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Trade in Commodities and Business Cycle Volatility[1]

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Abstract

This paper studies the role of differences in the patterns of production and international trade on the business cycle volatility of emerging and developed economies. We study a multi-sector small open economy in which firms produce and trade commodities and manufactures. We estimate the model to match key cross-sectional and time-series differences across countries. Emerging economies run trade surpluses in commodities and trade deficits in manufactures, while sectoral trade flows are balanced in developed economies. We find that these differences amplify the response of emerging economies to commodity price fluctuations. We show evidence consistent with this mechanism using cross-country data.

JEL Classification Codes: E32, F4, F41, F44

Keywords: International business cycles, output volatility, emerging economies

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1 Introduction

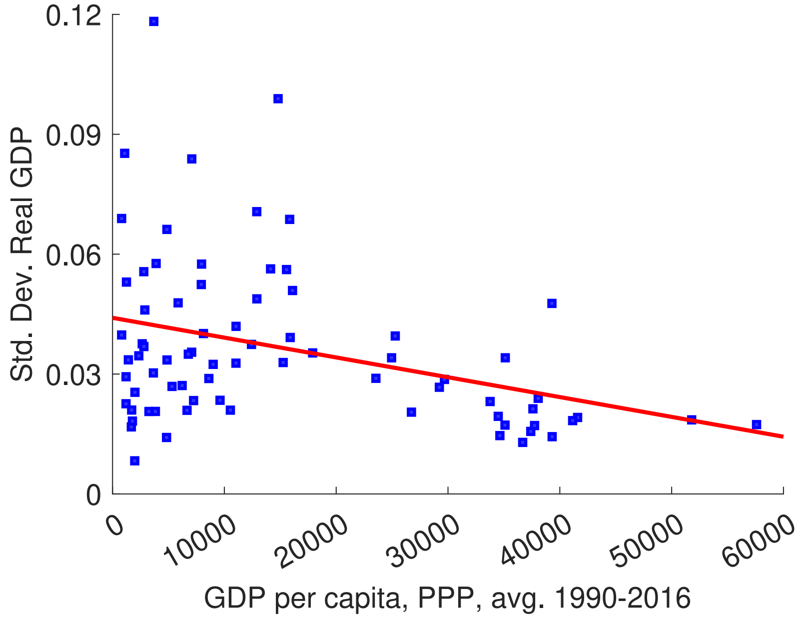
Emerging and developed economies differ systematically both along the cross-section and in their dynamics. On the one hand, as shown in Figure 1, there is a negative relationship between GDP per capita and the standard deviation of real GDP (Acemoglu and Zilibotti 1997 and Koren and Tenreyro 2007, among others).[1] On the other hand, a growing literature on structural transformation shows that emerging and developed economies specialize in the production of different types of goods (see Herrendorf et al. 2014 for an overview of this literature). In this paper, we show that cross-sectional differences in the patterns of production and trade between emerging and developed economies can account for a sizable share of the difference in business cycle volatility between them.

Our starting point is the observation that the structure of production and trade is systematically different between emerging and developed economies. First, emerging economies produce a larger share of tradable goods, making them more exposed to international price fluctuations. Second, these economies export relatively more commodities than manufactures, while the shares of commodities and manufactures in imports are similar to developed economies. Thus, emerging economies feature large sectoral trade imbalances. We document these patterns of production and trade using cross-country data and investigate their effect on the responsiveness of economies to changes in international relative prices.

To study the role of these cross-sectional differences on business cycle volatility, we set up a multi-sector small open economy that produces commodities, manufactures, and non-tradable goods. The model accounts for the cross-sectional patterns of production and trade observed in the data. In our model, an increase in the relative price of commodities raises the value of production and exports in emerging economies, while reducing the relative price of goods imported, triggering an economic boom. In contrast, in developed economies, these effects approximately offset each other and, thus, have a

[1] See also Da-Rocha and Restuccia (2006). For the data used in Figure 1, see Section 2.

Figure 1: Economic development and business cycle volatility



minimal impact on aggregate economic activity.

Our main contributions are twofold. First, we quantify the role of differences in the patterns of production and trade on business cycle volatility differences between emerging and developed economies. Second, we document that this mechanism is consistent with evidence from cross-country data. Thus, we contribute to understanding differences in business cycles between emerging and developed economies (e.g. Aguiar and Gopinath 2007, Neumeyer and Perri 2005) as well as the impact of terms of trade shocks (e.g. Schmitt-Grohé and Uribe 2018, Mendoza 1995) and commodity prices on economic activity (e.g. Fernández et al. 2018, Fernández et al. 2017, Drechsel and Tenreyro 2017).

In our multi-sector small open economy, firms produce commodities and manufactures using capital and labor. These goods can be traded internationally at prices taken as given from the rest of the world. Aggregate fluctuations are driven by shocks to aggregate productivity and to the relative price of commodities. Sectoral reallocation costs discipline the degree to which capital and labor can reallocate across sectors in response to shocks. In addition, we assume that domestic interest rates are a function of the world interest rate and a spread which varies systematically with domestic business cycles. This assumption is standard in the literature and allows us to study our mechanism in an economy that can account for salient features of emerging market business cycles, such as the counter-cyclicality of net exports and the high relative volatility of consumption.[2]

First, we investigate analytically the role of differences in the types of goods produced and consumed across countries in the response of output to changes in international relative prices. We show that international price fluctuations impact the incentives to accumulate physical capital and supply labor insofar as the composition of the consumption price index is different from the production price index; this is the case in emerging economies. We also show that international relative price shocks affect aggregate output by leading to changes in aggregate total factor productivity (TFP). In contrast to Kehoe and Ruhl (2008), in our economy, changes in international relative prices affect real GDP through changes in aggregate capital and labor, as well as by affecting aggregate TFP through the reallocation of production across sectors.

Second, we quantitatively investigate the extent to which systematic cross-sectional differences between emerging and developed economies can account for the difference in business cycle volatility observed between them. To do so, we first estimate an emerging and a developed economy to account for salient cross-sectional and time-series features observed in the data. In particular, we parameterize the economies to account for the share of commodities and manufactures in aggregate output as well as for the trade imbalances in the two sectors. Notice that the latter capture differences in the shares of commodities and manufactures in aggregate exports and imports.

To quantify the role of cross-sectional differences on aggregate volatility, we contrast the implications of our estimated emerging economy with a counter-factual economy that differs only in the parameters that control the patterns of production and trade. We re-estimate these parameters such that

[2]See, for example, Neumeyer and Perri (2005), Uribe and Yue (2006), Chang and Fernández (2013) and Drechsel and Tenreyro (2017).

the counter-factual economy matches the developed economy's cross-sectional moments mentioned above. That is, our counter-factual emerging economy's sectoral trade flows are largely balanced, and it produces a higher share of non-tradable goods and a lower share of commodities. We also do an analogous experiment for the estimated developed economy.

We find that cross-sectional differences in the patterns of production and trade can account for 29% of the difference in real GDP volatility between emerging and developed economies. In particular, given an emerging economy parameterized to match the standard deviation of real GDP in the data (equal to 4.21%), we find that real GDP volatility in the counter-factual emerging economy decreases to 3.63%. The analogous exercise based on the estimated developed economy implies that cross-sectional differences in the patterns of production and trade account for 39% of the difference in real GDP volatility. Thus, cross-sectional differences between emerging and developed economies have a significant impact on business cycle volatility.

Third, we investigate which features of our model are most important in accounting for our findings. We begin by showing that the implied volatility differences between developed and emerging economies are primarily accounted for by differences in their sectoral trade imbalances: Aggregate volatility is significantly reduced when the emerging economy is recalibrated to match the smaller manufacturing trade imbalance of developed economies. Differences in the size of the non-tradable sector between emerging and developed economies also play an important role.

Fourth, we compute impulse response functions and find that the importance of sectoral trade imbalances is driven by a higher response to commodity price shocks in emerging economies rather than by differences in their response to productivity shocks. Through a variance decomposition, we find that commodity price shocks account for 26.1% of the variance of real GDP in emerging economies while they only account for 10.7% of this variance in developed economies.

Fifth, we find that the key channels that account for the higher volatility of emerging economies in our model are also important in accounting for aggregate volatility in the data. In particular, we use cross-country regressions to document that aggregate real GDP volatility is positively associated with sectoral trade imbalances and negatively associated with the share of non-tradable goods. Importantly, we find that these relationships are robust to controlling for the countries' level of economic development.

Finally, we examine whether the implications of our model are quantitatively consistent with this evidence. To do so, we re-estimate our model for each of the 76 countries in our cross-country dataset and contrast the implications for each country with its empirical counterpart. We show that, indeed, our model is quantitatively consistent with the cross-country empirical relationship between sectoral imbalances and aggregate volatility.

Our paper contributes to a literature that investigates the impact of terms of trade shocks on business cycle fluctuations across countries. Early work by Mendoza (1995) and Kose (2002) showed that terms of trade shocks are an important source of business cycle volatility in emerging and developed economies. Schmitt-Grohé and Uribe (2018) use an extended version of the model developed by Mendoza (1995) to show that these implications are at odds with evidence from cross-country structural vector autoregressions. In a similar economic environment, we study the role of one specific source of terms of trade variability, shocks to commodity prices, in accounting for differences in business cycle volatility between emerging and developed economies. As mentioned above, we contribute to this literature by quantifying the impact of sectoral trade imbalances on business cycle volatility and documenting evidence consistent with this mechanism.

Our paper is also related to a rapidly growing literature that investigates complementary channels on the interaction between the production of commodities and business cycle dynamics, such as Fernández et al. (2017), Drechsel and Tenreyro (2017), Zeev et al. (2017), and Shousha (2016). Recent work by Fernández et al. (2018) documents that a common factor in commodity prices accounts for a significant fraction of output volatility, with heterogeneous effects across countries. Our paper shows that differences in the patterns of production and trade across countries also generate a heterogeneous response of aggregate fluctuations to common commodity price shocks.

Finally, a related literature investigates differences in economic fluctuations between emerging and developed economies along a broader set of business cycle moments. One mechanism examined in this literature is the role of differences in the productivity process underlying economic fluctuations across these economies (Aguiar and Gopinath 2007). Another channel emphasized is the role of borrowing costs in international markets and financial frictions (Neumeyer and Perri 2005; Uribe and Yue 2006).[3] Our model features differences in the responsiveness of interest rates to changes in economic activity in order to account for additional dimensions of business cycles in emerging economies emphasized in this literature.[4]

The rest of the paper is structured as follows. In Section 2, we document salient features of developed and emerging economies. In Section 3, we set up our model. In Section 4, we examine the mechanisms through which changes in international relative prices can affect real GDP in our model. In Section 5, we calibrate the model, present our results and study the mechanism behind them. In Section 6, we contrast the implications of our model with cross-country evidence. In Section 7, we present the main conclusions of the paper.

2 Volatility, production, and trade in emerging economies

In this section, we document salient features of emerging and developed economies. First, we present a well-known empirical fact: business cycles in emerging economies are more volatile than in developed ones. Then, we show that these two country groups also differ markedly along the cross-section: the production of commodities constitutes a larger share of economic activity in emerging economies than the production of manufactures, while the opposite

[3]Other papers that investigate differences in business cycles between emerging and developed economies include García-Cicco et al. (2010), Hevia (2014), and Comin et al. (2014).

[4]Chang and Fernández (2013) contrast the relative importance of the channels discussed above and show that a relationship between spreads and productivity plays a dominant role in accounting for emerging market business cycles.

is true in developed economies. Emerging economies also produce a higher share of tradable goods. Moreover, we show that these economies differ in the type of goods traded internationally: in emerging economies the compositions of exports and imports are quite different, while in developed economies the shares of commodities and manufactures are similar for both exports and imports. In subsequent sections, we use a structural model to investigate the extent to which these cross-sectional differences can account for the difference in business cycle volatility.

We use data from the World Development Indicators (WDI).[5] We restrict attention to annual data from 1970 to 2016. We classify countries into "Developed" and "Emerging" as follows: countries that are members of the OECD and have an average, PPP adjusted, GDP per capita higher than $25,000 in 2011 U.S. dollars are classified as "Developed." Countries that have an average, PPP adjusted, GDP per capita lower than $25,000 are classified as "Emerging."[6] To identify fluctuations at business cycle frequencies we use annual per capita variables and de-trend them applying the Hodrick-Prescott filter with smoothing parameter 100.[7]

We restrict the set of countries that we study to ensure the availability of data along the dimensions of interest. First, we restrict attention to countries with at least 25 years of consecutive annual observations for each of the business cycle variables that we examine in Section 2.1. We also exclude any country with cross-sectional variables observed for less than 15 years. In addition, we exclude countries that transitioned from communism to market economies in the 1990s.[8] Finally, we drop the U.S. and China, since we study a

[5] The data is publicly available at http://databank.worldbank.org/.

[6] For the purposes of this classification, the averages are taken over the period from 1990 to 2016. The PPP adjusted series in the WDI database start in 1990. Two developed countries (Greece and Israel) and two emerging countries (Portugal and South Korea) have average levels of volatility close to the cutoff. Dropping these countries does not materially affect any of our conclusions.

[7] The features of business cycles in emerging and developed countries that we discuss in this section are robust to using alternative de-trending schemes such as an HP-filter with smoothing parameter 6.25 or a band pass filter.

[8] These countries are the former Soviet and Yugoslav Republics as well as members of the Warsaw Pact (except East Germany).

small open economy throughout our quantitative analysis, and we drop countries with a population below 1 million. After applying these filters, our final sample consists of 56 emerging economies and 20 developed ones.[9]

See Section 1 of the Online Appendix for further details on the datasets and individual variables used throughout this section and the rest of the paper.

2.1 Business cycles in emerging economies are more volatile

We begin by contrasting the volatility of business cycles between emerging and developed economies. To do so, we focus on the standard deviation of annual real GDP fluctuations (percent deviations from trend) as our measure of business cycle volatility, and construct real GDP by deflating nominal GDP with the GDP deflator.

The first row of Table 1 reports the average volatility of real GDP corresponding to each country group. As previously documented in the literature, we observe that economic activity in emerging economies is more volatile than in developed ones: the average standard deviation of real GDP is 4.23% in emerging economies and 2.25% in developed countries. Thus, we observe that emerging economies are 1.98 percentage points more volatile than developed ones on average (that is, real GDP is 88% more volatile in emerging countries).

2.2 Emerging economies specialize in commodity production

We now contrast the types of goods and services produced by emerging and developed economies. We partition the aggregate value of goods and services produced by these countries into three groups: services, commodities and manufactured goods, where commodities consist of goods produced by the agricultural, mining, and fuel sectors.

The second and third rows of Table 1 report the average shares of commodities and manufactures in GDP, respectively, for each of these country groups. The share of commodities is much larger in emerging economies, 69%

[9]Results are robust to dropping countries with values of the standard deviation of real GDP above 8.5%, which are outliers in our data. These countries are Iran, Rwanda, Yemen, and Zimbabwe.

Table 1: GDP volatility and the type of goods produced and traded

	Developed Economies	Emerging Economies
GDP volatility (%)	2.25	4.23
	(1.71, 2.39)	(2.69, 5.30)
Share of Commodities in GDP	0.15	0.33
	(0.12, 0.17)	(0.25, 0.39)
Share of Manufactures in GDP	0.19	0.15
	(0.17, 0.21)	(0.12, 0.19)
Share of Services in GDP	0.67	0.51
	(0.64, 0.70)	(0.46, 0.56)
Share of Commodities	0.31	0.66
in Aggregate Exports	(0.14, 0.42)	(0.46, 0.87)
Share of Commodities	0.30	0.33
in Aggregate Imports	(0.24, 0.34)	(0.27, 0.40)
Net Exports of	-0.01	-0.11
Manufactures / GDP	(-0.05, 0.04)	(-0.15, -0.06)
Net Exports of	0.00	0.04
Commodities / GDP	(-0.04, 0.03)	(-0.02, 0.10)
Aggregate	-0.01	-0.07
Net Exports / GDP	(-0.03, 0.02)	(-0.12, -0.01)

Note: Averages computed across 56 emerging and 20 developed economies over the period 1970 to 2016, as described in the text. In parentheses we report the values corresponding to the 25th and 75th percentiles.

of total tradable goods, while only 44% of tradable output consists of commodities in developed economies. The third row shows that the total share of services is much lower in emerging than in developed economies (51% vs. 67%).

2.3 Emerging economies exhibit larger sectoral trade imbalances

We now contrast the types of goods that emerging and developed economies trade internationally. To do so, we report the average shares of commodities in aggregate exports and aggregate imports, respectively, in the fifth and sixth rows of Table 1.[10] On the one hand, we find that developed economies export and import very similar goods: On average, commodities make up 31% of aggregate exports and 30% of aggregate imports. In contrast, emerging economies export and import very different baskets of goods: On average, commodities make up 66% of aggregate exports but only 33% of aggregate imports.

In the seventh and eight rows of Table 1, we show that the differences in the types of goods that emerging and developed economies trade internationally lead to differences in sectoral trade deficits across these countries. While imports and exports of manufactures are roughly identical relative to GDP in developed economies, there is a sizable mismatch between them in emerging countries. In particular, while emerging economies exhibit, on average, a manufacturing trade deficit equal to 11 % of GDP, the average manufacturing trade deficit is only 1 % in developed economies. In contrast, while emerging economies are net exporters of commodities, trade of these goods in developed economies is largely balanced.

The final row of Table 1 reports the aggregate trade imbalances that follow from the sectoral trade patterns. While emerging economies exhibit an average aggregate trade deficit equal to 7% of GDP, the deficit is 1% in developed ones.[11]

3 Model

We study a small open economy model with three sectors that produce manufactures, commodities, and non-tradables. The small open economy and the rest of the world produce homogeneous commodities and manufactures, and these goods can be traded internationally. The economy is populated by a representative household, a representative producer of a tradable composite good, a representative producer of a final good, and representative producers of the three sectoral goods.

[10] Results look qualitatively similar when considering commodities excluding fuel.

[11] If we considered all countries in the world, trade should be balanced across all countries. This is not the case in our sample as we drop China and the U.S., among others.

Time is discrete. Each period a random event s_t is realized, and $s^t = (s_0, s_1, \ldots, s_t)$ denotes the history of events up to and including period t. The probability in period 0 of a particular history of events is $\pi_t(s^t)$, and s_0 is given. In general, allocations in period t are functions of the history s^t and of initial values of the capital stock K_0 and asset holdings B_0, but for notational convenience we suppress this dependence.

3.1 Households

We consider an economy populated by a representative infinitely lived household that derives utility from consumption of final goods C_t and disutility from labor N_t. In our baseline model, the utility function is given by

$$U_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{[C_t - \psi_u N_t^{\nu}]^{1-\gamma}}{1-\gamma}, \tag{1}$$

where β is the discount factor, γ is the coefficient of relative risk aversion, ψ_u is the weight on the disutility of labor, and ν determines the Frisch elasticity of labor supply. $\mathbb{E}_t[\cdot]$ denotes the expectation operator conditional on the information at time t. The preferences, that we refer to as GHH, follow the specification introduced by Greenwood et al. (1988). These preferences eliminate the wealth effect on labor supply and is now standard in the emerging market business cycles literature.[12]

The household accumulates the aggregate capital stock internally by investing final goods subject to an aggregate capital adjustment cost. In addition, the household chooses how to allocate next period's aggregate capital stock across sectors subject to sectoral reallocation costs, which require the household to pay in order to change the share of capital supplied to each sector. The evolution of the aggregate capital stock is then given by the following law of motion:

$$K_{t+1} = (1-\delta)K_t + I_t - \tfrac{\phi_K}{2}\left(\tfrac{K_{t+1}}{K_t} - 1\right)^2 K_t - \tfrac{\phi_K^X}{2}\left(\tfrac{K_{m,t+1}}{K_{t+1}} - \tfrac{K_{m,t}}{K_t}\right)^2 - \tfrac{\phi_K^X}{2}\left(\tfrac{K_{c,t+1}}{K_{t+1}} - \tfrac{K_{c,t}}{K_t}\right)^2, \tag{2}$$

[12] Some examples are Neumeyer and Perri (2005), Chang and Fernández (2013), and Drechsel and Tenreyro (2017).

where I_t is aggregate investment, $K_{x,t} \geq 0$ is the capital stock in sector $x \in \{m, c, n\}$ at the beginning of period t, δ is the depreciation rate of the stock of capital, and changes to the aggregate capital stock entail a quadratic adjustment cost governed by $\phi_K > 0$. The parameter ϕ_K^X controls the cost of adjusting the share of capital used in the three sectors.[13]

Similarly, households are endowed with a unit of time and choose the fraction of it to supply as labor, as well as the amount of labor supplied to each sector subject to reallocation costs. Every period households can vary the allocation of labor across sectors, but sectoral capital shares have to be chosen one-period ahead.

The household has access to international financial markets where it can trade a non-contingent bond that delivers one unit of the tradable composite good next period. B_{t+1} is the quantity of such bonds and q_t is the internationally given price which is discussed in detail in Section 3.5.

The household chooses the amount of consumption along with the aforementioned choices to maximize (1) subject to the capital evolution equation and budget constraint, given initial values of the capital stock K_0 and asset holdings B_0. The budget constraint is given by

$$\begin{aligned} p_t C_t + p_t I_t + p_{\tau,t} q_t B_{t+1} + p_t \sum_{x \in \{m,c\}} \frac{\phi_N^X}{2} \left(\frac{N_{x,t}}{N_t} - \frac{N_{x,t-1}}{N_{t-1}} \right)^2 \\ = \sum_{x \in \{m,c,n\}} w_{x,t} N_{x,t} + \sum_{x \in \{m,c,n\}} r_{x,t} K_{x,t} + \Pi_t + p_{\tau,t} B_t, \end{aligned} \tag{3}$$

where $N_{x,t} \in [0, 1]$ is the fraction of time spent working in sector $x \in \{m, c, n\}$. In sector x, the wage and the rental rate of capital are respectively $w_{x,t}$ and $r_{x,t}$. Π_t denotes the total profits transferred to the household from the ownership of all domestic firms, p_t is the price of the final good used for consumption and investment, and $p_{\tau,t}$ is the price of the tradable composite good. ϕ_N^X controls

[13]Given there are three sectors in our economy, specifying sectoral reallocation costs as a function of changes in the share of commodities and manufactures is without loss of generality.

the cost of adjusting the share of labor employed in the three sectors. All adjustment costs are denominated in units of final goods.

3.2 Firms

There are five types of goods produced in the economy: final goods, a tradable composite good, manufactures, commodities, and non-tradable goods. The tradable composite combines manufactures and commodities, while final goods are a composite good that combines tradable and non-tradable goods. Each good is produced by a representative firm.

3.2.1 Production of final goods

A representative firm produces final goods using a constant elasticity of substitution (CES) production function. To do so, it uses a tradable composite good and non-tradable goods as inputs. The demands for these goods are denoted by $X_{\tau,t}$ and $X_{n,t}$, respectively, and the production function is given by

$$G\left(X_{\tau,t}, X_{n,t}\right) = \left[\eta X_{\tau,t}^{\frac{\sigma-1}{\sigma}} + (1-\eta) X_{n,t}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

where σ is the elasticity of substitution between the two inputs,[14] and η determines the relative weight of tradable and non-tradable goods.

The representative producer of final goods takes the prices of the two inputs as given and solves the following problem:

$$\max_{X_{\tau,t}, X_{n,t} \geq 0} p_t G\left(X_{\tau,t}, X_{n,t}\right) - p_{\tau,t} X_{\tau,t} - p_{n,t} X_{n,t}, \tag{5}$$

where $p_{n,t}$ is the price of non-tradable goods. The solution to the final goods producers' problem determines the price level p_t, which is given by $p_t = \left[\eta^{\sigma} p_{\tau,t}^{1-\sigma} + (1-\eta)^{\sigma} p_{n,t}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$.

3.2.2 Production of tradable composite

A representative firm produces a tradable composite by combining manufactures and commodities purchased from domestic or international markets using

[14] For $\sigma = 1$, the final goods production function is Cobb-Douglas.

a CES production function. The demands for these goods are denoted by $X_{m,t}$ and $X_{c,t}$, respectively, and the production function is given by

$$H\left(X_{m,t},X_{c,t}\right) = \left[\eta_\tau X_{m,t}^{\frac{\sigma_\tau-1}{\sigma_\tau}} + (1-\eta_\tau)X_{c,t}^{\frac{\sigma_\tau-1}{\sigma_\tau}}\right]^{\frac{\sigma_\tau}{\sigma_\tau-1}}, \tag{6}$$

where σ_τ is the elasticity of substitution between the two inputs[15] and η_τ determines the relative weight of manufactures and commodities.

The representative producer takes the prices of the two inputs as given and solves the following problem:

$$\max_{X_{m,t},X_{p,t}\geq 0} p_{\tau,t}H\left(X_{m,t},X_{c,t}\right) - p_{m,t}X_{m,t} - p_{c,t}X_{c,t}, \tag{7}$$

where $p_{i,t}$ is the price of input $i \in \{m,c\}$. The solution to the problem for the producer of the tradable composite good determines its price $p_{\tau,t}$, which is given by $p_{\tau,t} = \left[\eta_\tau^{\sigma_\tau} p_{m,t}^{1-\sigma_\tau} + (1-\eta_\tau)^{\sigma_\tau} p_{c,t}^{1-\sigma_\tau}\right]^{\frac{1}{1-\sigma_\tau}}$.

3.2.3 Production of manufactures, commodities, and non-tradables

In each sector $x \in \{m,c,n\}$, a representative firm produces sector-specific goods using capital and labor with a decreasing returns to scale production technology.[16] For sector $x \in \{m,c,n\}$, the amount $Y_{x,t}$ produced is given by

$$Y_{x,t} = A_x Z_t \left(K_{x,t}^{\theta_x} N_{x,t}^{1-\theta_x}\right)^{\mu_x}, \tag{8}$$

where Z_t is a time-varying Hicks-neutral level of productivity that affects all sectors, A_x is a sector-specific and time-invariant level of productivity, $\theta_x \in [0,1]$ controls the share of capital in production, and $\mu_x \in (0,1)$ determines the degree of decreasing returns to scale.

The representative firm takes the prices of its output and factor inputs as

[15] For $\sigma_\tau = 1$, the production function for the tradable composite good is Cobb-Douglas.

[16] We assume that firms operate decreasing returns to scale technologies to ensure that, in equilibrium, we have a non-degenerate distribution of output across sectors for any combination of sectoral prices.

given and maximizes profits by solving

$$\max_{N_{x,t},K_{x,t}\geq 0} \pi_{x,t} = p_{x,t}Y_{x,t} - w_{x,t}N_{x,t} - r_{x,t}K_{x,t}. \tag{9}$$

The total amount of profits transferred to the households is then given by $\Pi_t = \pi_{m,t} + \pi_{c,t} + \pi_{n,t}$.

3.3 Productivity

The process for the time-varying level of productivity Z_t is given by

$$\log Z_t = \rho_z \log Z_{t-1} + \varepsilon_{z,t}, \tag{10}$$

where ρ_z denotes the persistence of productivity and $\varepsilon_{z,t} \sim N(0, \sigma_z^2)$.

3.4 International prices

We choose the price of manufactured goods to be the numeraire and set $p_{m,t} = 1$. The small open economy trades manufactures and commodities in international markets and takes the relative price of commodities $p_{c,t}$ as given exogenously. The process for this relative price is given by

$$\log p_{c,t} = \rho_c \log p_{c,t-1} + \varepsilon_{c,t}, \tag{11}$$

where ρ_c is the persistence of shocks to the relative price, and $\varepsilon_{c,t} \sim N(0, \sigma_c^2)$.

3.5 Interest rates and country risk

The bond price is measured in units of the tradable composite and is given by

$$\frac{1}{q_t} = 1 + r_t + \psi_r \left[e^{-\left(\tilde{B}_{t+1} - b\right)} - 1 \right], \tag{12}$$

where r_t is a country-specific interest rate. The last term in the equation ensures the stationarity of bond holdings, following Schmitt-Grohé and Uribe (2003), by making the bond price sensitive to the aggregate per capita level of foreign debt $\tilde{B}_{t+1}$ relative to the steady-state level $b \in \mathbb{R}$.[17] $\psi_r > 0$ determines

[17] Given the representative household assumption, $\tilde{B}_{t+1} = B_{t+1}$ in equilibrium.

the elasticity of the interest rate to changes in the debt level.

The interest rate r_t is a function of both the world interest rate r^* and a country-specific spread S_t.[18] The interest rate is then given by:

$$\ln(1+r_t) = \ln(1+r^*) + \ln S_t$$
$$\ln S_t = \eta_{\mathrm{GDP}} \ln\left(\frac{\mathrm{GDP}_t}{\mathrm{GDP}}\right),$$

where η_{GDP} determines the impact of changes in domestic economic activity (relative to steady-state) on the economy's borrowing costs in international financial markets.[19] This formulation is similar to the specification of interest rate spreads used by Chang and Fernández (2013), Neumeyer and Perri (2005), and Drechsel and Tenreyro (2017), among others. In contrast to these papers, we assume that spreads are driven by movements in GDP rather than solely by productivity or commodity price shocks. Differences in η_{GDP} across emerging and developed countries then provide a way to capture differences in the extent to which international borrowing costs depend on domestic conditions across countries at different stages of development.

3.6 Market clearing conditions

Market clearing in the manufacturing and commodity sectors requires that the amount of goods purchased by the producer of the tradable composite good equals the sum of domestic production and net imports of these goods. We let $M_{i,t}$ be the net amount imported in sector $i \in \{m, c\}$. $M_{i,t} > 0$ (< 0) implies that goods are imported (exported). The market clearing condition in sector i is then given by

$$X_{i,t} = Y_{i,t} + M_{i,t}. \tag{13}$$

For the non-tradable goods, tradable composite good, and final goods,

[18] We assume that the world interest rate is constant and determined by $\beta = 1/(1+r^*)$ to ensure the existence of a steady state.

[19] GDP_t is given by $p_{m,t}Y_{m,t} + p_{c,t}Y_{c,t} + p_{n,t}Y_{n,t}$.

demand has to equal domestic production:

$$X_{n,t} = Y_{n,t} \tag{14}$$

$$X_{\tau,t} = H\left(X_{m,t}, X_{c,t}\right) \tag{15}$$

$$C_t + I_t + \sum_{x\in\{m,c\}} \frac{\phi_N^X}{2}\left(\frac{N_{x,t}}{N_t} - \frac{N_{x,t-1}}{N_{t-1}}\right)^2 = G\left(X_{\tau,t}, X_{n,t}\right). \tag{16}$$

Finally, market clearing in the capital and labor markets requires that the amount of capital and labor supplied by the household equals the total demand by the producers of manufactures, commodities, and non-tradable goods:

$$K_t = \sum_{x\in\{m,c,n\}} K_{x,t} \tag{17}$$

$$N_t = \sum_{x\in\{m,c,n\}} N_{x,t}. \tag{18}$$

3.7 Definition of equilibrium

Given the international interest rate r^*, the productivity process in equation (10), and the process for the relative price of commodities in equation (11), an equilibrium of this economy consists of a set of aggregate allocations C_t, I_t, N_t, K_t, B_t, $X_{\tau,t}$, and NX_t; a set of sectoral allocations $N_{x,t}$, $K_{x,t}$, $X_{x,t}$, $Y_{x,t}$ for $x \in \{m,c,n\}$, and $M_{i,t}$ for $i \in \{m,c\}$; and prices q_t, p_t, $p_{\tau,t}$, $p_{n,t}$ $w_{x,t}$, and $r_{x,t}$ for $x \in \{m,c,n\}$ such that (*i*) given prices, the households' allocations solve the households' problem; (*ii*) given prices, the allocations of producers of manufactured goods, commodities, and non-tradable goods solve the producers' respective problems; (*iii*) given prices, the tradable composite goods producers' allocations solve the tradable composite goods producers' problem; (*iv*) given prices, the final goods producers' allocations solve the final goods producers' problem; and (*v*) markets clear.

4 Mechanism

In this section, we investigate the channels through which international relative prices affect real GDP in our model. To do so, we begin by describing our measurement of real GDP and defining a measure of TFP. We then discuss a special case that shows that our measure of TFP can be decomposed into an exogenous component driven by the process in equation (10) and an endogenous component driven by the reallocation of resources across sectors. Finally, we investigate the impact of changes in international relative prices on factors of production and aggregate productivity.

4.1 Real GDP

Real GDP is defined as the ratio between nominal GDP and the GDP deflator: Real $\text{GDP}_t = \frac{\text{GDP}_t}{P_t^{\text{GDP}}}$, where GDP_t is given by $p_{m,t}Y_{m,t}+p_{c,t}Y_{c,t}+p_{n,t}Y_{n,t}$ following the value-added approach.

To derive an expression of real GDP consistent with its empirical counterpart, we restrict attention to the GDP deflator as measured by statistical agencies. In particular, we follow the approach of the World Bank's Development Indicators (our source of data throughout the paper) and compute the GDP deflator as a Paasche index, defined as the ratio between GDP measured at current prices relative to GDP measured at base-year prices:

$$P_t^{\text{GDP}} = \frac{p_{m,t}Y_{m,t} + p_{c,t}Y_{c,t} + p_{n,t}Y_{n,t}}{p_{m,ss}Y_{m,t} + p_{c,ss}Y_{c,t} + p_{n,ss}Y_{n,t}},$$

where we define base-year prices to be given by their values in the deterministic steady state, denoted with the ss subscript.

Combining the expressions above, we have that real GDP is given by

$$\text{Real GDP}_t = p_{m,ss}Y_{m,t} + p_{c,ss}Y_{c,t} + p_{n,ss}Y_{n,t}. \tag{19}$$

Finally, we define TFP by expressing real GDP as a function of the aggregate capital stock and labor supply:

$$\text{Real GDP}_t = \text{TFP}_t K_t^{KS} N_t^{LS}, \tag{20}$$

where K_t denotes the aggregate stock of physical capital, N_t denotes the aggregate supply of labor, and KS and LS are, respectively, the capital and labor shares in the deterministic steady state.[20]

Under certain restrictions on the parameters, we can obtain a simple analytic expression for TFP. In particular, if we require that the capital intensities and returns to scale are equal across sectors (θ and μ, respectively), then the aggregate capital and labor shares are constant and equal to the shares in each sector. That is, the aggregate steady-state shares in equation (20) are then given by $KS = \theta\mu$ and $LS = (1-\theta)\mu$. We can then use the real GDP and TFP equations along with the sectoral production functions to express TFP as

$$\begin{aligned}\text{TFP}_t = Z_t \Bigg[& p_{m,ss} A_m \left(\frac{K_{m,t}}{K_t}\right)^{KS} \left(\frac{N_{m,t}}{N_t}\right)^{LS} \\ & + p_{c,ss} A_c \left(\frac{K_{c,t}}{K_t}\right)^{KS} \left(\frac{N_{c,t}}{N_t}\right)^{LS} + p_{n,ss} A_n \left(\frac{K_{n,t}}{K_t}\right)^{KS} \left(\frac{N_{n,t}}{N_t}\right)^{LS} \Bigg].\end{aligned} \tag{21}$$

That is, in this case, real GDP in our economy can be represented as an aggregate production function that uses aggregate capital and labor as its inputs, where TFP can be decomposed into an exogenous component Z_t and an endogenous component that depends on the shares of aggregate labor and capital allocated to each sector. Reallocation of resources across sectors thus affects measured TFP through this endogenous component. As a result, our economy features five alternative sources of real GDP fluctuations: (*i*) changes in the aggregate stock of physical capital, (*ii*) changes in the aggregate supply

[20] In particular, we define $KS = \frac{r_{m,ss}K_{m,ss}+r_{c,ss}K_{c,ss}+r_{n,ss}K_{n,ss}}{p_{m,ss}Y_{m,ss}+p_{c,ss}Y_{c,ss}+p_{n,ss}Y_{n,ss}}$ and $LS = \frac{w_{m,ss}N_{m,ss}+w_{c,ss}N_{c,ss}+w_{n,ss}N_{n,ss}}{p_{m,ss}Y_{m,ss}+p_{c,ss}Y_{c,ss}+p_{n,ss}Y_{n,ss}}$.

of labor, (*iii*) changes in the allocation of physical capital across sectors, (*iv*) changes in the allocation of labor across sectors, and (*v*) changes in exogenous productivity. While (*i*) and (*ii*) affect real GDP through the factors of production, (*iii*)-(*v*) affect it through TFP.[21]

4.2 International Relative Prices and Factors of Production

The expressions above show that changes in international relative prices may affect real GDP through two broad channels: either by affecting the factors of production or aggregate productivity. In this subsection, we show that the extent to which changes in international relative prices affect capital and labor depends on the degree to which they impact the production price index (PPI) relative to the consumption price index (CPI). To simplify the exposition, here we restrict attention to economies that operate under international financial autarky and we ignore the sectoral reallocation cost on labor.

Plugging the profits of sectoral producers into the household's budget constraint and using the results above, we have that $C_t + I_t = \frac{P_t^{\text{PPI}}}{P_t^{\text{CPI}}} \times \text{Real GDP}_t$, where P_t^{PPI} denotes the PPI given by the GDP deflator P_t^{GDP}, defined above, and P_t^{CPI} denotes the consumption (and investment) price index p_t faced by households.

This expression shows that the mapping between real GDP and aggregate consumption and investment depends on the relative price between production and consumption baskets. In particular, the relative price between goods produced and consumed regulates the returns to supplying additional units of labor as well as the extent to which output can be used to accumulate physical capital.

To illustrate these effects, consider the response of two counter-factual economies to a persistent increase in the price of commodities $p_{c,t}$. The first economy only produces commodities but consumes commodities, manufactures

[21] In our baseline calibration, we impose that the degree of returns to scale is the same across sectors but we allow capital intensities to differ. Therefore, while the decomposition in equation (21) does not hold, it is still the case that sectoral reallocation of resources affects measured TFP.

and non-tradables. In this economy, the relationship above boils down to

$$C_t + I_t = \frac{p_{c,t}}{P_t^{\text{CPI}}} \times \text{Real GDP}_t.$$

Thus, in this economy, an increase in the price of commodities $p_{c,t}$ triggers an increase in the price of production relative to consumption. Therefore, with a higher price of commodities, every unit produced can be transformed into physical capital and consumption at a higher rate, increasing the incentives to accumulate capital and supply labor.

The second economy only produces and consumes commodities. In this economy, the relationship above boils down to $C_t + I_t = \text{Real GDP}_t$. That is, changes in the price of commodities have no impact on equilibrium allocations. In contrast to the first economy, an increase in the price of commodities now increases the value of the production and consumption baskets by equal amounts; thus, the rate at which output may be transformed into consumption or investment goods remains unchanged and so do the returns to labor supply.

We conclude that the relative composition of consumption and production baskets play a fundamental role in the extent to which changes in international relative prices may affect capital accumulation and labor supply. In the model, the composition of consumption and production baskets is determined by the shares of value added in each of the sectors and the sectoral trade imbalances. In the quantitative section of the paper, we examine their impact on real GDP volatility.

4.3 International Relative Prices and Aggregate Productivity

We now examine the impact of changes in international relative prices on aggregate TFP. In equation (21), changes in international prices may only affect aggregate TFP insofar as they trigger changes in the share of capital and labor that is allocated across sectors. Thus, we now investigate the extent to which changes in international relative prices may lead to reallocation of production inputs across sectors.

To do so, we consider the response of two counter-factual economies to a persistent increase in the price of commodities $p_{c,t}$. The first economy produces non-tradables, commodities, and manufactures. In this economy, an increase in the price of commodities increases the returns to selling commodities relative to non-tradables or manufactures; thus, it triggers a reallocation of production inputs towards this sector. This response of the economy leads to a change in aggregate TFP, as implied by equation (21).

The second economy specializes in the production of commodities, and produces no non-tradables or manufactures. In this economy, aggregate TFP is given by $\text{TFP}_t = Z_t$. Thus, changes in international relative prices have no impact on aggregate TFP in this one-sector economy.

We conclude that the impact of international price movements on aggregate TFP depends crucially on the extent to which these trigger a reallocation of production inputs across sectors. In the following sections, we discipline the impact of international relative prices on aggregate TFP by estimating sectoral reallocation costs to capture the degree of cross-sectoral reallocation observed in the data.

In contrast to Kehoe and Ruhl (2008), we find that changes in the terms of trade may impact aggregate TFP as long as they are associated with the reallocation of production inputs across sectors. Thus, the distinguishing feature of our analysis is the existence of multiple sectors across which economic activity may reallocate in response to shocks. As we show above, in a one-sector version of our model, we find that terms-of-trade shocks do not impact aggregate TFP, as previously documented by Kehoe and Ruhl (2008). In Section 5.6 below, we investigate the importance of endogenous TFP fluctuations in accounting for business cycle volatility.

5 Quantitative Analysis

Following our discussion in the previous section, differences in the sectoral composition of production and trade between developed and emerging economies may affect how aggregate output responds to changes in international relative prices through two channels. First, the aggregate supply of capital and labor may respond to changes in the relative price between goods consumed and produced (Section 4.2). Second, aggregate TFP may respond to changes in the distribution of capital and labor across sectors (Section 4.3). In this section, we investigate the extent to which differences in the sectoral composition of production and trade can account for the higher business cycle volatility of emerging economies observed in the data.

To do so, we consider the model presented in Section 3 and estimate two economies: an emerging and a developed economy. We contrast the implications of these economies with those of counter-factual economies designed to isolate the impact on business cycle volatility of cross-sectoral differences in the composition of production and trade. We then investigate the differential impact of commodity price fluctuations across these economies as well as the relative role of the two channels described above.

5.1 Calibration

We now calibrate two economies: an emerging and a developed economy. To parameterize these economies, we partition the parameter space into three groups. The first group consists of predetermined parameters set to standard values from the literature. The second group consists of the parameters of the stochastic process for international relative prices, which are externally estimated. Finally, the third group is estimated jointly via simulated method of moments (SMM) to match salient features of the data. The first two groups of parameters are common across the two economies, while the latter group of parameters is economy-specific.

Unless otherwise specified, the data used to parameterize the model corresponds to the data sources described in Section 2 and in Section 1 of the Online Appendix. In particular, we classify countries as "Developed" or "Emerging" following our discussion in Section 2 and compute the relevant moments as averages across the countries in these groups.

5.1.1 Predetermined parameters

Panel A of Table 2 shows the set of predetermined parameters. These include the preference parameters, borrowing costs in international financial markets, and most of the technology parameters in the production functions for sectoral and final goods. A period in the model represents a quarter. We set the discount factor β to 0.98 and the risk aversion parameter γ to 2 as in Aguiar and Gopinath (2007). It follows that the world interest rate r^* that is consistent with a steady-state equilibrium is 2%. We set the parameter ν, that controls the elasticity of labor supply, equal to 1.455 as in Mendoza (1991) and Schmitt-Grohé and Uribe (2018). The parameter ψ_r that controls the debt elasticity of the interest rate is set to 0.001.[22]

We set the elasticity of substitution σ between tradable and non-tradable goods to 0.5, a value that falls well within the range estimated by Akinci (2017) and Stockman and Tesar (1995). We set the elasticity of substitution σ_τ between commodities and manufactures in the production of tradable goods to 1; that is, we assume Cobb-Douglas aggregation following numerous studies of multi-industry models of international trade such as Caliendo and Parro (2015) and Costinot and Rodríguez-Clare (2014). We follow Schmitt-Grohé and Uribe (2018) and set $\theta_m = \theta_c = 0.35$ and $\theta_n = 0.25$. We set μ_x to 0.85 across all sectors following Midrigan and Xu (2014) and Atkeson and Kehoe (2007). The capital depreciation rate δ is set to 0.05. Finally, we normalize the steady-state productivity in the production of commodities $A_c = 1$, and set the productivity of non-tradable goods $A_n = 1$.[23]

5.1.2 Price process

As described in Section 3, we let the price of manufacturing goods be the numeraire and specify a stochastic process to determine the evolution of commodity prices $p_{c,t}$. Then, we use data on the price of commodities relative to the price of manufactures to estimate this process.

To do so, we follow Gubler and Hertweck (2013) and use data from the "Producer Price Index - Commodity Classification" published by the Bureau of Labor Statistics. For commodity prices, we use the "PPI by Commodity

[22] We set this parameter to a sufficiently low value to ensure the stationarity of the model without affecting its implications for business cycles.

[23] In Section 4 of the Online Appendix, we study the sensitivity of our findings to alternative values of these parameters.

Table 2: Predetermined parameters

Parameter	Value	Source
β	0.98	Aguiar and Gopinath (2007)
γ	2	Aguiar and Gopinath (2007)
ν	1.455	Schmitt-Grohé and Uribe (2018)
σ	0.5	See Section 5.1.1
σ_τ	1	See Section 5.1.1
θ_n	0.25	Schmitt-Grohé and Uribe (2018)
$\theta_m = \theta_c$	0.35	Schmitt-Grohé and Uribe (2018)
μ	0.85	See Section 5.1.1
ψ_r	0.001	See Section 5.1.1
r^*	0.02	$1/\beta - 1$
δ	0.05	Aguiar and Gopinath (2007)
ρ_c	0.957	See Section 5.1.2
σ_c	0.059	See Section 5.1.2

for Crude Materials for Further Processing" index. As they discuss in detail, this index captures much of the variation in commodity prices of alternative indexes and is available for a longer time period.[24] For the price of manufactured goods we use the "PPI by Commodity for Finished Goods Less Food & Energy" index. This index is only available starting in 1974, so we estimate the parameters in equation (11) using data from the first quarter of 1974 to the last quarter of 2016.

We estimate this process via ordinary least squares (OLS). The bottom panel of Table 2 reports our estimates.

5.1.3 Jointly estimated parameters

We assume that all the aforementioned parameters are common across emerging and developed economies. For each of these economies, we estimate the remaining economy-specific parameters jointly via SMM. Table 3 and Table 4 report these parameters for the emerging and the developed economy, respectively.

[24] In addition, Gubler and Hertweck (2013) point out that this index is also used by Hanson (2004) and Sims and Zha (2006).

Time-series targets The top panel in Tables 3 and 4 presents the parameters used to target salient features of business cycles in emerging and developed economies. The parameters that we choose are the standard deviation σ_z and the persistence ρ_z of the productivity process; the sectoral and aggregate adjustment costs ϕ_N^X, ϕ_K^X, and ϕ_K; and the elasticity of interest rates to changes in economic activity η_{GDP}. The tables report the estimated parameters along with the target and model-implied moments at an annual frequency; we annualize the simulated series from our quarterly model before computing the corresponding moments.[25]

We choose the parameters of the productivity process to target the volatility and autocorrelation of real GDP. Therefore, our parametrization of the emerging and developed economies will feature business cycles that are as volatile as those in the data. The aggregate capital adjustment cost ϕ_K allows us to discipline the volatility of aggregate investment relative to real GDP. We do so to discipline the extent to which investment may respond to changes in the relative prices of consumption and production goods, a potentially important channel through which changes in international relative prices may affect aggregate output (Section 4.2).

The sectoral adjustment costs ϕ_N^X and ϕ_K^X allow us to discipline the degree of cross-sectoral reallocation of production inputs, and thus output, featured by the economies in response to aggregate shocks. Given the limited availability of time-series data on sectoral inputs across countries, we assume that $\phi_N^X = \phi_K^X$ and choose them to match the standard deviation of the log of the share of manufacturing output in aggregate GDP. Thus the sectoral adjustment costs control the extent to which international price movements affect aggregate TFP (Section 4.3).

As in Chang and Fernández (2013) and others, the elasticity of interest rates to changes in economic activity η_{GDP} allows us to discipline the cyclicality

[25]We solve the model using perturbation methods to compute a second-order approximation around the deterministic steady state. We compute 100 simulations of 188 quarters by simulating 1188 quarters starting at the steady state and dropping the initial 1000 periods. We annualize the simulations, detrend them using the HP-filter as we do in the data, and compute the average moments across the simulations.

Table 3: Estimated parameters: Emerging Economy

Parameter	Value	Target moment	Data	Model
		Time-series targets		
σ_z	0.012	Std. dev. real GDP	4.23	4.21
ρ_z	0.930	Autocorrelation real GDP	0.55	0.64
ϕ_K	7.669	Std. dev. investment / Std. dev. real GDP	3.90	3.89
$\phi_K^X = \phi_N^X$	99.219	Std. dev. share of manufactures in GDP	0.20	0.27
η_{GDP}	-0.084	Corr(NX/GDP,GDP)	-0.20	-0.21
		Std. dev. consumption / Std. dev. real GDP	1.34	1.28
		Std. dev. NX/GDP	3.44	3.45
		Cross-sectional targets		
A_m	0.890	Avg. share of manufactures in GDP	0.152	0.153
η	0.396	Avg. share of commodities in GDP	0.332	0.332
η_τ	0.471	Avg. manufactures NX/GDP	-0.107	-0.107
b	0.984	Avg. aggregate NX / GDP	-0.067	-0.067
ψ_u	0.401	Share of labor endowment used to work	—	1/3

of the trade balance. Finally, we target two additional business cycle moments that characterize salient dimensions along which business cycles in emerging economies differ from those of their developed counterparts. In particular, following Aguiar and Gopinath (2007), we target the standard deviation of consumption relative to the standard deviation of GDP, as well as the standard deviation of the net exports to GDP ratio.[26]

Cross-sectional targets We complete the parametrization of the emerging and developed economies by choosing the five remaining economy-specific parameters, A_m, η, η_τ, b, and ψ_u to match salient cross-sectional features. The bottom panel in Tables 3 and 4 presents the parameter values as well as the empirical and model-implied moments.

In particular, we choose A_m, η, η_τ, and b such that the steady states of these economies account for the following features reported in Table 1: (*i*) the average share of commodities in aggregate GDP, (*ii*) the average share of manufactures in aggregate GDP, (*iii*) the average net exports of manufactures

[26] Our estimation approach is, thus, overidentified as it features two more moments than parameters.

Table 4: Estimated parameters: Developed Economy

Parameter	Value	Target moment	Data	Model
		Time-series targets		
σ_z	0.0074	Std. dev. real GDP	2.25	2.26
ρ_z	0.909	Autocorrelation real GDP	0.58	0.59
ϕ_K	2.602	Std. dev. investment / Std. dev. real GDP	3.30	3.30
$\phi_K^X = \phi_N^X$	75.633	Std. dev. share of manufactures in GDP	0.19	0.19
η_{GDP}	-0.060	Corr(NX/GDP,GDP)	-0.28	-0.26
		Std. dev. consumption / Std. dev. real GDP	0.96	0.99
		Std. dev. NX/GDP	1.39	1.38
		Cross-sectional targets		
A_m	1.039	Avg. share of manufactures in GDP	0.188	0.188
η	0.152	Avg. share of commodities in GDP	0.146	0.146
η_τ	0.570	Avg. manufactures NX/GDP	-0.005	-0.005
b	0.096	Avg. aggregate NX / GDP	-0.005	-0.005
ψ_u	0.558	Share of labor endowment used to work	—	1/3

relative to GDP, and (*iv*) the average aggregate net exports to GDP ratio.[27] We choose ψ_u such that the household's steady-state share of time endowment devoted to work is equal to 1/3.

As can be seen in Tables 3 and 4, these five parameters allow us to match the five targets exactly. Intuitively, the productivity of the manufacturing sector A_m allows us to discipline the share of manufactures in aggregate GDP. Similarly, the share of non-tradables in the production of final goods η allows us to match the share of commodities (and tradables) in aggregate GDP.

Given the patterns of production implied by these parameters, the remaining two parameters allow us to discipline the sectoral and aggregate trade imbalances of the economy. First, the share of manufactures in the production of tradable goods η_τ controls the relationship between domestic demand and domestic production of manufactures; or, in other words, the sectoral trade imbalance in manufactures. Second, the steady-state level of bond-holdings controls the magnitude of aggregate trade imbalances that the economy needs to run to sustain such a financial position.

[27]Note that avg. manufactures NX/GDP + avg. commodities NX/GDP = avg. aggregate NX/GDP. Thus, insofar as our model matches moments (*iii*) and (*iv*), then it also matches the avg. commodities NX/GDP observed in the data.

5.2 Business cycle moments

We begin by contrasting salient features of business cycle fluctuations implied by our estimated economies with their empirical counterparts. In particular, we contrast the standard deviation, correlation with GDP, and autocorrelation of the following variables: real GDP, the net exports to GDP ratio, consumption, investment, labor, TFP, and commodity prices.[28,29]

Panel A of Table 5 reports the volatility of these variables. We observe that, as a result of our estimation approach, our estimated emerging and developed economies account well for the volatility of real GDP, consumption, investment, the net exports to GDP ratio and commodity prices observed in the data. Moreover, the estimated economies imply labor volatilities of a similar magnitude as in the data; however, our model features TFP fluctuations that are less volatile than their empirical counterpart.[30]

As shown in Panel B of the table, the cyclicality of these variables is also similar between our estimated economies and their empirical counterpart. Two exceptions are the cyclicality of labor and TFP, which are relatively more procyclical in our model than in the data. Finally, Panel C shows that our estimated economies can match the autocorrelation of these variables.

We conclude that our estimated economies can successfully account for salient features of business cycle fluctuations across emerging and developed economies.

5.3 Results

We now investigate the extent to which differences in the cross-sectional patterns of production and trade between emerging and developed economies account for the higher business cycle volatility of emerging economies. To do

[28] To ensure the comparability of results across economies, we use the same sequences of shocks to simulate each of the economies.

[29] All data series are as described in Section 2 except for labor (employment) and TFP which are obtained from the Penn World Tables 9.0.

[30] the standard deviation and autocorrelation of commodity prices are estimated at quarterly frequency but we report business cycle moments at annual frequency. This explains differences in the commodity price series between the model and the data.

Table 5: Business Cycle Moments

	GDP	NX/GDP	C	I	N	TFP	p_c
A. Volatility							
	Std. dev. (%)		Std. dev. relative to GDP				
	GDP	NX/GDP	C	I	N	TFP	p_c
			Emerging				
Data	4.23	3.44	1.34	3.90	0.57	0.96	5.01
Model	4.21	3.45	1.28	3.89	0.81	0.43	3.97
			Developed				
Data	2.25	1.39	0.96	3.30	0.78	0.70	9.41
Model	2.26	1.38	0.99	3.30	0.74	0.47	7.40
B. Correlation with GDP							
	GDP	NX/GDP	C	I	N	TFP	p_c
			Emerging				
Data	1.00	-0.20	0.61	0.65	0.22	0.77	0.11
Model	1.00	-0.21	0.76	0.79	0.95	0.79	0.24
			Developed				
Data	1.00	-0.28	0.72	0.83	0.68	0.69	0.10
Model	1.00	-0.26	0.90	0.82	0.98	0.88	0.11
C. Autocorrelation							
	GDP	NX/GDP	C	I	N	TFP	p_c
			Emerging				
Data	0.55	0.31	0.38	0.49	0.50	0.52	0.85
Model	0.64	0.57	0.58	0.55	0.60	0.50	0.82
			Developed				
Data	0.58	0.38	0.54	0.64	0.73	0.51	0.85
Model	0.59	0.58	0.59	0.55	0.58	0.47	0.82

Note: For net exports we compute the standard deviation of NX/GDP. For other variables X we compute the standard deviation of log(X) and divide by the standard deviation of log(GDP).

so, we contrast the implications of our estimated economies, described in the previous subsections, with counter-factual economies designed to isolate the role of differences in the cross-sectional patterns of production and trade.

In the top panel of Table 6, we consider our estimated emerging economy and investigate the extent to which the structure of production and trade affects its business cycle volatility. In particular, we consider a counter-factual

Table 6: Real GDP Volatility (%)

Emerging economy	4.21
With developed economy's structure of production and trade	
Real GDP volatility	3.63
Share of volatility gap explained	29%
Developed economy	2.26
With emerging economy's structure of production and trade	
Real GDP volatility	3.03
Share of volatility gap explained	39%

emerging economy with the same production and trade structure as the developed economy. In particular, the time-series parameters described in the first panel of Table 3 are kept fixed, but the cross-sectional parameters are recalibrated to match the developed economy's targets from the second panel of Table 4.[31]

The first row of Table 6 shows that our estimated emerging economy features the same standard deviation of real GDP as in the data. This is by construction, given that the parameters that govern the stochastic process for aggregate productivity are chosen to match the volatility and autocorrelation of real GDP in this economy.

The second row of Table 6 reports the business cycle volatility implied by our counter-factual emerging economy. We find that the standard deviation of real GDP decreases from 4.21% in our estimated emerging economy to 3.63% in the counter-factual emerging economy featuring the developed economy's structure of production and trade. That is, our model implies that differences in the cross-sectional patterns of production and trade can account for 29% of the business cycle volatility gap between emerging and developed economies.[32]

In the bottom panel of Table 6, we conduct a similar analysis of the

[31] In particular, we recalibrate A_m, η, η_τ, and b such that our counter-factual emerging economy accounts for the first four cross-sectional targets described in Table 4. We keep the preference parameter ψ_u unchanged, but our results are robust to recalibrating it.

[32] That is, $29\% = 100 \times \frac{(4.21-3.63)}{(4.23-2.26)}$, where the values in the denominator are those observed in the data.

relationship between the production and trade structure and business cycle volatility for our estimated developed economy. In particular, we consider a counter-factual developed economy that features the same production and trade structure as the emerging economy. The time-series parameters described in the first panel of Table 4 are kept fixed, but the cross-sectional parameters are recalibrated to match the emerging economy's targets from the second panel of Table 3.

The second row in the bottom panel of Table 6 reports the business cycle volatility implied by our counter-factual developed economy. We find that real GDP volatility increases from 2.26% in our estimated developed economy to 3.03% in the counter-factual economy featuring the emerging economy's structure of production and trade. That is, this exercise implies that differences in the cross-sectional patterns of production and trade can account for 39% of the business cycle volatility gap observed between emerging and developed economies.

We conclude that differences in the patterns of production and trade between emerging and developed economies can account for a substantial fraction of the volatility differences between them.[33] between emerging and developed economies in our model. In In the rest of this section, we investigate the key channels that account for these findings. In Section 6, we investigate the extent to which cross-sectional differences across individual countries — rather than country aggregates — account for country-by-country differences in business cycle volatility.

[33]In Section 3.3 of the Online Appendix, we complement this analysis by decomposing the output volatility gap among all its model determinants: cross-sectional moments, productivity process and adjustment costs, and sensitivity of interest rates to GDP fluctuations. We find that differences in the productivity process between emerging and developed economies account for an additional 33% to 49%, whereas differences in the process for interest rates account for an additional 15% to 33%.

Table 7: Real GDP Volatility Gap Decomposition (%)

	Std. dev.	Share of volatility gap
Emerging economy	4.21	—
With developed economy's features		
Mfct. NX/GDP	3.84	19%
Mfct. NX/GDP and non-tradable share	3.66	28%
Structure of production and trade	3.63	29%
Developed economy	2.26	—
With emerging economy's features		
Mfct. NX/GDP	2.56	15%
Mfct. NX/GDP and non-tradable share	2.82	28%
Structure of production and trade	3.03	39%

5.4 Which cross-sectional features are key in accounting for volatility differences between emerging and developed countries?

In the preceding analysis, the estimated and counter-factual economies are assumed to be identical except for the parameters that control the cross-sectional target moments. In this subsection, we investigate which of these differences are most important in accounting for the difference in volatility between them.[34]

We begin by examining the role played by sectoral trade imbalances. The second row in the top panel of Table 7 presents the business cycle volatility of a counter-factual economy that is almost identical to our estimated emerging economy, but where one of the cross-sectional targets is changed in the calibration of the cross-sectional parameters. These parameters are recalibrated to match (*i*) the net exports of manufactures to GDP ratio featured by developed economies, and (*ii*) the remaining cross-sectional moments of emerging economies.[35] All other parameters are kept unchanged at the values reported in Table 3. The second row in the bottom panel of Table 7 presents the implications of the analogous experiment for the developed economy.

The first column of Table 7 presents the volatility of real GDP correspond-

[34] See Section 3.2 of the Online Appendix for more details on the parametrization of each of these economies.

[35] Except for the preference parameter ψ_u which is kept fixed at its baseline value.

ing to each of these economies. We find that sectoral trade imbalances play a key role in accounting for differences between the estimated and the counter-factual economies examined in Table 6. In particular, recalibrating our estimated emerging economy to match the sectoral trade imbalance featured by developed economies reduces its real GDP volatility from 4.21% to 3.84%, explaining 66% of the volatility gap accounted for by the overall difference in the structure of production and trade. Similarly, recalibrating our estimated developed economy to match the sectoral trade imbalance of emerging economies increases the volatility of real GDP from 2.26% to 2.56%, explaining 38% of the volatility gap accounted for by the overall cross-sectional differences.

We then examine the cumulative role played by differences in the share of non-tradable goods between emerging and developed economies. The third row in the top panel of Table 7 presents the business cycle volatility implied by a counter-factual economy where the cross-sectional parameters are recalibrated to match (*i*) the net exports of manufactures to GDP ratio featured by developed economies, (*ii*) the share of non-tradable goods featured by developed economies, and (*iii*) the remaining cross-sectional moments of emerging economies. All other parameters are kept unchanged at the values reported in Table 3. The third row in the bottom panel of Table 7 presents the implications of conducting the analogous experiment based on the developed economy.

We find that the share of non-tradable goods also plays a significant role in accounting for the real GDP volatility differences between the estimated and the counter-factual economies. In particular, we find that recalibrating our estimated emerging economy to match both the sectoral trade imbalances and the share of non-tradable goods in developed economies reduces real GDP volatility from 4.21% to 3.66%. Thus, these two cross-sectional targets jointly explain 97% of the volatility gap accounted for by differences in the structure of production and trade. Similarly, recalibrating our estimated developed economy to also match the share of non-tradables of emerging economies increases the volatility of real GDP from 2.26% to 2.82%, explaining 72% of the volatility gap accounted for by differences in production and trade.

Table 8: Real GDP Variance Decomposition

	Commodity price shocks
Emerging economy	26.1%
Developed economy	10.7%

We conclude that sectoral trade imbalances play a fundamental role in accounting for the higher volatility of emerging economies while differences in the share of non-tradables also have a significant effect.

5.5 What is the role of commodity prices on real GDP volatility?

We now investigate the extent to which differences in the cross-sectional patterns of production and trade between emerging and developed economies lead to differences in real GDP volatility by affecting how the estimated economies respond to commodity price shocks.

Variance decomposition We begin by contrasting the share of real GDP fluctuations accounted for by commodity price shocks between the estimated emerging and developed economies. To do so, we conduct a variance decomposition analysis, which we execute by recomputing the implications of our estimated models under the assumption that commodity price shocks are the only shocks hitting our economies.[36]

In Table 8, we report the share of the variance of real GDP that is explained by shocks to commodity prices. We find that commodity price shocks play a more important role in accounting for business cycle fluctuations in emerging economies than in their developed counterparts. In particular, we find that 26.1% of the variance of real GDP is driven by commodity price shocks in emerging economies while this value is only 10.7% in developed economies. Interestingly, the greater importance of commodity price shocks in emerging economies results despite the higher estimated volatility and persistence of productivity shocks in these economies.

[36]Given that productivity and commodity price shocks are assumed to be orthogonal, this exercise is sufficient to identify the share of the variance explained by each of the shocks.

Impulse response functions We now investigate the mechanisms underlying the higher role of commodity prices on business cycle fluctuations in emerging economies. To do so, we first contrast the response of real GDP to productivity and commodity price shocks in emerging and developed economies. Then, we contrast the response of a broader set of variables to changes in commodity prices across the two estimated economies.

We compute impulse response functions for real GDP in the emerging and developed economies to the two shocks: (*i*) a positive aggregate productivity shock and (*ii*) a positive shock to the relative price of commodities. Crucially, we isolate the differential impact of the shocks across economies by considering identical paths of the shocked variables. We consider one-time one-standard-deviation orthogonal shocks to productivity and the relative price of commodities based on the productivity process estimated for the emerging economy.[37] Figures 2 and 3 plot the response to productivity and commodity price shocks, respectively.

Figure 2 shows that productivity shocks have a very similar impact on real GDP across the two economies. Given that the productivity path that we consider in this exercise is the same, this finding shows that the response to fluctuations in aggregate productivity is not significantly affected by the cross-sectional differences between our model economies. In contrast, Figure 3 shows that the response of emerging economies to commodity price shocks is substantially higher than in developed economies. These findings suggest that the higher business cycle volatility of the emerging economy is significantly accounted for by this economy's differential response to aggregate commodity price shocks.

We then contrast the response of a broader set of variables to changes in commodity prices across the two estimated economies. Figure 4 shows that shocks to the relative price of commodities have a substantial impact on key aggregate variables in the emerging economy but a significantly lower impact in the developed economy. First, note that the emerging economy exhibits a

[37]We compute impulse response functions based on a first-order approximation of the solution around the deterministic steady state.

Figure 2: Productivity Shock

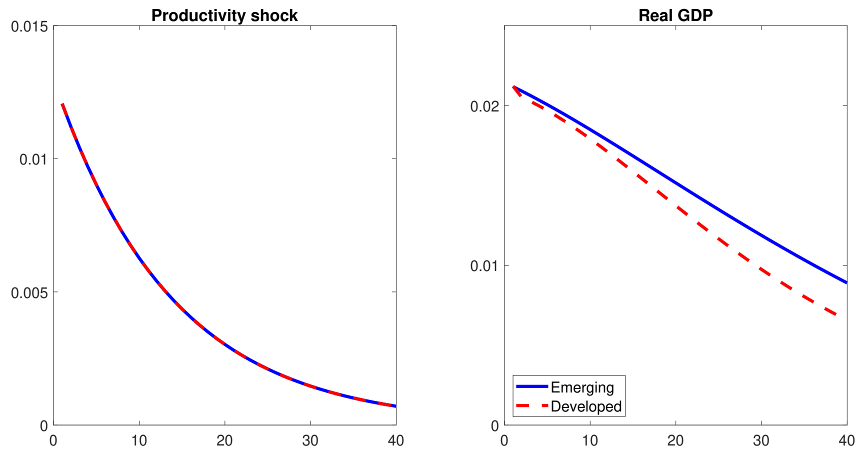
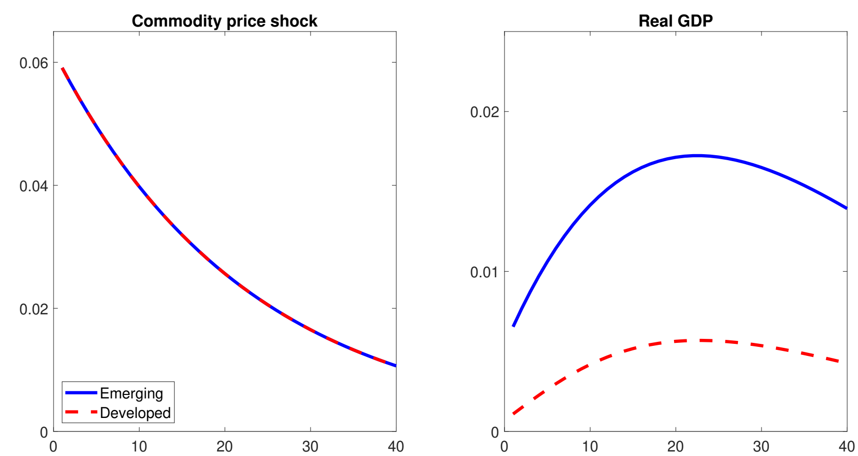
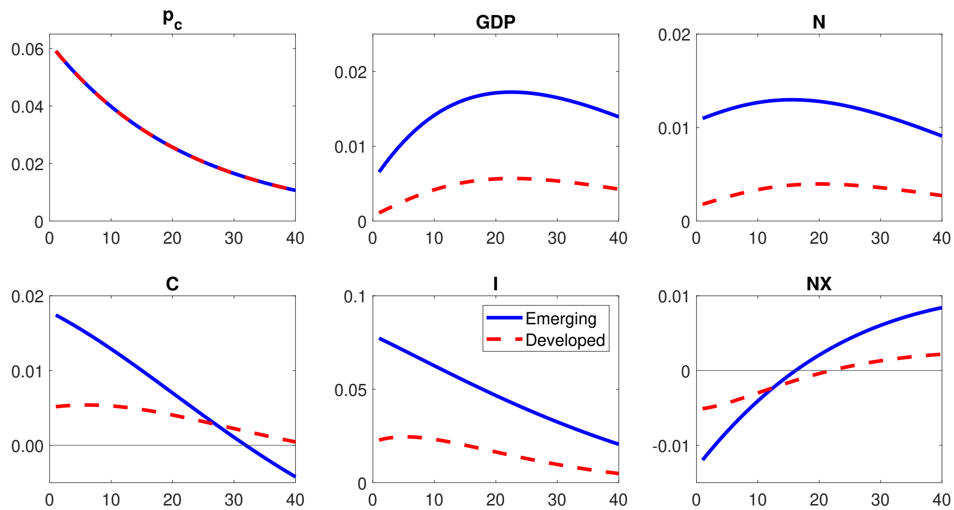


Figure 3: Commodity Price Shock



larger increase in labor supply and investment than the developed economy. Second, we observe that this larger increase in the factors of production in the emerging economy also lead to a large increase in real GDP and consumption in this economy. This higher response of consumption and investment in the emerging economy leads to a higher trade deficit on impact, which then becomes a surplus once GDP peaks. In contrast, the response of aggregate

Figure 4: Commodity Price Shock



variables in the developed economy is significantly milder. [38]

Our analysis in Section 5.4 suggests that differences in sectoral trade imbalances and the share of non-tradable goods are key in accounting for the role of commodity prices in emerging economies. The emerging economy features significant sectoral trade imbalances, and a positive commodity price shock increases the price of exports and decreases the price of imports. These changes have a positive wealth effect, which increases the relative price between goods produced and consumed, increasing economic activity. In contrast, in the developed economy, where sectoral trade is balanced, an increase in the relative price of commodities does not have a wealth effect, as the increase in the value of domestically produced commodities is almost exactly offset by the increase in the price paid to consume commodities.

5.6 What is the role of aggregate TFP on real GDP volatility?

Section 4 shows that changes in international relative prices may affect real GDP through two channels: either by affecting the supply of factors of produc-

[38] In Section 3.4 of the Online Appendix we also present the impulse response functions to productivity shocks for this broader set of variables.

Table 9: Standard Deviation relative to Real GDP

	Real GDP	K^{KS}	N^{LS}	Z_t	Endogenous TFP
Emerging economy	1.00	0.33	0.48	0.43	0.03
... without sectoral adj. costs	1.00	0.43	0.50	0.37	0.18
Developed economy	1.00	0.27	0.45	0.47	0.02
... without sectoral adj. costs	1.00	0.38	0.52	0.38	0.24

tion or by affecting aggregate TFP. Given the crucial role played by commodity price shocks in accounting for differences in business cycle volatility between emerging and developed economies (Section 5.5), we now investigate the importance of aggregate TFP relative to factors of production in accounting for these findings.

To do so, we decompose real GDP into four terms based on equation 20: the contribution of aggregate capital and labor, and the contribution of the exogenous and endogenous components of aggregate TFP.[39] Given this decomposition, we investigate their relative importance for aggregate volatility by computing the standard deviation of these four components relative to the standard deviation of real GDP for the estimated emerging and developed economies. The results are reported in Table 9.

The first and third rows of the table report the results for the estimated emerging and developed economies. We find that the endogenous TFP component features a much smaller volatility relative to GDP than the remaining three terms. These findings suggest that the key channel through which commodity price shocks lead to volatility differences between emerging and developed economies is by affecting the supply of factors of production (Section 4.2) rather than through endogenous TFP movements (Section 4.3).

The second and fourth rows of the table report the results corresponding to each of these economies when removing sectoral labor and capital adjustment costs while keeping all other parameters at their estimated values. Consistent with the discussion in Section 4.3, we find that the relative standard deviation

[39]The exogenous component of TFP is given by Z_t. Then, we compute the contribution of the endogenous components of aggregate TFP as: Endogenous $\text{TFP}_t = \frac{\text{Real GDP}_t}{Z_t K_t^{KS} N_t^{LS}}$.

of the endogenous TFP components increase substantially in the absence of sectoral adjustment costs.

We conclude that the importance of production factors relative to endogenous TFP movements underlying the volatility differences explained by our model are accounted by the sizable sectoral adjustment costs estimated for both emerging and developed economies.[40] Moreover, these findings show that, as discussed in Section 5.6 and in contrast to Kehoe and Ruhl (2008), our model implies that shocks to international relative prices lead to endogenous TFP fluctuations. These fluctuations may be particularly sizable in environments with low sectoral adjustment costs.

6 Cross-country Analysis

The quantitative analysis conducted in the previous section shows that differences in the patterns of production and trade between emerging and developed economies can account for a significant fraction of the higher volatility of emerging economies. One implication of this finding is that such a relationship should hold not only across country aggregates (i.e., emerging vs. developed economies), but also across individual countries. In particular, countries with more unbalanced sectoral trade flows (i.e., with a larger trade deficit in manufactures) should exhibit more volatile output. In this section, we investigate whether this is indeed the case in the data. Then, we contrast the empirical relationship observed in the data with its model counterpart.

6.1 Empirical Evidence

In this section, we use the cross-country panel dataset described in Section 2 to examine whether the systematic relationship between aggregate volatility and the patterns of production and trade implied by our model also holds in the data.

The analysis in Section 5.4 shows that economies with higher sectoral trade

[40] In Section 3.5 of the Online Appendix, we show that the implications of our model for the volatility of labor shares across sectors is consistent with the data. See Benguria et al. (2018) for evidence on the importance of labor market frictions that slow down the reallocation of labor across sectors.

imbalances are more vulnerable to changes in international relative prices and, thus, are associated with higher output volatility. We now evaluate the extent to which this relationship holds in the data by estimating an OLS regression of real GDP volatility on sectoral imbalances, as characterized by the absolute value of the manufacturing net exports to GDP ratio.[41]

We report the regression estimates in the first column of Table 10. The estimated relationship between sectoral trade imbalances and aggregate volatility across countries is positive and statistically significant at the 1% level. Moreover, this relationship is also economically significant: The beta coefficients reported show that a one-standard-deviation change in the manufacturing net exports to GDP ratio is associated with a 0.37-standard-deviation change in real GDP volatility.

While this evidence shows that sectoral trade imbalances are indeed associated with higher business cycle volatility, this may be due to the negative relationship between economic development and aggregate volatility, observed in Figure 1 and in the second column of Table 10. This could be the case since more developed economies display both lower sectoral trade imbalances and lower aggregate volatility. In the third column of Table 10, we find that sectoral trade imbalances remain statistically and economically significant even after controlling for countries' GDP per capita. Moreover, while more developed economies feature lower output volatility on average, this relationship is not statistically significant once we control for sectoral imbalances.

Our findings in Section 5 show that the share of non-tradables also plays an important role in accounting for output volatility differences in our model. In the fourth column of Table 10 we examine whether this is also the case in the data after controlling for the role of sectoral imbalances and economic development. As implied by the model, we find that both sectoral imbalances and the share of non-tradables are statistically and economically significant in

[41]In the model, it is the magnitude of sectoral trade imbalances that matter for volatility, not their sign. Therefore, we focus on the absolute value of sectoral trade imbalances in the regressions. In Section 3.7 of the Online Appendix, we show that these results are robust to restricting attention to countries with sectoral trade deficits.

Table 10: Cross-Country Evidence

Dependent variable: Std. dev. real GDP	(1)	(2)	(3)	(4)	(5)
(Abs) NX of Manufactures / GDP	0.37		0.31	0.33	0.28
	(0.001)		(0.008)	(0.009)	(0.025)
Share of Commodities in GDP					0.59
					(0.110)
Share of Manufactures in GDP					0.14
					(0.306)
Share of Non-Tradables in GDP				-0.47	
				(0.036)	
Aggregate NX/GDP					−0.06
					(0.697)
GDP per capita (log)		−0.27	−0.13	0.21	0.27
		(0.013)	(0.265)	(0.285)	(0.381)
R^2	0.14	0.07	0.15	0.26	0.24
# of Obs	76	76	76	76	76

Notes: a) "Abs" denotes the absolute value. b) Coefficients are all normalized (beta coefficients). c) All regressions include an intercept. d) The numbers in parentheses are p-values based on robust standard errors.

accounting for differences in output volatility.

Finally, in the fifth column of Table 10 we examine whether any of the additional cross-sectional moments used to estimate our model are also associated with real GDP volatility. We find that the relationship between sectoral trade imbalances and business cycle volatility is statistically and economically robust to controlling for these variables, while GDP per capita and the additional cross-sectional moments are not statistically significant.

6.2 Quantitative Analysis

The previous subsection shows that the key channels that account for the higher volatility of emerging economies in our model are also systematically associated with higher business cycle volatility in cross-country data. We now investigate the implications of our model for the volatility of real GDP in each of the 76 countries used to estimate the regression in Table 10.

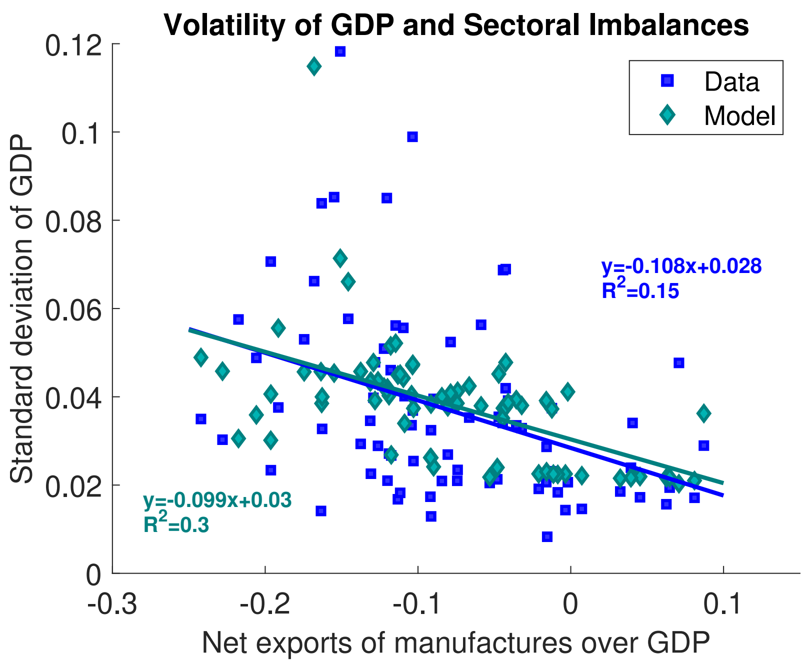
To do so, we re-estimate our model for each of the 76 countries in the cross-country dataset described in Section 2. We assume that each of the emerging economies only differs in the parameters used to discipline the cross-sectional moments reported in Table 3 while each of the developed economies only differs in the parameters used to discipline the cross-sectional moments reported in Table 4. In particular, the times-series parameters (i.e. productivity process, adjustment costs, and sensitivity of interest rates to output) are assumed to be common within emerging and developed economies, respectively, but are assumed to differ between the two groups as described in Section 5.1. Then, for each of the 76 economies in our dataset, we estimate the parameters A_m, η, η_τ, and b to match (i) the share of manufactures in GDP, (ii) the share of commodities in GDP, (iii) the manufacturing net exports to GDP ratio, and (iv) the aggregate net exports to GDP ratio.[42]

We contrast the implications of our 76 calibrated small open economies with their empirical counterparts along two dimensions. First, we examine their implications for the relationship between sectoral trade imbalances and real GDP volatility. To do so, in Figure 5 we use diamonds to represent the manufacturing net exports to GDP ratio and real GDP volatilities implied by our model for each of the countries, and we use squares to represent the values in the data.

We observe that both the data and the model imply a negative relationship between sectoral trade imbalances and aggregate volatility: Real GDP volatility decreases systematically as the manufacturing net exports to GDP ratio approaches zero (i.e, as the manufacturing net imports decrease). Moreover, we find that the relationship between sectoral imbalances and real GDP volatility implied by our model is quantitatively consistent with the empirical relationship between them: An increase in the manufacturing net exports to GDP ratio from -0.1 to 0.0 (i.e. a reduction in net imports of manufactures) is associated with a 1pp decrease in real GDP volatility in the model and 1.1pp decrease in the data. We interpret this finding as evidence of the success of

[42]We also assume that ψ_u is common within emerging and developed economies, but differs between them; we set it to its respective value reported in Tables 3 and 4. See Section 3.10 of the Online Appendix for country-specific parameters.

Figure 5



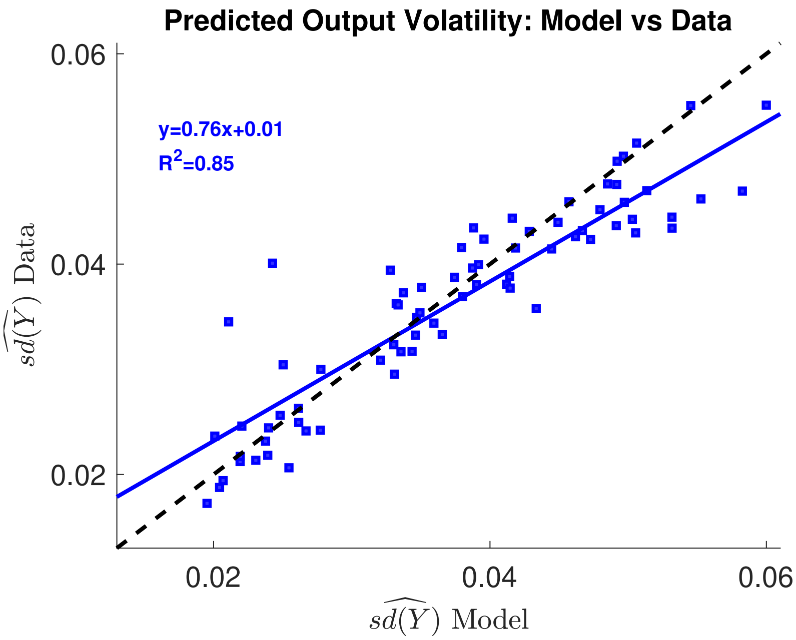
our model in capturing the average relationship between sectoral imbalances and aggregate volatility observed in the data.[43]

While the evidence presented in Figure 5 shows that the model and the data feature a very similar relationship between sectoral trade imbalances and aggregate volatility *on average*, it begs the question about whether this relationship also holds on a country-by-country basis. Thus, we now investigate the extent to which our model captures the empirical relationship between the four cross-sectional moments and real GDP volatility on a country-by-country basis.

To answer this question, we construct model-implied and empirical measures of predicted real GDP volatility given the four cross-sectional moments used to calibrate our model. To do so, we first regress real GDP volatility on the four cross-sectional variables that characterize each of our economies,

[43]Notice that the regression estimates presented in Figure 5 are different than those reported in the first column of Table 10: (*i*) the table reports beta coefficients; and (*ii*) the independent variable in the table is the absolute value of the ratio of manufacturing net exports to GDP.

Figure 6



using real and simulated data separately.[44] Then, we use the estimated regressions to compute predicted real GDP volatilities for each country given their cross-sectional moments. Finally, we contrast the empirical and model-implied predicted real GDP volatilities for each country.

Figure 6 plots the empirical and model-implied predicted real GDP volatilities for each of the 76 countries in our sample. We find that there is a strong systematic positive relationship between the aggregate volatilities predicted by our model and their empirical counterpart. In particular, we find that our model accounts for 85% of the variation in predicted real GDP volatility from a regression using our four cross-sectional target moments. We interpret this as evidence of the success of our model in accounting for the empirical cross-country relationship between the patterns of production and trade and aggregate real GDP volatility.

[44]Our model is sufficiently flexible to match each of the cross-sectional moments exactly. Thus, the real and simulated cross-sectional variables are identical.

7 Conclusion

In this paper, we investigate the extent to which salient cross-sectional differences between emerging and developed economies can account for the higher business cycle volatility of the former. Our starting point is the observation that while emerging economies produce and export systematically different goods than their developed counterparts, these economies consume and import very similar types of goods. Moreover, emerging economies also produce a higher share of tradable goods and, thus, are more exposed to changes in international relative prices.

We use a multi-sector small open economy model to show that these systematic differences between emerging and developed economies can affect their response to changes in international relative prices, amplifying business cycle volatility in emerging economies. We find that cross-sectional differences in the patterns of production and trade between developed and emerging economies can account for between 29% and 39% of the difference in business cycle volatility.

Our findings raise important questions left for future research. First, we take as given the differences in the structure of production and trade between emerging and developed economies. But our findings raise a deeper question: What forces are making emerging economies more commodity dependent in the first place? A better understanding of these forces could be important for designing policies aimed at reducing the vulnerability of emerging economies from international relative price fluctuations.

Second, we abstract from the interaction between government policies and the commodity price cycle. Yet, several countries have now implemented sovereign stabilization funds with the goal of moderating the cyclicality of government revenues in economies that export commodities. Thus, given a structure of production and trade, these policies might help to shield commodity exporters from commodity price shocks.

We conclude that cross-sectional differences in the patterns of production and trade between emerging and developed economies can account for a sizable share of the difference in business cycle volatility between them.

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