The Business Cycle Volatility Puzzle

Emerging vs Developed Economies *

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Abstract

We study the drivers of business cycle volatility differences between emerging and developed economies. We develop a multisector small open economy framework with heterogeneous firms and production linkages in which firms are subject to sectoral and firm-level TFP shocks and international prices shocks. Using sector-level, firm-level, and international trade data from various developed and emerging economies, we quantify the relevant model-based sufficient statistics. We find that differences in sectoral composition between emerging and developed economies can explain up to 75% of the excessive business cycle volatility in emerging economies, while disparities in the distribution of firms account for up to 10%, and the role of international prices shocks is negligible. Despite the significant influence of sectoral composition, the decrease in volatility observed in emerging economies over the past four decades cannot be attributed to changes in their economic structure.

Keywords: international business cycles, production structure, production networks, structural change.

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1 Introduction

Emerging economies are characterized by higher business cycle volatility compared with developed ones (Acemoglu and Zilibotti, 1997). This higher output volatility is mirrored by even greater private consumption volatility (Neumeyer and Perri, 2005; Aguiar and Gopinath, 2007), which affects households' welfare in emerging economies. Identifying the sources of this excessive volatility is crucial in determining whether policy interventions can mitigate it or if it is an inherent aspect of the development process. In this paper, we study the drivers of differences in aggregate output volatility between emerging and developed economies.

Extending Hulten's theorem (Hulten, 1978) to a multisector small open economy with heterogeneous firms and production linkages, we show that aggregate volatility can be decomposed into four channels: aggregate, sectoral, firm-level, and international prices. Our findings show that differences in the distribution of sectoral sales shares across countries can account for up to 68% of the greater total factor productivity (TFP) volatility and up to 75% of the higher output volatility observed in emerging economies. Additionally, differences in firm size distribution across countries contribute between 4% and 10%, while the importance of international prices is negligible, even when the aggregate labor supply is highly elastic. We argue that the strength of the sectoral channel is tied to structural change, as economic activity shifts to less volatile sectors (such as services) as countries grow. However, this channel cannot explain the observed decrease in volatility in emerging economies over time. Overall, our results suggest that while a significant portion of the excessive business cycle volatility in emerging economies may be inherent to the economic development process, its decline over the last 30-40 years was not.

In the model there are two sets of goods: those that can be traded internationally (tradables) and those that are only produced and consumed domestically (nontradables). Both types of goods can be used for production (intermediates) and for final consumption. Given that the economy is small, the prices of tradable goods are assumed to be exogenous, while the prices of nontradable goods are determined in equilibrium. Within each sector, firms produce a homogeneous good using a decreasing returns to scale technology that combines labor and intermediate inputs produced by other firms. As a result, there is an endogenous distribution of firms, and production across sectors is linked through firms' use of intermediate inputs. Firms' productivity is exogenous and consists of three components: economy-wide (aggregate), sectoral, and firm-specific. Finally, there is a representative household that owns all firms in the economy, supplies labor, and consumes both tradable and non-tradable goods.

We show that, in this rich environment, aggregate output volatility, up to a first-order approximation, can be explained by aggregate, sectoral, and firm-level TFP shocks (as in a closed economy) if households' labor supply is inelastic, while international prices shocks come into play if households' labor supply is elastic.[1] The importance of each channel depends on observable sufficient statistics that capture their direct and indirect impact on aggregate output, as well as on the preference parameters that determine the elasticity of households' labor supply.

Specifically, the aggregate channel depends on the volatility of economy-wide TFP shocks and the ratio of total sales to GDP (aggregate Domar weight). The sectoral channel depends on the variance and covariance matrix of sector-level TFP shocks and the distribution of sectoral sales shares (sectoral Domar weights). The firm-level channel is determined by the volatility of firm-specific TFP shocks and the concentration of firms' sales shares (firm-level Domar weights). Additionally, the importance of these three channels depends on the parameters that shape the utility function over consumption and leisure, which determine the elasticity of labor. Lastly, the relevance of the international prices channel is determined by the variance and covariance matrix of international prices, the distribution of sectoral trade imbalances, and, crucially, the parameters of households' preferences that govern the strength of the substitution and income effects. To understand how international prices shocks can affect aggregate output, consider an example where the economy is a net exporter of a tradable good, and its price rises. In this case, households' real income increases, leading to a change in aggregate output if households' labor supply responds to real income changes—i.e., if the income and substitution effects do not cancel each other out. Thus, if labor supply is inelastic, international prices shocks do not impact aggregate output.

To quantify the sufficient statistics, we use input-output data, firm-level microdata, disaggregated trade balance data, and long-run sectoral productivity and prices data. Our baseline sample includes 34 sectors across 36 countries (17 emerging and 19 developed), along with sales data for the top firms in each country. Our descriptive statistics show that emerging economies concentrate significantly more of their economic activity in volatile sectors, have a more concentrated firm size distribution at the top, measured by sales over GDP, and exhibit greater disaggregated trade imbalances. Through the lens of our model, these facts suggest that the sectoral, firm-level, and international prices channels can potentially contribute to the excessive volatility in emerging economies.

We use our model-based decomposition to evaluate the contribution of each channel

[1] More formally, we refer to labor as being *elastic* to income whenever preferences are such that the income and substitution effects do not cancel each other out, and *inelastic* when they do.

to the higher business cycle volatility in emerging economies. To isolate the contribution of the micro-composition of the economy, we assume that the volatility of sectoral and idiosyncratic TFP shocks is the same across emerging and developed economies.[2] First, we find that differences in the sectoral distribution of the economy explain as much as 75% of the excessive volatility in emerging economies. We show that this channel is closely tied to the structural transformation process, which posits that as economies develop, economic activity shifts away from agriculture and manufacturing (which have high TFP volatility) toward services sectors (which have low TFP volatility).[3] Moreover, we find that most of the sectoral channel is accounted for by differences in intermediate input usage between emerging and developed economies (i.e., indirect contribution), highlighting the importance of accounting for production linkages across sectors.

Next, we find that the firm-level channel plays a more limited role, explaining at most 10% of the excessive volatility in emerging economies. Despite this, we argue that if firm-level TFP shocks in emerging economies are moderately more volatile than in developed ones, the contribution of this channel could be substantially higher. Finally, we find that the international prices channel plays a negligible role under a wide range of parameters values. Even if labor is elastic to changes in real income, the reason why this channel plays a minor role is explained by two factors: first, although disaggregated trade imbalances are larger in emerging economies, they still remain small; second, price shocks across tradable sectors are not sufficiently correlated, reducing the potential significance of this channel.

Lastly, we document that the excessive business cycle volatility in emerging economies has been decreasing over the past 30 to 40 years. We conduct a time-series application of our model using historical input-output data and find that, although the sectoral channel explains a large portion of why emerging economies are more volatile, it does not contribute to the observed decline in excessive volatility over time. This suggests that the decrease in business cycle volatility in emerging economies over the past few decades may be explained by other factors, such as improved macroeconomic management, greater financial and trade integration, among others.

Related Literature and Contributions. The observation that emerging economies have higher business cycle volatility than developed economies [see, for example, Lucas (1988) and Acemoglu and Zilibotti (1997)] ignited a large body of work that studies potential explanations. First, many papers have focused on aggregate explanations,

[2] We discuss the potential role of intrinsic sectoral and firm-level volatility differences in additional exercises.

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

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 prices shocks [see, for example, Kohn, Leibovici and Tretvoll (2021)]. Second, a smaller set of papers have focused on the role of sectoral composition [Koren and Tenreyro (2007), Moro (2015), Da-Rocha and Restuccia (2006)].

Unlike previous studies on excessive business volatility in emerging economies, we provide a unique rich theoretical framework to study the role of economy-wide and international price shocks, as well as sectoral and firm-level distributions. We use model-induced sufficient statistics to quantify the contribution of each channel.[4] The sufficient statistics capture both the direct and indirect impacts of each channel and can be computed using sectoral data, firm-level microdata, and international trade data from several emerging and developed economies.

To derive the sufficient statistics, we extend Hulten's theorem (Hulten, 1978) to a small open economy framework. Our analytical results are related to those of Baqaee and Farhi (2024). While they focus on a multiple-economy setup, we focus on a small open economy setup with tradable (no market clearing, and thus exogenous prices) and non-tradable (only domestic market clearing) sectors, a non-degenerate distribution of firms within a sector, and elastic labor supply.

A few papers have focused on the role of sectoral composition in accounting for aggregate volatility differences between emerging and developed economies—one of the key channels we examine. Da-Rocha and Restuccia (2006) focuses on the role of the agricultural sector. Koren and Tenreyro (2007) study this channel using an atheoretical decomposition that weights the importance of sectoral productivity shocks by their employment shares, capturing approximately the direct impact of these shocks on aggregate output.[5] In contrast to this paper, our model-based volatility decomposition shows that sectoral Domar weights (i.e., sales shares) are the appropriate sufficient statistic for measuring the aggregate output and productivity impact of sectoral productivity shocks, as they reflect both the direct and indirect impact arising from production linkages across sectors (Hulten theorem).[6] We show that the contribution of

[4]Although they don't focus on differences between emerging and developed economies, Carvalho and Gabaix (2013) use a sufficient statistic approach to study the role of sectoral composition in changes in volatility over time for the US and other developed economies.

[5]In an economy without production linkages, the sufficient statistic is the value-added share (Hulten theorem). The employment share serves as a rough approximation of the value-added share under certain conditions. It is in this sense that we interpret the use of employment shares as an approximation of the direct impact of sectoral shocks.

[6]Our model also accounts for the role of preferences in output fluctuations—through the response of labor supply to shocks—an aspect that is overlooked in their empirical decomposition.

the sectoral channel is primarily driven by this indirect component.[7] Moro (2015) studies the relationship between structural transformation and differences in business cycle volatility between high- and upper-middle-income economies. While this paper is complementary to ours in examining the role of sectoral composition in explaining cross-country differences in GDP volatility, we additionally explore whether this channel accounts for the relative decline in GDP volatility in emerging economies compared to developed ones over time.[8] Furthermore, our sufficient-statistics approach enables us to cover a broader set of countries across the development spectrum and to work with a more disaggregated sectoral classification—key for assessing the role of production linkages.[9]

It is important to emphasize that, relative to this set of papers, our work also examines additional drivers of volatility beyond the sectoral composition channel—namely, the role of differences in firm size distribution between emerging and developed economies, as well as the impact of international price shocks on aggregate volatility.

Relative to the firm-level channel, to our knowledge, the role of differences in firm size distribution as a driver of aggregate volatility differences between emerging and developed economies has not been explored before.[10] While we find its impact to be limited, we argue that it could be more relevant if firm-level shocks in emerging economies are moderately more volatile.

One of our main analytical results shows that international prices shocks don't affect aggregate output when labor is inelastic. This neutrality of international prices shocks is related to other results by, for example, Kehoe and Ruhl (2008); Burstein and Cravino (2015); and Baqaee and Farhi (2024). We highlight the importance of households' preferences, particularly the responsiveness of labor supply to changes in real income, which is crucial for the transmission of international prices shocks to output.[11]

[7] In addition, there are several differences in their computations relative to ours. A key distinction in our analysis is that we fix the variance and covariance of sector-level shocks across countries, using long-run sectoral data employed in several previous studies, as discussed in our data section. This approach allows us to isolate the role of sectoral composition, conditional on the shocks, and mitigates potential issues associated with estimating volatility matrices from relatively short time series. Furthermore, there are important differences in the set of countries and the period covered. Once these are accounted for, our estimate of the contribution of the direct sectoral channel is consistent with their findings.

[8] Contemporaneous work by Mendoza-Fernández and Meyer (2024) shows that our novel findings regarding the relative decline in emerging market volatility hold across a broader set of emerging economies. Our sample is more limited due to the use of historical input-output tables.

[9] Moro (2015) uses a quantitative model of structural transformation with production linkages between two sectors (manufacturing and services), involving the calibration of a large set of parameters. Furthermore, for our analysis, it is important to take into account the covariance between sectors, which this paper abstracts from.

[10] Gabaix (2011) and di Giovanni and Levchenko (2012) also study the role of firm-level shocks but focus on developed economies and the differences between large and small countries, respectively.

[11] Several papers in the literature that study the transmission of commodity prices shocks to domestic output in open economies [see, for example, Shousha (2016); Drechsel and Tenreyro (2018); Kohn *et al.*

Finally, we also contribute empirically to this strand of literature. Consistent with previous studies that focus on the employment shares across sectors [see Koren and Tenreyro (2007)], we find that emerging economies, compared to developed ones, have larger sectoral Domar weights (sector-level sales as a proportion of total GDP) in more volatile sectors. Additionally, in line with previous work [see, for example, Kohn *et al.* (2021)], we observe that disaggregated trade imbalances in emerging economies are much larger than those in developed economies. Furthermore, we document that large firms in emerging economies exhibit higher concentration measures, such as the squared sum of their Domar weights (firm-level sales as a proportion of total GDP), compared to their counterparts in developed economies.

Organization. The rest of the paper is organized as follows: Section 2 describes the theoretical model and main proposition; Section 3 presents the data and documents the empirical patterns; Section 4 describes the results of the quantitative applications; Section 5 studies the time-series changes in volatility; and Section 6 concludes.

2 Theoretical Framework

We develop a multisector small open economy model with heterogeneous firms and production linkages. We use the model to decompose the volatility of GDP in aggregate, sectoral, firm-level, and international prices channel.

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 subset of nontradable sectors $\mathcal{S}^{NT}$ that can only be sold domestically and a subset of tradable sectors $\mathcal{S}^{T}$ that can be sold domestically and internationally. Then

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

where $S_{NT} + S_{NT} = N$ is the total number of sectors. The economy is relatively small and open, so tradable prices, p_s with $s \in \mathcal{S}^T$, are exogenous. Nontradable prices, p_s with $s \in \mathcal{S}^{NT}$, are determined in general equilibrium. Within each sector $s \in \mathcal{S}$ there is an arbitrarily finite number of heterogeneous firms $i \in \mathcal{I}_s$. The set of all firms in the

(2021)] use GHH preferences, which we show could significantly amplify their transmission by muting the income effects. On the other hand, our results are consistent with those of Huo, Levchenko and Pandalai-Nayar (2023), who find that international transmission is low for a relatively low elasticity of labor supply.

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 $I = \sum_s^N I_s$ is the total number of firms. Firms are linked through their production—i.e., firms buy intermediate goods from other firms—and act competitively. The economy is also populated by a representative household that owns all the firms, consumes, and supplies labor to firms. We next describe the firm and household problems, market-clearing conditions, and aggregates.

2.1.1 Firms

Each firm i in sector s produces homogeneous good s and chooses labor and intermediate inputs to maximize its profits, taking the price of the good produced, wages, and the 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 the 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's 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 of aggregate productivity $A = e^a$, sectoral productivity $\tilde{A}_s = e^{\tilde{a}_s}$, and firm-level idiosyncratic productivity $A_i = e^{a_i}$ components. Crucially, the function $F_s(.)$ exhibits decreasing returns to scale, and thus firms can be heterogeneous within a sector [see Hopenhayn (1992)].

2.1.2 Households

The representative household consumes tradable and nontradable goods, supplies labor to firms, and owns all the firms in the economy. The household maximizes its utility

$$\max_{\mathbf{C},L} \frac{\mathcal{C}(\mathbf{C})^{1-\sigma}}{1-\sigma} - \frac{L^{1+\frac{1}{\psi}}}{1+\frac{1}{\psi}},$$

subject to the budget constraint

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

where σ is the relative risk aversion parameter and ψ the labor-supply elasticity; $\mathcal{C}(.)$ is a homogeneous degree one aggregator over consumption choices $\{C_s\}_{s=1}^N$ with $\mathbf{C} = \begin{bmatrix} C_1 & \cdots & C_s & \cdots & C_N \end{bmatrix}$; L is the aggregate labor supply choice, $\mathbf{p}' \in \mathcal{R}_+^N$ consumption goods' prices, and B^* is the exogenous net transfers to the rest of the world (similar to Baqaee and Farhi (2024)). The household's earnings are the sum of labor income wL and firms' profits $\sum_{i\in\mathcal{I}} \pi_i$. Since firms have 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

Market clearing. First, the total amount of labor demanded by all firms in the economy has to equal the labor supplied by the representative household:

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

Next, for each nontradable sector the goods produced by firms within sector s have to equal household's and all firms' demand of sector s's good:

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

Finally, there is an aggregate external resource constraint such 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:

$$\sum_{s\in\mathcal{S}^T} p_s \left(\sum_{i\in\mathcal{I}_s} y_i - C_s - \sum_{i\in\mathcal{I}} X_{i,s} \right) = \sum_{s\in\mathcal{S}^T} b_s = B^*. \tag{5}$$

Gross domestic product. GDP in this economy is given by aggregate production net the use of intermediate inputs. Using the nontradable sector's market-clearing conditions (4) and that $\mathcal{C}(.)$ is homogeneous of degree 1, we can express the economy's GDP

$(\tilde{Y})$ as

$$\tilde{Y} = \mathbf{p}\mathbf{C}^{'} + B^{*} = wL + \sum_{i \in \mathcal{I}} \pi_i = \mathcal{C}\left(\mathbf{C}\right) + B^{*}, \tag{6}$$

which means that, different from a closed economy setup, in our small open economy GDP differs from welfare by the exogenous net exports.[12] Notice that $\tilde{Y}$ is the GDP deflated by the CPI index $P = P_{\mathcal{C}} = 1$, which is the numeraire, and denote GDP deflated by the production price index $P_{\mathcal{Y}}$ as $Y = \frac{P_{\mathcal{C}}}{P_{\mathcal{Y}}} \tilde{Y}$. Lemma 1 shows analytically what determines the difference between CPI inflation and the production price index change.

Lemma 1. *In an economy with shocks to* $\{A, \tilde{A}_s, A_i, \mathbf{p}^T\}$, *the GDP deflator growth is*

$$d \log P_{\mathcal{Y}} = \sum_{s \in \mathcal{S}^T} b_s d \log p_s. \tag{7}$$

where b_s *is the trade balance of sector* s*. The proof is in Appendix A.*

2.2 Competitive Equilibrium

Definition 1. *A competitive equilibrium is an allocation* $\left\{\{\mathbf{X}_i\}_{i \in \mathcal{I}}, \mathbf{C}, \{L_i\}_{i \in \mathcal{I}}, L\right\}$ *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 its utility,*
- *nontradable goods markets clear and labor market clears.*

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

2.3 Business Cycle Volatility

Before stating the main proposition, it is useful to define the relevant *Domar weights* in this economy. The Domar weight of firm $i \in \mathcal{I}_s$ is the sales share of firm i in GDP $(\tilde{Y})$ and denoted by λ_i—i.e., $\lambda_i \equiv \frac{p_s y_i}{\tilde{Y}}$. Then, it follows that the sectoral Domar weight for a sector s is $\Lambda_s \equiv \sum_{i \in \mathcal{I}_s} \lambda_i$ and the aggregate Domar weight is $\Lambda \equiv \sum_{i \in \mathcal{I}} \lambda_i$.

[12] Define the expenditure function of the household as $e(p, \mathcal{C}) = \sum_s p_s C_s$. Since $\mathcal{C}$ is homogeneous of degree 1, we have $e(p, \mathcal{C}) = \mathcal{C}e(p)$. Normalize the unit cost of consumption $e(p) = 1$ to obtain $\sum_i p_s C_s = \mathcal{C}$, [see, for example, Baqaee and Farhi (2024)].

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

$$d\log Y = \vartheta\left[\Lambda da + \sum_{s\in\mathcal{S}} \Lambda_s d\tilde{a}_s + \sum_{i\in\mathcal{I}} \lambda_i da_i\right] + (\vartheta - 1)\sum_{s\in\mathcal{S}^T} b_s d\log p_s, \tag{8}$$

where $\vartheta = \left(\frac{1+\psi}{1+\psi-\psi\alpha+\alpha\psi\sigma(1-b^*)}\right)$, $\alpha \in (0,1]$ is an aggregate scale parameter, and $b^* = \frac{B^*}{Y-B^*}$. Moreover, if firm-level shocks are uncorrelated and their volatility is the same for all firms, sectoral shocks can be correlated across sectors, and international prices shocks can be correlated across tradable goods, then the variance of GDP growth (in log differences) is

$$Var\,(d\log Y) = \underbrace{\vartheta^2\Lambda^2\sigma_A^2}_{aggregate} + \underbrace{\vartheta^2\mathbf{\Lambda}'\Omega_{\tilde{A}}\mathbf{\Lambda}}_{sectoral} + \underbrace{\vartheta^2\lambda'\lambda\,\sigma_{A_i}^2}_{firm\text{-}level} + \underbrace{(1-\vartheta)^2\,\mathbf{b}'\Omega_{\mathbf{p}^T}\mathbf{b}}_{int.\ prices} \tag{9}$$

where σ_A^2 is the variance of common (aggregate) TFP shocks, $\mathbf{\Lambda}$ the vector of sector-level Domar weights, $\Omega_{\tilde{A}}$ the covariance matrix of sectoral TFP shocks, λ the vector of firm-level Domar weights, σ_{A_i} the variance of firm-level shocks, $\mathbf{b}$ the vector of sectoral trade imbalances, and $\Omega_{\mathbf{p}^T}$ the covariance matrix of international prices shocks. Variance terms are computed for log changes. The proof is in Appendix A.

In Proposition 1, we extend Hulten's theorem to a small open economy with tradable and nontradable sectors, firm-level heterogeneity, and elastic aggregate labor supply. The proof utilizes the envelope condition of the planner's problem (see Appendix A) and it holds for a large family of models.[13]

To a first order, GDP growth and its volatility can be decomposed into four distinctive channels that depend on observable sufficient statistics and one term that summarizes how aggregate labor supply reacts to changes in real income. The channels in our proposition capture both direct and indirect transmission through production linkages and labor responses.

The first term in equation (9) corresponds to the aggregate channel, whose impact depends on the volatility of aggregate TFP shocks and the sum of all firms' Domar weights (aggregate sales share). The second and third terms in equation (9) correspond to 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 TFP shocks and the vector of sectoral Domar weights. The firm-level channel depends on the volatility of firm-level TFP shocks and the Herfindahl index of the firms' sales share. The last term in equation (9) describes the international prices chan-

[13]For example, our framework encompasses models in which the production structure can vary endogenously across countries given aggregate income levels and productivity differences across sectors. Our framework allows for production heterogeneity (Ngai and Pissarides, 2007) and homogeneous degree-one consumption functions, such as non-homothetic CES functions (Comin, Lashkari and Mestieri, 2021). The proposition also holds in an environment where capital is assumed fixed in the short-run—i.e., fixed upon impact of the shock, see vom Lehn and Winberry (2021) for reference.

nel, which depends on the variance and covariance matrix of tradable prices shocks and the vector of sectoral trade balances, scaled by $(1-\vartheta)$.

All four channels are scaled by parameter ϑ, which is determined by parameters of household's preferences and the aggregate trade balance. From equation (8), if $\vartheta > 1$ ($\vartheta < 1$), then TFP and international price shocks are amplified (dampened) by changes in the labor supply. A special case arises when $\vartheta = 1$, which we will characterize next.

Corollary 1. *For any combination of parameter values $\{b^*, \sigma, \psi\, \alpha\}$ such that $\vartheta = 1$, labor supply is not reponsive to real income changes. As a result, up to a first order, international prices shocks do not affect aggregate output volatility, which is given by:*

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

We will refer to the *fundamental* volatility as the aggregate output volatility when labor is inelastic $\vartheta = 1$, which can be interpreted as the aggregate TFP volatility, since it reflects the volatility of aggregate output when aggregate inputs (i.e., labor) are fixed. Equation (10) shows that when $\vartheta = 1$, we recover a variation of Hulten's theorem: To a first order, as in a closed economy setup, only TFP shocks (aggregate, sector-, and firm-level shocks) matter for aggregate output fluctuations, and the Domar weights summarize their importance. The neutrality of international prices shocks is related to the results in Kehoe and Ruhl (2008); Burstein and Cravino (2015); and Baqaee and Farhi (2024). For international prices shocks to matter, the aggregate labor supply must be elastic ($\psi \neq 0$) and the income and substitution effects cannot fully cancel each other.[14] Intuitively, when there is a trade imbalance $b_s \neq 0$ in sector s, a change in p_s changes the real income of the households, since the CPI index changes relative to the GDP deflator (see Lemma 1). If the supply of labor is elastic and the income and substitution effects are different, then L responds to the change in real income, which ultimately changes aggregate output.[15]

Let's now focus into the factors that determine the general equilibrium response of aggregate labor supply. In our setup, the Frisch elasticity is $\psi = \frac{\partial L}{\partial w}\frac{w}{L}$, yet labor response also relies on the elasticity of consumption to labor, denoted as $-\sigma\psi = \frac{\partial L}{\partial C}\frac{C}{L}$,

[14]In our setup, substitution and income fully cancel if there are log-preferences ($\sigma = 1$) and a balanced aggregate trade balance ($b^* = 0$).

[15]In our setup, international prices shocks could also explain aggregate output fluctuations through higher-order moments, such as reallocation. However, Kohn *et al.* (2021) find that the reallocation channel is the least relevant in their quantitative exercises. In our baseline theorem, the reallocation channel is muted since we focus on the first-order approximation. Moreover, we assume that international price shocks cannot affect aggregate output by influencing the TFP process directly, for example, through changes to innovation incentives, by altering financial conditions, as in Drechsel and Tenreyro (2018), or by affecting fiscal revenues and taxes. The study of these potential additional channels is beyond the scope of this paper.

which is muted under, for example, GHH preferences. In general equilibrium, the aggregate labor supply response also depends on resource constraints and technology. In our case, parameters α capture the scale of aggregate production, while b^* represents the long-run aggregate trade balance. The parameter ϑ summarize all these forces.

In the next section, we use a sufficient statistic approach, based on our theory, to quantify how much each channel drives the business cycle volatility differences between emerging and developed economies. Under this approach we don't need to fully calibrate the model to fit the distribution of firms, sectors, and trade imbalances.

3 Data

In this section, we describe the data used for our quantitative analysis and document the differences in the distribution of sectoral and firm-level Domar weights, as well as in disaggregated sectoral balances, between emerging and developed economies.

3.1 Data Description

Data Sources Sector-level sales data is sourced from the OECD Input-Output Tables spanning from 2005 to 2015, covering 36 sectors. After matching all the datasets we have 34 sectors. For the historical exercise we use sector-level sales from the historical World Input-Output Database (long-run WIOD, Version 1.1, March 2022 Release). Firm-level sales are obtained from Worldscope, which encompasses more than 90% of publicly held firms' market capitalization internationally over the past 20 to 30 years. Importantly, this dataset includes financial information for all domestic listed companies (including state-owned firms), and allows to separate sales by domestic subsidiaries, the ones consistent with our theory, from foreign ones. Table B.1 shows the sample selection criteria for Worldscope. Sectoral international trade flows data is sourced from UN Comtrade and merged with the input-output data. The long-run sectoral prices data is obtained from Jorgenson, Ho and Stiroh (2005) dataset, which we also use to estimate the sectoral TFP as in Carvalho and Gabaix (2013). Finally, we use aggregate GDP and TFP data from The World Bank's World Development Indicators (WDI) and Penn World Tables (PWT) version 10.01. More details regarding the data sources and variables used are provided in Appendix B.

Countries and Sectors Our baseline sample comprises 36 countries–17 emerging and 19 developed economies–and 34 sectors, of which 19 are tradable and 15 are nontradable. Appendix B.2 shows the complete list of countries and sectors in our baseline sample. We apply a similar sample selection criteria as Kohn *et al.* (2021), by excluding large open economies such as China and the US, ex-communist countries, and economies with an average population lower than 1 million. Additionally, we exclude countries that don't have disaggregated sectoral, firm-level, or trade data. We define developed economies as those members of the OECD with an average GDP per capita (PPP-adjusted in 2011 US dollars) higher than \$25,000, and emerging economies as those with a GDP per capita lower than \$25,000. We define tradable sectors as those in the primary and manufacturing categories, and nontradable sectors as those in services, which is standard in the literature.

3.2 Empirical Patterns

Aggregate Volatility It is well-documented that emerging economies exhibit significantly greater business cycle volatility compared to developed economies (see, for example, Acemoglu and Zilibotti (1997)). We compute the aggregate business cycle volatility as the variance of the observed annual growth in aggregate GDP per capita and aggregate TFP. During the period 1990-2019, the GDP and TFP volatilities are 2.3 and 3.3 times larger, respectively, in the median emerging economy than in the median developed economy. Moreover, Figure C.1 shows a clear negative relationship between business cycle volatility and per capita income level across countries.

Sectoral Sufficient Statistics The relevant statistics consist of the TFP covariance matrix $\Omega_{\tilde{A}}$ and the vector of sectoral sales shares (Domar weights) $\mathbf{\Lambda}$. In our baseline exercise, due to measurement concerns and to emphasize the role of the sectoral distribution, we assume the sectoral covariance matrix is common across countries.[16] To compute the sectoral TFP covariance matrix $\Omega_{\tilde{A}}$, we use long-run U.S. sector-level TFP as estimated in Carvalho and Gabaix (2013) using Jorgenson *et al.* (2005) data, from which we subtract the commonly correlated component across sectors.[17] Furthermore, since the sectoral TFP is potentially driven by firm-specific shocks, to mitigate this concern we subtract from the covariance matrix the contribution of firm-level shocks

[16] Using sector value-added and employment data from the Groningen Growth and Development Centre (GGDC) 10-Sector and Economic Transformation databases, EU KLEMS, and the OECD Structural Analysis (STAN) Database, we computed the sectoral volatility of value-added over employment at the country level from 1990 to 2016 for the Primary, Manufacturing, and Services sectors. We found that the volatility of the output-to-labor ratio in emerging economies is very similar in Agriculture to that of developed economies, and slightly larger in Manufacturing and Services. This suggests that there may be some heterogeneity in the shocks that could increase the importance of the sectoral channel. However, due to the absence of detailed sectoral prices and quantities data for emerging economies, we are unable to estimate sectoral TFP using standard accounting methods, and therefore we abstract from this source of heterogeneity in the volatility of sectoral TFPs across countries.

[17] To do this, we subtract year fixed effects from the sectoral TFP series. See Appendix B.

weighted by the relevant firm-to-sector multiplier.[18] The sectoral Domar weights are computed as the sales of the sector over GDP using the input-output matrices.

Pattern 1. *Sectoral Domar weights in emerging economies are concentrated in highly volatile sectors, whereas in developed economies they are concentrated in the least volatile sectors.*

Table C.4, Panel (a), summarizes the distribution of sectoral Domar weights in sectors belonging to the highest and lowest quartiles of sectoral volatility for both emerging and developed economies. The sum of Domar weights across the most volatile sectors (e.g, primary or manufacturing sectors) for the median emerging economy is 0.64, compared to 0.50 in developed economies. Similarly, the sum of Domar weights among the least volatile sectors (e.g., services sectors) is 0.68 in the median emerging economy versus 0.89 in the median developed economy.

Firm-level Sufficient Statistics The relevant firm-level statistics consist of the firms' volatility $\sigma^2_{A_i}$ and the vector of firms' Domar weights λ. Similar to sectoral volatility, due to data limitations, we assume that firm-level volatility is common across countries, which allows us to focus on the role of the distribution of firms. Thus, if top firms in emerging economies are intrinsically more volatile, our baseline results represent a lower bound on the importance of this channel. We discuss this further in our additional quantitative exercises. For firm-level volatility, we use the estimates by Gabaix (2011) of $\sigma_{A_i} = 0.12$. These estimates are based in firm-level sales of the top 100 firms in US. The correlations across firms are small, so the volatility is primarily capturing firm-specific shocks. The relevant sufficient statistic for this channel is the sum of the squared firm-level sales shares $(\lambda\lambda')$, which we measure using the vector of the top firms' sales relative to GDP, as discussed below.

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

Figure C.4 shows that in both emerging and developed economies, the cumulative sum of squared Domar weights flattens out when including at least the largest 20 firms. Consistent with Gabaix (2011), in our theory the concentration of sales among the largest firms in the economy is what matters for the impact of firms' idiosyncratic shocks on aggregate volatility. Furthermore, Table C.4, Panel (b) shows that sales within the largest firms are more concentrated in emerging economies, with the sum of Domar weights of the top 70 firms being 0.34 in emerging economies vs 0.27 in developed ones. This pattern remains robust across various thresholds of top firms.

[18] To accomplish this, we subtract from the diagonal elements of the matrix the firm-specific volatility, which is weighted by the sum of the squared sales of the firms over the sectoral-level sales (distinct from a Domar weight). This correction holds to a first order and implicitly assumes that the top firms share is the same across sectors. Results are almost identical without this correction.

Table 1: *Sectoral and firm distribution*

	Sum of Domar weights	
	Emerging	Developed
(a) Sector volatility		
Most volatile sectors	0.64 (0.60,0.70)	0.50 (0.43,0.55)
Least volatile sectors	0.68 (0.62,0.75)	0.89 (0.77,0.93)
(b) Firms' concentration		
Top firms	0.34 (0.20,0.44)	0.27 (0.20,0.34)

Source: Penn World Tables (PWT), OECD-IOT, Jorgenson *et al.* (2005) dataset, and Worldscope firm-level data.
Note: Panel (a) shows the sum of Domar weights across sector's volatility for the median emerging and developed economies. "Most volatile sectors" refer to sectors belonging to the highest quartile in volatility; "Least volatile sectors" refer to sectors belonging to the lowest quartile in volatility. Panel (b) shows the sum of Domar weights for top firms in the economy for the median emerging and developed economies. Top firms are the 70 largest firms in terms of sales. We report in parentheses values that correspond to the 25th and 75th percentiles.

International Trade Sufficient Statistics The relevant international trade statistics consist of the international prices' volatility $\Omega_{\mathbf{p}^T}$ and the vector of sectoral trade imbalances $\mathbf{b}$. The matrix $\Omega_{\mathbf{p}^T}$ is computed only for the tradable sectors and it is common across countries. In addition, the sectoral trade imbalances over GDP are computed for each country and tradable sector in our data. Figure C.5 shows the disaggregated sectoral trade imbalances for the tradable sectors for the median emerging and developed economies. We observe that trade imbalances are much larger in emerging economies. In addition, consistent with Kohn *et al.* (2021), while emerging economies are net exporters of primary goods and net importers of manufactures, developed economies are roughly balanced in the two sectors.

Pattern 3. *Emerging economies have larger sectoral trade imbalances than developed ones.*

Overall, emerging economies concentrate their economic activity in higher volatility sectors (e.g., primary sectors), have more concentration at the top of the firms' distribution, and they have larger trade imbalances across sectors. We use these model-based sufficient statistics to quantify the relevance of each channel in explaining why emerging economies are more volatile than developed ones.

4 Why Are Emerging Business Cycles More Volatile?

We first examine the extent to which each channel—sectoral, firm, and international prices—can account for the differences in business cycle volatility between emerging and developed economies. Second, we study how our results relate to the structural transformation process. Last, we discuss the role of correlated shocks and intrinsic firm-level volatility differences across countries.

4.1 Volatility Accounting

As emphasized in Section 2.3, our theory makes a clear distinction between aggregate TFP volatility (or *fundamental* volatlity, see Corollary 1) and aggregate output volatility, with the first one being independent of household preferences parameters. Thus, in what follows we conduct business cycle volatility accounting for aggregate TFP and aggregate output separately. [19] In both cases, we isolate the contribution of the micro-structure of the economy by assuming: (i) the sector-level covariance matrix is the same across countries; (ii) firm-level volatility is the same across firms and countries; and (iii) the sum of Domar weights for non-top firms tends to zero, as in the data. These assumptions imply that the contributions of the sectoral and firm-level channels are explained *only* by differences in the micro-structure of the economy, and not by intrinsic differences in sector- and firm-level volatility across countries.[20]

4.1.1 TFP Volatility

Using the fundamental volatility equation from the theory, we can express the difference in TFP volatility across emerging and developed economies as:

$$\sigma^2_{\text{EM}} - \sigma^2_{\text{DEV}} = \underbrace{\boldsymbol{\Lambda}'_{\text{EM}}\Omega_{\tilde{A}}\boldsymbol{\Lambda}_{\text{EM}} - \boldsymbol{\Lambda}'_{\text{DEV}}\Omega_{\tilde{A}}\boldsymbol{\Lambda}_{\text{DEV}}}_{\text{sectoral distribution}} + \underbrace{\left[\left(\lambda'\lambda\right)^{\text{top}}_{\text{EM}} - \left(\lambda'\lambda\right)^{\text{top}}_{\text{DEV}}\right]\sigma^2_{A_i}}_{\text{firm-level distribution}}$$
$$+ \underbrace{\Lambda^2_{\text{EM}}\sigma^2_{A,\text{EM}} - \Lambda^2_{\text{DEV}}\sigma^2_{A,\text{DEV}}}_{\text{residual aggregate}}, \tag{11}$$

where EM refers to the emerging economy statistics and DEV to the developed ones, and σ^2_i is the business cycle–TFP in our application–volatility of $i = \{\text{EM}, \text{DEV}\}$.

Decomposition (11) shows that aggregate TFP volatility can be expressed in terms of sufficient statistics that can be taken directly from the data: differences in the distribution of Domar weights across sectors and differences in the sum of the squared firm-level Domar weights. Notably, as discussed in the previous section, the international prices don't play a role in the fundamental volatility.

Table 2 reports our main findings. Differences in the distribution of sectors and firms

[19]Our main propositions show that the channels are linear in the variance of the log growth, allowing us to perform a volatility accounting exercise.

[20]We don't rule out that differences in intrinsic volatility can exist and might be relevant (see the discussion in Section 4.4).

can explain as much as 75% (68% sectoral and 7% firm-level) of the excessive aggregate volatility in emerging economies. Thus, the heterogeneity in sectoral composition across countries is a major driver of the higher volatility observed in emerging economies. This is consistent with the higher concentration of economic activity in volatile sectors in emerging economies, as noted in the previous section.

Table 2: *TFP Volatility accounting: Emerging vs Developed economies*

	Contribution		
	Sectoral	Firm-level	Aggregate
Baseline (median)	0.68	0.07	0.25
[P25,P75]	[0.44,0.68]	[-0.01,0.07]	[0.58,0.26]

Note: the contributions of each channel estimated using equation (11). To compute the country-group statistics, we first average each sufficient statistic across time for each country and then, for each sufficient statistics we take the median, 25th percentile, or 75th percentile across countries in each group (emerging or developed). Further details about the data and computation are in the text. In the "Baseline" model, median values of sufficient statistics across emerging and across developed economies are used to compute the contribution of each channel; "P25" ("P75") refers to the result for the exercise using the 25th (75th) percentile of the distribution of sectoral and firm-level Domar weights and TFP volatility across emerging and developed economies.

However, we find that the distribution of firms, although more concentrated at the top in emerging economies, does not explain much of the excessive volatility. Finally, as a residual, the aggregate component, which captures economy-wide shocks (e.g., monetary policy shocks, fiscal shocks) explain around 25% of the excessive TFP volatility in emerging economies.

4.1.2 GDP Volatility

Next, we study the contribution of each channel to differences in aggregate output volatility. Unlike total factor productivity (TFP), output fluctuations, to a first order, can also be influenced by variations in aggregate inputs such as labor. Consequently, the volatility of output depends on the micro shocks—sectoral, firm-level, and tradable prices—and how aggregate labor responds to them. We must then assign values to the parameters of the utility function and the long-run aggregate trade balance, as stated in our main Proposition 1. Moreover, in this case the international prices do play a role, through changes in real households' income that affects their labor supply decision.

We use a range of parameters that includes those often used in the macro literature. We assign a value of $\alpha = 2/3$ for the aggregate labor scale parameter and $b^* = -0.03$ for the trade balance parameter, consistent with the historical trade balances in our sample. We use a range of values for the Frisch elasticity, ψ, from 0.5 to 4, which includes common values used in the literature (see, for example, Huo *et al.* (2023); Schmitt-Grohé and Uribe (2018)). For the curvature of the utility of consumption, σ

(the inverse of the intertemporal elasticity of substitution), we use values ranging from 0.9 to 4, which contain standard values commonly used in the business cycle literature (see, for example, Aguiar and Gopinath (2007)). Analogously to our TFP volatility accounting, we can decompose the difference in output volatility using equation (9) for both emerging and developed economies. For this wide range of parameters the lowest multiplier ϑ is 0.38 and the maximum is 1.4.

Table 3: *GDP Volatility accounting: Emerging vs Developed economies*

	Contribution		
	Sectoral	Firm-level	Int. Prices
$\vartheta = 1$	0.41	0.04	0.006
max ϑ	0.75	0.07	0.002
min ϑ	0.06	0.01	0.000
$\{\sigma = 2; \psi = 1\}$	0.29	0.03	0.000
$\{\sigma = 0; \psi = 0.75\}$	1.02	0.10	0.000

Note: the contributions of each channel are estimated using equation (11) for different values of the parameters. Further details about the data and computation are in the text. Each exercises uses the median values of sufficient statistics across emerging and across developed economies are used to compute the contribution of each channel.

Table 3 shows the contribution of each channel for several sets of parameters. As expected, results vary significantly depending on the parameter values. The first line shows the contribution of each channel when labor supply is inelastic ($\vartheta = 1$).[21] The second line represents the maximum ϑ within the parameter range, while the third line shows the value for the minimum of this range. The last two lines consider two additional cases commonly used in the study of business cycle fluctuations: one with $\sigma = 2; \psi = 1$ and another where preferences follow GHH with $\psi = 0.75$.

Several observations. First, the international price channel is irrelevant irrespective of the parameters. Intuitively, through the lens of our model, when disaggregated trade imbalances are low, price volatility would need to be extremely large and correlated across sectors for this channel to have any explanatory power. Second, the sectoral channel plays a relevant role in most cases, except those where the transmission is significantly dampened due to a low Frisch elasticity and high consumption curvature (in third and fourth lines). Finally, the role of the firm distribution increases with a greater labor supply response, but it is limited to 10% at most in the range of parameters we study.

[21]Notice that the results when $\vartheta = 1$ differ from those presented in Table 2. The reason is because in Table 3, the denominator corresponds to observed differences in GDP volatility, whereas in Table 2, it corresponds to observed differences in TFP volatility.

Overall, we find that the sectoral channel is a significant factor in explaining why GDP is more volatile in emerging economies than in developed ones. In contrast, differences in firm distribution play a minor role, and international prices are irrelevant within the real income channel explored in this paper.

4.2 Direct and Indirect Sectoral Contributions

In this section, we decompose the total contribution of the sectoral channel into its direct and indirect components. A sector's value-added share captures the direct impact of productivity changes in that sector on the aggregate, while the sales share also accounts for the indirect impact that arise through production linkages. Since Hulten's theorem holds in our economy, the value-added share is the appropriate sufficient statistic in the absence of linkages, whereas the sales share is the relevant one when sectors are interconnected through the use of intermediate inputs.

Table C.3 presents the decomposition of the sectoral channel into direct and indirect. For both aggregate TFP volatility and different parameterizations of GDP volatility, the indirect channel plays a crucial role, accounting for more than 80% of the sectoral channel's total contribution in all cases.

What explains the large importance of the indirect sectoral channel? Table C.4 reports the ratio of Domar weights to value-added and its relationship with sectoral volatility in emerging and developed economies. A higher ratio indicates a stronger amplification through production linkages. The sectors where this amplification channel is the largest are also the most volatile, with a median Domar weight-to-value-added ratio of 2.27 in emerging economies and 2.72 in developed economies.[22] This pattern explains why, quantitatively, the indirect component plays such a dominant role in the sectoral channel.

4.3 Relation to Structural Transformation

We analyze which specific sectors are driving such a substantial contribution of the sectoral channel. As shown in the first three columns of Table 4, emerging economies tend to have relatively more sales shares in agriculture and manufacturing, which are the most volatile sectors. On the other hand, developed economies concentrate relatively more sales in services, which is a low-volatility sector. These patterns are consistent with the process of structural transformation, which has been widely studied in the macro-development literature (Herrendorf *et al.*, 2014). Structural transformation

[22] For the least volatile sectors, the ratio of Domar weight to value added is 1.66 in emerging economies and 1.83 in developed economies.

posits that as countries develop, they transition their production away from agriculture and manufacturing and toward services.

We conduct a counterfactual analysis to quantify the relative importance of each sector in explaining the excessive volatility observed in emerging economies. Results are reported in the fourth column of Figure 4. If differences in sectoral Domar weights arose only from agriculture, the sectoral channel would explain 51% of GDP volatility differences. If they arose only from manufacturing, the sectoral channel would contribute 70%. Lastly, if the only differences arose from services, the sectoral channel would yield a negative contribution of -54%, which implies that this sector plays a pivotal role in explaining aggregate TFP volatility in developed economies but not in emerging economies. These results suggests that differences in business cycle volatility between levels of development can emerge as an intrinsic part of the development process.

Table 4: *Sectoral channel decomposition*

	Domar W		Volatility	Contribution
	EM	DEV	(std)	to differences
Agriculture	0.20	0.05	0.10	51%
Manufacturing	0.59	0.42	0.08	70%
Services	1.04	1.32	0.05	-54%

Source: Authors' calculations based on OECD-IOT.
Note: The first column shows sectoral Domar weights for the median emerging (EM) and developed (DEV) economies; the second column shows sectoral TFP volatility; the third column shows the contribution of the sectoral channel (net cross-sector correlations) in the counterfactual scenario in which sale shares for all sectors but the one under analysis are the same in emerging and developed economies.

4.4 Discussion

Correlated vs. Uncorrelated Sectoral Shocks So far, in the analysis we have allowed for the possibility of sectoral TFP shocks to be correlated. Alternatively, we assume that sectoral TFP shocks are uncorrelated, and find that the sectoral channel explains 95% of excessive volatility in emerging economies. This very large contribution suggests that for very disaggregated sectors, as in our application, the correlations between sectors play a crucial role. More specifically, in our quantitative application, they dampen the importance of sectoral shocks in the aggregate, reducing their contribution by 27% in our baseline exercise. Thus, ignoring the potential correlation of sectoral TFP shocks would lead us to significantly overestimate the contribution of this channel.

Intrinsic Firm-level Volatility Differences In our baseline exercise, we find that the firm-level distribution, on its own, plays a minor role in explaining excessive volatility. However, emerging economies may be more volatile due to larger idiosyncratic shocks to firms. Estimating firm-level TFP volatility requires extensive data that we currently lack, so we rely on our theory to provide insights into the potential relevance of intrinsic differences in firms' shocks. To do this, we assume that the residual portion of the excessive volatility stems solely from intrinsic differences in firm-level volatility (i.e., we assume the aggregate channel is zero and that the residual is explained by the firm-level channel; see Appendix C.3.2 for details on the computation). In this exercise, we can estimate the firm-level volatility in emerging economies that would explain the residual difference in overall volatility. We find that the idiosyncratic volatility of firms in emerging economies would need to be approximately twice as high as in developed economies to account for the 25% of volatility not explained by differences in the sector and firm distributions. This suggests that the firm-level channel may be significantly more relevant if firms in emerging economies are even moderately more volatile.[23]

Crisis and Inflation Episodes One potential concern is that our baseline exercise includes countries that experienced extreme events, such as major crises or episodes of high inflation, which may distort the economic structure. To address this, we study how our results change when excluding countries that faced large financial crises—such as sovereign debt defaults—or episodes of high inflation during the sample period. To identify sovereign debt default episodes, we use the crisis dating data from Laeven and Valencia (2018). For inflation surge episodes, we follow a criterion similar to Blanco, Ottonello and Ranosova (2022), defining a high-inflation surge as a year in which inflation increases by more than 5 percentage points. The results and further discussion are provided in Appendix C.6. Overall, we find that the contribution of the sectoral channel remains relatively large across different samples, while the firm-level channel continues to play a limited role.

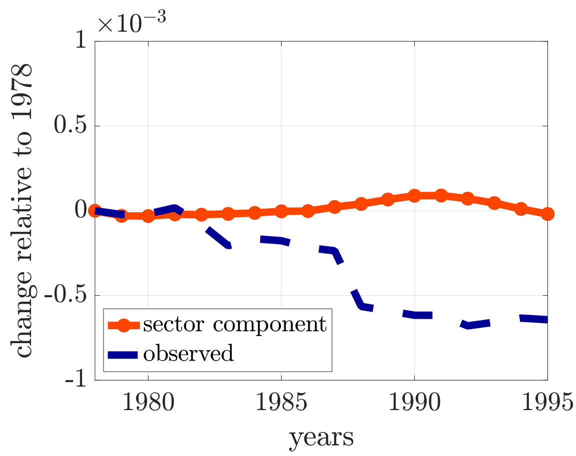
5 Time-series Analysis

Lastly, we study volatility differences between emerging and developed economies over time, and quantify the contribution of the sectoral channel in explaining the time series patterns. We document a significant reduction in TFP volatility in both emerging and developed economies during the period between 1978 and 1995 (See Appendix

[23] As a reference, Kochen (2023) estimates that the volatility (variance) of transitory firm-level TFP shocks in middle-income European economies is twice that in high-income European economies.

Figure C.2). Notably, this decline is more pronounced in emerging economies.[24] Using historical input-output data from WIOD, we employ our theoretical framework from Section 2 to examine how shifts in the sectoral structure of developed and emerging economies affected the *relative* reduction in TFP volatility in emerging economies. In calculating the time series of the sectoral channel, we allow Domar weights to vary over time, while keeping the covariance matrix of the sectoral TFP shocks ($\Omega_{\tilde{A}}$) fixed.

Figure 1: *TFP volatility and sectoral channel evolution*



Notes: This figure shows the evolution of the volatility driven by the sectoral distribution $\left(\boldsymbol{\Lambda}'_{\text{EM},t}\Omega_{\tilde{A}}\boldsymbol{\Lambda}_{\text{EM},t} - \boldsymbol{\Lambda}'_{\text{DEV},t}\Omega_{\tilde{A}}\boldsymbol{\Lambda}_{\text{DEV},t}\right)$ and the observed TFP volatility differences $(\sigma^2_{\text{EM}} - \sigma^2_{\text{DEV}})$ relative to base year 1978.

We find that the sectoral channel alone cannot account for the relative decrease in volatility in emerging economies, as illustrated in Figure 1. In fact, there is a surge in the relevance of the service sector in both emerging and developed economies, which may be a key driver of the substantial decrease in volatility observed in both types of economies —a phenomenon previously noted by Carvalho and Gabaix (2013) for the United States and other developed countries. Differently from our baseline exercise and its mapping to structural change, the results in this section suggest that the relative decline in volatility in emerging economies in the last 30-40 years do not seem inherent to the process of economic development. Instead, for example, improvements in macroeconomic policy management in emerging markets, globalization, and other economy-wide factors beyond the scope of this paper may contribute to this relative decline in volatility.

[24]In Appendix Table C.2, we use different samples to check for robustness and find that the relative decline in emerging economies business cycle is robust across samples. We focus on this period due to data availability.

6 Conclusion

In this paper, we study why emerging economies are more volatile than developed economies through the lens of a small open economy general equilibrium model with production linkages, tradable and nontradable sectors, heterogeneous firms within each sector, and elastic aggregate labor supply. Our main proposition shows that in this economy, aggregate output, to a first order, can fluctuate through four channels—aggregate, sectoral, firm-level, and international prices—which depend on observable sufficient statistics and parameters that summarize the responsiveness of aggregate labor to changes in households' real income.

Our quantitative application, using sector- and firm-level data from several countries, reveals that differences in sectoral and firm distribution between emerging and developed economies can explain around three-fourths of the greater business cycle volatility in emerging economies. However, changes in economic structure cannot explain why emerging economies have become relatively less volatile over time, which suggests there are other factors, such as improvements in macroeconomic management, driving the relative decline in volatility in these economies.

Our paper remains silent on why the microstructure of the economy (the distribution of sectors and firms) differs between emerging and developed economies. Whether these differences are driven by variations in natural endowments, skill distribution, market structure, inefficiencies, or standard income and relative price channels would have distinct normative implications. Additionally, we find that factors beyond economic structure are likely to explain why volatility has declined disproportionately more in emerging economies, raising the question of what is driving this trend–whether it is government policies or other factors not accounted for by our theory. We leave these interesting research avenues for future work.

References

ACEMOGLU, D. and ZILIBOTTI, F. (1997). Was Prometheus Unbound by Chance? Risk, Diversification, and Growth. *Journal of Political Economy*, **105** (4), 709–751.

AGUIAR, M. and GOPINATH, G. (2007). Emerging market business cycles: The cycle is the trend. *Journal of Political Economy*, **115** (1), 69–102.

BAQAEE, D. R. and FARHI, E. (2024). Networks, barriers, and trade. *Econometrica*, **92** (2), 505–541.

BLANCO, A., OTTONELLO, P. and RANOSOVA, T. (2022). *The dynamics of large inflation surges*. Tech. rep., National Bureau of Economic Research.

BURSTEIN, A. and CRAVINO, J. (2015). Measured Aggregate Gains from International Trade. *American Economic Journal: Macroeconomics*, **7** (2), 181–218.

CALVO, G. A., IZQUIERDO, A. and TALVI, E. (2006). Sudden Stops and Phoenix Miracles in Emerging Markets. *American Economic Review*, **96** (2), 405–410.

CARVALHO, V. and GABAIX, X. (2013). The Great Diversification and Its Undoing. *American Economic Review*, **103** (5), 1697–1727.

COMIN, D., LASHKARI, D. and MESTIERI, M. (2021). Structural change with long-run income and price effects. *Econometrica*, **89** (1), 311–374.

DA-ROCHA, J. M. and RESTUCCIA, D. (2006). The role of agriculture in aggregate business cycles. *Review of Economic Dynamics*, **9** (3), 455–482.

DI GIOVANNI, J. and LEVCHENKO, A. A. (2012). Country size, international trade, and aggregate fluctuations in granular economies. *Journal of Political Economy*, **120** (6), 1083–1132.

DRECHSEL, T. and TENREYRO, S. (2018). Commodity booms and busts in emerging economies. *Journal of International Economics*, **112** (C), 200–218.

GABAIX, X. (2011). The Granular Origins of Aggregate Fluctuations. *Econometrica*, **79** (3), 733–772.

HERRENDORF, B., ROGERSON, R. and VALENTINYI, Á. (2014). Chapter 6 - growth and structural transformation. In P. Aghion and S. N. Durlauf (eds.), *Handbook of Economic Growth*, *Handbook of Economic Growth*, vol. 2, Elsevier, pp. 855–941.

HOPENHAYN, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, **60** (5), 1127–1150.

HULTEN, C. R. (1978). Growth Accounting with Intermediate Inputs. *The Review of Economic Studies*, **45** (3), 511–518.

HUO, Z., LEVCHENKO, A. A. and PANDALAI-NAYAR, N. (2023). International Comovement in the Global Production Network, working paper.

JORGENSON, D., HO, M. S. and STIROH, K. (2005). *Productivity, Vol. 3 Information Technology and the American Growth Resurgence*. MIT Press.

KEHOE, T. J. and RUHL, K. J. (2008). Are Shocks to the Terms of Trade Shocks to Productivity? *Review of Economic Dynamics*, **11** (4), 804–819.

KOCHEN, F. (2023). Finance Over the Life Cycle of Firms, working paper.

KOHN, D., LEIBOVICI, F. and TRETVOLL, H. (2021). Trade in Commodities and Business Cycle Volatility. *American Economic Journal: Macroeconomics*, **13** (3), 173–208.

KOREN, M. and TENREYRO, S. (2007). Volatility and Development. *The Quarterly Journal of Economics*, **122** (1), 243–287.

LAEVEN, M. L. and VALENCIA, M. F. (2018). *Systemic banking crises revisited*. International Monetary Fund.

LUCAS, R. E. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, **22** (1), 3–42.

MENDOZA-FERNÁNDEZ, A. and MEYER, T. (2024). The emerging market great moderation. *Available at SSRN 4946632*.

MOBARAK, A. M. (2005). Democracy, Volatility, and Economic Development. *The Review of Economics and Statistics*, **87** (2), 348–361.

MORO, A. (2015). Structural change, growth, and volatility. *American Economic Journal: Macroeconomics*, **7** (3), 259–94.

NEUMEYER, P. A. and PERRI, F. (2005). Business Cycles in Emerging Economies: The Role of Interest Rates. *Journal of Monetary Economics*, **52** (2), 345–380.

NGAI, L. R. and PISSARIDES, C. A. (2007). Structural change in a multisector model of growth. *American Economic Review*, **97** (1), 429–443.

SCHMITT-GROHÉ, S. and URIBE, M. (2018). How important are terms-of-trade shocks? *International Economic Review*, **59** (1), 85–111.

SHOUSHA, S. (2016). Macroeconomic Effects of Commodity Booms and Busts: The Role of Financial Frictions, working paper.

URIBE, M. and YUE, V. Z. (2006). Country Spreads and Emerging Countries: Who Drives Whom. *Journal of International Economics*, pp. 6–36.

VEGH, C. A. and VULETIN, G. (2014). The Road to Redemption: Policy Response to Crises in Latin America. *IMF Economic Review*, **62** (4), 526–568.

VOM LEHN, C. and WINBERRY, T. (2021). The Investment Network, Sectoral Comovement, and the Changing U.S. Business Cycle*. *The Quarterly Journal of Economics*, **137** (1), 387–433.

Online Appendix
"The Business Cycle Volatility Puzzle: Emerging vs Developed Economies" by Lucia Casal and Rafael Guntin

A Proofs

A.1 Proof of Lemma 1

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

$$\mathrm{d}\ln P = \sum_{s\in\mathcal{S}^T} \frac{p_s C_s}{\sum_{s\in\mathcal{S}} p_s C_s} \mathrm{d}\log p_s, + \sum_{s\in\mathcal{S}^{NT}} \frac{p_s C_s}{\sum_{s\in\mathcal{S}} p_s C_s} \mathrm{d}\log p_s. \tag{12}$$

By definition, the nominal GDP is $\tilde{\mathcal{Y}} = \sum_{s\in\mathcal{S}} p_s\,(y_s - X_s)$, 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, scaling (12) by the ratio of total expenditure to GDP and using (12) $\mathrm{d}P = 0$, then

$$0 = \sum_{s\in\mathcal{S}^T} \frac{p_s C_s}{\tilde{\mathcal{Y}}} \mathrm{d}\log p_s + \sum_{s\in\mathcal{S}^{NT}} \frac{p_s C_s}{\tilde{\mathcal{Y}}} \mathrm{d}\log p_s. \tag{13}$$

The GDP deflator growth is

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

then using the non-tradable market clearing $y_s = C_s + X_s$ and (13), the GDP deflator growth is

$$\mathrm{d}\log P_{\mathcal{Y}} = \sum_{s\in\mathcal{S}^T} b_s \mathrm{d}\log p_s. \tag{14}$$

where $b_s \equiv \frac{(y_s - X_s - C_s)}{\tilde{\mathcal{Y}}}$.

$\square$

A.2 Proof of Proposition 1

Using the firms' optimal choices and market clearing conditions in the non-tradable sector and labor markets, we can write the aggregate production function as

$$\tilde{\mathcal{Y}}\left(\mathcal{A},\mathbf{p}^{T},L\right)=H\left(\mathcal{A},\mathbf{p}^{T},L\right)L^{\alpha}.$$

where $\alpha\in(0,1]$ is the scale parameter of the aggregate production function.

Assumption 1. *We assume that the aggregate production function satisfies the following assumption*

$$\frac{\partial H\left(\mathcal{A},\mathbf{p}^{T},L\right)}{\partial L}\rightarrow 0 \tag{15}$$

This assumption assures that aggregate labor endowment doesn't affect the allocations across firms, therefore aggregate TFP, in equilibrium.

Proof of Proposition 1. The economy is efficient then to show the SOC Hulten Theorem using the envelope conditions of the planner's problem. We do this in two steps, first, we show the standard Hulten theorem with fixed L, and then we find L to determine the total response of aggregate output.

Planner's problem. Using the aggregation properties, given L, the planner solves the following problem

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

where $\mathcal{A}_i=A\tilde{A}_sA_i$ 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 $\tilde{\mathcal{Y}}(A,\tilde{A}_s,A_i,\mathbf{p}^{T})/P_{\mathcal{Y}}=\mathcal{Y}(A,\tilde{A}_s,A_i,\mathbf{p}^{T})$ 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 $\mathbf{p}^{T}$.

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

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

The FOC with respect to consumption are

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

From the descentralized problem of the household the optimal conditions are

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

which implies that $\mu^T = 1$ and $\mu_s = p_s$. Then replacing in the envelope conditions of the planner's problem and rearranging terms using the definition of firm-level Domar weights, i.e.

$$\lambda_i \equiv \frac{p_s A \tilde{A}_s A_i F_s \left(L_i, \left\{ X_{i,j} \right\}_{j=1}^S \right)}{\tilde{\mathcal{Y}}},$$

then the optimal conditions are

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

The first order response of output, fixed L, to changes to shocks $\{A, \tilde{A}_s, A_i, \mathbf{p}^T\}$ is

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

Equation (16) is Hulten's theorem for our economy when labor is inelastic and GDP is deflated by the CPI.[25] Using the properties of the aggregate production function and for L fixed, we it is straightforward that $\mathrm{d} \log \tilde{Y} = \mathrm{d} \log H$.

Find L and Y response. Using Assumption 1 we solve for the household's L choice problem, such that

$$\max_L \frac{(HL^\alpha - B^*)^{1-\sigma}}{1-\sigma} - \frac{L^{1+\frac{1}{\psi}}}{1+\frac{1}{\psi}}$$

then the optimality condition is

$$H \left(\tilde{Y} - B^*\right)^{-\sigma} = L^{\frac{1}{\psi}+1-\alpha} \rightarrow \alpha^\psi \left(Y - B\right)^{-\psi\sigma} = H^{-\frac{1+\psi}{\alpha}} Y^{\frac{1+\psi-\psi\alpha}{\alpha}}$$

Next, using logs, first difference and log-linearizing $\log\left(\tilde{Y} - B^*\right)$[26]

$$\partial \ln Y = \left(\frac{1+\psi}{1+\psi-\psi\alpha+\alpha\psi\sigma\left(1-b^*\right)}\right) \partial \ln H,$$

where $b^* = \frac{B_0^*}{Y_0 - B_0^*}$. Last, using Lemma 1, we deflate $\tilde{Y}$ by the GDP deflator and using (16), then it follows that

$$\partial \log Y = \vartheta \left[\Lambda \partial a + \sum_{s\in\mathcal{S}} \Lambda_s \partial a_s + \sum_{i\in\mathcal{I}} \lambda_i \partial a_i\right] + (\vartheta - 1) \sum_{s\in\mathcal{S}^T} b_s \partial \log p_s.$$

where $\vartheta = \frac{1+\psi}{1+\psi-\psi\alpha+\alpha\psi\sigma(1-b^*)}$

□

B Data Appendix

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

[25]In a previous version of the theorem we consider shocks to B^*, but they don't affect real output when aggregate labor supply is inelastic. This result is consistent with the results by Burstein and Cravino (2015); Baqaee and Farhi (2024).

[26]Log approx for $\log\left(\tilde{Y} - B^*\right) - \log\left(\tilde{Y}_0 - B_0^*\right) = \frac{\tilde{Y}-\tilde{Y}_0}{\tilde{Y}_0 - B_0^*}$ then $\mathrm{d}\log\left(\tilde{Y} - B^*\right) = \left(\frac{\tilde{Y}_0}{\tilde{Y}_0 - B_0^*}\right) \mathrm{d}\log \tilde{Y}$. Due to Inada conditions we know $\tilde{Y} - B^* > 0$.

B.1 Data Sources by Channel

Business Cycle Volatility. For our baseline calculations, using PWT 10.01 we calculate the real GDP per capita by dividing the real GDP at constant prices (`rgdpna`) by the population (`pop`). Additionally, we use the TFP measure at constant prices (`rtfpna`). To determine income levels, we rely on output at current PPP (`cgdpo`). Furthermore, for certain computations such as country categorization and GDP ratios, we incorporate data from the GDP per capita PPP-adjusted in 2011 dollars, GDP in constant LCU, and GDP at current USD from the World Development Indicators (WDI). For our baseline calculations, we compute the volatility of TFP and output for the period 1990-2019 for each country. The volatility is the variance of aggregate output and TFP annual growth in logs.[27] To aggregate across regions, we compute the average across years within for each country, and then we calculate the country group moments.

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 as in Carvalho and Gabaix (2013) as the residual from standard gross-output accounting. 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 (34 sectors in total after sample selection).

To compute the long-run changes in Domar weights — in the time-series exercise — we use historical input-output data from WIOD, which covers the period 1965 to 2000. Domar weights are calculated using 8-year window, where the reference year is the 6th year (i.e., median year of the window).

[27] Results are unchanged if we use deviation from the HP trends, instead of annual growth.

Firm-level Channel. We use the Worldscope dataset to compute the firms' 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 shows our sample selection criteria for Worldscope.

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
Potential duplicates*	177,576	552,683
Irregular foreign sales shares (<0%, >100%)	179,141	373,542
Match with GDP data	126,115	247,427
Further refinements**	124,088	123,339
Match with baseline country sample	36,522	86,817

Source: Worldscope. *For example, we exclude observations for which `ITEM6027` indicates the location is in US (840). ** For better coverage in emerging economies we consider post-2010 firms and keep top country-years with at least 70 firms.

International Prices Channel. We use international trade sector-country data from UN Comtrade to compute the country-sector trade imbalances b_s. Trade imbalances b_s are defined as a sector s exports minus imports as a share of GDP. We construct the series consistent with the OECD tradable sectors. We use data from U.S. sector-level prices from Jorgenson *et al.* (2005) to compute the volatility of tradable sector prices. We deflate the time series by US CPI. The main advantage of using this dataset is that the international prices are compatible with our sectoral TFP data.

B.2 Countries and Sectors

Table B.2: *Countries in the baseline sample*

Emerging	Developed
Argentina	Australia
Brazil	Austria
Chile	Belgium
Colombia	Canada
Costa Rica	Switzerland
Indonesia	Germany
India	Denmark
South Korea	Spain
Morocco	Finland
Mexico	France
Malaysia	United Kingdom
Peru	Greece
Philippines	Israel
Portugal	Italy
Thailand	Japan
Turkey	Netherlands
South Africa	Norway
	New Zealand
	Sweden

Table B.3: *Tradable and nontradable OECD sectors*

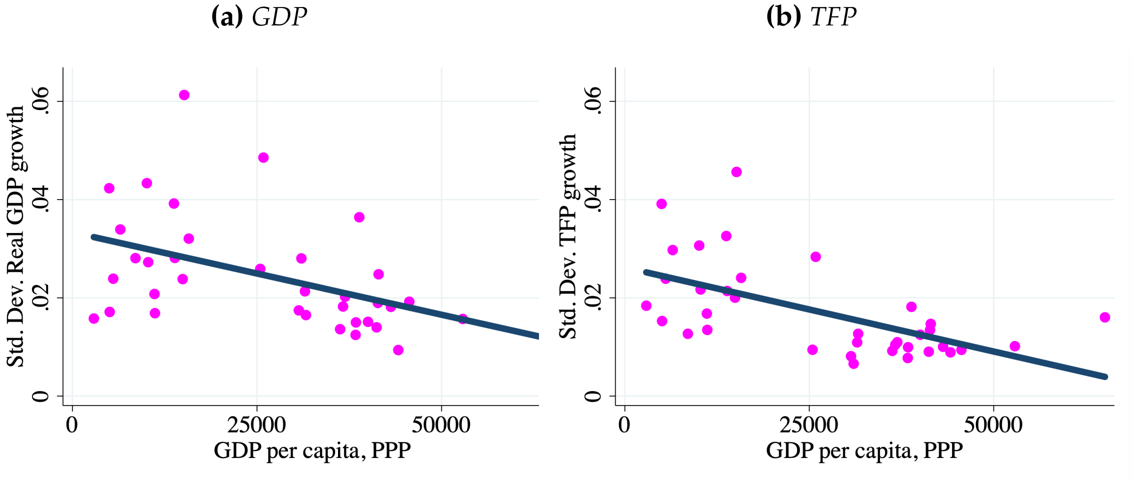
Tradables	Nontradables
Mining and ext.of energy prod	Electricity, gas, water supply
Coke and refined petroleum products	Other business sector services
Machinery and equipment	Financial and insurance activities
Other transport equipment	Wholesale and retail trade; repair of motor vehicles
Motor vehicles, 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 and Figures

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

C.1 Volatility and Development

Figure C.1: *Business Cycle Volatility and Development*



Notes: Panel (a) shows the relationship between GDP volatility and GDP per capita level. Panel (b) shows the relationship between TFP volatility and TFP per capita level. Period 1990-2019. Data source: Penn World Tables.

C.2 Structural Transformation and Business Cycle Volatility

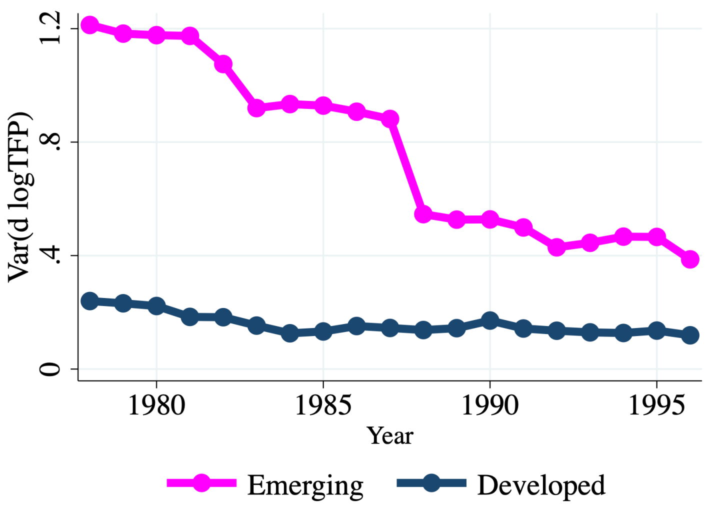
We describe the sample used in the exercise that uses historical input-output data from WIOD.

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

Figure C.2 documents that business cycle volatility has been decreasing over time in both emerging and developed economies.

Figure C.2: *Volatility Across Time*



Notes: The Figure shows the volatility of emerging and developed economies over time. The volatility at year t is computed for an 8-year window centered in year t. The variance is multiplied by 1000. Data source: Penn World Tables (PWT).

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*

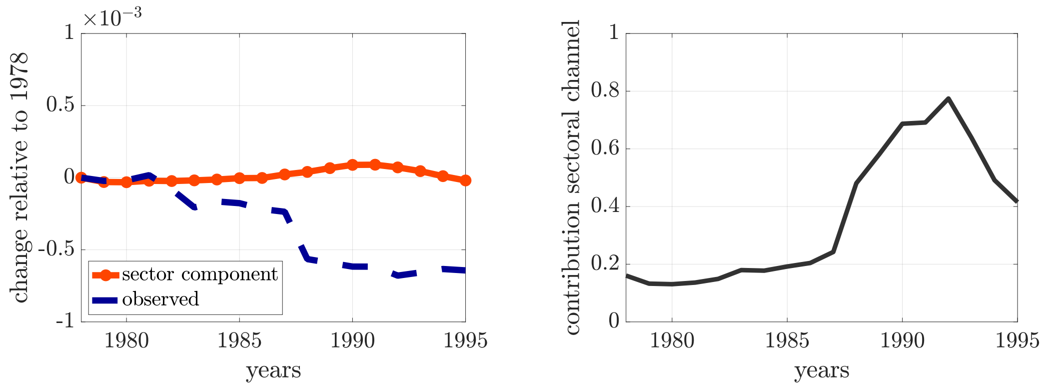
	Sample		
	Baseline	Long-run	Large*
$\left(\sigma^2_{\text{EM},1978} - \sigma^2_{\text{DEV},1978}\right)$	1.08	0.97	1.34
$\left(\sigma^2_{\text{EM},1995} - \sigma^2_{\text{DEV},1995}\right)$	0.53	0.33	0.92
$\Delta_{1978-1995}$	-0.55	-0.64	-0.42

Source: authors' calculations using WIOD and PWT data.
Notes: TFP volatility terms are expressed in 10^{-3} units. Baseline = sample for baseline exercise; Long-run = time-series sample; Large = 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.3: *Sectoral channel and relative decline in volatility*

(a) *TFP volatility and sectoral channel changes* **(b)** *Contribution to volatility differences*



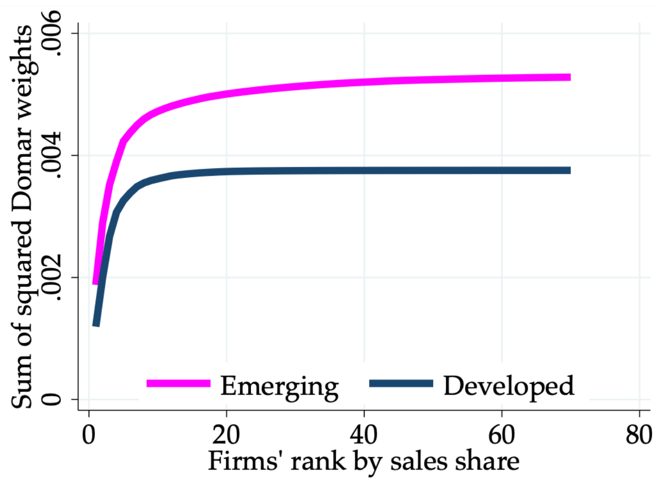
Notes: panel (a) shows the change of the sectoral channel $\left(\mathbf{\Lambda}'_{\mathrm{EM},t}\Omega_{\tilde{A}}\mathbf{\Lambda}_{\mathrm{EM},t} - \mathbf{\Lambda}'_{\mathrm{DEV},t}\Omega_{\tilde{A}}\mathbf{\Lambda}_{\mathrm{DEV},t}\right)$ and the observed $(\sigma^2_{\mathrm{EM},t} - \sigma^2_{\mathrm{DEV},t})$ 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.

C.3 Firm Distribution

C.3.1 Empirics

Figure C.4 shows that the sum of the squared Domar from the Top 1 to Top 70 firms by sales of their domestic establishments. The sum becomes flat after a low number of firms.

Figure C.4: *Cummulative sum of squared Domar weights: $\lambda\lambda'$*



Source: Worldscope.
Note: the figure shows the cummulative sum of squared Domar weights from the Top 1 to Top 70 firms in terms of sales by domestic establishments.

C.3.2 Intrinsic Volatility Differences

We explain briefly how we compute the intrinsic volatility implied by our quantitative exercise. To do this, first, we assume that the aggregate channel is muted, such that fundamental volatility differences are only explained by the sector- and firm-level shocks. Next, we assume that the sectoral volatility matrix and the developed economies firms' volatility are the same as in our baseline exercise, then we can show the idiosyncratic volatility in emerging can be backed-out from the following expression

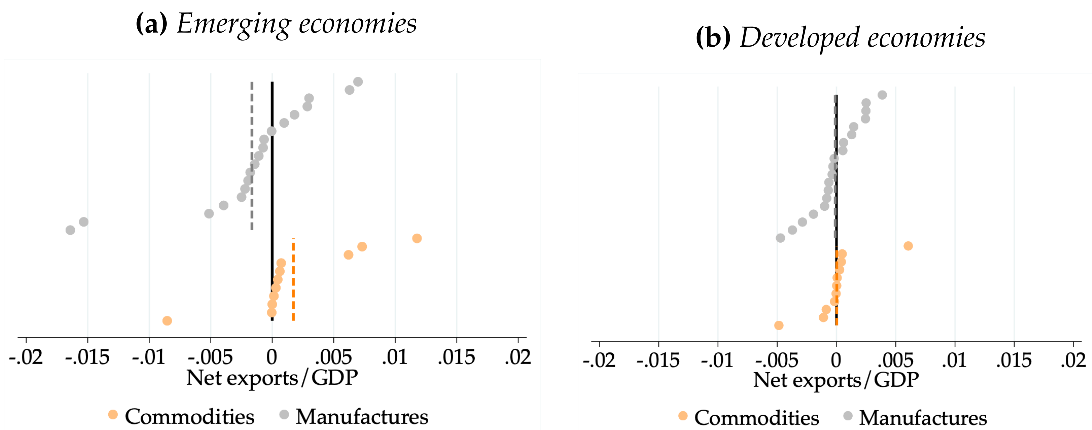
$$\sigma^2_{A_{\text{EM},i}} = \frac{(\sigma^2_{\text{EM}} - \sigma^2_{\text{DEV}}) - \left(\mathbf{\Lambda}'_{\text{EM}}\Omega_{\tilde{A}}\mathbf{\Lambda}_{\text{EM}} - \mathbf{\Lambda}'_{\text{DEV}}\Omega_{\tilde{A}}\mathbf{\Lambda}_{\text{DEV}}\right) + \left(\lambda'\lambda\right)^{\text{top}}_{\text{DEV}}\sigma^2_{A_{\text{DEV},i}}}{(\lambda'\lambda)^{\text{top}}_{\text{EM}}},$$

where all the terms in the RHS are observable.

C.4 Trade Flows

Figure C.5b shows the disaggregated trade imbalances for emerging and developed economies. Trade imbalances are sorted by commodities (primary goods) and manufactures, and order from larger to lower balance.

Figure C.5: *Sectoral trade imbalances (as % of GDP)*



Source: authors' calculations based on Comtrade.
Note: orange and gray dashed lines represent averages within commodities (primary goods) and manufactures' sectors respectively. Within each broad category, sectors are ordered by their net trade balance.

C.5 Sectoral Channel: Direct and Indirect Contributions

Table C.3: *Volatility accounting: Emerging vs Developed economies*

	Sectoral Channel Contribution		
	Total	Direct	Indirect
	TFP Volatility		
Baseline	0.68	0.07	0.61
	GDP Volatility		
$\vartheta = 1$	0.41	0.04	0.37
max ϑ	0.75	0.07	0.68
min ϑ	0.06	0.01	0.05
$\{\sigma = 2; \psi = 1\}$	0.29	0.05	0.24
$\{\sigma = 0; \psi = 0.75\}$	1.02	0.16	0.86

Note: the "Total" column shows the contribution of the sectoral channel estimated using equation (11), which includes both the direct component given by value added shares and the indirect component given by intermediate inputs linkages between sectors. The "Direct" column estimates equation (11) replacing sectoral Domar weights with sectoral value added shares. The "Indirect" column shows the magnitude of the total contribution that is not explained by the direct part. To compute the country-group statistics, we first average each sufficient statistic across time for each country and then, for each sufficient statistics we take the median across countries in each group (emerging or developed). The top panel includes the results for TFP volatility. In the "Baseline" model, median values of sufficient statistics across emerging and across developed economies are used to compute the contribution of the sectoral channel. The bottom panel includes the results for GDP volatility, for different values of the parameters. Further details about the data and computation are in the text.

Table C.4: *Sectoral distribution: Domar weights and value added shares*

	$\frac{\text{Domar W}}{\text{VA share}}$ ratio	
	Emerging	Developed
Most volatile sectors	2.27 (2.15,2.73)	2.72 (2.35,2.98)
Least volatile sectors	1.66 (1.61,1.80)	1.83 (1.74,1.95)

Source: Penn World Tables (PWT), OECD-IOT and Jorgenson *et al.* (2005) dataset.
Note: ratio of Domar weights over value added shares, across sector's volatility for the median emerging and developed economies. "Most volatile sectors" refer to sectors belonging to the highest quartile in volatility; "Least volatile sectors" refer to sectors belonging to the lowest quartile in volatility. We report in parentheses values that correspond to the 25th and 75th percentiles.

C.6 Crisis and Inflation Episodes

We study how our results change when excluding countries that faced large financial crises—such as sovereign debt defaults—or episodes of high inflation during the sample period. To identify sovereign debt default episodes, we use the crisis dating data from Laeven and Valencia (2018). To identify inflation surge episodes, we follow a similar criterion to Blanco *et al.* (2022), defining a high-inflation surge as a year in which inflation increases by more than 5 percentage points. Inflation data is from the World Bank's World Development Indicators (WDI).

Table C.5 lists the countries in our sample that experienced either a crisis or an inflation surge. All, except from Greece, are in the group of emerging economies. We exclude these countries and recompute the contribution of each channel to TFP and GDP volatility differences between emerging and developed economies. Table C.6 shows the results. For the GDP volatility accounting we consider the case of the fundamental volatility (i.e., $\vartheta = 1$).

Table C.5: *Countries that Face Extreme Events*

Sovereign Debt Default	Inflation Surge
Argentina	Argentina
Brazil	Brazil
Chile	Costa Rica
Costa Rica	Indonesia
Greece	India
Indonesia	Mexico
Morocco	Philippines
Mexico	Turkey
Peru	
Philippines	
Turkey	
South Africa	

Note: the table shows the countries that experience at least one sovereign default episode or an inflation surge episode, as defined in the text, from 1990 to 2019. The countries are included in our baseline sample.
Data sources: World Development Indicators and Laeven and Valencia (2018).

We find that the contribution of the sectoral channel to TFP volatility remains sizable, though it varies slightly across samples. When we exclude countries that experienced sovereign debt defaults, the sectoral contribution increases to 94%, compared to our baseline estimate of 68%. However, this change comes with a substantial reduction in the number of emerging economies in the sample—from 17 to 6. In contrast, when we exclude countries that experienced inflation surges during the sample period, the sectoral contribution declines to around 53%. The contribution of the firm-level channel ranges between 7% and 13%, similar to our baseline estimate of 7%.

When analyzing the contribution of the sectoral and firm-level channels to GDP volatility differences using the fundamental volatility decomposition (i.e., $\vartheta = 1$), we find that the results remain broadly stable across specifications. Compared to the baseline estimate of 41%, the sectoral channel accounts for 35% when excluding sovereign debt default episodes, and 32% when excluding inflation surge episodes. The firm-level channel accounts for 5% when excluding sovereign debt defaults and 4% when excluding inflation surges—both similar to the baseline value of 4%.

Table C.6: *Volatility accounting w/o extreme events: Emerging vs Developed economies*

	Contribution	
	Sectoral	Firm-level
a. TFP		
Baseline	0.68	0.07
Excluding Sov. Debt Default	0.94	0.13
Excluding Inflation Surges	0.53	0.07
b. GDP (fundamental volatility)		
Baseline	0.41	0.04
Excluding Sov. Debt Default	0.35	0.05
Excluding Inflation Surges	0.32	0.04

Note: in panel (a), we report the contributions to TFP volatility differences, and in panel (b), to GDP volatility under the case of fundamental volatility ($\vartheta = 1$). 'Baseline' refers to the main results reported in the paper; 'Excluding Sov. Debt Default' refers to results excluding countries that experienced a sovereign debt crisis during the sample period; and 'Excluding Inflation Surges' excludes countries with episodes of inflation surges, as defined in the text.

Overall, the baseline results—highlighting the relevance of the sectoral channel and the more limited role of cross-country differences in firm distribution—remain unchanged.