

Panel VAR Models for Nowcasting

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Abstract

This paper examines the out-of-sample forecasting performance of mixed-frequency panel VAR (pVAR) models for four key macroeconomic variables using data from four European economies. Our aim is to investigate the circumstances under which modelling interdependencies across countries improves forecasting with respect to standard single-country models. For a complete assessment, we evaluate point, directional and also interval and density forecasts. Overall, the empirical results provide mixed evidence in favour of pVAR models.

Keywords: Panel data, Vector Autoregressions, Nowcasting, Timely Estimates, Forecasting.

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Contents

1	Introduction	2
2	Methodology	4
2.1	pVAR	4
2.2	Exogenous Variables and Factors	6
2.3	Mixed-Frequency	8
3	Data Description	9
3.1	Targets	9
3.2	Predictors	10
3.3	Transformations	10
3.4	Time Span	11
3.5	Data Summary	11
4	Forecasting Setup	12
4.1	Direct Forecasts	12
4.2	Forecasting Exercise	12
4.3	Forecast Evaluation	13
4.4	Settings	15
4.4.1	Models	15
4.4.2	pVAR Specifications	16
4.4.3	Forecasting Horizons	17
5	Summary of Results	17
5.1	Reading a Table	17
5.2	Averaging Across Forecast Horizons	19
6	Conclusions	22
7	Appendix	49
7.1	List of Models	49

7.2	Estimation of pVAR Models in R	51
7.2.1	Strengths	51
7.2.2	Weaknesses	52
7.2.3	Example Code for Estimation	53
7.2.4	R Code Used in this Paper	53

1 Introduction

The literature on Panel Vector Autoregressive (pVAR) models has been gradually increasing over the past decades mainly due to the wide applicability of these models. pVAR models combine the simplicity of Vector Autoregressive (VAR) models with the rich information provided by panel data, permitting joint modelling of several countries or sectors, at the macro level, or firms or households, at the micro level. These features are very relevant for official statistics, due to 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.

In the context of official statistics, pVARs models are particularly appealing for nowcasting and the construction of flash estimates for key economic indicators, using large information sets and taking into account cross-country interdependencies. Both features are indeed potentially relevant to improve upon current methods, often based on small sets of single-country data, which makes flash estimates inaccurate in the presence of global shocks, like it happened in the recent financial crisis when flash estimates had to be often and repeatedly revised.

VAR models are already often used in official statistics, as they can capture linear interdependencies among multiple time series, without requiring deep knowledge on the factors affecting a variable, as it is instead usually the case in, e.g., 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 in official statistical agencies. In fact, VAR models only require the specification of a set of variables that are assumed to interact dynamically.

However, in the global economic framework we live in, and given the large degree of economic integration across countries, 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)¹ with standard time series VAR models, yielding the pVAR models.

pVAR models have been gradually increasing in popularity in the fields of empirical economics and economic statistics during the past decade. Two factors explaining their increasing adoption in empirical applications are their ability to capture interdependencies and the availability of freeware software.² However, before considering pVAR models as a tool really suited for official statistics, and in particular for flash estimation and nowcasting, their forecasting performance needs to be carefully investigated and assessed.

This paper complements the review of theoretical and empirical articles on panel VARs by Kapetanios et al. (2019) and is specifically concerned with the examination of 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 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

¹Also see Chudik and Pesaran (2015) for a survey on panel data models.

²Love 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 ECB BEAR toolbox built in MATLAB also includes procedures for pVAR models; see Dieppe et al. (2016) for more information.

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 UMI-DAS 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 this paper is organised as follows. Section 2 introduces the methodological framework. Section 3 briefly explains the datasets. Section 4 discusses the forecasting algorithm and forecast evaluation statistics. Section 5 presents the main results. Section 6 summarizes the main findings and offers the conclusions. In the Appendix we review the already existing open source software solutions for estimation of pVAR models, mainly focusing on the R programming language that is particularly suited for statistical computing.

2 Methodology

2.1 pVAR

A pVAR model is similar in many ways to a standard VAR or VAR with exogenous regressors (VARX), as variables are still treated as endogenous and interdependent. However, a cross-sectional dimension is added, which can account for joint modelling $i = 1, \dots, N$ units. Units can be, for example, countries, sectors, markets or combinations of them. In our forecasting setup, which follows in a later section, i corresponds to countries.

A pVAR(p) model of $i = 1, \dots, N$ units can be represented as:

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

where $i = 1, \dots, N$, $t = 1, \dots, T$ and μ_i captures the unit-specific effects. Therefore, a pVAR(p) can be also seen as a combination of single equation dynamic panel data models (DPM).

Assumption 1 *The disturbances, ε_{it} , have the following properties:*

1. $E(\varepsilon_{it}) = 0$,
2. $E(\varepsilon_{it}\varepsilon'_{it}) = \Sigma_{\varepsilon,ii}$,
3. $E(\varepsilon_{it}\varepsilon'_{it-s}) = 0$ for $s \neq t$.

In the above setup we see that ε_{it} is zero mean, uncorrelated and homoscedastic across time for each unit. Yet, the errors can be correlated both across variables for the same unit and across units, i.e., $E(\varepsilon_{it}\varepsilon'_{jt}) = \Sigma_{\varepsilon,ij}$.

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

$$y_{it} = \mu_i + \sum_{l=1}^p A_l y_{it-l} + \sum_{k=0}^s C_k s_{t-k} + \varepsilon_{it}. \quad (2)$$

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 heteroscedastic, (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 (2), or Equation (1), is a useful extension of VAR models. In particular:

1. The autoregressive structure allows *all* endogenous variables of each unit to enter the model (capturing *interdependencies* across variables *within and across each unit*).
2. The inclusion of a unit fixed effect, μ_i , captures all unobservable time-invariant factors at unit level (allowing for *heterogeneity*).

As in panel models, the coefficient matrices (A_l, 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.

We can further extend the model in Equation (2) to allow the exogenous variables to be specific across units, i.e.:

$$y_{it} = \mu_i + \sum_{l=1}^p A_l y_{it-l} + \sum_{k=0}^s C_k s_{it-k} + \varepsilon_{it}. \quad (3)$$

The models in Equations (1) to (3) can be estimated using OLS or GMM (as described in Sigmund and Ferstl (2019) and Kapetanios et al. (2019)).

2.2 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 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 $R \times 1$, can be captured by a $r \times 1$ vector of unobserved factors $F_t = (F_{1t} \cdots F_{rt})'$, i.e.,

$$\tilde{x}_t = \Lambda' F_t + e_t, \tag{4}$$

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 (4) 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:

$$V(r) = \min_{\Lambda, F} \frac{1}{RT} \sum_{i=1}^N \sum_{t=1}^T (\tilde{x}_{it} - \lambda'_i F_t)^2, \quad (5)$$

where λ_i is an $r \times 1$ vector of loadings that represent the N columns of $\Lambda = (\lambda_1 \cdots \lambda_R)$. One, non-unique, solution of (5) 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 (3), 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.

2.3 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:

$$y_{it_{f_y}} = \mu_i + \sum_{l=1}^p A_l y_{it-l} + \sum_{k=0}^s C_k s_{it-k_{f_y}} + \varepsilon_{it}, \quad (6)$$

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:

$$s_{it_{f_y}} = \sum_{j=1}^J \beta_j(L) s_{it_{f_s}} \quad (7)$$

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:

$$s_{it_{f_y}} = \beta_1(L) s_{it_{f_s}}^1 + \beta_2(L) s_{it_{f_s}}^2 + \dots + \beta_J(L) s_{it_{f_s}}^J. \quad (8)$$

J now corresponds to the duration of f_y in f_s terms and $s_{it_{f_s}}^J$ 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 (1) and (3), using both methods in Equations (7) and (8) to handle mixed frequencies, when necessary.

3 Data Description

3.1 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).³ The data has been downloaded using Macrobond Software⁴.

3.2 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.

3.3 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

³It must be noted that we use CPI instead of the Harmonised CPI for comparability reasons between the UK and the euro area countries.

⁴Macrobond 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.

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., McCracken 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.

3.4 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]).⁵

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).

3.5 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.

⁵The out-of-sample sizes of this subsection refer to the $h = 1$ case. For larger h , the out-of-sample size decreases accordingly.

4 Forecasting Setup

4.1 Direct Forecasts

The models we use in the forecasting exercise are those described in Equations (1) and (3). 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 (7) and (8).

The models in Equations (1) and (3) can be re-written as simple linear regressions of the form:

$$y = \mu + X\beta + \varepsilon, \quad \mathbb{E}[\varepsilon|X] = 0, \quad \mathbb{E}[\varepsilon^2|X] = \sigma^2, \quad (9)$$

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 $t = 1, \dots, T$, $\hat{\gamma}_h$ denotes the parameter estimate which is obtained by regressing $Z_{t=\{h+1, \dots, T\}}$ on $F_{t=\{1, \dots, T-h\}}$. 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.

4.2 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 models⁶. In our experiments, $T^{OUT} = 127$ for the monthly targets (IP, UNR, CPI) and

⁶The 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.

$T^{OUT} = 31$ 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 $T_1^{IN} = \{1, \dots, (T - T^{OUT} + 1)\}$. Then, we estimate the parameters and produce the h -step ahead forecasts from various models.
3. We repeat Step 2 in a recursive manner, i.e. $T_2^{IN} = \{1, \dots, (T - T^{OUT} + 2)\}$ and generally $T_j^{IN} = \{1, \dots, (T - T^{OUT} + j)\}$. We stop when $T_j^{IN} = \{1, \dots, (T - h)\}$, as we always need the true value of the next period to evaluate the nowcasts.

At the end of the above recursive procedure, we end up with $(T^{OUT} - h)$ forecasts for each model under consideration.

4.3 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:

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

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

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:

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

where

$$\begin{aligned}\bar{d} &= \frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} d_t, \\ d_t &= |e_{1,t}| - |e_{2,t}|, \text{ corresponding to MAE} \\ d_t &= e_{1,t}^2 - e_{2,t}^2, \text{ corresponding to RMSFE} \\ LRV_{\bar{d}} &= \gamma_0 + 2 \sum_{v=1}^{\infty} \gamma_v, \quad \gamma_v = cov(d_t, d_{t-v}),\end{aligned}$$

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:

$$SSR_j = \frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} I[sgn(\Delta y_{t+h}) = sgn(\hat{y}_{t+h} - y_t)], \quad (10)$$

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:

$$CR_j = \frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} I [q_{\alpha_1, \hat{y}_{t+h}} \leq y_{t+h} \leq q_{\alpha_2, \hat{y}_{t+h}}], \quad (11)$$

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.

4.4 Settings

4.4.1 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.

4.4.2 pVAR Specifications

In our pVAR models, our panel consists of $i = \{1, 2, 3, 4\}$ economies: DE, FR, IT and the UK. In all VARX⁷ and pVARX specifications the exogenous variables include: (i) the first PCA factor extracted from the set of macro and 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.

It is important to notice that we estimate the pVAR(1) models using GMM as discussed in Sigmund and Ferstl (2019). However, given that the corresponding

⁷Using a maximum order of 6 (which means that for the target variable equation we can have a maximum of 3 variables \times 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.

package in R does not allow for flexible direct forecasting using exogenous variables, we also use OLS. See the Appendix for more details.

4.4.3 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.

5 Summary of Results

5.1 Reading a Table

Empirical results are summarized in the 22 Tables at the end of the document. They present point and directional forecasts (4 variables \times 4 economies), coverage rates as a way to evaluate the precision of the density forecasts, and summary results. Density forecast plots for each model, forecast horizon, target variable and country are available upon request. 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 (7) and (8).

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.

5.2 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 RMSFE 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.

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- 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.

6 Conclusions

This paper complements the overview of theoretical and empirical contributions related to panel VAR models by Kapetanios et al. (2019) and is concerned with the examination of pVAR models in out-of-sample forecasting applications, using data from European countries. 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 when analysing multiple markets in a single economy, or across different integrated economies, or for a different set of variables, or to construct coincident or leading indexes rather than nowcasts or forecasts.

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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)-MF-T2	Linear Regression using the first lag of y, Macro/Finance predictors (UMIDAS)
AR(1)-G-T2	Linear Regression using the first lag of y, Google predictors (UMIDAS)
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)-MF-T2	Vector Autoregressive model, P=1 with Macro/Finance predictors (UMIDAS) as exogenous
VARX(1)-G-T2	Vector Autoregressive model, P=1 with Google predictors (UMIDAS) 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
PVARX(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 (avg) 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

Legend.

	h=1						h=3						h=6						h=12						
	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	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	1.000	1.000	0.504	NA	NA
AR(1)	0.984	0.988	0.389	0.386	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	0.365	0.362	0.448	1.004	1.004	0.999	0.487	0.450
LR-MF-T1	0.997	0.994	0.373	0.300	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	1.013	1.067	0.397	0.703	0.424
LR-MF-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	1.073	1.102	0.397	0.081	0.235
LR-MFG-T2	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	1.005	1.005	0.516	0.623	0.442
AR(1)-MF-T1	1.005	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	1.088	0.496	0.328	0.358	1.021	1.084	0.381	0.568	0.347
AR(1)-MFG-T1	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	1.090	1.130	0.397	0.653	0.208
AR(1)-MF-T2	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	1.035	1.073	0.444	0.399	0.334
AR(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	1.176	1.230	0.435	0.241	0.254	1.064	1.144	0.429	0.286	0.321
VARX(1)-MFG-T1	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	1.064	1.180	0.468	0.090	0.232
VARX(1)-MF-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	1.155	1.282	0.389	0.039	0.121
VARX(1)-G-T2	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	1.006	1.009	0.563	0.683	0.500
VARX(1)-MFG-T2	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	1.010	1.014	0.579	0.528	0.322
PVAR(1)-GMM	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	0.605	0.421	1.016	1.038	0.470	0.682	0.348	1.017	1.009	0.476	0.470	0.676
PVAR(1)-OLS	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	0.915	0.631	1.133	1.123	0.504	0.154	0.179	1.010	1.013	0.500	0.426	0.375
PVAR(1)-OLS	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	0.744	0.229	1.032	1.045	0.504	0.457	0.313	1.014	1.027	0.484	0.425	0.461
PVAR(1)-OLS	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	1.024	1.027	0.484	0.425	0.461

Table 8: Industrial Production Growth, FR.

	h=1			h=3			h=6			h=12					
	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	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
AR(1)	1.000	1.000	0.571	NA	NA	1.000	1.000	0.516	NA	NA	1.000	1.000	0.438	NA	NA
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	0.495	0.325	0.100
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
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
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
LR-G-T2	1.012	1.047	0.476	0.661	0.693	1.016	0.973	0.548	0.712	0.530	1.020	1.010	0.512	0.361	0.570
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
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
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
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
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
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
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
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
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
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
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
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
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
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
PVAR(1)-GMM	1.039	1.160	0.683	0.024	0.210	0.990	0.983	0.556	0.702	0.591	0.963	0.959	0.446	0.046	0.054
PVAR(1)-OLS	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
PVARX(1)-OLS-CFE-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
PVARX(1)-OLS-CFE-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
PVARX(1)-OLS-CFE-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
PVARX(1)-OLS-CFE-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
PVARX(1)-OLS-CFE-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
PVARX(1)-OLS-CFE-MFG-T2	0.987	1.001	0.508	0.669	0.964	1.019	0.980	0.548	0.576	0.563	1.023	1.024	0.479	0.520	0.547

Table 9: Industrial Production Growth, IT.

	h=1						h=3						h=6						h=12					
	MAE	RMSFE	SSR	DMI	DM1	DM2	MAE	RMSFE	SSR	DMI	DM1	DM2	MAE	RMSFE	SSR	DMI	DM1	DM2	MAE	RMSFE	SSR	DMI	DM1	DM2
Naive	1.647	1.593	0.222	0.000	0.000	0.000	1.504	1.507	0.387	0.000	0.000	0.000	1.293	1.247	0.521	0.003	0.018	0.018	1.717	1.626	0.278	0.000	0.000	0.000
AR(1)	1.000	1.000	0.643	NA	NA	NA	1.000	1.000	0.621	NA	NA	NA	1.000	1.000	0.479	NA	NA	NA	1.000	1.000	0.730	NA	NA	NA
LR-MF-T1	1.017	1.044	0.444	0.372	0.062	1.063	1.063	1.046	0.540	0.085	0.137	0.992	0.992	1.006	0.446	0.715	0.671	0.671	1.074	1.058	0.435	0.036	0.036	0.005
LR-G-T1	1.020	1.041	0.429	0.510	0.064	1.066	1.066	1.063	0.452	0.003	0.001	0.984	0.984	0.996	0.521	0.425	0.601	0.601	1.037	1.043	0.504	0.202	0.014	0.014
LR-MFG-T1	1.015	1.043	0.429	0.648	0.109	1.061	1.048	1.048	0.516	0.099	0.117	0.984	0.984	0.998	0.488	0.421	0.748	0.748	1.065	1.058	0.574	0.045	0.045	0.006
LR-MF-T2	1.048	1.083	0.484	0.201	0.025	1.089	1.068	1.068	0.516	0.017	0.043	0.994	0.994	1.029	0.471	0.855	0.181	0.181	1.107	1.088	0.461	0.029	0.018	0.018
LR-G-T2	1.035	1.049	0.468	0.290	0.053	1.057	1.060	1.060	0.427	0.039	0.007	0.970	0.970	1.017	0.512	0.288	0.382	0.382	1.043	1.030	0.513	0.156	0.234	0.234
LR-MFG-T2	1.075	1.099	0.516	0.085	0.019	1.079	1.069	1.069	0.460	0.039	0.047	0.989	0.989	1.046	0.496	0.793	0.174	0.174	1.131	1.107	0.513	0.107	0.115	0.115
AR(1)-MF-T1	0.999	1.004	0.627	0.360	0.700	0.999	0.993	0.993	0.597	0.949	0.733	1.004	1.004	1.006	0.446	0.673	0.367	0.367	1.027	1.019	0.730	0.155	0.050	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	0.997	0.529	0.900	0.744	0.744	0.994	1.006	0.722	0.705	0.669	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	0.998	1.000	0.488	0.897	0.985	0.985	1.015	1.021	0.739	0.444	0.195	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	1.008	1.030	0.463	0.757	0.066	0.066	1.058	1.048	0.652	0.023	0.021	0.021	
AR(1)-G-T2	1.010	0.995	0.611	0.385	0.711	0.997	1.012	0.605	0.835	0.386	0.984	0.984	1.016	0.554	0.501	0.454	0.454	0.999	0.987	0.722	0.922	0.253	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	1.000	1.045	0.496	0.997	0.204	0.204	1.112	1.077	0.643	0.209	0.282	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	1.029	1.019	0.355	0.086	0.297	0.297	1.014	1.016	0.704	0.378	0.344	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	1.035	1.021	0.430	0.131	0.351	0.351	1.042	1.037	0.713	0.014	0.024	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	1.029	1.017	0.397	0.215	0.435	0.435	1.003	1.021	0.730	0.906	0.418	0.418	
VARX(1)-MFG-T1	1.012	1.011	0.571	0.385	0.576	1.003	1.008	0.581	0.883	0.725	1.029	1.029	1.016	0.405	0.310	0.547	0.547	1.028	1.039	0.730	0.217	0.132	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	1.029	1.045	0.405	0.430	0.122	0.122	1.091	1.082	0.643	0.002	0.005	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	1.009	1.029	0.471	0.741	0.266	0.266	1.003	1.010	0.704	0.912	0.672	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	1.020	1.057	0.446	0.639	0.185	0.185	1.165	1.121	0.643	0.119	0.134	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	0.973	0.986	0.471	0.377	0.531	0.531	1.019	1.018	0.504	0.497	0.359	0.359	
PVAR(1)-OLS	0.991	0.991	0.659	0.476	0.336	1.007	1.004	0.645	0.240	0.286	1.000	1.000	0.996	0.463	0.992	0.689	0.689	1.008	1.012	0.704	0.457	0.163	0.163	
PVARX(1)-OLS	0.999	0.998	0.659	0.350	0.867	1.006	1.002	0.581	0.608	0.859	1.022	1.022	1.020	0.438	0.121	0.146	0.146	1.032	1.025	0.687	0.104	0.019	0.019	
PVARX(1)-OLS	0.987	0.983	0.667	0.355	0.121	1.006	0.999	0.629	0.418	0.805	1.008	1.008	1.000	0.455	0.429	0.973	0.973	1.003	1.010	0.722	0.846	0.402	0.402	
PVARX(1)-OLS	0.996	0.991	0.659	0.782	0.466	1.003	0.996	0.573	0.828	0.728	1.029	1.029	1.024	0.455	0.088	0.152	0.152	1.029	1.023	0.704	0.068	0.024	0.024	
PVARX(1)-OLS	0.998	0.998	0.635	0.874	0.880	1.010	1.003	0.629	0.422	0.808	1.030	1.030	1.026	0.413	0.083	0.091	0.091	1.039	1.031	0.670	0.117	0.040	0.040	
PVARX(1)-OLS	0.985	0.981	0.659	0.280	0.086	1.003	0.995	0.645	0.727	0.485	0.997	0.997	1.000	0.471	0.809	0.975	0.975	1.001	1.003	0.704	0.949	0.849	0.849	
PVARX(1)-OLS	0.994	0.988	0.635	0.721	0.445	1.003	0.993	0.637	0.812	0.545	1.029	1.029	1.031	0.430	0.096	0.067	0.067	1.031	1.019	0.678	0.131	0.188	0.188	

Table 13: Unemployment Rate (Difference), IT.

	h=1					h=3					h=6					h=12									
	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	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	0.634	0.011					
AR(1)	1.000	1.000	0.365	NA	NA	1.000	1.000	0.258	NA	NA	1.000	1.000	0.372	NA	NA	1.000	1.000	0.365	NA	NA					
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	0.331	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	0.366	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	0.760	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	0.429	0.489	0.949	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 14: Unemployment Rate (Difference), UK.

	h=1				h=3				h=6				h=12							
	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2
Naive	1.331	1.341	0.302	0.001	0.001	1.562	1.502	0.413	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	NA	NA	1.000	1.000	0.508	NA	NA	1.000	1.000	0.579	NA	NA	1.000	1.000	0.574	NA	NA
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	0.391	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	0.374	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)-OLS	1.033	1.022	0.452	0.095	0.134	1.038	1.041	0.524	0.334	0.410	1.010	1.158	0.421	0.074	0.189	1.093	1.117	0.557	0.293	0.333
PVARX(1)-OLS	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)-OLS	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)-OLS	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)-OLS	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)-OLS	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)-OLS	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 15: CPI Growth (Inflation), DE.

	h=1						h=3						h=6						h=12						
	MAE	RMSFE	SSR	DMI	DM1	DM2	MAE	RMSFE	SSR	DMI	DM1	DM2	MAE	RMSFE	SSR	DMI	DM1	DM2	MAE	RMSFE	SSR	DMI	DM1	DM2	
Naive	1.298	1.350	0.198	0.001	0.000	0.000	1.401	1.351	0.403	0.000	0.000	0.000	1.304	0.545	0.003	0.008	0.008	1.032	1.084	0.635	0.824	0.523	NA	NA	
AR(1)	1.000	1.000	0.611	NA	NA	NA	1.000	1.000	0.500	NA	NA	1.000	1.000	0.562	NA	NA	1.000	1.000	0.626	NA	NA	NA	NA	NA	
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	1.004	1.004	0.548	0.696	0.617
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	1.016	0.548	0.696	0.617	1.017	1.058	0.508	0.677	0.137
LR-MFG-T1	1.047	1.079	0.500	0.267	0.049	1.006	1.022	0.492	0.164	0.280	1.097	1.071	0.521	0.169	0.264	1.038	1.083	0.557	0.260	0.277	1.047	1.079	0.500	0.267	0.049
LR-MF-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	1.060	1.078	0.524	0.268	0.154
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	0.995	0.999	0.667	0.833	0.947
AR(1)-MF-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	0.998	1.005	0.651	0.936	0.823
AR(1)-G-T1	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	1.002	0.996	0.619	0.912	0.815
AR(1)-MF-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	1.043	1.033	0.587	0.334	0.407
AR(1)-G-T2	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	1.052	1.108	0.611	0.268	0.115
VAR(1)	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	1.062	1.120	0.603	0.205	0.114
VARX(1)-MF-T1	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	1.007	1.052	0.603	0.845	0.186
VARX(1)-MFG-T1	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	1.281	1.328	0.603	0.002	0.008
VARX(1)-G-T1	1.002	1.044	0.603	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	1.002	1.044	0.603	0.938	0.138
VARX(1)-MFG-T2	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	0.989	1.050	0.667	0.783	0.212
VARX(1)-G-T2	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	1.023	1.070	0.563	0.544	0.072
PVAR(1)-GMM	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	1.031	1.067	0.540	0.918	0.166
PVAR(1)-OLS	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	1.005	1.067	0.540	0.918	0.166
PVARX(1)-OLS	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	1.045	1.169	0.508	0.052	0.005
PVAR(1)-OLS	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	1.002	1.044	0.603	0.938	0.138
PVARX(1)-OLS	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	1.023	1.070	0.563	0.544	0.072
PVARX(1)-OLS	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	1.031	1.073	0.659	0.446	0.084
PVARX(1)-OLS	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	1.078	1.158	0.508	0.104	0.004
PVARX(1)-OLS	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	1.005	1.067	0.540	0.918	0.166
PVARX(1)-OLS	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	1.101	1.169	0.508	0.052	0.005

Table 17: CPI Growth (Inflation), IT.

	h=1						h=3						h=6						h=12						
	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2	MAE	RMSFE	SSR	DMI	DM2
	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	1.029	1.034	0.557	0.573	0.479	0.878	0.863	0.652	0.134	0.087
Naive	1.000	1.000	0.508	NA	NA	1.000	1.000	0.452	NA	NA	1.000	1.000	0.661	NA	NA	1.000	1.000	0.600	NA	NA	1.000	1.000	0.600	NA	NA
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	0.878	0.863	0.652	0.134	0.087
LR-G-T1	0.973	0.992	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	0.553	0.973	0.973	0.548	0.937	0.522
LR-MFG-T1	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	1.062	1.055	0.591	0.315	0.290
LR-MF-T2	0.968	0.957	0.619	0.272	0.068	0.992	0.970	0.629	0.877	0.369	0.906	0.980	0.620	0.876	0.439	0.862	0.834	0.696	0.016	0.011	0.862	0.834	0.696	0.016	0.011
LR-G-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	0.939	0.904	0.678	0.314	0.090
LR-MFG-T2	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	1.016	1.019	0.557	0.324	0.416
AR(1)-MF-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	0.959	0.935	0.643	0.033	0.092
AR(1)-G-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	0.981	0.951	0.617	0.014	0.205
AR(1)-MFG-T1	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	1.085	1.068	0.609	0.271	0.260
AR(1)-MF-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	0.856	0.829	0.722	0.006	0.006
AR(1)-G-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	0.941	0.912	0.687	0.185	0.057
AR(1)-MFG-T2	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	1.105	1.287	0.652	0.358	0.327
VAR(1)	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	1.126	1.294	0.661	0.299	0.303
VARX(1)-MF-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	1.074	1.264	0.626	0.576	0.420
VARX(1)-G-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	1.106	1.267	0.626	0.447	0.404
VARX(1)-MFG-T1	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	1.254	1.711	0.635	0.305	0.316
VARX(1)-MF-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	1.056	1.488	0.730	0.800	0.437
VARX(1)-G-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	1.169	1.816	0.713	0.571	0.376
VARX(1)-MFG-T2	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	1.005	0.626	0.809	0.431	1.203	1.005	0.626	0.809	0.431
PVAR(1)-GMM	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	1.003	1.005	0.626	0.809	0.431
PVARX(1)-OLS	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	1.018	1.018	0.591	0.417	0.457	1.018	1.018	0.591	0.417	0.457
PVAR(1)-OLS	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	0.995	0.976	0.635	0.716	0.107
PVARX(1)-OLS	0.980	0.977	0.548	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	0.937	0.906	0.704	0.027	0.009
PVAR(1)-OLS	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	0.971	0.925	0.696	0.259	0.000

Table 18: CPI Growth (Inflation), UK.

7 Appendix

7.1 List of Models

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)-MF-T2	Linear Regression using the first lag of y, Macro/Finance predictors (UMIDAS)
AR(1)-G-T2	Linear Regression using the first lag of y, Google predictors (UMIDAS)
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)-MF-T2	Vector Autoregressive model, P=1 with Macro/Finance predictors (UMIDAS) as exogenous
VARX(1)-G-T2	Vector Autoregressive model, P=1 with Google predictors (UMIDAS) 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
PVARX(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 (avg) 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

Legend.

7.2 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.

7.2.1 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 laptop⁸).

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.

7.2.2 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 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.

⁸Exact machine specifications: Intel Core i7-6600U @ 2.60GHz, 16GB RAM.

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.

7.2.3 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
                             )
```

7.2.4 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.

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