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Keywords: Global inflation, conditional heteroskedasticity, inflation forecasting.

JEL classification: E31, E37, F41

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1 Introduction

Price stability has become an important mandate of many central banks around the world since the 1980s. It is now widely accepted that decision making becomes more complex in high and persistent inflation scenarios, as inflation may cloud public confidence as well as economic agents' assessments of future economic activity (Golob, 1994). Moreover, low inflation seems to promote growth and support sustainable employment in the long run (Bernanke, 2007). Thus, it is not surprising that a lot of effort has been devoted to the development of models that can accurately explain the dynamics of inflation rates.

In this article we contribute to the inflation literature by proposing and estimating a multivariate model of inflation with conditionally heteroskedastic common and country-specific components. The model is estimated in one-step by means of Quasi Maximum Likelihood (QML) which allows us to take time-series and cross-sectional information of (time-varying) first and second order moments into account and jointly estimate all parameters of the model. We analyze various specifications of the full model both in-sample and out-of-sample.

Our inflation model is motivated by the fact that it has become more difficult in the last decades to find economic models which can accurately describe the *ex-ante* dynamics of inflation (Stock and Watson, 2007). A possible reason given in the inflation literature to the 'unpredictability' phenomenon is that inflation expectations seem to be now anchored over the long term, that is, inflation is relatively insensitive to the arrival of new information. Rather, agents appear to stick to their long-run reference of inflation when making their forecasts (Mishkin, 2007). This, in turn, would explain why empirical studies have found that the Phillips curve has become flatter and why oil shocks and other macroeconomic variables have relatively less explanatory power than in the past (Hooker, 2002). Nevertheless, while inflation expectations seem to be relatively more anchored than in the past, some suggest that the anchoring is somewhat imperfect. In other words, agents seem to set expectations to a long term trend but unanticipated shocks can cause temporary deviations from this trend (Gurkaynak et al., 2005).

Stock and Watson (2007) (SW henceforth) formalized an elegant statistical model that accurately describes the dynamics of inflation in the United States (US) and that sheds light on the hypothesis of imperfect anchoring of expectations. The SW model decomposes inflation rates in the US into two components: a permanent and a transitory component which can also be interpreted as a time-varying trend and a cycle. Following Bernanke (2007), the SW model shows that there has been a moderation in the level of variability of trend inflation since the 1980's suggesting that innovations to inflation expectations are much more likely to be transitory now than three decades ago. However, the variability of the trend in inflation, although lower, remains positive which suggests that long-run expectations are not perfectly anchored.

Along the lines of SW, a study by Broto and Ruiz (2009) (BR henceforth) finds evidence that inflation rates can be modeled by means of conditionally heteroskedastic permanent and transitory components. Interestingly, BR find that volatility of inflation seems to exhibit asymmetric effects, that is, high (low) inflation today leads to high (low) volatility of inflation tomorrow. This finding can be related to the literature on inflation uncertainty which suggests the that high inflation can increase inflation uncertainty (Friedman, 1977; Golob, 1994).

An interesting study by Ciccarelli and Mojon (2010) (CM henceforth) recently documented comovements of inflation amongst OECD economies. We interpret their result as evidence of a common time-varying trend of inflation, very much in the spirit of the SW and BR decompositions but with a more concrete economic interpretation: global inflation rates are driven by a highly persistent common stochastic trend. Moreover, similar to the finding by Cogley et al. (2010) for the US, CM show that inflation gaps of their model (given by the spread of global inflation rates to the common global trend) shows some persistent autoregressive properties. The model by CM not only provides evidence on international comovement and error correction of inflation but also seems to outperform standard benchmarks (such as an autoregressive model of inflation and a random walk) in out-of-sample analyzes.

Cecchetti et al. (2007) (CHKSW henceforth) use the SW model to extract smoothed estimates of the transitory and permanent components of inflation for the G7 countries, as well as their time-varying volatilities. Smoothed estimates of the permanent components are very similar across G7 countries, reinforcing the evidence of a global trend in inflation reported by CM. Moreover, CHKSW also provide some evidence on comovements in the *volatility* of the permanent components of global inflation rates. In fact, the results of CHKSW document the 'Great Moderation' of inflation volatility in most of the G7 economies. Thus, it seems that the comovement of global inflation rates is not only apparent in their first order moments but also in their second order moments.

Overall, the results of the studies by SW, BR, CPS, CM and CHKSW seem to point to the same direction: inflation rates in various countries can be described by a permanent-transitory component specification and the permanent component along with its volatility seem to be common amongst OECD economies. The time-series evidence also fits well to the hypothesis on (imperfect) anchoring of inflation expectations over the long-term which partially explains the so-called 'Great Moderation'. In addition, if global and national inflation volatility are indeed time-varying, global models of inflation with time-varying volatility can also contribute to the burgeoning literature on inflation uncertainty. An accurate estimate of inflation uncertainty would imply that consumers and businesses could better plan for the future (Golob, 1994).

The specification proposed in this study is rich in the sense that it incorporates all the empirical determinants of inflation rates set forth by SW, BR, CPS, CM and CHKSW into a compact global inflation model. To preview some of our results, we find that the estimated common inflation component can explain on average more than 50% of the variability of national inflation in the G7. The estimated volatility of the common inflation component captures the international effects of the 'Great Moderation' and of the 'Great Recession'. Various model specifications considered fit well the first and second order dynamics of inflation in the G7. The model also shows promising capabilities for forecasting inflation in several countries.

The article is organized as follows. In the next section we describe our empirical model. Section 3 describes the data set used and the estimation methodology employed. Section 4 presents the forecasting design. Section 5 discusses the results of our analysis and the last section concludes with some final remarks.

2 The model

We consider the following specification of inflation, denoted π_{it}, for $i = 1, ..., N$ cross-sectional members and $t = 1, ..., T$ time periods:

$$\pi_{it} = \lambda_i g_t + f_{it}, \tag{1}$$

where g_t and f_{it} are, respectively, common and country-specific latent components and λ_i is the so-called loading coefficient. The components g_t and f_{it} follow autoregressive processes of order one, i.e.

$$\begin{aligned} g_t &= (1-\rho)\mu + \rho g_{t-1} + \epsilon_t, & (2) \\ f_{it} &= \phi_i f_{it-1} + u_{it}, & (3) \end{aligned}$$

where ρ and ϕ_i are parameters such that $|\rho| < 1$ and $|\phi_i| < 1$, and the disturbance terms ϵ_t, u_{it} and u_{jt}, $i \neq j$ are uncorrelated and have zero-mean. Note then, that $E[\pi_{it}] = \lambda_i \mu$ is the unconditional mean of each inflation rate π_{it} in our set up in the case $|\rho| < 1$. The common component g_t follows from the time series evidence on the existence of a world trend documented by CM whereas the autoregressive country-specific component f_{it} stems from both CM and CPS who show that inflation gaps display serial correlation. Our set up for inflation implies the following error correction model (ECM) obtained from the above system for each i:

$$\Delta\pi_{it} = \varphi_i f_{it-1} + \lambda_i \Delta g_t + u_{it}, \tag{4}$$

where $\Delta\pi_{it} = \pi_{it} - \pi_{it-1}$ is the change in inflation, $f_{it} = \pi_{it} - \lambda_i g_t$ is the so-called error correction term, $\Delta g_t = g_t - g_{t-1}$ is the change in the common inflation component and $\varphi_i = (\phi_i - 1)$ is the error correction parameter. In a nutshell, the ECM suggests that inflation rates are mean-reverting to their long-run reference level g_t with the speed of adjustment given by φ_i. Furthermore, note that if we assume a random walk specification for the common component g_t, i.e. $\rho = 1$, then the variables π_{it} would be integrated of order one, denoted $I(1)$, as they would be explained by a non-stationary component (g_t) and a stationary component (f_{it}). However, as long as $\varphi_i < 0$ ($|\phi_i| < 1$), model (4) is stable and country inflation π_{it} is said to be *cointegrated* to the common inflation component g_t with cointegrating (long-run) parameter λ_i, denoted $CI(1, -\lambda_i)$ for short. It is also worth noting that in the cointegration case $\rho = 1$, the shock ϵ_t has a permanent effect on inflation π_{it} while the country specific shock u_{it} has a temporary (mean-reverting) effect.

Following the empirical evidence documented by SW, BR and CHKSW, we assume that ϵ_t and u_{it} are conditionally heteroskedastic:

$$\epsilon_t \sim N(0, v_t), \tag{5}$$

$$u_{it} \sim N(0, \omega_{it}). \tag{6}$$

Along the lines of BR who find evidence of asymmetry in inflation volatility (higher (lower) inflation today can generate higher (lower) inflation volatility tomorrow), we employ a Quadratic Generalized Autoregressive Conditionally Heteroskedastic specification of order one (QGARCH(1,1) henceforth) for v_t and ω_{it}, i.e.

$$v_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 v_{t-1} + \alpha_3 \epsilon_{t-1}, \tag{7}$$

$$\omega_{it} = \beta_{i0} + \beta_{i1} u_{it-1}^2 + \beta_{i2} \omega_{it-1} + \beta_{i3} u_{it-1}, \tag{8}$$

where the parameters $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ and $\beta_{i0}, \beta_{i1}, \beta_{i2}, \beta_{i3}$ satisfy the usual conditions to guarantee positivity of v_t and ω_{it} (Sentana, 1995). Under the QGARCH(1,1) specification, conditional variances have different responses to shocks of the same magnitude but different sign (Broto and Ruiz, 2009).

Note that the empirical model (1)-(6) is general enough to nest other interesting specifications analyzed in previous studies. For instance, when $|\rho| < 1$ and ϵ_t and u_{it} are homoskedastic, we end up with the global specification proposed by CM.[1] Similar to BR, we may obtain a permanent-transitory component specification for each country from the above system if $g_t = g_{it}$, $\rho = 1$, $\phi_i = 0$ and $\lambda_i = 1$. Moreover, if $g_t = g_{it}$, $\rho = 1$, $\phi_i = 0$ and $\lambda_i = 1$, but v_t and ω_{it}

[1]Note, however, that CM do a multi-step approach to estimate their error-correction model whereas our approach estimates *all* parameters jointly.

have an integrated stochastic volatility formulation we arrive at the specification used in SW and CHKSW.

Collecting the equations (1)-(8) for all i leads to the following compact state-space representation of a multivariate inflation model with conditionally heteroskedastic disturbances:

$$\Pi_t = AS_t, \quad (9)$$

$$S_t = BS_{t-1} + \xi_t, \qquad \xi_t \sim N(0, Q_t), \quad (10)$$

where $\Pi_t = (\pi_{1t}, ..., \pi_{Nt})'$ is the vector of inflation rates, $S_t = (g_t, f_{1t}, ..., f_{Nt})'$ is the state vector containing the common (global henceforth) component and the country-specific components, and $\xi_t = (\epsilon_t, u_{1t}, ..., u_{Nt})'$ is the vector of state disturbances. The matrix $A = [\Lambda, I_N]$ links the observations to the unobserved states, where $\Lambda = (\lambda_1, ..., \lambda_N)'$ is the vector of loading coefficients and I_N is an identity matrix of order N. Moreover, $B = \text{diag}(\rho, \phi_1, ..., \phi_N)$ is a diagonal state transition matrix and $Q_t = \text{diag}(v_t, \omega_{1t}, ..., \omega_{Nt})$ is a diagonal covariance matrix whose elements are defined in (7) and (8). In the subsequent sections we describe the estimation approach of the state space model in (9)-(10) and the out-of-sample analysis designed for this study.

3 Data and estimation approach

The dataset comprises quarterly data on the Consumer Price Index (CPI) denoted P_{it} for OECD economies in the G7 (Canada, France, Germany, Italy, Japan, United Kingdom and United States). The full sample period runs from Q1-1960 to Q4-2009 and the data have been obtained from the OECD Statistics Portal.[2] We employ year-on-year (yoy) inflation rates, i.e. $\pi_{it} = 100 \times (\ln P_{it} - \ln P_{it-4})$ to avoid seasonalities (Ciccarelli and Mojon, 2010).

Model (9)-(10) is estimated by means of Quasi Maximum Likelihood. Note, that if $\xi_t = (\epsilon_t, u_{1,t}, ..., u_{N,t})'$ were observed, the model (9)-(10) would be conditionally Gaussian and the Kalman filter would be the optimal filter in the sense that it would yield minimum mean square estimates of the states $S_t = (g_t, f_{1,t}, ..., f_{N,t})'$. However, the disturbances ξ_t are unobserved and

[2] See http://www.oecd.org/statsportal for further details.

equations (7)-(8) cannot be computed. Harvey et al. (1992) propose to substitute ϵ_t and u_{it} in (7) and (8) by their conditional expectations, i.e.

$$
\begin{aligned}
v_t &= \alpha_0 + \alpha_1 E\left[\epsilon_{t-1}^2 | \Pi_{t-1}\right] + \alpha_2 v_{t-1} + \alpha_3 E\left[\epsilon_{t-1} | \Pi_{t-1}\right], &(11)\\
\omega_{it} &= \beta_{i0} + \beta_{i1} E\left[u_{it-1}^2 | \Pi_{t-1}\right] + \beta_{i2}\omega_{it-1} + \beta_{i3} E\left[u_{it-1} | \Pi_{t-1}\right]. &(12)
\end{aligned}
$$

In this approach, the state vector is augmented with the disturbances ξ_t such that the Kalman filter recursions can be used to compute the expectations in (11) and (12). The augmented measurement and state transition equations are then given by

$$
\begin{aligned}
\Pi_t &= A^* S_t^* = [A, 0_{N,N+1}] S_t^*, \\
S_t^* &= \begin{bmatrix} S_t \\ \xi_t \end{bmatrix} = \begin{bmatrix} B & 0_{N+1,N+1} \\ 0_{N+1,N+1} & 0_{N+1,N+1} \end{bmatrix} \begin{bmatrix} S_{t-1} \\ \xi_{t-1} \end{bmatrix} + \begin{bmatrix} I_{N+1} \\ I_{N+1} \end{bmatrix} \xi_t. \qquad (13)
\end{aligned}
$$

Although the conditional distribution of ξ_t given ξ_{t-1} is assumed to be normal with mean zero and variance Q_t, the distribution of ξ_t conditional on past observations is unknown, as knowledge of past observations does not imply knowledge of past disturbances. Harvey et al. (1992) propose to treat the augmented state space (13) as if it were conditionally Gaussian and to use the Kalman filter to obtain an approximate likelihood function based on the prediction errors decomposition:

$$
\log L(\Gamma | \underline{\Pi}) = -\frac{NT}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(|\Sigma_t|) - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t' \Sigma_t^{-1}\varepsilon_t, \qquad (14)
$$

where $\underline{\Pi} = (\Pi_1, ..., \Pi_T)'$ are the observations, ε_t are the innovations and Σ_t their corresponding variances. The Quasi-Maximum Likelihood estimates of Γ are obtained by maximizing the Gaussian log-likelihood in (14) (see, for instance, Kim and Nelson (1999) for further details).

The vector of parameters to be estimated in the full version of model (9)-(10) is given by:

$$
\Gamma = (1, ..., \lambda_N^*, \mu, \rho, \phi_1, ..., \phi_N, \alpha_0, \alpha_1, \alpha_2, \alpha_3, \beta_{01}, ..., \beta_{0N}, \beta_{11}, ..., \beta_{1N}, \beta_{21}, ..., \beta_{2N}, \beta_{31}, ..., \beta_{3N})', \qquad (15)
$$

where we normalize the loading coefficients with respect to the loading coefficient of the US, i.e. $\lambda_i^* = \lambda_i/\lambda_1$ for $i = 2, ..., N$. As introduced previously, our model is rich in the sense that it allows us to analyze various nested specifications. In our in-sample and out-of-sample analysis we study other submodels within the fully parameterized model. The different specifications analyzed are denoted M1 to M6 and are displayed in Table 1.

We used Principal Component Analysis (PCA) to find initial values for the loading matrix Λ, and an Ordinary Least Squares (OLS) regression of the first principal component on its lagged values to obtain an initial value for the autoregressive parameter ρ of the global component. Given the PCA estimate of Λ and g_t, we computed an estimate for $f_{it} = \pi_{it} - \lambda_i g_t$, $i = 1, ..., N$, and subsequently estimated the autoregressive (AR) coefficients ϕ_i by means of an OLS regression of the estimate for f_{it} on f_{it-1}. These initial values are used as starting point in the BFGS (Broyden, 1970) numerical optimization routine, used to maximize (14) with a homoskedastic version of our model (9)-(10), i.e. with $Q_t = Q$. This restricted version of the model (denoted M1) is conditionally Gaussian, and the Kalman filter is the optimal filter for its estimation. The ML estimates of the subset parameter vector $\Gamma^{(1)}$ obtained from the estimation of M1 are used to initialize the estimation of two larger models: M2 which contains GARCH effects only in the country-specific components f_{it} and M3 which contains GARCH effects only in the global component g_t. Initial values for GARCH parameters are obtained by estimating GARCH processes with estimates of ϵ_t and u_{it} computed from M1. The QML parameter estimates $\Gamma^{(2)}$ and $\Gamma^{(3)}$ obtained from M2 and M3, respectively, are subsequently used to initialize the estimation of the other model specifications considered: M4 (with GARCH(1,1) in g_t and f_{it}), M5 (with IGARCH(1,1) in g_t and f_{it}) and M6 (with QIGARCH(1,1) in g_t and f_{it}).

4 Out-of-sample analysis

The proposed model is also tested out-of-sample to shed light on its capabilities for forecasting inflation. The out-of-sample period chosen for backtesting the model runs from Q1-1985 to Q4-2009 which covers the second half of our sample.[3] In what follows we describe the forecasting

[3]Other samples yielded qualitatively similar results and can be provided upon request.

methodology employed for single and combined forecasts and the forecast evaluation.

4.1 Single forecasts

Let τ denote the forecast origin. The out-of-sample forecasting analysis consists of estimating the parameter vector $\Gamma^{(l)}$ of model l up to time $\tau = R$ and using observations $\tau = R, R+1, ..., T-h$ to obtain forecasts $\hat{\pi}_{i\tau+h|\tau}$ and $\Delta\hat{\pi}_{i\tau+h|\tau}$ recursively for horizons $h = 1, 4, 8$, i.e. quarterly, annually and bi-annually yoy-inflation, based on the Kalman filter estimates $\hat{g}_\tau$ and $\hat{f}_{i\tau}$. Due to the computationally intensive estimation procedure, we do not re-estimate parameters at each τ in order to save on computational time.

Forecasts of inflation $\hat{\pi}_{i\tau+h|\tau}$ for each i, τ and h are obtained as

$$\hat{\pi}_{i\tau+h|\tau} = \hat{\lambda}_i^* \hat{g}_{\tau+h|\tau} + \hat{f}_{i\tau+h|\tau}, \tag{16}$$

$$\hat{g}_{\tau+h|\tau} = \hat{\mu} + \hat{\rho}^h \hat{g}_\tau, \tag{17}$$

$$\hat{f}_{i\tau+h|\tau} = \hat{\phi}_i^h \hat{f}_{i\tau}. \tag{18}$$

We obtain forecasts of inflation changes $\Delta\hat{\pi}_{i\tau+h|\tau}$ for each i, τ and h as

$$\Delta\hat{\pi}_{i\tau+h|\tau} = \hat{\lambda}_i^* \Delta\hat{g}_{\tau+h|\tau} + \Delta\hat{f}_{i\tau+h|\tau}, \tag{19}$$

$$\Delta\hat{g}_{\tau+h|\tau} = (\hat{\rho} - 1)\hat{\rho}^{h-1} \hat{g}_\tau, \tag{20}$$

$$\Delta\hat{f}_{i\tau+h|\tau} = (\hat{\phi}_i - 1)\hat{\phi}_i^{h-1} \hat{f}_{i\tau}. \tag{21}$$

From an economic perspective, forecasts of inflation $\hat{\pi}_{i\tau+h|\tau}$ might be more interesting than forecast of inflation changes $\Delta\hat{\pi}_{i\tau+h|\tau}$ as they have a straight forward interpretation. However, recent studies have suggested that accurate forecasts of the direction of inflation changes can shed light (ex-ante) onto the type of monetary policy needed (i.e. tight versus loose) which motivates us to also analyze them here (Sinclair et al., 2006).

4.2 Combined forecasts

An important result from the methodological literature on forecasting is that a linear combination of two or more forecasts may yield more accurate predictions than using only a single forecast (Granger, 1989; Newbold and Harvey, 2002; Aiolfi and Timmermann, 2006). In particular, there is recent evidence that combining forecast of nested models can significantly improve forecasting precision upon forecasts obtained from single model specifications (Clark and McCracken, 2009). Therefore, our proposed inflation model provides a good platform to test out-of-sample complementarities between alternative nested models (Table 1) via forecast combinations.

Combinations of inflation forecasts obtained from various models for each $i = 1, ..., N$ are given by:

$$\hat{y}_{i\tau+h|\tau} = \widehat{\boldsymbol{w}}'_{i\tau+h|\tau}\widehat{\boldsymbol{\eta}}_{i\tau+h|\tau}, \tag{22}$$

where $\hat{y}_{i\tau+h|\tau}$ is the combined forecast of inflation (inflation change), $\widehat{\boldsymbol{\eta}}_{i\tau+h|\tau}$ is a vector that collects forecasts of inflation (inflation change) of model l and $\widehat{\boldsymbol{w}}_{i\tau+h|\tau}$ is a vector that collects the weights attached to each model l.

The weights $\widehat{w}_{l,i\tau+h|\tau}$, $l = 1, ..., 5$, are computed based on alternative criteria that measure the out-of-sample performance of each inflation (inflation change) forecast l. Note, however, that since a forecaster would only have information available up to the forecast origin τ, the sub-sample for forecast selection and computation of weights must contain data on or before that period. Thus, we start by setting equal weights to all forecasts until the weighting schemes could be based on the evaluation of *realized* forecast errors. This procedure guarantees that we use only information available up to a particular period τ to set weights of forecasts for period $\tau + h$. The following 5 alternative combination strategies $c = \{1, 2, ..., 5\}$ are considered:

1. *Simple average (AFC)*: Various studies have demonstrated that simple averaging of a multitude of forecasts works well in relation to more sophisticated weighting schemes (Newbold and Harvey, 2002; Clark and McCracken, 2009). Therefore, the first scheme that we use is of averaging all the forecasts obtained from the different models considered.

2. *Thick-modeling approach with OLS weights (TFC)*: A study by Granger and Jeon (2004) proposes the so-called thick modeling approach (TMA) which consists of selecting the z-percent of the best forecasting models in the sub-sample period for model evaluation, according to the root mean square error (RMSE) criterion. We use the selection process of Granger and Jeon and subsequently compute weights by means of OLS regressions along with the constraint that the weights are all positive and sum up to one. The z-percent of top forecasts selected is set to 2 (i.e. about z=35%).

3. *Rank-weighted combinations (RFC)*: The RFC scheme, suggested by Aiolfi and Timmermann (2006), consists of first computing the RMSE of all models in the sub-sample period for evaluation. Defining $RANK_{h,i\tau}(l)$ as the rank of the l-th model based on its historical RMSE performance up to time τ for horizon h, the weight for the l-th forecast is then calculated as: $\widehat{w}_{l,i\tau+h|\tau} = RANK_{h,i\tau}(l)^{-1}/\sum_l RANK_{h,i\tau}(l)^{-1}$.

4. *RMSE-weighted combinations (MFC)*: The MFC weighting scheme is similar to RFC and consists of computing the RMSE of all selected models l and setting the weight of the l-th model as $\widehat{w}_{l,i\tau+h|\tau} = RMSE_{h,i\tau}(l)^{-1}/\sum_l RMSE_{h,i\tau}(l)^{-1}$.

5. *Frequency combinations (FFC)*: The FFC scheme consists of assigning to each l-th forecast, a weight equal to a model's empirical frequency of minimizing the squared forecast error over realized past forecasts.

4.3 Forecast evaluation

In order to evaluate forecasts of inflation we employ mean squared forecast errors (MSE) and mean absolute forecast errors (MAE). MSE and MAE of a particular model are given in percentage of the MSE and MAE of either an autoregressive model of order one (AR) or a random walk model (RW). More precisely, let $\tilde{\tau} = 1, ..., \mathcal{T}$ denote an out-of-sample forecast observation with $\mathcal{T} = T - R - h$. Let '$\bullet$' and '0' indicate a particular competing model and the benchmark, respectively. Forecast errors of model '$\bullet$' for country i are computed as

$$\hat{e}_{i\tilde{\tau}}(\bullet) = \pi_{i\tilde{\tau}} - \hat{\pi}_{i\tilde{\tau}}(\bullet). \tag{23}$$

The MSE and MAE of model '•' are:

$$\bar{d}_i(\bullet) = \mathcal{T}^{-1} \sum_{\tilde{\tau}} d_{i\tilde{\tau}}(\bullet), \tag{24}$$

with $d_{i\tilde{\tau}}(\bullet) = \hat{e}_{i\tilde{\tau}}(\bullet)^2$ for MSE or $d_{i\tilde{\tau}}(\bullet) = |\hat{e}_{i\tilde{\tau}}(\bullet)|$ for MAE. The average performance of a competing model specification is given in relation to $\bar{d}_i(0)$, obtaining relative MSEs or MAEs:

$$\overline{dr}_i(\bullet) = \frac{\bar{d}_i(\bullet)}{\bar{d}_i(0)}, \tag{25}$$

where $\bar{d}_i(0)$ is defined as in (24). Thus, $\overline{dr}_i(\bullet)$ values below one indicate a superior performance of a particular model '•' against the benchmark '0' in terms of MSE or MAE. Note that (25) computed with $d_{i\tilde{\tau}}(\bullet) = \hat{e}_{i\tilde{\tau}}(\bullet)^2$ and $d_{i\tilde{\tau}}(0) = \hat{e}_{i\tilde{\tau}}(0)^2$ in (24) is related to the so-called out-of-sample R^2 as $R^2_{OS,i} = 1 - \overline{dr}_i(\bullet)$.

In order to analyze whether model '0' has a statistically equal predictive accuracy to model '•', we employ the modified Diebold Mariano (DM) test of Harvey et al. (1997). We address the issue of forecast complementarities between '0' and '•' by means of the forecast encompassing test proposed by Harvey et al. (1998). Lastly, we analyze the out-of-sample performance of our model for forecasting the direction of change of inflation $\Delta\pi_{it+h}$ by means of the directional-accuracy test of Pesaran and Timmermann (1995).

5 Results

In this section we discuss the main results of our study. We consider first the in-sample results (Tables 2 to 7) and subsequently the out-of-sample results (Tables 8 to 13).

5.1 In-sample results

Tables 6 and 7 display the parameter estimation results for the full sample period Q1-1960 to Q4-2009. The first specification (M1) considers the multivariate inflation model with an AR world component and homoskedastic shocks, i.e. $|\rho| < 1$, $\alpha_k = 0$ and $\beta_{ik} = 0$ for $k = 1, 2$

and all i. Note, then, that this model is a variant of the global inflation model proposed by CM (estimated in one step). We find for this version of the model that the normalized loading coefficients $\hat{\lambda}_i^*$ and autoregressive coefficients $\hat{\phi}_i$ are all statistically different from zero at the 5% level. The estimate $\hat{\rho}$ in M1 is very close to one, indicating that the global inflation component possibly follows a random walk process. This result suggests that the inflation rates of the G7 might be cointegrated with the global inflation component since the estimated autoregressive parameters $\hat{\phi}_i$ are all less than one (Table 3). The case of $\rho = 1$ is supported by unit root tests and cointegration tests presented in Tables 2 and 3. In fact, imposing $\rho = 1$ yields a higher log-likelihood value for M2-M6 than for M1 (Table 5).[4] Thus, models M2 to M6 assume a cointegrated model of G7 inflation, that is we set $\rho = 1$.

Model 2 (M2) assumes that $\alpha_k = 0$ for $k = 1, 2$, i.e. GARCH effects only in the country-specific components f_{it}. For the latter model, we find that the loading coefficients $\hat{\lambda}_i^*$ and autoregressive coefficients $\hat{\phi}_i$ are statistically different from zero as in the case of M1. However, (G)ARCH parameters of the country-specific components f_{it} are statistically insignificant in most countries. Moreover, in several countries the restriction $\beta_{1,i} + \beta_{2,i} < 1$ is almost binding suggesting that conditional volatility could be better approximated by an Integrated GARCH (IGARCH) process. Interestingly, the latter results corroborates the model of SW who specify conditional variances by means of integrated stochastic volatility processes.

Model 3 (M3) considers a heteroskedastic global inflation component g_t but homoskedastic country-specific components f_{it}, i.e. $\alpha_k \neq 0$ and $\beta_{ik} = 0$ for $k = 1, 2$ and all i. The latter model yields parameter estimates $\hat{\lambda}_i^*$ and $\hat{\phi}_i$ that are statistically different from zero in all countries at conventional significance levels. Interestingly, M3 clearly shows that the world component g_t exhibits time-varying volatility v_t as all GARCH parameters are statistically different from zero (Table 7).

Model 4 (M4) assumes GARCH specifications for the global g_t and the country-specific f_{it} components, i.e. $\alpha_k \neq 0$ and $\beta_{ik} \neq 0$ for $k = 1, 2$ and all i. However, as in the case of M2, (G)ARCH parameter estimates of the country-specific shocks are not statistically different from zero at the 5% level in most countries and the restrictions on these parameters are also almost

[4] A higher log likelihood is also obtained for the homoskedastic case with $\rho = 1$. Results can be provided upon request.

binding in several countries.

Given the results on M2 and M4, we have imposed the restrictions $\alpha_2 = 1 - \alpha_1$ and $\beta_{i2} = 1 - \beta_{i1}$ throughout in Models 5 (M5) and 6 (M6) which specifies conditional variances as (Q)IGARCH processes. As expected, the parameters of the integrated conditional variances in M5 and M6 are found to be statistically different from zero in most countries and for the world component. In fact, the model incorporating IGARCH and asymmetric variance effects (M6) yields the highest log-likelihood value out of all models considered (Table 5). Moreover, M6 displays evidence of asymmetry in volatility at the 5% level in most countries which suggests that high (low) inflation can generate high (low) inflation uncertainty. The relationship between inflation and inflation volatility seems to be positive in all countries except for Canada. Interestingly, the pass-through of inflation to inflation volatility is highest in France, Canada and Japan which are also the three countries with the fastest speed of adjustment $\varphi_i = \phi_i - 1$ according to M6.

Figure 1 displays the filtered estimates of the country specific components for the G7 economies obtained from M6 which is the full model. To save on space, we only present the figures for M6 although similar plots are also obtained for other versions of the model and can be provided upon request. Similar to CM, our global inflation estimate ($\hat{g}_t$) suggests a highly significant international co-movement of inflation for the G7. The figure also shows the mean reverting features of the country-specific error correction terms ($\hat{f}_{it} = \pi_{it} - \hat{\lambda}_i^* \hat{g}_t$) suggesting that global inflation is 'attractive' as proposed by CM. Visually, mean reversion seems to be fastest (slowest) for France and Canada (USA and Italy) which is in line with their fast (slow) speed of adjustment φ_i. Thus, it appears that France and Canada (USA and Italy) display a relatively low (high) level of price 'stickiness' according to the data with M6 as underlying model.

Table 4 shows the results of a variance decomposition of M1 (the stationary case). We find that the global inflation component explains on average more than 50% of national inflation rate fluctuations, while a similar analysis for international business cycles shows that a global business cycle component accounts on average for only 30% of the variance of industrial production growth in OECD countries (Kose et al., 2008).

Figure 2 displays the conditional variance estimates for the G7 obtained from M6. Similar plots are also obtained for other versions of the model. Note that the volatility of the global component captures the effect of the 'Great Moderation' but also shows a relative increase in 'world' inflation volatility after the start of the 'Great Recession'. Interestingly, the effect of the 'Great Recession' in US national inflation volatility is affected not only via an increase in the volatility of the global component, but also via the increase in the volatility of its country-specific component.

Lastly, Figure 3 shows time-varying correlations obtained from our multivariate inflation model for particular pairs of countries. Note that in all cases shown, the correlation of inflation rates has increased in comparison to previous periods since the start of the 'Great Recession'. In fact, in some cases, the correlation level has come back to pre-'Great Moderation' levels.

Summing up, our proposed multivariate inflation model seems to describe the mean and variance dynamics of inflation in the G7. However, some specifications seem to fit the data better than others in-sample. In the next section we explore the out-of-sample implications of the alternative specifications analyzed and their complementarities.

5.2 Out-of-sample results

In this section we discuss the out-of-sample performance of the various model specifications considered and of combined forecasts, respectively. Tables 8 to 10 display the forecasting results of the single model specifications. Tables 12 to 13 display the results on forecast combinations.

5.2.1 Single models

M1 which assumes homoskedastic (autoregressive) global and country-specific components, yields relative MSEs (with RW as benchmark) which are below one for all countries except for France. Forecasts of M1 encompass information of the RW forecasts according to the HLN statistic in all countries except for France (Table 10). The latter result suggests that combining forecasts of a RW and M1 for France would significantly improve inflation forecasts obtained exclusively from M1 for this particular country. M1 also yields forecasts of inflation changes that can accurately predict the direction of inflation change with a 95% confidence level in Germany ($h = 1, 4$), Italy ($h = 8$) and in the UK ($h = 4, 8$) (Table 10).

Turning to M2, which assumes a random walk global component and GARCH variances in the country-specific components, we find that the MSEs results improve upon M1 for most countries considered and at most forecasting horizons (Table 8). As for M1, we also find that only in the case of France it would be possible to improve inflation forecasts at certain horizons by means of a linear combination of forecasts obtained from M2 and RW according to the HLN statistic (Table 10). Results on directional accuracy for M2 remain similar to those of M1 in Germany and the UK.

Accounting for conditional heteroskedasticity in the global component only (M3) yields somewhat higher relative MSEs in relation to M2 in most countries (Table 8). M3 forecast encompasses the RW benchmark in most cases except of Japan at $h = 1, 4$. Results on directional accuracy for M3 show that the direction of inflation changes can be accurately predicted with this specification in the USA ($h = 4$), Germany ($h = 4$) and Italy ($h = 4$). The model with GARCH specifications in all shocks (M4) yields lower relative MSEs than M1 and M3 (Table 8). M4 forecast encompasses the RW model in most countries except for France. Results on directional accuracy for M4 remain qualitatively similar to M1 and M2 (Table 10).

We find that M5 which restricts shocks to have IGARCH variances yields a qualitatively similar out-of-sample performance to M4 in terms of relative MSEs. However, restricting the model to have IGARCH variances results in better forecasts than M1-M3 in terms of relative MSEs (Table 8). Results on forecast encompassing and directional accuracy remain similar to all other models for M5. Lastly, M6 which accounts for asymmetric effects in the variance of the shocks usually yields the best performance in terms of MSEs in relation to other models at most forecasting horizons. The out-of-sample performance of the alternative model specifications seems to be consistent with the in-sample fit of each model as given by the likelihood values in Table 5.

The previous forecasting results for inflation are qualitatively similar when comparing the performance *across* models by means of MAEs (Table 8 and Table 9). However, relative MAEs are usually larger than MSEs when comparing both measures. Moreover, it is worth noting that MSEs and MAEs relative to AR increase in relation to MSEs and MAEs relative to RW. This suggests that the AR benchmark is more difficult to beat than the RW benchmark which corroborates previous studies on inflation forecasting (Ciccarelli and Mojon, 2010).

Summing up, we find that the multivariate inflation specification for the G7 performs well out-of-sample in relation to the standard benchmarks of the literature. This can be appreciated visually at the aggregate level in Figures 4 and 5 which display (by means of boxplots) the cross-section of relative MSEs for selected model specifications. In particular, we find that the model with a common non-stationary component and QIGARCH shocks (M6) leads to better forecasts than other nested specifications considered.

5.2.2 Combined forecasts

Tables 12 to 13 display the results of the forecast combination exercise. As is usually the case in the forecasting literature, simple averaging of the forecasts (AFC) yields good results when compared against more sophisticated methods (e.g. TFC, MFC, FFC). We find that combining forecasts improve upon forecasts of several single models at various forecasting horizons. For instance, in the USA, simple averaging of the forecasts (AFC) and the forecast combination based on rank weights (RFC) improves upon M1 and M3 in terms of relative MSEs and MAEs. Similarly, relative MSEs and MAEs of models M1 and M4 for Germany are improved by most forecast combination strategies. In the case of France, where relative MSEs and MAEs are found greater than one in all model specifications, TFC and FFC usually improve relative MSEs and MAEs of most single models (although these quantities are still greater than one). The overall benefits of combining forecast can be appreciated in Figures 4 and 5 which show that relative MSEs remain similar to the 'best' model specifications but improve upon the 'worst' model specifications. Indeed, in several countries there is an increase in the number of rejections of the DM test in relation to single models.

The results on the HLN and PT test remain, however, qualitatively similar to those of single models. As in the case of single models, MSEs and MAEs relative to the RW benchmark are somewhat lower than those relative to the AR model, suggesting again that the AR model is harder to beat.

6 Conclusion

We contribute to the empirical inflation literature by proposing and estimating a multivariate model of inflation with conditionally heteroskedastic common and country-specific components. Our empirical specification is rich in the sense that it incorporates all the determinants of inflation that reconcile the empirical evidence set forth by SW, BR, CPS, CM and CHKSW. The model is estimated in one-step by means of QML and we analyze various specifications of the full model both in-sample and out-of-sample. In general, we find that the proposed model (with some parameter restrictions) fits the data quite well and has good forecasting performance relative to the RW, AR and a variant of the benchmark proposed by CM.

We find that the estimated global inflation trend can explain on average more than 50% of the variability of national inflation in the G7. The volatility of the global inflation trend captures the international effects of the 'Great Moderation' and of the 'Great Recession'. We also find that there is an increase in correlation of inflation for certain country pairs since the start of the 'Great Recession'. Moreover, there is evidence of asymmetry in inflation volatility which is consistent with the idea from Friedman (1977) that higher inflation levels lead to greater uncertainty about future inflation.

An interesting extension to this model would be to allow for stochastic volatility in the shocks. Furthermore, it would be interesting to investigate the dynamics of world volatility of various macro variables. We leave these issues for future research.

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A Time varying correlations

Time varying correlations of the model based on the parameter estimates are computed as:

$$\widehat{\text{Cor}}_{t-1}(\pi_{it}, \pi_{jt}) = \frac{\widehat{\text{Cov}}_{t-1}[\pi_{it}, \pi_{jt}]}{\sqrt{\widehat{\text{Var}}_{t-1}[\pi_{it}]}\sqrt{\widehat{\text{Var}}_{t-1}[\pi_{jt}]}},$$

with

$$\widehat{\text{Var}}_{t-1}[\pi_{it}] = \hat{\lambda}_i^2\hat{\rho}^2 P_{t-1}^{gg} + \hat{\lambda}_i^2\hat{v}_t + 2\hat{\lambda}_i\hat{\phi}_i\hat{\rho}P_{t-1}^{gf_i} + \hat{\phi}_i^2 P_{t-1}^{f_if_i} + \hat{\omega}_{it}, \quad (26)$$

$$\widehat{\text{Cov}}_{t-1}[\pi_{it}, \pi_{jt}] = \hat{\lambda}_i\hat{\lambda}_j(\hat{\rho}^2 P_{t-1}^{gg} + \hat{v}_t) + \hat{\lambda}_i\hat{\rho}\hat{\phi}_j P_{t-1}^{gf_j} + \hat{\lambda}_j\hat{\rho}\hat{\phi}_i P_{t-1}^{gf_i} + \hat{\phi}_i\hat{\phi}_j P_{t-1}^{f_if_j}, \quad (27)$$

where P_{t-1}^{ij} is the period $t-1$ covariance between the estimates of states i and j.

Figure 1: Fitted global inflation component $\hat{g}_t$ and country-specific components $\hat{f}_{it}$ (error correction terms). Dashed red lines correspond to 95% confidence intervals

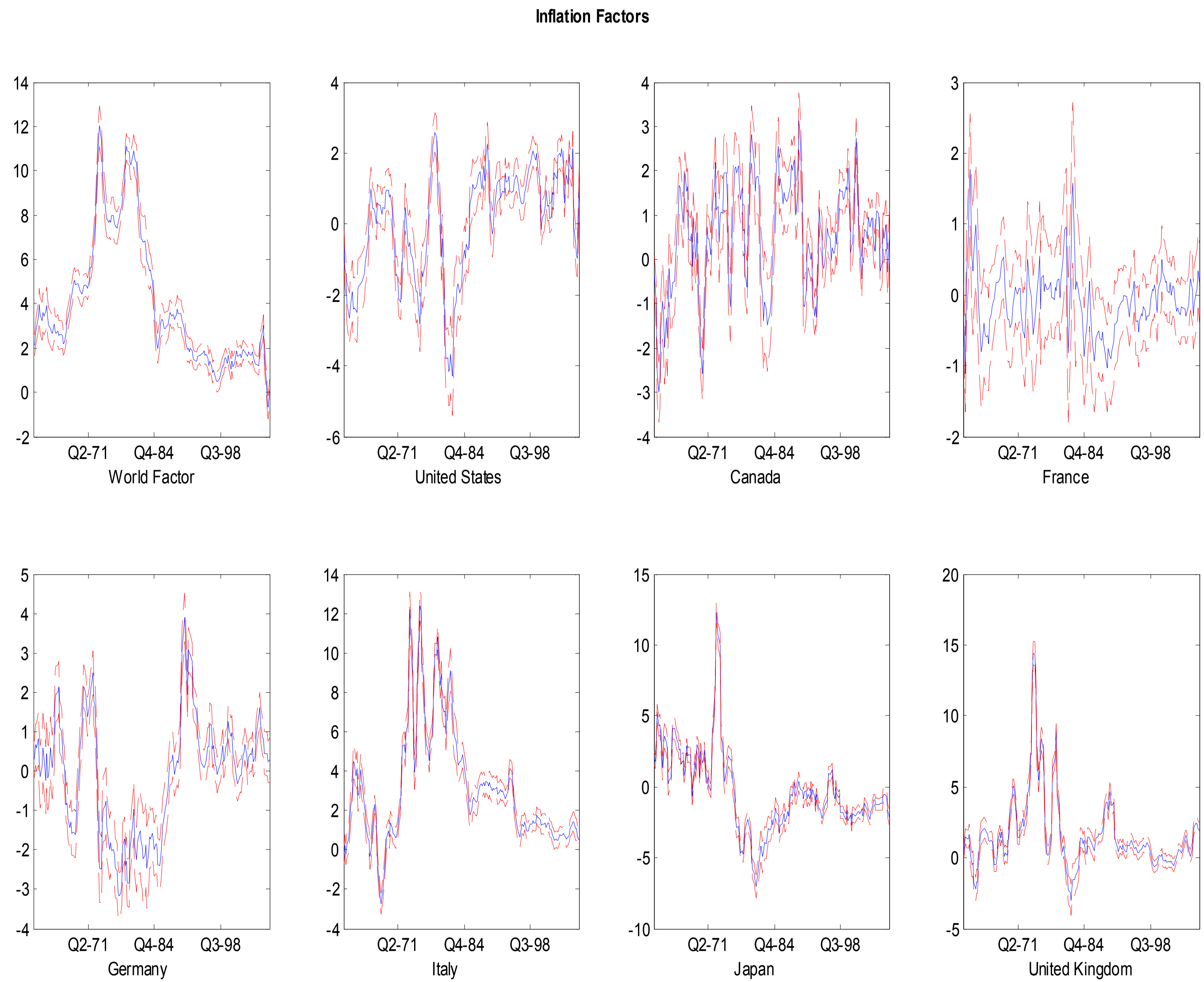


Figure 2: Fitted QIGARCH(1,1) volatilities of the global inflation component $\hat{g}_t$ and country-specific components $\hat{f}_{it}$ (error correction terms).

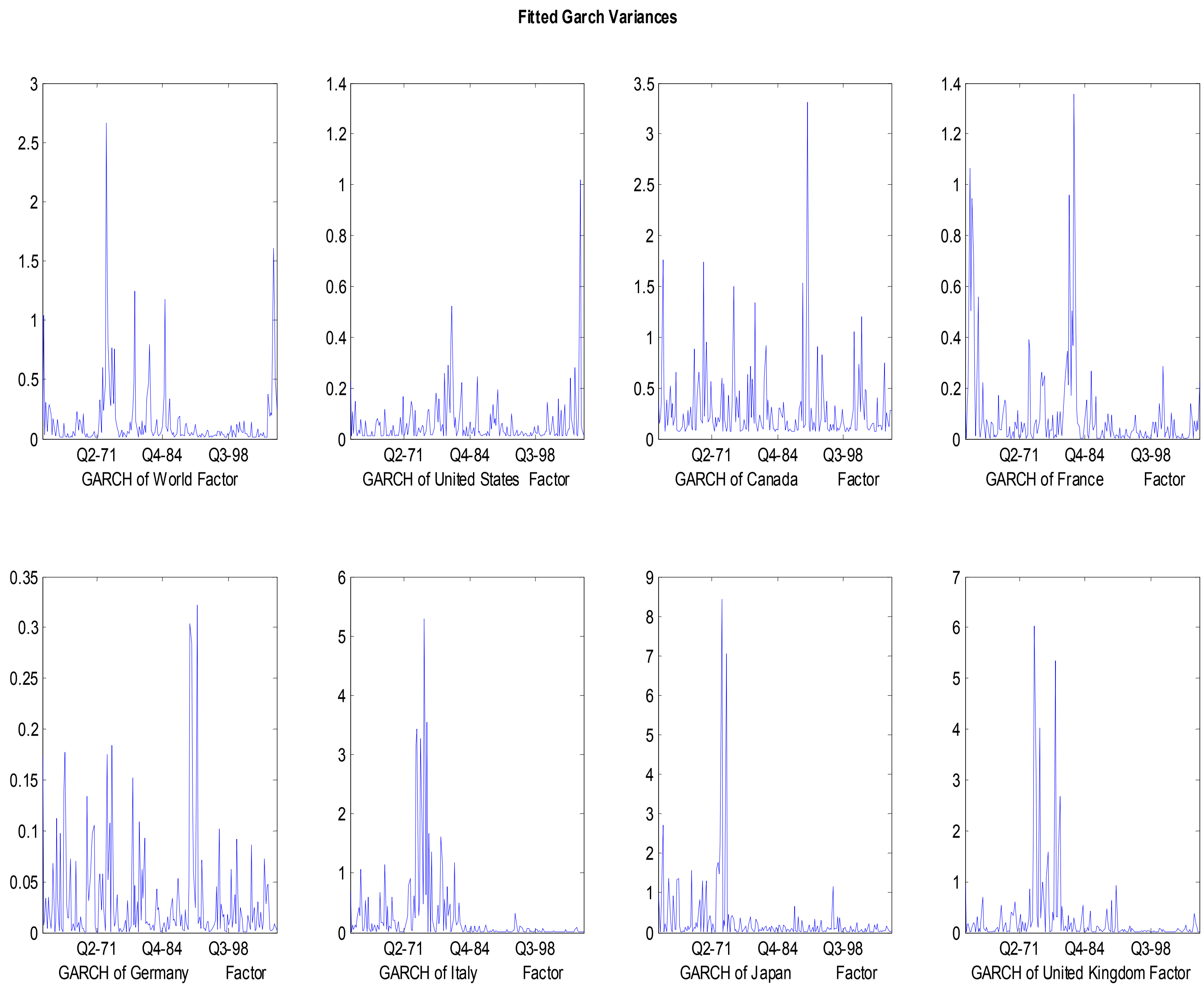


Figure 3: Fitted conditional correlations of inflation for selected country pairs.

Figure 4: Boxplots of the cross-section of relative MSEs for selected models (random walk benchmark). Note: The box has lines at the lower quartile, median, and upper quartile values. The whiskers show the extent of the rest of the data. Outliers are data with values beyond the ends of the whiskers. Boxplots are in the same scale for easy comparability.

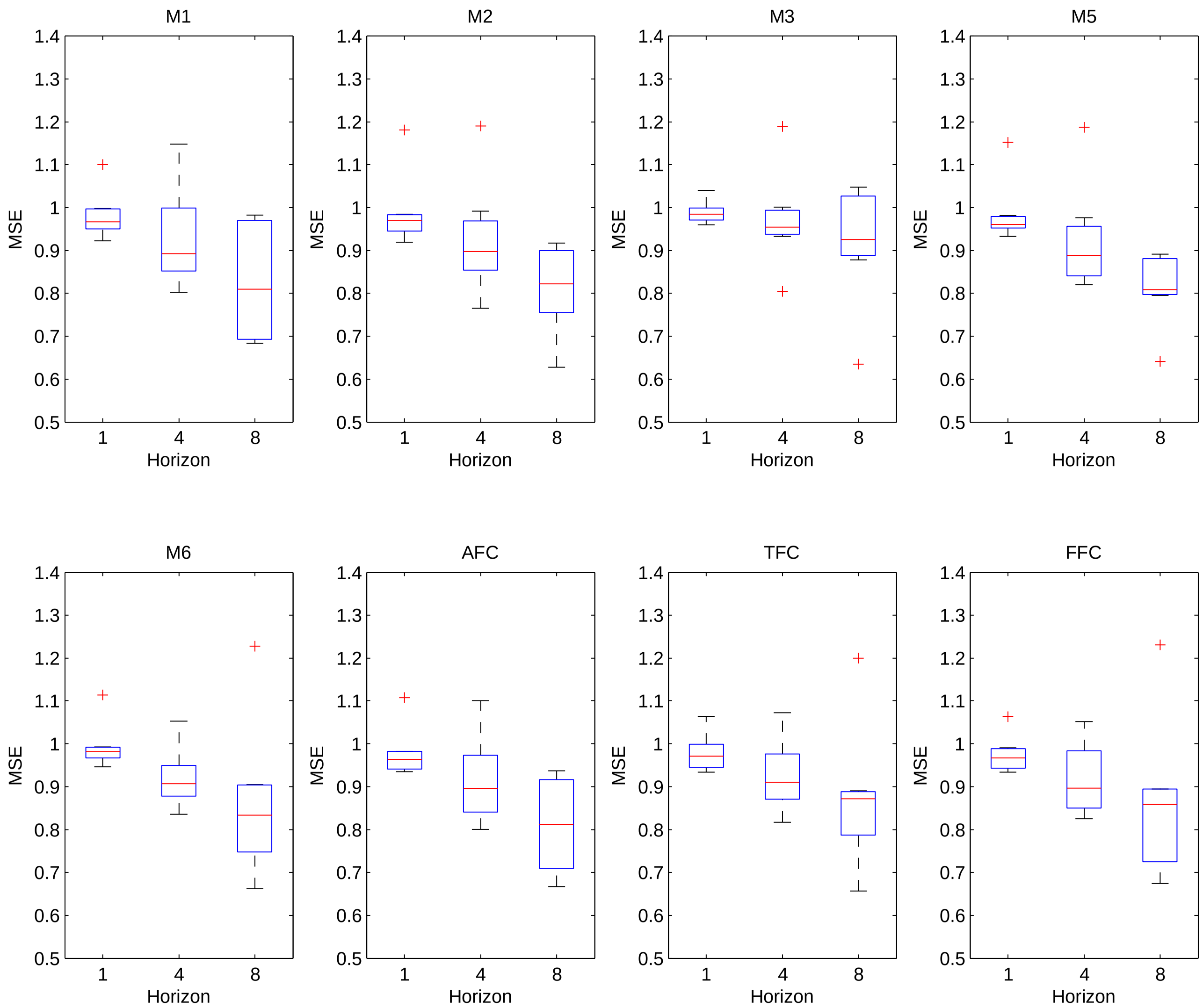
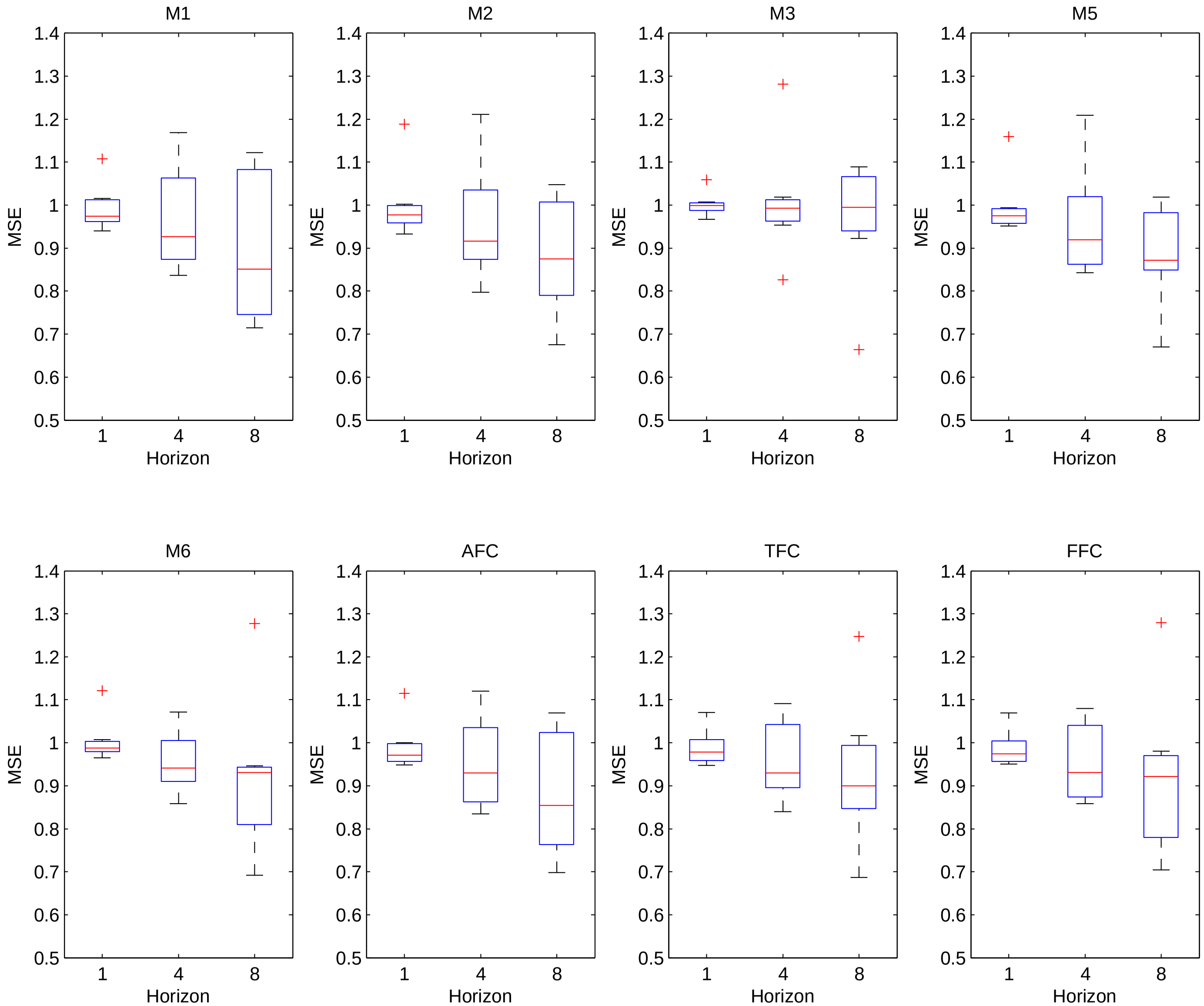


Figure 5: Boxplots of the cross-section of relative MSEs for selected models (autoregressive benchmark). For further notes see Figure 4



Model	Parameter space
M1: AR g_t, AR f_{it}, CV g_t and f_{it}	$\Gamma^{(1)} = (1, ..., \lambda_N^*, \mu, \rho, \phi_1, ..., \phi_N, \alpha_0, 0, 0, 0, \beta_{01}, ..., \beta_{0N}, 0, ..., 0, 0, ..., 0, 0, ..., 0)'$
M2: RW g_t, AR f_{it}, CV g_t and GARCH(1,1) f_{it}	$\Gamma^{(2)} = (1, ..., \lambda_N^*, 0, 1, \phi_1, ..., \phi_N, \alpha_0, 0, 0, 0, \beta_{01}, ..., \beta_{0N}, \beta_{11}, ..., \beta_{1N}\beta_{21}, ..., \beta_{2N}, 0, ..., 0)'$
M3: RW g_t, AR f_{it}, GARCH(1,1) g_t and CV f_{it}	$\Gamma^{(3)} = (1, ..., \lambda_N^*, 0, 1, \phi_1, ..., \phi_N, \alpha_0, \alpha_1, \alpha_2, \alpha_3, 0, ..., 0, 0, ..., 0, 0, ..., 0, 0, ..., 0)'$
M4: RW g_t, AR f_{it}, GARCH(1,1) g_t and f_{it}	$\Gamma^{(4)} = (1, ..., \lambda_N^*, 0, 1, \phi_1, ..., \phi_N, \alpha_0, \alpha_1, \alpha_2, 0, \beta_{01}, ..., \beta_{0N}, \beta_{11}, ..., \beta_{1N}\beta_{21}, ..., \beta_{2N}, 0, ..., 0)'$
M5: RW g_t, AR f_{it}, IGARCH(1,1) g_t and f_{it}	$\Gamma^{(5)} = (1, ..., \lambda_N^*, 0, 1, \phi_1, ..., \phi_N, \alpha_0, \alpha_1, 1-\alpha_1, 0, \beta_{01}, ..., \beta_{0N}, \beta_{11}, ..., \beta_{1N}, 1-\beta_{11}, ..., 1-\beta_{1N}, 0, ..., 0)'$
M6: RW g_t, AR f_{it}, QIGARCH(1,1) g_t and f_{it}	$\Gamma^{(6)} = (1, ..., \lambda_N^*, 0, 1, \phi_1, ..., \phi_N, \alpha_0, \alpha_1, 1-\alpha_1, \alpha_3, \beta_{01}, ..., \beta_{0N}, \beta_{11}, ..., \beta_{1N}, 1-\beta_{11}, ..., 1-\beta_{1N}, \beta_{31}, ..., \beta_{3N})'$

Table 1: Parameter spaces of the alternative model specifications. Note: AR: autoregressive, RW: random walk, CV: constant variance

	US	Canada	France	Germany	Italy	Japan	UK
τ_{ADF}	-2.168	-1.498	-0.974	-2.122	-1.016	-1.885	-1.619

Table 2: Results from Augmented Dickey-Fuller test with 4 lags and a constant term. 10% critical value of τ_{ADF} is -2.569.

Null Hypothesis	J_{trace}	J_{max}
$r = 0$	169.255	53.311
crit 90%	120.367	43.295
crit 95%	125.619	46.230
crit 99%	135.982	52.307
$r = 1$	115.944	44.693
crit 90%	91.109	37.279
crit 95%	95.754	40.076
crit 99%	104.964	45.866
$r = 2$	71.2510	28.633
crit 90%	65.820	31.238
crit 95%	69.819	33.878
crit 99%	77.820	39.369
$r = 3$	42.618	18.140
crit 90%	44.493	25.124
crit 95%	47.855	27.586
crit 99%	54.682	32.717

Table 3: Results from cointegration tests.

Model	US	Canada	France	Germany	Italy	Japan	UK
M1	78.78%	88.32%	95.36%	53.37%	90.47%	45.18%	79.17%

Table 4: Share of national inflation variance explained by the global inflation component

Model	$\log L$
M1	-1468.041
M2	-1266.156
M3	-1453.968
M4	-1236.072
M5	-1243.685
M6	-1214.944

Table 5: Likelihood value for each model

Country	Model	$\hat{\lambda}_i^*$	$\hat{\phi}_i$	$\hat{\beta}_{0i}$	$\hat{\beta}_{1i}$	$\hat{\beta}_{2i}$	$\hat{\beta}_{3i}$
USA	M1	1.000	0.968	0.487	—	—	—
			(0.028)	(0.035)			
	M2	1.000	0.922	0.155	0.290	0.651	—
			(0.055)	(0.115)	(0.373)	(0.297)	
	M3	1.000	0.913	0.542	—	—	—
			(0.032)	(0.029)			
	M4	1.000	0.955	0.119	0.204	0.752	—
			(0.050)	(0.139)	(0.342)	(0.245)	
	M5	1.000	0.937	0.104	0.305	—	—
			(0.030)	(0.032)	(0.103)		
	M6	1.000	0.957	0.099	0.239	—	0.020
			(0.023)	(0.028)	(0.085)		(0.064)
CAN	M1	0.771	0.863	0.608	—	—	—
		(0.094)	(0.046)	(0.035)			
	M2	0.969	0.850	0.515	0.279	0.711	—
		(0.138)	(0.081)	(0.340)	(0.460)	(1.095)	
	M3	1.045	0.877	0.631	—	—	—
		(0.075)	(0.036)	(0.030)			
	M4	0.904	0.857	0.526	0.218	0.710	—
		(0.292)	(0.125)	(0.356)	(0.586)	(1.063)	
	M5	0.908	0.852	0.225	0.492	—	—
		(0.085)	(0.047)	(0.062)	(0.161)		
	M6	0.875	0.920	0.297	0.599	—	-0.180
		(0.122)	(0.046)	(0.099)	(0.308)		(0.096)
FRA	M1	0.933	0.926	0.391	—	—	—
		(0.116)	(0.037)	(0.030)			
	M2	1.119	0.931	0.133	0.450	0.440	—
		(0.380)	(0.223)	(0.568)	(0.989)	(1.010)	
	M3	1.533	0.987	0.352	—	—	—
		(0.128)	(0.014)	(0.040)			
	M4	1.019	0.797	0.159	0.840	0.150	—
		(0.228)	(0.266)	(0.542)	(1.811)	(0.967)	
	M5	0.998	0.917	0.143	0.610	—	—
		(0.096)	(0.052)	(0.033)	(0.192)		
	M6	1.152	0.668	0.124	0.784	—	0.219
		(0.115)	(0.090)	(0.024)	(0.150)		(0.001)
GER	M1	0.525	0.946	0.423	—	—	—
		(0.078)	(0.024)	(0.024)			
	M2	0.729	0.938	0.153	0.134	0.720	—
		(0.392)	(0.089)	(0.145)	(0.141)	(0.196)	
	M3	0.740	0.966	0.439	—	—	—
		(0.093)	(0.023)	(0.024)			
	M4	0.608	0.926	0.192	0.145	0.655	—
		(0.267)	(0.094)	(0.107)	(0.303)	(0.319)	
	M5	0.644	0.916	0.109	0.272	—	—
		(0.076)	(0.032)	(0.039)	(0.128)		
	M6	0.724	0.944	0.070	0.153	—	0.054

		(0.086)	(0.021)	(0.019)	(0.038)		(0.001)
ITA	M1	1.133	0.932	0.823	—	—	—
		(0.184)	(0.043)	(0.049)			
	M2	0.735	0.974	0.086	0.350	0.640	—
		(0.224)	(0.044)	(0.624)	(1.000)	(0.982)	
	M3	1.676	0.921	0.825	—	—	—
		(0.135)	(0.035)	(0.045)			
	M4	0.769	0.984	0.085	0.380	0.610	—
		(0.431)	(0.030)	(0.618)	(1.004)	(0.972)	
	M5	0.740	0.977	0.085	0.371	—	—
		(0.101)	(0.013)	(0.024)	(0.076)		
	M6	0.820	0.983	0.084	0.339	—	0.098
		(0.110)	(0.010)	(0.021)	(0.065)		(0.001)
JAP	M1	1.240	0.977	0.945	—	—	—
		(0.214)	(0.017)	(0.052)			
	M2	0.813	0.936	0.257	0.279	0.671	—
		(0.340)	(0.062)	(0.129)	(0.167)	(0.142)	
	M3	1.955	0.990	0.942	—	—	—
		(0.275)	(0.020)	(0.053)			
	M4	0.795	0.927	0.240	0.306	0.659	—
		(0.414)	(0.096)	(0.221)	(0.199)	(0.265)	
	M5	0.807	0.941	0.221	0.329	—	—
		(0.140)	(0.030)	(0.045)	(0.061)		
	M6	0.926	0.923	0.228	0.258	—	0.231
		(0.132)	(0.020)	(0.041)	(0.050)		(0.001)
GRB	M1	1.079	0.906	0.966	—	—	—
		(0.152)	(0.034)	(0.052)			
	M2	0.925	0.908	0.128	0.280	0.710	—
		(0.676)	(0.191)	(1.143)	(0.998)	(0.981)	
	M3	1.472	0.948	0.988	—	—	—
		(0.159)	(0.028)	(0.050)			
	M4	0.862	0.929	0.117	0.260	0.730	—
		(0.285)	(0.070)	(1.138)	(0.999)	(0.919)	
	M5	0.840	0.923	0.108	0.267	—	—
		(0.108)	(0.034)	(0.033)	(0.060)		
	M6	0.960	0.928	0.094	0.248	—	0.093
		(0.125)	(0.031)	(0.027)	(0.048)		(0.001)

Table 6: In-sample estimation results per country for the various model specifications. For acronyms see Table 1.

g_t	Model	μ	ρ	α_0	α_1	α_2	α_3
FAC	M1	3.399 (2.544)	0.989 (0.009)	0.492 (0.055)	—	—	—
	M2	—	1.000	0.415 (0.155)	—	—	—
	M3	—	1.000	0.104 (0.047)	0.038 (0.012)	0.308 (0.156)	—
	M4	—	1.000	0.133 (0.351)	0.820 (1.168)	0.170 (0.996)	—
	M5	—	1.000	0.130 (0.033)	0.784 (0.187)	—	—
	M6	—	1.000	0.137 (0.026)	0.887 (0.108)	—	0.086 (0.046)

Table 7: In-sample estimation results of the global inflation component for the various model specifications. For acronyms see Table 1.

	h	1	4	8	1	4	8
Country	Model	MSE			MAE		
USA	M1	0.996	**0.972**	**0.936**	1.001	**0.990**	0.976
	M2	0.981	**0.898**	**0.848**	1.019	0.984	0.942
	M3	0.996	**0.973**	0.967	1.004	0.995	1.003
	M4	0.981	**0.896**	**0.836**	1.011	0.977	0.930
	M5	0.981	**0.898**	**0.850**	1.011	0.981	0.939
	M6	0.982	0.898	0.905	1.027	1.001	0.970
CAN	M1	**0.967**	**0.880**	0.810	0.984	0.961	0.946
	M2	**0.952**	**0.849**	0.801	0.982	0.950	0.940
	M3	**0.983**	**0.933**	0.878	0.993	**0.975**	0.977
	M4	0.944	**0.816**	0.804	0.985	0.938	0.933
	M5	0.949	**0.827**	0.805	0.986	0.945	0.941
	M6	**0.987**	**0.952**	0.900	0.994	**0.981**	0.972
FRA	M1	1.101	1.148	1.702	1.053	1.147	1.295
	M2	1.181	1.190	1.571	1.097	1.155	1.233
	M3	1.000	1.001	1.048	1.002	1.011	1.038
	M4	1.188	1.162	1.596	1.105	1.157	1.245
	M5	1.152	1.187	1.630	1.087	1.179	1.255
	M6	1.114	1.053	1.228	1.050	1.085	1.108
GER	M1	0.967	**0.843**	**0.683**	0.976	**0.898**	**0.827**
	M2	0.971	**0.873**	**0.739**	0.980	**0.920**	**0.862**
	M3	0.960	**0.804**	**0.635**	0.972	**0.869**	**0.795**
	M4	0.963	**0.832**	**0.670**	0.971	**0.889**	**0.814**
	M5	0.961	**0.820**	**0.641**	0.969	**0.876**	**0.796**
	M6	0.971	**0.836**	**0.661**	0.974	**0.879**	**0.804**
ITA	M1	**0.922**	**0.892**	**0.717**	**0.964**	**0.936**	0.909
	M2	**0.943**	**0.903**	0.823	**0.971**	0.950	0.923
	M3	0.968	0.955	0.920	**0.985**	0.983	0.982
	M4	0.928	**0.880**	0.799	0.967	0.941	0.923
	M5	0.933	**0.889**	0.809	**0.968**	0.944	0.921
	M6	0.946	**0.907**	0.834	0.972	0.951	0.925
JAP	M1	0.998	1.008	0.982	1.002	0.998	0.999
	M2	0.985	0.992	0.917	1.000	1.004	0.988
	M3	1.041	1.189	1.404	1.034	1.147	1.265
	M4	0.973	0.959	0.857	0.998	1.031	1.003
	M5	0.976	0.976	0.891	0.999	1.043	1.027
	M6	0.965	0.943	0.815	0.994	1.009	0.980
GRB	M1	0.945	**0.803**	**0.685**	0.977	**0.925**	**0.859**
	M2	0.920	0.766	0.628	0.968	0.906	**0.820**
	M3	0.985	0.952	0.925	1.003	1.015	1.026
	M4	0.926	0.769	0.629	0.967	**0.908**	**0.822**
	M5	0.961	0.882	0.795	0.987	**0.956**	**0.912**
	M6	**0.993**	0.871	0.725	1.000	0.971	0.838

Table 8: Results on forecasting accuracy of inflation models with random walk benchmark. The table shows MSE and MAE for the various model specifications relative to MSE and MAE of a random walk model for horizons $h = 1, 4, 8$. Entries in **bold** denote statistical significance at the 10% level according to the Diebold Mariano test. For acronyms see Table 1.

Country	Model	MSE h=1	MSE h=4	MSE h=8	MAE h=1	MAE h=4	MAE h=8
USA	M1	1.001	0.992	0.966	1.003	0.992	0.988
	M2	0.986	**0.916**	**0.875**	1.021	0.986	0.954
	M3	1.002	0.993	0.998	1.006	0.997	1.015
	M4	0.987	**0.915**	**0.863**	1.013	0.979	0.942
	M5	0.987	**0.917**	**0.877**	1.013	0.983	0.951
	M6	0.987	0.917	0.934	1.029	1.003	0.982
CAN	M1	**0.972**	**0.898**	0.852	0.987	0.968	0.958
	M2	**0.957**	**0.867**	0.842	0.984	0.957	0.952
	M3	**0.988**	**0.953**	0.923	**0.996**	0.982	0.990
	M4	0.949	**0.833**	0.845	0.988	0.945	0.945
	M5	0.954	**0.845**	0.846	0.989	0.952	0.953
	M6	**0.992**	**0.972**	0.946	**0.997**	0.988	0.984
FRA	M1	1.108	1.169	1.770	1.056	1.159	1.320
	M2	1.189	1.212	1.634	1.100	1.167	1.257
	M3	1.007	1.019	1.089	1.004	1.021	1.058
	M4	1.195	1.183	1.659	1.108	1.169	1.269
	M5	1.160	1.209	1.694	1.089	1.192	1.280
	M6	1.121	1.072	1.277	1.052	1.096	1.129
GER	M1	0.974	**0.866**	**0.714**	0.980	**0.911**	**0.841**
	M2	0.978	**0.897**	**0.773**	0.985	**0.933**	**0.876**
	M3	0.967	**0.827**	**0.664**	0.977	**0.882**	**0.808**
	M4	0.970	**0.855**	**0.701**	0.976	**0.902**	**0.827**
	M5	0.968	**0.843**	**0.671**	0.974	**0.889**	**0.809**
	M6	0.978	**0.859**	**0.691**	0.978	**0.891**	**0.817**
ITA	M1	**0.941**	0.927	0.773	**0.975**	0.954	0.943
	M2	0.962	**0.938**	0.887	0.982	0.968	0.957
	M3	0.987	0.992	0.991	0.996	1.002	1.018
	M4	0.946	0.914	0.861	0.978	0.959	0.957
	M5	0.952	0.923	0.872	0.979	0.962	0.955
	M6	0.965	**0.942**	**0.899**	0.984	0.970	0.959
JAP	M1	1.016	1.086	1.122	1.012	1.034	1.078
	M2	1.003	1.068	1.048	1.010	1.040	1.066
	M3	1.059	1.281	1.604	1.044	1.189	1.365
	M4	0.990	1.034	0.979	1.007	1.068	1.082
	M5	0.994	1.052	1.018	1.009	1.081	1.108
	M6	0.983	1.016	0.931	1.003	1.046	1.057
GRB	M1	0.959	**0.837**	0.737	0.977	**0.926**	**0.860**
	M2	0.933	**0.798**	0.676	0.968	**0.907**	**0.820**
	M3	0.999	0.993	0.995	1.003	1.016	1.027
	M4	0.939	0.802	0.677	**0.967**	**0.909**	**0.822**
	M5	**0.975**	**0.920**	**0.855**	**0.987**	**0.957**	**0.912**
	M6	1.008	0.908	0.780	1.000	0.972	0.838

Table 9: Results on forecasting accuracy of inflation models with autoregressive benchmark. The table shows MSE and MAE for the various model specifications relative to MSE and MAE of an autoregressive model of order one for horizons $h = 1, 4, 8$. Entries in **bold** denote statistical significance at the 10% level according to the Diebold Mariano test. For acronyms see Table 1.

Country	h / Model	HLNAR 1	HLNAR 4	HLNAR 8	HLNRW 1	HLNRW 4	HLNRW 8	PT 1	PT 4	PT 8
USA	M1	0.337	-0.374	-0.363	-0.653	-1.857	-1.673	0.166	1.587	-0.187
	M2	-0.065	-0.786	-0.193	-0.110	-0.734	0.017	-0.543	1.092	0.101
	M3	0.545	-0.342	0.287	-0.561	-1.686	-0.802	-0.189	2.407	0.346
	M4	-0.234	-1.101	-0.773	-0.286	-1.020	-0.524	0.078	1.092	-0.246
	M5	-0.265	-1.071	-0.680	-0.309	-0.982	-0.395	0.078	1.092	-0.246
	M6	0.217	-0.330	1.028	0.204	-0.282	1.176	-0.286	0.876	0.937
CAN	M1	-1.091	-1.258	-0.532	-1.010	-1.192	-0.482	0.955	-0.046	-0.743
	M2	-0.959	-0.989	-0.173	-0.891	-0.955	-0.168	1.191	0.430	-1.349
	M3	-1.273	-1.399	-0.821	-1.275	-1.366	-0.826	0.502	0.556	-0.655
	M4	-0.361	-0.730	0.308	-0.332	-0.701	0.261	0.704	0.032	-1.021
	M5	-0.467	-0.784	0.180	-0.438	-0.758	0.145	0.704	0.032	-1.021
	M6	-1.545	-1.539	-1.141	-1.334	-1.462	-1.032	0.618	-0.458	-0.446
FRA	M1	2.617	2.121	1.817	2.580	1.987	1.786	-0.545	0.776	0.773
	M2	2.797	1.984	1.614	2.777	1.895	1.573	-0.823	0.662	-0.250
	M3	1.091	1.111	1.239	0.220	0.233	0.944	1.258	-0.427	-1.128
	M4	2.896	1.740	1.647	2.879	1.639	1.613	0.119	1.078	-0.269
	M5	3.235	1.971	1.689	3.264	1.867	1.648	-1.145	0.854	-0.533
	M6	2.920	1.985	1.951	2.937	1.726	1.917	0.337	1.299	-0.539
GER	M1	-0.330	-1.928	-2.094	-0.263	-1.587	-1.730	1.931	2.690	1.096
	M2	-0.655	-2.167	-2.124	-0.537	-1.744	-1.707	1.931	2.690	1.096
	M3	-0.123	-2.271	-2.322	-0.065	-1.786	-1.808	2.606	2.630	0.631
	M4	-0.280	-1.786	-1.961	-0.193	-1.430	-1.519	1.681	2.690	1.096
	M5	-0.203	-1.790	-2.063	-0.125	-1.447	-1.668	1.379	2.354	0.806
	M6	0.215	-0.972	-1.557	0.257	-0.735	-1.100	1.379	2.354	0.806
ITA	M1	-1.007	-0.586	-0.921	-1.161	-0.979	-1.200	1.175	0.106	2.051
	M2	-1.038	-1.046	-0.716	-0.990	-1.029	-0.626	0.484	0.385	0.394
	M3	-0.726	-0.217	0.098	-1.149	-1.124	-0.974	1.280	1.892	1.693
	M4	-0.831	-0.811	-0.286	-0.790	-0.783	-0.198	0.484	0.385	0.394
	M5	-0.941	-0.914	-0.471	-0.896	-0.889	-0.385	0.484	0.385	0.394
	M6	-0.976	-0.998	-0.593	-0.949	-0.993	-0.533	0.484	0.385	0.394
JAP	M1	1.198	1.553	1.108	0.137	0.527	0.249	-0.021	0.010	0.011
	M2	0.831	1.379	1.248	0.039	0.599	0.452	0.984	1.050	0.023
	M3	2.465	2.705	2.672	2.204	2.568	2.819	-0.021	0.010	0.011
	M4	1.184	1.579	1.838	0.764	1.009	1.071	1.643	0.876	0.029
	M5	1.286	1.741	2.003	0.868	1.166	1.228	1.643	0.876	0.029
	M6	0.747	1.239	1.281	0.259	0.627	0.521	2.181	1.652	1.012
GRB	M1	-0.326	-1.164	-0.997	-0.587	-1.206	-1.047	1.049	1.993	2.319
	M2	-0.500	-0.998	-1.170	-0.388	-0.768	-0.937	1.796	0.704	3.030
	M3	0.808	0.912	0.987	-0.014	-0.127	-0.004	-0.771	-0.390	1.026
	M4	-0.389	-1.079	-1.227	-0.319	-0.810	-1.006	2.352	1.265	2.289
	M5	-1.425	-1.805	-1.701	-1.101	-1.131	-1.092	2.228	0.704	2.586
	M6	0.973	0.636	0.391	1.005	0.721	0.614	1.249	0.023	1.847

Table 10: Results on forecast encompassing and directional accuracy of inflation models. The table displays the results on the forecast encompassing test of Harvey et al. (1998) with respect to the autoregressive (HLNAR) and random walk (HLNRW) benchmarks, and the directional-accuracy test of Pesaran and Timmermann (1995) (PT). For acronyms see Table 1.

Country	h Model	MSE 1	MSE 4	MSE 8	MAE 1	MAE 4	MAE 8
USA	AFC	0.983	**0.913**	**0.857**	1.005	0.980	**0.940**
	TFC	1.004	0.911	0.872	1.013	0.989	0.956
	RFC	0.986	**0.920**	**0.886**	1.002	0.983	0.957
	MFC	0.983	**0.913**	**0.860**	1.005	**0.980**	0.942
	FFC	0.985	**0.930**	**0.893**	1.002	0.985	0.960
CAN	AFC	**0.960**	**0.866**	0.812	0.983	0.952	0.944
	TFC	**0.953**	**0.873**	0.881	0.985	0.941	0.955
	RFC	**0.958**	**0.863**	0.812	0.984	0.946	0.940
	MFC	**0.960**	**0.868**	0.817	**0.983**	0.952	0.945
	FFC	**0.962**	**0.895**	0.895	0.985	0.960	0.975
FRA	AFC	1.108	1.101	1.409	1.055	1.117	1.172
	TFC	1.064	1.072	1.200	1.026	1.093	1.106
	RFC	1.105	1.104	1.377	1.054	1.113	1.166
	MFC	1.105	1.098	1.379	1.054	1.114	1.161
	FFC	1.063	1.052	1.231	1.031	1.074	1.103
GER	AFC	0.964	**0.832**	**0.668**	0.973	**0.888**	**0.813**
	TFC	0.971	**0.818**	**0.657**	0.974	**0.880**	**0.810**
	RFC	0.966	**0.830**	**0.679**	0.972	**0.885**	**0.821**
	MFC	0.964	**0.832**	**0.668**	0.973	**0.888**	**0.813**
	FFC	0.967	**0.835**	**0.674**	0.975	**0.891**	**0.817**
ITA	AFC	**0.935**	**0.896**	**0.792**	**0.967**	**0.944**	0.917
	TFC	0.943	0.924	0.806	0.978	0.964	0.971
	RFC	**0.935**	**0.894**	0.796	**0.969**	**0.941**	0.938
	MFC	**0.935**	**0.896**	0.794	**0.967**	0.944	0.919
	FFC	**0.934**	**0.896**	0.793	**0.966**	0.944	0.937
JAP	AFC	0.983	0.993	0.937	1.002	1.030	1.029
	TFC	0.984	0.993	0.890	1.005	1.049	1.033
	RFC	0.981	0.989	0.900	1.003	1.036	1.024
	MFC	0.983	0.992	0.928	1.002	1.029	1.025
	FFC	0.991	1.002	0.858	1.007	1.025	0.979
GRB	AFC	0.935	**0.801**	**0.681**	0.976	**0.929**	**0.859**
	TFC	**0.934**	**0.870**	**0.781**	**0.963**	**0.923**	**0.890**
	RFC	0.955	**0.811**	**0.718**	0.990	**0.937**	**0.893**
	MFC	0.935	**0.808**	**0.692**	0.976	0.928	**0.863**
	FFC	0.937	0.825	**0.702**	0.978	**0.944**	**0.869**

Table 11: Results on forecasting accuracy of combinations of inflation models with random walk benchmark. The table shows MSE and MAE for the various forecast combination schemes relative to MSE and MAE of a random walk model for horizons $h = 1, 4, 8$. Entries in **bold** denote statistical significance at the 10% level according to the Diebold Mariano test. AFC = simple average, TFC: thick modeling with OLS, RFC: rank weighted, MFC: RMSE weighted, FFC: frequency weighted.

Country	h / Model	MSE 1	MSE 4	MSE 8	MAE 1	MAE 4	MAE 8
USA	AFC	0.988	**0.932**	**0.885**	1.007	0.982	**0.952**
	TFC	1.010	0.930	0.900	1.015	0.990	0.968
	RFC	0.991	**0.939**	**0.915**	1.004	0.984	0.969
	MFC	0.988	**0.932**	**0.888**	1.007	0.982	0.954
	FFC	0.990	**0.950**	0.922	1.005	0.987	0.973
CAN	AFC	**0.965**	**0.885**	0.853	0.986	0.960	0.956
	TFC	**0.958**	**0.891**	0.926	0.988	0.948	0.967
	RFC	**0.963**	**0.881**	0.853	0.987	0.953	0.952
	MFC	**0.965**	**0.886**	0.859	0.986	0.959	0.957
	FFC	**0.967**	**0.914**	0.941	0.988	0.967	0.988
FRA	AFC	1.115	1.121	1.465	1.058	1.129	1.195
	TFC	1.071	1.092	1.248	1.029	1.104	1.128
	RFC	1.113	1.124	1.432	1.057	1.125	1.189
	MFC	1.112	1.117	1.434	1.057	1.126	1.184
	FFC	1.070	1.071	1.280	1.034	1.085	1.125
GER	AFC	0.971	**0.855**	**0.698**	0.978	**0.901**	**0.827**
	TFC	0.978	**0.840**	**0.686**	0.978	**0.893**	**0.824**
	RFC	0.973	**0.853**	**0.710**	0.977	**0.897**	**0.835**
	MFC	0.971	**0.855**	**0.698**	0.978	**0.901**	**0.827**
	FFC	0.974	**0.858**	**0.704**	0.979	**0.904**	**0.831**
ITA	AFC	**0.954**	**0.930**	**0.854**	**0.978**	**0.962**	0.951
	TFC	0.962	0.960	0.868	0.990	0.983	1.007
	RFC	**0.954**	**0.928**	**0.858**	**0.980**	**0.959**	0.973
	MFC	**0.954**	**0.930**	0.855	**0.978**	**0.962**	0.954
	FFC	**0.953**	**0.931**	**0.854**	0.978	0.962	0.972
JAP	AFC	1.001	1.070	1.070	1.012	1.067	1.110
	TFC	1.001	1.070	1.017	1.015	1.088	1.115
	RFC	0.999	1.066	1.028	1.013	1.074	1.105
	MFC	1.001	1.069	1.060	1.012	1.067	1.106
	FFC	1.009	1.079	0.980	1.017	1.062	1.056
GRB	AFC	0.948	**0.835**	**0.733**	0.976	**0.930**	**0.860**
	TFC	**0.948**	**0.907**	**0.840**	**0.962**	**0.924**	**0.891**
	RFC	0.969	**0.846**	**0.772**	**0.989**	**0.938**	**0.894**
	MFC	**0.949**	**0.842**	0.744	0.976	**0.929**	**0.864**
	FFC	0.951	**0.860**	**0.755**	0.978	**0.945**	**0.869**

Table 12: Results on forecasting accuracy of combinations of inflation models with autoregressive benchmark. The table shows MSE and MAE for the various forecast combination schemes relative to MSE and MAE of a random walk model for horizons $h = 1, 4, 8$. Entries in **bold** denote statistical significance at the 10% level according to the Diebold Mariano test. AFC = simple average, TFC: thick modeling with OLS, RFC: rank weighted, MFC: RMSE weighted, FFC: frequency weighted.

Country	h / Model	HLNAR 1	HLNAR 4	HLNAR 8	HLNRW 1	HLNRW 4	HLNRW 8	PT 1	PT 4	PT 8
USA	AFC	-0.438	-1.261	-1.266	-0.499	-1.165	-0.892	-0.219	1.382	-0.246
	TFC	1.202	-0.746	-0.154	0.697	-0.715	0.041	-0.174	1.092	0.101
	RFC	-0.403	-1.164	-0.663	-0.562	-1.115	-0.514	0.085	1.092	0.101
	MFC	-0.435	-1.242	-1.183	-0.497	-1.151	-0.832	-0.219	1.382	-0.246
	FFC	-0.526	-1.280	-0.710	-0.635	-1.226	-0.527	-0.219	1.092	0.101
CAN	AFC	-1.053	-1.206	-0.492	-1.033	-1.159	-0.466	0.930	-0.302	-0.894
	TFC	-1.176	-0.948	-0.008	-1.136	-0.989	-0.123	0.921	-0.242	-0.511
	RFC	-0.998	-1.225	-0.558	-0.942	-1.179	-0.520	0.930	-0.016	-1.223
	MFC	-1.065	-1.241	-0.493	-1.044	-1.191	-0.470	0.930	-0.302	-0.894
	FFC	-1.122	-1.272	-0.183	-1.052	-1.232	-0.314	0.930	-0.302	-0.874
FRA	AFC	2.888	1.860	1.671	2.872	1.696	1.623	-0.296	0.714	0.082
	TFC	2.035	2.278	1.968	1.972	2.048	1.921	2.389	1.078	-0.116
	RFC	2.720	1.682	1.682	2.694	1.530	1.635	-0.828	0.662	-0.231
	MFC	2.859	1.904	1.680	2.844	1.692	1.621	-0.296	0.714	0.082
	FFC	1.940	1.988	1.803	1.880	1.706	1.717	-0.555	0.452	0.414
GER	AFC	-0.243	-1.882	-2.101	-0.168	-1.505	-1.638	1.596	2.037	1.074
	TFC	-0.243	-2.053	-2.027	-0.189	-1.619	-1.578	1.633	3.138	0.806
	RFC	-0.262	-1.778	-2.037	-0.191	-1.414	-1.568	1.633	2.354	0.806
	MFC	-0.243	-1.883	-2.100	-0.169	-1.506	-1.635	1.596	2.037	1.074
	FFC	-0.241	-1.912	-2.105	-0.173	-1.531	-1.635	1.633	2.037	1.074
ITA	AFC	-1.317	-1.314	-1.189	-1.225	-1.253	-1.048	1.534	-0.068	0.179
	TFC	-0.493	-0.110	-0.341	-0.693	-0.437	-0.551	0.153	0.201	0.718
	RFC	-1.224	-1.145	-0.967	-1.175	-1.201	-0.959	0.093	0.034	1.113
	MFC	-1.314	-1.302	-1.161	-1.223	-1.245	-1.037	1.534	-0.395	0.179
	FFC	-1.259	-1.196	-0.907	-1.192	-1.256	-0.951	0.166	-0.101	-0.380
JAP	AFC	1.072	1.622	1.749	0.503	0.983	1.045	0.984	1.050	0.023
	TFC	1.346	1.839	1.710	0.845	1.223	0.954	1.337	1.215	0.427
	RFC	1.128	1.711	1.715	0.596	1.052	0.924	1.337	1.050	0.023
	MFC	1.069	1.613	1.715	0.499	0.970	0.992	0.984	1.050	0.023
	FFC	1.152	1.625	1.194	0.549	0.925	0.310	0.984	1.050	0.016
GRB	AFC	-0.572	-1.105	-1.202	-0.471	-0.848	-0.982	2.352	0.588	2.670
	TFC	-1.505	-2.152	-0.946	-1.387	-1.374	-0.930	1.596	0.054	2.831
	RFC	-0.461	-1.265	-1.077	-0.463	-1.030	-0.944	1.227	1.968	2.269
	MFC	-0.599	-1.167	-1.219	-0.497	-0.885	-0.987	2.352	0.588	2.670
	FFC	-0.358	-0.869	-1.203	-0.279	-0.645	-0.953	1.763	0.390	2.453

Table 13: Results on forecast encompassing and directional accuracy of combinations of inflation models. The table displays the results on the forecast encompassing test of Harvey et al. (1998) with respect to the autoregressive (HLNAR) and random walk (HLNRW) benchmarks, and the directional-accuracy test of Pesaran and Timmermann (1995) (PT). AFC = simple average, TFC: thick modeling with OLS, RFC: rank weighted, MFC: RMSE weighted, FFC: frequency weighted.