International Journal of Forecasting 33 (2017) 76–89

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

A comparative assessment of alternative ex ante measures of inflation uncertainty

Matthias Hartmann[a,*], Helmut Herwartz[b], Maren Ulm[b]

[a] Ruprecht-Karls-University Heidelberg, Alfred-Weber-Institute for Economics, Bergheimer Strasse 58, 69115 Heidelberg, Germany
[b] Georg-August-University Goettingen, Department of Economics, Germany

ARTICLE INFO

Keywords:
Uncertainty measurement
Ex ante and ex post inflation uncertainty
Disagreement
Out-of-sample forecasting
Economic crisis

ABSTRACT

The existence of unconventional monetary and fiscal policy arrangements in industrialized economies has been raising concerns about the future evolution of inflation rates ever since the onset of the financial and sovereign debt crisis in 2008. However, the question of how inflation uncertainty should be quantified is an open issue. We assess the informative content of alternative ex ante quantifications of inflation uncertainty by predicting ex post squared inflation forecast errors in an out-of-sample forecasting contest. We find that the average across distinct models' levels of ex ante uncertainty offers a greater predictive content than other uncertainty measures based on the cross-sectional variance of point forecasts, GARCH or stochastic volatility models.

1. Introduction

Ever since the outbreak of the financial and sovereign debt crisis, a growing body of theoretical and empirical literature has documented the effects of macroeconomic uncertainty. For example, Bloom (2009) and Jurado, Ludvigson, and Ng (2015) investigate the influence of uncertainty on real economic activity. Bloom (2009) explains this linkage through firms' investment decisions, which can be affected by uncertainty regarding the future payoffs of physical investment projects. Early contributions with an explicit focus on uncertainty about future inflation are those by Friedman (1977) and Okun (1971). Friedman (1977) highlights the detrimental effects of inflation uncertainty (IU in what follows) on aggregate investment and output. One reason for the sustained interest in IU might be the ongoing dispute about the sources of the so-called Great Moderation. The Great Moderation describes a secular containment of inflation fluctuations that has been observed across industrialised economies over recent decades (Benati, 2008; Herrera & Pesavento, 2009; Lahiri & Sheng, 2010; McConnell & Perez-Quiros, 2000). However, empirical studies of the causes and effects of IU face the problem that IU is unobservable.

The aim of this study is to evaluate a broad range of the measures of IU that are employed at present. Conceptually, most IU statistics are derived from either dynamic specifications such as (G)ARCH and stochastic volatility (SV) models, or the information provided by forecast surveys (Giordani & Söderlind, 2003; Lahiri & Sheng, 2010; Zarnowitz & Lambros, 1987). Representatives of the former category draw upon historical time series information. In contrast, survey-based approaches often approximate IU by the cross-sectional dispersion of point forecasts or by the average over survey participants' individual uncertainty, as derived from density forecasts (Giordani & Söderlind, 2003; Rich & Tracy, 2003). The high predictive content of survey-based point forecasts for inflation is

* Corresponding author. Fax: +49 621 54 3649.
E-mail addresses: matthias.hartmann@awi.uni-heidelberg.de (M. Hartmann), hherwartz@uni-goettingen.de (H. Herwartz), maren.ulm@wiwi.uni-goettingen.de (M. Ulm).

http://dx.doi.org/10.1016/j.ijforecast.2016.08.005
0169-2070/

documented by Ang, Bekaert, and Wei (2007), for example. Hence, this approach also seems promising as a means of quantifying IU. Clements (2014) compares measures of the ex ante forecast uncertainties derived from survey-based density forecasts of inflation and output growth with those of the ex post (i.e., realised) uncertainties that are derived from forecast errors. The relative magnitudes of ex ante and ex post IU can be interpreted as a metric of over- or under-confidence. Clements (2014) finds that the ex ante and ex post uncertainty are related only weakly, especially at short forecast horizons. Since survey-based and time series methods aggregate information in distinct ways (Batchelor & Dua, 1996; Mankiw & Reis, 2004), they will often provide diverging estimates of IU. Moreover, as was argued by Lahiri and Sheng (2010), choosing between these two approaches might be most difficult during turbulent periods.

This study assesses IU statistics from both the survey-based and time series categories according to their performances as predictor variables. Similarly to Clements (2014), the ex ante IU is related to the ex post IU. The ex post (i.e., realised) IU is obtained as squared inflation forecast errors. We then forecast the ex post IU using alternative ex ante IU measures, and rank them in terms of the predictive content of each. The comparability between the time series and disparity-type IU statistics is improved by using the predictions of various econometric forecasting models to represent the inflation expectations of surveyed experts. The first advantage of this approach is that differences in the predictive content cannot arise due to the use of distinct information sets, as both the time series based approaches and the dispersion statistics rely on the same historical time series information. Second, the consideration of a larger cross-section of economies is facilitated, since survey data on IU for sufficiently long time periods are available only for the Euro area and the US. Similarly, Branch (2004) and Brock and Hommes (1997) model the heterogeneity of expectations in terms of a finite number of prediction models. In contrast to other studies that evaluate alternative IU statistics, our investigation is based on a large-scale international data set, covering 18 industrialised economies and a sample period between 1997 and 2014. This allows us to compare the features and relative performances of IU measures during the time following the onset of the financial and sovereign debt crisis in 2007, as well as during the less turbulent period before.

We find that IU predictions that are based on the average uncertainty of alternative models are most accurate for predicting ex post squared inflation forecast errors. This statistic also corresponds most clearly to the ex post uncertainty if in-sample statistics like the R^2 are considered. In a descriptive analysis of the proposed IU statistics, the correlation coefficients reveal that the IU estimates that belong to the time series and dispersion categories process information in similar ways. However, each quantification of IU also shows idiosyncratic characteristics, which might explain the superior predictive performance of the average uncertainty statistic. Moreover, we enable a comparison with the model-based IU statistics by computing the disagreement among forecasters from the *Consensus Economics* survey with regard to their inflation expectations. The disagreement derived from *Consensus Economics* data is correlated positively with the model-based disagreement and the average uncertainty implied by the individual models. For all IU quantifications, a strong increase in uncertainty is observed at the outbreak of the global financial crisis. Interestingly, unlike for countries that are characterized by relatively low inflation rates, we do not find evidence of a substantial decline in IU after 2009 in high-inflation economies.

In Section 2, we introduce six competing IU metrics. In Section 3, we describe the relationship between the ex ante and ex post IU that is employed to assess the predictive content of alternative IU statistics. Moreover, the data set and the IU measures are described. An introduction to the forecasting design and a discussion of the comparisons between the ex ante and ex post IU follow in Section 4. Section 5 summarises and concludes. The alternative forecasting models that are used to substitute survey forecasts are outlined in the Appendix.

2. Measuring IU

There is no one way to define or quantify IU. Thus, we seek to determine the ex ante IU statistic that has the highest predictive content among a set of alternatives that have been proposed in the literature. We evaluate IU measures that mimic commonly-used dynamic and disparity approaches. Following, e.g., Branch (2004), Brock and Hommes (1997) and Hamilton (1985), we compute measures of disparity by replacing survey expectations with forecasts that are derived from a variety of econometric (time series) models. This procedure allows us to analyse a larger cross-section of economies, since typical forecast surveys such as the *Survey of Professional Forecasters* are only available for the US or the Euro area. Moreover, this approach guarantees an equal timing of the information sets underlying both time series based and disparity type IU measures. In what follows, six distinct IU statistics are reviewed. We begin by considering time series based methods, which include GARCH and stochastic volatility (SV) models, then go on to illustrate approaches that are based on the dispersion of individual forecasts. All measures are ex ante quantifications of IU. Several of the IU statistics discussed below are based (at least partly) on the linear autoregressive (AR) model, a specification that is used frequently for inflation forecasting. The comparably strong predictive performances of AR and random walk specifications for inflation processes have been documented in several empirical studies, including those by Canova (2007) and Stock and Watson (2007, 2008). The AR scheme is formulated as

$$\pi_{t+\ell} = \mu + \alpha_{11}(L)\pi_t + \varepsilon_{t+\ell}, \quad t = \tau - B + 1, \dots, \tau, \quad (1)$$

where $\varepsilon_{t+\ell} \sim (0, \sigma_\varepsilon^2)$, L denotes the lag operator, i.e., $L^n\pi_t = \pi_{t-n}$, and $\alpha_{11}(L) = \alpha_{11,0} + \alpha_{11,1}L + \cdots + \alpha_{11,P}L^P$. The lag order P is selected by means of the AIC, with the maximum order set to $P^{\max} = 12$. We consider the forecast horizons $\ell \in \{1, 3, 6, 12\}$ and alternative lengths of a (rolling) estimation sample $B \in \{72, 108\}$. The out-of-sample forecasts implied by (1) are denoted by $\hat{\pi}_{\tau+\ell|\tau}$, where $\tau = T_0 - \ell - P, \dots, T - \ell$ is the rolling