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Forecasting toolbox for Cyprus GDP growth

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Forecasting Toolbox for Cyprus GDP Growth

Elena Andreou* ***Andros Kourtellos***† ***Nicoletta Pashourtidou***‡

Abstract

We use regression-based methods for predicting the quarterly real economic activity of Cyprus using a large panel of time-series and new statistical methods. In particular, we employ various forecast combinations as well as dynamic factor models that allow us to deal with the curse of dimensionality. Our results show that factor augmented regressions or their combinations can provide substantial gains over traditional benchmarks for forecasting real GDP growth in Cyprus.

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Μοντέλα πρόβλεψης του ρυθμού μεταβολής του ΑΕΠ στην Κύπρο

ΠΕΡΙΛΗΨΗ

Στόχος της μελέτης είναι η εφαρμογή μεθόδων που βασίζονται σε μοντέλα παλινδρόμησης, καθώς και σε καινούριες στατιστικές μεθόδους για την πρόβλεψη του τριμηνιαίου ρυθμού μεταβολής της οικονομικής δραστηριότητας (ΑΕΠ σε σταθερές τιμές) στην Κύπρο. Στην ανάλυση χρησιμοποιείται ένας μεγάλος αριθμός τριμηνιαίων εγχώριων και διεθνών μακροοικονομικών σειρών για την περίοδο 1995:1-2009:3. Συγκεκριμένα, η μελέτη επικεντρώνεται

- στην κατασκευή τριμηνιαίων παραγόντων (factors) που συνοψίζουν τις πληροφορίες ενός μεγάλου αριθμού μακροοικονομικών σειρών, και

- στη διερεύνηση της ικανότητας πρόβλεψης του ρυθμού μεταβολής του ΑΕΠ μέσω ενός μεγάλου αριθμού μοντέλων όπως (α) μοντέλα μιας μεταβλητής (AR, Random Walk, Moving Average), (β) μοντέλα τύπου ADL (Autoregressive Distributed Lag) που περιέχουν ξεχωριστά διάφορες μακροοικονομικές σειρές ή τριμηνιαίους παράγοντες και (γ) συνδυασμούς προβλέψεων που προέρχονται από τα πιο πάνω μοντέλα (forecast combinations).

Τα αποτελέσματα της ανάλυσης δείχνουν ότι μοντέλα που περιέχουν τριμηνιαίους παράγοντες ή συνδυασμοί προβλέψεων από τέτοια μοντέλα δίνουν σημαντικά καλύτερες προβλέψεις σε σχέση με δυναμικά μοντέλα που χρησιμοποιούνται παραδοσιακά για σκοπούς πρόβλεψης. Επίσης, μοντέλα που περιλαμβάνουν διεθνείς μεταβλητές σχετικές με την οικονομική δραστηριότητα, όπως δείκτες οικονομικού κλίματος και δείκτες του ρυθμού μεταβολής του ΑΕΠ της ΕΕ, Ευρωζώνης, Ην. Βασιλείου και της Ελλάδας φαίνεται να δίνουν αρκετά καλές προβλέψεις για το ρυθμό μεταβολής του ΑΕΠ της Κύπρου.

CONTENTS

1 Introduction

Nowadays thousands of economic time series are available online in real time. Can these be used for economic forecasting and monitoring forecasts in real time? One problem with this proposal is that it is against the principle of parsimony. In fact forecasters are faced with the curse of dimensionality caused by the number of alternative predictors and by model uncertainty. There are two methods to turn the curse into a blessing. The first method combines information using factor models. Factor models are a useful way of summarizing the information in hundreds of time-series by extracting their common component or covariation in a handful of factors and hence achieving a great reduction in dimensionality. Factor models are widely used in central banks and research institutions as a forecasting tool and have been used to predict real and nominal variables. For the US, see for example Stock and Watson (1999), Stock and Watson (2002a), Stock and Watson (2002b), D'Agostino, Surico, and Giannone (2009). For the euro area, see for example Forni, Hallin, Lippi, and Reichlin (2000), Forni, Hallin, Lippi, and Reichlin (2003), Marcellino, Stock, and Watson (2006), and Banerjee, Marcellino, and Masten (2005). For the UK, Artis, Banerjee, and Marcellino (2002). The second method combines information across different forecasts; see Timmermann (2006).

In this paper we construct factors based on 95 leading indicators to forecast Cyprus GDP growth. We then compare the predictive performance of forecast combinations of factor augmented AR models for GDP growth along with forecast combinations of ADL models based on indicators in order to provide robust and accurate forecasts for economic activity. Our results suggest some interesting findings for forecasting the Cyprus GDP growth. In particular, we find that forecast combinations and in particular factor augmented AR models can yield substantial forecasting gains against the traditional univariate benchmarks. Forecast combination methods that heavily discount the past observations such as the Recently Best method appear to perform the best. Moreover, our findings suggest that forecasting gains are mainly driven by the class of international activity-based indicators for all forecasting horizons, $h = 1, 2$, and 4 quarters. The classes of financial-international and UK predictors, such as the UK GDP and an economic sentiment indicator, tourist arrivals from the UK and the exchange rate of British pound to Euro, also contribute to the predictive ability of forecast combinations for the shorter horizons of $h = 1$ and $h = 2$ quarters.

The paper is organized as follows. In section 2 we describe our basic models. In sections 2 and 5 we present our factor analysis and forecast combination methods, respectively. Section 3 and section 6 present our data and empirical results, respectively. Section 7 concludes.

2 Methodology

Suppose we wish to forecast a variable 1-step ahead observed at some low frequency, for instance quarterly real GDP growth, denoted by Y_{t+1}. We express the growth in annualized units $Y_{t+1} = 400ln(GDP_{t+1}/GDP_t) = 400\Delta ln(GDP_{t+1})$. In the absence of any other information the simplest univariate model that we can estimate is the constant growth model (2.1) - RW model for GDP

$$Y_{t+1} = \mu + u_{t+1}. \tag{2.1}$$

It is typical for time series variables to allow for autocorrelation in Y_{t+1} using the AR model (2.2)

$$Y_{t+1} = \mu + \sum_{j=0}^{p_Y-1} \alpha_j Y_{t-j} + u_{t+1}. \tag{2.2}$$

Suppose now we have at our disposal quarterly macroeconomic and financial series that are considered as useful predictors, denoted by X_t. Higher frequency variables can be averaged to quarterly frequency, albeit temporal aggregation issues.[1] A simple framework for assessing predictive content is the dynamic linear predictive regression model or Augmented Distributed Lag, $ADL(p_Y, q_X)$, regression model relating the future value of Y to the current

[1]For example Andreou, Ghysels, and Kourtellos (2010a) show that the estimated slope coefficient of a regression model that imposes a standard aggregation scheme (and ignore the fact that processes are generated from a mixed data environment) yield asymptotically inefficient (at best) and in many cases inconsistent estimates. Both inefficiencies and inconsistencies can have adverse effects on forecasting. On the other Andreou, Ghysels, and Kourtellos (2010b) illustrates the value of daily information in terms of improving traditional forecasts based on aggregated data using Mi(xed) Da(ta) S(ampling) - MIDAS - regressions. The MIDAS regression forecasting approach is pursued in future work.

value of X and past values of Y

$$Y_{t+1} = \mu + \sum_{j=0}^{p_Y-1} \alpha_{j+1} Y_{t-j} + \sum_{j=0}^{q_X-1} \beta_j X_{t-j} + u_{t+1}. \tag{2.3}$$

This regression is fairly parsimonious as it only requires $p_Y + q_X + 1$ regression parameters to be estimated. The economic significance of X_t as a predictor can be assessed using the estimate of the standard deviation of u_{t+1}. Given that the conditional variance of the error term u_{t+1} can depend on X_t (heteroskedasticity) and/or be correlated with its previous values (autocorrelation), we often use a t-statistic based on heteroskedasticity and autocorrelation consistent (HAC) standard errors in the presence of reasonably large time series. Note that this model nests the simple predictive regression when $\alpha_j = 0$ for $j = 0, \ldots, p_Y - 1$ as well as the AR model (2.2) when $\beta_j = 0$ for $j = 0, \ldots, p_Y - 1$.

Equation (2.3) applies to forecasts one period ahead, but it can easily be modified for multistep-ahead forecasts by replacing Y_{t+1} with the appropriate h-period ahead value, where the dependent variable in (2.4) becomes $Y_{t+h} = (400/h)ln(GDP_{t+h}/GDP_t) = (400/h)\Delta ln(GDP_{t+h})$. Then the h-step ahead ADL regression model becomes

$$Y_{t+h} = \mu + \sum_{j=0}^{p_Y-1} \alpha_{j+1} Y_{t-j} + \sum_{j=0}^{q_X-1} \beta_j X_{t-j} + u_{t+h}. \tag{2.4}$$

As a final note of this section we point out that this study is based on direct forecasts as opposed to iterated. While direct forecasts can be less efficient they are robust to model misspecification; see for example Marcellino, Stock, and Watson (2006).

3 Data

We focus on forecasting the Cyprus quarterly real GDP growth rate as it is one of the key macroeconomic measures in the literature. Figure 1 plots the series of interest, namely real GDP growth (quarter-on-quarter) over the available sample period. The most noticeable slowdown in economic activity was registered in 2009 and it was due to the international financial crisis that affected Cyprus with a time lag.

The data set contains 95 series over the period 1995Q1-2009Q3. The variables consist of measures of aggregate and sectoral economic activity, productivity and labour cost indices, employment (aggregate and sectoral) and unemployment, measures of external trade and tourism, price indices, interest rates, exchange rates, stock exchange indices (domestic and foreign), a number of international commodity price indices (e.g. gold, silver, oil) and various foreign economic activity measures and indicators (e.g. euro area real GDP and economic sentiment indicator). Due to data availability these series are at quarterly frequency and are obtained from the following data sources: Cyprus Statistical Service, IMF International Financial Statistics, Global Financial Data, Eurostat and European Commission (DG-ECFIN). The series are seasonally adjusted and expressed in first differences of logarithms or first differences of levels. All variables used in the analysis together with the transformations applied are shown in A1.

Using a recursive estimation method we provide pseudo out-of-sample forecasts (see also for instance, Stock and Watson (2002b) and Stock and Watson (2003)) to evaluate the predictive ability of our models for various forecasting horizons $h = 1$, 2, and 4.[2] The total sample size, $T+h$, is split into the period used to estimate the models, and the period used for evaluating the forecasts. The estimation period spans $1995Q1 - 2001Q4$ and the forecast evaluation period is from 2001$Q4$+h to 2009$Q3$-h.

In assessing the forecast accuracy of each model we use the root mean squared forecast error (RMSFE) as follows:

$$RMSFE_{i,t} = \sqrt{\frac{1}{t - T_0 + 1} \sum_{\tau=T_0}^{t} (y^h_{\tau+h} - \widehat{y}^h_{i,\tau+h|\tau})^2} \tag{3.1}$$

where $t = T_1, \ldots, T_2$. T_0 is the point at which the first individual pseudo out-of sample forecast is computed. In our sample $T_0 = 2002 : Q1$, $T_1 = 2002 : Q1 + h$, and $T_2 = 2009 : Q3 - h$. [3]

[2]Due to sample limitations we do not use a rolling forecasting method.

[3]In the forecast evaluation exercise where different combination forecasts are considered the forecast evaluation period over which the relative MSEs are computed is restricted to begin from 2002Q4+$h + nprb$, where $nprb$ is the number of periods for the Recently Best forecast combination which is set equal to 4.

4 Factor analysis

Recently, a large body of work has developed factor model techniques that are tailored to exploit a large cross-sectional dimension; see for instance, Bai and Ng (2002), Bai (2003), Forni, Hallin, Lippi, and Reichlin (2000), Forni, Hallin, Lippi, and Reichlin (2005), Stock and Watson (1989), Stock and Watson (2003), Andreou, Ghysels, and Kourtellos (2010b) among many others. These factors are usually estimated at quarterly frequency using a large panel and then these estimated factors augment the standard AR and ADL models to obtain the Factor AR (FAR) and Factor ADL (FADL) models, respectively.

Following this literature we construct quarterly factors from our dataset of 95 series to augment the AR regression model with quarterly factors. Due to the small time series sample we do not consider more than one factor in a forecasting equation, but use again forecast combinations of regressions based on each factor.

The next issue is how we construct the factors. We estimate the factors using a Dynamic Factor Model (DFM) with time-varying factor loadings, which is given by the following static representation:

$$\begin{aligned} X_t &= \Lambda_t F_t + e_t && (4.1) \\ F_t &= \Phi_t F_{t-1} + \eta_t && (4.2) \\ e_{it} &= a_{it}(L) e_{it-1} + \varepsilon_{it}, \quad i = 1, 2, ..., N, && (4.3) \end{aligned}$$

where $X_t = (X_{1t}, ..., X_{Nt})'$, F_t is the r-vector of static factors, Λ_t is a $N \times r$ matrix of factor loadings, $e_t = (e_{1t}, ..., e_{Nt})'$ is an N-vector of idiosyncratic disturbances, which can be serially correlated and (weakly) cross-sectionally correlated. Note that the static representation in equation (4.1) can be derived from the DFM assuming finite lag lengths and VAR factor dynamics in the factors where F_t contains the lags (and possibly leads) of the dynamic factors. Although generally the number of factors from a DFM and those from a static one differ, we have that $r = d(s+1)$ where r and d are the numbers of static and dynamic factors, respectively, and s is the order of the dynamic factor loadings. Moreover, empirically static and dynamic factors produce rather similar forecasts (Bai and Ng (2008)).

This particular factor model enjoys the following two advantages. First, it allows for the possibility that the factor loadings change over time (compared to the standard DFMs), which may address potential instabilities during our sample period (see Theorem 3, p. 1170, in Stock and Watson (2002a)). Hence, the extracted common factors can be robust to instabilities in individual time-series, if such instability is small and sufficiently dissimilar among individual variables, so that it averages out in the estimation of common factors. Second, the errors, ε_{it} are allowed to be conditionally heteroskedastic and serially and cross-correlated (see Stock and Watson (2002a) for the full set of assumptions).

Under these assumptions we estimate the factors using a principal component method that involves cross-sectional averaging of the individual predictors. An advantage of this estimation approach is that it is nonparametric and therefore we do not need to specify any additional auxiliary assumptions required by state space representations which may be more prone to misspecification error.[4] DFM using principal components yield consistent estimates of the common factors if $N \to \infty$ and $T \to \infty$. The condition $N/\sqrt{T} \to \infty$ ensures that the estimated coefficients of the forecasting equations are consistent and asymptotically Normal with standard errors, which are not subject to the estimation error from the DFM model estimation in the first stage.[5]

There are various approaches to choosing the number of factors. One approach is to use the information criteria (ICP) proposed by Bai and Ng (2002). Panel A of Table 1 shows the values of the ICP criteria, the estimated eigenvalues and the standardized estimated eigenvalues that correspond to different number of estimated factors. The three ICP criteria yield different estimates of the number of factors. ICP2 and ICP1 suggest one and two factors, respectively, while ICP3 estimates five factors, i.e. the maximum number of factors employed in the estimation. Therefore to choose the number of quarterly factors we assess the marginal contribution of the k^{th} principal component in explaining the total variation. We opt to examine forecast combinations of up to 5 quarterly factors in all exercises since we have found that overall this number explains a sufficiently large percentage of the cross-sectional variation. In particular, the first factor captures nearly 34% of this variation while the fifth explains about 11%.

Panel B of Table 1 presents the distribution of the sums of squared loadings over the different categories of variables and the five factors. The first factor loads mainly on domestic activity variables, international activity and international financial series. The second factor

[4]State space models and the associated Kalman filter are based on linear Gaussian models. Non-Gaussian state space models are numerically much more involved, see e.g. Smith and Miller (1986), Kitagawa (1987), and the large subsequent literature - see the recent survey of Johannes and Polson (2006).

[5]Although the parametric AR assumption for F_t and e_{it} is not needed to estimate the factors, such assumptions can be useful when discussing forecasts using factors.

correlates mostly with labour market variables and the third with domestic activity, labour market and international financial variables. These results suggest the use of at most five factors which are subsequently used, one at a time, in forecasting equations. Figure 2 shows the evolution of the first five factors over time. All series plotted are standardized so that they have a mean of zero and a variance of one.

Having obtained these quarterly common factors we extend the AR and ADL regression models. Equation (2.2) generalizes to the $FAR(p_Y, p_F)$ model

$$Y_{t+1} = \mu + \sum_{k=0}^{p_Y-1} \alpha_k Y_{t-k} + \sum_{k=0}^{p_F-1} \beta_k F_{t-k} + u_{t+1}. \tag{4.4}$$

In ongoing work we also extend the ADL model in (2.3) by augmenting it with quarterly factors. The $FADL(p_Y, p_F, q_X)$ model is given by

$$Y_{t+1} = \mu + \sum_{k=0}^{p_Y-1} \alpha_k Y_{t-k} + \sum_{k=0}^{p_F-1} \beta_k F_{t-k} \sum_{k=0}^{p_X-1} \gamma_k X_{t-k} + u_{t+1}. \tag{4.5}$$

5 Forecast combinations

There is a large and growing literature that suggests that forecast combinations can provide more accurate forecasts by using evidence from all the models considered rather than relying on a specific model. Areas of applications include output growth (Stock and Watson (2004)), inflation (Stock and Watson (2008)), exchange rates (Wright (2008)), and stock returns (Avramov (2002)). Timmermann (2006) provides an excellent survey of forecast combination methods. One justification for using forecast combinations methods is the fact that in many cases we view models as approximations because of the model uncertainty that forecasters face due to the different set of predictors, the various lag structures, and generally the different modeling approaches. Furthermore, forecast combinations can deal with model instability and structural breaks under certain conditions. For example, Hendry and Clements (2004) argue that under certain conditions forecast combinations provide robust forecasts against deterministic structural breaks when individual forecasting models are misspecified while Stock and Watson (2004) find that forecast combination methods and especially simple strategies such as equally weighting schemes (Mean) can produce more stable forecasts than individual forecasts. In contrast, Aiolfi and Timmermann (2006) show that combination strategies based on some pre-sorting into groups can lead to better overall forecasting performance than simpler ones in an environment with model instability. Although there is a consensus that forecast combinations improve forecast accuracy there is no consensus concerning how to form the forecast weights.

Given M approximating models and associated forecasts, combination forecasts are (time-varying) weighted averages of the individual forecasts,

$$\widehat{f}_{M,t+h|h} = \sum_{i=1}^{M} \widehat{\omega}_{i,t}\widehat{y}_{i,t+h|t}, \tag{5.1}$$

where the weights $\widehat{\omega}_{i,t}$ on the i^{th} forecast in period t depends on the historical performance of the individual forecast.

In this paper we consider mainly two families of forecast combination methods: (i) Simple combination forecasts and (ii) Discounted MSFE forecasts. Simple combination forecasts include the Mean, the Trimmed Mean (with 5% symmetric trimming), and the Median. According to Timmermann (2006) while equal weighting methods such as the Mean are simple to compute and perform well, they can also be optimal under certain conditions. Nevertheless, equal weighting methods ignore the historical performance of the individual forecasts in the panel. To account for the historical performance of each individual forecast we use the Discounted MSFE method employed by Stock and Watson (2004) and Stock and Watson (2008). This method computes the combination forecast as a weighted average of the individual forecasts, where the weights are inversely proportional to the discounted MSFE (DMSFE) or the square of the discounted MSFE (2DMSFE), using a discount factor of $\delta = 0.9$ in order to attach greater weight to the recent forecast accuracy of the individual model.

$$\begin{aligned} \widehat{\omega}_{i,t} &= \frac{\left(\lambda_{i,t}^{-1}\right)^{\kappa}}{\sum_{j=1}^{n}(\lambda_{j,t}^{-1})^{\kappa}} && (5.2) \\ \lambda_{i,t} &= \sum_{\tau=T_0}^{t-h} \delta^{t-h-\tau}(y_{\tau+h}^{h} - \widehat{y}_{i,\tau+h|\tau}^{h})^2, && (5.3) \end{aligned}$$

where $\delta = 0.90$ and $\kappa = 1, 2$. Although we focus on $\delta = 0.9$, we also considered discount factors of $\delta = 1$ and 0.95 but the results remained qualitatively the same.[6]

In future work we also plan to employ Information criteria based forecast combination methods. In these methods the weights are based on an in-sample model fit and include Mallows Model Averaging (Hansen (2008)) and Bayesian Model Averaging (e.g. Avramov (2002), Stock and Watson (2006), and Wright (2008))among others.

6 Empirical results

In this section we discuss the forecasting performance of various families of models and different sets of quarterly predictors for forecasting the quarterly Cyprus real GDP growth rate.

We start with Table 2, which presents RMSFEs relative to the RW benchmark for several benchmark models for three forecasting horizons, $h = 1$, 2, and 4 quarters ahead. For the RW we report the absolute RMSFE. We include two autoregressive models with fixed lags (AR(1) and AR(4)), two autoregressive models based on AIC and BIC (AR(AIC) and AR(BIC)), and three moving average models including the specification proposed by Nelson and Schwert (1977). The results illustrate that it is hard to beat the RW model since neither the AR nor the MA models can yield gains over the RW benchmark.

Table 3 presents our main findings. This table presents RMSFEs for forecast combinations for real GDP growth relative to the RMSFE of RW for 1-, 2-, and 4-step. Panel A includes forecast combination results on 78 leading indicators (GDP and its 16 subaggregates are excluded) across *all* models, across univariate models, and across ADL models. The results show that forecast combinations of *all* or ADL models can improve the forecasting ability of the RW, especially in the case of $h = 1$. In particular, we find that the Recently Best forecast combination of models that includes ADL (*all* or ADL) yields the highest gains. It provides 18% gains over the RW and 28% over the benchmark of AR(1) in the case of $h = 1$. For $h = 4$ the Recently Best forecast combination yields about 20% gains over the benchmark of RW and AR(1). This implies that for $h = 1$ and $h = 4$ the 78 indicators entail valuable predictive information beyond the information of the univariate models. For $h = 2$ Recently Best forecast combinations provide about 10% gains over the RW benchmark. Most of the

[6]Note that the case of no discounting $\delta = 1$ corresponds to the Bates and Granger (1969) optimal weighting scheme when the individual forecasts are uncorrelated.

remaining forecast combination methods shown in Panel A give relatively smaller gains over the RW benchmark. This can be attributed to the turbulent period of our sample and to the role of factor models which can be an additional method to efficiently summarize information in the panel before applying forecast combinations. [7]

Panel B of Table 3 presents RMSFEs for forecast combinations for up to 5 factors. Interestingly, we find that forecast combinations of factor augmented AR models (FAR) yield forecasting gains at all forecast horizons, especially for the Recently Best method. For $h = 1$ and $h = 2$, FAR models can yield as much as 44% and 29% gains, over the RW benchmark, respectively. For Recently Best the largest gains for $h = 1$ and $h = 2$ are given by forecast combinations of models based on the first factor or by forecast combinations of the first two. On the contrary the largest gains for $h = 4$ are given by forecast combinations of all five factors. Overall given the uncertainty we face in selecting the number of factors, the strategy of using the first three factors provides the best results for longer forecasting horizons and large gains for $h = 1$, albeit not the largest. We should point out that the performance of 2DMSFE with a discount factor $\delta = 0.9$ also exhibits large gains for the various combinations of factors.

More importantly, the overall performance of forecast combinations based on the factor model against those based on ADL or univariate is remarkable. Figures 3-5 present the RMSFE of Recently Best forecast combinations across *all*, *univariate*, *ADL*, and *Factor 1* relative to the RMSFE of the RW benchmark, for $h = 1$, $h = 2$, and $h = 4$, respectively. Interestingly, in the case of $h = 1$ we see that combinations of FAR models provide substantial gains against alternative combinations over the entire evaluation period. While these gains appear to shrink towards the end of the sample, they are still large. For instance, *Factor 1* provides gains of about 32% to 62% over forecast combinations based on *ADL* models. While this finding appears to hold for longer horizons the gains are smaller. In the case of $h = 4$ we also note that after mid 2008 *ADL* forecast combinations appear to work better implying that *ADL* models include useful information for prediction, especially during the recent financial crisis. This finding suggests that one maybe able to further improve the Cyprus GDP growth forecasts using $FADL$ models that always include a quarterly factor, as well as for instance, international activity measures, financial indicators domestic or international. We plan to investigate these models in future research.

[7] It may also suggest that more work needs to be done in terms of finding better leading indicators for Cyprus GDP growth.

Table 4 presents RMSFEs for forecast combinations using 7 different classes of our 78 leading indicators that correspond to four domestic classes of variables (activity, financial, labor market, trade and tourism) and three international classes (activity, financial, and UK). Figures 6-8 present the corresponding RMSFE of Recently Best forecast combinations using ADL models for the various sectors relative to the RMSFE of the RW benchmark. We find that the gains in the predictive ability of Cyprus GDP growth using *all* 78 indicators are mainly driven by the activity-international. More importantly, activity international is the only class that provides substantial gains for all three horizons. Using the Recently Best method we can obtain as much as 34% for $h = 1$, 38% for $h = 2$ and 25% for $h = 4$ gains over the RW benchmark. Interestingly, activity-domestic contributes the least in those gains. The financial-international and UK are also important classes for $h = 1$ and $h = 2$ with gains as much as 24%.

In terms of best predictors we should mention that the class of activity-international includes EU, UK, and Greek economic activity sentiment indices as well as GDP growth measures. The complete set of results for each predictor are presented in the appendix; see Table A2.

7 Conclusion

We studied how to incorporate the information from a large number of time-series for forecasting quarterly real GDP growth of Cyprus using forecast combinations as well as dynamic factor models.

Overall, we find that factor combinations of factor augmented, FAR, models, provide substantial forecast gains against various benchmark forecasts as well as forecast combinations of ADL models. These gains are especially large in the case of one-step ahead forecasts. These gains appear to be mainly driven by the first two quarterly factors and by the sector of activity international, which includes variables such as the EU, UK, and Greek economic activity indices as well as GDP growth measures. The predictors of UK and the international financial sectors are the next set of best predictors.

Figure 1: Cyprus Real GDP Growth

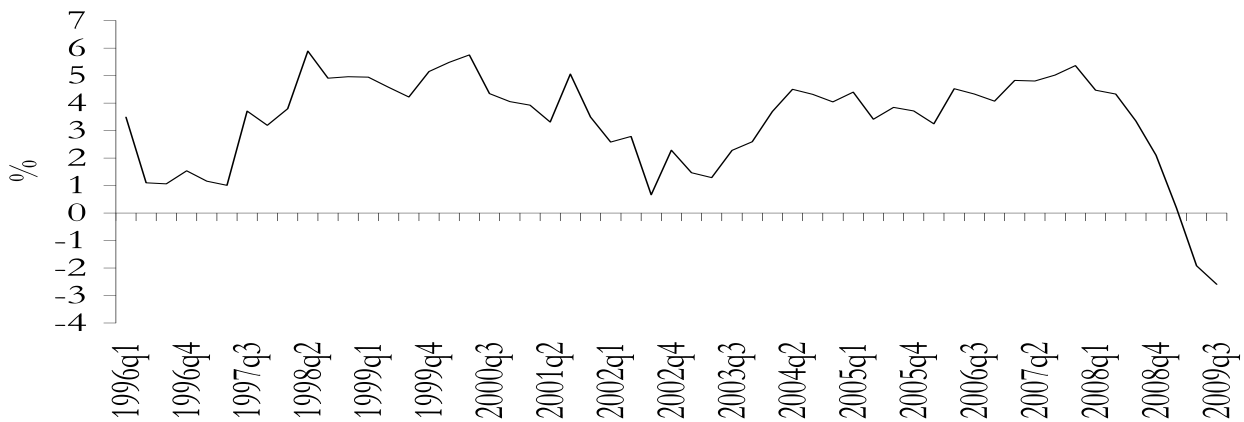
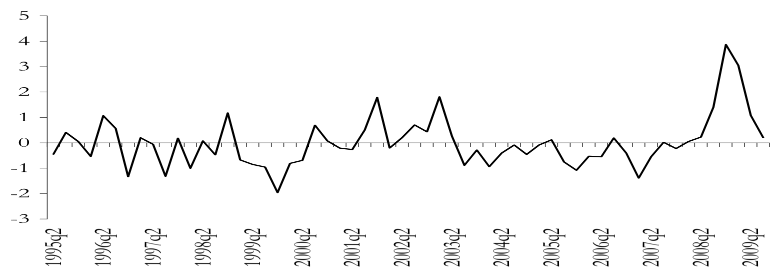
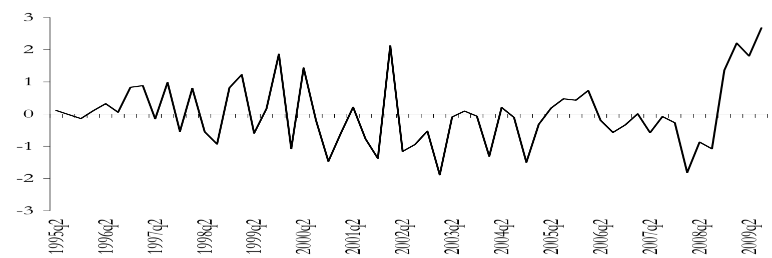


Figure 2: The five quarterly factors

(a) 1*st* Factor

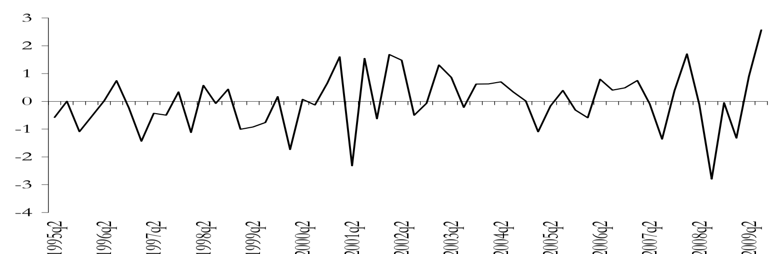


(b) 2*nd* Factor



(c) 3*rd* Factor

(d) 4*th* Factor



(e) 5*th* Factor

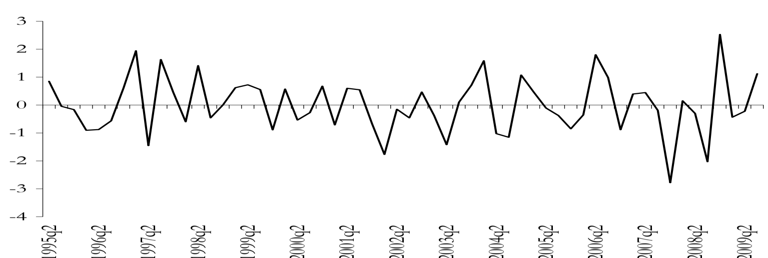


Figure 3: Relative RMSFE of forecast combinations - h = 1

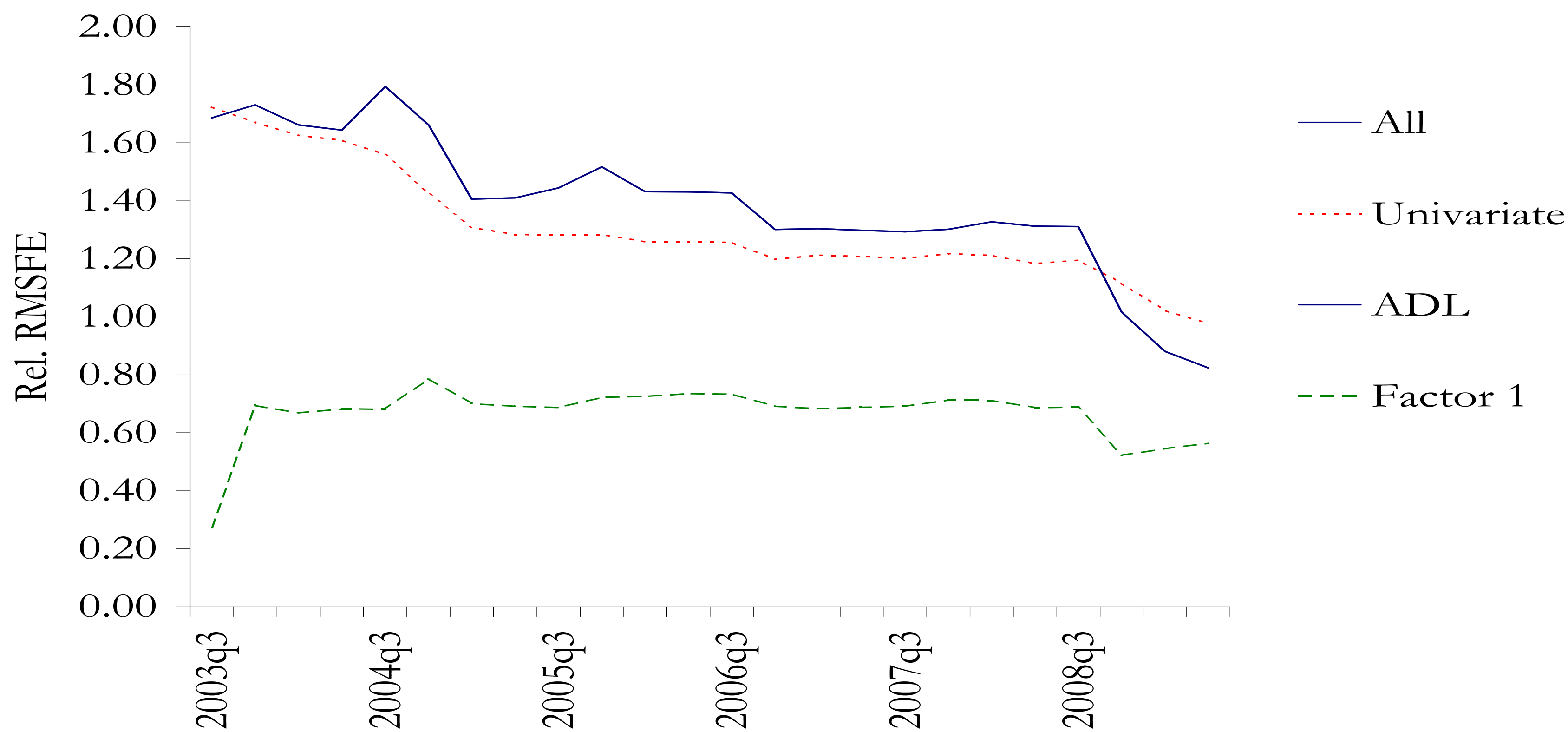


Figure 4: Relative RMSFE of forecast combinations - h = 2

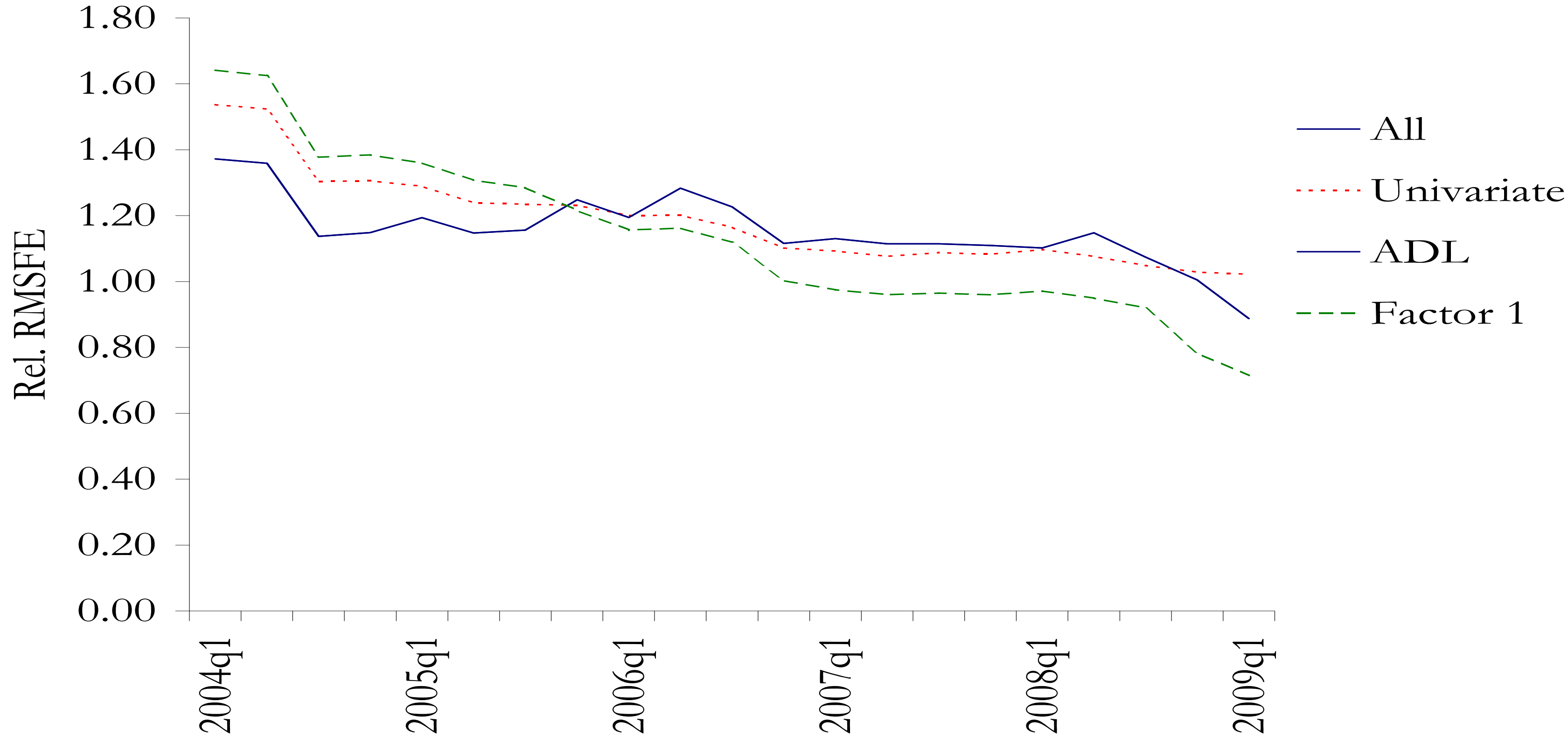


Figure 5: Relative RMSFE of forecast combinations - h = 4

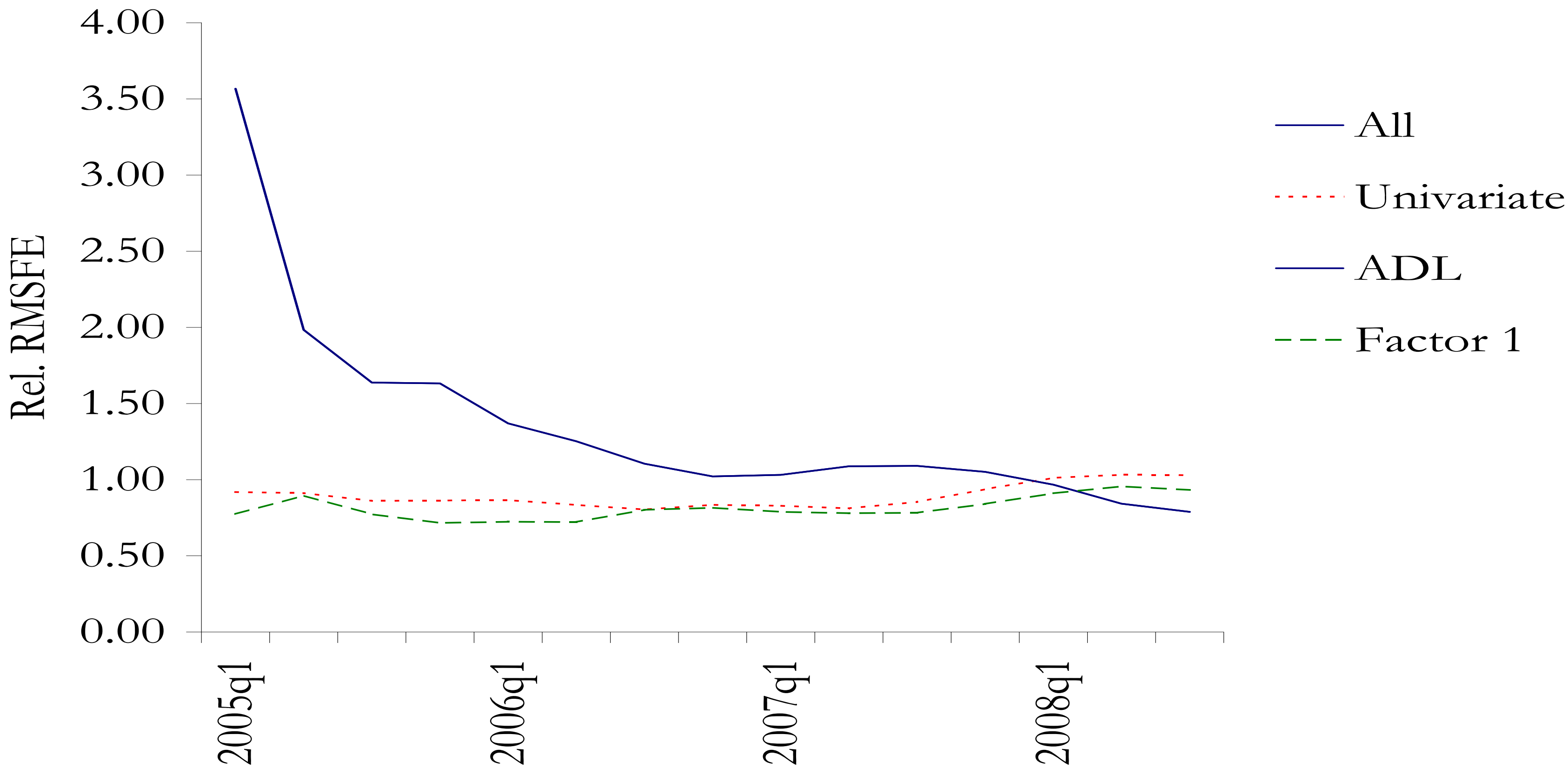


Figure 6: Relative RMSFE of forecast combinations - h = 1

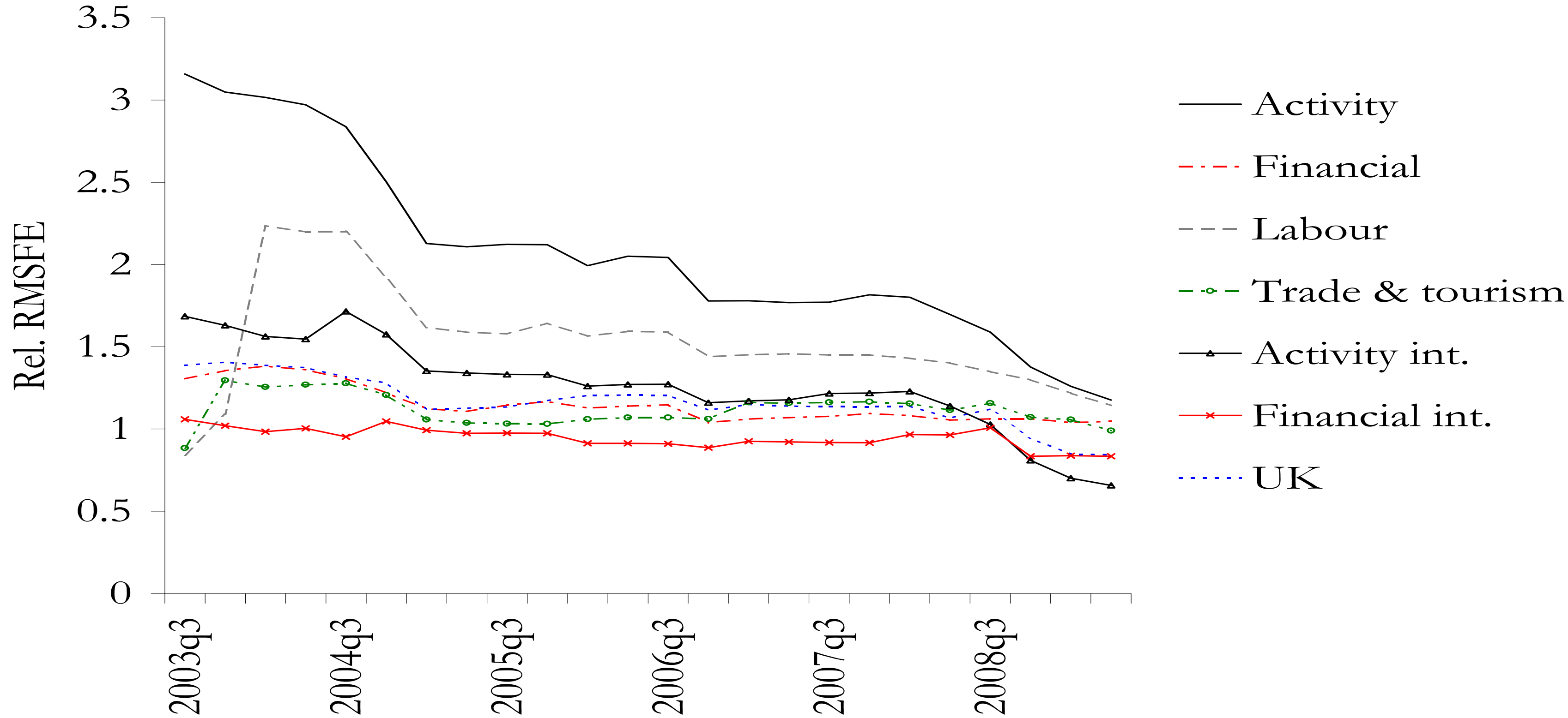


Figure 7: Relative RMSFE of forecast combinations - h = 2

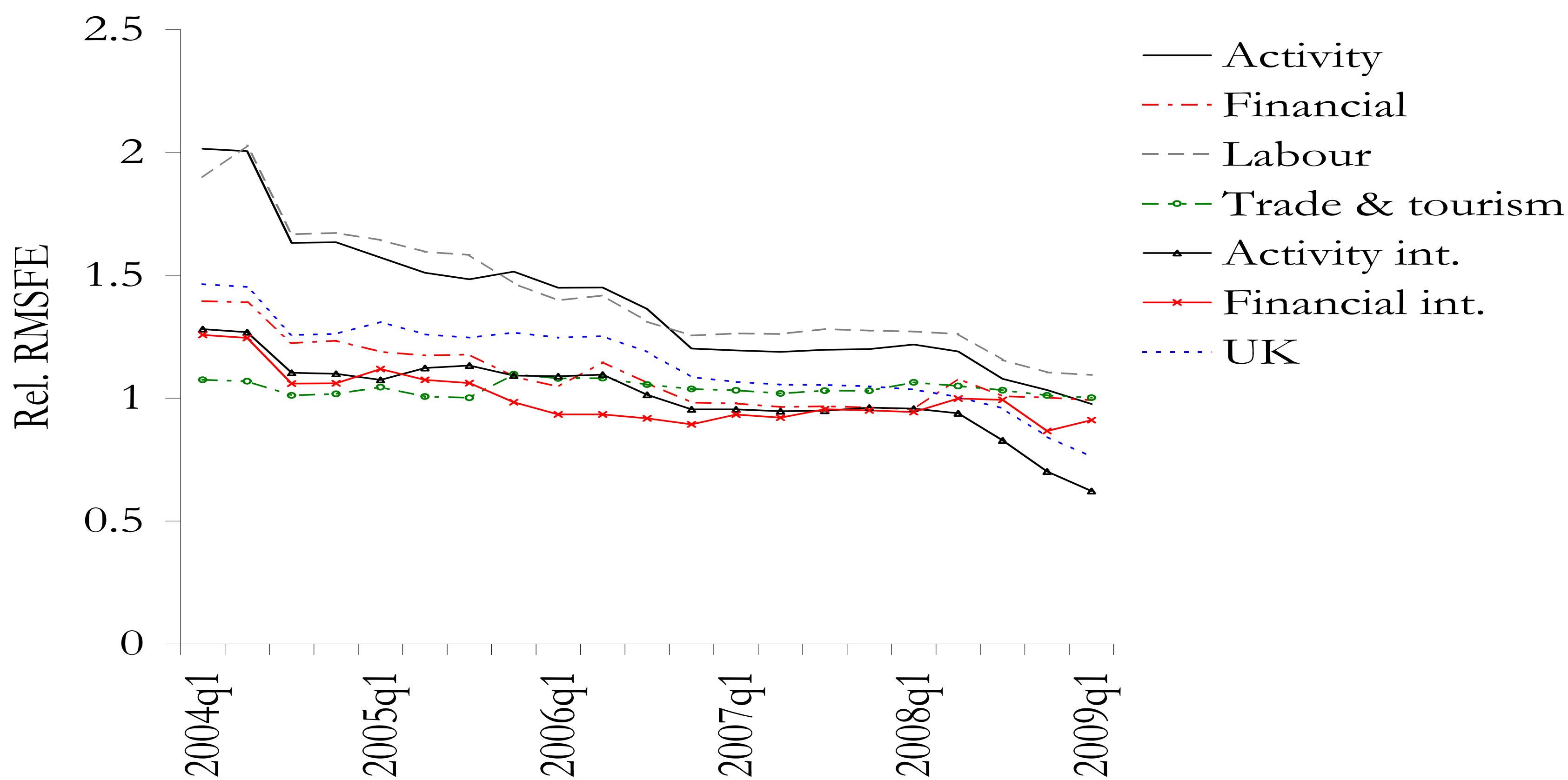


Figure 8: Relative RMSFE of forecast combinations - h = 4

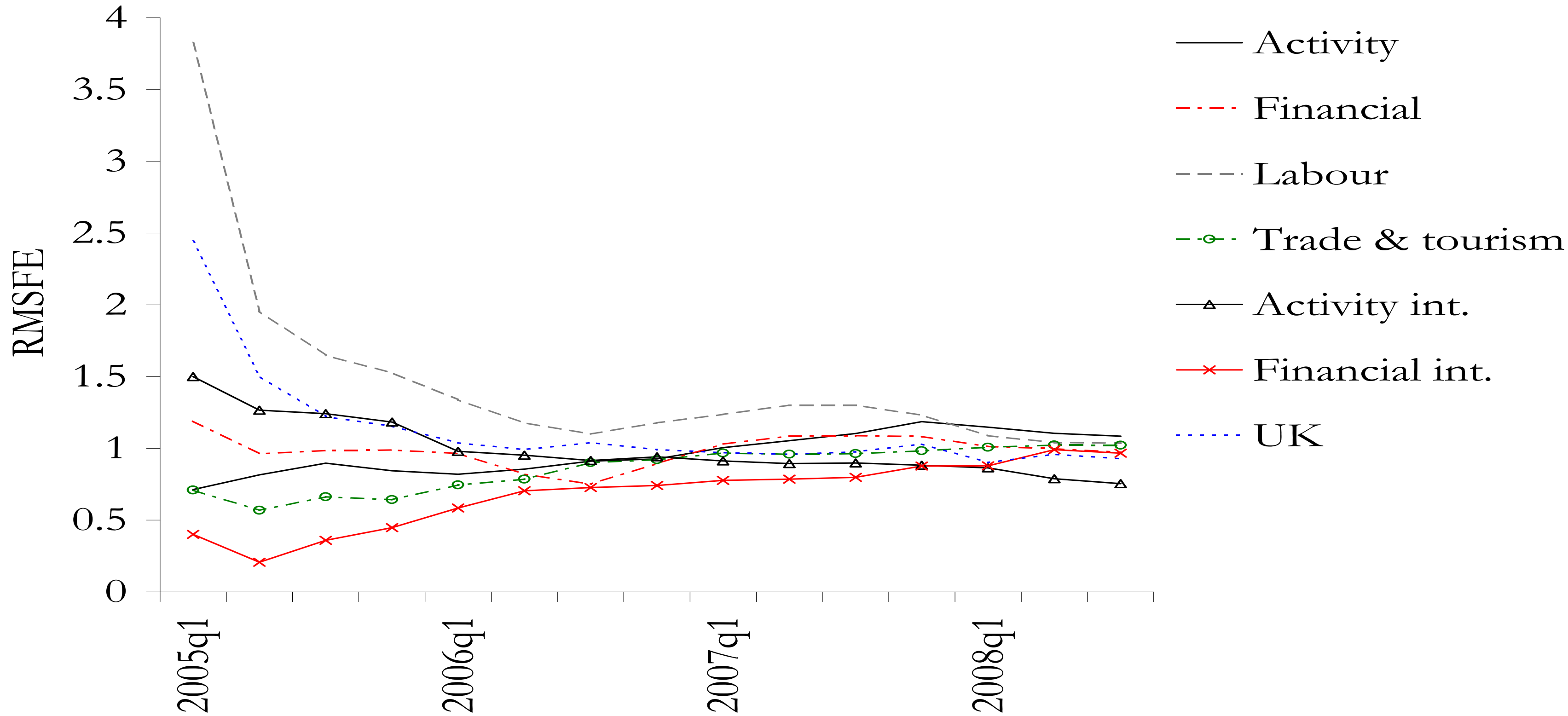


Table 1: Factor analysis

Factors are obtained from a Dynamic Factor Model (DFM) with time-varying factor loadings appearing in equations (4.1)-(4.3). The factors are estimated using a principal component method that involves cross-sectional averaging of the individual predictors. Panel A shows results of the ICP criteria for the first five factors as well as the corresponding standardized eigenvalues. The percentage of total variance in the 95 series accounted for by the first 5 factors is 37%. The sum of squared residuals is 2301. Panel B provides the sum of squared loadings for the 7 main sectors of the Cyprus economy.

Panel A: ICP criteria and Eigenvalue analysis

Number of factors	ICP1	ICP2	ICP3	Std. eigenvalues
0	-0.017	-0.017	-0.017	-
1	-0.061	-0.048	-0.090	34.0
2	-0.067	-0.041	-0.126	22.2
3	-0.064	-0.025	-0.153	18.4
4	-0.044	0.009	-0.163	13.8
5	-0.016	0.050	-0.164	11.5

Panel B: Sum of squared loadings

Category	Number of series	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Activity variables	30	25.5	19.4	25.1	46.3	46.6
Labour	26	14.2	44.1	27.5	20.9	25.9
Trade, tourism	6	8.7	1.4	3.6	3.7	8.2
Financial variables (domestic)	10	8.9	10.3	14.8	5.9	1.9
Prices	2	1.3	5.1	0.7	1.2	1.1
Financial variables (international)	14	20.5	13.4	22.4	9.2	14.0
International activity variables	7	21.0	6.3	5.9	12.8	2.3
All series	95	100	100	100	100	100

Table 2: Benchmark Models

This table presents RMSFEs for real GDP growth relative to the RMSFE of RW for 1-, 2-, and 4-step ahead forecasts. RW is at absolute values. The estimation period is 1995:Q1 to 2001:Q4 while the forecasting period is 2001:Q4 + h to 2009:Q3 - h. For ADL models the choice of the number of lags is carried out separately for the lag dependent and the independent variable. "NS" denotes the Nelson and Schwert (1977) MA model. The entries below one imply improvements compared to the benchmark.

	h = 1	h=2	h=4
RW	2.90	2.72	2.40
AR(1)	1.14	1.01	1.01
AR(4)	1.03	0.97	1.02
AR(AIC)	1.00	1.02	1.01
AR(BIC)	1.05	1.00	1.01
MA(1), θ=0.25	1.83	1.96	2.14
MA(1), θ=0.65	3.64	3.99	4.65
MA(2)_NS θ_1=0.487; θ_2=0.158	3.55	4.19	5.11

Table 3: Forecast combinations and factors

This table presents RMSFEs for real GDP growth relative to the RMSFE of RW for 1-, 2-, and 4-step. The results refer to forecast combinations of various methods. Panel A includes forecast combination results on 78 leading indicators while Panel B presents our forecast combinations for up to 5 factors.

Panel A: Univariate and ADL models

	All			*Univariate*			*ADL*		
Forecasting horizon	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
Mean	0.95	0.95	0.97	1.46	1.51	1.62	0.95	0.95	0.98
Median	1.00	0.99	1.01	1.00	0.99	1.00	1.00	0.99	1.01
Recently best	0.82	0.89	0.79	0.98	1.02	1.03	0.82	0.89	0.79
Trimmed mean	0.96	0.96	0.98	1.32	1.33	1.36	0.97	0.97	0.99
DiscMSE (κ=1, δ=0.90)	0.90	0.94	0.97	1.03	1.00	1.00	0.90	0.94	0.97
DiscMSE (κ=2, δ=0.90)	0.83	0.91	0.95	1.02	1.00	1.01	0.83	0.91	0.95
DiscMSE (κ=1, δ=0.95)	0.92	0.94	0.97	1.03	1.00	1.00	0.91	0.94	0.97
DiscMSE (κ=2, δ=0.95)	0.86	0.92	0.96	1.03	1.00	1.01	0.86	0.92	0.96
DiscMSE (κ=1, δ=1.00)	0.93	0.94	0.98	1.03	1.00	1.00	0.92	0.94	0.97
DiscMSE (κ=2, δ=1.00)	0.89	0.92	0.97	1.03	1.00	1.01	0.89	0.92	0.97

Panel B: FAR models

	Factor 1			*Factors 1-2*			*Factors 1-3*			*Factors 1-4*			*Factors 1-5*		
Forecasting horizon	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
Mean	0.63	0.74	0.93	0.76	0.90	0.94	0.72	0.86	0.91	0.80	0.89	0.95	0.86	0.90	0.91
Median	0.63	0.74	0.93	0.76	0.90	0.94	0.72	0.86	0.93	0.90	0.92	0.94	0.97	0.95	0.92
Recently best	0.56	0.71	0.93	0.56	0.72	0.95	0.62	0.76	0.86	0.62	0.76	0.86	0.62	0.80	0.83
Trimmed mean	0.63	0.74	0.93	0.76	0.90	0.94	0.73	0.85	0.92	0.82	0.90	0.96	0.88	0.91	0.92
DiscMSE (κ=1, δ=0.90)	0.62	0.74	0.93	0.69	0.88	0.94	0.68	0.84	0.90	0.73	0.87	0.93	0.78	0.89	0.89
DiscMSE (κ=2, δ=0.90)	0.61	0.75	0.93	0.64	0.86	0.94	0.65	0.82	0.88	0.68	0.86	0.90	0.71	0.88	0.88
DiscMSE (κ=1, δ=0.95)	0.62	0.75	0.93	0.70	0.87	0.94	0.68	0.84	0.90	0.74	0.87	0.93	0.79	0.88	0.90
DiscMSE (κ=2, δ=0.95)	0.62	0.75	0.93	0.66	0.86	0.93	0.66	0.82	0.89	0.70	0.86	0.91	0.73	0.88	0.89
DiscMSE (κ=1, δ=1.00)	0.63	0.75	0.93	0.71	0.87	0.94	0.69	0.84	0.90	0.76	0.87	0.93	0.81	0.88	0.90
DiscMSE (κ=2, δ=1.00)	0.63	0.76	0.93	0.68	0.86	0.93	0.67	0.82	0.89	0.72	0.86	0.91	0.75	0.87	0.89

Table 4: Sectoral analysis

This table presents RMSFEs for real GDP growth relative to the RMSFE of RW for 1-, 2-, and 4-step ahead forecasts.

Panel A. Domestic variables

	Activity			*Financial*			*Labour market*			*Trade and tourism*		
Forecasting horizon	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
Mean	1.03	1.01	1.02	0.99	0.95	0.98	1.01	1.00	1.01	0.99	1.02	1.01
Median	1.03	1.01	1.01	1.01	0.98	0.99	1.00	1.01	1.01	0.98	1.01	1.01
Recently best	1.18	0.98	1.08	1.05	0.99	0.97	1.14	1.09	1.04	0.99	1.00	1.02
Trimmed mean	1.03	1.01	1.02	1.00	0.96	0.98	1.01	1.00	1.01	0.99	1.02	1.01
DiscMSE (κ=1, δ=0.90)	1.04	1.01	1.02	0.99	0.95	0.98	1.01	1.00	1.01	0.99	1.02	1.01
DiscMSE (κ=2, δ=0.90)	1.05	1.01	1.02	0.99	0.94	0.97	1.01	1.01	1.02	0.99	1.02	1.01
DiscMSE (κ=1, δ=0.95)	1.04	1.01	1.02	0.99	0.95	0.98	1.01	1.00	1.01	0.99	1.02	1.01
DiscMSE (κ=2, δ=0.95)	1.05	1.01	1.02	0.99	0.94	0.97	1.01	1.01	1.02	0.98	1.02	1.01
DiscMSE (κ=1, δ=1.00)	1.04	1.01	1.02	0.99	0.95	0.98	1.01	1.00	1.01	0.99	1.02	1.01
DiscMSE (κ=2, δ=1.00)	1.05	1.01	1.02	0.99	0.94	0.97	1.01	1.01	1.02	0.98	1.02	1.01

Panel B. International variables

	Activity			*Financial*			*UK*		
Forecasting horizon	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
Mean	0.59	0.68	0.86	0.95	0.95	0.96	0.85	0.88	0.95
Median	0.63	0.65	0.88	0.96	0.99	1.00	0.86	0.90	0.96
Recently best	0.66	0.62	0.75	0.83	0.91	0.97	0.84	0.76	0.93
Trimmed mean	0.60	0.67	0.86	0.95	0.96	0.96	0.85	0.88	0.95
DiscMSE (κ=1, δ=0.90)	0.58	0.66	0.84	0.93	0.93	0.96	0.83	0.86	0.95
DiscMSE (κ=2, δ=0.90)	0.58	0.65	0.81	0.91	0.92	0.95	0.81	0.84	0.95
DiscMSE (κ=1, δ=0.95)	0.59	0.67	0.84	0.93	0.93	0.96	0.83	0.86	0.95
DiscMSE (κ=2, δ=0.95)	0.59	0.66	0.82	0.91	0.91	0.95	0.82	0.85	0.95
DiscMSE (κ=1, δ=1.00)	0.59	0.67	0.85	0.93	0.93	0.96	0.84	0.86	0.95
DiscMSE (κ=2, δ=1.00)	0.59	0.67	0.83	0.91	0.91	0.95	0.83	0.85	0.95

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Table A1: List of Variables

Description	Abbreviation	Transformation
National Accounts		
Gross Domestic Product (EUR mn - constant 2005 prices: c.p.)	GDPcp	Δln
GDP-Agriculture, hunting, forestry and fishing (EUR mn - c.p.)	AHFFcp	Δln
GDP-Mining, quarrying, manufacturing, and electricity, gas & water supply (EUR mn - c.p.)	MQMEGWScp	Δln
GDP-Construction (EUR mn - c.p.)	CONSTcp	Δln
GDP-Wholesale-retail trade, hotels-restaurants, transport-storage-communication (EUR mn - c.p.)	WRTHRTSCcp	Δln
GDP-Financial intermediation,real estate, renting and business activities (EUR mn - c.p.)	FIRERBcp	Δln
GDP-Public administration-defence, education-health-social work, other community social, personal sevices and private households with employed persons (EUR mn - c.p.)	PADEHScp	Δln
GDP-Final Consumption Expenditure (EUR mn - c.p.)	FCEcp	Δln
GDP-Exports of goods and services (EUR mn - c.p.)	EOGScp	Δln
GDP-Imports of goods and services (EUR mn - c.p.)	IOGScp	Δln
Total Gross Fixed Capital Formation (GFCF) (EUR mn - c.p.)	TGFCF	Δln
GFCF- Products of agriculture, fisheries and aquaculture (EUR mn - c.p.)	GFCFafa	Δln
GFCF- Equipment:metal product and machinery (EUR mn - c.p.)	GFCFepm	Δln
GFCF-Equipment:transport equipment (EUR mn - c.p.)	GFCFte	Δln
GFCF-Construction:housing (EUR mn - c.p.)	GFCFca	Δln
GFCF-Construction:other construction (EUR mn - c.p.)	GFCFcoc	Δln
GFCF-Other products (EUR mn - c.p.)	GFCFop	Δln
Retail trade, manufacturing, mining		
Turnover Value Index of retail trade (2005=100)	TVIRT	Δln
Turnover Volume Index of retail trade (2005=100)	TVOIRT	Δln
Registration of motor vehicles (passenger cars)	RMV	Δln
Registration of motor vehicles (light goods vehicles,except for public use)	RMV2	Δln
Volume Index of Manufacturing Production act (2005=100)	VIMP	Δln
Production Volume Index of Mining and Quarrying act (2005=100)	PVIMQ	Δln

Table continued on next page ...

Table A1 continued

Description	Abbreviation	Transformation
Energy		
Electricity consumption(EUR 000's)	EAC	Δln
Electricity consumption (act 000's kWh)	EACkwc	Δln
Electricity production (act 000's kWh)	EACkwp	Δln
Total Sales of Petroleum Products (000's m.t.)	TSP	Δln
Construction		
Local cement sales (m.ton)	LCS	Δln
Building permits authorised (act no)	BPAN	Δln
Building permits authorised (EUR 000's)	BPAM	Δln
Labour cost and productivity		
Nominal Unit Labour Cost Index: NSA	NULC	Δln
Real Unit Labour Cost Index: NSA	ULCI	Δln
Real Labour Productivity Per Hour Worked Index: NSA	RLPPH	Δln
Real Labour Productivity Per Person Employed Index: NSA	RLPPP	Δln
Index of labour cost in construction (2005=100)	ILCC	Δln

Table A1 continued

Description	Abbreviation	Transformation
Employment		
Total Registered Unemployed (act number)	TRU	Δln
Vacancies Notified (act number)	VAC	Δln
Vacancies Outstanding (act number)	OVAC	Δln
Employment-Total (000's)	EMP	Δln
Employment-Agriculture, Hunting and Forestry (000's)	EMPAHF	Δln
Employment-Fishing (000's)	EMPF	Δln
Employment-Mining and Quarrying (000's)	EMPMQ	Δln
Employment-Manufacturing (000's)	EMPMAN	Δln
Employment-Electricity, Gas and Water (000's)	EMPEGW	Δln
Employment-Construction (000's)	EMPCON	Δln
Employment-Wholesale-retail trade; Repair of motorvechicles, motorcycles and personal household goods (000's)	EMPWRT	Δln
Employment-Hotels and Restauarants (000's)	EMPHR	Δln
Employment-Transport Storage and Communication (000's)	EMPTSC	Δln
Employment-Financial Intermediation (000's)	EMPFI	Δln
Employment-Real estate, renting and business activities (000's)	EMPRRB	Δln
Employment-Public administration and defence; Compulsory social security (000's)	EMPPAD	Δln
Employment-Education (000's)	EMPEDU	Δln
Employment-Health and social work (000's)	EMPHSW	Δln
Employment-Other community, social and personal service activities (000's)	EMPOCS	Δln
Employment-Private households with employed persons (000's)	EMPPH	Δln
Total foreign workers in Cyprus	TFW	Δln

Table A1 continued

Description	Abbreviation	Transformation
Trade and tourism		
Total imports (act EUR mn)	TI	$\Delta \ln$
Total exports (incl.shipstores) (act EUR mn)	TE	$\Delta \ln$
Re-exports (act EUR mn)	REX	$\Delta \ln$
Imports of Petroleum for home consumption (EUR 000's)	IPHC	$\Delta \ln$
Tourist arrivals	TARR	$\Delta \ln$
Tourist arrivals from UK	TARUK	$\Delta \ln$
Deposits, reserves, interest rates		
Deposit Money Banks: Assets - EUR	DMBA	$\Delta \ln$
Deposit Money Banks: Liabilities - EUR	DMBL	$\Delta \ln$
International Reserves - EUR	IRES	$\Delta \ln$
Gold national valuation - EUR	GNVAL	$\Delta \ln$
Personal Lending Rate	PLR	Δ
1-year Time Deposits	1YTD	Δ
Price indices		
Consumer Price Index	CPIa	$\Delta \ln$
Price Index of construction materials (2005=100)	PICM	$\Delta \ln$
Cyprus stock exchange		
CSE All Share Composite	CSEA	$\Delta \ln$
SE Banks Index	CSEB	$\Delta \ln$
SE Hotels Index	CSEH	$\Delta \ln$
SE Investment Companies	CSEIC	$\Delta \ln$

Table A1 continued

Description	Abbreviation	Transformation
Exchange rates		
YEN to EUR	YENEUR	$\Delta\ln$
US to EUR	USEUR	$\Delta\ln$
UK to EUR	UKEUR	$\Delta\ln$
International financial indices		
ATHEX Composite- Price Index	ATHEX	$\Delta\ln$
DAX 30 Performance - Price Index	DAX30	$\Delta\ln$
FTSE 100 - Price Index	FTSE100	$\Delta\ln$
France CAC 40 - Price Index	FRCAC40	$\Delta\ln$
Brent Crude Oil (EUR)-Commodity Prices	BCO	$\Delta\ln$
Crude Oil Futures (EUR) -Futures Contracts	COF	$\Delta\ln$
Gold Bullion Price-New York (EUR/Ounce) -Commodity Price	GBNY	$\Delta\ln$
Dow Jones World Basic Materials Index (EUR) - Sector Indices-Materials	DJWB	$\Delta\ln$
Corn Oil Price, Wet Mill, Chicago (Cents/Pound) (EUR) -Commodity Prices	COPWM	$\Delta\ln$
Silver Cash Price (EUR/Ounce) -Commodity Prices	SCP	$\Delta\ln$
Wheat #2 Cash Price (EUR/Bushel) -Commodity Prices	WCP	$\Delta\ln$
International economic activity indices		
EU27-Gross Domestic Product (EUR mn - c.p.)	GDPcpEU27	$\Delta\ln$
EA-Gross Domestic Product (EUR mn - c.p.)	GDPcpEA	$\Delta\ln$
UK-Gross Domestic Product (EUR mn - c.p.)	GDPcpUK	$\Delta\ln$
EU27-Economic Sentiment Indicator	ESIEU	Δ
EA-Economic Sentiment Indicator	ESIEA	Δ
GR-Economic Sentiment Indicator	ESIGR	Δ
UK-Economic Sentiment Indicator	ESIUK	Δ

Table A2: All models

This table reports the RMSFEs of ADL models for real GDP growth that use alternative individual predictors, relative to the RW for 1-, 2- and 4-step. RW is at absolute values.

	Model	h = 1	h = 2	h = 4		Model	h = 1	h = 2	h = 4
1	RW	2.90	2.72	2.40	24	ADL(AIC)_rec_EMPEDU	1.12	1.03	1.03
2	ADL(AIC)_rec_1YTD	1.17	1.05	1.03	25	ADL(AIC)_rec_EMPEGW	1.04	1.00	1.00
3	ADL(AIC)_rec_ATHEX	0.80	0.79	0.87	26	ADL(AIC)_rec_EMPF	1.04	0.99	1.02
4	ADL(AIC)_rec_BCO	0.99	1.12	1.01	27	ADL(AIC)_rec_EMPFI	1.05	1.04	1.04
5	ADL(AIC)_rec_BPAM	1.02	1.05	1.13	28	ADL(AIC)_rec_EMPHR	1.15	1.00	0.99
6	ADL(AIC)_rec_BPAN	1.07	1.04	1.02	29	ADL(AIC)_rec_EMPHSW	1.03	1.05	1.01
7	ADL(AIC)_rec_COF	0.99	1.07	1.01	30	ADL(AIC)_rec_EMPMAN	1.03	1.04	1.02
8	ADL(AIC)_rec_COPWM	1.11	1.18	1.02	31	ADL(AIC)_rec_EMPMQ	1.00	1.04	1.02
9	ADL(AIC)_rec_CPIA	1.03	1.08	0.94	32	ADL(AIC)_rec_EMPOCS	1.06	0.96	1.01
10	ADL(AIC)_rec_CSEA	0.93	0.89	0.93	33	ADL(AIC)_rec_EMPPAD	1.56	1.28	1.01
11	ADL(AIC)_rec_CSEB	0.95	0.90	0.92	34	ADL(AIC)_rec_EMPPH	1.22	1.07	1.02
12	ADL(AIC)_rec_CSEH	1.00	1.00	1.00	35	ADL(AIC)_rec_EMPRRB	0.95	1.04	1.01
13	ADL(AIC)_rec_CSEIC	0.95	0.92	0.93	36	ADL(AIC)_rec_EMPTSC	1.22	1.07	1.03
14	ADL(AIC)_rec_DAX30	0.84	0.87	0.94	37	ADL(AIC)_rec_EMPWRT	0.96	1.03	1.03
15	ADL(AIC)_rec_DJWB	0.77	0.75	0.88	38	ADL(AIC)_rec_ESIEA	0.66	0.58	0.71
16	ADL(AIC)_rec_DMBA	1.04	0.99	0.98	39	ADL(AIC)_rec_ESIEU	0.64	0.55	0.76
17	ADL(AIC)_rec_DMBL	0.99	0.97	0.97	40	ADL(AIC)_rec_ESIGR	0.80	0.83	0.93
18	ADL(AIC)_rec_EAC	1.13	1.02	1.01	41	ADL(AIC)_rec_ESIUK	0.75	0.77	0.94
19	ADL(AIC)_rec_EACKWC	1.03	0.99	1.01	42	ADL(AIC)_rec_F01 (Factor 1)	0.59	0.72	0.93
20	ADL(AIC)_rec_EACKWP	1.10	1.00	1.04	43	ADL(AIC)_rec_F02 (Factor 2)	1.00	1.14	0.93
21	ADL(AIC)_rec_EMP	1.00	1.10	1.03	44	ADL(AIC)_rec_F03 (Factor 3)	0.70	0.69	0.81
22	ADL(AIC)_rec_EMPAHF	1.17	1.07	1.08	45	ADL(AIC)_rec_F04 (Factor 4)	1.03	0.99	1.07
23	ADL(AIC)_rec_EMPCON	0.99	1.03	1.03	46	ADL(AIC)_rec_F05 (Factor 5)	1.23	0.99	0.78

Table continued on next page ...

Table A2 continued

	Model	h = 1	h = 2	h = 4		Model	h = 1	h = 2	h = 4
47	ADL(AIC)_rec_FRCAC40	0.86	0.86	0.83	72	ADL(AIC)_rec_TFW	1.01	1.05	1.01
48	ADL(AIC)_rec_FTSE100	0.84	0.73	0.90	73	ADL(AIC)_rec_TI	0.95	1.07	1.01
49	ADL(AIC)_rec_GBNY	1.02	1.04	1.08	74	ADL(AIC)_rec_TRU	1.00	0.98	1.02
50	ADL(AIC)_rec_GDPCPEA	0.62	0.65	0.93	75	ADL(AIC)_rec_TSP	1.18	1.01	1.02
51	ADL(AIC)_rec_GDPCPEU27	0.67	0.65	0.87	76	ADL(AIC)_rec_TVIRT	1.08	0.92	1.01
52	ADL(AIC)_rec_GDPCPUK	0.91	0.84	0.95	77	ADL(AIC)_rec_TVOIRT	1.13	0.96	1.00
53	ADL(AIC)_rec_GNVAL	1.12	1.03	1.04	78	ADL(AIC)_rec_UKEUR	1.10	1.07	0.99
54	ADL(AIC)_rec_ILCC	1.28	1.03	1.03	79	ADL(AIC)_rec_ULCI	1.16	0.98	1.02
55	ADL(AIC)_rec_IPHC	0.97	1.02	1.02	80	ADL(AIC)_rec_USEUR	1.15	1.10	1.01
56	ADL(AIC)_rec_IRES	1.01	0.97	1.04	81	ADL(AIC)_rec_VAC	1.03	1.05	1.01
57	ADL(AIC)_rec_LCS	1.02	1.08	1.02	82	ADL(AIC)_rec_VIMP	1.02	1.06	1.01
58	ADL(AIC)_rec_NULC	1.17	1.07	1.08	83	ADL(AIC)_rec_WCP	1.03	1.14	1.07
59	ADL(AIC)_rec_OVAC	0.91	0.99	1.02	84	ADL(AIC)_rec_YENEUR	1.09	1.07	1.07
60	ADL(AIC)_rec_PICM	1.24	1.16	0.98	85	ADL(BIC)_rec_1YTD	1.24	1.04	1.03
61	ADL(AIC)_rec_PLR	1.02	0.79	0.97	86	ADL(BIC)_rec_ATHEX	0.85	0.84	0.86
62	ADL(AIC)_rec_PVIMQ	1.12	1.04	1.01	87	ADL(BIC)_rec_BCO	1.04	1.00	1.01
63	ADL(AIC)_rec_REX	1.00	1.03	1.02	88	ADL(BIC)_rec_BPAM	1.08	1.01	1.00
64	ADL(AIC)_rec_RLPPH	0.99	1.01	1.01	89	ADL(BIC)_rec_BPAN	1.08	1.01	1.01
65	ADL(AIC)_rec_RLPPP	0.98	1.02	1.02	90	ADL(BIC)_rec_COF	1.05	1.04	1.01
66	ADL(AIC)_rec_RMV2	1.02	1.02	1.03	91	ADL(BIC)_rec_COPWM	1.04	0.99	1.02
67	ADL(AIC)_rec_RMV	1.07	1.07	1.06	92	ADL(BIC)_rec_CPIA	1.05	1.11	1.00
68	ADL(AIC)_rec_SCP	1.05	0.98	0.94	93	ADL(BIC)_rec_CSEA	0.94	0.90	0.93
69	ADL(AIC)_rec_TARR	1.13	1.05	1.05	94	ADL(BIC)_rec_CSEB	1.02	0.91	0.92
70	ADL(AIC)_rec_TARUK	0.92	0.99	1.00	95	ADL(BIC)_rec_CSEH	1.00	0.99	1.00
71	ADL(AIC)_rec_TE	1.00	1.05	1.02	96	ADL(BIC)_rec_CSEIC	1.03	0.89	0.93

Table A2 continued

	Model	h = 1	h = 2	h = 4		Model	h = 1	h = 2	h = 4
97	ADL(BIC)_rec_DAX30	0.90	0.91	0.95	119	ADL(BIC)_rec_EMPTSC	1.11	1.07	1.03
98	ADL(BIC)_rec_DJWB	0.85	0.82	0.89	120	ADL(BIC)_rec_EMPWRT	0.99	1.01	1.03
99	ADL(BIC)_rec_DMBA	1.06	1.02	0.98	121	ADL(BIC)_rec_ESIEA	0.68	0.60	0.73
100	ADL(BIC)_rec_DMBL	1.10	0.99	0.97	122	ADL(BIC)_rec_ESIEU	0.64	0.57	0.78
101	ADL(BIC)_rec_EAC	1.10	1.04	1.01	123	ADL(BIC)_rec_ESIGR	0.89	0.86	0.93
102	ADL(BIC)_rec_EACKWC	1.04	1.01	1.01	124	ADL(BIC)_rec_ESIUK	0.74	0.82	0.97
103	ADL(BIC)_rec_EACKWP	1.03	1.00	1.02	125	ADL(BIC)_rec_F01	0.71	0.78	0.93
104	ADL(BIC)_rec_EMP	0.99	1.01	1.03	126	ADL(BIC)_rec_F02	1.02	1.04	0.99
105	ADL(BIC)_rec_EMPAHF	1.12	1.02	1.07	127	ADL(BIC)_rec_F03	0.80	0.93	0.92
106	ADL(BIC)_rec_EMPCON	1.03	1.04	1.03	128	ADL(BIC)_rec_F04	1.09	1.03	1.07
107	ADL(BIC)_rec_EMPEDU	1.10	1.03	1.03	129	ADL(BIC)_rec_F05	1.19	0.96	0.78
108	ADL(BIC)_rec_EMPEGW	1.14	0.98	1.00	130	ADL(BIC)_rec_FRCAC40	0.98	0.86	0.86
109	ADL(BIC)_rec_EMPF	1.12	1.01	1.02	131	ADL(BIC)_rec_FTSE100	0.89	0.81	0.89
110	ADL(BIC)_rec_EMPFI	1.07	1.03	1.01	132	ADL(BIC)_rec_GBNY	1.06	1.01	1.02
111	ADL(BIC)_rec_EMPHR	1.00	1.02	1.00	133	ADL(BIC)_rec_GDPCPEA	0.57	0.62	0.93
112	ADL(BIC)_rec_EMPHSW	1.04	1.01	1.01	134	ADL(BIC)_rec_GDPCPEU27	0.61	0.62	0.89
113	ADL(BIC)_rec_EMPMAN	1.07	1.01	1.02	135	ADL(BIC)_rec_GDPCPUK	0.86	0.88	0.97
114	ADL(BIC)_rec_EMPMQ	1.06	1.03	1.02	136	ADL(BIC)_rec_GNVAL	1.11	1.01	1.04
115	ADL(BIC)_rec_EMPOCS	1.04	0.99	1.01	137	ADL(BIC)_rec_ILCC	1.16	1.01	1.03
116	ADL(BIC)_rec_EMPPAD	1.48	1.20	1.01	138	ADL(BIC)_rec_IPHC	1.02	1.00	1.02
117	ADL(BIC)_rec_EMPPH	1.11	1.02	1.00	139	ADL(BIC)_rec_IRES	0.93	1.03	1.04
118	ADL(BIC)_rec_EMPRRB	0.99	1.00	1.01	140	ADL(BIC)_rec_LCS	1.04	1.00	1.04

Table A2 continued

	Model	h = 1	h = 2	h = 4
141	ADL(BIC)_rec_NULC	1.12	1.04	1.02
142	ADL(BIC)_rec_OVAC	0.99	0.98	1.02
143	ADL(BIC)_rec_PICM	1.18	1.14	0.98
144	ADL(BIC)_rec_PLR	1.16	1.04	1.04
145	ADL(BIC)_rec_PVIMQ	1.17	1.04	1.01
146	ADL(BIC)_rec_REX	1.05	1.01	1.02
147	ADL(BIC)_rec_RLPPH	1.06	1.01	1.01
148	ADL(BIC)_rec_RLPPP	1.09	1.01	1.02
149	ADL(BIC)_rec_RMV2	1.06	0.99	1.03
150	ADL(BIC)_rec_RMV	1.05	1.05	1.02
151	ADL(BIC)_rec_SCP	1.04	0.96	0.94
152	ADL(BIC)_rec_TARR	1.13	1.05	1.03
153	ADL(BIC)_rec_TARUK	0.99	0.99	1.00
154	ADL(BIC)_rec_TE	1.05	1.01	1.02
155	ADL(BIC)_rec_TFW	1.07	1.02	1.01
156	ADL(BIC)_rec_TI	0.95	1.05	1.01
157	ADL(BIC)_rec_TRU	0.98	0.93	1.02
158	ADL(BIC)_rec_TSP	1.06	0.99	1.02
159	ADL(BIC)_rec_TVIRT	1.04	1.01	1.01
160	ADL(BIC)_rec_TVOIRT	1.06	1.02	1.01
161	ADL(BIC)_rec_UKEUR	1.04	1.06	0.99
162	ADL(BIC)_rec_ULCI	1.18	0.99	1.02
163	ADL(BIC)_rec_USEUR	1.05	1.01	1.01
164	ADL(BIC)_rec_VAC	1.05	1.02	1.01
165	ADL(BIC)_rec_VIMP	1.05	0.98	1.01
166	ADL(BIC)_rec_WCP	1.04	1.01	1.07
167	ADL(BIC)_rec_YENEUR	1.08	1.03	1.05

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