New methods for timely estimates

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Abstract

We provide a survey of the literature on panel vector autoregression (pVAR) models and of their main characteristics. We also assess the possible gains pVAR models might yield for flash estimation, now-casting and economic short-term (point and density) forecasting, and discuss some yet unexploited applications where pVAR models could be effectively used in official statistics. Next, we examine empirically the out-of-sample forecasting performance of mixed-frequency pVAR models for four key macroeconomic variables using data for four European economies. We evaluate point, directional and also interval and density forecasts. Overall, the empirical results provide mixed evidence in favour of pVAR models but suggest that at least for point forecasts they can be more accurate than VAR models.

Keywords: Panel data, Vector Autoregressions, Timely Estimates, Forecasting, Official statistics.

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Abbreviations

BVAR	Bayesian vector autoregression
CPI	Consumer Price Index
DPM	Dynamic Panel Data
DSGE	Dynamic Stochastic General Equilibrium
GDP	Gross Domestic Product
GMM	Generalised Method of Moments
GVAR	Global Vector Autoregressive
IP	Industrial production
MIP	Macroeconomic Imbalances Procedure
pVAR	panel Vector Autoregression
SDG	sustainable development goals
TVpVAR	Time Varying pVAR
UNR	Unemployment rate
VAR	Vector Autoregressive
VECM	Vector Error Correction Model

Country codes

DE	Germany
FR	France
IT	Italy
UK	United Kingdom

1 Introduction

A decade ago, the Great Recession highlighted two important facts, among others. First, a severe shock in a sector of an economy can affect a number of other sectors (domestic spillover effect) and, eventually, the economy as a whole. The mortgage subprime crisis is a representative example. Second, an economy in recession can also affect the growth rate or other key macroeconomic indicators of other related economies (international spillover effect), which was also the case during the Euro Area sovereign debt crisis initiated by Greece in 2010. These facts illustrate the concept of *interdependency*. Sectors and markets in a country are interdependent and also sectors and markets of one country might be interdependent with sectors and markets of another country. Therefore, it is now a necessity for macroeconomic analysts and official statisticians to take this global perspective into account when compiling and using key macroeconomic indicators. Discarding this global dimension could lead to producing biased and misleading indicators, which could affect the effectiveness of economic and monetary policies. For example, during the financial crisis, early estimates of several economic indicators had to be substantially revised afterwards. Similar interdependencies exist at a more micro level, for example among firms or banks or households, but in this paper we focus on the macro level from the perspective of official statistical agencies.

Long and Plosser (1983) is one of the first papers to provide evidence that domestic interdependencies affect the business cycle. Spillovers from the financial sector to the real economy have been observed during the 2007–08 economic and financial crisis and investigated in the academic literature (see Stock and Watson (2012) and Cicarelli *et al.* (2016) among others). A number of studies have also showed that increasing levels of trade and financial market integration result in an increase of interdependencies among developed countries as well as an increase of interdependencies between developed and developing economies (see Kose *et al.* (2003), Pesaran *et al.* (2004), Canova and Pappa (2007), Kose and Prasad (2010) and Canova and Ciccarelli (2012), among others). Macroeconomic analysis and the preparation of official statistics, particularly when focusing on flash estimation, nowcasting and short-term forecasting, should model these complex relations. As already said, failing to do so might lead to biased and inefficient estimates and, consequently, ineffective policies.

The literature suggests two main methodologies that can incorporate interdependencies in modelling. First, the multi-sector, multi-market, multi-country Dynamic Stochastic General Equilibrium (DSGE) models are suggested. This type of models has been extensively used in practice by central banks but not by official statistical agencies. In fact, DSGE models can offer recommendations and easy-to-interpret answers to policy-related questions but they impose many restrictions which do not always meet the characteristics of the data. Such restrictions are, in most cases, derived from macroeconomic theories and, consequently, contradict one of the basic principles of official statistics, i.e., impartiality. Furthermore in a recent study which focuses on the analysis of business cycles, Andrl *et al.* (2017) argue that most DSGE models do not feature a structural shock that dominates the cyclical frequencies of consumption, investment, output, hours worked, and inflation, and therefore most DSGE models are likely to be misspecified, which makes them not particularly suited for the construction of official statistics without major modifications.

The second strand of the literature focuses on Vector Autoregressive (VAR) models. VAR models are used to capture linear interdependencies among multiple time series, without requiring deep knowledge about the factors affecting a variable, as it is instead usually the case in structural simultaneous equation models. From a statistical point of view, VAR models can be considered as an approximation to the MA infinite representation implied by the Wold theorem for stationary variables. As such, they are theoretically well grounded and for this reason, combined with their good fit for several types of macroeconomic data and ease of implementation, they are often used also in official statistical agencies. In fact, VAR models only require the specification of a set of variables that are assumed to interact dynamically. VAR models are essentially data driven and they do not require the use of any restrictions coming from economic theories. Consequently they are fully in line with official statistics principles.

In the global context described above, the researcher must use an extended version of VAR models, leading to a multi-sector, multi-market, multi-country specification. This cannot be accomplished by standard VAR techniques, as the number of parameters of the resulting VAR would be too large, it grows quadratically with the number of variables (the so-called *curse of dimensionality*). Hence, specific techniques are needed.

The seminal papers by Anderson and Hsiao (1982) and Holtz-Eakin *et al.* (1988) formulate the combination of panel data (multi-sector, multi-market, multi-country)([5]) with standard time series VAR models, yielding the so-called Panel VAR (pVAR). pVAR models have been gradually increasing in popularity in the field of empirical economics and economic statistics during the past decade. Two factors explaining the increasing popularity of pVARs in empirical applications are their ability to capture interdependencies and the availability of freeware software for their implementation.([6])

The main purpose of this paper is to offer an extensive review of pVAR models, followed by a detailed empirical evaluation of their forecasting performance for several macroeconomic variables and countries. As mentioned, given their flexibility, these models could be also adopted by official statistical agencies both to improve nowcasts and flash estimates for national variables, basing them on an extended information set, and to provide a comprehensive statistical coverage across countries or markets. Following Canova and Ciccarelli (2013), we show how pVAR models can (i) capture both static and dynamic interdependencies, (ii) treat the links across units in an unrestricted fashion, (iii) easily incorporate time variation in the coefficients and in the variance of the shocks, and (iv) account for cross-sectional dynamic heterogeneities. Next, we discuss the estimation of pVAR models in Bayesian and non-Bayesian frameworks. Further, we compare pVARs to alternative models, such as Global VARs (GVARs) or large scale Bayesian VARs, and review the empirical use of pVAR models in economic forecasting and business cycle analysis. As we discuss later, the use of pVAR models for nowcasting and forecasting has just started, providing an excellent timing for further work in this area but also the need for a careful evaluation to assess their applicability and usefulness for official statistical agencies. Potential applications of PVAR models in official statistics are shortly discussed later.

Even though we extensively discuss the properties of pVAR models in later sections, it is useful to point out from the start their differences with respect to the single country VAR specifications. Standard VARs model all variables as endogenous and interdependent, however they do not offer the flexibility of a cross-sectional dimension. pVARs on the other hand still treat all variables as endogenous and interdependent but also add a cross-sectional dimension, which can account for, say, N units. These units can be, for example, countries, sectors, markets or combinations of them. GVAR (Global Vector Autoregressive) models, which are probably the methodology closest to the pVAR, can be considered as a collection of unit specific VARs where an unobservable common factor is included. A common technique is to proxy this factor with cross-unit averages. Therefore, a GVAR can be viewed as a restricted large scale VAR where variables of different units are weighted. This means that GVARs impose a particular structure on the interdependencies in the data, which makes them easier to estimate but also more prone to misspecification. Large Bayesian VARs could in principle be used to jointly model all variables for all units of interest, yet imposing some additional structure related to the panel dimension could improve efficiency of estimation and forecasting.

Moving to the empirical application, we examine the out-of-sample forecasting performance of pVAR models for key economic variables of European countries. The choice of this region is of particular importance as it consists of separate economies which are integrated to a large extent (no customs, single currency for many of them, etc.). From an official statistics point of view, analysing data of integrated economies requires to capture the potential underlying interdependencies and exploit them in the context of estimation and forecasting. Our four target

([5]) Also see Chudik and Pesaran (2015) for a survey on panel data models.

([6]) Love and Zicchino (2006), which is one of the first papers to widely share STATA program codes, has more than 1,100 citations. As these models have increased in popularity, Abrigo and Love (2015) have prepared a suite of computational procedures for STATA and Sigmund and Ferstl (2019) prepared a suite of procedures for R. The European Central Bank (ECB) BEAR toolbox built in MATLAB also includes procedures for pVAR models; see Dieppe *et al.* (2016) for more information.

variables are: (i) the quarterly Gross Domestic Product growth, (ii) the monthly Industrial Production growth, (iii) the first difference of the monthly Unemployment Rate and (iv) the period-to-period Inflation based on the monthly Consumer Prices Indices. Our set of countries consists of Germany, France, Italy and the UK.

We start with a set of standard models which includes univariate autoregressive and VAR models. Then, we extend these models including factors extracted from a higher frequency set of macroeconomic and financial predictors as well as big textual data. To overcome the difficulty of mixed-frequency we employ the bridge and UMIDAS approaches. Finally, we compare the out-of-sample forecasting performance of the standard models to simple and factor-augmented pVAR models. Therefore, we contribute to the academic literature and to the discussion on the usefulness of pVARs in the context of official statistics in two ways: (i) we apply for the first time mixed-frequency pVAR models, and (ii) we provide a comprehensive forecasting evaluation of standard and pVAR models using point, directional and density forecasts.

The rest of the paper is organised as follows: Section 2 provides a description of various specifications and Section 3 is concerned with various estimation techniques for pVAR models. Section 4 discusses how pVAR models could be used in forecasting. Section 5 provides a discussion of various empirical applications based on pVAR models and of possible uses in official statistics. Section 6 introduces the models used in the empirical application. Section 7 briefly explains the datasets. Section 8 discusses the forecasting algorithm and forecast evaluation statistics. Section 9 presents the main results. Section 10 summarizes the main findings and offers the conclusions.

2 Description of pVAR models

2.1 Standard VAR models

Time series VARs are now a standard tool in macroeconomic analysis. They model all variables as endogenous and interdependent and provide an intuitive output for policy recommendations (e.g., based on impulse response analysis, forecast error variance decomposition, etc.). A VAR of order p, VAR(p), takes the following form:

$$Y_t = \mu + \sum_{l=1}^{p} A_l Y_{t-l} + \varepsilon_t, \tag{1}$$

where Y_t is a $(G \times 1)$ vector of endogenous variables, μ is a $(G \times 1)$ vector of constants, A_l is a time-invariant $(G \times G)$ matrix of coefficients, $l = 1, ..., p$, ε_t is a $G \times 1$ vector of errors and $t = 1, \ldots, T$.

Assumption 1 *The vector of errors, ε_t, has the following properties:*

1. $E(\varepsilon_t) = 0,$
2. $E(\varepsilon_t \varepsilon'_t) = \Sigma_\varepsilon$ *which is a $G \times G$ positive-semidefinite matrix, and*
3. $E(\varepsilon_t \varepsilon'_{t-s}) = 0$ *for $s \neq t$.*

Typically, the Y_t variables are assumed to be weakly stationary and the VAR(p) model is interpreted as an approximation to the $\mathrm{MA}(\infty)$ representation for Y_t implied by the Wold theorem. Yet, integrated variables (driven by stochastic trends) can be also considered. If the integrated variables are also co-integrated, namely driven by a limited number of common stochastic trends so that specific linear combinations of them are stationary (the error correction terms), the VAR can be transformed into a Vector Error Correction Model (VECM). If the integrated variables are not co-integrated, then a VAR in their first differences suffices (and is equivalent to a VECM with no cointegration). Additional details on VAR(p) models can be found in standard academic textbooks (see, e.g., Lütkepohl (2005) and Canova (2007) among others).

In a common extension of VAR(p) models, the G variables in Y_t are assumed to be linear functions of some predetermined exogenous variables S_t. In this case, the VAR(p) model of Equation (1) becomes the VARX(p) model:

$$Y_t = \mu + \sum_{l=1}^{p} A_l Y_{t-l} + \sum_{k=0}^{s} C_k S_t + \varepsilon_t, \quad (2)$$

where S_t is a $(K \times 1)$ vector of exogenous variables, C_k is a time-invariant $(G \times K)$ matrix of coefficients and Assumption 1 holds. The model allows to include *s* lags of S_t. VARX(p) models have been used, for example, in the analysis of the effects of monetary policy (see Cushman and Za (1997) among others), or in the measurement of the effects of global variables (e.g., commodity prices or world productivity) on domestic economies (see, e.g., Kilian and Vega (2011)).

2.2 Standard pVAR models

A pVAR model is similar in many ways to a standard VAR or VARX, as variables are still treated as endogenous and interdependent. However, we can now add a cross-sectional dimension, which can account for $i=1,\ldots,N$ units. Units can be, for example, countries, sectors, markets or combinations of them. A pVAR(p) model of $i=1,\ldots,N$ units can be represented as:

$$y_{it} = \mu_i + \sum_{l=1}^{p} A_l y_{it-l} + \varepsilon_{it}, \quad (3)$$

where $i=1,\ldots,N$, $t=1,\ldots,T$ and μ_i captures the unit-specific effects. Therefore, a pVAR(p) can be seen as a combination of a single equation dynamic panel data model (DPM) and a VAR(p) model. Assumption 1 now becomes:

Assumption 2 *The disturbances,* ε_{it}, *have the following properties:*

1. $E\left(\varepsilon_{it}\right)=0,$
2. $E\left(\varepsilon_{it}\varepsilon'_{,it}\right)=\Sigma_{\varepsilon}$ *which is a* $G \times G$ *positive-semidefinite matrix, and*
3. $E\left(\varepsilon_{it}\varepsilon'_{,it-s}\right)=0$ *for* $s \neq t$.

In the above setup we see that ε_{it} is uncorrelated across time, but can be correlated across units, i.e. $E\left(\varepsilon_{it}\varepsilon'_{jt}\right)=\Sigma_{\varepsilon,ij}$.

In a similar fashion to VARX(p) models, we can include exogenous variables in pVAR(p) models as well (pVARX(p)). The specification now becomes:

$$y_{it} = \mu_i + \sum_{l=1}^{p} A_l y_{it-l} + \sum_{k=0}^{s} C_k s_{t-k} + \varepsilon_{it}. \quad (4)$$

Notice that in this case, the exogenous variables are *common to all units*.

Following Sigmund and Ferstl (2019), we can further extend the model in Equation (4) including a vector of *M* predetermined variables which are potentially correlated with past errors. Therefore, in total we consider $(M+K)$ predetermined variables where only K are strictly exogenous. The model now becomes:

$$y_{it} = \mu_i + \sum_{l=1}^{p} A_l y_{it-l} + \sum_{m=0}^{q} B_m x_{t-m} + \sum_{k=0}^{s} C_k s_{t-k} + \varepsilon_{it}, \tag{5}$$

where x_t is a vector of $(M \times 1)$ predetermined variables common to all units which are potentially correlated with past errors and s_t is the $(K \times 1)$ vector of strictly exogenous variables common to all units. B_m and C_k are $(G \times M)$ and $(G \times K)$ coefficient matrices respectively. We allow q and s past lags of x_t and s_t respectively. However, to simplify our notation, we consider that $q = s = 0$ and therefore Equation (5) takes the following simpler form:

$$y_{it} = \mu_i + \sum_{l=1}^{p} A_l y_{it-l} + Bx_t + Cs_t + \varepsilon_{it}, \tag{6}$$

where A_l, B and C are $(G \times G)$, $(G \times M)$ and $(G \times K)$ coefficient matrices respectively.

Following Binder *et al.* (2005), the fixed effects specification allows more flexibility as no restrictions need to be placed on the probability distribution function generating the individual-specific effects μ_i. It can then be allowed, for example, that (i) the individual effects are dependently distributed, (ii) the individual effects are heteroskedastic, (iii) the individual effects are (more generally) characterised by a joint probability distribution function with the number of unknown parameters increasing at the same rate as the number of cross-sectional observations in the panel, (iv) the individual effects do not have moments, and (v) the individual effects and the disturbances are correlated.

We can already see that the model in Equation (5), or Equation (3), is a useful extension of VAR models. In particular:

1. The autoregressive structure allows *all* endogenous variables of each unit to enter the model (therefore, it captures *interdependencies* across variables *within each unit*);
2. the panel allows the explicit inclusion of a fixed effect, μ_i, which captures all unobservable time-invariant factors at unit level (*heterogeneity*).

As in panel models, the coefficient matrices (A_l, B_m, C_k) are assumed to be the same across units. This reduces the parameter dimensionality and makes the model estimable also for a large number of units, *N*. On the other hand, if this restriction is not satisfied, the estimated parameters can be biased and inconsistent.

2.3 Dynamic Interdependencies and a generalised framework

We can further extend the pVAR models we described above to permit the modelling of interdependencies across units. Following Canova and Ciccarelli (2013), consider that Y_t is the stacked version of y_{it} for each unit i, i.e. $Y_t = \left(y'_{1t}, \ldots, y'_{Nt}\right)'$ The model in Equation (3) can now be written as:

$$y_{it} = \mu_i + \sum_{l=1}^{p} A_{i,l} Y_{t-1} + \varepsilon_{it}, \tag{7}$$

where notice that A_i may also depend on the unit. Similarly, the model in Equation (5) now becomes:

$$y_{it} = \mu_i + \sum_{l=1}^{p} A_{i,l} Y_{t-1} + \sum_{m=0}^{q} B_{i,m} x_{t-m} + \sum_{k=0}^{s} C_{i,k} s_{t-k} + \varepsilon_{it},$$

or, considering $q=s=0$ as in Equation (6):

$$y_{it}=\mu_i+\sum_{l=1}^{p}A_{i,l}Y_{t-1}+B_i x_t+C_i s_t+\varepsilon_{it}. \tag{8}$$

We can now see that in this setup:

1. The autoregressive structure allows *all* endogenous variables to enter the model *for unit* i allowing to capture *dynamic interdependencies*, i.e. modelling interdependencies across different units,
2. ε_{it} are generally correlated across *i* capturing *static interdependencies*, and
3. the intercept, the coefficients and the variance of the shocks ε_{it} might be unit specific, allowing for substantial *cross-sectional heterogeneity*, i.e. different unit characteristics can be modelled.

The above features differentiate standard single country VAR models, which have been mainly used in macroeconomic and financial analysis, from pVAR models, which have been used in more micro-related studies (see, e.g., the seminal paper by Holtz-Eakin *et al.* (1988) or cross-country analyses. From a different perspective, a pVAR such as that in (8) is similar to a large scale VAR where both dynamic and static interdependencies across units are allowed for. Yet, as we will see, some restrictions on the model parameters are needed to limit their number and make the model estimable. It is also easy to see that the models in Equations (3) and (5) are nested in the model of Equation (8), which can be considered as a general framework.

As Canova and Ciccarelli (2013) explain, not all three characteristic features of the pVAR models described in Equations (7) and (8) are needed for all applications. For example, one possibility is to examine if a model without dynamic interdependencies is sufficient to characterise the data under analysis. This is a typical setup for small units that are not expected to have any effects on other units, but shocks in different units have a common component. Another restricted specification nested in this framework, and often used in practice, is one where all interdependencies are omitted and cross-sectional slope homogeneity is assumed. This is a standard setup in many micro studies, but it can be problematic in macroeconomic analyses dealing with countries or regions, due to their heterogeneity.

Micro and macro panel approaches have different targets, and therefore borrowing models with specific features from one literature is not always straightforward. In particular, the cross-sectional dimension is usually large in micro studies and small or moderate in macro studies. On the contrary, micro panels have short time series dimension while macro panels have moderate time series dimension.

2.4 Time varying coefficients

The academic literature as well as practical applications in many policy-making institutions (such as Central Banks), argue that a constant parameter approach to econometric modelling might be useful for a first look at the data and the relationships between the underlying variables. However, the economy is a complex system vulnerable to internal and external shocks, whose transmission can change over time due to institutional changes or other developments such as globalization. Therefore, the applied researcher may have to include *parameter time variation* as an extra feature in her macroeconomic analysis.

Time varying coefficients have been studied in the standard VAR literature. Many studies use VAR specifications where the coefficients follow a random walk process, see, among others, Cogley and Sargent (2005), Primiceri (2005), Gallí and Gambetti (2009), and a more recent forecasting application in D'Agostino *et al*. (2013), whereas others, such as Sims and Zha (2006), model the coefficients as Markov switching processes. The specification of pVAR models can also be extended to incorporate time dynamics; see, among others, Canova and Ciccarelli (2004), Canova *et al.* (2007), Canova and Ciccarelli (2009), Canova *et al*. (2012), Koop and Korobilis (2013), Koop and Korobilis (2016) and more recently Koop and Korobilis (2018).

We can extend the model in Equations (7) and (8) and write the Time Varying pVAR (TVpVAR) model as:

$$y_{it}=\mu_{it}+\sum_{l=1}^{p} A_{it,l}Y_{t-1}+\varepsilon_{it}, \quad (9)$$

and similarly,

$$y_{it}=\mu_{it}+\sum_{l=1}^{p} A_{it,l}Y_{t-1}+\sum_{m=0}^{q} B_{it,m}x_{t-m}+\sum_{k=0}^{s} C_{it,k}s_{t-k}+\varepsilon_{it},$$

which, if $q=s=0$, becomes:

$$y_{it}=\mu_{it}+\sum_{l=1}^{p} A_{it,l}Y_{t-1}+B_{it}x_t+C_{it}s_t+\varepsilon_{it}. \quad (10)$$

All coefficients are now allowed to vary across time for both endogenous and exogenous variables. Actually, the models are typically completed with specifications for the temporal evolution of the time-varying parameters, which can be interpreted as a set of state equations. The latter, combined with the models that are the observation equations, form large state space systems. A common choice is to model all time-varying parameters as independent random walks, in order to limit the number of additional parameters. Factor models are another option for the same reason.

TVpVARs have been employed to study time varying business cycle features of vectors of countries and changing patterns in the transmission of shocks across variables or units. Time variation in pVAR models is useful and adds realism to the model. However, it is in general costly in terms of estimation, the more so the larger the model, and pVAR models can be very large.

2.5 A Simple example

In this section we provide an example to familiarise the reader with the general specifications of pVAR models discussed in the previous sections. We consider the simple case where we have $N=2$ units, $G=2$ endogenous variables and no exogenous variables i.e. $M=K=0$. Also, for simplicity, we set $p=1$.

2.5.1 PVAR(1) WITHOUT DYNAMIC INTERDEPENDENCIES

Without dynamic interdependencies, we can describe this bivariate pVAR(1) model, based on Equation (3), with the following system of equations, for $i=1,2$:

$$y_{1,it} = \mu_{1,i}+A_{11}y_{1,it-1}+A_{12}y_{2,it-1}+\varepsilon_{1,it},$$

$$y_{2,it} = \mu_{2,i}+A_{21}y_{1,it-1}+A_{22}y_{2,it-1}+\varepsilon_{2,it}.$$

In the notation above, we use the subscript $(v,\ it)$ which denotes the endogenous variable $v=\{1,2\}$, the unit dimension $i=\{1,2\}$ and the time dimension $t=1,\ldots,T$. We can equivalently write this model in matrix form as:

$$\begin{bmatrix} y_{1;it} \\ y_{2;it} \end{bmatrix}=\begin{bmatrix} \mu_{1;i} \\ \mu_{2;i} \end{bmatrix}+\begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}\begin{bmatrix} y_{1;it-1} \\ y_{2;it-1} \end{bmatrix}+\begin{bmatrix} \varepsilon_{1;it} \\ \varepsilon_{2;it} \end{bmatrix},$$

with $\Sigma_{\varepsilon}=\begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$. If we have one weakly exogenous variable $(M=1)$ that is common to all units, we can extend this model and write:

$$\begin{bmatrix} y_{1;it} \\ y_{2;it} \end{bmatrix} = \begin{bmatrix} \mu_{1;i} \\ \mu_{2;i} \end{bmatrix} + \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} y_{1;it-1} \\ y_{2;it-1} \end{bmatrix} + \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} x_{1,t} + \begin{bmatrix} \varepsilon_{1;it} \\ \varepsilon_{2;it} \end{bmatrix},$$

when Assumption 2 holds.

2.5.2 PVAR(1) WITH DYNAMIC INTERDEPENDENCIES AND TIME VARIATION

Next, let us consider the pVAR model in the generalised framework with dynamic interdependencies. Using the model described in Equation (8) and, continuing the same examples with N=2 units, G=2 endogenous variables, M=1 common weakly exogenous variable and p=1. Using the (v, it) subscript notation, we can write the *unit by unit* system of equations for variable v=1 as:

$$y_{1,1t} = \mu_{1,1} + A_{11,11} y_{1,1t-1} + A_{11,12} y_{2,1t-1} + A_{11,21} y_{2,1t-1} + A_{11,22} y_{2,2t-1} + B_{11,1} x_{1,t} + \varepsilon_{1,1t},$$

$$y_{1,2t} = \mu_{1,2} + A_{12,11} y_{1,1t-1} + A_{12,12} y_{2,1t-1} + A_{12,21} y_{2,1t-1} + A_{12,22} y_{2,2t-1} + B_{12,1} x_{1,t} + \varepsilon_{1,2t}.$$

Similarly, the unit by unit system of equations for variable v=2 is:

$$y_{2,1t} = \mu_{2,1} + A_{21,11} y_{1,1t-1} + A_{21,12} y_{2,1t-1} + A_{21,21} y_{2,1t-1} + A_{21,22} y_{2,2t-1} + B_{21,1} x_{1,t} + \varepsilon_{2,1t},$$

$$y_{2,2t} = \mu_{2,2} + A_{22,11} y_{1,1t-1} + A_{22,12} y_{2,1t-1} + A_{22,21} y_{2,1t-1} + A_{22,22} y_{2,2t-1} + B_{22,1} x_{1,t} + \varepsilon_{2,2t}.$$

The residuals are characterised by the following variance-covariance matrices:

$$\Sigma_{11} = \begin{bmatrix} \sigma_{11;11} & \sigma_{11;12} \\ \sigma_{11;21} & \sigma_{11;22} \end{bmatrix} and \Sigma_{22} = \begin{bmatrix} \sigma_{22;11} & \sigma_{22;12} \\ \sigma_{22;21} & \sigma_{22;22} \end{bmatrix}.$$

Using the matrix form we can write the full model with dynamic interdependencies as:

$$\begin{bmatrix} y_{1;1t} \\ y_{1;2t} \\ y_{2;1t} \\ y_{2;2t} \end{bmatrix} = \begin{bmatrix} \mu_{1;1} \\ \mu_{1;2} \\ \mu_{2;1} \\ \mu_{2;2} \end{bmatrix} + \begin{bmatrix} A_{11;11} & A_{11;12} & A_{11;21} & A_{11;22} \\ A_{12;11} & A_{12;12} & A_{12;21} & A_{12;22} \\ A_{21;11} & A_{21;12} & A_{21;21} & A_{21;22} \\ A_{22;11} & A_{22;12} & A_{22;21} & A_{22;22} \end{bmatrix} \begin{bmatrix} y_{1;1t-1} \\ y_{1;2t-1} \\ y_{2;1t-1} \\ y_{2;2t-1} \end{bmatrix} + \begin{bmatrix} B_{11;1} \\ B_{12;1} \\ B_{21;1} \\ B_{22;1} \end{bmatrix} x_{1,t} + \begin{bmatrix} \varepsilon_{1;1t} \\ \varepsilon_{1;2t} \\ \varepsilon_{2;1t} \\ \varepsilon_{2;2t} \end{bmatrix}, \quad (11)$$

and,

$$\Sigma_{\varepsilon} = \begin{bmatrix} \sigma_{11;11} & \sigma_{11;12} & \sigma_{12;11} & \sigma_{12;12} \\ \sigma_{11;21} & \sigma_{11;22} & \sigma_{12;21} & \sigma_{12;22} \\ \sigma_{21;11} & \sigma_{21;12} & \sigma_{22;11} & \sigma_{22;12} \\ \sigma_{21;21} & \sigma_{21;22} & \sigma_{22;21} & \sigma_{22;22} \end{bmatrix}.$$

Adding time variation yields:

$$\begin{bmatrix} y_{1;1t} \\ y_{1;2t} \\ y_{2;1t} \\ y_{2;2t} \end{bmatrix} = \begin{bmatrix} \mu_{1;1t} \\ \mu_{1;2t} \\ \mu_{2;1t} \\ \mu_{2;2t} \end{bmatrix} + \begin{bmatrix} A_{11;11;t} & A_{11;12;t} & A_{11;21;t} & A_{11;22;t} \\ A_{12;11;t} & A_{12;12;t} & A_{12;21;t} & A_{12;22;t} \\ A_{21;11;t} & A_{21;12;t} & A_{21;21;t} & A_{21;22;t} \\ A_{22;11;t} & A_{22;12;t} & A_{22;21;t} & A_{22;22;t} \end{bmatrix} \begin{bmatrix} y_{1;1t-1} \\ y_{1;2t-1} \\ y_{2;1t-1} \\ y_{2;2t-1} \end{bmatrix} + \begin{bmatrix} B_{11;1t} \\ B_{12;1t} \\ B_{21;1t} \\ B_{22;1t} \end{bmatrix} x_{1,t} + \begin{bmatrix} \varepsilon_{1;1t} \\ \varepsilon_{1;2t} \\ \varepsilon_{2;1t} \\ \varepsilon_{2;2t} \end{bmatrix}, \quad (12)$$

with

$$\Sigma_{\varepsilon t}=\begin{bmatrix} \sigma_{11;11;t}\sigma_{11;12;t}\sigma_{12;11;t}\sigma_{12;12;t} \\ \sigma_{11;21;t}\sigma_{11;22;t}\sigma_{12;21;t}\sigma_{12;22;t} \\ \sigma_{21;11;t}\sigma_{21;12;t}\sigma_{22;11;t}\sigma_{22;12;t} \\ \sigma_{21;21;t}\sigma_{21;22;t}\sigma_{22;21;t}\sigma_{22;22;t} \end{bmatrix}.$$

The above specification allows for time variation in the parameters. As we provide a general overview of pVAR models, we do not specify equations for the evolution of the time varying parameters as this changes across different applications. A common example, which we discuss later, is to assume a unit root model for the parameters. Heteroskedastic residuals are also accommodated. As we can see, for each period, every individual equation comprises of $(NGp+M)=(2\cdot2\cdot1+1)=5$ coefficients to estimate. For each unit we have $v\,(NGp+M)=2\,(2\cdot2\cdot1+1)=10$ coefficients to estimate, and the full model comprises of $Nv\,(NGp+M)=20$ coefficients (for each period).

2.6 A Comparison with alternative methodologies

We have so far described the features of pVAR models and explained why they are attractive in practice: they allow modelling dynamic and static interdependencies across units, typically with a parsimonious parameterization. In that perspective, pVAR models are unique and fill a gap where other methodologies are not very successful. Nevertheless, in this part of the study, we briefly discuss the characteristics of other methodologies and compare them to pVARs. In our discussion we closely follow the analysis in Canova and Ciccarelli (2013) and compare pVAR models to three main competitors: (i) Large Scale VARs, (ii) Spatial VARs, and (iii) Global VARs. Some researchers also argue that pVAR models can be compared to Dynamic Factor Analysis (DFA). However, the factors in GVAR models can be estimated using static or dynamic principal components, therefore the resulting model can be considered as a factor augmented VAR. In this way, factor models are discussed as part of the general GVAR context.

2.6.1 LARGE SCALE VARS

Large scale Bayesian VARs([7]) allow for static and dynamic interdependencies but the researcher gives no consideration to the panel dimension of the data. All variables are treated in the same — common — way regardless of whether they belong to a unit or not (though particular specifications of the priors could be used to emphasize either within or cross unit relationships). Given the large scale of the model, a frequentist (classical) approach to the estimation becomes unfeasible, whereas, as we will see in the next section, some pVAR specifications allow for classical estimation methods to be applied. Still, even if the panel dimension is not specifically modelled, large scale Bayesian VARs have been proved to be useful in forecasting; see, among others, Carriero et al. (2010), Banbura et al. (2010), etc. Time variation has also been examined in Bayesian VARs (see, e.g., Koop and Korobilis (2013) and Koop and Korobilis (2016)) and has also been used in forecasting exercises with encouraging results (see, e.g., Koop and Korobilis (2018)). Therefore, if the applied researcher is not particularly interested in the panel dimension, Bayesian VARs could be a relevant alternative to the use of pVARs. However, it must be highlighted that Large Bayesian VARs still do not account for the cross-sectional relations between units as pVARs do.

2.6.2 SPATIAL VARS

VAR models have also been used in the spatial econometric literature; see Anselin (2010) for a comprehensive review. In this case, dimensionality restrictions must be directly imposed to make estimation feasible. For simplicity, consider one lag of the dependent variables and no deterministic components. A spatial VAR(1) has the following form:

$$\begin{aligned} Y_t &= \rho S_1 Y_{t-1} + u_t \\ u_t &= S_2 \varepsilon_t \end{aligned}$$

([7]) See De Mol et al. (2008) for an introduction.

where S_1 and S_2 are fixed matrices of weights. These matrices define the transmission process of shocks from one unit to other 'neighbouring' areas. For example, consider that there is a shock in unit i. The spatial VAR structure (conditional on the specification for S matrices) implies that this shock will be transmitted after one period to unit j only if j is a neighbour of i. If j is not a neighbour (or a more distant neighbour) the shock might still be transmitted but it might take longer.

Overall, we think spatial VAR models have three main disadvantages:

1. The weight matrices have to be chosen prior to the estimation. Different specification of S by different researchers might result in different conclusions for the same dataset.
2. Borders in economics are not clearly defined as in geography. For example, in a monetary union, country borders do not obstacle the transmission of economics shocks.
3. The approach is more difficult to implement when y_{it} is a vector of variables since different elements of y_{it} might have different relationships across units.

2.6.3 GLOBAL VARS

Global VAR (GVAR) models have been introduced by by Dees et al. (2007) and they are probably the methodology closest to the pVARs discussed above. We consider a GVAR as a collection of unit specific VARs where an unobservable common factor is included. Consider the structure described in Equation (3) and add a new vector of unobservable variables, f_t. Then,

$$y_{it}=\mu_i+\sum_{l=1}^{p} A_{i,l}y_{it-l}+H_i f_t+\varepsilon_{it}. \tag{13}$$

Equation (13) describes a collection of unit specific VARs linked together by the presence of unobservable variables. Unobservable factors is one of the disadvantages of this method, as they complicate estimation. The model could be extended using lags of f_t, however, as in Canova and Ciccarelli (2013), we do not include lags for reasons of simplicity.

A commonly used technique is to proxy f_t with cross-unit averages of y_{it} (and any exogenous variables if present). Thus, rather than estimating Equation (13), one could estimate:

$$y_{it}=\mu_i+\sum_{l=1}^{p} A_l y_{it-l}+H_i y^*_{it}+\varepsilon_{it}, \tag{14}$$

where $y^*_{it}=\sum_{j=1}^{N} s_{ij}y_{jt}$ with $s_{ii}=0$ and s_{ij} is a set of country-specific weights which reflect the relative importance of the unit in the aggregate. Alternatively, factors can also be extracted using static or dynamic principal components. Then, as discussed in Pesaran et al (2004), the estimation of the model in Equation (14) is equivalent to estimating a large scale VAR of the form:

$$Y_t=\sum_{l=1}^{p} D_l Y_{t-1}+u_t,$$

where $I-D_l$ is a $NG\times1$ matrix whose typical i-th element is $1-D_{il}s_i$, for $l=1,..,p$. Therefore, a GVAR can be viewed as a restricted large scale VAR where variables of different units are weighted according to s_i. This means that GVAR imposes a particular structure on the interdependencies in the data. This is easier to estimate, however it makes GVAR models more prone to misspecification when economic relationships are not theoretically (or otherwise clearly) defined. Because of this potential misspecification, pVAR models could offer robust modelling in complex economic analysis. GVAR models could also be estimated in a Bayesian setup; Cuaresma et al. (2016) for more details in estimation and forecasting.

2.6.4 TWO MAIN TYPES OF PVAR MODELS

As already mentioned in the Introduction, interdependencies can be observed and modelled at macroeconomic as well as at microeconomic level. For this reason, since the beginning, the pVAR literature has generated two quite well distinct strands: one dealing with macroeconomic applications and the other with microeconomic ones. Even if this paper is mainly focused on macroeconomic applications, we consider of a certain interest, especially in the perspective of using PVAR models in official statistics, to spend some words on microeconomic pVAR models.

Microeconomic pVARs can be viewed as a particular variant of restricted pVAR models. These are models, as the name suggests, commonly applied in microeconomics since the work of Holtz-Eakin et al. (1988), which due to historical data restrictions - namely small or moderate T but large N panels - impose different restrictions from macroeconomic pVAR models on the unrestricted pVAR models.

The asymptotic properties of microeconomic pVAR models, in contrast to the macroeconomic pVAR models, rely on fixed *T* and large *N*. Letting *N* tend to infinity is a reasonable assumption in many microeconomic applications, modelling individual firms in a whole economy for example, but less plausible when modelling countries or sectors.

The restrictions imposed in microeconomic pVAR models are typically cross-sectional homogeneity restrictions $Ap, jj = Ap, kk, \forall p = 1, \ldots, P$ but where $Ao, jj \neq 0$ as individual **fixed-effects** are included, as is common in microeconometric models, to pick up time-invariant cross-sectional heterogeneities among individual firms, banks, households, workers, etc.

3 Estimation

In this section we provide an overview on estimation of pVAR models and discuss some technical aspects. Following the structure we have in Section 2, we distinguish three cases: (i) pVAR models without dynamic interdependencies, (ii) pVAR models with dynamic interdependencies, and (iii) pVAR models with dynamic interdependencies and time varying coefficients.

3.1 pVAR without dynamic interdependencies

3.1.1 GMM ESTIMATION

A standard estimation method for panel models is the Generalised Method of Moments (GMM); see, e.g., Arellano and Bond (1991). In the seminal paper, paper, Holtz Eakin et al. (1988) use a first difference GMM estimator which uses lags of the endogenous variables as instruments. There also exists the system GMM estimator, see, e.g., Blundell and Bond (1988) and more recently, Hayakawa (2016), which uses additional moment conditions based on information contained in the levels. Binder et al. (2005) extend the equation-by-equation estimator of Holtz-Eakin et al. (1988) for a pVAR(1) model with only endogenous variables. Sigmund and Ferstl (2019) further extend the work of Binder et al. (2005) to allow more lags of order *p*, and weakly and strictly exogenous variables.

Starting with Equation (6) and following Binder et al. (2005), μ_i's can be eliminated by taking first differences:

$$\Delta y_{it} = \sum_{l=1}^{p} A_l \Delta y_{it-l} + B\Delta x_{it} + C\Delta s_{it} + \Delta\varepsilon_{it}, t=p+1,\dots,T. \quad (15)$$

Following Sigmund and Ferstl (2019), we can write the first difference GMM conditions as:

$$\begin{aligned} E\left(\Delta\varepsilon_{it} y_{ij}^{'}\right) &= 0, j=1,\dots,T-2, \\ E\left(\Delta\varepsilon_{it} x_{ij}^{'}\right) &= 0, j=1,\dots,T-1, \\ E\left(\Delta\varepsilon_{it} s_{it}^{'}\right) &= 0. \end{aligned}$$

Then, we can redefine Equation (15) by stacking over *t* obtaining:

$$\Delta\mathcal{Y}_i = \sum_{l=1}^{p} A_l \Delta\mathcal{Y}_{i,l} + \Delta\mathcal{X}_i B^{'} + \Delta\mathcal{S}_i C^{'} + \Delta\mathcal{E}_i$$

and also consider

$$Q_i = \begin{bmatrix} q'_{i;p+2} & 0 & \cdots & 0 \\ 0 & q'_{i;p+3} & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & q'_{i;T} \end{bmatrix}$$

where

$$q'_{i,t} = \left(y'_{it-p-1}, y'_{it-p-2}, \ldots, x'_{it-1}, x'_{it-2}, \ldots, x'_{i1}, \Delta s'_{it}\right)$$

Then, the stacked moment conditions for unit i are given by:

$$E\left(Q'_i\left(\Delta \mathcal{E}_i\right)\right)=0.$$

Subsequently, the first difference GMM function is defined as:

$$\hat{g}(\Phi) = \frac{1}{N}\sum_{i=1}^{N} \hat{g}_i(\Phi),$$

$$\hat{g}_i(\Phi) = \left(Q_i \otimes I_{G\times G}\right) vec\left(\Delta \mathcal{E}_i\right),$$

where $I_{G\times G}$ is the $G\times G$ identity matrix and Φ denotes the parameter vector. This function states that the sample average $\hat{g}_i(\Phi)$ is close to the true parameter, Φ_0, given that

$$\Delta \mathcal{E}_i = \Delta \mathcal{W}_i - \Delta \mathcal{W}_{-,i} \Phi_0$$

where

$$\mathcal{W}_i = \mathcal{Y}_i$$

And

$$\Delta \mathcal{W}_{-,i} = \left(\Delta \mathcal{Y}_{i-1}, \Delta \mathcal{X}_i, \Delta \mathcal{S}_i\right)$$

.

Following Binder et al. (2005), the GMM estimator is consistent if all eigenvalues of Φ fall inside the unit circle, but breaks down if some eigenvalues of Φ are equal to unity. It is also important to notice that the efficiency of GMM estimators depends on the correlations between instruments $\mathcal{W}_i$ and the regressors $\Delta \mathcal{W}_{-,i}$.

3.1.2 PARTIAL POOLING

As discussed in Canova and Ciccarelli (2013), the GMM estimation, which requires differencing as discussed in the previous subsection, throws away some information and may make inference less accurate when the ignored information is important for the parameters of interest. In this section we closely follow Canova and Ciccarelli (2013) to discuss the method of 'partial pooling'.

This method may help to improve the coefficient estimates for moderate values of *T* and *N* and when dynamic heterogeneity is suspected. For simplicity, consider the model in Equation (3): $y_{it} = \mu_i + \sum_{l=1}^{p} A_l y_{it-l} + \varepsilon_{it}$. A standard format leading to partial pooling is a random coefficient model. We can also allow the slope parameters to potentially be unit specific, i.e.,

$$y_{it} = \mu_i + \sum_{l=1}^{p} A_{i,l} y_{it-l} + \varepsilon_{it}. \tag{16}$$

If we impose that

$$\alpha_i = \overline{\alpha} + \upsilon_i \tag{17}$$

Where $\alpha_i = \left(vec\left(A_{i,l}\right)' vec\left(\mu_i\right) \right)'$ and $\upsilon_i \sim N(0, \Sigma_\upsilon)$, we can construct an estimator which partially pools the information present in different units. Equation (17) allows the coefficients to be different across units, but they are drawn from a distribution with a constant mean and variance across i.

GLS Estimation

A straightforward way in frequentist econometrics is to substitute Equation (17) in Equation (16) and apply the GLS estimator proposed by Swamy (1970). In particular, combining these two equations and stacking across time, we have:

$$\begin{aligned} y_i &= R_i \overline{\alpha} + u_i, \\ u_i &= R_i \upsilon_i + \varepsilon_i, \end{aligned}$$

where R_i is the matrix containing the right hand side variables. We have that:

$$\begin{aligned} E\left(u_i u_i'\right) &= R_i \Sigma_\upsilon R_i' + \sigma_{ii} I \\ &\equiv \Pi_i. \end{aligned}$$

Stacking across i we have

$$y = R\overline{\alpha} + u$$

Where

$$\Pi = \begin{bmatrix} \Pi_1 & 0 & \cdots & 0 \\ 0 & \Pi_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & \Pi_N \end{bmatrix}.$$

Then,

$$\begin{aligned} \overline{\alpha}_{GLS} &= \left(R'\Pi^{-1}R\right) R'\Pi^{-1} y \\ &= \left(\sum_{i=1}^{N} R_i' \Pi_i^{-1} R_i \right)^{-1} \sum_{i=1}^{N} R_i' \Pi_i^{-1} y_i \\ &= \sum_{i=1}^{N} W_i \hat{\alpha}_i, \end{aligned} \tag{18}$$

indicating that $\overline{\alpha}_{GLS}$ is the weighted average of the panel-specific OLS estimates. As we see, only the mean $\overline{\alpha}$ is estimated. An estimate of the amount of cross-sectional heterogeneity is difficult to obtain, since Σ_υ enters in a complicated way in the variance of the composite error term. The Bayesian approach we describe below is an attractive alternative. Another interesting reference in this context is Juodis (2018), who uses first difference transformations for estimation and inference in pVAR(1) models.

Bayesian Approach

Following Canova and Ciccarelli (2013), the alternative Bayesian approach is to treat Equation (17) as an exchangeable prior. This prior is combined with the likelihood of the data to obtain the posterior distribution of the individual α_i, as well as the average $\overline{\alpha}$. Therefore, in this setup we allow for dynamic heterogeneity to be captured by the model. If ε_i and u_i are normally distributed and $\overline{\alpha}$ and Σ_υ known, then, conditional on the initial observations, the posterior for α_i is normal with mean:

$$\alpha_i = \left(R_i \hat{\Sigma}_i^{-1} R_i + \Sigma_\upsilon^{-1}\right)^{-1} \left(R_i \hat{\Sigma}_{i,ols}^{-1} R_i \hat{\alpha}_i + \Sigma_\upsilon^{-1} \overline{\alpha}\right) \quad (19)$$

where R_i is the matrix containing the variables in the right hand of the equation, α_i is the OLS estimate of α_i and $\hat{\Sigma}_i$ is the OLS estimate of Σ_i .

It is important for the applied researcher to focus on three important issues regarding this Bayesian approach:

1. The formulae are valid only when $\overline{\alpha}$ and Σ_υ are known. As this is not the usual case in practice, one should specify a prior distribution for these unknowns and use a Gibbs sampler to construct draws for the marginal of α_i
2. The mean of the posterior $\tilde{\alpha}_i$ collapses to a standard OLS estimator if heterogeneity is large, i.e. $\Sigma_\upsilon \to \infty$.
3. As described in Equation (18), the GLS estimator for the mean effect is the average of the posterior means of the individual units.

3.2 pVAR with dynamic interdependencies

Next, we turn to the estimation of a pVAR model with dynamic interdependencies. The estimation problem in this case becomes more complicated as the dimension of the model increases; we have $(N \cdot G \cdot p)$ coefficients in each equation. One way to solve this problem is to decrease the dimension of the model by focusing on modelling specific links across units only. For example, we can argue that only unit *j* enters the equations of unit *i*. However, in practice there is no efficient way of doing this that does not involve data mining; even if we use data mining the whole approach is not robust. Another approach is to group cross-sectional units and assume random coefficients within each group but no relationships across groups. An example of this approach has been used in Canova (2004). This setup, however, applies to cases where dynamic interdependencies are excluded.

Canova and Ciccarelli (2004) and Canova and Ciccarelli (2009) have suggested a shrinkage approach to deal with the curse of dimensionality and allow the estimation of dynamic interdependencies; see also Canova and Ciccarelli (2013) and Del Negro and Schorfheide (2010) for more details. For simplicity, consider the model described in Equation (7). We rewrite the model in a simultaneous equation format:

$$Y_t = Z_t \alpha + U_t, \quad (20)$$

where $Z_t = I_{N \times G} \otimes R_t'$, $R_t = (I, Y_{t-1}', Y_{t-2}', .., Y_{t-p}')$, $\alpha = \left(\alpha_1', \alpha_2', ..., \alpha_N'\right)$ and α_i are vectors containing stacked the *G* rows of $\left(\mu_i, A_i\right)$. Then, we can focus on α and assume that α depends on a vector θ which is of a much lower dimension and takes the (linear) form:

$$\alpha = \Xi_1 \theta_1 + \Xi_2 \theta_2 + \Xi_3 \theta_3 + \Xi_4 \theta_4 + \ldots + e_t, \quad (21)$$

where Ξ_j is the coefficient matrix of the θ_j factor, capturing the determinants of α for $j=1,2,...$. For example, θ_1 could capture the components in the coefficient vector which are common across units and variables, θ_2 could capture the components in the coefficient vector which are common within units, θ_3 could capture the components in the coefficient vector which are variable specific and θ_4 could capture the components in the lagged coefficients.

This factorisation solves the problem of dimensionality as well as eases the computational burden. It also allows to interpret an overparameterized VAR into a parsimonious Seemingly Unrelated Regression (SUR) model, where the regressors are averages of certain right-hand side variables. Using Equation (21) we can write Equation (20) as

$$Y_t = \sum_{j=1}^{r} \mathcal{Z}_{jt}\theta_j + \gamma_t \qquad (22)$$

where $\mathcal{Z}_{jt}=Z_t\Xi_j$ captures the common, unit specific, variable specific, and lag specific information for $j=\{1,..,4\}$ and $\gamma_t=U_t+Z_te_t$. As Canova and Ciccarelli (2013) discuss, the model in Equation (22) has a slow moving average structure that allows to capture low frequency movements, which can be an important factor for example for medium term forecasting exercises.

To illustrate the above, we can revisit the example described in Equation (11). Consider that $\alpha=(A_{11,11}, ..., A_{22,22})'$ is a 16×1 vector. If we are not interested in modelling all these aspects, we can reduce the computational burden and dimension of the model using the factorisation described in Equation (21) and write:

$$\alpha=\Xi_1\theta_1+\Xi_2\theta_2+\Xi_3\theta_3+e_t$$

where e_t captures the unaccounted features. Then,

$$\begin{aligned}
\underset{(16\times1)}{\Xi_1} &= I_{16\times1}\\
\underset{(16\times2)}{\Xi_2} &= \begin{bmatrix} \iota_1 & 0\\ \iota_1 & 0\\ 0 & \iota_2\\ 0 & \iota_2 \end{bmatrix}\\
\underset{(16\times2)}{\Xi_3} &= \begin{bmatrix} \iota_3 & 0\\ 0 & \iota_4\\ \iota_3 & 0\\ 0 & \iota_4 \end{bmatrix}
\end{aligned}$$

with $\iota_1=(1100)'$, $\iota_2=(0011)'$, $\iota_3=(1010)'$ and $\iota_4=(0101)'$, to capture the common, unit specific and variable specific information.

3.2.1 OLS ESTIMATION

To estimate the model in Equation (22) we can simply stack the *t* observations in a vector to obtain:

$$Y = \sum_{j=1}^{r} \mathcal{Z}_j\theta_j + \gamma. \qquad (23)$$

We can now see that the initial large-scale pVARX models have been transformed to a parsimoniously parameterised SUR model. If the factorisation in Equation (21) is exact, then the error term in Equation (23) is uncorrelated with the regressors and OLS estimation is suited to obtain θ and consequently α. When the factorisation allows for an error component, e_t, then γ_t has a heteroskedastic covariance matrix, which needs to be taken into account.

3.2.2 BAYESIAN APPROACH

In a Bayesian framework, we can construct the posterior of unknowns easily. Let $e_t \sim N\left(0, \Sigma_\upsilon \otimes V\right)$ and restrict $V = \sigma^2 I$. Then, $\upsilon_t \sim N\left(0, \sigma_t \Sigma_\upsilon\right)$ where $\sigma_t = \left(I + \sigma^2 R_t' R_t\right)$. If the prior for $\left(\theta, \Sigma_\upsilon, \sigma^2\right)$ is, for example, of the semi-conjugate type: $\theta \sim N\left(\theta_0, \Omega_0\right), \Sigma_u^{-1} \sim W\left(z_0, Q_0\right), \sigma^2 \sim G\left(0.5\alpha_0, 0.5\alpha_0 s^2\right)$ where $(\theta_0, \Omega_0, z_0, Q_0, \alpha_0, s^2)$ are known quantities and W denotes the Wishart distribution and G the Gamma distribution, then one can use the Gibbs sampler to obtain samples of $(\theta, \Sigma_\upsilon, \sigma^2)$ from their joint posterior distribution; see Canova and Ciccarelli (2013) for more details. Also, see Korobilis (2016) for a discussion on prior selection for pVAR models.

3.3 pVAR with dynamic interdependencies and time variation

Finally, we discuss the estimation of the model under the generalised framework introduced in Equations (9) and (10). In the previous subsection we have illustrated how dynamic interdependencies significantly increase the dimension of the model and reviewed some methods to deal with the curse of dimensionality and reduce the computational burden. It is easy to understand that allowing the parameters to vary across time further adds to the dimensionality problem. Consider the simultaneous equation model described in Equation (20) and allow the coefficients to vary across time. Then we can write:

$$Y_t = Z_t \alpha_t + U_t, \qquad (24)$$

where now $\alpha_t = (\alpha'_{1t}, \alpha'_{2t}, \ldots, \alpha'_{Nt})$ and α_{it} are vectors containing stacked the G rows of $\left(\mu_i, A_{it}\right)$ (or more generally $\left(\mu_i, A_{it}, B_{it}, C_{it}\right)$). Both methods are analysed in Canova and Ciccarelli (2013).

3.3.1 A PANEL-TYPE HIERARCHICAL PRIOR

We assume α_t to be the sum of two independent components: a unit specific component which is time invariant and a common across units but time-varying component. In particular,

$$\alpha_{it} = \delta_i + \lambda_t.$$

An exchangeable prior is assumed for δ_i with

$$\delta_i = \overline{\delta} + \upsilon_i, \upsilon_i \sim N\left(0, \Sigma_\upsilon\right)$$

where a further layer of dimensionality reducing hierarchy can be specified by setting $\overline{d} \sim N\left(w, \Theta\right)$. λ_t is assumed to follow an AR(1) process of the form:

$$\lambda_t = (1-\rho)\lambda_0 + \rho\lambda_{t-1} + e_t,$$

where additional assumptions on Σ_υ, ρ, λ_0 and e_t complete the specification of the prior. The structure of the model can be summarised with the following hierarchical scheme:

$$Y_t = Z_t\delta + Z_t S_N \lambda_t + U_t;\quad U_t \sim N(0;\Sigma_\upsilon);$$
$$\delta = S_N \overline{\delta} + \zeta;\qquad \zeta \sim N(0;\Upsilon);$$
$$\overline{\delta} = \omega + \xi;\qquad \xi \sim N(0;\Theta);$$
$$\lambda_t = (1-\rho)\lambda_0 + \rho\lambda_{t-1} + e_t;\ e_t \sim N(0;\Sigma_e);$$

where $S_N = e_n \otimes I;\ e_n = vec(1,1,\ldots,1)$, and $\Upsilon = I \otimes \Sigma_\iota$. Canova and Ciccarelli (2004) discuss how to construct the posterior distributions for the parameters of interest, under several prior assumptions on the variance covariance matrices Σ_υ, Υ, Θ and Σ_e, the mean vector ω and on the initial λ_0, using the Gibbs sampler.

3.3.2 FACTORISATION

The second possibility is to allow for time variation in the factorisation we described in Equation (21). We can now write:

$$\alpha_t = \sum_j \Xi_j \theta_{jt} + e_t, \tag{25}$$

where Ξ_j are matrices with ones and zeros and θ_{jt} are time-varying factors. One straightforward way to model the stochastic process θ_{jt} is to assume that

$$\theta_t = \theta_{t-1} + \eta_t, \tag{26}$$

where $\theta_t = (\theta_{1t}, \theta_{2t}, \ldots)'$, $\eta_t \sim N(0, \Omega_t)$, Ω_t is block diagonal and U_t, e_t and η_t are mutually independent. To allow estimation of the specification described in Equations (24), (25) and (26), we need assumptions on the error terms U_t and e_t. We can let $U_t \sim N(0, \Sigma_u)$ and $e_t \sim N(0, \Sigma_u \otimes V)$ where $V = \sigma^2 I$. Then the parameterised model has the state-space representation:

$$Y_t = (Z_t \Xi)\theta_t + \gamma_t;\ \gamma_t = U_t + Z_t e_t;\ with\ \gamma_t \sim N(0; \sigma_t \Sigma_\upsilon)$$
$$\theta_t = \theta_{t-1} + \eta_t;\qquad \eta_t \sim N(0; \Omega_t)$$

where $\sigma_t = I + \sigma^2 Z'_t Z_t$. Bayesian estimation requires that the priors for Σ_υ, Ω_t, σ^2 and θ_0 are specified. Alternatively, one can use the Kalman filter algorithm.

3.4 Seven panel and large-scale VAR priors

In previous sub-sections we have clearly shown how solving the so called course of dimensionality problem is essential of making PVAR models estimable. We have also already introduced a couple of priors to be used in different contexts. In this sub-section we provide some details on various priors which have been proposed in the literature. The selection of the most appropriate prior is crucial since, using different priors, can lead to substantially different results.

We follow Korobilis (2016) who considers, and develops, a range of parametric and semiparametric priors for PVAR models. These also subsume the priors proposed and used by Canova and Ciccarelli (2013) and Korobilis (2016).

Korobilis (2016) considers the following 7 priors, the first 4 of which are designed specifically for PVAR models rather than large-scale BVAR models:

1. SSSS: the Stochastic Search Specification Selection (S^4) prior of Korobilis (2016),
2. CC: The factor shrinkage prior of Canova and Ciccarelli (2013),
3. BGCS: Bayesian Factor Clustering and Selection as in Korobilis (2016),
4. BMixS: Bayesian Mixture Shrinkage as in Korobilis (2016),
5. SSVS: Stochastic Search Variable Selection,
6. GLP: Hierarchical Minnesota prior as in Korobilis (2016),
7. OLS: unrestricted estimation, equivalent to a diffuse prior.

4 Forecasting with pVAR models

In this section we focus on forecasting with pVAR models. Based on our discussion on the estimation of pVAR models, it can be easily seen that, even though pVAR models seem complicated in their initial specification, they can be essentially treated as standard VARs and estimated using both frequentist and Bayesian approaches (see, e.g., our analysis for Equation (23)). In this perspective, existing forecasting techniques available in graduate econometric textbooks can be directly applied in the pVAR context. For simplicity, let us focus on the model described in Equation (20), assuming that factorisation is exact, i.e. $e_t=0$ in Equation (21) and $\gamma=\varepsilon$ in Equation (23).

Let us assume we are at time period t. As discussed in the previous section, stacking across $t=1,2,..,T$, we can compute the OLS estimate of Equation (23), $Y=Z\theta+\gamma$, and obtain:

$$\hat{\theta}=\left(Z'Z\right)^{-1}Z'Y,$$

which can in turn provide us with:

$$\hat{\alpha}=\Xi\hat{\theta},$$

Subsequently, using Equation (20), we can compute:

$$\hat{\varepsilon}_t=Y_t-Z_t\hat{\alpha}$$

and therefore $\hat{\Sigma}_\varepsilon$.

Since the original model in Equation (7) is a pVAR without exogenous variables, we could calculate the forecasts iteratively.

In the case of a pVARX model, as the one presented in Equation (8), the applied researcher might find it easier to compute direct forecasts(8), as follows. For the *h*-step ahead forecast(9):

1. Stack $Y_{t=\{h,\dots,T\}}\equiv\tilde{Y}$ and $Z_{t=\{1,\dots,T-h\}}\equiv\tilde{Z}$ and obtain $\tilde{\theta}=\left(\tilde{Z}'\tilde{Z}\right)^{-1}\tilde{Z}'\tilde{Y}$.
2. Consequently, calculate $\tilde{\alpha}=\Xi\tilde{\theta}$ and $\tilde{\varepsilon}_t=Y_t-Z_t\tilde{\alpha}$.

(8) See Marcellino et al. (2006) for a discussion on iterative and direct forecasting approaches.

(9) Also see Greenaway-McGrevy (2013).

3. Then, calculate $\hat{Y}_{T+h}=Z_T\tilde{\alpha}$.

If the pVAR model is correctly specified, we expect that $E\left[Y_{T+h}-\hat{Y}_{T+h}\right]=0$. Assuming a known distribution about the forecast error, for example Gaussian or t-student, allows us to also construct density and interval forecasts using standard procedures. Density and interval forecasts can be also obtained without making an assumption about the distribution of ε_t, by bootstrapping the realized forecast errors.

From a Bayesian perspective, point and density forecasts can be also obtained as in the standard SUR literature; Percy (1992), Canova and Ciccarelli (2004), Canova and Ciccarelli (2009), Koop and Korobilis (2013), Koop and Korobilis (2016), Koop and Korobilis (2018), among others. Following Percy. (1992), consider that we have observed the data for $Z_1,\ldots,Z_{T+1}$, and we want to derive the one-step ahead forecast for Y_T, i.e. Y_{T+1}, based on the training data $\mathcal{F}=\{Y_1,\ldots,Y_T,Z_1,\ldots,Z_T\}$. Then, the predictive density in this case is of the form:

$$f\left(Y_{T+1}|Z_{T+1},\mathcal{F}\right)\propto\int_{\alpha}\int_{\Phi}|\Phi|^{(T-p)/2}\exp\left\{-\frac{1}{2}\sum_{t=1}^{T+1}\left(Y_t-Z_t\alpha\right)'\Phi\left(Y_t-Z_t\alpha\right)\right\}d\Phi d\alpha,$$

which can be further generalised for Y_{T+h}. Then the Gibbs sampler or a first order approximation can be further applied; see Percy. (1992) and also Canova and Ciccarelli (2009) for more details on conditional forecasts based on MCMC routines.

5 Use of pVAR models in the literature

In this section of the paper we discuss the uses of pVAR models in practice, with the aim of providing evidence useful to assess their potential relevance also for applications related to economic data in official statistical agencies. Our review aims to be up-to-date and focuses on the most representative papers in each area. In general, we distinguish economic applications in three main fields: (i) business cycle analysis and average effects estimation, (ii) shocks transmission and modelling of heterogeneities, and (iii) nowcasting and forecasting, where the latter is of more direct use for possible applications in an official statistics context but the former can provide evidence on the suitability of pVARs as models for properly capturing interdependencies. To be able to fully understand the potential uses of pVAR models, we must bear in mind our discussion regarding the advantages of pVAR models as analysed in previous sections.

In particular, pVAR models combine characteristics from VAR and panel data models. A panel could consist of multiple markets and/or sectors in an economy, and can also include multiple economies. To capture all possible interactions, pVAR models allow for the modelling of interdependencies across all units in a system of economies (dynamic interdependencies) as well as across units within an economy (static interdependencies). They also allow for dynamic heterogeneities and time variation. Therefore, this flexible nature of pVAR models makes them suitable for empirical economic and statistical applications.

We can anticipate that the applications discussed in this section overall suggest that pVAR models could be a useful tool for official statistical agencies which often need to provide a comprehensive view across multiple markets within the same country, across countries or both. pVAR models allow to analyse panels of macro and micro variables, focus on the cross-sectional dimension that is often ignored by other models, permit the analysis of spill-over effects across sectors, markets or countries, and, finally, can improve flash estimation and short-term forecasting in the presence of integrated sectors and economies.

5.1 Business cycles and average effects

One of the most representative examples in the application of pVAR models is the analysis of business cycles, and in particular of convergence issues. Canova et al.

(2007) investigate the similarities and convergence of cycles in a panel of G7 countries. Their findings confirm the pattern of a common, ‘*world*’, cycle which has a greater influence on the individual cycles when compared to the country-specific indicators. They find no major evidence of structural changes or an effect from the euro adoption in the late 1990s. They consider a time varying pVAR model, similar to the one described in equation (10) with no strictly exogenous factors, under a Bayesian framework.

In a later paper, Canova and Ciccarelli (2012) apply a similar analysis to a panel of 16 Mediterranean countries. In contrast to Canova et al. (2007), idiosyncratic components have more impact on the cyclical fluctuation of many countries and cycles convergence/divergence is only local land transitory. The model here is also a Bayesian time varying pVAR.

Next, Canova and Pappa (2005) focus on the impact of fiscal restrictions on the business cycle features of macro variables using a sample of 48 U.S. states. Using a pVAR model, they report similarities in second moments of macro variables and in the transmission properties of fiscal shocks across states with different fiscal constraints. The cyclical response of expenditure differs in size and sometimes in sign, but heterogeneity within groups makes point estimates statistically insignificant. Canova and Pappa (2007) study the effect of regional expenditure and revenue shocks on price differentials for 47 U.S. states and 9 EU countries. Using pVAR modelling, they investigate average effects finding that expansionary fiscal shocks produce positive price differential responses, while distortionary balance budget shocks produce negative price differential responses.

Koutsomanoli-Filippaki and Mamatzakis (2009) study the dynamic interactions between risk and efficiency. First, they estimate three alternative measures of bank performance by employing a directional distance function framework. Then, they calculate a Merton-type bank default risk. Finally, they employ pVAR models to examine the underlying relationships between efficiency and risk without applying any a priori restrictions. Most evidence shows that the effect of a one standard deviation shock of the distance to default on inefficiency is negative and substantial.

Canova (2005) and Rebucci (2010) use pVAR models to examine whether shocks generated outside of a country (or an area) dominate the variability of domestic variables. Canova (2005) studies whether US shocks are transmitted to 8 Latin American countries finding that US monetary shocks produce significant fluctuations in Latin America, but real demand and supply shocks do not. Rebucci (2010) assesses the role of external and policy factors for growth variability using 18 developing economies from 1965 to 1992. The main findings are that (i) temporary external shocks are an important determinant of medium to long-run growth variability, and (ii) high inflation countries are more vulnerable to external shocks than others.

Ciccarelli et al. (2013) use a pVAR model to analyse how financial fragility has affected the transmission mechanism of the single Euro area monetary policy. The analysis shows that, on average, the monetary transmission mechanism is time-varying and influenced by the financial fragility of the sovereigns, banks, firms and households. The impact of monetary policy on aggregate output is stronger during the financial crisis, especially in countries facing increased sovereign financial distress.

Apostolakis and Papadopoulos (2018) use a pVAR model to investigate the relationship among financial stress, inflation and growth in 19 advanced economies over the 1999–2016 period. Their analysis shows negative responses of the macroeconomic variables to financial stress shocks. Lof and Malinen (2014) estimate pVAR models to analyse the relationship between sovereign debt and economic growth. Using data on 20 developed countries, they find no evidence for a robust effect of debt on growth. Instead, there is evidence of a significant reverse effect of growth on debt, which also explains the negative relationship.

5.2 Shocks transmission, heterogeneities & macroeconomic applications

The construction of pVAR models also allows to analyse the transmissions of idiosyncratic shocks across units and time. Canova et al. (2012) examine how shocks in U.S. interest rates can potentially affect European economies, including seven EMU countries and three non-EMU, and how German shocks which simultaneously increase domestic output, employment, consumption and investment are transmitted to the remaining economies in the panel.

Ciccarelli et al. (2016) investigate the commonalities and spillovers in macro-financial linkages and compare the transmission of real and financial shocks focusing on the Great recession. They find that country-specific factors remain important, which is consistent with the heterogeneous behavior observed across countries over time, and also find that spillovers across countries and between real and financial variables are key to explain economic fluctuations. A shock to a variable in a given country affects all other countries in the system, and the transmission seems to be more direct and immediate between financial variables than between real variables. Their analysis is based on a Bayesian pVAR.

Beetsma and Giuliadori (2011) examine the transmission of government spending shocks using data for 14 economies modelled with a pVAR. They find evidence that an increase in government purchases raises output, consumption and investment and reduces the trade balance. Benetrix and Lane (2015) focus on the Great

Recession investigating the cross-country dispersion in fiscal outcomes. Based on a panel model they find that declines in the overall and structural fiscal balances were larger for countries experiencing larger increases in unemployment and where credit growth during the pre-crisis period was more rapid. In both the above cases, we can infer that a pVAR model could be applied returning more robust results.

Boubtane et al. (2013) use a pVAR model to examine the interaction between immigration and host country economic conditions. Their data includes 22 OECD countries over the period 1987–2009. The empirical findings suggest that there is evidence of migration contribution to host economic prosperity; positive impact on GDP per capita and negative impact on aggregate unemployment, native — and foreign — born unemployment rates.

pVAR models can be also used to examine the effects of dynamic heterogeneity and convergence of clubs, to group units or to measure their differences; see, e.g., Canova (2005). De Graeve and Karas (2014) empirically test theories of bank runs using a structural panel VAR to extract runs from deposit market data. Identification exploits cross-sectional heterogeneity in deposit insurance: they identify bank runs as adverse deposit market supply shocks hitting uninsured banks harder compared to insured. They study the behavior of uninsured banks with bad and good fundamentals. Empirical evidence suggests that they both experience runs, but deposit outflows at the former are more severe.

Lee (2007) use a pVAR approach in the Korean housing market finding that (i) public and private housing investment Granger-cause each other with an asymmetric pattern; and (ii) the crowding-out effect rises with the housing availability ratio; it grows rapidly as the housing availability ratio gets closer to 100 %, which offers useful policy implications for public housing policies in fast-growing regions or countries.

Kim and Lee (2008) investigates the macroeconomic effects of demographic changes, focusing on saving rates and current account balances. Using a pVAR approach they find evidence that an increase in the dependency rate significantly lowers public saving rates and a higher dependency rate significantly worsens current account balances.

Love and Zicchino (2006) also employ a pVAR model to examine the dynamic relationship between firms' financial conditions and investment. They conclude that the impact of financial factors on investment is significantly larger in countries with less developed financial systems. This result further confirms the importance of financial development in improving capital allocation and growth. Jouida (2018) investigates the dynamic relationship between diversification, capital structure and profitability. A pVAR model using data for 412 French financial institutions for a period of 10 years provides evidence of reverse causality between these variables.

Grossman et al. (2014) study the dynamics of the overall exchange rate volatility using pVAR models on a panel including 29 economies. The study reveals interesting dynamic interrelationships between macroeconomic as well as financial variables and exchange rate volatility. Instead, there is, on average, little evidence of significant differences in the responses of macroeconomic and financial variables to the overall volatility.

Guerello (2014) use a pVAR model to investigate the risk taking channel in the Euro Area. According to prior expectations based on an extended DSGE model, the analysis demonstrates that the monetary policy incentives bank risk taking by increasing the bank leverage, but it is not able to influence the level of credit risk. However, deeper investigations indicates the Taylor gap adds to the bank risk appetite in all its forms, while regarding the reactions to target variables, movements in the interest rate smooth the bank risk.

Landesmann and Leitner (2015) use a pVAR model to analyse the role of EU labour market mobility, specifically cross-border mobility by migrants, in labour market adjustments and, vice versa, how labour market developments across the EU in terms of relative wage differences, differences in activity rates, in labour productivity differentials and in human capital structures affect labour mobility.

Attinasi and Metelli (2016) study the effects of fiscal consolidation on the debt-to-GDP ratio of 11 Euro area countries. They employ a fiscal pVAR model which allows to trace out the dynamics of the debt-to-GDP ratio following a fiscal shock and to disentangle the main channels through which fiscal consolidation affects the debt ratio. Their main finding is that when consolidation is implemented via a cut in government primary spending, the debt ratio, after an initial increase, falls to below its pre-shock level. When instead the consolidation is implemented via an increase in government revenues, the initial increase in the debt ratio is stronger and, eventually, the debt ratio reverts to its pre-shock level, resulting in what we call self-defeating austerity.

Berdiev and Saunoris (2016) use a pVAR to examine the dynamic relationship between financial development and the shadow economy using data for 161 countries over the period 1960–2009. Using impulse response functions they find that financial development reduces the size of the shadow economy. Moreover, there is some evidence that a shock to shadow economy inhibits financial development.

Goes (2016) builds a pVAR model for a short panel of 119 countries over 10 years and finds that exogenous shocks to a proxy for institutional quality have a positive and statistically significant effect on GDP per capita. On average, a 1 % shock in institutional quality leads to a peak 1.7 % increase in GDP per capita after six years.

Gnimassoun and Mignon (2016) investigate the interactions between three key macroeconomic imbalances: current-account discrepancies (external imbalances), output gaps (internal imbalances), and exchange-rate misalignments. Using a pVAR model for 22 industrialised during 1980–2011, they find that macroeconomic imbalances strongly interact through a causal relationship. If current-account disequilibria threaten the stability of the global economy, their origin can be found in internal imbalances and exchange-rate misalignments: positive output-gap shocks as well as currency overvaluation deepen current-account deficits.

Jawadi et al. (2016) use a pVAR to assess the macroeconomic impact of fiscal policy and monetary policy shocks for five key emerging market economies: Brazil, Russia, India, China and South Africa. Their results show that monetary contractions lead to a fall in real economic activity and tighten liquidity market conditions, while government spending shocks have strong Keynesian effects.

5.3 Nowcasting and Forecasting: A Growing Topic

Another area where pVAR models could be effectively used, and is currently growing, is the construction of leading indicators and forecasting. Panel models have been used in forecasting, however not in a VAR setup; see Baltagi (2008) who provides a survey of forecasting with panel data investigating the forecasting ability of heterogeneous and homogeneous panel data models in out-of-sample cross-validation experiments. There are only a few papers which deal with the topic of forecasting using pVAR models and virtually none on the topic of nowcasting. The closest literature is the forecasting of economic variables using aggregates and disaggregates. pVAR models offer a solution to this debate as the interdependencies and heterogeneities are captured along with common factors (if any). Canova and Ciccarelli (2009) use a Bayesian time varying parameter pVAR model to construct leading or coincident indicators. More recently, Dees and Guntner (2017) employ a pVAR model to estimate and forecast inflation dynamics in four different sectors: industry, services, construction and agriculture. Their data is based on the four largest Euro area member states: France, Germany, Italy and Spain. By modelling inflation together with real activity, employment and wages at the sectoral level, pVAR allows to disentangle the role of unit labour costs and profit margins as the fundamental determinants of price dynamics on the supply side. In out-of-sample forecast comparisons, the pVAR approach performs well against popular alternatives, especially at a short forecast horizon and relative to standard VAR forecasts based on aggregate economy-wide data.

From a technical perspective, Koop and Korobilis (2013), Koop and Korobilis (2016) and Koop and Korobilis (2018) further extend the Bayesian methods to allow for Dynamic Model Averaging (DMA), with encouraging results in forecasting macroeconomic targets, e.g., inflation as in Koop and Korobilis (2018).

As it can be seen from the previous discussion, evaluating the predictive gains of pVAR models for nowcasting and short-term forecasting in panels of interdependent groups (such as the EU or EA member states or across US states) has just started, providing an excellent timing for further work in this area but also the need for a careful evaluation to assess their applicability and usefulness for official statistical agencies.

5.4 The potential usefulness of PVAR models for official statistics

Since the end of the 20th century, advance statistical and econometric techniques started to be integrated into official statistics, complementing traditional methods; mainly to deal with some new priorities, such as the improvement of the timeliness of macroeconomic indicators, the construction of higher frequency indicators and the development of new policy relevant kind of indicators. In the last two decades a further impulse to the incorporation of new econometric tools in official statistics was originated by two additional factors: the continuous growth of the amount of available data (both from traditional and alternative sources, such as big data) and the need of taking into account globalization effects and interdependencies among economic sectors, markets, regions, countries, etc. when constructing statistical indicators.

Both macroeconomic and microeconomic PVAR models have appealing features which could make them, from the theoretical point of view, able of providing a relevant contribution in dealing with almost all new challenges mentioned above.

In Sections 4 and 5.2 we have already discussed in details how both point and density nowcasts, flash estimates and short-term forecasts can be constructed. We have also discussed the advantages offered by PVAR models with respect to other competing approaches. The main added value of PVAR models in this field is represented by the incorporation of both static and dynamic interdependencies as well as of cross-sectional heterogeneities within the forecasting scheme. This multivariate framework cam provide a methodologically sound and robust alternative to the never ending debate between direct and indirect approaches to the construction of nowcasts for the Euro area and its member countries, as well as for individual countries and their regions. Similar considerations apply to the estimation of cyclical patterns and the output-gap at geographically aggregated and disaggregated levels. Furthermore, in Section 5.1 we have also shown how pVAR models can give the possibility of identifying, estimating and analyzing shocks transmission mechanisms and cyclical contagion.

Concerning the development of new indicators, pVAR models could be used to construct indicators of stress, vulnerability, fragility, disequilibrium, etc. These indicators could be of high interest for macroeconomic stability policies and for the Macroeconomic Imbalances Procedure (MIP) of the European Union. By contrast, the usefulness of pVAR models to develop new sustainable development goals (SDG) related indicators needs to be further investigated. We are not aware of any empirical applications of PVARs in the SDG context, maybe due to the very limited number of temporal observations.

Finally, microeconomic PVAR models appear, theoretical speaking, an ideal tool to deal with microdata coming either by sampling surveys or administrative registers as well as from big data sources. They could help in conducting in-depth investigations of the behaviour of individual consumers, retail trade sales, employed and unemployed individuals, firms, etc. They could also contribute to the construction of some new bottom-up based indicators such as poverty risk, well-being, and many others.

Obviously, before considering pVAR models as a tool really suited for official statistics, their performance needs to be carefully investigated and assessed by means of a set of empirical studies covering all areas discussed above.

6 Should we use pVAR models?

So far we have reviewed the growing literature on pVAR models and provides an overview for applied researchers in official statistical agencies and similar institutions. pVAR models should be adopted when the researcher wants to model interdependencies in different units, allowing at the same time for dynamic heterogeneity.

We first introduced the standard VAR models and next their panel extension. Then, we discussed various pVAR specifications, including static and dynamic interdependencies as well as time variation. We discussed that, even though pVAR models might be complex in their initial setup, factorisation methods allow to transform large scale pVARX models into standard SUR models, where existing methods from the frequentist and Bayesian econometrics literature can be directly applied. For example, OLS can be straightforwardly applied and point and density forecasts can be easily obtained.

Finally, this paper provides a discussion of a large number of studies which show that pVAR and pVARX models are useful in three main areas: (i) evaluation of the effects of economic policy, (ii) analysis of business cycles fluctuations and convergence issues and (iii) forecasting. While forecasting is of more direct use for possible applications in an official statistics context, the analysis of business cycles fluctuations and similar empirical applications can provide evidence on the suitability of pVARs as models for properly capturing interdependencies.

The area related to forecasting and nowcasting with pVARs models is rather novel. Hence, in the next section we aim to bridge this gap in the macroeconomic nowcasting literature and investigate the nowcasting performance of pVAR models for a system of interconnected economies, such as economies of countries belonging to the Euro area or to the EU. Macroeconomic nowcasting in Euro area economies is particularly promising, as the monetary policy for these countries is common and they are highly integrated, so that they should share common factors, Ξ_{common}. The use of a larger information set and the modeling of cross-country interdependencies could lead to improved nowcasts and short-term forecasts, possibly enhancing the quality of official flash estimates for key economic variables such as GDP.

7 Methodology used in our empirical study

7.1 pVAR

As already analysed in Section 2.2, a pVAR model is similar in many ways to a standard VAR or VAR with exogenous regressors, as variables are still treated as endogenous and interdependent adding a cross-sectional dimension, which can account for joint modelling of i=1,…,N units. For our empirical study we employ the pVAR model discussed in Equation (4) allowing the exogenous variables to be specific across units, i.e.:

$$y_{it}=\mu_i+\sum_{l=1}^{p}A_l y_{it-l}+\sum_{k=0}^{s}C_k s_{it-k}+\varepsilon_{it}. \quad (27)$$

As mentioned earlier in this study, this model can be estimated using OLS or GMM (as described in Sigmund and Ferstl (2017) and Kapetanios et al. (2017)). In our empirical study we use both estimation methods.

7.2 Exogenous variables and factors

In economic applications, the number of exogenous variables in panel (and pVAR) models is relatively small and targeted. For example, Arellano and Bond (1991) use a panel data model for the employment in the UK. Their model aims to explain current employment levels using past values of employment (two lags), current and first lag of wages and output and current value of capital (i.e. three exogenous variables). Dahlberg and Johansson (2000) use a pVAR to model the total expenditures, total own-source revenues and intergovernmental grants using data on 265 Swedish municipalities across 9 years without exogenous variables at all. Exogenous variables are also problematic in a forecasting context, as their future values are needed for the computation of the forecasts. This issue can be addressed either by augmenting the pVAR model with auxiliary models for the exogenous variables, or by using external forecasts (e.g., from institutions or from surveys), or by adopting a direct forecasting approach.

In out-of-sample forecasting applications, the researcher also often faces a trade-off between the use of a large information set and the difficulty of variable selection. To overcome this difficulty, Stock and Watson (2002a) and Stock and Watson (2002b) suggest to extract unobserved factors from of a rich set of macroeconomic and financial predictors in order to reduce the number of variables while preserving the relevant information; see, e.g., Kapetanios et al. (2017) for a comprehensive discussion. Specifically, in an effort to keep the dimension of the pVAR model relatively small and to be in line with the forecasting literature, we will employ static Principal Component Analysis (PCA) to extract a few factors from a large set of potential predictors, and add them as exogenous regressors in a pVARX.

The defining characteristic of most factor methods is that relatively few summaries of the many available variables are used in forecasting equations, which thereby become standard forecasting equations as they only involve a few explanatory variables. Consider a set of R predictors, x_t.The main assumption is that the co-movements across the (weakly stationary and standardised) predictor variables x_t, where $x_t=(x_{1t}\cdots x_{Rt})'$ is a vector of dimension $R\times1$, can be captured by a $r\times1$ vector of unobserved factors $F_t=(F_{1t}\cdots F_{rt})'$, i.e.,

$$\tilde{x}_t=\Lambda' F_t+e_t, \tag{28}$$

Where $\tilde{x}_t$ may be equal to x_t or may involve other variables, such as lags, leads or products of the elements of x_t, and Λ is an $r\times R$ matrix of parameters describing how the individual indicator variables relate to each of the r factors, which we denote with the terms 'loadings'. In (28) e_t is a zero-mean $I(0)$ vector of errors that represent, for each indicator variable, the fraction of dynamics unexplained by F_t, the 'idiosyncratic components'. The number of factors is assumed to be finite. The use of PCA for the estimation of factor models is, by far, the most popular method. It has been popularised by Stock and Watson (2002a) and Stock and Watson (2002b), in the context of large data sets, although the idea had been well established in the traditional multivariate statistical literature. The method of principal components is simple. Estimates of Λ and the factors F_t are obtained by solving:

$$V(r)=\min_{\Lambda,F}\frac{1}{RT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\tilde{x}_{it}-\lambda_i' F_t)^2, \tag{29}$$

where λ_i is an $r\times1$ vector of loadings that represent the N columns of $\Lambda=(\lambda_1\cdots\lambda_R)$. One, non-unique, solution of (29) can be found by taking the eigenvectors corresponding to the r largest eigenvalues of the second moment matrix $X'X$, which then are assumed to represent the rows in Λ, and the resulting estimate of Λ provides the forecaster with an estimate of the r factors $\hat{F}_t=\hat{\Lambda}\tilde{x}_t$. To identify the factors up to a rotation, the data are usually normalised to have zero mean and unit variance prior to the application of principal components. We note that factor estimates obtained via PCA estimation are $\min(\sqrt{R},T)$-consistent. Further, if $\sqrt{T}/R=o(1)$, using estimated factors rather than true factors in predictive regressions produces negligible estimation errors.

Therefore, in the context of Equation (27), s_{it} can be a set of specific variables or a set of factors estimated as the principal components of a much larger set of indicators.

7.3 Mixed-Frequency

We now turn our attention to the frequency of s_{it}. Usually, s_{it} is expressed in the same frequency as y_{it}. However, there can be cases where s_{it} is sampled at higher frequency than y_{it}. For example y_{it} could be quarterly and s_{it} could be monthly. Or, y_{it} could be monthly and s_{it} could be weekly. To overcome this difficulty, we introduce the mixed-frequency pVAR model defined as:

$$y_{it_{f_y}}=\mu_i+\sum_{l=1}^{p}A_l y_{it-l}+\sum_{k=0}^{s}C_k s_{it-k_{f_y}}+\varepsilon_{it}, \tag{30}$$

where y_{it} is expressed in its natural frequency f_y and s_{it} (which is of higher frequency, i.e. $f_s>f_y$) has been aggregated to match f_y. To handle the mixed frequency, we use two approaches. First, we define:

$$s_{it_{f_y}}=\sum_{j=1}^{J}\beta_j(L)s_{it_{f_s}} \tag{31}$$

with $J=f_s/f_y$. For example, if $y_{it_{f_y}}$ is quarterly and $s_{it_{f_s}}$ is monthly then $J=3$. Furthermore, if $\beta_1=\beta_2=\beta_3=1/3$, $s_{it_{f_y}}$ is constructed by taking quarterly averages of the monthly values. Second, we adopt the Unrestricted Mixed Data Sampling approach (see Foroni et al. (2015)), so that:

$$s_{it_{f_y}} = \beta_1(L) s^{1,it_{f_s}} + \beta_2(L) s^{2,it_{f_s}} + \ldots + \beta_J(L) s^{J,it_{f_s}}. \qquad (32)$$

J now corresponds to the duration of f_y in f_s terms and $s^J_{it_{f_s}}$ denotes the corresponding J–th observation. For example, if $y_{it_{f_y}}$ is quarterly and $s_{it_{f_s}}$ is monthly then J=3 because we have 3 months (f_s terms) in a quarter (f_y). Therefore, in the spirit of Unrestricted Mixed Data Sampling, $s_{it_{f_s}}$ is split into three corresponding (sub-) variables where each variable holds the first, second and third month of each quarter across time. Similarly, if $y_{it_{f_y}}$ is monthly and $s_{it_{f_s}}$ is weekly, then J=4, assuming that we have 4 weeks in a month. Hence, $s_{it_{f_s}}$ is split into four corresponding (sub-) variables where each variable holds the first, second, third and fourth week of each month across time.

In what follows we employ the models described in Equations (3) and (27), using both methods in Equations (31) and (32) to handle mixed frequencies, when necessary.

8 Data description

8.1 Targets

We consider the four largest European economies: Germany (DE), France (FR), Italy (IT) and the UK. For each of them, we have collected data on the quarterly GDP growth rate and three other key economic indicators: the monthly industrial production (IP), monthly unemployment rate (UNR) and the monthly Consumer Price Index (CPI). The data has been downloaded using Macrobond Software([10]).

8.2 Predictors

Our set of monthly macroeconomic predictors includes various coincident and leading indicators plus additional key economic variables for each country. Specifically, we consider the following categories: Bank Lending Rate, Bankruptcies, Building Permits, Capital Flows, Car Registrations, Construction Output, Consumer Credit, Core Consumer Prices, various CPI components, Crude Oil Production, Export Prices, Exports, Factory Orders, Gasoline Prices, House Price Index, Import Prices, Imports, Job Vacancies, Manufacturing Production, Mining Production, Money Supply M1, M2 and M3, New Orders, Private Sector Credit, Producer Prices, Steel Production, Youth Unemployment Rate, Consumer Confidence Indicators and various surveys.

Our set of daily and weekly variables includes mainly financial indicators: interest rates at various maturities and spreads, equity indexes, volatility indexes.

We also consider a big data-based uncertainty indicator using Google searches. For more details on the construction of this index see Kapetanios et al. (2017). Kapetanios et al. (2017) find that big data based uncertainty indicators are sometime useful in single country analyses to improve the forecasts of our same four variables. Here we want to assess whether and to what extent they are useful in a panel context.

8.3 Transformations

To ensure that the variables under analysis are stationary, a pre-requisite for several of the econometric methods we implement, we use a set of transformations, which include: (i) log, (ii) log difference (log growth), (iii) first difference, and (iv) percentage change. The specific transformation for each variable follows standard practice in the literature, see, e.g., Mc Cracken and Ng (2016) as well as Stock and Watson (2002a) and Stock and Watson (2002b) among others. In our exercise, we forecast the period-to-period log growth of GDP, IP and CPI and the period-to-period first difference of UNR.

([10]) Macrobond is not a data provider. They offer proprietary data aggregation solutions. The actual data is sourced from official statistics agencies (e.g., the ONS, IStat, etc.) and therefore is expected to be similar to the data used by Eurostat.

8.4 Time span

In particular, we have a total number of 53 quarterly observations (after stationarity transformations). Using an initial in-sample size of 22 observations (from 2004-06-30 [2004Q2] to 2009-09-30 [2009Q3]) we have a remaining out-of-sample size of 31 observations (from 2009-12-31 [2009Q4] to 2017-06-30 [2017Q2])([11]).

For our monthly variables we have a total number of 163 observations (after stationarity transformations). Using an initial in-sample size of 36 observations (from 2004-02-29 to 2007-01-31) we have a remaining out-of-sample size of 127 observations (from 2007-02-28 to 2017-08-31).

8.5 Data summary

In total we have:

- 119 variables for DE,
- 111 variables for FR,
- 62 variables for IT, and
- 108 variables for the UK,
- 53 quarterly observations and 163 monthly observations.

([11]) The out-of-sample sizes of this subsection refer to the *h*=1 case. For larger *h*, the out-of-sample size decreases accordingly.

9 Forecasting setup

9.1 Direct forecasts

The models we use in the forecasting exercise are those described in Equations (3) and (27). To deal with mixed-frequencies we translate the higher-frequency variables to their lower-frequency counterparts using the averaging (avg) and Unrestricted Mixed Data Sampling (UMIDAS) transformations described in Equations (31) and (32).

The models in Equations (3) and (27) can be re-written as simple linear regressions of the form:

$$y=\mu+X\beta+\varepsilon,\ E[\varepsilon|X]=0, E[\varepsilon^2|X]=\sigma^2, \tag{33}$$

where y is the corresponding stacked vector of y_{it}, X is the stacked vector of past lags of y_{it} and/or s_{it} and μ denotes the vector of fixed-effects. Hence, we can employ these predictive regressions to produce the out-of-sample forecasts using the direct (projection) method.

In the direct forecasting approach, say for a simple model $Z_t=\gamma F_t+u_t$ for $t=1,..,T$, $\hat{\gamma}_h$ denotes the parameter estimate which is obtained by regressing $Z_{t=\{h+1,..,T\}}$ on $F_{t=\{1,..,T-h\}}$. Then this estimate is used to calculate $\hat{Z}_{t+h}=\hat{\gamma}_h F_t$. The direct approach is computationally efficient and it does not require the specification of models for the exogenous variables. It is less efficient than the iterated approach but can be more robust in the presence of model misspecification.

9.2 Forecasting exercise

The forecasting exercise is based on the algorithm described in the following steps.

1. We leave a number of observations, T^{OUT}, out-of-sample, in order to use them in the evaluation of the nowcasting performance of the different models[12]. In our experiments, T^{OUT}=127 for the monthly targets (IP, UNR, CPI) and T^{OUT}=31 for the quarterly target (GDP) for h=1. For larger h the out-of-sample size decreases accordingly.
2. The initial sample we use in the first round of estimation is $T_1^{IN}=\{1,..,\left(T-T^{OUT}+1\right)\}$. Then, we estimate the parameters and produce the h-step ahead forecasts from various models.

(12) The researcher can choose the desired out-of-sample size for the exercise. We choose our T^{OUT} so that the initial in-sample allows enough observations for our estimators to converge.

3. We repeat Step 2 in a recursive manner, i.e. $T_2^{IN}=\{1,.., \left(T\text{-}T^{OUT}+2\right)\}$ and generally $T_j^{IN}=\{1,.., \left(T\text{-}T^{OUT}+j\right)\}$. We stop when $T_j^{IN}=\{1,.., (T\text{-}h)\}$, as we always need the true value of the next period to evaluate the nowcasts.
4. At the end of the above recursive procedure, we end up with (T^{OUT}-h) forecasts for each model under consideration.

9.3 Forecast evaluation

Once we have computed $(T^{OUT}-h)$ forecasts for each model, we evaluate the forecasting performance using the mean absolute error and the root mean squared forecast error statistics, defined as:

$$MAE_{j,h} = \frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} \left| e_{j,t} \right|,$$

$$RMSFE_{j,h} = \left(\frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} e_{j,t}^2 \right)^{\frac{1}{2}},$$

where e_j is the out-of-sample forecast error (in levels) for model j. All our tables present the MAE and RMSFE relative to an AR(1), which serves as our benchmark. We further calculate the Diebold and Mariano (1995 statistic for predictive accuracy as follows:

$$DM = \frac{\overline{d}}{\left(\widehat{LRV}_{\overline{d}}/T\right)^{1/2}},$$

where

$$\overline{d} = \frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} d_t,$$

$$d_t = \left| e1,t \right| - \left| e2,t \right| correspondingtoMAE$$

$$d_t = e_{1,t}^2 - e_{2,t}^2, correspondingtoRMSFE$$

$$LRV_{\overline{d}} = \gamma_0 + 2 \sum_{v=1}^{\infty} \gamma_v, \gamma_v = cov(d_t, d_{t-v}),$$

for candidate models 1 and 2 (model 2 always being the AR(1) benchmark). We use the two-sided test where the null hypothesis states equal predictive ability between models:

- $H_0 : E[d_t] = 0$,
- $H_A : E[d_t] \neq 0$.

In the tables we report the p-value of the test.

To evaluate the directional forecasts of each model we use the Sign Success Ratio (SSR) which is defined as the proportion of instances that the direction of the forecasts from each model is the same to the direction of the actual values. This is given by:

$$SSR_j = \frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} I\left[sgn(\Delta y_{t+h}) = sgn(\hat{y}_{t+h} - y_t)\right], \tag{34}$$

where $sgn(\bullet)$ denotes the sign operator and $I(\bullet)$ is an indicator variable which takes the value 1 if the signs are equal and 0 otherwise. For example, in the case of GDP, we evaluate whether the sign of the actual growth in GDP between period t and period $t+h$ is the same as the forecasted sign. Sign forecasts can be interesting in the context of official statistics to communicate whether key indicators are expected to improve or deteriorate over a given period.

Finally, in separate tables we assess the density forecasting of various methods reporting the 68 % and 90 % coverage rates (CR) for each model and forecasting horizon. We calculate the coverage rates as:

$$CR_j = \frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} I\left[q_{\alpha_1, \hat{y}_{t+h}} \le y_{t+h} \le q_{\alpha_2, \hat{y}_{t+h}}\right], \tag{35}$$

where $I(\bullet)$ is an indicator variable which takes the value 1 if the true value, $\hat{y}_{t+h}$ lies within the density estimate interval $[q_{\alpha_1}, \hat{y}_{t+h}, q_{\alpha_2}, \hat{y}_{t+h}]$ and zero otherwise. We report two intervals 68 % and 90 % using $\{q_{\alpha_1}, q_{\alpha_2}\} = \{0.16, 0.84\}$ and $\{\alpha_1, \alpha_2\} = \{0.05, 0.95\}$ levels.
The quantiles are obtained by parametric bootstrapping (using the estimated model parameters for each model and drawing from the distribution of the errors). It is also worth mentioning that the averages of the resulting empirical distributions are in general quite similar to the point forecasts obtained with the analytical formulae. We also mention that interval forecasts are of interest in the context of official statistics as a way to communicate easily the extent of the uncertainty around the flash estimates of short-term forecasts of the variables. Hence, it is important to assess whether the measured uncertainty is reliable, in the sense that the actual coverage rates are close to the nominal ones.

9.4 Settings

9.4.1 MODELS

Our set of models consists of: naive forecasts and autoregressive model of order 1 (which is also our main benchmark), linear regressions using the first lag, exogenous factors and different mixed-frequency transformations, single-country vector autoregression models of order 1 using exogenous factors and different mixed-frequency transformations, and pVAR models using exogenous factors and different mixed-frequency transformations. As exogenous factors, we use principal components extracted from the large macro-finance datasets, with or without the Google uncertainty index for each country separately. In total, we have 29 models, a summary description can be found in the legend in the Appendix while in the next subsection we provide details on the pVAR specifications.

9.4.2 PVAR SPECIFICATIONS

In our pVAR models, our panel consists of $i = \{1,2,3,4\}$ economies: DE, FR, IT and the UK. In all VARX([13]) and pVARX specifications the exogenous variables include: (i) the first PCA factor extracted from the set of macro and

([13]) Using a maximum order of 6 (which means that for the target variable equation we can have a maximum of 3 variables □ 6 lags = 18 predictors), the Schwarz information criterion suggests that the optimal order is P=1 for almost all combinations of countries and variables. Therefore, we choose to use the VAR(1) and VARX(1) models. We also choose to use pVAR(1) and pVARX(1) to facilitate the direct comparison between time-series and panel data approaches in forecasting. All codes are provided by the authors and the applied researcher could experiment with higher orders bearing in mind the tradeoff between parsimony and forecast error; i.e. we need a parsimonious model which provides robust forecasts in multiple setups and its results can be explained from an economic perspective, rather than specific (and possibly very different) models for each case with forecast output which can be result of data mining.

financial predictors, (ii) the Google trends, (iii) their combination. However, in pVAR models, for each case we have different specifications regarding the endogenous variables.

In particular:

1. for quarterly GDP growth we use a pVAR(1) model for the four economies based on a standard macro VAR using the GDP, CPI and interest rate as endogenous variables. The CPI and the interest rate have been transformed to quarterly frequency using quarterly averages.
2. For monthly IP growth we also use a pVAR(1) based on a standard macro VAR using the IP, CPI and the interest rate as endogenous variables.
3. For monthly UNR we use a pVAR(1) where the endogenous variables are UNR, IP and CPI.
4. For monthly CPI we use the pVAR model mentioned above where the endogenous variables are CPI, IP and the interest rate.
5. It is important to notice that we estimate the pVAR(1) models using GMM as discussed in Sigmund and Ferstl (2017). However, given that the corresponding package in R does not allow for flexible direct forecasting using exogenous variables, we also use OLS. See the Appendix for more details.

9.4.3 FORECASTING HORIZONS

In our experiments we use short-run forecasting with h={1,2,3,4} step-ahead for the quarterly target and h={1,3,6,12} step-ahead for the monthly target.

10 Summary of results

10.1 Reading a table

We complement this paper with 16 tables in the Appendix presenting results for the point and directional forecasts (4 variables X 4 economies), 4 tables with coverage rates as a way to evaluate the precision of the density forecasts, 2 tables with summary results, and two documents with the corresponding density forecast plots for each model, forecast horizon, target variable and country (2,304 figures in total). Below, we provide a short summary of the results organised by variable.

Each of the tables presenting the evaluation of the point and directional forecasts is organised in four panels:

- for h={1,2,3,4} step-ahead quarterly target forecasting, and
- for h={1,3,6,12} step-ahead monthly target forecasting.

For each h we report the MAE and RMSFE relative to the AR(1) benchmark and the actual SSR. We also report the p-values of the Diebold and Mariano (1995) statistic, henceforth DM, with absolute and squared errors which can be associated to the MAE and RMSFE statistics respectively (even though, strictly speaking, DM tests compare MSFEs rather than RMSFEs). A model outperforms the benchmark if the relative MAE and RMSFE are less than 1 and the corresponding p-values are smaller than the required statistical level of significance (i.e. for 10 % level the p-value has to be smaller than 0.1 to reject the null hypothesis of equal predictive ability).

In Tables 1 to 18, the competing models are organised in five panels:

- first, there are the standard Naive and AR(1) models,
- then, we have simple linear regressions (LR) using only the extracted factors from the set of macroeconomic and financial predictors (MF), the Google Trends (G), and their combination (MFG),
- then, there is the combination of LR models including a past lag (AR(1) term) in the equation,
- then, we have the single-country VAR(1) and VARX(1) models using MF, G, and MFG as exogenous variables, and
- finally, we have the pVAR(1) using GMM for estimation (and no exogenous factors) and pVAR(1) and pVARX(1) using OLS and country fixed-effects (OLSCFE) which is more flexible and allows the direct forecasting using MF, G and MFG as exogenous factors.

Tables 19 to 22 present the actual coverage rates of the 68 % and 90 % interval forecasts obtained from the entire density forecasts. These tables are organised in a slightly different way. Each table has four panels, one panel for each of the four economies under consideration. Each panel then presents the two coverage rates for h=1,2,3,4 step-ahead (for the quarterly GDP) and h=1,3,6,12 step-ahead for the monthly variables.

For all of these models, the issue of mixed-frequency between the dependent and the exogenous variables is solved employing either the averaging (T1) or the UMIDAS (T2) transformations, as explained in Equations (31) and (32).

Example: using the previously mentioned notation, we can denote the pVAR with p=1 lag, estimated using OLS Country Fixed-Effects, including the factors extracted from Macro/Finance and Google predictors as exogenous, and using the mixed-frequency averaging transformation as PVARX(1)-OLSCFE-MFG-T1.

10.2 Averaging across forecast horizons

In an effort to provide an overall evaluation of the competing methodologies, we comment on the performance of the various models when averaged across all forecast horizons: *h*=1,2,3,4 for quarterly GDP growth and *h*=1,3,6,12 for the three monthly targets.

Table 1 presents the average relative MAE and RMSFE for each target variable and economy combination. We have highlighted with bold facetype font all models which have an average relative MAE or RMSFE which is smaller than unity; this means that every model with an average relative MAE/RMSFE below unity produces forecasts which outperform -on average- the benchmark.

The top left panel of Table 1 provides the average results for each country when the GDP growth is the target variable. We see that for Germany, LR-MF-T1 and AR(1)-MF-T1 have smaller forecast error compared to the benchmark. PVARX(1)-OLSCFE-MF-T1 slightly outperforms these models with a relative MAE of 0.963 and an RMSFE of 0.986. Including the Google trends indicator, PVARX(1)-OLSCFE-MFG-T1, only marginally improves the forecast accuracy return a MAE and RMSFE of 0.954 and 0.960 respectively. For the case of France, we see that none of the VAR or pVAR models outperforms the simpler methods. Linear regressions, LR-MF-T1, LR-G-T1 and LR-MFG-T1 seem to have the smallest error across all horizons. Based on MAE, we see that PVAR(1)-OLSCFE has smallest forecast error for Italy (the MAE value is 0.967); this does not improve when the Google trends indicator is included. Finally, for the UK we see that the AR(1) benchmark consistently outperforms the rest. It is interesting to note that for all the countries under consideration the pVAR forecasts are generally more accurate than the VAR forecasts. This provides evidence in favour of modeling the cross-country relationships.

In the top right panel of Table 1, we have the corresponding average results for the Industrial Production growth target. It is obvious that the results for pVAR models are favourable for Germany; interestingly we observe that the models with Google trends are better compared to the Macro/Finance models (PVARX(1)-OLSCFE-G-T1 has 0.986 and 0.983 MAE and RMSFE respectively, compared to 1.007 and 1.000 of which correspond to PVARX(1)-OLSCFE-MF-T1). For France and the UK, we see that PVAR(1)-GMM outperforms the benchmark and all other competing models. Also for Industrial Production the PVAR is generally better than the VAR.

Turning to the bottom left panel of Table 1, we see more evidence in favour of pVAR models when the target variable is the (first difference of the) Unemployment Rate. For Germany, the model with the smallest average error across all forecast horizons is PVAR(1)-GMM using MAE and PVARX(1)-OLSCFE-G-T1 using RMSFE with 0.825 and 0.985 values respectively. AR(1)-MF-T1 and VARX(1)-MF-T1 seem to be the best models for France, however, we also see that PVARX(1)-OLSCFE-MF-T1 has a small RMSFE of 0.967. For Italy, the best performing methods are PVARX(1)-OLSCFE-G-T1 and PVARX(1)-OLSCFE-G-T2, but only with marginal gains. Finally, for the UK we have a clear result in favour of pVAR models which all have the smallest forecast error. PVAR(1)-GMM has the smallest MAE (0.919), whereas PVAR(1)-OLSCFE has the smallest RMSFE (0.978). The addition of Macro/Finance factors or Google trends does not seem to significantly improve these results. Also for the Unemployment Rate, the pVARs seem in general to perform better than the VARs, confirming the importance of modelling the cross-country relationships.

The bottom right panel of Table 1 provides the results when the target variable is the CPI growth (inflation). We see that the AR(1) benchmark is the best performing method for Germany and Italy. However, for France we have that PVARX(1)-OLSCFE-G-T2 and PVARX(1)-OLSCFE-MFG-T2 have the smallest MAE and RMSFE, even though the gains with respect to the benchmark are small. Interestingly, it must be highlighted that the pVAR models with Google trends only has slightly better results. The same is also true for the case of the UK where pVAR models are good performers, however the model with the smallest error is LR-G-T2 with 0.955 and 0.935 MAE and RSMFE respectively. The ranking of VARs and pVARs is less clear-cut, with the former often only slightly worse than the latter, and both models generally worse than the AR benchmark. This different relative performance of the pVAR models for inflation, and the very good performance of simple AR models, can be attributed to the persistence of this variable, which makes its own lag the dominant predictor.

Table 2 presents the absolute distance from the nominal 68 % and 90 % levels of the average density forecasts across all forecast horizons. Similarly to Table 1, we have highlighted with bold facetype font the model with the smallest distance to the nominal values. It is important to notice that, in this table, we are looking for the models which have values very close to 0 meaning that their coverage rates are very close to the actual levels.

Starting from the top left panel of Table 2 with the GDP coverage rate results, we see that only VAR models for France, Italy and the UK have accurate coverage rates. This is not the case for the Industrial Production results in the top right panel. We now see that for Germany and Italy, pVAR models offer accurate coverage rates together with LR models. AR and VAR models have better performance for France and the UK targets. Looking at the bottom left panel of Table 2, we see that for the Unemployment Rate pVAR models offer accurate coverage rates for France and Italy. In the bottom right panel of Table 2, we see that pVAR models along with LR, AR and VAR models have all accurate coverage rates for Germany, however for the other countries targets, none of the models seem to work well. Some LR, AR and VAR models return accurate coverage rates for 68 % for the UK. From Table 2, it also emerges that the relative performance of VARs and pVARs in terms of coverage rates is rather different from that in terms of MAE and RMSFE. Indeed, though there are various exceptions, VARs often provide more accurate coverage than pVARs. A possible explanation for this finding is that pVAR models are much more heavily parameterized than VARs, and estimation uncertainty can enlarge too much the forecast distributions.

Finally, we summarise all the above findings below. Starting with Table 1, we see that -on average across all horizons- pVAR/pVARX models produce satisfactory forecasts for the following cases:

- GDP: DE and IT.
- IP: DE (mainly) and only PVAR(1)-GMM for FR, IT and the UK.
- UNR: DE, FR and the UK.
- CPI: FR and the UK.

Comparing VAR/VARX models to their pVAR/pVARX counterparts, we see that -on average across all horizons-, pVAR/pVARX models provide better forecasts and outperform both the benchmark and the VAR models.

From Table 2, we see that the minimum absolute distance between actual and nominal coverage rates are obtained by the pVAR/pVARX models in the following cases:

- IP: DE and IT (only PVARX(1)-OLSCFE-G-T2).
- UNR: FR and IT.
- CPI: DE.

The above findings offer some evidence that pVAR/pVARX models should be -at least- included in the toolkit of models from the applied researcher.

11 Conclusions

This report reviews the theoretically and empirically the panel VAR models using out-of-sample forecasting applications with data from European countries. From an official statistical agencies point of view, analysing data of integrated economies requires to capture the potential underlying interdependencies and exploit them in the context of estimation and forecasting. We use four of the most important macroeconomic variables as targets and the four largest European economies. Our set of standard models includes univariate autoregressive and VAR models. We extend these models by including factors extracted from a higher frequency set of macroeconomic and financial predictors as well as indicators extracted big textual datasets. To overcome the difficulty of mixed-frequency we employ the bridge and UMIDAS approaches. Finally, we compare the out-of-sample forecasting performance of the standard single country models to that of corresponding simple and factor-augmented pVAR models. We consider point, directional, interval and density forecasts, with associated measures of mean squared forecast errors, sign success ratios, actual coverage rates and graph of the forecast densities.

Based on the detailed empirical analysis we have conducted, we can say that we find mixed evidence in favour of pVAR models. They seem to improve the point forecasts at longer horizons, the directional forecasts across most horizons, and the coverage rates of interval forecasts for a few variables and countries. In all cases, a careful selection of the proper specification of the pVAR model is required, as it is also the case for standard single-country models.

Another interesting finding is that pVAR models are generally better than VAR models in terms of RMSFE and MAE for most of the variables and countries we have considered. Yet, in several cases they are outperformed by VARs in terms of coverage rates, possibly because classical estimation of their larger number of parameters increases too much the forecast uncertainty.

Additional empirical analyses could shed light on whether forecast combination of pVAR models or Bayesian estimation might prove to be useful. Also, pVAR models could be of further interest to official statistical agencies when analysing multiple markets in a single economy, or across different integrated economies, of for a different set of variables, or to construct coincident or leading indexes rather than nowcasts or forecasts.

Overall, we certainly believe that official statistical agencies should have the pVAR methodology as part of their toolbox and modelling strategy, but clearly they should not rely exclusively on these methods.

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12 Appendix

12.1 Estimation of pVAR Models in R

Love and Zicchino (2006) was the first paper to widely share their STATA program codes. Because of this fact, this paper now counts more than 1 100 citations. As these models have increased in popularity, Abrigo and Love (2015) have prepared a suite of computational procedures for STATA and Sigmund and Ferstl (2019) prepared a suite of procedures for R. The ECB BEAR toolbox built in MATLAB also includes procedures for pVAR models; see Dieppe et al. (2016) for more information.

Currently, the 'panelvar' package of Sigmund and Ferstl (2019) is the only library which can be used for the estimation of pVAR models in R. Sigmund and Ferstl (2019) properly explain the theoretical as well as practical aspects of their package. Here, instead of repeating Sigmund and Ferstl (2019) and explaining the underlying theory of pVAR models estimations, we take a different approach and discuss the strengths and weaknesses of the package.

12.1.1 STRENGTHS

1. The package contains two different estimation approaches: the first difference GMM estimator of Holtz-Eakin et al. (1988) as well as the system GMM estimator of Blundell and Bond (1988).
2. The Hansen overidentification test, lag selection criteria and stability test of the pVAR polynomial are also provided in the package.
3. The package can handle orthogonal and generalised impulse response functions, bootstrapped confidence intervals for impulse response analysis and forecast error variance decompositions.
4. The package handles both 'first difference' and 'forward orthogonal deviations' transformations.
5. The main function 'pvargmm' is easy to use and the estimation is relatively fast (a dataset of 3 000 observations is estimated in about 15–20 second using a standard-type office laptop14).
6. The researcher has great flexibility in various settings such as about the transformation, the use of the System GMM estimator, the application of PCA to instruments matrix and the maximum and minimum number of instruments for dependent variables.

12.1.2 WEAKNESSES

1. The package has been built for estimation and fully serves that purpose. It has not been built or optimised for panel forecasting. Therefore, to use the 'pvargmm' and perform iterative forecasting (as the direct forecasting is not feasible in the way the package is set up) requires many additional lines of coding, given that the actual

([14]) Exact machine specifications: Intel Core i7-6600U @ 2.60GHz, 16GB RAM.

iterative forecasting algorithm needs to be written from scratch.

2. Depending on the nature of the (forecasting) exercise, the researcher needs to experiment with various settings about the transformation, the use of the System GMM estimator, the application of PCA to instruments matrix, etc.

Let us be more specific about the forecasting problems we might face using the panelvar package. Let us distinguish two models: (i) one with no exogenous variables, and (ii) one which includes exogenous variables. First, for both models we can use the corresponding in-sample data and proceed with the estimation. This will return us the vector of estimated coefficients.

Using the first model with no exogenous variables, one could use the autoregressive coefficients and iteratively produce $\hat{Y}_{t+1}$, using the observed Y_t data; here Y_t denotes the stacked vector of endogenous variables. Then, produce $\hat{Y}_{t+2}$ using the estimated $\hat{Y}_{t+1}$ and Y_t (if the order is greater than 1). Then, produce $\hat{Y}_{t+3}$ using the estimated $\hat{Y}_{t+2}$ and past values if necessary. Therefore, in this case the panelvar package can be used, only requiring the research to write a small piece of code implementing the iterative forecasting process described above.

If instead exogenous variables are included in the model, then the iterative forecasting procedure would require Y_t (which is observed) and X_{t+1} for the exogenous variables (which is not observed). This would require the researcher to separately forecast $\hat{X}_{t+1}$. In principle, this can be done either by means of an auxiliary model, or by taking external forecasts, for example from international organizations or consensus. While both methods could increase forecast accuracy, they could also decrease it when the forecasts for the exogenous variables are inaccurate. As a third option, direct forecasting (based on the projection method) could be used. Unfortunately, the panelvar package in its current form does not support the direct forecasting approach due to problems with the estimation of the underlying regression model with lagged variables.

12.1.3 EXAMPLE CODE FOR ESTIMATION

The following excerpt is directly taken from the helpfile of the package.

```
data('Dahlberg')
ex1_dahlberg_data <- pvargmm(dependent_vars = c('expenditures', 'revenues', 'grants'),
                             lags = 1,
                             transformation = 'fod',
                             data = Dahlberg,
                             panel_identifier=c('id', 'year'),
                             steps = c('twostep'),
                             system_instruments = FALSE,
                             max_instr_dependent_vars = 99,
                             max_instr_predet_vars = 99,
                             min_instr_dependent_vars = 2L,
                             min_instr_predet_vars = 1L,
                             collapse = FALSE
```

12.1.4 R CODE USED IN THIS PAPER

We have written many programs to produce the results for this paper. First, we have separate files for quarterly and monthly targets. Then, we have separate files for the standard models (Naive, AR, VAR) and for the pVAR models. In the pVAR models we have different (sub-) files for the out-of-sample forecasting using the GMM estimation from the ‘panelvar’ model and for the OLS estimation. We also have different files with the functions which produce the figures with the density forecasts as well as the output tables (i.e. results post-processing files).

For all the above reasons, instead of putting our code into a separate Annex, we will share all files (programs and data) with Eurostat so that all researchers could replicate and extend this research.

13 Tables

Model legend	Summary description of the model
Naive	Value of the last period
AR(1)	Autoregressive model, P=1 (Benchmark)
LR-MF-T1	Linear Regression using Macro/Finance predictors (avg)
LR-G-T1	Linear Regression using Google predictors (avg)
LR-MFG-T1	Linear Regression using Macro/Finance & Google predictors (avg)
LR-MF-T2	Linear Regression using Macro/Finance predictors (UMIDAS)
LR-G-T2	Linear Regression using Google predictors (UMIDAS)
LR-MFG-T2	Linear Regression using Macro/Finance & Google predictors (UMIDAS)
AR(1)-MF-T1	Linear Regression using the first lag of y, Macro/Finance predictors (avg)
AR(1)-G-T1	Linear Regression using the first lag of y, Google predictors (avg)
AR(1)-MFG-T1	Linear Regression using the first lag of y, Macro/Finance & Google predictors (avg)
AR(1)-MFG-T2	Linear Regression using the first lag of y, Macro/Finance & Google predictors (UMIDAS)
VAR(1)	Vector Autoregressive model, P=1
VARX(1)-MF-T1	Vector Autoregressive model, P=1 with Macro/Finance predictors (avg) as exogenous
VARX(1)-G-T1	Vector Autoregressive model, P=1 with Google predictors (avg) as exogenous
VARX(1)-MFG-T1	Vector Autoregressive model, P=1 with Macro/Finance & Google predictors (avg) as exogenous
VARX(1)-MFG-T2	Vector Autoregressive model, P=1 with Macro/Finance & Google predictors (UMIDAS) as exogenous
PVAR(1)-GMM	Panel Vector Autoregression, P=1, GMM Country Fixed-Effects estimation
PVAR(1)-OLSCFE	Panel Vector Autoregression, P=1, simple OLS Country Fixed-Effects estimation
PVARX(1)-OLSCFE-MF-T1	Panel Vector Autoregression, P=1, simple OLS Country Fixed-Effects estimation, with Macro/Finance predictors (avg) as exogenous
PVARX(1)-OLSCFE-G-T1	Panel Vector Autoregression, P=1, simple OLS Country Fixed-Effects estimation, with Google predictors (avg) as exogenous
PVARX(1)-OLSCFE-MFG-T1	Panel Vector Autoregression, P=1, simple OLS Country Fixed-Effects estimation, with Macro/Finance & Google predictors as exogenous
PVARX(1)-OLSCFE-MF-T2	Panel Vector Autoregression, P=1, simple OLS Country Fixed-Effects estimation, with Macro/Finance predictors (UMIDAS) as exogenous
PVARX(1)-OLSCFE-G-T2	Panel Vector Autoregression, P=1, simple OLS Country Fixed-Effects estimation, with Google predictors (UMIDAS) as exogenous
PVARX(1)-OLSCFE-MFG-T2	Panel Vector Autoregression, P=1, simple OLS Country Fixed-Effects estimation, with Macro/Finance & Google predictors (UMIDAS) as exogenous

Table 1: Averages of relative MAE/RMSFE across forecasting horizons

	GDP								IP							
	DE		FR		IT		UK		DE		FR		IT		UK	
	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE
Naive	**0.992**	**0.990**	1.220	1.195	1.027	1.076	1.474	1.402	1.384	1.302	1.443	1.407	1.394	1.385	1.405	1.384
AR(1)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LR-MF-T1	0.965	0.945	0.962	0.919	0.994	1.076	1.028	1.020	1.007	1.023	1.016	1.026	1.008	0.999	1.011	1.012
LR-G-T1	1.065	1.112	0.950	0.903	1.049	1.064	1.053	1.052	0.995	0.989	1.002	0.999	1.001	0.993	1.002	1.005
LR-MFG-T1	1.013	1.046	0.993	0.944	1.058	1.143	1.106	1.091	1.048	1.070	1.035	1.046	1.013	1.001	1.019	1.019
LR-MF-T2	1.121	1.085	1.335	1.361	1.526	2.344	1.120	1.078	1.054	1.073	1.033	1.063	1.034	1.033	1.058	1.058
LR-G-T2	1.072	1.103	1.128	1.096	1.205	1.213	1.158	1.136	1.024	1.011	1.039	1.032	1.038	1.028	1.028	1.043
LR-MFG-T2	1.164	1.130	1.488	1.517	1.641	2.352	1.355	1.284	1.121	1.130	1.091	1.129	1.079	1.074	1.086	1.091
AR(1)-MF-T1	1.005	0.971	1.003	**0.983**	1.042	1.108	1.019	**0.993**	1.033	1.060	1.021	1.036	1.012	1.012	1.023	1.023
AR(1)-G-T1	1.092	1.147	1.031	1.031	1.078	1.077	1.060	1.046	1.019	1.015	1.007	1.008	1.003	1.003	1.010	1.010
AR(1)-MFG-T1	1.056	1.063	1.034	1.012	1.089	1.178	1.103	1.068	1.069	1.103	1.038	1.052	1.015	1.013	1.031	1.032
AR(1)-MF-T2	1.160	1.147	1.405	1.414	1.552	2.340	1.110	1.058	1.076	1.104	1.044	1.076	1.038	1.043	1.068	1.061
AR(1)-G-T2	1.103	1.167	1.196	1.296	1.257	1.274	1.153	1.144	1.049	1.034	1.045	1.045	1.041	1.046	1.046	1.056
AR(1)-MFG-T2	1.251	1.231	1.644	1.670	1.714	2.503	1.381	1.288	1.141	1.153	1.104	1.143	1.080	1.093	1.100	1.098
VAR(1)	1.137	1.168	1.136	1.175	1.660	2.162	1.083	1.089	1.026	1.045	1.080	1.112	1.060	1.085	1.029	1.049
VARX(1)-MF-T1	1.144	1.135	1.172	1.157	1.707	2.294	1.111	1.096	1.043	1.062	1.091	1.136	1.047	1.076	1.049	1.055
VARX(1)-G-T1	1.251	1.352	1.161	1.199	1.729	2.312	1.156	1.160	1.041	1.055	1.102	1.158	1.056	1.083	1.041	1.056
VARX(1)-MFG-T1	1.222	1.278	1.182	1.171	1.757	2.402	1.258	1.231	1.074	1.097	1.121	1.199	1.046	1.071	1.059	1.062
VARX(1)-MF-T2	1.350	1.401	1.502	1.522	1.752	2.366	1.197	1.135	1.088	1.111	1.108	1.171	1.085	1.119	1.102	1.110
VARX(1)-G-T2	1.229	1.345	1.300	1.388	1.604	2.022	1.297	1.284	1.063	1.064	1.148	1.204	1.093	1.125	1.090	1.114
VARX(1)-MFG-T2	1.372	1.496	1.614	1.690	2.104	2.896	1.512	1.398	1.152	1.162	1.186	1.294	1.133	1.170	1.170	1.193
PVAR(1)-GMM	1.906	1.690	1.460	1.370	1.288	1.307	1.505	1.463	**0.953**	**0.937**	**0.981**	**0.969**	**0.998**	1.020	**0.985**	**0.981**
PVAR(1)-OLSCFE	1.014	1.037	1.057	1.063	**0.967**	1.087	1.108	1.086	**0.988**	**0.985**	1.017	1.021	1.036	1.033	1.005	1.010
PVARX(1)-OLSCFE-MF-T1	**0.963**	**0.986**	1.064	1.065	1.038	1.197	1.105	1.076	1.007	1.000	1.044	1.043	1.029	1.024	1.019	1.018
PVARX(1)-OLSCFE-G-T1	1.020	1.041	1.104	1.100	**0.980**	1.115	1.101	1.086	**0.986**	**0.983**	1.018	1.022	1.031	1.027	1.010	1.014
PVARX(1)-OLSCFE-MFG-T1	**0.954**	**0.960**	1.099	1.090	1.067	1.243	1.102	1.077	1.005	**0.998**	1.048	1.046	1.025	1.016	1.023	1.022
PVARX(1)-OLSCFE-MF-T2	1.029	1.069	1.141	1.162	1.176	1.456	1.072	1.055	1.007	1.010	1.044	1.050	1.035	1.027	1.027	1.021
PVARX(1)-OLSCFE-G-T2	1.034	1.040	1.192	1.178	**0.995**	**1.095**	1.125	1.109	**0.993**	**0.984**	1.031	1.030	1.033	1.031	1.015	1.018
PVARX(1)-OLSCFE-MFG-T2	1.026	1.048	1.258	1.261	1.181	1.441	1.081	1.073	1.015	1.010	1.061	1.061	1.032	1.021	1.035	1.030

Table 1: Averages of relative MAE/RMSFE across forecasting horizons (continued)

	UNR								CPI							
	DE		FR		IT		UK		DE		FR		IT		UK	
	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE	MAE	RMSFE
Naive	**1.073**	**1.243**	1.020	1.056	1.540	1.493	1.108	1.171	1.415	1.402	1.214	1.190	1.262	1.272	1.260	1.232
AR(1)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LR-MF-T1	1.173	1.364	1.042	0.996	1.037	1.038	1.036	1.043	1.020	1.013	1.020	1.012	1.011	1.020	1.007	1.013
LR-G-T1	1.096	1.117	1.116	1.077	1.027	1.036	1.040	1.042	1.024	1.022	1.005	0.998	1.011	1.016	0.998	0.986
LR-MFG-T1	1.269	1.421	1.064	1.017	1.031	1.037	1.049	1.053	1.043	1.040	1.023	1.010	1.016	1.024	1.004	0.998
LR-MF-T2	1.256	1.524	1.071	1.038	1.059	1.067	1.060	1.070	1.048	1.074	1.032	1.021	1.047	1.051	1.026	1.045
LR-G-T2	1.108	1.150	1.134	1.096	1.026	1.039	1.044	1.059	1.030	1.039	1.004	0.997	1.016	1.025	0.955	0.935
LR-MFG-T2	1.386	1.598	1.112	1.072	1.069	1.080	1.083	1.100	1.099	1.141	1.026	1.023	1.057	1.062	0.983	0.987
AR(1)-MF-T1	1.117	1.252	0.957	**0.946**	1.007	1.005	1.006	**0.998**	1.029	1.023	1.008	1.008	1.014	1.015	1.004	1.012
AR(1)-G-T1	1.080	1.100	1.024	1.013	0.999	1.001	1.012	1.014	1.027	1.026	0.997	0.996	1.008	1.005	0.992	0.985
AR(1)-MFG-T1	1.239	1.367	0.979	0.963	1.002	1.004	1.018	1.013	1.060	1.060	1.012	1.005	1.017	1.018	0.999	0.995
AR(1)-MF-T2	1.197	1.412	0.995	0.997	1.025	1.033	1.040	1.028	1.060	1.093	1.022	1.018	1.063	1.056	1.035	1.051
AR(1)-G-T2	1.094	1.128	1.054	1.035	0.997	1.003	1.024	1.037	1.041	1.047	0.993	0.996	1.015	1.013	0.963	0.942
AR(1)-MFG-T2	1.354	1.552	1.044	1.035	1.040	1.048	1.065	1.069	1.116	1.169	1.011	1.018	1.065	1.062	0.996	0.999
VAR(1)	0.992	1.007	1.010	0.998	1.014	1.013	1.006	1.006	1.050	1.065	1.044	1.047	1.051	1.058	1.073	1.128
VARX(1)-MF-T1	1.154	1.303	0.959	0.944	1.024	1.019	1.007	1.002	1.093	1.121	1.044	1.048	1.077	1.099	1.088	1.157
VARX(1)-G-T1	1.091	1.118	1.035	1.010	1.011	1.015	1.019	1.021	1.058	1.069	1.037	1.036	1.060	1.068	1.070	1.125
VARX(1)-MFG-T1	1.262	1.410	0.983	0.962	1.018	1.018	1.020	1.017	1.098	1.127	1.036	1.033	1.087	1.111	1.087	1.154
VARX(1)-MF-T2	1.226	1.464	1.002	0.998	1.043	1.051	1.045	1.035	1.124	1.178	1.060	1.073	1.115	1.136	1.145	1.280
VARX(1)-G-T2	1.104	1.145	1.060	1.031	1.010	1.019	1.032	1.047	1.081	1.106	1.033	1.034	1.059	1.066	1.060	1.195
VARX(1)-MFG-T2	1.378	1.604	1.054	1.042	1.064	1.070	1.070	1.074	1.143	1.215	1.047	1.062	1.118	1.144	1.120	1.311
PVAR(1)-GMM	0.825	1.018	0.992	0.979	1.023	1.029	0.919	0.988	**1.193**	**1.154**	**1.061**	**1.033**	**1.166**	1.148	**1.214**	**1.131**
PVAR(1)-OLSCFE	0.982	0.981	1.011	0.978	**1.001**	1.001	0.978	0.978	**1.066**	**1.084**	1.009	1.010	1.062	1.068	1.008	1.006
PVARX(1)-OLSCFE-MF-T1	**1.013**	**1.025**	1.003	0.967	1.015	1.011	0.976	0.983	1.085	1.104	1.015	1.016	1.066	1.077	1.009	1.008
PVARX(1)-OLSCFE-G-T1	0.981	0.985	1.031	0.997	**1.001**	0.998	0.991	0.989	**1.082**	**1.092**	1.006	1.006	1.059	1.065	1.000	0.994
PVARX(1)-OLSCFE-MFG-T1	**1.016**	**1.031**	1.031	0.994	1.014	1.009	0.988	0.994	1.099	**1.113**	1.012	1.011	1.069	1.073	1.002	0.996
PVARX(1)-OLSCFE-MF-T2	1.022	1.037	1.014	0.989	1.019	1.015	1.000	1.006	1.096	1.130	1.005	1.012	1.094	1.111	1.014	1.017
PVARX(1)-OLSCFE-G-T2	0.989	0.998	1.061	1.006	**0.997**	**0.995**	0.986	0.989	**1.080**	**1.092**	0.984	0.991	1.059	1.065	0.983	0.967
PVARX(1)-OLSCFE-MFG-T2	1.034	1.057	1.066	1.020	1.014	1.008	1.004	1.013	1.111	1.142	0.985	0.995	1.095	1.103	0.988	0.981

Table 2: **Absolute distance of average coverage rates across forecasting horizons from nominal levels**

	GDP								IP							
	DE		FR		IT		UK		DE		FR		IT		UK	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.252	0.100	0.159	0.066	0.216	0.100	**0.009**	**0.009**	0.127	0.092	0.113	0.088	0.148	0.158	0.104	0.086
AR(1)	0.278	0.100	0.245	0.092	0.311	0.100	0.144	0.076	0.053	**0.003**	0.082	0.049	**0.000**	0.031	0.059	0.014
LR-MF-T1	0.262	0.100	0.262	0.092	0.253	0.083	0.169	0.067	0.036	**0.003**	0.083	0.038	**0.000**	0.027	0.032	0.010
LR-G-T1	0.253	0.092	0.270	0.100	0.285	0.100	0.176	0.058	0.061	**0.000**	0.100	0.049	0.024	0.029	0.040	0.023
LR-MFG-T1	0.212	0.092	0.237	0.084	0.219	0.092	0.117	0.050	0.018	0.021	0.083	0.040	0.011	0.029	0.033	**0.006**
LR-MF-T2	0.121	0.076	0.067	0.023	0.149	0.040	0.084	0.049	0.012	0.017	0.075	0.030	0.014	0.051	0.018	0.015
LR-G-T2	0.260	0.092	0.209	0.100	0.209	0.083	0.065	0.032	0.028	0.013	0.022	0.026	0.005	0.060	0.047	0.000
LR-MFG-T2	0.128	0.058	0.020	0.013	0.115	0.018	0.029	0.063	0.031	0.054	0.017	**0.005**	0.031	0.086	0.005	0.011
AR(1)-MF-T1	0.262	0.100	0.245	0.084	0.252	0.083	0.111	0.067	0.042	0.023	0.077	0.039	0.010	0.027	0.052	**0.008**
AR(1)-G-T1	0.261	0.092	0.228	0.092	0.277	0.100	0.117	0.058	0.042	**0.009**	0.088	0.047	0.012	0.033	0.059	**0.008**
AR(1)-MFG-T1	0.229	0.092	0.229	0.076	0.235	0.083	0.101	0.050	0.028	0.030	0.073	0.038	**0.006**	0.029	0.048	**0.008**
AR(1)-MF-T2	0.138	0.042	0.075	**0.006**	0.133	0.032	0.068	0.051	**0.008**	0.023	0.068	0.032	0.014	0.045	0.020	**0.007**
AR(1)-G-T2	0.225	0.083	0.184	0.066	0.175	0.083	0.023	0.023	0.022	0.027	0.023	0.024	**0.004**	0.068	0.018	0.003
AR(1)-MFG-T2	0.103	0.017	0.037	0.038	0.072	0.027	0.097	0.054	0.046	0.060	**0.005**	**0.005**	0.051	0.098	0.019	0.017
VAR(1)	0.210	0.074	0.175	0.067	0.105	**0.005**	0.127	0.026	0.049	0.017	0.061	0.030	**0.002**	0.049	0.028	**0.002**
VARX(1)-MF-T1	0.136	0.066	0.134	0.076	0.073	0.014	0.069	0.017	0.018	0.031	0.050	0.024	0.010	0.051	0.036	0.011
VARX(1)-G-T1	0.176	0.066	0.168	0.067	0.080	**0.005**	0.118	0.025	0.041	0.021	0.053	0.028	0.014	0.049	0.034	**0.002**
VARX(1)-MFG-T1	0.110	0.066	0.143	0.076	0.089	**0.004**	**0.009**	0.017	**0.000**	0.045	0.038	0.024	**0.008**	0.053	0.023	**0.009**
VARX(1)-MF-T2	0.054	0.043	**0.010**	0.055	0.022	0.020	0.025	0.026	**0.004**	0.047	0.042	0.026	0.041	0.068	**0.002**	0.019
VARX(1)-G-T2	0.159	0.066	0.107	0.049	0.046	**0.005**	0.014	**0.010**	**0.003**	0.043	**0.002**	**0.003**	0.025	0.068	**0.003**	0.023
VARX(1)-MFG-T2	0.010	0.034	0.079	0.113	0.086	0.087	0.199	0.096	0.050	0.080	0.015	0.001	0.055	0.108	0.048	0.038
PVAR(1)-GMM	0.225	0.037	0.079	0.038	0.253	0.075	0.052	0.045	**0.005**	0.019	0.024	0.029	0.015	0.049	0.025	**0.004**
PVAR(1)-OLSCFE	0.269	0.091	0.244	0.076	0.276	0.082	0.153	0.075	0.073	**0.000**	0.098	0.053	0.019	0.025	0.057	0.027
PVARX(1)-OLSCFE-MF-T1	0.260	0.083	0.228	0.076	0.226	0.082	0.144	0.075	0.046	**0.009**	0.069	0.045	0.010	0.023	0.058	0.020
PVARX(1)-OLSCFE-G-T1	0.260	0.083	0.227	0.076	0.285	0.082	0.145	0.083	0.081	**0.002**	0.096	0.053	0.021	0.021	0.063	0.026
PVARX(1)-OLSCFE-MFG-T1	0.261	0.092	0.210	0.076	0.243	0.082	0.127	0.075	0.052	**0.007**	0.063	0.040	0.016	0.021	0.066	0.022
PVARX(1)-OLSCFE-MF-T2	0.252	0.083	0.176	0.067	0.226	0.048	0.135	0.075	0.055	0.011	0.077	0.047	0.010	0.023	0.081	0.022
PVARX(1)-OLSCFE-G-T2	0.260	0.100	0.177	0.084	0.276	0.082	0.144	0.067	0.071	**0.006**	0.076	0.051	**0.006**	0.023	0.074	0.031
PVARX(1)-OLSCFE-MFG-T2	0.244	0.091	0.142	0.067	0.217	0.048	0.160	0.075	0.059	**0.007**	0.055	0.051	**0.002**	0.028	0.089	0.020

Table 2: Absolute distance of average coverage rates across forecasting horizons from nominal levels (continued)

	UNR								CPI							
	DE		FR		IT		UK		DE		FR		IT		UK	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.238	0.083	0.039	0.045	0.285	0.227	**0.006**	0.158	0.183	0.100	0.157	0.133	0.213	0.195	0.088	0.089
AR(1)	0.233	0.085	0.057	0.018	0.047	0.049	0.072	0.087	0.032	0.010	0.084	0.049	0.117	0.100	0.047	0.027
LR-MF-T1	0.212	0.056	0.052	0.012	0.049	0.061	0.109	0.086	0.033	**0.000**	0.106	0.048	0.141	0.114	0.030	0.018
LR-G-T1	0.222	0.079	0.059	0.016	0.052	0.061	0.076	0.067	0.041	**0.004**	0.092	0.053	0.121	0.092	0.014	0.025
LR-MFG-T1	0.186	0.048	0.037	0.019	0.059	0.053	0.106	0.090	0.032	0.012	0.108	0.068	0.145	0.114	0.020	0.029
LR-MF-T2	0.190	0.052	0.017	0.016	0.078	0.076	0.115	0.121	0.025	0.014	0.117	0.088	0.143	0.132	**0.002**	0.051
LR-G-T2	0.209	0.073	0.038	0.033	0.066	0.078	0.106	0.083	0.028	**0.008**	0.086	0.068	0.154	0.096	**0.000**	0.014
LR-MFG-T2	0.141	0.027	0.026	0.043	0.107	0.097	0.132	0.151	0.011	0.037	0.118	0.112	0.181	0.153	0.023	0.037
AR(1)-MF-T1	0.198	0.056	0.042	0.016	0.051	0.051	0.077	0.105	0.018	**0.004**	0.091	0.051	0.140	0.112	0.032	0.031
AR(1)-G-T1	0.217	0.075	0.022	0.025	0.029	0.051	0.065	0.089	0.020	**0.002**	0.088	0.047	0.124	0.104	0.026	0.020
AR(1)-MFG-T1	0.178	0.054	0.019	0.026	0.050	0.047	0.073	0.105	**0.005**	0.010	0.094	0.059	0.143	0.118	0.016	0.028
AR(1)-MF-T2	0.186	0.052	0.022	0.025	0.071	0.066	0.116	0.142	0.020	**0.008**	0.116	0.092	0.152	0.141	**0.007**	0.055
AR(1)-G-T2	0.199	0.070	**0.000**	0.051	0.087	0.061	0.085	0.101	0.010	0.012	0.080	0.065	0.168	0.114	**0.002**	0.014
AR(1)-MFG-T2	0.133	0.023	0.014	0.053	0.098	0.095	0.134	0.155	**0.005**	0.045	0.107	0.118	0.192	0.161	0.025	0.065
VAR(1)	0.233	0.083	0.033	0.025	0.062	0.063	0.095	0.105	0.015	0.019	0.104	0.074	0.148	0.132	0.016	0.049
VARX(1)-MF-T1	0.202	0.052	0.019	0.014	0.074	0.061	0.107	0.120	**0.000**	0.031	0.101	0.084	0.154	0.140	**0.004**	0.060
VARX(1)-G-T1	0.203	0.077	0.012	0.031	0.064	0.055	0.095	0.105	0.011	0.014	0.100	0.078	0.152	0.130	**0.003**	0.053
VARX(1)-MFG-T1	0.174	0.054	0.013	0.025	0.074	0.053	0.109	0.117	**0.007**	0.023	0.109	0.081	0.153	0.141	**0.009**	0.059
VARX(1)-MF-T2	0.187	0.043	**0.006**	0.021	0.090	0.082	0.117	0.146	**0.000**	0.043	0.116	0.114	0.172	0.154	0.048	0.088
VARX(1)-G-T2	0.186	0.066	**0.006**	0.051	0.095	0.078	0.107	0.113	**0.008**	0.033	0.107	0.085	0.177	0.137	0.025	0.051
VARX(1)-MFG-T2	0.120	0.017	0.026	0.054	0.134	0.110	0.134	0.158	**0.007**	0.057	0.142	0.145	0.184	0.184	0.074	0.090
PVAR(1)-GMM	0.259	0.100	0.086	**0.004**	0.084	0.039	0.132	0.078	0.157	0.018	0.099	0.083	0.168	0.184	0.130	0.084
PVAR(1)-OLSCFE	0.250	0.094	**0.002**	0.038	**0.007**	0.027	0.103	0.093	0.011	**0.002**	0.071	0.051	0.109	0.103	0.045	0.024
PVARX(1)-OLSCFE-MF-T1	0.234	0.087	0.017	0.037	0.016	0.031	0.089	0.093	**0.008**	0.014	0.079	0.055	0.103	0.116	0.036	0.033
PVARX(1)-OLSCFE-G-T1	0.248	0.092	**0.004**	0.034	**0.001**	0.029	0.110	0.098	**0.006**	**0.008**	0.079	0.047	0.111	0.107	0.034	0.023
PVARX(1)-OLSCFE-MFG-T1	0.236	0.087	0.013	0.050	**0.006**	0.027	0.092	0.089	**0.003**	0.015	0.081	0.054	0.109	0.111	0.034	0.025
PVARX(1)-OLSCFE-MF-T2	0.240	0.089	0.021	0.041	0.016	0.038	0.091	0.089	0.030	0.013	0.073	0.047	0.124	0.097	0.032	0.029
PVARX(1)-OLSCFE-G-T2	0.240	0.092	0.012	0.027	0.010	0.019	0.089	0.095	0.018	**0.001**	0.051	0.041	0.103	0.090	0.039	0.012
PVARX(1)-OLSCFE-MFG-T2	0.230	0.089	0.046	0.048	0.020	0.035	0.075	0.076	0.027	**0.001**	0.063	0.048	0.129	0.099	0.051	0.021

Table 3: GDP Growth, DE

	h=1					h=2					h=3					h=4				
	MAE	**RMSFE**	**SSR**	**DM1**	**DM2**	**MAE**	**RMSFE**	**SSR**	**DM1**	**DM2**	**MAE**	**RMSFE**	**SSR**	**DM1**	**DM2**	**MAE**	**RMSFE**	**SSR**	**DM1**	**DM2**
Naive	0.967	0.985	0.433	0.859	0.928	1.008	0.980	0.414	0.975	0.930	0.829	0.850	0.607	0.505	0.618	1.166	1.145	0.370	0.522	0.592
AR(1)	1.000	1.000	0.367	:	:	1.000	1.000	0.724	:	:	1.000	1.000	0.643	:	:	1.000	1.000	0.481	:	:
LR-MF-T1	1.039	0.946	0.433	0.721	0.461	0.950	0.922	0.586	0.523	0.308	0.916	0.923	0.607	0.391	0.462	0.956	0.989	0.370	0.594	0.863
LR-G-T1	1.166	1.147	0.467	0.106	0.075	1.189	1.293	0.414	0.104	0.122	0.992	1.054	0.357	0.940	0.711	0.912	0.953	0.519	0.403	0.504
LR-MFG-T1	0.981	0.926	0.567	0.887	0.470	1.091	1.159	0.621	0.272	0.191	0.995	1.066	0.393	0.962	0.659	0.983	1.033	0.481	0.847	0.711
LR-MF-T2	1.153	1.091	0.333	0.389	0.529	1.207	1.096	0.621	0.232	0.525	1.230	1.177	0.464	0.076	0.025	0.896	0.977	0.444	0.240	0.438
LR-G-T2	1.004	1.025	0.733	0.965	0.726	1.171	1.268	0.379	0.088	0.120	1.087	1.065	0.500	0.574	0.738	1.025	1.053	0.370	0.882	0.689
LR-MFG-T2	1.090	1.025	0.400	0.595	0.864	1.326	1.232	0.621	0.014	0.000	1.294	1.207	0.571	0.154	0.226	0.945	1.055	0.444	0.763	0.695
AR(1)-MF-T1	1.032	0.925	0.400	0.785	0.407	0.994	0.980	0.414	0.952	0.851	0.993	0.970	0.536	0.933	0.687	1.001	1.009	0.481	0.935	0.019
AR(1)-G-T1	1.026	1.053	0.400	0.427	0.340	1.219	1.363	0.621	0.121	0.183	1.100	1.153	0.607	0.270	0.267	1.022	1.018	0.519	0.637	0.616
AR(1)-MFG-T1	1.001	0.921	0.567	0.996	0.460	1.183	1.303	0.414	0.112	0.107	1.053	1.036	0.643	0.294	0.286	0.986	0.992	0.519	0.856	0.905
AR(1)-MF-T2	1.142	1.089	0.367	0.411	0.532	1.300	1.217	0.552	0.114	0.196	1.262	1.247	0.464	0.000	0.162	0.936	1.035	0.556	0.302	0.738
AR(1)-G-T2	0.948	0.997	0.467	0.490	0.970	1.214	1.360	0.517	0.106	0.167	1.181	1.189	0.607	0.114	0.303	1.070	1.123	0.370	0.630	0.304
AR(1)-MFG-T2	1.123	1.051	0.400	0.462	0.722	1.511	1.495	0.621	0.000	0.004	1.388	1.283	0.571	0.040	0.035	0.981	1.095	0.407	0.910	0.445
VAR(1)	1.091	1.038	0.500	0.517	0.734	1.160	1.212	0.483	0.386	0.206	1.212	1.258	0.571	0.134	0.059	1.083	1.166	0.593	0.649	0.345
VARX(1)-MF-T1	0.994	0.938	0.567	0.968	0.596	1.222	1.177	0.379	0.224	0.170	1.253	1.241	0.536	0.214	0.094	1.108	1.184	0.593	0.576	0.313
VARX(1)-G-T1	1.129	1.132	0.567	0.383	0.412	1.428	1.614	0.552	0.032	0.144	1.317	1.454	0.571	0.056	0.159	1.130	1.209	0.593	0.505	0.217
VARX(1)-MFG-T1	0.992	0.949	0.467	0.958	0.648	1.424	1.565	0.483	0.038	0.132	1.311	1.354	0.571	0.163	0.091	1.159	1.244	0.556	0.454	0.170
VARX(1)-MF-T2	1.176	1.048	0.367	0.179	0.615	1.512	1.482	0.483	0.040	0.044	1.225	1.289	0.536	0.053	0.003	1.488	1.786	0.556	0.117	0.234
VARX(1)-G-T2	1.078	1.099	0.467	0.592	0.554	1.466	1.653	0.483	0.029	0.128	1.230	1.468	0.643	0.291	0.310	1.142	1.160	0.519	0.085	0.000
VARX(1)-MFG-T2	1.145	1.025	0.433	0.283	0.810	1.666	1.703	0.483	0.013	0.050	1.044	1.157	0.607	0.751	0.190	1.633	2.099	0.481	0.242	0.322
PVAR(1)-GMM	1.792	1.639	0.400	0.000	0.000	1.809	1.605	0.448	0.000	0.000	1.959	1.695	0.714	0.000	0.000	2.064	1.819	0.333	0.000	0.000
PVAR(1)-OLSCFE	0.996	0.949	0.500	0.959	0.441	1.111	1.080	0.448	0.093	0.115	0.940	1.044	0.571	0.569	0.798	1.010	1.074	0.593	0.938	0.516
PVARX(1)-OLSCFE-MF-T1	0.915	0.874	0.433	0.405	0.104	1.004	0.981	0.483	0.967	0.857	0.935	1.032	0.536	0.528	0.840	0.997	1.057	0.593	0.983	0.591
PVARX(1)-OLSCFE-G-T1	0.981	0.961	0.433	0.829	0.605	1.158	1.161	0.448	0.009	0.027	0.938	0.996	0.536	0.547	0.982	1.004	1.043	0.556	0.976	0.709
PVARX(1)-OLSCFE-MFG-T1	0.870	0.833	0.433	0.242	0.061	1.031	1.026	0.448	0.735	0.751	0.926	0.974	0.500	0.490	0.854	0.989	1.009	0.556	0.932	0.946
PVARX(1)-OLSCFE-MF-T2	0.903	0.883	0.433	0.349	0.128	1.073	1.103	0.414	0.311	0.141	0.994	1.077	0.536	0.943	0.496	1.145	1.213	0.593	0.228	0.174
PVARX(1)-OLSCFE-G-T2	1.026	0.976	0.533	0.792	0.774	1.147	1.152	0.379	0.016	0.011	0.917	0.972	0.571	0.519	0.853	1.044	1.059	0.556	0.731	0.634
PVARX(1)-OLSCFE-MFG-T2	0.929	0.868	0.467	0.558	0.179	1.116	1.147	0.448	0.258	0.187	0.928	0.984	0.464	0.517	0.881	1.133	1.194	0.519	0.052	0.058

Table 4: GDP Growth, FR

	h=1					h=2					h=3					h=4				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.277	1.211	0.233	0.070	0.090	1.125	1.110	0.586	0.466	0.487	1.112	1.142	0.571	0.608	0.517	1.366	1.319	0.370	0.127	0.125
AR(1)	1.000	1.000	0.500	:	:	1.000	1.000	0.586	:	:	1.000	1.000	0.464	:	:	1.000	1.000	0.519	:	:
LR-MF-T1	0.990	0.920	0.533	0.936	0.583	0.984	0.956	0.448	0.905	0.734	0.914	0.839	0.643	0.412	0.359	0.960	0.963	0.593	0.096	0.116
LR-G-T1	0.950	0.867	0.567	0.663	0.411	0.932	0.931	0.448	0.542	0.537	0.919	0.843	0.607	0.444	0.383	1.000	0.973	0.407	0.998	0.793
LR-MFG-T1	1.021	0.963	0.433	0.877	0.817	1.004	0.962	0.414	0.976	0.769	0.933	0.850	0.607	0.517	0.385	1.013	1.000	0.556	0.782	1.000
LR-MF-T2	1.101	1.009	0.533	0.565	0.965	1.314	1.377	0.552	0.206	0.135	1.270	1.309	0.464	0.238	0.225	1.656	1.751	0.556	0.007	0.113
LR-G-T2	1.065	0.994	0.600	0.428	0.922	1.216	1.209	0.414	0.000	0.001	1.017	0.911	0.607	0.867	0.545	1.216	1.269	0.296	0.167	0.047
LR-MFG-T2	1.181	1.144	0.400	0.362	0.529	1.432	1.481	0.483	0.158	0.117	1.427	1.372	0.607	0.033	0.091	1.911	2.071	0.370	0.016	0.087
AR(1)-MF-T1	1.001	0.957	0.567	0.990	0.621	1.021	0.984	0.414	0.837	0.877	1.016	1.015	0.679	0.273	0.399	0.976	0.978	0.630	0.462	0.189
AR(1)-G-T1	1.033	1.038	0.533	0.070	0.028	1.013	1.036	0.517	0.867	0.619	1.016	1.007	0.536	0.492	0.670	1.062	1.045	0.333	0.027	0.170
AR(1)-MFG-T1	1.028	1.003	0.533	0.791	0.975	1.047	1.001	0.414	0.610	0.994	1.030	1.022	0.679	0.289	0.352	1.032	1.021	0.556	0.395	0.553
AR(1)-MF-T2	1.198	1.099	0.467	0.225	0.572	1.295	1.346	0.483	0.248	0.176	1.411	1.412	0.536	0.024	0.060	1.714	1.797	0.481	0.003	0.100
AR(1)-G-T2	1.128	1.227	0.567	0.063	0.203	1.181	1.277	0.414	0.033	0.123	1.132	1.144	0.607	0.091	0.224	1.345	1.538	0.296	0.179	0.226
AR(1)-MFG-T2	1.340	1.238	0.400	0.046	0.140	1.476	1.507	0.483	0.095	0.082	1.699	1.650	0.571	0.000	0.015	2.063	2.285	0.333	0.010	0.045
VAR(1)	1.039	1.133	0.567	0.574	0.279	1.140	1.233	0.517	0.066	0.086	1.201	1.200	0.464	0.086	0.025	1.163	1.135	0.556	0.277	0.300
VARX(1)-MF-T1	1.148	1.108	0.567	0.189	0.129	1.226	1.226	0.483	0.031	0.017	1.171	1.173	0.464	0.286	0.229	1.142	1.120	0.593	0.286	0.317
VARX(1)-G-T1	1.082	1.173	0.600	0.268	0.218	1.164	1.262	0.448	0.136	0.111	1.205	1.205	0.464	0.087	0.042	1.192	1.156	0.593	0.220	0.295
VARX(1)-MFG-T1	1.194	1.142	0.600	0.086	0.076	1.193	1.227	0.414	0.095	0.006	1.180	1.174	0.464	0.266	0.243	1.163	1.140	0.630	0.247	0.309
VARX(1)-MF-T2	1.248	1.180	0.467	0.151	0.263	1.422	1.449	0.552	0.063	0.073	1.477	1.502	0.500	0.012	0.071	1.862	1.958	0.593	0.009	0.035
VARX(1)-G-T2	1.206	1.360	0.633	0.086	0.197	1.207	1.382	0.379	0.111	0.136	1.358	1.290	0.464	0.035	0.056	1.429	1.522	0.333	0.004	0.082
VARX(1)-MFG-T2	1.393	1.280	0.467	0.039	0.168	1.494	1.620	0.517	0.071	0.100	1.776	1.785	0.464	0.012	0.030	1.793	2.074	0.259	0.062	0.113
PVAR(1)-GMM	1.491	1.378	0.200	0.014	0.004	1.355	1.327	0.552	0.031	0.023	1.437	1.301	0.571	0.016	0.051	1.558	1.475	0.333	0.050	0.014
PVAR(1)-OLSCFE	0.994	1.009	0.567	0.949	0.880	1.125	1.187	0.483	0.392	0.183	1.086	1.023	0.500	0.592	0.895	1.021	1.033	0.667	0.866	0.753
PVARX(1)-OLSCFE-MF-T1	1.032	1.010	0.567	0.725	0.867	1.118	1.183	0.448	0.450	0.213	1.061	1.008	0.500	0.723	0.964	1.045	1.059	0.556	0.686	0.532
PVARX(1)-OLSCFE-G-T1	1.013	1.031	0.567	0.885	0.600	1.142	1.194	0.448	0.274	0.132	1.135	1.065	0.464	0.486	0.739	1.124	1.109	0.630	0.390	0.458
PVARX(1)-OLSCFE-MFG-T1	1.039	1.006	0.567	0.670	0.934	1.102	1.175	0.448	0.483	0.217	1.110	1.046	0.464	0.600	0.822	1.144	1.132	0.519	0.301	0.338
PVARX(1)-OLSCFE-MF-T2	1.034	0.986	0.567	0.735	0.875	1.252	1.378	0.414	0.157	0.088	1.111	1.050	0.571	0.541	0.808	1.168	1.234	0.519	0.020	0.098
PVARX(1)-OLSCFE-G-T2	1.119	1.092	0.567	0.362	0.449	1.235	1.329	0.379	0.056	0.006	1.180	1.083	0.571	0.030	0.518	1.233	1.205	0.481	0.021	0.036
PVARX(1)-OLSCFE-MFG-T2	1.098	1.038	0.600	0.577	0.858	1.345	1.466	0.345	0.047	0.031	1.214	1.135	0.607	0.058	0.429	1.377	1.405	0.444	0.000	0.011

Table 5: GDP Growth, IT

	h=1					h=2					h=3					h=4				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	0.843	1.012	0.467	0.306	0.938	0.896	0.943	0.483	0.692	0.797	1.038	1.093	0.464	0.863	0.591	1.331	1.255	0.407	0.246	0.258
AR(1)	1.000	1.000	0.467	:	:	1.000	1.000	0.483	:	:	1.000	1.000	0.464	:	:	1.000	1.000	0.333	:	:
LR-MF-T1	1.119	1.304	0.367	0.421	0.155	0.968	1.028	0.690	0.724	0.795	0.869	0.952	0.714	0.197	0.746	1.019	1.021	0.556	0.769	0.787
LR-G-T1	1.079	1.185	0.400	0.485	0.127	1.001	0.957	0.517	0.987	0.379	1.106	1.068	0.500	0.398	0.621	1.010	1.044	0.519	0.914	0.665
LR-MFG-T1	1.185	1.425	0.367	0.259	0.068	1.020	1.042	0.621	0.797	0.514	0.990	1.033	0.679	0.939	0.817	1.038	1.072	0.481	0.732	0.576
LR-MF-T2	1.431	1.990	0.500	0.160	0.206	1.678	3.028	0.724	0.233	0.283	1.454	2.510	0.571	0.271	0.309	1.540	1.847	0.704	0.209	0.282
LR-G-T2	1.226	1.289	0.500	0.146	0.087	1.154	1.206	0.621	0.262	0.032	1.185	1.179	0.536	0.154	0.248	1.255	1.179	0.481	0.017	0.094
LR-MFG-T2	1.561	2.436	0.467	0.174	0.208	1.777	2.708	0.621	0.069	0.236	1.598	2.436	0.679	0.206	0.303	1.628	1.828	0.593	0.107	0.199
AR(1)-MF-T1	1.069	1.140	0.367	0.392	0.204	1.100	1.167	0.586	0.156	0.257	0.909	1.057	0.607	0.000	0.692	1.090	1.069	0.444	0.024	0.253
AR(1)-G-T1	1.050	1.094	0.433	0.416	0.254	1.038	1.001	0.483	0.233	0.945	1.149	1.132	0.429	0.289	0.442	1.075	1.081	0.333	0.167	0.247
AR(1)-MFG-T1	1.120	1.291	0.400	0.334	0.086	1.132	1.186	0.552	0.022	0.135	0.962	1.107	0.571	0.754	0.411	1.141	1.128	0.407	0.055	0.240
AR(1)-MF-T2	1.241	1.736	0.367	0.359	0.233	1.817	3.195	0.690	0.160	0.259	1.511	2.477	0.571	0.237	0.291	1.637	1.951	0.704	0.172	0.280
AR(1)-G-T2	1.162	1.204	0.467	0.228	0.144	1.273	1.384	0.621	0.090	0.044	1.239	1.239	0.429	0.084	0.205	1.353	1.270	0.370	0.002	0.002
AR(1)-MFG-T2	1.456	2.467	0.433	0.291	0.246	1.902	2.898	0.621	0.041	0.205	1.738	2.636	0.536	0.027	0.236	1.759	2.013	0.556	0.148	0.229
VAR(1)	1.037	1.095	0.333	0.660	0.374	1.637	2.039	0.448	0.148	0.236	1.783	2.123	0.607	0.089	0.220	2.184	3.389	0.519	0.331	0.309
VARX(1)-MF-T1	1.267	1.519	0.333	0.131	0.135	1.280	1.521	0.586	0.336	0.239	2.127	2.915	0.607	0.147	0.272	2.155	3.223	0.481	0.313	0.304
VARX(1)-G-T1	1.102	1.176	0.367	0.302	0.137	1.671	2.147	0.448	0.162	0.247	1.937	2.503	0.607	0.118	0.244	2.206	3.422	0.630	0.326	0.306
VARX(1)-MFG-T1	1.326	1.577	0.300	0.071	0.065	1.298	1.559	0.552	0.336	0.239	2.236	3.211	0.607	0.165	0.277	2.166	3.259	0.519	0.314	0.301
VARX(1)-MF-T2	1.202	1.693	0.400	0.439	0.182	1.817	2.521	0.621	0.026	0.134	2.127	2.746	0.679	0.091	0.227	1.862	2.505	0.593	0.261	0.292
VARX(1)-G-T2	1.118	1.247	0.533	0.472	0.169	1.269	1.609	0.517	0.435	0.288	2.071	2.554	0.643	0.063	0.224	1.957	2.677	0.370	0.273	0.298
VARX(1)-MFG-T2	2.011	2.759	0.400	0.021	0.081	1.907	2.611	0.517	0.012	0.120	2.335	3.067	0.643	0.037	0.147	2.163	3.148	0.593	0.246	0.280
PVAR(1)-GMM	1.372	1.671	0.333	0.071	0.157	1.208	1.240	0.448	0.141	0.276	1.258	1.178	0.393	0.100	0.091	1.316	1.139	0.593	0.115	0.363
PVAR(1)-OLSCFE	0.988	1.029	0.333	0.877	0.723	0.727	0.756	0.517	0.062	0.092	0.868	0.937	0.571	0.202	0.376	1.285	1.624	0.481	0.535	0.357
PVARX(1)-OLSCFE-MF-T1	1.157	1.270	0.300	0.177	0.075	0.793	0.850	0.483	0.112	0.178	0.847	0.961	0.607	0.168	0.677	1.356	1.707	0.519	0.469	0.339
PVARX(1)-OLSCFE-G-T1	0.996	1.033	0.367	0.953	0.684	0.740	0.767	0.483	0.068	0.091	0.867	0.958	0.571	0.185	0.631	1.319	1.703	0.481	0.525	0.358
PVARX(1)-OLSCFE-MFG-T1	1.186	1.309	0.333	0.129	0.061	0.807	0.856	0.483	0.124	0.163	0.868	1.000	0.571	0.231	0.999	1.407	1.807	0.556	0.448	0.339
PVARX(1)-OLSCFE-MF-T2	1.295	1.522	0.333	0.064	0.082	0.928	1.208	0.448	0.729	0.579	1.004	1.157	0.571	0.982	0.552	1.478	1.936	0.556	0.467	0.336
PVARX(1)-OLSCFE-G-T2	0.952	1.010	0.300	0.597	0.910	0.797	0.870	0.517	0.141	0.048	0.932	0.996	0.643	0.508	0.967	1.298	1.506	0.481	0.430	0.344
PVARX(1)-OLSCFE-MFG-T2	1.227	1.419	0.300	0.116	0.051	1.007	1.306	0.517	0.972	0.431	1.005	1.191	0.643	0.973	0.454	1.483	1.848	0.519	0.408	0.325

Table 6: GDP Growth, UK

	h=1					h=2					h=3					h=4				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.357	1.376	0.400	0.029	0.054	1.741	1.648	0.276	0.000	0.000	1.189	1.150	0.750	0.435	0.471	1.611	1.435	0.556	0.003	0.049
AR(1)	1.000	1.000	0.300	:	:	1.000	1.000	0.759	:	:	1.000	1.000	0.607	:	:	1.000	1.000	0.778	:	:
LR-MF-T1	0.906	0.899	0.400	0.315	0.209	1.073	1.074	0.379	0.179	0.113	1.007	0.980	0.714	0.781	0.372	1.124	1.127	0.481	0.253	0.004
LR-G-T1	0.855	0.893	0.233	0.024	0.022	1.088	1.088	0.517	0.281	0.216	1.093	1.080	0.571	0.214	0.202	1.175	1.147	0.556	0.335	0.288
LR-MFG-T1	0.910	0.928	0.433	0.341	0.404	1.155	1.144	0.448	0.072	0.077	1.118	1.079	0.500	0.158	0.391	1.243	1.213	0.556	0.202	0.128
LR-MF-T2	0.869	0.885	0.433	0.175	0.175	1.190	1.176	0.276	0.032	0.021	1.170	1.068	0.607	0.174	0.488	1.250	1.182	0.556	0.180	0.093
LR-G-T2	0.865	0.906	0.533	0.030	0.029	1.147	1.138	0.483	0.025	0.036	1.266	1.227	0.429	0.062	0.093	1.353	1.273	0.481	0.096	0.102
LR-MFG-T2	0.950	0.985	0.467	0.648	0.859	1.369	1.325	0.483	0.000	0.001	1.526	1.352	0.321	0.000	0.006	1.575	1.474	0.481	0.055	0.058
AR(1)-MF-T1	1.024	0.992	0.367	0.734	0.899	1.055	1.034	0.655	0.053	0.150	1.018	0.980	0.679	0.481	0.375	0.978	0.964	0.778	0.660	0.177
AR(1)-G-T1	1.011	1.015	0.300	0.505	0.254	1.085	1.066	0.621	0.064	0.190	1.097	1.080	0.429	0.160	0.167	1.048	1.022	0.667	0.706	0.816
AR(1)-MFG-T1	1.024	1.020	0.367	0.770	0.794	1.134	1.124	0.552	0.034	0.066	1.156	1.081	0.429	0.037	0.332	1.098	1.049	0.667	0.599	0.704
AR(1)-MF-T2	1.020	0.992	0.367	0.777	0.895	1.211	1.161	0.448	0.018	0.083	1.177	1.080	0.571	0.166	0.418	1.031	0.999	0.778	0.772	0.988
AR(1)-G-T2	1.052	1.048	0.333	0.199	0.092	1.179	1.171	0.655	0.041	0.083	1.313	1.294	0.500	0.069	0.117	1.069	1.064	0.704	0.738	0.657
AR(1)-MFG-T2	1.121	1.104	0.400	0.236	0.217	1.454	1.384	0.517	0.000	0.003	1.620	1.428	0.286	0.000	0.009	1.328	1.237	0.741	0.187	0.260
VAR(1)	1.077	0.999	0.400	0.472	0.989	1.082	1.143	0.552	0.276	0.089	1.191	1.231	0.571	0.121	0.291	0.980	0.985	0.778	0.444	0.465
VARX(1)-MF-T1	1.029	0.987	0.433	0.830	0.910	1.153	1.185	0.483	0.078	0.085	1.233	1.236	0.536	0.109	0.271	1.031	0.978	0.852	0.619	0.548
VARX(1)-G-T1	1.098	1.011	0.333	0.375	0.899	1.144	1.196	0.483	0.153	0.075	1.281	1.373	0.393	0.080	0.271	1.101	1.058	0.630	0.333	0.347
VARX(1)-MFG-T1	1.041	1.011	0.433	0.765	0.920	1.252	1.265	0.517	0.038	0.061	1.412	1.420	0.429	0.034	0.232	1.327	1.228	0.704	0.119	0.080
VARX(1)-MF-T2	0.987	0.960	0.467	0.924	0.734	1.330	1.288	0.345	0.000	0.001	1.329	1.232	0.536	0.037	0.126	1.142	1.061	0.815	0.254	0.493
VARX(1)-G-T2	1.173	1.103	0.400	0.187	0.312	1.217	1.250	0.621	0.100	0.032	1.392	1.417	0.429	0.091	0.171	1.406	1.368	0.519	0.159	0.082
VARX(1)-MFG-T2	1.107	1.082	0.500	0.478	0.480	1.555	1.471	0.483	0.002	0.001	1.734	1.536	0.286	0.000	0.007	1.653	1.502	0.667	0.019	0.066
PVAR(1)-GMM	1.248	1.245	0.367	0.042	0.019	1.438	1.480	0.414	0.007	0.000	1.550	1.471	0.714	0.005	0.000	1.784	1.656	0.593	0.002	0.000
PVAR(1)-OLSCFE	1.107	1.024	0.400	0.091	0.626	1.102	1.160	0.552	0.232	0.071	1.186	1.139	0.607	0.011	0.021	1.038	1.023	0.778	0.443	0.609
PVARX(1)-OLSCFE-MF-T1	1.076	1.004	0.300	0.282	0.947	1.102	1.147	0.517	0.232	0.112	1.202	1.137	0.571	0.024	0.021	1.041	1.018	0.815	0.569	0.704
PVARX(1)-OLSCFE-G-T1	1.104	1.025	0.400	0.095	0.602	1.082	1.148	0.586	0.350	0.074	1.197	1.159	0.607	0.004	0.015	1.020	1.013	0.815	0.769	0.815
PVARX(1)-OLSCFE-MFG-T1	1.070	1.002	0.300	0.333	0.968	1.104	1.147	0.517	0.249	0.102	1.215	1.157	0.536	0.011	0.018	1.020	1.004	0.741	0.834	0.945
PVARX(1)-OLSCFE-MF-T2	1.045	0.998	0.367	0.547	0.977	1.033	1.084	0.517	0.720	0.175	1.106	1.091	0.500	0.087	0.128	1.104	1.046	0.778	0.054	0.289
PVARX(1)-OLSCFE-G-T2	1.120	1.033	0.367	0.076	0.495	1.136	1.191	0.517	0.159	0.036	1.209	1.171	0.536	0.015	0.055	1.036	1.043	0.815	0.600	0.439
PVARX(1)-OLSCFE-MFG-T2	1.044	1.012	0.300	0.600	0.857	1.100	1.141	0.414	0.272	0.033	1.106	1.112	0.500	0.185	0.114	1.074	1.029	0.815	0.214	0.657

Table 7: Industrial Production Growth, DE

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.405	1.332	0.286	0.000	0.001	1.307	1.183	0.508	0.001	0.029	1.388	1.302	0.554	0.000	0.023	1.435	1.389	0.478	0.000	0.013
AR(1)	1.000	1.000	0.468	:	:	1.000	1.000	0.460	:	:	1.000	1.000	0.455	:	:	1.000	1.000	0.591	:	:
LR-MF-T1	0.893	0.879	0.556	0.012	0.064	0.979	0.980	0.484	0.037	0.057	0.991	0.987	0.554	0.666	0.315	1.167	1.245	0.530	0.368	0.376
LR-G-T1	0.968	0.979	0.429	0.277	0.422	0.989	0.970	0.556	0.361	0.180	1.013	1.003	0.471	0.509	0.895	1.010	1.005	0.504	0.718	0.822
LR-MFG-T1	0.907	0.881	0.524	0.027	0.074	0.989	0.989	0.532	0.370	0.371	1.061	1.071	0.463	0.025	0.145	1.234	1.338	0.565	0.290	0.324
LR-MF-T2	0.954	0.950	0.492	0.239	0.285	1.035	1.025	0.379	0.324	0.594	1.055	1.036	0.446	0.184	0.167	1.172	1.281	0.557	0.278	0.258
LR-G-T2	0.975	0.989	0.413	0.434	0.676	1.007	0.986	0.613	0.734	0.578	1.058	1.029	0.512	0.093	0.321	1.057	1.038	0.435	0.285	0.299
LR-MFG-T2	0.989	0.982	0.500	0.787	0.743	1.049	1.003	0.460	0.232	0.939	1.168	1.145	0.504	0.010	0.027	1.278	1.390	0.478	0.077	0.131
AR(1)-MF-T1	0.916	0.904	0.556	0.054	0.123	1.002	1.017	0.492	0.867	0.243	1.023	1.020	0.496	0.051	0.353	1.190	1.296	0.609	0.337	0.337
AR(1)-G-T1	1.011	1.005	0.452	0.163	0.265	1.012	1.008	0.460	0.083	0.020	1.032	1.031	0.529	0.069	0.124	1.022	1.015	0.539	0.083	0.147
AR(1)-MFG-T1	0.929	0.907	0.532	0.098	0.139	1.013	1.027	0.508	0.488	0.183	1.082	1.099	0.512	0.067	0.197	1.251	1.379	0.548	0.284	0.313
AR(1)-MF-T2	0.990	0.987	0.500	0.802	0.781	1.046	1.047	0.427	0.195	0.352	1.076	1.063	0.471	0.048	0.089	1.192	1.318	0.539	0.268	0.245
AR(1)-G-T2	1.027	1.020	0.452	0.142	0.066	1.029	1.021	0.508	0.143	0.152	1.082	1.058	0.521	0.025	0.065	1.060	1.037	0.478	0.132	0.135
AR(1)-MFG-T2	1.037	1.026	0.508	0.394	0.655	1.056	1.024	0.444	0.231	0.647	1.183	1.167	0.479	0.009	0.035	1.291	1.394	0.504	0.091	0.137
VAR(1)	1.026	1.045	0.444	0.284	0.119	1.045	1.076	0.435	0.146	0.250	1.019	1.023	0.421	0.393	0.034	1.017	1.038	0.522	0.629	0.382
VARX(1)-MF-T1	0.957	0.938	0.516	0.393	0.361	1.059	1.121	0.435	0.351	0.303	1.028	1.019	0.380	0.313	0.363	1.127	1.170	0.565	0.328	0.307
VARX(1)-G-T1	1.040	1.053	0.429	0.138	0.076	1.067	1.091	0.403	0.060	0.205	1.038	1.024	0.455	0.109	0.076	1.020	1.051	0.504	0.627	0.261
VARX(1)-MFG-T1	0.971	0.946	0.532	0.569	0.438	1.096	1.165	0.452	0.218	0.274	1.054	1.037	0.471	0.018	0.019	1.176	1.242	0.574	0.301	0.287
VARX(1)-MF-T2	1.016	1.009	0.460	0.735	0.884	1.108	1.132	0.427	0.025	0.066	1.080	1.065	0.421	0.064	0.071	1.147	1.240	0.626	0.260	0.222
VARX(1)-G-T2	1.054	1.066	0.421	0.084	0.040	1.061	1.078	0.492	0.010	0.106	1.076	1.060	0.438	0.065	0.027	1.062	1.052	0.504	0.222	0.204
VARX(1)-MFG-T2	1.064	1.050	0.452	0.222	0.472	1.141	1.133	0.468	0.007	0.106	1.168	1.138	0.421	0.031	0.046	1.238	1.329	0.548	0.095	0.162
PVAR(1)-GMM	0.885	0.900	0.690	0.003	0.090	0.981	0.951	0.540	0.260	0.082	0.972	0.948	0.529	0.240	0.154	0.975	0.951	0.470	0.400	0.192
PVAR(1)-OLSCFE	0.963	0.953	0.444	0.073	0.211	1.000	1.000	0.452	0.867	0.926	0.988	0.977	0.446	0.423	0.003	1.001	1.012	0.522	0.915	0.521
PVARX(1)-OLSCFE-MF-T1	0.935	0.919	0.484	0.031	0.152	1.004	1.015	0.427	0.579	0.139	0.994	0.978	0.446	0.664	0.096	1.093	1.088	0.522	0.257	0.303
PVARX(1)-OLSCFE-G-T1	0.959	0.948	0.468	0.050	0.164	0.999	1.002	0.427	0.292	0.853	0.987	0.974	0.455	0.427	0.018	0.997	1.009	0.478	0.870	0.557
PVARX(1)-OLSCFE-MFG-T1	0.932	0.914	0.524	0.020	0.121	1.002	1.017	0.411	0.735	0.180	0.994	0.976	0.438	0.653	0.122	1.092	1.086	0.478	0.236	0.289
PVARX(1)-OLSCFE-MF-T2	0.957	0.962	0.492	0.224	0.561	1.020	1.035	0.379	0.100	0.009	0.987	0.977	0.471	0.498	0.127	1.065	1.067	0.574	0.473	0.477
PVARX(1)-OLSCFE-G-T2	0.965	0.951	0.492	0.094	0.164	1.009	1.002	0.427	0.026	0.000	0.990	0.981	0.455	0.473	0.556	1.009	1.001	0.470	0.639	0.988
PVARX(1)-OLSCFE-MFG-T2	0.953	0.954	0.524	0.182	0.479	1.038	1.044	0.419	0.010	0.073	0.990	0.983	0.446	0.584	0.174	1.078	1.061	0.487	0.332	0.456

Table 8: Industrial Production Growth, FR

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.567	1.516	0.278	0.000	0.000	1.371	1.296	0.516	0.000	0.000	1.279	1.286	0.521	0.016	0.022	1.556	1.529	0.417	0.000	0.000
AR(1)	1.000	1.000	0.532	:	:	1.000	1.000	0.468	:	:	1.000	1.000	0.479	:	:	1.000	1.000	0.504	:	:
LR-MF-T1	0.984	0.988	0.389	0.396	0.540	1.024	1.070	0.460	0.614	0.344	0.978	0.971	0.537	0.170	0.099	1.079	1.073	0.565	0.362	0.448
LR-G-T1	1.000	0.999	0.413	0.997	0.906	1.007	1.008	0.444	0.518	0.511	0.995	0.991	0.463	0.673	0.581	1.004	0.999	0.487	0.450	0.900
LR-MFG-T1	0.997	0.994	0.373	0.900	0.773	1.048	1.101	0.492	0.350	0.261	0.999	0.993	0.504	0.918	0.637	1.097	1.095	0.539	0.323	0.400
LR-MF-T2	1.013	1.067	0.397	0.703	0.406	1.022	1.089	0.565	0.718	0.424	1.004	0.993	0.512	0.891	0.793	1.095	1.104	0.417	0.342	0.364
LR-G-T2	1.039	1.018	0.500	0.133	0.427	1.042	1.053	0.387	0.095	0.199	1.020	1.011	0.471	0.492	0.693	1.054	1.046	0.487	0.344	0.408
LR-MFG-T2	1.073	1.102	0.397	0.081	0.235	1.118	1.192	0.427	0.103	0.189	1.054	1.049	0.463	0.180	0.076	1.118	1.172	0.522	0.311	0.216
AR(1)-MF-T1	0.990	0.994	0.437	0.543	0.742	1.034	1.087	0.452	0.518	0.321	0.991	0.993	0.455	0.451	0.384	1.070	1.070	0.522	0.370	0.406
AR(1)-G-T1	1.005	1.005	0.516	0.623	0.442	1.018	1.014	0.444	0.094	0.185	1.004	1.004	0.446	0.376	0.337	1.004	1.008	0.487	0.512	0.118
AR(1)-MFG-T1	1.002	1.001	0.389	0.899	0.979	1.061	1.114	0.444	0.261	0.255	1.002	1.002	0.413	0.808	0.756	1.088	1.093	0.496	0.328	0.358
AR(1)-MF-T2	1.021	1.084	0.381	0.568	0.347	1.035	1.107	0.556	0.593	0.385	1.023	1.012	0.446	0.403	0.494	1.098	1.101	0.452	0.316	0.337
AR(1)-G-T2	1.046	1.034	0.516	0.084	0.277	1.063	1.076	0.411	0.044	0.142	1.014	1.023	0.479	0.638	0.264	1.059	1.050	0.496	0.234	0.293
AR(1)-MFG-T2	1.090	1.130	0.397	0.053	0.208	1.143	1.217	0.427	0.072	0.155	1.050	1.054	0.430	0.166	0.007	1.135	1.172	0.522	0.269	0.228
VAR(1)	1.036	1.077	0.508	0.388	0.322	1.092	1.136	0.411	0.160	0.262	1.053	1.045	0.504	0.059	0.068	1.141	1.189	0.426	0.247	0.240
VARX(1)-MF-T1	1.035	1.073	0.444	0.399	0.334	1.105	1.200	0.435	0.241	0.265	1.048	1.039	0.455	0.062	0.090	1.176	1.230	0.435	0.241	0.254
VARX(1)-G-T1	1.064	1.147	0.476	0.277	0.303	1.116	1.182	0.363	0.131	0.249	1.057	1.050	0.479	0.030	0.058	1.170	1.252	0.435	0.246	0.254
VARX(1)-MFG-T1	1.064	1.144	0.429	0.286	0.321	1.144	1.283	0.419	0.193	0.269	1.049	1.039	0.446	0.015	0.065	1.229	1.329	0.461	0.247	0.269
VARX(1)-MF-T2	1.064	1.162	0.389	0.223	0.132	1.091	1.220	0.484	0.336	0.307	1.082	1.056	0.438	0.057	0.031	1.196	1.247	0.383	0.223	0.229
VARX(1)-G-T2	1.111	1.180	0.468	0.090	0.232	1.145	1.214	0.371	0.039	0.119	1.086	1.083	0.471	0.027	0.034	1.248	1.340	0.530	0.155	0.231
VARX(1)-MFG-T2	1.155	1.282	0.389	0.039	0.121	1.200	1.366	0.444	0.090	0.190	1.115	1.103	0.496	0.008	0.002	1.274	1.426	0.522	0.198	0.230
PVAR(1)-GMM	0.970	0.945	0.635	0.546	0.333	0.998	0.991	0.516	0.899	0.434	0.973	0.964	0.471	0.025	0.075	0.983	0.976	0.452	0.071	0.053
PVAR(1)-OLSCFE	1.006	1.009	0.563	0.683	0.500	1.030	1.020	0.492	0.179	0.208	1.010	1.015	0.455	0.635	0.431	1.024	1.039	0.452	0.514	0.325
PVARX(1)-OLSCFE-MF-T1	1.007	1.003	0.516	0.761	0.903	1.033	1.040	0.524	0.357	0.225	1.002	1.009	0.455	0.938	0.639	1.135	1.122	0.504	0.134	0.172
PVARX(1)-OLSCFE-G-T1	1.010	1.014	0.579	0.528	0.322	1.034	1.023	0.468	0.150	0.190	1.011	1.015	0.463	0.605	0.421	1.016	1.038	0.470	0.682	0.348
PVARX(1)-OLSCFE-MFG-T1	1.017	1.009	0.476	0.470	0.676	1.039	1.044	0.460	0.287	0.198	1.003	1.009	0.455	0.915	0.631	1.133	1.123	0.504	0.154	0.179
PVARX(1)-OLSCFE-MF-T2	1.010	1.024	0.452	0.735	0.503	1.027	1.030	0.524	0.480	0.344	1.009	1.026	0.446	0.744	0.229	1.129	1.120	0.452	0.169	0.193
PVARX(1)-OLSCFE-G-T2	1.014	1.013	0.500	0.426	0.375	1.062	1.048	0.403	0.024	0.035	1.017	1.016	0.446	0.541	0.479	1.032	1.045	0.504	0.457	0.313
PVARX(1)-OLSCFE-MFG-T2	1.024	1.027	0.484	0.425	0.461	1.064	1.054	0.484	0.104	0.114	1.016	1.029	0.421	0.622	0.229	1.141	1.135	0.504	0.138	0.164

Table 9: Industrial Production Growth, IT

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.391	1.448	0.270	0.000	0.000	1.239	1.218	0.508	0.031	0.054	1.347	1.318	0.496	0.001	0.002	1.598	1.556	0.374	0.000	0.005
AR(1)	1.000	1.000	0.571	:	:	1.000	1.000	0.516	:	:	1.000	1.000	0.438	:	:	1.000	1.000	0.617	:	:
LR-MF-T1	0.980	0.979	0.500	0.539	0.489	1.021	1.018	0.516	0.377	0.390	0.985	0.971	0.645	0.325	0.100	1.047	1.026	0.452	0.000	0.016
LR-G-T1	0.985	1.004	0.444	0.491	0.840	1.001	0.982	0.548	0.958	0.532	0.992	0.982	0.496	0.413	0.192	1.026	1.005	0.426	0.158	0.290
LR-MFG-T1	0.982	0.988	0.508	0.616	0.725	1.037	1.016	0.524	0.207	0.553	0.987	0.974	0.653	0.370	0.143	1.048	1.027	0.461	0.000	0.002
LR-MF-T2	1.003	1.013	0.571	0.947	0.717	1.043	1.068	0.556	0.566	0.431	0.986	0.984	0.537	0.674	0.590	1.104	1.068	0.417	0.003	0.014
LR-G-T2	1.012	1.047	0.476	0.661	0.093	1.016	0.973	0.548	0.712	0.530	1.020	1.010	0.512	0.361	0.570	1.105	1.080	0.383	0.025	0.074
LR-MFG-T2	1.052	1.075	0.532	0.260	0.073	1.081	1.059	0.613	0.307	0.473	1.011	1.017	0.521	0.648	0.383	1.171	1.145	0.357	0.005	0.030
AR(1)-MF-T1	0.993	0.989	0.540	0.788	0.648	1.041	1.045	0.573	0.050	0.098	0.998	0.995	0.537	0.869	0.560	1.017	1.021	0.652	0.310	0.241
AR(1)-G-T1	1.000	1.007	0.532	0.957	0.410	1.013	1.003	0.548	0.415	0.804	1.005	1.002	0.438	0.030	0.468	0.994	1.000	0.591	0.264	0.911
AR(1)-MFG-T1	0.994	0.995	0.548	0.838	0.869	1.050	1.041	0.565	0.062	0.100	1.001	0.997	0.537	0.898	0.592	1.015	1.021	0.652	0.259	0.129
AR(1)-MF-T2	1.009	1.021	0.619	0.812	0.566	1.060	1.092	0.573	0.381	0.281	0.997	1.006	0.537	0.957	0.893	1.084	1.053	0.504	0.066	0.115
AR(1)-G-T2	1.015	1.047	0.571	0.401	0.020	1.033	1.001	0.532	0.399	0.967	1.039	1.046	0.421	0.059	0.093	1.078	1.089	0.539	0.070	0.150
AR(1)-MFG-T2	1.044	1.074	0.571	0.307	0.069	1.100	1.090	0.556	0.210	0.254	1.030	1.051	0.529	0.461	0.325	1.145	1.155	0.530	0.027	0.066
VAR(1)	1.042	1.116	0.524	0.240	0.104	1.063	1.069	0.492	0.011	0.014	1.061	1.059	0.405	0.025	0.043	1.074	1.097	0.565	0.265	0.258
VARX(1)-MF-T1	1.023	1.061	0.556	0.523	0.243	1.056	1.078	0.556	0.095	0.050	1.032	1.051	0.463	0.121	0.027	1.078	1.112	0.565	0.318	0.272
VARX(1)-G-T1	1.045	1.128	0.500	0.235	0.086	1.047	1.052	0.492	0.123	0.028	1.062	1.054	0.421	0.018	0.026	1.070	1.097	0.574	0.261	0.256
VARX(1)-MFG-T1	1.027	1.067	0.532	0.480	0.236	1.046	1.057	0.532	0.192	0.035	1.034	1.047	0.471	0.085	0.014	1.075	1.112	0.583	0.288	0.263
VARX(1)-MF-T2	1.053	1.110	0.603	0.246	0.139	1.097	1.136	0.548	0.185	0.159	1.035	1.063	0.545	0.382	0.143	1.156	1.167	0.530	0.107	0.136
VARX(1)-G-T2	1.065	1.176	0.508	0.126	0.041	1.080	1.051	0.492	0.107	0.244	1.087	1.097	0.421	0.051	0.043	1.140	1.175	0.522	0.047	0.120
VARX(1)-MFG-T2	1.097	1.182	0.587	0.072	0.077	1.128	1.131	0.548	0.122	0.135	1.071	1.107	0.521	0.102	0.038	1.235	1.260	0.496	0.023	0.073
PVAR(1)-GMM	1.039	1.160	0.683	0.624	0.210	0.990	0.983	0.556	0.702	0.591	0.963	0.959	0.446	0.046	0.054	1.001	0.978	0.365	0.834	0.318
PVAR(1)-OLSCFE	1.003	1.035	0.452	0.921	0.573	1.000	0.995	0.524	0.999	0.832	1.046	1.029	0.438	0.191	0.447	1.094	1.072	0.539	0.014	0.015
PVARX(1)-OLSCFE-MF-T1	0.979	0.982	0.579	0.420	0.444	1.004	0.994	0.581	0.808	0.795	1.028	1.013	0.488	0.314	0.635	1.106	1.104	0.530	0.079	0.066
PVARX(1)-OLSCFE-G-T1	1.003	1.035	0.460	0.925	0.587	0.997	0.988	0.524	0.895	0.605	1.045	1.027	0.455	0.190	0.464	1.077	1.059	0.539	0.014	0.003
PVARX(1)-OLSCFE-MFG-T1	0.980	0.980	0.548	0.452	0.441	1.002	0.987	0.573	0.927	0.597	1.027	1.012	0.496	0.318	0.671	1.091	1.087	0.539	0.115	0.089
PVARX(1)-OLSCFE-MF-T2	0.989	0.997	0.563	0.722	0.899	1.019	0.996	0.597	0.440	0.884	1.020	1.023	0.496	0.592	0.569	1.113	1.093	0.522	0.059	0.033
PVARX(1)-OLSCFE-G-T2	1.002	1.038	0.484	0.958	0.530	1.003	0.981	0.492	0.926	0.492	1.045	1.026	0.488	0.214	0.529	1.083	1.082	0.513	0.014	0.002
PVARX(1)-OLSCFE-MFG-T2	0.987	1.001	0.508	0.699	0.964	1.019	0.980	0.548	0.576	0.563	1.023	1.024	0.479	0.520	0.547	1.097	1.080	0.487	0.073	0.023

Table 10: Industrial Production Growth, UK

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.628	1.527	0.270	0.000	0.000	1.248	1.302	0.581	0.013	0.007	1.342	1.339	0.545	0.000	0.001	1.402	1.366	0.522	0.000	0.000
AR(1)	1.000	1.000	0.508	:	:	1.000	1.000	0.500	:	:	1.000	1.000	0.504	:	:	1.000	1.000	0.513	:	:
LR-MF-T1	0.964	0.978	0.500	0.149	0.392	1.001	1.009	0.492	0.967	0.582	1.012	1.009	0.512	0.720	0.619	1.068	1.053	0.548	0.278	0.383
LR-G-T1	0.985	0.992	0.389	0.489	0.731	1.008	1.009	0.540	0.697	0.643	1.022	1.019	0.488	0.490	0.416	0.994	1.000	0.530	0.642	0.996
LR-MFG-T1	0.968	0.984	0.516	0.224	0.541	1.012	1.015	0.524	0.604	0.505	1.029	1.023	0.463	0.362	0.286	1.067	1.052	0.530	0.347	0.420
LR-MF-T2	0.985	0.976	0.571	0.700	0.551	1.029	1.033	0.524	0.495	0.480	1.058	1.079	0.537	0.086	0.071	1.162	1.146	0.461	0.125	0.198
LR-G-T2	0.994	1.020	0.524	0.861	0.600	1.009	1.030	0.589	0.800	0.447	1.043	1.024	0.504	0.265	0.373	1.065	1.097	0.513	0.110	0.176
LR-MFG-T2	1.025	1.020	0.563	0.592	0.634	1.054	1.069	0.532	0.317	0.245	1.093	1.103	0.521	0.119	0.104	1.173	1.171	0.478	0.124	0.135
AR(1)-MF-T1	0.979	0.989	0.492	0.266	0.556	1.014	1.009	0.452	0.007	0.367	1.006	1.003	0.512	0.287	0.425	1.092	1.090	0.513	0.300	0.349
AR(1)-G-T1	1.006	1.005	0.524	0.336	0.352	1.013	1.007	0.476	0.316	0.602	1.017	1.015	0.496	0.470	0.459	1.006	1.013	0.522	0.726	0.388
AR(1)-MFG-T1	0.983	0.994	0.492	0.399	0.746	1.020	1.017	0.419	0.168	0.360	1.022	1.019	0.504	0.333	0.333	1.099	1.098	0.539	0.345	0.364
AR(1)-MF-T2	1.008	0.990	0.563	0.803	0.756	1.048	1.031	0.484	0.208	0.443	1.035	1.059	0.496	0.084	0.036	1.182	1.165	0.478	0.112	0.182
AR(1)-G-T2	1.031	1.033	0.540	0.258	0.131	1.025	1.033	0.524	0.418	0.278	1.035	1.018	0.521	0.316	0.471	1.095	1.139	0.522	0.141	0.210
AR(1)-MFG-T2	1.048	1.031	0.540	0.222	0.378	1.083	1.072	0.573	0.068	0.144	1.075	1.075	0.512	0.192	0.133	1.194	1.214	0.522	0.156	0.187
VAR(1)	1.063	1.118	0.524	0.243	0.259	1.035	1.029	0.500	0.139	0.273	1.015	1.017	0.479	0.247	0.030	1.004	1.031	0.565	0.779	0.181
VARX(1)-MF-T1	1.023	1.048	0.492	0.570	0.325	1.055	1.058	0.508	0.094	0.284	1.017	1.019	0.496	0.430	0.236	1.100	1.096	0.522	0.281	0.332
VARX(1)-G-T1	1.065	1.113	0.508	0.205	0.230	1.047	1.030	0.468	0.054	0.207	1.043	1.038	0.446	0.000	0.000	1.011	1.042	0.530	0.678	0.186
VARX(1)-MFG-T1	1.022	1.048	0.500	0.571	0.278	1.061	1.054	0.427	0.036	0.222	1.042	1.037	0.438	0.190	0.000	1.112	1.107	0.504	0.317	0.355
VARX(1)-MF-T2	1.052	1.061	0.532	0.322	0.377	1.064	1.034	0.500	0.103	0.380	1.114	1.177	0.512	0.058	0.071	1.176	1.167	0.496	0.116	0.163
VARX(1)-G-T2	1.076	1.106	0.492	0.112	0.090	1.090	1.129	0.508	0.259	0.259	1.048	1.047	0.488	0.050	0.003	1.147	1.174	0.513	0.093	0.162
VARX(1)-MFG-T2	1.094	1.085	0.492	0.067	0.104	1.106	1.102	0.524	0.056	0.155	1.167	1.229	0.529	0.055	0.048	1.315	1.355	0.522	0.179	0.212
PVAR(1)-GMM	0.936	0.930	0.722	0.106	0.103	1.016	1.016	0.444	0.360	0.324	1.002	0.998	0.479	0.957	0.899	0.987	0.980	0.565	0.532	0.310
PVAR(1)-OLSCFE	1.007	1.020	0.500	0.689	0.177	1.000	1.004	0.476	0.965	0.107	1.013	1.004	0.471	0.326	0.723	1.000	1.014	0.539	0.990	0.252
PVARX(1)-OLSCFE-MF-T1	0.981	0.993	0.532	0.428	0.697	1.014	1.019	0.476	0.354	0.136	1.010	1.005	0.488	0.476	0.657	1.069	1.056	0.513	0.060	0.104
PVARX(1)-OLSCFE-G-T1	1.013	1.025	0.492	0.454	0.099	1.005	1.005	0.468	0.711	0.570	1.015	1.007	0.488	0.213	0.504	1.009	1.020	0.470	0.567	0.051
PVARX(1)-OLSCFE-MFG-T1	0.985	1.000	0.508	0.540	0.996	1.017	1.020	0.484	0.271	0.127	1.013	1.008	0.496	0.347	0.470	1.077	1.062	0.461	0.061	0.102
PVARX(1)-OLSCFE-MF-T2	0.981	0.975	0.563	0.498	0.297	1.021	1.003	0.524	0.447	0.909	1.027	1.032	0.463	0.319	0.138	1.077	1.074	0.470	0.005	0.007
PVARX(1)-OLSCFE-G-T2	1.011	1.028	0.500	0.561	0.096	1.007	1.009	0.452	0.669	0.561	1.016	1.003	0.496	0.320	0.815	1.028	1.033	0.487	0.173	0.138
PVARX(1)-OLSCFE-MFG-T2	0.986	0.985	0.563	0.642	0.530	1.037	1.014	0.500	0.247	0.629	1.031	1.037	0.463	0.310	0.130	1.084	1.083	0.443	0.024	0.067

Table 11: Unemployment Rate (Difference), DE

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.130	1.292	0.270	0.220	0.003	1.090	1.235	0.250	0.360	0.030	1.112	1.300	0.339	0.278	0.007	0.961	1.146	0.443	0.762	0.155
AR(1)	1.000	1.000	0.262	:	:	1.000	1.000	0.315	:	:	1.000	1.000	0.289	:	:	1.000	1.000	0.304	:	:
LR-MF-T1	1.092	1.219	0.317	0.284	0.206	0.971	1.040	0.347	0.771	0.813	1.340	1.688	0.306	0.125	0.138	1.288	1.511	0.261	0.274	0.277
LR-G-T1	1.150	1.199	0.246	0.064	0.041	1.200	1.279	0.290	0.002	0.002	1.049	1.025	0.314	0.196	0.440	0.983	0.967	0.322	0.310	0.243
LR-MFG-T1	1.220	1.240	0.278	0.010	0.017	1.187	1.203	0.323	0.030	0.069	1.357	1.709	0.298	0.129	0.155	1.313	1.532	0.243	0.268	0.271
LR-MF-T2	1.141	1.343	0.310	0.157	0.232	1.114	1.368	0.339	0.420	0.340	1.459	1.838	0.240	0.085	0.126	1.312	1.549	0.278	0.263	0.239
LR-G-T2	1.166	1.224	0.270	0.050	0.025	1.200	1.276	0.282	0.004	0.003	1.010	1.029	0.306	0.758	0.138	1.054	1.068	0.304	0.348	0.361
LR-MFG-T2	1.272	1.282	0.325	0.001	0.004	1.385	1.598	0.306	0.038	0.100	1.557	1.984	0.289	0.072	0.111	1.329	1.528	0.278	0.239	0.221
AR(1)-MF-T1	1.009	1.071	0.349	0.850	0.344	0.943	0.984	0.379	0.542	0.911	1.324	1.640	0.289	0.137	0.138	1.193	1.312	0.252	0.266	0.270
AR(1)-G-T1	1.116	1.117	0.310	0.027	0.037	1.176	1.254	0.315	0.006	0.005	1.017	1.022	0.347	0.337	0.280	1.009	1.006	0.296	0.116	0.238
AR(1)-MFG-T1	1.166	1.164	0.325	0.008	0.023	1.190	1.215	0.315	0.025	0.044	1.361	1.736	0.306	0.156	0.165	1.238	1.355	0.261	0.240	0.252
AR(1)-MF-T2	1.069	1.195	0.381	0.304	0.216	1.072	1.328	0.355	0.616	0.382	1.456	1.793	0.298	0.086	0.123	1.193	1.332	0.261	0.271	0.247
AR(1)-G-T2	1.104	1.115	0.325	0.054	0.036	1.190	1.259	0.306	0.006	0.004	1.015	1.054	0.339	0.663	0.149	1.067	1.084	0.322	0.096	0.209
AR(1)-MFG-T2	1.219	1.225	0.349	0.001	0.004	1.400	1.650	0.331	0.040	0.112	1.586	1.998	0.314	0.075	0.111	1.213	1.334	0.243	0.232	0.209
VAR(1)	0.965	0.973	0.341	0.264	0.397	0.986	1.016	0.371	0.699	0.612	1.034	1.040	0.289	0.173	0.202	0.982	0.999	0.339	0.631	0.991
VARX(1)-MF-T1	1.021	1.088	0.357	0.696	0.346	0.985	1.019	0.347	0.886	0.902	1.394	1.765	0.273	0.134	0.156	1.214	1.341	0.304	0.306	0.281
VARX(1)-G-T1	1.104	1.100	0.325	0.127	0.144	1.211	1.300	0.306	0.008	0.004	1.059	1.065	0.314	0.082	0.071	0.989	1.008	0.330	0.752	0.855
VARX(1)-MFG-T1	1.180	1.184	0.357	0.016	0.030	1.219	1.272	0.306	0.031	0.044	1.422	1.829	0.281	0.150	0.182	1.228	1.357	0.313	0.283	0.262
VARX(1)-MF-T2	1.074	1.205	0.381	0.313	0.256	1.081	1.332	0.355	0.603	0.369	1.529	1.950	0.289	0.096	0.135	1.221	1.370	0.296	0.273	0.230
VARX(1)-G-T2	1.099	1.099	0.365	0.147	0.151	1.214	1.296	0.347	0.013	0.005	1.058	1.099	0.347	0.346	0.159	1.045	1.088	0.330	0.217	0.048
VARX(1)-MFG-T2	1.239	1.249	0.373	0.002	0.005	1.409	1.704	0.331	0.049	0.115	1.614	2.085	0.331	0.084	0.122	1.249	1.378	0.270	0.207	0.186
PVAR(1)-GMM	1.011	1.132	0.222	0.879	0.037	0.856	1.095	0.218	0.100	0.279	0.813	1.030	0.355	0.127	0.825	0.620	0.813	0.330	0.003	0.377
PVAR(1)-OLSCFE	0.960	0.958	0.381	0.121	0.135	0.976	0.989	0.395	0.314	0.590	1.013	0.998	0.331	0.589	0.934	0.977	0.978	0.348	0.172	0.429
PVARX(1)-OLSCFE-MF-T1	0.966	0.966	0.365	0.235	0.323	0.975	0.997	0.403	0.362	0.895	1.053	1.053	0.281	0.222	0.228	1.059	1.083	0.313	0.455	0.372
PVARX(1)-OLSCFE-G-T1	0.960	0.963	0.349	0.224	0.264	0.955	0.994	0.379	0.136	0.740	1.016	0.999	0.355	0.511	0.951	0.992	0.987	0.339	0.611	0.565
PVARX(1)-OLSCFE-MFG-T1	0.979	0.977	0.365	0.557	0.556	0.961	1.009	0.395	0.312	0.725	1.049	1.045	0.314	0.255	0.263	1.077	1.093	0.322	0.380	0.347
PVARX(1)-OLSCFE-MF-T2	0.987	0.996	0.357	0.719	0.921	0.973	0.988	0.387	0.335	0.703	1.063	1.085	0.306	0.185	0.094	1.064	1.080	0.313	0.265	0.226
PVARX(1)-OLSCFE-G-T2	0.964	0.975	0.389	0.283	0.451	0.958	1.005	0.331	0.101	0.765	1.021	1.014	0.364	0.611	0.684	1.014	1.000	0.296	0.370	0.987
PVARX(1)-OLSCFE-MFG-T2	1.014	1.032	0.397	0.764	0.548	0.968	1.010	0.323	0.349	0.738	1.074	1.097	0.331	0.111	0.029	1.082	1.089	0.322	0.084	0.165

Table 12: Unemployment Rate (Difference), FR

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	0.472	0.736	0.278	0.000	0.002	1.084	1.023	0.290	0.408	0.854	1.129	1.135	0.364	0.323	0.286	1.395	1.329	0.339	0.025	0.005
AR(1)	1.000	1.000	0.310	:	:	1.000	1.000	0.339	:	:	1.000	1.000	0.355	:	:	1.000	1.000	0.322	:	:
LR-MF-T1	1.257	1.161	0.444	0.001	0.037	0.922	0.890	0.387	0.180	0.088	0.959	0.935	0.331	0.389	0.256	1.032	1.000	0.365	0.560	0.999
LR-G-T1	1.346	1.269	0.373	0.000	0.006	1.080	1.063	0.395	0.134	0.237	1.050	1.029	0.372	0.202	0.185	0.987	0.947	0.357	0.639	0.000
LR-MFG-T1	1.266	1.163	0.444	0.001	0.029	0.943	0.925	0.419	0.311	0.110	1.012	0.977	0.331	0.762	0.600	1.036	1.002	0.348	0.520	0.981
LR-MF-T2	1.266	1.171	0.429	0.002	0.073	0.936	0.944	0.411	0.309	0.268	1.019	1.015	0.331	0.666	0.774	1.064	1.020	0.322	0.363	0.816
LR-G-T2	1.360	1.281	0.365	0.000	0.004	1.074	1.068	0.411	0.186	0.210	1.052	1.039	0.364	0.156	0.041	1.049	0.995	0.417	0.002	0.869
LR-MFG-T2	1.278	1.173	0.460	0.002	0.060	0.970	1.016	0.468	0.648	0.845	1.092	1.060	0.339	0.071	0.283	1.108	1.039	0.357	0.000	0.389
AR(1)-MF-T1	0.999	0.968	0.429	0.968	0.316	0.884	0.855	0.387	0.085	0.130	0.961	0.957	0.355	0.234	0.332	0.986	1.003	0.339	0.744	0.954
AR(1)-G-T1	1.010	1.010	0.349	0.290	0.232	1.036	1.014	0.379	0.131	0.336	1.025	1.023	0.364	0.200	0.083	1.025	1.005	0.339	0.128	0.775
AR(1)-MFG-T1	1.003	0.975	0.405	0.892	0.443	0.917	0.890	0.395	0.171	0.149	1.008	0.990	0.355	0.564	0.637	0.986	0.996	0.339	0.764	0.934
AR(1)-MF-T2	1.008	0.997	0.500	0.878	0.968	0.917	0.920	0.403	0.191	0.208	1.044	1.052	0.347	0.460	0.399	1.013	1.020	0.330	0.762	0.686
AR(1)-G-T2	1.059	1.034	0.389	0.070	0.203	1.043	1.021	0.403	0.384	0.649	1.035	1.040	0.331	0.120	0.010	1.078	1.044	0.443	0.000	0.019
AR(1)-MFG-T2	1.064	1.023	0.452	0.242	0.779	0.957	0.994	0.452	0.491	0.922	1.102	1.087	0.347	0.101	0.183	1.055	1.035	0.357	0.299	0.175
VAR(1)	1.040	0.999	0.381	0.133	0.974	1.009	1.010	0.315	0.615	0.496	0.984	0.984	0.430	0.372	0.252	1.005	0.997	0.409	0.825	0.876
VARX(1)-MF-T1	1.014	0.973	0.405	0.635	0.451	0.891	0.860	0.363	0.103	0.135	0.947	0.950	0.380	0.143	0.302	0.984	0.996	0.365	0.816	0.939
VARX(1)-G-T1	1.054	1.012	0.397	0.057	0.601	1.060	1.024	0.306	0.084	0.297	1.005	1.004	0.355	0.714	0.587	1.022	1.001	0.409	0.523	0.981
VARX(1)-MFG-T1	1.024	0.983	0.413	0.444	0.639	0.926	0.895	0.371	0.241	0.172	0.996	0.981	0.397	0.864	0.464	0.985	0.989	0.365	0.825	0.849
VARX(1)-MF-T2	1.012	1.002	0.444	0.832	0.982	0.918	0.926	0.419	0.215	0.243	1.036	1.049	0.372	0.521	0.438	1.044	1.016	0.339	0.513	0.779
VARX(1)-G-T2	1.099	1.035	0.389	0.009	0.220	1.056	1.021	0.347	0.298	0.647	1.011	1.021	0.364	0.667	0.187	1.073	1.047	0.391	0.002	0.009
VARX(1)-MFG-T2	1.066	1.035	0.437	0.256	0.693	0.959	0.991	0.411	0.532	0.888	1.081	1.079	0.347	0.197	0.264	1.112	1.065	0.348	0.057	0.168
PVAR(1)-GMM	1.184	1.134	0.349	0.033	0.093	0.997	1.008	0.427	0.970	0.880	0.928	0.934	0.471	0.373	0.361	0.857	0.838	0.374	0.128	0.201
PVAR(1)-OLSCFE	1.082	1.017	0.381	0.052	0.610	0.987	0.977	0.331	0.657	0.340	0.966	0.957	0.430	0.222	0.123	1.007	0.961	0.400	0.862	0.191
PVARX(1)-OLSCFE-MF-T1	1.064	0.989	0.421	0.142	0.775	0.924	0.944	0.403	0.025	0.043	0.939	0.902	0.364	0.315	0.230	1.087	1.031	0.417	0.190	0.628
PVARX(1)-OLSCFE-G-T1	1.137	1.072	0.397	0.011	0.105	1.002	0.995	0.347	0.961	0.847	0.964	0.955	0.438	0.223	0.098	1.021	0.968	0.383	0.614	0.333
PVARX(1)-OLSCFE-MFG-T1	1.132	1.054	0.413	0.017	0.234	0.951	0.972	0.403	0.200	0.346	0.940	0.906	0.380	0.321	0.256	1.101	1.042	0.391	0.174	0.550
PVARX(1)-OLSCFE-MF-T2	1.076	1.018	0.429	0.104	0.710	0.925	0.947	0.387	0.047	0.113	0.952	0.925	0.347	0.443	0.374	1.103	1.067	0.383	0.093	0.288
PVARX(1)-OLSCFE-G-T2	1.139	1.061	0.429	0.009	0.130	1.020	0.987	0.347	0.612	0.655	0.973	0.956	0.413	0.409	0.133	1.110	1.018	0.365	0.024	0.668
PVARX(1)-OLSCFE-MFG-T2	1.149	1.068	0.468	0.012	0.219	0.961	0.967	0.355	0.396	0.356	0.946	0.915	0.347	0.471	0.387	1.207	1.131	0.365	0.007	0.120

Table 13: Unemployment Rate (Difference), IT

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.647	1.593	0.222	0.000	0.000	1.504	1.507	0.387	0.000	0.000	1.293	1.247	0.521	0.003	0.018	1.717	1.626	0.278	0.000	0.000
AR(1)	1.000	1.000	0.643	:	:	1.000	1.000	0.621	:	:	1.000	1.000	0.479	:	:	1.000	1.000	0.730	:	:
LR-MF-T1	1.017	1.044	0.444	0.572	0.062	1.063	1.046	0.540	0.085	0.137	0.992	1.006	0.446	0.715	0.671	1.074	1.058	0.435	0.036	0.005
LR-G-T1	1.020	1.041	0.429	0.510	0.064	1.066	1.063	0.452	0.003	0.001	0.984	0.996	0.521	0.425	0.601	1.037	1.043	0.504	0.202	0.014
LR-MFG-T1	1.015	1.043	0.429	0.648	0.109	1.061	1.048	0.516	0.099	0.117	0.984	0.998	0.488	0.421	0.748	1.065	1.058	0.574	0.045	0.006
LR-MF-T2	1.048	1.083	0.484	0.201	0.025	1.089	1.068	0.516	0.017	0.043	0.994	1.029	0.471	0.855	0.181	1.107	1.088	0.461	0.029	0.018
LR-G-T2	1.035	1.049	0.468	0.290	0.053	1.057	1.060	0.427	0.039	0.007	0.970	1.017	0.512	0.288	0.382	1.043	1.030	0.513	0.156	0.234
LR-MFG-T2	1.075	1.099	0.516	0.085	0.019	1.079	1.069	0.460	0.039	0.047	0.989	1.046	0.496	0.793	0.174	1.131	1.107	0.513	0.107	0.115
AR(1)-MF-T1	0.999	1.004	0.627	0.960	0.700	0.999	0.993	0.597	0.949	0.733	1.004	1.006	0.446	0.673	0.367	1.027	1.019	0.730	0.155	0.050
AR(1)-G-T1	1.003	0.996	0.667	0.742	0.545	0.999	1.005	0.613	0.792	0.306	0.998	0.997	0.529	0.900	0.744	0.994	1.006	0.722	0.705	0.669
AR(1)-MFG-T1	0.999	1.002	0.595	0.956	0.905	0.996	0.995	0.613	0.860	0.828	0.998	1.000	0.488	0.897	0.985	1.015	1.021	0.739	0.444	0.195
AR(1)-MF-T2	1.014	1.042	0.611	0.586	0.179	1.020	1.013	0.621	0.371	0.566	1.008	1.030	0.463	0.757	0.066	1.058	1.048	0.652	0.023	0.021
AR(1)-G-T2	1.010	0.995	0.611	0.585	0.711	0.997	1.012	0.605	0.835	0.386	0.984	1.016	0.554	0.501	0.454	0.999	0.987	0.722	0.922	0.253
AR(1)-MFG-T2	1.028	1.048	0.579	0.419	0.246	1.018	1.021	0.605	0.449	0.402	1.000	1.045	0.496	0.997	0.204	1.112	1.077	0.643	0.209	0.282
VAR(1)	1.007	1.006	0.595	0.577	0.547	1.006	1.013	0.621	0.532	0.091	1.029	1.019	0.355	0.086	0.297	1.014	1.016	0.704	0.378	0.344
VARX(1)-MF-T1	1.013	1.014	0.579	0.474	0.336	1.004	1.003	0.556	0.873	0.876	1.035	1.021	0.430	0.131	0.351	1.042	1.037	0.713	0.014	0.024
VARX(1)-G-T1	1.006	1.001	0.603	0.735	0.965	1.006	1.019	0.581	0.441	0.046	1.029	1.017	0.397	0.215	0.435	1.003	1.021	0.730	0.906	0.418
VARX(1)-MFG-T1	1.012	1.011	0.571	0.585	0.576	1.003	1.008	0.581	0.883	0.725	1.029	1.016	0.405	0.310	0.547	1.028	1.039	0.730	0.217	0.132
VARX(1)-MF-T2	1.027	1.051	0.611	0.350	0.133	1.027	1.026	0.589	0.291	0.279	1.029	1.045	0.405	0.430	0.122	1.091	1.082	0.643	0.002	0.005
VARX(1)-G-T2	1.019	1.001	0.587	0.411	0.943	1.011	1.037	0.613	0.422	0.155	1.009	1.029	0.471	0.741	0.266	1.003	1.010	0.704	0.912	0.672
VARX(1)-MFG-T2	1.046	1.058	0.563	0.222	0.180	1.025	1.044	0.589	0.368	0.182	1.020	1.057	0.446	0.639	0.185	1.165	1.121	0.643	0.119	0.134
PVAR(1)-GMM	1.051	1.067	0.270	0.172	0.027	1.051	1.044	0.508	0.078	0.058	0.973	0.986	0.471	0.377	0.531	1.019	1.018	0.504	0.497	0.359
PVAR(1)-OLSCFE	0.991	0.991	0.659	0.476	0.336	1.007	1.004	0.645	0.240	0.286	1.000	0.996	0.463	0.992	0.689	1.008	1.012	0.704	0.457	0.163
PVARX(1)-OLSCFE-MF-T1	0.999	0.998	0.659	0.950	0.867	1.006	1.002	0.581	0.608	0.859	1.022	1.020	0.438	0.121	0.146	1.032	1.025	0.687	0.104	0.019
PVARX(1)-OLSCFE-G-T1	0.987	0.983	0.667	0.355	0.121	1.006	0.999	0.629	0.418	0.805	1.008	1.000	0.455	0.429	0.973	1.003	1.010	0.722	0.846	0.402
PVARX(1)-OLSCFE-MFG-T1	0.996	0.991	0.659	0.782	0.466	1.003	0.996	0.573	0.828	0.728	1.029	1.024	0.455	0.088	0.152	1.029	1.023	0.704	0.068	0.024
PVARX(1)-OLSCFE-MF-T2	0.998	0.998	0.635	0.874	0.880	1.010	1.003	0.629	0.422	0.808	1.030	1.026	0.413	0.083	0.091	1.039	1.031	0.670	0.117	0.040
PVARX(1)-OLSCFE-G-T2	0.985	0.981	0.659	0.280	0.086	1.003	0.995	0.645	0.727	0.485	0.997	1.000	0.471	0.809	0.975	1.001	1.003	0.704	0.949	0.849
PVARX(1)-OLSCFE-MFG-T2	0.994	0.988	0.635	0.721	0.445	1.003	0.993	0.637	0.812	0.545	1.029	1.031	0.430	0.096	0.067	1.031	1.019	0.678	0.131	0.188

Table 14: Unemployment Rate (Difference), UK

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.087	1.142	0.190	0.289	0.067	0.971	1.072	0.395	0.782	0.396	1.151	1.213	0.264	0.241	0.067	1.225	1.259	0.339	0.034	0.011
AR(1)	1.000	1.000	0.365	:	:	1.000	1.000	0.258	:	:	1.000	1.000	0.372	:	:	1.000	1.000	0.365	:	:
LR-MF-T1	1.077	1.109	0.405	0.128	0.009	1.038	1.029	0.347	0.419	0.507	0.992	0.980	0.430	0.900	0.701	1.038	1.052	0.339	0.654	0.617
LR-G-T1	1.098	1.119	0.349	0.042	0.005	1.043	1.042	0.371	0.295	0.305	1.025	1.021	0.380	0.556	0.589	0.994	0.985	0.391	0.911	0.755
LR-MFG-T1	1.084	1.109	0.389	0.091	0.011	1.050	1.039	0.331	0.283	0.382	1.007	0.991	0.430	0.911	0.848	1.056	1.075	0.435	0.543	0.512
LR-MF-T2	1.087	1.123	0.476	0.125	0.010	1.099	1.085	0.379	0.103	0.117	1.004	1.007	0.413	0.947	0.904	1.050	1.065	0.426	0.638	0.623
LR-G-T2	1.109	1.161	0.357	0.045	0.012	1.046	1.047	0.387	0.247	0.190	1.052	1.036	0.421	0.050	0.224	0.968	0.993	0.383	0.516	0.834
LR-MFG-T2	1.112	1.159	0.468	0.074	0.012	1.129	1.113	0.363	0.051	0.090	1.045	1.044	0.405	0.432	0.372	1.048	1.086	0.400	0.652	0.518
AR(1)-MF-T1	1.000	0.997	0.421	0.982	0.799	1.005	0.988	0.290	0.860	0.599	0.981	0.965	0.488	0.507	0.291	1.038	1.042	0.339	0.340	0.335
AR(1)-G-T1	1.007	1.005	0.389	0.509	0.698	1.009	1.011	0.258	0.243	0.194	1.005	1.013	0.405	0.619	0.233	1.026	1.028	0.383	0.338	0.302
AR(1)-MFG-T1	1.005	1.001	0.405	0.757	0.924	1.011	0.998	0.282	0.657	0.888	0.992	0.978	0.463	0.745	0.366	1.063	1.075	0.365	0.115	0.195
AR(1)-MF-T2	1.014	1.009	0.492	0.624	0.688	1.085	1.053	0.274	0.066	0.212	1.004	1.001	0.430	0.915	0.973	1.059	1.051	0.409	0.222	0.292
AR(1)-G-T2	1.029	1.050	0.413	0.202	0.283	1.034	1.033	0.355	0.170	0.259	1.019	1.027	0.421	0.285	0.169	1.013	1.041	0.374	0.677	0.199
AR(1)-MFG-T2	1.041	1.057	0.460	0.272	0.256	1.111	1.093	0.306	0.048	0.144	1.049	1.044	0.405	0.258	0.333	1.061	1.081	0.409	0.336	0.152
VAR(1)	0.993	1.008	0.429	0.749	0.597	1.011	1.012	0.339	0.589	0.521	1.005	0.996	0.430	0.779	0.721	1.015	1.010	0.365	0.128	0.135
VARX(1)-MF-T1	0.991	1.005	0.413	0.701	0.772	1.011	0.998	0.315	0.750	0.939	0.980	0.958	0.430	0.636	0.352	1.047	1.047	0.374	0.214	0.282
VARX(1)-G-T1	0.997	1.013	0.413	0.907	0.468	1.023	1.023	0.323	0.191	0.080	1.013	1.007	0.421	0.390	0.412	1.042	1.042	0.357	0.158	0.216
VARX(1)-MFG-T1	0.995	1.010	0.413	0.839	0.607	1.018	1.007	0.298	0.574	0.786	0.990	0.969	0.430	0.766	0.400	1.078	1.081	0.365	0.043	0.161
VARX(1)-MF-T2	1.009	1.008	0.484	0.774	0.754	1.098	1.069	0.282	0.053	0.164	1.013	1.002	0.471	0.720	0.949	1.059	1.059	0.435	0.224	0.245
VARX(1)-G-T2	1.021	1.064	0.444	0.530	0.222	1.057	1.046	0.371	0.004	0.018	1.030	1.023	0.405	0.117	0.018	1.020	1.055	0.365	0.566	0.146
VARX(1)-MFG-T2	1.033	1.061	0.444	0.451	0.236	1.130	1.110	0.331	0.027	0.090	1.052	1.041	0.446	0.292	0.451	1.063	1.084	0.417	0.345	0.145
PVAR(1)-GMM	1.015	1.059	0.254	0.782	0.260	0.926	1.004	0.355	0.180	0.944	0.892	0.974	0.380	0.098	0.638	0.842	0.913	0.348	0.086	0.285
PVAR(1)-OLSCFE	0.970	0.980	0.429	0.218	0.307	0.983	0.988	0.339	0.582	0.667	0.963	0.963	0.438	0.158	0.140	0.995	0.979	0.374	0.943	0.702
PVARX(1)-OLSCFE-MF-T1	0.948	0.961	0.397	0.043	0.058	0.970	0.975	0.347	0.429	0.489	0.949	0.941	0.438	0.255	0.187	1.037	1.056	0.357	0.702	0.625
PVARX(1)-OLSCFE-G-T1	0.982	0.987	0.444	0.558	0.577	1.011	1.011	0.306	0.747	0.681	0.970	0.966	0.455	0.243	0.144	1.000	0.991	0.357	0.998	0.855
PVARX(1)-OLSCFE-MFG-T1	0.957	0.964	0.421	0.161	0.137	0.997	0.998	0.290	0.930	0.950	0.957	0.948	0.421	0.336	0.231	1.042	1.068	0.374	0.645	0.532
PVARX(1)-OLSCFE-MF-T2	0.954	0.958	0.444	0.146	0.093	1.000	0.990	0.298	0.994	0.802	0.991	0.994	0.405	0.801	0.882	1.054	1.081	0.417	0.624	0.543
PVARX(1)-OLSCFE-G-T2	0.988	0.982	0.452	0.695	0.443	1.024	1.017	0.371	0.490	0.536	0.968	0.976	0.372	0.278	0.265	0.963	0.981	0.374	0.489	0.522
PVARX(1)-OLSCFE-MFG-T2	0.952	0.954	0.468	0.200	0.116	1.035	1.020	0.290	0.398	0.620	1.000	1.004	0.364	0.993	0.938	1.031	1.074	0.365	0.705	0.462

Table 15: CPI Growth (Inflation), DE

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.331	1.341	0.302	0.001	0.001	1.562	1.502	0.411	0.000	0.000	1.427	1.417	0.413	0.000	0.000	1.339	1.349	0.504	0.003	0.006
AR(1)	1.000	1.000	0.492	:	:	1.000	1.000	0.508	:	:	1.000	1.000	0.579	:	:	1.000	1.000	0.574	:	:
LR-MF-T1	1.034	1.022	0.444	0.138	0.348	1.026	1.018	0.516	0.563	0.741	1.036	1.023	0.479	0.022	0.224	0.985	0.988	0.591	0.571	0.608
LR-G-T1	1.020	1.017	0.349	0.197	0.180	1.018	1.011	0.468	0.469	0.591	1.027	1.028	0.488	0.072	0.035	1.032	1.032	0.478	0.558	0.608
LR-MFG-T1	1.054	1.046	0.452	0.025	0.038	1.029	1.022	0.492	0.547	0.699	1.041	1.043	0.421	0.015	0.127	1.048	1.047	0.539	0.326	0.446
LR-MF-T2	1.039	1.059	0.421	0.194	0.141	1.102	1.148	0.468	0.254	0.303	1.048	1.095	0.471	0.302	0.309	1.002	0.996	0.504	0.941	0.851
LR-G-T2	1.038	1.036	0.476	0.062	0.028	1.035	1.040	0.403	0.266	0.182	1.023	1.042	0.471	0.397	0.038	1.022	1.036	0.487	0.611	0.574
LR-MFG-T2	1.086	1.137	0.437	0.043	0.051	1.137	1.218	0.444	0.168	0.228	1.077	1.125	0.471	0.095	0.114	1.095	1.082	0.600	0.189	0.330
AR(1)-MF-T1	1.033	1.028	0.476	0.144	0.269	1.039	1.030	0.532	0.377	0.587	1.037	1.031	0.504	0.122	0.200	1.010	1.005	0.600	0.139	0.439
AR(1)-G-T1	1.011	1.017	0.500	0.286	0.040	1.017	1.011	0.484	0.092	0.312	1.021	1.026	0.554	0.256	0.127	1.061	1.051	0.557	0.216	0.235
AR(1)-MFG-T1	1.052	1.051	0.460	0.020	0.033	1.046	1.038	0.548	0.355	0.531	1.041	1.060	0.488	0.087	0.118	1.103	1.093	0.574	0.155	0.184
AR(1)-MF-T2	1.049	1.070	0.429	0.108	0.114	1.110	1.162	0.532	0.214	0.278	1.055	1.117	0.521	0.301	0.291	1.025	1.025	0.522	0.232	0.069
AR(1)-G-T2	1.035	1.037	0.540	0.054	0.010	1.046	1.044	0.476	0.046	0.138	1.026	1.048	0.554	0.365	0.072	1.057	1.056	0.574	0.158	0.255
AR(1)-MFG-T2	1.097	1.151	0.500	0.026	0.042	1.157	1.243	0.444	0.125	0.209	1.076	1.150	0.529	0.151	0.147	1.135	1.133	0.617	0.155	0.218
VAR(1)	1.040	1.043	0.516	0.327	0.423	1.054	1.093	0.540	0.440	0.362	0.995	1.002	0.587	0.390	0.550	1.112	1.122	0.539	0.284	0.271
VARX(1)-MF-T1	1.081	1.124	0.468	0.167	0.263	1.064	1.044	0.556	0.321	0.518	1.056	1.045	0.529	0.161	0.114	1.172	1.270	0.548	0.287	0.271
VARX(1)-G-T1	1.053	1.064	0.500	0.234	0.267	1.061	1.093	0.492	0.385	0.349	1.018	1.025	0.570	0.300	0.123	1.100	1.095	0.548	0.298	0.287
VARX(1)-MFG-T1	1.099	1.146	0.492	0.101	0.178	1.059	1.040	0.556	0.358	0.558	1.095	1.101	0.521	0.125	0.082	1.140	1.221	0.530	0.306	0.287
VARX(1)-MF-T2	1.067	1.128	0.476	0.304	0.170	1.146	1.184	0.500	0.220	0.257	1.072	1.093	0.512	0.145	0.180	1.212	1.306	0.504	0.236	0.263
VARX(1)-G-T2	1.085	1.091	0.508	0.089	0.161	1.094	1.142	0.492	0.223	0.199	1.016	1.043	0.545	0.558	0.074	1.128	1.149	0.583	0.276	0.293
VARX(1)-MFG-T2	1.109	1.188	0.500	0.114	0.063	1.186	1.236	0.484	0.113	0.191	1.080	1.131	0.512	0.106	0.063	1.198	1.304	0.539	0.229	0.286
PVAR(1)-GMM	1.275	1.235	0.548	0.002	0.003	1.185	1.145	0.444	0.018	0.049	1.173	1.142	0.463	0.005	0.055	1.139	1.092	0.496	0.093	0.247
PVAR(1)-OLSCFE	1.033	1.022	0.452	0.095	0.134	1.038	1.041	0.524	0.334	0.410	1.101	1.158	0.421	0.074	0.189	1.093	1.117	0.557	0.293	0.333
PVARX(1)-OLSCFE-MF-T1	1.062	1.071	0.476	0.034	0.019	1.038	1.045	0.532	0.325	0.419	1.103	1.143	0.405	0.019	0.151	1.136	1.157	0.539	0.204	0.249
PVARX(1)-OLSCFE-G-T1	1.055	1.042	0.460	0.017	0.021	1.036	1.040	0.548	0.376	0.440	1.104	1.150	0.405	0.064	0.181	1.134	1.135	0.574	0.111	0.182
PVARX(1)-OLSCFE-MFG-T1	1.084	1.092	0.476	0.008	0.006	1.036	1.045	0.548	0.351	0.434	1.105	1.139	0.421	0.018	0.143	1.171	1.178	0.548	0.101	0.141
PVARX(1)-OLSCFE-MF-T2	1.022	1.039	0.484	0.536	0.368	1.045	1.056	0.500	0.307	0.351	1.163	1.243	0.397	0.013	0.084	1.155	1.183	0.565	0.250	0.285
PVARX(1)-OLSCFE-G-T2	1.064	1.045	0.444	0.023	0.074	1.013	1.037	0.435	0.817	0.589	1.102	1.161	0.421	0.116	0.182	1.141	1.127	0.600	0.080	0.212
PVARX(1)-OLSCFE-MFG-T2	1.047	1.064	0.429	0.232	0.222	1.035	1.059	0.492	0.560	0.466	1.168	1.252	0.405	0.032	0.086	1.194	1.194	0.591	0.138	0.214

Table 16: CPI Growth (Inflation), FR

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.502	1.483	0.302	0.000	0.000	1.567	1.380	0.468	0.000	0.000	1.144	1.206	0.545	0.000	0.030	0.644	0.689	0.835	0.025	0.034
AR(1)	1.000	1.000	0.381	:	:	1.000	1.000	0.419	:	:	1.000	1.000	0.579	:	:	1.000	1.000	0.696	:	:
LR-MF-T1	0.997	0.999	0.381	0.836	0.934	1.001	0.999	0.435	0.906	0.757	1.035	1.008	0.579	0.068	0.457	1.047	1.043	0.670	0.144	0.158
LR-G-T1	0.990	0.992	0.556	0.532	0.483	0.989	0.991	0.540	0.366	0.100	1.035	1.011	0.471	0.054	0.575	1.005	0.998	0.583	0.798	0.893
LR-MFG-T1	1.004	1.000	0.548	0.857	0.989	1.007	1.000	0.524	0.709	0.988	1.056	1.019	0.521	0.095	0.421	1.026	1.022	0.583	0.499	0.537
LR-MF-T2	0.978	0.987	0.492	0.396	0.513	1.031	1.014	0.516	0.215	0.388	1.061	1.028	0.554	0.031	0.104	1.058	1.053	0.478	0.136	0.161
LR-G-T2	0.994	0.985	0.532	0.820	0.619	1.018	1.016	0.468	0.337	0.258	1.038	1.001	0.521	0.133	0.971	0.965	0.987	0.574	0.556	0.816
LR-MFG-T2	0.983	0.977	0.571	0.652	0.470	1.049	1.057	0.492	0.155	0.143	1.076	1.025	0.570	0.041	0.247	0.996	1.033	0.522	0.966	0.696
AR(1)-MF-T1	1.009	1.008	0.365	0.546	0.545	1.012	1.008	0.355	0.154	0.090	1.003	0.997	0.587	0.836	0.414	1.008	1.018	0.713	0.728	0.389
AR(1)-G-T1	1.003	1.004	0.548	0.830	0.712	0.996	1.001	0.508	0.711	0.929	1.017	1.000	0.521	0.279	0.994	0.970	0.981	0.713	0.104	0.000
AR(1)-MFG-T1	1.017	1.011	0.500	0.435	0.539	1.016	1.009	0.460	0.366	0.304	1.031	1.001	0.554	0.271	0.968	0.984	0.998	0.696	0.531	0.922
AR(1)-MF-T2	0.988	0.997	0.444	0.619	0.891	1.053	1.031	0.476	0.048	0.077	1.017	1.014	0.512	0.563	0.442	1.029	1.030	0.670	0.412	0.304
AR(1)-G-T2	1.003	0.995	0.563	0.918	0.869	1.021	1.024	0.444	0.245	0.170	1.024	1.000	0.545	0.360	0.990	0.924	0.965	0.713	0.034	0.348
AR(1)-MFG-T2	0.989	0.981	0.603	0.773	0.554	1.062	1.065	0.460	0.075	0.085	1.041	1.021	0.512	0.332	0.402	0.953	1.004	0.626	0.398	0.930
VAR(1)	1.031	1.012	0.373	0.036	0.252	1.016	1.006	0.435	0.667	0.743	1.090	1.129	0.537	0.373	0.341	1.040	1.042	0.713	0.276	0.168
VARX(1)-MF-T1	1.033	1.022	0.349	0.054	0.149	1.025	1.012	0.444	0.516	0.523	1.070	1.102	0.521	0.386	0.306	1.049	1.054	0.722	0.234	0.157
VARX(1)-G-T1	1.028	1.012	0.500	0.240	0.446	1.032	1.017	0.516	0.444	0.389	1.088	1.104	0.504	0.305	0.362	1.000	1.012	0.739	0.998	0.592
VARX(1)-MFG-T1	1.034	1.023	0.492	0.194	0.256	1.045	1.030	0.524	0.366	0.261	1.061	1.058	0.512	0.309	0.331	1.004	1.021	0.696	0.913	0.540
VARX(1)-MF-T2	1.022	1.012	0.508	0.437	0.579	1.054	1.030	0.492	0.062	0.162	1.105	1.158	0.496	0.337	0.287	1.060	1.089	0.661	0.349	0.201
VARX(1)-G-T2	1.041	1.012	0.548	0.235	0.707	1.051	1.040	0.460	0.226	0.079	1.086	1.098	0.554	0.280	0.355	0.954	0.986	0.722	0.345	0.727
VARX(1)-MFG-T2	1.020	0.998	0.627	0.625	0.964	1.074	1.076	0.484	0.114	0.042	1.112	1.133	0.496	0.243	0.278	0.983	1.041	0.626	0.814	0.553
PVAR(1)-GMM	1.049	1.036	0.643	0.279	0.326	1.056	1.026	0.444	0.243	0.396	1.079	1.036	0.554	0.002	0.015	1.059	1.036	0.635	0.206	0.307
PVAR(1)-OLSCFE	1.000	0.992	0.516	0.986	0.500	0.995	0.994	0.435	0.525	0.403	1.024	1.026	0.554	0.457	0.445	1.019	1.028	0.704	0.641	0.477
PVARX(1)-OLSCFE-MF-T1	1.009	1.006	0.452	0.591	0.705	0.998	0.999	0.403	0.833	0.853	1.011	1.015	0.545	0.669	0.591	1.041	1.043	0.687	0.457	0.341
PVARX(1)-OLSCFE-G-T1	1.010	0.996	0.492	0.592	0.718	0.997	0.995	0.468	0.753	0.516	1.024	1.023	0.545	0.439	0.497	0.993	1.009	0.670	0.839	0.790
PVARX(1)-OLSCFE-MFG-T1	1.021	1.010	0.516	0.290	0.526	1.001	1.000	0.419	0.895	0.954	1.012	1.012	0.537	0.628	0.661	1.015	1.024	0.670	0.766	0.564
PVARX(1)-OLSCFE-MF-T2	0.988	0.993	0.532	0.544	0.666	0.996	1.001	0.484	0.791	0.897	0.992	1.009	0.521	0.850	0.806	1.044	1.045	0.678	0.508	0.368
PVARX(1)-OLSCFE-G-T2	0.978	0.965	0.548	0.421	0.095	0.998	1.001	0.500	0.880	0.913	1.034	1.024	0.545	0.336	0.522	0.925	0.973	0.722	0.128	0.527
PVARX(1)-OLSCFE-MFG-T2	0.980	0.970	0.563	0.459	0.144	1.004	1.010	0.508	0.815	0.413	1.004	1.008	0.512	0.931	0.833	0.952	0.989	0.704	0.520	0.827

Table 17: CPI Growth (Inflation), IT

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.298	1.350	0.198	0.001	0.000	1.401	1.351	0.403	0.000	0.000	1.318	1.304	0.545	0.003	0.008	1.032	1.084	0.635	0.824	0.523
AR(1)	1.000	1.000	0.611	:	:	1.000	1.000	0.500	:	:	1.000	1.000	0.562	:	:	1.000	1.000	0.626	:	:
LR-MF-T1	1.008	1.050	0.492	0.830	0.174	0.976	0.988	0.476	0.074	0.525	1.041	1.029	0.545	0.400	0.499	1.020	1.015	0.539	0.247	0.329
LR-G-T1	1.035	1.069	0.397	0.289	0.028	0.995	0.995	0.484	0.701	0.720	1.009	0.995	0.488	0.562	0.676	1.004	1.004	0.548	0.696	0.617
LR-MFG-T1	1.017	1.058	0.508	0.677	0.137	0.979	0.993	0.540	0.164	0.724	1.045	1.028	0.496	0.317	0.467	1.022	1.016	0.574	0.194	0.338
LR-MF-T2	1.047	1.079	0.500	0.267	0.049	1.006	1.022	0.492	0.761	0.280	1.097	1.071	0.521	0.169	0.264	1.038	1.033	0.557	0.260	0.277
LR-G-T2	1.033	1.059	0.508	0.408	0.139	0.999	1.003	0.524	0.921	0.845	1.019	1.011	0.446	0.262	0.498	1.014	1.025	0.557	0.799	0.569
LR-MFG-T2	1.060	1.078	0.524	0.268	0.154	1.014	1.030	0.565	0.391	0.129	1.115	1.082	0.479	0.084	0.140	1.038	1.057	0.635	0.540	0.430
AR(1)-MF-T1	0.995	0.999	0.667	0.833	0.947	0.983	1.002	0.548	0.167	0.901	1.053	1.045	0.570	0.320	0.337	1.025	1.013	0.635	0.067	0.188
AR(1)-G-T1	1.009	1.007	0.611	0.074	0.077	1.005	1.005	0.548	0.364	0.278	1.014	1.009	0.554	0.058	0.072	1.003	1.001	0.635	0.683	0.735
AR(1)-MFG-T1	0.998	1.005	0.651	0.936	0.823	0.987	1.008	0.565	0.351	0.677	1.059	1.047	0.587	0.245	0.280	1.023	1.012	0.635	0.075	0.211
AR(1)-MF-T2	1.033	1.035	0.635	0.335	0.232	1.019	1.040	0.500	0.279	0.073	1.113	1.091	0.471	0.110	0.184	1.087	1.056	0.635	0.257	0.279
AR(1)-G-T2	1.002	0.996	0.619	0.912	0.815	1.012	1.015	0.573	0.223	0.135	1.035	1.025	0.521	0.026	0.027	1.009	1.017	0.617	0.853	0.620
AR(1)-MFG-T2	1.043	1.033	0.587	0.334	0.407	1.026	1.048	0.532	0.143	0.032	1.149	1.113	0.471	0.036	0.080	1.044	1.053	0.696	0.533	0.438
VAR(1)	1.022	1.054	0.587	0.413	0.053	1.006	1.004	0.516	0.416	0.296	1.034	1.037	0.529	0.433	0.327	1.143	1.135	0.565	0.155	0.196
VARX(1)-MF-T1	1.052	1.108	0.611	0.268	0.115	1.039	1.071	0.516	0.439	0.372	1.075	1.076	0.562	0.324	0.300	1.142	1.140	0.600	0.189	0.206
VARX(1)-G-T1	1.032	1.065	0.587	0.262	0.040	1.017	1.012	0.516	0.145	0.093	1.036	1.036	0.579	0.325	0.216	1.154	1.159	0.574	0.152	0.216
VARX(1)-MFG-T1	1.062	1.120	0.603	0.205	0.114	1.048	1.078	0.532	0.348	0.321	1.084	1.079	0.562	0.260	0.247	1.155	1.165	0.591	0.186	0.227
VARX(1)-MF-T2	1.078	1.141	0.619	0.146	0.110	1.080	1.111	0.516	0.133	0.177	1.132	1.122	0.479	0.092	0.159	1.168	1.172	0.609	0.187	0.202
VARX(1)-G-T2	1.007	1.052	0.603	0.845	0.186	1.029	1.024	0.548	0.104	0.056	1.068	1.058	0.504	0.098	0.046	1.132	1.131	0.583	0.236	0.237
VARX(1)-MFG-T2	1.065	1.131	0.651	0.291	0.182	1.095	1.122	0.508	0.083	0.150	1.175	1.157	0.463	0.033	0.074	1.135	1.166	0.635	0.296	0.259
PVAR(1)-GMM	1.281	1.328	0.603	0.002	0.008	1.139	1.101	0.403	0.093	0.217	1.130	1.087	0.628	0.093	0.359	1.114	1.077	0.513	0.130	0.510
PVAR(1)-OLSCFE	1.002	1.044	0.603	0.938	0.138	1.018	1.023	0.573	0.429	0.224	1.064	1.069	0.496	0.285	0.211	1.162	1.135	0.617	0.030	0.037
PVARX(1)-OLSCFE-MF-T1	0.989	1.050	0.667	0.783	0.212	1.027	1.034	0.605	0.384	0.271	1.072	1.076	0.479	0.254	0.196	1.176	1.146	0.600	0.015	0.027
PVARX(1)-OLSCFE-G-T1	1.023	1.070	0.563	0.544	0.072	1.017	1.022	0.573	0.476	0.259	1.069	1.069	0.488	0.255	0.202	1.128	1.100	0.635	0.053	0.049
PVARX(1)-OLSCFE-MFG-T1	1.031	1.073	0.659	0.446	0.084	1.025	1.033	0.581	0.414	0.284	1.076	1.074	0.479	0.231	0.187	1.144	1.112	0.626	0.029	0.039
PVARX(1)-OLSCFE-MF-T2	1.078	1.158	0.508	0.104	0.004	1.031	1.038	0.597	0.380	0.310	1.071	1.067	0.496	0.316	0.230	1.197	1.183	0.548	0.030	0.035
PVARX(1)-OLSCFE-G-T2	1.005	1.067	0.540	0.918	0.166	1.035	1.031	0.605	0.258	0.299	1.057	1.068	0.496	0.335	0.250	1.139	1.094	0.609	0.009	0.047
PVARX(1)-OLSCFE-MFG-T2	1.101	1.169	0.508	0.052	0.005	1.045	1.047	0.621	0.237	0.224	1.070	1.064	0.529	0.331	0.272	1.162	1.131	0.626	0.010	0.073

Table 18: CPI Growth (Inflation), UK

	h=1					h=3					h=6					h=12				
	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2	MAE	RMSFE	SSR	DM1	DM2
Naive	1.455	1.477	0.270	0.000	0.000	1.546	1.471	0.395	0.000	0.000	1.162	1.118	0.603	0.144	0.270	0.878	0.863	0.652	0.134	0.087
AR(1)	1.000	1.000	0.508	:	:	1.000	1.000	0.452	:	:	1.000	1.000	0.661	:	:	1.000	1.000	0.609	:	:
LR-MF-T1	0.982	1.006	0.508	0.260	0.712	1.001	1.011	0.565	0.981	0.627	1.019	1.001	0.463	0.555	0.962	1.029	1.034	0.557	0.573	0.479
LR-G-T1	0.973	0.982	0.540	0.194	0.260	0.995	0.995	0.476	0.482	0.314	1.046	1.016	0.372	0.071	0.505	0.978	0.950	0.600	0.544	0.053
LR-MFG-T1	0.973	0.992	0.595	0.282	0.700	1.003	1.015	0.500	0.892	0.509	1.038	1.012	0.430	0.268	0.558	1.003	0.973	0.548	0.937	0.522
LR-MF-T2	0.981	1.042	0.548	0.659	0.473	1.019	1.036	0.597	0.630	0.316	1.043	1.045	0.479	0.245	0.181	1.062	1.055	0.591	0.315	0.290
LR-G-T2	0.968	0.957	0.619	0.272	0.068	0.992	0.970	0.629	0.877	0.369	0.996	0.980	0.620	0.876	0.439	0.862	0.834	0.696	0.016	0.011
LR-MFG-T2	0.969	1.012	0.651	0.495	0.845	1.008	1.008	0.661	0.901	0.860	1.015	1.025	0.620	0.789	0.514	0.939	0.904	0.678	0.314	0.090
AR(1)-MF-T1	0.995	1.010	0.571	0.730	0.476	1.006	1.017	0.556	0.774	0.468	0.998	1.000	0.579	0.934	0.984	1.016	1.019	0.557	0.324	0.416
AR(1)-G-T1	0.985	0.986	0.540	0.504	0.382	1.005	1.006	0.460	0.474	0.382	1.020	1.012	0.628	0.014	0.009	0.959	0.935	0.643	0.033	0.092
AR(1)-MFG-T1	0.982	0.996	0.643	0.489	0.844	1.016	1.024	0.524	0.523	0.361	1.018	1.011	0.562	0.513	0.520	0.981	0.951	0.617	0.014	0.205
AR(1)-MF-T2	0.994	1.048	0.563	0.898	0.411	1.028	1.044	0.573	0.497	0.228	1.032	1.043	0.537	0.433	0.131	1.085	1.068	0.609	0.271	0.260
AR(1)-G-T2	0.980	0.966	0.619	0.484	0.148	1.002	0.984	0.597	0.964	0.654	1.015	0.988	0.653	0.386	0.200	0.856	0.829	0.722	0.006	0.006
AR(1)-MFG-T2	0.978	1.020	0.651	0.636	0.745	1.025	1.029	0.645	0.713	0.579	1.041	1.037	0.628	0.519	0.330	0.941	0.912	0.687	0.185	0.057
VAR(1)	1.023	1.021	0.548	0.345	0.254	1.032	1.030	0.444	0.240	0.143	1.133	1.175	0.636	0.193	0.269	1.105	1.287	0.652	0.358	0.327
VARX(1)-MF-T1	1.017	1.020	0.540	0.528	0.367	1.034	1.049	0.492	0.145	0.015	1.176	1.267	0.636	0.328	0.313	1.126	1.294	0.661	0.299	0.303
VARX(1)-G-T1	1.005	1.004	0.603	0.864	0.874	1.042	1.034	0.419	0.116	0.087	1.157	1.199	0.645	0.129	0.241	1.074	1.264	0.626	0.576	0.420
VARX(1)-MFG-T1	0.996	1.004	0.611	0.910	0.880	1.047	1.055	0.484	0.079	0.041	1.201	1.289	0.612	0.272	0.293	1.106	1.267	0.626	0.447	0.404
VARX(1)-MF-T2	1.035	1.081	0.508	0.466	0.193	1.082	1.087	0.516	0.063	0.010	1.208	1.243	0.587	0.150	0.171	1.254	1.711	0.635	0.305	0.316
VARX(1)-G-T2	0.983	0.980	0.611	0.638	0.510	1.044	1.096	0.589	0.602	0.474	1.158	1.217	0.661	0.201	0.304	1.056	1.488	0.730	0.800	0.437
VARX(1)-MFG-T2	0.998	1.041	0.611	0.960	0.519	1.058	1.083	0.645	0.501	0.331	1.257	1.305	0.653	0.115	0.179	1.169	1.816	0.713	0.571	0.376
PVAR(1)-GMM	1.204	1.134	0.730	0.001	0.014	1.211	1.119	0.540	0.000	0.017	1.240	1.130	0.512	0.000	0.016	1.203	1.141	0.583	0.000	0.065
PVAR(1)-OLSCFE	1.011	1.010	0.540	0.226	0.337	0.993	0.991	0.484	0.425	0.307	1.026	1.017	0.645	0.236	0.375	1.003	1.005	0.626	0.809	0.431
PVARX(1)-OLSCFE-MF-T1	1.006	1.012	0.587	0.589	0.329	0.988	0.988	0.492	0.200	0.146	1.025	1.014	0.636	0.354	0.528	1.018	1.018	0.591	0.417	0.457
PVARX(1)-OLSCFE-G-T1	0.995	0.999	0.563	0.721	0.943	0.990	0.992	0.460	0.300	0.338	1.037	1.023	0.628	0.098	0.285	0.979	0.963	0.652	0.175	0.123
PVARX(1)-OLSCFE-MFG-T1	0.991	1.001	0.611	0.595	0.920	0.986	0.988	0.484	0.150	0.097	1.037	1.019	0.620	0.172	0.417	0.995	0.976	0.635	0.716	0.107
PVARX(1)-OLSCFE-MF-T2	0.980	1.012	0.548	0.471	0.688	0.995	1.011	0.556	0.804	0.535	1.039	1.022	0.570	0.371	0.467	1.041	1.021	0.609	0.212	0.426
PVARX(1)-OLSCFE-G-T2	0.983	0.977	0.595	0.390	0.150	0.980	0.971	0.581	0.378	0.064	1.031	1.013	0.669	0.268	0.658	0.937	0.906	0.704	0.027	0.009
PVARX(1)-OLSCFE-MFG-T2	0.963	0.986	0.611	0.218	0.668	0.980	0.995	0.605	0.510	0.824	1.038	1.019	0.612	0.421	0.622	0.971	0.925	0.696	0.259	0.000

Table 19: Density Coverage Rates. GDP Growth

	DE								FR							
	h=1		h=2		h=3		h=4		h=1		h=2		h=3		h=4	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.935	1.000	0.933	1.000	0.966	1.000	0.893	1.000	0.839	0.968	0.833	1.000	0.862	0.931	0.821	0.964
AR(1)	0.968	1.000	0.933	1.000	0.966	1.000	0.964	1.000	0.871	0.968	0.933	1.000	0.931	1.000	0.964	1.000
LR-MF-T1	0.871	1.000	0.967	1.000	0.966	1.000	0.964	1.000	0.871	0.968	0.967	1.000	0.966	1.000	0.964	1.000
LR-G-T1	0.935	1.000	0.900	0.967	0.931	1.000	0.964	1.000	0.935	1.000	0.933	1.000	0.966	1.000	0.964	1.000
LR-MFG-T1	0.806	1.000	0.900	0.967	0.931	1.000	0.929	1.000	0.839	0.935	0.900	1.000	0.966	1.000	0.964	1.000
LR-MF-T2	0.613	0.903	0.867	1.000	0.759	1.000	0.964	1.000	0.742	0.935	0.700	0.967	0.724	0.931	0.821	0.857
LR-G-T2	0.968	1.000	0.900	0.967	0.966	1.000	0.929	1.000	0.935	1.000	0.833	1.000	0.966	1.000	0.821	1.000
LR-MFG-T2	0.645	0.935	0.867	0.967	0.828	0.931	0.893	1.000	0.677	0.935	0.667	0.933	0.690	0.931	0.607	0.750
AR(1)-MF-T1	0.871	1.000	0.967	1.000	0.966	1.000	0.964	1.000	0.839	0.935	0.967	1.000	0.931	1.000	0.964	1.000
AR(1)-G-T1	0.968	1.000	0.900	0.967	0.931	1.000	0.964	1.000	0.871	0.968	0.867	1.000	0.931	1.000	0.964	1.000
AR(1)-MFG-T1	0.806	1.000	0.900	0.967	0.966	1.000	0.964	1.000	0.839	0.903	0.900	1.000	0.931	1.000	0.964	1.000
AR(1)-MF-T2	0.645	0.871	0.833	0.967	0.828	0.966	0.964	0.964	0.774	0.903	0.700	1.000	0.724	0.862	0.821	0.857
AR(1)-G-T2	0.968	1.000	0.900	0.967	0.897	0.966	0.857	1.000	0.871	0.968	0.833	0.967	0.931	0.966	0.821	0.964
AR(1)-MFG-T2	0.645	0.839	0.800	0.933	0.793	0.931	0.893	0.964	0.613	0.871	0.700	0.967	0.690	0.862	0.571	0.750
VAR(1)	0.903	1.000	0.900	0.967	0.862	0.966	0.893	0.964	0.903	0.968	0.900	0.933	0.724	0.966	0.893	1.000
VARX(1)-MF-T1	0.774	0.968	0.733	0.967	0.862	0.966	0.893	0.964	0.774	0.935	0.867	0.967	0.724	1.000	0.893	1.000
VARX(1)-G-T1	0.903	0.968	0.800	0.967	0.828	0.966	0.893	0.964	0.839	0.968	0.900	0.933	0.759	0.966	0.893	1.000
VARX(1)-MFG-T1	0.742	0.968	0.733	0.967	0.793	0.966	0.893	0.964	0.806	0.903	0.833	1.000	0.759	1.000	0.893	1.000
VARX(1)-MF-T2	0.516	0.839	0.733	0.800	0.828	0.897	0.857	0.893	0.677	0.871	0.633	0.933	0.690	0.828	0.679	0.750
VARX(1)-G-T2	0.903	0.968	0.767	0.967	0.793	0.966	0.893	0.964	0.806	0.968	0.867	0.900	0.724	0.966	0.750	0.964
VARX(1)-MFG-T2	0.613	0.839	0.600	0.800	0.724	0.931	0.821	0.893	0.581	0.839	0.733	0.833	0.517	0.724	0.571	0.750
PVAR(1)-GMM	0.581	0.935	0.467	0.867	0.379	0.828	0.393	0.821	0.613	0.903	0.633	0.933	0.621	0.828	0.536	0.786
PVAR(1)-OLSCFE	0.968	1.000	0.967	1.000	0.931	0.966	0.929	1.000	0.935	0.935	0.900	0.967	0.931	1.000	0.929	1.000
PVARX(1)-OLSCFE-MF-T1	0.968	0.968	0.933	1.000	0.931	0.966	0.929	1.000	0.871	0.935	0.900	0.967	0.931	1.000	0.929	1.000
PVARX(1)-OLSCFE-G-T1	0.968	1.000	0.933	0.967	0.931	0.966	0.929	1.000	0.903	0.935	0.900	0.967	0.897	1.000	0.929	1.000
PVARX(1)-OLSCFE-MFG-T1	0.968	0.968	0.900	1.000	0.931	1.000	0.964	1.000	0.871	0.935	0.900	0.967	0.862	1.000	0.929	1.000
PVARX(1)-OLSCFE-MF-T2	0.968	0.968	0.900	1.000	0.931	1.000	0.929	0.964	0.871	0.935	0.833	0.933	0.828	1.000	0.893	1.000
PVARX(1)-OLSCFE-G-T2	0.968	1.000	0.933	1.000	0.931	1.000	0.929	1.000	0.839	0.968	0.867	0.967	0.793	1.000	0.929	1.000
PVARX(1)-OLSCFE-MFG-T2	0.968	1.000	0.833	1.000	0.931	1.000	0.964	0.964	0.839	0.935	0.833	0.933	0.759	1.000	0.857	1.000

Table 19: Density Coverage Rates. GDP Growth (continued)

	IT								UK							
	h=1		h=2		h=3		h=4		h=1		h=2		h=3		h=4	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.935	1.000	0.967	1.000	0.862	1.000	0.821	1.000	0.677	0.871	0.533	0.833	0.759	0.966	0.786	0.893
AR(1)	1.000	1.000	1.000	1.000	0.966	1.000	1.000	1.000	0.710	0.935	0.867	0.967	0.862	1.000	0.857	1.000
LR-MF-T1	0.903	0.968	0.933	1.000	0.966	0.966	0.929	1.000	0.806	0.935	0.833	0.967	0.862	1.000	0.893	0.964
LR-G-T1	1.000	1.000	1.000	1.000	0.931	1.000	0.929	1.000	0.871	0.935	0.867	0.967	0.828	0.966	0.857	0.964
LR-MFG-T1	0.839	0.968	0.900	1.000	0.966	1.000	0.893	1.000	0.774	0.903	0.800	0.967	0.828	1.000	0.786	0.929
LR-MF-T2	0.871	0.968	0.800	0.900	0.897	0.966	0.750	0.929	0.774	0.935	0.667	0.967	0.759	0.966	0.857	0.929
LR-G-T2	0.935	1.000	0.867	0.933	0.862	1.000	0.893	1.000	0.806	0.935	0.733	0.967	0.690	0.897	0.750	0.929
LR-MFG-T2	0.839	0.871	0.767	0.833	0.862	0.931	0.714	0.893	0.710	0.903	0.667	0.900	0.586	0.793	0.643	0.750
AR(1)-MF-T1	0.935	1.000	0.900	0.967	0.966	0.966	0.929	1.000	0.645	0.903	0.833	0.967	0.828	1.000	0.857	1.000
AR(1)-G-T1	0.968	1.000	1.000	1.000	0.931	1.000	0.929	1.000	0.742	0.935	0.833	0.967	0.793	0.966	0.821	0.964
AR(1)-MFG-T1	0.935	1.000	0.900	0.967	0.931	0.966	0.893	1.000	0.710	0.871	0.800	0.967	0.828	1.000	0.786	0.964
AR(1)-MF-T2	0.871	0.968	0.767	0.900	0.828	0.931	0.786	0.929	0.710	0.903	0.667	0.933	0.759	0.966	0.857	1.000
AR(1)-G-T2	0.968	1.000	0.767	0.933	0.828	1.000	0.857	1.000	0.710	0.935	0.733	0.933	0.655	0.897	0.714	0.929
AR(1)-MFG-T2	0.839	0.871	0.767	0.833	0.690	0.897	0.714	0.893	0.645	0.903	0.667	0.867	0.448	0.759	0.571	0.857
VAR(1)	0.968	1.000	0.800	0.900	0.621	0.862	0.750	0.857	0.742	0.871	0.800	0.900	0.828	0.931	0.857	1.000
VARX(1)-MF-T1	0.839	0.968	0.767	0.933	0.655	0.897	0.750	0.857	0.581	0.839	0.800	0.900	0.724	0.966	0.893	0.964
VARX(1)-G-T1	0.935	1.000	0.733	0.900	0.655	0.862	0.714	0.857	0.742	0.871	0.767	0.900	0.828	0.966	0.857	0.964
VARX(1)-MFG-T1	0.903	0.968	0.733	0.933	0.690	0.862	0.750	0.821	0.581	0.839	0.700	0.933	0.724	0.931	0.679	0.964
VARX(1)-MF-T2	0.903	0.935	0.567	0.900	0.586	0.793	0.750	0.893	0.645	0.871	0.667	0.900	0.724	0.931	0.786	1.000
VARX(1)-G-T2	0.871	1.000	0.767	0.900	0.552	0.828	0.714	0.893	0.742	0.871	0.733	0.900	0.621	0.897	0.679	0.893
VARX(1)-MFG-T2	0.613	0.871	0.533	0.767	0.552	0.759	0.679	0.857	0.581	0.839	0.467	0.833	0.414	0.759	0.464	0.786
PVAR(1)-GMM	0.903	0.968	0.933	0.967	0.931	0.966	0.964	1.000	0.613	0.903	0.600	0.833	0.655	0.862	0.643	0.821
PVAR(1)-OLSCFE	1.000	1.000	1.000	1.000	0.966	1.000	0.857	0.929	0.774	0.968	0.767	0.967	0.862	0.966	0.929	1.000
PVARX(1)-OLSCFE-MF-T1	0.903	1.000	0.967	1.000	0.897	1.000	0.857	0.929	0.774	0.968	0.800	0.967	0.828	0.966	0.893	1.000
PVARX(1)-OLSCFE-G-T1	1.000	1.000	1.000	1.000	0.966	1.000	0.893	0.929	0.742	0.968	0.800	1.000	0.828	0.966	0.929	1.000
PVARX(1)-OLSCFE-MFG-T1	0.935	1.000	0.967	1.000	0.897	1.000	0.893	0.929	0.742	0.968	0.800	0.967	0.793	0.966	0.893	1.000
PVARX(1)-OLSCFE-MF-T2	0.903	0.968	0.967	0.967	0.931	0.966	0.821	0.893	0.774	0.935	0.800	1.000	0.759	0.966	0.929	1.000
PVARX(1)-OLSCFE-G-T2	1.000	1.000	0.967	1.000	0.966	1.000	0.893	0.929	0.774	0.935	0.800	0.967	0.828	0.966	0.893	1.000
PVARX(1)-OLSCFE-MFG-T2	0.935	0.968	0.933	0.967	0.897	0.966	0.821	0.893	0.806	0.935	0.833	1.000	0.793	0.966	0.929	1.000

Table 20: Density Coverage Rates. Industrial Production Growth

	DE								FR							
	h=1		h=3		h=6		h=12		h=1		h=3		h=6		h=12	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.543	0.764	0.568	0.872	0.566	0.770	0.534	0.828	0.520	0.787	0.592	0.832	0.656	0.828	0.500	0.802
AR(1)	0.724	0.913	0.728	0.912	0.754	0.885	0.724	0.879	0.740	0.953	0.760	0.952	0.770	0.943	0.776	0.948
LR-MF-T1	0.701	0.898	0.712	0.920	0.754	0.910	0.698	0.862	0.756	0.953	0.768	0.928	0.779	0.951	0.750	0.922
LR-G-T1	0.732	0.913	0.736	0.912	0.746	0.893	0.750	0.879	0.772	0.953	0.760	0.944	0.795	0.951	0.793	0.948
LR-MFG-T1	0.693	0.906	0.704	0.904	0.730	0.869	0.664	0.836	0.764	0.953	0.752	0.936	0.787	0.951	0.750	0.922
LR-MF-T2	0.654	0.913	0.704	0.880	0.721	0.885	0.690	0.853	0.764	0.929	0.752	0.936	0.762	0.934	0.741	0.922
LR-G-T2	0.717	0.913	0.720	0.888	0.713	0.885	0.681	0.862	0.740	0.929	0.752	0.944	0.697	0.951	0.621	0.879
LR-MFG-T2	0.638	0.890	0.672	0.848	0.648	0.820	0.638	0.828	0.724	0.921	0.720	0.928	0.697	0.926	0.647	0.845
AR(1)-MF-T1	0.709	0.898	0.736	0.896	0.746	0.885	0.698	0.828	0.748	0.961	0.776	0.928	0.770	0.934	0.733	0.931
AR(1)-G-T1	0.717	0.913	0.728	0.912	0.738	0.877	0.707	0.862	0.756	0.953	0.752	0.944	0.770	0.943	0.793	0.948
AR(1)-MFG-T1	0.709	0.898	0.720	0.896	0.730	0.877	0.672	0.810	0.740	0.961	0.760	0.936	0.787	0.934	0.724	0.922
AR(1)-MF-T2	0.646	0.913	0.688	0.880	0.721	0.869	0.698	0.845	0.764	0.937	0.752	0.936	0.770	0.934	0.707	0.922
AR(1)-G-T2	0.709	0.898	0.712	0.880	0.713	0.861	0.672	0.853	0.724	0.937	0.736	0.944	0.713	0.943	0.638	0.871
AR(1)-MFG-T2	0.622	0.874	0.656	0.848	0.656	0.820	0.603	0.819	0.701	0.913	0.712	0.928	0.705	0.926	0.621	0.853
VAR(1)	0.701	0.890	0.736	0.904	0.730	0.885	0.750	0.853	0.740	0.945	0.744	0.928	0.738	0.926	0.741	0.922
VARX(1)-MF-T1	0.669	0.858	0.696	0.888	0.738	0.885	0.690	0.845	0.717	0.945	0.752	0.920	0.746	0.918	0.707	0.914
VARX(1)-G-T1	0.701	0.890	0.736	0.896	0.713	0.885	0.733	0.845	0.732	0.937	0.736	0.936	0.730	0.918	0.733	0.922
VARX(1)-MFG-T1	0.646	0.835	0.688	0.880	0.697	0.885	0.690	0.819	0.709	0.937	0.728	0.928	0.738	0.926	0.698	0.905
VARX(1)-MF-T2	0.646	0.850	0.688	0.864	0.713	0.861	0.690	0.836	0.717	0.929	0.752	0.928	0.746	0.934	0.672	0.914
VARX(1)-G-T2	0.693	0.874	0.688	0.872	0.680	0.844	0.672	0.836	0.669	0.929	0.728	0.928	0.713	0.918	0.603	0.836
VARX(1)-MFG-T2	0.622	0.811	0.648	0.840	0.631	0.836	0.621	0.793	0.654	0.913	0.712	0.920	0.672	0.926	0.621	0.845
PVAR(1)-GMM	0.732	0.898	0.672	0.888	0.672	0.877	0.664	0.862	0.724	0.929	0.680	0.920	0.705	0.926	0.707	0.940
PVAR(1)-OLSCFE	0.748	0.913	0.720	0.888	0.803	0.902	0.741	0.897	0.764	0.953	0.736	0.952	0.820	0.959	0.793	0.948
PVARX(1)-OLSCFE-MF-T1	0.724	0.921	0.704	0.896	0.803	0.893	0.672	0.853	0.717	0.961	0.736	0.936	0.828	0.959	0.716	0.922
PVARX(1)-OLSCFE-G-T1	0.748	0.913	0.736	0.888	0.803	0.910	0.759	0.897	0.772	0.953	0.728	0.944	0.811	0.959	0.793	0.957
PVARX(1)-OLSCFE-MFG-T1	0.724	0.921	0.728	0.896	0.803	0.902	0.672	0.853	0.724	0.961	0.712	0.936	0.820	0.959	0.716	0.905
PVARX(1)-OLSCFE-MF-T2	0.732	0.913	0.696	0.888	0.795	0.893	0.716	0.862	0.732	0.953	0.760	0.952	0.803	0.959	0.733	0.922
PVARX(1)-OLSCFE-G-T2	0.740	0.913	0.728	0.912	0.787	0.910	0.750	0.888	0.732	0.953	0.720	0.936	0.811	0.959	0.759	0.957
PVARX(1)-OLSCFE-MFG-T2	0.748	0.921	0.712	0.896	0.779	0.885	0.716	0.871	0.693	0.961	0.720	0.936	0.811	0.959	0.716	0.948

Table 20: Density Coverage Rates. Industrial Production Growth (continued)

	IT								UK							
	h=1		h=3		h=6		h=12		h=1		h=3		h=6		h=12	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.535	0.717	0.560	0.808	0.574	0.746	0.457	0.698	0.449	0.780	0.664	0.848	0.607	0.828	0.586	0.802
AR(1)	0.661	0.882	0.664	0.880	0.697	0.844	0.698	0.871	0.717	0.906	0.728	0.912	0.762	0.918	0.750	0.922
LR-MF-T1	0.646	0.898	0.664	0.856	0.697	0.869	0.716	0.871	0.709	0.921	0.736	0.912	0.721	0.918	0.681	0.888
LR-G-T1	0.701	0.882	0.712	0.864	0.697	0.861	0.707	0.879	0.717	0.929	0.744	0.920	0.721	0.910	0.698	0.931
LR-MFG-T1	0.646	0.898	0.688	0.856	0.705	0.861	0.724	0.871	0.717	0.913	0.744	0.912	0.730	0.910	0.664	0.888
LR-MF-T2	0.654	0.866	0.640	0.832	0.689	0.861	0.681	0.836	0.693	0.890	0.696	0.896	0.713	0.893	0.690	0.862
LR-G-T2	0.701	0.827	0.648	0.872	0.689	0.844	0.664	0.819	0.717	0.913	0.736	0.904	0.730	0.902	0.724	0.879
LR-MFG-T2	0.638	0.827	0.616	0.784	0.689	0.836	0.655	0.810	0.677	0.898	0.696	0.904	0.689	0.902	0.638	0.853
AR(1)-MF-T1	0.638	0.882	0.656	0.872	0.680	0.869	0.707	0.871	0.717	0.921	0.736	0.912	0.770	0.918	0.707	0.879
AR(1)-G-T1	0.669	0.866	0.688	0.872	0.697	0.852	0.716	0.879	0.724	0.906	0.736	0.920	0.746	0.902	0.750	0.905
AR(1)-MFG-T1	0.646	0.898	0.656	0.856	0.689	0.861	0.707	0.871	0.717	0.921	0.744	0.920	0.754	0.902	0.698	0.888
AR(1)-MF-T2	0.669	0.858	0.640	0.848	0.672	0.852	0.681	0.862	0.677	0.906	0.704	0.904	0.730	0.902	0.690	0.862
AR(1)-G-T2	0.677	0.843	0.680	0.840	0.664	0.828	0.681	0.819	0.677	0.913	0.688	0.912	0.721	0.885	0.707	0.879
AR(1)-MFG-T2	0.622	0.811	0.600	0.792	0.664	0.795	0.629	0.810	0.669	0.898	0.664	0.920	0.672	0.893	0.638	0.819
VAR(1)	0.669	0.858	0.656	0.856	0.697	0.844	0.690	0.845	0.701	0.898	0.688	0.896	0.730	0.902	0.716	0.897
VARX(1)-MF-T1	0.630	0.850	0.664	0.864	0.689	0.836	0.698	0.845	0.709	0.898	0.720	0.896	0.738	0.902	0.698	0.862
VARX(1)-G-T1	0.654	0.866	0.656	0.864	0.680	0.836	0.672	0.836	0.717	0.898	0.712	0.912	0.705	0.885	0.724	0.914
VARX(1)-MFG-T1	0.638	0.858	0.672	0.864	0.680	0.828	0.698	0.836	0.709	0.898	0.728	0.904	0.705	0.902	0.672	0.862
VARX(1)-MF-T2	0.630	0.858	0.632	0.848	0.639	0.811	0.655	0.810	0.661	0.890	0.680	0.912	0.680	0.869	0.690	0.853
VARX(1)-G-T2	0.677	0.850	0.640	0.840	0.656	0.828	0.647	0.810	0.685	0.890	0.688	0.888	0.680	0.877	0.655	0.853
VARX(1)-MFG-T2	0.598	0.803	0.640	0.776	0.631	0.795	0.629	0.793	0.630	0.866	0.656	0.912	0.648	0.869	0.595	0.802
PVAR(1)-GMM	0.661	0.843	0.656	0.848	0.672	0.852	0.672	0.862	0.756	0.921	0.696	0.896	0.689	0.902	0.681	0.897
PVAR(1)-OLSCFE	0.677	0.898	0.688	0.864	0.705	0.877	0.724	0.862	0.740	0.913	0.744	0.920	0.738	0.951	0.724	0.922
PVARX(1)-OLSCFE-MF-T1	0.661	0.898	0.688	0.872	0.705	0.885	0.707	0.853	0.764	0.913	0.736	0.920	0.738	0.951	0.716	0.897
PVARX(1)-OLSCFE-G-T1	0.677	0.906	0.696	0.872	0.705	0.877	0.724	0.862	0.717	0.921	0.760	0.920	0.746	0.951	0.750	0.914
PVARX(1)-OLSCFE-MFG-T1	0.677	0.898	0.696	0.872	0.705	0.885	0.707	0.862	0.756	0.913	0.768	0.928	0.738	0.943	0.724	0.905
PVARX(1)-OLSCFE-MF-T2	0.669	0.898	0.672	0.872	0.713	0.877	0.707	0.862	0.787	0.937	0.744	0.928	0.762	0.943	0.750	0.879
PVARX(1)-OLSCFE-G-T2	0.685	0.898	0.688	0.864	0.697	0.877	0.672	0.871	0.732	0.929	0.752	0.920	0.754	0.951	0.776	0.922
PVARX(1)-OLSCFE-MFG-T2	0.661	0.874	0.656	0.864	0.713	0.869	0.698	0.879	0.795	0.929	0.728	0.920	0.787	0.943	0.767	0.888

Table 21: Density Coverage Rates. Unemployment Rate (Difference)

	DE								FR							
	h=1		h=3		h=6		h=12		h=1		h=3		h=6		h=12	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.937	0.992	0.944	1.000	0.902	0.984	0.888	0.957	0.913	0.953	0.744	0.864	0.631	0.836	0.586	0.767
AR(1)	0.921	1.000	0.944	1.000	0.951	0.992	0.836	0.948	0.724	0.882	0.712	0.888	0.754	0.877	0.759	0.879
LR-MF-T1	0.929	0.984	0.944	0.992	0.877	0.943	0.819	0.905	0.701	0.890	0.672	0.904	0.762	0.869	0.793	0.888
LR-G-T1	0.913	0.984	0.888	0.984	0.918	1.000	0.888	0.948	0.780	0.890	0.736	0.888	0.664	0.861	0.776	0.897
LR-MFG-T1	0.898	0.969	0.896	0.992	0.861	0.943	0.810	0.888	0.724	0.890	0.672	0.896	0.697	0.861	0.776	0.879
LR-MF-T2	0.921	0.992	0.928	0.976	0.836	0.934	0.793	0.905	0.677	0.890	0.656	0.904	0.705	0.852	0.750	0.888
LR-G-T2	0.890	0.984	0.888	0.984	0.926	0.992	0.853	0.931	0.772	0.882	0.720	0.864	0.680	0.844	0.698	0.879
LR-MFG-T2	0.835	0.984	0.872	0.944	0.820	0.918	0.759	0.862	0.646	0.890	0.632	0.856	0.664	0.811	0.672	0.871
AR(1)-MF-T1	0.906	0.992	0.944	0.992	0.877	0.951	0.784	0.888	0.709	0.882	0.672	0.904	0.721	0.861	0.784	0.888
AR(1)-G-T1	0.906	0.984	0.904	0.984	0.943	0.992	0.836	0.940	0.709	0.874	0.672	0.888	0.705	0.861	0.724	0.879
AR(1)-MFG-T1	0.898	0.992	0.896	0.992	0.861	0.951	0.776	0.879	0.709	0.874	0.664	0.896	0.656	0.836	0.767	0.888
AR(1)-MF-T2	0.898	0.992	0.928	0.976	0.844	0.943	0.793	0.897	0.669	0.882	0.656	0.912	0.705	0.828	0.776	0.879
AR(1)-G-T2	0.874	0.992	0.896	0.984	0.926	0.992	0.819	0.914	0.724	0.843	0.616	0.840	0.689	0.852	0.690	0.862
AR(1)-MFG-T2	0.819	0.984	0.856	0.944	0.828	0.910	0.750	0.853	0.669	0.874	0.632	0.856	0.639	0.795	0.724	0.862
VAR(1)	0.921	1.000	0.960	0.992	0.934	0.992	0.836	0.948	0.709	0.890	0.680	0.872	0.713	0.869	0.750	0.871
VARX(1)-MF-T1	0.921	0.992	0.952	0.992	0.861	0.943	0.793	0.879	0.685	0.890	0.648	0.904	0.721	0.861	0.741	0.888
VARX(1)-G-T1	0.890	1.000	0.872	0.984	0.934	0.992	0.836	0.931	0.709	0.874	0.632	0.880	0.713	0.861	0.716	0.862
VARX(1)-MFG-T1	0.874	0.992	0.880	0.992	0.869	0.943	0.793	0.888	0.693	0.874	0.656	0.896	0.680	0.852	0.741	0.879
VARX(1)-MF-T2	0.913	0.992	0.936	0.984	0.852	0.926	0.767	0.871	0.709	0.906	0.600	0.912	0.697	0.828	0.690	0.871
VARX(1)-G-T2	0.874	1.000	0.872	0.984	0.926	0.984	0.793	0.897	0.693	0.843	0.632	0.848	0.689	0.844	0.681	0.862
VARX(1)-MFG-T2	0.843	0.976	0.824	0.936	0.836	0.910	0.698	0.845	0.685	0.858	0.584	0.888	0.656	0.803	0.690	0.836
PVAR(1)-GMM	0.906	1.000	0.952	1.000	0.951	1.000	0.948	1.000	0.740	0.906	0.760	0.880	0.770	0.902	0.793	0.897
PVAR(1)-OLSCFE	0.937	1.000	0.944	1.000	0.943	0.992	0.897	0.983	0.685	0.858	0.640	0.832	0.705	0.877	0.681	0.879
PVARX(1)-OLSCFE-MF-T1	0.929	1.000	0.920	0.992	0.934	0.984	0.871	0.974	0.669	0.858	0.656	0.880	0.672	0.885	0.655	0.828
PVARX(1)-OLSCFE-G-T1	0.937	1.000	0.944	0.992	0.934	0.992	0.897	0.983	0.693	0.874	0.640	0.840	0.730	0.869	0.672	0.879
PVARX(1)-OLSCFE-MFG-T1	0.929	1.000	0.928	0.992	0.934	0.984	0.871	0.974	0.654	0.866	0.672	0.856	0.705	0.861	0.638	0.819
PVARX(1)-OLSCFE-MF-T2	0.929	1.000	0.928	1.000	0.926	0.984	0.897	0.974	0.661	0.843	0.664	0.880	0.656	0.885	0.655	0.828
PVARX(1)-OLSCFE-G-T2	0.921	1.000	0.920	0.992	0.934	0.992	0.905	0.983	0.701	0.882	0.656	0.856	0.738	0.885	0.672	0.871
PVARX(1)-OLSCFE-MFG-T2	0.913	1.000	0.912	1.000	0.918	0.984	0.897	0.974	0.654	0.874	0.632	0.848	0.648	0.877	0.603	0.810

Table 21: Density Coverage Rates. Unemployment Rate (Difference) (continued)

	IT								UK							
	h=1		h=3		h=6		h=12		h=1		h=3		h=6		h=12	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.362	0.654	0.456	0.656	0.426	0.754	0.336	0.629	0.748	0.858	0.712	0.784	0.631	0.697	0.603	0.629
AR(1)	0.630	0.866	0.648	0.848	0.623	0.836	0.629	0.853	0.606	0.850	0.616	0.824	0.623	0.803	0.586	0.776
LR-MF-T1	0.622	0.850	0.632	0.832	0.648	0.836	0.621	0.836	0.606	0.835	0.536	0.808	0.574	0.811	0.569	0.802
LR-G-T1	0.638	0.835	0.632	0.840	0.639	0.844	0.603	0.836	0.606	0.835	0.608	0.832	0.607	0.836	0.595	0.828
LR-MFG-T1	0.598	0.866	0.624	0.832	0.639	0.852	0.621	0.836	0.606	0.827	0.536	0.816	0.566	0.795	0.586	0.802
LR-MF-T2	0.606	0.827	0.600	0.840	0.607	0.828	0.595	0.802	0.606	0.795	0.544	0.784	0.582	0.754	0.526	0.784
LR-G-T2	0.614	0.835	0.624	0.832	0.607	0.820	0.612	0.802	0.583	0.827	0.560	0.784	0.566	0.828	0.586	0.828
LR-MFG-T2	0.575	0.819	0.592	0.824	0.607	0.811	0.517	0.759	0.622	0.787	0.504	0.720	0.533	0.730	0.534	0.759
AR(1)-MF-T1	0.614	0.866	0.640	0.848	0.639	0.828	0.621	0.853	0.654	0.843	0.568	0.800	0.615	0.787	0.578	0.750
AR(1)-G-T1	0.646	0.850	0.672	0.840	0.639	0.836	0.647	0.871	0.661	0.850	0.616	0.832	0.607	0.803	0.578	0.759
AR(1)-MFG-T1	0.638	0.850	0.640	0.856	0.631	0.844	0.612	0.862	0.677	0.850	0.576	0.792	0.607	0.787	0.569	0.750
AR(1)-MF-T2	0.630	0.850	0.648	0.848	0.615	0.828	0.543	0.810	0.598	0.843	0.552	0.744	0.590	0.738	0.517	0.707
AR(1)-G-T2	0.598	0.858	0.616	0.832	0.598	0.820	0.560	0.845	0.630	0.835	0.584	0.784	0.598	0.803	0.569	0.776
AR(1)-MFG-T2	0.614	0.819	0.616	0.832	0.631	0.811	0.466	0.759	0.583	0.843	0.536	0.720	0.541	0.730	0.526	0.690
VAR(1)	0.630	0.843	0.632	0.824	0.582	0.836	0.629	0.845	0.598	0.819	0.576	0.824	0.607	0.787	0.560	0.750
VARX(1)-MF-T1	0.606	0.843	0.640	0.848	0.574	0.828	0.603	0.836	0.591	0.835	0.560	0.800	0.590	0.762	0.552	0.724
VARX(1)-G-T1	0.614	0.850	0.640	0.824	0.598	0.852	0.612	0.853	0.606	0.819	0.568	0.816	0.607	0.795	0.560	0.750
VARX(1)-MFG-T1	0.622	0.850	0.632	0.840	0.566	0.852	0.603	0.845	0.606	0.819	0.560	0.792	0.582	0.787	0.534	0.733
VARX(1)-MF-T2	0.630	0.819	0.640	0.840	0.574	0.820	0.517	0.793	0.583	0.835	0.552	0.712	0.590	0.754	0.526	0.716
VARX(1)-G-T2	0.598	0.827	0.600	0.840	0.574	0.803	0.569	0.819	0.583	0.843	0.560	0.752	0.598	0.787	0.552	0.767
VARX(1)-MFG-T2	0.614	0.811	0.608	0.840	0.557	0.803	0.405	0.707	0.591	0.819	0.528	0.720	0.541	0.730	0.526	0.698
PVAR(1)-GMM	0.583	0.874	0.600	0.856	0.598	0.852	0.603	0.862	0.598	0.835	0.544	0.824	0.541	0.820	0.509	0.810
PVAR(1)-OLSCFE	0.701	0.906	0.696	0.888	0.656	0.836	0.638	0.862	0.598	0.866	0.576	0.824	0.590	0.779	0.543	0.759
PVARX(1)-OLSCFE-MF-T1	0.701	0.898	0.704	0.896	0.623	0.828	0.629	0.853	0.614	0.866	0.592	0.808	0.631	0.787	0.526	0.767
PVARX(1)-OLSCFE-G-T1	0.717	0.906	0.704	0.888	0.656	0.828	0.638	0.862	0.614	0.882	0.568	0.808	0.574	0.779	0.526	0.741
PVARX(1)-OLSCFE-MFG-T1	0.724	0.898	0.712	0.904	0.623	0.836	0.638	0.853	0.622	0.906	0.592	0.800	0.631	0.787	0.509	0.750
PVARX(1)-OLSCFE-MF-T2	0.701	0.890	0.704	0.896	0.607	0.836	0.647	0.828	0.614	0.874	0.616	0.816	0.590	0.787	0.534	0.767
PVARX(1)-OLSCFE-G-T2	0.709	0.906	0.696	0.912	0.639	0.852	0.638	0.853	0.606	0.882	0.584	0.776	0.607	0.779	0.569	0.784
PVARX(1)-OLSCFE-MFG-T2	0.709	0.882	0.696	0.896	0.615	0.844	0.621	0.836	0.661	0.906	0.600	0.784	0.607	0.803	0.552	0.802

Table 22: Density Coverage Rates. CPI Growth (Inflation)

	DE								FR							
	h=1		h=3		h=6		h=12		h=1		h=3		h=6		h=12	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.551	0.827	0.408	0.752	0.475	0.787	0.552	0.836	0.402	0.677	0.240	0.656	0.631	0.795	0.819	0.940
AR(1)	0.724	0.906	0.680	0.896	0.730	0.926	0.716	0.914	0.583	0.850	0.576	0.856	0.615	0.852	0.612	0.845
LR-MF-T1	0.709	0.898	0.696	0.896	0.705	0.910	0.741	0.897	0.575	0.874	0.576	0.856	0.541	0.861	0.603	0.819
LR-G-T1	0.717	0.890	0.720	0.896	0.713	0.902	0.733	0.897	0.575	0.866	0.568	0.848	0.598	0.836	0.612	0.836
LR-MFG-T1	0.701	0.882	0.720	0.880	0.721	0.902	0.707	0.888	0.559	0.843	0.552	0.840	0.566	0.828	0.612	0.819
LR-MF-T2	0.693	0.890	0.688	0.872	0.713	0.893	0.724	0.888	0.583	0.811	0.544	0.816	0.549	0.828	0.578	0.793
LR-G-T2	0.709	0.882	0.704	0.896	0.713	0.893	0.707	0.897	0.551	0.843	0.544	0.824	0.607	0.844	0.672	0.819
LR-MFG-T2	0.677	0.858	0.648	0.864	0.680	0.869	0.672	0.862	0.551	0.764	0.536	0.808	0.525	0.803	0.638	0.776
AR(1)-MF-T1	0.693	0.898	0.672	0.888	0.721	0.926	0.707	0.905	0.567	0.850	0.560	0.856	0.607	0.869	0.621	0.819
AR(1)-G-T1	0.709	0.890	0.672	0.896	0.746	0.926	0.672	0.897	0.583	0.850	0.568	0.856	0.598	0.861	0.621	0.845
AR(1)-MFG-T1	0.685	0.882	0.688	0.880	0.721	0.918	0.647	0.879	0.575	0.827	0.552	0.848	0.598	0.852	0.621	0.836
AR(1)-MF-T2	0.693	0.906	0.672	0.864	0.721	0.910	0.716	0.888	0.559	0.795	0.528	0.800	0.582	0.836	0.586	0.802
AR(1)-G-T2	0.693	0.874	0.664	0.896	0.713	0.885	0.690	0.897	0.567	0.827	0.544	0.824	0.607	0.852	0.681	0.836
AR(1)-MFG-T2	0.693	0.874	0.640	0.856	0.713	0.844	0.655	0.845	0.551	0.748	0.528	0.792	0.566	0.803	0.647	0.784
VAR(1)	0.709	0.866	0.680	0.880	0.738	0.926	0.655	0.853	0.551	0.827	0.552	0.824	0.590	0.844	0.612	0.810
VARX(1)-MF-T1	0.677	0.874	0.656	0.872	0.697	0.902	0.690	0.828	0.543	0.835	0.552	0.808	0.598	0.811	0.621	0.810
VARX(1)-G-T1	0.701	0.874	0.688	0.880	0.746	0.926	0.629	0.862	0.559	0.811	0.536	0.824	0.615	0.844	0.612	0.810
VARX(1)-MFG-T1	0.677	0.874	0.672	0.888	0.689	0.885	0.655	0.862	0.551	0.819	0.520	0.800	0.582	0.820	0.629	0.836
VARX(1)-MF-T2	0.677	0.874	0.672	0.832	0.697	0.893	0.672	0.828	0.535	0.803	0.544	0.760	0.590	0.803	0.586	0.776
VARX(1)-G-T2	0.677	0.874	0.688	0.872	0.721	0.869	0.664	0.853	0.551	0.811	0.536	0.808	0.566	0.811	0.638	0.828
VARX(1)-MFG-T2	0.685	0.850	0.640	0.840	0.705	0.844	0.664	0.836	0.512	0.740	0.488	0.768	0.525	0.754	0.629	0.759
PVAR(1)-GMM	0.543	0.858	0.488	0.888	0.492	0.885	0.569	0.897	0.591	0.803	0.584	0.816	0.590	0.820	0.560	0.828
PVAR(1)-OLSCFE	0.701	0.898	0.704	0.904	0.697	0.902	0.664	0.905	0.591	0.850	0.584	0.856	0.615	0.852	0.647	0.836
PVARX(1)-OLSCFE-MF-T1	0.685	0.858	0.696	0.904	0.689	0.893	0.681	0.888	0.583	0.850	0.568	0.848	0.615	0.852	0.638	0.828
PVARX(1)-OLSCFE-G-T1	0.677	0.890	0.696	0.896	0.697	0.893	0.672	0.888	0.583	0.866	0.576	0.856	0.590	0.861	0.655	0.828
PVARX(1)-OLSCFE-MFG-T1	0.669	0.882	0.704	0.904	0.697	0.893	0.664	0.862	0.591	0.858	0.568	0.848	0.598	0.869	0.638	0.810
PVARX(1)-OLSCFE-MF-T2	0.748	0.890	0.704	0.912	0.697	0.877	0.690	0.871	0.591	0.866	0.584	0.840	0.615	0.885	0.638	0.819
PVARX(1)-OLSCFE-G-T2	0.701	0.921	0.704	0.928	0.697	0.877	0.690	0.879	0.669	0.874	0.584	0.848	0.590	0.869	0.672	0.845
PVARX(1)-OLSCFE-MFG-T2	0.756	0.913	0.712	0.944	0.689	0.877	0.672	0.862	0.622	0.866	0.584	0.848	0.607	0.885	0.655	0.810

Table 22: Density Coverage Rates. CPI Growth (Inflation) (continued)

	IT								UK							
	h=1		h=3		h=6		h=12		h=1		h=3		h=6		h=12	
	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %	68 %	90 %
Naive	0.480	0.685	0.360	0.656	0.467	0.705	0.560	0.776	0.559	0.740	0.480	0.736	0.607	0.836	0.724	0.931
AR(1)	0.575	0.819	0.560	0.792	0.557	0.795	0.560	0.793	0.717	0.874	0.728	0.872	0.721	0.885	0.741	0.862
LR-MF-T1	0.512	0.787	0.568	0.792	0.541	0.762	0.534	0.802	0.693	0.874	0.712	0.888	0.721	0.893	0.716	0.871
LR-G-T1	0.567	0.819	0.552	0.808	0.541	0.803	0.578	0.802	0.677	0.890	0.720	0.872	0.713	0.861	0.664	0.879
LR-MFG-T1	0.520	0.780	0.560	0.784	0.525	0.779	0.534	0.802	0.685	0.866	0.728	0.872	0.713	0.877	0.672	0.871
LR-MF-T2	0.528	0.772	0.560	0.760	0.500	0.730	0.560	0.810	0.646	0.850	0.712	0.864	0.705	0.836	0.664	0.845
LR-G-T2	0.535	0.811	0.520	0.808	0.525	0.795	0.526	0.802	0.661	0.898	0.648	0.864	0.721	0.869	0.690	0.914
LR-MFG-T2	0.449	0.732	0.528	0.768	0.484	0.721	0.534	0.767	0.646	0.866	0.632	0.856	0.689	0.852	0.664	0.879
AR(1)-MF-T1	0.535	0.795	0.576	0.792	0.525	0.770	0.526	0.793	0.709	0.858	0.720	0.880	0.705	0.893	0.716	0.845
AR(1)-G-T1	0.559	0.819	0.536	0.800	0.541	0.779	0.586	0.784	0.693	0.882	0.736	0.872	0.705	0.877	0.690	0.888
AR(1)-MFG-T1	0.535	0.795	0.552	0.784	0.516	0.762	0.543	0.784	0.669	0.858	0.728	0.864	0.705	0.885	0.681	0.879
AR(1)-MF-T2	0.535	0.764	0.576	0.768	0.492	0.721	0.509	0.784	0.654	0.843	0.704	0.864	0.672	0.844	0.664	0.828
AR(1)-G-T2	0.512	0.787	0.504	0.792	0.516	0.779	0.517	0.784	0.669	0.890	0.656	0.872	0.713	0.869	0.672	0.914
AR(1)-MFG-T2	0.433	0.740	0.544	0.784	0.459	0.672	0.517	0.759	0.646	0.843	0.640	0.856	0.689	0.795	0.647	0.845
VAR(1)	0.559	0.787	0.528	0.800	0.533	0.770	0.509	0.716	0.693	0.858	0.720	0.856	0.648	0.844	0.724	0.845
VARX(1)-MF-T1	0.535	0.780	0.528	0.784	0.525	0.754	0.517	0.724	0.677	0.850	0.704	0.856	0.648	0.828	0.707	0.828
VARX(1)-G-T1	0.551	0.787	0.520	0.792	0.549	0.787	0.491	0.716	0.701	0.850	0.720	0.848	0.656	0.828	0.655	0.862
VARX(1)-MFG-T1	0.528	0.772	0.520	0.776	0.533	0.754	0.526	0.733	0.677	0.843	0.712	0.840	0.639	0.820	0.655	0.862
VARX(1)-MF-T2	0.504	0.764	0.520	0.768	0.500	0.721	0.509	0.733	0.638	0.835	0.672	0.840	0.582	0.754	0.638	0.819
VARX(1)-G-T2	0.543	0.756	0.488	0.792	0.508	0.770	0.474	0.733	0.669	0.843	0.656	0.856	0.631	0.836	0.664	0.862
VARX(1)-MFG-T2	0.504	0.677	0.520	0.776	0.467	0.689	0.491	0.724	0.638	0.827	0.608	0.832	0.557	0.754	0.621	0.828
PVAR(1)-GMM	0.496	0.717	0.520	0.728	0.525	0.713	0.509	0.707	0.528	0.819	0.544	0.816	0.549	0.811	0.578	0.819
PVAR(1)-OLSCFE	0.622	0.835	0.560	0.800	0.566	0.787	0.534	0.767	0.709	0.882	0.744	0.872	0.713	0.869	0.733	0.879
PVARX(1)-OLSCFE-MF-T1	0.606	0.819	0.576	0.808	0.590	0.787	0.534	0.724	0.701	0.874	0.728	0.880	0.721	0.869	0.716	0.845
PVARX(1)-OLSCFE-G-T1	0.598	0.811	0.568	0.808	0.566	0.787	0.543	0.767	0.724	0.890	0.744	0.872	0.705	0.869	0.681	0.879
PVARX(1)-OLSCFE-MFG-T1	0.591	0.819	0.576	0.808	0.574	0.787	0.543	0.741	0.724	0.890	0.728	0.880	0.721	0.869	0.681	0.862
PVARX(1)-OLSCFE-MF-T2	0.583	0.819	0.560	0.832	0.574	0.811	0.509	0.750	0.693	0.898	0.728	0.888	0.721	0.852	0.707	0.845
PVARX(1)-OLSCFE-G-T2	0.646	0.827	0.536	0.816	0.582	0.803	0.543	0.793	0.732	0.890	0.768	0.896	0.705	0.869	0.672	0.897
PVARX(1)-OLSCFE-MFG-T2	0.583	0.819	0.504	0.808	0.582	0.820	0.534	0.759	0.764	0.906	0.784	0.896	0.713	0.852	0.664	0.862

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