The evolving impact of global, region-specific and country-specific uncertainty*

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Abstract

We develop a dynamic factor model with time-varying parameters and stochastic volatility, estimate it using a large panel of macroeconomic and financial data for 22 countries and decompose the variance of each variable in terms of contributions from uncertainty common to all countries ('global uncertainty'), region-specific uncertainty and country-specific uncertainty. Among other findings, the estimates suggest that global uncertainty plays a primary role in explaining the volatility of inflation, interest rates and stock prices, although to a varying extent over time, while all uncertainty components are found to play a non-negligible role for real economic activity, credit and money for most countries.

JEL Codes: C15,C32, E32

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1 Introduction

After a period characterised by increasing macroeconomic stability observed in several advanced economies from the mid- to late 1980s onwards, known as the Great Moderation, the world economy has experienced a substantial increase in financial and macroeconomic volatility. Such heightened volatility resulted from the global financial crisis starting in the summer of 2007, a major global recession between 2008 and 2009 and regional crises such as the sovereign debt crisis in Europe starting in 2010. The prolonged adverse effects of these developments, despite the implementation of several unconventional monetary policy measures by the major central banks around the world, have led to a marked increase in the degree of uncertainty prevailing in several countries, which is likely to be a significant factor behind the slow pace of the recent recoveries observed in several advanced economies.

As a result, the analysis of the role of volatility and uncertainty in the macroeconomy has regained a prominent role in recent years. This is reflected in the publication of several studies on the role of uncertainty shocks during the course of the past decade (see Bloom, 2014, for a recent overview of this literature). Several of these studies conclude that unexpected large changes in uncertainty (or the closely related concepts of risk and volatility) represent an important source of macroeconomic fluctuations (see for example Bloom, 2009, Bloom et al., 2018, and Christiano et al., 2014) and also explain a significant fraction of the contraction in real GDP observed during the latest global recession of 2008-2009, known as the Great Recession (see for example Bloom et al., 2018, and Stock and Watson, 2012).

From a policy perspective, measuring, monitoring and analysing the impact of uncertainty is very important for various reasons. First, uncertainty can affect the macroeconomy through several channels, whether it reflects exogenous factors such as natural disasters or geopolitical turmoil, thus representing a source of macroeconomic fluctuations, or whether it arises as an endogenous response to other macroeconomic forces, such as specific aggregate demand shocks or aggregate supply shocks, thus contributing to amplify their effects. Indeed, heightened uncertainty can transmit through the macroeconomy by affecting spending decisions of households and firms, for example inducing them to postpone consumption and investment, as well as financial markets, for example if expected asset price volatility leads to increased risk premia which are then transmitted to higher cost of credit to families and companies. Second, the degree of macroeconomic uncertainty and volatility may affect the effectiveness of economic policies. For example, slowdowns characterised by a high degree of uncertainty might require a more substantial monetary policy stimulation package as well as a stronger fiscal policy response to support the economy and achieve a desired increase in aggregate demand compared to recessions coinciding with a more muted degree of uncertainty (Aastveit et al., 2017; Ricco et al., 2016). As a result, the assessment of macroeconomic uncertainty is very much at the centre of attention of policymakers, as discussed in speeches of central bankers (Bernanke, 2007; Carney, 2016; Praet, 2015) and in policy articles (ECB, 2016; Haddow et al., 2013; Kose and Terrones, 2012).

Against this background, the purpose of this paper is to provide estimates of common global, common regional and country-specific macroeconomic uncertainty and to assess the economic impact of the associated uncertainty shocks. More precisely, we address the following two questions. Do fluctuations in uncertainty that are common among advanced economies or common to specific regions such as the Euro Area, North-America or Asia matter more for macroeconomic volatility than country-specific uncertainty shocks? Has the relative importance of these different sources of uncertainty changed over time? In order to carry out this investigation, we build a dynamic factor model with time-varying factor loadings and stochastic volatility allowing for the estimation of uncertainty that is common across a large set of advanced economies, uncertainty that is common to specific regions (Euro Area, other European countries, North-America, Asia and Oceania) and country-specific uncertainty. We then calculate the contribution of each of these components to the volatility of a large range of macroeconomic and financial series for each country in the panel. The time-varying factor loadings imply that we can assess if the relative importance of these components has changed over time. This represents an advantage compared to the alternative approach adopted often in the literature which consists first in deriving one estimate of macroeconomic uncertainty and then using it as if it were an observable time series within an econometric model such as a recursive VAR to derive inference on the effects of uncertainty shocks on the economy (see for example Caggiano et al., 2014, Basu and Bundick, 2017, Bachman et al., 2013, and Gilchrist et al., 2014, in addition to several of the above-mentioned papers). As noted by Carriero et al. (2016), such a two-step approach has several limitations, including possible omitted variable bias and non-fundamentalness of the errors, linked to the fact that the second step is typically based on small scale VAR models. Our approach allows to overcome such limitations, as the derivation of the uncertainty measures and the inference on the associated uncertainty shocks are derived within a coherent econometric framework including several variables, thereby increasing the reliability of the estimates. Moreover, to the best of our knowledge, this paper is the first to provide a comprehensive estimate of common macroeconomic uncertainty and its economic impact at regional level, along with corresponding estimates for global common macroeconomic uncertainty and country-specific macroeconomic uncertainty. The analysis is based on a large set of quarterly financial and macroeconomic variables spanning from 1960 to 2016 for 22 OECD countries, including eleven Euro Area economies, five other European countries and six other countries. For each of the 22 countries we consider 20 variables and the sample is completed with 20 additional international variables, some referring to prices of commodities such as oil, gas and gold, while other ones representing a small sample of long time series for selected indicators for a number of emerging economies. Overall, 460 time series are included in the sample. It should be noted that among the different empirical measures or proxies of uncertainty proposed in the literature (see Bloom, 2014, for a detailed discussion and overview), the estimated uncertainty based on our approach can be associated to the category of measures related to the volatility in the data.[1] More precisely, the estimated uncertainty based on our approach is defined as the volatility of shocks (i.e. the unforecastable component) to global, regional and country-specific economic conditions.

The main results of the empirical analysis are the following. First, all the uncertainty measures display significant recurrent fluctuations, with evidence of alternating periods of high and low persistent uncertainty found for most cases. A historical perspective appears to be very informative, showing for example that the most recent temporary but marked increase in macroeconomic uncertainty associated to the global economic and financial crisis of 2008/2009, which can be observed in most estimates of uncertainty (global, for most regions and for most countries), is not unprecedented and indeed often comparable to uncertainty increases emerging during the first half of the 1970s and early 1980s. Second, we find that all uncertainty measures appear to be strongly countercyclical, with periods of marked increased uncertainty often emerging just before or during the vast majority of recessions, and a strong positive correlation of these measures with inflation. Third, the relative importance of the various uncertainty measures in explaining the volatility of the variables considered appears to differ both over time, geographically (across country and re-

[1]As noted by Bloom (2014), the justification for using estimates of uncertainty related to the volatility in the data is associated to the fact that more volatile data tends to be more difficult to forecast. At the same time, it should be recognised that conceptually there can be instances when uncertainty might increase even in the absence of major changes in actual volatility.

gion) and for different variables, but all of them - global uncertainty, region-specific uncertainty and country-specific uncertainty - play a non-negligible role in most cases. Specifically, for real economic activity, credit and money all components appear to be important in most countries, while the volatility of inflation, interest rates and stock prices seems to be driven primarily by the global common uncertainty component in most countries, although to a varying extent over time. By contrast, region-specific uncertainty drives most of the exchange rate volatility especially for all Euro Area countries and for the countries in North-America and Oceania, while for the other countries either country-specific or idiosyncratic uncertainty prevail in importance.

This paper is closely related to various recent developments in the empirical macroeconomic literature. The aim of the paper is similar in spirit to the work on international business cycles (see for example Kose et al., 2003) and the research on inflation co-movements (see Mumtaz and Surico, 2012) that has sought to establish the importance of a common factor in explaining the movements in these variables. We focus on comovement in the second moment and show that this feature is important. Our analysis is also closely related to the recent literature that has focused on estimating proxies for economic uncertainty for the purposes of monitoring its evolution and deriving estimates of their impact on the economy. Much of this literature has focused on deriving uncertainty measures for the US economy (see for example Carriero et al., 2015, Carriero et al., 2016, and Jurado et al., 2015, which also include an overview of this literature), although a number of recent studies have also provided estimates of global uncertainty along with related country-specific uncertainty measures (Cesa-Bianchi et al, 2014; Berger et al., 2016; Ozturk and Sheng, 2017; Mumtaz and Theodoridis, 2017). However, there is a lack of estimates of common region-specific uncertainty, despite the obvious fact that some sources of uncertainty for several economies in specific regions are common, including the Euro Area as a result of the process of European economic and monetary integration and of the monetary policy changes of the European Central

Bank. One exception is represented by Baker et al. (2016), which however derive a measure of European economic policy uncertainty, based on newspaper articles regarding policy-related economic uncertainty, instead of European or Euro Area macroeconomic uncertainty.[2] In contrast to these studies, we investigate the role of alternative sources of uncertainty with special attention to sources of *common* movements in uncertainty, by explicitly accounting for uncertainty common to various regions as well as uncertainty that is common across the entire set of countries. Moreover, we focus on common *macroeconomic* uncertainty reflected in real and nominal aggregate variables as well as in financial variables. Finally, our analysis is a generalisation of the investigation by Mumtaz and Theodoridis (2017) as we use a substantially more comprehensive data set, also allow for common region-specific uncertainty and allow for time-varying parameters in the factor model.

Our results have potentially important policy implications. Indeed, accounting for different sources of uncertainty can inform the assessment of the macroeconomic landscape and the optimal policy response. For example, if increased macroeconomic uncertainty is predominantly driven by the country-specific uncertainty component then a set of domestic policy measures might represent the most appropriate response to mitigate its potentially adverse effects. By contrast, if the regional common uncertainty component is the main driver of a specific macroeconomic uncertainty spike observed in several countries of that region, then a set of coordinated policy measures by national authorities of that region might be warranted. Finally, heightened macroeconomic uncertainty driven mainly by the global uncertainty component in specific periods might be beyond the control of national or even regional policy authorities (such as the European Central Bank for the Euro Area countries) if acting in isolation and might require, under specific circumstances, coordinated policy responses at global level. By showing the changing role of the different components of

[2] See in particular the European Economic Policy Uncertainty Index, which runs from January 1997 onwards and is based on data for Germany, France, the UK, Italy, Spain and the Netherlands. The index can be found in the website associated to the paper Baker et al., (2016): http://www.policyuncertainty.com/europe_monthly.html. For other Euro Area uncertainty measures under development see ECB (2016).

uncertainty in explaining the volatility of several core macroeconomic variables, we suggest that it is important to monitor all three sources of uncertainty, global, region-specific and country-specific, in order to understand developments in macroeconomic fluctuations as well as inflation and financial cycles, and inform the economic policy process.

The paper is organised as follows: Section 2 introduces the empirical model and provides details on the estimation method, the model specification and the dataset used. The results from the empirical model are presented in Section 3, including uncertainty estimates and the role of uncertainty shocks via a variance decomposition analysis. Section 4 provides conclusions. A supplemental appendix includes various annexes that provide further details on the model, the data and results. More specifically, Annex I includes a detailed description of the technical aspects of the model estimation, Annex II describes in detail the data set, while Annex III reports a more comprehensive set of results.

2 Global, region-specific and country-specific uncertainty

In this section we describe the econometric model used and provide some details on the estimation and the dataset. Annex I provides more details on the technical aspects of the estimation.

2.1 The model

In order to estimate country-specific, region-specific and global (also referred to as 'world') measures of uncertainty, we use a dynamic factor model with time-varying volatility and time-varying factor loadings. The factor model is defined as:

$$X_{it} = B_{i,t}^{W} F_t^{W} + B_{i,t}^{R} F_t^{R} + B_{i,t}^{C} F_t^{C} + v_{it} \tag{1}$$

where X_t is a $N \times 1$ panel of macroeconomic and financial data for the set of industrialised countries described below, with $t = 1, .., T$ with the subscript $i = 1, .., N$ indexing each series. This panel of data is summarised by four components: a set of K factors common to all countries $\underbrace{F_t^W}_{K \times 1}$, a set of K region-specific factors $\underbrace{F_t^R}_{K \times 1}$, a set of K country-specific factors $\underbrace{F_t^C}_{K \times 1}$ and idiosyncratic components $\underbrace{v_t}_{N \times 1}$. The factor loadings are denoted by the $N \times K$ matrices B_t^J, where $J = W, R, C$ with i denoting the loadings associated with each series.

The dynamics of the world, regional and the country factors, respectively, are described by the VAR process :

$$F_t^J = c^J + \sum_{j=1}^{P} \beta_j^J F_{t-j}^J + \left(\Omega_t^J\right)^{1/2} e_t^J \tag{2}$$

The idiosyncratic components have an AR transition equation:

$$v_{it} = \sum_{m=1}^{M} \rho_j v_{it-j} + h_{it}^{1/2} \varepsilon_{it} \tag{3}$$

Following Del Negro and Otrok (2008), we allow for time-varying factor loadings. Collecting the factor loadings at time t in a vector $B_{i,t} = \begin{pmatrix} vec\left(B_{i,t}^W\right) \\ vec\left(B_{i,t}^R\right) \\ vec\left(B_{i,t}^C\right) \end{pmatrix}$, the law of motion describing their time-variation is given by:

$$B_{i,t} = B_{i,t-1} + \left(Q_i^B\right)^{1/2} U_{it} \tag{4}$$

Note that the error terms in the transition equations (equations 2 and 3) are heteroscedastic. The error covariance matrices are defined as:

$$\Omega_t^J = \left(A^J\right)^{-1} H_t^J \left(A^J\right)^{-1\prime} \tag{5}$$

where A^J are lower triangular matrices and H_t^J are diagonal matrices:

$$H_t^J = diag(S_k^J \lambda_t^J) \tag{6}$$

The time-varying volatility is captured by the scalar process $\underbrace{\lambda_t^J}_{1\times1}$ with S_k representing scaling factors for $k = 1, 2, ...K$. The log of the common stochastic volatility $\ln \lambda_t^J$ evolves as the AR(1) process:

$$\ln \lambda_t^J = \alpha^J + \beta^J \ln \lambda_{t-1}^J + \left(Q^J\right)^{1/2} \eta_t^J \tag{7}$$

The structure defined by equation 5 suggests that λ_t^J captures the overall or common volatility in the orthogonalized residuals of the VAR models. As explained in Carriero et al. (2015), the common volatilities can be interpreted as the average of the variance of the shocks with equal weight given to each individual volatility. Note that the errors to equation 2 represent the shocks to 'world', region and country factors. Thus, $\lambda_t^W, \lambda_t^R, \lambda_t^C$ capture the average volatility of the unpredictable part of the global, the region-specific and the country-specific components, respectively. We interpret these volatilities as measures of uncertainty associated with global economic conditions, region-wide economic conditions and country-specific economic conditions. This underlying intuition is related to the procedure used in Jurado et al. (2015) to estimate US economic uncertainty. The uncertainty measure in that study is the average time-varying variance in the unpredictable component of a large set of real and financial time-series. The volatility specification in our factor model has a similar intepretation – it attempts to capture the average volatility in the shocks to the factors that summarise real and financial conditions.

The variance of the shocks to the idiosyncratic components is also assumed to be heteroscedastic, with h_{it} evolving as a stochastic volatility process

$$\ln h_{it} = a_i + b_i \ln h_{it-1} + q_i^{1/2} n_{it} \tag{8}$$

Finally, the disturbances of the model are assumed to be mutually uncorrelated and normally distributed:

$$\begin{pmatrix} e_t^J \\ \varepsilon_{it} \\ U_{it} \\ \eta_t^J \\ n_{it} \end{pmatrix} \tilde{} N \left(\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} I_K & 0 & 0 & 0 & 0 \\ 0 & I_N & 0 & 0 & 0 \\ 0 & 0 & I_{3(K(KP+1))} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \right)$$

The proposed model is an extended version of factor model used in Del Negro and Otrok (2008). We generalise the formulation of Del Negro and Otrok (2008) in three ways. First, as our interest centers on measures of macroeconomic uncertainty, our data set contains a range of macroeconomic and financial variables. In contrast, Del Negro and Otrok (2008) focus only on real GDP growth.[3] Given the range of series included in X_{it}, the number of factors in each category is larger than 1. The factor dynamics are described by a VAR where the volatility of the shocks changes according to the common volatility specification shown in equations 5 to 7. In contrast, Del Negro and Otrok (2008) consider one global and one European factor for real activity with each factor following an AR process with stochastic volatility. Our general set-up for the volatility of the transition equation shocks allows us to estimate measures of uncertainty that incorporate information regarding uncertain conditions in a range of macroeconomic and financial variables.

[3]Similar considerations apply to Mumtaz and Surico (2012) and Berger et al. (2016), as these studies focus on the volatility of the unpredictable component of inflation or output growth factors.

Our model is related to Mumtaz and Theodoridis (2017), but extends their work in two important dimensions. First, we allow time-variation in the factor loadings. As we show below, this feature is supported by measures of model fit. More importantly, restricting this time-variation affects the estimates of uncertainty in important ways. Suppressing time-variation in the factor loadings imparts more variation in the measures of uncertainty, possibly reflecting a bias in estimating the common components. When considering the aftermath of important events such as the global financial crisis, estimates from the restricted model appear to suggest a rapid fall in uncertainty. This is in contrast to the estimates from the proposed model which suggests that uncertainty remained elevated after these events. This highlights the important point that models designed to measure uncertainty can provide inaccurate results if time-variation in volatility reflects a bias due to suppressed time-variation in the conditional mean. In an important contribution, Breitung and Eickmeier (2011) show that when structural breaks in factor loadings are ignored, the common component is not adequately captured by the same number of factors as in a fixed-factor loadings model. This has important implications in our modelling framework as far as the definition of uncertainty measures is concerned. For example, if time-variation in the factor loadings is erroneously ignored, then the results in Breitung and Eickmeier (2011) suggest that F_t^W may not be an adequate summary of global economic conditions. As a consequence the volatility of shocks to F_t^W may be a biased measure of global uncertainty.

As a secondary contribution, note that the data set used in our study represents a substantial improvement over the panel employed by Mumtaz and Theodoridis (2017). The data set in the latter paper is dominated by series from countries such as the US, UK and Australia. In contrast, our data set is based on a larger number of countries (22 versus 11 in Mumtaz and Theodoridis, 2017) and keeps the number of series uniform across countries. This makes it less likely that common factors simply reflect countries with a larger number of series.

2.2 Variance decomposition

The structure of the model implies that the unconditional variance of each series can be written as a function of Ω_t^J $(J = W, R, C)$ and h_t. In particular for the ith series at time t, the variance is defined as :

$$var\left(X_{it}\right) = \left(B_{i,t}^W\right)\Theta_t^W\left(B_{i,t}^W\right)' + \left(B_{i,t}^R\right)\Theta_t^R\left(B_{i,t}^R\right)' + \left(B_i^C\right)\Theta_t^C\left(B_i^C\right)' + var\left(v_{it}\right) \tag{9}$$

where $\Theta_t^J = diag\left(var\left(F_t^J\right)\right)$. The variance terms Θ_t^J on the RHS of equation 9 can be calculated using the standard VAR formula for the unconditional variance. Note that these variance terms are time-varying as they are functions of $\lambda_t^W, \lambda_t^R, \lambda_t^C$ and h_{it} respectively. The volatility of each series in our panel is thus driven by uncertainty that is common to all countries, uncertainty that is common to specific regions (Euro Area, other Europe, North-America, Asia and Oceania), uncertainty that is country-specific and a residual term that captures sectoral volatility and data uncertainty. Our framework, therefore, allows us to calculate how volatility of key series (such as GDP growth, CPI inflation, interest rates, credit and stock market prices) is driven by uncertainty that is common to all countries and uncertainty that is region-, country- and series-specific. As we allow for time-varying factor loadings, the contribution of each of these components is time-varying.

Note that the variance of X_{it} in equation 9 is derived under the assumption of 'anticipated utility' (see e.g. Cogley and Sargent, 2008). Under this assumption, the factor loadings are fixed at their estimated value at each point in time and their stochastic process does not enter the computation. Within the context of a Markov decision problem, Cogley and Sargent (2008) show that anticipated utility provides an accurate approximation. Given this result, this assumption is frequently employed in the calculation of variances in time-varying parameter models.[4]

[4] See Cogley, Primiceri and Sargent (2010) for a recent example.

2.3 Estimation, identification and model specification

The factor model described in equations 1 to 8 is estimated via Gibbs sampling. Annex I provides details on the priors and the conditional posterior distributions. A summary of the procedure is provided here.

As discussed extensively in Del Negro and Otrok (2008), a number of identification issues have to be resolved in the factor model with stochastic volatility and time-varying factor loadings. First, the scale of the factors is unidentified. Following Del Negro and Otrok (2008), we fix the scale by assuming a fixed initial value for the stochastic volatilities λ_t^J and h_{it}. In addition, the sign of the time-varying factor loadings $B_{i,t}$ is not identified separately from the factors F_t^J. In their application, Del Negro and Otrok (2008) monitor the Gibbs draws of the loadings and factors for this problem and find that their algorithm is unaffected by this issue. However, unlike Del Negro and Otrok (2008), our aim is not to recover $B_{i,t}$ and F_t^J separately. The objects of interest for our study are the stochastic volatilities λ_t^J and the variance decomposition in equation 9. The former is unaffected by the sign of the factor and the latter depends on the product of the factor and the loadings.

2.4 Gibbs algorithm

The prior distributions used in our study are fairly standard. In time-varying parameter models, the prior for the variance of the shock to the transiton equation (i.e. Q_i^B in equation 4) for the time-varying coefficients can be important. We follow Cogley and Sargent (2005) and assume that this prior distribution is inverse Wishart with scale matrix $Q_{i,0}^B = V_{i,0}^B \times T_0 \times \kappa$ and degrees of freedom $\dim Q_{i,0}^B + 1$. Note that as in Cogley and Sargent (2005), $V_{i,0}^B$ denotes the OLS estimate of the variance of the factor loadings obtained using a principal component estimate of the factors over a training sample of $T_0 = 40$ observations. The scaling factor κ is set equal to the value typically used in the time-varying VAR literature: 3.5×10^{-4}. In Annex I we provide a sensitivity analysis that suggests that the main results are not sensitive to this choice.

The Gibbs algorithm consists of the following main steps:

1. Conditional on a draw for the factors, the stochastic volatilities and Q_i^B, the model collapses to a sequence of N time-varying regressions in equation 1. As these are linear state-space models, the Carter and Kohn (1994) algorithm can be used to draw the time-varying loadings from the conditional posterior distribution.

2. Conditional on the time-varying loadings, the error variances Ω_t^J, h_{it} and the coefficients of the transition equations 2 and 3, the model, again, has a linear state-space representation. The draw from the conditional posterior distribution of F_t^J is carried out using the Carter and Kohn (1994) algorithm.

3. Conditional on equations 2 and 3 and the parameters of the transition equations 7 and 8, the model can be written as a sequence of non-linear state-space models. The states (i.e. the stochastic volatilties) are drawn using the particle Gibbs sampler introduced in Andrieu et al. (2010) and Lindsen et.al. (2014).

4. All the remaining time-invariant coefficients and variances have standard conditional posteriors and can be easily drawn from their respective distributions.

In the benchmark specifications, we use 20,000 replications and base our inference on the last 1,000 replications. The inefficiency factors calculated using the retained draws (see Annex I) are fairly low providing support for convergence of the algorithm.

In Annex I we present results from a Monte-Carlo experiment that shows that this proposed algorithm displays reasonable small sample performance. In particular, we generate artificial data from a simple version of the proposed model. The Gibbs algorithm outlined above is then used to approximate the posterior distribution of the parameters. The estimated uncertainty measures and the variance decomposition are close to the true values. This experiment is also used to examine the consequences of erroneously assuming fixed factor loadings. When a model with fixed factor loadings is estimated using the artificial data, the resulting uncertainty measures deviate substantially from the true values. As discussed above, this may be because the common components are not captured sufficiently with the given number of factors when time-variation in factor loadings is ignored.

2.5 Model Specification

In order to maintain parsimony, the lag lengths in the VARs (L) are fixed at 2. In addition, we allow for first order serial correlation in the idiosyncratic errors v_{it}. In the benchmark model, we fix the number of common, region-specific and country-specific factors to 3. By choosing a relatively large number of factors in each category, our aim is to capture global, regional and country-specific economic conditions as accurately as possible from our data that contains a range of macroeconomic and financial time-series.[5]

We use the deviance information criterion (DIC) to compare the fit of the benchmark model with an alternative that restricts the factor loadings to be fixed across time (as in Mumtaz and Theodoridis, 2017). Introduced by Spiegelhalter et.al (2002), the DIC is defined as:

$$DIC = \bar{D} + p_D. \tag{10}$$

[5] This implies that each series for each country loads on 9 factors. Given that we only have 20 series per country, we consider this as the upper limit on the number of factors.

The first term is $\bar{D} = E\left(-2\ln f\left(\tilde{y}|\Xi^m\right)\right) \approx \frac{1}{M}\sum_m \left(-2\ln f\left(\tilde{y}|\Xi^m\right)\right)$, where $f\left(\tilde{y}|\Xi^m\right)$ is the likelihood evaluated at the draws of the parameters Ξ from the Gibbs sampler.[6] This term measures goodness of fit. The second term p_D is defined as a measure of the number of effective parameters in the model. A model is preferred if its DIC is smaller. The estimated DIC for the restricted model is 8605.04. This estimate is substantially larger than the DIC for the benchmark model that is estimated to be 8045.45. Therefore, allowing for time-varying factor loadings leads to an improvement in model fit.[7]

2.6 Data

The data includes a large set of quarterly financial and macroeconomic variables spanning from the first quarter of 1960 to the fourth quarter of 2016 for 22 OECD countries, including eleven Euro Area economies (Germany, France, Italy, Spain, the Netherlands, Belgium, Austria, Finland, Greece, Ireland and Portugal), five other European countries (the UK, Sweden, Denmark, Switzerland and Norway), two North-American countries (the US and Canada), two Asian countries (Japan and South Korea) and two Oceanian countries (Australia and New Zealand). For each of the 22 countries we consider 20 variables, ranging from real economic activity variables (real GDP, real private consumption expenditure, real gross fixed capital formation, industrial production, retail sales), consumer prices (CPI), labour market variables (employment and the unemployment rate), asset prices (stock market prices and house prices), interest rates (short-term interest rates and long-term interest rates), credit market variables (total credit to the private sector and bank loans to the non-financial private sector), money (narrow money and broad money), international

[6] We compute the likelihood conditional on the state variables via the prediction error decomposition. Due to the large number of state variables, efforts to compute the likelihood using the particle-filter were unsuccessful. As a result, the estimated DIC is approximate. See Chan and Grant (2016).

[7] Ando (2011) proposes a version of the DIC that is less likely to lead to overfitting. For the benchmark model the criterion of Ando (2011) is estimated to be 8067.02 while for the restricted model this estimate is 9671.15. This provides further support for the benchmark model.

trade variables (real exports and real imports) and exchange rates (the nominal effective exchange rate and the US dollar exchange rate). The sample is completed with 20 more international variables, including 8 times series referring to international prices of commodities such as crude oil, natural gas, agricultural products (food, beverages and raw materials), fertilizers and metals (precious metals and other metals and minerals), and 12 time series for selected indicators available over the time span mentioned above for a number of emerging economies (China, India, Turkey, Mexico and South Africa). Overall, 460 time series are included in the sample. Annex II provides details on the data definitions and sources.

3 Empirical results

3.1 Estimates of uncertainty components

The measures of macroeconomic uncertainty based on the dynamic factor model are represented by the posterior estimates of the common standard deviation of the shocks to the global factors $(\lambda_t^W)^{1/2}$, the posterior estimates of the common standard deviation of the shocks to the regional factors $(\lambda_t^R)^{1/2}$and the posterior estimates of the common standard deviation of the shocks to the country-specific factors $(\lambda_t^C)^{1/2}$, for $C = 1, 2, ..22$. They are displayed in Figure 1 (global), Figure 2 (Euro Area), Figure A in Annex III (other regions) and Figures B and C in Annex III (countries).

Figure 1 displays the global uncertainty measure, along with global recessions as dated by the IMF and several selected events which arguably have a global nature or relevance, either relating to major economic events (dashed vertical lines) or associated to major geopolitical events with significant economic implications such as turmoil in the Middle East with implications for global oil prices (dotted vertical lines). A visual inspection of the figure suggests that global uncertainty spikes are often associated to recessions, as most global recessions are preceded (mid-1970s and early 1980s) or accompanied (2009) by marked increases in global macroeconomic uncertainty. The early 1990s global recession appears to represent an exception, possibly explained by the fact that in some countries such as the US the recession and associated increased uncertainty took place earlier (around 1991) than in most European countries, where the expansionary effect of German re-unification more than offset the decline in Euro Area foreign demand and implied that a recession was experienced only later (1992 or 1993). As expected, the largest increase in global macroeconomic uncertainty can be observed in 2008, as most countries in the sample experienced increased financial volatility, banking crises and a major recession, although the spike does not seem to be significantly higher than those observed in the first half of the 1970s or early 1980s. The strong but only temporary increase in our global uncertainty measure in 2008 may be a factor behind the slow pace of the sub-sequent recoveries observed in several advanced economies due to possible long-lasting effects on real economic and labour variables reflecting hysteresis effects. Major geopolitical events leading to marked adverse oil price shocks in the mid-1970s and 1979-1980 appear to be factors which can be associated to significant increases in global macroeconomic uncertainty, but in more recent decades similar events seem to have a more limited effect, possibly due to the increased resilience of advanced economies to oil price shocks. Indeed, as discussed in Blanchard and Gali (2007) and Blanchard and Riggi (2103), although in recent years the global economy has witnessed various oil shocks of sign and magnitude comparable to those of the 1970s, their macroeconomic impact has been much more limited. Among the major economic events, while several appear to have had a limited impact on global macroeconomic uncertainty, including the Asian financial crisis starting in 1997 and the start of the Dotcom bubble crash around 2000, other ones such as financial turbulence in housing markets and interbank money markets leading to the start of the financial crisis in the summer of 2007 appear to coincide with a marked increase in global macroeconomic uncertainty.

<Figure 1 around here>

A comparison of the dynamics of the common global uncertainty measure with an alternative global uncertainty measures is presented in the top panel of Figure D of Annex III (with all indices reported in standardised form, i.e. demeaned and divided by their respective standard deviation, to enhance the comparison). More precisely, the chart shows the estimated common global uncertainty measure along with the Global News Index (GNI) of Baker, Bloom and Davis (2016) and the Geopolitical Risk Index (GRI) of Caldara and Iacoviello (2018). The correlation of our measure with the GNI measure from 1997 (i.e. the starting point of the latter) onwards is close to zero (-0.06), which is not surprising as the GNI measure is based on news references on specific uncertainty aspects, in particular relating to economic policies. The correlation of our measure with the GRI measure from 1985 (i.e. the starting point of the benchmark version of the latter) onwards is small and negative (-0.22), signalling that the two measures capture clearly different phenomena. Overall, the differences across these indicators can be associated to the fact that they aim at capturing different aspects of global uncertainty: macroeconomic versus economic policy and/or geopolitical risk, such that they could be seen as providing complementary, rather than substitute, information.

In Annex I (Figure I.9), we show a comparison between the estimate of global uncertainty from the benchmark model and this estimate obtained from a version of the model that restricts the factor loadings to be fixed across time. Restricting the time-variation in the factor loadings has important implications for the estimated uncertainty measure. In particular, the estimate from the restricted model appears to be more volatile than the benchmark estimate. This is evident from the behaviour of the measure during the two large increases in global uncertainty that occurred in the early 1980s and during the global financial crisis. In both cases, the restricted model suggests that the increase in uncertainty is substantially less persistent than the benchmark case depicted in Figure 1. One possible reason for this difference may be that by erroneously restricting the factor loadings to be fixed across time, the uncertainty estimates from the restricted model are biased as they are based on the volatility of shocks to factors that do not fully capture the common component (see Breitung and Eickmeier, 2011).

Among the region-specific common uncertainty measures, a particularly interesting one to analyse is that for the Euro Area, given the multiple steps toward economic and monetary integration that the countries that adopted the Euro have implemented over the past decades. The common Euro Area uncertainty measure is shown in Figure 2, along with Euro Area recessions as identified by the CEPR Euro Area Business Cycle Dating Committee (grey shaded areas) and several selected events which arguably have a Euro Area nature, either relating to the process of European economic and monetary integration (dashed vertical lines) or associated to changes in the ECB monetary policy (dotted vertical lines). Also in this case it appears that heightened uncertainty is often associated to recessions, as it can be found in coincidence with all of the recessionary periods reported, with the exception of the last recession in the sample (2011-2013), which arguably was experienced by most Euro Area countries in somewhat different periods and with different intensity (severity and duration), a fact reflected in the different dynamics of the country-specific uncertainty measures (Figure B in Annex III). In contrast to the case of the global uncertainty measure, the increase in Euro Area uncertainty which can be observed during the 2008-2009 recession is not the highest by historical standards, being clearly more limited than that observed in the mid-1970s. Overall, the increased uncertainty in 2008-2009 appears to include a stronger global component than a regional common component, suggesting that it can be associated to multiple causes and channels of transmission with a marked international component. At the same time, significant increases in 2008-2009 can be observed not only for the Euro

Area common uncertainty measure, but also for other region-specific measures such as those for North-America and Asia (Figure A in Annex III), indicating that the impact of the Great Recession was felt globally but to a different degree in different areas. As regards the effects of specific events relating to European integration, it can be observed that the ERM crises of late 1992 and mid-1993 coincide with increased Euro Area uncertainty, but these events also overlap with the early 1990s Euro Area recession. While for several years the ECB operated in an environment characterised by low uncertainty, this is less the case since 2007. At the same time, it appears that the inception of the European sovereign debt crisis in 2010 and the re-intensification of the crisis in 2012 are not associated with increased common Euro Area uncertainty. This could be explained by the fact that not only such episodes had distinctively heterogeneous effects across Euro Area countries, but it can also be argued that the impact on uncertainty was mitigated by some timely policy measures, such as the introduction of the Securities Markets Programme (SMP), the joint EC/ECB/IMF programme of financial assistance to Greece in the summer of 2010 and then the ECB's announcement of the Outright Monetary Transactions (OMT) in the summer of 2012.

<Figure 2 around here>

The estimated common Euro Area uncertainty measure appears to display markedly different dynamics than other Euro Area or European uncertainty measures (second top panel of Figure D in Annex III). This applies to both the VSTOXX index and a weighted average of the Economic Policy Uncertainty (EPU) index of Baker, Bloom and Davis (2016) for the largest Euro Area economies (Germany, France, Italy and Spain). The former is a stock market implied volatility (of the EURO STOXX 50® Index) measure and can be characterised as a financial market uncertainty measure. Its correlation with the common Euro Area uncertainty measure based on our model from 2000 (i.e. the starting period of the VSTOXX) onwards is highly significant (0.63), but also suggests that about one third of the time they move in different direction. This is not surprising, as our measure includes some financial variables but also a majority of macroeconomic variables, such that we characterise our measure as a macroeconomic uncertainty measure. The correlation of our measure with the Euro Area EPU index (available from 2001 onwards) is low (0.22), as in the case of the global uncertainty measures. Similar differences can also be detected between the US-specific uncertainty estimate and alternative uncertainty measures proposed for the US (see the lower panels of Figure D in Annex III).[8]

The country-specific estimates of macroeconomic uncertainty confirm that most recessionary episodes are accompanied by a rise in country-specific macroeconomic uncertainty, unless they coincide with a rise in either global or region-specific macroeconomic uncertainty (see Figures B and C in Annex III). However, several episodes of heightened uncertainty can also be detected coinciding with other events which are not classified as recessions. An example of such episode is represented by the German re-unification of 1990, which gave rise to a significant increase in the German-specific uncertainty measure, not surprisingly given the unique nature of such event. For several country-specific uncertainty measures, as is the case for the global and regions-specific uncertainty measures, it is noticeable that the 1970s was the decade characterised by the highest degree of volatility, often more marked than during the period of the recent economic and financial crisis, which highlights the importance to undertake such analysis with a historical sample spanning several decades to assess recent developments in a broader perspective.

[8]For instance, the correlation between the US-specific uncertainty measure and the corresponding one of Jurado et al. (2015) is 0.37, that with the VIX is 0.15 and those with the economic policy uncertainty indices for the US of Baker, Bloom and Davis (2016) are -0.25 for the historical index (available from 1971 to 2014) and 0.21 for the baseline index (available from 1985 onwards) (all standardised indices).

3.2 Co-movement of uncertainty

In order to assess to which extent the uncertainty measures relate to each other, it can be instructive to look at the cross-correlations between pairs of uncertainty measures. These are reported in Table A of Annex III.

The correlation between the global common uncertainty measure and the region-specific uncertainty measures is on average around 0.50, a similar figure found for the average correlation between pairs of region-specific measures. While these numbers indicate a significant degree of co-movement among international uncertainty measures, they also suggests that they often capture different components of overall macroeconomic uncertainty, as about half of the time they move in different direction. The global measure and the region-specific measures are also correlated with the country-specific measures (on average about 0.30 for the global and about 0.40 for the region-specific), confirming however that more than half of the time they move in different direction, thereby indicating that they often capture different components of overall uncertainty.

As regards the country-specific macroeconomic uncertainty measures, the average cross-correlation for all pairs of measures is 0.32. Among Euro Area countries the average cross-correlation is only marginally higher (0.35), while it is lower among the countries grouped under the "other Europe" region (0.26) and the Asian region (0.10), in contrast to the strong pairs of correlations between US and Canada and Australia and New Zealand (around 0.60 for both pairs).

The estimates of uncertainty clearly point to a negative correlation with real economic activity growth and a positive co-movement with inflation. The countercyclical nature of uncertainty is confirmed by the negative correlations found for most measures with real GDP growth, both at country level and at aggregate global or Euro Area level (for which aggregate real GDP are readily available, in contrast to the other regions). Indeed, as shown in Table B of Annex III, the contemporaneous correlations between the uncertainty measures and real GDP quarterly growth of the corresponding country or area (first column) is in most cases negative and clearly significant.

Another feature which emerges from these estimates is the strong positive correlation with inflation, which is in most cases of a magnitude (in absolute value) even greater than that between uncertainty and real GDP growth (second column in Table B of Annex III).

3.3 Variance decomposition

In order to assess the extent to which shocks to the different uncertainty components drive the overall volatility of key macroeconomic and financial variables, forecast error variance decompositions are considered. More precisely, using equation 9 the unconditional variance of each variable is decomposed into the contributions of the various uncertainty components (global: λ_t^W, region-specific: λ_t^R and country-specific: λ_t^C, for $C = 1, 2, ..22$) with the residual capturing the idiosyncratic, or variable-specific, volatility. Since the variances in the model are time-varying, the implied decomposition changes over time as well, and it is instructive to assess both the average contributions over the whole sample period as well as the evolution over time of these contributions.

Starting with real economic activity, Table 1 reports the average variance decomposition for a set of real economic activity variables, namely nine variables ranging from real GDP and its components real consumption and real investment to employment and industrial production (detailed results for most of the specific variables in this set are reported in Tables C to G in Annex III). Specifically, the table reports the average contributions (averages of median, 16th percentile and 84th percentile) over the whole sample period of each uncertainty component to real economic activity for each country, region and for the whole world. Looking at overall averages (last row), for all countries and over the whole sample period it appears that idiosyncratic uncertainty explains 56% of total volatility of real economic activity, much more than country-specific uncertainty (16%), region-specific uncertainty (12%) and global uncertainty (16%). Most likely, such a high importance of the idiosyncratic component is to a large extent due to the structure of the data used, an interpretation that can be supported by a comparison of our results with those of Mumtaz and Theodoridis (2017), who find on average a significantly smaller contribution of such component. First, our dataset is much larger (460 time series compared to 243 in Mumtaz and Theodoridis, 2017), implying that the cross-sectional variation is harder to explain with a limited number of factors. Second, our panel is balanced (that is, we use the same number of time series for each of the 22 countries), in contrast to Mumtaz and Theodoridis (2017), who use an unbalanced panel with many more time series present for the US, UK and Australia, and accordingly find very small contributions of the idiosyncratic component to GDP fluctuations for these countries but not for the other ones in their sample.[9] The relative importance of the various uncertainty components does not seem to differ much across countries, except that for the groups of countries in the North-American and Asian regions the region-specific uncertainty component seems to be more important (just above 40% for both regions). The finding that uncertainty of real economic activity for the US and Canada has a strong region-specific component is not too surprising once we note the very high correlation of macroeconomic variables for these two neighbouring economies. Such correlation could result from either US shocks being transmitted very quickly to the Canadian economy, such that with quarterly data the impact would appear simultaneous, from domestic structural shocks correlated across the two countries or from common region-specific structural shocks (associated for example to the introduction of, and modifications to, bilateral trade agree-

[9] To assess this interpretation, we estimated our model with the dataset of Mumtaz and Theodoridis (2017) and setting the number of factors to 4 as in their paper, and found a much smaller role for the idiosyncratic components with global, regional and country-specific uncertainty explaining a proportion of GDP variance that exceeds 50 percent for 9 out of 11 countries (results available upon request). At the same time, the adoption of time-varying factor loadings in our model, in contrast to Mumtaz and Theodoridis (2017), may also play a role in explaining the importance of the idiosyncratic component. Indeed, our model allows the importance of the different sources of uncertainty to change not only through a change in the volatility of factors but also through their impact on the series. This extra flexibility, which as discussed is supported by the data, may imply that the contributions can change quickly and this may reduce their average over time.

ments). Since we do not identify structural shocks, we cannot distinguish among these scenarios, and are in this respect agnostic.[10] For most countries idiosyncratic uncertainty is clearly the most important source of volatility of real economic activity, but also the other three uncertainty components play a significant role in most cases. Looking at contributions over time, it appears that global uncertainty (especially for European countries) and country-specific uncertainty (except for the Asian countries) have gradually become less important on average, while idiosyncratic uncertainty (except for the North-American countries) seems to play a gradually more important role (Figure 3).

<Table 1 and Figure 3 around here>

As regards consumer price inflation, on average for the majority of countries idiosyncratic uncertainty is also the most important driver of volatility, with global uncertainty representing the second most important component in most cases (Table 2). By contrast, country-specific uncertainty and region-specific uncertainty seem to explain minor fractions of volatility, with few exceptions (notably region-specific uncertainty for the Asian countries appears also important). The importance of global uncertainty for consumer price inflation volatility is in line with the findings of Ciccarelli and Mojon (2010) and Mumtaz and Surico (2012), who provide empirical evidence on the importance of the common international component of inflation, suggesting that inflation in industrialized countries is largely a global phenomenon. From a historical perspective, it is noticeable that the importance of global uncertainty in explaining inflation increased during the 1980s and 1990s, but since then is has become less important on average, although remaining clearly significant (Figure 4).

[10] Our reluctance to take a stand on the interpretation of such correlation also reflects the fact that the macroeconomic literature does not seem to provide clear-cut guidance on the driving forces of these strong comovements (see, for example, Justiniano and Preston, 2010).

<Table 2 and Figure 4 around here>

For short-term interest rate volatility, global uncertainty is the most important driver on average as well as for most countries and regions (Table 3). A similar picture emerges for long-term interest rate volatility (Table H in Annex III). By contrast, region-specific and country-specific uncertainty appear to be of negligible importance. For most countries, the role of global uncertainty in explaining interest rate volatility has even increased over time (Figure 5). This evidence on the importance of the global uncertainty component for interest rate volatility is in line with the evidence reported in some studies on the existence of a global yield curve (Diebold et al., 2008), along with the declining path of interest rates observed in most countries over the past four decades.

<Table 3 and Figure 5 around here>

Stock price volatility also appears to be driven first and foremost by global uncertainty, followed in importance by idiosyncratic uncertainty, for most countries on average (Table 4). At the same time, the contribution of region-specific uncertainty seems to be non-negligible for several countries. By contrast, country-specific uncertainty seems to play a negligible role in stock price volatility in all countries. Over time, global uncertainty seems to have been gaining importance in driving stock price volatility on average, with signs of slight diminishing importance only over the past decade (Figure 6). The relevance of the global uncertainty component for stock price volatility supports the view on the presence of a global financial cycle discussed in some recent studies (Miranda-Agrippino and Rey, 2015). This evidence is somewhat in contrast to the case of house price volatility, for which the evidence points to the overwhelming importance of the idiosyncratic uncertainty component for most countries (see detailed results in Table I and Figure K in Annex III).

<Table 4 and Figure 6 around here>

As regards other variables, for credit volatility all four uncertainty components seem to play a non-negligible role on average for most countries and regions (Tables J and K and Figures L and M in Annex III). By contrast, for monetary aggregates the idiosyncratic uncertainty component appears to be the most important driver of volatility, with however a non-negligible role also for all the other components in most cases (Tables L and M and Figures N and O in Annex III). Finally, in contrast to the other variables, the evidence for exchange rate volatility differs markedly across groups of countries. Indeed, region-specific uncertainty is clearly the most important source of exchange rate volatility for all Euro Area countries, as well as for the countries in the North-America and Oceania groups (Table N in Annex III), with its relevance strongly increasing over the past three decades (Figure P in Annex III). For the other European countries, the country-specific uncertainty component is the main driver of exchange rate fluctuations, while for Asian countries it is the idiosyncratic uncertainty component to play a major role in explaining exchange rate volatility.

4 Conclusions

In this paper we build a dynamic factor model with time-varying factor loadings and stochastic volatility allowing for the estimation of uncertainty that is common across a large set of advanced economies, uncertainty that is common at regional level and country-specific uncertainty. On the basis of a large sample of data comprising 460 quarterly time series for financial and macroeconomic variables for 22 OECD countries spanning from 1960 to 2016, we provide estimates of these three different components of macroeconomic uncertainty, quantify their impact in explaining the volatility of aggregate real and nominal variables and assess their changing role over time.

Overall, we find that all uncertainty estimates display significant recurrent fluctuations and that the marked increase in macroeconomic uncertainty associated to the global economic and financial crisis of 2008/2009, which can be observed in the global common uncertainty measure, some of the region-specific uncertainty measures as well as in most country-specific uncertainty measures, is not unprecedented and indeed often comparable to uncertainty increases emerging during the first half of the 1970s and early 1980s. Moreover, we find that all uncertainty measures appear to be strongly countercyclical, with periods of marked increased uncertainty often emerging just before or during most recessions, and a strong positive correlation of these measures with inflation. Finally, the relative importance of the various uncertainty measures in explaining the volatility of the variables considered appears to differ somewhat over time and across country and region, but all of them - global uncertainty, region-specific uncertainty and country-specific uncertainty - play a non-negligible role in most cases, including for real economic activity, credit and money. Global common uncertainty appears to play a primary role in explaining the volatility of inflation, interest rates and stock prices in most countries, although to a varying extent over time. Region-specific uncertainty drives most of the exchange rate volatility for all Euro Area countries as well as countries in North-America and Oceania, while for the other countries either country-specific or idiosyncratic uncertainty prevail in importance.

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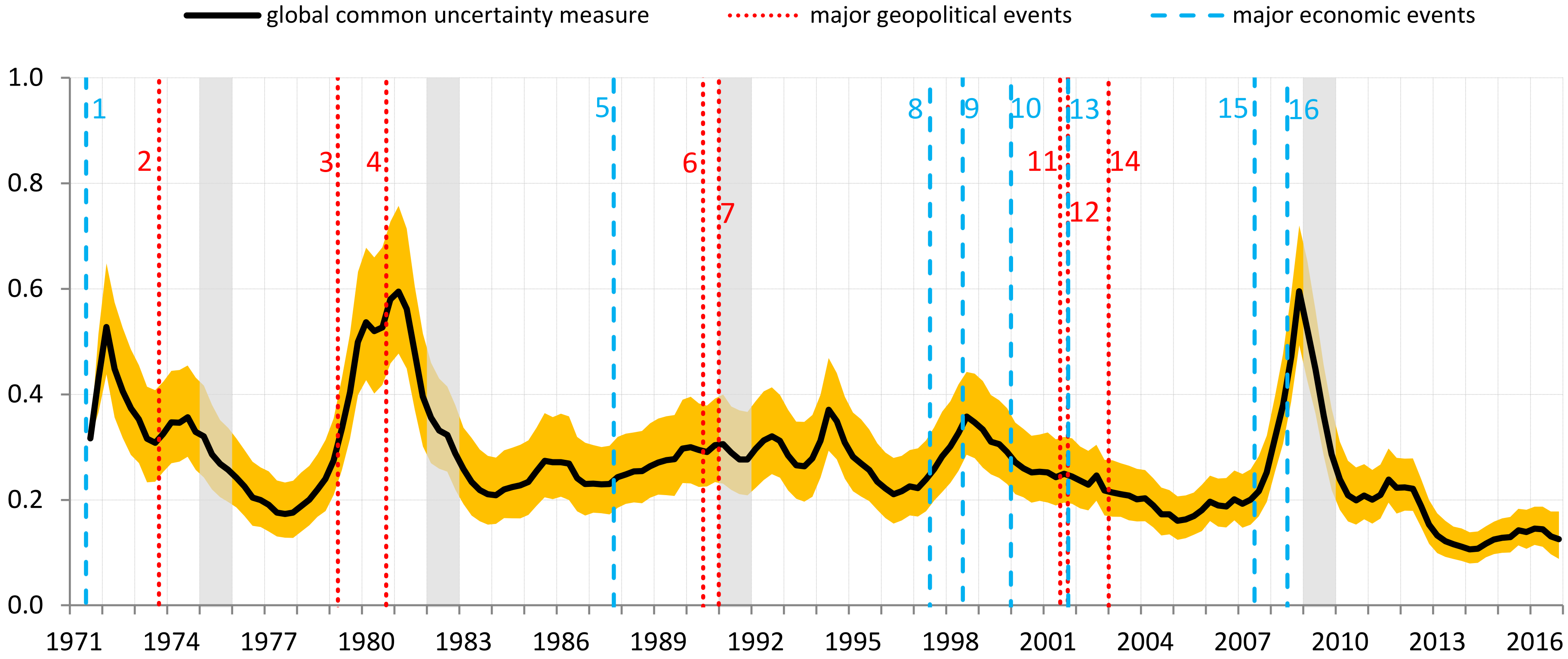
Chart 1 – Global uncertainty

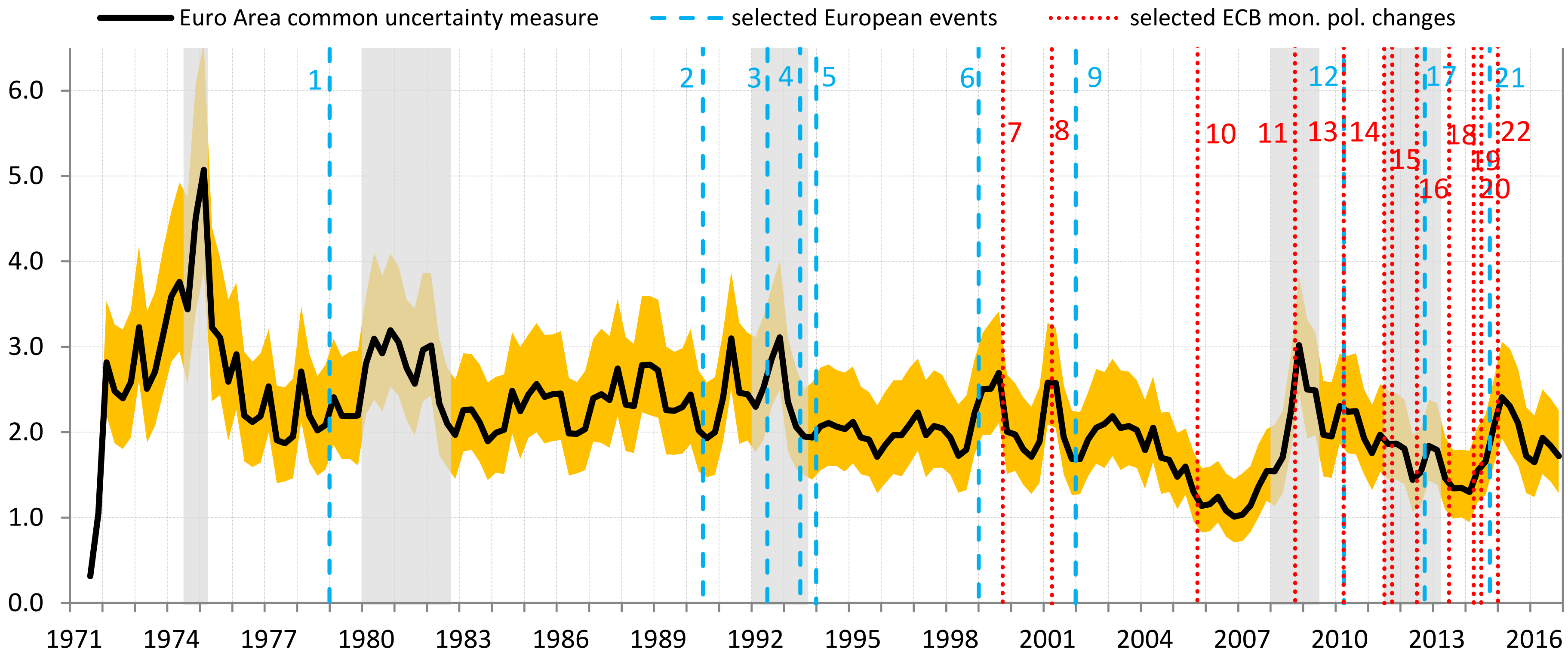


Source: Own estimates, IMF.

Notes: Estimate of the common standard deviation of shocks to the world factors (median and 68 percentile band). Grey areas delimit global recessions as dated by the IMF (April 2009 World Economic Outlook, Box 1.1. on Global Business Cycles). Events associated to vertical dashed and dotted lines are:

1	August 1971: End of Bretton Woods system	9	August 1998: Russian financial crisis
2	October 1973: Arab-Israel conflict and OPEC oil embargo	10	March 2000: Start of Dotcom bubble crash
3	April 1979: Iranian revolution and end of monarchy in Iran	11	September 2001: US terrorist attacks
4	September 1980: Invasion of Iran by Iraq, leading to the Iran-Iraq war	12	October 2001: Start of war in Afghanistan
5	October 1987: Black Monday	13	December 2001: Argentina's debt default
6	August 1990: Invasion of Kuwait by Iraq	14	March 2003: Start of Second Persian Gulf War
7	January-February 1991: First Persian Gulf war	15	August 2007: Start of financial crisis
8	July 1997: Start of Asian financial crisis	16	September 2008: Lehman Brothers bankruptcy

Chart 2 – Euro Area uncertainty



Source: CEPR and own calculations.

Notes: Estimate of the common standard deviation of shocks to the Euro Area factors (median and 68 percentile band). Grey areas delimit Euro Area recessions as dated by the CEPR Euro Area Business Cycle Dating Committee. Events associated to vertical dashed and dotted lines are:

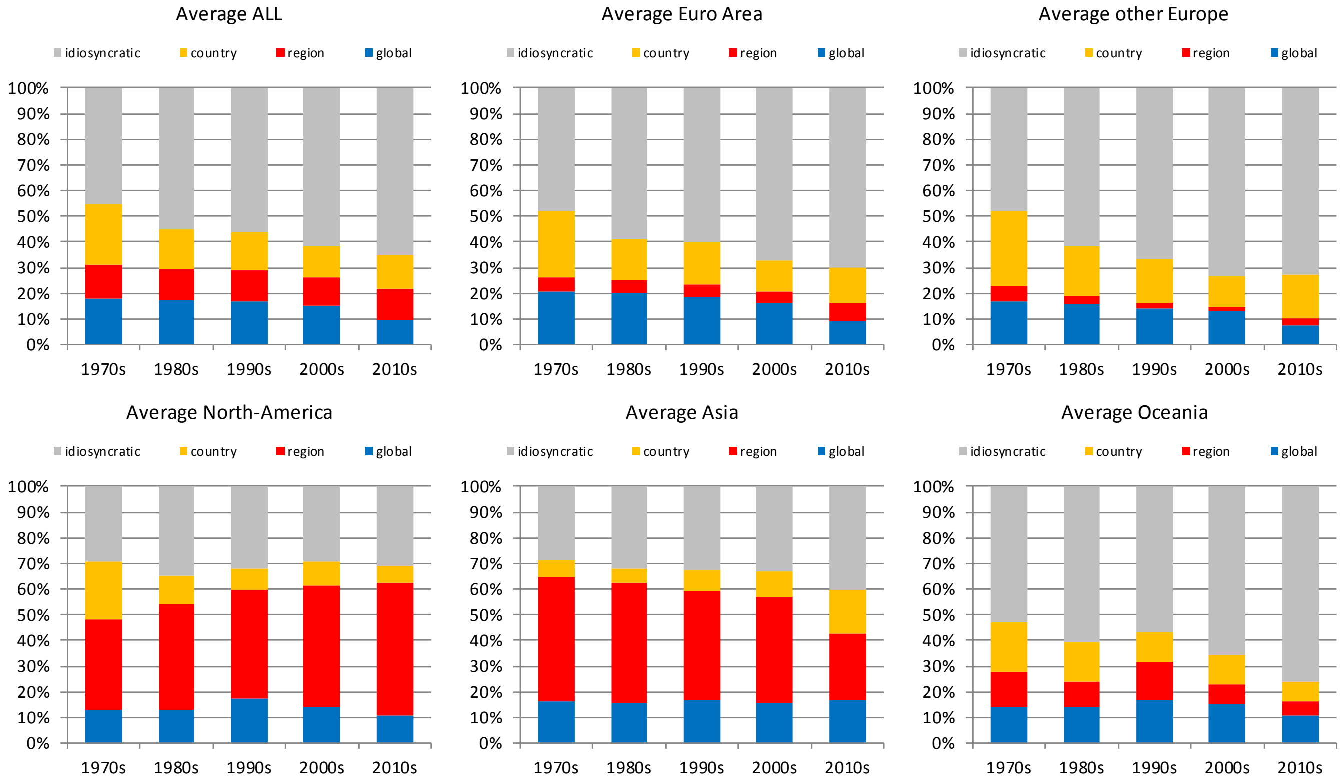
1	March 1979: Creation of the European Monetary System (EMS)	12	May 2010: ECB introduces SMP programme
2	July 1990: Start of Stage One of EMU	13	May 2010: Sovereign debt crisis (Greece IMF/ECB/EC programme)
3	September 1992: Exchange Rate Mechanism (ERM) crisis	14	August 2011: ECB reactivates SMP programme
4	August 1993: ERM currency fluctuation bands increased to 15%	15	December 2011: ECB announces two 3yLTROs
5	January 1994: Start of Stage Two of EMU	16	August 2012: OMTs announcement
6	January 1999: Start of Stage III of EMU	17	October 2012: Inauguration of European Stability Mechanism (ESM)
7	November 1999: Start of ECB interest rate tightening cycle	18	July 2013: ECB introduces forward guidance
8	May 2001: Start of ECB interest rate loosening cycle	19	June 2014: ECB announces TLTROs and cuts DFR to negative levels
9	January 2002: Euro cash changeover	20	September 2014: ECB announces CBPP3 and ABSPP and cuts DFR
10	December 2005: Start of ECB interest rate tightening cycle	21	November 2014: SSM enters into force
11	October 2008: Start of ECB interest rate loosening cycle	22	January 2015: ECB announces expanded Asset Purchase Programme

Table 1 – Variance decompositions: contributions of uncertainty components to the volatility of real economic activity growth

	global			region-specific			country-specific			idiosyncratic
	16^{th} p.	median	84^{th} p.	16^{th} p.	median	84^{th} p.	16^{th} p.	median	84^{th} p.	residual*
Germany	8%	16%	28%	5%	9%	15%	10%	20%	33%	56%
France	10%	18%	32%	5%	9%	16%	8%	16%	28%	57%
Italy	10%	18%	32%	3%	6%	11%	6%	13%	23%	64%
Spain	10%	18%	31%	2%	4%	7%	11%	19%	30%	59%
Netherlands	11%	19%	32%	4%	7%	13%	9%	18%	31%	56%
Belgium	17%	27%	42%	2%	4%	7%	10%	18%	29%	51%
Austria	13%	20%	32%	3%	7%	12%	3%	8%	15%	65%
Finland	9%	16%	28%	2%	3%	6%	8%	14%	25%	67%
Greece	7%	13%	23%	1%	3%	5%	13%	23%	40%	62%
Ireland	6%	13%	24%	1%	3%	6%	10%	19%	32%	65%
Portugal	9%	16%	29%	1%	3%	7%	10%	17%	28%	63%
UK	7%	12%	23%	1%	3%	5%	11%	20%	32%	65%
Sweden	8%	15%	27%	2%	3%	7%	12%	23%	38%	59%
Denmark	9%	15%	25%	1%	3%	6%	14%	22%	32%	60%
Switzerland	7%	14%	25%	2%	3%	7%	9%	15%	23%	68%
Norway	7%	13%	24%	2%	4%	7%	5%	14%	25%	70%
US	7%	15%	29%	23%	41%	60%	6%	15%	30%	30%
Canada	7%	13%	24%	28%	45%	61%	3%	9%	18%	33%
Japan	8%	15%	27%	19%	34%	51%	6%	14%	27%	37%
Australia	10%	16%	27%	4%	9%	17%	8%	16%	29%	59%
New Zealand	7%	13%	24%	6%	12%	22%	5%	11%	19%	64%
Korea	10%	17%	29%	35%	51%	65%	1%	4%	9%	28%
Av. Euro Area	10%	18%	30%	3%	5%	10%	9%	17%	28%	60%
Av. other Europe	8%	14%	25%	2%	3%	6%	10%	19%	30%	64%
Av. North-America	7%	14%	27%	25%	43%	61%	5%	12%	24%	31%
Av. Asia	9%	16%	28%	27%	42%	58%	4%	9%	18%	33%
Av. Oceania	8%	15%	26%	5%	11%	20%	6%	13%	24%	61%
Average ALL	9%	16%	28%	7%	12%	19%	8%	16%	27%	56%

Notes: Contributions of the global, region-specific, country-specific and idiosyncratic components to the variance of real economic activity growth (average of contributions to real GDP growth, real private consumption growth, real gross fixed capital formation, employment growth, unemployment rate, industrial production growth, retail sales growth, real export growth and real import growth) over the whole sample period 1971Q1-2016Q4. * Idiosyncratic contribution derived as residual.

Chart 3 – Variance decompositions: contributions of uncertainty components to the volatility of real economic activity growth over time



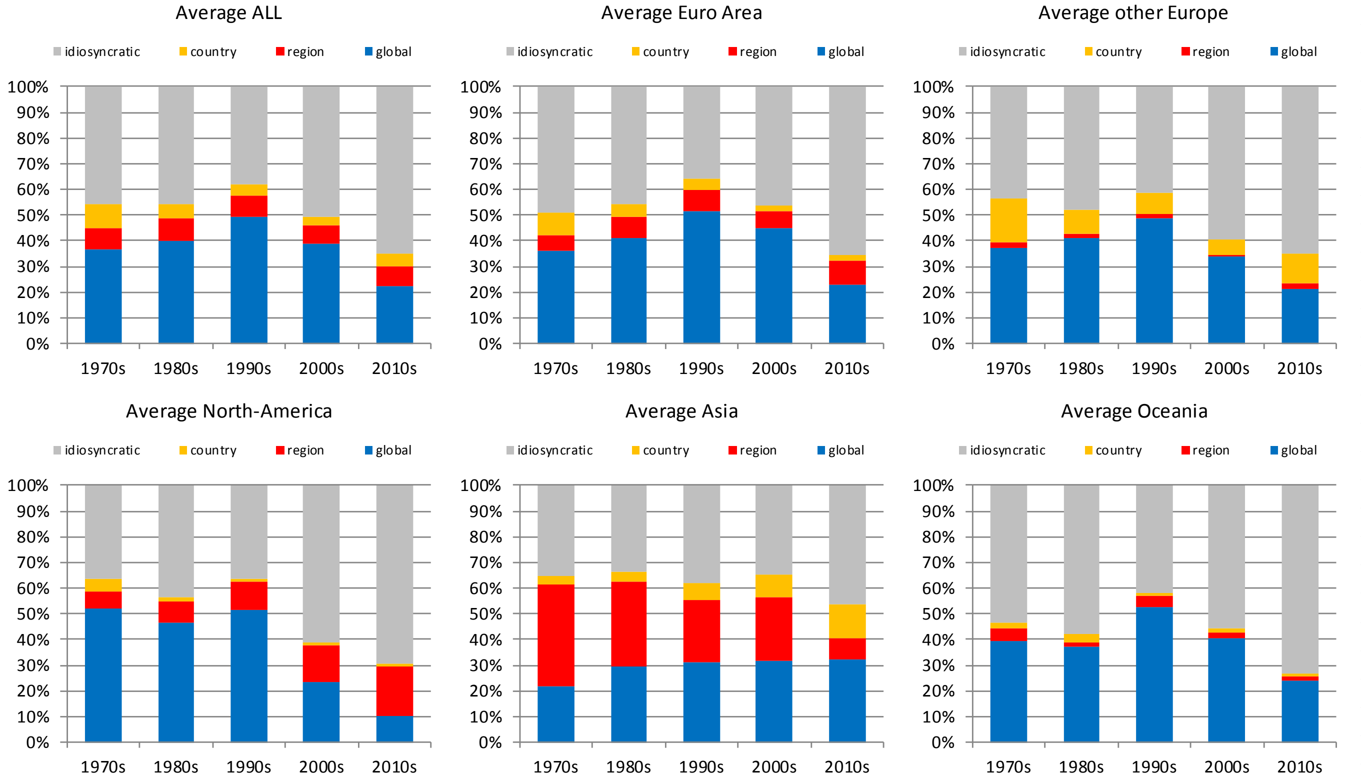
Notes: Contributions of the global, region-specific, country-specific and idiosyncratic components to the variance of real economic activity growth. 1970s: average 1971Q1-1979Q4, 1980s: average 1980Q1-1989Q4, 1990s: average 1990Q1-1999Q4, 2000s: average 2000Q1-2009Q4, 2010s: average 2010Q1-2016Q4.

Table 2 – Variance decompositions: contributions of uncertainty components to the volatility of CPI inflation

	global			region-specific			country-specific			idiosyncratic
	16th p.	median	84th p.	16th p.	median	84th p.	16th p.	median	84th p.	residual*
Germany	6%	18%	41%	5%	12%	26%	2%	7%	19%	63%
France	38%	61%	81%	2%	7%	17%	0%	0%	1%	32%
Italy	43%	63%	81%	1%	4%	10%	0%	0%	2%	33%
Spain	25%	43%	65%	1%	4%	9%	1%	3%	9%	50%
Netherlands	22%	40%	64%	6%	15%	30%	1%	4%	11%	41%
Belgium	13%	30%	56%	2%	6%	16%	0%	2%	7%	62%
Austria	9%	24%	49%	5%	15%	36%	8%	21%	43%	39%
Finland	31%	53%	76%	2%	6%	14%	1%	3%	10%	38%
Greece	14%	31%	57%	1%	5%	12%	0%	3%	17%	62%
Ireland	21%	43%	70%	3%	7%	16%	1%	3%	10%	47%
Portugal	27%	45%	65%	1%	4%	10%	1%	4%	13%	48%
UK	16%	35%	63%	0%	1%	3%	3%	11%	27%	53%
Sweden	21%	43%	69%	0%	1%	4%	1%	5%	19%	51%
Denmark	25%	46%	72%	0%	1%	5%	6%	16%	31%	37%
Switzerland	17%	33%	55%	0%	1%	3%	2%	6%	14%	60%
Norway	14%	32%	57%	1%	3%	8%	3%	12%	32%	53%
US	21%	41%	64%	4%	14%	38%	0%	2%	8%	43%
Canada	19%	37%	60%	2%	8%	29%	1%	2%	7%	53%
Japan	7%	21%	50%	10%	28%	56%	3%	11%	30%	39%
Australia	15%	32%	58%	1%	5%	14%	1%	3%	9%	61%
New Zealand	27%	48%	71%	0%	2%	6%	0%	1%	4%	49%
Korea	14%	37%	67%	9%	26%	55%	1%	2%	7%	34%
Av. Euro Area	23%	41%	64%	3%	8%	18%	1%	5%	13%	47%
Av. other Europe	19%	38%	63%	0%	2%	4%	3%	10%	25%	51%
Av. North-America	20%	39%	62%	3%	11%	34%	0%	2%	7%	48%
Av. Asia	11%	29%	58%	9%	27%	56%	2%	7%	18%	37%
Av. Oceania	21%	40%	64%	1%	3%	10%	0%	2%	7%	55%
Average ALL	20%	39%	63%	3%	8%	19%	2%	6%	15%	48%

Notes: Contributions of the global, region-specific, country-specific and idiosyncratic components to the variance of CPI inflation over the whole sample period 1971Q1-2016Q4. * Idiosyncratic contribution derived as residual.

Chart 4 – Variance decompositions: contributions of uncertainty components to the volatility of CPI inflation over time



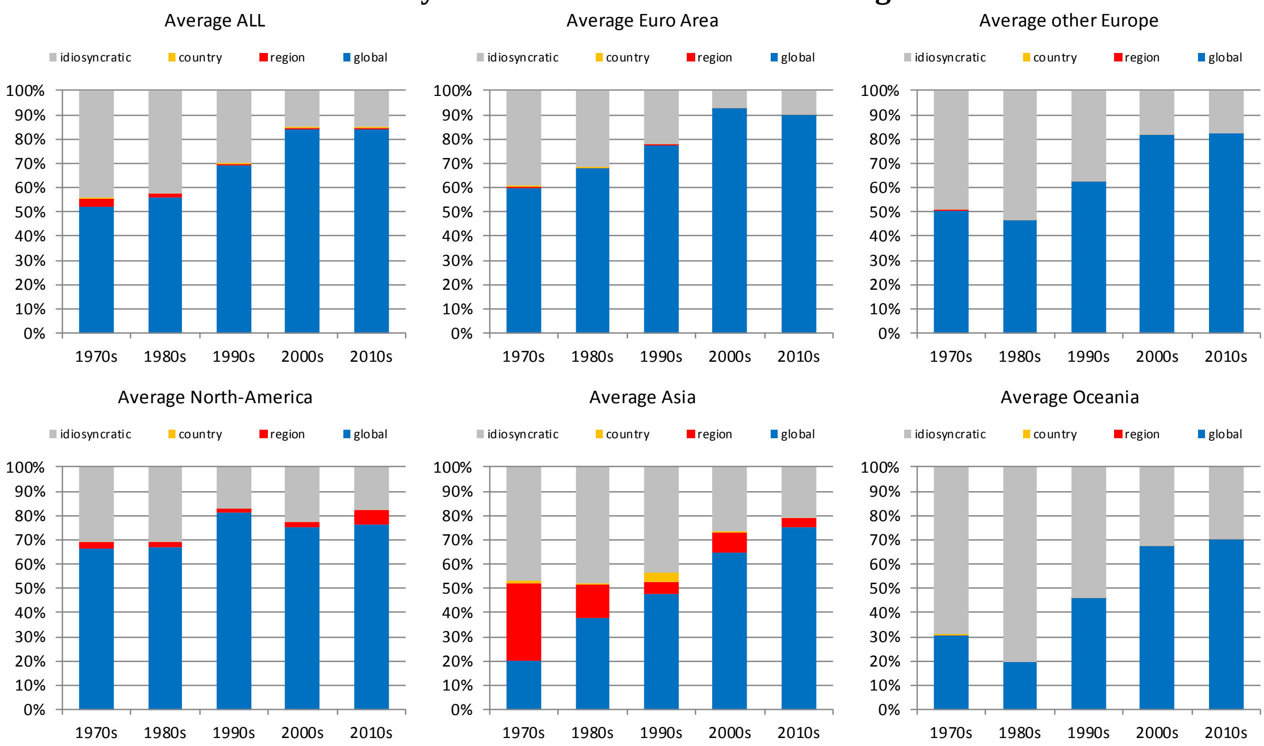
Notes: Contributions of the global, region-specific, country-specific and idiosyncratic components to the variance of CPI inflation. 1970s: average 1971Q1-1979Q4, 1980s: average 1980Q1-1989Q4, 1990s: average 1990Q1-1999Q4, 2000s: average 2000Q1-2009Q4, 2010s: average 2010Q1-2016Q4.

Table 3 – Variance decompositions: contributions of uncertainty components to the volatility of short-term interest rate changes

	global			region-specific			country-specific			idiosyncratic
	16^{th} p.	median	84^{th} p.	16^{th} p.	median	84^{th} p.	16^{th} p.	median	84^{th} p.	residual*
Germany	61%	84%	95%	0%	0%	0%	0%	0%	1%	16%
France	79%	91%	97%	0%	0%	0%	0%	0%	0%	8%
Italy	82%	91%	97%	0%	0%	1%	0%	0%	0%	8%
Spain	67%	84%	92%	0%	0%	1%	0%	0%	0%	16%
Netherlands	75%	88%	96%	0%	0%	1%	0%	0%	0%	11%
Belgium	75%	89%	96%	0%	0%	0%	0%	0%	0%	11%
Austria	54%	73%	89%	0%	0%	1%	0%	0%	0%	26%
Finland	9%	28%	52%	0%	0%	0%	0%	0%	0%	72%
Greece	52%	75%	92%	0%	0%	1%	0%	1%	11%	23%
Ireland	69%	83%	93%	0%	0%	1%	0%	0%	1%	17%
Portugal	37%	59%	80%	0%	0%	0%	0%	0%	3%	40%
UK	39%	65%	85%	0%	0%	1%	0%	0%	1%	34%
Sweden	53%	72%	87%	0%	0%	1%	0%	0%	1%	28%
Denmark	77%	89%	96%	0%	0%	0%	0%	0%	0%	11%
Switzerland	38%	64%	85%	0%	0%	0%	0%	0%	0%	36%
Norway	7%	27%	60%	0%	0%	0%	0%	0%	0%	72%
US	27%	62%	86%	1%	3%	9%	0%	0%	1%	35%
Canada	67%	85%	95%	1%	3%	9%	0%	0%	0%	13%
Japan	3%	27%	65%	0%	6%	37%	0%	0%	1%	68%
Australia	28%	50%	70%	0%	0%	0%	0%	0%	0%	50%
New Zealand	19%	41%	65%	0%	0%	1%	0%	0%	0%	59%
Korea	46%	69%	86%	7%	20%	42%	1%	2%	7%	8%
Av. Euro Area	60%	77%	89%	0%	0%	1%	0%	0%	2%	23%
Av. other Europe	43%	64%	82%	0%	0%	0%	0%	0%	1%	36%
Av. North-America	47%	73%	90%	1%	3%	9%	0%	0%	1%	24%
Av. Asia	25%	48%	76%	4%	13%	40%	0%	1%	4%	38%
Av. Oceania	23%	45%	68%	0%	0%	1%	0%	0%	0%	55%
Average ALL	48%	68%	84%	0%	2%	5%	0%	0%	1%	30%

Notes: Contributions of the global, region-specific, country-specific and idiosyncratic components to the variance of short-term interest rate changes over the whole sample period 1971Q1-2016Q4. * Idiosyncratic contribution derived as residual.

Chart 5 – Variance decompositions: contributions of uncertainty components to the volatility of short-term interest rate changes over time



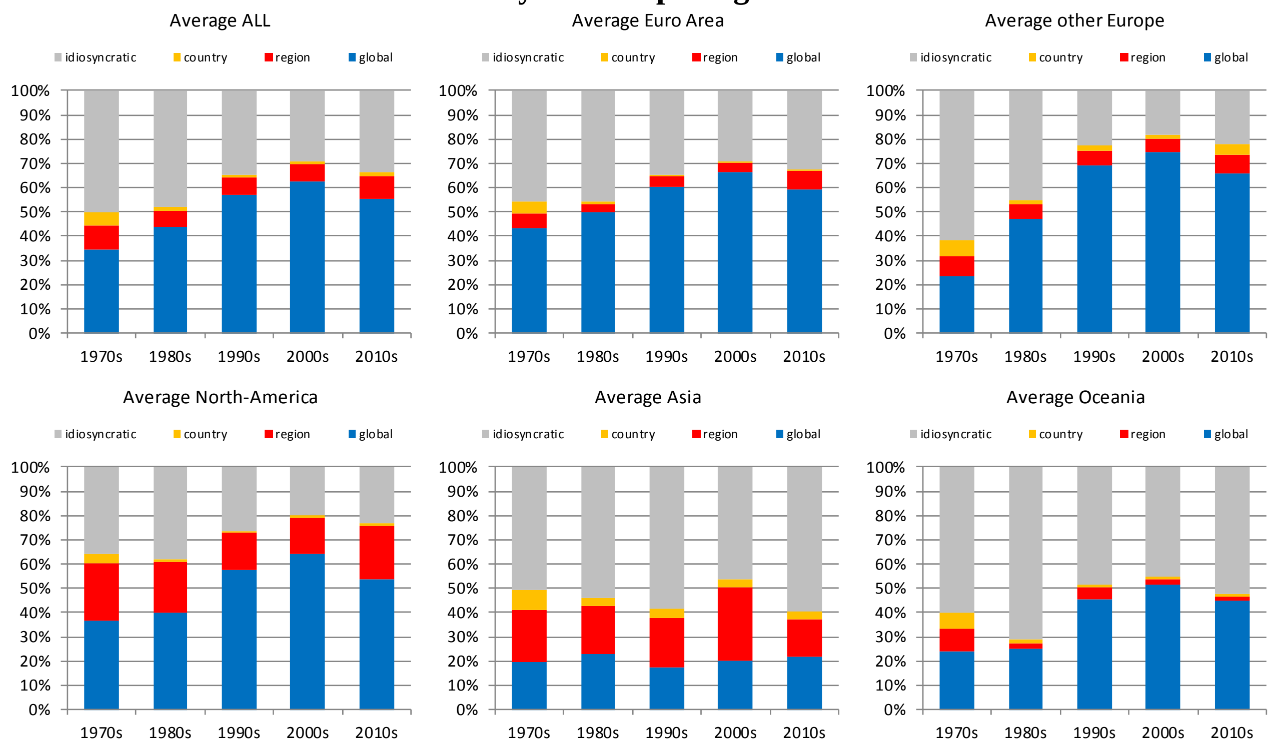
Notes: Contributions of the global, region-specific, country-specific and idiosyncratic components to the variance of short-term interest rate changes. 1970s: average 1971Q1-1979Q4, 1980s: average 1980Q1-1989Q4, 1990s: average 1990Q1-1999Q4, 2000s: average 2000Q1-2009Q4, 2010s: average 2010Q1-2016Q4.

Table 4 – Variance decompositions: contributions of uncertainty components to the volatility of stock price growth

	global			region-specific			country-specific			idiosyncratic
	16th p.	median	84th p.	16th p.	median	84th p.	16th p.	median	84th p.	residual*
Germany	62%	79%	91%	2%	6%	13%	0%	1%	3%	14%
France	66%	83%	93%	2%	6%	15%	0%	0%	1%	11%
Italy	42%	62%	80%	2%	4%	11%	0%	0%	1%	34%
Spain	10%	22%	43%	0%	1%	2%	0%	1%	3%	77%
Netherlands	65%	81%	92%	3%	8%	18%	0%	0%	1%	11%
Belgium	51%	69%	84%	2%	5%	11%	0%	0%	2%	26%
Austria	46%	66%	84%	2%	6%	13%	0%	1%	4%	27%
Finland	31%	53%	75%	2%	7%	16%	1%	2%	7%	38%
Greece	5%	13%	26%	0%	0%	1%	0%	1%	7%	85%
Ireland	36%	58%	78%	2%	6%	14%	1%	4%	13%	31%
Portugal	16%	30%	50%	2%	4%	9%	1%	4%	13%	62%
UK	39%	58%	77%	3%	7%	16%	1%	3%	11%	31%
Sweden	40%	58%	76%	4%	9%	19%	1%	4%	14%	29%
Denmark	37%	52%	69%	2%	5%	11%	1%	4%	9%	39%
Switzerland	38%	59%	79%	3%	8%	18%	1%	3%	8%	30%
Norway	38%	55%	74%	1%	3%	8%	0%	1%	6%	41%
US	30%	53%	76%	6%	20%	47%	0%	1%	9%	25%
Canada	24%	48%	74%	5%	17%	43%	0%	2%	6%	33%
Japan	11%	25%	48%	2%	11%	33%	1%	3%	10%	61%
Australia	36%	56%	76%	0%	2%	7%	1%	3%	9%	39%
New Zealand	9%	20%	41%	2%	6%	15%	1%	2%	6%	72%
Korea	6%	16%	36%	14%	33%	60%	2%	6%	15%	45%
Av. Euro Area	39%	56%	73%	2%	5%	11%	0%	1%	5%	38%
Av. other Europe	38%	57%	75%	2%	6%	14%	1%	3%	9%	34%
Av. North-America	27%	51%	75%	5%	19%	45%	0%	1%	7%	29%
Av. Asia	9%	20%	42%	8%	22%	47%	1%	4%	13%	53%
Av. Oceania	23%	38%	58%	1%	4%	11%	1%	2%	7%	55%
Average ALL	34%	51%	69%	3%	8%	18%	1%	2%	7%	39%

Notes: Contributions of the global, region-specific, country-specific and idiosyncratic components to the variance of stock price growth over the whole sample period 1971Q1-2016Q4. * Idiosyncratic contribution derived as residual.

Chart 6 – Variance decompositions: contributions of uncertainty components to the volatility of stock price growth over time



Notes: Contributions of the global, region-specific, country-specific and idiosyncratic components to the variance of stock price growth. 1970s: average 1971Q1-1979Q4, 1980s: average 1980Q1-1989Q4, 1990s: average 1990Q1-1999Q4, 2000s: average 2000Q1-2009Q4, 2010s: average 2010Q1-2016Q4.