corporate bond spread shocks and by over twice as much as sovereign bond spread shocks. In the top row of Figure 1, the output response reaches a trough of -0.50, -0.29, and -0.77 percentage points to an $\triangle EFI$, $\triangle EMBI$, and EqR shock, whereas output growth is lowered by 0.40, 0.23, and 0.69 percentage points in the bottom row.

Figure 2: Impulse response functions of GDP growth to global risk shocks



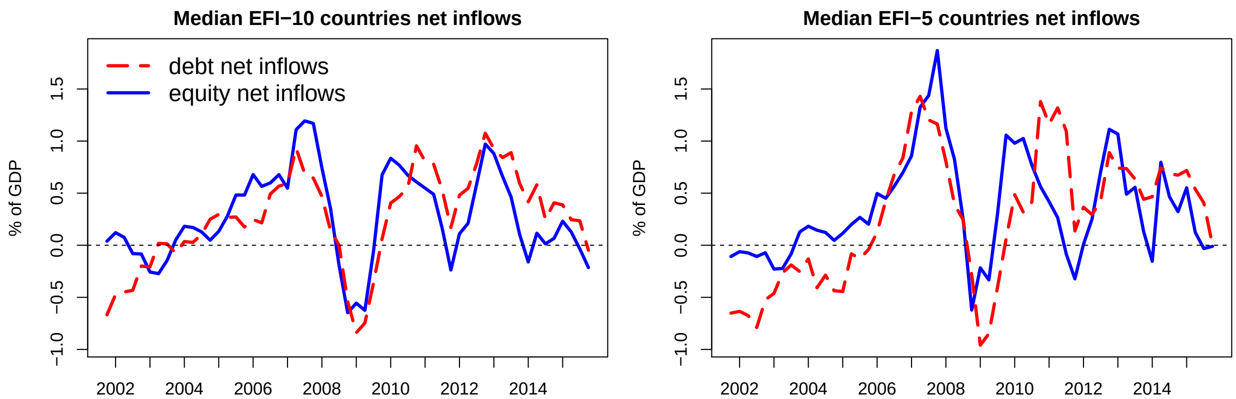
Notes: The figure shows impulse response functions of annual real GDP growth to a one standard deviation $\triangle GR$ shock, proxied by $\triangle VIX$ in Panel A and $\triangle Baa$ in Panel B. The baseline responses are depicted with a solid line. The dashed line represents a counterfactual scenario, when $\triangle EFI$ (M1), $\triangle EMBI$ (M2), and EqR (M3) is assumed not to respond to changes in $\triangle GR$. M1, M2, and M3 in given columns denote 3-variable panel structural VAR models 1,2, and 3 shown in Table 2, estimated over the 1999Q2-2017Q2 period for EFI-10 countries. The shaded areas represent 95% confidence bands obtained with bootstrapping.

4 Transmission

In this section, we provide evidence suggesting that the larger impact of equity return shocks on EME economic activity is due to equity returns transmitting global risk shocks more effectively than corporate and sovereign bond spreads. Moreover, we show that equity flows play a key role in international capital flows.

We consider a counterfactual experiment where, similarly to CFP, we assume that the local financial variable ($\triangle EFI$, $\triangle EMBI$, or EqR) in the 3-variable PSVAR models (M1-M3) does not directly respond to movements in global financial risk. The counterfactual impulse response functions of EME output growth to global risk shocks are shown in Figure 2 with red dashed lines. Compared to the baseline responses depicted with blue solid lines, the output response in model M3 is significantly muted under the counterfactual scenario,

Figure 3: Net equity and debt inflows to EMEs as a percentage of GDP



Notes: EFI-5 countries include Brazil, Chile, Malaysia, Mexico, and Philippines. EFI-10 countries include Colombia, Peru, Russia, South Africa, Turkey, and EFI-5 countries. Flows and GDP are measured in US dollars and over the 2001Q1-2015Q4 period. Net inflows denote moving averages over the last four quarters and are constructed as the difference between non-resident portfolio inflows to and outflows from EMEs. Inflows are sourced from Cerutti, Claessens, and Puy (2019). Outflows are authors' own calculation using data from IMF's Balance of Payment (BOP) database.

when EqR is assumed not to propagate fluctuations in global risk. However, when $\triangle EFI$ (M1) or $\triangle EMBI$ (M2) is not allowed to respond to changes in global risk, the baseline and counterfactual responses of output are rather similar; especially given the considerable overlap of the confidence bands.

Table 3 presents the variance decomposition results of the counterfactual exercise for models M1-M3. When we shut off the response of equity returns to global risk, the contribution of global risk shocks to EME macroeconomic fluctuations decreases by over a half compared to the baseline case, while the contribution of equity return shocks increases sizeably. The contribution of corporate and sovereign bond spread shocks, however, remains similar under the counterfactual scenario. The results point to the association of the forward looking nature of stock prices with economic activity to be a key propagation mechanism of global risk shocks to EMEs. This is in line with Asis et al. (2021), who document that the sensitivity of equity returns to global financial conditions can exacerbate firms' default risk in EMEs.

Our findings are also consistent with Bathia, Bouras, Demirer, and Gupta (2020) who show that EME stock market returns are highly sensitive to cross-border equity and bond flows, and with Fink and Schüler (2015) who show that capital flows in and out of EMEs are crucial in transmitting US financial stress shocks to emerging countries. We provide corroborating evidence in Figure 3 revealing that net equity portfolio inflows to EMEs are similar in size to net debt inflows. With more refined data, Hevia and Neumeyer (2020) and Matthews (2020) use the Institute of International Finance's daily flow tracker to show that equity flows to EMEs account for a disproportionately larger share of total portfolio flows than debt flows during crises such as the Global Financial Crisis and the COVID-19 Crisis.

Overall, we demonstrate that equity returns contain information about aggregate economic activity in EMEs beyond the informational content already embedded in corporate and sovereign bond spreads. The analysis points to some degree of market segmentation between equity and debt markets in EMEs, consistent with the presence of slow-moving capital in equity and debt markets presented in Pitkäjärvi et al. (2020).

5 Conclusion

Caballero et al. (2019) show that corporate bond spreads in EMEs have a predictive power for future economic activity and account for a sizeable fraction of macroeconomic fluctuations, even after controlling for the effects of the well-known sovereign bond spreads. We demonstrate that the behavior of EME equity returns is a more important factor in predicting and accounting for movements of economic activity in emerging countries, and for propagating the fluctuations in global financial conditions to these economies.

Declaration of Interest

All authors declare that they have no relevant information or potential conflicts of interest to disclose.

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Online Appendix (not for publication)

In the Online Appendix, we present results analogous to those in the main text but using EFI-5 countries (Brazil, Chile, Malaysia, Mexico, Philippines), instead of EFI-10 countries.

Table A.1: Forecasting regressions (EFI-5)

Spec.4 with EqR	h=1: $\triangle GDP^k_{t+1}$	h=2: $\triangle GDP^k_{t+2}$	h=3: $\triangle GDP^k_{t+3}$	h=4: $\triangle GDP^k_{t+4}$	h=5: $\triangle GDP^k_{t+5}$
$\triangle EFI^k_t$	-0.068	-0.21	-0.26*	-0.25	-0.17
	(-0.79)	(-1.51)	(-1.91)	(-1.47)	(-1.06)
$\triangle EMBI^k_t$	0.061	0.11	0.099	0.067	-0.00087
	(0.67)	(0.71)	(0.64)	(0.36)	(-0.00)
EqR^k_t	0.022***	0.039***	0.045***	0.037***	0.010
	(6.10)	(5.27)	(4.85)	(3.29)	(0.62)
$\triangle VIX_t$	0.0048	0.058**	0.11***	0.093**	0.035
	(0.34)	(2.12)	(3.09)	(2.55)	(0.70)
$\triangle Baa_t$	-0.24	-0.65	-1.16**	-1.27*	-0.59
	(-1.17)	(-1.64)	(-2.01)	(-1.76)	(-0.94)
R^2	0.839	0.612	0.453	0.256	0.121
Adjusted R^2	0.826	0.581	0.409	0.195	0.048
Observations	334	329	325	319	314
Spec.4 (CFP)	h=1: $\triangle GDP^k_{t+1}$	h=2: $\triangle GDP^k_{t+2}$	h=3: $\triangle GDP^k_{t+3}$	h=4: $\triangle GDP^k_{t+4}$	h=5: $\triangle GDP^k_{t+5}$
$\triangle EFI^k_t$	-0.11	-0.29*	-0.35**	-0.32*	-0.19
	(-1.19)	(-1.83)	(-2.31)	(-1.79)	(-1.10)
$\triangle EMBI^k_t$	0.022	0.041	0.016	0.00050	-0.018
	(0.26)	(0.27)	(0.09)	(0.00)	(-0.09)
EqR^k_t					
$\triangle VIX_t$	-0.00054	0.048	0.094**	0.083*	0.032
	(-0.03)	(1.37)	(2.08)	(1.97)	(0.68)
$\triangle Baa_t$	-0.25	-0.67	-1.19*	-1.28	-0.59
	(-1.12)	(-1.45)	(-1.79)	(-1.62)	(-0.92)
R^2	0.826	0.572	0.397	0.219	0.118
Adjusted R^2	0.812	0.538	0.349	0.155	0.045
Observations	334	329	325	319	314

Notes: The table reports estimated coefficients, and t-statistics in parenthesis, from a dynamic panel regression specified in equation (1) in the main text, with the dependent variable being future annual real GDP growth ($\triangle GDP^k{}_{t+h}$) measured in percentages. The EFI-5 sample is balanced over the 1999Q2-2017Q1 period and includes Brazil, Chile, Malaysia, Mexico, and Philippines. $\triangle EFI$ and $\triangle EMBI$ refer to annual percentage point changes in country-specific corporate and sovereign bond spreads. EqR denotes equity returns measured as annual percent log changes in country-specific stock market prices. $\triangle VIX$ and $\triangle Baa$ stand for annual changes in the US option-implied S&P 500 index volatility and in the difference between the Moody's US Baa Corporate and 10-year Treasury rates, expressed in percentage points. *, **, and *** indicate significance level at 10%, 5%, and 1%. The bottom panel replicates the results of Caballero et al. (2019) for their specification 4. The top panel adds equity returns to the specification.

Table A.2: Variance decomposition of GDP growth (EFI-5)

Panel A: Global Risk (GR) is proxied by VIX					
3-variable PSVAR models	GDP shock	VIX shock	EFI shock	EMBI shock	EqR shock
M1(CFP):[$\triangle GDP_t^k, \triangle GR_t, \triangle EFI_t^k$]	0.56	0.41	0.03	-	-
M2(CFP):[$\triangle GDP_t^k, \triangle GR_t, \triangle EMBI_t^k$]	0.52	0.44	-	0.03	-
M3:[$\triangle GDP_t^k, \triangle GR_t, EqR_t^k$]	0.47	0.34	-	-	0.18
5-variable PSVAR models	GDP shock	VIX shock	EFI shock	EMBI shock	EqR shock
M4:[$\triangle GDP_t^k, \triangle GR_t, \triangle EFI_t^k, \triangle EMBI_t^k, EqR_t^k$]	0.46	0.32	0.05	0.00	0.16
M5:[$\triangle GDP_t^k, \triangle GR_t, EqR_t^k, \triangle EFI_t^k, \triangle EMBI_t^k$]	0.46	0.32	0.01	0.00	0.21
M6:[$\triangle GDP_t^k, \triangle GR_t, \triangle EMBI_t^k, \triangle EFI_t^k, EqR_t^k$]	0.46	0.32	0.04	0.01	0.16
M7:[$\triangle GDP_t^k, \triangle GR_t, EqR_t^k, \triangle EMBI_t^k, \triangle EFI_t^k$]	0.46	0.32	0.01	0.00	0.21
Average across M1-M7	0.48	0.35	0.03	0.01	0.18
Panel B: Global Risk (GR) is proxied by US Baa spread					
3-variable PSVAR models	GDP shock	Baa shock	EFI shock	EMBI shock	EqR shock
M1(CFP):[$\triangle GDP_t^k, \triangle GR_t, \triangle EFI_t^k$]	0.40	0.59	0.01	-	-
M2(CFP):[$\triangle GDP_t^k, \triangle GR_t, \triangle EMBI_t^k$]	0.63	0.36	-	0.00	-
M3:[$\triangle GDP_t^k, \triangle GR_t, EqR_t^k$]	0.36	0.51	-	-	0.12
5-variable PSVAR models	GDP shock	Baa shock	EFI shock	EMBI shock	EqR shock
M4:[$\triangle GDP_t^k, \triangle GR_t, \triangle EFI_t^k, \triangle EMBI_t^k, EqR_t^k$]	0.37	0.51	0.03	0.00	0.10
M5:[$\triangle GDP_t^k, \triangle GR_t, EqR_t^k, \triangle EFI_t^k, \triangle EMBI_t^k$]	0.37	0.51	0.00	0.00	0.12
M6:[$\triangle GDP_t^k, \triangle GR_t, \triangle EMBI_t^k, \triangle EFI_t^k, EqR_t^k$]	0.37	0.51	0.02	0.01	0.10
M7:[$\triangle GDP_t^k, \triangle GR_t, EqR_t^k, \triangle EMBI_t^k, \triangle EFI_t^k$]	0.37	0.51	0.00	0.00	0.12
Average across M1-M7	0.41	0.50	0.01	0.00	0.11

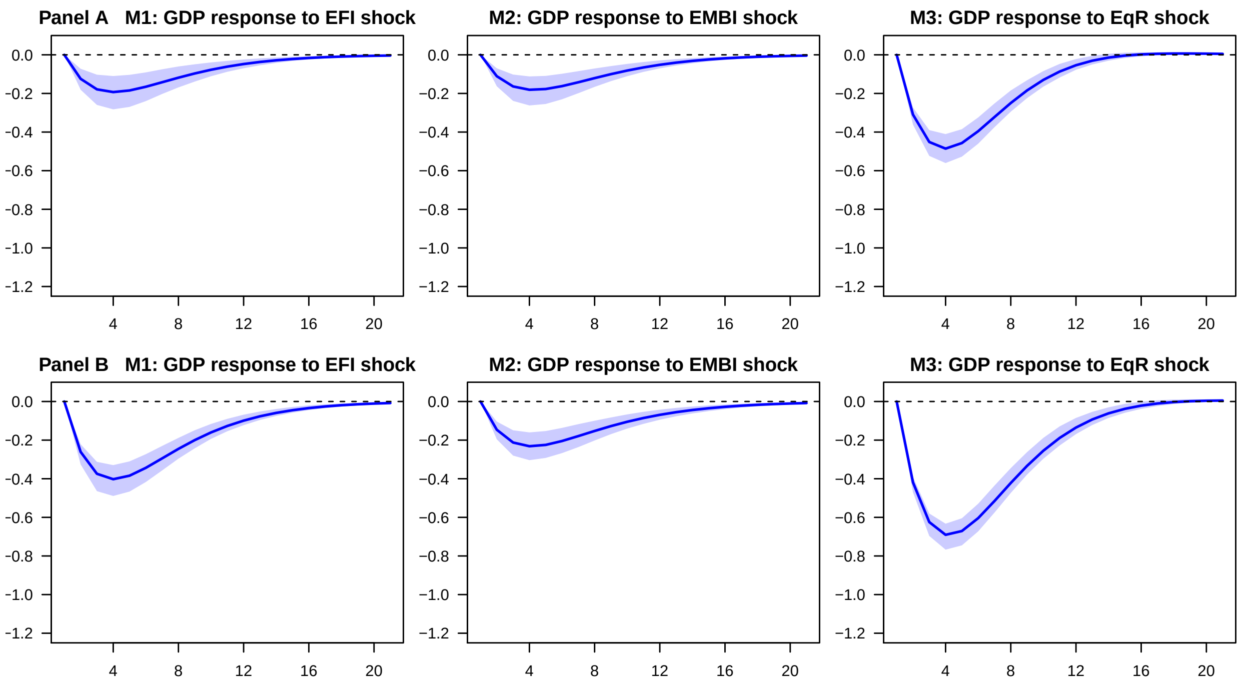
Notes: The table shows the forecast error variance decomposition, i.e., the fraction of real GDP growth variance explained by GDP, VIX, Baa, EFI, EMBI, and EqR shocks across 3-variable and 5-variable panel structural VAR models M1-M7. The sample period is 1999Q2-2017Q1 and includes EFI-5 countries.

Table A.3: Variance decomposition of GDP growth: counterfactual analysis (EFI-5)

Panel A: Global Risk (GR) is proxied by VIX					
Model	GDP shock	VIX shock	EFI shock	EMBI shock	EqR shock
M1	0.56	0.41	0.03	-	-
M1 counterfactual	0.65	0.31	0.03	-	-
M2	0.52	0.44	-	0.03	-
M2 counterfactual	0.62	0.35	-	0.03	-
M3	0.47	0.34	-	-	0.18
M3 counterfactual	0.61	0.15	-	-	0.24
Panel B: Global Risk (GR) is proxied by US Baa spread					
Model	GDP shock	Baa shock	EFI shock	EMBI shock	EqR shock
M1	0.40	0.59	0.01	-	-
M1 counterfactual	0.47	0.51	0.02	-	-
M2	0.63	0.36	-	0.00	-
M2 counterfactual	0.65	0.35	-	0.00	-
M3	0.36	0.51	-	-	0.12
M3 counterfactual	0.55	0.26	-	-	0.19

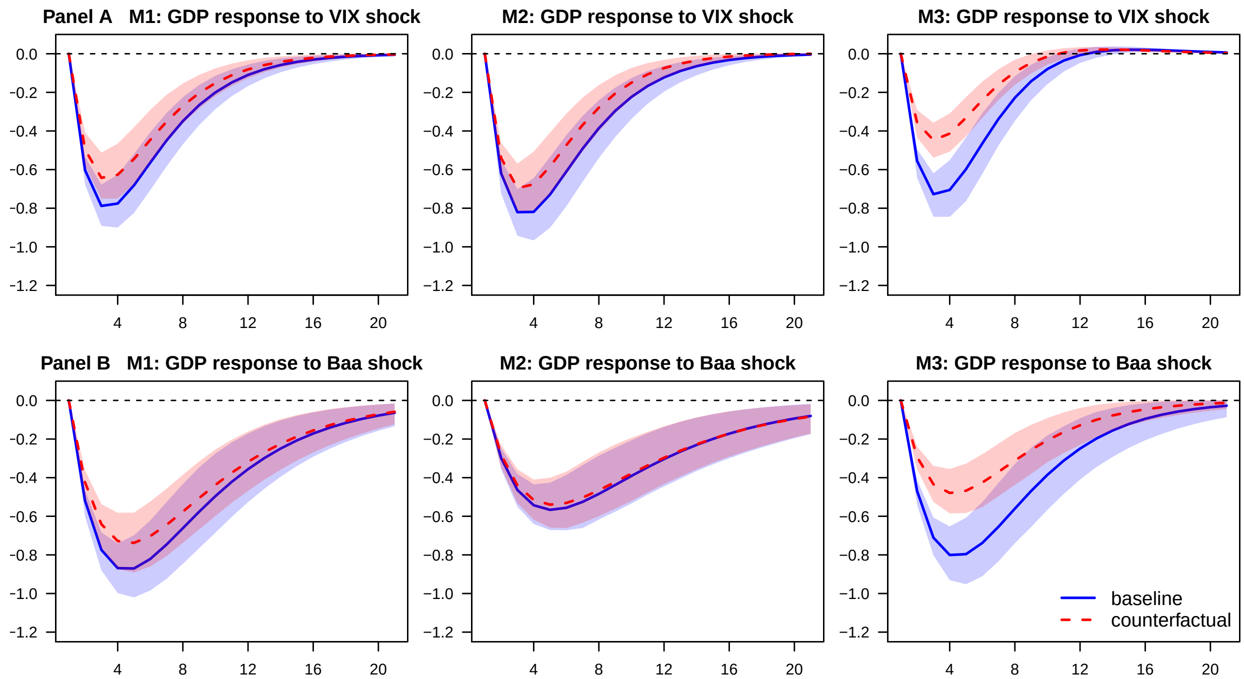
Notes: The table shows the fraction of real GDP growth variance explained by GDP, VIX, EFI, EMBI, and EqR shocks. M1-M3 denote baseline models, which allow feedback from changes in global risk to EFI, EMBI, or EqR. M1 counterfactual - M3 counterfactual denote models when EFI, EMBI, or EqR is assumed not to respond directly to changes in global risk, measured by the VIX index in Panel A and by the US Baa spread in Panel B. The sample period is 1999Q2-2017Q1 and includes EFI-5 countries.

Figure A.1: Impulse response functions of GDP growth to domestic financial variable shocks (EFI-5)



Notes: The figure shows impulse response functions of annual real GDP growth to a one standard deviation $\triangle EFI$, $\triangle EMBI$, and EqR shock. EqR displays a negative shock for comparison. M1, M2, and M3 in given columns denote 3-variable panel structural VAR models 1,2, and 3 shown in Table 2, estimated over the 1999Q2-2017Q2 period for EFI-5 countries. Global risk (GR) is proxied by the VIX index (VIX) in Panel A and by the US Baa corporate spread (Baa) in Panel B. The shaded areas represent 95% confidence bands obtained with bootstrapping.

Figure A.2: Impulse response functions of GDP growth to global risk shocks (EFI-5)



Notes: The figure shows impulse response functions of annual real GDP growth to a one standard deviation $\triangle GR$ shock, proxied by $\triangle VIX$ in Panel A and $\triangle Baa$ in Panel B. The baseline responses are depicted with a solid line. The dashed line represents a counterfactual scenario, when $\triangle EFI$ (M1), $\triangle EMBI$ (M2), and EqR (M3) is assumed not to respond to changes in $\triangle GR$. M1, M2, and M3 in given columns denote 3-variable panel structural VAR models 1,2, and 3 shown in Table 2, estimated over the 1999Q2-2017Q2 period for EFI-5 countries. The shaded areas represent 95% confidence bands obtained with bootstrapping.