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ECB FOOTPRINTS ON INFLATION FORECAST UNCERTAINTY

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ECB footprints on inflation forecast uncertainty

Svetlana Makarova*

Abstract

The main scope of the paper is to evaluate the hypothesis that the monetary policy of the European Central Bank leads to convergence in bank-induced effects in inflation forecast uncertainty for euro area countries. Inflation forecast uncertainty is measured by the root mean squared pseudo *ex-post* errors of inflation forecasts net of the ARCH-GARCH effects. A bootstrap-type test is proposed for testing convergence of growth of the cross-country uncertainty ratio, understood as the fraction of the estimated policy effects in inflation uncertainty. Results obtained from monthly data for 16 countries for the period January 1991 to November 2014 and with forecast horizons from 1 to 18 months show strong evidence of such convergence among the euro area countries to a common level.

JEL Codes: F14, F43, O57

Keywords: inflation ex-post uncertainty, monetary policy, country effects, inflation forecasting

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The author is solely responsible for all remaining deficiencies.

Non-technical summary

This paper attempts to shed new light on the “one size fits all” hypothesis. This hypothesis describes a possible real interest rate effect in the presence of regional inflation differentials and was formulated by then Chief Economist of the European Central Bank, ECB, Otmar Issing in 2005. He questioned the traditional wisdom that an interest rate set by a single central bank would affect economic growth in countries with relatively low and relatively high inflation in diametrically opposed ways, leading to divergence in growth and increasing uncertainty about inflation. Issing’s reinterpretation was that investment decisions are based on *ex-ante* rather than *ex-post* real interest rates, or expected rather than historical inflation. If expected inflation is not idiosyncratic, then its dispersion between countries will not increase, and there will be no divergence in growth.

The evidence so far has been mixed, which makes it difficult either to disprove or to confirm Issing’s hypothesis by evaluating the traditional convergence hypothesis. This paper suggests a new approach to this puzzle that focuses on reducing macroeconomic uncertainty to a degree rather than on convergence in the level of inflation or uncertainty itself.

The traditional approach to measuring inflation uncertainty is to calculate a measure of its variability, meaning the variability of ex-post forecast error of inflation, and then evaluate changes in it over time. In periods of low inflation, other approaches are needed. In this paper, the main inference is based on the entire distribution of forecast errors, rather than on the dispersion of those errors alone. The weighted skew normal distribution (WSN) is fitted to pseudo *ex-post* forecast errors for annual inflation measured monthly. The parameters of the WSN can be interpreted as reflecting the influence of monetary policy on uncertainty. This allows the relative effectiveness of such a policy in reducing uncertainty to be evaluated.

Verification of the hypothesis that ECB monetary policy is creating cross-country convergence in reducing inflation uncertainty is the main topic of this paper. One measure of such effects is called the *uncertainty ratio,* which shows how far the uncertainty might be affected by monetary policy. If Issing’s arguments are correct, the necessary condition for the one size fits all hypothesis is that the uncertainty ratios across the euro area countries should converge to a common level. A common level like this for the uncertainty ratio is called the Common Uncertainty Reduction Effect in this paper (CURE), and convergence to the CURE is called CURE-convergence. If CURE-convergence exists, it documents the long-run tendency for monetary policy outcomes to be unified across countries.

The empirical model for testing CURE-convergence consists of regressing the rate of growth in the uncertainty ratio computed for different forecast horizons on the initial conditions and on controls variables that include the interaction terms of the initial conditions with dummies for countries and forecast horizons. The construction of this is to some extent technically similar to that of fixed effect panel data models. However, the model is static by its nature as it has two cross-sectional dimensions, rather than cross-sectional and time series. In this case, the traditional standard errors of the estimates are not valid, as the distributions of the uncertainty ratios for different forecast horizons are usually not normal and might be highly interdependent. Consequently, it has been decided to apply the moving blocks bootstrap method for computing them.

Monthly data on annual inflation for the 16 euro area countries for the period January 1991 to November 2014 was used for empirical evaluation of the CURE-convergence hypothesis. Several models with difference combinations of controls variables were estimated and in all cases the estimated coefficients under the initial condition were close to each other and significantly negative. This suggests robustness of the specification and also provides strong evidence in favour of the CURE-convergence hypothesis among the euro area countries.

The results obtained show support for Issing's "one size fits all" conjecture, albeit not in the absolute sense. There are no clear signs of homogeneity being achieved in the levels of inflation uncertainty across the euro area countries. Fiscal and institutional discrepancies within the Union are still too large for this sort of convergence. The idiosyncratic effects on inflation uncertainty still exist and might even cause divergence within that uncertainty. However, it is argued here that without the monetary policy of the ECB this divergence would have been worse. The CURE-convergence, which is the tendency of the relative ECB policy effects on inflation uncertainty to be unified across countries, is clearly detected. This may be a sign of institutional adjustment and also of some effectiveness in monetary policy.

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1 Introduction

One of the principal arguments for how the European Monetary Union can be economically effective in the allocative sense was made in 2005 in the speech by Otmar Issing, then Chief Economist of the European Central Bank (ECB), at the *International Research Forum on Monetary Policy*. In this speech (Issing, 2005) he reinforced his earlier arguments (see Issing, 2001) in favour of the "one size fits all" hypothesis for the single interest rate policy of the ECB. His main argument came from a reinterpretation of the real interest rate effect on growth when there are regional inflation differentials (see e.g. Caporale and Kontonikas, 2009). In the original interpretation, an interest rate determined by a single central bank would negatively affect economic growth in countries with low inflation, as the real interest rate for these countries would be relatively high. At the same time, the opposite effect would appear in countries with high inflation and a relatively lower real interest rate, leading to divergence in growth and increasing uncertainty about inflation. Issing's counterargument was that investment decisions are based on *ex-ante* rather than *ex-post* real interest rates, or expected rather than historical inflation. If expected inflation is not idiosyncratic, then its dispersion between countries will not increase and no divergence in growth will occur.

Ten years after the speech the empirical evidence has been mixed. Some signs of inflation convergence were noticed some five years after the creation of the euro (Mongelli and Vega, 2006; Busetti et al., 2007) and were confirmed later (Lopez and Papell, 2012), but the empirical confirmation of real sphere convergence in the euro area is less evident. Although there are some signs that there was convergence in output and unemployment before 2007, substantial divergence has been observed after that date (see Estrada et al., 2013; Monfort et al., 2013). This makes it difficult either to disprove or to confirm Issing's hypothesis by evaluating the traditional convergence hypothesis.

However, convergence in levels of inflation does not necessarily imply that inflation uncertainty converges as well. This paper attempts to shed new light on the "one size fits all" hypothesis and provide empirical evidence of a different type based on an evaluation of the effects of monetary policy on inflation uncertainty. The logic here is that Issing's (2005) conjecture that investment decisions are based on an *ex-ante* real interest rate reflecting the entire euro area implies that there is some uncertainty about future euro inflation. There may be some external factors, fiscal or political, which increase inflation uncertainty from its relatively low level. In this context the question arises of whether the economic policy of the euro area can successfully reduce the uncertainty by a similar proportion across countries. In a way this also relates to the conjecture of Arnold and Lemmen (2008) that, within the euro area, "inflation uncertainty may increase in countries that have a smaller influence on ECB policy".

The traditional approach to measuring inflation uncertainty is to calculate a measure of its variability and then evaluate changes in it over time (see e.g. Caporale et al., 2012; Lopez and Papell, 2012). As high inflation usually corresponds to higher dispersion of inflation, *ex-post* or *ex-ante*, periods of high inflation were historically associated with higher uncertainty. Other approaches are needed, however, in the current economic realities when the level of inflation is low. There is a growing literature discussing different approaches to defining and measuring inflation uncertainty and, more generally, macroeconomic uncertainty (see e.g.

Giordani and Söderlind, 2003; Baker et al., 2015; Jurado et al., 2015; Makarova, 2014, for a comprehensive discussion and overview). At the same time, literature is scarce on the relation between growth and inflation uncertainty, especially when inflation is low. Inflation uncertainty is generally regarded as being detrimental to growth, either directly through the effect on long-term interest rates (see Golob, 1994), or indirectly as a component of macroeconomic uncertainty, where it affects long-term transactional insurance and option costs (Bloom, 2014).

Verification of the hypothesis that ECB monetary policy is creating cross-country convergence in reducing inflation uncertainty is the main topic of this paper. It is important to note that convergence in reducing uncertainty resulting from a policy action is not the same as convergence in uncertainty itself nor, indeed, in levels of inflation. In this paper, inflation uncertainty is expressed by the dispersion of inflation forecast errors (see e.g. Clements, 2014). To facilitate the measurement of inflation uncertainty reduction, the weighted skew normal distribution, WSN (see Charemza et al., 2015) is fitted to pseudo *ex-post* forecast errors for annual inflation measured monthly. According to Charemza et al. (2015), the parameters of the WSN can be interpreted as reflecting the monetary policy influence on uncertainty. This allows the relative effect of such a policy in reducing uncertainty to be evaluated. One measure of such effects is called the *uncertainty ratio*. If Issing's arguments are correct, the necessary condition for the one size fits all hypothesis is that the uncertainty ratios across the euro area countries should converge to a common level. A common level like this for the uncertainty ratio is called the Common Uncertainty Reduction Effect in this paper (CURE), and convergence to the CURE is called CURE-convergence. If CURE-convergence exists, it documents the long-run tendency for monetary policy outcomes to be unified across countries.

The empirical model for testing CURE-convergence consists of regressing the rate of growth in the uncertainty ratio computed for different forecast horizons on the initial conditions. The construction of this is to some extent technically similar to the fixed effect panel data models. However, the model is static by its nature as it has two cross-sectional dimensions, rather than cross-sectional and time series. In this case, the traditional standard errors of the estimates are not valid, as the distributions of the uncertainty ratios for different forecast horizons are usually not normal and are highly interdependent. Consequently, it has been decided to apply the moving blocks bootstrap method for computing them (see Gonçalves, 2011). The main message of the paper is that, despite the obstacles caused by the global financial crisis in 2007–2011 and the euro area debt crisis that has been bubbling away since 2009, monetary policy in the euro area provides strong and statistically significant support for CURE-convergence. This in turn provides indirect evidence in favour of Issing's one size fits all hypothesis.

The further structure of the paper is as follows. Section 2 discusses possible reasons for the divergence in inflation uncertainty given the convergence in levels. Section 3 applies some simple measures of inflation uncertainty and, without formal testing, illustrates the existence of such divergence in the euro area. Section 4 proposes a formal model for testing the convergence in reducing inflation uncertainty that is due to monetary policy and discusses its stochastic assumptions and estimation. Section 5 gives the main empirical results, and Section 6 concludes.

2 ECB monetary policy and inflation uncertainty

It is generally, albeit not universally, agreed that growth benefits from a reduction in macroeconomic uncertainty, a substantial component of which is inflation uncertainty (see e.g. Bloom, 2014; Vavra, 2014; Jurado et al., 2015). The literature that directly covers the link between monetary policy and inflation uncertainty is limited and somewhat contradictory. Greenspan (2004) argues that monetary policy in the US led to price stability and a reduction in uncertainty. Evidence for the European countries on the relation between monetary policy, inflation and inflation uncertainty is mixed. Bekaert et al. (2013) argue that lax monetary policy lowers uncertainty, but as the point of inflation targeting is to reduce inflation uncertainty (see Wright, 2008), the one size fits all policy loosely implies that the effects of the ECB decisions should be equally beneficial (or, if the decisions are wrong, equally harmful) to all members of the euro area. This policy, however, does not mean that inflation uncertainty should be identical in all euro countries (see e.g. Fountas et al., 2004).

There are numerous factors which cause inflation uncertainty to be different across the region. The heterogeneity of inflation uncertainty in a cross section of countries can be explained by the following main factors:

(i) A different level of inflation in each country. The level of inflation is often different between countries because of heterogeneous long-run factors like consumers' preferences, tax structures, asynchronous business cycles, employment structure, foreign trade diversification, the structure of credit channels and others. According to the Friedman-Ball hypothesis (Ball, 1992; Friedman, 1977), countries with a higher level of inflation should also have higher inflation uncertainty. The Friedman-Ball hypothesis is an alternative to the Cukierman-Meltzer (1986) hypothesis that positive causality goes from inflation uncertainty to inflation. In either case, it would be expected that high inflation uncertainty would be observed in times of high inflation and low inflation uncertainty in times of low inflation.

(ii) Various idiosyncratic factors which might not change the level of inflation, and so not trigger the Friedman-Ball effect, but may affect uncertainty in a direct way. The factors here include political uncertainty (for a theoretical treatment see Davig et al., 2011), a lack of fiscal transparency or discipline, an unclear legal structure for long-term investment, unemployment threats, corrupt credit and microfinance channels, and others. These factors are predominantly country-specific, affecting uncertainty differently in different countries and resulting in heterogeneity in country-relative risk regimes (see Belke and Kronen, 2016; Delrio, 2016).

Regarding (i), there is strong empirical support for the Friedman-Ball and Cukierman-Meltzer hypotheses for the euro countries until 2010 (see e.g. Caporale et al., 2012). As mentioned in Section 1 above, there is also some evidence of convergence in inflation levels in the euro area countries (Lopez and Papell, 2012) so it might be expected that inflation uncertainty would decrease in time. This, however, does not seem to have been the case. There is some econometric evidence suggesting that in at least some euro area countries inflation uncertainty has risen in recent years despite the continuously low level of inflation (see Chowdhury and Sarkar, 2013). From more recent non-econometric accounts of growing macroeconomic uncertainty, which indicate inflation uncertainty without any expectation of a substantial rise in inflation itself (see e.g. European Commission, 2015), it becomes evident that the link between inflation and inflation uncertainty appears to have been broken, particularly between October 2011 and October 2013. Growing inflation uncertainty coinciding with a low level of inflation in this period indicates that factors in (ii) were gaining in importance, particularly the political and fiscal uncertainty.

In the light of the above, it might be interesting to find out not just by how much inflation uncertainty in each country is reduced by ECB policy, but how effective this policy was in balancing uncertainty reduction across the euro area countries. Long-term success here should result in some convergence of measures for this reduction across countries.

3 Measuring uncertainty

There are two widely used ways of measuring inflation uncertainty. One is based on the inference of dispersion between forecasts and in some cases on direct expressions of uncertainty in surveys of professional forecasters (see e.g. Giordani and Söderlind, 2003; Patton and Timmermann, 2010), sometimes in combination with *ex-post* forecast uncertainty computed using past forecast errors (Lahiri et al., 2014). However, survey-based measures often suffer from cross-section and time series heterogeneity, time inconsistency and possible herd behaviour among individual forecasters (see Andrade and Bihan, 2013; Makarova, 2014; Clements, 2015). The other approach defines inflation uncertainty as the conditional variance of AR-GARCH or VAR-GARCH models (see e.g. Fountas et al., 2006), or as their corresponding stochastic volatility component in unobserved components or stochastic volatility models (e.g. Wright, 2011). Though this approach is less demanding for data, it narrows the scope of uncertainty to what is embedded within the model and can be explained by the past.

The concept of inflation uncertainty used here is *ex-post* forecast uncertainty, conveyed by the dispersion of past forecast errors made in an econometric model (see Clements, 2014). *Ex-post* forecast uncertainty is easy to compute, and its interpretation is straightforward. It does not depend on the size and quality of the pool of forecasters and is free from political, emotional and sociological bias. The disadvantages of this approach are the rather tight assumptions about the homogeneity and ergodicity of the distribution of forecast errors. Uncertainty is model-dependent, and quite frequently the number of observations used for computing the uncertainty measure of individual *ex-post* forecast errors is small.

To obtain observations on uncertainty, let us first define the concept of a baseline inflation forecast for time $t+h$ as being publically available to all agents at time t. The series of such forecasts has been computed in the *pseudo out of sample* way, so they are obtained in continuously expanding windows (see Stock and Watson (2007)), as:

$$e_{t+h|t} = \pi_{t+h} - \hat{\pi}_{t+h|t} \ , \qquad\qquad t = t_0,\ t_0+1, \ldots, T-h, \tag{1}$$

where h denotes the forecast horizon, $h = 1, \ldots, H$; π_t is the observed headline HICP inflation at time *t*; $\hat{\pi}_{t+h|t}$ is the baseline *h*-step ahead point forecast from the ARIMA-GARCH model, estimated with the use of data prior to *t*; $e_{t+h|t}$ are the baseline forecast errors of the forecast made in time *t* for $t+h$; T is the total length of the data series, and data for the period from 1 to t_0 are used for the initial model estimation. It is further assumed that this forecast is a “common knowledge” forecast that does not constitute information relevant for monetary policy but can be improved upon by ECB forecasters.

Evidently the choice of model used for computing the baseline forecast is, to an extent, arbitrary, and selecting another model might lead to a different series of baseline forecast errors being obtained. It has been decided to use the ARIMA-GARCH model due to its simplicity, flexibility, low computational costs and, above all, the fact that this model often outperforms more complex multivariate models in its forecasting properties (see Bjørnland et al., 2012; Buelens, 2012; Clark and Ravazzolo, 2014; Mitchell et al., 2015).

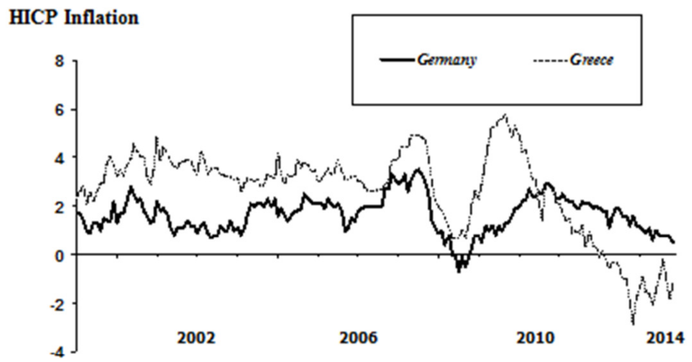
A single observation on the *h*-steps ahead uncertainty in time *t* is defined as:

$$u_{t,h} = e_{t+h|t}\left(\sigma_{t,h} / \sqrt{\hat{\sigma}^2_{t+h|t}}\right) \quad , \tag{2}$$

where $\hat{\sigma}^2_{t+h|t}$ is the *h*-step ahead forecast of GARCH conditional variance and $\sigma_{t,h}$ is the unconditional standard deviation of $e_{t+h|t}$. The *ex-post* forecast uncertainty at time t ($t = t_0 + h + \Delta - 1, \ldots, T$) for forecast horizon h is defined as the root mean square error (RMSE) of $u_{t,h}$ over the moving time windows of bandwidth Δ that starts from $t_0 + h$ and runs to $T - \Delta + 1$.

The baseline forecast errors (1) have been obtained by estimating the ARIMA(*p*, 1)-GARCH(1,1) model at the maximum likelihood for 16 of the 18 euro area countries (excluding Cyprus and Slovakia, for which there have been convergence problems in the estimation due to the small number of observations), using monthly data on the annual HICP inflation downloaded from Eurostat. Data series for all the countries end in November 2014 and start between January 1991 and January 1996. Detailed data spans and country abbreviations are given in Appendix A. For all the countries, inflation has been found to be integrated of order 1. Therefore models have been estimated in first differences (details of the unit root testing, which allows for the existence of structural breaks, are available on request). The lag length of the ARIMA process has been chosen as the minimum for which autocorrelation of the residuals (up to order 12) is jointly insignificant at the 5% significance level. The first recursion uses the first 20% of the observations in each series, but not more than 80. Column 5 in Table A1 (see Appendix A) shows the numbers of one-step ahead forecasts made for each country and also indicates the date that is associated with the first one-step ahead forecast error for each country. For the two-step ahead forecast errors the start date is one month later, and so forth. For each forecast, the *ex-post* forecast errors given by (1) and observations on uncertainty (2) have been calculated. Finally, for each set, the RMSE of $u_{t,h}$ has been computed in rolling windows as described above, as the measure of uncertainty. With identical window bandwidth of $\Delta = 120$ for calculating RMSE for different countries and different forecast horizons, it gives a different start date for the RMSEs and a different number of observations (details are shown in Table A1, column 6).

Figure 1 compares HICP inflation for Germany and Greece (upper panel) and France and Italy (lower panel), from 2000m01 until 2014m11. Figure 2 plots the corresponding RMSEs of $u_{t,h}$ for these countries for *h*=1.



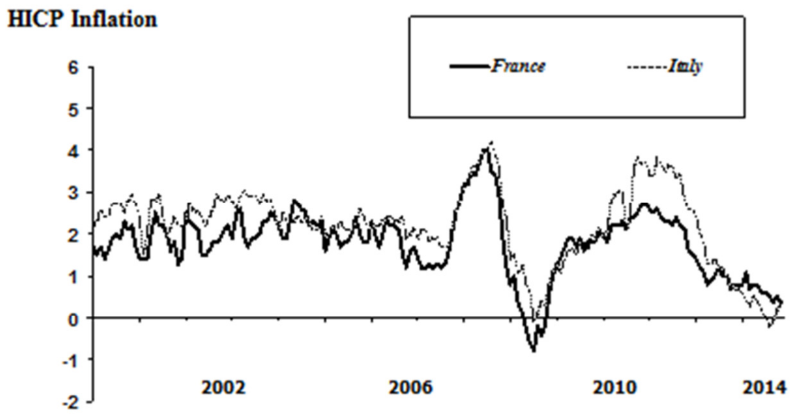
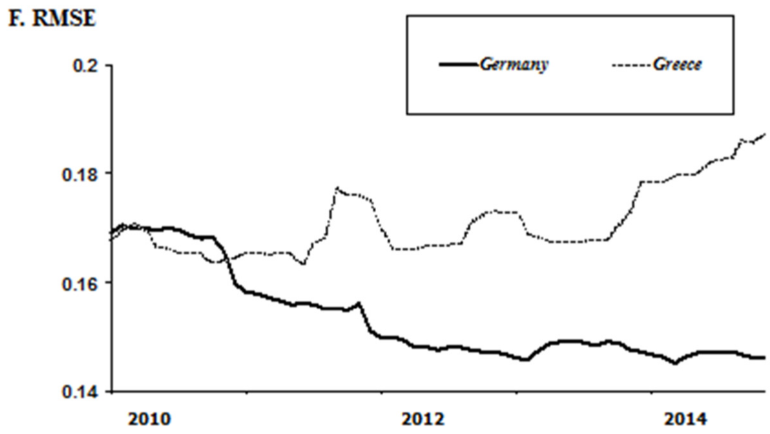


Figure 1: HICP inflation for Germany, Greece, France and Italy



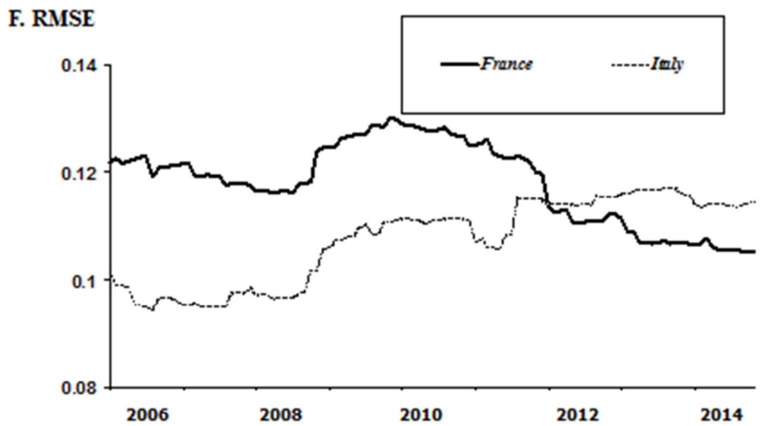


Figure 2: Forecast uncertainty (RMSE): Germany, Greece France and Italy, forecast horizon h=1

Figure 1 indicates the presence of pairwise inflation convergence in levels of HICP inflation for the pairs of countries shown. This is in line with the Monfort et al. (2013) conjecture of the existence of different convergence clubs in the euro area. It appears that Germany and

Greece are in different convergence clubs and Italy and France are in the same one. However, Figure 2 shows that there is an evident divergence in inflation uncertainty for the same period and the same countries. For Germany and France lower inflation is associated with lower uncertainty, thus confirming the Friedman-Ball or Cukierman-Meltzer hypotheses. For Greece and Italy, however, it is the opposite; low inflation corresponds to increased uncertainty.

Bearing in mind the purpose of this paper, there is no need to pursue by formal testing the question of the convergence of inflation and inflation uncertainty any further. More evidence in favour of such divergence can be drawn from the time series of the RMSEs given in Appendix B (Figure B1 for inflation and Figures B2–B3 for RMSEs for the forecast horizons h=1 and h=12 respectively). While we might observe convergence in levels of inflation in the euro area, there is clearly a divergence in inflation uncertainty. Developing from the discussion in Section 2 above it can be argued that factors beyond the Friedman-Ball or Cukierman-Meltzer hypotheses are responsible for this divergence. Most likely these factors are related to the widely understood lack of fiscal discipline. Detailed analysis of this is, however, outside the scope of this paper.

4 Uncertainty and monetary policy

If monetary policy is to be effective in reducing uncertainty, the RMSEs of the $u_{t,h}$ s, should be smaller than the RMSEs computed for the hypothetical uncertainty that is free from the effects of monetary policy. Unlike the $u_{t,h}$ s, this uncertainty is unobservable in the sense that it cannot be retrieved from forecast errors. Strictly speaking, it would have been observable if the monetary policy had not been implemented, as in that case it would coincide with $u_{t,h}$. However, under the additional assumption that for each county and each horizon h, uncertainty $u_{t,h}$ follows the weighted skew normal distribution, WSN, it is possible to derive an approximation of the distribution of this uncertainty and therefore to estimate the ratio of its variance to $RMSE(u_{t,h})$. The WSN random variable U used for such approximation is defined by:

$$U = X + a \cdot Y \cdot I_{Y>m} + b \cdot Y \cdot I_{Y<k}, \qquad (X,Y) \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{bmatrix}\right), \tag{3}$$

where $I_{\{\bullet\}}$ is the indicator function of a set $\{\bullet\}$, $a, b, m, k \in \mathrm{R}$, and $-1 < \rho < 1$, while X is the random component that is unpredictable from the baseline forecast. As the baseline forecast is made using common information that is publically available, X is not predictable if only publically available information is used. However, the monetary policy decision makers might have some partial knowledge represented by $\rho > 0$. The random variable Y represents forecasts (strictly speaking, corrections to the baseline forecast) made by the ECB forecasters and delivered to the Governing Council of the ECB. If these forecasts show that inflation exceeds the thresholds, that is $Y>m$ or $Y<k$, the Governing Council undertakes either an anti-inflationary policy with strength a, or a pro-inflationary policy with strength b respectively. In this set up it is also natural to assume that a<0, b<0, m>0 and k<0. This explanation is fairly simplified, especially in the context of ECB action based on a set of inflation forecasts from different countries rather than a single, homogeneous signal about inflation. As the WSN distribution is fitted for each country separately, its parameters correspond to the country effect of the single ECB decision and the thresholds correspond to the weights given to inflation information from each country in the aggregate one size fits all decision. It is also assumed that the variances of *X* and *Y* are identical and equal to σ^2.

The WSN distribution defined by (3) is parametrised by six parameters. In order to increase the efficiency of estimation and avoid identification problems, it has been decided to reduce the number of estimated parameters to three, namely α, β and σ. The ECB forecast signals are seen as large enough to act upon if they exceed one standard deviation. So in the estimation, $\hat{m}$ and $\hat{k}$ are set to $\pm\hat{\sigma}$, where $\hat{\sigma}$ denotes the estimate of σ. The parameter ρ reflects how much predictability is left in *X* and at the same time it indicates how accomplished the forecasts in *Y* are. If *X* is completely unpredictable or if the ECB forecasters who deliver *Y* are ignorant, then $\rho = 0$. If *X* is fully predictable by the ECB forecasters, then $\rho = 1$. Moreover, for the thresholds-symmetric case when $k = -m$, the variance of the WSN distribution decreases monotonically up to the point given by the constraint $-2\rho = \alpha + \beta$ (see Charemza et al., 2015). Consequently, low values of ρ implicitly constrain the strength of monetary policy in reducing uncertainty. A sensible choice seems to be $\rho = 0.75$, which reflects a reasonable forecasting power of the ECB forecasters and a potential policy strength. Other values of ρ have also been tried in the robustness check but without much effect on the outcome.

The estimates of a, b and σ in (3) are obtained using data on $\{u_{t,h}\}$ separately for each country and each horizon *h*, in rolling windows of length $\Delta = 120$. For each country and each forecast horizon (with country and forecast horizon indices omitted to simplify the notation) this gives the series of estimates $\{\hat{a}(j)\}$, $\{\hat{b}(j)\}$ and $\{\hat{\sigma}(j)\}$ where the j-th estimate corresponds to the period between $(t_0 + h + j - 1)$ and $(t_0 + h + j + \Delta - 2)$, when $j = 1,...,(T - t_0 - h - \Delta + 2)$. For clarity of notation, each estimate is assigned to the right end of the interval it corresponds to and is re-denoted as $\hat{a}_s \equiv \hat{a}(j), \hat{b}_s \equiv \hat{b}(j)$, $\hat{\sigma}_s \equiv \hat{\sigma}(j)$, where $s = t_0 + h + j + \Delta - 2$ ($s = t_0 + h + \Delta - 1,...,T$). The random variable which is WSN-distributed with these parameters is denoted as $U_{s,h}$ (the country index is omitted for simplicity). The estimation method used here is the simulated minimum distance estimation (SMDE) method (see Charemza et al., 2012). Appendix C contains a brief description of the SMDE method and the aggregated results of fitting the WSN distribution to one-step ahead uncertainties (Table C1).

The random variable *V* that approximates the distribution of the hypothetical uncertainty that is free from the effects of monetary policy can be recovered from the WSN distribution fitted to *ex-post* forecast errors $u_{t,h}$ (separately for each country and each forecast horizon *h*) by removing from U most of the predictable components, some of which are still left due to the possible monetary policy feedback, so that

$$V = U - E(X \mid Y) = U - \rho Y = X - \rho Y + a \cdot Y \cdot I_{Y>m} + b \cdot Y \cdot I_{Y<k} . \quad (4)$$

The random variable V defined by (4) above is also of the WSN type, and its parameters and thus the variance of V, Var(V), can be expressed via the parameters of U, meaning via a, b, m, k ρ and σ. This is done in rolling windows (again, for each country and each forecast horizon h separately) that correspond to the estimates $\{\hat{a}(j)\}$, $\{\hat{b}(j)\}$, $\{\hat{\sigma}(j)\}$, where $s = t_0 + h + j + \Delta - 2$, ($s = t_0 + h + \Delta - 1, ..., T$). The ratio of the variance of the corresponding V to the RMSE of the observed *ex-post* errors $u_{t,h}$ s can then be computed for each window. This ratio is called the *uncertainty ratio* and is defined as (see Charemza et al., 2015):

$$\mathrm{UR}_{i,h}(s) = \mathrm{Var}(V) / \mathrm{RMSE}(U), \qquad h = 1, 2, ..., H, \tag{5}$$

where i stands for the country (i=1,…,16), and $s = t_0 + h + \Delta - 1, ..., T$. $\mathrm{UR}_{i,h}(s)$, referred further simply as UR, represents an approximation of the fraction of uncertainty reduced as the result of action taken in response to the forecast signals based on the information in Y. In other words, it shows the footprints of monetary policy in the uncertainty. For simplicity of notation, country indicators (i) and the window which the uncertainty ratio corresponds to (s), are omitted from the right-hand side of (5). It is also worth noting that there are different numbers of observations on inflation for different countries as the data begin at different points in time, which means that the first time moment for which the uncertainty ratio can be computed $s = t_0 + h + \Delta - 1$ is different for each country. This is accounted for in the further empirical analysis.

The uncertainty ratio $\mathrm{UR}_{i,h}(s)$ defined by (5) can be expressed via ρ, set to 0.75 for each country and each forecast horizon, the estimated parameters $\{\hat{a}(j)\}$, $\{\hat{b}(j)\}$ and $\{\hat{\sigma}(j)\}$, and the thresholds $\hat{m}$ and $\hat{k}$, which are set to $\pm\hat{\sigma}$.[1] The explicit formula is given in Appendix D. The immediate interpretation of the uncertainty ratio, UR, that follows from (5) is that if the policy is effective in reducing uncertainty than the UR is greater than unity.

Figure 3 shows the time paths of the development of the uncertainty ratio for h=1 for selected euro area countries: Germany and Greece (upper panel) and France and Italy (lower panel) for the same periods as in Figure 2 in Section 3, which is 2009m10 to 2014m11 for Germany and Greece, and 2005m11 to 2014m11 for France and Italy.

Apart from two turbulent periods for France in the beginning of 2012 and the end of 2013, the URs for all four countries are above unity. The dynamics of the URs for the other euro area countries (see Figure B4 in Appendix B) are less clear, indicating periods of different gains in the sense of reductions in uncertainty policy. It can also be noticed that periods of relative success in reducing uncertainty for some of the countries correspond to periods of ineffectiveness for others. This seems to be quite natural. Countries may have different capacity for inflation uncertainty reduction as there are various idiosyncratic factors (see Section 2). ɪt is not realistic to expect that the ECB policy will be effective in reducing uncertainty in the absolute sense by leading to an increase in the UR in all countries. A more plausible hypothesis could therefore be relative policy effectiveness through the convergence of the URs to a common level across the euro area countries.

[1] Other settings have also been used. The results do not differ markedly from those presented here.

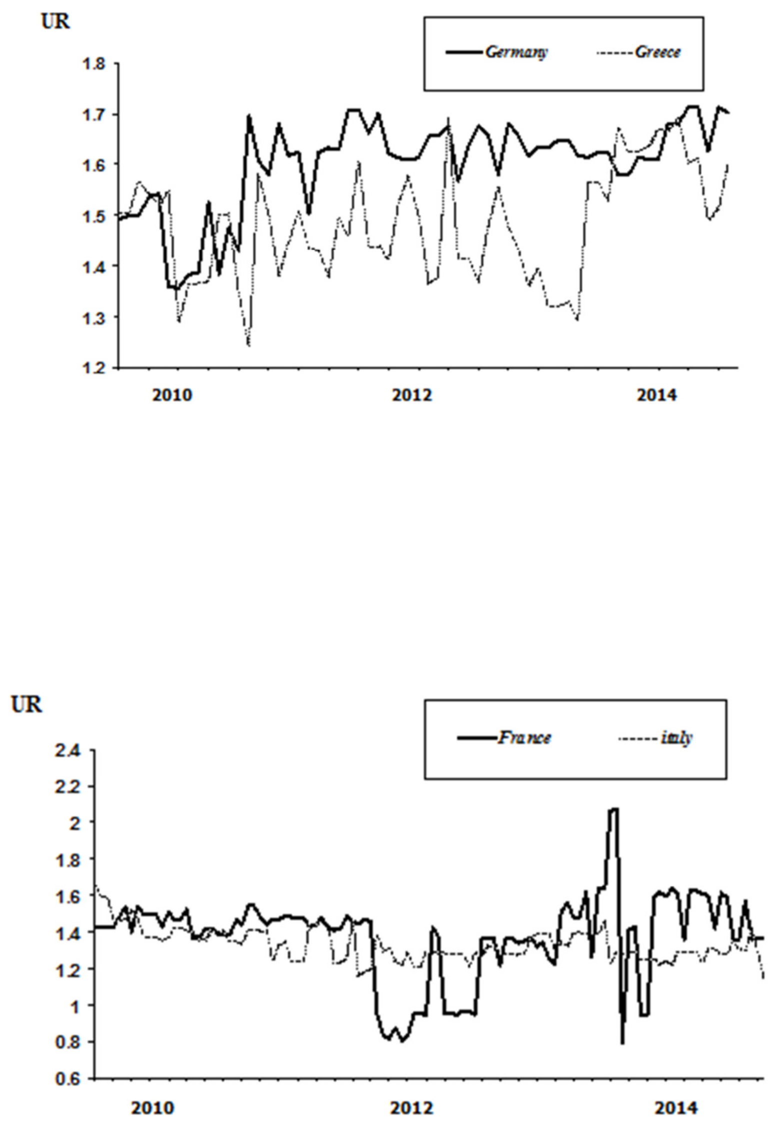


Figure 3: Uncertainty ratio (UR) for selected euro area countries, forecast horizon h=1

5 The CURE-convergence test

To test the CURE-convergence hypothesis formally, let us consider a hypothetical level of UR that is identical for all the euro area countries. Convergence to such UR is called the *common uncertainty reduction effect* and is abbreviated as CURE-convergence. In order to test for it, the following model has been estimated:

$$g_{i,h} = \alpha_i + \beta \cdot \mathrm{UR}^0_{i,h} + x'_{i,h}\gamma + \varepsilon_{i,h} \quad , \qquad i = 1, 2, ..., N \ , \quad h = 1, 2, ..., H \ , \qquad (6)$$

where $g_{i,h}$ is the average rate of growth of $\mathrm{UR}_{i,h}$ for country *i* and forecast horizon *h* over the period that is common to all countries starting on 2010m12 for *h*=1, 2011m01 for *h*=2 etc. All periods end in 2014m11. The number of countries is $N = 16$; the number of forecast horizons is $H = 18$. $\mathrm{UR}^0_{i,h}$ is the initial level of $\mathrm{UR}_{i,h}$; α_is denote country-specific effects resulting from the factors discussed in Section 2 that affect the uncertainty ratio in individual countries and are assumed to be constant for each forecast horizon *h*; β is the coefficient which decides the CURE-convergence hypothesis, and more specifically, the CURE-convergence hypothesis is confirmed if β is significantly negative. Vector $x_{i,h}$ is a $q \times 1$ vector of other variables on which the rates of growth of $\mathrm{UR}_{i,h}$ are conditioned with the corresponding vector of parameters γ, and $\varepsilon_{i,h}$ is the error term. Other specifications that include time-specific effects have also been tried, but these effects turned out to be statistically insignificant. In the model discussed below, the variables in $x_{i,h}$ contain products of $\mathrm{UR}^0_{i,h}$ and some country dummies or horizon dummies.

Model (6) resembles the simple fixed-effect panel data growth model (see Barro and Sala-i-Martin, 1995; Islam, 1995). In fact, model (6) is not a panel data model as the dependence is on the forecast horizon rather than on time. Hence it is a static cross-section model in its essence. However, the possible mutual dependence of multi-level forecasts is expected to be transmitted into the dependence of URs for different forecast horizons, which might create effects similar to that of the time effect in panel data models with heteroscedasticity and autocorrelation.

Further difficulties in testing are caused by the fact that the distributions of $\varepsilon_{i,h}$ are likely to be non-normal, heteroscedastic and "autodependent", meaning they have dependence on different forecast horizons, possibly nonlinear, due to the non-normality of the residuals. This might affect the estimates of the standard errors of $\varepsilon_{i,h}$ and consequently distort the testing results for the parameters. To ease this problem, the standard errors and consequently the *p*-values of the significance statistics have been estimated by applying the moving blocks bootstrap, MBB (see Gonçalves, 2011), for data ordered by forecast horizon.

Following Gonçalves, the MBB algorithm consists of the following steps:

(1) For each *h*, stack observations on $g_{i,h}$ and $z_{i,h} = [UR^{(0)}_{i,h}, x'_{i,h}]'$ in a $N \cdot (p+2)$ vector $\Gamma_h = [g_{1,h}, z'_{1,h}, g_{2,h}, z'_{2,h}, ..., g_{I,h}, z'_{I,h}]'$, where p denotes the number of regressors in $x_{i,h}$.

(2) Define block length $\ell = H/\kappa$ such that $1 \le \ell \le H$ and H is divisible by an integer κ. Then create a block B_j of ℓ consecutively stacked vectors of Γ_h as $\mathrm{B}_j = [\Gamma_j, \Gamma_{j+1}, ..., \Gamma_{j+l-1}]$, $j = 1, 2, ... T - \ell + 1$. If $\kappa = T$, so if $\ell = 1$, MBB becomes a standard *i.i.d.* bootstrap on data ordered by forecast horizon. If $\kappa = 1$, so if $\ell = H$, no bootstrap is performed. The length recommended by Gonçalves (2011) for the blocks of samples with a time dimension close to 25 (in this case the forecast horizon dimension) is $\ell \approx 2.5$. Because of this, it has been decided to use $\ell = 2$ as the number of forecast horizons is equal to 18. The results for $\ell = 3$, not reported here, are very similar.

(3) From a set of $H - \ell + 1$ of such overlapping blocks, draw a uniformly distributed sample with replacement on $\{1, 2, ..., l\}$ of κ of them and, for this pseudo (bootstrapped) sample, estimate the parameters in (6). Due to the pseudo-sample nature rather than true sample nature of the draws, the ordinary Student-*t* ratios are not valid, as the OLS covariance matrix of the residuals is inconsistent. Gonçalves (2011) provides a formula for the long-run asymptotic covariance matrix for MBB pseudo-samples, which can be used for computing Student-*t* ratios in each draw. Such estimates of the covariance matrix are robust to cross-sectional and between-forecast horizon dependence of unknown form. The robustness does not depend on the assumption of normality for the error terms.

(4) Repeat (3) many times, collect Gonçalves' *t*-ratios, and use them for computing *p*-values for particular estimates. Note that the direct estimate of standard errors of the parameters obtained across the pseudo-sample is not valid. In the results presented here the total number of valid bootstraps, excluding the cases where singularity has been obtained, is set at 10,000.

Table 1 provides a summary of the output for the estimates of model (6) under various specifications of $x_{i,h}$. The notation here is as follows. Products of $\mathrm{UR}^0_{i,h}$ and country dummies are denoted as $\mathrm{UR}^0 * \mathrm{AA}$, where AA is the two-digit country code explained in Appendix A. Products of $\mathrm{UR}^0_{i,h}$ and horizon dummies are denoted as $\mathrm{UR}^0 * h\mathrm{NN}$, where NN denotes an integer indicating the forecast horizon of between 1 and 18. The HAC *p*-values for the ordinary not-bootstrapped fixed-effects OLS estimates and MBB *p*-values for $l = 2$ are given beneath the parameter estimates in the first and second rows respectively[2]. Country effects α_i are jointly significant in all models, and so for clarity of presentation they are not included in Table 1.

The results given in Table 1 indicate, not surprisingly, that the omission of the products of $\mathrm{UR}^0_{i,h}$ and country/forecast horizon dummies causes substantial underestimation of the speed of the convergence parameter β, in comparison with all the other specifications or models. The estimates of β for all the other models (except Model 6) are close to each other, negative and significant. This suggests the specification is robust in its estimates in models with the $\mathrm{UR}^0_{i,h}$ and dummy product variables and also strongly supports the existence of CURE-convergence in the period between December 2010 and November 2014.

[2] Computations have been made using GAUSS. The procedures for computing the HAC standard errors, are written by Seung Chen Ahn and available at: http://www.public.asu.edu/~miniahn/ecn726/ecn_726.htm#syllabus. Codes are available on request.

Table 1: Summary of models' estimation

Regressor	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$\mathrm{UR}^{0}_{i,h}$	–1.106* (0.018) (0.330)	–1.795*+ (0.007) (0.000)	–1.778*+ (0.007) (0.000)	–1.786*+ (0.007) (0.000)	–1.761*+ (0.007) (0.000)	–1.357*+ (0.006) (0.042)
$\mathrm{UR}^{0} \times \mathrm{DE}$		1.464*+ (0.004) (0.000)	1.474*+ (0.004) (0.000)	1.479*+ (0.008) (0.000)	1.523*+ (0.005) (0.000)	1.661*+ (0.001) (0.003)
$\mathrm{UR}^{0} \times \mathrm{ES}$		1.871*+ (0.010) (0.000)	1.912*+ (0.011) (0.006)	1.919*+ (0.023) (0.011)	2.010*+ (0.012) (0.001)	2.490*+ (0.000) (0.000)
$\mathrm{UR}^{0} \times \mathrm{FR}$				0.463 (0.256) (0.119)		
$\mathrm{UR}^{0} \times \mathrm{GR}$		1.377*+ (0.011) (0.042)	1.385*+ (0.011) (0.026)	1.391*+ (0.019) (0.024)	1.444*+ (0.012) (0.000)	1.671*+ (0.001) (0.000)
$\mathrm{UR}^{0} \times \mathrm{IT}$				–0.567 (0.306) (0.283)		
$\mathrm{UR}^{0} \times h1$		0.210+ (0.173) (0.000)	0.202+ (0.185) (0.000)	0.203+ (0.205) (0.002)	0.180+ (0.221) (0.002)	
$\mathrm{UR}^{0} \times h2$		0.146*+ (0.001) (0.001)	0.143*+ (0.002) (0.001)	0.140*+ (0.004) (0.002)	0.133*+ (0.004) (0.002)	0.107* (0.014) (0.379)
$\mathrm{UR}^{0} \times h3$			–0.037 (0.163) (0.296)	–0.037 (0.194) (0.305)	–0.043 (0.142) (0.210)	
$\mathrm{UR}^{0} \times h6$					–.030 (0.132) (0.131)	
R^2	0.342	0.453	0.454	0.456	0.461	0.427

Note: Dependent variable: $g_{i,h}$, average growth rate of uncertainty ratio for country i (i=1,…,16) and forecast horizon h (h=1,…,18). Total number of observations: 288.

Comments to Table 1:
1) HAC p-values and MBB p-values for 2 blocks bootstrap are given in brackets beneath the parameter estimates in the first and second rows respectively.
2) * indicates 5% significance according to the OLS HAC standard errors and Student-t ratios.
3) + indicates 5% significance according to MBB standard errors.
4) Country effects are jointly significant in all models. Therefore they are not included in the table.

Throughout the models, the cross-effects of $\mathrm{UR}_{i,h}^{0}$ are stable and significant, as are the dummies for Germany and Greece, which are two extreme countries in the euro area. They are also positive, though smaller than the corresponding $(-\beta)$ estimates, which suggests slower convergence in the effects of ECB monetary policy in reducing uncertainty at the opposite ends of the spectrum for the EU. For the middle-ground countries like France and Italy, the cross-effects are small and insignificant. This is also true for other countries in the euro area (not reported here) except for Spain, which exhibits a strongly positive and significant effect in all the specifications reported here. The possible reason for this is the large RMSEs in absolute terms (not reported here), which are much larger than those of other countries, which suggests a bad fit of the forecasting model. Anyway, the magnitude of the estimated coefficient for the cross-effect for Spain is similar to that of $(-\beta)$, so its overall effect on the CURE-convergence is likely to be neutral.

The relevance of using the MBB covariance matrix for computing the Student-*t* statistics is shown by the results obtained for $\mathrm{UR}^{0} \times h1$, which indicates the individual cross-effect of the one-step ahead forecast. Although its coefficient is not large and, judging by the HAC estimates of its standard error, not significant, it knots together the nonlinear dependencies of the model. Its removal in Model 6 changes substantially the estimates of the remaining parameters of the model and, most notably, biases the value of β towards zero. It is interesting to note that this is the only variable across the specifications which is significant according to the MBB estimates of the covariance matrix and not the HAC results. With $\mathrm{UR}^{0} * h1$ present, cross effects of other forecast horizons and $\mathrm{UR}_{i,h}^{0}$, except $\mathrm{UR}^{0} * h2$, are not significant (these results are equally not reported here).

6 Conclusions

The results of this paper are quite supportive of Issing's "one size fits all" conjecture, albeit not in the absolute sense. There are clearly no signs of homogeneity being achieved in inflation uncertainty across the euro area countries. This is not only a case of Greece versus the rest of the euro area, as it also applies to more stable countries like France and Italy. Fiscal and institutional discrepancies within the Union are still too large for this sort of convergence. The idiosyncratic effects on inflation uncertainty still exist and might even cause divergence in it. However, it is argued here that without the monetary policy of the ECB it would have been worse. The CURE-convergence, which is the tendency of the relative ECB policy effects on inflation uncertainty to be unified across countries, is clearly detected. This may be a sign of institutional adjustment and also of some effectiveness in monetary policy. At the same time, the results presented here do not confirm the Arnold and Lemmen (2008) conjecture that inflation uncertainty across the euro area countries is negatively related to the degree of their influence on ECB policy. On the contrary, this paper provides statistical evidence for the long-run tendency of the ECB's monetary policy to affect inflation uncertainty in all countries in an equal way, regardless of their influence.

On the methodological side, the paper uses a cross-section model which exhibits heterogeneity similar to that of the fixed effects panel data models and can be used for analysing forecast effects jointly for different horizons. However, the stochastic structure of such models can be quite complicated and might require the application of methods allowing for nonlinear dependence. The two-step method applied here for estimating the forecasting model first and then analysing the distributions of forecast errors constitutes a novel approach, though it might not be the most efficient. However, the joint estimation of the ARMA-GARCH model with skew-normal uncertainty still poses some statistical questions, which have not yet been fully resolved.

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Appendix A: Data description

For all countries, the last observation is in November 2014.

Of the 18 countries in the euro area, Cyprus and Slovakia were the two countries for which the maximum likelihood ARIMA-GARCH model estimation failed and no convergence was achieved. Therefore these countries have been excluded, so the number of countries considered is 16.

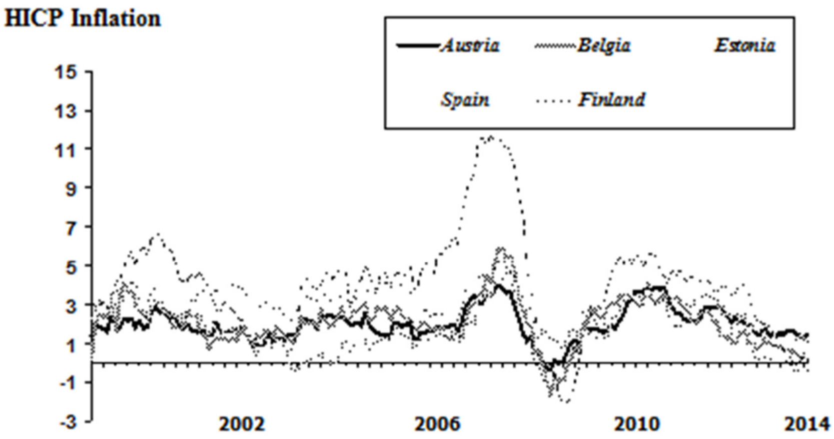
The common date for all countries for which $\mathrm{UR}_{i,1}$ is computed (the date of $\mathrm{UR}_{i,1}^{0}$) is December 2010. That means the date for $\mathrm{UR}_{i,2}^{0}$ is January 2011 etc.

Note that the RMSEs are computed using moving windows of $\Delta = 120$. Therefore the number of observations for each country in columns (5) and (6) in Table A1 differs by 118.

Table A1: Description of data spans and recursions

Country	**Code**	**Date of first observation**	**Number of observations**	**Date of the first observation on one-step ahead forecast $u_{t,1}$ / number of observations**	**Date of the first observation on RMSE of one-step ahead forecast $u_{t,1}$ / number of observations**
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Austria	AT	1991m01	287	1995m11 / 229	2005m10 / 111
Belgium	BE	1992m01	275	2000m07 / 173	2010m06 / 55
Germany	DE	1996m01	227	1999m11 / 181	2009m10 / 63
Estonia	EE	1996m01	227	1999m11 / 181	2009m10 / 63
Spain	ES	1993m01	263	1999m09 / 183	2009m08 / 64
Finland	FI	1991m01	287	1995m11 / 229	2005m10 / 111
France	FR	1991m01	287	1995m11 / 229	2005m10 / 111
Greece	GR	1991m01	287	1995m11 / 229	2005m10 / 111
Ireland	IE	1996m01	227	1999m11 / 181	2009m10 / 63
Italy	IT	1991m01	287	1995m11 / 229	2005m10 / 111
Luxembourg	LU	1996m01	227	2000m03 / 177	2010m02 / 59
Latvia	LT	1997m01	215	2000m08 / 172	2010m07 / 54
Malta	MT	1997m01	215	2002m11 / 145	2010m12 / 49
Netherlands	NL	1991m01	287	1995m11 / 229	2005m10 / 111
Portugal	PT	1991m01	287	1995m11 / 229	2005m10 / 111
Slovenia	SL	1996m01	227	1999m11 / 181	2009m10 / 63

Appendix B: Inflation, forecast uncertainty and uncertainty ratios for euro area countries



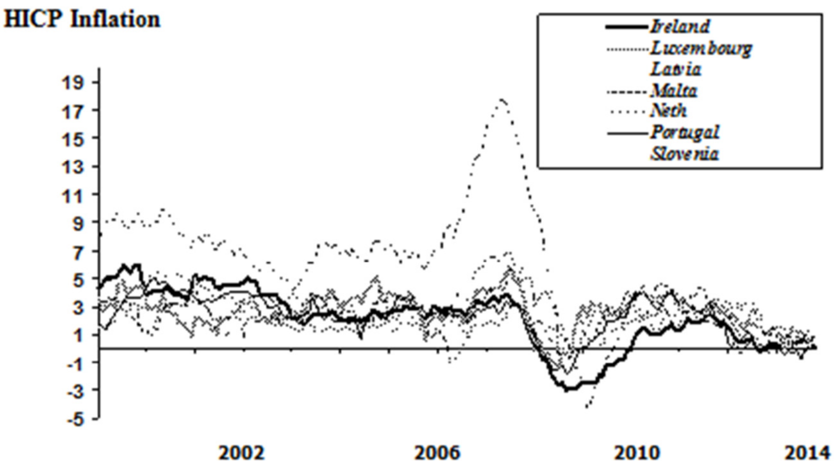
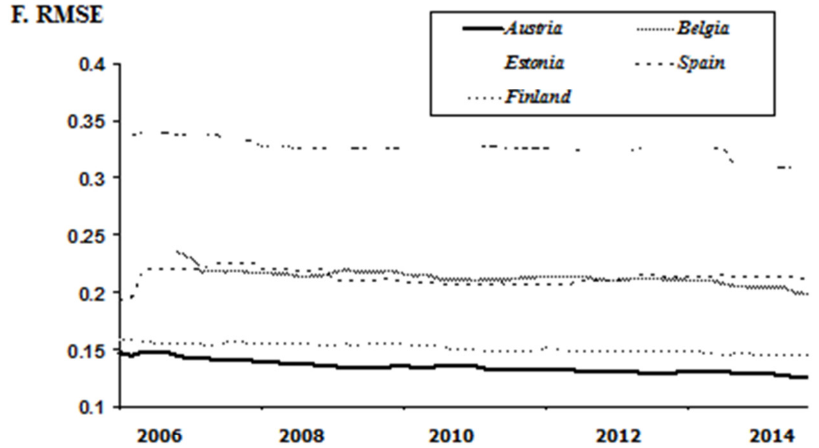


Figure B1: HICP inflation for euro area countries other than Germany, Greece, France and Italy



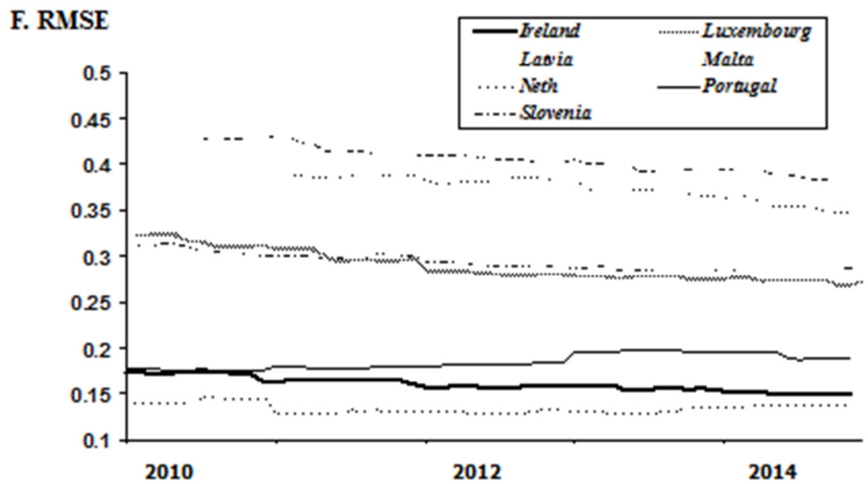
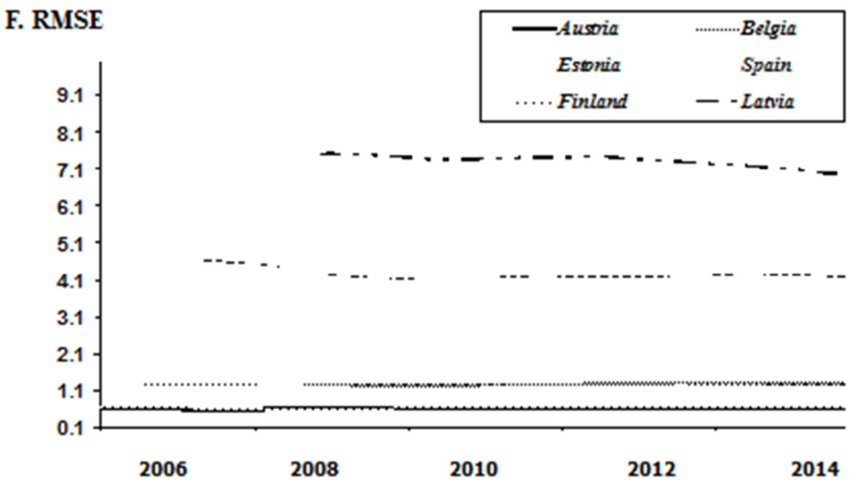


Figure B2: Forecast uncertainty (RMSE) for euro area countries other than Germany, Greece, France and Italy, forecast horizon *h*=1



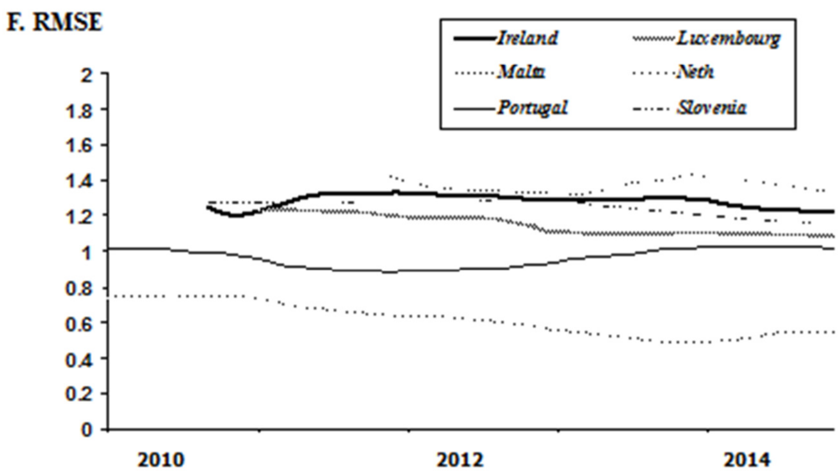
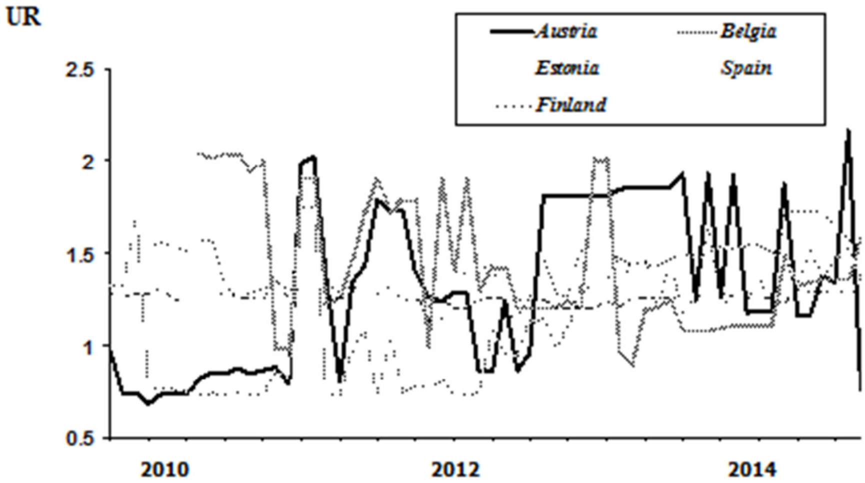


Figure B3: Forecast uncertainty for euro area countries other than Germany, Greece, France and Italy, forecast horizon *h*=12



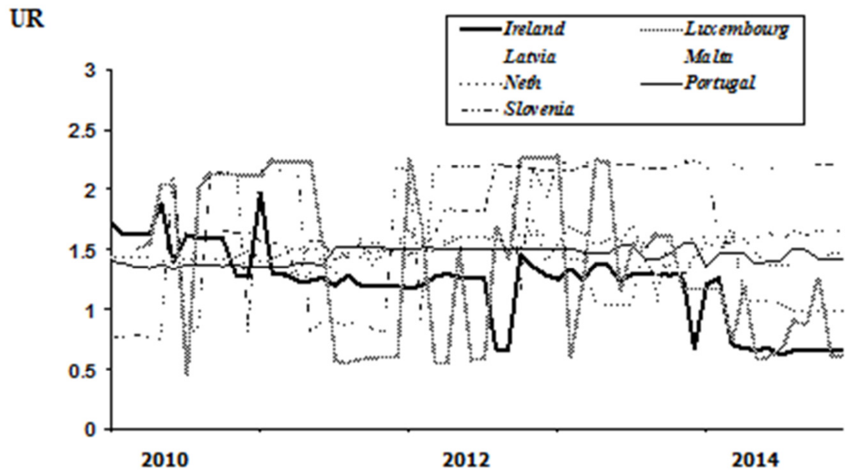


Figure B4: Uncertainty ratio (UR) for selected euro area countries other than Germany, Greece, France and Italy, forecast horizon *h*=1

Appendix C: Estimates of the parameters in (3) by the simulated minimum distance method (SMDE)

The SMDE estimates of a vector of parameters ω $(\omega \in \Omega \subset \mathrm{R}^k)$, introduced by Charemza et al. (2012), are given by:

$$\hat{\omega}_n^{SMDE} = \arg\min_{\omega \in \Omega} \left\{ \mu_w \left(d(g_n\,,\, f_{t,\omega}) \right)_{r=1}^{R} \right\} \quad , \tag{C1}$$

where $f_{t,\omega}$ is the approximation of the *pdf*, f_ω, of a random variable obtained by generating $r = 1,\ldots,R$ replications (drawings) from a distribution with the parameters ω, g_n denotes the density of the empirical sample of size n, μ_w is an aggregation operator based on R replications, which deals with the problem of the 'noisy' criterion function (median, in this case), and $d(\bullet,\bullet)$ is the distance measure. This approach is similar to that of Dominicy and Veredas (2013).

Table C1: Aggregate results of the estimation of WSN parameters for one-step ahead uncertainties. Averages across rolling windows

Country (1)	**Code** (2)	**Average** $(-\hat{a})$ (3)	**Average** $(-\hat{b})$ (4)	**Average** $\hat{\sigma}$ (5)
Austria	AT	0.49	0.92	0.15
Belgium	BE	0.43	1.06	0.24
Germany	DE	0.62	0.88	0.21
Estonia	EE	0.03	1.57	0.30
Spain	ES	0.30	1.14	0.21
Finland	FI	0.21	1.07	0.16
France	FR	0.44	0.90	0.15
Greece	GR	0.37	1.15	0.20
Ireland	IE	0.56	0.56	0.20
Italy	IT	0.25	1.17	0.12
Luxembourg	LU	0.77	0.84	0.30
Latvia	LT	0.94	1.47	0.44
Malta	MT	0.28	1.39	0.42
Netherlands	NL	0.71	0.51	0.15
Portugal	PT	0.27	1.22	0.20
Slovenia	SL	0.80	1.15	0.33

Following Cressie and Read (1984), the distance measure is defined as:

$$d(d_n\,,\, f_{t,\omega}) = \frac{1}{\lambda_{CR}(\lambda_{CR}+1)} \sum_{i=1}^{m+1} g_n(i) \left[\left(\frac{g_n(i)}{f_{t,\omega}(i)} \right)^{\lambda_{CR}} - 1 \right] \quad , \tag{C2}$$

For $\lambda_{CR} = 1$ formula (C2) gives the Pearson χ^2 (*PCS*) measure, for $\lambda_{CR} = -1/2$ the Hellinger twice squared distance (*HD*) and for $\lambda_{CR} = -2$ the Neyman χ^2 measure (*NCS*). For $\lambda_{CR} \to 0$

and $\lambda_{CR} \to -1$ the continuous limits of the right-hand side expression in (C2) are respectively the likelihood disparity (*LD*) and the Kullback-Leibler divergence (*KLD*) statistics. Cressie and Read (1984) advocate setting $\lambda_{CR} = 3/2$. Although the minimum distance estimators have been computed for all the λ_{CR}s listed above, for further inference it has been decided to concentrate on the *HD* distance estimator. Its properties have been well researched in the context of skew normal distributions (see Greco, 2011), and it is known that it is reasonably robust to the presence of outliers, which might appear in a large sample of inflation forecast errors, especially for longer forecast horizons. Minimisation of (C1) has been made by a grid search.

Appendix D: Formula for computing the uncertainty ratio UR

For the WSN random variable defined by (3), the corresponding uncertainty ratio can be explicitly expressed via its parameters as

$$\mathrm{UR} = 1 + 2\frac{\rho[|a|D_{m,\sigma} + |b|D_{k,\sigma} - \rho/2] - [a\varphi(m/\sigma) - b\varphi(k/\sigma)]^2}{1 - 2\rho\left(|a|D_{m,\sigma} + |b|D_{k,\sigma}\right) + W_{m,k,\sigma}\cdot\left(|a|D_{m,\sigma} + |b|D_{k,\sigma}\right)^2},$$

where φ and Φ denote respectively the density and cumulative distribution functions of the standard normal distribution, $D_{x,\sigma} = \int_{|x/\sigma|}^{+\infty} t^2\varphi(t)dt$ and

$$W_{m,k,\sigma} = \left[D_{m,\sigma}\varphi^2(k/\sigma) + D_{k,\sigma}\varphi^2(m/\sigma)\right] / \left[D_{m,\sigma}\varphi(k/\sigma) + D_{k,\sigma}\varphi(m/\sigma)\right]^2 .$$

The derivation of this formula and some analytical properties of the UR are discussed in Charemza, Díaz and Makarova (2015).

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