Global Macroeconomic Uncertainty

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Abstract

We measure global real and nominal macroeconomic uncertainty and analyze its impact on individual countries' macroeconomic performance. Global uncertainty is measured through the conditional variances of global factors in inflation and output growth, estimated from a bivariate dynamic factor model with $GARCH$ errors. The impact of global uncertainty is measured by including the conditional variances as regressors. We refer to this as a dynamic factor $GARCH$-in-mean model. Global real uncertainty spikes around the mid-70s and during the Great Recession. Global nominal uncertainty declines in the 90s and increases during the Great Recession. We find significant influence of global macroeconomic uncertainty on output growth and/or inflation in all countries of our sample except Germany.

JEL classification: F44, C32

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1 Introduction

The Great Recession that started in the US as a Subprime crisis, spread quickly around the world and had a global impact. The quick expansion of the crisis has rekindled interest in investigating shock transmission mechanisms. The direct contagion channel via real and financial linkages results to have limited explanatory power. Recent research on the topic has identified indirect contagion channels as a second category of transmission mechanisms, that is related to variables' second moments. It includes contagion channels via credit or liquidity risk, or more generally, uncertainty.

This paper engages in the investigation of the role and importance of uncertainty studying the global aspect of the trade-off between uncertainty and macroeconomic performance. We propose a model to estimate a measure for global macroeconomic uncertainty and its impact on individual countries' macroeconomic performance.

In order to estimate a measure of global uncertainty and investigate its impact on macroeconomic fluctuations we set up a bivariate dynamic factor model (DFM) that decomposes inflation and output growth into country-specific and global components. The conditional variances of all factors are modeled as Generalized Autoregressive Conditional Heteroscedasticity ($GARCH$) processes and interpreted as reflecting uncertainty in the underlying factor. Thus we can distinguish between country-specific and global uncertainty. Following the $GARCH$-in-mean approach, we include the conditional variance of the global factors as a measure of global real and nominal uncertainty in the mean equations of each country and estimate its impact on the dependent macro variables simultaneously.

The contribution of this paper is twofold. First, the paper estimates a measure of global macroeconomic uncertainty. Specifically it identifies global real and nominal uncertainty. Both measures are, by construction, orthogonal to country-specific real and nominal uncertainty. Second, the paper provides an extension to the discussion about the importance of real and nominal uncertainty for macroeconomic performance. It extends the literature by focussing on the effect of global uncertainty for the conditional mean of inflation and output growth. If global uncertainty is found to be important, than domestic policy aiming at reducing uncertainty can only be partially successful.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature, Section 3 introduces the model and elaborates on our estimation methodology, Section 4 presents the estimation results, and Section 5 concludes.

2 Literature

When investigating the expansion of the Great Recession, Rose and Spiegel (2010) and Kamin and DeMarco (2012) find that there is little relation between the dimension of cross-border financial linkages or trade shares that countries have with the US and the extent to what they were affected by the Great Recession. This limited explanatory power of direct contagion channels implies that there must be other transmission mechanisms accounting for the substantial business cycle synchronicity in this time. Regarding the idea of a global dimension of risk or a global risk factor, in a theoretical approach, Bacchetta et al. (2012) develop a concept of self-fulfilling risk panics. They state that changes in macro fundamentals do not give a sufficient explanation for the geographic extent of the Great Recession or the 2010 Eurozone debt crisis. In their approach a weak fundamental in one country (e.g. the health of financial institutions in the US, the scale of debt in Greece) suddenly becomes a focal point of fear everywhere. This fundamental then takes on the role of a coordination device for a self-fulfilling shift in risk perceptions, even without any dramatic or sudden change in the fundamental itself. In a further approach on uncertainty related contagion, Kannan and Kohler-Geib (2009) propose a transmission channel which they call the 'uncertainty channel of contagion'. In their model an unanticipated crisis in one country raises investors doubts about available information on fundamentals and leads them to make decisions that increase the probability of a crisis in a second country where they invest.

Regarding the role of uncertainty as a driver of business cycle fluctuations, Bloom (2009) argues that heightend uncertainty leads firms to delay their decisions on investment and hiring and therefore economic slow downs could be driven by a combination of first and second moment shocks.[1] Bloom et al. (2012) show uncertainty to be strongly counter-

[1]The theoretical relationship between nominal and real uncertainty and the performance of macroeconomic variables received attention already starting with Friedman (1977) in his Nobel lecture. There exists a large body of work - such as Cukierman and Meltzer (1986), Black (1987) and Devereux (1989) - that

cyclical and using various measures of uncertainty they find that positive shocks to uncertainty lead to a temporary fall in output and investment. Addressing doubts regarding the causality of uncertainty and growth, Baker and Bloom (2013) prove empirically that rising uncertainty is driving recessions and is not an outcome of economic slowdowns. Fernandez-Villaverde et al. (2011) complement Blooms' work by identifying an additional mechanism through which time-varying volatility has a first moment impact. They show how changes in the volatility of real interest rates have a quantitatively important effect on business cycle fluctuations of emerging economies that rely on foreign debt to smooth consumption and to hedge against idiosyncratic productivity shocks. In times of highly volatile real interest rates, the economy lowers its outstanding debt by cutting consumption. Moreover, real activity is slowing down since foreign debt becomes a less attractive hedge for productivity shocks and investment falls. Stock and Watson (2012) also highlight the importance of time-varying second moments when examining the dynamics of the 2007-2009 US recession. Considering six major shocks - oil, monetary policy, productivity, uncertainty, liquidity risk and fiscal policy - in which they use Bloom's uncertainty series as a measure for uncertainty - they identify heightened uncertainty and liquidity risk as the dominant driving shocks of the crisis.

The prevalent empirical approach to measuring uncertainty in macroeconomic variables is to use the time-varying conditional variance of the series.[2] The important difference about using the standard deviation of a variable or the conditional variance estimated with $GARCH$ techniques is that moving standard deviation measures include variability and uncertainty of a variable, although the variability is predictible. $GARCH$ techniques allow for the separation between anticipated and unanticipated changes and focus on the variance of unpredictible innovations. Typically univariate or bivariate $GARCH$ models are used to model time variation in the conditional variance.

To investigate the impact of real and nominal uncertainty on macroeconomic performance different empirical approaches have been developed. The most relevant for this paper

contributes to the understanding of potential connections. For an overview see Grier and Perry (2000).

[2]Economists have proposed different measures of uncertainty in different frameworks. Bloom (2009) creates an uncertainty measure coming from the volatility of stock markets, called the VIX. Popescu and Smets (2010) refer to the disagreement among forecasters as uncertainty whereas Fernandez-Villaverde et al. (2011) concentrate on a measure of interest-rate volatility.

are $GARCH$-in-mean models. This simultanous approach includes uncertainty, proxied by the conditional variance from the $GARCH$ models, as an explanatory variable in the mean equation.[3] Grier and Perry (2000), Grier et al. (2004) and Bredin and Fountas (2009) use bivariate $GARCH$-in-mean models of inflation and output growth to investigate the effects of macroeconomic uncertainty on the performance of the dependent series. Grier and Perry (2000), Grier et al. (2004) focus on post-war US data, the investigation of Bredin and Fountas (2009) is for the European Union. But generally this work focuses on estimating uncertainty and its potential influence on a national level and no attention is paid on the transmission of uncertainty and a potentially important global aspect of the relationship between uncertainty and macroeconomic performance. There exist also a number of studies using univariate settings, but Grier et al. (2004) highlight the importance of a bivariate approach. Univariate models do not consider the potential joint determination of output growth and inflation and do not account for spillovers.

Another important and rich strand of literature related to this paper is on the comovement of macroeconomic variables. We know that macroeconomic variables are highly correlated over developed countries. Whereas comovement in macroeconomic variables has been examined intensively, less attention has been paid on the correlation of uncertainty. Using dynamic latent factor models, Kose et al. (2003) estimate common components in macroeconomic aggregates and interpret the common factor across countries as the world business cycle. They find that it accounts for high shares of volatility in the economic activity of developed economies. Similarly Neely and Rapach (2008), Ciccarelli and Mojon (2010) and Mumtaz and Surico (2012) focus on the contribution of global inflation to fluctuations in national inflation rates and find inflation to be a common phenomenon to a substantial extent. Mumtaz et al. (2011) provide an even more general analysis, by jointly identifying international comovements in output growth and inflation in a bivariate DFM. Thereby they fill a gap studying the correlations between national real and nominal variables across countries.

[3]Another approach using $GARCH$ methods is a two step procedure. A $GARCH$ model is estimated and in a second step Granger-causality tests are performed to test for potentially bi-directional causality. See Grier and Perry (1998), Fountas et al. (2006) or Fountas and Karanasos (2007) for examples. Another simultanous approach is a stochastic volatility in mean model, used for example by Berument et al. (2009).

3 Econometric model

The goal of the paper is to identify global real and nominal uncertainty and to analyze its impact on countries' macroeconomic performance. We follow the literature by measuring uncertainty through a $GARCH$ specification of the error term's variance. The main difficulty is that the mean equation from which the error term is obtained must contain a measure of global inflation and global output on the left hand side. The predominant approach for measuring common factors in macroeconomic data across countries are DFM. The specific DFM model outlined in this section seeks to pursue the following objectives simultaneously. First, it identifies a common inflation factor and a common factor in output growth and separates them from a factor specific to each country and each series. Second, it allows the variances of the common and country-specific factors' error terms to vary over time according to $GARCH$ processes which we interpret as uncertainties in the underlying factor. Third, the model estimates the impact of global real and nominal uncertainty on countries' output growth and inflation rates. We refer to this as a dynamic factor $GARCH$-in-mean model.

3.1 A bivariate dynamic factor $GARCH$-in-mean model

Starting point of the econometric framework is a bivariate dynamic latent factor model. We denote y_{it} as output growth and π_{it} as inflation in country i at time t, where $i = 1, ..., N$ and $t = 1, ..., T$. The mean equation is specified as

$$\begin{bmatrix} y_{it} \\ \pi_{it} \end{bmatrix} = \begin{pmatrix} \Gamma_i^y & 0 \\ 0 & \Gamma_i^\pi \end{pmatrix} \begin{bmatrix} R_t^y \\ R_t^\pi \end{bmatrix} + \begin{bmatrix} I_{it}^y \\ I_{it}^\pi \end{bmatrix} \tag{1}$$

where R_t^y denotes the common factor in output growth and R_t^π denotes the common inflation factor. I_{it}^y and I_{it}^π are idiosyncratic or country-specific factors in output growth and inflation respectively. Γ_i^y and Γ_i^π denote the country-specific factor loadings. The common factors in inflation and output growth are modeled as independent AR processes of order p:

$$R_t^y = \sum_{k=1}^{p} \rho_k R_{t-k}^y + \varepsilon_t^y \tag{2}$$

$$R_t^\pi = \sum_{k=1}^{p} \theta_k R_{t-k}^\pi + \varepsilon_t^\pi. \tag{3}$$

The error terms ε_t^y and ε_t^π are white noise processes with $\varepsilon_t^y, \varepsilon_t^\pi \sim N(0,1))$, i.e

$$\varepsilon_t^y = [\sigma_t^y]^{\frac{1}{2}} \, v_t^y \tag{4}$$

$$\varepsilon_t^\pi = [\sigma_t^\pi]^{\frac{1}{2}} \, v_t^\pi, \tag{5}$$

where v_t^y, $v_t^\pi \sim i.i.d.(0,1)$ and where the conditional variances σ_t^y and σ_t^π follow $GARCH(1,1)$ processes,

$$\sigma_t^y = V_{t-1}\left(\varepsilon_t^y\right) = \alpha_0^y + \alpha_1^y \varepsilon_{t-1}^{y2} + \alpha_2^y \sigma_{t-1}^y \tag{6}$$

$$\sigma_t^\pi = V_{t-1}\left(\varepsilon_t^\pi\right) = \alpha_0^\pi + \alpha_1^\pi \varepsilon_{t-1}^{\pi 2} + \alpha_2^\pi \sigma_{t-1}^\pi. \tag{7}$$

The idiosyncratic factors follow bivariate VAR(p) processes

$$x_{it} = \sum_{k=1}^{p} \Phi_k^i x_{it-k} + \eta_{it}, \qquad \eta_{it} \sim N\left(0, H_{it}\right) \tag{8}$$

where

$$x_{it} = \begin{bmatrix} I_{it}^y \\ I_{it}^\pi \end{bmatrix}, \quad \Phi_k^i = \begin{bmatrix} \phi_{k11}^i & \phi_{k12}^i \\ \phi_{k21}^i & \phi_{k22}^i \end{bmatrix}, \quad \eta_t = \begin{bmatrix} \eta_{it}^y \\ \eta_{it}^\pi \end{bmatrix}, \quad H_{it} = \begin{bmatrix} h_{it}^y & h_{it}^{y\pi} \\ h_{it}^{y\pi} & h_{it}^\pi \end{bmatrix}.$$

We impose a constant conditional correlation (CCC) $GARCH(1,1)$ structure on the conditional covariance matrix H_t. The conditional variances and the conditional covariance are given by

$$h_{it}^y = \beta_{i0}^y + \beta_{i1}^y \eta_{it-1}^{y2} + \beta_{i2}^y h_{it-1}^y \tag{9}$$

$$h_{it}^\pi = \beta_{i0}^\pi + \beta_{i1}^\pi \eta_{it-1}^{\pi 2} + \beta_{i2}^\pi h_{it-1}^\pi \tag{10}$$

$$h_{it}^{y\pi} = \rho_i \sqrt{h_{it}^y h_{it}^\pi} \tag{11}$$

The model differs in two points from a standard DFM. First, by modeling output growth and inflation for each country simultaneously it constitutes a bivariate factor model. Following Mumtaz et al. (2011) we assume that the common factors are orthogonal. The country-specific output growth and inflation factor are allowed to be correlated within each country. The orthogonality of the common factors allows for (time-varying) variance decomposition into common vs. idiosyncratic factors. Second, the conditional variances of all factors are time-varying and follow $GARCH$ processes. We interpret the $GARCH$ series as uncertainty in the underlying factor, i.e. σ_t^y and σ_t^π measure uncertainty in the common or global factors of output growth and inflation. Thus, we refer to them as global real and nominal uncertainty. In order to analyze the impact of global uncertainty on individual countries' macroeconomic performance we augment equation (1) to include σ_t^y and σ_t^π as explanatory variables, i.e.

$$\begin{bmatrix} y_{it} \\ \pi_{it} \end{bmatrix} = \begin{pmatrix} \Gamma_i^y & 0 \\ 0 & \Gamma_i^\pi \end{pmatrix} \begin{bmatrix} R_t^y \\ R_t^\pi \end{bmatrix} + \begin{pmatrix} \delta_{11}^i & \delta_{12}^i \\ \delta_{21}^i & \delta_{22}^i \end{pmatrix} \begin{bmatrix} \sigma_t^y \\ \sigma_t^\pi \end{bmatrix} + \begin{bmatrix} I_{it}^y \\ I_{it}^\pi \end{bmatrix}. \tag{12}$$

The coefficients δ^i capture the sensitivity of output growth and inflation in country i to global real and nominal uncertainty. In order to keep the model tractable we focus on the impact of global uncertainty. Including country-specific uncertainties as additional $GARCH$-in-mean variables would increase the number of parameters to be estimated significantly.

3.2 Identification

For the empirical model to be identified we impose the following restrictions. First, note that we can multiply and divide the terms $\Gamma_i^y R_t^y$ and $\Gamma_i^\pi R_t^\pi$ by any constant and obtain a different decomposition of y_{it} and π_{it}. This identification problem, known as the scale problem in factor models, states that the factor's variance and the factor loadings are not separately identified. The scale problem is solved by imposing an unconditional variance of unity on the shocks to the two common factors. This amounts to setting $\alpha_0^y = 1 - \alpha_1^y - \alpha_2^y$ in equation (6) and $\alpha_0^\pi = 1 - \alpha_1^\pi - \alpha_2^\pi$ in equation (7). Second, the signs of the factor loadings and the factors are not identified since the likelihood remains the same if we multiply both Γ_i^y and R_t^y (or Γ_i^π and R_t^π) by -1. Therefore, we impose the restrictions $\Gamma_i^y > 0$ and $\Gamma_i^\pi > 0$. Further parameter restrictions are imposed on the parameters in the $GARCH$ equations in order to ensure that all $GARCH$ series are non-negative and stationary. Thus, we restrict $0 < \alpha_1^m < 1$, $0 < \alpha_2^m < 1$, and $0 < \alpha_1^m + \alpha_2^m < 1$ for $m = \{y, \pi\}$. Similarly $\beta_{i0}^m > 0$, $0 < \beta_{i1}^m < 1$, $0 < \beta_{i2}^m < 1$, and $0 < \beta_{i1}^m + \beta_{i2}^m < 1$ for $m = \{y, \pi\}$.

3.3 Estimation

The vast majority of the DFM literature employs a Gibbs sampling scheme in order to estimate the factors and the parameters.[4] Gibbs sampling is a Bayesian estimation technique that belongs to the class of Markov Chain Monte Carlo (MCMC) methods. Instead of evaluating the full joint posterior distribution directly, the Gibbs sampler is an iterative procedure that simulates from conditional densities which have known analytical solutions. This property of sampling from conditional densities is known as *conjugacy*. The sequential drawing of conditional densities yields random draws of the models' posterior density.[5] However the presence of $GARCH$ effects makes the use of Gibbs sampling impossible. The reason is that in a $GARCH$ model the conditional variance is a function of the conditional mean. The conditional posterior density of the conditional mean contains the conditional variance which itself depends on the conditional mean. Hence the conditional posterior density does not belong to a class of know densities, i.e. there is no conjugacy.[6] As a consequence the estimation procedure for the dynamic factor $GARCH$-in-mean model needs to evaluate the full joint posterior.[7]

The estimation technique used in this paper is a Metropolis-Hastings (MH) algorithm. Similar to the Gibbs sampler the MH algorithm is a Markov chain algorithm which draws from the exact posterior density. The basic idea of the MH algorithm is to draw samples from a proposal density and then apply an acceptance rule to decide if a draw belongs

[4] While the likelihood function of a DFM model can easily be calculated using the Kalman filter, the numerical optimization is cumbersome when the number of parameter to be estimated is large.

[5] A textbook treatment of DFM estimation using the Gibbs sampler is given by Kim and Nelson (1999).

[6] Gibbs sampling can work well even in DFM models with time-varying variances. For instance DFM with stochastic volatilities can be estimated using Gibbs sampling. The crucial point here is that the time-varying variance is a function of the error term and thus of the conditional mean.

[7] Bauwens and Lubrano (1998) combine the Gibbs sampler with a deterministic integration rule in order to estimate $GARCH$ models. However, this so called Griddy-Gibbs sampling algorithm is computational intensive.

to the exact posterior density. If a draw does not get accepted the previous draw is kept thereby creating dependence in the sample. MH algorithm are widely used in applied econometrics, e.g. Geweke (1995) has proposed it for the estimation of $GARCH$ models. While the MH algorithm performs well in small or medium size models it often fails in high dimensional models. If the dimension of the posterior distribution is large, the acceptance rates of new draws from the posterior distribution is close to zero implying very low mixing of the Markov chain and thus inefficient estimation (see e.g. Au and Beck, 2001). The most commonly used variants of the MH algorithm to solve high dimensional problems are the adaptive MH and the component wise MH algorithm. The former updates the covariance matrix of the proposal distribution within the sampling process by using the empirical covariance of the chain created so far (see e.g. Haario et al., 2001). The adjustment to the MH algorithm used here is the component-wise approach where only parts of the Markov chain are updated in one iteration.[8]

To be more specific, let $\Theta_n = (\Theta_{n1}, \ldots, \Theta_{nd})$ be a Markov chain of dimension d. The component wise MH algorithm divides the elements of Θ_n into z components, denoted by Θ_{nj}. Θ_{n-j} denotes all components except the jth component, i.e.

$$\Theta_{n-j} = (\Theta_{n1}, \ldots, \Theta_{nj-1}, \Theta_{nj+1}, \ldots, \Theta_{nz}) . \tag{13}$$

Let $\theta_{n1}, \ldots, \theta_{nz}$ be the state of the components $\Theta_{n1}, \ldots, \Theta_{nz}$ at time n and θ'_{n-j} be the state of θ_{n-j} after updating the components $1, \ldots, j-1$. The component wise MH algorithm is as follows. For each $j = 1, \ldots, z$

1. Simulate a candidate ζ_{nj} from a proposal density $\psi\left(\cdot \mid \theta_{nj}, \theta'_{n-j}\right)$.

2. Compute the acceptance probability γ according to

$$\gamma = \min\left\{\frac{p\left(\zeta_{nj} \mid \theta'_{n-j}\right)\psi\left(\theta_{nj} \mid \zeta_{nj}, \theta'_{n-j}\right)}{p\left(\theta_{nj} \mid \theta'_{n-j}\right)\psi\left(\zeta_{nj} \mid \theta_{nj}, \theta'_{n-j}\right)}, 1\right\} \tag{14}$$

   where $p(\cdot)$ denotes the posterior density. Thus, $p\left(\theta_{nj} \mid \theta'_{n-j}\right)$ is the full conditional posterior distribution for the components Θ_{nj} given the current state θ'_{n-j} of all

[8] These two variants may also be applied simultaneously (see e.g. Haario et al., 2005).

other components.

3. Set $\Theta_{n+1j} = \zeta_{nj}$ if the candidate is accepted, otherwise set $\Theta_{n+1j} = \Theta_{nj}$.

The number of parameter in each component is not necessarily equal. While there is no fixed rule as to how many parameters should be in one component, a general guideline is that parameters which are highly correlated should be sampled together. Therefore we form the components such that the number of parameters in one component is not larger than five but still sample parameters that are likely to be correlated jointly (e.g. the AR coefficients of each factor, the $GARCH$ parameters for a given factor etc.).

The sampling procedure requires the calculation of the posterior density given a certain draw of parameters. The posterior density is the product of the likelihood function and the prior distribution. As common in the DFM literature we use normal priors for all non-variance parameters. The priors in the $GARCH$ equations follow inverse Gamma distributions. All priors are non-informative.

In order to construct the importance function we first approximate the two common factors by the first principal components of output growth and inflation and estimate two $AR(p)$-$GARCH(1,1)$ models. Given the approximations of the common factors and their conditional variances, the model reduces to N independent vector moving average process with exogenous variables and a CCC-$GARCH(1,1)$ error variance structure. We estimate them country by country using maximum likelihood (ML). The importance function is then assumed to be multivariate normally distributed with the mean and variances coming from the ML estimation.[9]

In order to calculate the likelihood function we first put the model given by equations (2)-(12) in state space form. In particular, we estimate a *conditionally* Gaussian linear state space system including time-varying conditional variances (see Harvey, 1989). In Appendix B we report the state space representation of the model. Given the assumption of stationarity the initialization of the filter is non-diffuse. The time-varying conditional variances complicate the otherwise standard state space framework. To deal with this we follow the approach by Harvey et al. (1992) and augment the state vector with the shocks ε_t^y, ε_t^π, η_{it}^y and η_{it}^π. The Kalman filter then provides estimates of the conditional variance

[9]We investigated the accuracy of the procedure by simulating the model for various parameter specifications and found that the approximation using principal components and ML estimation works well.

of the shocks, i.e. estimates for σ_t^y, σ_t^π, h_{it}^y, and h_{it}^π. We refer to Appendix A for more details on the approach followed.

To deal with potential computational difficulties that are caused by the relatively large dimension of the observation vector we follow the univariate approach to multivariate filtering and smoothing as presented by Koopman and Durbin (2000) and Durbin and Koopman (2001, chapter 6). A major advantage of this approach is that we can avoid taking the inverse of the variance matrix of the one-step-ahead prediction errors. We refer to Koopman and Durbin (2000) for the filtering recursion and for the calculation of the likelihood.

4 Data and estimation results

4.1 Data

The deseasonalized data are from the OECD Main Economic Indicators. As an approximation for output growth we use the annualized monthly difference of logarithmized industrial production data and for inflation we use the annualized monthly difference of the logarithmized consumer price index.[10] All series are demeaned.[11] The data covers the period from January 1965 to June 2012. The sample includes nine industrialized countries, Canada, France, Germany, Italy, Japan, Netherlands, Spain, United Kingdom, and the United States.[12] Given the $GARCH$ structure of the model the data should be of a relatively high frequency. In fact the $GARCH$-in-mean literature discussed in section 2 typically uses monthly data as this is the highest frequency for which output growth and inflation data are available. Data availability is also the limiting factor regarding the choice of countries to be included in the sample. However the nine countries used here represent a share of about 80 per cent of OECD countries GDP.

[10] Data on producer prices are only available for a substantially shorter time period and are therefore neglected.

[11] We alternativly computed the local means using a Baxter-King high-pass filter as well as a Hodrick-Prescott filter and obtained similar results.

[12] Following Morley et al. (2011) we tested to interpolate some outliers in the inflation series to not allow them to dominate the results. We replaced them with the Median of the six adjacent observations that were not outliers themselves and obtained similar results. The outliers are Canada 1991:1, 1994:1, Germany 1991:1-1991:12, Japan 1997:3 and UK 1990:7.

4.2 Estimation results

This section presents the results of the model given by equations (2)-(12). The order of autocorrelation, i.e. p, is set to four. Table 3 presents tests for autocorrelation, heteroscedasticity, and normality conducted on the one-step ahead prediction errors obtained from the estimation of the state space model. We refer to Durbin and Koopman (2001, p.34) for a discussion of these tests in a state space model. First, from the Ljung-Box tests for autocorrelation we note that the null hypothesis of no autocorrelation is not rejected at the conventional level of significance at most lags in the majority of countries, except for output growth in France and Spain. This suggests that a sufficient number of lags has been included. Second we test for heteroscedasticity conducting Ljung-Box tests for autocorrelation on the *squared* prediction errors. The results of these tests indicate some serial dependence in the *squared* prediction errors only for Italy in output growth and for Japan in inflation. Overall, the $GARCH$ processes capture the time-varying conditional heteroscedasticity that is present in the data. Third, normality of the prediction errors is strongly rejected. This is due to the $GARCH$ effects which render the unconditional distributions of the error terms in the state space system non-Gaussian. While the model is assumed to be conditionally Gaussian, it is clearly unconditionally non-Gaussian.

[Figure 1 about here.]

[Table 1 about here.]

Figure 1 shows the common factors in output growth and inflation in the period from January 1968 to June 2012 estimated by our model. Although the common factors are not in the focus of our analysis, the global uncertainty measures are based on them. The common output growth factor exhibits relatively small persistence as measured by the sum of the AR coefficients (see Table 1). It exhibits some downturns just before the mid 70s and during the end of the 70s and the early 80s. These fluctuations may be attributed to the first and second oil crisis, since most of the countries in the sample are oil importers. After the mid 80s the unconditional variance of common output growth declines until the recent

Great Recession. This phenomenon, known as the Great Moderation, has been found in the data of various industrialized countries (see Stock and Watson (2005)). The strongest decline in common output growth is during 2007-2009, the period of the Great Recession. Turning to the common inflation factor, it is estimated to be relatively persistent. Similarly to the common factor in output growth, it exhibits large fluctuations from the early 70s until the mid 80s. In this period, generally labelled as the Great Inflation, many countries experienced high inflation rates along with high unemployment rates. Thus, the two common factors capture major economic fluctuations that were common to the countries in our sample and which are well established in the literature.

[Figure 2 about here.]

Figure 2 presents the corresponding estimates of global real uncertainty and global nominal uncertainty. It shows a substantial increase in global real uncertainty in the 70s during the time of the oil price shocks. The sharpest spike in global real uncertainty can be clearly identified in 2008, during the Great Recession. In 2007, when the subprime crisis started in the US, only country-specific uncertainty in the US increases (see Figure 5), while in 2008, when the crisis spread globally and the Great Recession started, global real uncertainty raises substantially whereas country-specific US uncertainty decreases at the same time. Thus our uncertainty measures capture the evolution of the Great Recession and indicate that global uncertainty in fact played a role in its expansion process. Furthermore global real uncertainty decreases in the period from the mid 80s until the Great Recession. This supports the idea of the Great Moderation and shows that not only unconditional macroeconomic volatility but also uncertainty has declined in industrialized countries in this time period.

The oil price shocks and the Great Recession also increase global nominal uncertainty to a substantial extent. In times of the Great Inflation, global nominal uncertainty stays at an elevated level and in the early 90s it spikes again. While global real uncertainty vanishes very quickly, global nominal uncertainty exhibits much more persistence. This can be also seen in Table 1. The sum of the $ARCH$ and the $GARCH$ parameter in the conditional variance equation, which can be interpreted as a measure of persistence, is higher for the conditional variance of the common inflation factor as compared to the conditional variance of the common output factor. Thus, global nominal uncertainty is highly persistent while global real uncertainty is more volatile.[13]

[Table 2 about here.]

Table 2 displays the estimates of the *GARCH*-in-mean parameters. The means and associated quantiles of the parameters' posterior distributions are illustrated. The *GARCH*-in-mean effects reflect the relevance of global uncertainty for the individual countries' performance of output growth and inflation.

First we consider the effect of global real uncertainty on average output growth. Our results show evidence for a negative relationship between global real uncertainty and output growth and therefore support Bloom's theory of a "wait-and-see" effect for Canada, Italy, Japan and Spain as the *GARCH*-in-mean parameter are negative and significant for these countries. This implies that an increase in global real uncertainty leads to a slowdown in economic activity in these countries and that events causing global real uncertainty can be transmitted to these countries via an uncertainty channel. The *GARCH*-in-mean parameter reporting the effect of global real uncertainty on output growth is also significant but positive for the Netherlands, implying an increase in output when global real uncertainty rises. The effect of increased global real uncertainty on inflation is positive and significant for the Netherlands, Spain and UK whereas it is significantly negative for France.

An increase in global nominal uncertainty affects output growth on a country level positively in Italy, Japan and Spain. We find evidence for a negative and significant effect in the Netherlands and UK. Results are quite mixed here, but still indicate that global nominal uncertainty has an impact in the majority of countries in our sample. Nominal uncertainty on a global dimension is also related to changes in national inflation rates in the majority of countries. Japan, the Netherlands, Spain and UK show evidence for a significant and negative relationship, implying that heightened inflation uncertainty on a

[13] In fact the persistence in global nominal uncertainty is close to one. However, a near-integrated or integrated GARCH processes causes no specific inference problems. An IGARCH model can be estimated like any other GARCH model (see Enders (2004, pp. 140–141)).

global level decreases the inflation rates in those countries, whereas for France and Italy we find significant results for the opposite effect.

In sum, our parameter estimates point to a significant impact of global real and nominal uncertainty on the business cycle and inflation performance in the majority of countries in our sample. Although the $GARCH$-in-mean parameter show an overall mixed picture, especially concerning the direction of the uncertainty effects, there is empirical evidence that global real uncertainty has a negative effect for individual countries' output growth. However, with the exception of Germany, global macroeconomic uncertainty affects all countries in our sample. Thus, our results indicate that there exists a global dimension of uncertainty and that it should be taken into account in the analysis of individual countries' macroeconomic performance.

5 Conclusion

The quick expansion of the Great Recession and the limited explanatory power of direct contagion channels have rekindled interest in alternative shock transmission channels. The focus of this paper is on uncertainty as an indirect transmission mechanism and the impact of global macroeconomic uncertainty factors on individual countries' macroeconomic performance. In order to estimate a measure of global real and nominal uncertainty we set up a bivariate Dynamic Factor $GARCH$-in-mean model. The conditional variances of all factors are modeled as $GARCH$ processes and interpreted as uncertainty in the corresponding factor. The global uncertainty measures are included in the mean equation as explanatory variables to quantify their influence on output growth and inflation of the individual countries. The model is estimated using a Metropolis-Hastings algorithm. Global real uncertainty is found to be high during the mid 70s and during the Great Recession while it is low from the mid 80s until 2008. Global nominal uncertainty exhibits substantial persistence and spikes during the time of the Great Inflation and the Great Recession. We find significant influence of global macroeconomic uncertainty on output growth and/or inflation in almost all countries in our sample. The strongest evidence is on global real uncertainty, which negatively affects individual countries' output growth.

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Appendices

Appendix A Details on estimation

The model for $N = 9$ countries can be written in state space representation of the following form

$$u_t = Z\Omega_t + AX_t \tag{A-1}$$

$$\Omega_t = W\Omega_{t-1} + K\vartheta_t, \qquad \vartheta_{t|t-1} \sim N(0, Q_t), \qquad t = 1, ..., T \tag{A-2}$$

The *measurement equation* (A-1) relates the vector of the observable variables output growth y and inflation π, $u_t = [y_{1t} \dots y_{9t} \quad \pi_{1t} \dots \pi_{9t}]'$, to the unobservable factors, that are captured in the state vector Ω_t. The exact specification of the state vector Ω_t for $i = 1, ..., N$ and $m = \{y, \pi\}$ is given by

$$\Omega_t = \left[I_i^y \dots \quad R^y \dots \quad \eta_i^y \dots \quad \varepsilon^{Ry} \quad I_i^\pi \dots \quad R^\pi \dots \quad \eta_i^\pi \dots \quad \varepsilon^{R\pi}\right]',$$

with

$$I_i^m = [I_{it}^m \quad I_{it-1}^m \quad I_{it-2}^m \quad I_{it-3}^m], \eta_i^m = [\eta_{it}^m \quad \eta_{it-1}^m \quad \eta_{it-2}^m \quad \eta_{it-3}^m],$$

$$R^m = [R_t^m \quad R_{t-1}^m \quad R_{t-2}^m \quad R_{t-3}^m], \varepsilon^{Rm} = \left[\varepsilon_t^{Rm} \quad \varepsilon_{t-1}^{Rm} \quad \varepsilon_{t-2}^{Rm} \quad \varepsilon_{t-3}^{Rm}\right]$$

Z is a matrix of dimension 18×100 containing the factor loadings $(\beta_1, \dots, \beta_9, \kappa_1, \dots, \kappa_9)$. The *state equation* (A-2) reflects the dynamic structure of the system. A includes the $GARCH$-in-Mean parameters (δ_{11}^1, ..., δ_{22}^9), that measure to what extent the dependent variable moves with the global uncertainty measures, the time-varying conditional variances of the common factors $\sigma_{yt}, \sigma_{\pi t}$, captured by vector X_t. The transition matrix W contains the AR parameter ρ_k and θ_k of the common factor in output growth and inflation and all VAR parameter $\phi_{k,11}, \dots, \phi_{k,22}$ of the country-specific factors. The covariance matrix Q is defined as a diagonal matrix, containing the time-varying conditional variances on the diagonal. For $i = 1, \dots, N$ we have

$$diag(Q) = [h_{it}^y \quad \sigma_t^y \quad h_{it}^\pi \quad \sigma_t^\pi]'$$

where $\sigma_t^m = \alpha_0^m + \alpha_1^m \varepsilon_{t-1}^{m2} + \alpha_2^m \sigma_{t-1}^y$ with $\alpha_0^m = (1 - \alpha_1^m - \alpha_2^m)$ and $h_{it}^m = \beta_{i0}^m + \beta_{i1}^m \eta_{it-1}^{m2} + \beta_{i2}^m h_{it-1}^m$.

K is a 100×20 matrix relating the state vector Ω to ϑ.

The $GARCH$ effects imply time-varying conditional variances σ_t^y, σ_t^π, h_{it}^y and h_{it}^π and complicate the state space framework. To deal with this we follow the approach by Harvey et al. (1992) and include the shocks ε_t^y, ε_t^π, η_{it}^y and η_{it}^π in the state vector. We note then that σ_t^y, σ_t^π, h_{it}^y and h_{it}^π and therefore Q_{t+1} are functions of the unobserved states ε_t^y, ε_t^π, η_{it}^y and η_{it}^π. Harvey et al. (1992) replace σ_{t+1}^y, σ_{t+1}^π, h_{it+1}^y and h_{it+1}^π in the system by

$$\sigma_{t+1}^{y^*} = \alpha_0^y + \alpha_1^y \varepsilon_t^{y^*2} + \alpha_2^y \sigma_t^{y^*}, \tag{A-3}$$

$$\sigma_{t+1}^{\pi^*} = \alpha_0^\pi + \alpha_1^\pi \varepsilon_t^{\pi^*2} + \alpha_2^\pi \sigma_t^{\pi^*}, \tag{A-4}$$

$$h_{it+1}^{y^*} = \beta_{i0}^y + \beta_{i1}^y \eta_{it}^{y^*2} + \beta_{i2}^y h_{it}^{y^*}, \tag{A-5}$$

$$h_{it+1}^{\pi^*} = \beta_{i0}^\pi + \beta_{i1}^\pi \eta_{it}^{\pi^*2} + \beta_{i2}^\pi h_{it}^{\pi^*}, \tag{A-6}$$

where the unobserved ε_t^{y2}, $\varepsilon_t^{\pi 2}$, $\eta_{it}^{\pi 2}$ and η_{it}^{y2} are replaced by their conditional expectations $\varepsilon_t^{y*2} = E_t\varepsilon_{it}^2$, $\varepsilon_t^{\pi*2} = E_t\varepsilon_t^{\pi 2}$, $\eta_{it}^{y*2} = E_t\eta_{it}^{y2}$ and $\eta_{it}^{\pi*2} = E_t\eta_{it}^{\pi 2}$. Note that $E_t\varepsilon_t^{y2} = [E_t\varepsilon_t^y]^2 + \left[E_t(\varepsilon_t^y - E_t\varepsilon_t)^{y2}\right]$, $E_t\varepsilon_t^{\pi 2} = [E_t\varepsilon_t^\pi]^2 + \left[E_t(\varepsilon_t^\pi - E_t\varepsilon_t)^{\pi 2}\right]$, $E_t\eta_{it}^{y2} = [E_t\eta_{it}^y]^2 + \left[E_t(\eta_{it}^y - E_t\eta_{it}^y)^2\right]$ and $E_t\eta_{it}^{\pi 2} = [E_t\eta_{it}^\pi]^2 + \left[E_t(\eta_{it}^\pi - E_t\eta_{it}^\pi)^2\right]$where the quantities between square brackets are period t Kalman filter output (conditional means and variances of the states ε_t^y, ε_t^π, η_{it}^y and η_{it}^π). Thus, given $\sigma_t^{y^*}$, $\sigma_t^{\pi^*}$, $h_{it}^{y^*}$ and $h_{it}^{\pi^*}$ (which are initialized by the unconditional variances of ε_t^y , ε_t^π, η_{it}^y and η_{it}^π, i.e. $\varphi_{\varepsilon y}^2$, $\varphi_{\varepsilon\pi}^2$, $\varphi_{\eta yi}^2$, $\varphi_{\eta\pi i}^2$) and given the Kalman filter output from period t, namely $E_t(\Omega_t)$ and $V_t(\Omega_t)$, we can calculate σ_{t+1}^{y*}, $\sigma_{t+1}^{\pi*}$, h_{it+1}^{y*}, $h_{it+1}^{\pi*}$ and the system matrix Q_{t+1} which makes it possible to calculate $E_t(\Omega_{t+1})$, $V_t(\Omega_{t+1})$ and $E_{t+1}(\Omega_{t+1})$, $V_{t+1}(\Omega_{t+1})$.

Following Harvey et al. (1992) we proceed as though the state space model with $GARCH$ errors is conditionally Gaussian while this is not strictly the case. The reason is that knowledge of past observations does not imply knowledge of the past disturbances ε_t^y, ε_t^π, η_{it}^y, η_{it}^π and thus ε_t^{y2}, $\varepsilon_t^{\pi 2}$, η_{it}^{y2}, $\eta_{it}^{\pi 2}$ since the latter need to be replaced by ε_t^{y*2}, $\varepsilon_t^{\pi*2}$, η_{it}^{y*2} and $\eta_{it}^{\pi*2}$. This implies that the Kalman filter is *quasi*-optimal and the likelihood is an approximation. Monte Carlo simulations conducted by Harvey et al. (1992) suggest that this method works rather well for our available sample size.

Appendix B Diagnostic tests and Graphs

[Table 3 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

Figure 1: Common factors

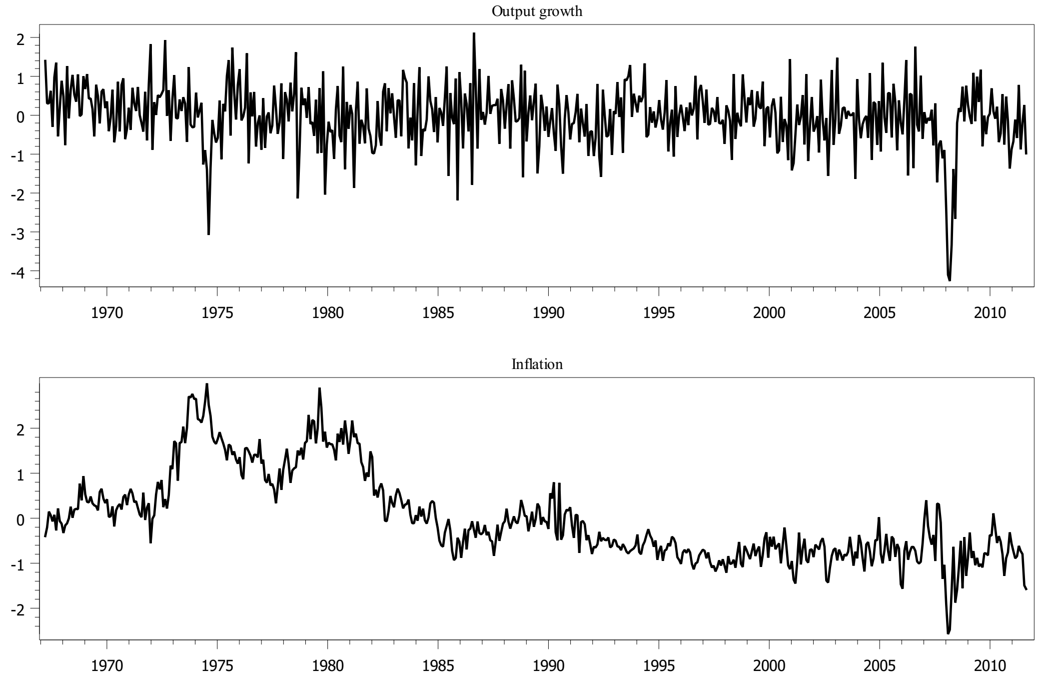

Figure 2: Global uncertainty

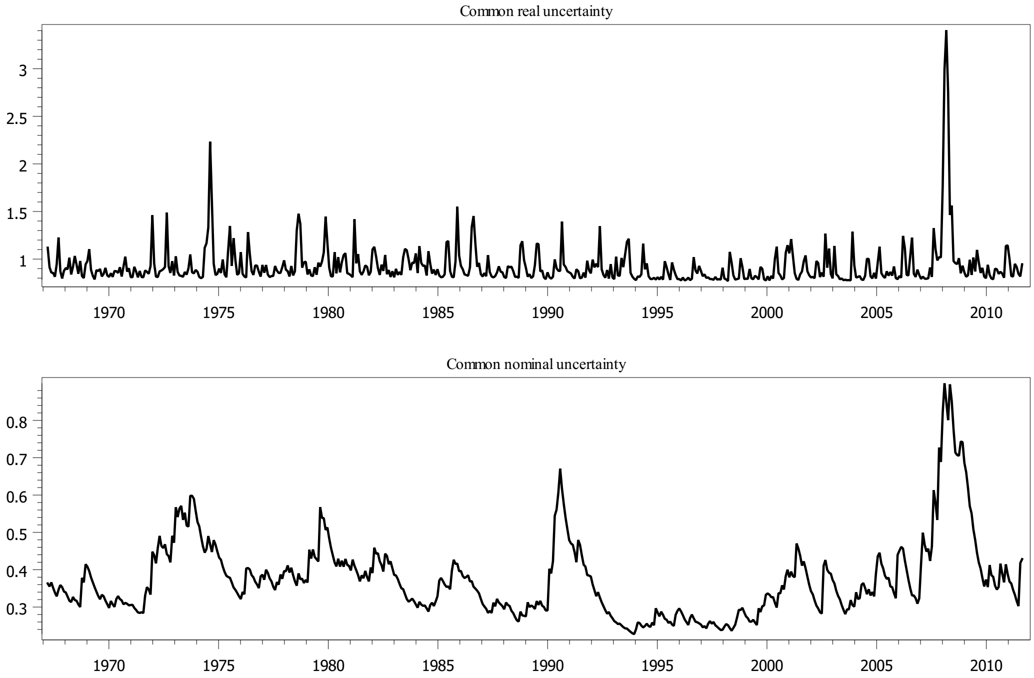

Figure 3: Country-specific factors: output growth

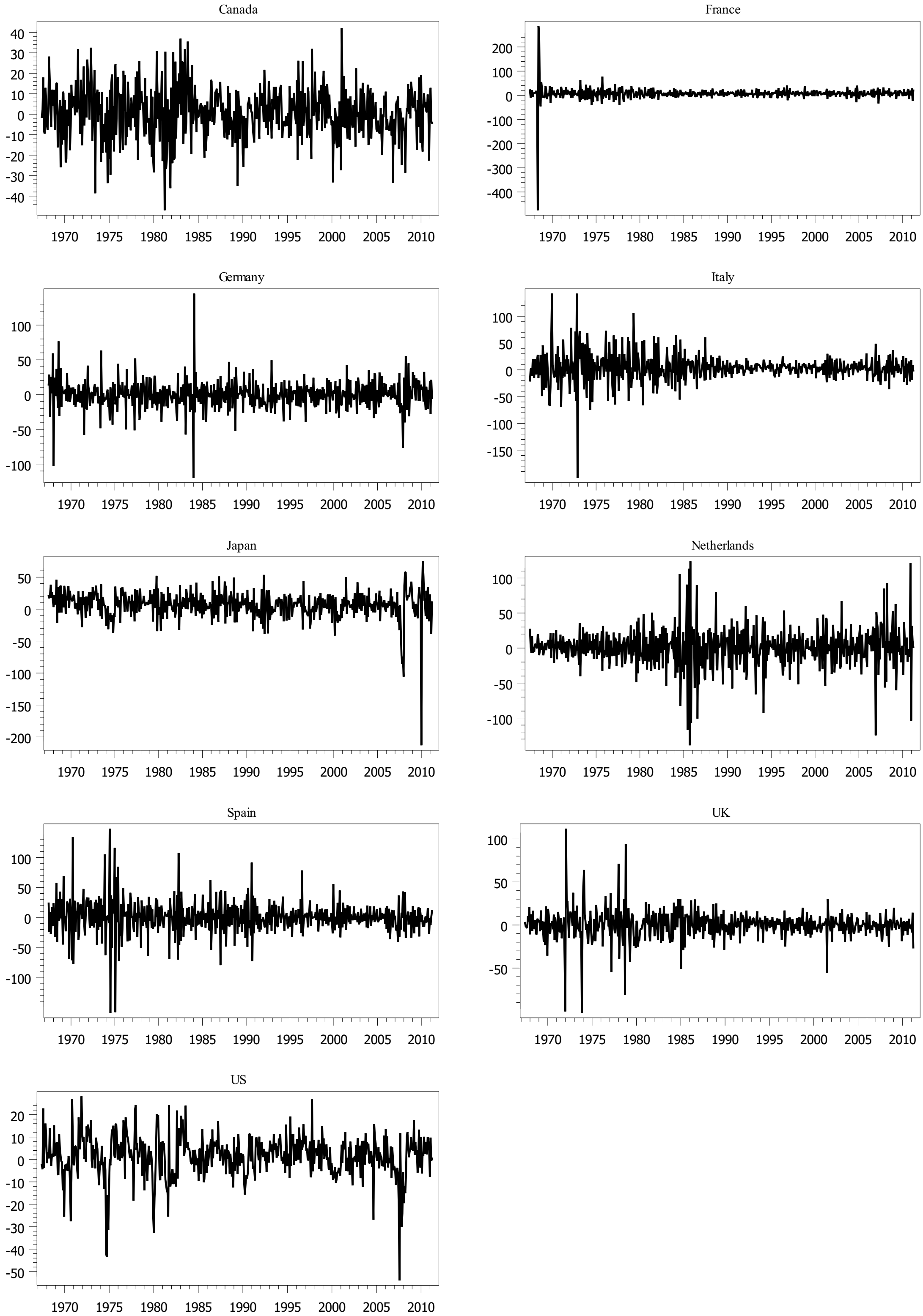

Figure 4: Country-specific factors: inflation

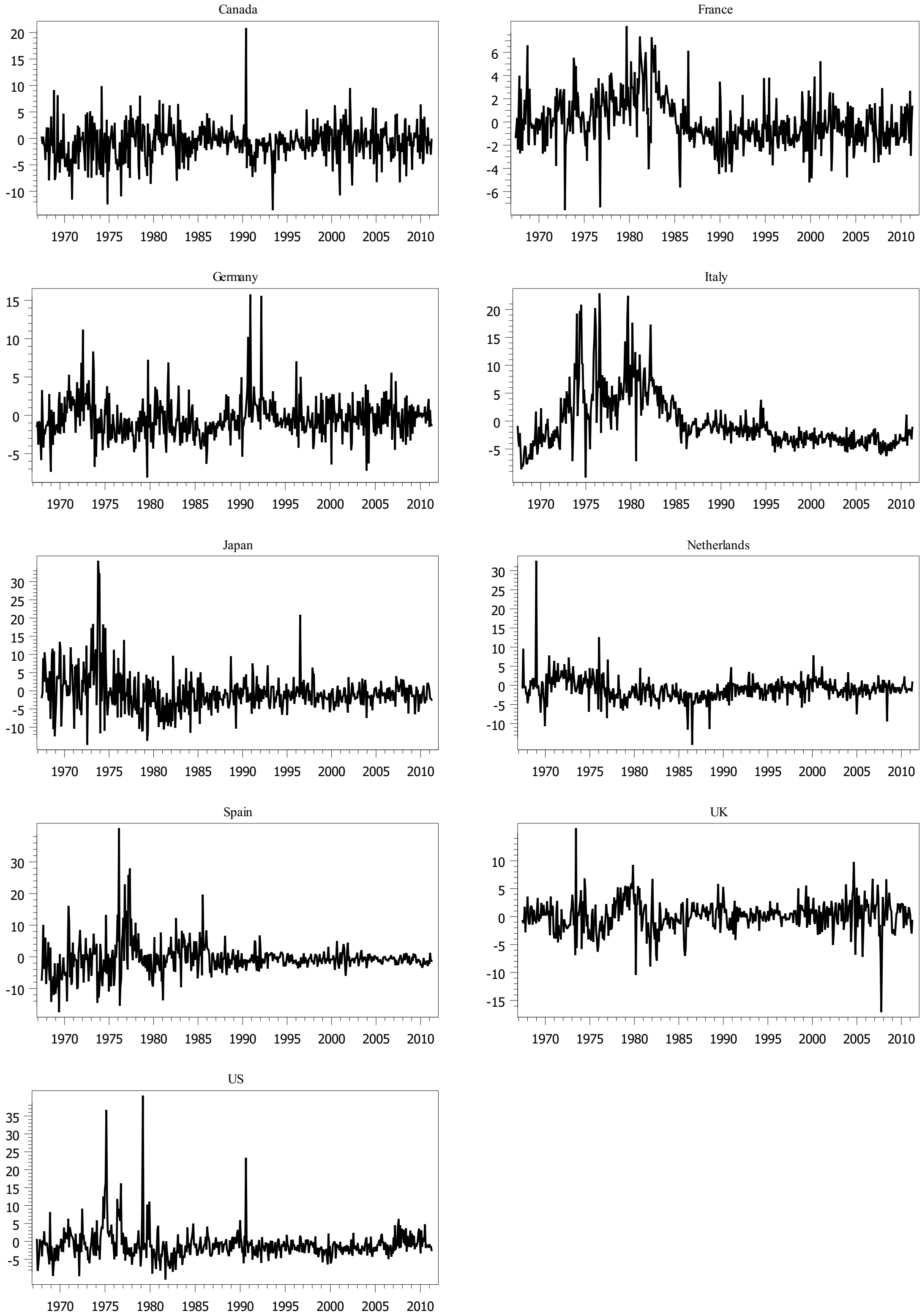

Figure 5: Country-specific uncertainties: output growth

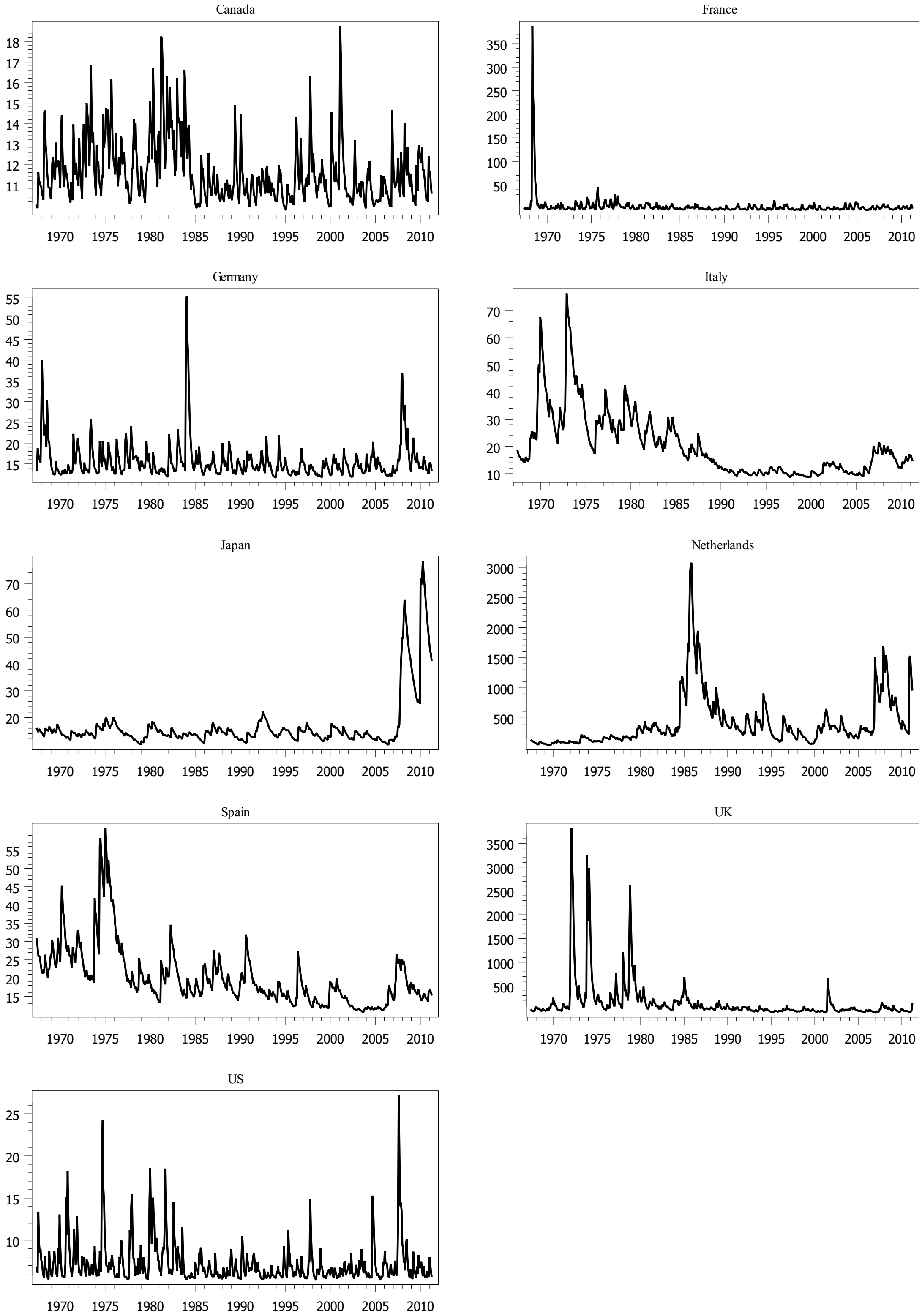

Figure 6: Country-specific uncertainties: inflation

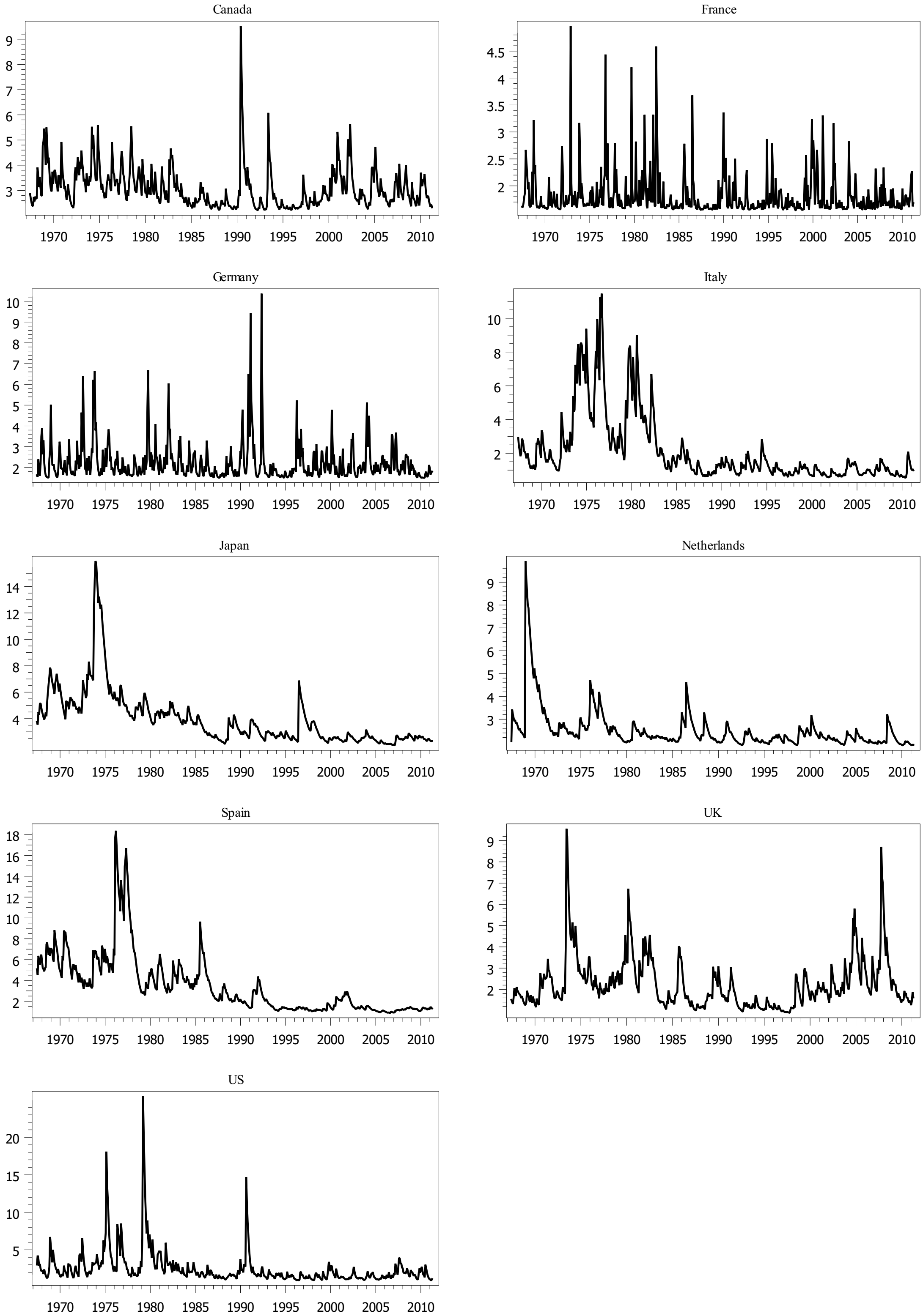

Table 1: Common factor AR(4)-$GARCH$(1,1) parameter

Common Factor Output Growth
$R^y_t = -0.228R^y_{t-1} + 0.026R^y_{t-2} + 0.179R^y_{t-3} + 0.062R^y_{t-4} + \varepsilon^y_t$
$\sigma^y_t = 0.468 + 0.420\varepsilon^{y2}_{t-1} + 0.112\sigma^y_{t-1}$
Common Factor Inflation
$R^\pi_t = 0.547R^\pi_{t-1} + 0.066R^\pi_{t-2} + 0.217R^\pi_{t-3} + 0.125R^\pi_{t-4} + \varepsilon^\pi_t$
$\sigma^\pi_t = 0.004 + 0.189\varepsilon^{\pi 2}_{t-1} + 0.807\sigma^\pi_{t-1}$

Table 2: $GARCH$-in-Mean effects

	Global real uncertainty on		Global nominal uncertainty on	
	Output Growth δ_{11}^{i}	Inflation δ_{12}^{i}	Output Growth δ_{21}^{i}	Inflation δ_{22}^{i}
Canada	-1.49	0.05	-0.50	0.59
	[-2.05, -0.93]	[-0.12, 0.22]	[-2.92, 1.89]	[-0.42, 1.58]
France	0.00	-0.31	1.06	2.11
	[-0.48, 0.48]	[-0.44, -0.17]	[-0.88, 3.03]	[1.15, 3.06]
Germany	-0.48	0.03	0.17	-0.20
	[-1.07, 0.13]	[-0.08, 0.14]	[-2.05, 2.40]	[-1.00, 0.61]
Italy	-1.76	-0.20	7.50	2.09
	[-2.28, -1.24]	[-0.28, -0.11]	[5.66, 9.28]	[0.83, 3.34]
Japan	-1.10	-0.15	4.47	-1.36
	[-1.87, -0.34]	[-0.33, 0.03]	[1.94, 7.02]	[-2.42, -0.29]
Netherlands	1.43	0.27	-4.07	-1.61
	[0.75, 2.07]	[0.07, 0.48]	[-6.15, -1.96]	[-2.76, -0.49]
Spain	-0.76	0.17	2.16	-2.85
	[-1.24, -0.28]	[0.04, 0.31]	[0.25, 4.07]	[-3.56, -2.15]
UK	0.04	0.15	-2.78	-1.39
	[-0.32, 0.40]	[0.03, 0.27]	[-4.40, -1.16]	[-2.04, -0.74]
US	-0.23	-0.25	0.61	0.45
	[-0.72, 0.28]	[-0.42, -0.09]	[-1.40, 2.61]	[-0.87, 1.76]

Notes: Intervals for 80% coverage are shown in parentheses.

Table 3: Specification tests

	CAN	FRA	GER	ITA	JAP	NL	SPA	UK	US
country-specific Ljung-Box test for autocorrelation$^{(a),(b)}$									
Output Growth									
lag 1	0.086	14.536	0.361	3.750	1.883	6.560	20.465	1.605	2.129
	[0.769]	[0.000]	[0.548]	[0.053]	[0.170]	[0.010]	[0.000]	[0.205]	[0.144]
lag 4	0.978	15.431	1.647	4.219	5.185	7.996	20.666	3.818	3.655
	[0.913]	[0.004]	[0.800]	[0.377]	[0.269]	[0.092]	[0.000]	[0.431]	[0.455]
lag 12	22.559	27.103	4.589	14.450	10.318	10.582	27.184	7.116	13.603
	[0.032]	[0.007]	[0.970]	[0.273]	[0.588]	[0.565]	[0.007]	[0.850]	[0.327]
Inflation									
lag 1	0.000	0.202	0.194	1.902	3.580	1.055	0.087	1.344	0.006
	[0.999]	[0.653]	[0.660]	[0.168]	[0.058]	[0.304]	[0.768]	[0.246]	[0.938]
lag 4	3.662	8.259	4.246	13.34	4.137	11.067	17.35	2.398	2.411
	[0.454]	[0.083]	[0.374]	[0.010]	[0.388]	[0.026]	[0.002]	[0.663]	[0.661]
lag 12	30.169	26.514	19.215	53.604	42.783	23.996	33.756	38.803	11.667
	[0.003]	[0.009]	[0.083]	[0.000]	[0.000]	[0.020]	[0.001]	[0.000]	[0.473]
country-specific Ljung-Box test for heteroscedasticity$^{(a),(c)}$									
Output Growth									
lag 1	0.141	0.004	0.058	15.036	0.003	0.063	4.947	0.898	2.256
	[0.707]	[0.952]	[0.810]	[0.000]	[0.954]	[0.801]	[0.026]	[0.343]	[0.133]
lag 4	6.47	0.197	0.135	30.53	3.467	0.318	4.951	0.913	3.797
	[0.167]	[0.995]	[0.998]	[0.000]	[0.483]	[0.989]	[0.292]	[0.923]	[0.434]
lag 12	24.82	0.377	0.207	36.34	3.554	3.184	5.018	0.947	10.50
	[0.016]	[1.000]	[1.000]	[0.000]	[0.990]	[0.994]	[0.957]	[1.000]	[0.572]
Inflation									
lag 1	0.072	0.170	0.568	0.757	46.653	0.029	0.012	2.752	0.395
	[0.789]	[0.680]	[0.451]	[0.384]	[0.000]	[0.865]	[0.912]	[0.097]	[0.530]
lag 4	0.974	0.696	1.044	2.384	46.75	0.097	26.32	3.329	0.621
	[0.914]	[0.952]	[0.903]	[0.666]	[0.000]	[0.999]	[0.000]	[0.504]	[0.961]
lag 12	3.057	5.926	4.765	16.47	47.01	0.587	26.38	10.56	2.107
	[0.995]	[0.920]	[0.965]	[0.171]	[0.000]	[1.000]	[0.009]	[0.567]	[0.999]
country-specific test for normality$^{(a),(d)}$									
Output Growth									
	10.1	95754.6	20751.1	87.1	63770.8	1115.5	1165021.0	119116.8	244.7
	[0.006]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Inflation									
	306.2	588.6	357.5	33.4	8273.9	42984.6	122060.4	53.0	879.5
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

(a) p-values are in square brackets
(b) The null hypothesis is no autocorrelation in the one-step-ahead prediction error
(c) The null hypothesis is homoscedasticity in the one-step-ahead prediction error
(d) The null hypothesis is normality of the one-step-ahead prediction error