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Fluctuations in global output volatility ☆

Lorenzo Ductor [a,*], Danilo Leiva-León [b]

[a] University of Granada, Department of Economic Theory and History, 18071 Granada, Spain
[b] Banco de España, Alcalá 48, 28014 Madrid, Spain

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ABSTRACT

In this paper, we dissect the time-varying output volatility of the main world economies to study its dynamics, spillovers, and determinants, from a global perspective. Our analysis relies on a hierarchical volatility factor model and Bayesian model averaging. We show that the increasing comovement observed in international macroeconomic volatility is substantially larger in developing than in developed countries. Instead, developed countries have exhibited more asymmetric volatility shocks than developing countries in recent times. We also show that, although the downward trend in global volatility is related with increasing trade, idiosyncratic changes in volatility are highly influenced by domestic monetary policies. However, due to the declining role played by these idiosyncratic components over time, policymakers currently face greater constraints when it comes to stabilizing output fluctuations.

1. Introduction

Changes in macroeconomic volatility at the international level have important implications for the global economy. They may affect financial markets, by generating investor uncertainty (Arellano et al., 2019), and influence capital flows, leading to changes in the indebtedness position of a country (Fogli and Perri, 2015). Also, it is crucial to account for changes in volatility at the global level when assessing downside risks associated with the world economy outlook (Adrian et al., 2019). To mitigate the adverse effects of macroeconomic volatility, governments and central banks tend to rely on stabilization policies. However, the effectiveness of such policies would heavily depend on the extent to which macroeconomic volatility of a given country is mainly driven by domestic or foreign developments.

Ever since the structural decline in the output volatility of the U.S. economy beginning in the mid-80s was first documented by Kim and Nelson (1999) and Pérez-Quirós and McConnell (2000), there has been increasing interest in understanding the dynamics and sources of changes in macroeconomic volatility. This phenomenon, also referred to as the *Great Moderation*, is not unique to the U.S.; it has also been documented in other advanced economies (Blanchard and Simon,

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* Corresponding author.
E-mail addresses: lductor@ugr.es (L. Ductor), danilo.leiva@bde.es (D. Leiva-León).

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2001 and Everaert and Iseringhausen, 2018), suggesting potential similarities in output volatility across countries (Stock and Watson, 2005 and Mumtaz and Musso, 2019). Yet the studies that have found commonalities in macroeconomic volatility have focused on a small set of countries, only composed of advanced economies, making it difficult to derive broader implications for the world economy, and precluding them to assess spillovers between regions of different degrees of economic development.

In this paper, we study the dynamics, propagation and sources of changes in macroeconomic volatility from a global perspective, by relying on information from 42 developed and developing economies. In particular, we focus on decomposing the overall output volatility across countries into underlying global, regional and idiosyncratic components, to assess changes in their respective contributions over time. We also characterize time-varying volatility spillovers throughout the world economy. Lastly, we identify the main macroeconomic factors influencing changes in the overall and idiosyncratic volatility of output both across countries and over time.

We proceed in two steps. First, we propose a hierarchical factor structure to summarize the underlying volatility of output growth fluctuations across countries into a small number of common (global and regional) volatility factors that are allowed to be endogenously interrelated. This modelling strategy permits us evaluate the influence of domestic and foreign developments on national macroeconomic volatility, and assessing the evolving strength of volatility spillovers at the regional level. Second, we focus on identifying the main factors associated with changes in macro volatility across countries from among those commonly proposed in the literature. These factors are associated to trade openness, financial integration, exchange rate, terms of trade, fiscal and monetary policies, and technology shocks. In doing so, we adopt an agnostic perspective and rely on Bayesian Model Averaging (BMA) panel data regressions to account for model uncertainty.[1]

Our results provide a comprehensive description of both propagation and transmission mechanism of international macroeconomic volatility. We show that, for a given country, sectors which are more open to trade are less associated with the other sectors of their economy, i.e. they have a lower sectoral composition overlap with the rest of the economy. These sectors are likely to be influenced more by global shocks to the industry and less by domestic cycles. Therefore, greater dissimilarity among the sectors of an economy (facilitated through trade) diminishes overall volatility. Consequently, the sustained increase in world trade observed in recent decades has substantially contributed to a decline in macroeconomic volatility across both developed and developing economies around the globe. However, there are important differences in the declining pattern of macroeconomic volatility between countries with different degrees of development. In particular, episodes of high volatility have become both more extreme and frequent in developed than in developing countries. Also, the increasing commonality in the level of volatility associated to developing countries has been substantially larger than in developed countries.

Despite the overall decline in macroeconomic volatility worldwide, countries have been subject to temporary increases in the size of output fluctuations, which are not necessarily related to economic recessions. Instead, they are also related to episodes of political instability, structural changes, foreign shocks, and high uncertainty. These episodes have induced substantial changes to global and regional common factors driving macroeconomic volatility at the international level. Our analysis provides a narrative associated to countries and events that led to major changes in common volatility factors. Regarding volatility spillovers at the regional level, our estimates suggest that North America, Asia and Oceania are not significantly affected by the volatility originated in other regions of the world. However, Europe and South America are highly influenced by North American volatility developments.

The role of these global and regional factors in shaping volatility across countries has substantially evolved over time. We document that the generalized and persistent decline in output volatility across both developed and developing economies has been driven by a markedly downward trend over time in the global volatility component, implying that GDP growth across the major world economies share a common feature that can be interpreted as a "global moderation" of international output fluctuations. Moreover, we show that, despite the declining levels of global volatility, the exposure of countries' volatility to those global developments has steadily increased over time. This finding suggests that countries' GDP growth has become more synchronized in second order moments, revealing a new level of interconnectedness in the global economy. Conversely, the contribution of the regional volatility component has remained relatively steady over time. Hence, the increasing contribution of the global component has been offset by a substantial decline in the importance of the role played by idiosyncratic volatility component.

These idiosyncratic components identify changes in output volatility that can be attributed to events occurred in a given country that are unrelated to global or regional developments, such as domestic economic policies. We show that changes in the idiosyncratic volatility component are related to the volatility in monetary policy across countries, acting as an effective business cycle stabilization tool at the global level. However, due to the substantial decline in the role played by the idiosyncratic volatility component, policymakers currently face greater constraints than in the past when it comes to stabilizing output fluctuations.

Our paper is related to two strands of the literature. First, the literature focused on evaluating common patterns in macroeconomic volatility and the propagation of shocks, from a global perspective. Similarities in output volatility have been studied by Del Negro and Otrok (2008) for the G7 economies.[2] We provide a global assessment of common patterns in macroe-

[1] We also use the second and third lags of the regressors as instrumental variables to account for reverse causality.

[2] Also, Mumtaz and Theodoridis (2017),Everaert and Iseringhausen (2018), Carriero et al. (2020),Berger et al. (2016), Mumtaz and Musso (2019) have performed similar studies for 11, 16, 19, 20, and 22 advanced economies, respectively.

conomic volatility by addressing the *propagation* of volatility shocks between a large set of 42 developed and developing countries. In terms of modelling strategy, some studies have used mean factor models with stochastic volatility, while others have relied on volatility factor models, which have different implications. In particular, Mumtaz and Theodoridis (2017) and Mumtaz and Musso (2019), following the line of Del Negro and Otrok (2008), focus on analyzing the "volatility of the comovement" by estimating the time-varying volatility of innovations associated with common components in mean, finding that these common factors play an important role in driving international output volatility. However, their approach does not address commonalities in the cross-sectional profiles of output variation, that is, "comovement of the volatility", which is the focus of our paper. Our work is also related with the literature on uncertainty, see Baker et al. (2016). Also, Londono and Wilson (2018) have assessed the relationship between global output volatility and economic policy uncertainty, and Ozturk and Sheng (2018) has documented changes in global uncertainty. Our paper does not focus on the lack of predictability in business cycles, which is the foundation of uncertainty. Instead, we assess the nature and dynamics of change in business cycle fluctuations, which entails the measurement of volatility.

The second strand of the literature to which our paper belongs is focused on evaluating the effect of specific economic factors on output volatility. Previous studies have shown the importance of several economic factor on output volatility, such as trade and terms of trade (Giovanni and Levchenko, 2009), financial openness (Buch et al., 2005 and Andrés et al., 2008), government expenditure (Fatás and Mihov, 2001), monetary policy (Sutherland, 1996). Despite the large literature dedicated to studying the underlying determinants of output volatility, previous studies have typically focused on analyzing a particular determinant of volatility without accounting for the influence of other potential factors. The only exception is Malik and Temple (2009), who use a Bayesian Model Averaging approach to study the structural determinants of output volatility. However, the authors focus only on developing countries, and more importantly, they focus on explaining only the level (averaged over time) of output volatility and not its dynamics. To the best of our knowledge, ours is the first study to identify the main macroeconomic factors that explain changes over time in both total and idiosyncratic output volatility, accounting for model uncertainty.

The rest of the paper is organized as follows. Section 2 describes the empirical framework used for measuring and decomposing international volatility fluctuations. Section 3 assesses the global propagation of macroeconomic volatility. Section 4 investigates the main underlying economic factors associated with changes in volatility worldwide. Section 5 concludes.

2. Measuring similarities in volatility

In this section, we describe the framework used for jointly estimating output volatility across countries, decomposing it into global, regional and idiosyncratic components, and assessing how volatility spillovers propagate at the international level. In sum, this framework allows us to analyze the VOLatility Transmission Across Grouped Economies, therefore, we refer to it as the VOLTAGE model.

Within this context, it is important to distinguish between comovements in mean and in volatility, and their corresponding implications. In a recent study, Ductor and Leiva-Leon (2016) documented that after the early 2000s, it became more common for economies to fall into recession and engage in economic expansion in a synchronous way. Hence, if this pattern persists during future episodes of global recessions, the number of countries affected by contractionary shocks will be similar to or even larger than those affected during the "Great Recession". These assessments are based on the synchronization of business cycle phases, which rely on first order moments of output growth. However, it remains uncertain whether the severity of GDP downturns is more or less likely to be similar across countries in forthcoming global recessions. While an adverse scenario for the global economy is one in which most countries enter recessionary phases, an even more drastic scenario would arise if the magnitudes of those downturns in GDP were similarly large across countries. Therefore, it is crucial to assess common patterns in the width of international output growth fluctuations, that is, second order moments, by also accounting for similarities in first order moments.

The data employed to estimate the proposed model consists of quarterly real GDP growth of different countries.[3] This growth rate was computed based on the quarterly GDP at constant 2010 prices in U.S. dollars. The data was gathered from Datastream, which has the largest coverage of countries and periods. Since information at a higher frequency allows us to characterize volatility patterns with more precision, we rely on data at the quarterly rather than at the annual frequency. Based on data availability, our sample covers $N = 42$ countries from four world regions: North America, South America, Europe, and a joint region composed of countries in Asia and in Oceania. The list of countries along with the corresponding regions is reported in Table 1. The sample period runs from 1981:Q1 until 2019:Q4.

Let $y_{i_k,t}$ be the annual growth rate of quarterly real GDP of country i, which belongs to region k, at time t. We assume that it is driven by a mean global factor, $\bar{g}_t$, a mean regional factor, $\bar{h}_{k,t}$, and an idiosyncratic component $u_{i_k,t}$, as follows,

$$y_{i_k,t} = \bar{\gamma}_{i_k}\bar{g}_t + \bar{\lambda}_{i_k}\bar{h}_{k,t} + u_{i_k,t}, \tag{1}$$

[3] Figure A17 in Online Appendix J shows the real GDP growth rates for each country in the sample. It is important to acknowledge potential inaccuracies regarding quarterly GDP data provided by national statistical agencies of some countries. Although, using quarterly data is essential in order to provide as precise as possible estimates of output volatility.

Table 1
List of Countries: Period 1981Q1-2019Q4.

North America	South America	Europe			Asia + Oceania	
Canada	Argentina	Austria	Greece	Norway	Australia	Japan
Mexico	Brazil	Belgium	Iceland	Portugal	China(1988Q1)	New Zealand
United States	Chile	Denmark	Ireland	Spain	Hong Kong	Philippines(1982Q1)
	Peru	Finland	Italy	Sweden	India(1997Q2-)	Kazakhstan(1995Q3)
	Venezuela(2019Q1)	France	Luxembourg	Switzerland	Indonesia	Russia(1990Q2)
		Germany	Netherlands	United Kingdom	Israel(1996Q1)	Singapore
					South Korea	Taiwan
					Thailand(1994Q1)	Turkey(1988Q2)

Note. The table reports the list of countries used in the empirical analysis along with their corresponding geographic region. Starting period for countries with missing observations in parenthesis, except for Venezuela, which corresponds to the end sample period.

where $\bar{\gamma}_{i_k}$ and $\bar{\lambda}_{i_k}$ are the corresponding factor loadings, for $i_k = 1, 2, \ldots, n_k$ and $k = 1, \ldots, K, n_k$ is the number of countries that belong to region k, and K is the total number of regions under analysis. Note that the terms $u_{i_k,t}$ represent country-specific output growth fluctuations after removing common patterns in the mean. We impose as little structure in the dynamics of the mean factors as possible since our main focus is on the comovement of volatility. Therefore, we use a non-parametric method, principal component analysis, to extract mean factors.[4] In doing so, our main volatility estimates would be less subject to misspecification issues in modeling the mean factors.[5]

Accordingly, in order to investigate volatility commonalities over and above mean commonalities, we focus on the terms, $u_{i_k,t}$, and model its time-varying volatility of as follows,

$$u_{i_k,t} = e^{\frac{1}{2}F_{i_k,t}} \varepsilon_{i_k,t}, \tag{2}$$

where $\varepsilon_{i_k,t} \sim N(0,1), F_{i_k,t}$ is a latent variable, and $\sigma_{i_k,t} = e^{\frac{1}{2}F_{i_k,t}}$ denotes the time-varying standard deviation associated with country i_k. Typically, $F_{i_k,t}$ is assumed to be an independent univariate autoregressive processes. However, given our multi-country environment, we are interested in decomposing $F_{i_k,t}$ into its global, regional and idiosyncratic components across countries. That is, we decompose country i_k log-volatility as follows,

$$F_{i_k,t} = \gamma_{i_k} g_t + \lambda_{i_k} h_{k,t} + \chi_{i_k,t}, \tag{3}$$

for $i_k = 1, 2, \ldots, n_k$ and $k = 1, \ldots, K$. The term, g_t denotes the global volatility factor, while $h_{k,t}$ denotes the volatility factor associated with the group of countries that belong to region k, and $\chi_{i_k,t}$ denotes the idiosyncratic, or country-specific, volatility component of country i that belongs to region k.

The global factor measures common changes in the overall degree of countries' macroeconomic volatility around the world. Conversely, the regional factors account for common patterns in the volatility of countries in a given region, after accounting for patterns in global volatility. Finally, the idiosyncratic component identifies volatility changes that can be attributed entirely to country-specific developments. The coefficients γ_{i_k} and λ_{i_k} are the corresponding factor loadings and measure the strength of the comovement between the country-specific volatility and the volatility factors at the global and regional level, respectively.

Eq. (3) provides a decomposition of fluctuations in macroeconomic volatility from a contemporaneous perspective, but it remains silent about potential non-contemporaneous feedback effects of volatility shocks. Hence, for a more comprehensive evaluation of the importance of global and regional factors in countries' macroeconomic volatility, the latent variables driving both types of factors are assumed to evolve according to a stationary vector autoregression (VAR),

$$\begin{bmatrix} g_t \\ h_{1,t} \\ \vdots \\ h_{K,t} \end{bmatrix} = \Phi \begin{bmatrix} g_{t-1} \\ h_{1,t-1} \\ \vdots \\ h_{K,t-1} \end{bmatrix} + \zeta_t, \tag{4}$$

where the innovations are assumed to be normally distributed, $\zeta_t \sim N(0, \Sigma)$.[6] The dynamics of the idiosyncratic volatility components are given by independent stationary autoregressive processes,

$$\chi_{i_k,t} = \varphi_{i_k} \chi_{i_k,t-1} + \xi_{i_k,t}, \tag{5}$$

where the innovations are assumed to be normally distributed, $\xi_{i_k,t} \sim N(0, \sigma^2_{i_k})$, and cross-sectionally uncorrelated.

[4] Prior to the application of the principal component analysis, the data on output growth is standardized. Also, to deal with missing data in the extraction of the common factors in the mean, we apply probabilistic principal component analysis.

[5] Online Appendix C provides a series of exercises for robustness purposes where several modelling assumptions are relaxed.

[6] We also considered the case when log-volatility factors depend not only on their past values, but also on past values of the mean factor as a robustness test. The results are commented in the empirical Section 4.2.1.

To identify the factors and factor loadings, we follow Bai and Wang (2015) and impose two types of restrictions: first, the covariance matrix of the innovations in the VAR is an identity matrix, $\Sigma = I_{K+1}$, and second, specific factor loadings, γ_{1_1} and $\{\lambda_{1_k}\}_{k=1}^{K}$, are assumed to be lower-triangular matrices with strictly positive diagonal terms.[7]

The model is estimated using Bayesian methods. In particular, we rely on the Gibbs sampler to provide robust inference on all the elements of the model, that is, latent variables and parameters.[8] The proposed estimation algorithm, along with information on the prior distributions, is detailed Online Appendix A.

3. Dissecting international macroeconomic volatility

The purpose of this section is threefold. First, we identify changes over time in macroeconomic volatility across both developed and developing economies to unveil key similarities and differences. Second, we seek to gain an understanding of the sources of those changes by disentangling them into domestic and foreign contributions. Third, we characterize macroeconomic volatility spillovers throughout the global economy.

3.1. Cross-country heterogeneity

We extract commonalities in the volatility profiles of country-specific GDP fluctuations after removing the common patterns in the mean.[9] The VOLTAGE model is employed to estimate the volatility, $\sigma^2_{i_k,t}$, of the 42 countries in our sample, and the corresponding cross-sectional distribution over time is plotted in Fig. 1. Chart A plots the world time-varying second moment distribution, showing two salient features. First, the median of the cross-sectional distribution exhibits a downward trend, pointing to a moderation of business cycle fluctuations across the major world economies. Second, the cross-sectional dispersion of volatility profiles has decreased over time, indicating an increasing commonality in the level of volatility over time. To provide a clearer visualization of the changes in international volatility dynamics, we compute the kernel densities associated with all the realizations of volatility, both across time and countries, during each decade in our sample, that is, 1980s, 1990s, 2000s and 2010s. Fig. A17 shows that the world volatility distribution has shrunk and displaced towards the left, features consistent with a lower level and higher comovement of volatility, respectively.

Next, we analyze the key differences in international volatility between developed and developing countries. In doing so, we first compute the same cross-sectional distribution of volatility profiles, differentiating between the two groups of economies.[10] The corresponding densities are plotted in charts B and C of Fig. 1, respectively, suggesting that, despite the common decline in the level of volatility, there might be important differences in the volatility changes associated to developed and developing countries.

We compute statistics that measure four key features of the volatility distributions both across groups of countries and over time. Chart A of Fig. 2 reports the mode of the distributions, corroborating the decline in the level of volatility, and moreover, showing that such decline has taken place in both developed and developing countries. Chart B of Fig. 2 reports the variance of the distributions, which provide information regarding the degree of commonality in the level of volatility across countries. The estimates indicate that the increase in world volatility commonalities is mainly attributed to developing countries since the variance has substantially declined over time. Instead, volatility commonalities in developed economies have remained relatively stable over time, sowing a subtle reduction with time. Finally, charts C and D of Fig. 2 report the skewness and kurtosis of the distributions, respectively, indicating that temporary episodes of high volatility, relative to their historical trends, have become more extreme, and more frequent, in developed than in developing countries. This can be inferred from the increasing (declining) trend in both skewness and kurtosis of distributions associated to developed (developing) countries, suggesting that developed economies have exhibited more asymmetric volatility shocks than developing economies in recent times. Overall, the statistics reported in Fig. 2 unveil important differences between macroeconomic volatility of developed and developing countries that have not been previously documented in the literature, since previous studies focused solely on advanced economies.

[7] The identification scheme proposed in Bai and Wang (2015) has been proven to work in a context of linear factor models. Despite the fact that the proposed volatility factor model is nonlinear, those identification restrictions still uniquely identify the factors and factor loadings because the model can be alternatively expressed in a log-linearized representation, which is used to generate inferences from the latent variables (Kim et al., 1998), as shown in Appendix A.

[8] It is important to note that Carriero et al. (2018) and Carriero et al. (2020) rely on Particle Gibbs sampling to estimate volatility factor models. Instead, we propose an algorithm that relies on standard Gibbs sampling steps to simulate the posterior density of the volatility factor model. This algorithm also allows us to deal with missing observations, which is a common problem in multi-country quarterly GDP data.

[9] Before assessing common patterns in second order moments, extract the common factors in the mean from the GDP growth of the 42 countries in our sample, as described in Eq. (1), and report them in Fig. A1 of the Online Appendix B. The estimates show that the global factor closely resemble the dynamics of the real world activity, while the regional factors are consistent with several salient features of the business cycles in those regions. Kose et al. (2003),Kose et al. (2012), and Ductor and Leiva-Leon (2016) provide a more in-depth assessment of changes in the comovement of mean output growth at the international level, which are in line with our mean factor estimates.

[10] The classification of countries between developed and developing ones is based on the IMF's definition. The IMF's classification of countries is not stable over time: Greece and Portugal were reclassified from developing to developed in 1989, and Singapore, South Korea and Israel were added in 1997 as developed (Nielsen, 2011).

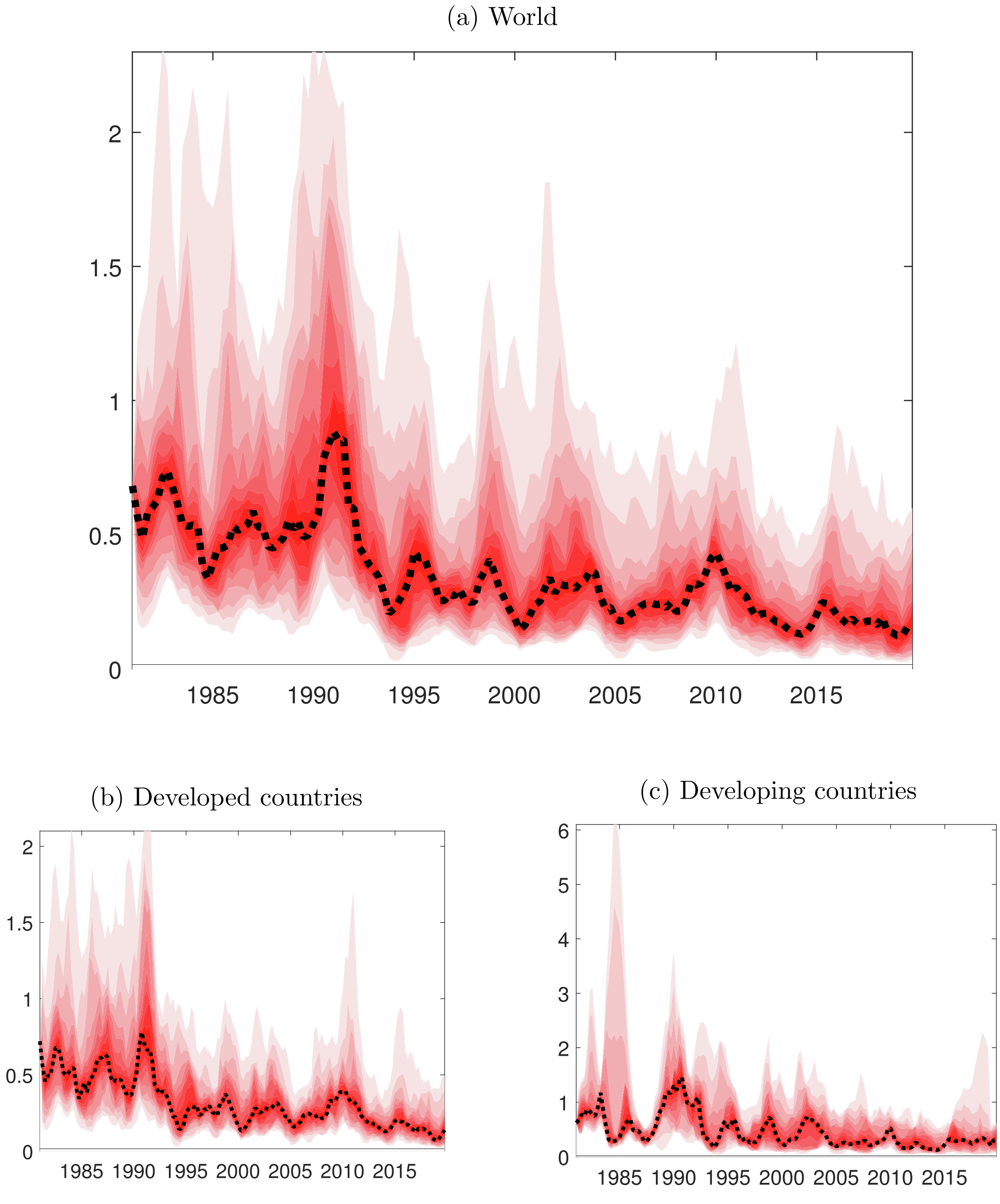


Fig. 1. Time-varying volatility across countries. Note. The time-varying volatilities for each country are estimated jointly by using the VOLTAGE model, proposed in Section 2. Chart A plots the cross-sectional distribution of time-varying volatilities for all the countries in our sample, that is, including developed and developing economies. Chart B and Chart C plot the cross-sectional distributions of time-varying volatilities for only developed and developing countries, respectively. The black lines represent the median of the corresponding time-varying distribution.

3.2. Dynamics and spillovers

After documenting a substantial heterogeneity of macroeconomic volatility profiles in countries with different levels of development, we turn to define the underlying sources that generate such heterogeneity. The main advantage of the employed econometric framework is its ability to endogenously decompose time-varying volatility estimates into the contributions of global, regional and country-specific, or idiosyncratic, developments. The time-varying standard deviation associated with country i_k can be compactly expressed as,

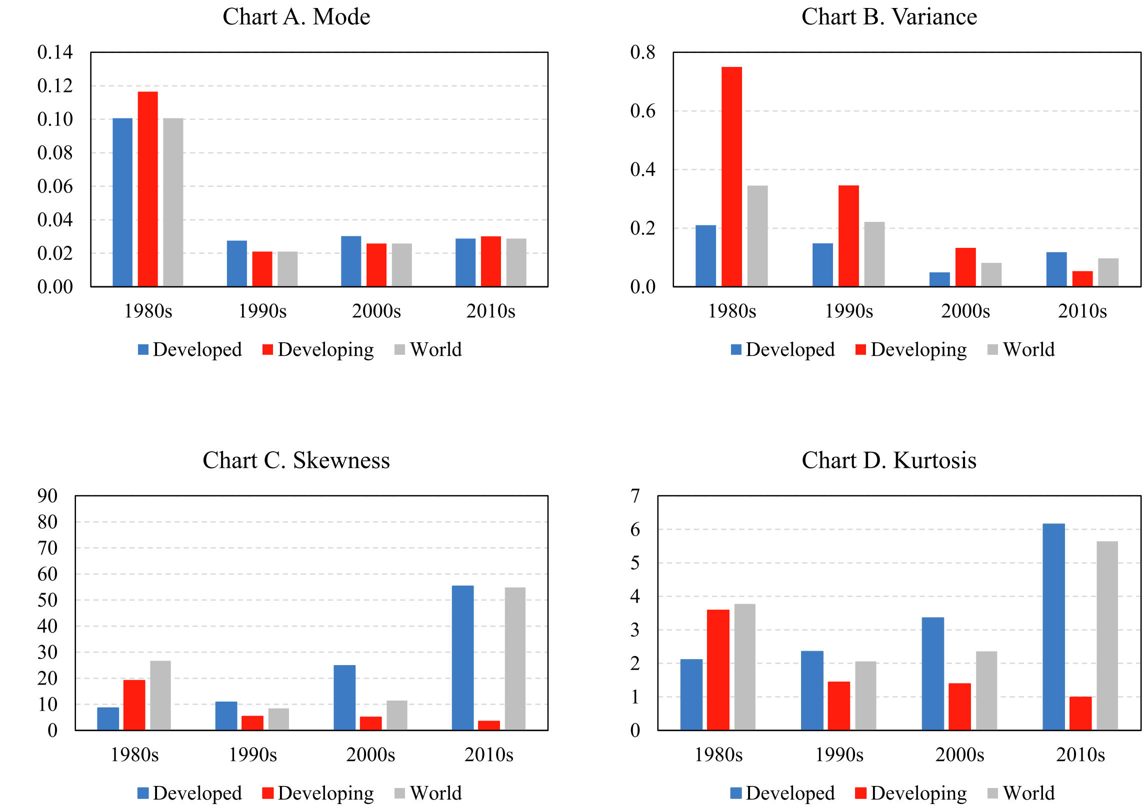


Fig. 2. Statistics of densities of international macroeconomic volatility. Note. Charts A, B, C and D report the mode, variance, skewness and kurtosis, respectively, associated to all the realizations of time-varying macroeconomic volatility across developed (blue bars) and developing (red bars) countries, and the world (grey bars), which is defined as the joint set of developed and developing countries in our sample. The distributions are computed for each decade. The measures of volatilities are based on the VOLTAGE model estimates.

$$\sigma_{i_k,t} = \sigma_{g,t}^{\gamma_{i_k}} \sigma_{h_k,t}^{\lambda_{i_k}} \sigma_{\chi_{i_k},t}, \tag{6}$$

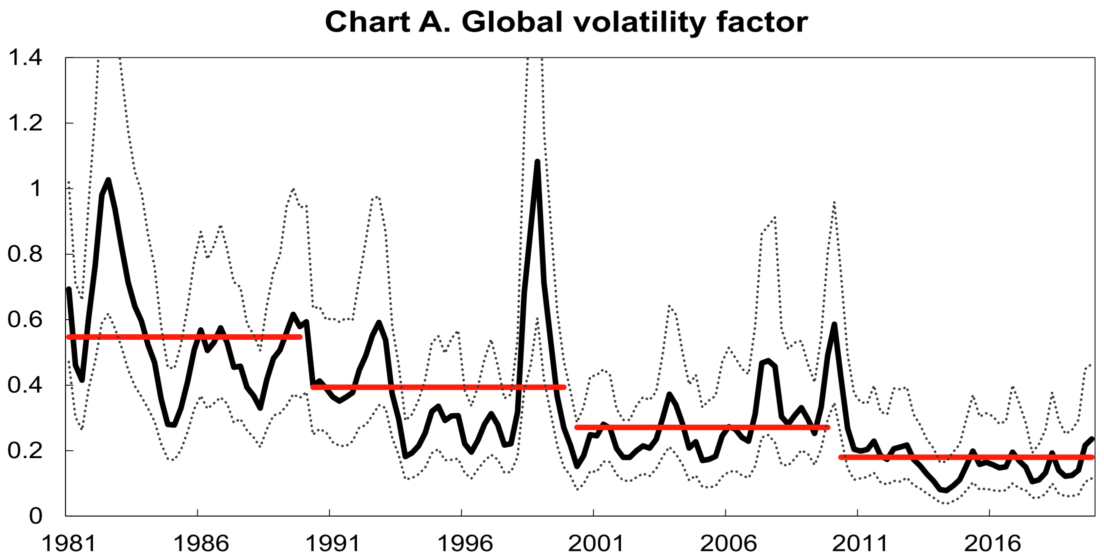
where $\sigma_{g,t} = e^{\frac{1}{2}g_t}, \sigma_{h_k,t} = e^{\frac{1}{2}h_{k,t}}$, and $\sigma_{\chi_{i_k},t} = e^{\frac{1}{2}\chi_{i_k,t}}$ denote the corresponding global, regional and idiosyncratic components, respectively.

Previous related works have focused on describing the dynamics of these common components and their effect on macroeconomic variables across countries (Mumtaz and Theodoridis, 2017 and Mumtaz and Musso, 2019), which are highly relevant issues. However, that type of analysis unveils only one side of the coin, since no information is provided about the country, or set of countries, mainly driving such common components, information that is crucial to measure volatility spillovers. In this section, we examine the dynamics of common volatility factors, and more importantly, we provide a narrative associated to countries and events that led to major changes in global and regional volatility factors.

Chart A of Fig. 3 plots the dynamics of the global volatility component, showing a marked decreasing trend over time. Such a persistent decline indicates a common feature in GDP growth across the major world economies that can be interpreted as a global moderation of international output fluctuations. This result is robust to a series of changes in the modelling specifications. Fig. 4 shows the dynamics of the global volatility component obtained with a model where both mean and volatility factors are jointly estimated, in a Bayesian fashion, assuming similar autoregressive dynamics. These estimates are consistent with the message from our benchmark specification, suggesting a persistent decline in global volatility. In addition, we employ two alternative specifications which consist on, first, extracting volatility factors from raw data, without accounting for factors in the mean, and second, taking into account the endogenous interdependence between mean and volatility factors. All the estimates, which are reported in Online Appendix C for the sake of space, point to a "global moderation" of international business cycles. Given that there are several ways to decompose common, regional and idiosyncratic volatility, we build the rest of our analysis on the estimates from our benchmark specification, for the sake of parsimony, and place alternative more complex modelling strategies as robustness exercises.

The features displayed in Figs. 3 and 4 are consistent with the downward trend in the cross-sectional distribution of volatility shown in Fig. 1, suggesting that this global component plays a key role in determining the decline in international

(a) Dynamics



(b) Historical decomposition

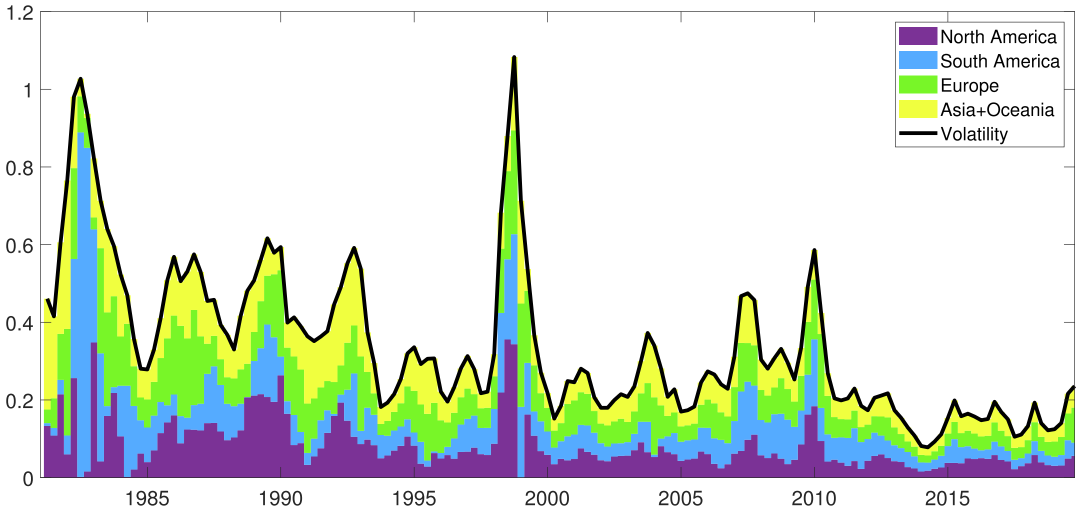


Fig. 3. Global volatility. Note.Chart A plots the global volatility factor and red horizontal lines make reference to the average volatility over the corresponding period. The solid line represents the median of the posterior distribution and the dotted lines make reference to the 68 percent credible set of the posterior distribution. Chart B plots the global volatility factor along with the corresponding historical data decomposition. The contributions associated to each country are computed based on the algorithm proposed in Koopman and Harvey (2003). Then, the average contribution of countries in a given region are reported for ease of exposition.

volatility fluctuations, in line with Mumtaz and Musso (2019). Also, our estimates are consistent with features reported in previous studies by Imbs (2007) and Gorodnichenko and Ng (2017), who find that volatility factors tend to be countercyclical and persistent.

Next, we examine the extent to which the decline in the global volatility component is driven by countries from different regions of the world. In doing so, we follow the line of Koopman and Harvey (2003) to decompose the latent factors into the contributions associated with each country's observable real activity.[11] This allows us to disentangle the contribution made by

[11] Broto and Pérez-Quirós (2015) relied on a somewhat related approach to study contagion among sovereign CDS spreads during the European debt crisis.

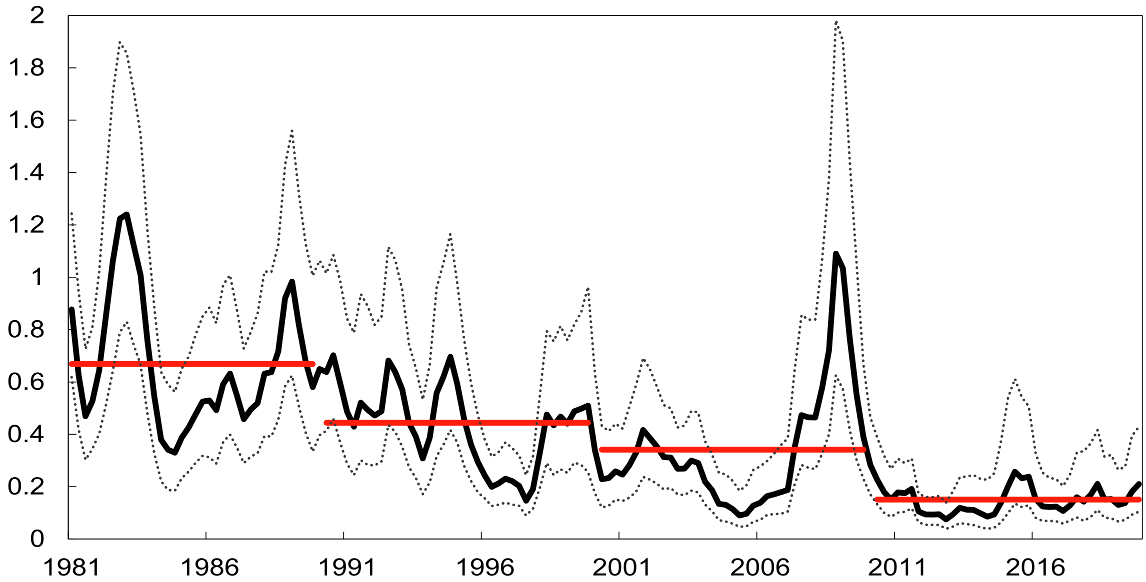


Fig. 4. Global Volatility: alternative model specification. Note. The figure plots the global volatility factor obtained with filtering techniques by jointly estimating mean and volatility factors, assuming similar autoregressive dynamics, VAR(1), for both types of factors. The solid line represents the median of the posterior distribution and the dotted lines make reference to the 68 percent credible set of the posterior distribution. Red horizontal lines make reference to the average volatility over the corresponding period.

each region to the changes in the global volatility component. In particular, we express the state vector containing the latent log-volatilities, both factors and the idiosyncratic components, a_t, as a weighted average of the observed data,

$$a_t = \sum_{j=1}^{t-1} w_j u^*_{i_k,t}, \tag{7}$$

where $u^*_{i_k,t} = \ln(u^2_{i_k,t})$, and the weights, denoted by w_j, can be computed by backward recursion.[12]

Chart B of Fig. 3 also shows the historical data decomposition of the global volatility factor. Note that the persistent decline in global volatility is not associated to a specific region, since all four regions under consideration have significantly contributed to the downward trend, suggesting that the moderation of macroeconomic fluctuations can be considered a global phenomenon. Regarding global volatility fluctuations, a temporary increase can be seen in the early 1980s, which coincides with a significant contribution of the South American region. This period was known as South America's "Lost Decade". Another increase in global volatility is observed in the early 1990s. During this period, most of the Western world suffered a recession. Furthermore, around that time, German reunification was taking place, which had significant economic implications for several European countries. The sudden increase in global volatility observed in the late 1990s can be explained as the result of spillover effects from the severe Asian crisis to advanced economies through the global markets. Finally, another increase in global volatility took place between 2007 and 2010, with all regions contributing almost equally. This last increase can be associated with the high levels of uncertainty caused by the adverse effects of the Great Recession.[13]

3.3. Domestic and foreign influences

The effectiveness of stabilization policies could heavily depend on the extent to which the macroeconomic volatility of a given country is mainly driven by domestic or foreign developments. Since both global and regional macroeconomic volatility have evolved substantially over time, it is important to assess each country's degree of exposure to fluctuations in these common factors.[14] Therefore, we compute the contribution of global, regional and idiosyncratic components to the output volatility of each country. The standard deviation of country i_k, $\sigma_{i_k,t}$, can be expressed as,

[12] The weights are obtained by iterating the equations, $w_j = B_{t,j}K_j$, and $B_{t,j-1} = B_{t,j}F - w_jG$, with $B_{t|t-1} = I$, for $j = t-1, t-2, \ldots, 1$, where K_j denotes the Kalman gain, and F and G are the matrices corresponding to the transition and measurement equations of the state space representation, respectively, as defined in Appendix A. Also, notice that Koopman and Harvey (2003) provide algorithms for computing the weights implicitly assigned to the observed data when estimating the latent variables in a linear state-space model. Although the VOLTAGE model works under nonlinear dynamics, it can be expressed in a linearized form by following Kim et al. (1998).

[13] For the sake of space, Online Appendix D provides a detailed narrative of the dynamics of regional and idiosyncratic volatility components.

[14] The regional volatility factors are show in Fig. A5 of Online Appendix D.1, while the idiosyncratic volatility components are shown in Online Appendix D.2, for the sake of space.

$$\sigma_{i_k,t} = S^{global}_{i_k,t} + S^{region}_{i_k,t} + S^{country}_{i_k,t}, \quad (8)$$

where $S^{global}_{i_k,t}$, $S^{region}_{i_k,t}$, and $S^{country}_{i_k,t}$ denote the share of the global, regional and idiosyncratic components in total volatility, respectively, for each period of time. The expression for each share is derived in the Online Appendix E.[15]

The historical volatility decomposition for all the countries in our sample is plotted in Figs. A9–A11 of the Appendix E, due to space constraints. The figures provide a comprehensive picture of the total time-varying output volatility for each country, along with the corresponding contributions of the global, regional and idiosyncratic components. This information represents a valuable asset for policymakers interested in making timely assessments of the size and sources of fluctuations in macroeconomic volatility for a given country. That is, to disentangle the part of macroeconomic volatility that is due to purely idiosyncratic (domestic) factors from the part that can be attributed to regional or global (foreign) developments. Moreover, notice that the VOLTAGE framework is able to provide a comprehensive assessment of volatility spillovers across countries. In particular, the effect that a shock originated in a given country, or set of countries, have on the common volatility factors can be traced through the historical data decomposition (Eq. (7)), and the effect that changes in those common factors have on the volatility of another country, or set of countries, can be mapped with the historical variance decomposition (Eq. (8)).

To illustrate the overall patterns of the historical variance decompositions, we summarize all the information in Figs. A9–A11, from quarters to decades, and from countries to regions. Accordingly, the first four bars (from left to right) in Chart A of Fig. 5 plot the contribution of the global component, averaged across all the countries in our sample, for the 1980s, 1990s, 2000s and 2010s, respectively. A striking finding is the increase over time in the average contribution of the global component to the volatility across countries, despite the decrease in global volatility documented in Section 3.1. To investigate whether this characteristic is specific to a subset of countries or if it is a feature that applies worldwide, we repeat the same exercise but separately for each of the four defined regions, that is, North America, South America, Europe and Asia + Oceania. The results presented in Chart A of Fig. 5 show that the increase in the contribution of the global component over time occurred in all four regions under study, implying that this is a systemic feature of international business cycle fluctuations.

Given that the contributions of the three components of volatility are expressed as shares of total volatility, and that the global component has increased over time, we assess whether this increase has been offset by a decline in the contribution of the regional component, the idiosyncratic component, or both. Chart B of Fig. 5 plots the average contribution of the regional component, both across countries in a region and over quarters in a decade. The figure shows that the sensitivity of output volatility to regional developments has generally remained relatively stable over time, with the exception of the Asia + Oceania region, which shows increasing sensitivity. This is of particular importance given the increasing protagonism that China and India are gaining in shaping the world business cycle. On the contrary, the average contribution of the idiosyncratic component has persistently declined over time for all the regions, as can be seen in Chart C of Fig. 5.

The overall pattern of the contributions in Fig. 5 show that, on average, the regional component accounted for 37 percent of output volatility fluctuations between 1981 and 2019. The global component accounted for 26 percent of volatility dynamics in the 1980s, but during the 2010s it accounted for 42 percent. In other words, despite the substantial decline in global volatility (documented in Section 3.1), its influence on output volatility across countries has significantly increased. On the other hand, the contribution of idiosyncratic developments has dropped substantially, from 41 percent in the 1980s to 18 percent in the 2010s. This pattern has been roughly similar for North America, South America and Europe. However, the role of the regional component has increased in Asia + Oceania, while the idiosyncratic component has become progressively less important. These results imply that, compared to the 1980s or 1990s, policymakers currently face greater constraints on their use of the appropriate tools to stabilize output fluctuations.

Global factors, based on strong common patterns, are usually interpreted as a summary of external influences that countries cannot manage or control, but that at the same time play a critical role in determining country-specific developments (Rey, 2013). Therefore, it is relevant to assess how unexpected increases in the global component can propagate through countries' macroeconomic volatility. This information could also help policymakers, especially from international organizations, to provide an accurate assessment of risks when analyzing the global economic outlook. In Online Appendix F we illustrate the key role played by global shocks in influencing country-specific macroeconomic volatility by employing impulse response analysis.[16]

4. What explains changes in volatility?

In this section, we assess the most robust factors associated to changes in output volatility. We use Bayesian Model Averaging (hereafter, BMA) to deal with model uncertainty. The reasoning for doing so is that there are many potential factors that could affect volatility, however, the theoretical literature provides limited guidance on the specification of the volatility regression. BMA addresses model uncertainty by weighting the various models based on fit and then averaging the parameter estimates they produce.

[15] The shares are defined as, $S^{global}_{i_k,t} = \sigma_{i_k,t}^{\frac{\left|\frac{\gamma_{i_k} g_t}{2\times \log(\sigma_{i_k,t})}\right|}{\alpha_t}}$, $S^{region}_{i_k,t} = \sigma_{i_k,t}^{\frac{\left|\frac{\lambda_{i_k} h_{k,t}}{2\times \log(\sigma_{i_k,t})}\right|}{\alpha_t}}$, and $S^{country}_{i_k,t} = \sigma_{i_k,t}^{\frac{\left|\frac{\chi_{i_k,t}}{2\times \log(\sigma_{i_k,t})}\right|}{\alpha_t}}$, where $\alpha_t = \left|\frac{\gamma_{i_k} g_t}{2\times \log(\sigma_{i_k,t})}\right| + \left|\frac{\lambda_{i_k} h_{k,t}}{2\times \log(\sigma_{i_k,t})}\right| + \left|\frac{\chi_{i_k,t}}{2\times \log(\sigma_{i_k,t})}\right|$.

[16] Since the VOLTAGE model allows for endogenous interdependencies between the common factors of volatility, collected in $H_t = (g_t, h_{1,t}, \ldots, h_{K,t})'$, we are able to apply all the standard practices used in VAR and factor-augmented VAR models to perform structural analysis.

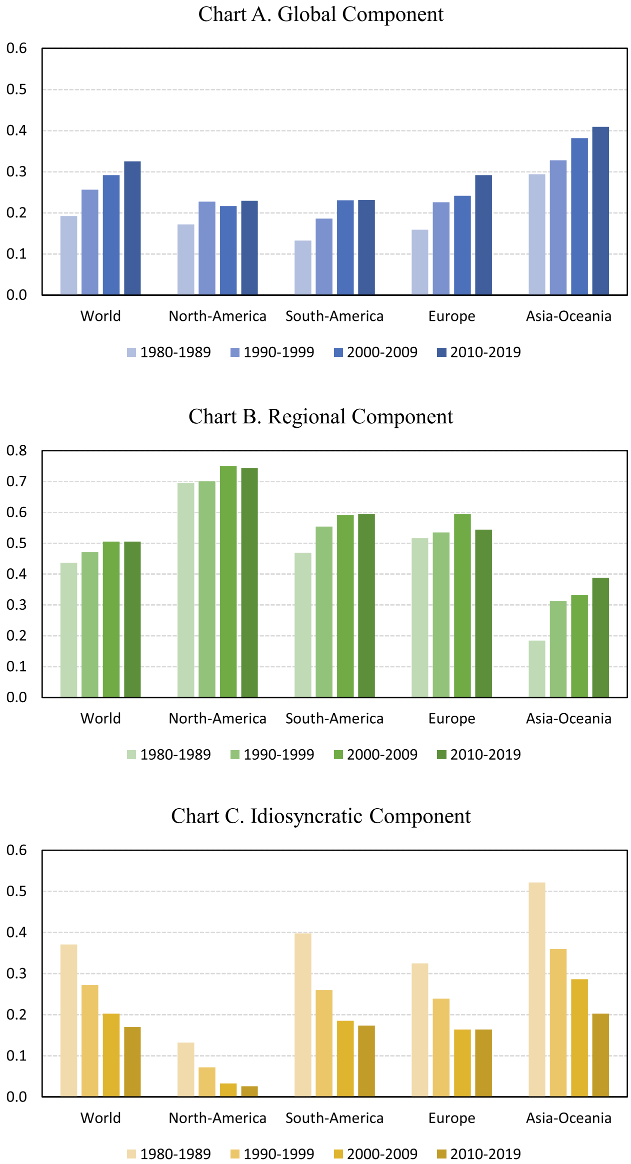


Fig. 5. Contribution of volatility components across regions and over time. Note. Chart A, B and C plot the average contribution of the global, regional and idiosyncratic components, respectively, on output volatility. For ease of exposition, each bar in each chart reports the average contribution across countries in a given region and across periods in a given decade.

There is ample literature suggesting different potential factors that could explain variation in volatility. Table 2 defines the factors that we consider in our analysis and their theoretically expected effect on volatility. We present further details about the explanatory factors in the Online Appendix G.

4.1. Model uncertainty

Following Ductor and Leiva-Leon (2016) we use a BMA panel data approach to deal with model uncertainty in assessing the most robust factors associated to output volatility at the global level. Accordingly, the output volatility model is defined as

$$\sigma_{it} = \rho\sigma_{it-1} + \sigma(x_k)_{it}\beta^k + \mu_t + \alpha_i + \upsilon_{it}, \tag{9}$$

where σ_{it} is the quarterly average volatility of economic growth in country i in year t, obtained using the framework proposed in Section 2, and as shown in Figs. A9–A11. We acknowledge the potential inefficiency of our estimates due to the measurement error being associated with the dependent variable. The term $\sigma(x_k)_{it}$ includes a set of potential factors

Table 2
Potential explanatory factors of macroeconomic volatility.

Variable	Transformation	Source	Description	Expected Sign
Trade openness	$T_{it} = \frac{E_{it}+I_{it}}{GDP_{it}}$	WDI	E_{it} is the total exports from country i in year t, I_{it} denotes total imports to country i in year t, and GDP_{it} is the nominal GDP in country i in year t	Ambiguos
Financial Openness	$F_{it} = \frac{A_{it}+L_{it}}{GDP_{it}}$	WDI	A_{it} is total assets to GDP and L_{it} is liquid liabilities to GDP in country i	Ambiguos
Terms of trade volatility	$\sigma(tot)_{it} = (log(tot_{it}) - log(tot_{it-1}))^2$	PWT 9.0	Square of the first differences in log of tot_{it} from $t-1$ to t	Positive
Exchange rate volatility	$\sigma(xr)_{it} = (log(xr_{it}) - log(xr_{it-1}))^2$	PWT 9.0	Exchange rate defined as national currency units per U.S. dollar. Volatility defined as the square of the first differences in log of tot_{it} from $t-1$ to t	Positive
Fiscal policy shocks	$Log(gov)$	PWT 9.0	Share of government consumption	Ambiguous
Monetary policy shocks	$\sigma(int)_{it} = \left(\frac{int_{it}-int_{it-1}}{int_{it-1}}\right)^2$	WDI	Square of the growth rate of the short-term lending interest rates	Ambiguous
Technology shocks	$\sigma(TFP)_{it} = \left(\frac{TFP_{it}-TFP_{it-1}}{TFP_{it-1}}\right)^2$	PWT 9.0	Square growth rate of TFP, TFP is the variable *ctfp* in PWT.	Positive

Note. As a measure of financial globalization, we use a financial openness indicator based on Lane and Milesi-Ferretti (2007). Terms of trade is defined as $tot_{it} = \frac{PE_{it}}{PI_{it}}$, the ratio between the price level of exports and imports in country i in year t. The square of the growth rate is a standard proxy for volatility (Alizadeh et al., 2002), in the field of finance. Both measures of volatility $\sigma(tot)$ and $\sigma(xr)$ test the importance of supply shocks in explaining changes in output volatility over time. To account for the potential effect of fiscal policy on volatility we use the share of government consumption, as in Fatas and Mihov (2013). TFP is computed using output-side real GDP, capital stock, labor input and the share of labor income of employees and self-employed workers in GDP. For a detailed description of the TFP variable, see Feenstra et al. (2015). WDI: World Development Indicators, PWT: Penn World Table.

associated with volatility, as defined in Section 4. We include time (year) dummies in all the regressions, μ_t, to account for time aggregate effects, i.e. unobservables affecting all countries, such as oil prices. We also include country dummies, α_i, to capture all time-invariant factors of the countries, such as geographical location. υ_{it} is the disturbance term.[17] The main idea of the BMA approach is to compute a weighted average of the conditional estimates across all possible models resulting from different combinations of the regressors. The weights are the probabilities, obtained using Bayes' rule that each model is the "true" model given the data. We use the priors specified in Magnus et al. (2010). In particular, Magnus et al. (2010) consider uniform priors on the model space, so each model has the same probability of being the true one. Moreover, they use a Zellner's g-prior structure for the regression coefficients and set the hyperparameter $g = \frac{1}{max(N,K^2)}$, as in Fernandez et al. (2001), where K is the number of regressors and N the number of observations.[18] This hyperparameter measures the degree of prior uncertainty on coefficients.

In the next section, we present the estimates of the *posterior inclusion probability (PIP)* of an explanatory factor, which can be interpreted as the probability that a particular regressor belongs to the true model of international output volatility. We also present results on the posterior mean, the coefficients averaged over all models, and the posterior standard deviation, which describes the uncertainty in the parameters and the model.

4.2. Results

In this section we present the results of estimating model in Eq. (9) using total output volatility and the idiosyncratic component of output volatility as dependent variables.

4.2.1. Total output volatility

We first present results for all the countries in a static panel, without lags of output volatility as regressors. Table 3 reports the estimates of the output volatility models obtained using the BMA panel approach over the 1981–2017 period for 37 emerging and advanced economies. Column 1 presents the PIP of each potential determinant of output volatility of the static model. The rule of thumb is that a factor is considered very robust if the PIP is greater than or equal to 0.80. We find that the most robust factors are exchange rate volatility and trade openness. Although our results cannot be interpreted in a causal sense due to simultaneity problems, we find that exchange rate volatility is positively associated with output volatility, while trade openness is negatively related with output volatility, as shown by the posterior mean, reported in column 2 of the table. Next, we control for output volatility dynamics by adding the lag of output volatility as a regressor in our BMA approach. The number of lags was selected according to the PIP criteria.[19] Columns 4–6 of Table 3 presents the results of

[17] Using a BMA approach, Malik and Temple (2009) find that remote countries exhibit greater output volatility. However, they focus on time-invariant drivers of the constant volatility, using only cross-sectional information. Our paper, on the other hand, analyzes the factors related to changes in volatility, which can be interpreted as its short-run dynamics.

[18] For robustness, we also consider a beta-binomial prior for the model space and different forms of the hyperparameter g. The results are quantitatively the same and presented in Appendix H.

[19] We also consider specifications with two lags of the output volatility, but the PIP of the second lag is very low.

the BMA in the dynamic panel setting. The results of the dynamic model are qualitatively similar to those of the static model. A one standard deviation increase in exchange rate volatility is associated with an increase in output volatility of 0.09 standard deviations, while a one standard deviation increase in trade openness is related to a decline in output volatility of 0.29 standard deviations.

We acknowledge the potential presence of biases in our results due to simultaneity issues. Therefore, we also attempt to account for the simultaneity between output volatility and its potential determinants by using an instrumental variable (IV) BMA approach. In particular, we deal with simultaneity problems by regressing each factor, including the lag of output volatility, on its second, third and fourth lags to purge the contemporaneous correlation with output volatility, i.e. we use lags of the regressors as instrumental variables, in line with the ample literature on empirical macroeconomics. We then apply our BMA strategy to the predicted regressors. The results presented in columns 7–9 of Table 3 show that once we account for simultaneity issues between the regressors and output volatility the only robust factors are its own lag and trade openness. In particular, the results show that a one standard deviation increase in trade openness leads to a decline in output volatility of 0.23 standard deviations. This is in line with the results reported in Mumtaz and Theodoridis (2017), who show using a two-country DSGE model that increases in trade openness lead to closer movements in output volatility. They also show that trade is one of the main mechanism explaining the increase over time in common uncertainty: higher trade openness leads consumers hedge against future risk about expected utility by transferring resources to other countries. The results are also consistent with Cavallo (2008), who provided evidence that the effect of trade openness on output volatility is negative. Giovanni and Levchenko (2009) show that sectors that rely on imports from other countries are less correlated with the other sectors of their economy.[20] Thus, sectors that depend on trade are mainly affected by global shocks to the industry and are less exposed to the domestic cycle (Kraay and Ventura, 2007), a mechanism that reduces overall volatility.[21]

In Online Appendix I, we test if the aforementioned mechanism is present in our sample and if it is the main driver of the negative association between trade and overall volatility. For this purpose, we use detailed World Input–Output (IO) tables, with available data on 34 sectors between 1995 and 2011, to analyze whether sectors that rely more on imports are less correlated with other sectors of their economy, and whether this lower comovement among the sectors of an economy diminishes the overall level of volatility. We show that sectors which are more open to trade are less associated with the other sectors of their economy, i.e. they have a lower sectoral composition overlap with the rest of the economy. These sectors are likely to be in influenced more by global shocks to the industry and less by domestic cycles. Therefore, greater dissimilarity among the sectors of an economy (facilitated through trade) diminishes overall volatility.

Our study confirms the importance of trade in explaining global volatility and provide evidence about the mechanisms through which trade is associated with output volatility. It also shows that other factors, including fiscal, monetary policy, financial instruments and technological shocks are not robustly associated with total output volatility, from a global perspective.

4.2.2. Idiosyncratic component of output volatility

Adrian et al., 2019 report that countries' exposure to the global price of risk interact with monetary, fiscal, and prudential stabilization policies. However, as previously postulated, the effectiveness of such stabilization policies might heavily depend on the extent to which macroeconomic volatility is mainly driven by the idiosyncratic component. In previous sections, we have characterized the time-varying influence of the idiosyncratic component on total output volatility across countries. We now investigate the main economic factors associated with changes in the idiosyncratic component of output volatility. This analysis is crucial in helping policy makers to determine the effectiveness of governmental and central bank stabilization policies aimed at reducing the adverse effects of macroeconomic volatility. Therefore, we apply our (IV) BMA strategy to identify the most robust factors of the idiosyncratic component of countries' volatility, instead of the total output volatility.

The main results, presented in Table 4, show that, unlike the case of total output volatility, we find that interest rate volatility is the most robust factor of the idiosyncratic component. A one standard deviation increase in the interest rate is related to an increase in the idiosyncratic component of output volatility of 0.15 standard deviations. Also, we find that the changes in government expenditure do not seem to have a significant influence on output volatility. Accordingly, from a global perspective, these results seem to imply that when central banks rely on substantial variations in the policy rate to stabilize the economy, these actions translate into significant changes in the idiosyncratic volatility component, which in turn influence the total output volatility.

As shown in Figs. A9–A11, the magnitude of such idiosyncratic influence can significantly vary both across countries and over time. Fig. A18 shows world maps with a detailed description of the share of idiosyncratic volatility components, which can be interpreted as the "space for action" that policy makers across countries may have in order to stabilize output fluctuations with more effectiveness. The figures shows that despite of the overall decline in the idiosyncratic share over time, there is a substantial heterogeneity across countries.

[20] Giovanni and Levchenko, 2009 also find that sectors displaying more openness to trade are more volatile and that trade facilitates specialization. These two mechanisms predict a positive effect of trade on volatility. Trade may also reduce the exposure of the economy to financial crises such as sudden stops and currency crashes (Cavallo and Frankel, 2008).

[21] In a recent study, Miyamoto and Nguyen (2019) use a multi-sector multi-country international business cycle model to show that changes in the international input–output linkages lead to a sizeable drop in output volatility across countries.

Table 3
Factors associated with volatility: A BMA approach. Period: 1981–2017.

Models:	(1)	(2) Static	(3)	(4)	(5) Dynamic	(6)	(7)	(8) Dynamic-IV	(9)
	PI prob.	Pt. Mean	Pt. Std.	PI prob.	Pt. Mean	Pt. Std.	PI prob.	Pt. Mean	Pt. Std.
Volatility$_{t-1}$	–	–	–	1	0.59	0.03	1	0.51	0.03
Exchange rate vol.	1	0.13	0.03	1	0.09	0.02	0.04	0.01	0.10
Trade Openness	0.99	−0.43	0.12	0.94	−0.29	0.11	0.80	−0.23	0.14
TFP volatility	0.58	0.04	0.04	0.69	0.04	0.03	0.06	0.01	0.03
Financial Integration	0.19	−0.02	0.05	0.04	−0.00	0.01	0.03	−0.00	0.01
Government cons.	0.41	0.04	0.06	0.13	0.01	0.02	0.06	0.01	0.01
Interest volatility	0.03	−0.00	0.01	0.03	0.00	0.01	0.04	0.00	0.01
Terms of trade vol.	0.04	−0.00	0.1	0.03	−0.00	0.01	0.24	0.11	0.23
Observations	1010	1010	1010	973	973	973	820	820	820
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note. All the variables are standardized. The dependent variable is economic growth volatility. Columns 1, 2 and 3 present the posterior inclusion probability, the posterior mean and the posterior standard deviation of the static model, respectively. Columns 4, 5 and 6 present the posterior inclusion probability, the posterior mean and the posterior standard deviation of the dynamic model, respectively. Columns 7, 8 and 9 present the posterior inclusion probability, the posterior mean and the posterior standard deviation of the IV-Dynamic model, respectively. In this model the explanatory variables are the predicted values of regressing the explanatory factors on its second, third and fourth lags. The sample includes 37 countries. The results are obtained by using a uniform prior for the prior model probability and a BRIC prior for the hyperparameter that measures the degree of prior uncertainty on coefficients, $g = 1/max(N, K^2)$.

Table 4
Factors associated with idiosyncratic volatility: An IV-BMA approach. Dynamic panel. Period: 1985–2017.

	PI prob.	Pt. Mean	Pt. Std.
Volatility$_{t-1}$	1.00	0.76	0.03
Interest volatility	0.82	0.15	0.09
Trade Openness	0.41	−0.11	0.14
Financial Integration	0.40	−0.06	0.08
Government cons.	0.21	0.02	0.04
Exchange rate vol.	0.11	0.09	0.32
TFP volatility	0.09	0.02	0.07
Terms of trade volatility	0.04	0.01	0.07
Observations	862	862	862
Year FE	✓	✓	✓
Country FE	✓	✓	✓

Note. Model estimated in first differences. The explanatory variables are the predicted values of regressing the explanatory factors on its second and third lags. Column 1 presents the posterior inclusion probability. Column 2 shows the posterior mean. Column 3 reports the posterior standard deviation. The sample includes 37 countries. The dependent variable is economic growth idiosyncratic volatility. The results are obtained by using a uniform prior for the prior model probability and a BRIC prior for the hyperparameter that measures the degree of prior uncertainty on coefficients, $g = 1/max(N, K^2)$.

Overall, the results show that the factor most associated with total output volatility is trade openness. We also find that the most robust factors of the idiosyncratic component of output volatility are trade openness and interest rate volatility. The latter underscores the relevance of monetary policy in stabilizing output fluctuations at the global level.

5. Conclusions

We show that the decline in macroeconomic volatility previously documented in the literature for developed countries has also been exhibited by developing countries, becoming a "global moderation" phenomenon. Although, there are important differences across economies. The increasing comovement observed in international macroeconomic volatility is substantially larger in developing than in developed countries. Instead, temporary episodes of high volatility have become both more extreme and frequent in developed than in developing countries. Regarding volatility spillovers at the regional level, our estimates suggest that North America, Asia and Oceania are not significantly affected by the volatility originated in other regions of the world. However, Europe and South America are highly influenced by North American volatility developments.

We also show that, although the downward trend exhibited by global volatility is mainly explained by an increasing trade openness, idiosyncratic macroeconomic volatility fluctuations are highly influenced by domestic monetary policies, acting as an effective business cycle stabilization tool at the global level. However, due to the substantial decline in the role played by the idiosyncratic volatility component over time, policymakers currently face greater constraints than in the past when it comes to stabilizing output fluctuations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jimonfin.2021.102533.

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