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Abstract

We rely on a hierarchical volatility factor approach to estimate and decompose time-varying second moments of countries output growth into global, regional and idiosyncratic contributions. We document a “global moderation” of international business cycles, defined as a persistent decline in macroeconomic volatility across the main world economies. This decline in volatility was induced by a reduction in the underlying global component, uncovering a new level of interconnection of the world economy. After assessing the importance of different economic factors, we find that the reduction in overall countries macroeconomic volatility can be mainly explained by the increasing trade openness exhibited in recent decades. Likewise, the idiosyncratic component of countries volatility is also influenced by domestic monetary policies.

Keywords: output volatility, factor model, model uncertainty.

JEL classification: C11, C32, F44, E32.

Resumen

Este trabajo se basa en un enfoque de factores de volatilidad para estimar y descomponer segundos momentos, cambiantes en el tiempo, del crecimiento del PIB a través de países en contribuciones globales, regionales e idiosincrásicas. Los resultados documentan una moderación global de los ciclos económicos internacionales, definida como una disminución persistente de la volatilidad macroeconómica en las principales economías del mundo. Esta disminución de la volatilidad ha sido inducida por una reducción del componente subyacente global, y desvela un nuevo nivel de interconexión de la economía mundial. Después de evaluar la importancia de diferentes factores económicos, se encuentra que la reducción de la volatilidad macroeconómica de los países puede explicarse principalmente por la creciente apertura comercial habida en las últimas décadas. Asimismo, se encuentra que el componente idiosincrásico de la volatilidad de los países también está influenciado por las políticas monetarias internas.

Palabras clave: volatilidad del PIB, modelo de factores, incertidumbre de modelización.

Códigos JEL: C11, C32, F44, E32.

1 Introduction

Changes in macroeconomic volatility at the international level have important implications for the global economy. They may affect financial markets, by inducing uncertainty to investors (Arellano et al. (2019)), and capital flows, leading to changes in the indebtedness position of a country (Fogli and Perri (2015)). Moreover, accounting for changes in volatility at the global level is important when assessing downside risks associated to 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. Therefore, decomposing the fluctuations in macroeconomic volatility into global, regional and idiosyncratic contributions, along with a thoroughly assessment of its potential drivers, would provide valuable information for a better understanding of the global economy interconnections.

Since the structural reduction in output volatility of the U.S. economy, that started in the mid 80s, was documented by Kim and Nelson (1999) and Pérez-Quirós and McConnell (2000), there has been an increasing interest in understanding the dynamics and sources of changes in macroeconomic volatility. This phenomenon, also called as the *Great Moderation*, is not a unique feature of the U.S., since it is also documented in other advanced economies (Blanchard and Simon (2001) and Everaert and Iseringhausen (2018)), suggesting potential commonalities in output volatility across countries (Stock and Watson (2005) and Mumtaz and Theodoridis (2017)). Yet these studies on commonalities in macroeconomic volatility have focused on a small set of countries, mainly composed by advanced economies, precluding them to derive comprehensive implications for the world economy. Therefore, a relevant question that emerges is whether such a reduction in output volatility is a unique characteristic of developed countries or if it also involves developing countries, making it a systemic global feature.

In this paper, we study the dynamics, propagation and sources of changes in macroeconomic volatility from a global perspective. In particular, we focus on, first, decomposing output volatility across countries into underlying global, regional and idiosyncratic components, to assess changes in their contribution over time. Second, characterizing how volatility shocks propagate throughout the world economy. Third, identifying the main macroeconomic factors that explain changes in the volatility of output both across countries and over time.

We proceed in two steps. First, we introduce an econometric framework referred to as the VOLTAGE (VOLatility Transmission Across Grouped Economies) model to estimate, decompose and analyze the propagation of output volatility across countries. The VOLTAGE model relies on a hierarchical volatility factor structure to simultaneously infer and summarize the underlying volatilities of the output growth of a set of countries into a small number of common factors. Second, we focus on identifying the main explanatory factors of changes in macro volatility across countries among the drivers commonly proposed in the literature. These potential drivers are trade openness, financial integration, exchange rate volatility, terms of trade volatility, fiscal, monetary policy 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. We also use the second and third lags of the potential drivers as instrumental variable to account for reverse causality.

Our results indicate that temporary increases in global volatility are not always necessarily related to economic recessions. Instead, they seem to be more generally related to episodes of instabilities, structural changes, high uncertainty and large foreign shocks. We document a generalized and persistent decline in output volatility across both developed and developing economies. Such a decline is driven by a markedly downward trend over time in the global volatility component, implying that GDP growth across the main world economies share a feature in common 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, implying that countries GDP growth has become more synchronized in second order moments and uncovering a new level of interconnection of the global economy. Instead, the contribution of the regional volatility component has remained relatively steady over time. Hence, the increasing contribution of the global component has been compensated by a substantial decline in the importance of the idiosyncratic volatility component.

The results on the drivers of short-run fluctuations in volatility indicate that exchange rate volatility and trade openness are the most robust explanatory factors. However, once we account for endogeneity issues the only robust driver of international macro volatility is the level of trade openness. In particular, we show that the systemic decline in macro volatility across countries can be explained by the increasing trade openness across countries observed during recent decades. Using the World Input-Output database, we provide evidence that the main mechanism through which trade openness negatively affect volatility is that sectors that rely on imports for their production process are likely to depend more on global shocks to the industry and less to domestic cycles (Kraay and Ventura, 2007).[1] Thus, trade facilitates higher dissimilarity among the sectors of an economy, diminishing overall volatility. Finally, we document that changes in the idiosyncratic volatility component are not only explained by trade openness but also by the volatility in the monetary policy across countries, acting as an effective business cycle stabilization tool, at the global level. Although, policy makers are currently more constrained than in the past to stabilize output fluctuations due to the substantial decline in the importance of the idiosyncratic volatility component.

Our paper is related to two strands of the literature. First, the literature focused on evaluating common patterns in macroeconomic volatility, and its shock propagation, from a global perspective. Commonalities in output volatility have been studied by Stock and Watson (2005) and Del Negro and Otrok (2008) for the G7 economies, and by Mumtaz and Theodoridis (2017), Everaert and Iseringhausen (2018) and Carriero et al. (2018a) for 11, 16 and 19 advanced economies, respectively. Up to our knowledge, this is the first study in providing a *global* assessment of commonalities in macroeconomic volatility, by addressing the volatility shock propagation between a large set of advanced and emerging economies.[2]

Our work is also related to the growing literature on economic uncertainty. There are numerous proxies for economic uncertainty, based on news (Baker et al. (2016)), the dispersion of earnings forecast, the dispersion of productivity shocks, the dispersion between forecasters for economic variables, stock market volatility or GDP volatility, among others.[3] Carriero et al. (2018b) focus on measuring uncertainty and its effect on the U.S. economy by using a large VAR model with errors whose stochastic volatility is driven by two common and interrelated unobservable factors, representing aggregate macroeconomic and financial uncertainty. Recently, Carriero et al. (2018a) employ such framework to eval-

[1]We use the World Input-Output Database 2013 release. The data covers 27 EU countries and 13 other major countries in the world for the period from 1995 to 2011 (Timmer et al., 2015).

[2]Mumtaz and Theodoridis (2017), following the line of Del Negro and Otrok (2008), estimate the time-varying volatility of innovations associated to common mean factors or idiosyncratic terms, finding that common components play an important role in driving cross-country output volatility. Everaert and Iseringhausen (2018) use a factor-augmented dynamic panel data model with time-varying parameters to analyze changes in volatility, finding a reduction in the volatility of domestic shocks, which is consistent with Stock and Watson (2005). However, these articles do not examine the propagation of volatility shocks systematically.

[3]See Bloom (2014) for a review of the literature.

uate commonalities in macroeconomic uncertainty for advanced economies, finding that uncertainty shocks lower output, stock prices, and in some economies lead to an easing of monetary policy.

Second, the literature focused on evaluating the effect of specific economic factors on output volatility. *Trade* and *Terms of trade shocks* have been documented as important sources of output volatility in previous studies. Giovanni and Levchenko (2009) find a positive and economically significant relationship between trade openness and aggregate volatility.[4] Using a small open economy real business cycle model, Mendoza (1995) estimates that roughly one-half of the variation in aggregate output in a sample of the G7 and 23 developing economies can be attributed to terms of trade shocks. Kose (2002) applies a similar framework and finds that terms of trade shocks can explain almost all of the variance in output in small open developing economies. Another important factor considered in previous studies is *financial openness*. Buch et al. (2005) found that financial openness increases business cycle volatility in the decades before the 1990s but it has a cushioned effect in the 1990s. There is also a large literature pointing to the importance of *government expenditure* on output volatility. Buch et al. (2005) and Fatás and Mihov (2001), among others, found that large governments are associated with less volatile economies.[5] Fatás and Mihov (2003) provide empirical evidence that governments that intensively rely on discretionary spending induce significant macroeconomic volatility which lowers economic growth.[6] *Monetary policy shocks* also affect output volatility and its effect depend on the degree of financial integration of the economy (Buch et al. (2005), Sutherland (1996), Obstfeld and Rogoff (1976)).

Despite the large literature dedicated to study the underlying drivers of output volatility, previous studies have typically focused on analyzing a particular driving factor of volatility without accounting for the implications of other potential factors. The only exception is Malik and Temple (2009), who use a Bayesian Model Averaging approach to study the structural drivers 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, we are the

[4]Giovanni and Levchenko (2012) show that the effect of trade shocks to large firms on aggregate volatility explain two empirical stylised facts: smaller countries are more volatile and more open countries are more volatile.

[5]Andrés et al. (2008) analyze how alternative models of the business cycle can replicate this empirical finding.

[6]The authors emphasize the importance of political factors in the fiscal policy conduct: institutional arrangements that constrain discretion allow to reduce macroeconomic volatility.

first to identify the main macroeconomic factors that explain changes over time in output volatility accounting for model uncertainty and reverse causality.

The paper is organized as follows. Section 2 proposes the empirical framework to measure and decompose global volatility fluctuations. Section 3 describes the dynamics and assess the propagation of macroeconomic volatility. Section 4 investigates the main underlying economic factors that could explain changes in volatility worldwide. Section 5 concludes.

2 Measuring Commonalities in Volatility

In this section, we propose a framework that is suitable to jointly estimate output volatility across countries, decompose it into global, regional and idiosyncratic components, and assess how volatility shocks propagate at the international level. Specifically, the proposed empirical framework relies on a hierarchical factor structure, that is designed to simultaneously (i) estimate and summarize the output volatilities of a large set of economies into a small number of factors, both global and regional, (ii) identify changes in the contribution of the global, regional and idiosyncratic components to the output volatility of countries over time, and (iii) provide a detailed assessment of the transmission of output volatility shocks at different levels of disaggregation. In sum, we introduce a framework that is well suited to analyze the VOLatility Transmission Across Grouped Economies, henceforth, it will be referred to as the VOLTAGE model.

Within this context, it is important to distinguish between comovements in mean and in volatility, and their corresponding implications. Recently, Ductor and Leiva-Leon (2016) have documented that after the early 2000s, economies tend to fall in recessions, and rise in expansions, in a synchronous way more often than before that time. Hence, if this pattern persists during future episodes of global recessions, the number of countries affected by contractionary shocks will be similar or even larger than during the "Great Recession". These assessments are based on synchronization of business cycle phases, which rely on first order moments of output growth. However, it still remains uncertain whether the severity of GDP downturns is more or less likely to be similar across countries during next global recessions. If an adverse scenario for the global economy is when most of the countries enter recessionary phases, an even more drastic scenario is when, in addition, the magnitudes of those downturns in GDP are similarly large across countries. Therefore, it is crucial to assess commonalities in the width of international output growth fluctuations, that is, second order moments, by also accounting for commonalities in first order moments.

Our modelling strategy closely follows the work of Kose et al. (2003), who rely on a factor structure to decompose real activity growth across countries into global, regional and idiosyncratic components. However, the authors focus solely on measuring commonalities in the mean, leaving unaddressed potential volatility comovements. Therefore, we extend their analysis by also disentangling commonalities in the time-varying macroeconomic volatility profiles across countries. Consequently, our focus is on "comovement of the volatility", and not on "volatility of the comovement". In particular, previous studies, following the line of Del Negro and Otrok (2008), have focused on modelling the time-varying volatility of common mean factors extracted from the data. However, such a modelling strategy is not designed to measure the extent to which volatility profiles across countries are alike over time, which is one of the goals of this paper. Instead, the VOLTAGE model is specifically intended to address commonalities of time-varying volatility measures.

The data employed to estimate the proposed model consists of quarterly real GDP growth of different countries. This growth rate was computed based on the quarterly GDP at standardized constant prices in US 2010 dollars. The data was gathered from Datastream, which has the largest coverage of countries and periods. Since information at a higher frequency allow 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 regions of the world, North America, South America, Europe, and a joint region composed by countries located in Asia and in Oceania. The list of countries along with the corresponding regions is reported in Table 1. The sample period spans from 1981:Q1 until 2016:Q3.

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,

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

where $\bar{\gamma}_{i_k}$ and $\bar{\lambda}_{i_k}$ are the corresponding factor loadings, for $i_k = 1, 2, ..., n_k$ and $k = 1, ..., K$, n_k is the number of countries that belong to region k, and K is the total number of considered regions. Notice 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 in the volatility. Therefore, we extract mean factors non-parametrically by relying on principal components.[7] This would preclude our main estimates of being significantly affected by any misspecification in modelling the mean factors.[8]

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 to country i_k. Typically, $F_{i_k,t}$ is assumed to be an independent univariate autoregressive processes. This functional form was initially used as an approximation to the stochastic volatility diffusion by Chesney and Scott (1989) and Hull and White (1987).[9] However, given our multi-country environment, we are interested in decomposing $F_{i_k,t}$ into its common, regional and idiosyncratic components across countries.[10] That is, we decompose country i_k log-volatility as follows,

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

for $i_k = 1, 2, ..., n_k$ and $k = 1, ..., K$. The term, g_t denotes the global volatility factor, while $h_{k,t}$ denotes the volatility factor associated to 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. Instead, the regional factors account for the commonalities in the volatility patterns between countries located in a given region, after accounting for global volatility commonalities. Finally, the idiosyncratic component identifies volatility changes that can be purely attributed to country-specific developments. The coefficients γ_{i_k} and λ_{i_k} are the corresponding factor loadings and measure the strength of the comove-

[7]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.

[8]However, as a robustness exercises of the empirical analysis, we also extract the mean factors with filtering techniques by assuming autoregressive dynamics, showing that, besides increasing parameter uncertainty, our main results remain unchanged.

[9]Recent examples of such a modelling strategy are Del Negro and Otrok (2008) and Everaert and Iseringhausen (2018).

[10]Such a decomposition is closer to the work by Carriero et al. (2018b), who focuses on measuring U.S. macroeconomic and financial uncertainty by relying on VAR models.

ment between the country-specific volatility and the volatility factors, both at the global and regional level, respectively.

Equation (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, to evaluate the importance of the global volatility factor on countries macroeconomic volatility from a more comprehensive perspective, the latent variables driving both the global and regional volatility factors are assumed to evolve according to a stationary vector autorregresion (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, $\zeta_t \sim N(0, \Sigma)$. This assumption allows us to perform any type of structural analysis typically employed in a linear VAR context, but in a perspective of second order moments.[11] 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.

To achieve identification of 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 equals to 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.[12] The first restriction facilitates the type of structural analysis that can be performed with the model since the innovations, ζ_t, are orthogonal by construction[13]

[11] 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 exercise. The results are shown in the empirical Section 3.2.1.

[12] 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 it is shown in Appendix A.1.

[13] However, notice that since the innovations ζ_t are orthogonal by assumption, they can be directly interpreted as structural innovations in an "artificial" way. Therefore, it is important to acknowledge this feature in the interpretations derived from any shock decomposition associated to the VAR defined in Equation (4). Also, notice that if one is interested in allowing Σ to be unrestricted in order to impose a given identification scheme for the structural shocks, it can be also done by imposing stronger restrictions in the matrix of factor loadings, as it is shown in Bai and Wang (2015).

The proposed VOLTAGE model is suited for a wide range of applications, since it allows to perform all the types of analyses typically done in the literature of dynamic factor models and structural vector autoregressions, but for the volatility of data instead of the raw data itself. Therefore, it can be used to provide a comprehensive assessment on the propagation pattern of volatility shocks in large dimensional settings.

The model is estimated with 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. Moreover, the proposed estimation algorithm allows us to deal with missing observations, which is a typical problem in multi-country GDP data at the quarterly frequency. The Appendix A.1 reports the details about the estimation procedure.

3 Global, Regional and Idiosyncratic Volatility

The purpose of this section is threefold. First, inferring changes over time in macroeconomic volatility across both developed and developing economies. Second, understanding the sources of those changes by disentangling them into domestic and foreign contributions. Third, assessing how macroeconomic volatility shocks propagate throughout the global economy.

Prior to investigating commonalities in second order moments, it is important to account for commonalities in first order moments. We extract the common factors in the mean from the GDP growth of the 42 countries in our sample, as described in Equation 1. The estimates show that the global factor resembles fairly well the dynamics of the world real activity, while the regional factors are consistent with several salient features of the business cycles in those regions, such as, the prolonged slow down in Europe since the late 2000s, the severe recession in Asia due to the 1997 Financial Crisis, the recent downturn of economic conditions in South America, and the reduction of real activity fluctuations in North America. Since the focus of this paper is on commonalities in volatility, for the sake of space, we report the mean factor estimates in A1. Kose et al. (2003), Kose et al. (2012), and Ductor and Leiva-Leon (2016) provide a deeper assessment on changes in the comovement of mean output growth at the international level, which is aligned with our mean factor estimates.

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. 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 Figure 1. Chart A plots the world time-varying second moments 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 main world economies. Second, the cross-sectional dispersion of volatility profiles has decreased over time, indicating an increase in the comovement of international macroeconomic volatility over time. Moreover, in order to assess whether these two features are consistent with only highly industrialized countries, we compute the same cross-sectional distribution, but differentiating between developed and developing economies, plotted in charts B and C, of Figure 1, respectively. The charts indicate these two features of macroeconomic volatility, downward trend and higher comovement, are present in both developed and developing countries.

To address whether such an increasing comovement in volatility across countries, obtained with the VOLTAGE model, is an artefact of relying on a factor structure in modelling second moments, we perform a robustness exercise. We assume no factor structure, and estimate the time-varying volatility associated to each country, independently, by fitting univariate stochastic volatility processes to each term $u_{i_k,t}$. The results reported in Figure A2, show the same features obtained with the framework based on factor structure, indicating an inherent pattern of real activity at the international level. Overall, these results show that countries macroeconomic volatility has persistently reduced over time and become more similar worldwide.

In a recent work, Adrian et al. (2019) show substantial changes over time in the predictive distribution of U.S. GDP growth by relying on quantile regressions.[14] Also, Adrian et al. (2018) document similar patterns at the international level by using quantile panel regressions. Regarding GDP second moments across countries, Figure 1 suggests that the world macroeconomic volatility distribution is remarkably right-skewed and exhibited substantial changes over time. To analyze in depth these patterns, we compute the kernel

[14] In particular, they show that lower quantiles of GDP growth tend to vary with financial conditions, especially, when they are deteriorating, while upper quantiles tend to be stable over time.

densities associated to all the realizations of volatility, both across time and countries, within each decade in our sample, that is, 1980s, 1990s, 2000s and 2010s. Chart A of Figure 2 shows that the world volatility distribution is becoming more right-skewed with time. This pattern occurs independently on whether we focus only on developed or developing countries, as shown in Charts B and C.[15] This left-displacement of the distribution can be interpreted as a reduction in the world macroeconomic risk. That is, the realizations of large and atypical macroeconomic fluctuations across countries has become less frequent during recent times.

3.2 Dissecting Volatility

The main advantage of the VOLTAGE framework is its ability to endogenously decompose time-varying volatility estimates into the contributions associated to global, regional and country-specific, or idiosyncratic, development. The time-varying standard deviation associated to country i_k can be compactly expressed as,

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

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. Next, we proceed to examine in detail each of these components and their implications.

3.2.1 Global Component

Chart A of Figure 3 plots the dynamics of the global volatility component, showing a markedly decreasing trend over time. In particular, during the 1980s the average global volatility was 0.50 standardized units, in the 1990s the average volatility declined to 0.35, similarly, during the 2000s it continued decreasing reaching 0.20, to finally remain at 0.14 standard units during the 2010s. Such a persistent decline, which illustrates our first main result, implies that GDP growth across the main world economies share a feature in common that can be interpreted as a global moderation of international output fluctuations. This feature is consistent with the downward trend in the cross-sectional distribution of volatility shown in Figure 1, suggesting an important role for this global component in

[15] As a robustness exercise, we also compute the corresponding kernel densities of the time-varying volatilities obtained with univariate stochastic volatility models. The results, shown in Figure A3, point to the same conclusions.

determining international volatility fluctuations. This phenomenon is analyzed in details in section 3.2.2.[16]

Next, we examine up to which extent the decline in the global volatility component has been induced by both, developed and developing economies. For this purpose, we proceed to disentangle the contribution of each region to the changes exhibited by the global volatility component. This analysis also allows to identify the regions associated with the temporary increase in global volatility depicted in Figure 1.

We follow the line of Koopman and Harvey (2003) to decompose the latent factors into the contributions associated to each of the observable countries real activity. In particular, we express the state vector containing the latent log-volatilities, both factors and idiosyncratic, 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.[17] To facilitate the interpretation of the decomposition, we group all the country-specific contributions associated to a particular region.

Chart B of Figure 3 shows the historical data decomposition of the global volatility factor. Notice that the persistent decline in global volatility is not associated to a specific region, since all the four regions have, in general, significantly contributed to the downward trend, suggesting that the moderation of macroeconomic fluctuations can be considered as a global phenomenon.

[16] We provide additional evidence on the declining pattern of global macroeconomic volatility based on three robustness exercises. First, to avoid potential misspecifications in the extraction of the mean common factors, we fit the VOLTAGE model directly to output growth fluctuations, $y_{i_k,t}$. Figure A4 plots the estimated global volatility, also showing a persistent declining, with a significant increase during the Great Recession. Second, we estimate the mean and volatility common factors jointly, with Bayesian methods, assuming similar autoregressive dynamics for both types of factors. Figure A5 indicates that, despite increasing the uncertainty around the estimates, the declining pattern in global volatility is also present. Third, to account for the dependence of between the volatility and the mean we allow the volatility factors to depend on their past values and on the lagged mean factors, that is, $H_t = \Phi H_{t-1} + \Lambda \bar{X}_{t-1} + \zeta_t$, where the log-volatility factors are given by $H_t = (g_t, h_{1,t}, ..., h_{K,t})'$ and the mean factors are collected in $\bar{X}_t = (\bar{g}_t, \bar{h}_{1,t}, ..., \bar{h}_{K,t})'$. Figure A6 also shows a persistent decline of the global volatility. These three exercises provide robust evidence on the importance of the global component in the downward trend pattern of macro volatility across countries.

[17] The weights are obtained by iterating the equations, $w_j = B_{t,j} K_j$, and $B_{t,j-1} = B_{t,j} F - w_j G$, with $B_{t|t-1} = I$, for $j = t-1, t-2, ..., 1$, 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.1. 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).

Regarding global volatility fluctuations, it shows a temporary increase in the early 1980s, which is accompanied by a significant contribution of the South American region. This is associated by the period called as the "Lost Decade". Another increase in global volatility is observed in the early 1990s. During this period, most of the Western world suffered a recession. Also, around the same time the German reunification was taking place. This event had significant economic implications for several European countries. The sudden increase in global volatility observed in the late 1990s can be rationalized as the result of spillover effects of the severe Asian crisis to advanced economies through the global markets. Finally, there is another increase in global volatility that took place between 2007 and 2010, when all the regions contributed almost equally, and that can be associated to the high levels of uncertainty caused by the adverse effects of the Great Recession.

3.2.2 Regional Components

The regional volatility factors are intended to capture commonalities in output volatility across countries after accounting for global patterns. We restrict to a definition of groups based on geographic location of countries since it facilitates the interpretation of the regional factors, and therefore, the subsequent structural analysis. Figure 4 shows the regional volatility components along with their corresponding historical data decompositions. Chart A plots the volatility factor of the North American region, which exhibits three significant increases. In 1984, all the economies of the region experienced a significant boom leading to substantial magnitudes of real activity fluctuations. Instead, in 1991, the opposite scenario occurred, when U.S. and Canada enter a recessionary phase. The third increase can be attributed to the so called "Tequila Crisis" originated in Mexico. Despite those specific periods, the volatility in North America has remained relatively stable over time, which is consistent with Gadea et al. (2018), who showed that since the Great Moderation, U.S. output growth has remained subdued despite the loss of the Great Recession. Also, the corresponding decomposition shows that North American volatility is almost no influence by the volatility of other regions.

Chart B of Figure 4 plots the volatility of South America. This region presents several temporal increases in volatility, two of them are of a large magnitude. First, the rise in volatility around the early 1990s is associated to economic upswings in the region due to policies focused on the liberalization and privatization to incentivize a free market economy. Instead, the rise occurred in the early 2000s can be associated to, first, large fluctuations in the output of Venezuela induced by oil price shocks, and second, uncertainty in the Argentine economy due to unexpected regulations of its financial system to avoid bank runs. Similarly to the case of global volatility, temporary increases in regional volatility are not only related to recessions, but also to large upward fluctuations and to foreign shocks. The decomposition reveals that North American developments has had a substantial influence in the volatility of South America during those periods.

Chart C of Figure 4 plots the volatility of the European region. The most significant episodes of high volatility occurred, first, during the early 1990s European recession, as dated by the Euro Area Business Cycle Dating Committee. Second, during the Sovereign Debt Crisis in the early 2010s, event that led to a pronounced declines in real activity for several countries of the region. Again, the influence of North American developments have played a substantial role in the volatility of Europe. Finally, Chart D of Figure 4 plots the volatility associated to the region of Asia+Oceania. The figure shows more frequent changes in the level of aggregate volatility than for the other regions, such as the one occurred in the early 2000s, period in which the Turkish economy went through a severe crisis leading to financial and political instability and to further panic in the markets. In contrast to South America and Europe, the volatility in Asia+Oceania is mainly driven by its own developments, being almost no influence by North America.

It is important to notice that all these temporary increases in both global and regional volatility are not necessarily related to economic recessions. Instead, they seem to be more generally related to episodes of instabilities, structural changes, and high uncertainty.

3.2.3 Idiosyncratic Components

The idiosyncratic volatility component captures changes in output volatility that can be attributed to events occurred in a given country and that are unrelated to global or regional developments, such as domestic economic policies. The estimated idiosyncratic volatilities, which are plotted in Figures A7 to A9 of the Appendix for the sake of space, show substantial heterogeneity across countries. For some economies, the idiosyncratic volatility has remained relatively stable over time, these are the cases of Canada, Mexico, Belgium or Japan. Instead, other economies exhibit several changes in the idiosyncratic component of output volatility, for example, Peru, Germany, Norway or China. Also, some countries, such as Ireland and Finland, show a stable pattern with a sudden substantial increase due to the 2015 tax inversion practices, in the former case, and to the early 1990s country-specific depression, in the later.

3.3 Sources of Fluctuations

The effectiveness of stabilization policies would depend on the extent to which 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 the degree of exposition that each country has to fluctuations in these common factors. 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 can be expressed as,

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

where $S^{global}_{i_k,t}$, $S^{region}_{i_k,t}$, and $S^{country}_{i_k,t}$ correspond to the share of the global, regional and idiosyncratic components to the total volatility, respectively, for each period of time. The expression for each share is derived in the Appendix A.2.[18]

The historical volatility decomposition of four selected countries, United States, United Kingdom, Chile and Japan, is plotted in Figure 5.[19] The figure shows that, in all the four cases, the volatility has exhibited a downward trend, the contribution of the idiosyncratic component has lost strength over time, while the contribution of the global component has increased in recent decades. These results would imply that policy makers of these countries are currently more constrained to stabilize output fluctuations, by using appropriate tools, than during the 1980s or 1990s. The historical volatility decomposition for all the countries in our sample is plotted in figures A10 to A12 of the Appendix, due to space constraints. The figures show a comprehensive description of the total time-varying output volatility for each country, along with its corresponding contributions of the global, regional and idiosyncratic components. This information represents a valuable asset for policy makers, who are interested in performing timely assessments about the size and sources of fluctu-

[18] 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 $\alpha_t = \left|\frac{\gamma_{i_k} g_t}{2\times log(\sigma_{i_k,t})}\right| + \left|\frac{\lambda_{i_k} h_{k,t}}{2\times log(\sigma_{i_k,t})}\right| + \left|\frac{\chi_{i_k,t}}{2\times log(\sigma_{i_k,t})}\right|$.

[19] These countries were selected due to their large size, in economic terms, and because they belong to different geographical regions.

ations 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.

To illustrate the overall patterns, we summarize all the information in figures A10 to A12, from quarters to decades, and from countries to regions. Accordingly, the first four bars (from left to right) in Chart A of Figure 6 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. This feature constitutes our second main result, which consists of a persistently increasing sensitivity of macro volatility to global developments. To investigate if this is a particular characteristic of a subset of countries or if it is worldwide feature, we repeat the same exercise by, separately, using averages across countries that belong only to each of the four predetermined regions, that is, North America, South America, Europe and Asia+Oceania. The results presented in the subsequent piles of bars plotted in Chart A of Figure 6 show that the increase in the contribution of the global component over time occurred in the four regions under consideration, implying that this is a systemic feature of international business cycle fluctuations.

Given that the contributions of the three components of volatility are expressed in terms of shares, and that the global component has increased over time, we assess whether such an increase has been compensated by a decline in the contribution of the regional component, or in the idiosyncratic component, or in both. Chart B of Figure 6 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, in general, has remained relatively stable over time, with the exception of the Asia+Oceania region, which has experienced an increasing sensitivity. Instead, the average contribution of the idiosyncratic component has persistently declined over time for all the regions, as can be seen in Chart C of Figure 6.

The overall pattern of the contributions in Figure 6 show that, on average, regional commonalities account for 37 percent of output volatility fluctuations between 1981 and 2016. Global commonalities accounted for 26 percent of volatility dynamics in the 1980s, but during the 2010s it accounts for 42 percent. That is, despite the substantial decline in global volatility (documented in Section 3.1), its influence on output volatility across countries has significantly increased. Instead, 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, regional commonalities in Asia+Oceania have increased, while the idiosyncratic component has been significantly loosing importance, pointing to a higher integration in macro volatility both at the regional and global level for this specific set of countries.

3.4 Shocks Propagation

Economic factors, such as international trade, capital flows, financial integration, common sectoral composition, have contributed to take the main world economies to a high level of interconnectedness (Ductor and Leiva-Leon, 2016). The previous sections of this paper have documented an additional layer of economies interconnection, which is based on the importance of a global component in determining changes in countries macroeconomic volatility. 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 an important role in determining country-specific developments (Rey (2013)). This section provides an assessment on how unexpected increases in the global component can propagate through countries macroeconomic volatility. This information could also help policy makers, especially from international organizations, to provide accurate assessment of risks when inferring the outlook of the global economy.

Since the VOLTAGE model allows for endogenous interdependencies between the common factors of volatility, collected in $H_t = (g_t, h_{1,t}, ..., h_{K,t})'$, we are able to apply all the standard practices used in VAR and FAVAR models to perform structural analysis. In particular, we rely on the notion of generalized impulse response functions and use the difference between $E(\sigma_{i_k,t+j}|\zeta_t = 1, \psi_{t-1})$ and $E(\sigma_{i_k,t+j}|\zeta_t = 0, \psi_{t-1})$ as our measure of impulse response, where ψ_{t-1} denotes all the accumulated information up to time $t-1$.[20] Accordingly, to obtain the responses of country-specific volatilities to a one-time unexpected increases in the volatility factors, we project the impulse response function associated to the VAR equation by using the corresponding factor loadings,

[20]Notice that it is not necessary to follow the generalized impulse response function approach of Koop et al. (1996), since the VAR model in H_t is linear and the associated disturbances are Gaussian. Instead, given that the nonlinear mapping between H_t and the volatility component is known, we compute the linear impulse responses Θ_j and map them using the corresponding exponential function.

$$\frac{\partial \sigma_{i_k,t+j}}{\partial \zeta_t'} = exp\left(\frac{1}{2}\left(\gamma_{i_k}\Theta_{j[g]} + \lambda_{i_k}\Theta_{j[h_k]}\right)\right) - 1, \tag{9}$$

for countries $i_k = 1, 2, ..., n_k$, located in regions $k = 1, ..., K$, for horizon path $j = 1, 2, ..., J$, where $\Theta_{j[z]}$ denotes the row of Θ_j that corresponds to the latent factor $z = \{g, h_1, ..., h_K\}$, and where $\Theta_j = \frac{\partial H_{t+j}}{\partial \zeta_t'}$.[21]

The responses of country-specific volatilities to a global shock are reported in Figure (7), showing substantial heterogeneity. In particular, all the three countries composing the Noth American region are highly sensitive to global shocks. For countries in South America, Chile is the most responsive to unexpected global developments, while the other countries of the region present a lower and relatively similar responsiveness. In the case of Europe, most of the countries experience a significant sensitivity to global shocks, with the exception of Iceland and Norway. Also, most of the countries that belong to the Asia+Oceania region are highly sensitive to global volatility shocks, in particular, Indonesia and China. This impulse response pattern illustrates the high importance of global shocks in influencing country-specific macroeconomic volatility.

Lastly, we adopt a more aggregate and dynamic perspective in the assessment of shock propagation and analyze how the influence of global shocks on regional developments has evolved over time. Once the impulse responses Θ_j have been estimated, it is possible to quantify how much a given structural shock explains the historically dynamics of the log-volatility factors, collected in H_t, by approximating them as follows,

$$H_t \approx \sum_{j=0}^{t-1} \Theta_j \zeta_{t-j}, \tag{10}$$

and then computing the corresponding decomposition. Figure 8 plots the shock decomposition of both global and regional log-volatility factors showing a striking feature, which consists of an increasing contribution over time of global shocks to the volatility dynamics of all the regions, and more importantly, to the volatility dynamics of the global factor. This feature corroborates our second main result, which pointed to an increasing importance of the global component. In others words, these results show strong evidence that

[21] To identify the latent factors from the factor loadings we follow the line of Bai and Wang (2015) and assume that $\Sigma = I_{K+1}$. An advantage of this identification scheme is that it provides shocks, ζ_t, that are orthogonal by construction. This feature is also applied in Bai and Wang (2015) to assess spillovers in international bond yields by employing a dynamic factor model in first moments.

global macro volatility has become "more global", indicating a more interrelated global economy in terms of aggregate risks.

4 What Does Explain Changes in Volatility?

In this section, we assess the most robust factors explaining 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 theorical literature provides only weak 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 across models.

4.1 Explanatory Factors

There is ample literature suggesting different potential factors that could explain variation in volatility. These factors can be categorized as follows:

1) *Trade openness.* The theoretical relationship between trade openness and output fluctuations is ambiguous. Trade may affect volatility through three main different channels (Giovanni and Levchenko, 2009): (i) trade openness may expose industries to external shocks leading to higher volatility (Newbery and Stiglitz, 1984); (ii) trade may increase specialization and lead to a less diversified production structure, increasing volatility; (iii) trade can change co-movement between sectors within the economy; sectors that are more open to trade will depend more on global shocks to the industry than to domestic cycle, this may reduce volatility (Kraay and Ventura, 2007).

To compute trade openness we use data on exports and imports and define trade openness in year t as,

$$T_{it} = \frac{E_{it} + I_{it}}{GDP_{it}} \tag{11}$$

where 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.

2) *Financial integration.* Theoretically, the impact of financial integration on output volatility is ambiguous. Evans and Hnatkovska (2014) and Kose et al. (2006) emphasize two main channels through which larger international financial integration may affect output volatility: (i) consumption paths will be less correlated with country-specific shocks, since

financial instruments facilitates risk-sharing by households; (ii) greater financial integration increases production specialization within countries, magnifying the effect of industry-specific shocks and their transmission across countries. The first channel predicts a negative effect on macroeconomic volatility while the second a positive.

As a measure of financial globalization, we use a financial openness indicator based on Lane and Milesi-Ferretti (2007). This indicator is defined as the volume of a country's assets and liabilities as a share of GDP:[22]

$$F_{it} = \frac{A_{it} + L_{it}}{GDP_{it}} \tag{12}$$

where A_{it} is total assets to GDP and L_{it} is liquid liabilities to GDP in country i. This variable has been extensively used in the literature and is considered a good measure in comparison to available alternatives.

3) *Supply shocks.* To capture supply shocks we consider exchange rate volatility and terms of trade volatility. Changes in the exchange rate and terms of trade affect output through two main channels: (i) fluctuations in the exchange rate and term of trades alter imports and hence affects real domestic income; (ii) inflationary pressures through fluctuations in domestic spending.

To compute terms of trade we use price level of imports and exports from the Penn World Table 9.0. Formally, the terms of trade is defined as,

$$tot_{it} = \frac{PE_{it}}{PI_{it}} \tag{13}$$

where PE_{it} and PI_{it} are the price level of exports and imports in country i at year t, respectively. Since these prices are available per year we compute the volatility at period t as the square of the first differences in log of tot_{it} from $t-1$ to t,

$$\sigma(tot)_{it} = (log(tot_{it}) - log(tot_{it-1}))^2 \tag{14}$$

The square of the growth rate is a standard proxy of volatility in finance (Alizadeh et al., 2002). We also obtain the exchange rate, defined as national currency units per U.S. dollar, from the Penn World table 9.0 and compute exchange rate volatility as,

[22]The original indicator constructed by Lane and Milesi-Ferretti (2007) is based on country's foreign assets and liabilities. Unfortunately, we do not have data on foreign assets and liabilities.

$$\sigma(xr)_{it} = (log(xr_{it}) - log(xr_{it-1}))^2 \tag{15}$$

We use both volatilities $\sigma(tot)$ and $\sigma(xr)$ to test the importance of supply shocks in explaining changes in output volatility over time.

4) *Fiscal policy shocks.* In theory, governments may use discretionary changes to smooth out fluctuations in output. Some of these discretionary changes include expansionary spending and tax cuts in recessions and contractionary policy in expansions. However, there is no agreement as to whether fiscal policy volatility increases or decreases macroeconomic volatility. Gali (1994) show that both low income tax rate and higher share of government expenditure are asssociated with low output volatility in a real business cycle model, however, the predicted effects are small. Fatás and Mihov (2003) and Fatás and Mihov (2001) provide empirical evidence that governments that intensively rely on discretionary spending induce significant macroeconomic volatility. Fernández-Villaverde et al. (2015) find that unexpected changes in fiscal volatility can have a sizable adverse effect on economic activity. Andrés et al. (2008) found a negative effect of government size on business cycle volatility. Grechyna (2019) shows that higher fraction of discretionary public spending in total public spending, other things being equal, leads to more volatile business cycles.

To account for the potential effect of fiscal policy on volatility we use the share of government consumption as in Fatas and Mihov (2013). This variable is obtained from the Penn World Table 9.0. Since government consumption is only available per year we compute the volatility at period t as the squared of growth of government expenditure from $t-1$ to t,

$$\sigma(gov)_{it} = \left(\frac{gov_{it} - gov_{it-1}}{gov_{it-1}}\right)^2 \tag{16}$$

5) *Monetary policy shocks.* The impact of monetary policy shocks on output volatility has been extensively study. Traditional models suggest that monetary contractions (expansions) should increase interest rate (decrease), lower (raise) prices and reduce (increase) real output. Thus, changes in interest rate volatility may also affect output volatility. Fernández-Villaverde et al. (2011) consider a non-linear small open economy DSGE model to show that as real interest rate volatility increases, countries reduce their foreign debt by reducing consumption. Thus, investment falls, as foreign debt becomes a less attractive hedge for productivity shocks, leading to a fall in output. Empirically, Mumtaz and

Zanetti (2013) using a SVAR with stochastic volatility found that the nominal interest rate, inflation, and output growth fall after an increase in the volatility of monetary policy.[23]

We measure monetary policy volatility using the square of the growth rate of the short-term lending interest rates obtained from the World Bank Development Indicator. Formally,

$$\sigma(int)_{it} = \left(\frac{int_{it} - int_{it-1}}{int_{it-1}}\right)^2 \tag{17}$$

where int_{it} is the short-term interest rate at year t in country i.

6) *Technology shocks.* The role of technology shocks in business cycle fluctuations has been widely studied in the real business cycle models that followed the seminal work by Kydland and Prescott (1982). Overall, there is consensus in the literature that expansions in output, at least in the medium-long run, are caused by TFP increases that derive from technical progress (Rebelo, 2005). Prescott (1986) estimated that technology shocks could account for around 75% of business cycle fluctuations. Changes in technology factor productivity could then be an important factor leading to changes in output volatility.

Total factor productivity (hereafter TFP) level was obtained from the Penn World Table 9.0 (variable *ctfp*). It 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.[24] We then measure volatility in TFP as the square growth rate of TFP,

$$\sigma(TFP)_{it} = \left(\frac{TFP_{it} - TFP_{it-1}}{TFP_{it-1}}\right)^2 \tag{18}$$

where TFP_{it} is the TFP at year t in country i.

4.2 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 explanatory factors of output volatility at the global level. Accordingly, the output volatility model is defined as

$$\sigma_{it} = \rho\sigma_{it-1} + \sigma(x_k)_{it}\beta^k + \mu_t + \alpha_i + v_{it}, \tag{19}$$

where σ_{it} is the quarterly average volatility of economic growth in country i at year t, as obtained with the framework proposed in Section 2, and shown in figures A10-A12.

[23] There is ample empirical literature examining the impact of monetary policy shock on output, see surveys in Christiano et al. (1999) and Bagliano and Favero (1998).

[24] For a detailed description, see Feenstra et al. (2015).

We acknowledge the potential inefficiency of our estimates due to the measurement error associated to the dependent variable. Therefore, we perform a series of robustness tests to assess the reliability of our results. The term $\sigma(x_k)_{it}$ includes a set of potential drivers as defined in Section 4.1. 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. α_i captures all time invariant factors of the countries, such as geographical location; v_{it} is the disturbance term.[25] 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 Baye's 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) considers 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 sets 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.[26] 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.

4.3 Main Drivers of Volatility

We first present results for all the countries in a static panel, without lags of output volatility as regressors. Table 2 reports the estimates of the output volatility model obtained by using the BMA panel approach over the 1981-2014 period for 37 emerging and advanced economies. Column 1 presents the posterior inclusion probability of each potential driver of output volatility. The rule of thumb is that a factor is considered very robust if the PIP is greater or equal to 0.80. We find that the most robust explanatory factors are exchange rate

[25]Using a BMA approach, Malik and Temple (2009) find that remote countries exhibit greater output volatility. However, Malik and Temple (2009) focus on time-invariant drivers of the constant volatility, using only cross-sectional information. Instead, our paper analyses the drivers of changes in volatility, which can be interpreted as its short-run dynamics.

[26]We also consider a beta-binomial prior for the model space and different forms of the hyperparameter g in the robustness section.

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. In particular, a one standard deviation increase in exchange rate volatility is associated with an increase in output volatility of 0.12 standard deviations, while a one standard deviation increase in trade openness is related to a decline in output volatility of 0.57 standard deviations. This is in line with the results found in Cavallo (2008), who provided evidence that the effect of trade openness on output volatility is negative. Sectors that are more open to trade are less correlated with other sectors of the economy and will be mainly affected by shocks to the industry rather than to domestic cycle (Giovanni and Levchenko (2009), Kraay and Ventura (2007)).[27] Moreover, trade may reduce the exposure of the economy to financial crises like sudden stops and currency crashes (Cavallo and Frankel, 2008).

Next, we control for the dynamics in output volatility by adding the lag of output volatility as a regressor in our BMA approach. The number of lags was selected according to the posterior inclusion probability criteria.[28] Table 3 presents the results of the BMA in the dynamic panel setting. The results of the dynamic model are qualitatively and quantitatively similar to the static model.

We check the robustness of the results to different priors in the BMA model and to different methods to identify the most robust drivers of output volatility. First, we present results for an analysis using an alternative prior for the model probability: the beta-binomial prior proposed by Ley and Steel (2009), which reduces the effect of imposing a particular prior model size on the posterior probabilities. Furthermore, we present robustness check for different forms of the hyperparameter governing the variance, g. In particular, we use the unit information prior (UIP), which set g equal to the number of observations for all models, and a hyper-g-prior, which assumes that the hyperparameter g is not fixed across all the candidate models, but it is adjusted by using Bayesian updating, see Ley and Steel (2012). The results, presented in Figure A13 of the Online Appendix, show that the main findings are robust to the specification of the model and hyperparameter priors. Overall, we find that the most robust drivers of international output volatility, in the static and dynamic models, are the same regardless of the model and hyperparameter priors. Sec-

[27] We test if this mechanism is presented in our sample in the next section.

[28] We also consider specifications with two lags of the output volatility, but the posterior inclusion probability of the second lag was very low.

ond, we also check if our results hold when using alternative methods to deal with model uncertainty. In doing so, we use the least squares (WALS) method introduced by Magnus et al. (2010), where the rule of thumb is that an explanatory factor is considered robust if the t-statistics is above 2 in absolute value. The results, presented in Tables A1-A2 of the Online Appendix, show that the most robust explanatory factors are exchange rate volatility and trade openness. These factors are the same as those found using the BMA approach.

We acknowledge the potential presence of biases in our results due to simultaneity issues. Therefore, we also attempt to account for the simultaneity problem between output volatility and its explanatory factors by using an instrumental variable (IV) BMA approach. In particular, we deal with simultaneity problems by regressing each factor on their second and third lags to purge of the contemporaneous correlation with output volatility, i.e. we use lags of the potential drivers as instrumental variables in line with the ample literature in empirical macroeconomics. We then apply our BMA strategy on the predicted drivers. The results presented in Table 4 show that once we account for simultaneity issues between the regressors and output volatility the only robust drivers are its own lag and trade openness. In particular, the results show that a one standard deviation increases in trade openness leads to a decline in output volatility of 0.33 standard deviations.

Adrian et al. (2019) document that countries exposures to the global price of risk interact with monetary, fiscal, and prudential stabilization policies. However, as previously postulated, the effectiveness of such stabilization policies would 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 driving changes in the idiosyncratic component of output volatility. This analysis is crucial for policy makers to determine the effectiveness of governmental and central banks stabilization policies aiming at reducing the adverse effects of macroeconomic volatility. Therefore, we apply our (IV) BMA strategy to identify the most robust drivers of the idiosyncratic component of countries volatility, instead of the total output volatility.

The main results, presented in Table 5, show that, similarly to the case of total output volatility, trade openness is a robust driver of the idiosyncratic volatility component. A one standard deviation in trade openness lead to a decline in the idiosyncratic volatility of 0.48

standard deviations. More importantly, in contrast to the case of total output volatility, we find that interest rate volatility is an additional robust driver 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 0.21 standard deviations. Also, we find that the changes in government expenditure volatility does not seem to have a significantly influence on output volatility. Accordingly, from a global perspective, these results would imply that when central banks rely on substantial variations in the policy rate to stabilize the economy, these actions would translate into significant changes in the idiosyncratic volatility component, which would end up influencing the total output volatility. As shown in figures A10 to A12, the magnitude of such influence can significantly vary both across countries and over time.

Overall, the most robust driving factor of total output volatility is trade openness. We also find that the most robust driver of the idiosyncratic component of output volatility are trade openness and interest rate volatility. The latter shows the high relevance of monetary policies in stabilizing output fluctuations at the global level.

4.4 Macroeconomic Volatility and Trade Openness

Section 4.3 shows that trade openness has a negative effect on total macroeconomic volatility and its idiosyncratic component. In this section, we focus on studying the mechanism through which trade could negatively affect volatility. Giovanni and Levchenko (2009) show that sectors that rely on imports from other countries are less correlated with the other sectors of the economy. Thus, sectors that depend on trade are mainly affected by global shocks to the industry and are less exposed to domestic cycle (Kraay and Ventura, 2007), a mechanism that reduces overall volatility. Giovanni and Levchenko (2009) also found that sectors more open to trade are more volatile and that trade facilitates specialization. These two mechanisms predict a positive effect of trade on volatility. Recently, Miyamoto and Nguyen (2019) show, using a multi-sector multi-country international business cycle model, that changes in the international input-output linkages led to a sizeable drop in output volatility across countries.[29]

In this section, we use detailed World Input-Output (IO) tables, based on 34 sectors, available between 1995 and 2011 to analyze if sectors that rely more on imports are less

[29] Also, Mumtaz and Theodoridis (2017) rely on two-country DSGE model to illustrate that increases in trade openness lead to closer movements in output volatility.

correlated with the other sectors of the economy and if this lower comovement among the sectors of an economy diminish the overall level of volatility. For this purpose, we first compute, for each of the 34 sectors of a country and year, the share of output produced using imports from other countries, this is what we call *import share*, $I_{j,i,t}$, where j denotes a sector, i a country and t the year. We then compute the overlap in the composition of a sector j and another sector k of a country using the cosine similarity measure. This measure is computed as the cosine of two different vectors. One of the vectors, $x^j_{c;i,t}$, includes the share of inputs used by sector j from each sector c of country i at t. This captures the inputs used from other sectors of the economy in the production of the good deliver by sector j. The other vector, $x^k_{c;i,t}$, contains the share of inputs used by sector k from each sector c of country i at t. Using these two vectors, the cosine similarity measure is computed as:

$$w_{jk;i,t} = \frac{\sum_c x^j_{c;i,t} x^k_{c;i,t}}{\sqrt{\sum_c \left(x^j_{c;i,t}\right)^2 \sum_f \left(x^k_{c;i,t}\right)^2}}.$$

This commonality composition index takes a value from 0 to 1. The higher the index, the stronger the sectoral composition overlap between sector j and sector k. We then take the average of this overlap across all the sectors k to obtain a similarity measure of sector j with respect to the other sectors of the economy, $\bar{w}_{j,i,t}$.

We present in Figure 9 the correlation between import shares of a sector, $I_{j,i,t}$, and its average sectoral composition overlap with respect to the other sectors of the economy, $\bar{w}_{j;i,t}$. This allows to illustrate the association between import shares and similarities between the different sectors of an economy. The figure shows that in most of the countries the association between the import shares of a sector and its similarities in sectoral composition with the rest of the economy is negative, except in China and India, where the correlation is positive and persistent. We then estimate the relationship between average similarity in sectoral composition and import shares as follows:

$$\bar{w}_{j,i,t} = \rho I_{j,i,t} + \theta HI_{j,i,t} + \gamma_j + \mu_i \delta_t + u_{jit}, \tag{20}$$

where $\bar{w}_{j,i,t}$ is the average of the commonality composition index between sector j and the other sectors of the economy i at year t. $I_{j,i,t}$ is the import share of sector j of economy i at period t. $HI_{j,i,t}$ is the Herfindahl-Hirschman index (HHI) of production shares in sector j of economy i at year t. The HHI is obtained as the sum of the squared of the imputs shares used by sector j from the other sectors of the economy i at period t. A higher value of HHI represents a more specilized (less diversified) sector. γ_j are sectors fixed effects and account for any inherent technological feature of industries such as R&D intensity, capital, skilled and unskilled labor intensity, and many others. $\mu_i\delta_t$ are country-time fixed effects. These interacted fixed effects would absorb not just inherent country characteristics, but also the average effect of time-varying country characteristics, such as overall level of development, growth, macroeconomic volatility, financial liberalization, monetary and fiscal policy changes and many others. Column 1 of Table 6 presents the results of estimating the model in Equation (20) using the estimator proposed by Correia (2016) to absorb high-dimensional fixed effects. The results show a negative relationship between import share and the similarity composition index, that is, sectors that rely more on imports have a lower degree of similarity composition with the rest of the economy.

Finally, we test if this negative association between import share and similarity is the main mechanism explaining the negative effect of trade on overall volatility. For this, we estimate the relationship between similarity in the composition of a sector with the rest of the economy and overall volatility, controlling for the dynamics of volatility through its lagged value, specialization, year dummies, sector fixed effects and country fixed effects. The main specification is,

$$\sigma_{it} = \rho\sigma_{it-1} + \beta_1 \bar{w}_{j,i,t} + \beta_2 HI_{j,i,t} + \gamma_j + \alpha_i + \mu_t + v_{it}, \tag{21}$$

where $\bar{w}_{j,i,t}$, $I_{j,i,t}$ and $HI_{j,i,t}$ are defined as the model in Equation (20). γ_j are sectors fixed effects, μ_i denotes country fixed effects and δ_t are yearly dummies to control for time effects.[30] The results presented in column 2 of Table 6 shows that higher degree of similarity in the composition of the different sectors of an economy is associated with higher volatility. In column 3, we analyze if trade is the main channel through which similarity in the composition of sectors affects volatility. For this purpose, we purge of the trade effect from the similarity composition index by taking the residuals from model in Equation (20). The coefficient of similarity composition in the volatility model becomes economically and statistically insignificant, suggesting that trade is the main mediating factor in the association between similarity composition and volatility.

[30] Note that the unit of analysis is economy i and year t since volatility is defined at the economy level. Thus, we cannot include country-year fixed effects.

The findings presented in this section support the hypothesis that sectors more open to trade are less associated with the other sectors of the economy, i.e. have a lower sectoral composition overlap with the rest of the economy. These sectors, are likely to depend more on global shocks to the industry and less to domestic cycles. Therefore, higher dissimilarity among the sectors of an economy (facilitated through trade) diminishes overall volatility. Figure 10 shows a measure of the world trade, computed by the World Bank, along with the global volatility factor, showing a negative correlation (-0.73). Based on the previous exercises, we argue that the downturn in global volatility can be mainly explained by the increasing degree of trade openness exhibit by the main world economies during recent decades.

5 Conclusions

This paper provides a comprehensive assessment of the dynamics, propagation and drivers of macroeconomic volatility from an global perspective. We propose the VOLTAGE econometric framework to estimate and decompose the time-varying volatility of output growth across developed and developing countries into global, regional, and idiosyncratic components. Three main results emerge from the analysis. First, GDP growth across the main world economies, both developed and developing, share a feature in common that can be interpreted as a "global moderation" of international output fluctuations. Second, despite such a decline in global volatility, there has been a systemic increasing sensitivity of macro volatility to global developments. Third, the decline in the global macroeconomic volatility can be mainly attributed to the increasing levels of countries trade openness. The idiosyncratic component of countries volatility is also influenced by changes in the monetary policies, acting as an effective stabilization tool, but not to changes in the fiscal policies.

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Tables and Figures

Table 1: List of Countries

North America	South America	Europe			Asia + Oceania		
Canada	Argentina	Austria	Greece	Norway	Australia	Japan	South Korea
Mexico	Brazil	Belgium	Iceland	Portugal	China	New Zealand	Taiwan
United States	Chile	Denmark	Ireland	Spain	Hong Kong	Philippines	Thailand
	Peru	Finland	Italy	Sweden	India	Kazakhstan	Turkey
	Venezuela	France	Luxembourg	Switzerland	Indonesia	Russia	
		Germany	Netherlands	United Kingdom	Israel	Singapore	

Note: The table reports the list of countries used in the empirical analysis along with their corresponding geographic region.

Table 2: Drivers of volatility: A BMA approach. Static panel. Period: 1981-2014

	PI prob.	Pt. Mean	Pt. Std.
Exchange rate vol.	1.00	0.124	0.027
Trade Openness	1.00	-0.570	0.118
TFP volatility	0.30	0.018	0.032
Financial Integration	0.15	-0.018	0.049
Government cons. volatility	0.05	0.001	0.008
Interest volatility	0.03	-0.00001	0.004
Term of trade volatility	0.04	-0.0005	0.005
Year FE	✓	✓	✓
Country FE	✓	✓	✓

All the variables are standardized. 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 and 940 observations. The dependent variable is economic growth 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, $g = 1/max(N, K^2)$.

Table 3: Drivers of volatility: A BMA approach. Dynamic panel. Period: 1982-2014

	PI prob.	Pt. Mean	Pt. Std.
Volatility$_{t-1}$	1.00	0.588	0.027
Exchange rate vol.	1.00	0.094	0.022
Trade Openness	0.98	-0.369	0.111
TFP volatility	0.26	0.013	0.025
Term of trade volatility	0.04	-0.0004	0.004
Financial Integration	0.04	-0.001	0.012
Interest volatility	0.03	0.0002	0.036
Government cons. volatility	0.03	-0.0001	0.0042
Year FE	✓	✓	✓
Country FE	✓	✓	✓

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 and 902 observations. The dependent variable is economic growth volatility. The dependent variable is economic growth 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, $g = 1/max(N, K^2)$.

Table 4: Drivers of volatility: An IV-BMA approach. Dynamic panel. Period: 1982-2014

	PI prob.	Pt. Mean	Pt. Std.
Volatility$_{t-1}$	1.00	0.499	0.027
Trade Openness	0.94	-0.329	0.128
Term of trade volatility	0.45	0.281	0.350
Interest volatility	0.10	0.008	0.028
Exchange rate vol.	0.08	0.061	0.256
Government cons. volatility	0.05	0.0095	0.0664
TFP volatility	0.04	-0.004	0.034
Financial Integration	0.04	0.0007	0.011
Year FE	✓	✓	✓
Country FE	✓	✓	✓

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 and 902 observations. The dependent variable is economic growth volatility. The dependent variable is economic growth 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, $g = 1/max(N, K^2)$.

Table 5: Drivers of idiosyncratic volatility: An IV-BMA approach. Dynamic panel. Period: 1982-2014

	PI prob.	Pt. Mean	Pt. Std.
Volatility$_{t-1}$	1.00	0.633	0.029
Trade Openness	1.00	-0.476	0.110
Interest volatility	0.92	0.206	0.085
Exchange rate vol.	0.35	0.533	0.823
Financial Integration	0.31	-0.042	0.070
Term of trade volatility	0.13	0.057	0.175
TFP volatility	0.08	0.015	0.065
Government cons. volatility	0.05	0.0088	0.0661
Year FE	✓	✓	✓
Country FE	✓	✓	✓

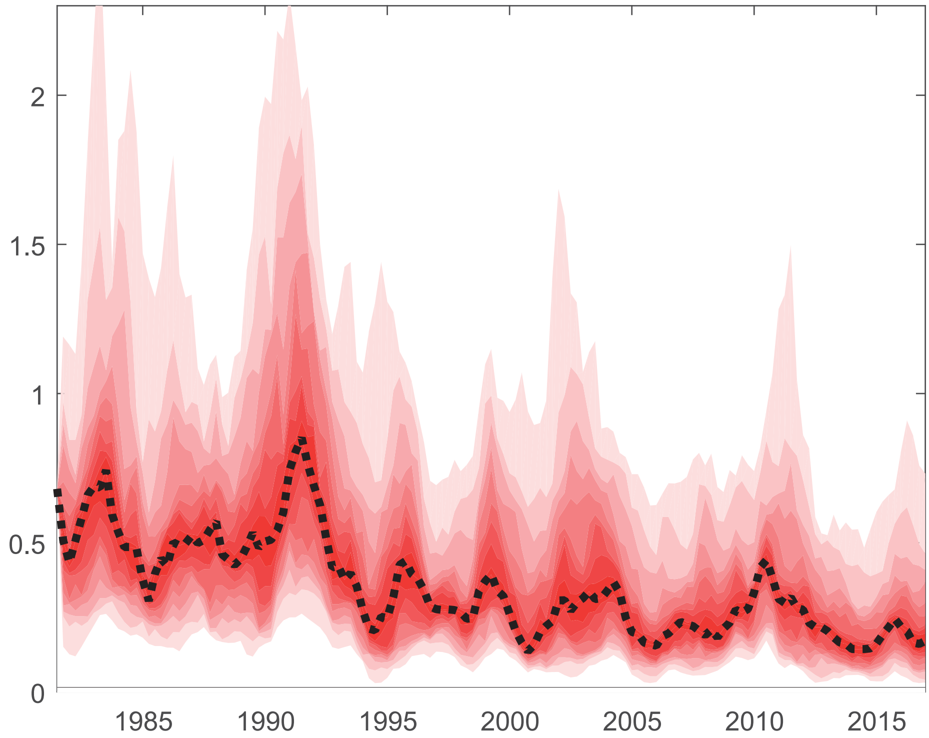
The explanatory variables are the predicted values of regressing the explanatory factors on its second and third lags. Column 1 presents the posterior inclusion probability. Column 2 shows the posterior mean. Column 3 reports the posterior standard deviation. The sample includes 37 countries and 902 observations. 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, $g = 1/max(N, K^2)$.

Table 6: Trade, sectoral composition and volatility

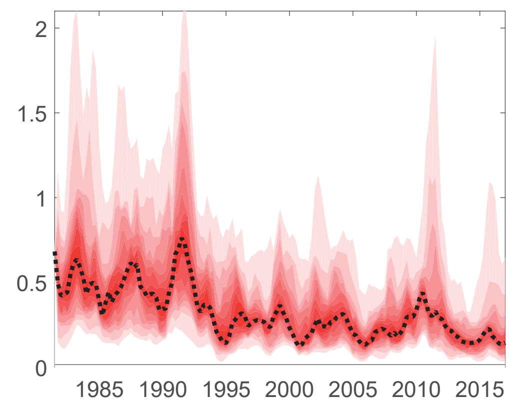
	(1)	(2)	(3)
Dependent var.:	Similarity	Volatility	Volatility
Import Share	-0.011**		
	(0.005)		
Specialization	-0.483***	0.092***	0.042
	(0.011)	(0.032)	(0.027)
Volatility_{t-1}		0.720***	0.719***
		(0.012)	(0.012)
Similarity		0.104***	
		(0.031)	
Similarity Res.			0.000
			(0.035)
Constant	0.420***	0.210***	0.254***
	(0.003)	(0.018)	(0.012)
Observations	16,109	15,059	15,059
Adjusted R-squared	0.708	0.772	0.772
Sector FE	✓	✓	✓
Country-Year FE	✓		
Year FE		✓	✓
Country FE		✓	✓

Column 1 presents the results of estimating the similarity in sectoral composition model. Column 2 and 3 show the results of estimating total macroeconomic volatility. In column 3, *SimilarityRes.* is estimated by regressing the similarity index on import share, specialization, sector fixed effects, country fixed effects, year fixed effects and country-year fixed effects. The sample includes 28 countries. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

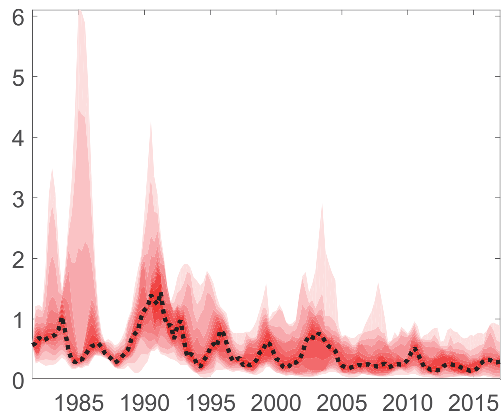
Figure 1: Time-varying volatility across countries



(b) Developed countries



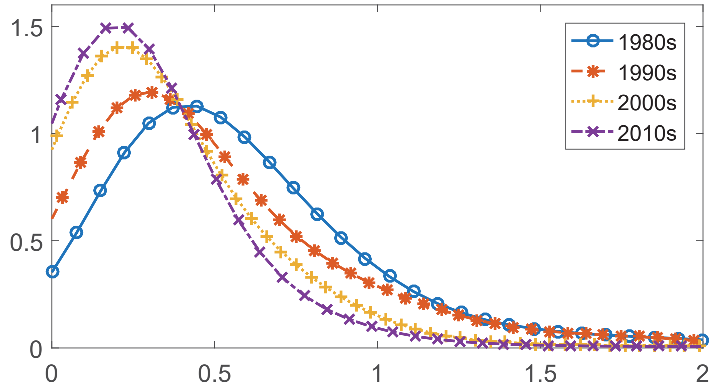
(c) Developing countries



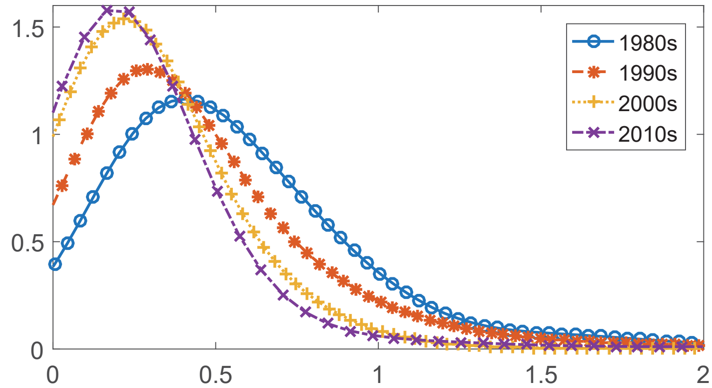
Note: The time-varying volatilities for each country are estimated jointly by using the VOLTAGE model, proposed in Section 2. Chart A plots the cross-sectional distribution of time-varying volatilities for all the countries in our sample, that is, including developed and developing economies. Chart B 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.

Figure 2: Densities of international macroeconomic volatility

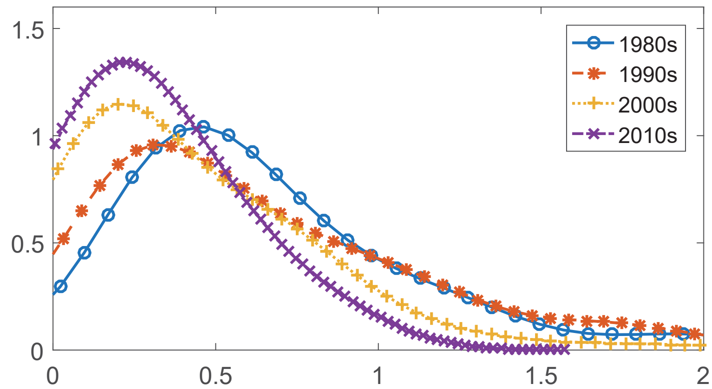
(a) World



(b) Developed countries



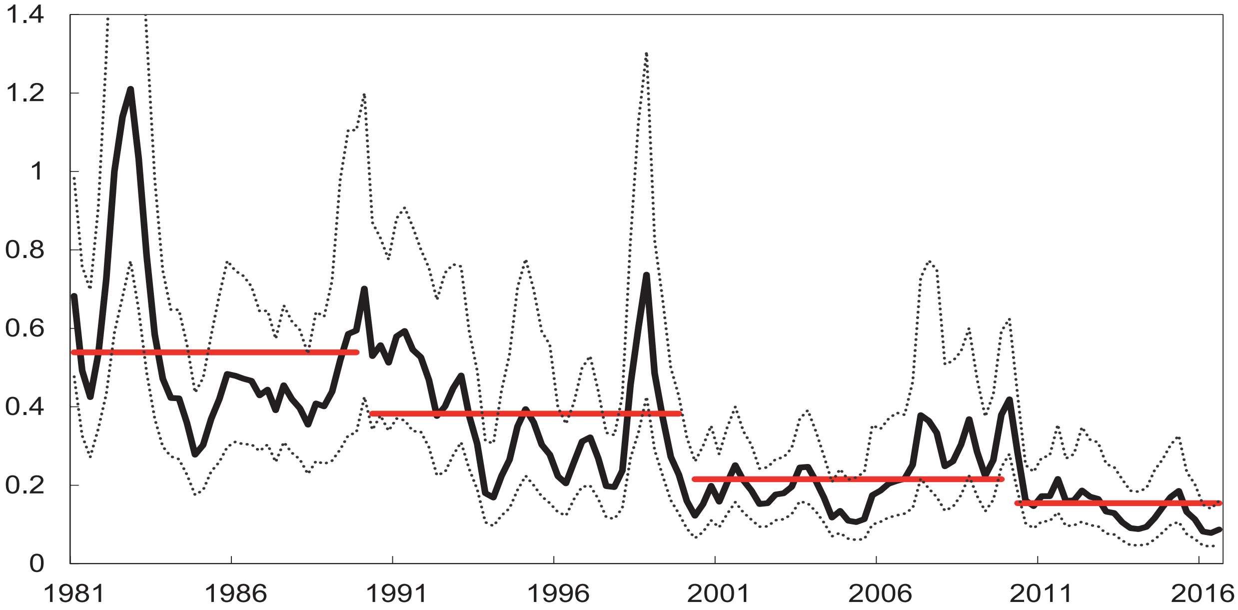
(c) Developing countries



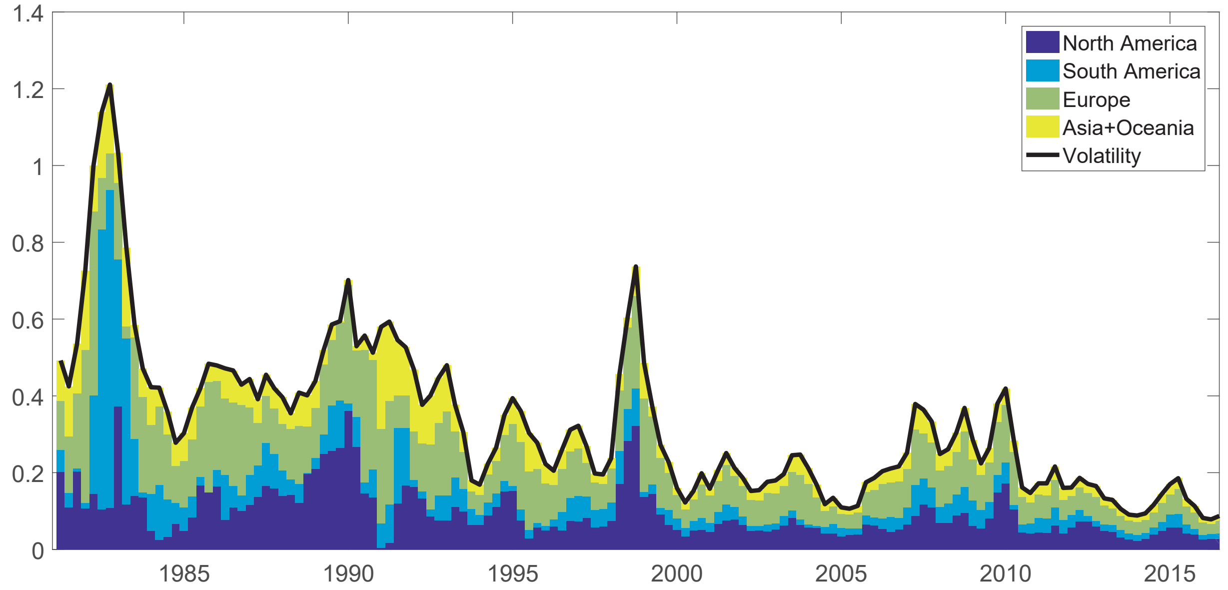
Note: The figure shows the kernel densities associated to all the realizations of time-varying macroeconomic volatility, both across time and countries, within each decade in our sample, that is, 1980s, 1990s, 2000s and 2010s. The measures of volatilities are based on VOLTAGE model estimates. Chart A shows the densities containing information from all the countries in our sample, while densities in Chart B and C only contain information from developed and developing countries, respectively.

Figure 3: Global volatility

(a) Estimated global volatility factor

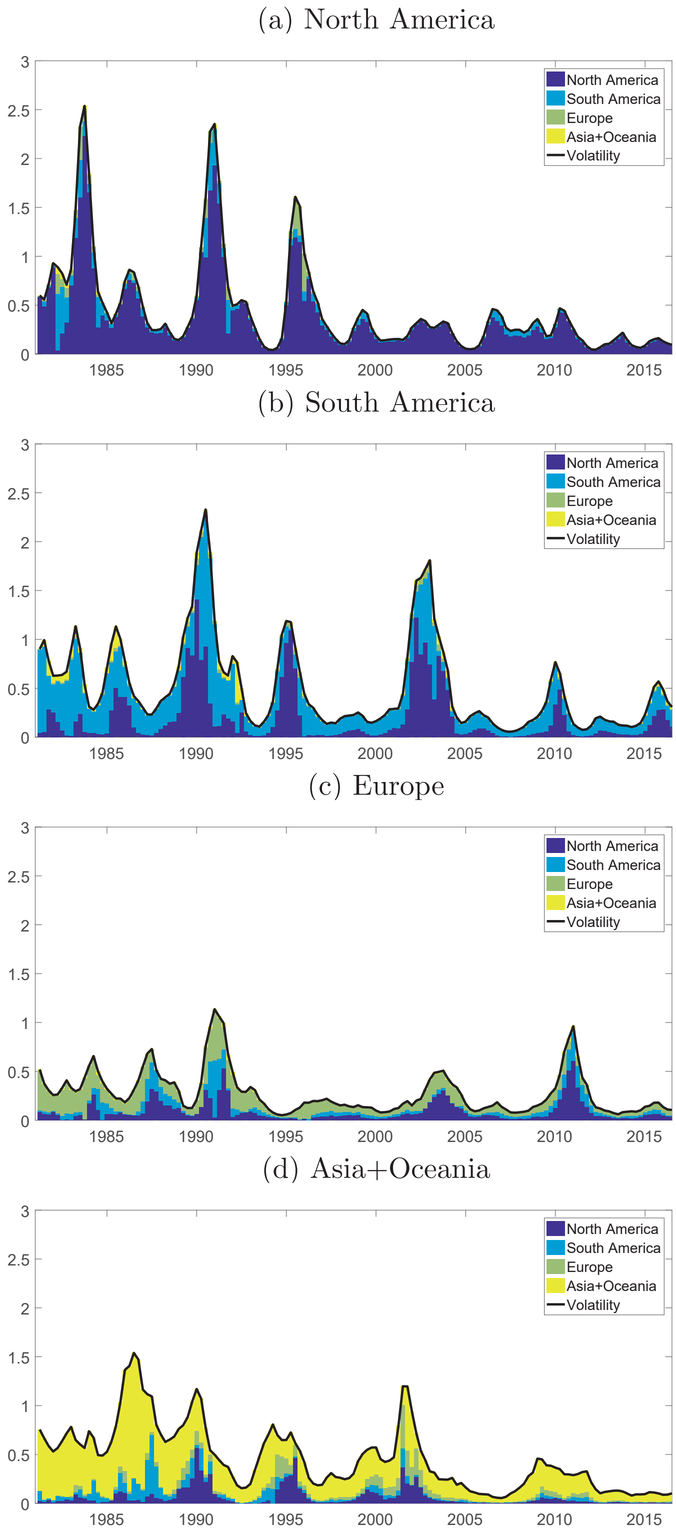


(b) Historical data decomposition of the global volatility factor



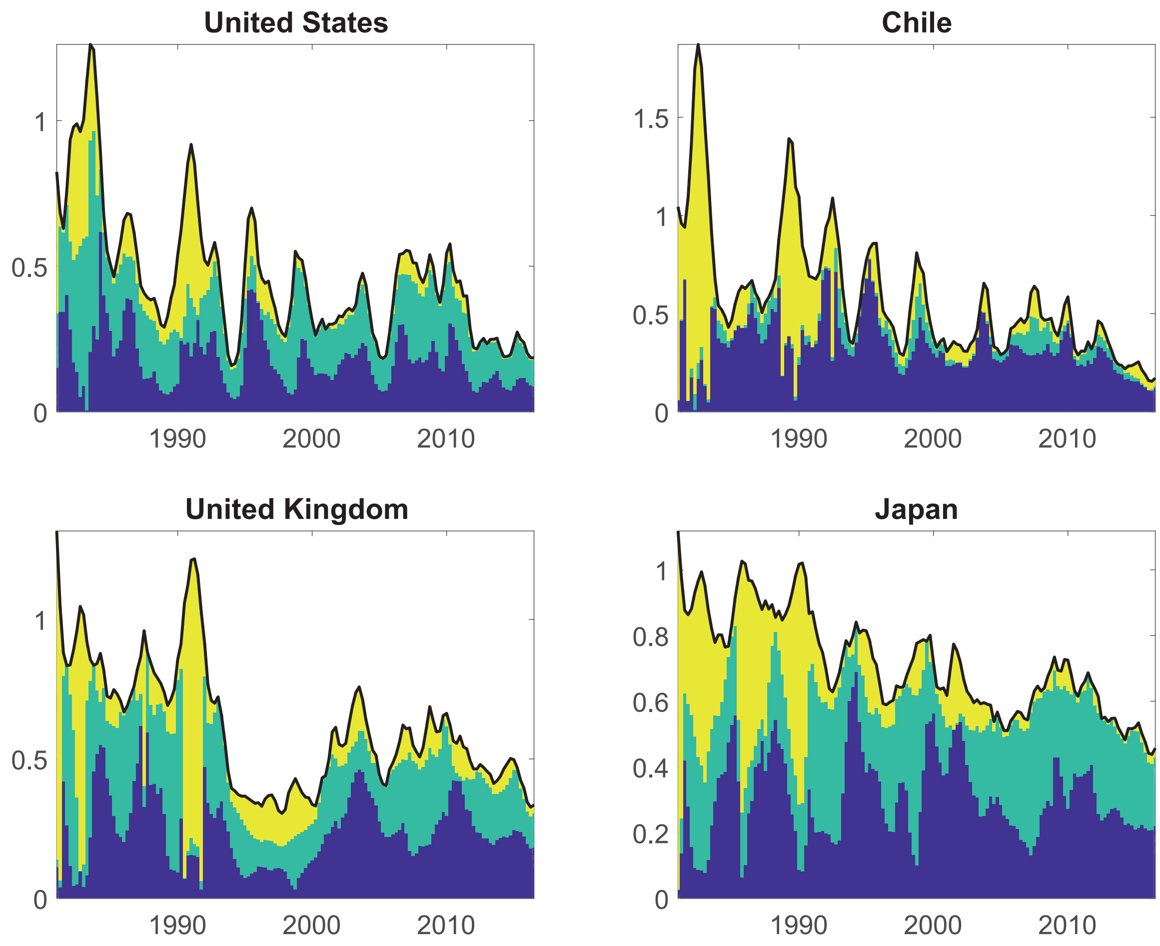
Note: Chart A plots the global volatility factor. The solid line represents the median of the posterior distribution and the dotted lines make reference to the 68 percent credible set of the posterior distribution. Red lines make reference to the average volatility over the corresponding period. Chart B plots the average contribution of countries in a given region for the construction of the global volatility factor. The contributions associated to each country are computed based on the algorithm proposed in Koopman and Harvey (2003).

Figure 4: Regional volatility



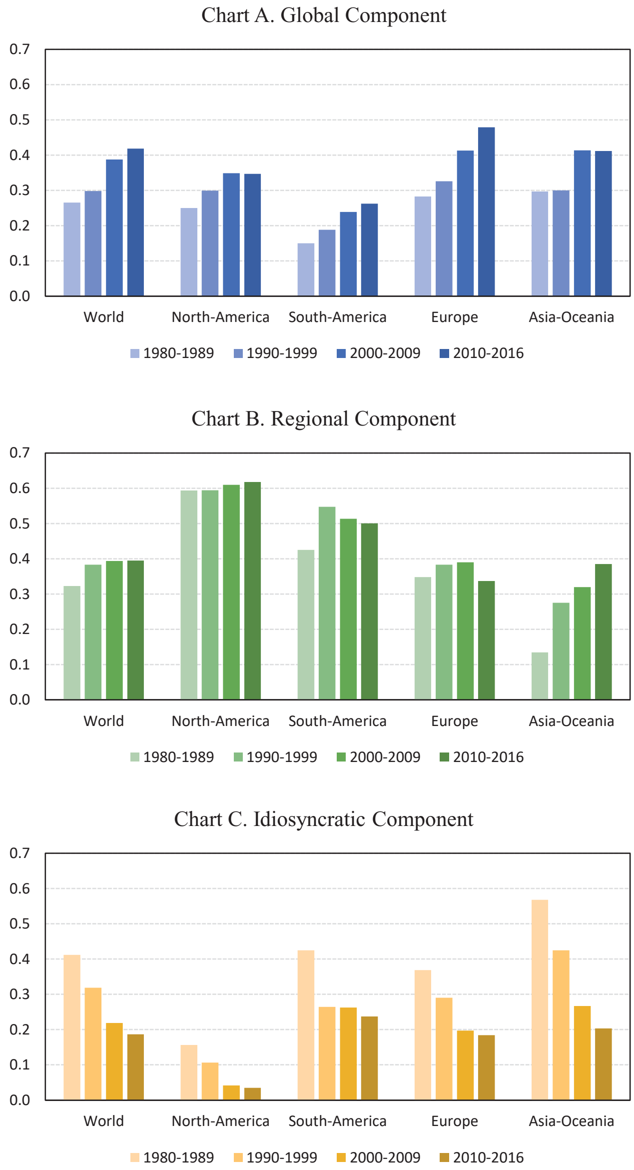
Note: Charts A, B, C, and D plot the volatility factor corresponding to the different regions under study along with the corresponding historical data decomposition, computed based on the algorithm proposed in Koopman and Harvey (2003).

Figure 5: Historical volatility decomposition: selected examples



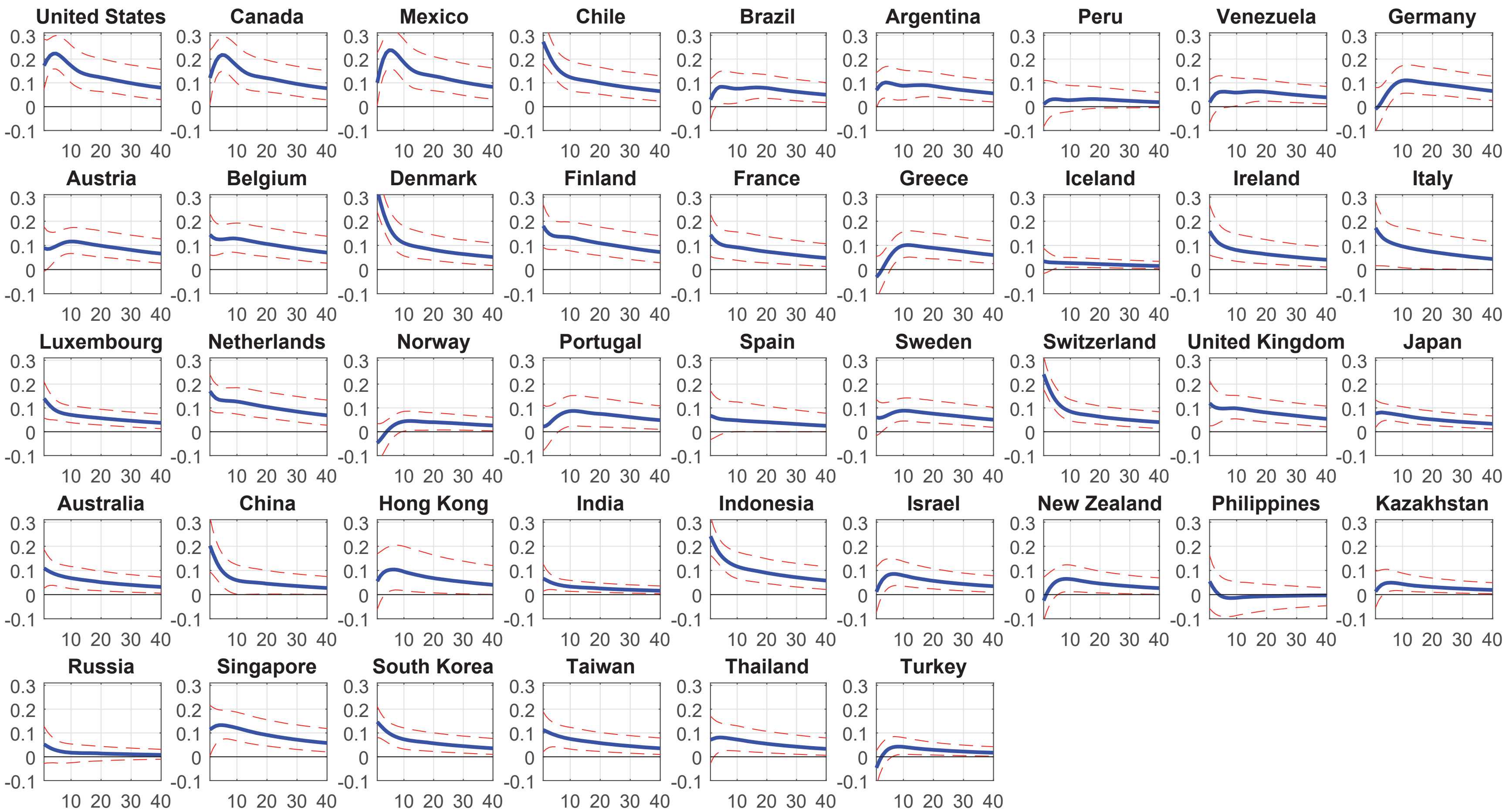
Note: The figure plots the estimated time-varying volatility for four selected countries. Black lines plot the estimated total volatility. Blue, green and yellow areas correspond to the global, regional and idiosyncratic components, respectively. The information regarding all the countries in our sample can be found in figures A10-A12 of the Online Appendix.

Figure 6: Contribution of volatility components across regions and over time



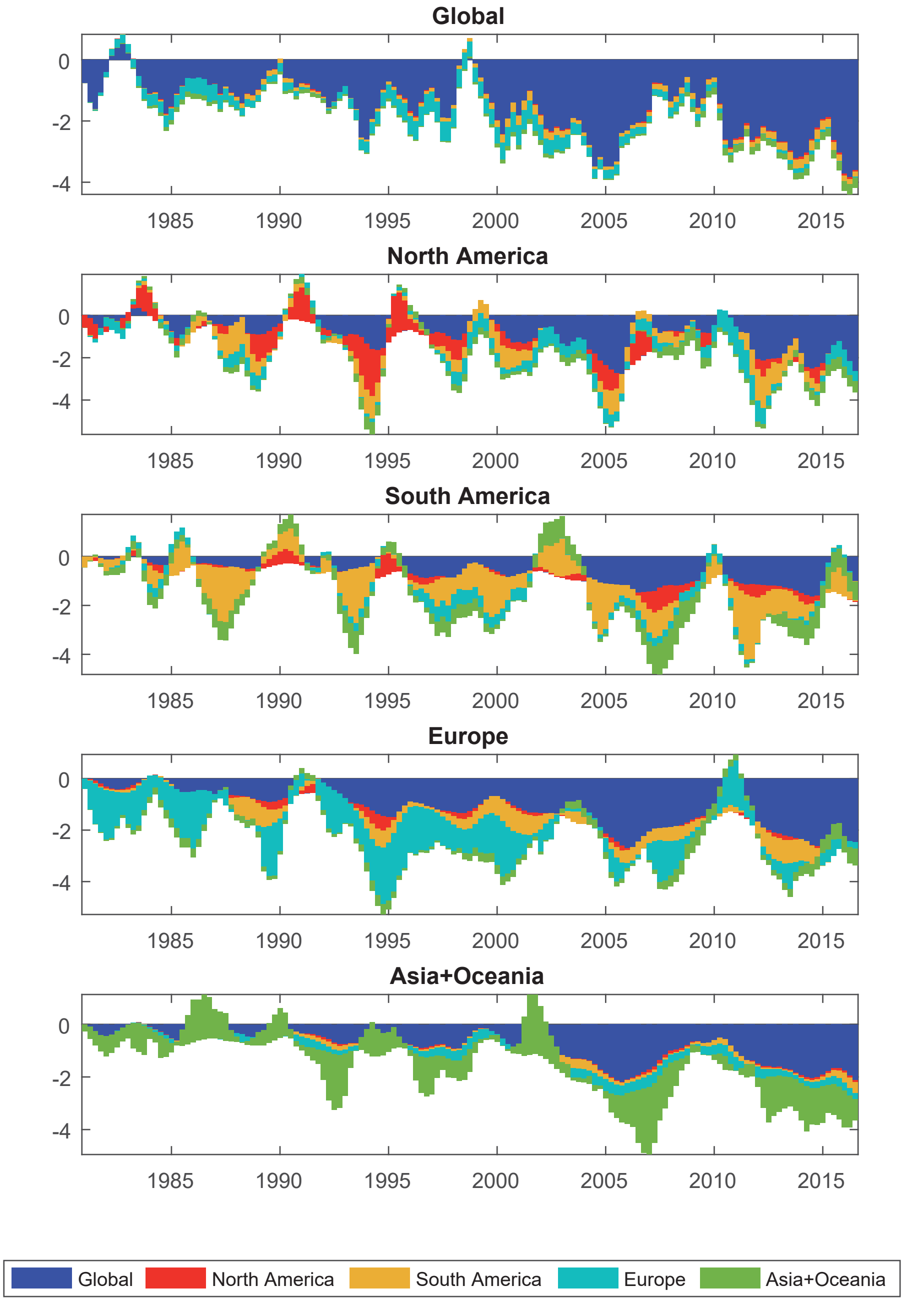
Note: Chart A, B and C plot the average contribution of the global, regional and idiosyncratic components, respectively, on output volatility. For ease of exposition, each bar in each chart reports the average contribution across countries in a given region and across periods in a given decade.

Figure 7: Response of country-volatility to global shocks



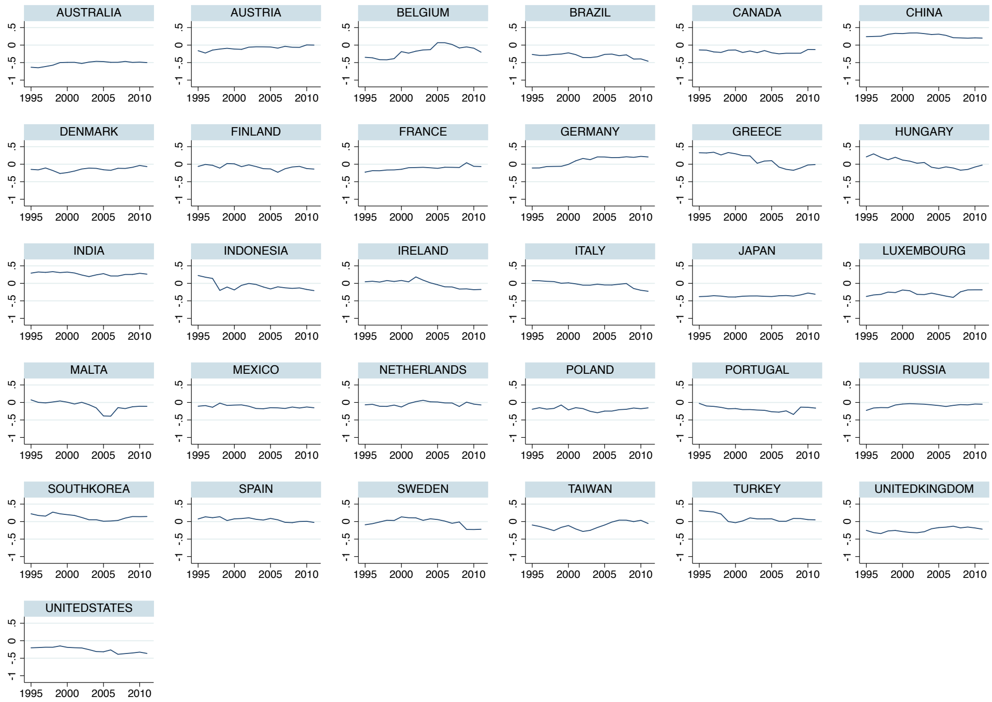
Note: The figure plots the responses of the country-specific volatilities to a unit shock in the global factor. Blue solid lines represent the median of the corresponding posterior distribution, and red dashed lines make reference to the 68th confidence set.

Figure 8: Historical shock decomposition of log-volatility factors



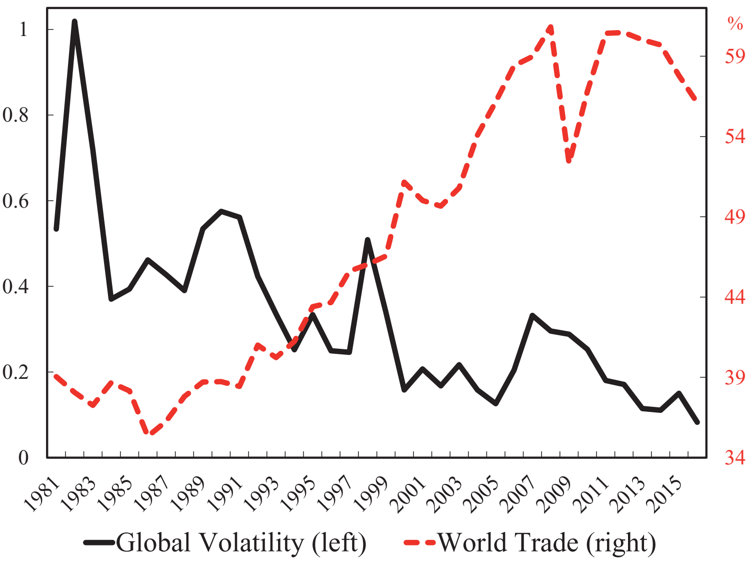
Note: The figure plots the historical shock decomposition of the VAR, in Equation (4), which involves the latent log-volatility factors. The shock decomposition is performed based on Equation (10).

Figure 9: Correlation between import shares of a sector and its similarities in sectoral composition with the other sectors of an economy



Note: Correlation between import shares of a sector and its average degree of similarity with respect to the other sectors of the economy. Correlation obtained using 34 sectors per country per year. Source: World Input-Output tables.

Figure 10: Global volatility and world trade



Note: The figure plots the global volatility factor and world trade as share of GDP (computed by the Word Bank), at the annual frequency.

A Online Appendix - Not for Publication

A.1 Estimation Algorithm

The proposed algorithm relies on Bayesian methods and uses the Gibss sampler to simulate the posterior distribution of parameters and latent variables involved in the VOLTAGE model. Let the vectors of observed and latent variables be defined as $\widetilde{Y}_T = \{u_{1_1,t}, ..., u_{n_1,t}, ..., u_{1_K,t}, ..., u_{n_K,t}\}_{t=1}^{T}$, $\widetilde{g}_T = \{g_t\}_{t=1}^{T}$, $\widetilde{h}_{k,T} = \{h_{k,t}\}_{t=1}^{T}$, $\widetilde{\chi}_{i_k,T} = \{\chi_{i_k,t}\}_{t=1}^{T}$, and $\widetilde{d}_{i_k,T} = \{d_{i_k,t}\}_{t=1}^{T}$, where $d_{i_k,t}$ is an auxiliary random variable used to define the state of the time-varying volatility, for $i_k = 1, 2, ..., n_k$ and $k = 1, 2, ..., K$. The algorithm consists of the following steps:

- ***Step 1***: Sample $\widetilde{g}_T$, $\widetilde{h}_{k,T}$ and $\widetilde{\chi}_{i_k,T}$ from $P(\widetilde{g}_T, \widetilde{h}_{k,T}, \widetilde{\chi}_{i_k,T} | \gamma_{i_k}, \lambda_{i_k}, \Phi, \Sigma, \varphi_{i_k}, \sigma^2_{i_k}, \widetilde{d}_{i_k,T}, \widetilde{Y}_T)$

First, the logarithms to the squares of both sides of equation (2) are taken,

$$u^*_{i_k,t} = \gamma_{i_k} g_t + \lambda_{i_k} h_{k,t} + \chi_{i_k,t} + \varepsilon^*_{i_k,t}, \tag{22}$$

where $u^*_{i_k,t} = \ln(u^2_{i_k,t})$ and $\varepsilon^*_{i_k,t} = \ln(\varepsilon^2_{i_k,t})$.[31] Then, the volatility factor model, in equations (2)-(5), is casted in a state space representation with measurement equation given by,

$$\underbrace{\begin{bmatrix} u^*_{1_1,t} \\ \vdots \\ u^*_{n_1,t} \\ u^*_{1_2,t} \\ \vdots \\ u^*_{n_2,t} \\ \vdots \\ u^*_{1_K,t} \\ \vdots \\ u^*_{n_K,t} \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} \gamma_{1_1} & \lambda_{1_1} & \cdots & 0 & 1 & & & & & & & \\ \vdots & \vdots & \ddots & \vdots & & \vdots & & & & & & \\ \gamma_{n_1} & \lambda_{n_1} & \cdots & 0 & & & 1 & & & [\mathbf{0}] & & \\ \gamma_{1_2} & 0 & \cdots & 0 & & & & & & & & \\ \vdots & \vdots & \ddots & \vdots & & & & \ddots & & & & \\ \gamma_{n_2} & 0 & \cdots & 0 & & & & & \ddots & & & \\ \vdots & \vdots & \ddots & \vdots & & & & & & & & \\ \gamma_{1_K} & 0 & \cdots & \lambda_{1_K} & & & [\mathbf{0}] & & & 1 & & \\ \vdots & \vdots & \ddots & \vdots & & & & & & & \vdots & \\ \gamma_{n_K} & 0 & \cdots & \lambda_{n_K} & & & & & & & & 1 \end{bmatrix}}_{G} \underbrace{\begin{bmatrix} g_t \\ h_{1,t} \\ \vdots \\ h_{K,t} \\ \chi_{1_1,t} \\ \vdots \\ \chi_{n_1,t} \\ \vdots \\ \vdots \\ \chi_{1_K,t} \\ \vdots \\ \chi_{n_K,t} \end{bmatrix}}_{a_t} + \underbrace{\begin{bmatrix} \varepsilon^*_{1_1,t} \\ \vdots \\ \varepsilon^*_{n_1,t} \\ \varepsilon^*_{1_2,t} \\ \vdots \\ \varepsilon^*_{n_2,t} \\ \vdots \\ \varepsilon^*_{1_K,t} \\ \vdots \\ \varepsilon^*_{n_K,t} \end{bmatrix}}_{U_t}, \tag{23}$$

[31] In practice we set $u^*_{i_k,t} = \ln(u^2_{i_k,t} + c)$, with c being the offset constant to avoid numerical problems when $u^*_{i_k,t}$ is close to zero (set to 10^{-4}).

and transition equation defined as,

$$\underbrace{\begin{bmatrix} g_t \\ h_{1,t} \\ \vdots \\ h_{K,t} \\ \chi_{1_1,t} \\ \vdots \\ \chi_{n_1,t} \\ \vdots \\ \vdots \\ \chi_{1_K,t} \\ \vdots \\ \chi_{n_K,t} \end{bmatrix}}_{a_t} = \underbrace{\begin{bmatrix} \phi_{g,g} & \phi_{g,1} & \cdots & \phi_{g,K} & & & & & & & & \\ \phi_{1,g} & \phi_{1,1} & \cdots & \phi_{1,K} & & & & & & & & \\ \vdots & \vdots & \ddots & \vdots & & & & & & [\mathbf{0}] & & \\ \phi_{K,g} & \phi_{K,1} & \cdots & \phi_{K,K} & & & & & & & & \\ & & & & \varphi_{1_1} & & & & & & & \\ & & & & & \ddots & & & & & & \\ & & & & & & \varphi_{n_1} & & & & & \\ & & & & & & & \ddots & & & & \\ & & & & & & & & \ddots & & & \\ & & [\mathbf{0}] & & & & & & & \varphi_{1_K} & & \\ & & & & & & & & & & \ddots & \\ & & & & & & & & & & & \varphi_{n_K} \end{bmatrix}}_{F} \underbrace{\begin{bmatrix} g_{t-1} \\ h_{1,t-1} \\ \vdots \\ h_{K,t-1} \\ \chi_{1_1,t-1} \\ \vdots \\ \chi_{n_1,t-1} \\ \vdots \\ \vdots \\ \chi_{1_K,t-1} \\ \vdots \\ \chi_{n_K,t-1} \end{bmatrix}}_{a_{t-1}} + \underbrace{\begin{bmatrix} \zeta_t \\ \zeta_{1,t} \\ \vdots \\ \zeta_{K,t} \\ \xi_{1_1,t} \\ \vdots \\ \xi_{n_1,t} \\ \vdots \\ \vdots \\ \xi_{1_K,t} \\ \vdots \\ \xi_{n_K,t} \end{bmatrix}}_{V_t}. \tag{24}$$

Notice that although the state-space in equations (23)-(24) is linear, the disturbances associated to the measurement equation, $\varepsilon^*_{i_k,t}$, are not Gaussian. Therefore, since the idiosyncratic disturbances, $\varepsilon_{i_k,t}$, are assumed to be independent from each other, we model the distribution of each $\varepsilon^*_{i_k,t}$ as a mixture of Normal distributions, conditional on the auxiliary random variable $d_{i_k,t} \in \{1, 2, ..., 7\}$, where

$$(\varepsilon^*_{i_k,t} | d_{i_k,t} = \kappa) \sim N(m_\kappa, \upsilon^2_\kappa),$$

for $i_k = 1, 2, ..., n_k$, and $k = 1, ..., K$. Hence, the distribution of $\varepsilon^*_{i_k,t}$ can be expressed as

$$f(\varepsilon^*_{i_k,t}) = \sum_{\kappa=1}^{7} q_\kappa f_N(\varepsilon^*_{i_k,t} | m_\kappa - 1.2704, \upsilon^2_\kappa),$$

where f_N denotes a Normal distribution, q_κ is given by the $P(d_{i_k,t} = \kappa)$, and the values q_κ, m_κ and υ^2_κ are known, since they are calibrated in Kim et al. (1998).

Consequently, conditional on $d_{i,t}$, equations (23)-(24) constitute an approximate linear and Gaussian state-space model and the Carter and Kohn (1994) simulation smoother is applied to generate inferences of the volatility factors and idiosyncratic volatility components.

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Consequently, conditional on $d_{i,t}$, equations (23)-(24) constitute an approximate linear and Gaussian state-space model and the Carter and Kohn (1994) simulation smoother is applied to generate inferences of the volatility factors and idiosyncratic volatility components. In dealing with missing observations in Y_t, we follow the approach in Bańbura et al. (2015), which consists on apply the Kalman filter to a modified state space representation in which (i) the rows of the factor loading matrix and (ii) rows and columns of the measurement equation covariance matrix, that correspond to missing observations, are removed.

- ***Step 2***: Sample φ_{i_k} from $P(\varphi_{i_k}|\widetilde{\chi}_{i_k,T}, \sigma^2_{i_k}, \widetilde{Y}_T)$

To sample the autoregressive coefficient we use a normal prior distribution, $N(\underline{\varphi}, \underline{\varsigma})$, with $\underline{\varphi} = 0.9$ and $\underline{\varsigma} = 1$, and generate draws from the posterior distribution

$$\varphi_{i_k} \sim N(\bar{\varphi}, \bar{\varsigma}),$$

where

$$\begin{aligned} \bar{\varphi} &= (\underline{\varsigma}^{-1} + Z'Z)^{-1}(\underline{\varsigma}^{-1}\underline{\varphi} + Z'W) \\ \bar{\varsigma} &= (\underline{\varsigma}^{-1} + Z'Z)^{-1}, \end{aligned}$$

with $Z = \left\{\frac{\chi_{i_k,t}}{\sigma_{i_k}}\right\}_{t=1}^{T-1}$, and $W = \left\{\frac{\chi_{i_k,t}}{\sigma_{i_k}}\right\}_{t=2}^{T}$. Additionally, we only retain the draws that comply with the stationarity condition of the autoregressive process $\chi_{i_k,t}$.

- ***Step 3***: Sample $\sigma^2_{i_k}$ from $P(\sigma_{i_k}|\widetilde{\chi}_{i_k,T}, \varphi_{i_k}, \widetilde{Y}_T)$

To sample the variance of the idiosyncratic volatility innovations we use an inverse Gamma prior distribution, $IG(\underline{\eta}, \underline{v})$, with $\underline{\eta} = 3$ and $\underline{v} = 0.1 \times (\underline{\eta} - 1)$, as in Chan and Hsiao (2001), and generate draws from the posterior distribution

$$\sigma_{i_k} \sim IW(\bar{\eta}, \bar{v}),$$

where

$$\begin{aligned}
\bar{\eta} &= \underline{\eta} + T \\
\bar{v} &= \underline{v} + (\chi_{i_k,t} - \varphi_{i_k}\chi_{i_k,t-1})'(\chi_{i_k,t} - \varphi_{i_k}\chi_{i_k,t-1}).
\end{aligned}$$

- ***Step 4***: Sample γ_{i_k} and λ_{i_k} from $P(\gamma_{i_k}, \lambda_{i_k}|\widetilde{g}_T, \widetilde{h}_{k,T}, \widetilde{\chi}_{i_k,T}, \widetilde{d}_{i_k,T}, \widetilde{Y}_T)$

Conditional on $d_{i_k,t}$, the variance of $\varepsilon^*_{i_k,t}$ is known (see Kim et al. (1998)), and draws of the vector of factor loadings, $\beta_{i_k} = (\gamma_{i_k}, \lambda_{i_k})'$, can be generated independently for each $u^*_{i_k,t}$. Then, a normal prior distribution, $N(\underline{\beta}, \underline{c})$, with prior hyper-parameters $\underline{\beta} = (0,0)'$ and $\underline{c} = I_2$ is used, and draws of the factor loadings are generated from the posterior distribution

$$\beta_{i_k} \sim N(\bar{\beta}, \bar{c}),$$

where

$$\begin{aligned}
\bar{\beta} &= (\underline{c}^{-1} + X^{\ddagger\prime} X^{\ddagger})^{-1}(\underline{c}^{-1}\underline{\beta} + X^{\ddagger\prime} Y^{\ddagger}) \\
\bar{c} &= (\underline{c}^{-1} + X^{\ddagger\prime} X^{\ddagger})^{-1},
\end{aligned}$$

with $X^{\ddagger} = \left\{ \frac{g_t}{std(\varepsilon^*_{i_k,t})}, \frac{h_{k,t}}{std(\varepsilon^*_{i_k,t})} \right\}_{t=1}^{T}$, and $Y^{\ddagger} = \left\{ \frac{u^*_{i_k,t} - \chi_{i_k,t}}{std(\varepsilon^*_{i_k,t})} \right\}_{t=1}^{T}$. The same procedure is applied for $i_k = 1, 2, ..., n_k$ and $k = 1, ..., K$.

- ***Step 5***: Sample Φ from $P(\Phi|\widetilde{h}_{k,T}, \Sigma, \widetilde{Y}_T)$

To sample the autoregressive coefficients of the VAR, we rely on Minnesota priors based on random walk processes. Hence, for $vec(\Phi)$ it is assumed a prior normal distribution $N(\underline{\Pi}, \underline{\Upsilon})$, where $\underline{\Pi} = vec(I_K)$, and the $\underline{\Upsilon}$ is given according to the following equations,

$$\begin{cases} (\delta_1)^2, & if \quad i=j \\ \left(\frac{\varsigma_i \delta_1 \delta_2}{\varsigma_j}\right)^2, & if \quad i \neq j, \end{cases}$$

with i referring to the dependent variable in that equation and j referring to the independent variable in that equation. The hyper-parameters are set to $\delta_1 = 0.1$, and $\delta_2 = 1$, and ς_i and ς_j denote the diagonal elements of the scale matrix I_K. Accordingly, the autoregressive coefficients are sampled from the following posterior distribution,

$$vec(\Phi) \sim N(\bar{\Pi}, \overline{\Upsilon}),$$

where

$$\begin{aligned} \bar{\Pi} &= \left(\underline{\Upsilon}^{-1} + \Omega^{-1} \otimes H_{t-1}^{'} H_{t-1}\right)^{-1} \left(\underline{\Upsilon}^{-1}\underline{\Pi} + \Omega^{-1} \otimes H_{t-1}^{'} H_t\right) \\ \overline{\Upsilon} &= \left(\underline{\Upsilon}^{-1} + \Omega^{-1} \otimes H_{t-1}^{'} H_{t-1}\right)^{-1}, \end{aligned}$$

and $H_t = (g_t, h_{1,t}, ..., h_{K,t})'$.

- ***Step 6***: Sample $\widetilde{d}_{i_k,T}$ from $P(\widetilde{d}_{i_k,T}|\gamma_{i_k}, \lambda_{i_k}, \widetilde{g}_T, \widetilde{h}_{k,T}, \widetilde{\chi}_{i_k,T}, \widetilde{Y}_T)$

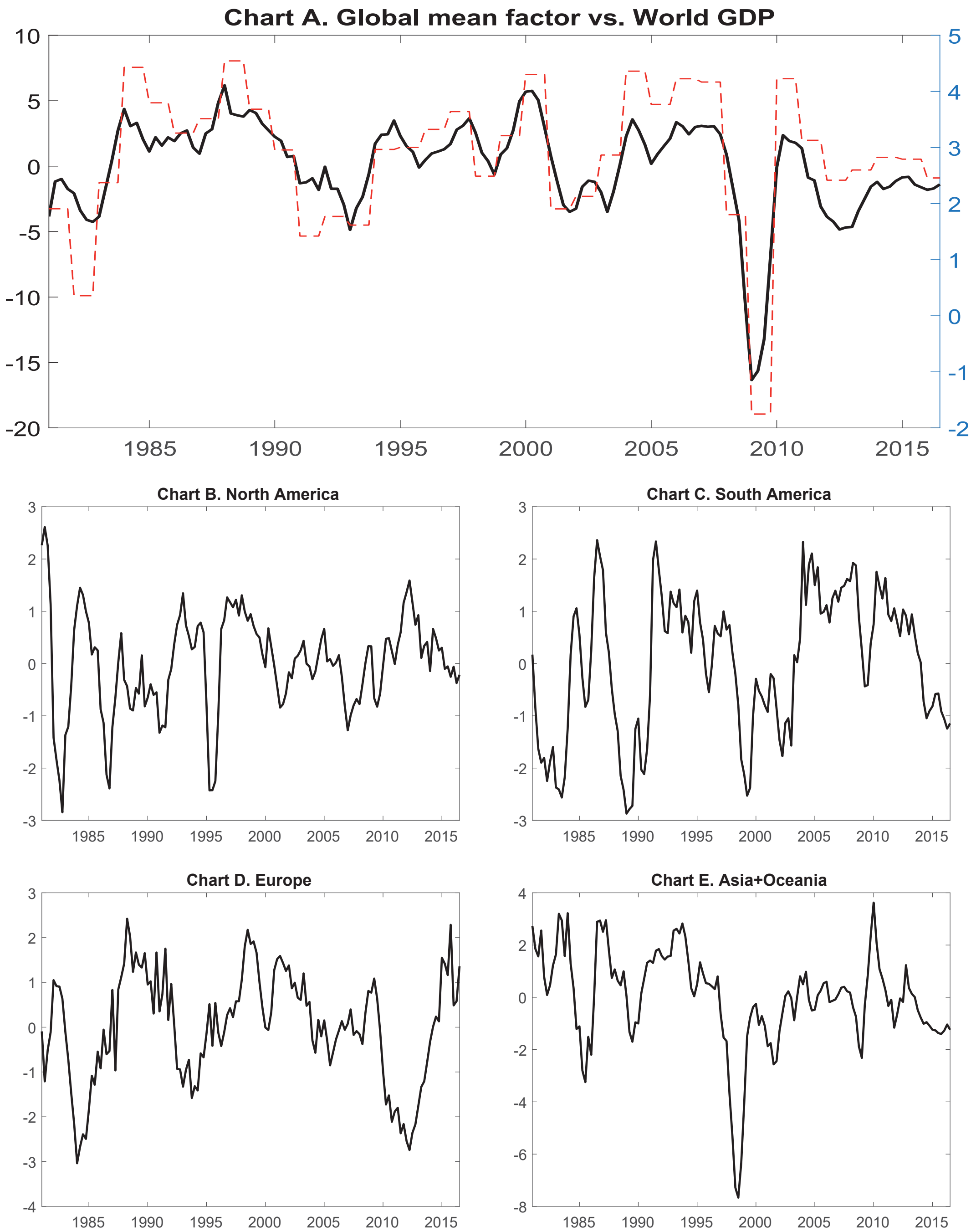
To generate draws of the auxiliary variables $\widetilde{d}_{i_k,T}$ we follow the line of Kim et al. (1998) and Primiceri (2005), and generate independent draws for each i_k from the discrete density,

$$P(d_{i_k,t} = \kappa \mid u^*_{i_k,t}, \gamma_{i_k} g_t + \lambda_{i_k} h_{k,t} + \chi_{i_k,t}) \propto q_\kappa f_N(u^*_{i_k,t} \mid \gamma_{i_k} g_t + \lambda_{i_k} h_{k,t} + \chi_{i_k,t} + m_\kappa - 1.2704, \upsilon^2_\kappa),$$

where $m_\kappa$and υ^2_κ are known for $\kappa = 1, 2, ..., 7$, see Kim et al. (1998).

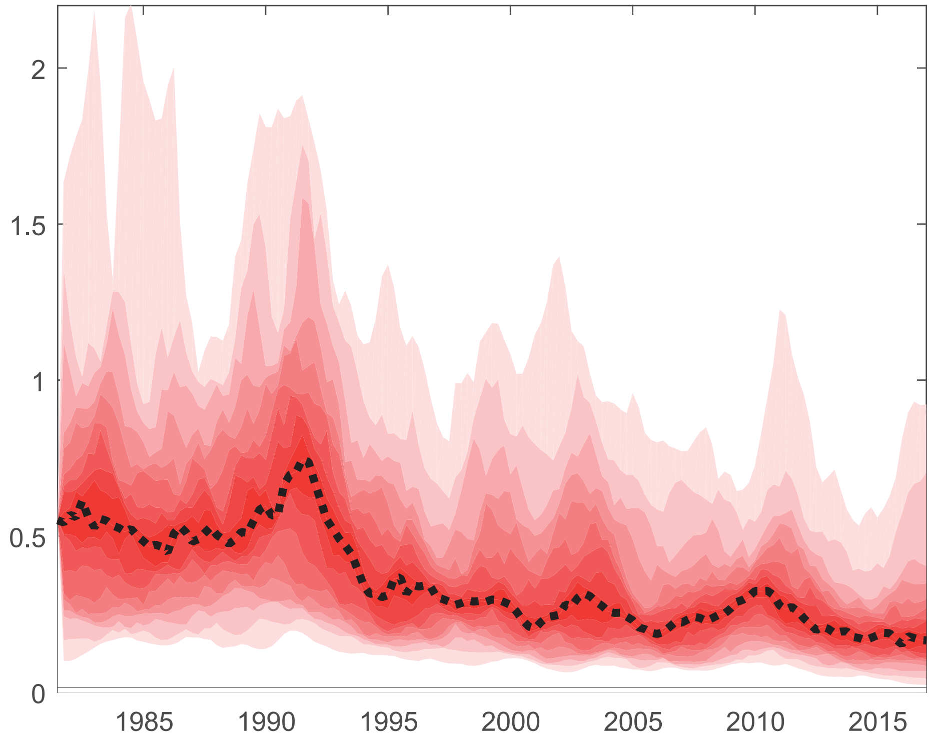
To approximate the posterior distribution of both the parameters and latent variables involved in the model, each step of the algorithm is recursively repeated $M = 20,000$ times, discarding the first $m = 10,000$ iterations to ensure convergence.

Figure A1: Global and regional mean factors

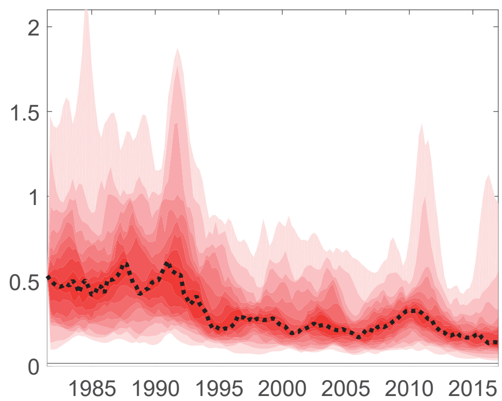


Note: Chart A plots the global mean factor (solid black line) aligned to the left axis and the world real GDP (dashed red line), computed by the World Bank, aligned with the right axis. Charts B, C, D, and E plot the corresponding regional mean factors.

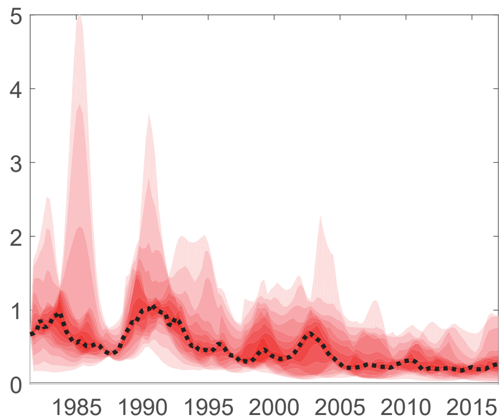
Figure A2: Independent time-varying volatilities across countries



(b) Developed countries



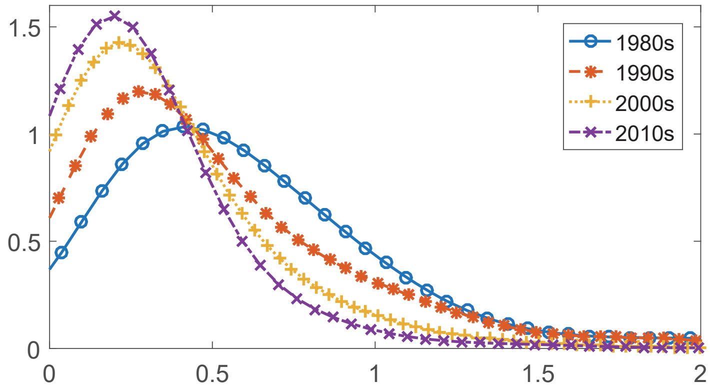
(c) Developing countries



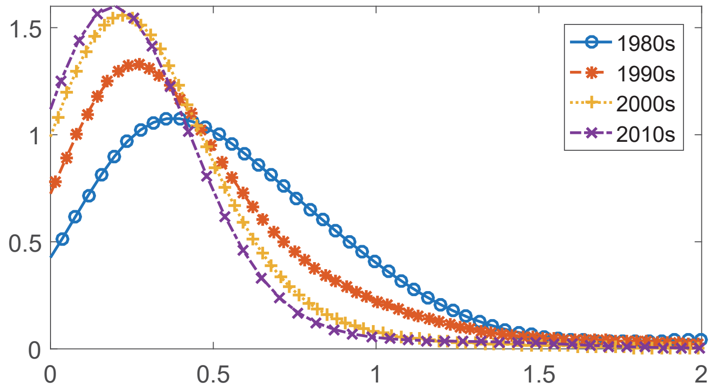
Note: The time-varying volatilities for each country are estimated by using a univariate stochastic volatility model fitted to each term $u_{i_k,t}$, independently. Chart A plots the cross-sectional distribution of time-varying volatilities for all the countries in our sample, that is, including developed 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.

Figure A3: Robustness on the densities of international macroeconomic volatility

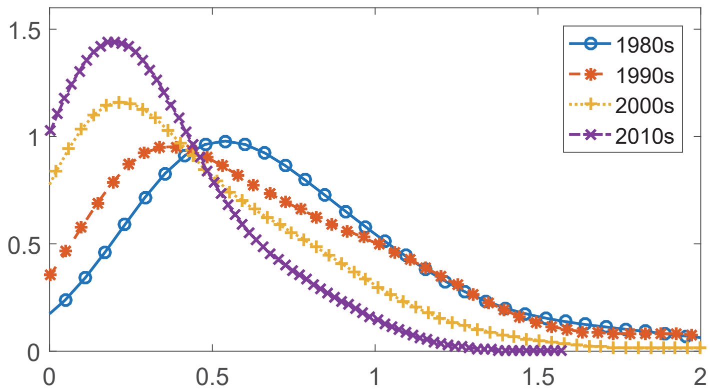
(a) World



(b) Developed countries

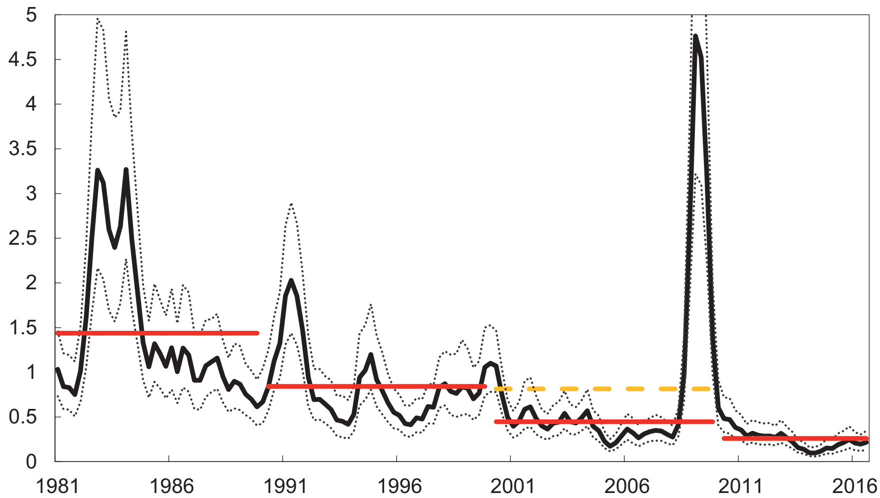


(c) Developing countries



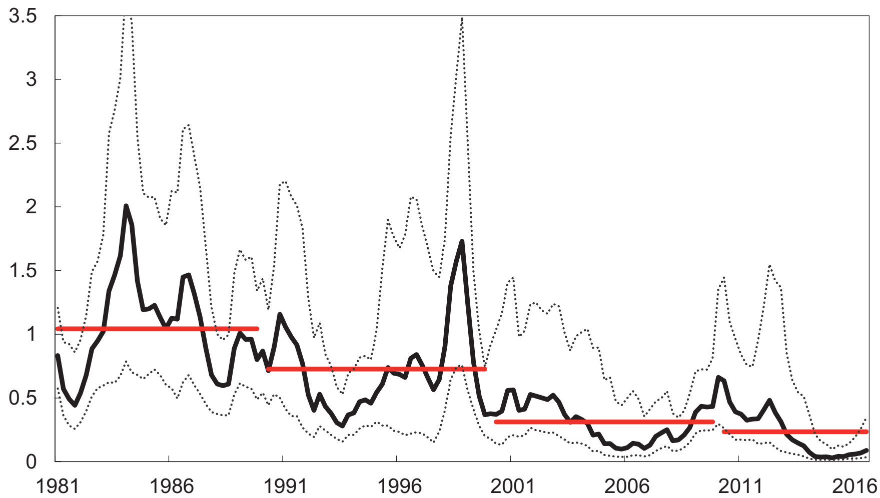
Note: The figure shows the kernel densities associated to all the realizations of time-varying macroeconomic volatility, both across time and countries, within each decade in our sample, that is, 1980s, 1990s, 2000s and 2010s. The measures of volatilities are based on independent univariate stochastic volatility model estimates. Chart A shows the densities containing information from all the countries in our sample, while densities in Chart B and C only contain information from developed and developing countries, respectively.

Figure A4: Global volatility: based on GDP growth fluctuations



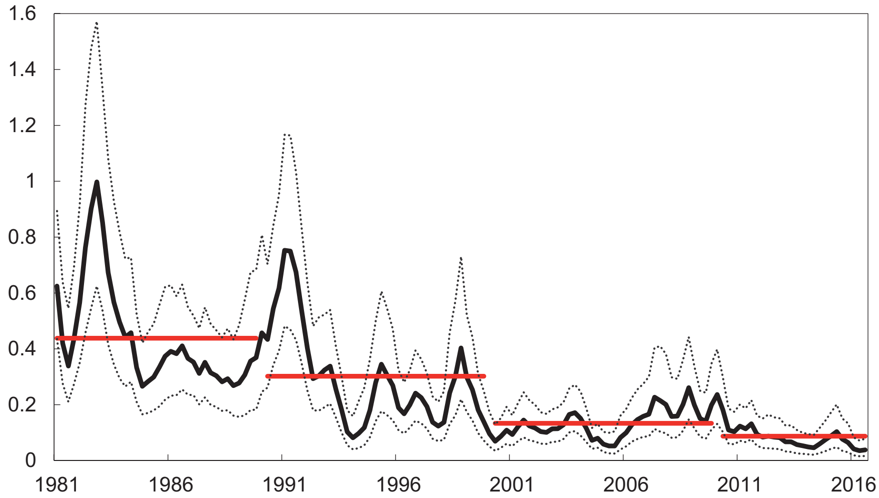
Note: The figure plots the global volatility factor obtained by applying the VOLTAGE model to output growth fluctuation $y_{i_k,t}$. The solid line represents the median of the posterior distribution and the dotted lines make reference to the 68 percent credible set of the posterior distribution. Red lines make reference to the average volatility over the corresponding period. Yellow segment is computed by including the Great Recession episode (2008-2009), while corresponding red segment excludes such period.

Figure A5: Global Volatility: based on joint estimation



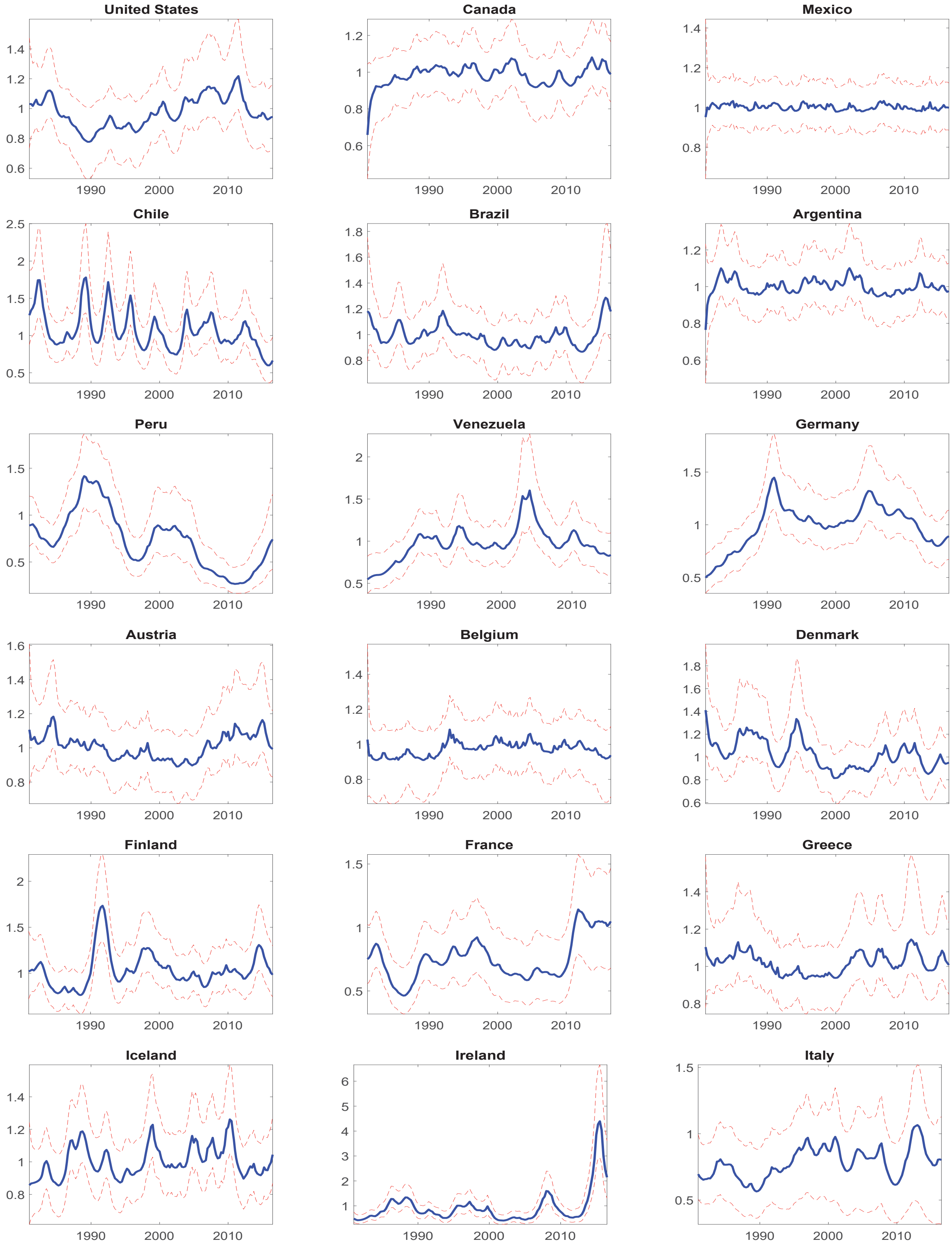
Note: The figure plots the global volatility factor obtained by applying jointly estimating mean and volatility factors, assuming similar autoregressive dynamics, VAR(1), for both types of factors. The solid line represents the median of the posterior distribution and the dotted lines make reference to the 68 percent credible set of the posterior distribution.

Figure A6: Global volatility: based on mean-dependence



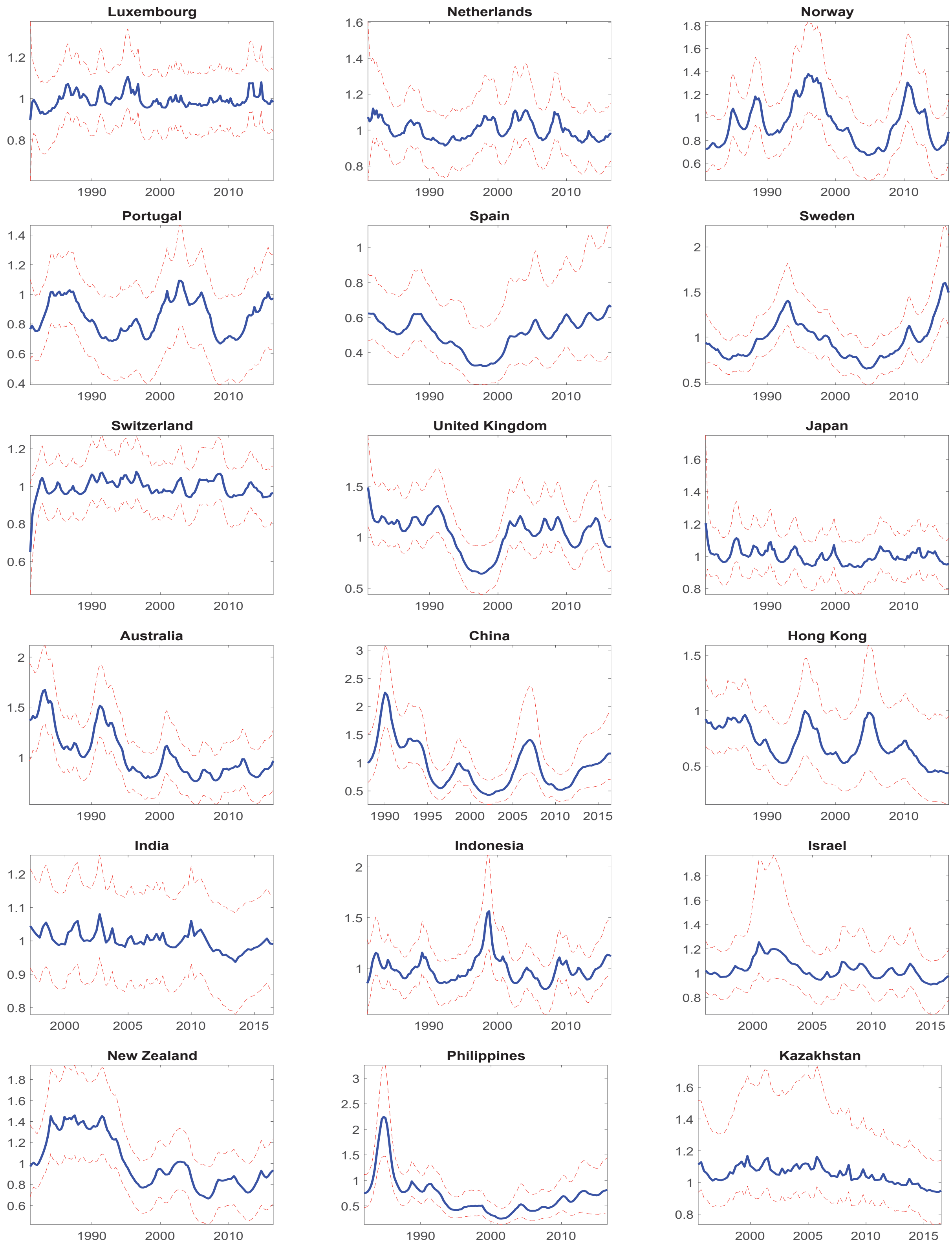
Note: The figure plots the global volatility factor obtained by allowing the volatility factors to depend on their past values and on the lagged mean factors, that is, $H_t = \Phi H_{t-1} + \Lambda \bar{X}_{t-1} + \zeta_t$, where the log-volatility factors are given by $H_t = (g_t, h_{1,t}, ..., h_{K,t})'$ and the mean factors are collected in $\bar{X}_t = (\bar{g}_t, \bar{h}_{1,t}, ..., \bar{h}_{K,t})'$.

Figure A7: Idiosyncratic volatility



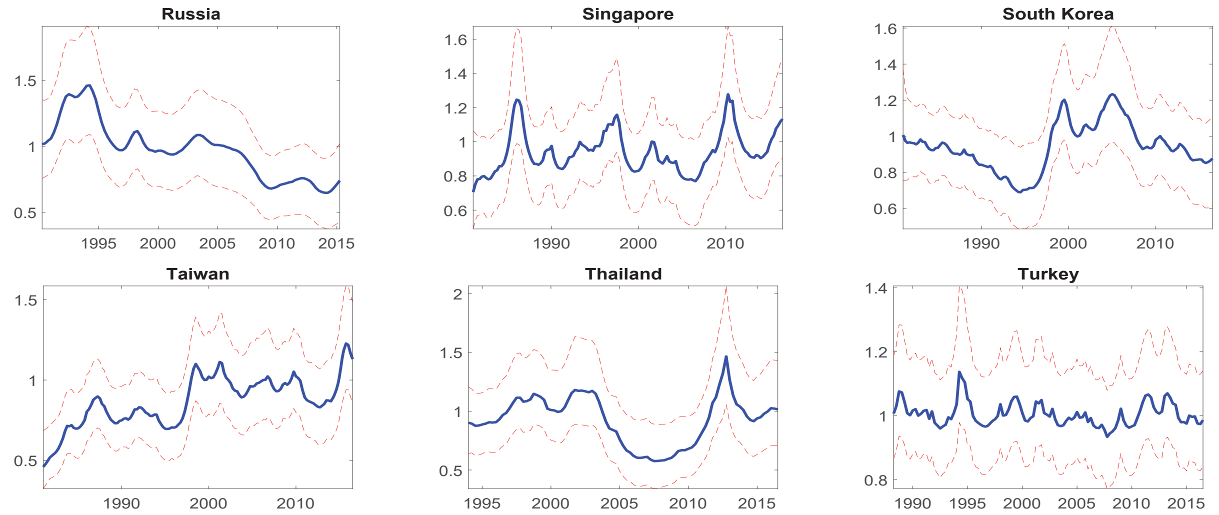
Note: The figure plots the estimated time-varying idiosyncratic volatility for each country. Solid lines make reference the median of the corresponding posterior distribution. Dotted lines refer to the 68 percent credible set of the posterior distribution.

Figure A8: Idiosyncratic volatility (cont.)



Note: The figure plots the estimated time-varying idiosyncratic volatility for each country. Solid lines make reference the median of the corresponding posterior distribution. Dotted lines refer to the 68 percent credible set of the posterior distribution.

Figure A9: Idiosyncratic volatility (cont.)



Note: The figure plots the estimated time-varying idiosyncratic volatility for each country. Solid lines make reference the median of the corresponding posterior distribution. Dotted lines refer to the 68 percent credible set of the posterior distribution.

A.2 Linearization of Historical Decomposition

Although the functional form of the volatility is exponential, we are interested in expressing the total output volatility into sums, rather than products, of its corresponding components, for ease of interpretation. Hence, we take logarithms to the standard deviation, $\sigma_{i_k,t} = e^{\frac{1}{2}F_{i_k,t}}$, and express it in shares.

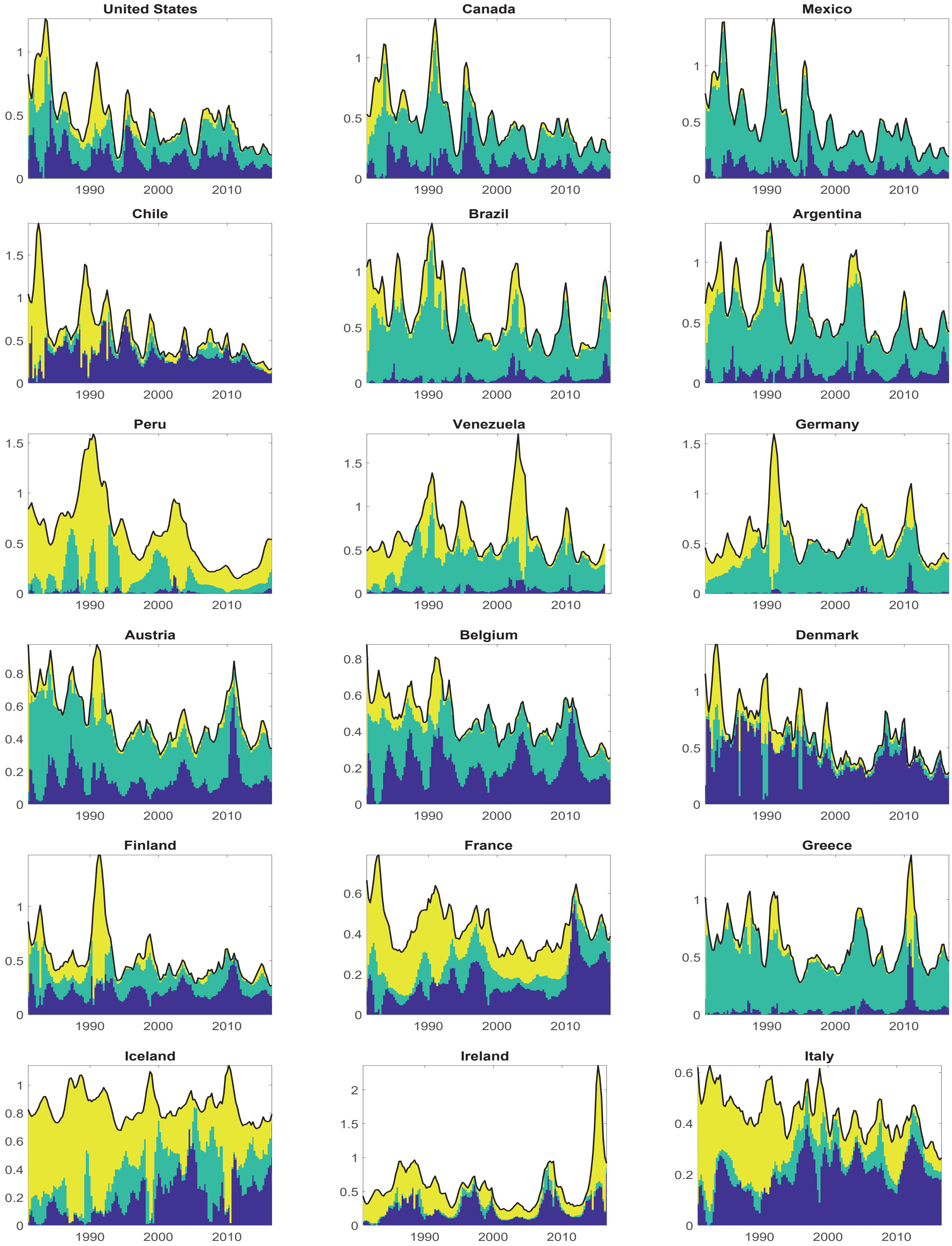
$$\begin{aligned} log(\sigma_{i_k,t}) &= \frac{\gamma_{i_k} g_t}{2} + \frac{\lambda_{i_k} h_{k,t}}{2} + \frac{\chi_{i_k,t}}{2} \\ 1 &= \frac{\gamma_{i_k} g_t}{2 \times log(\sigma_{i_k,t})} + \frac{\lambda_{i_k} h_{k,t}}{2 \times log(\sigma_{i_k,t})} + \frac{\chi_{i_k,t}}{2 \times log(\sigma_{i_k,t})}. \end{aligned}$$

However, since the volatility only takes non-negative values, we express the shares in absolute terms.

$$\begin{aligned} \alpha_t &= \left|\frac{\gamma_{i_k} g_t}{2 \times log(\sigma_{i_k,t})}\right| + \left|\frac{\lambda_{i_k} h_{k,t}}{2 \times log(\sigma_{i_k,t})}\right| + \left|\frac{\chi_{i_k,t}}{2 \times log(\sigma_{i_k,t})}\right| \\ 1 &= \frac{\left|\frac{\gamma_{i_k} g_t}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t} + \frac{\left|\frac{\lambda_{i_k} h_{k,t}}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t} + \frac{\left|\frac{\chi_{i_k,t}}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t} \\ \sigma_{i_k,t} &= \sigma_{i_k,t}\frac{\left|\frac{\gamma_{i_k} g_t}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t} + \sigma_{i_k,t}\frac{\left|\frac{\lambda_{i_k} h_{k,t}}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t} + \sigma_{i_k,t}\frac{\left|\frac{\chi_{i_k,t}}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t} \\ \sigma_{i_k,t} &= S^{global}_{i_k,t} + S^{region}_{i_k,t} + S^{country}_{i_k,t}, \end{aligned}$$

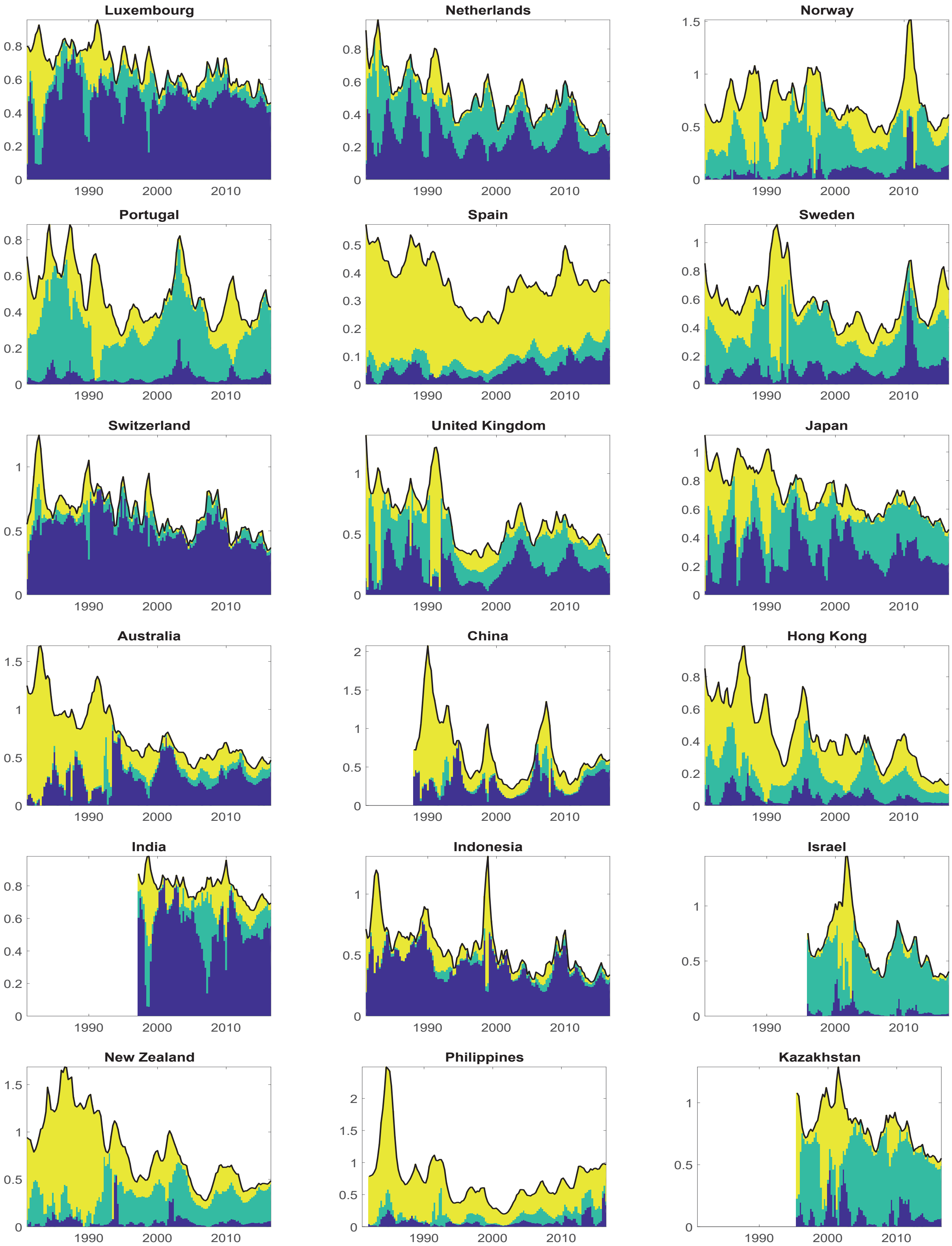
where $S^{global}_{i_k,t} = \sigma_{i_k,t}\frac{\left|\frac{\gamma_{i_k} g_t}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t}$, $S^{region}_{i_k,t} = \sigma_{i_k,t}\frac{\left|\frac{\lambda_{i_k} h_{k,t}}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t}$, and $S^{country}_{i_k,t} = \sigma_{i_k,t}\frac{\left|\frac{\chi_{i_k,t}}{2 \times log(\sigma_{i_k,t})}\right|}{\alpha_t}$ correspond to the contributions of the global, regional and idiosyncratic components, respectively.

Figure A10: Historical volatility decomposition



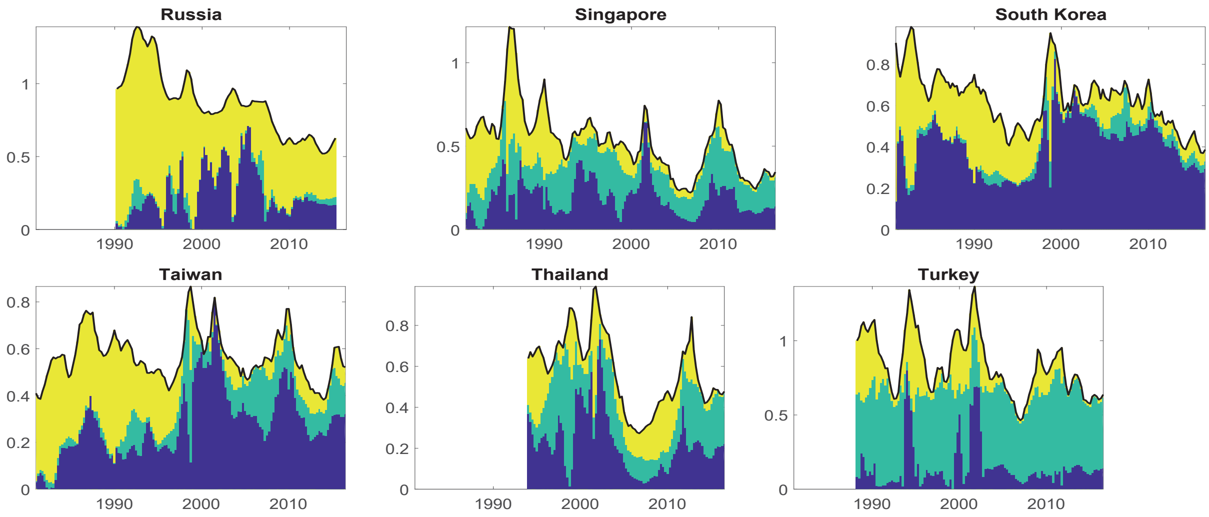
Note: The figure plots the estimated time-varying volatility for each country. Black lines plot the estimated total volatility. Blue, green and yellow areas correspond to the global, regional and idiosyncratic components, respectively.

Figure A11: Historical volatility decomposition (cont.)



Note: The figure plots the estimated time-varying volatility for each country. Black lines plot the estimated total volatility. Blue, green and yellow areas correspond to the global, regional and idiosyncratic components, respectively.

Figure A12: Historical volatility decomposition (cont.)



Note: The figure plots the estimated time-varying volatility for each country. Black lines plot the estimated total volatility. Blue, green and yellow areas correspond to the global, regional and idiosyncratic components, respectively.

Table A1: Drivers of volatility: A WALS approach. Static panel. Period: 1981-2014

	Coefficient	Std. error	t-statistic
Exchange rate vol.	0.083	0.025	3.391
Trade Openness	-0.429	0.117	-3.671
TFP volatility	0.053	0.027	1.928
Financial Integration	-0.09	0.056	-1.599
Government cons. volatility	0.014	0.026	0.533
Term of trade volatility	-0.009	0.024	-0.375
Interest volatility	-0.003	0.018	-0.158
Year FE	✓	✓	✓
Country FE	✓	✓	✓

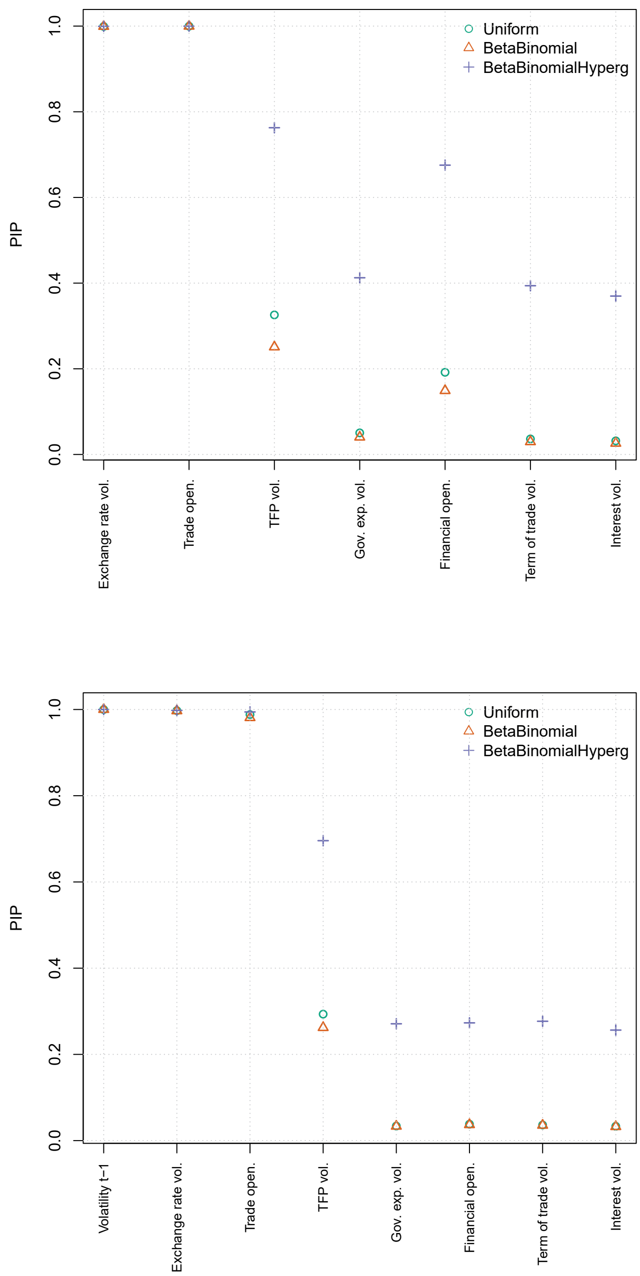
The sample includes 53 countries and 1185 observations. The dependent variable is economic growth volatility.

Table A2: Drivers of volatility: A WALS approach. Dynamic panel. Period: 1982-2014

	Coefficient	Std. error	t-statistic
Volatility$_{t-1}$	0.545	0.027	20.355
Trade Openness	-0.417	0.093	-4.486
Exchange rate vol.	0.077	0.018	4.168
TFP volatility	0.049	0.02	2.385
Term of trade volatility	-0.014	0.02	-0.666
Interest volatility	0.011	0.019	0.6157
Financial Integration	-0.004	0.053	-0.083
Government cons. volatility	-0.013	0.021	-.0629
Year FE	✓	✓	✓
Country FE	✓	✓	✓

The sample includes 53 countries and 1130 observations. The dependent variable is economic growth volatility.

Figure A13: Drivers of volatility: PIP using different priors



Note: The bottom plot includes lagged volatility as regressor.

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