The Business Cycle Volatility Puzzle

Emerging vs Developed Economies *

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Abstract

We study the drivers of the business cycle volatility differences between emerging and developed economies. We develop a heterogeneous firms and multi-sector small open economy framework with production linkages in which firms are subject to economy-wide, sectoral, firm-level, and tradable prices shocks. Using input-output sector-level data and firm-level micro data from various developed and emerging economies, we quantity the relevant model-based sufficient statistics and find that differences in the sectoral composition and in the distribution of firms explain roughly half of the excessive business cycle volatility in emerging economies. However, in the time-series, we find that changes in the economic structure cannot explain the relative decline in the business cycle volatility in emerging economies over the past few decades.

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1 Introduction

Emerging economies exhibit greater volatility in gross domestic output (GDP) compared to developed economies (Acemoglu and Zilibotti, 1997). Furthermore, this higher output volatility is mirrored by even greater private consumption volatility (Neumeyer and Perri, 2005; Aguiar and Gopinath, 2007). If households prefer to smooth consumption, then excessive output volatility is depressing households' welfare in emerging economies. To assess whether policy interventions can mitigate the volatility of output or if such extra volatility is an inherent part of the development process, a crucial first step is to investigate what are the main drivers of the volatility differences between emerging and developed economies.[1]

Motivated by this, in this paper we study the factors that drive the differences in aggregate output volatility between emerging and developed economies. To accomplish this, we develop a small open economy model with a rich economic structure and heterogeneous firms which are subject to multiple types of shocks. Based on this framework, we derive observable sufficient statistics that account for the volatility of aggregate output. Our findings reveal that disparities in the economic structure, such as the distribution of sectors and firms, account for nearly half of the excessive volatility observed in emerging economies. However, changes in the economic structure cannot account for the observed decline in the excessive volatility of emerging economies over time. Our model-based sufficient statistic approach is different from previous paper which do an empirical exercise or rely on a calibrated model.

Our analysis is based on a multi-sector small open economy model with heterogenous firms and production linkages (Baqaee and Farhi, 2019, 2021). In the economy, there is a set of goods that can be traded internationally (tradables), and a set of goods which are only consumed and produced domestically (nontradables). Since the economy is relatively small, the prices of tradable goods are assumed to be exogenous. Within each sector, firms produce a homogeneous good with a decreasing returns to scale technology that uses labor and intermediate inputs produced by other firms. Thus, in our framework, there is an endogenous distribution of firms and the production across sectors is linked through the firms' use of intermediate inputs. Firms' productivity is exogenous and has three components: aggregate (i.e., common to all firms and sectors), sectoral, and firm-specific. Last, there is a representative household who owns all the firms in the economy, supplies labor inelastically, and consumes tradable and nontradable goods.

[1] Acemoglu and Zilibotti (1997) argue that, in the process of developing, economies transition from volatile output to stable growth.

We show that in this framework aggregate output volatility can be decomposed into three channels that depend on sufficient statistics, to a first order approximation. The decomposition is derived as an extension of the seminal Hulten (1978) theorem to a small open economy setup with tradable and non-tradable sectors and within sector's firm heterogeneity. On one hand, the aggregate channel depends on aggregate sales over GDP and aggregate TFP volatility. On the other hand, we divide the channel related to the micro-structure of the economy in two: a sectoral and a firm-level channel. The sectoral channel depends on the sector-level TFP volatilities and the distribution of sales shares (Domar weights) across sectors, and the firm-level channel depends on the idiosyncratic TFP volatility and how concentrated are firms' sales across large firms in the economy.

In our main application, we quantify how much each channel contributes to differences in GDP volatility between emerging and developed economies. We compute the model-induced sufficient statistics using aggregate, input-output production, and firm-level data for 10 emerging and 19 developed economies. To isolate the contribution of the micro-composition of the economy, we assume that sectoral and idiosyncratic TFP volatilities are the same across emerging and developing economies, so the sectoral and firm-level channels are only driven by differences in the distribution of sales shares across sectors and firms. We find that differences in the sectoral distribution of the economy explain as much as 43% of the excessive volatility in emerging economies, the firm-level channel explains 6%, and the (residual) aggregate channel explains the remaining 51%.

Our model indicates the relevance of the sectoral and firm-level channels depend on the sales share distribution of sectors and firms, respectively, then we proceed to document for each channel what are the empirical patterns across emerging and developed economies.

Regarding the sectoral channel, we document that sectoral sales shares in emerging economies are concentrated in highly volatile sectors, whereas in developed economies they are concentrated in the least volatile sectors, which explains the significant contribution of the sectoral channel in our main quantitative exercise. These findings are related to the structural transformation process, which reallocates economic activity away from agriculture and manufacturing (high volatility) and towards services (low volatility) as countries develop.[2] We run a counterfactual analysis to estimate the contribution of each set of sectors in explaining volatility differences between emerging and developed economies, and find that agriculture contributes 46%, manufacturing contributes 53%, and services contributes -46%. A negative contribution means

[2]See Herrendorf, Rogerson and Ákos Valentinyi (2014) for a review of the literature.

that this last sector plays a crucial role in explaining output volatility in developed economies but not in emerging ones.

Regarding the distribution of firms, using firm-level data, we document that the sales within the largest firms are more concentrated in emerging economies which, through the lens of our model, suggests that firms' idiosyncratic shocks could influence aggregate output more in emerging economies than in developed.

Lastly, we take a time-series approach and study how the excessive business cycle volatility in emerging economies evolved over the last decades and what was the role of the changes in the economic structure.[3] We document that since the late 1970s, in both group of countries, output has become less volatile, but the volatility has decline more rapidly in emerging economies. We find that changes in the sectoral composition of the economy don't contribute to explain this relative decline, which suggests that other channels should explain the disproportional reduction of output volatility in emerging economies during this period.

Related Literature and Contributions. The observation that emerging economies have a higher business cycle volatility than developed economies [see, for example, Lucas (1988, p4) and Acemoglu and Zilibotti (1997)] ignited a large body of work that studies potential explanations. First, many papers have focused on aggregate explanations such as more frequent or larger financial shocks [Neumeyer and Perri (2005), Uribe and Yue (2006), Calvo, Izquierdo and Talvi (2006), and others], more persistent TFP processes [Aguiar and Gopinath (2007)], procyclical fiscal and monetary policy [Vegh and Vuletin (2014)], more institutional instability [Mobarak (2005)], and higher exposure to commodity price shocks [see, for example, Kohn, Leibovici and Tretvoll (2021)]. Second, a smaller set of papers have focused on the role of sector-level shocks and sectoral differences across emerging and developed economies [see, for example, Da-Rocha and Restuccia (2006) and Koren and Tenreyro (2007)].[4] In our paper, we combine these different views – aggregate and micro explanations – in a unique theoretical framework.

Unlike previous studies on the excessive business volatility in emerging economies, we use model-induced sufficient statistics to quantify the contribution of each channel.[5] These statistics can be computed using input-output data and firm-level micro

[3] It is well documented that economic activity in emerging and developed economies has shifted from the primary to the service sectors [see, for a recent reference, Huneeus and Rogerson (2020)].

[4] Although it doesn't focus on differences between emerging and developed economies, Carvalho and Gabaix (2013) studies the role of sectoral composition in changes in volaility across time for the US and other developed economies.

[5] For example, Koren and Tenreyro (2007) uses an atheoretical approach to study the role of the eco-

data from several emerging and developed economies. To derive the sufficient statistics, we extend Hulten (1978)'s theorem to our small open economy framework.

Our variation of Hulten's theorem is different from Baqaee and Farhi (2021). While they focus on a multiple economy setup, we focus on a small open economy setup with tradable (no market clearing, prices are exogenous) and nontradable sectors (only domestic market clearing) and a non-degenerate distribution of firms within a sector.

Although it is well-known that there are differences in the distribution of firms between developed and advanced economies, to our knowledge, this is the first paper that studies how these differences account for the excessive volatility of output in emerging economies. Related papers, Gabaix (2011) and di Giovanni and Levchenko (2012) also study the role of firm-level shocks, but focus in developed economies and in the differences between large and small countries, respectively.

Finally, our empirical contribution is to document that, in emerging economies, the sectoral sales tend to be more concentrated in the most volatile sectors and the firms' sales tend to be more concentrated in the largest firms.

Organization. The rest of the paper is organized as follows: Section 2 describes the theoretical model and main proposition, Section 3 includes the quantitative application and the empirical patterns, Section 4 describes the time-series analysis, and Section 5 concludes.

2 Theoretical Framework

We develop a multi-sector small open economy model with heterogeneous firms and production linkages that we use to decompose volatility of GDP in aggregate, sectoral, and firm-level channels.

2.1 Environment

In the economy, there is a discrete number of sectors $s \in \mathcal{S}$ where $\mathcal{S}$ can be partitioned into a sub-set of nontradable sectors $\mathcal{S}^{NT}$ which can only be sold domestically and a sub-set of tradable sectors $\mathcal{S}^{T}$ which can be sold domestically and internationally, then

$$\mathcal{S} = \left\{ \underbrace{1, ..., S_{NT}}_{\mathcal{S}^{NT}}, \underbrace{S_{NT}+1, ..., S_T + S_{NT}}_{\mathcal{S}^{T}} \right\},$$

nomic structure. In spite of this, our main findings regarding the economic structure are in line with theirs.

where $S_{NT} + S_{NT} = N$ is the total number of sectors.

The economy is relatively small, so tradable prices, p_s with $s \in \mathcal{S}^T$, are taken as exogenous. Within each sector $s \in \mathcal{S}$ there is an arbitrary finite number of heterogeneous firms $i \in \mathcal{I}_s$. The set of all firms in the economy is

$$\mathcal{I} = \left\{ \underbrace{1, 2, ..., I_1}_{\mathcal{I}_1}, \underbrace{I_1 + 1, ..., I_2 + I_1}_{\mathcal{I}_2}, ..., \underbrace{\sum_{s=1}^{N-1} I_s + 1, ..., \sum_{s=1}^{N} I_s}_{\mathcal{I}_N} \right\},$$

where $\mathcal{I}$ is the total number of firms in the economy. Firms in sector $s \in \mathcal{S}$ produce an homogenous good, combining labor and intermediate inputs, and sell it at price p_s taking it as given (i.e., act competitively). The goods produced by domestic firms are consumed by the household and used by the firms to produce. In the case of tradable goods, they can be exported (i.e., part of them are not consumed domestically), and household and firms can import them for their consumption.[6] To produce, firms use also domestic labor which is provided inelastically by the household.

There are five exogenous forces that could potentially generate output fluctuations in this economy: aggregate, sectoral and firm-level shocks to firms' production, tradable prices shocks, and aggregate trade balance shocks.

2.1.1 Firms

Each firm i in sector s produces an homogenous good s, and chooses labor and intermediate inputs to maximize its profits, taking the price of the good produced, wages and prices of intermediate inputs as given. Then the problem of firm i in sector s is

$$\pi_i = \max_{L_i, \mathbf{X}_i} p_s y_i - wL_i - \mathbf{p}\mathbf{X}_i^{'}, \tag{1}$$

where y_i is the output produced by firm i, L_i is labor demanded by firm i at wage w, and $\mathbf{X}_i = \begin{bmatrix} X_{i,1} & \cdots & X_{i,s} & \cdots & X_{i,N} \end{bmatrix}$ are the intermediate inputs demanded by firm i at prices $\mathbf{p} = \begin{bmatrix} p_1 & \cdots & p_s & \cdots & p_N \end{bmatrix}$, where $X_{i,j}$ denotes firm i's demand of sector j intermediate good. The production function of firm i in sector s is

$$y_i = \mathcal{A}_i F_s \left(L_i, \mathbf{X}_i \right),$$

where $\mathcal{A}_i = \exp(a + \tilde{a}_s + a_i)$ is an exogenous productivity shifter composed by aggregate productivity $A = e^a$, sectoral productivity $\tilde{A}_s = e^{\tilde{a}_s}$ and firm-level idiosyncratic

[6] We abstract from trade costs, so it is not necessary to keep track of the consumption, input, or production origin.

productivity $A_i = e^{a_i}$ components. Crucially, we assume that the function $F_s(.)$ exhibits decreasing returns to scale, so there can be firm heterogeneity within sector even if the good is homogeneous [see Hopenhayn (1992)].

2.1.2 Households

We consider a representative household who consumes tradable and nontradable goods, supplies one unit of labor inelastically to domestic firms, and owns all the firms in the economy. The household maximizes constant returns to scale utility $U(.)$ over consumption choices $\mathbf{C}$, i.e.,

$$\max_{\mathbf{C}} U(\mathbf{C})$$

subject to the budget constraint

$$\mathbf{p}\mathbf{C}^{'} + B^* \leq w + \sum_{i \in \mathcal{I}} \pi_i, \tag{2}$$

where $\mathbf{C} = \begin{bmatrix} C_1 & \cdots & C_s & \cdots & C_N \end{bmatrix}$ with C_s being household's consumption of sectoral good s, $\mathbf{p}$ vector of consumption goods prices, and B^* are exogenous net transfers to the rest of the world [similar to Baqaee and Farhi (2021)]. Households earnings are the sum of labor income w and the sum of all the firms' profits $\sum_{i \in \mathcal{I}} \pi_i$. Since firms' produce with a decreasing returns to scale technology, profits are weakly positive, i.e., $\pi_i \geq 0 \;\; \forall i \in \mathcal{I}$.

2.1.3 Market Clearing and Aggregation

Labor market clearing requires that total amount of labor demanded by each firm i within all the sectors $s \in \mathcal{S}$ equals total amount of labor supplied by the representative household, wich is normalized to 1:

$$\sum_{i \in \mathcal{I}} L_i = 1. \tag{3}$$

Market clearing for each nontradable sector $s \in \mathcal{S}^{NT}$ requires that goods produced by the set of firms $\mathcal{I}_s$ within sector s equals demand in sector s, which is composed by the amount of good s consumed by households and the amount of good s demanded as intermediate input from all firms in the economy,

$$\sum_{i \in \mathcal{I}_s} y_i = C_s + \sum_{i \in \mathcal{I}} X_{i,s} \qquad \text{if } \; s \in \mathcal{S}_{NT}. \tag{4}$$

The aggregate resource constraint condition for this small open economy states that aggregate consumption plus exogenous aggregate net exports equals aggregate production across all sectors $s \in \mathcal{S}$ net of the use of intermediate inputs demanded from and to all sectors:

$$\mathbf{p}\mathbf{C}^{'} + B^{*} = \sum_{s\in\mathcal{S}} p_s \sum_{i\in\mathcal{I}_s} \mathcal{A}_i F_s\left(L_i, \mathbf{X}_i\right) - \sum_{i\in\mathcal{I}} \mathbf{p}\mathbf{X}_i^{'}. \tag{5}$$

Combining equation 5 with the nontradable sector's market clearing conditions 4, we obtain the following aggregate resource constraint for the set of tradable sectors $\mathcal{S}^T$:

$$\sum_{s\in\mathcal{S}^T} p_s \left(\sum_{i\in\mathcal{I}_s} y_i - C_s - \sum_{i\in\mathcal{I}} X_{i,s}\right) = B^{*}, \tag{6}$$

which states that the sum of production across all tradable sectors net of aggregate consumption of these sectors and aggregate demand of intermediate inputs from these sectors equals aggregate net exports in the small open economy.

Gross domestic product (GDP) in this economy is given by aggregate production net of the use of intermediate inputs. Combining equation 5 with the nontradable sector's market clearing conditions 4, we can express GDP as

$$GDP = \mathbf{p}\mathbf{C}^{'} + B^{*} = w + \sum_{i\in\mathcal{I}} \pi_i.$$

Furthermore, given the assumption that the utility function exhibits constant returns to scale [7] and that the aggregate price index is the numeraire, we obtain that

$$GDP = U\left(\mathbf{C}\right) + B^{*}, \tag{7}$$

which means that, different from a closed economy setup, in our small open economy GDP differs from welfare by the exogenous net exports. Moreover, in Lemma 1, we show that GDP is different from the GDP deflated by the GDP deflator.

2.2 Competitive Equilibrium

In this section we define the competitive equilibrium for this economy.

Definition 1. *A competitive equilibrium is an allocation* $\left\{\{\mathbf{X}_i\}_{i\in\mathcal{I}}, \mathbf{C}, \{L_i\}_{i\in\mathcal{I}}\right\}$ *with exogenous productivity shifter* $\mathcal{A}_i = A\tilde{A}_s A_i$*, tradable prices* $\mathbf{p}^T$*, aggregate net exports* B^**, and prices* $\{\mathbf{p}, w\}$ *such that*

- *given prices* $\mathbf{p}$ *and* w*, firms maximize their profits,*
- *given* $\mathbf{p}$*,* w *and* B^**, the representative household maximizes her utility,*
- *the nontradable goods and labor markets clear.*

The economy is efficient so the competitive equilibrium allocations coincide with the allocations of the planner's problem.

[7] Define the expenditure function of the household as $e(p, U) = \sum_s p_s C_s$. Since U is homogeneous of degree 1, we have $e(p, U) = Ue(p)$. Normalize the unit cost of consumption $e(p) = 1$ to obtain $\sum_i p_s C_s = U$, [Baqaee and Farhi (2021)].

2.3 Business Cycle Volatility Decomposition

Before stating the main proposition of the paper, it is useful to define formally the relevant Domar Weights in this economy.

Definition 2. *The Domar Weight of firm $i \in \mathcal{I}_s$ is the sales share of firm i in GDP (Y) and denoted by λ_i, i.e.,*

$$\lambda_i \equiv \frac{p_s y_i}{Y}. \tag{8}$$

It then follows that the Sectoral Domar Weight for a sector s is defined as $\Lambda_s \equiv \sum_{i \in \mathcal{I}_s} \lambda_i$ and the Aggregate Domar Weight is defined as $\Lambda \equiv \sum_{i \in \mathcal{I}} \lambda_i$.

In Proposition 1 we show that GDP growth can be decomposed into three distinctive channels which depend on observable sufficient statistics.

Proposition 1. *The first order response of output $Y(.)$ to changes in $\{A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T\}$ is*

$$d\log Y(B^*, \mathbf{p}^T, A, \tilde{A}_s, A_i) = \Lambda da + \sum_{s \in \mathcal{S}} \Lambda_s d\tilde{a}_s + \sum_{i \in \mathcal{I}} \lambda_i da_i \tag{9}$$

where Λ is the aggregate Domar weight, Λ_s is the Domar weight of sector s, and λ_i is the Domar weight of firm i. Moreover, assuming firm-level shocks are uncorrelated and their volatility is common across firms, and allowing for correlation across sector-level shocks, then the variance of GDP growth (in log differences) is

$$Var\left(d\log Y\right) = \underbrace{\Lambda^2 \sigma_A^2}_{aggregate} + \underbrace{\mathbf{\Lambda}' \Omega_{\tilde{A}} \mathbf{\Lambda}}_{sectoral} + \underbrace{\left(\lambda' \lambda\right) \sigma_{A_i}^2}_{firm\text{-}level} \tag{10}$$

where σ_A^2 is the variance of common (aggregate) TFP shocks, $\mathbf{\Lambda}$ is the vector of sector-level Domar weights, $\Omega_{\tilde{A}}$ is the covariance matrix of sectoral TFP shocks, λ is the vector of firm-level Domar weights, and σ_{A_i} is the variance of firm-level shocks. The variance terms are constructed using log changes. The proof is in Appendix A.

The first channel is the aggregate channel, whose impact depends on the volatility of the aggregate TFP shocks and the sum of the total sales shares (i.e., Domar weights). The second and third terms are the channels related to the micro-structure of the economy at the *sector*- and *firm*-level, respectively. The sectoral channel depends on the variance and covariance matrix of sector-level shocks, and the vector of sectoral Domar weights. The firm-level channel depends on the volatility of firm-level shocks and the herfindahl index of the firm's sale share.

In a closed economy, the celebrated Hulten (1978)'s Theorem states that the Domar weight of a firm or sector summarizes the importance of the firm/sector's TFP shock on aggregate output. In Proposition 1, we show that this result also holds in a small open economy setup where tradable sector prices are exogenous (i.e., no market clearing in the tradable sectors).

Moreover, we show that in this framework aggregate balance B^* shocks and international prices $\mathbf{p}^T$ shocks don't affect aggregate output to a first order. Intuitively, an increase in output from an increase in B^* is fully compensated by a tightening of the aggregate resource constraint. This result is analogous to the ones in Baqaee and Farhi (2021) and Burstein and Cravino (2015). For the case of the international prices shocks, changes in these prices will affect the difference between the CPI and GDP deflator (see Lemma 1 in Appendix A) but will not change real aggregate output once we deflate it by the GDP deflator. This is a result of the inelastic supply of labor and the first order approximation.[8]

In the next section, we use the decomposition (10) to quantify the difference in aggregate output volatility between emerging and advanced economies.

3 Quantitative Application

In this section, we first describe the sample and data sources. Next, using our theoretical framework, we quantify the contribution of the aggregate, sectoral-, and firm-level channels in explaining the excessive business cycle volatility in emerging economies. Finally, we decompose the contribution of each channel, documenting new empirical facts on emerging and developed economies.

3.1 Sample and Data Sources

Sample We start by empirically defining emerging and developed economies and tradable and nontradable sectors. For the definition of the country groups, we follow Kohn *et al.* (2021), and define developed economies as those members of OECD with average PPP adjusted GDP per capita higher than \$25,000, and emerging economies as those countries with average PPP adjusted GDP per capita lower than \$25,000.[9] We follow the standard in the literature and define tradable sectors as those belonging to the commodities and manufacturing categories, and nontradable sectors as those belonging to services. After combining all the data sources for each of the four channels (described below) we end up with a sample of 10 emerging and 19 developed

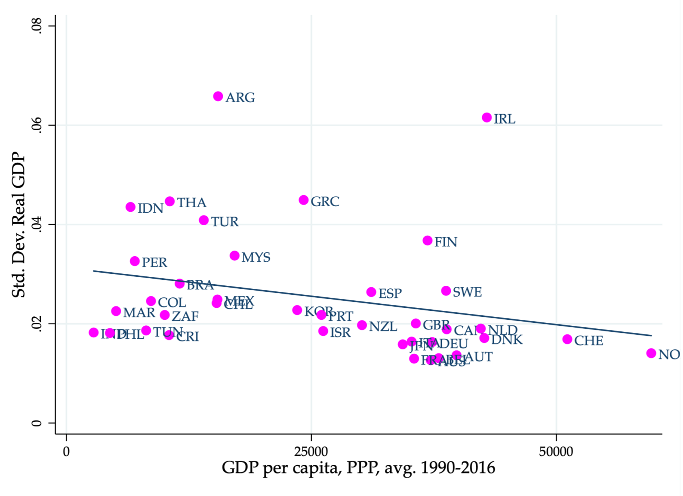
[8] Other papers [see, for example, Kohn *et al.* (2021)] find that commodity prices shocks can change aggregate output because they can induce changes in the use of aggregate inputs and the reallocation of inputs across sectors. In this paper, we abstract from this.

[9] Following Kohn *et al.* (2021) we exclude from the sample large open economies such as China and US and ex-communist countries.

economies.[10]

Data Sources and Data Moments To estimate each countries' business cycle volatility we use GDP data from the World Development Indicators (WDI) for the period 1970-2016. The business cycle volatility indicator is computed as standard in the literature, by calculating the variance of the cyclical component of GDP. [11]

Figure 1: Business cycle volatility across the development spectrum



Source: authors' calculations based on World Development Indicators (WDI).

In Figure 1 we document the negative relation between GDP volatility and GDP levels, a well-known empirical pattern that lies on the core of all the studies that try to explain aggregate volatility in emerging economies [see Acemoglu and Zilibotti (1997) for an early reference]. In our sample, the median emerging economy has 2.2 times the business cycle volatility of the median developed economy.

We combine data from several data sources to compute the sufficient statistics to quantify each channel's contribution.

For the sectoral channel, we use the OECD input-output tables to compute the sectoral Domar weights vector $\mathbf{\Lambda}_c$ for 36 (tradable and nontradable) sectors for each country. To compute the sectoral TFP covariance matrix $\Omega_{\tilde{A}}$ we use updated[12] sector-level TFP estimates from Jorgenson, Ho and Stiroh (2005) net of the commonly correlated component across sectors.[13] We assume that volatility of TFP is the same for same sec-

[10]See the list of countries and sectors in the sample in Appendix B.2.

[11]For consistency, we detrend aggregate output using the same methodology as the one used to compute volatility of sectoral TFP, which consists on computing the variance of log-differences.

[12]Although the original paper was published in 2005, the authors have been updating the data repository to include data for subsequent years.

[13]To do so, we substract the year fixed-effects from the sectoral TFP series.

tors across countries, and equal to the one in US. This highlights the role of sectoral composition and allows us to use the best estimates possible for long-run TFP sectoral volatility. [14]

For the aggregate channel, we use the sectoral Domar weights from the OECD input-output tables to estimate the aggregate Domar weight Λ_c.

For the firm-level channel, we use data from Worldscope, which covers more than 90% of publicly held firms market cap internationally, to compute the Domar weight of the largest 70 firms λ_c for each country.[15] The great advantage of the Worldscope dataset is that it allows us to distinguish between sales done by domestic and international subsidiaries, so we can compute the economically relevant firm-level Domar weights (i.e., using only sales by domestic subsidiaries). We use the baseline estimates from Gabaix (2011) to compute the firm-level TFP volatility $\sigma^2_{A_i}$, which we assume common across firms in both emerging and developed economies.

3.2 Cross-Sectional Quantitative Analysis

We use the framework in Section 2 to quantify the contribution of each channel to the excessive volatility in emerging economies. To isolate the contribution of the micro-structure of the economy we assume: (i) sector-level covariance matrix is the same across countries, (ii) firm-level volatility is the same across countries, and (iii) the sum of domar weights for non-top firms tends to zero. Notice that these assumptions imply that the contribution of the sectoral and firm-level channels are explained *only* by differences in the micro-structure of the economy, instead of intrinsic differences in sector- and firm-level volatility across countries.[16] Using these assumptions and the decomposition (10), we can write the differences in output volatility between emerging and developed economies as

$$\begin{aligned}
&\mathrm{Var}\left(\mathrm{d}\log Y_{\mathrm{EM}}\right) - \mathrm{Var}\left(\mathrm{d}\log Y_{\mathrm{DEV}}\right) = \\
&\qquad \underbrace{\boldsymbol{\Lambda}_{\mathrm{EM}}^{'}\Omega_{\tilde{A}}\boldsymbol{\Lambda}_{\mathrm{EM}} - \boldsymbol{\Lambda}_{\mathrm{DEV}}^{'}\Omega_{\tilde{A}}\boldsymbol{\Lambda}_{\mathrm{DEV}}}_{\text{sectoral distribution}} + \underbrace{\left[\left(\lambda'\lambda\right)^{\mathrm{top}}_{\mathrm{EM}} - \left(\lambda'\lambda\right)^{\mathrm{top}}_{\mathrm{DEV}}\right]\sigma^2_{A_i}}_{\text{firm-level distribution}} \\
&\qquad + \underbrace{\Lambda^2_{\mathrm{EM}}\sigma^2_{A,\mathrm{EM}} - \Lambda^2_{\mathrm{DEV}}\sigma^2_{A,\mathrm{DEV}}}_{\text{residual aggregate}}.
\end{aligned} \tag{11}$$

[14] This point discussed later in the results and in appendix A.

[15] As studied by Gabaix (2011), if there is a fat-tailed distribution of firms' sale shares in the economy, when it comes to the firm-level channel, what matters for the impact of firms' idiosyncratic shocks on aggregate volatility is how concentrated are sales among the largest firms in the economy.

[16] We don't rule out that differences in intrinsic volatility may exist and be relevant. See next subsection's discussion.

Decomposition (11) shows that aggregate output volatility differences can be explained by differences in the distribution of domar weights across sectors, differences in the herfindahl index of firm-level domar weights, and a residual component common to all sectors and firms.

Using the data sources described in Section 5, we compute the sufficient statistics to quantify the contribution of each channel. We find that differences in the distribution of sectors and firms can explain much as 48% (43% sectoral and 5% firm-level) of the excessive aggregate output volatility in emerging economies. The rest (52%) is explained by the residual aggregate channel.

The Role of Correlated Sectoral Shocks If we assume that sectoral TFP shocks are uncorrelated, we find the sectoral channel explains 83% of the excessive output volatility in emerging economies. Thus, the sectoral channel's contribution is significantly smaller if we take into account that sector-level TFP shocks can be correlated. Intuitively, this happens because in emerging economies there is a higher economic weight in sectors where shocks have a relatively lower correlation to other sectors.

Firm-Level Intrinsic Volatility Differences Aggregate output in emerging economies could be more volatile because firms idiosyncratic shocks are more volatile in emerging economies. Using our data we cannot measure directly the differences in firm-level volatility, but we can infer them indirectly using our framework. To do this, we assume that the residual portion of the excessive volatility comes only from *intrinsic* differences in firm-level volatility, i.e., formally $\sigma_{A_i,\text{EM}} \neq \sigma_{A_i,\text{DEV}}$ and $\sigma_{A,\text{EM}} = \sigma_{A,\text{DEV}}$. Under these assumptions, we find that the idiosyncratic volatility of firms in emerging economies has to be 31% higher than in developed economies. This number is comparable to previous findings that use firm-level data.[17]

3.3 Decomposing the contribution of each channel

In this section, we document two new empirical patterns that drive the contribution of the sectoral and firm-level channels.

3.3.1 Sectoral Channel

Pattern 1. *Sectoral Domar weights in emerging economies are concentrated in highly volatile sectors (e.g., manufacturing and agricultural sectors), whereas in developed economies they are concentrated in the least volatile sectors (e.g., services sectors).*

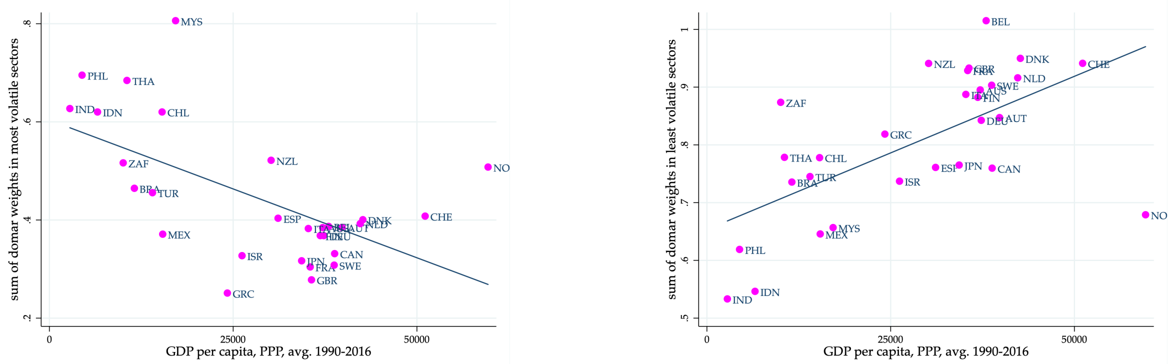
[17] See, for example, Kochen (2023) estimates for a set of developed and emerging European economies.

This pattern explains the important contribution of the sectoral channel, and is represented in Figure 2. In left panel 2a, we show a negative correlation between GDP per capita levels and the sum of sectoral Domar weights of the sectors that belong to the highest quartile of sectoral volatility. In contrast, in right panel 2b we show a positive correlation between income per capita levels and the sum of sectoral Domar weights for those sectors that belong to the lowest quartile of sectoral volatility.

Translated in terms of equation (11), emerging economies are characterized by higher Domar weights $\sum_{i\in\mathcal{I}_s}\lambda_i$ in sectors with higher TFP volatility $\sigma^2_{\tilde{A}_s}$, whereas developed economies are characterized by higher Domar weights $\sum_{i\in\mathcal{I}_s}\lambda_i$ in sectors with lower TFP volatility $\sigma^2_{\tilde{A}_s}$, leading to a high contribution of the sectoral channel in explaining aggregate volatility differences.

Figure 2: Sectoral compositional differences across the development spectrum

(a) *GDP vs sales shares in most volatile sectors* **(b)** *GDP vs sales shares in least volatile sectors*



(c) *Sector-level Domar weights*

	Emerging	Developed
Sum of Domar weigths of most volatile sectors	0.62 (0.46,0.68)	0.38 (0.32,0.40)
Sum of Domar weigths of least volatile sectors	0.70 (0.62,0.78)	0.89 (0.77,0.93)

Source: authors' calculations based on World Development Indicators (WDI) and Jorgenson *et al.* (2005) dataset.
Note: most volatilie sectors refer to the sectors belonging to the highest quartile in volatility; least volatile sectors refer to the sectors belonging to the lowest quartile in volatility; in panel (c) we report in parentheses the values corresponding to the 25th and 75th pct, and the most and least volatile sectors refer to the sectors belonging to the highest and lowest quartile of volatility.

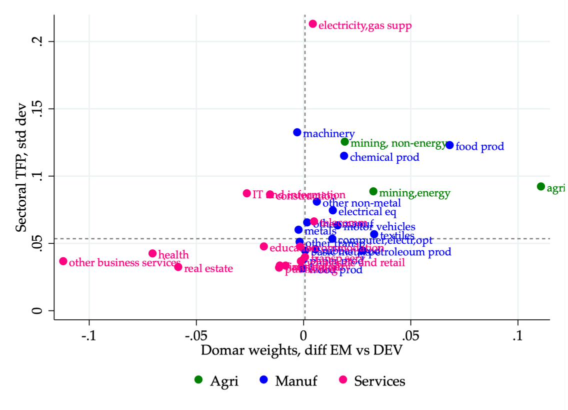
Panel 2c summarizes the distribution of sectoral Domar weigths in the most and least volatile sectors for emerging and developed economies. The sum of Domar weights across the most volatile sectors for the median emerging economy is 0.62 compared to 0.38 in developed economies, and the sum of Domar weights among the least volatile sectors is 0.70 in the median emerging economy vs 0.89 in the median developed economy.

In light of the quantitative findings in Section 3.2, we further analyze which specific sectors are driving such a substantial contribution of the sectoral channel.

Structural Transformation In Figure 3a we plot, for each sector, its TFP volatility (in standard deviations) against the differences in its sales shares between emerging and developed economies. We find that agriculture and food production (i.e., primary sectors) are among the most volatile sectors, and also the ones where sales shares are largest in emerging economies relative to developed ones. On the other hand, health, business and real estate sectors are the least volatile and the ones where sales share are largest in developed economies relative to emerging ones.

Figure 3: Business cycle volatility and structural transformation

(a) *Sectoral volatility and differences in sales shares*



(b) *Sectoral channel decomposition*

	Domar W EM	Domar W DEV	Volatility (std)	Contribution to differences
Agriculture	0.21	0.05	0.10	46%
Manufacturing	0.62	0.42	0.08	53%
Services	1.00	1.32	0.06	-46%
Total				57%

Source: authors' calculations based on World Development Indicators (WDI) and Jorgenson *et al.* (2005) dataset.
Note: in panel (b), the first column shows the sectoral Domar weights; the second column shows the sectoral TFP volatility; and the third column shows the contribution of the sectoral channel (net of cross-sector correlations) in the counterfactual scenario in which the sale shares for all sectors but the one under analysis are the same in emerging and developed economies.

These sectoral composition patterns can be mapped to the process of structural transformation –widely studied in the development literature– which states that agriculture has relatively more importance in the least-developed economies, services sectors have relatively more importance in the most-developed economies, and the relationship between development and manufacturing follows a hump shape. For a more direct link, we aggregate sectors in agriculture, manufacturing and services and compute their sales share in emerging and developed economies, and their sectoral TFP volatility. As shown in the first three columns of Figure 3b, emerging economies tend to have relatively more sales share in agriculture and manufacturing, which are the most volatile sectors. In the case of services, the balance leans towards developed economies, which tend to concentrate relatively more sales in this low volatile aggregate sector.

We then estimate the relative importance of each aggregate sector in explaining the excessive volatility in emerging economies. To do so, we run the following counterfactual exercise: for each sector (i.e., agriculture, manufacturing and services) we estimate what would the sectoral channel contribute to explain differeces in output volatility if the only sectoral composition differences came from that sector (i.e., if the sale shares for all sectors but the one under analysis were the same in emerging and developed economies). The results are shown in the fourth column of Figure 3b. If the only sectoral differences came from agriculture, then the sectoral channel would contribute 46% in explaining volatility differences. If, instead, the only sectoral differences came from manufacturing, the sectoral channel would explain 53% of the excessive volatility in emerging economies, meaning that the largest differences between emerging and developed come from this aggregate sector. Last, if the only sectoral differences came from services, then the sectoral channel would contribute with a negative 46%, meaning that this sector plays a crucial role in exlpaining output volatility in developed economies, but not so in emerging ones.

In turn, Figure 3 can be interpreted as suggestive evidence that the process of structural transformation has implications on business cycle volatility differences between emerging and developed economies.

3.3.2 Firm-level Channel

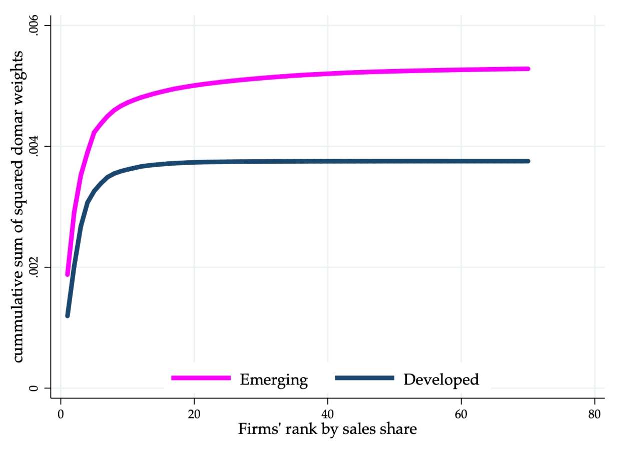
Pattern 2. *Firm-level Domar weights within the largest firms are more concentrated in emerging than developed economies.*

This pattern drives the contribution of the firm-level channel. Through the lens of our model, a higher concentration of sales in fewer large firms implies that shocks that hit large firms, given the same firm-level shocks volatility, would have a higher impact on emerging economies aggregate volatility than on developed.

Using firm-level data from Worldscope, we analyze how concentrated are the sales shares across the largest firms in the economy [see, for reference, Gabaix (2011)]. In Figure 4, we show the cummulative sum of squared Domar weights for the Top 1st to Top 70th firms in emerging and developed economies.[18] Two aspects are worth noticing. First, as Figure 4a shows, the sum becomes flat when roughly more than 15 firms are included, which implies that idiosyncratic shocks to firms at the bottom of the distribution are negligible in the aggregate, and therefore have no implications for differences between emerging and developed economies. Second, sales within the largest firms are more concentrated in emerging economies, with the sum of Domar weights of the top 70 firms being 0.48 in emerging economies vs 0.36 in developed ones (Figure 4b).

Figure 4: Firm distribution differences across the development spectrum

(a) *Cummulative sum of squared Domar weights*



(b) *Firm-level Domar weights*

	Emerging	Developed
Sum of Domar weigths of top 70 largest firms	0.48 (0.24,0.55)	0.36 (0.29,0.49)

Source: authors' calculations based on Worldscope firm level data.
Note: in panels (a) we show the cummulative sum of squared Domar weights from the Top 1 to Top 70 firms in terms of sales ;in panel (b) we report in parentheses the values corresponding to the 25th and 75th pct, and Top 70 largest firms are defined in terms of sales by domestic establishments.

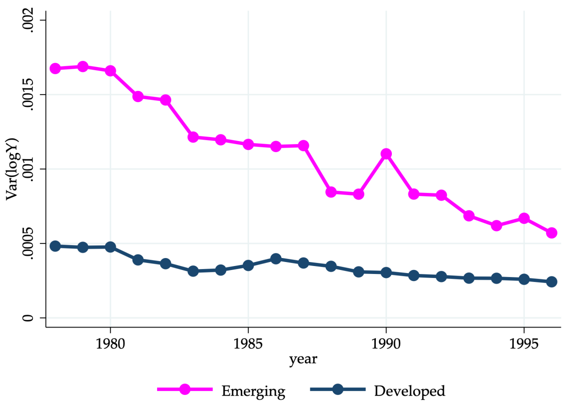
[18] As mentioned before, for multinational firms (i.e., with establishments in many countries) we use the sales by domestic establishments to compute the economically relevant firm-level Domar weights.

4 Time-Series Quantitative Analysis

In our main analysis stated in Section 3, we find that differences in the economic structure of developed and emerging economies explain a significant fraction of their output volatility differences. In this section, we study how these volatility differences evolved over time and what role did the economic structure played.

Figure 5: Aggregate volatility and structural transformation

(a) *Output volatility*



(b) *Sectoral Domar weights*

	Emerging			Developed		
	1978	1995	Δ	1978	1995	Δ
Agriculture	0.21	0.12	-0.09	0.13	0.07	-0.06
Manufacturing	0.70	0.65	-0.05	0.73	0.55	-0.18
Services	0.87	1.12	0.25	1.10	1.26	0.16

Source: authors' calculations based on World Development Indicators (WDI) and World Input-Output Database (WIOD) data. Notes: in panel (a), we show the evolution of the GDP volatility in Emerging and Developed economies. We compute the volatility of output $Var_t(\log Y_c)$ using a 15-year window with t being the median year in the window. The classification of countries is the same as in the baseline exercises, but the set of countries used is limited to those with WIOD data. In panel (b), we show the Domar weights for the agriculture, manufacturing and services sectors for 1978 and 1995 and their change in this period by country groups. The Domar weights $\Lambda_{sc,t}$ are computed using a 11-year window, where t is the median date of the window. Further details of the data and sample are available in the text and the Appendix C.1.

First, in Figure 5a, we show the evolution of output volatility between 1978 and 1995. During this period, both emerging and developed economies reduced significantly their output volatility. Moreover, we observe a stronger decline of output volatility in emerging than developed economies.[19]

[19]In Appendix C.1, we use different samples to check for robustness and find that the decline in

Next, using historical input-output data from the World Input-Output Database (WIOD) we study, for the same period, the changes in the economies' sectoral composition. Figure 5b shows that in both emerging and developed economies the Domar weights of the service sectors increments substantially, while there is a decrease in the weights of the manufacturing and agricultural sectors. Moreover, the reduction in the Domar weight of the manufacturing sectors is more than three times larger in developed economies, whereas the reduction in the Domar weight of the agricultural sector is slightly larger in emerging economies. These patterns are consistent with previous evidence on the rise of the service economy and the deindustrialization of developed economies.

Lastly, using our theoretical framework from Section 2, we study the role of changes in the sectoral structure of developed and emerging economies in the *relative* decline of output volatility in emerging economies.[20] To compute the time series of the sectoral channel we let the Domar weights to vary across time $\Lambda_{sc,t}$ and use the covariance matrix of the sectoral TFP shocks $\Omega_{\tilde{A}}$ which we assume fixed over time. We find that the sectoral channel can't explain the relative decline in output volatility in emerging economies (see figure C.1a in Appendix C.1). This suggests that other drivers should explain the relative decline (e.g., improvements in macroeconomic policy management in emerging markets). As a counterpart, the contribution of the sectoral channel in explaining the differences between emerging and developed economies becomes increasingly more important over time (see figure C.1b).

5 Conclusion

In this paper, we study how business cycle volatility differences between emerging and developed economies can be explained by three channels: aggregate shocks, and the micro-structure of the economy at the sector and firm-level.

We build a multi-sector small open economy model with heterogenous firms and production linkages. Different from previous literature, we construct a consistent and unified framework to decompose aggregate output volatility in the three channels that depend only in terms of sufficient statistics (i.e., no need to calibrate parameters and estimate full model), which allows for a quantitative application that includes a broad set of countries.

output volatility is robust across both groups of economies, and the relatively larger decline in emerging economies is robust but weaker.

[20]The surge in the relevance of the service sector could be a relevant driver of the observed sharp decline in output volatility in both types of economies [as observed by Carvalho and Gabaix (2013) for U.S. and other developed economies].

In the quantitative application, we combine aggregate, input-outputs and firm level data for 10 emerging and 19 developed economies to compute the contribution of each channel. We find that differences in the sectoral composition of the economies play a significant role, and explain as much as 43% of the differences in output volatility. Differences in the distribution of firms contribute by 5%, thus the remaining 51% is explained by the residual aggregate component. Moreover, we document that there is a decrease of the excessive volatility of output in emerging economies over time, but sectoral changes don't play a relevant role, despite their importance in explaining the cross-section.

The paper remains silent on why the micro-structure of the economy (distribution of sectors and firms) differs between emerging and developed economies. Whether differences are driven by heterogeneity in natural endowments, skills distribution, market structure, or inefficiencies, would have different normative implications. We left this for future research.

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Appendices

A Theory Appendix

A.1 Proof of Lemma 1

Lemma 1. *If we assume shocks to* $\{A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T\}$ *we have that the GDP deflator is*

$$d\log P_{\mathcal{Y}} = \sum_{s\in\mathcal{S}^T} b_s d\log p_s. \tag{12}$$

where b_s *is the trade balance of sector* s*.*

Proof. Changes in CPI can be defined as

$$\mathrm{d}\ln P = \sum_{s\in\mathcal{S}} \frac{p_s C_s}{\sum_{s\in\mathcal{S}} p_s C_s} \mathrm{d}\log p_s,$$

which can be split in different sectors as

$$\mathrm{d}\ln P = \sum_{s\in\mathcal{S}^T} \frac{p_s C_s}{\sum_{s\in\mathcal{S}} p_s C_s} \mathrm{d}\log p_s, + \sum_{s\in\mathcal{S}^{NT}} \frac{p_s C_s}{\sum_{s\in\mathcal{S}} p_s C_s} \mathrm{d}\log p_s. \tag{13}$$

By definition, the nominal GDP is

$$\tilde{\mathcal{Y}} = \sum_{s\in\mathcal{S}} p_s \left(y_s - X_s\right)$$

where $X_s = \sum_{i\in\mathcal{I}} X_{i,s}$ and $y_s = \sum_{i\in\mathcal{I}_s} y_i$ aggregated to the sector-level. Notice that nominal GDP and GDP deflated by CPI are the same since the CPI is normalized to 1 (i.e., $\mathrm{d}\ln P = 0$). Furthermore, we can use the CPI definition (13) and scale it by the ratio of total expenditure to GDP, such that

$$\frac{\sum_{s\in\mathcal{S}} p_s C_s}{\tilde{\mathcal{Y}}} \mathrm{d}\ln P = \sum_{s\in\mathcal{S}^T} \frac{p_s C_s}{\tilde{\mathcal{Y}}} \mathrm{d}\log p_s + \sum_{s\in\mathcal{S}^{NT}} \frac{p_s C_s}{\tilde{\mathcal{Y}}} \mathrm{d}\log p_s. \tag{14}$$

The GDP deflator can be defined as

$$\mathrm{d}\log P_{\mathcal{Y}} = \sum_{s\in S} \frac{p_s \left(y_s - X_s\right)}{\tilde{\mathcal{Y}}} \mathrm{d}\log p_s,$$

then using the non-tradable market clearing $y_s = C_s + X_s$, we can rewrite the GDP deflator as

$$\mathrm{d}\log P_{\mathcal{Y}} = \sum_{s\in\mathcal{S}^{NT}} \frac{p_s C_s}{\tilde{\mathcal{Y}}} \mathrm{d}\log p_s + \sum_{s\in\mathcal{S}^T} \frac{p_s \left(y_s - X_s\right)}{\tilde{\mathcal{Y}}} \mathrm{d}\log p_s$$

then substituing with CPI expression we have

$$\mathrm{d}\log P_{\mathcal{Y}} = \frac{\sum_{s\in\mathcal{S}} p_s C_s}{\tilde{\mathcal{Y}}}\mathrm{d}\log P - \sum_{s\in\mathcal{S}^T} \frac{p_s C_s}{\tilde{\mathcal{Y}}}\mathrm{d}\log p_s + \sum_{s\in\mathcal{S}^T} \frac{p_s\left(y_s - X_s\right)}{\tilde{\mathcal{Y}}}\mathrm{d}\log p_s$$

using the fact that $\mathrm{d}\log P = 0$ and $b_s \equiv \frac{(y_s - X_s - C_s)}{\tilde{\mathcal{Y}}}$ then the GDP deflator is

$$\mathrm{d}\log P_{\mathcal{Y}} = \sum_{s\in\mathcal{S}^T} b_s \mathrm{d}\log p_s. \tag{15}$$

□

We owe the proof of Lemma 1 to Alvaro Silva.

A.2 Proof of Proposition 1

Proof. The economy is efficient then to show the SOC Hulten Theorem setup the planner's problem. The planner maximizes household consumption subject to the market clearing for every nontradable good, labor market clearing and the aggregate resource constraint. Differently from Baqaee and Farhi (2021) since X^* is exogenous for our setup the planner's problem is equivalent to a problem where total GDP is maximized.

Planner's problem

$$\begin{aligned}
\tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T) = & \max_{\{X_{i,s}\}, L_i, C_s} U\left(\{C_s\}_{s=1}^S\right) + B^* \\
& + \sum_{s\in\mathcal{S}^{NT}} \mu_s \left[\sum_{i\in\mathcal{I}_s} \mathcal{A}_i F_s\left(L_i, \{X_{i,j}\}_{j=1}^S\right) - C_s - \sum_{j\in\mathcal{S}}\sum_{i\in\mathcal{I}_j} X_{i,s}\right] \\
& + \lambda\left(1 - \sum_{j\in\mathcal{S}}\sum_{i\in\mathcal{I}_j} L_i\right) \\
& + \mu^T\left[\sum_{s\in\mathcal{S}^T} p_s \left(\sum_{i\in\mathcal{I}_s} \mathcal{A}_i F_s\left(L_i, \{X_{i,j}\}_{j=1}^S\right) - C_s - \sum_{j\in\mathcal{S}}\sum_{i\in\mathcal{I}_j} X_{i,s}\right) - B^*\right]
\end{aligned}$$

where $\mathcal{A}_i = A\tilde{A}_s A_i$ if the TFP shifter, μ_s is the lagrange multiplier on the market clearing condition of nontradable sector $s \in \mathcal{S}^T$, λ is the multiplier on the labor supply constraint, and μ^T the mutiplier on the tradable sectors aggregate resource constraint. Notice that $\tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)/P_{\mathcal{Y}} = \mathcal{Y}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)$ where $\tilde{\mathcal{Y}}$ is the nominal GDP (or deflated by CPI), $P_{\mathcal{Y}}$ is the GDP deflator , and $\mathcal{Y}$ is the real GDP deflated by the GDP deflator. Finally, the net external balance are B^* and the tradable sectors prices are $\mathbf{p}^T$.

Optimal conditions

First the envelope conditions for $A, \tilde{A}_s, A_{is}, B^*$and p_s for $s \in \mathcal{S}^T$:

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial A} = \sum_{s \in \mathcal{S}^{NT}} \mu_s \sum_{i \in \mathcal{I}_s} \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right) + \mu^T \sum_{s \in \mathcal{S}^T} p_s \sum_{i \in \mathcal{I}_s} \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial \tilde{A}_s} = \mathbf{1}_{s \in \mathcal{S}^{NT}} \mu_s \sum_{i \in \mathcal{I}_s} A A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right) + \mathbf{1}_{s \in \mathcal{S}^T} \mu^T p_s \sum_{i \in \mathcal{I}_s} A A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial A_i} = \mathbf{1}_{s \in \mathcal{S}^{NT}} \mu_s A \tilde{A}_s F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right) + \mathbf{1}_{s \in \mathcal{S}^T} \mu^T p_s A \tilde{A}_s F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial p_s} = \mu^T \left(A \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right) - C_s - \sum_{j \in \mathcal{S}} \sum_{i \in \mathcal{I}_j} X_{i,s} \right)$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial B^*} = 1 - \mu^T$$

The FOC with respect to consumption are

$$\frac{\partial U \left(\{C_s\}_{s=1}^S \right)}{\partial C_s} = \mathbf{1}_{\mathbf{s} \in \mathcal{S}^{\mathbf{NT}}} \mu_s + \mathbf{1}_{s \in \mathcal{S}^T} \mu^T p_s$$

From the descentralized problem of the household the optimal conditions are

$$\frac{\partial U \left(\{C_s\}_{s=1}^S \right)}{\partial C_s} = p_s$$

which implies that $\mu^T = 1$ and $\mu_s = p_s$. Then replacing in the envelope conditions of the planner's problem:

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial A} = \sum_{s \in \mathcal{S}} p_s \sum_{i \in \mathcal{I}_s} \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial \tilde{A}_s} = p_s \sum_{i \in \mathcal{I}_s} A A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial A_{is}} = p_s A \tilde{A}_s F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial p_s} = A \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right) - C_s - \sum_{j \in \mathcal{S}} \sum_{i \in \mathcal{I}_j} X_{i,s}$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial B^*} = 0$$

Rearranging terms and defining the Domar weight of firm $i \in \mathcal{I}_s$ as $\lambda_i \equiv \frac{p_s A \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)}{\tilde{\mathcal{Y}}}$ then we have:

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)/\tilde{\mathcal{Y}}}{\partial A/A} = \frac{\sum_{s \in \mathcal{S}} p_s \sum_{i \in \mathcal{I}_s} A \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)}{\tilde{\mathcal{Y}}} = \sum_{s \in \mathcal{S}} \sum_{i \in \mathcal{I}_s} \lambda_i$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)/\tilde{\mathcal{Y}}}{\partial \tilde{A}_s/\tilde{A}_s} = \frac{p_s \sum_{i \in \mathcal{I}_s} A \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S \right)}{\tilde{\mathcal{Y}}} = \sum_{i \in \mathcal{I}_s} \lambda_i$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)/\tilde{\mathcal{Y}}}{\partial A_i/A_i} = \frac{p_s A \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S\right)}{\tilde{\mathcal{Y}}} = \lambda_i$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)/\tilde{\mathcal{Y}}}{\partial p_s/p_s} = \frac{p_s \left(A \tilde{A}_s A_i F_s \left(L_i, \{X_{i,j}\}_{j=1}^S\right) - C_s - \sum_{j\in\mathcal{S}} \sum_{i\in\mathcal{I}_j} X_{i,s}\right)}{\tilde{\mathcal{Y}}} \equiv b_s$$

$$\frac{\partial \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T)}{\partial B^*} = 0$$

The first order response of output to changes in $A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T$ is

$$\partial \log \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T) = \sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{I}_s} \lambda_i \partial a + \sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{I}_s} \lambda_i \partial \tilde{a}_s + \sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{I}_s} \lambda_i \partial a_i + \sum_{s\in\mathcal{S}} b_s \partial \log p_s.$$

Using Lemma 1 and the fact that

$$\partial \log \mathcal{Y}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T) = \partial \log \tilde{\mathcal{Y}}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T) - \partial \log P_{\mathcal{Y}}$$

we can derive the decomposition for log changes of real GDP deflated by the GDP deflator

$$\partial \log \mathcal{Y}(A, \tilde{A}_s, A_i, B^*, \mathbf{p}^T) = \sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{I}_s} \lambda_i \partial a + \sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{I}_s} \lambda_i \partial \tilde{a}_s + \sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{I}_s} \lambda_i \partial a_i. \tag{16}$$

□

B Data Appendix

In this Appendix, we explain the data sources, measurement and sampling used.

B.1 Data Sources by Channel

Business Cycle (GDP) Volatility. We use the GDP in constant LCU series from World Development Indicators (WDI) for the period 1970-2016 to compute the volatility of GDP for each country.

Sectoral Channel. Given the lack of long time series of sectoral productivity across countries, we assume sectoral volatilities to be the same across developed and emerging economies. We use the dataset from Jorgenson *et al.* (2005) to construct the sector-level TFP series. To remove the common component of TFP growth we run the following regression

$$\mathrm{dlog}(A_{st}) = \alpha_t + \mathrm{dlog}(\tilde{A}_{st}),$$

where $\mathrm{d}x_t = x_t - x_{t-1}$, A_{st} are the observed sectoral TFPs, α_t time (year) FE, and the residual $\mathrm{dlog}(\tilde{A}_{st})$ is the sectoral TFP used in the estimation of the covariance matrices.

We construct a crosswalk from the 77 sectors in Jorgenson *et al.* (2005) to compute the average sectoral volatility for each of the 36 OECD sectors.

We use the OECD input output tables to estimate the sectoral Domar weights for emerging and developed economies. For each sector we compute the share of gross output on aggregate value added (GDP), for both tradable and nontradable sectors (36 sectors in total).

To compute the long-run changes in Domar weights — in Section 4 — we use historical input-output data from WIOD, which covers the period 1965 to 2000. Domar weights are calculated using 11-year window, where the reference year is the 6th year (i.e., median year of the window).

Firm-level Channel . We use the Worldscope dataset to compute the firm's Domar weights λ_i. Worldscope contains financial statements of up to 90,000 public companies in both emerging and developed economies. The main advantage of Worldscope is that it covers both emerging and developed economies and distinguishes between domestic and foreign sales for each company, where domestic sales are sales done by establishments located in the country. Domestic sales are computed as 1 minus the share of foreign sales (1-`ITEM8731`) times total sales in USD (`ITEM7240`). Finally, the Domar weight is computed as the domestic sales over GDP from WDI in current USD.

Table B.1: Sample Selection: Worldscope

Criteria	drop	sample
Year $\geq$ 2000	341,292	1,223,875
Missing sales data	223,855	1,000,020
Domestic sales data	269,761	730,259
Duplicates	177,576	552,683
Irregular foreign sales shares (<0%, >100%)	177,576	373,542
Top 70 firms per country-year	250,203	123,339
Country sample	36,522	86,817

Table B.1 shows our sample selection criteria in Worldscope.

B.2 Countries and Sectors

Table B.2: Countries in the Baseline Sample

Emerging	Developed
Brazil	Australia
Chile	Austria
Indonesia	Belgium
India	Canada
Mexico	Denmark
Malaysia	Finland
Philippines	France
Thailand	Greece
Turkey	Germany
South Africa	Ireland
	Israel
	Italy
	Japan
	Netherlands
	Norway
	Spain
	Sweden
	Switzerland
	United Kingdom

Table B.3: Tradable and Nontradable OECD Sectors

Tradables	Nontradables
Mining and ext.of energy prod	Electricity, gas, water supply
Coke and refined petroleum products	Other business sector services
Machinery and equipment	Financial and insurance activities
Other transport equipment	Wholesale and retail trade; repair of motor vehicles
Motor vehicles, trailers and semi-trailers	Public admin. and defence; compulsory social security
Chemicals and pharmaceutical products	Publishing, audiovisual and broadcasting activities
Electrical equipment	Real estate activities
Textiles, wearing apparel, leather and related products	Construction
Fabricated metal products	Telecommunications
Basic metals	Arts, entertainment, recreation and other service activities
Mining support service activities	Transportation and storage
Other non-metallic mineral products	Human health and social work
Rubber and plastic products	Accommodation and food services
Other manufacturing	Education
Computer, electronic and optical products	IT and other information services
Wood products	
Paper products and printing	
Agriculture, forestry and fishing	
Mining and ext.of non-energy prod	

C Additional Exercises

In this section, we provide further detail of the additional exercises.

C.1 Structural Transformation and Business Cycle Volatility

We describe the sample used in the exercise that uses historical input-output data from WIOD.

Table C.1: Countries in the Long-Run Sample

Emerging	Developed
Brazil	Australia
India	Austria
Korea	Belgium
Mexico	Canada
Portugal	Denmark
	Finland
	France
	Germany
	Greece
	Ireland
	Italy
	Japan
	Netherlands
	Spain
	Sweden
	United Kingdom

Next, we perform a robustness check for different sample selections of the evolution of the relative volatility of emerging economies.

Table C.2: Changes in Volatility Differences: Sample Robustness

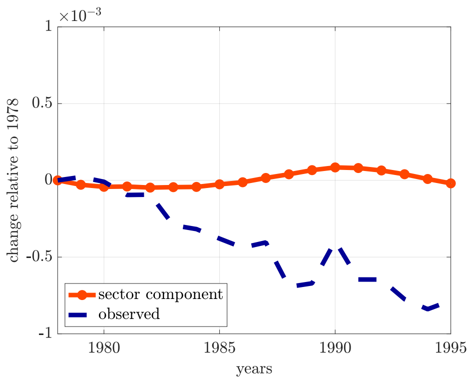
	sample		
	baseline	long-run	large*
$\left(\sigma^2_{\text{EM},1978} - \sigma^2_{\text{DEV},1978}\right)$	1.20	0.74	0.97
$\left(\sigma^2_{\text{EM},1995} - \sigma^2_{\text{DEV},1995}\right)$	0.41	0.60	0.59
$\Delta_{1978-1995}$	-0.79	-0.15	-0.38

Source: authors' calculations using WIOD and WDI data. Notes: volatility terms are expressed in 10^{-3} units.
*baseline sample in Kohn *et al.* (2021)

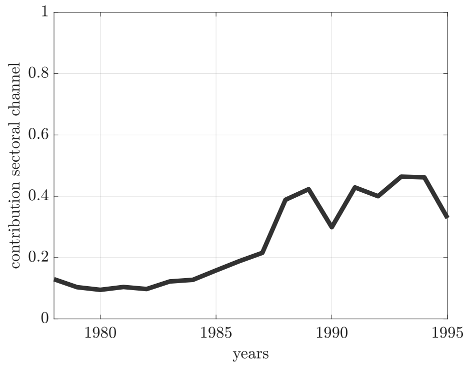
Finally, we compute the exercise using the theoretical framework. We compare the changes in relative volatility driven only by the sectoral channel and the observed decline, and we compute the contribution of the channel in explaining the level of the excessive volatility in emerging economies.

Figure C.1: Sectoral Channel and Relative Decline in Volatility

(a) *Output volatility and Sectoral Channel changes*



(b) *Contribution to volatility differences*



Notes: panel (a) shows the change of the sectoral channel $\left(\mathbf{\Lambda}'_{\mathrm{EM},\mathbf{t}}\Omega_{\tilde{A}}\mathbf{\Lambda}_{\mathrm{EM},\mathbf{t}} - \mathbf{\Lambda}'_{\mathrm{DEV},\mathbf{t}}\Omega_{\tilde{A}}\mathbf{\Lambda}_{\mathrm{DEV},\mathbf{t}}\right)$ and the observed $(\sigma^2_{\mathrm{EM},t} - \sigma^2_{\mathrm{DEV},t})$ relative to base year 1978. Panel (b) shows the evolution of the contribution of the sectoral channel to the volatility differences between emerging and developed economies.