

Fluctuations in Global Macro Volatility*

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Abstract

This paper investigates the dynamics, propagation and drivers of macroeconomic volatility from a global perspective. A hierarchical volatility factor model is designed to estimate and decompose the time-varying volatility of output growth across countries into global, regional, and idiosyncratic components. We find that the global volatility component has been systematically declining over time, which is consistent with a “global moderation” of international business cycles. Despite the declining levels of global volatility, the exposure of countries 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. Moreover, the level of trade openness seems to be the most robust explanatory factor of changes in output volatility worldwide.

Keywords: Output Volatility, Factor Model, Model Uncertainty.

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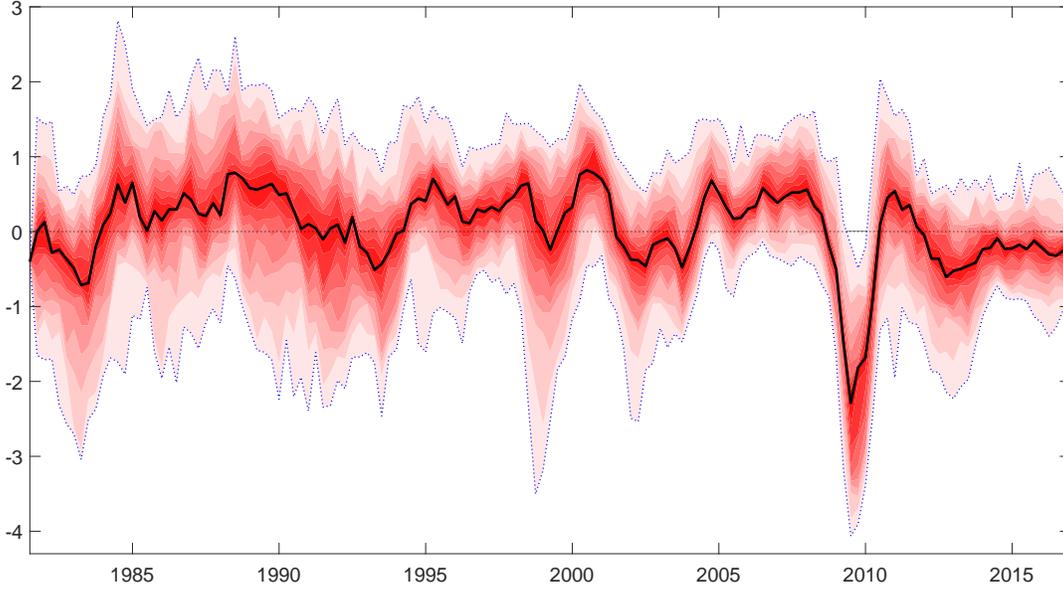
1 Introduction

Since the structural reduction in output volatility of the U.S. economy, occurred in the mid 1980s and commonly known as the Great Moderation ([Kim and Nelson \(1999\)](#) and [Pérez-Quirós and McConnell \(2000\)](#)), there has been an increasing interest in analyzing the dynamics and sources of changes in macroeconomic volatility. The Great Moderation is not a unique feature of the U.S. and is also documented in other advanced economies ([Blanchard and Simon \(2001\)](#) and [Everaert and Iseringhausen \(2018\)](#)), suggesting potential commonalities and spillovers in output volatility across countries. Based on these findings, a relevant question that emerges is whether such a reduction in output volatility is a unique feature of developed countries or it also involves developing countries, making it a systemic pattern of the global economy. Moreover, understanding the fluctuations and spillovers of output volatility has important implications for policy makers ([Stock and Watson \(2005\)](#)) responsible for designing and implementing policies that improve economic stability. This is particularly the case after the Great Recession showed the severe adverse effects that an interconnected world economy may be exposed to.

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 simultaneous way more often than before that time. This result has important implications when inferring the outlook of the global economy. For example, if global synchronization remains at high levels when the next global recession will occur, the number of countries potentially affected by the recession will be similar or even larger than in the previous global recession.

These assessments are based on synchronization of expected real activity, that is, on first order moments of output growth. However, it still remains uncertain whether the severity of GDP downturns will be similar or not across countries. If an adverse scenario for the global economy is when most of the countries enter recessionary phases, an even more adverse scenario is when, additionally, 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 of global real activity to design policies that promote economic stability. Also, macroeconomic fluctuations are major “market movers”, since perceptions and expectations of economic trends

Figure 1: Distribution of GDP growth across countries



Note: The fan chart plots the real GDP growth cross-section distribution of countries listed in Table 1. The solid black line makes reference to the median of the distribution. The dotted blue lines indicate the corresponding 5th and 95th percentile of the distribution.

affect the fundamental value of all traded securities. Thus, measuring and understanding the sources of macroeconomic volatility from a global perspective also has important implications for traders and financial analysts.

Figure 1 plots the real GDP growth cross-sectional distribution over 42 countries for each time period from 1981:Q1 until 2016:Q3, showing a salient feature.¹ The tails of the distribution in the early part of the sample are much wider than the tails during the last part of the sample. This implies that the magnitude of international output fluctuations, in general, seems to have decreased over time. Although, there have been some particular episodes in which the distribution has widen temporarily, for example, during the 1998, 2001-2002, and 2008-2009 global recessions, as dated by the IMF. Another important feature that can be seen in Figure 1 is the negative skewness of the cross-sectional distribution, which is more accentuated in the first part of the sample, indicating stronger down-side risks in global real activity.²

¹The list of countries is available in Table 1.

²This asymmetric feature is observed for the case of the U.S. Adrian et al. (2018) 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.

Motivated by these features, we investigate, from a rigorous perspective, if there has been a structural decline in global macroeconomic volatility. More importantly, we assess the underlying sources and propagation of those changes in volatility. In particular, the analysis proposed in this paper has three main goals. First, decomposing output volatility across countries into underlying global, regional and idiosyncratic components, and 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 over time and across countries.

In doing so, 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 investigate what are the most robust driving macroeconomic factors that explain changes in output volatility across countries by relying on panel regressions that account for model uncertainty and potential reverse causality.

Our results indicate that temporary increases in global volatility are not always 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 markedly decreasing trend over time exhibited by the global volatility component. Such a persistent decline 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 narrowing over time of the tails of the GDP growth distribution across countries, shown in Figure 1. Moreover, the persistent decline in global volatility is systemic, since all regions (North America, South America, Europe, Asia and Oceania) have significantly contributed to its reduction.

We find an asymmetric propagation pattern of macro volatility shocks, in particular, unexpected global developments affect regional ones, but not viceversa. Also, we document an increasing contribution over time of global shocks to the volatility dynamics of the global

factor. In other words, we show strong evidence that global macro volatility has become “more global”. Moreover, 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.

Lastly, we focus on identifying the main explanatory factors of changes in macro volatility across countries among the determinants commonly studied in the literature, which is described below. These potential determinants 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. The results indicate that exchange rate volatility and trade openness are the most robust explanatory factors. However, once we account for endogeneity issues the only robust determinant of international macro volatility is the level of *trade openness*.

The literature on the estimation of output volatility from a global perspective and the propagation of its shocks is scarce. [Everaert and Iseringhausen \(2018\)](#) partially addressed these issues by using a factor-augmented dynamic panel data model with time-varying parameters to analyze changes in volatility between 16 advanced economies, finding a reduction in the volatility of domestic shocks, which is consistent with [Stock and Watson \(2005\)](#). However, by focusing only on advanced economies, their study is not able to assess the role that global developments may play in the propagation of volatility shocks between advanced and emerging economies from a structural perspective. We contribute to this literature by proposing an approach to assess the propagation of structural volatility shocks, and that can be used in a wide range of applications. Our work also contributes 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 Recently, [Carriero et al. \(2018\)](#) focus on measuring uncertainty and its effect on the U.S. economy by using a large VAR

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

model with errors whose stochastic volatility is driven by two common and interrelated unobservable factors, representing aggregate macroeconomic and financial uncertainty. As explained below, since their framework is related to ours in spirit, the measures of global and regional volatility computed in this paper can be alternatively interpreted as a proxies for global and regional macroeconomic uncertainty.

When assessing commonalities and spillovers in output volatility is also important to understand the main channels through which volatility shocks propagate across countries. There is ample literature evaluating the effect of specific macroeconomic 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 \(1976\)](#)).

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.

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

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 determinants. The only exception is [Malik and Temple \(2009\)](#), who use a Bayesian Model Averaging approach to study the structural determinants of output volatility. However, [Malik and Temple \(2009\)](#), first, focus only on developing countries, and second, the authors only explain the level (averaged over time) of volatility and not its dynamics. To the best of our knowledge, we are the first to identify the main macroeconomic factors that explain changes over time in output volatility worldwide.

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

2 Measuring Global Volatility

Understanding and assessing time varying output volatility and the propagation of volatility shocks across countries is crucial for policy makers, especially at international organizations, when performing risk assessments on the outlook of the global economy. However, measuring output volatility and assessing volatility spillovers in a multi-country environment is a challenge, since volatilities are latent variables that need to be estimated.⁷ In this paper, we contribute to overcome these challenges by proposing 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 across countries.

The proposed empirical framework relies on a hierarchical factor structure, that is designed to jointly (i) estimate and summarize the output volatilities of a large set of

⁷A simple way of estimating time-varying output volatility is by computing it based on rolling windows. However, this measure can be highly sensitive to the size of the chosen window and it could provide imprecise estimates if the sample size is too short, as it is the case for some emerging countries.

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) assess the transmission of output volatility shocks across both developed and developing countries. In sum, we introduce a framework that is well suited to analyze the VOLatility Transmission Across Grouped Economies, henceforth, it will be referred as the VOLTAGE model.

We restrict to the use of quarterly real GDP data instead of annual data because information at a higher frequency allow us to characterize volatility patterns with more precision. Our data 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 of the Online Appendix, and the sample period from 1981:Q1 until 2016:Q3.⁸ Although the focus of the analysis is on commonalities in volatilities (second order moments), it is important to, first, account for commonalities in the mean (first order moments). Therefore, we start by extracting global and regional components in the mean across countries output growth by using principal component analysis.⁹ 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 .¹⁰ Then, output growth is decomposed into a mean global factor, \bar{g}_t , a mean regional factor, $\bar{h}_{k,t}$, and an idiosyncratic component $u_{i_k,t}$, as follows,

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

where $\bar{\gamma}_{i_k}$ and $\bar{\lambda}_{i_k}$ are the corresponding factor loadings, for $i_k = 1, 2, \dots, n_k$ and $k = 1, \dots, K$, where n_k is the number of countries that belong to region k , and K is the total number of considered regions.

In order to investigate volatility commonalities over and above mean commonalities, we focus on the terms, $u_{i_k,t}$, which are country-specific output growth fluctuations after purging off common patterns in the mean. Therefore, we model the stochastic volatility

⁸The data was gathered from different sources, such as the World Bank, Datastream, among others.

⁹To deal with missing data in the extraction of the common factors in the mean, we apply probabilistic principal component analysis.

¹⁰The data is standardized prior to the application of the principal component analysis.

of, $u_{i_k,t}$, as,

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

where $\varepsilon_{i_k,t} \sim N(0, 1)$ and $F_{i_k,t}$ is the latent variable that refers to the log-volatility. Typically, $F_{i_k,t}$ is assumed to be a univariate stationary process. However, given our multi-country environment, we are interested in decomposing $F_{i_k,t}$ into its common, regional and idiosyncratic components across countries, that is,

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

for $i_k = 1, 2, \dots, n_k$ and $k = 1, \dots, K$. 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 changes in the overall degree of the world macroeconomic volatility, while the regional factors account for the commonalities in the volatility patterns between countries located in a given region, and 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 comovement between the country-specific volatility and the volatility factors.

To assess the propagation pattern of volatility shocks across the different regions of the world, the latent variables driving the global and regional volatility factors are assumed to evolve according to a stationary vector autorregresion,

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

where the innovations are assumed to be normally distributed, $\zeta_t \sim N(0, \Sigma)$. This assumption allows to perform any type of structural analysis typically employed in a linear VAR context. Similarly, the dynamics of the idiosyncratic volatility components are given by

independent stationary autoregressive processes,

$$\chi_{i_k,t} = \varphi_{i_k} \chi_{i_k,t-1} + \xi_{i_k,t}, \quad (5)$$

where the innovations are assumed to be normally distributed, $\xi_{i_k,t} \sim N(0, \sigma_{i_k}^2)$, and cross-sectionally uncorrelated, $Cov(\xi_{i_k,t}, \xi_{-i_k,t}) = 0$. To achieve identification of factors and factor loadings, we follow [Bai and Wang \(2015\)](#) and impose restrictions to the covariance matrix of the innovations: first, the covariance matrix of the innovations in the VAR equals to an identity matrix, $\Sigma = I_{K+1}$, and second, some factor loadings, γ_{1_1} and $\{\lambda_{1_k}\}_{k=1}^K$, are lower-triangular matrices with strictly positive diagonal terms.¹¹ The first type of restrictions facilitate the structural analysis that can be performed with the model since the the innovations, ζ_t , are structural by construction and no additional assumptions about the ordering of the elements in the VAR or signs in the relationship between structural shocks need to be made.¹²

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 for the 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, parameters, and consequently, impulse responses. Moreover, the proposed estimation algorithm allows us to deal with missing observations, which is a typical problem in multi-country data. The Online Appendix A.1 reports the details about the estimation procedure.

¹¹The 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, as in [Kim et al. \(1998\)](#).

¹²However, 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 \(2015\)](#).

3 Dynamics and Propagation of Volatility

The purpose of this section is threefold. First, inferring changes in global macroeconomic volatility since the Great Moderation. Second, understanding the sources of these changes from an international perspective. 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. Chart A of Figure 2 shows the global mean factor extracted from the GDP growth of the 42 countries in our sample, as described in equation 1. The chart also plots the world GDP growth, computed by the World Bank, showing that the common factor resembles fairly well the dynamics of the world real activity. Similarly, Charts B, C, D and E of Figure 2 plot the extracted regional mean factors for North America, South America, Europe and Asia+Oceania, respectively. The charts 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. Additional features of the commonalities in the mean can be discussed, however, since the focus of this paper is on the commonalities in volatility, the rest of the analysis is dedicated to that aim.¹³

3.1 Time Variation

We extract commonalities in the volatility profiles of country-specific GDP fluctuations after purging off the common patterns in the mean. Chart A of Figure 3 plots the dynamics of the global volatility factor, 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 down to 0.20, to finally remain in 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

¹³For a deeper assessment on changes in the comovement of mean output growth at the international level, see [Del Negro and Otrok \(2008\)](#) and [Ductor and Leiva-Leon \(2016\)](#).

of international output fluctuations. This feature is consistent with the narrowing between the upper and lower bounds of cross-country GDP growth distribution, shown in Figure 1.

Despite the overall declining pattern, global volatility has also exhibited sudden and temporary increases over time. To identify the regions associated with those temporary fluctuations in global volatility, the common factor is decomposed into the contributions of each region. We follow the line of [Koopman and Harvey \(2003\)](#) to decompose the latent factor into the contributions associated to each of the observables, which in this case are countries.¹⁴ To facilitate the interpretation of the decomposition, we group all the country-specific contributions associated to each region. Chart B of Figure 3 shows the historical data decomposition of the global volatility factor. The figure shows a temporary increase in volatility 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”. During that period, countries of the region reached a point where their foreign debt exceeded their earning power, precluding them to repay the debt. This situation led to declines in income and imports, high levels of unemployment, drops in real wages, and consequently, to a stagnation of economic growth.

Another increase in global volatility is observed in the early 1990s, when the oil price shock lead to a deterioration of consumers and business confidence and caused a recession in the U.S. ([Walsh, 1993](#)). Most of the Western world also suffered a recession in this period due to restrictive monetary policy by central banks to deal with concerns associated to high inflation. Another event that could explained the increase in global volatility in the early 1990s is the German reunification. This event had significant economic implications for several European countries, specially for those countries that have their currencies pegged to the European Currency Unit.

The sudden increase in global volatility observed in the late 1990s can be associated to the severe Asian financial crisis, although Chart B of Figure 3 shows that the contribution of the Asia+Oceania region to the global volatility is small.¹⁵ The increase in global

¹⁴[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. \(1998\)](#).

¹⁵This low contribution is explained by the fact that recessionary effects, measured by first order moments

volatility is the result of spillover effects of that event to advanced economies through the global financial markets. This is consistent with the high levels of stock market volatility, measured by the VIX, reported around that time.

Finally, there is another mild 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. However, all these temporary increases in global volatility are not necessarily related to economic recessions. Instead, they seem to be more related to episodes of instabilities, structural changes, and high uncertainty. Another important finding illustrated in Chart B of Figure 3 is that the persistent decline in global volatility is not associated to a specific region, since all regions have, in general, significantly contributed to the reduction in global volatility.

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.¹⁶ Chart A of Figure 4 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 from a sudden devaluation of the Mexican Peso. Despite those specific periods, the volatility in North America has remained relatively stable over time, which is consistent with Gadea et al. (2018), where it is shown that since the Great Moderation, U.S. output growth has remained subdued despite the loss of the Great Recession.

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.

commonalities in Chart E of Figure 2, are already accounted for.

¹⁶Kose et al. (2003) also decompose the output growth across countries into global and regional factors. However, they focus on commonalities in the mean rather than in the volatility.

Instead, the rise occurred in the early 2000s can be attributed 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.

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. 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 sever crisis leading to financial and political instability and to further panic in the markets.

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. The estimated idiosyncratic volatilities, which are plotted in Figures A1 to A3 of the Online Appendix for the sake of brevity, 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 change due to the 2015s tax inversion practices, in the former case, and to the early 1990s country-specific depression, in the later.

3.2 Sources of Fluctuations

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 proposed framework allows us to easily compute the historical volatility decomposition for each country. Let $\sigma_{i_k,t} = e^{\frac{1}{2}F_{i_k,t}}$ denote the output volatility of country i_k , it can be expressed as

$$\sigma_{i_k,t} = S_{i_k,t}^{global} + S_{i_k,t}^{region} + S_{i_k,t}^{country}, \quad (6)$$

where $S_{i_k,t}^{global}$, $S_{i_k,t}^{region}$, and $S_{i_k,t}^{country}$ 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 Online Appendix A.2.¹⁷

The historical volatility decomposition for each country in the sample is plotted in figures A4 to A6 of the Online Appendix plot, 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 may represent a valuable asset for policy makers, who are interested in performing timely assessments about the size and sources of fluctuations in macroeconomic volatility for a given country, that is, to disentangle the part of macroeconomic volatility that is due to purely idiosyncratic factors from the part that can be attributed to regional or global spillovers.

For ease of interpretation, we summarize all the information in figures A4 to A6, from quarters to decades, and from countries to regions. Accordingly, the first four bars (from left to right) in Chart A of Figure 5 plot the contribution of the global component, averaged across all the countries in our sample, for the 1980s, 1990s, 2000s and 2010s, respectively. A striking finding is the increase over time in the average contribution of the global component to the volatility across countries, despite the decrease in global volatility documented in section 3.1. 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 feature of a subset of countries or if it is indeed a systemic feature across all the main world economies, we repeat the same exercise by, separately, using averages across

¹⁷In particular, $S_{i_k,t}^{global} = \sigma_{i_k,t} \frac{\left| \frac{\gamma_{i_k} g t}{2 \times \log(\sigma_{i_k,t})} \right|}{\alpha_t}$, $S_{i_k,t}^{region} = \sigma_{i_k,t} \frac{\left| \frac{\lambda_{i_k} h_{k,t}}{2 \times \log(\sigma_{i_k,t})} \right|}{\alpha_t}$, and $S_{i_k,t}^{country} = \sigma_{i_k,t} \frac{\left| \frac{\chi_{i_k,t}}{2 \times \log(\sigma_{i_k,t})} \right|}{\alpha_t}$, where $\alpha_t = \left| \frac{\gamma_{i_k} g t}{2 \times \log(\sigma_{i_k,t})} \right| + \left| \frac{\lambda_{i_k} h_{k,t}}{2 \times \log(\sigma_{i_k,t})} \right| + \left| \frac{\chi_{i_k,t}}{2 \times \log(\sigma_{i_k,t})} \right|$.

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 5 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 5 plots the average contribution of the regional component, both across countries in a region and over quarters in a decade. The figure shows that the sensitivity of output volatility to regional developments, 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 5.

The overall pattern of the contributions in Figure 5 show that regional commonalities account for about 35 percent of output volatility fluctuations. Global commonalities accounted for about 25 percent of volatility dynamics in the 1980s, but currently it accounts for about 45 percent. Instead, the contribution of idiosyncratic developments has dropped substantially from about 40 percent in the 1980s, to 20 percent in the present time. This pattern has been roughly similar for South America and Europe. However, regional commonalities in North America seems to dominate volatility fluctuations, and in Asia+Oceania the idiosyncratic component has been significantly losing importance, pointing to a higher integration in macro volatility both at the regional and at the global level.

It is important to notice that despite the substantial decline in global volatility (documented in Section 3.1), its influence on output volatility across countries has significantly increased. This result shows that the reduction in the magnitude of real activity fluctuations has become a global phenomenon.

3.3 Spillovers at the Global Level

This section is devoted to provide a comprehensive assessment about how macroeconomic volatility shocks propagate through the global economy. The motivation relies on the existing high level of interconnectedness between economies at the global level, due to factors such as international trade, foreign exchange markets, commodity prices, among many others. The specific channels through which such spillovers may be generated are studied in Section 4. For now, we concentrate on addressing two questions which, to the best of our knowledge, have not been studied in the literature. First, do we observe output volatility spillovers across countries? Second, if this is the case, how do these spillovers propagate from regional to global volatility? from global to regional volatility? or between the different regions? These are important questions whose answers could help policy makers, especially from international organizations, to provide accurate assessment of risks when inferring the outlook of the global economy. Therefore, in order to provide a full picture of the propagation pattern of volatility shocks we characterize it at two levels. First, we show how volatility shocks propagate between aggregate regional and global components. Second, we adopt a more disaggregated perspective, and investigate how unexpected increases in global volatility propagate through country-specific volatility.

Since the VOLTAGE model allows for endogenous interdependencies between the common factors of volatility, we are able to apply all the standard practices used in VAR and FAVAR models to perform structural analysis. In particular, given the dynamics described in Equation (4), the response, j periods ahead, of each element in $H_t = (g_t, h_{1,t}, \dots, h_{K,t})'$ to a one-time impulse in the structural shock ζ_t , can be defined as,¹⁸

$$\frac{\partial H_{t+j}}{\partial \zeta'_t} = \Theta_j, \quad (7)$$

for the horizon path $j = 1, 2, \dots, J$.

¹⁸To identify the latent factor from the factor loadings we assume that $\Sigma = I_{K+1}$. An advantage of this identification scheme is that it provides shocks, ζ_t , that can be interpreted as structural by construction. This feature is also applied in [Bai and Wang \(2015\)](#) to assess spillovers in international bond yields by employing a linear dynamic factor model.

Notice that the output volatility of country i_k can be compactly expressed as,

$$\sigma_{i_k,t} = \sigma_{g,t}^{\gamma_{i_k}} \sigma_{h_k,t}^{\lambda_{i_k}} \sigma_{\chi_{i_k},t}, \quad (8)$$

where $\sigma_{g,t} = \exp\left(\frac{1}{2}g_t\right)$, $\sigma_{h_k,t} = \exp\left(\frac{1}{2}h_{k,t}\right)$ and $\sigma_{\chi_{i_k},t} = \exp\left(\frac{1}{2}\chi_{i_k,t}\right)$ denote the global, regional and idiosyncratic volatility components, respectively. For ease of interpretation, we are interested in recovering the responses of the volatility components $(\sigma_{g,t}, \sigma_{h_k,t}, \sigma_{\chi_{i_k},t})$, and not the responses of the volatility factors $(g_t, h_{k,t}, \chi_{i_k,t})$, to a given structural shock. Therefore, we rely on the notion of generalized impulse response function. In particular, we define the difference between $E(\sigma_{z,t+j}|\zeta_t = 1, \psi_{t-1})$ and $E(\sigma_{z,t+j}|\zeta_t = 0, \psi_{t-1})$ as our measure of impulse response, where ψ_{t-1} denotes all the cumulated information up to time $t - 1$.¹⁹ Accordingly, the impulse response function for the volatility components is defined as,

$$\frac{\partial \sigma_{z,t+j}}{\partial \zeta_t'} = \exp\left(\frac{1}{2}\Theta_{j[z]}\right) - 1, \quad (9)$$

for $z = \{g, h_1, \dots, h_K\}$, and where $\Theta_{j[z]}$ denotes the row of Θ_j that corresponds to the latent factor z .

Chart A of Figure (6) plots the responses of the volatility associated to the four regions of the world to a shock in global volatility. The results show that all regions are significantly affected by global shocks. In particular, the regions of North America and Europe show the largest, most significant and persistent responses. For the case of the volatility of Asia+Oceania region, although being significantly affected by global shocks, their effect tends to fade out sooner than for North America and Europe. Instead, the volatility of South America responds significantly to global shocks but with certain delay. Despite the heterogeneous pattern of the responsiveness, it can be clearly seen that unexpected increases in global volatility have sizeable and long-lasting effects on the volatility across regions.

Charts B, C, D and E of Figure (6) plot the response patterns to a volatility shock

¹⁹We do not need 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.

in the regions of North America, South America, Europe and Asia+Oceania, respectively. Interestingly, the results indicate that regional volatility shocks are not significantly propagated across different regions, since the distribution of the estimated responses are mostly centered at zero, with the only exception of a response to its own shock. This lead us to our third main results, which consists of uncovering an asymmetric propagation pattern of macro volatility shocks in that unexpected global developments affect regional ones, but not viceversa, moreover, volatility shocks are propagated through the global component and not directly from one region to another. Hence, the dynamics of the global volatility component is shown to be crucial in determining the fluctuations of regional volatility. To investigate further this issue, we analyze how the influence of global shocks on regional developments has changed over time.

Once the impulse responses Θ_j have been estimated, it is possible to quantify how much a given structural shock explains of the historically fluctuations of the log-volatility factors. This can be done by approximating the factors in H_t as,

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

and then computing the corresponding historical decomposition. Figure 7 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 global macro volatility has become “more global”, indicating a more interrelated global economy in terms of aggregate risks.

Next, we provide a deeper assessment about the effects of global volatility shocks by looking at the heterogeneous response across countries. This information help us to identify the most and least sensitive economies to global shocks. To obtain the responses of country-specific volatilities to a one-time unexpected increases in the volatility factor, we project

the impulse response function in Equation (9) by using the corresponding factor loadings,

$$\frac{\partial \sigma_{i_k, t+j}}{\partial \zeta_t'} = \exp\left(\frac{1}{2}(\gamma_{i_k} \Theta_{j[g]} + \lambda_{i_k} \Theta_{j[h_k]})\right) - 1, \quad (11)$$

for countries $i_k = 1, 2, \dots, n_k$, located in regions $k = 1, \dots, K$.

The responses of country-specific volatilities to a global shock are reported in Figure (8), showing substantial heterogeneity. In particular, all the three countries composing the North 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 Norway and Portugal, whose volatility is mainly driven by the regional component, and Iceland and Spain, whose idiosyncratic volatility dynamics are the most predominant, as it is shown in figures A4-A6 of the Online Appendix.

4 What Does Explain Changes in Macro 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 theoretical 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 Data

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,

$$T_{it} = \frac{E_{it} + I_{it}}{GDP_{it}} \quad (12)$$

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.

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:²⁰

$$F_{it} = \frac{A_{it} + L_{it}}{GDP_{it}} \quad (13)$$

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 term 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

²⁰The 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.

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,

$$tot_{it} = \frac{PE_{it}}{PI_{it}} \quad (14)$$

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 ,

$$\sigma(tot)_{it} = (\log(tot_{it}) - \log(tot_{it-1}))^2 \quad (15)$$

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,

$$\sigma(xr)_{it} = (\log(xr_{it}) - \log(xr_{it-1}))^2 \quad (16)$$

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 associated 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. Recently, [Grechyna \(2017\)](#) 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 \(2013\)](#).²¹ 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 ,

$$\sigma(gov)_{it} = \left(\frac{gov_{it} - gov_{it-1}}{gov_{it-1}} \right)^2 \quad (17)$$

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.²²

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,

$$\sigma(int)_{it} = \left(\frac{int_{it} - int_{it-1}}{int_{it-1}} \right)^2 \quad (18)$$

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

²¹The share of government consumption is obtained from the Penn World Table 9.0.

²²There is ample empirical literature examining the impact of monetary policy shock on output, see surveys in [Christiano et al. \(1999\)](#) and [Bagliano and Favero \(1998\)](#).

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.²³ We then measure volatility in TFP as the square growth rate of TFP,

$$\sigma(TFP)_{it} = \left(\frac{TFP_{it} - TFP_{it-1}}{TFP_{it-1}} \right)^2 \quad (19)$$

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 drivers of output volatility at the global level. Accordingly, the output volatility model is defined as

$$\sigma_{it} = \rho\sigma_{it-1} + \sigma(x_k)_{it}\beta^k + \mu_t + \alpha_i + v_{it}, \quad (20)$$

where σ_{it} is the quarterly average volatility of economic growth in country i at year t , as obtained with the methodology proposed in Section 2, and shown in figures A4-A6. 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 test to assess the reliability of our results. The term $\sigma(x_k)_{it}$ includes a set of potential determinants 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

²³For a detailed description, see Feenstra et al. (2015).

the disturbance term.²⁴ 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.²⁵ 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 a determinant, which can be interpreted as the probability that a particular regressor belongs to the true output volatility model. 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 Results

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 determinant 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 determinants are exchange rate volatility and trade openness. Although our results cannot be interpreted in a causal sense due to simultaneity problems we find that exchange rate volatility, is positively associated with output volatility, while trade openness is negatively related with output volatility as shown by the posterior mean, see column 2. In particular, a one

²⁴Malik and Temple (2009) find using a BMA approach that remote countries suffer greater output volatility. Malik and Temple (2009) focuses on time invariant determinants of volatility using cross section while our paper analyses the determinants of volatility in the short-run.

²⁵We also consider a beta-binomial prior for the model space and different forms of the hyperparameter g in the robustness section.

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 \(2007\)](#)). 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.²⁶ [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 determinants of output volatility. First, we present results for an analysis using an additional 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 : 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 A7](#) of the Online Appendix, show that the main findings are robust to the specification of the model and hyperparameter priors. The most robust determinants of fluctuations in business cycle synchronization, in the static and dynamic models, are the same regardless of the model and hyperparameter priors. Second, we also check if our results hold using other methods to deal with model uncertainty. We use the least squares (WALS) method introduced by [Magnus et al. \(2010\)](#), the rule of

²⁶We also consider specifications with two lags of the output volatility, but the posterior inclusion probability of the second lag was very low.

thumb is that a 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 determinants are exchange rate volatility and trade openness. These determinants are the same as those found using the BMA approach.

Finally, we attempt to account for the simultaneity problem between output volatility and its determinants by using an IV-BMA approach. In particular, we deal with simultaneity problems by regressing each determinant on their second and third lags to purge off contemporaneous correlation with business cycle volatility, i.e. we use lags of the determinants as instrumental variables in line with ample literature in empirical macroeconomics. We then apply our BMA strategy on the predicted determinants. The results presented in Table 4 shows that once we account for simultaneity issues between the determinant and business cycle volatility the only robust drivers of business cycle volatility are its lag and trade openness. The results show that a one standard deviation increases in trade openness leads to a decline in output volatility of 0.33 standard deviations.

Overall, the most robust factor of output volatility are trade openness and exchange rate volatility. However, the latter is not a relevant explanatory factor once we account for endogeneity, suggesting that exchange rate and business cycle volatilities are simultaneously determined.

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. Four main results emerge from the analysis. First, GDP growth across the main world economies 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, we uncover an asymmetric propagation pattern of macro volatility

shocks in that unexpected global developments affect regional ones, but not viceversa, moreover, volatility shocks are propagated through the global component and not directly from one region to another. Fourth, the most robust explanatory factor of changes in output volatility worldwide is found to be the level of trade openness.

References

- Adrian, T., N. Boyarchenko, and D. Giannone (2018). Vulnerable growth. *American Economic Review* (Forthcoming). [2](#)
- Alizadeh, S., M. W. Brandt, and F. X. Diebold (2002). Range-based estimation of stochastic volatility models. *The Journal of Finance* *57*(3), 1047–1091. [4.1](#)
- Andrés, J., R. Doménech, and A. Fatás (2008). The stabilizing role of government size. *Journal of Economic Dynamics and Control* *32*(2), 571–593. [5](#), [4.1](#)
- Bagliano, F. C. and C. A. Favero (1998). Measuring monetary policy with var models: An evaluation. *European Economic Review* *42*(6), 1069–1112. [22](#)
- Bai, J. and P. Wang (2015). Identification and bayesian estimation of dynamic factor models. *Journal of Business & Economics Statistics* *33*(2), 221–240. [2](#), [11](#), [12](#), [18](#)
- Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics* *131*(4), 1593–1636. [1](#)
- Bañbura, M., D. Giannone, and M. Lenza (2015). Conditional forecasts and scenario analysis with vector autoregressions for large cross-sections. *International Journal of Forecasting* *31*(3), 739–756. [A.1](#)
- Blanchard, O. and J. Simon (2001). The long and large decline in u.s. output volatility. *Brookings Papers on Economic Activity* (1), 135–164. [1](#)
- Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives* *28*(2), 153–76. [3](#)
- Buch, C. M., J. Döpke, and C. Pierdzioch (2005). Financial openness and business cycle volatility. *Journal of International Money and Finance* *24*(5), 744–765. [1](#)
- Carriero, A., T. Clark, and M. Marcellino (2018). Measuring uncertainty and its impact on the economy. *Review of Economics and Statistics* Forthcoming. [1](#)
- Carter, C. and R. Kohn (1994). On gibbs sampling for state space models. *Biometrika* *81*(2), 541–553. [A.1](#)
- Cavallo, E. A. (2008). Output volatility and openness to trade: a reassessment. *Economia* *9*(1), 105–138. [4.3](#)
- Cavallo, E. A. and J. A. Frankel (2008). Does openness to trade make countries more vulnerable to sudden stops, or less? using gravity to establish causality. *Journal of International Money and Finance* *27*(8), 1430–1452. [4.3](#)
- Chan, J. and C. Hsiao (2001). Estimation of stochastic volatility models with heavy tails and serial dependence. In *Bayesian Inference in the Social Sciences*, Volume 2014, pp. 159–180. John Wiley & Sons, New York. [A.1](#)
- Christiano, L. J., M. Eichenbaum, and C. L. Evans (1999). Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics* *1*, 65–148. [22](#)
- Del Negro, M. and C. Otrok (2008). Dynamic factor models with time-varying parameters: Measuring changes in international business cycles. *Federal Bank of New York Staff Reports* *326*. [13](#)
- Ductor, L. and D. Leiva-Leon (2016). Dynamics of global business cycle interdependence. *Journal of International Economics* *102*, 110–127. [1](#), [13](#), [4.2](#)
- Evans, M. D. and V. V. Hnatkovska (2014). International capital flows, returns and world financial integration. *Journal of International Economics* *92*(1), 14–33. [4.1](#)
- Everaert, G. and M. Iseringhausen (2018). Measuring the international dimension of output volatility. *Journal of International Money and Finance* *81*, 20–39. [1](#), [1](#)

- Fatás, A. and I. Mihov (2001). Government size and automatic stabilizers: international and intranational evidence. *Journal of International Economics* 55(1), 3–28. [1](#), [4.1](#)
- Fatás, A. and I. Mihov (2003). The case for restricting fiscal policy discretion. *The Quarterly Journal of Economics* 118(4), 1419–1447. [1](#), [4.1](#)
- Fatas, A. and I. Mihov (2013). Policy volatility, institutions, and economic growth. *Review of Economics and Statistics* 95(2), 362–376. [4.1](#)
- Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015). The next generation of the penn world table. *American Economic Review* 105(10), 3150–82. [23](#)
- Fernandez, C., E. Ley, and M. F. Steel (2001). Benchmark priors for bayesian model averaging. *Journal of Econometrics* 100(2), 381–427. [4.2](#)
- Fernández-Villaverde, J., P. Guerrón-Quintana, K. Kuester, and J. Rubio-Ramírez (2015). Fiscal volatility shocks and economic activity. *The American Economic Review* 105(11), 3352–3384. [4.1](#)
- Fernández-Villaverde, J., P. Guerrón-Quintana, J. F. Rubio-Ramírez, and M. Uribe (2011). Risk matters: The real effects of volatility shocks. *American Economic Review* 101(6), 2530–61. [4.1](#)
- Gadea, M. D., A. Gomez-Loscoc, and G. Perez-Quiros (2018). Great moderation and great recession: From plain sailing to stormy seas? *International Economic Review* (Forthcoming). [3.1](#)
- Gali, J. (1994). Government size and macroeconomic stability. *European Economic Review* 38(1), 117–132. [4.1](#)
- Giovanni, J. d. and A. A. Levchenko (2009). Trade openness and volatility. *The Review of Economics and Statistics* 91(3), 558–585. [1](#), [4.1](#), [4.3](#)
- Giovanni, J. d. and A. A. Levchenko (2012). Country size, international trade, and aggregate fluctuations in granular economies. *Journal of Political Economy* 120(6), 1083–1132. [4](#)
- Grechyna, D. (2017). Mandatory spending, political polarization and macroeconomic volatility. *Mimeo*. [4.1](#)
- Kim, C.-J. and C. Nelson (1999). Has the u.s. economy become more stable? a bayesian approach based on a markov-switching model of the business cycle. *The Review of Economics and Statistics* 81(4), 608–616. [1](#)
- Kim, S., N. Shepard, and S. Chib (1998). Stochastic volatility: Likelihood inference and comparison with arch models. *The Review of Economic Studies* 65(3), 361–393. [11](#), [14](#), [A.1](#), [A.1](#)
- Koop, G., H. Pesaran, and S. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74(1), 119–147. [19](#)
- Koopman, S. J. and A. Harvey (2003). Computing observation weights for signal extraction and filtering. *Journal of Economic Dynamics and Control* 27(7), 1317–1333. [3.1](#), [14](#), [??](#)
- Kose, M. A. (2002). Explaining business cycles in small open economies: How much do world prices matter? *Journal of International Economics* 56(2), 299–327. [1](#)
- Kose, M. A., C. Otrok, and C. Whiteman (2003). International business cycles: World, region and country-specific factors. *American Economic Review* 93(4), 1216–1239. [16](#)
- Kose, M. A., E. S. Prasad, and M. E. Terrones (2006). How do trade and financial integration affect the relationship between growth and volatility? *Journal of international Economics* 69(1), 176–202. [4.1](#)
- Kraay, A. and J. Ventura (2007). Comparative advantage and the cross-section of business cycles. *Journal of the European Economic Association* 5(6), 1300–1333. [4.1](#), [4.3](#)
- Kydland, F. E. and E. C. Prescott (1982). Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society*, 1345–1370. [4.1](#)

- Lane, P. R. and G. M. Milesi-Ferretti (2007). The external wealth of nations mark ii: Revised and extended estimates of foreign assets and liabilities, 1970–2004. *Journal of international Economics* 73(2), 223–250. [4.1](#), [20](#)
- Ley, E. and M. F. Steel (2009). On the effect of prior assumptions in bayesian model averaging with applications to growth regression. *Journal of applied econometrics* 24(4), 651–674. [4.3](#)
- Ley, E. and M. F. Steel (2012). Mixtures of g-priors for bayesian model averaging with economic applications. *Journal of Econometrics* 171(2), 251–266. [4.3](#)
- Magnus, J. R., O. Powell, and P. Prüfer (2010). A comparison of two model averaging techniques with an application to growth empirics. *Journal of econometrics* 154(2), 139–153. [4.2](#), [4.3](#)
- Malik, A. and J. R. Temple (2009). The geography of output volatility. *Journal of Development Economics* 90(2), 163–178. [1](#), [24](#)
- Mendoza, E. (1995). The terms of trade, the real exchange rate, and economic fluctuations. *International Economic Review* 36(1), 101–137. [1](#)
- Mumtaz, H. and F. Zanetti (2013). The impact of the volatility of monetary policy shocks. *Journal of Money, Credit and Banking* 45(4), 535–558. [4.1](#)
- Newbery, D. M. and J. E. Stiglitz (1984). Pareto inferior trade. *The Review of Economic Studies* 51(1), 1–12. [4.1](#)
- Obstfeld, M. and K. Rogoff (1976). Exchange rate dynamics redux. *Journal of Political Economy* 103(3), 624–660. [1](#)
- Pérez-Quirós, G. and M. McConnell (2000). Output fluctuations in the united states: What has changed since the early 1980’s? *American Economic Review* 90(5), 1464–1476. [1](#)
- Prescott, E. C. (1986). Theory ahead of business-cycle measurement. In *Carnegie-Rochester conference series on public policy*, Volume 25, pp. 11–44. Elsevier. [4.1](#)
- Primiceri, G. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies* 72(3), 821–852. [A.1](#)
- Rebelo, S. (2005). Real business cycle models: past, present and future. *The Scandinavian Journal of Economics* 107(2), 217–238. [4.1](#)
- Stock, J. and M. Watson (2005). Understanding changes in international business cycle dynamics. *Journal of the European Economic Association* 3(5), 968–1006. [1](#), [1](#)
- Sutherland, A. (1996). Financial market integration and macroeconomic volatility. *The Scandinavian Journal of Economics*, 521–539. [1](#)
- Walsh, C. E. (1993). What caused the 1990-1991 recession? *Economic Review. Federal Reserve Bank of San Francisco* (2). [3.1](#)

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: Determinants of BC 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

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: Determinants of BC 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

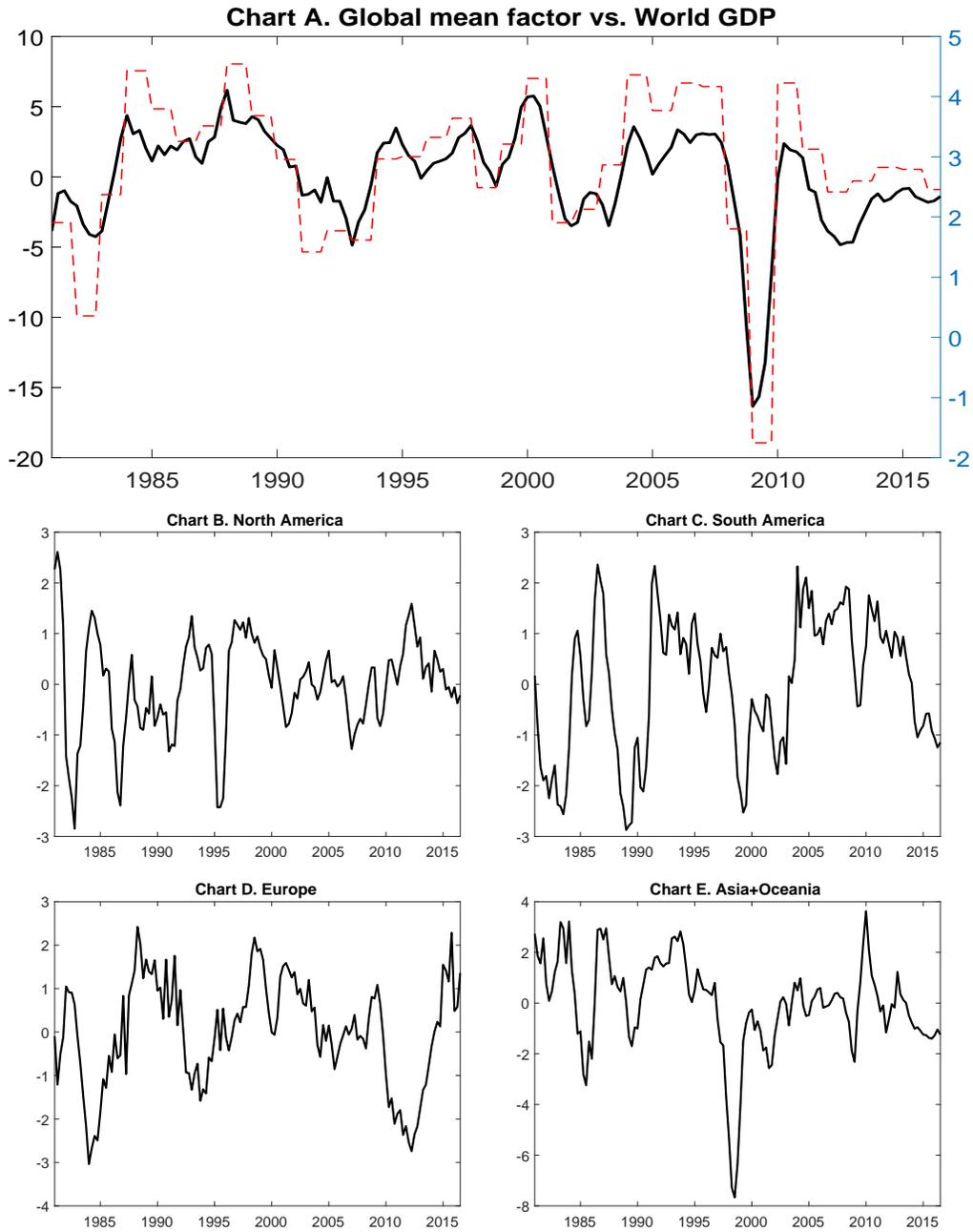
Column 1 presents the posterior inclusion probability. Column 2 shows the posterior mean. Column 3 reports the posterior standard deviation. The sample includes 37 countries and 902 observations. The dependent variable is economic growth volatility. The results are obtained by using a uniform prior for 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: Determinants of BC 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

The explanatory variables are the predicted values of regressing the determinants 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 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, $g = 1/\max(N, K^2)$.

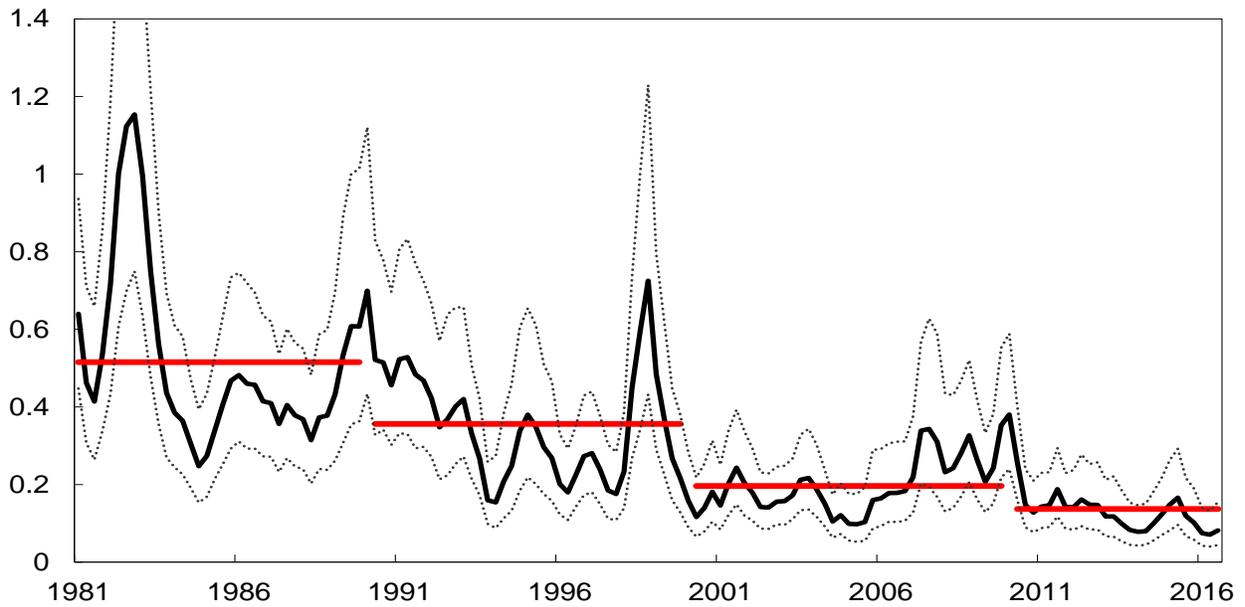
Figure 2: Global and regional mean factors



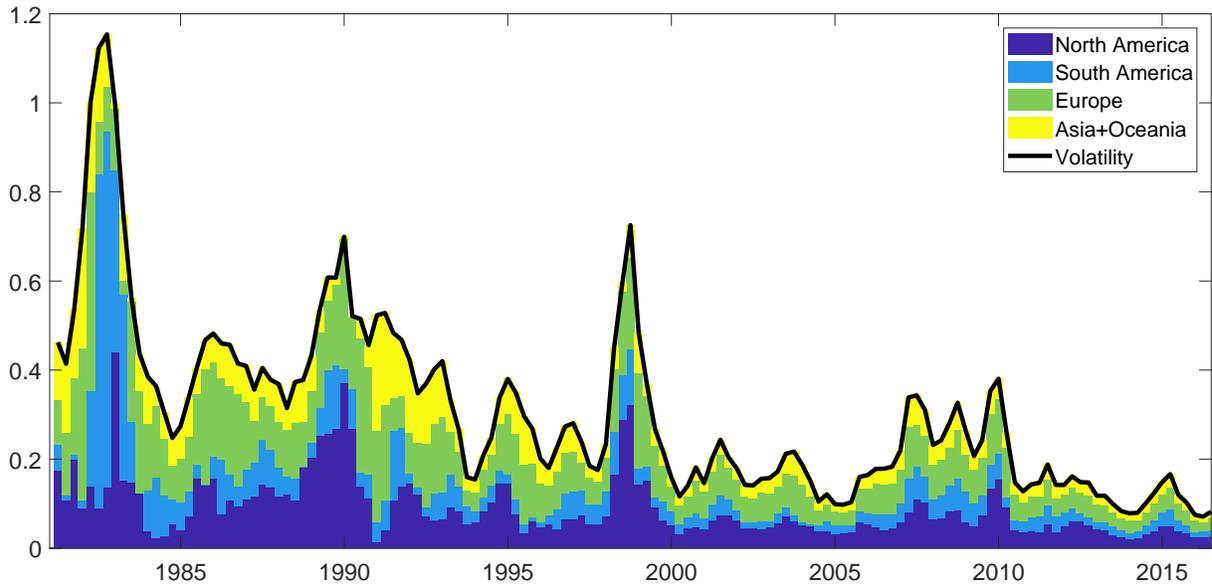
Note: Chart A plots the global mean factor (solid black line) aligned to the left axis and the world real GDP (dashed red line) aligned with the right axis. Charts B, C, D, and E plot the corresponding regional mean factors.

Figure 3: Global volatility

(a) Estimated global volatility factor

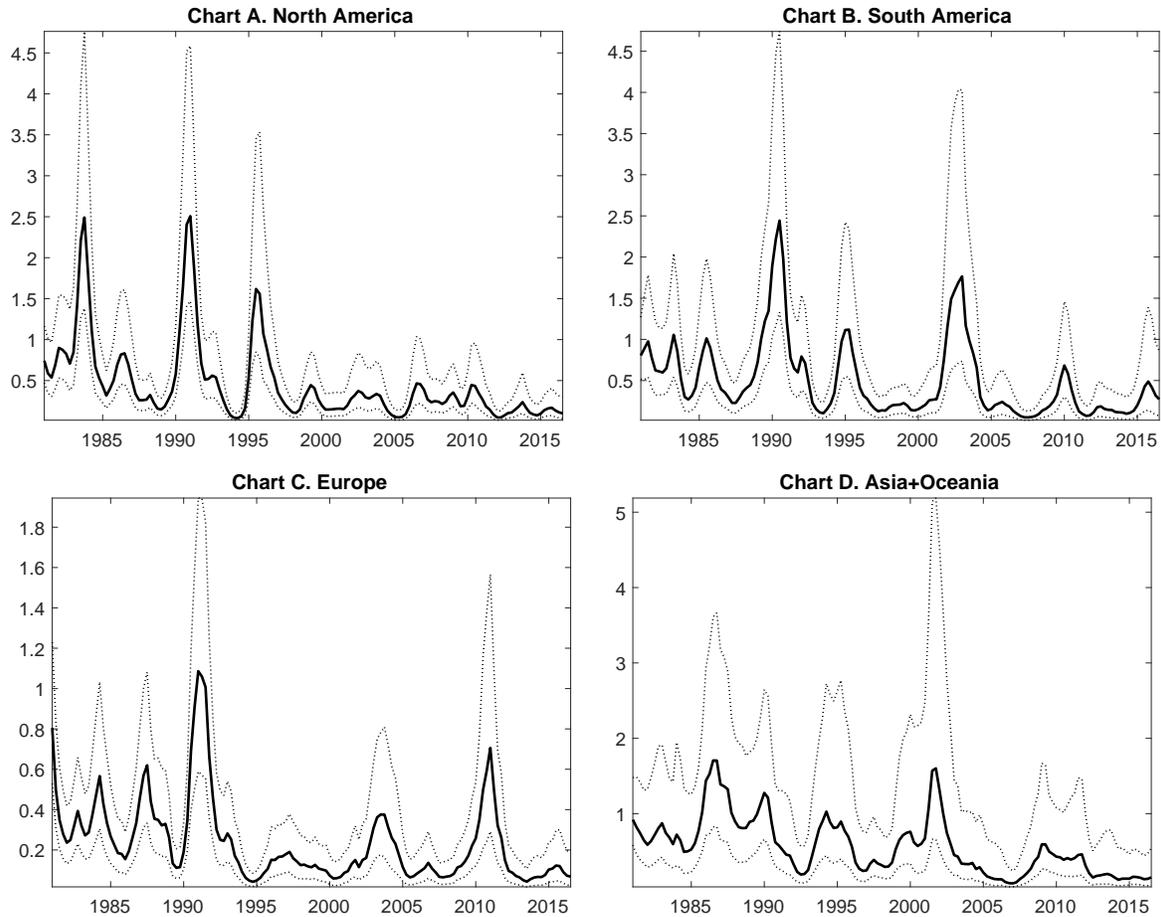


(b) Historical data decomposition of the global volatility factor



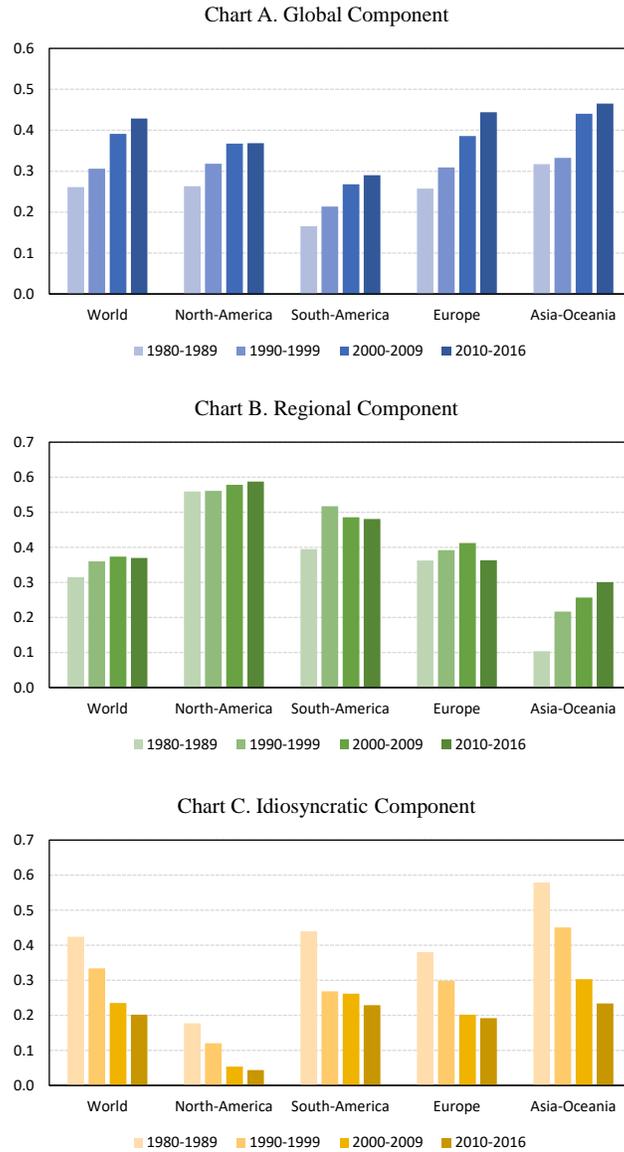
Note: Chart A plots the global volatility factor. The solid line represents the median of the posterior distribution and the dotted lines make reference to the 68 percent credible set of the posterior distribution. Red lines make reference to the average volatility over the corresponding period. Chart 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 factors



Note: Charts A, B, C, and D plot the volatility factor corresponding to the different regions under study. Solid lines represent the median of the corresponding distribution and dotted lines make reference to the 68 percent credible set of the posterior distribution.

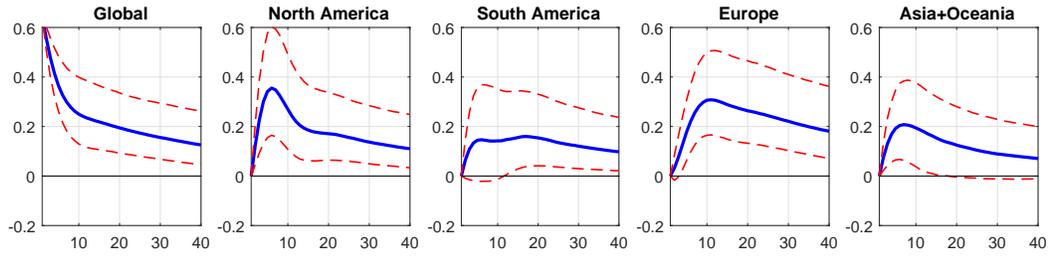
Figure 5: Contribution of volatility components across regions and over time



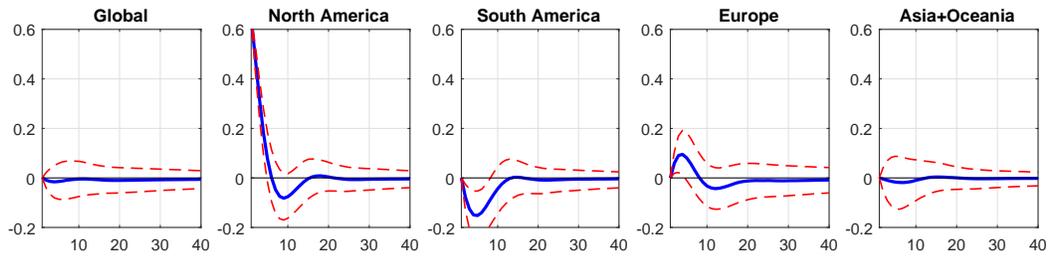
Note: Chart A, B and C plot the average contribution of the global, regional and idiosyncratic components, respectively, on output volatility. For ease of exposition, each bar in each chart reports the average contribution across countries in a given region and across periods in a given decade.

Figure 6: Propagation pattern of aggregate volatility shocks

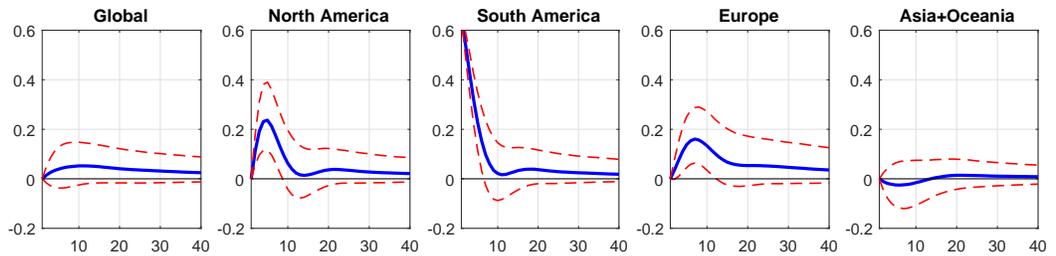
(a) Responses to a shock in global volatility



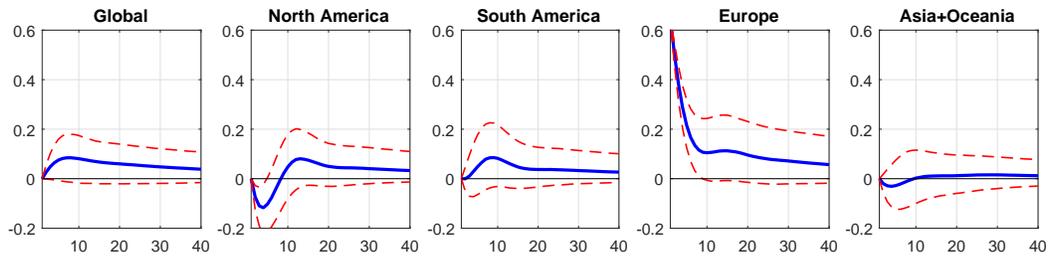
(b) Responses to a shock in the volatility of North America



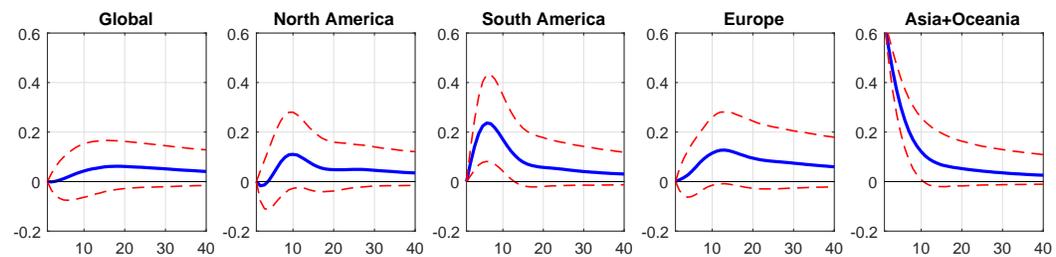
(c) Responses to a shock in the volatility of South America



(d) Responses to a shock in the volatility of Europe

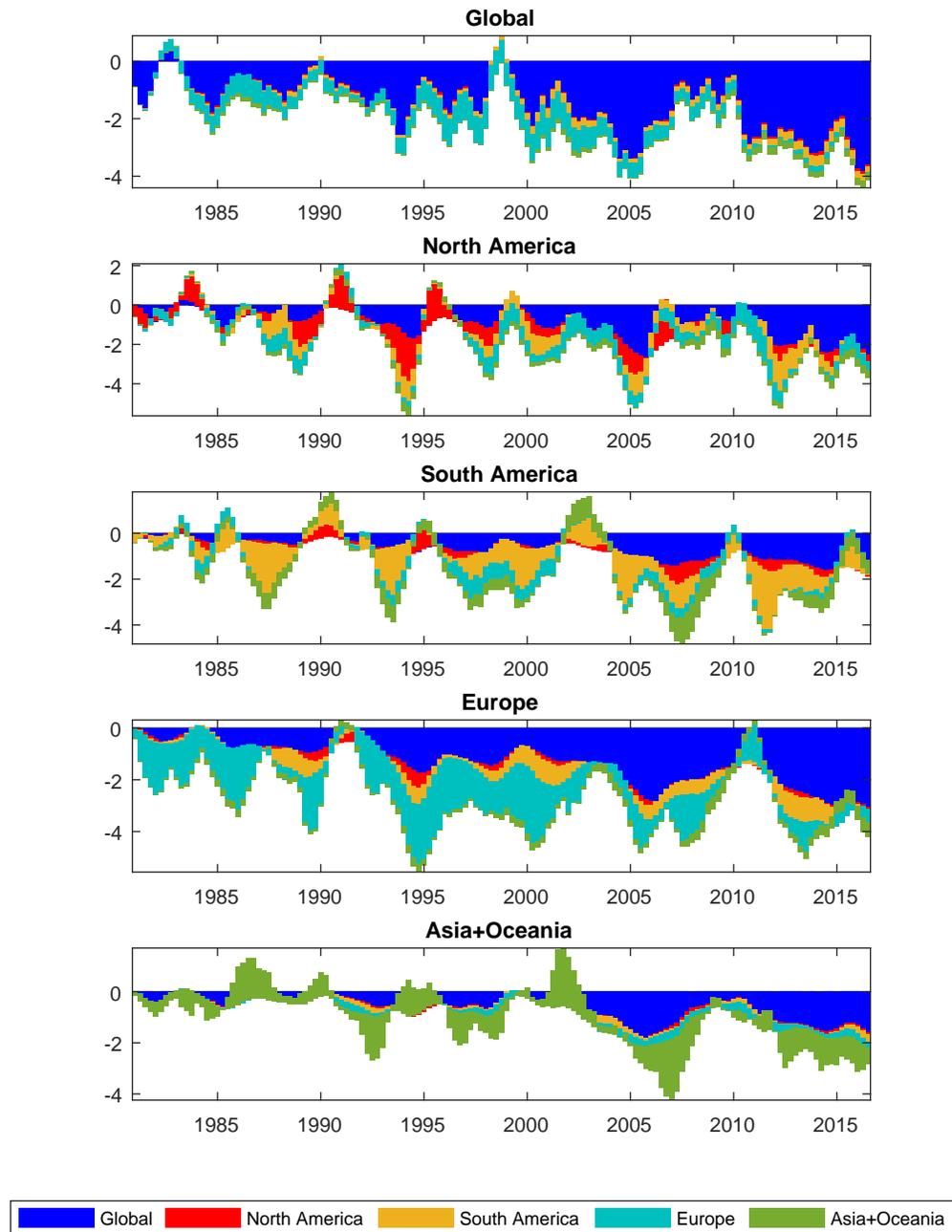


(e) Responses to a shock in the volatility of Asia+Oceania



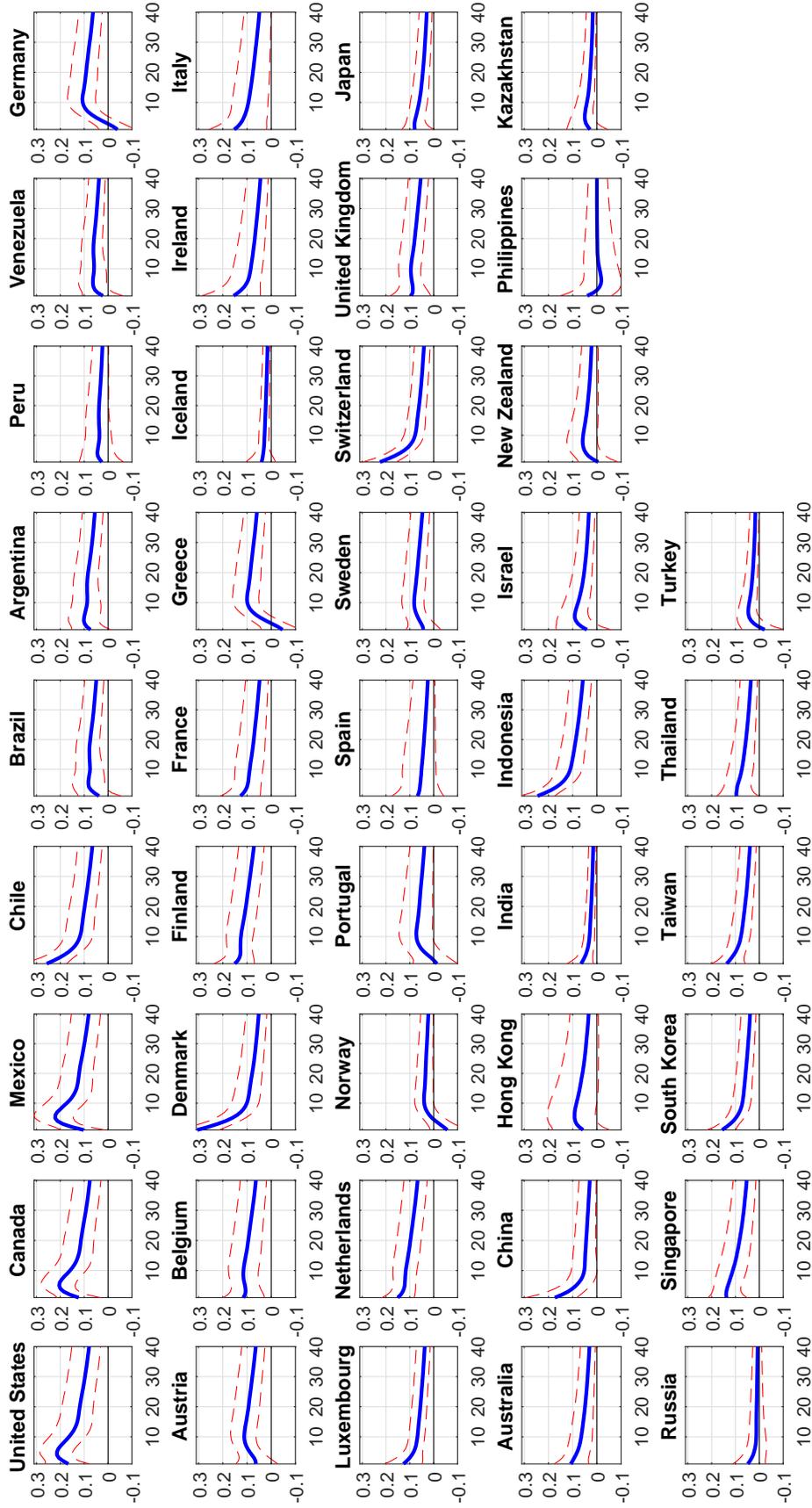
Note: The figure plots the responses of the global and regional volatilities to a unit shock of the underlying factor. Blue solid lines represent the median of the corresponding posterior distribution, and red dashed lines make reference to the 68th confidence set.

Figure 7: 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 8: 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.

A Online Appendix

A.1 Estimation Algorithm

The proposed algorithm relies on Bayesian methods and uses the Gibbs 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 $\tilde{Y}_T = \{u_{1,1,t}, \dots, u_{n_1,t}, \dots, u_{1_K,t}, \dots, u_{n_K,t}\}_{t=1}^T$, $\tilde{g}_T = \{g_t\}_{t=1}^T$, $\tilde{h}_{k,T} = \{h_{k,t}\}_{t=1}^T$, $\tilde{\chi}_{i_k,T} = \{\chi_{i_k,t}\}_{t=1}^T$, and $\tilde{d}_{i_k,T} = \{d_{i_k,t}\}_{t=1}^T$, where $d_{i_k,t}$ is an auxiliary random variable used to define the state of the time-varying volatility, for $i_k = 1, 2, \dots, n_k$ and $k = 1, 2, \dots, K$. The algorithm consists of the following steps:

- **Step 1:** Sample $\tilde{d}_{i_k,T}$ from $P(\tilde{d}_{i_k,T} | \gamma_{i_k}, \lambda_{i_k}, \tilde{g}_T, \tilde{h}_{k,T}, \tilde{\chi}_{i_k,T}, \tilde{Y}_T)$

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

$$u_{i_k,t}^* = \gamma_{i_k} g_t + \lambda_{i_k} h_{k,t} + \chi_{i_k,t} + \varepsilon_{i_k,t}^*, \quad (21)$$

where $u_{i_k,t}^* = \ln(u_{i_k,t}^2)$ and $\varepsilon_{i_k,t}^* = \ln(\varepsilon_{i_k,t}^2)$.²⁷ Then, to generate draws of the auxiliary variables $\tilde{d}_{i_k,T}$ we follow the line of [Kim et al. \(1998\)](#) and [Primiceri \(2005\)](#), and generate independent draws for each i_k from the discrete density,

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

where m_κ and v_κ^2 are known for $\kappa = 1, 2, \dots, 7$, see [Kim et al. \(1998\)](#).

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

To sample the autoregressive coefficient we use a normal prior distribution, $N(\underline{\varphi}, \underline{\varsigma})$, with $\underline{\varphi} = 0.95$ and $\underline{\varsigma} = 0.1$, and generate draws from the posterior distribution

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

²⁷In practice we set $u_{i_k,t}^* = \ln(u_{i_k,t}^2 + c)$, with c being the offset constant to avoid numerical problems when $u_{i_k,t}^*$ is close to zero (set to 10^{-4}).

where

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

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 $\sigma_{i_k}^2$ from $P(\sigma_{i_k}^2 | \tilde{\chi}_{i_k,T}, \varphi_{i_k}, \tilde{Y}_T)$

To sample the variance of the idiosyncratic volatility innovations we use an inverse Gamma prior distribution, $IG(\underline{\eta}, \underline{v})$, with $\underline{\eta} = 10$ 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 $P(\gamma_{i_k}, \lambda_{i_k} | \tilde{g}_T, \tilde{h}_{k,T}, \tilde{\chi}_{i_k,T}, \tilde{d}_{i_k,T}, \tilde{Y}_T)$

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

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

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 $i_k = 1, 2, \dots, n_k$ and $k = 1, \dots, K$.

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

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,

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

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,

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

where

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

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

- **Step 6:** Sample $\tilde{g}_T, \tilde{h}_{k,T}$ and $\tilde{\chi}_{i_k,T}$ from $P(\tilde{g}_T, \tilde{h}_{k,T}, \tilde{\chi}_{i_k,T} | \gamma_{i_k}, \lambda_{i_k}, \Phi, \Sigma, \varphi_{i_k}, \sigma_{i_k}^2, \tilde{d}_{i_k,T}, \tilde{Y}_T)$

The volatility factor model, in equations (2)-(5), is casted in a state space representation

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 $d_{i_k,t} \in \{1, 2, \dots, 7\}$, where

$$(\varepsilon_{i_k,t}^* | d_{i_k,t} = \kappa) \sim N(m_\kappa, v_\kappa^2),$$

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

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

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 v_κ^2 are known, since they are calibrated in [Kim et al. \(1998\)](#).

Consequently, conditional on $d_{i,t}$, equations (22)-(23) 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.

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.

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 devia-

tion, $\sigma_{i_k,t} = e^{\frac{1}{2}F_{i_k,t}}$, 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.

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

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

A.3 Additional Tables and Figures

Table A1: Determinants of BC 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

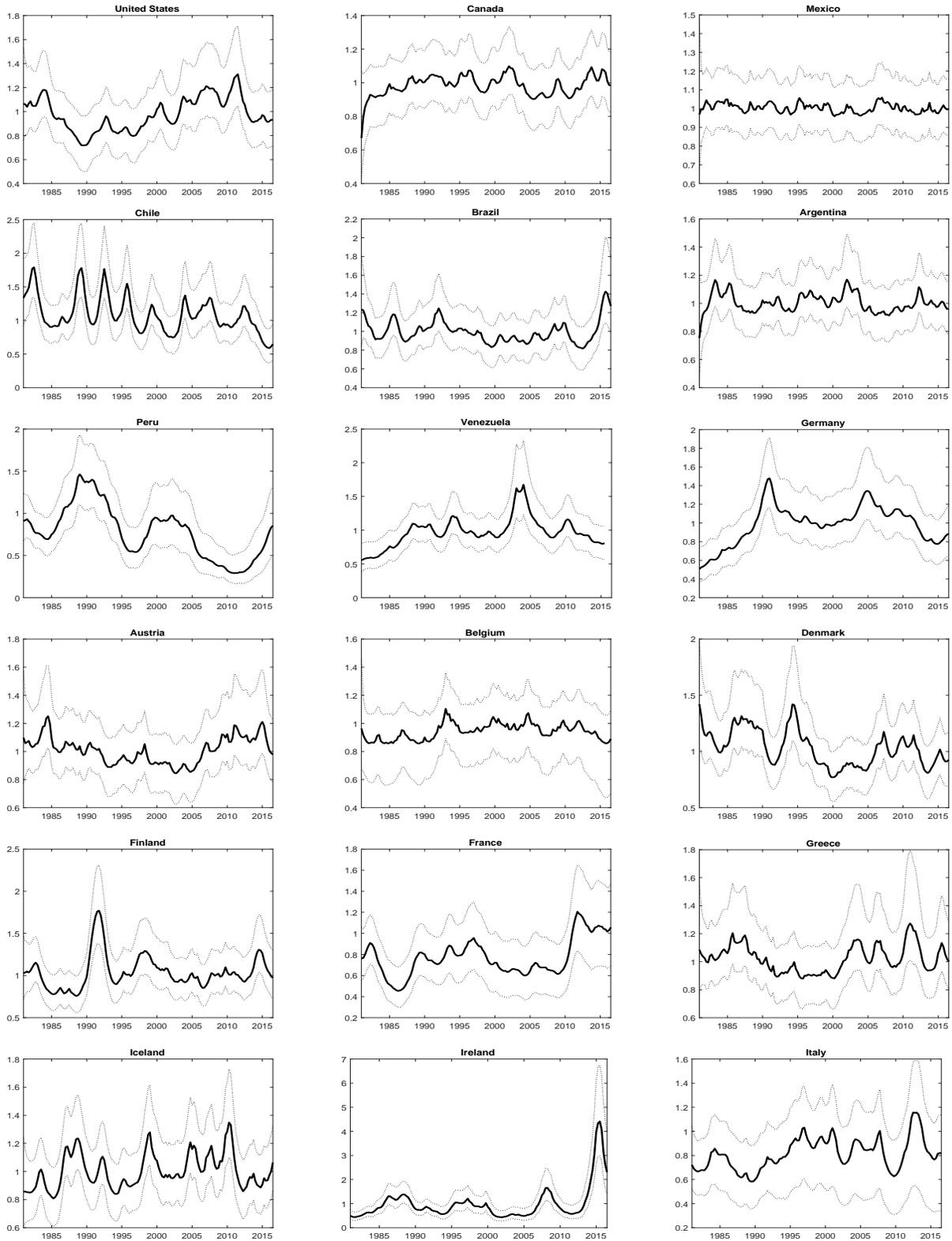
The sample includes 53 countries and 1185 observations. The dependent variable is economic growth volatility.

Table A2: Determinants of BC 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	-0.629

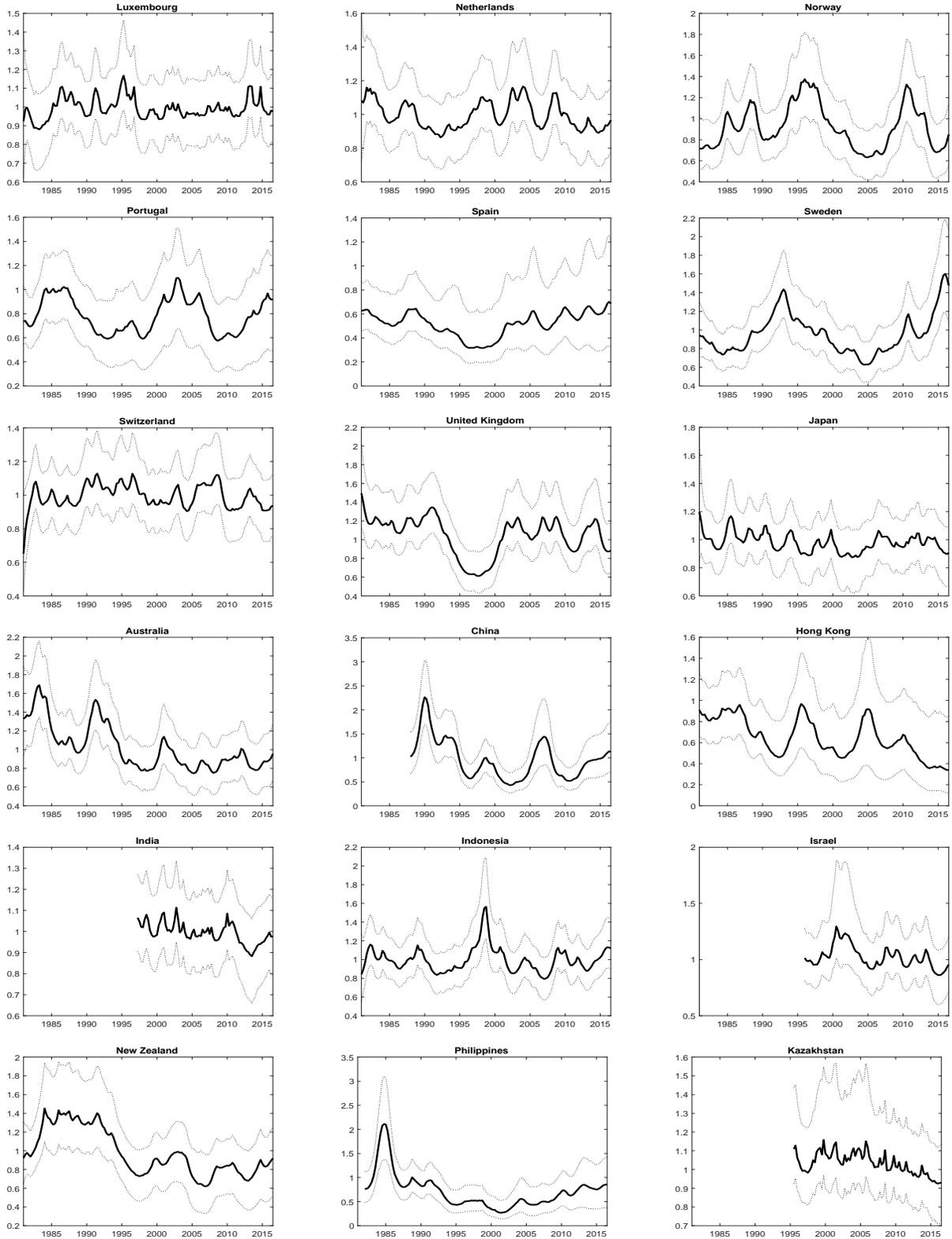
The sample includes 53 countries and 1130 observations. The dependent variable is economic growth volatility.

Figure A1: Idiosyncratic volatility



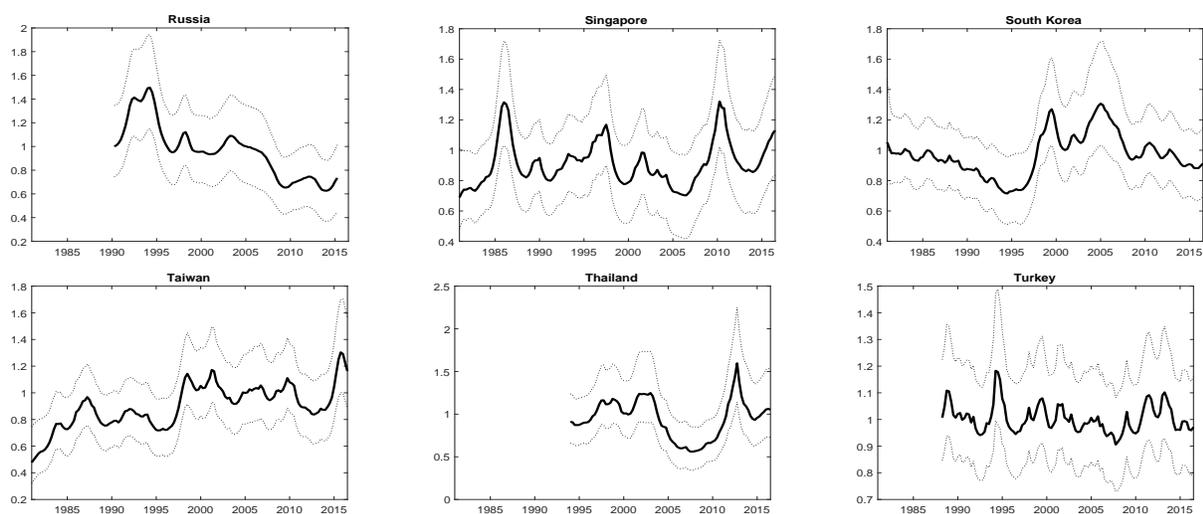
Note: The figure plots the estimated time-varying idiosyncratic volatility for each country. Solid lines make reference the median of the corresponding posterior distribution. Dotted lines refer to the 68 percent credible set of the posterior distribution.

Figure A2: Idiosyncratic volatility (cont.)



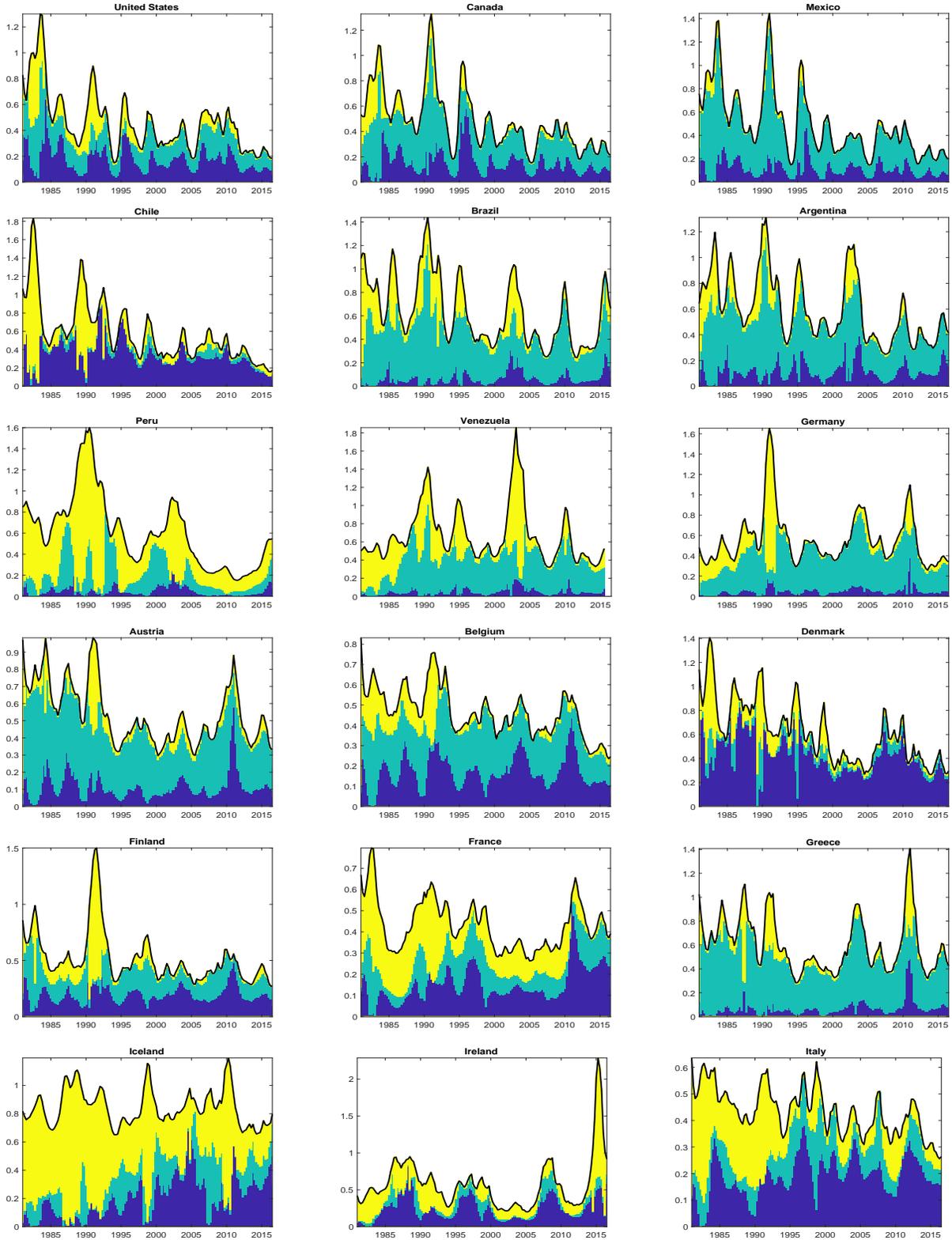
Note: The figure plots the estimated time-varying idiosyncratic volatility for each country. Solid lines make reference the median of the corresponding posterior distribution. Dotted lines refer to the 68 percent credible set of the posterior distribution.

Figure A3: Idiosyncratic volatility (cont.)



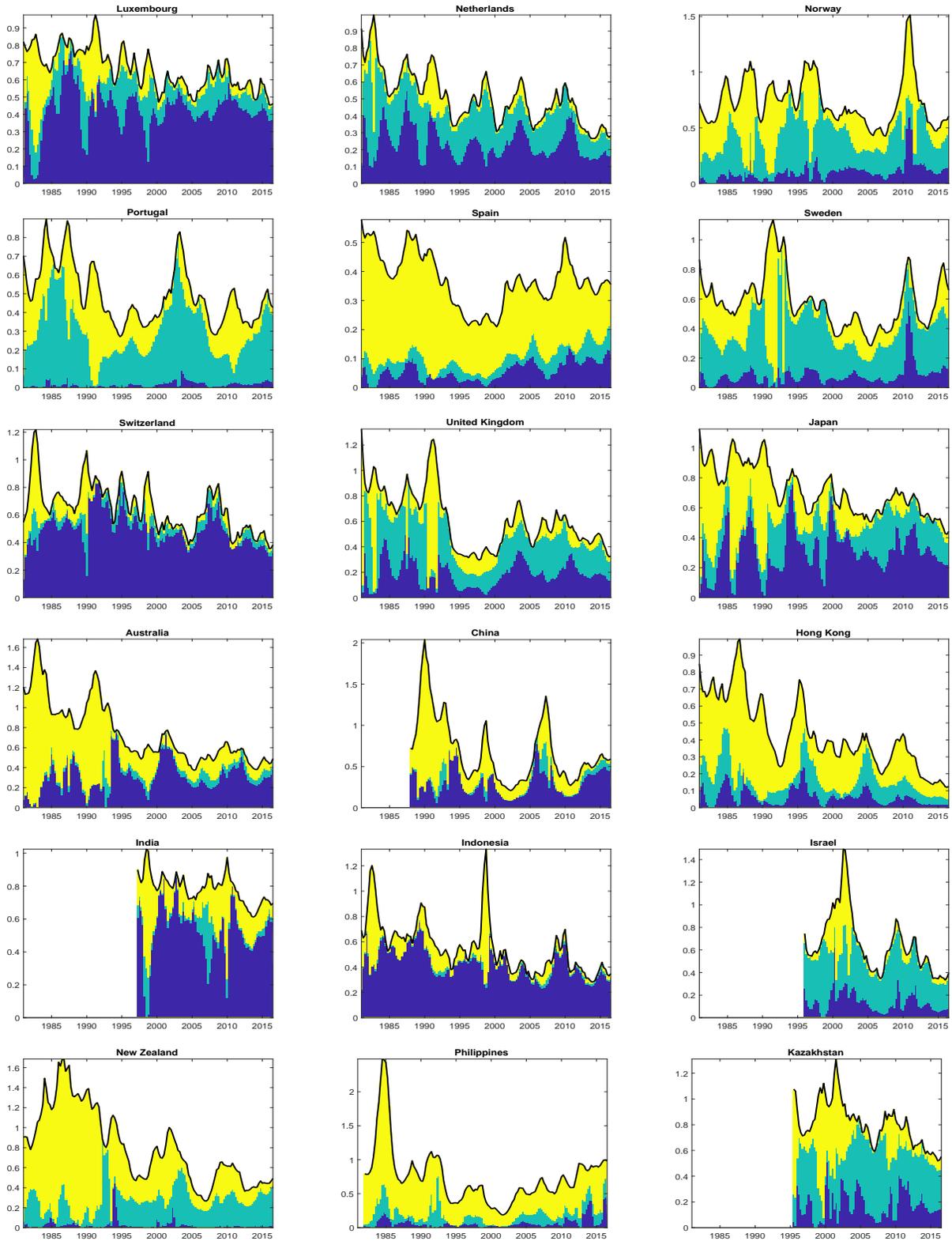
Note: The figure plots the estimated time-varying idiosyncratic volatility for each country. Solid lines make reference the median of the corresponding posterior distribution. Dotted lines refer to the 68 percent credible set of the posterior distribution.

Figure A4: Historical volatility decomposition



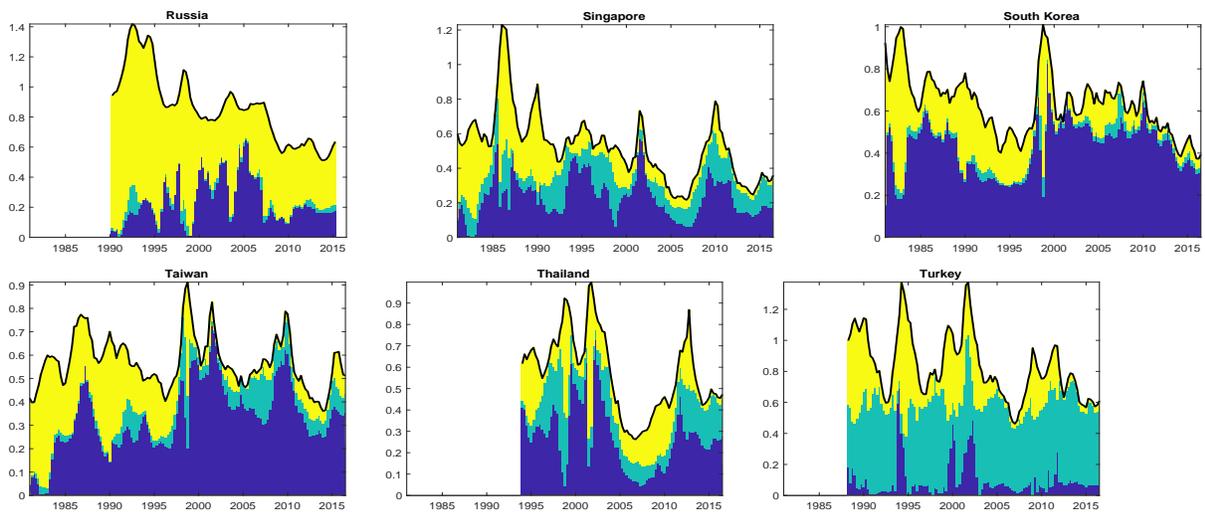
Note: The figure plots the estimated time-varying volatility for each country. Black lines plot the estimated total volatility. Blue, green and yellow areas correspond to the global, regional and idiosyncratic components, respectively.

Figure A5: Historical volatility decomposition (cont.)



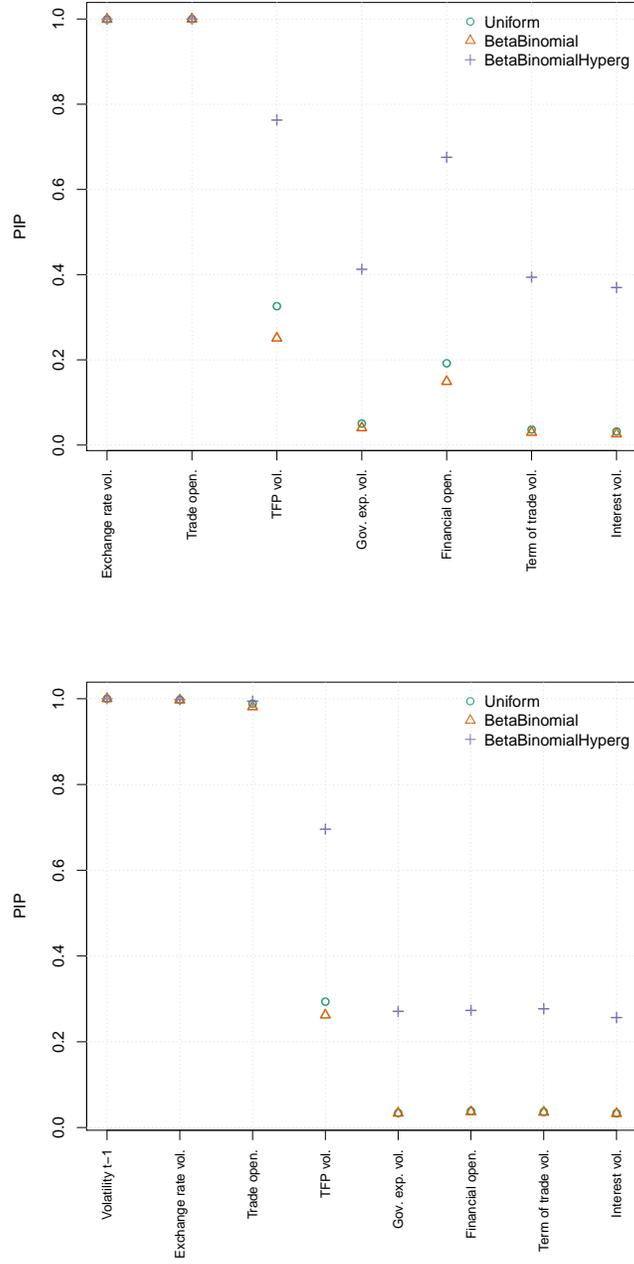
Note: The figure plots the estimated time-varying volatility for each country. Black lines plot the estimated total volatility. Blue, green and yellow areas correspond to the global, regional and idiosyncratic components, respectively.

Figure A6: 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 A7: Determinants of volatility: PIP using different priors



Note: The bottom plot includes lagged volatility as regressor.