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A FORECASTING EXERCISE FOR OUTPUT AND INFLATION IN CYPRUS

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A FORECASTING EXERCISE FOR OUTPUT AND INFLATION IN CYPRUS[1]

Z. G. Kontolemis, N. Pashourtidou, C. S. Savva and A. Tsiaklis

Abstract

The accurate and timely forecasting of key macroeconomic variables is critical for policy makers, businesses and households. From the perspective of policy makers, it is important for the prompt, and informed, pursue of government policies, while from the perspective of business and households forecasting the macroeconomy is crucial for financial planning.

This paper is the first in a series of papers that will follow, based on research undertaken at the Economics Research Centre which aims to investigate alternative models/methodologies for the construction of short-term forecasts for the Cyprus economy. This study is a preliminary attempt to assess the usefulness of quarterly macroeconomic data for Cyprus, for the period 1995Q1-2008Q4, in simple time series models, in the context of a forecasting exercise for GDP growth and inflation.

We explore the role of a large number of variables such as measures of output/income, employment and trade, price and stock exchange indices, interest rates and exchange rates and international variables, in the construction of forecasts for growth and inflation. Furthermore, we investigate the usefulness of "common factors" extracted from a large dataset (of about 100 variables) by means of principal component analysis. Common factors are a limited number of indices which summarize all the useful information embodied in a large number of series.

The results show that a number of common factors, mainly those relating to output and international variables and to prices, are among the best predictors of output growth and inflation, especially for one and two quarter forecasting horizons. For longer forecasting horizons, i.e. four quarters ahead the Turnover Index of Hotels and Restaurants and the Harmonised Consumer Price Index of Water Supply give the lowest mean-square-forecast-error forecasts for GDP growth and inflation, respectively. Nevertheless, some of the models that perform the best in terms of out-of-sample forecasting, suffer in terms of in-sample parameter stability and/or in-sample predictive content. Specifications that exhibit both good forecasting performance and parameter stability include Tourist Arrivals form the UK and a common factor, in modelling output growth and inflation, respectively. These models can be closely monitored on a regular basis to evaluate their usefulness for real-time forecasting.

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ΠΕΡΙΛΗΨΗ

Η πρόκληση για ακριβείς προβλέψεις, κυρίως όσον αφορά στον πληθωρισμό και στην οικονομική ανάπτυξη, είναι ιδιαίτερα σημαντική για μια μικρή, ανοικτή οικονομία, η οποία είναι ευάλωτη σε εξωγενείς παράγοντες, όπως για παράδειγμα οι οικονομικές κρίσεις. Μια τέτοια οικονομία αποτελεί και η περίπτωση της Κύπρου, με τους εξωγενείς παράγοντες να έχουν μεγάλες επιπτώσεις στην οικονομική ανάπτυξη του νησιού.

Το άρθρο αυτό είναι το πρώτο μιας σειρά άρθρων που θα ακολουθήσουν, βασισμένα σε έρευνα που διεξάγει το Κέντρο Οικονομικών Ερευνών η οποία στοχεύει στη διερεύνηση εναλλακτικών μοντέλων/μεθοδολογιών για την κατασκευή βραχυπρόθεσμών προβλέψεων για την κυπριακή οικονομία. Η παρούσα μελέτη αποτελεί μια προκαταρκτική προσπάθεια να αξιολογηθεί η χρησιμότητα τριμηνιαίων μακροοικονομικών στοιχείων της Κύπρου, για την περίοδο 1995-2008, σε απλά μοντέλα χρονοσειρών για τον υπολογισμό προβλέψεων για το ρυθμό μεταβολής του ΑΕΠ και τον πληθωρισμό.

Εξετάζεται ο ρόλος ενός μεγάλου αριθμού μεταβλητών, όπως δείκτες προϊόντος/εισοδήματος, απασχόλησης, εμπορίου, τιμών και χρηματιστηρίου, επιτόκια και συναλλαγματικές ισοτιμίες καθώς και διεθνείς μεταβλητές, στην κατασκευή προβλέψεων για το ρυθμό ανάπτυξης και τον πληθωρισμό. Επιπλέον μελετάται η χρησιμότητα των κοινών παραγόντων που εξάγονται από ένα μεγάλο αριθμό μεταβλητών. Οι κοινοί παράγοντες αποτελούν ένα μικρό αριθμό δεικτών οι οποίοι συνοψίζουν όλες τις χρήσιμες πληροφορίες που εμπεριέχονται σε ένα μεγάλο αριθμό σειρών που υπάρχουν στη βάση δεδομένων.

Τα αποτελέσματα δείχνουν ότι κάποιοι κοινοί παράγοντες, κυρίως αυτοί που σχετίζονται με το προϊόν, τις διεθνείς μεταβλητές και τις τιμές δίνουν τις καλύτερες προβλέψεις για το ρυθμό μεταβολής του ΑΕΠ και τον πληθωρισμό, ειδικά για ορίζοντα ενός και δύο τριμήνων μπροστά. Για μεγαλύτερους ορίζοντες, για παράδειγμα τέσσερα τρίμηνα μπροστά, ο Δείκτης Κύκλου Εργασιών Ξενοδοχείων και Εστιατορίων και ο Εναρμονισμένος Δείκτης Τιμών Νερού παράγουν τις καλύτερες προβλέψεις για το ρυθμό μεταβολής του ΑΕΠ και τον πληθωρισμό, αντίστοιχα. Κάποια από τα μοντέλα που δίνουν καλές προβλέψεις παρουσιάζουν αστάθεια στις εκτιμημένες παραμέτρους. Μοντέλα που περιλαμβάνουν τις Αφίξεις Τουριστών από το Ηνωμένο Βασίλειο και ένα κοινό παράγοντα για τη μοντελοποίηση του ρυθμού μεταβολής του ΑΕΠ και του πληθωρισμού αντίστοιχα, παράγουν καλές προβλέψεις και παρουσιάζουν ταυτόχρονα διαχρονική σταθερότητα στις παραμέτρους. Τέτοια μοντέλα θα μπορούσαν να παρακολουθούνται σε τακτική βάση ούτως ώστε να αξιολογηθεί η χρησιμότητά τους για σκοπούς πρόβλεψης.

CONTENTS

1. INTRODUCTION

The accurate and timely forecasting of key macroeconomic variables is critically important for policy makers, businesses and households. From the perspective of policy makers, it is important for the prompt, and informed, pursue of government policies, while from the perspective of business and households forecasting the macroeconomy is crucial for financial planning. This challenge is particularly important for a small, open economy, highly dependent on external demand and vulnrable to exogenous economic shocks.

The production and publication of macroeconomic forecasts for Cyprus is relatively scarce. Government services publish economic forecasts on a biannual basis, while the Central Bank of Cyprus also publishes forecasts for a small number of aggregate variables. International organisations and the European Commission also publish forecasts for Cyprus on a biannual basis. Thus, with the exception of the forecasts made by international organisations, there is a need for a more independent provision of macroeconomic analysis and forecasting. In addition, these forecasts are produced using simple national accounts-type models, without explicitly modelled behavioural econometric equations for the economy.[2]

This paper attempts to assess the usefulness of Factor Models in forecasting output growth and inflation in Cyprus. These models have been proved very sucessful in the literature. The idea here is simple and relies on the utilisation of a very large number of macroeconomic time series, to extract a limited number of indices (the common factors), which are supposed to contain all the useful information embodied in all time series. These indices, or factors, are then used to forecast GDP, or inflation, using simple, or more complex, econometric models.

There has been a large number of papers dealing with factor models in econometrics (see for example Stock and Watson, 1998, 1999 and 2002, and references therein).

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[2] To our knowledge, some attempts have been made for the development and estimation of various macroeconomic models for the economy of Cyprus. For instance Karamanou, Mitsis and Pashardes (2003) use simultaneous equations to describe the general equilibrium. Andreou, Spanos and Syrichas (1997) and Christofides, Kourtellos and Stylianou (2006) use classical VAR models to describe several sectors of the Cyprus economy such as the monetary sector (through the modelling of the relationship between the GDP, Money Supply, Interest Rates and Prices). Christosfides and Vrahimis (2006) employ a VAR model to identify the relationship between prices and wages. Nonetheless, those models have not been used for the systematic forecasting of macroeconomic variables.

These papers use factor models to combine information from large panels of macroeconomic data for the United States and then use the estimated factors to forecast a number of macroeconomic series. Overall these results suggest that these models are efficient, in terms of time and cost, and produce better forecasts compared with a range of alrnetives, particulalry when it comes to forecasting inflation. Similarly, Forni et al. (2001) and Marcellino, Stock, and Watson (2003) use factor models to analyze large panels of euro-area data, while Artis, Banerjee, and Marcellino (2005) use factor models to forecast economic and financial variables for the United Kingdom, and also report impressive results.

This paper undertakes a simple exercise, following the work of Stock and Watson (2003), to evaluate the usefulness of a number of models for short-term forecasting of output and inflation. This analysis uses quarterly data of as many as 104 variables from Cypriot economy, over 1995-2008. The results suggest that the common factor approach and some tourism-related variables can be very useful in predicting future output growth. Also, in the case of inflation, the common factor approach and various subcategories of the Harmonised consumer price index improve the predictive power of the models employed.

The rest of the paper is structured as follows: Section 2 provides information on the data and Section 3 describes the methodology. Section 4 discusses the results of the empirical analysis and Section 5 concludes the paper.

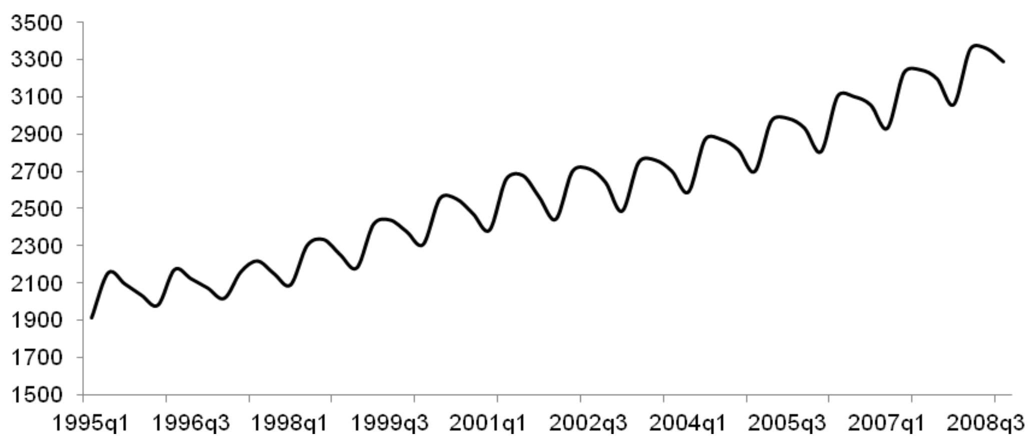
2. DATASET DESCRIPTION

Quarterly time series data for the Cypriot economy, covering the period 1995 to 2008, were obtained from four main sources: The Statistical Service of Cyprus, the International Monetary Fund IFS database, the Global Financial Data database and the DataStream. The compiled database comprises of a total of 104 variables; these are listed in the Appendix 1.

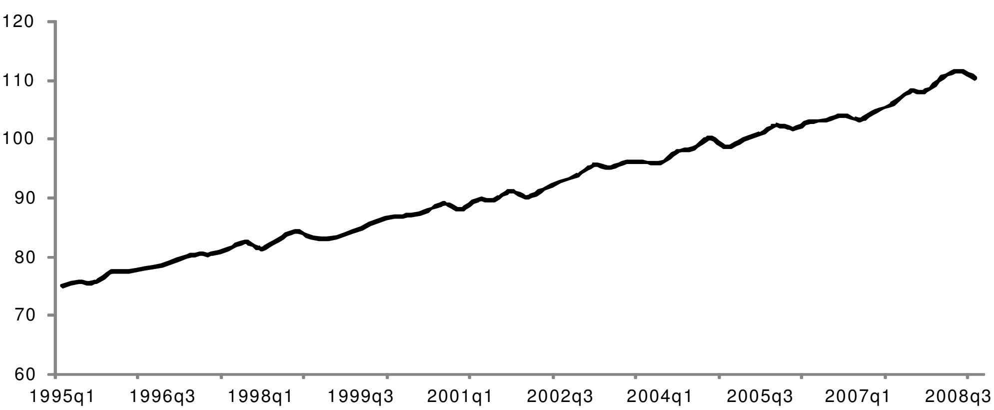
The data were transformed as follows (see Stock and Watson, 2003): first, extreme observations (outliers) were replaced with an interpolated value constructed as the median of the values within three periods on either side of the outlier. Second, series with significant seasonal variation were seasonally adjusted. Seasonal variation was determined by a pre-test (regressing an appropriately differenced version of the series on a set of seasonal dummies) carried out at the 10-percent level. Seasonal adjustment was carried out using a linear approximation to X11 for quarterly series with endpoints calculated using autoregressive forecasts and backcasts. Third, when the data were available on a monthly basis, the data were aggregated to quarterly observations. For indices, quarterly aggregates were formed as averages of the monthly values. For all other series, the last monthly value of the quarter was used as the quarterly value. Fourth, in most of the cases the data were transformed by taking logarithms and the highly persistent or trending variables were differenced. In Figure 1, for example, we present the series for Real Gross Domestic Product (GDP) and Consumer Price Index (CPI) in levels. Clearly both variables are trending upwards while GDP shows significant seasonal variation. Therefore, in order to be able to forecast these variables, we remove seasonality (which is only apparent in GDP), take logarithms and first differences.

Figure 1. Real Gross Domestic Product and Consumer Price Index

(a) Gross Domestic Product



(b) Consumer Price Index



3. METHODOLOGY

Below we outline the methodology we employ in constructing and evaluating forecasts.

3.1 Models

Suppose we want to know whether a candidate variable, X_t is useful for forecasting a variable of interest, Y_t. A simple framework for assessing predictive content is the linear regression model relating the future value of Y_t to the current value of X_t.

$$Y_{t+1} = \beta_0 + \beta_1 X_t + u_{t+1} \qquad (1)$$

where β_0 and β_1 are unkown parametrers and u_t is the error term. If $\beta_1 \neq 0$ then the current value of X_t can be used to forecast the value of Y_t in the next period. Nevertheless, since autocorrelation is a common feature in time series data, Y_{t+1} is most probably correlated with its own past values. Therefore, equation (1) should be modified to include lagged values of Y_t. In the same manner, additional lagged values of X_t might also be useful predictors. This leads to the extension of (1) to the well-known autoregressive distributed lag (ADL) model.

$$Y_{t+1} = \beta_0 + \beta_1 (L) X_t + \beta_2 (L) Y_t + u_{t+1} \quad (2)$$

Equation (2) can be applied for h-step ahead forecasting and takes the following form:

$$Y_{t+h}^h = \beta_0 + \beta_1 (L) X_t + \beta_2 (L) Y_t + u_{t+h}^h \quad (3)$$

Finally, we can use an alternative specification in which we will be able to examine the predictive content of X_t after controlling for the past values of Y_t and past values of a third predictor Z_t. This is done by augmenting (3) to include lags of Z_t:

$$Y_{t+h}^h = \beta_0 + \beta_1 (L) X_t + \beta_2 (L) Y_t + \beta_3 (L) Z_t + u_{t+h}^h \quad (4)$$

The stability of the coefficients in the forecasting relationships 2, 3, and 4 can be assessed by a variety of methods. These methods are discussed in Section 4.

3.2 Out-of-sample Measures of Predictive Content

To evaluate the predictive power of alternative models, we produce pseudo-out-of-sample forecasts based on real-time (dynamic) forecasting. The period used for forecast evaluation purposes is 2008Q1- 2008Q4. To produce the forecast for 2008Q1 we estimate the model using data through 2007Q4, and then repeat this throughout the evaluation period, moving ahead one quarter at a time, thereby producing a sequence of pseudo-out-of-sample forecasts. To identify the appropriate lag order for the out-of-sample forecasting exercise we use the Akaike information criterion (AIC), which is estimated using data available prior to making the forecast, i.e. using only the data available through 2007Q4.

A common way to assess the performance of the pseudo out-of-sample forecasts is to compute the mean squared forecast error of a candidate forecast (forecast i), relative to a benchmark (forecast 0). For instance, think of a simple univariate autoregression model and its forecasts as the benchmark model (forecast 0). Then think of an alternative univariate model augmented by a candidate variable (or a combination of variables) and its forecasts (forecast i). Then, the h-step ahead mean squared forecast error (MSFE) of forecast i, relative to that of the benchmark forecast, is:

$$\frac{\frac{1}{T_2 - T_1 - h + 1}\sum_{t=T_1}^{T_2-h}\left(Y_{t+h}^{h} - \hat{Y}_{t+h|t}^{h}\right)^2}{\frac{1}{T_2 - T_1 - h + 1}\sum_{t=T_1}^{T_2-h}\left(Y_{t+h}^{h} - \hat{Y}_{0,t+h|t}^{h}\right)^2} \qquad (5)$$

where T_1 and T_2 - h are respectively the first and last dates over which the pseudo out-of-sample forecast is computed (so that forecasts are computed for dates t = T_1+h,..., T_2). If its relative MSFE is less than one, the candidate forecast is estimated to have performed better than the benchmark.

3.3 Common Factors

Simple ADL models allow us to assess the usefulness of a small number of variables, at a time, in forecasting inflation or output. In practice many variables can be useful at the same time, as also seen in real time policy making a large number (hundreds and sometimes thousands) of economic time series are monitored in real time.

We therefore examine the usefulness of factor models, which can typically handle information from a large number of data series, from which a limited number of factors can be extracted. These factors which, in principle, should contain all the useful information can be used for forecasting. Thus, we utilise all variables in the dataset to obtain k common factors (F_t) which summarise the behaviour of all available macro series. Common factors are estimated by principal component analysis.[3]

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[3] For further details we refer to Appendix 2 and Stock and Watson (2005).

In the literature usually two or three common factors are found to account for more than 80% of the variablility of the dataset (Bernanke, Boivin and Elliaz, 2005). Although the Bai and Ng (2002) selection criterion is a good way to determine the appropriate number of common factors, we opted to employ ten factors. Table 1 reports the percentage of the variance in the data explained by each one of the ten factors, as well as the cumulative percentage of variance in the observed series that is accounted for by all ten factors.

Table 1: Percentage of Total Variance in the Dataset Explained by Factors

Factor	Percentage of total variance (%)
1	9.21
2	7.43
3	7.07
4	6.22
5	5.81
6	4.65
7	4.22
8	3.88
9	3.51
10	3.43
All ten factors	55.43

By employing this number of factors, we are able to evaluate their forecasting ability vis-à-vis individual marco variables in the dataset. Thus, the estimated common factors ($\hat{F}_t$) are incorporated (one at a time) in an ADL model and equation (4) takes the following form[4]:

$$Y_{t+h}^{h} = \beta_0 + \beta_1(L)\hat{F}_t + \beta_2(L)Y_t + u_{t+h}^{h} \quad (4')$$

By estimating the correlation of each factor with the various categories of variables in our sample, we are able to identify groups of macro variables that a factor describes better. For instance the first factor is highly correlated with nternational variables (such as crude oil futures, brend crude oil prices, etc) and output variables (such as GDP) with correlatoin around 0.70. Therefore, Factor 1 can be viewed as “International and Output Factor”. Similarly, Factor 2 is highly correlated with CPI variables with

[4] Forecasting is carried out in a two-step process: First the factors are estimated using the whole dataset, then estimated factors are used to forecast Y_{t+1}.

correlation around 0.80, Factor 3 correlates highly with interest rates (0.80), Factor 4 with stock market series (0.60) and Factor 5 with employment (0.70).[5]

4. EMPIRICAL ANALYSIS

4.1 Forecasting Models

In this section we employ equations (3) and (4) to examine the predictive content of the variables in our sample, and in the case of common factors we use equation (4').

The dependent variables are transformed to eliminate stochastic and deterministic trends. The logarithm of output is always treated as integrated of order one I(1), so that Y_t is the quarterly rate of growth of output at an annual rate. The multistep forecasts examine the predictability of the logarithm of the level of the variable of interest, after imposing the I(1) constraint. For output, we consider cumulative growth, at an annual percentage growth rate of output over the h periods, so $Y_{t+h}=(400/h)\ln(Q_{t+h}/Q_t)$, where Q_t denotes the level of the real output series. For prices, we consider the h-period rate of inflation $(400/h)\ln(P_{t+h}/P_t)$, where P_t is the price level; upon imposing the I(1) constraint, this yields the dependent variable, $P_{t+h}=(400/h)\ln(P_{t+h}/P_t)-400\ln(P_t/P_{t+1})$.

For the pseudo out-of-sample analysis, the lag length is data dependent, chosen using the AIC, so that the model could adapt to potentially different dynamics over time. For the univariate forecasts, the AIC-determined lag length was restricted to be between zero and four. For the bivariate forecasts, between zero and four lags of Y_t were considered, and between one and four lags of X_t (or $\hat{F}_t$) were considered. For the trivariate forecasts, between zero and four lags of Y_t were considered, and between one and four lags for each of X_t and Z_t were considered.

The pseudo out-of-sample statistics are based on forecasts computed for each model, horizon, and series being forecasted. The model estimation and selection is recursive (uses all available prior data) as the forecasting exercise proceeds through time. We computed the sample relative MSFE defined in (5), relative to the AR benchmark, where both models have recursive AIC lag length selection. For all series, the out-of-sample forecasting exercise begins in the first quarter of 2007 and continues through the end of the sample period. This means that the first forecast is based on

[5] The correlations of factors with all the variables in the dataset as well as factor loadings are available upon request.

approximately twelve years of data, after accounting for differencing and initial conditions.

Table 2 and Table 3 summarize the empirical results of the forecasting exercise for output growth and inflation, respectively, using individual predictors including estimated factors. Forecasts were computed for one- two- and four-step ahead. The description of the variables that appear in Table 2 and 3 can be found in Appendix 1. The entries shown in bold correspond to models that outperform the benchmark in a particular quarter.

As we can see from the results of Table 2, a number of variables consistently outperform univariate forecasts for all forecasting horizons. These are the All Share Composite Index of Cyprus Stock Exchange (CSEA), FTSE 20 (CSE20), the Cyprus Stock Exchange Banks Index (CSEB), Dow Jones World Basic Materials Index (DJWB) and the common factor variables (Factor 1 and 2). In addition to the above, some other variables have good forecasting ability only for some of the three horizons considered. In particular, for one-quarter ahead forecasts the lowest mean square forecast error model is the ADL that includes Factor 1, followed by the model with Dow Jones World Basic Materials Index (DJWB), the Value Added of Agriculture and Fishing (AFFH) and the stock exchange variables CSEA and CSE20. Other relatively good predictors of GDP growth for one-step ahead forecasting include the number of Outstanding Vacancies (OVAC) and, to a lesser extent, Factor 2.

For two-quarter ahead the best performer is the model with Factor 1 followed by the specification with Dow Jones World Basic Materials Index (DJWB), the stock exchange variables (CSE20, CSEA and CSEB) and Employment in Community, Social and Personal Services (EMPCSP).

The factor variables are not ranked among the top predictors for longer horizons, i.e. four-quarter ahead. Nevertheless, the ADL models with Factor 1, 2, 5 and 6 outperform the benchmark, but variables such as the Turnover Index of Hotels and Restaurants (TIHR), Tourist Arrivals from the UK (TARUK), some stock exchange variables (CSE20 and CSEB) and the Dow Jones World Basic Materials Index (DJWB) do a better job than common factors in forecasting output growth.

Overall, for one and two quarters ahead forecasts Factor 1 has the best predictive ability, while for four quarters ahead, Turnover Index of Hotels and Restaurants (TIHR) appears to be the best predictor. Generally, our results support the findings of Sock and Watson (2002) and Artis, Banerjee and Marcellino (2005) among others who find that factor models lead to better forecasts.

Table 2 Mean Square Forecast Errors: Output Growth

Indicator	Forecast Horizon		
	1 quarter ahead	2 quarters ahead	4 quarters ahead
	Root Mean Square Forecast Error (MSFE)		
Univariate Autoregression	0.005	0.008	0.010
Univariate Forecasts	MSFE Relative to Univariate Autoregression		
$(1-L)^2 q_t = \varepsilon_t$	1.294	1.679	2.477
$(1-L^4)^2 q_t = \varepsilon_t$	2.439	1.640	1.359
$(1-L) q_t = \alpha + \varepsilon_t$	1.000	1.007	1.104
Bivariate Forecasts	MSFE Relative to Univariate Autoregression		
TGFCF	1.193	1.123	1.156
GFCFafa	1.029	1.032	1.000
GFCFep	1.090	1.083	1.056
GFCFte	1.516	1.545	1.018
GFCFca	1.232	1.329	1.589
GFCFcoc	1.128	1.205	1.037
GFCFop	1.115	1.146	1.318
RMV	1.121	**0.957**	1.281
RMV2	1.003	1.024	**0.990**
LCS	1.312	1.072	1.176
EAC	1.001	1.014	1.012
EACkwc	1.126	1.049	1.027
EACkwp	1.005	1.065	**0.973**
BPAN	1.011	1.056	1.445
BPAM	1.083	**0.963**	1.347
BPm^2	1.170	1.253	**0.971**
VIMP	1.029	1.013	1.041
PVIMQ	1.485	1.300	1.051
AME	1.052	1.052	**0.984**
AHFF	**0.964**	1.147	1.008
MQMEGWS	1.049	1.121	1.005
CONST	1.193	1.310	1.343
WRTHRTSC	1.099	1.139	**0.993**
FIRERB	1.372	1.203	1.051
PADEHS	1.100	1.163	1.548
FCE	1.172	**0.962**	1.016
EOGS	1.085	1.089	**0.980**
IOGS	1.027	1.027	1.242
TSP	1.003	1.056	**0.979**
VIPC	1.025	1.014	**0.980**
PICM	1.515	1.232	1.293
ILCC	1.269	1.056	1.012
IOUP	1.070	1.241	1.722
ISMRM	1.017	**0.996**	1.001
TVWTC	1.065	1.162	1.012
TVIRT	1.039	1.011	**0.994**

Indicator	Forecast Horizon		
	1 quarter ahead	2 quarters ahead	4 quarters ahead
Bivariate Forecasts	MSFE Relative to Univariate Autoregression		
TVOIRT	1.073	1.093	**0.973**
TIHR	1.136	1.497	**0.837**
TICOBA	1.262	1.115	1.197
TVITSC	1.281	1.374	1.016
POP	1.506	1.510	1.351
TRU	1.055	1.041	**0.990**
VAC	1.003	1.021	**0.989**
OVAC	**0.976**	1.024	**0.979**
NULC	1.038	1.010	1.022
RLPPH	1.145	1.068	1.025
RLPPP	1.226	1.113	1.055
ULCI	1.120	1.044	1.069
EMPT	1.002	1.001	**0.997**
EMPA	1.039	1.116	1.005
EMPMQ	1.030	**0.965**	1.011
EMPM	1.397	1.253	1.083
EMPEGW	1.052	1.076	1.010
EMPCON	1.046	1.018	1.041
EMPWRT	1.029	1.040	**0.989**
EMPHR	1.000	1.002	**0.995**
EMPTSC	1.020	1.011	**0.993**
EMPFIR	1.007	**0.998**	**0.969**
EMPCSP	1.029	**0.950**	**0.985**
TFW	1.054	1.000	1.012
TI	1.051	1.031	1.230
TE	1.156	1.059	1.244
REX	1.068	1.019	1.409
TARR	1.364	1.374	1.047
TARUK	1.231	1.115	**0.910**
IPHC	1.089	1.012	1.008
DMBA	1.026	1.018	1.015
DMBL	1.019	1.013	1.036
INTR	1.184	1.018	1.013
GNVA	1.016	1.174	1.007
CPI	1.041	**0.990**	**0.968**
HCPI	1.045	1.008	**0.965**
HCPIC	1.058	1.003	1.213
HCPIE	**0.998**	1.028	1.005
HCPIEN	1.070	1.050	**0.997**
HCPIF	1.007	1.003	**0.998**
HCPIH	1.103	1.060	**0.981**
HCPIIG	1.041	1.095	1.055
HCPIMC	1.291	1.138	1.256
HCPIPP	1.133	1.100	1.070
HCPIT	1.090	**0.969**	**0.980**

Indicator	Forecast Horizon		
	1 quarter ahead	2 quarters ahead	4 quarters ahead
Bivariate Forecasts	MSFE Relative to Univariate Autoregression		
HCPIWS	1.603	1.211	1.527
CSEA	**0.972**	**0.925**	**0.946**
CSE20	**0.973**	**0.912**	**0.933**
CSEB	**0.997**	**0.947**	**0.940**
CSEH	1.023	1.022	1.037
CSEIC	**0.993**	1.013	**0.975**
PLR	1.696	1.517	1.648
IOR	1.666	1.763	2.374
MLR	1.710	2.540	3.341
1YTD	2.490	3.923	4.998
YENE	1.255	**0.997**	**0.990**
USEU	1.106	1.023	1.009
UKEU	1.014	**0.984**	1.077
SWEU	1.636	1.134	1.130
CANEU	1.060	1.006	1.103
BCO	1.026	1.020	1.042
COF	1.130	1.047	1.125
GBNY	1.011	1.026	1.070
DJWB	**0.941**	**0.899**	**0.938**
COP	1.019	**0.973**	**0.995**
SCP	1.030	**0.952**	**0.941**
WCP	1.085	1.007	1.193
Factor 1	**0.917**	**0.830**	**0.954**
Factor 2	**0.979**	**0.954**	**0.956**
Factor 3	1.203	1.188	1.229
Factor 4	1.254	1.098	1.136
Factor 5	1.044	1.008	**0.992**
Factor 6	1.139	1.039	**0.957**
Factor 7	1.139	1.191	1.014
Factor 8	1.036	1.010	1.030
Factor 9	1.192	1.039	1.011
Factor 10	1.036	1.005	1.006

Note: q_t denotes GDP.

From Table 3 we can see that bivariate ADL models of inflation with output (GDPcp), the Volume Index of Manufacturing Production (VIMP), the Index of Labour Cost in Construction (ILCC), various subcategories of the Harmonised Consumer Price Index relating to electricity (HCPIE), energy (HCPIEN) and industrial goods (HCPIIG), as well as Factor 2 outperform the benchmark model in all forecasting horizons. Moreover, for one-quarter ahead forecasts the best predictor of inflation is Factor 2, which appears to incorporate the information of individual price indices. Several Harmonised Price Indices subcategories relating to food (HCIF), industrial goods (HCPIIG), and energy (HCPIEN) follow in terms of performance in forecasting inflation one-quarter ahead.

The models with the smallest mean square forecast error for two-quarter ahead inflation forecasts are the bivariate ADLs that include the price indices for electricity (HCPIE) and energy (HCPIEN). The Wheat Cash Price (WCP), the Harmonised Price Index of Water Supply (HCPIWS) and the Crude Oil Future Contracts (COF) as well as Factors 1 and 2 are also relatively good predictors of inflation in the short-run. As in the case of output growth forecasts, the models with factor variables are outperformed by other bivariate ADLs with individual macro series in forecasting inflation four-quarters ahead. Such models are those that include the Harmonised Price Index of Water Supply (HCPIWS), the number of Outstanding Vacancies (OVAC), the Value Added of Agriculture and Fishing (AFFH) and the Wheat Cash Price (WCP). Out of all factors used, the most informative in predicting inflation four-quarters ahead is Factor 5 followed by Factor 2.

To sum up, the inclusion of factors in ADL models for output growth and inflation lead to better forecasts (i.e. lower mean square forecast error) than those obtained by univariate autoregressions or by a number of ADLs that include individual macro series, especially in short horizons, i.e. one or two quarters ahead. For four-quarter ahead forecasts other macro variables, such as the turnover index of hotels and restaurants and the water supply price index seem, to be more useful in forecasting output growth and inflation, respectively.

Table 3. Mean Square Forecast Errors: Inflation

Indicator	Forecast Horizon		
	1 quarter ahead	2 quarters ahead	4 quarters ahead
	Root Mean Square Forecast Error (MSFE)		
Univariate Autoregression	0.007	0.010	0.012
Univariate Forecasts	MSFE Relative to Univariate Autoregression		
$(1\text{-}L)^2 q_t = \varepsilon_t$	1.800	1.831	3.065
$(1\text{-}L^4)^2 q_t = \varepsilon_t$	2.707	1.984	1.602
$(1\text{-}L) q_t = \alpha + \varepsilon_t$	1.072	**0.868**	1.022
Bivariate Forecasts	MSFE Relative to Univariate Autoregression		
GDPcp	**0.992**	**0.967**	**0.964**
TGFCF	1.147	1.090	1.033
GFCFafa	1.133	1.219	1.152
GFCFepm	1.362	1.151	1.041
GFCFte	1.007	**0.944**	**0.973**
GFCFca	1.051	1.132	1.492
GFCFcoc	1.089	1.295	1.142
GFCFop	1.116	1.327	1.420
RMV	1.142	1.096	1.039
RMV2	1.003	1.035	1.111
LCS	1.194	1.035	1.057
EAC	1.047	1.021	1.001
EACkwc	1.010	**0.995**	1.013
EACkwp	1.144	1.007	1.076
BPAN	1.084	1.024	1.011
BPAM	1.057	1.023	1.007
BPm2	1.148	1.039	1.012
VIMP	**0.978**	**0.983**	**0.987**
PVIMQ	1.071	1.025	1.008
AME	1.015	1.019	1.003
AHFF	1.006	**0.974**	**0.904**
MQMEGWS	1.114	1.067	1.153
CONST	1.147	1.109	1.375
WRTHRTSC	1.013	**0.983**	**0.955**
FIRERB	1.165	1.065	1.129
PADEHS	1.118	1.078	1.203
FCE	1.012	1.002	1.003
EOGS	1.107	1.014	1.076
IOGS	1.138	1.002	1.008
TSP	1.089	1.023	1.011
VIPC	1.045	**0.949**	**0.991**
PICM	1.064	1.230	1.092
ILCC	**0.973**	**0.965**	**0.972**
IOUP	1.029	1.038	1.012
ISMRM	1.121	1.067	1.059
TVWTC	1.141	1.001	**0.961**

Indicator	Forecast Horizon		
	1 quarter ahead	2 quarters ahead	4 quarters ahead
Bivariate Forecasts	MSFE Relative to Univariate Autoregression		
TVIRT	1.062	1.075	1.061
TVOIRT	1.044	1.130	**0.987**
TIHR	1.065	1.003	**0.991**
TICOBA	1.129	1.045	1.186
TVITSC	1.044	1.015	**0.979**
POPcy	1.051	1.135	1.220
TRU	1.009	1.045	1.064
VAC	1.048	1.021	**0.973**
OVAC	1.062	**0.954**	**0.845**
NULC	1.024	1.013	**0.997**
RLPPH	1.001	1.040	1.049
RLPPP	1.006	1.138	**0.982**
ULCI	1.058	1.122	1.139
EMPT	1.000	1.043	**0.992**
EMPA	**0.999**	1.010	**0.998**
EMPMQ	1.090	**0.979**	1.084
EMPM	1.024	1.041	1.200
EMPEGW	1.084	1.099	1.110
EMPCON	**0.963**	1.009	**0.974**
EMPWRT	1.110	1.089	1.094
EMPHR	1.027	**0.957**	1.005
EMPTSC	1.058	1.045	**0.981**
EMPFIR	1.050	1.008	1.017
EMPCSP	1.123	**0.997**	1.034
TFW	1.012	1.029	1.046
TI	1.045	1.019	1.044
TE	1.080	1.053	1.096
REX	1.095	1.018	1.108
TARR	1.011	1.087	1.020
TARUK	1.004	**0.948**	**0.948**
IPHC	1.058	1.087	1.098
DMBA	1.150	**0.947**	1.118
DMBL	1.130	**0.943**	1.078
INTR	1.073	**0.955**	**0.986**
GNVA	1.010	**0.978**	**0.977**
HCPI	1.083	**0.962**	**0.960**
HCPIC	**0.988**	1.002	1.028
HCPIE	**0.978**	**0.767**	**0.988**
HCPIEN	**0.952**	**0.770**	**0.953**
HCPIF	**0.937**	**0.967**	1.016
HCPIH	1.088	1.012	**0.989**
HCPIIG	**0.939**	**0.936**	**0.998**
HCPIMC	1.195	1.430	1.214
HCPIPP	1.290	1.201	1.105

Indicator	Forecast Horizon		
	1 quarter ahead	2 quarters ahead	4 quarters ahead
Bivariate Forecasts	MSFE Relative to Univariate Autoregression		
HCPIT	1.137	**0.973**	1.050
HCPIWS	1.091	**0.890**	**0.792**
CSEA	1.065	1.013	1.028
CSE20	1.078	1.022	1.029
CSEB	1.119	1.041	1.039
CSEH	1.048	**0.982**	**0.997**
CSEIC	**0.953**	1.003	1.003
PLR	1.068	1.051	1.052
IOR	1.236	1.378	1.205
MLR	1.102	1.162	1.320
YTD	1.112	1.245	1.919
YENE	**0.990**	1.027	1.095
USEU	1.227	1.159	1.186
UKEU	1.115	1.145	1.087
SWEU	1.029	1.090	1.031
CANEU	1.052	1.048	1.007
BCO	1.069	**0.968**	**0.988**
COF	1.038	**0.929**	1.001
GBNY	1.233	1.021	1.178
DJWB	1.308	1.050	1.130
COP	1.245	1.222	1.160
SCP	1.021	1.171	1.092
WCP	1.008	**0.889**	**0.917**
Factor 1	1.041	**0.932**	1.043
Factor 2	**0.669**	**0.935**	**0.958**
Factor 3	1.176	1.246	1.470
Factor 4	1.125	1.157	1.272
Factor 5	1.156	1.013	**0.933**
Factor 6	1.049	1.052	1.015
Factor 7	1.108	**0.950**	1.004
Factor 8	1.207	1.036	1.156
Factor 9	1.045	1.009	1.009
Factor 10	1.034	1.022	1.013

Note: q_t denotes inflation.

4.2 In-Sample Tests for Predictive Content and Instability

In this section we investigate the predictive content of the variables in the sample and the stability of regression coefficients using the Granger causality test statistic (GC) and the Quandt (1960) likelihood ratio statistic (QLR), respectively.[6] We use the heteroskedasticity-robust Granger-causality test statistic, computed in an one-step ahead regression, and the Quandt (1960) likelihood ratio test for coefficient stability, computed over all possible break dates in the central 70 percent of the sample. The Granger-causality statistic tests the null hypothesis that the variables in the sample do not have any predictive content, while the QLR statistic tests the null hypothesis of constant regression coefficients against the alternative that the regression coefficients vary over time.[7,]

Table 4 presents the p-values for the Granger Causality (first and third column) and QLR (second and fourth column) test for growth and inflation. The high frequency of rejection of the Granger causality test indicates that a large number of bivariate relations have substantial in-sample predictive content. On the other hand, the QLR statistic detects instability in a large number of these relations.

For output growth the Granger Causality test rejects the null hypothesis of no predictive content (at 5% level of significance) for the specifications that include the following variables: value added for different subsectors of the economy[8], the Index of Labour Cost (ILCC) and Output Prices (IOUP) in Construction, the Turnover Volume Index for Retail Trade (TVOIRT) and for Hotels and Restaurants (TIHR), Employment in Hotels and Restaurants (EMPHR) and in the Financial and Real Estate sector (EMPFIR), Tourist Arrivals from the UK (TARUK), Gold National Valuation (GNVA), the Harmonised Consumer Price indices of Communications (HCPIC) and Water Supply (HCPIWS), the Dow Jones Wold Basic Materials Index (DJWB) and Factor 8. However, only the Value Added for Mining, Quarrying, Manufacturing, Electricity, Gas and Water Supply (MQMEGWS) and for Wholesale and Retail Trade, Hotels and Restaurants, Transport and Communications (WRTHRTSC), Tourist Arrivals from the UK (TARUK), Gold National Valuation and Factor 8 have stable coefficients according to the QLR statistic. Out of all these variables only Tourist Arrivals from the UK

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[6] Again we follow Stock and Watson (2003).

[7] For further details on these statistics and their distributional assumptions, see Stock and Watson (1998, 2002a) and Andrews (1993).

[8] Value added in Agriculture, Hunting, Forestry and Fishing (AHFF), Mining, Quarrying, Manufacturing, Electricity, Gas and Water Supply (MQMEGWS), Financial Intermediation, Real Estate, Renting and Business Activities (FIRERB) and Wholesale and Retail Trade, Hotels and Restaurants, Transport and Communications (WRTHRTSC).

(TARUK) and the Value Added of Wholesale and Retail Trade, Hotels and Restaurants, Transport and Communication (WRTHRTSC) correspond to ADLs that perform better than the benchmark, and this occurs solely for four-quarter ahead forecasts. In the cases of bivariate ADLs that outperform the benchmark for all horizons in the out-of sample forecasting exercise we observe either non-rejection of non-causality (stock exchange variables CSEA, CSE20 and CSEB) and/or rejection of the hypothesis of stable coefficients (stock exchange variables CSEA, CSE20 and DJWB and Factors 1 and 2).

For inflation, Granger Causality test rejects the null for the combinations of CPI with the following variables: GDP, a gross fixed capital formation subcategory (GFCFop), the value (EAC) and quantity (EACkwp) of Electricity Consumption, the Production Volume Index of Mining and Quarrying (PVIMQ), the Value Added of Financial, Real Estate and Other Business Activities (FIRERB), the Number of Vacancies Outstanding (OVAC), an index of labour productivity per person employed (RLPPP), Total Employment (EMPT) and employment in various subsectors[9], International Reserves (INTR), Gold National Valuation (GNVA), various subcategories of harmonised consumer price index[10], the Cyprus Stock Exchange Index for Hotels (CSEH) and Investment Companies (CSEIC), the exchange rate of yen (YENE) and Swiss franc (SWEU) to euro, a number of international variables[11], Factor 2, 5 and 10.

However, in bivariate models that include the Number of Vacancies Outstanding (OVAC), Employment in Construction (EMPCON), the price index for industrial goods (HCPIIG) and water supply (HCPIWS), the exchange rate of Swiss franc to euro (SWEU) and Brent Crude Oil Commodity Prices (BCO), the stability of coefficients is rejected at 5% level.

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[9] Employment in construction (EMPCON), Hotels and Restaurants (EMPHR), Transport/Storage/Communications (EMPTSC), Financial, Real Estate and Other Business Activities (EMPFIR), Community in Social and Personal Services (EMPCSP).

[10] Harmonised Consumer Price Index for Energy (HCPIEN), Food (HCPIF), Industrial Goods (HCPIIG), Transport (HCPIT) and Water Supply (HCPIWS).

[11]Brent Crude Oil Commodity Prices (BCO), Crude Oil Future Contracts (COF), Corn Oil Price (COP) and Wheat Cash Price (WCP).

Table 4: Granger Causality and QLR P-Values – Bivariate Models

	Output		Inflation	
	GC	QLR	GC	QLR
GDP	-	-	**0.00**	**0.61**
TGFCF	0.40	0.00	0.64	0.70
GFCFafa	0.39	0.00	0.82	0.67
GFCFep	0.95	0.00	0.88	0.17
GFCFte	0.36	0.03	0.17	0.20
GFCFca	0.17	0.01	0.63	0.21
GFCFcoc	0.41	0.01	0.81	0.04
GFCFop	0.17	0.00	**0.02**	**0.89**
RMV	0.10	0.58	0.35	0.85
RMV2	0.14	0.05	0.66	0.47
LCS	0.29	0.24	0.15	0.02
EAC	0.81	0.83	**0.04**	**0.87**
EACkwc	0.43	0.78	0.39	0.35
EACkwp	0.12	0.00	**0.03**	**0.18**
BPAN	0.45	0.86	0.14	0.04
BPAM	0.67	0.03	0.34	0.40
BPm^2	0.06	0.13	0.49	0.01
VIMP	0.05	0.60	0.21	0.42
PVIMQ	0.19	0.00	**0.00**	**0.79**
AME	0.91	0.19	0.57	0.81
AHFF	0.00	0.03	0.84	0.44
MQMEGWS	**0.01**	**0.93**	0.78	0.22
CONST	0.23	0.05	0.11	0.12
WRTHRTSC	**0.02**	**0.18**	0.72	0.96
FIRERB	0.00	0.00	**0.01**	**0.75**
PADEF	0.24	0.00	0.80	0.05
FCE	0.18	0.56	0.37	0.78
EOGS	0.10	0.08	0.22	0.86
IOGS	0.27	0.00	0.26	0.39
TSP	0.08	0.06	0.41	0.32
VIPC	0.12	0.00	0.90	0.58
PICM	0.28	0.00	0.62	0.16
ILCC	0.01	0.00	0.77	0.71
IOUP	**0.04**	**0.45**	0.54	0.54
ISMRM	0.85	0.66	0.85	0.88
TVWTC	0.33	0.69	0.10	0.69
TVIRT	0.08	0.00	0.77	0.70
TVOIRT	0.01	0.00	0.29	0.47

	Output		Inflation	
	GC	QLR	GC	QLR
TIHR	0.00	0.00	0.21	0.53
TICOBA	0.96	0.30	0.29	0.26
TVITSC	0.18	0.00	0.49	0.80
POP	0.53	0.43	0.23	0.12
TRU	0.32	0.06	0.53	0.26
VAC	0.56	0.00	0.09	0.15
OVAC	0.20	0.00	0.05	0.01
NULC	0.38	0.94	0.35	0.91
RLPPH	0.47	0.00	0.22	0.62
RLPPP	0.70	0.00	**0.04**	**0.70**
ULCI	0.29	0.32	0.40	0.70
EMPT	0.07	0.02	**0.01**	**0.50**
EMPA	0.08	0.02	0.51	0.60
EMPMQ	0.63	0.00	0.50	0.20
EMPM	0.28	0.00	0.48	0.45
EMPEGW	0.31	0.00	0.53	0.00
EMPCON	0.78	0.04	0.00	0.03
EMPWRT	0.42	0.00	0.38	0.51
EMPHR	0.04	0.00	**0.01**	**0.50**
EMPTSC	0.38	0.00	**0.00**	**0.52**
EMPFIR	0.01	0.00	**0.00**	**0.44**
EMPCSP	0.05	0.00	**0.00**	**0.95**
TFW	0.89	0.17	0.19	0.93
TI	0.51	0.00	0.26	0.64
TE	0.38	0.03	0.93	0.08
REX	0.37	0.00	0.87	0.11
TARR	0.70	0.04	0.90	0.63
TARUK	**0.00**	**0.16**	0.64	0.49
IPHC	0.84	0.05	0.95	0.25
DMBA	0.42	0.12	0.34	0.12
DMBL	0.56	0.22	0.30	0.15
INTR	0.58	0.00	**0.01**	**0.97**
GNVA	**0.00**	**0.86**	**0.00**	**0.32**
CPI	0.08	0.00	-	-
HCPI	0.10	0.00	0.70	0.06
HCPIC	0.04	0.00	0.19	0.58
HCPIE	0.12	0.00	0.38	0.25
HCPIEN	0.80	0.00	**0.01**	**0.69**
HCPIF	0.60	0.00	**0.02**	**0.97**

	Output		Inflation	
	GC	QLR	GC	QLR
HCPIH	0.72	0.00	0.69	0.16
HCPIIG	0.24	0.00	0.00	0.04
HCPIMC	0.30	0.00	0.16	0.85
HCPIPP	0.81	0.00	0.91	0.31
HCPIT	0.28	0.00	**0.00**	**0.54**
HCPIWS	0.00	0.01	0.00	0.01
CSEA	0.34	0.00	0.36	0.27
CSE20	0.33	0.00	0.46	0.31
CSEB	0.29	0.78	0.97	0.05
CSEH	0.05	0.00	**0.00**	**0.76**
CSEIC	0.22	0.00	**0.00**	**0.61**
PLR	0.26	0.00	0.52	0.73
IOR	0.60	0.00	0.26	0.08
MLR	0.30	0.00	0.28	0.64
1YTD	0.27	0.00	0.19	0.43
YENE	0.35	0.00	**0.02**	**0.46**
USEU	0.57	0.00	0.53	0.79
UKEU	0.22	0.00	0.82	0.07
SWEU	0.07	0.00	0.00	0.09
CANEU	0.43	0.00	0.81	0.30
BCO	0.74	0.00	0.09	0.05
COF	0.72	0.00	**0.04**	**0.16**
GBNY	0.57	0.03	0.12	0.06
DJWB	0.01	0.00	0.33	0.09
COP	0.16	0.00	**0.03**	**0.37**
SCP	0.16	0.25	0.24	0.59
WCP	0.39	0.00	**0.00**	**0.23**
Factor 1	0.24	0.00	0.24	0.50
Factor 2	0.81	0.00	**0.01**	**0.94**
Factor 3	0.14	0.01	0.63	0.83
Factor 4	0.20	0.00	0.90	0.00
Factor 5	0.24	0.00	**0.01**	**0.65**
Factor 6	0.43	0.02	0.50	0.52
Factor 7	0.91	0.05	0.59	0.47
Factor 8	**0.04**	**0.24**	0.14	0.12
Factor 9	0.28	0.00	0.74	0.00
Factor 10	0.53	0.55	**0.02**	**0.56**

Note: The cases where the null hypothesis of non-causality is rejected (p-value < 0.05) but the null of the stability coefficients is not rejected (p-value > 0.05) are shown in bold.

Moreover, the ADLs for inflation that include GDP, an index of labour productivity (RLPPP), employment variables[12], International Reserves (INTR), Gold National Valuation (GNVA), price indices for energy (HCPIEN), food (HCPIF) and transport (HCPIT), the Cyprus Stock Exchange Index for Hotels (CSEH) and Investment Companies (CSEIC), the exchange rate of yen to euro (YENE), Crude Oil Future Contracts (COF), Wheat Cash Price (WCP), Factor 2 and Factor 5 have lower mean square forecast error than the univariate autoregression in at least one of the forecast horizons considered. In the case of the bivariate models for inflation with GDP, the price index for energy (HCPIEN) and Factor 2, the models are found to reject the null of non-causality, to have stable coefficients and to beat the benchmark model in the out-of-sample forecasting exercise for all horizons.

Table 5 summarizes the results of Granger Causality and QLR tests presented in Table 4. In particular the table shows the percentage of the bivariate models that reject the null of non-causality, the percentage of the bivariate models that reject the null of stability of the regression parameters, the proportion of the models that reject both of the above hypotheses, as well as the product of the first two percentages mentioned above.

Table 5: Summary of Granger Causality and QLR Test Statistics

Output				Inflation			
GC	QLR	C&Q	CxQ	GC	QLR	C&Q	CxQ
0.168	0.735	0.106	0.123	0.274	0.124	0.035	0.034

Note: The figures in each cell show the fraction of bivariate models with significant (5%) GC statistics (column label GC), significant (5%) QLR statistics (column label QLR), significant GC and QLR statistics (column label G&Q) and the product of the first and second (column label GxQ).

For output the null hypothesis of no predictive content is rejected in about 17% of models, while for inflation the same hypothesis is rejected more frequently in approximately 27% of cases. The QLR test detects parameter instability in 70% of estimated relations of output with macro variables, but only in 12% of inflation models.

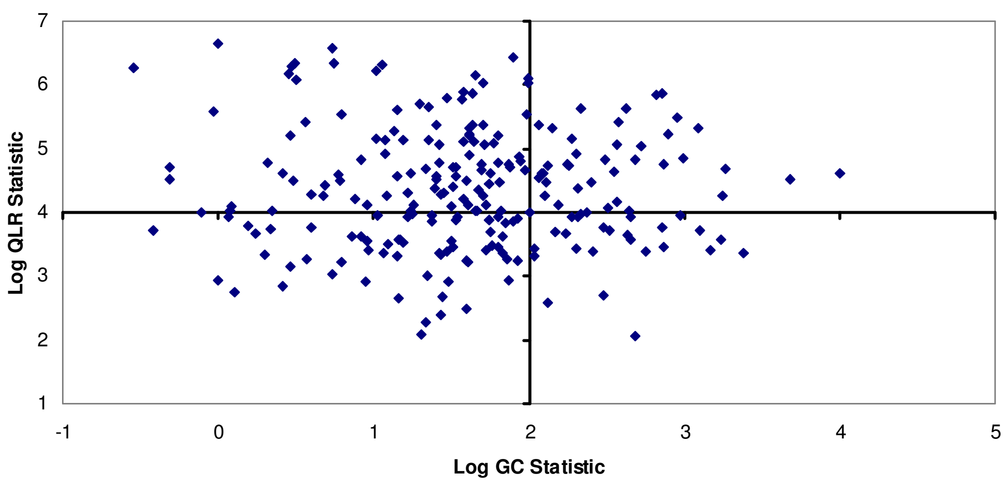
[12] Total Employment (EMPT) and Employment in Hotels and Restaurants (EMPHR), Transport/Storage/Communications (EMPTSC) and in Community in Social and Personal Services (EMPCSP).

Thus, there seems to be greater instability in the models for output growth than in those for inflation, which is the opposite of what Stock and Watson (2003) find.

Looking at the relationship between the outcomes of Granger Causality and QLR tests we can see that the joint probability of both tests rejecting (reported in the third and seventh column of Table 5) is quite close to the product of the marginal probabilities (shown in the fourth and eighth column of Table 5). Thus, the rejections of the non-causality hypothesis and the rejections of the null of stable regression parameters seem to be approximately independently.

The scatterplot of Granger Causality and QLR statistics shown in Figure 2 also depicts the lack of a relationship between the two statistics and therefore the absence of dependence of the predictive content of variables in the models on whether the coefficients in these models are stable or not.

Figure 2: Scatter plot of Granger Causality and QLR Statistics



5. CONCLUDING REMARKS

This paper draws heavily on the work of Stock and Watson (2003) to undertake a similar forecasting exercise for output growth and inflation, using quarterly macroeconomic data for the Cyprus economy for the period 1995Q1-2008Q4. Instead of focusing on the usefulness of asset prices in the construction of forecasts for growth and inflation as in Stock and Watson (2003), we explore a large number of alternative macroeconomic series, such as measures of output/income, employment and trade, price and stock exchange indices, interest rates and exchange rates, as well as international variables.

We also investigate the role of common factors extracted from a large dataset (of about 100 variables) by means of principal component analysis. The results show that a number of common factors, mainly those relating to output and international variables and to prices, are found to be among the best predictors (i.e. low relative mean square forecast error) of output growth and inflation, especially for one and two quarter forecasting horizons.

Other variables that are found to lead to relatively low mean-square-forecast-error forecasts for GDP growth four quarters ahead are the Turnover Index of Hotels and Restaurants (TIHR) and Tourist Arrivals from the UK (TARUK). This finding reflects the fact that Cyprus is an open economy, largely dependant on tourism, mostly form the UK. Therefore, the potential usefulness of other international and UK variables needs to be explored further.

For inflation two-quarter ahead forecasts, the minimum mean-square-forecast-error models are those that include the Harmonised Price Index of Electricity (HCPIE) and Energy (HCPIEN). The best predictor of inflation four quarters ahead appears to be the Harmonised Price Index of Water Supply (HCPIWS).

Nevertheless, some of the models that perform the best in terms of out-of-sample forecasting, suffer in terms of in-sample parameter stability and/or in-sample predictive content. The in-sample stability of the estimated parameters is found to bear no relation with the in-sample predictive content (Granger causality) of the variables.

For output growth, specifications that exhibit both good forecasting performance and parameter stability include Tourist Arrivals form the UK (TARUK) or the Value Added of Wholesale and Retail Trade, Hotels and Restaurants, Transport and Communications (WRTHRTC). For inflation the stable models that predict well consist of a common factor (Factor 2) or the Harmonised Consumer Price of Energy (HCPIEN). These models can be closely monitored on a regular basis to evaluate their usefulness for real-time forecasting.

The empirical results of the paper suggest that the factor models framework might constitute a promising strategy to follow in the effort of constructing forecasts for the Cyprus economy. In such a framework one can exploit the information from a large number of indicators (domestic, foreign and international) which are available, in the case of Cyprus, for a relatively small number of periods.

This study is a preliminary attempt of the Economics Research Centre to assess the usefulness of macroeconomic data for Cyprus in simple time series models, in the context of a forecasting exercise for GDP growth and inflation. This paper is the first in a series of papers that will follow, based on research undertaken in the Centre that intends to investigate alternative models/methodologies for the construction of short-term forecasts for output growth and inflation. The ultimate aim is the regular production and publication of reliable quarterly forecasts for aggregate series of the Cyprus economy as a whole (for example GDP growth, inflation, unemployment, etc), as well as for variables relating to particular sectors of economic activity (for example tourism, financial services, retail trade, etc). This line of applied research on the Cyprus economy will seek to fill a gap in Cyprus, namely the availability of macroeconomic forecasts produced by independent organizations, that can be used for financial planning by the private sector and policy makers.

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APPENDIX 1: LIST OF VARIABLES IN THE DATASET

Real Output and Income		Indicator	Transformation Code
1.	Real Gross Domestic Product (GDP)	GDP	5
2.	Total Gross Fixed Capital Formation (GFCF)	TGFCF	5
3.	GFCF - Products of agriculture, fisheries & aquaculture	GFCFafa	2
4.	GFCF - Equipment: metal product & machinery	GFCFep	5
5.	GFCF - Equipment: transport equipment	GFCFte	5
6.	GFCF - Construction: housing	GFCFca	5
7.	GFCF - Construction: other construction	GFCFcoc	5
8.	GFCF - Other products	GFCFop	5
9.	Registration of motor vehicles (passenger cars)	RMV	5
10.	Registration of motor vehicles (light goods vehicles, except for public use)	RMV2	5
11.	Local cement sales (millions of tons)	LCS	5
12.	Electricity consumption (€000's)	EAC	5
13.	Electricity consumption (act 000's kWh)	EACkwc	5
14.	Electricity production (act 000's kWh)	EACkwp	5
15.	Building permits authorized (act no)	BPAN	5
16.	Building permits authorised (€000's)	BPAM	5
17.	Building permits authorised (area m2)	BPm^2	5
18.	Volume Index of Manufacturing Production act (2000=100)	VIMP	5
19.	Production Volume Index of Mining & Quarrying act (2000=100)	PVIMQ	5
20.	Average Monthly Earnings	AME	5
21.	GDP - Agriculture, hunting, forestry & fishing	AHFF	5
22.	GDP - Mining, quarrying, manufacturing, electricity, gas & water supply	MQMEGWS	5
23.	GDP – Construction	CONST	5
24.	GDP – Wholesale, retail trade, hotels, restaurants, transport & communication	WRTHRTSC	5
25.	GDP - Financial intermediation, real estate, renting & business activities	FIRERB	5
26.	GDP - Public administration & defense	PADEF	5
27.	GDP - Final Consumption Expenditure	FCE	5
28.	GDP - Exports of goods & services	EOGS	5
29.	GDP - Imports of goods & services	IOGS	5
30.	Total Sales of Petroleum Products (millions of tons)	TSP	5
31.	Volume Index of production in construction	VIPC	5
32.	Price Index of main construction materials	PICM	5
33.	Index of labor cost in construction	ILCC	5
34.	Index of output prices in construction	IOUP	5
35.	Turnover Value Index of sale, maintenance & repair of motor vehicles	ISMRM	5
36.	Turnover Value Index of wholesale trade & commission trade	TVWTC	5
37.	Turnover Value Index of retail trade	TVIRT	5
38.	Turnover Volume Index of retail trade	TVOIRT	5

39.	Turnover Index of hotels & restaurants	TIHR	5
40.	Turnover Index of computers & other business activities	TICOBA	5
41.	Turnover value index in transport, storage & communication	TVITSC	5
Employment and Hours			
42.	Population	POP	5
43.	Total Registered Unemployed (act number)	TRU	5
44.	Vacancies Notified (act number)	VAC	5
45.	Vacancies Outstanding (act number)	OVAC	5
46.	Nominal Unit Labor Cost Index	NULC	5
47.	Real Labor Productivity Per Hour Worked Index	RLPPH	5
48.	Real Labor Productivity Per Person Employed Index	RLPPP	5
49.	Real Unit Labor Cost Index	ULCI	5
50.	Total Employment	EMPT	5
51.	Employment - Agriculture, Forestry & Fishing	EMPA	5
52.	Employment - Mining & Quarrying	EMPMQ	5
53.	Employment – Manufacturing	EMPM	5
54.	Employment - Electricity, Gas & Water	EMPEGW	5
55.	Employment – Construction	EMPCON	5
56.	Employment - Wholesale & Retail Trade	EMPWRT	5
57.	Employment - Hotels & Restauarants	EMPHR	5
58.	Employment - Transport Storage & Communication	EMPTSC	5
59.	Employment - Financial Intermediation, Real Estate & Business Activities	EMPFIR	5
60.	Employment - Community, Social & Personal Services	EMPCSP	5
61.	Total foreign workers in Cyprus	TFW	5
Trade			
62.	Total imports	TI	5
63.	Total exports	TE	5
64.	Re-exports	REX	5
65.	Tourist arrivals	TARR	5
66.	Tourist arrivals from the UK	TARUK	5
67.	Imports of Petroleum for home consumption (€000's)	IPHC	5
Money and Credit Quantity Aggreagates			
68.	Deposit Money Banks: Assets	DMBA	5
69.	Deposit Money Banks: Liabilities	DMBL	5
70.	International Reserves	INTR	5
71.	Gold national valuation	GNVA	5
Price Indices			
72.	Consumer Price Index	CPI	5
73.	Harmonised Consumer Price Index (HCPI)	HCPI	5
74.	HCPI – Communications	HCPIC	5
75.	HCPI – Electricity	HCPIE	5

76.	HCPI – Energy	HCPIEN	5
77.	HCPI – Food	HCPIF	5
78.	HCPI - Health	HCPIH	5
79.	HCPI - Industrial Goods	HCPIIG	5
80.	HCPI - Motor Cars	HCPIMC	5
81.	HCPI - Pharmaceutical Products	HCPIPP	5
82.	HCPI - Transport	HCPIT	5
83.	HCPI - Water Supply	HCPIWS	5
Stock Prices			
84.	Cyprus Stock Exchange (All Share Composite)	CSEA	5
85.	CSE - FTSE-20	CSE20	5
86.	CSE - Banks Index	CSEB	5
87.	CSE - Hotels Index	CSEH	5
88.	CSE - Investment Companies	CSEIC	5
Interest Rates			
89.	Personal Lending Rate	PLR	1
90.	3-month Interbank Offer Rate	IOR	1
91.	Mortgage Lending Rate	MLR	1
92.	1-year Time Deposits	1YTD	1
Exchange Rates			
93.	YEN to EUR	YENE	5
94.	US to EUR	USEU	5
95.	UK to EUR	UKEU	5
96.	SW to EUR	SWEU	5
97.	CAN to EUR	CANEU	5
International Variables			
98.	Brent Crude Oil Commodity Prices	BCO	5
99.	Crude Oil Futures Contracts	COF	5
100.	Gold Bullion Price	GBNY	5
101.	Dow Jones World Basic Materials Index	DJWB	5
102.	Corn Oil Price	COP	5
103.	Silver Cash Price	SCP	5
104.	Wheat Cash Price	WCP	5

Notes: (1) GDP for the economy as a whole and GDP for sectors of economic activity (value added) is expressed in constant prices of 2000. (2) Transformation codes are as follows: 1=Level, 2=First difference and 5=First difference of logarithms.

APPENDIX 2: THE FACTOR MODEL

Let X_t be the N-macroeconomic variables to be modelled, observed for $t=1,...,T$. X_t admits an approximate linear dynamic factor representation with r common factors, F_t if:

$$X_{it} = \lambda_i(L) f_t + e_{it} \qquad \text{(A2.1)}$$

for $i=1,...,N$, where e_{it} is an idiosyncratic disturbance with limited cross-sectional and temporal dependence, and $\lambda_i(L)$ are lag polynomials in non-negative powers of L. If $\lambda_i(L)$ have finite orders of at most q, equation (A2.1) can be rewritten as,

$$X_t = \Lambda F_t + e_t \qquad \text{(A2.2)}$$

where $F_t = (f'_t,\dots, f'_{t-q})'$ is $r \times 1$, where $r \le (q+1)\bar{r}$, and the i_{th} row of Λ in (A2.2) is $(\lambda_{i0},\dots, \lambda_{iq})$.

The factors provide a summary of the information in the data set, and can therefore be expected to be useful for forecasting. From a more structural point of view, the factors can be considered as the driving forces of the economy. In both cases, it is extremely important to have accurate estimators of the factors. Stock and Watson (1998) show that, under some technical assumptions (restrictions on moments and stationarity conditions), the column space spanned by the dynamic factors f_t can be estimated consistently by the principal components of the X's. A condition that is worth mentioning is that the number of factors included in the estimated model has to be equal or larger than the true number.

To determine the appropriate number of factors to be included in the model we apply the Bai and Ng (2002) selection criteria. These criteria add penalty terms to the minimised objective function. The penalty depends on N and T and the number of factors included in the model in such a way as to ensure consistency, i.e., the true number of factors is selected with probability one when N and T diverge. The criteria are asymptotically equivalent, but can differ in finite samples for different specifications of the penalty term.

In addition to the Bai and Ng (2002) criterion, we opted to include in the model 10 factors, in order to get the maximum predictive information from the factors.

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