Revealing forecaster's preferences: a Bayesian multivariate loss function approach

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Abstract

Revealing the underlying preferences of a forecaster has always been at the core of much controversy. Herein, we build on the multivariate loss function concept and propose a flexible and multivariate family of likelihoods. This allows examining whether a vector of forecast errors, along with control variables, shapes forecaster's preferences and, therefore, the underlying multivariate, non-separable, loss function. We estimate the likelihood function using Bayesian exponentially tilted empirical likelihood (BETEL), which reveals the shape of the parameter and the power of the multivariate loss function. In the empirical section, the reported evidence reveals that the EU Commission forecasts are predominantly asymmetric, leaning towards optimism in the year ahead, whilst a correction towards pessimism occurs in the current year forecast. There is some variability of this asymmetry across Member States, with forecasts, i.e. GDP growth, for large Member States exhibiting more optimism.

Keywords: Forecasting, multivariate loss function, Bayesian analysis, asymmetric preferences, EU Commission forecasts.

JEL Classifications: C32, C53, E27, E37.

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1. Introduction

Given the importance of forecasting in economics, in finance and operational research, it is hardly surprising that testing for the underlying statistical properties of forecasts has a long tradition that can be traced back to Theil (1966). Mincer and Zarnowitz, (1969) offered a way of streamlining this procedure by testing whether forecast errors have zero mean and are uncorrelated with information available at the time that forecasts are formed. Such testing implicitly assumes that the forecaster has an underlying loss function that is symmetric and quadratic.[1] The symmetry of the underlying loss function of the forecaster is a very strong assumption as in the presence of asymmetry in the loss function previous tests are losing validity. If indeed the underlying loss function of the forecaster is asymmetric then the standard Theil-Mincer-Zarnowitz tests for efficiency are biased and thereby misleading (see also Clements, 2015). Elliott et al. (2005 and 2008) propose tests that allow the estimation of the shape parameter of an underlying loss function, and thereby reveal whether the latter is symmetric, or not.[2] Knowing the shape of the loss function is important, as it reveals the forecaster's underlying preferences and thus its behaviour.[3]

The results presented in this paper complement previous studies and fill the gap in the literature by providing estimations of the underlying multivariate loss function parameter, including whether it is linear or non-linear, as well allowing for examining the impact of control variables on the shape of the loss function. Moreover, we propose a flexible likelihood function, which is consistent with the multivariate loss function of Komunjer and Owyang (2012). This likelihood function is estimated using Bayesian techniques of the multivariate loss as a Bayesian exponentially tilted

[1] The role of underlying behaviour of the forecaster or the judgment of the forecaster has been gained prominent attention in recent years (see Leitner and Leopold-Wildburger, 2011; Athanasopoulos, et al. 2017). Its significance for operational research has also been recognised (Hämäläinen, Luoma, & Saarinen, 2013; Petropoulos et al., 2016 and 2014; Sagaert, et al. 2018; Athanasopoulos, et al. 2017), where the main objective has been to identify behavioural aspects in forecasting performance.

[2] Based on such testing, previous studies emerged, which test the underlying shape of the loss function for a variety of forecasts (see Christodoulakis and Mamatzakis, 2008 and 2009).

[3] The hypothesis of rational forecasts has been prominent in economic theory and modelling since Lucas' report (1972). Rational expectations crucially depend on the shape of the loss function, which is assumed to be symmetric and mostly non-linear and specifically quadratic (Elliott et al. 2005 and 2008; Komunjer and Owyang, 2012). In the event that the underlying loss function is asymmetric, the forecaster will show preferences for example to positive forecast errors compared to negative forecast errors. Elliott et al. (2005) argue that if such preferences are not widely known then forecasts are not rational.

empirical likelihood (BETEL).[4] In addition, our proposed modelling allows for inferences of whether the shape of the multivariate loss function is linear or non-linear. In some detail, our contribution to the literature is fourfold: first, we opt for a Bayesian estimation of a flexible likelihood multivariate loss function. Second, the proposed likelihood function accommodates the estimation of the power of the underlying loss function. Our modelling also allows for control variables that would explain the shape of the multivariate loss function in single stage estimation. Third, we provide Monte Carlo evidence that the proposed BETEL likelihood function estimation is unbiased and consistent. Finally, we provide empirical evidence for the underlying properties of the EU Commission forecasts that have been the centre of much attention since the financial meltdown in 2009 and the bail out of several euro-area Member States thereafter. Our sample covers the period from the 1969–2014 and refers to estimations of current year and year-ahead forecasts. We examine the EU Commission forecasts using the proposed BETEL multivariate loss function estimation, which does not rely on implicitly assuming additive separability across forecast errors. The results show that EU forecasts are predominantly asymmetric, and to an extent, in which this information is not disclosed, they are not rational, and in addition linearity is also not present. The EU forecasts lean towards optimism in years ahead, whereas they correct somewhat this optimism towards pessimism in the current-year forecasts. We also reveal that for large Member States forecasts lean towards optimism, which has certain policy implications. Our multivariate loss function analysis reveals that EU Commission forecasts should be interpreted with caution, as they tend to be rather optimistic, in particular with respect to GDP growth. Since the GDP growth forecasts are key for the assessment of the national economic policy of the EU Member States, and in particular in the Euro Area, optimistic forecasts allow for certain leeway against tougher fiscal consolidation in order to meet the targets set by the EU treaty. In addition, Commission's forecasts also act as a benchmark upon which the conditionality imposed to financial constraint EU Member States is assessed. Such forecasts form the base of measuring any '*fiscal and financial gap*' of the stressed

[4] Bekiros and Paccagnini (2014) develop an interesting modeling of Bayesian forecasting based on factor-augmented vector autoregressive DSGE models, whilst Groen and Kaptenaions (2016) propose principal components and Bayesian regressions for data reach macroeconomic forecasting.

Member States that could, in turn, lay the base for requesting corrective actions, such as fiscal adjustment and appropriate structural reforms. Therefore, from an economic policy point of view, it is imperative that the EU Commission forecasts do not suffer from deviations from asymmetry, leaning towards, for example, optimism.

The rest of the paper follows with Section 2, which presents a new family of flexible likelihood multivariate loss function of forecasts. Section 3 provides data sources and discusses the EU Commission forecasts, whilst Section 4 provides the empirical results. Finally, the last section offers some concluding remarks.

2. Methodology: asymmetry in the loss function of forecast errors

The starting point of testing for asymmetry in the loss function is the equation provided by Elliott et al. (2005). The authors propose the following loss function:

$$L(e;\alpha,p)=\left[\alpha+(1-2\alpha)I(e\leq 0)\right]\cdot\exp\left(-|e|^{p}\right), \quad (1)$$

where e is the forecast error, α (alpha) is the asymmetry parameter, and p is the parameter that nests the case of both linear and non-linear underlying loss function.

A drawback of the above loss function is that it is univariate. A univariate loss function implicitly assumes additive separability across forecast errors. This assumption could result in a bias in the estimation of the asymmetry (Komunjer and Owyang 2012). Komunjer and Owyang (2012) proposed a new family of multivariate loss functions to test the rationality of a vector of forecast errors without assuming additive separability across such errors. They also derive a GMM test for multivariate forecast rationality that allows the forecaster's loss to be non-separable across variables and considers forecast estimation uncertainty.

2.1 A Bayesian multivariate loss function

We build on Komunjer and Owyang (2012) and propose a Bayesian multivariate likelihood loss function. Suppose the forecast error is $\mathbf{e} \in \mathbb{R}^n$. Define the l_p-norm of any vector $\mathbf{u} \in \mathbb{R}^n$ as $\|\mathbf{u}\|_p = \left(\sum_{i=1}^{p} |u_i|^p\right)^{1/p}$, where $p \geq 1$. In the limit, we have $\|\mathbf{u}\|_\infty = \max_{i=1,\ldots,n} : |u_i|$.

Moreover, as in Komunjer and Owyang (2012), we consider the potential non-separability of a multivariate loss function by rewriting the loss function of equation (1) following Koenker and Bassett (1978) quantile estimation as:

$$L_p(\tau, e) = 2[1 - \alpha + \tau\mathbf{1}\ (e)]|e|^p, \tag{2}$$

where $\tau = 2\alpha - 1$, and $0 < \alpha < 1$ is the shape parameter of the univariate loss function, $p \geq 1$, p=1 if the loss function is linear and p=2 if is quadratic, whilst $\mathbf{1}$ is an indicator function $\mathbf{1}: \mathbb{R} \longrightarrow [0,1]$.[5] When $\boldsymbol{\tau} = 0$ the loss function is symmetric. Both the direction and the magnitude of the n-vector τ , influence the degree of asymmetry in the forecaster's loss.

For simplicity of the presentation we follow the formulation of the multivariate loss of Komunjer and Owyang (2012), given as follows:

$$\mathrm{L}_{\mathrm{p}}\left(\boldsymbol{\tau}, \mathbf{e}\right) = \left(\|\mathbf{e}\|_{\mathrm{p}} + \tau'\mathbf{e}\right) \cdot \|\mathbf{e}\|_{\mathrm{p}}^{\mathrm{p}-1}, \tag{3}$$

where $\boldsymbol{\tau} \in \mathbb{R}^n$ with $\|\boldsymbol{\tau}\|_{\mathrm{p}} < 1$.

Moreover, we define a multivariate density for the forecast error as follows:

$$f\left(\mathbf{e}; \boldsymbol{\tau}, p, \mathbf{H}\right) \propto \exp\left\{-\left(\|\mathbf{He}\|_p + \boldsymbol{\tau}'\mathbf{He}\right) \cdot \|\mathbf{He}\|_p^{p-1}\right\}, \tag{4}$$

[5] In the univariate case, given an exponent p, $1 \leq p < \infty$, Elliott et al (2005) asymmetry parameter τ, $-1 \leq \tau \leq 1$ could be mapped as a non-negative function of a scalar error $e_t \in \mathbb{R}^4$. There are many losses based on this mapping that are flexible to represent the absolute value or quadratic losses along with asymmetries. Komunjer and Owyang (2012) extend the univariate family of losses to a vector-valued argument $e_t \in \mathbb{R}^n$. For this $\| e_t \|_p$ denote the l_p-norm of any n-vector $e_t = ((e_t)_1, \ldots, (e_t)_n)$` $\in \mathbb{R}^n$.

for a certain lower diagonal matrix $\mathbf{H}$, such that $\mathbf{H}'\mathbf{H} \equiv \boldsymbol{\Sigma}$, can be interpreted as the scale matrix of the forecast error.

The density is then:

$$f(\mathbf{e};\boldsymbol{\tau},p,\mathbf{I}) \propto \exp\left\{-\left(\|\mathbf{e}\|_p + \boldsymbol{\tau}'\mathbf{e}\right)\cdot\|\mathbf{e}\|_p^{p-1}\right\}, \quad (5)$$

where the integrating constant is denoted by $C_{\boldsymbol{\tau},p}$, that is $\int_{\mathbb{R}^n} \exp\left\{-\left(\|\mathbf{e}\|_p + \boldsymbol{\tau}'\mathbf{e}\right)\cdot\|\mathbf{e}\|_p^{p-1}\right\} d\mathbf{e} = C_{\boldsymbol{\tau},p}$.

For the general form of the density it then follows easily that we must have:

$$f(\mathbf{e};\boldsymbol{\tau},p,\mathbf{H}) = C_{\boldsymbol{\tau},p}^{-1}|\boldsymbol{\Sigma}|^{-1/2}\exp\left\{-\left(\|\mathbf{He}\|_p + \boldsymbol{\tau}'\mathbf{He}\right)\cdot\|\mathbf{He}\|_p^{p-1}\right\}. \quad (6)$$

Suppose for a time series $\mathbf{y}_{t+1}$ the forecasts are $\hat{\mathbf{f}}_{t+1,t}$. The forecasts are symmetric if:

$$\hat{\mathbf{f}}_{t+1,t} = \underset{\mathbf{f}_{t+1,t}}{\arg\min} : E\left[L_p\left(\boldsymbol{\tau}_0, \mathbf{y}_{t+1} - \mathbf{f}_{t+1,t}\right) \mid I_t\right], \quad (7)$$

where I_t denotes the information set.

To test for asymmetry in forecast errors Komunjer and Owyang (2012) proceed using GMM estimation with a vector of instruments $\mathbf{x}_t$. This defines:

$$\mathbf{g}_p(\boldsymbol{\tau};\mathbf{e}_{t+1},\mathbf{x}_t) = \left\{p\nu_p(\mathbf{e}_{t+1}) + \boldsymbol{\tau}\|\mathbf{e}_{t+1}\|_p^{p-1} + (p-1)\boldsymbol{\tau}'\mathbf{e}_{t+1}\|\mathbf{e}_{t+1}\|_p^{-1}\nu_p(\mathbf{e}_{t+1})\right\} \otimes \mathbf{x}_t. \quad (8)$$

With the orthogonality conditions as:

$$E\mathbf{g}_p(\boldsymbol{\tau};\mathbf{e}_{t+1},\mathbf{x}_t) = \mathbf{0}. \quad (9)$$

The GMM problem is then:

$$\min_{\tau,\|\tau\|_p<1} : \sum_{t=1}^{T}\left[\mathbf{g}_p(\boldsymbol{\tau};\mathbf{e}_{t+1},\mathbf{x}_t)\right]'\boldsymbol{\Omega}^{-1}\left[\mathbf{g}_p(\boldsymbol{\tau};\mathbf{e}_{t+1},\mathbf{x}_t)\right], \quad (10)$$

where $\boldsymbol{\Omega} = E\left\{\left[\mathbf{g}_p\left(\boldsymbol{\tau};\mathbf{e}_{t+1},\mathbf{x}_t\right)\right]\left[\mathbf{g}_p\left(\boldsymbol{\tau};\mathbf{e}_{t+1},\mathbf{x}_t\right)\right]'\right\}$.

In our context, since we have defined the multivariate density of forecast errors, we propose the following likelihood function:

$$LF(\boldsymbol{\theta};\mathbf{X}) = \prod_{t=1}^{T} f\left(\mathbf{e}_t;\boldsymbol{\tau},p,\mathbf{H}\right) = C_{\boldsymbol{\tau},p}^{-T}\left|\mathbf{H}\right|^{-T/2}\exp\left\{-\sum_{t=1}^{T}\left(\left\|\mathbf{He}_t\right\|_p + \boldsymbol{\tau}'\mathbf{He}_t\right)\cdot\left\|\mathbf{He}_t\right\|_p^{p-1}\right\}, \quad (11)$$

where $\mathbf{X} = \{\mathbf{x}_t; t = 1,\ldots,T\}$ is a vector of instruments $\mathbf{x}_t$ and $\boldsymbol{\theta} = \left[\boldsymbol{\tau}', p, vec(\mathbf{H})'\right]'$ is our parameter vector.

Note that our focus is on τ, where $\tau = 2\alpha - 1$, and $0 < \alpha < 1$, which is the shape parameter of the loss function. Also, it is worth noticing that we treat p as an unknown parameter, although Komunjer and Owyang (2012) consider it as known. In this paper, p is estimated. Thus, if $p > 1$ the above loss function is entirely new. For $p = 1$ it can be used to define geometric quantiles as in Chaudhuri (1996).

Given a prior $\pi\left(\boldsymbol{\theta}\right)$ the posterior distribution is proportional to the following expression, by Bayes' theorem:

$$\pi\left(\boldsymbol{\theta} \mid \mathbf{X}\right) \propto \pi\left(\boldsymbol{\theta}\right)\cdot C_{\boldsymbol{\tau},p}^{-T}\left|\mathbf{H}\right|^{-T/2}\exp\left\{-\sum_{t=1}^{T}\left(\left\|\mathbf{He}_t\right\|_p + \boldsymbol{\tau}'\mathbf{He}_t\right)\cdot\left\|\mathbf{He}_t\right\|_p^{p-1}\right\}. \quad (12)$$

We use a standard prior of the form:

$$\pi(\boldsymbol{\theta}) = \pi(\boldsymbol{\tau})\pi(p)\pi(\mathbf{H}) = I\left(\left\|\boldsymbol{\tau}\right\|_p < 1\right)\cdot \mathrm{I}(p \geq 1)\cdot\left|\boldsymbol{\Sigma}\right|^{-(n+1)/2}, \quad (13)$$

where $I(\times)$ denotes the indicator function. The constant of integration $C_{\tau,p}$ is computed using numerical integration as in Genz and Malik (1980) for high-dimensional techniques.

To analyse the posterior, we use Monte Carlo sampling, which produces draws $\left\{\boldsymbol{\theta}^{(s)}, s = 1,\dots,S\right\}$ that converge in posterior distribution. Specifically, we use Markov chain Monte Carlo (MCMC, Hastings, 1970, Tierney, 1994, Geweke, 1999), which consists of two major steps:[6]

(i) The different elements of $\mathbf{H} = \left\{\mathrm{h}_1, \dots, \mathrm{h}_{\mathrm{n(n+1)/2}}\right\}$ and parameter p are sampled using a hit-and-run algorithm (Andersen and Diaconis, 2007, Belisle, Romeijn and Smith, 1993, see also Roberts and Gilks, 1994).

(ii) The elements of $\boldsymbol{\tau}$ are sampled from their posterior conditional distribution which is given by:

$$\pi\left(\boldsymbol{\tau} \mid \mathbf{X}, p, \mathbf{H}\right) \propto \exp\left\{-\sum\nolimits_{t=1}^{T} \boldsymbol{\tau}'\mathbf{He}_t \cdot \left\|\mathbf{He}_t\right\|_p^{p-1}\right\} I\left(\left\|\boldsymbol{\tau}\right\|_p < 1\right) \equiv \exp\left\{-\boldsymbol{\tau}'\mathbf{s}\right\} I\left(\left\|\boldsymbol{\tau}\right\|_p < 1\right), \quad (14)$$

where $\mathbf{s} = \left\|\mathbf{He}_t\right\|_p^{p-1} \cdot \sum_{t=1}^{T} \mathbf{He}_t$. The form of the posterior conditional distribution suggests that it is feasible to employ the hit-and-run algorithm for simplicity.

To describe the algorithm, suppose $f(\mathbf{x})$ is a density in $\mathbb{R}^m$ and let $D_p = \left\{x \in \mathbb{R}^m : \left\|x\right\|_p \le 1\right\}$. Given an existing draw $\mathbf{x}^{(s)} \in D_p$, the next draw is $x^{(s+1)} = x^{(s)} + \lambda \mathbf{d}$ where $\mathbf{d}$ has a uniform distribution over D_p and λ is generated from the distribution whose density is:

$$f_\lambda\left(\lambda\right) = \frac{f(\mathbf{x} + \lambda \mathbf{d})}{\int f(\mathbf{x} + r\mathbf{d})\, dr}. \quad (15)$$

Then the sequence of $\left\{\mathbf{x}^{(s)}\right\}$ will converge in total variation norm to the posterior (Belisle, Romeijn and Smith, 1993).

6 For more details on the Markov chain Monte Carlo method employed herein please see Appendix A.

2.2 The Posterior analysis using Bayesian Exponentially Tilted Empirical Likelihood

The GMM technique proposed by Komunjer and Owyang (2012) lends itself to an empirical likelihood generalization of their multivariate loss function. The Bayesian generalization of empirical likelihood is known as Bayesian exponentially tilted empirical likelihood (BETEL):

$$E\left[\mathbf{g}\left(\mathbf{X}_t;\boldsymbol{\theta}\right)\right]=0, \qquad (16)$$

The sample moment conditions are:

$$\mathbf{G}\left(\theta;\mathbf{X}\right)=T^{-1}\sum_t\left[\mathbf{g}\left(\mathbf{X}_t;\boldsymbol{\theta}\right)\right]=0. \qquad (17)$$

The empirical likelihood (Kitamura and Stutzer, 1997) is:

$$\begin{gathered} EL(\boldsymbol{\theta})=\max_{\{p_t\}_{t=1}^{T}}:\prod_{t=1}^{T}p_t; \\ \sum_{t=1}^{T}p_t\mathbf{g}(\mathbf{X}_t;\boldsymbol{\theta})=0, \\ t_i\geq 0,\forall t=1,\ldots,T,\sum_{t=1}^{T}p_t=1. \end{gathered} \qquad (18)$$

Suppose $\hat{p}_t(\theta)$ is the solution to the exponentially tilted empirical likelihood (ETEL) problem:

$$\min_{\{p_t\}_{i=1}^{N}}:\sum_{t=1}^{T}p_t\ln(p_t), \qquad (19)$$

subject to:

$$\sum_{i=1}^{N}p_t\mathbf{g}(\mathbf{X}_t;\boldsymbol{\theta})=0_M,\ p_t\geq 0,\forall t=1,\ldots,T,\sum_{t=1}^{T}p_t=1, \qquad (20)$$

The ETEL approach uses exponential tilting (ET) for the implied probabilities and empirical likelihood (EL) for the criterion function. If we introduce Lagrange multipliers $\boldsymbol{\lambda}(\boldsymbol{\theta})$ for the equality constraints in (5) we have:

$$\hat{p}_i(\boldsymbol{\theta}) = \frac{\exp\left\{\boldsymbol{\lambda}(\boldsymbol{\theta})'\mathbf{g}(\mathbf{X}_t;\boldsymbol{\theta})\right\}}{\sum_{j=1}^{N}\exp\left\{\boldsymbol{\lambda}(\boldsymbol{\theta})'\mathbf{g}(\mathbf{X}_j;\boldsymbol{\theta})\right\}}, t = 1,...,T, \quad (21)$$

where the Lagrange multipliers $\lambda(\boldsymbol{\theta})$ are given by:

$$\boldsymbol{\lambda}(\boldsymbol{\theta}) = \arg\min_{\Lambda} : T^{-1}\sum_{t=1}^{T}\exp\left\{\boldsymbol{\Lambda}'\mathbf{g}(\mathbf{X}_t;\boldsymbol{\theta})\right\}. \quad (22)$$

Schennach (2005) proposed the following empirical Bayesian posterior known as BETEL:

$$\pi(\boldsymbol{\theta} \mid \mathbf{X}) \propto \pi(\boldsymbol{\theta}) \cdot \prod_{t=1}^{T} \hat{p}_t(\boldsymbol{\theta}). \quad (23)$$

To obtain draws that converge in distribution to the posterior we use a MCMC technique, which is described in some detail in Appendix A. This is a Hamiltonian Monte Carlo method that uses local information about the gradient and the Hessian of the log posterior and converges rather fast.

3. Data set: the EU Commission forecasts

In our empirical application, we focus on macro financial time series forecasting of the EU Commission since such forecasts have gained prominent significance in recent years. This is so, as several euro-area Member States have received financial assistance from the EU, but also the IMF, which has involved strong conditionality, mostly fiscal, and economic assessment in real time. Such Member States are Greece, Ireland and Portugal, whilst other Member States (see Italy and Spain) have been under close scrutiny given their underlying financial and sovereign economic weaknesses. Given the scale of the provided financial assistance across the EU, the Commission's forecasts act as a benchmark upon which the conditionality imposed to EU Member States is assessed. Crucially, forecasts facilitate the assessment analysis regarding the '*fiscal and financial gap*' of the stressed Member States that could, in turn, lay the base for requesting corrective actions, such as fiscal adjustment and appropriate structural reforms.[7]

Herein, we focus on the annual EU Commission forecasts as reported semi-annually in spring and autumn, focusing on current year and year-ahead forecasts.[8] In line with Keerman (1999) and Christodoulakis and Mamatzakis (2008) and (2009), the current-year forecast is the first estimation in time, as published in the EU spring forecasts of the same year, whilst the forecast of the year ahead comes from the EU autumn forecasts and represents the following year.[9] Along these lines, the realisation or actual forecast variable of the current year is reported in the spring the year ahead, whereas the realisation of the year-ahead forecast is reported in the autumn the year ahead. For reasons of data availability over time, we shall consider the EU-12, excluding Member States that joined the EU later than 1995.[10] To this end, our time series sample spans from 1969 to 2014, the longer possible period for EU forecasts.

Diagram 1 presents the forecast errors, defined as forecast minus realisation, for the main variables of our empirical testing. However, for prolonged periods there is fluctuation of forecast errors around zero, since financial crisis forecast errors appear to pick. For example, growth forecast errors are positive and large in the aftermath of the financial crisis, indicating over-prediction and thus optimism, in particular for the year ahead forecast. This over-prediction in the growth rate was somewhat corrected in 2011 during the euro-area sovereign debt crisis, but it has reoccurred since. The growth is the corner stone of the DG ECFIN of the EU Commission forecasts exercise

7 Previous research (see Christodoulakis and Mamatzakis 2008 and 2009) shows that the EU Commission forecasts have been optimistic. In particular regarding growth for some large Member States. It would be of interest, therefore, to examine whether our empirical test based on a multivariate loss function would provide further evidence of asymmetry or whether asymmetry is subdued within a multivariate framework as demonstrated by Komunjer and Owyang (2012).

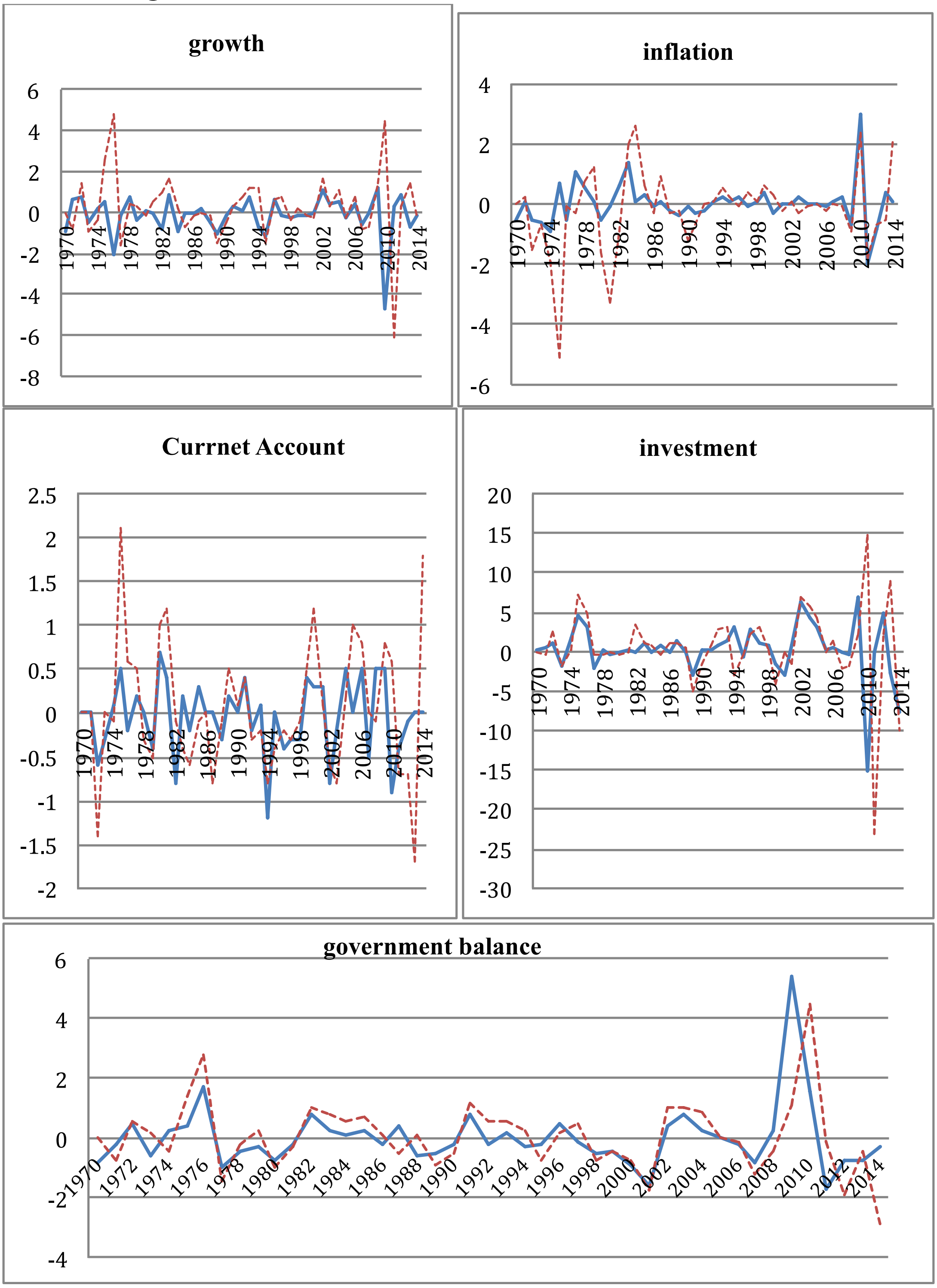
8 One of the advantages of using EU Commission forecasts is that they are widely considered as independent compared to the corresponding national forecasts. EU forecasts act as the benchmark in the assessment of the EU's national economies. National forecasts might not be independent and, therefore, could lean towards optimism. For example, additional ex-ante fiscal consolidation measures would be warranted in the case of under forecasting GDP growth so as to meet the government balance target of 3% of GDP, ceteris paribus revenue and expenditure elasticities, as well as fiscal multipliers. Similarly, under forecasting GDP growth for EU Member States in financial assistance programs, such as Greece where enhanced conditionality is imposed, would imply additional fiscal consolidation.

9 The DG ECFIN is responsible for providing the EU Commission forecasts in spring and autumn each year.

10 Forecasts at EU level would refer to EU-12 thereafter.

as it plays a crucial role in the ex-ante assessment of the EU's Member States. Positive forecast errors in the growth would suggest that the DG ECFIN allows some leeway to Member States towards optimism.

Diagram 1. EU-12 Current- and Year-Ahead Forecast Errors.



Note: solid and dash lines refer to current-year and year-ahead forecast errors respectively.

Moreover, some descriptive evidence of optimism in the growth forecast by the DG ECOFIN is reported in Diagram 1. The outcome of the euro-area GDP growth recorded a decline by 0.4% in 2012 (see Diagram 1), whereas it was forecasted a year earlier by DG ECFIN to increase by 1.8%. This is, indeed, a large forecast error. Descriptive statistics show positive forecast errors, defined as forecast minus realisation, and thus over-prediction and optimism, in particular in the years following the financial meltdown in 2009. Optimism in growth forecasting would imply optimism in other variable too, most importantly the government balance. The government balance is the key variable in terms of the annual assessment of the EU's Member States. Member States must follow the fiscal rule of having deficit less than 3% of GDP as stated in the EU treaty, so much so for Member States that have received financial assistance in recent years and are subjected to strong conditionality.

Regarding the inflation, a prudent economic agent may exhibit higher aversion to positive forecast errors versus negative ones of the same size. This would imply that the agent could assign higher loss for over-prediction (versus under-prediction). Similarly, for a government balance a prudent economic agent may exhibit higher aversion to negative forecast errors versus positive ones of the same size, reflecting higher loss for under-prediction.[11] Diagram 1 shows that forecast errors of government balances take negative values since 2010, implying persistence towards under prediction since the financial crisis, especially in the case of year ahead forecasts. The financial crisis has led to the euro area sovereign debt crisis characterised by large fiscal imbalances. The EU Commission fiscal forecasts appear to be rather optimistic during recent recession EU episodes. Along these lines forecast errors for investment also exhibit negative values in recent years.

Another interesting finding from Diagram 1 is that there is some variability between current-year and year-ahead forecast errors. For example, for the growth rate, investment and the current account balance, since 2010 the forecast error appears to be higher for the year-ahead forecast than that of the current-year forecast. This might

[11] Note that government deficit carries a negative sign. Negative forecast errors would mean that fiscal balances turn out to be worse than forecasted.

imply that EU Commission preferences could vary between year-ahead and current-year forecasts.

Given this preliminary descriptive evidence, it would be of interest to test for asymmetries in the underlying loss function of the EU Commission forecasts, whether univariate or multivariate. The variables of our analysis are GDP, government balance, current account, inflation, investment and unemployment.[12]

4. Empirical Results

In this section, we report estimations of *alphas* (α), the asymmetry parameter from the likelihood function of equation (11), which will reveal the underlying shape of the EU Commission forecasts, both for univariate as well multivariate loss function case. In the estimation of *alphas,* we employ the Bayesian exponentially tilted empirical likelihood (BETEL). As a first empirical exercise, we perform the univariate loss function and then compare the results with the multivariate case in a second stage. In a third stage, control variables are employed to assert their impact on alphas. Finally, we provide Monte Carlo evidence of the efficiency of our estimation method and compare it with the efficiency of Komunjer and Owyang (2012) method.

4.1. The shape of the loss function: the univariate case

Note that using our univariate loss function in Equation (2), we initially get estimates of *'τ'* as well as its median and standard errors. Having derived *'τ'* we proceed with estimation of *alphas* 'α' from $\tau = 2\alpha - 1$. Simply, if $0 < \alpha < 1$ and different than 0.5, it implies asymmetry in the shape of the underlying loss function. Also, note that we impose no restrictions on whether the flexible loss functions is linear or non-linear.[13]

In Table 1 we report *alphas,* 'α', for the GDP growth for both the case of year ahead and the current year forecasts. Perhaps not surprisingly, the results show that the underlying loss function of the EU Commission for GDP growth is asymmetric for all Member States, but a few (see Germany for the current-year forecast, Netherlands and

[12] We select forecasts and the corresponding realisations in line with Artis (1996), Keereman (1999) and (2003), and Christodoulakis and Mamatzakis (2008) and (2009).
[13] The power of the loss function is given as $p \geq 0$.

France for the year-ahead forecast). It is also striking that *alphas* take values less than 0.5 in most of the Member States for the year-ahead forecast GDP growth. Moreover, if alpha, 'α' takes a value less than 0.5 then the EU Commission will have directional preferences in favour of over-prediction of GDP growth and thus optimism, otherwise it has preferences in favour of under-prediction in GDP growth and thus pessimism. The results show that the EU Commission is pessimistic for Germany and Greece for the year-ahead forecast. The Greek case is of interest as pessimism prevails also in the current year. Such pessimism in the growth forecast would imply that the EU Commission in its assessment of the state of the Greek economy would request for enhanced fiscal consolidation efforts. On the other hand, the EU Commission preferences lean towards optimism for Belgium, Denmark, Ireland, Spain, Luxemburg, Portugal, UK and EU-12 for the year ahead. For the current-year forecast, the EU Commission shifts its preferences against over-prediction towards pessimism for Germany, Spain, Denmark, France, Ireland, Italy, Luxemburg, UK and EU. These results show that that the EU Commission takes a rather more conservative stand and exhibit pessimistic preferences for current year compared to year-ahead GDP growth forecasts. This evidence shows that the EU Commission has two faces when it comes to forecasts, which depend on the forecasting horizon. In general, it casts an optimistic preference for the year ahead and corrects this towards pessimism for the current year. Similar to Janus, whose two faces allows him to look at opposite directions at the same time, the EU Commission forecasts exhibit two opposite preferences at the same time. The EU forecasts offer an optimistic glimpse of the year ahead but correct to pessimism for the current year.

TABLE 1: GDP forecast errors for the univariate loss function.

	Current year			Year ahead		
	$\hat{\alpha}$	Med.	SE	$\hat{\alpha}$	Med.	SE
BE	0.4515	0.4435	0.0963	0.4249	0.4233	0.08387
DK	0.5629	0.5626	0.08301	0.4364	0.4344	0.07877
DE	0.5224	0.5222	0.0813	0.5911	0.5935	0.07493
EL	0.6512	0.6512	0.007361	0.6502	0.6503	0.006259
ES	0.6995	0.6997	0.005971	0.3128	0.3129	0.006787
FR	0.5859	0.5867	0.1006	0.5388	0.5382	0.08597
IE	0.5306	0.537	0.09577	0.3777	0.3787	0.1176
IT	0.6156	0.6133	0.08761	0.494	0.4926	0.08854
LU	0.6238	0.6251	0.08184	0.4401	0.443	0.09328
NL	0.4609	0.4592	0.08413	0.5025	0.5042	0.08474
PT	0.3074	0.3074	0.006232	0.3088	0.3089	0.006119
UK	0.7549	0.7562	0.07497	0.4502	0.4501	0.08059
EU	0.6056	0.6019	0.0905	0.465	0.4648	0.07637

Note: Estimations of the shape parameter, '*alpha*' $\hat{\alpha}$, of a univariate loss function. In the table we report posterior means, posterior medians and posterior standard deviations. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable loss, function.

Previous evidence, see Christodoulakis and Mamatzakis (2008) and (2009), provide estimates of *alphas* and therefore the shape parameter of a univariate loss function, opting for the Elliott et al. (2005) GMM estimation, imposing either a linear or a quadratic loss function. The authors report asymmetry for large Member States towards optimism compared to small Member States of the EU. Our findings complement previous evidence and show that asymmetry in the EU Commission forecasts is dominant for all EU Member States, but two, and there is a shift in the direction of preferences from the year ahead to the current year forecasts.[14]

[14] Our method allows to estimate posterior density of *ps*, and thus testing whether the underlying loss function is linear or quadratic, rather than imposing such functional form as in Elliott et al. (2005) and Komunjer and Owyang (2012). In order to facilitate the presentation of our findings we opt not to report *ps*. In the majority of testing, the loss function deviates from being quadratic. Results are available on request. Appendix B reports Diagrams B1 to B6 with densities of *alphas* and *ps* for the EU forecasts. These diagrams show that for most forecasts, whether current year or year ahead, the loss function is neither symmetric nor linear.

Table 2 reports the univariate loss function shape parameter, *alphas*, for the government balance. With the exception of Italy and Portugal, the loss function of the EU leans towards under-prediction, and thus optimism, for the year-ahead forecast. Notice that under-predicting government balance implies that Member States of the EU would have certain leeway when it comes to the required fiscal adjustment. This strong under-prediction for the year-ahead forecast shifts to over-prediction in the current-year forecast, for example in Belgium, Germany, Greece and Ireland. A familiar pattern, once more, is observed as the directional preferences of the EU Commission lean towards optimism for the year-ahead forecast, whereas such preferences are corrected towards pessimism in the current-year forecast.

TABLE 2: Government balance forecast errors for the univariate loss function.

	Current year			**Year ahead**		
	$\hat{\alpha}$	Med.	SE	$\hat{\alpha}$	Med.	SE
BE	0.8961	0.9351	0.1028	0.3897	0.3905	0.07985
DK	0.4913	0.4889	0.09429	0.4697	0.4703	0.09994
DE	0.8942	0.9087	0.07137	0.4308	0.4365	0.1394
EL	0.6948	0.6949	0.005375	0.3615	0.3615	0.006503
ES	0.3321	0.332	0.006244	0.3193	0.3194	0.006619
FR	0.3914	0.3926	0.08525	0.4257	0.4219	0.07785
IE	0.6011	0.6019	0.06204	0.4462	0.4439	0.07433
IT	0.4547	0.4543	0.0569	0.56	0.5663	0.06317
LU	0.4143	0.4183	0.09309	0.3737	0.3664	0.1371
NL	0.3026	0.2996	0.09729	0.3661	0.3686	0.08971
PT	0.7309	0.731	0.005018	0.6914	0.6915	0.00633
UK	0.3929	0.39	0.07897	0.4992	0.4964	0.0975
EU	0.3253	0.3221	0.07543	0.4451	0.4475	0.08983

Note: Estimations of the shape parameter, '*alpha*' $\hat{\alpha}$, of a univariate loss function. In the table we report posterior means, posterior medians and posterior standard deviations. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable loss, function.

Table 3 reports *alphas* for inflation. Strikingly, for all but one case (that is for Netherlands), the loss function exhibits preferences towards over-prediction for the year-ahead forecast. These preferences shift, once more, towards under-prediction for the current year forecast. Notably, for some EU Member States, such as Greece, Germany and Italy, the over-prediction in inflation for the year-ahead forecast becomes under-prediction in the current year. Inflation forecasts are of economic significance as they affect all nominal macroeconomic variables, notably government debt; for example, higher inflation would assert a positive impact on debt. Since Greece and Italy hold high government debts, over-prediction in inflation in the year ahead would imply lower measurement of nominal government debts as percentage of GDP, which could ease pressure on fiscal consolidation efforts. However, current-year preferences towards under-prediction of inflation forecasts would have the opposite impact.

TABLE 3: Inflation forecast errors for the univariate loss function.

	Current year			**Year ahead**		
	$\hat{\alpha}$	Med.	SE	$\hat{\alpha}$	Med.	SE
BE	0.4951	0.4954	0.0873	0.5643	0.5627	0.0887
DK	0.5519	0.5686	0.1235	0.5698	0.5734	0.07239
DE	0.4429	0.4377	0.08266	0.6002	0.603	0.1052
EL	0.3574	0.3574	0.006413	0.6438	0.6438	0.006368
ES	0.7062	0.7061	0.006159	0.7342	0.7343	0.00516
FR	0.4726	0.4719	0.08324	0.592	0.5924	0.08206
IE	0.5046	0.506	0.08991	0.651	0.6536	0.08098
IT	0.4019	0.4046	0.08341	0.6825	0.6835	0.07027
LU	0.5553	0.5572	0.08849	0.8163	0.8163	0.005063
NL	0.5194	0.5212	0.08523	0.4449	0.4466	0.08681
PT	0.7177	0.7177	0.005222	0.7075	0.7076	0.00587
UK	0.4992	0.4988	0.07739	0.5851	0.5809	0.08709
EU	0.4948	0.503	0.1023	0.5428	0.5409	0.07744

Note: Estimations of the shape parameter, '*alpha*' $\hat{a}$, of a univariate loss function. In the table we report posterior means, posterior medians and posterior standard deviations. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable loss, function.

Table, 4, 5 and 6 report results ('*alphas')* for unemployment, investment and current account, respectively. Unemployment is of interest as the revealed preferences lean towards pessimism in the year ahead, whilst this pessimism is subdued in most cases in the current year. For example, in the case of unemployment the EU Commission assigns higher loss when the forecast for unemployment in the year ahead is lower than the actual unemployment. This preference is reversed in the current-year unemployment forecast. Forecasts regarding investment in the year ahead show a moderate preference towards optimism compared to unemployment and current account (CA).

TABLE 4: Unemployment forecast errors for the univariate loss function.

	Current year			Year ahead		
	$\hat{\alpha}$	Med.	SE	$\hat{\alpha}$	Med.	SE
BE	0.4687	0.4621	0.1222	0.2776	0.2765	0.07661
DK	0.5826	0.5922	0.08451	0.4501	0.451	0.07938
DE	0.3639	0.3638	0.09121	0.3968	0.3996	0.08237
EL	0.6344	0.6344	0.006729	0.3778	0.3778	0.007258
ES	0.6797	0.6798	0.007146	0.3242	0.3241	0.006171
FR	0.5644	0.5661	0.1029	0.3123	0.3123	0.07187
IE	0.5132	0.5073	0.1002	0.369	0.3671	0.06544
IT	0.5282	0.5292	0.07564	0.3918	0.3939	0.07847
LU	0.5761	0.5855	0.0974	0.3594	0.3495	0.09029
NL	0.4866	0.4864	0.07089	0.4083	0.4074	0.07782
PT	0.2972	0.2971	0.005568	0.3016	0.3015	0.005938
UK	0.8142	0.8196	0.07425	0.3524	0.3545	0.07073
EU	0.6479	0.6526	0.08211	0.3606	0.3659	0.08307

Note: Estimations of the shape parameter, '*alpha*' $\hat{\alpha}$, of a univariate loss function. In the table we report posterior means, posterior medians and posterior standard deviations. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable loss, function.

TABLE 5: Investment forecasts errors for the univariate loss function.

	Current year	Year ahead

	$\hat{\alpha}$	Med.	SE	$\hat{\alpha}$	Med.	SE
BE	0.7031	0.7063	0.1120	0.6098	0.6098	0.08577
DK	0.6757	0.6749	0.08033	0.6737	0.6769	0.07189
DE	0.4376	0.4336	0.07502	0.5163	0.5158	0.07245
EL	0.6141	0.6142	0.009726	0.3559	0.3559	0.006354
ES	0.7164	0.7165	0.005414	0.3253	0.3254	0.006384
FR	0.5181	0.518	0.07874	0.4936	0.4931	0.07454
IE	0.3449	0.3409	0.0319	0.3668	0.3705	0.09573
IT	0.6278	0.6218	0.0213	0.5638	0.5632	0.07017
LU	0.487	0.4885	0.0701	0.5873	0.5869	0.06369
NL	0.5264	0.5234	0.08467	0.4986	0.4993	0.06524
PT	0.3365	0.3365	0.006715	0.3163	0.3163	0.006127
UK	0.58	0.5789	0.07894	0.536	0.533	0.07355
EU	0.4979	0.4941	0.07688	0.472	0.4688	0.06823

Note: Estimations of the shape parameter, '*alpha*' $\hat{\alpha}$, of a univariate loss function. In the table we report posterior means, posterior medians and posterior standard deviations. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable loss, function.

TABLE 6: Current Account forecast errors for the univariate loss function.

	Current year			Year ahead		
	$\hat{\alpha}$	Med.	SE	$\hat{\alpha}$	Med.	SE
BE	0.4621	0.4622	0.1053	0.613	0.633	0.2066
DK	0.537	0.5381	0.11	0.4464	0.4467	0.08437
DE	0.5634	0.5686	0.08848	0.3795	0.38	0.08415
EL	0.3211	0.3211	0.006034	0.344	0.3439	0.006119
ES	0.6778	0.6778	0.006572	0.3266	0.3267	0.006132
FR	0.5278	0.523	0.1066	0.7097	0.7201	0.1252
IE	0.5937	0.5985	0.07943	0.462	0.4602	0.09556
IT	0.6513	0.6532	0.0956	0.4932	0.4942	0.08275
LU	0.5318	0.5413	0.08546	0.455	0.4555	0.07426
NL	0.4186	0.4172	0.08615	0.3429	0.3434	0.09538
PT	0.2959	0.2958	0.005907	0.3096	0.3096	0.005841
UK	0.5694	0.5782	0.1247	0.4573	0.4582	0.0921
EU	0.7061	0.7114	0.1324	0.3609	0.3599	0.0936

Note: Estimations of the shape parameter, '*alpha*' $\hat{\alpha}$, of a univariate loss function. In the table we report posterior means, posterior medians and posterior standard deviations. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable loss, function.

Overall, we observe clearly for most variables that the EU Commission preferences are optimistic in the year ahead and turn pessimistic in the current-year forecast. An exception to this behaviour refers to unemployment and CA, but even for such variables' asymmetry is observed. We turn, next, to the multivariate loss function.

4.2. Multivariate loss function for a vector of forecast errors across variables

In this section, we employ the multivariate likelihood loss function in equation (11) and the Bayesian exponentially tilted empirical likelihood (BETEL) as derived from Equation (16) to estimate *alphas,* which are the shape parameters of the multivariate loss function. To the best of our knowledge, this is the first study that examines multivariate loss function for the EU Commission forecasts. Given asymmetries across the EU reported in the previous section, when a univariate loss function is employed, the results for the multivariate loss function would shed new light into whether those asymmetries persist or are lessened in the multivariate loss function case.[15]

Table 7(a) reports the posterior mean of the shape parameter, *alpha*, of the multivariate loss function that includes a vector of forecast errors of all EU Commission forecasts, namely GDP growth, inflation, government balance, unemployment, investment and current account. Note that we report the shape parameter of the multivariate, non-separable, loss function using as instruments a constant and one lag as in Komunjer and Owyang (2012).[16]

[15] It is worth noting that, in an early study, Kirchgassner and Muller (2006) propose a vector rationality test subject to the strong assumption that the underlying losses are additive separable and quadratic in individual variables. This is rather a restrictive assumption as it regards, for example, that the marginal loss for A's country forecast is independent of the B's country forecast despite both countries being members of the same union, such as the EU. Thus, under the assumption of separable loss, no interactions between different forecasts are present. Non-separable loss functions are of importance, as there must exist complementarities in the utility function of the EU Commission across countries. Komunjer and Owyang (2012) show that assuming additive separability of the underlying loss function will result to bias. To this end, any asymmetry found in the first step of our univariate rationality test could be biased if in a multivariate rationality test the asymmetry is restrained due to the non-separability of the underlying loss function based on n-variate. Komunjer and Owyang (2012) further argue that the asymmetries observed within a univariate loss function would be abridged at a multivariate loss function.

[16] In Appendix C, we report *alphas*, but also *ps*, for different instrument sets to test for the consistency of our results. That is we opt for one and two lags of all variables in the multivariate, non-separable, loss function.

TABLE 7 (a): Multivariate, non-separable, loss function across forecast errors in GDP growth, inflation, government balance, unemployment, investment and Current Account: the asymmetry parameter '*alpha*'.

	Current year			Year ahead		
	$\hat{\alpha}$	Med.	SE	$\hat{\alpha}$	Med.	SE
BE	0.4375	0.4303	0.0871	0.4329	0.4243	0.0892
DK	0.4577	0.4528	0.0985	0.4312	0.4321	0.0944
DE	0.5359	0.5346	0.0796	0.6004	0.6024	0.0742
EL	0.6565	0.6630	0.0186	0.6561	0.6643	0.0172
ES	0.3358	0.3465	0.0096	0.3184	0.3260	0.0119
FR	0.5923	0.5942	0.1124	0.5534	0.5412	0.1002
IE	0.5427	0.5434	0.1086	0.3899	0.3852	0.1342
IT	0.6161	0.6198	0.0950	0.4980	0.5037	0.0902
LU	0.6310	0.6333	0.0953	0.4432	0.4489	0.1069
NL	0.4653	0.4633	0.0966	0.5072	0.5098	0.0899
PT	0.3111	0.3156	0.0103	0.3175	0.3106	0.0066
UK	0.7568	0.7607	0.0752	0.4552	0.4603	0.0837
EU	0.6253	0.6154	0.0907	0.4661	0.4710	0.0807

Note: Estimations of the shape parameter, '*alpha*', of a multivariate, non-separable, loss function across forecast errors in GDP growth, inflation, government balance, unemployment, investment and Current Account. In the table we report posterior means, posterior medians and posterior standard deviations. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union.
The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable loss, function.

Our results from Table 7(a) show that asymmetries are also observed in the multivariate loss function. Moreover, results show that there is asymmetry towards over prediction of the vector of forecast errors of the EU Commission in eight out of twelve Member States, and the EU overall, in the case of the year-ahead forecasts. On the other hand, the EU Commission forecasts lean towards under-prediction in the case of the current-year forecasts. For Greece, the EU Commission forecasts show preferences towards under-prediction, and this is true to a lesser extent for Germany and France. For some other Member States preferences lean towards over-prediction also in the current year (see Belgium, Denmark, Spain, Netherlands and Portugal). Only for Netherlands a symmetric multivariate, non-separable, loss function is reported for the year ahead, but becomes asymmetric in the current year. Clearly, overall the multivariate loss function of the EU Commission forecasts does not seem to correct for the asymmetry observed in the univariate loss function. So, asymmetry prevails.

Table 7(b) reports the estimates of the *ps* of the multivariate loss function, providing information on whether is linear or nonlinear. Our results show that the underlying multivariate loss function is close to linearity for only a few EU Member States. Most EU Member States have a non-linear loss function, notably Greece, Portugal and Spain. For Ireland, also in the year ahead forecast, *p* the loss function takes values close to two and thereby the underlying multivariate loss would be quadratic.

TABLE 7 (b): Multivariate, non-separable loss function, across forecast errors in GDP growth, inflation, government balance, unemployment, investment and Current Account: the '*ps*'.

	Current year			**Year ahead**		
	p	Med.	SE	*p*	Med.	SE
BE	1.269	1.224	0.320	1.263	1.216	0.325
DK	1.261	1.222	0.332	1.268	1.225	0.327

DE	1.082	1.064	0.222	0.935	0.913	0.214
EL	0.017	0.023	0.011	0.012	0.020	0.011
ES	0.012	0.023	0.003	0.014	0.022	0.005
FR	1.158	1.139	0.265	1.203	1.162	0.307
IE	1.312	1.265	0.365	2.105	1.851	1.767
IT	1.079	1.032	0.309	1.235	1.206	0.302
LU	1.137	1.112	0.261	1.493	1.428	0.451
NL	1.247	1.208	0.329	1.207	1.168	0.301
PT	0.010	0.015	0.004	0.018	0.011	0.001
UK	1.097	1.052	0.308	0.885	0.869	0.194
EU	1.119	1.075	0.273	0.976	0.965	0.205

Note: Estimations of the '*ps*' of a multivariate, non-separable, loss function across forecast errors in GDP growth, inflation, government balance, unemployment, investment and Current Account. In the table we report posterior means, posterior medians and posterior standard deviations. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable, loss function.

4.4. Multivariate loss function for a vector of forecast errors across countries

In the previous section, we reveal the underlying multivariate loss function per EU Member State across different macro-finance variables. In this section we shift our attention to a multivariate loss function per macro-finance variable across EU Member States. We perform this testing to justify whether the EU Commission preferences regarding macro-finance forecasting are shaped considering economic conditions across Member States, and not just on one Member States. Note that the EU Commission forecasts are part of DG ECFIN mandate, and in particular they fall within the fiat of national desks of DG ECFIN of the EU Commission. As such, they are form in vacuum. EU DG ECFIN national desks employ several national experts to form Commission forecasts for every EU Member State. Some of those experts are EU nationals of the EU Member State in question. In this the case a consistency cross check exercise across national desks within the DG ECFIN would take place in every forecasting round (see Keereman, 2003) and before publishing such forecasts. As such, consultation might affect the shape of the loss function of forecasts, and therefore, an appropriate way to deal with it is to test for asymmetries for a multivariate loss function across EU Member States. Thus, we estimate a multivariate, non-separable, loss function per EU forecast across Member States.

Table 8(a) reports *alphas* of this multivariate loss likelihood per variable across all the EU-12 Member States. As previously, we employ a constant and one forecast error as instruments.[17] Once more, our results show that asymmetries in the multivariate loss function exist. Interestingly, preferences lean towards over-prediction, and thus optimism, for all variables but inflation, in the year ahead forecast. For government balance this over-prediction persists also in the current year forecast. But, for GDP growth, current account and unemployment in the EU Commission preferences shift towards under-prediction and thus pessimism for the current year. For government balance, we get deviation from symmetry towards under-prediction, for both the current year and the year ahead. Therfore, there is a certain degree of optimism for government balance, a key variable in the annual macroeconomic monitoring of the state of national EU economies, in particular for the euro-area countries. For investment, and to a less extend for inflation, we observe symmetry.

**TABLE 8 (a): Multivariate loss function, non-separable loss function, in f
errors across EU Member States: the asymmetry parameter *'alpha'*.**

	Current year			Year ahead	
	$\hat{\alpha}$	Med.	SE	$\hat{\alpha}$	Med.
INF	0.524	0.533	0.108	0.558	0.553
INV	0.506	0.502	0.078	0.484	0.470
GBAL	0.336	0.329	0.072	0.451	0.449
UN	0.657	0.656	0.085	0.377	0.386

[17] Appendix C reports the shape parameters and *ps* for instruments of one and two lags of all variables in the multivariate, non-separable, loss function.

CA	0.716	0.725	0.145	0.376	0.367	0.103
GDP	0.621	0.618	0.084	0.467	0.471	0.088

Note: In the table we report posterior means, posterior medians and posterior standard deviations. Estimations of the '*alpha*' of a multivariate, non-separable, loss function that is a function of forecast errors in the selected variables (i.e. INF inflation) across all Member States in our sample (namely Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxemburg, Netherlands, Portugal, United Kingdom). INF notes inflation, INV is investment, GBAL is the government balance, UN is unemployment, CA is current account and GDP is GDP growth. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable, loss function.

Table 8(b) shows that the loss function is not linear but close to linear, with the exception of CA, where a quadratic loss function is reported for current year, and to a lesser extent in the year ahead.

TABLE 8 (b): Multivariate loss function, non-separable loss function, in forecast errors across EU Member States: '*ps*' across all EU Member States.

	Current year			Year ahead		
	p	Med.	SE	*p*	Med.	SE
INF	0.692	0.675	0.229	0.901	0.858	0.225
INV	0.725	0.709	0.161	0.730	0.720	0.158
GBAL	0.969	0.952	0.216	1.317	1.279	0.311
UN	1.050	1.034	0.238	0.618	0.602	0.176
CA	2.004	2.285	1.933	1.647	1.549	0.583
GDP	1.111	1.087	0.290	0.985	0.955	0.212

Note: In the table we report posterior means, posterior medians and posterior standard deviations. Estimations of the '*ps*' of a multivariate, non-separable, loss function across Member States of EU (namely Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxemburg, Netherlands, Portugal, United Kingdom). INF notes inflation, INV is investment, GBAL is the government balance, UN is unemployment, CA is Current Account, and GDP is GDP growth. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable loss, function.

4.5. Multivariate loss function with covariates

In the previous section, we showed that national desks in the DG ECFIN proceed with a consultation over their forecasts, which ultimately shape their loss functions. In this section, given the flexibility of our loss function, which allows covariates in a single stage estimation, we run regressions to examine which of the national forecasts affect the most the EU Commission forecasts and thereby its underlying loss function.

4.5.1. The EU multivariate loss function regression

Table 9 reports the regressions from the likelihood function in Equation (11) of the EU forecasts for each variable in our sample.[18] Note that we report results for an instrument set that includes a constant and one lag in variables.[19]

TABLE 9: Multivariate loss function regressions of the EU Commission forecasts across EU Member States.

Dependent	INF		GBAL		CA		INV		UN		GDP	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-sta
C	-0.030	-0.573	0.098	1.280	-0.026	-0.689	-0.109	-0.631	-0.018	-0.792	0.028	0.76
lag	0.040	0.452	0.006	0.076	0.009	-0.056	0.056	1.239	-0.009	-0.627	0.012	0.03
BE	0.009	0.141	0.047	1.469	0.086	2.999	0.031	0.713	0.049	1.189	0.083	2.26
DK	0.022	0.292	0.015	0.072	0.025	0.819	-0.005	-0.746	0.039	1.171	-0.024	-1.1
DE	0.238	2.290	0.287	5.938	0.321	10.499	0.292	7.584	0.256	9.273	0.229	4.84
EL	0.034	0.726	0.045	2.116	-0.023	-1.633	0.022	0.906	0.053	2.951	-0.005	-0.4
ES	0.083	0.583	0.016	0.337	0.027	0.611	0.091	1.958	0.090	3.801	0.024	0.67
FR	0.387	3.325	0.173	3.315	0.110	2.620	0.364	4.613	0.269	7.222	0.224	4.63
IE	0.007	0.084	0.002	-0.083	0.037	1.565	0.038	1.779	0.035	2.098	0.035	1.97
IT	0.155	2.730	-0.014	-3.825	0.269	9.960	0.124	2.489	0.121	4.288	0.193	8.11
LU	-0.081	-0.826	0.022	0.577	0.002	-0.665	0.001	-0.890	-0.017	-0.346	0.016	0.87
NL	0.186	2.030	0.101	2.469	0.052	2.253	0.010	-0.091	0.099	3.694	0.098	2.21
PT	-0.004	-0.252	0.052	1.381	0.115	4.447	0.024	0.497	0.066	1.973	-0.008	-0.4
UK	0.111	2.177	0.213	6.205	0.153	6.791	0.158	4.083	0.135	3.123	0.194	7.41
alpha	0.367	0.110	0.660	0.296	0.614	0.264	0.462	0.293	0.436	3.934	0.563	0.26
ps	0.924	0.268	1.475	1.313	1.325	0.096	1.621	1.436	1.337	0.873	1.619	1.22

Note: Forecast errors are for the year ahead. Similar regressions are available under request for current year forecasts. BE is Belgium, DK Denmark, DE Germany, EL Greece, ES Spain, FR France, IE Ireland, IT Italy, LU Luxemburg, NL Netherlands, PT Portugal, UK United Kingdom, EU European Union. Dependent variable is EU forecast error. INF notes inflation, INV is investment, GBAL is the government balance, UN is unemployment, CA is Current Account, and GDP is GDP growth. C refers to constant, Lag counts for the lagged dependent variable that is included to observe any persistence. The instrument set includes: Constant and one lag of all variables in the multivariate, non-separable, loss function.

A strong result emerges from Table 9. National forecasts of large economies in the EU such as Germany and France appear to predominantly shape the loss function of the EU Commission forecasts across all macro-finance variables. Some other national forecasts, such as the UK, Italy, Netherlands, Germany and Belgium, also assert a statistical and economic significant effect on, for example, the EU Commission GDP growth forecast. Perhaps not surprisingly, when it comes to EU Commission government-balance forecasts, the Greek national forecasts assert a statistically significant effect, however, it is not of the same magnitude as the one of large

[18] Along with the regression results we estimate '*alphas*' of a multivariate, non-separable, loss of the EU forecast errors as function of forecast errors of all Member States in our sample (namely Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxemburg, Netherlands, Portugal, United Kingdom). Our results confirmed the findings of Table 8(a), since asymmetry is observed in all variables, but investment.

[19] Appendix C, see Table C9, reports the shape parameters and *ps* for instruments of one and two lags.

economies such as Germany, France and the UK. It is of interest that Italy's national forecasts on the EU Commission inflation forecast carries a negative sign. This last finding is in line with Keereman (1999). In terms of the shape of the multivariate loss function, *alphas* (see Table 9) show that asymmetry prevails, in line with previous sections. Again, for most of the variables the EU Commission forecasts lean towards over-prediction and thus optimism. Table 9 also reports the results for ρs, which indicate a non-linear multivariate loss function.

Overall, the above evidence reinforces the view that EU forecasts are not formed in a vacuum and a univariate loss function would fail to pick the '*true*' directional preferences. In fact, we provide evidence that the shape of the multivariate loss function of the EU Commission forecasts is strongly correlated with national forecasts of large EU economies. The sign of such correlation is mostly positive, though some negative correlations are also observed.

4.5.2. National multivariate loss function regressions

Given that we find evidence of the importance of some large Member States of the EU in shaping the loss function of the DG ECFIN forecasts, we further explore whether such asymmetries prevail at national level. Table 10 reports multivariate loss function regressions for the large Member States of the EU. In order to facilitate the presentation, we focus on the main DG ECFIN forecast variable, the GDP growth. We investigate the covariance between the GDP forecast error and the rest of macro-finance variables per EU Member State. The instrument set includes a constant and one lag.[20]

TABLE 10: Multivariate loss function regressions of GDP forecast errors for selected EU Member States.

	EU		**DE**		**FR**		**IT**		**NL**		**UK**	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
C	0.30	2.45	0.66	3.21	0.18	0.85	0.82	2.16	0.27	1.36	0.01	0.16
lag	-0.13	-1.31	-0.29	-2.42	-0.11	-0.63	-0.18	-1.02	-0.44	-3.72	-0.10	-1.09
INF	0.01	0.13	0.52	1.97	-0.06	-0.42	0.14	0.61	0.27	1.01	-0.39	-3.76
GBAL	0.93	7.27	0.63	3.61	0.64	3.41	-0.03	-1.38	0.58	5.78	0.28	2.81
CA	0.18	0.81	0.19	1.13	0.13	0.60	-0.17	-0.75	0.22	2.41	-0.28	-2.97

[20] Appendix C reports the shape parameters and *ps* for instruments of one and two lags.

UN	0.11	1.03	-0.30	-1.51	0.00	-0.02	-0.17	-1.42	-0.23	-1.82	-0.08	-0.38
alpha	0.30	7.05	0.46	2.81	0.46	1.75	0.35	3.89	0.56	3.94	0.34	2.13
ps	1.19	2.95	1.90	2.03	2.89	2.03	1.01	4.34	2.27	1.21	1.56	1.93

Note: Forecast errors are for year ahead. Similar regressions are available under request for current year forecasts. DE Germany, FR France, IT Italy, NL Netherlands, UK United Kingdom, EU European Union. Dependent variable is forecast error in GDP growth. INF notes inflation, INV is investment, GBAL is the government balance, UN is unemployment, CA is current account, and GDP is GDP growth. C refers to constant, Lag counts for the lagged dependent variable that is included to observe any persistence. The instruments used are: Constant and one lag of all variables in the multivariate, non-separable, loss function.

Interestingly, forecast errors in government balances assert a positive and statistically significant impact on growth forecast errors in all countries, but Italy (though it is insignificant). This result implies that fiscal imbalances would increase forecast errors in GDP growth that in turn allows certain leeway in the required fiscal consolidation. On the other hand, there is a negative correlation between inflation and GDP growth forecast error in the UK, insinuating some type of underlying supply shocks. Lagged GDP forecast errors have a negative and significant effect on present forecast errors in Germany and Netherlands.

The results for *alphas* show, once more, asymmetry in the underlying multivariate loss function towards preferences that leans to over-prediction and thus optimism for all large EU Member States, but Netherlands, whilst *ps* indicate nonlinearities.

4.6 Monte Carlo Validation of the multivariate loss

As part of validating the accuracy and consistency of our estimation method we proceed with the Markov chain Monte Carlo (MCMC). Here we follow exactly the data generating process as in Table 2 of Komunjer and Owyang (2012).[21] Table 11 reports results from the MCMC. We use 60,000 MCMC iterations. For brevity, we report only the relative mean square error (MSE thereafter) from the separable (multivariate loss function) to the non-separable (univariate loss) case. Table 11 provides evidence showing that our proposed Bayesian estimation performance is comparable to Komunjer and Owyang (2012). All standard deviations of our estimation are always lower than those of Komunjer and Owyang (2012).

21 Moreover, Komunjer and Owyang (2012) presented results from 1000 Monte Carlo replications for five different instruments. They show that mis-specification exists when the loss is assumed as univariate compared to the true multivariate loss function.

Table 11. Comparison of relative MSE with Komunjer and Owyang (2012).

	Komunjer and Owyang (2012) Multivariate Loss			Present Multivariate Loss		
Instrument set	τ_1	τ_2	τ_3	τ_1	τ_2	τ_3
1	15.09	109.79	132.98	4.12	11.12	13.05
2	17.14	108.61	134.23	4.33	12.05	14.54
3	18.49	106.49	128.50	4.71	14.17	17.21
4	20.06	105.25	122.48	6.87	17.36	21.12
5	16.88	106.24	131.97	5.12	15.55	15.59
Posterior analysis	-	-	-	4.12	11.22	13.05

Notes: The row headed *'posterior analysis'* gives results for posterior means derived using MCMC. The other elements are derived from BETEL using the instrument sets described in the first column and they are exactly the same as in Komunjer and Owyang (2012), Table 2.

Moreover, the reported MSE simulations prove that falsely adopting a univariate loss function could disguise the fact that forecast errors are not independent and as such the true underlying loss function could be mis-specified, along with its shape. Our new multivariate loss function offers an efficient way to correct for this mis-specification.

5. Conclusion

In this paper we propose a multivariate, non-separable, loss likelihood function, where a vector of forecast errors is present. Control variables are also present in the loss function. We show that the Bayesian generalization of an empirical likelihood known as Bayesian exponentially tilted empirical likelihood (BETEL) is more efficient than the standard likelihood function in the literature. In an empirical application, we focus on testing for asymmetries in the EU Commission forecasts, given their importance due to strong conditionality imposed to some euro-area Member States that have been under financial distress. The reported evidence shows that the EU Commission forecasts are predominantly asymmetric, leaning towards optimism in the year-ahead forecasts, and towards pessimism in the current year, in particular for the GDP growth and the government balance. We also find that size matters as large Member States of the EU have a dominant role in shaping the multivariate loss function of the EU Commission forecasts and in turn the EU Commission's preferences lean towards optimism regarding large EU Member States forecasts. The EU forecasts should be interpreted with caution as they predominantly project a promising picture with regards to the EU economy, yet the EU growth remains anaemic since the financial crisis. It would benefit the implementation of an economic policy to shed new lights when it comes to forecasting that would correct for asymmetries in EU Commission forecasts.

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