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Thesis Title: *"Direct vs. Iterated forecasts for the U.S. GDP growth rate."*

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ABSTRACT

The aim of this study is twofold. First, we investigate the predictive role of some economic and financial variables for the U.S. economic activity at short-term forecast horizons. We do this by generating recursively out-of-sample forecasts in the context of simple autoregressive models. Second, the main goal is to compare two forecasting methods, namely the iterated and the direct approach, regarding their forecasting ability for the U.S. GDP growth rate. We initially review the voluminous literature on this topic. We then set the theoretical framework for our empirical analysis. Afterwards, we undertake an empirical analysis using quarterly data for a span of up to 41 years (1973-2013). Empirical results indicate that none of the candidate variables is systematically an efficient predictor of the U.S output growth. Finally, we find that direct forecasts are superior to iterated forecasts at all forecast horizons.

Keywords: iterated forecasts, direct forecasts, recursive scheme, output growth

1. INTRODUCTION

Nowadays, output growth is studied by many researchers in order to forecast the economic progress of countries. In most economic studies that deal with out-of sample forecasts, it has been indicated that forecasts of macroeconomic variables such as Gross Domestic Product (GDP) and other variables (industrial production) which essentially measure and approximate the output, add important and useful content to the growth of countries' economic activity. Particularly, GDP, as an index, reveals the economic and financial situation of a country and many researchers deal with predictions of a country's output in order to examine its economic growth. Thus, GDP is significant for the evaluation and estimation of national economic development and performance of a whole country indicating the success or failure of its economic policy.

In addition, output as a general definition, is the aggregate economic activity of a country taking place in a specific period of a year. Output captures and characterizes much more efficiently the broadest coverage of an economy than any other macroeconomic variable. It also measures the value of all final goods and services of a nation produced in a specific period of a year. It is noteworthy to mention that among all macroeconomic variables, GDP used as a proxy of output, is the most often used variable for forecasting the economic growth of a country. According to many researchers, a precise prediction of a country's GDP is very helpful to approximate its future economic situation.

Methods for forecasting output growth have been examined by many researchers. Thus, many forecasting approaches have been proposed, especially for (pseudo) out-of-sample projections. Literature survey includes a number of alternative forecasting methods. Most of them are presented in the following section. Although forecasting methods are implemented to predict the same economic variable, their results may differ because each method is usually fitted in different econometric models.

The most common multi-period ("h"-step) forecasting approaches in the literature are the iterated method (step by step forecasting process) and the direct method. Iterated multi-period forecasts are made using a one-period ahead model, iterated forward for the desired number of periods, whereas direct forecasts are made using a horizon-specific estimated model, where the dependent variable is the multi-period ahead value being forecasted.

In our study, we focus on univariate, and bivariate linear autoregressive models. Furthermore, using the simple AutoRegressive model (AR) as a benchmark model and augmenting it with an individual economic or financial variable each time, we make multi-step out-of sample predictions. In contrast, we generate iterated out-of-sample forecasts employing the one-step benchmark AR model as analyzed in the section of methodology.

The primary aim of this study is to compare the benchmark AR model to its alternative augmented models. In this context, we choose a battery of economic and financial variables to include as predictors in alternative models. We examine if candidate indicators have predictive power over the benchmark model. However, the notion that financial and economic variables contain information to forecast real economic activity is still controversial. Moreover, it is not necessary for any candidate predictor to be statistically significant in-sample in order to add effectively predictive content to the benchmark. Statistical significance satisfies only the sufficient condition in order for a variable to be an efficient predictor. It is based on in-sample estimations and non existence of it does not influence the predictive ability and power of the candidate variable. Furthermore, before choosing the appropriate variables, we have to test if variables are stationary either in levels or in first differences. Our augmented autoregressive models include variables which are stationary in first differences. Despite the fact that a widely literature exists on the choice of candidate variables, there is little consensus as to what the appropriate variables should be. As a result, the selection of the most suitable predictors is a difficult process and becomes more complicated due to the fact that some candidate indicators are not well adjusted to the models as theory argues.

This is the fundamental reason why some candidate variables are discarded and not implemented in our analysis. In our case, we end up incorporating quarterly data of stock market returns (S&P 500 composite index), commodity prices-indices (gold prices, agriculture index), exchange rates (trade weighted U.S dollar index), monetary aggregates (M1 monetary stock) and macroeconomic variables (Consumer Price Index) into our models. So, these are the candidate indicators which may or may not add predictive content to the benchmark model. The forecasting results may differ in each case and depend on the approach employed in each different model.

The second goal of our study is to compare the direct method against the iterated approach. In other words we evaluate the forecasting ability of each approach by means of the Mean Squared Forecast Error criterion (MSFE). According to the theory, the best dynamic autoregressive model is the one which provides the largest reduction in MSFE. Consequently, the best forecasting method is the one that has the smallest MSFE. This forecasting approach is more suitable and precise for predicting the U.S. growth rate.

Our results indicate that in the vast majority of cases, economic and financial variables add little predictive content over that contained in the benchmark model. Some U.S. variables are useful for the 1-quarter horizon while other variables offer forecasting improvements at some longer horizons. Then, we show that direct forecasts outperform the iterated forecasts.

The remaining of the study is organized as follows: Section 2 describes and analyzes the literature review. Section 3 presents the econometric methodology while Section 4 describes the data and presents our empirical results. The conclusions are discussed and summarized in Section 5.

2. LITERATURE SURVEY

There is a vast literature on the prediction of output growth either in theoretical or empirical level, using asset prices and financial variables (term spreads, house prices interest rates, default spreads, monetary aggregates and exchange rates), stock market indexes, commodity prices (gold, oil, silver), and other economic indicators as predictors. The present literature survey refers and analyzes the results of various studies which make (pseudo) out-of-sample forecasts for the main macroeconomic variables, especially GDP, using either the iterated or the direct forecasting approach.

The basic idea of this section is to present studies which include at least one of the two following tasks. The first task compares the iterated method with the direct approach regarding the forecasting accuracy of AR models for the economic activity, while the second task detects the exogenous macroeconomic variables that embody predictive content to the autoregressive (AR, VAR, ARIMA) models and consequently, improve their forecasting ability. Interest rates, short term rates (Bernanke and Blinder, 1992) and more usually term spreads (Harvey, 1988, Stock and Watson, 1989 and Davis and Fagan, 1997) are efficient indicators which succeed in forecasting output growth. However, Haubrich and Dombrosky (1996) found that these asset prices have no predictive ability for the U.S. output growth. Moreover, Fama (1990), Barro (1990), Lee (1992), Estrella and Mishkin (1998), Hassapis and Kalyvitis (2002), Hassapis (2003) argued that stock market returns are basic and effective indicators of output growth and enhance output forecasts.

In the majority of studies in the literature, univariate, bivariate and multivariate autoregressive models are constructed for generating multi-period forecasts for the real economic activity. These alternative AR models implement either the iterated forecasting method or the direct one. There are several studies that compare these two forecasting methods. We take as our starting point the paper of Marcellino, Stock and Watson (2006). They employ 170 major U.S. macroeconomic variables estimated in autoregressive form by using AR and VAR models. The dataset includes monthly time series over the period of 1959:1 to 2002:12 and most of them were able to improve the forecasting performance of output growth. Their study compares iterated and direct forecasts by means of the MSFE measure and discusses which of the two multi-period forecasting methods leads to smaller forecast errors. Univariate, bivariate and multivariate autoregressive equations with fixed lag order (k) are considered using the Akaike Information Criterion (AIC) or, alternatively, the Bayes Information Criterion (BIC). Multi-period forecasts are estimated for horizons of 3, 6, 12, and 24 months by using the two methods. As a result, the authors find that iterated forecasts tend to have smaller Mean Squared Forecasting Errors (MSFE) than direct forecasts in the case of AIC. One additional result of this study is the fact that the forecasting performance, using the direct method, gets worse rapidly as the forecast horizon increases.

Furthermore, Ghysels, Rubia and Valkanov (2009) have conducted a battery of (pseudo) out-of sample multi-period forecasts by using both the iterated and direct methods.[1] Their study involves daily returns of the U.S. stock market portfolio from 1963:6 to 2007:12. The main goal of this study is to forecast the volatilities of 21 portfolio returns (market plus 20 portfolios), at various forecast horizons, with these two approaches. Furthermore, they implement the consistent loss function of MSFE, to assess the accuracy of volatility forecasts. Comparisons between these approaches lead to two main inferences: i) direct forecasts tend to dominate iterated forecasts only if model misspecification exists. In this case, the direct method is more robust to bias than the iterated method, ii) the iterated model tends to dominate only if it is unbiased and estimation efficiency is assumed.

[1] Ghysels, Rubia and Valkanov (2009) have also employed the Mixed Data Sampling (MIDAS) approach which is used for the cases where the frequency of the data differs.

Moreover, Chow and Choy (2008) focus on the use of a dynamic factor model in which they implement macroeconomic variables (real GDP, asset prices, interest rates) of a small open economy, namely Singapore. In addition, quarterly data spanning the period of 1993:1 to 2006:4 are used as indicators to forecast Singapore's economic cycles. Different models are estimated for each forecasting method (iterated and direct). In the case of the latter forecasting method, an augmented vector autoregressive model (FAVAR) is estimated for forecasting output growth. On the other hand, a univariate autoregressive model (AR) and vector autoregressive models (VAR) are used for the direct forecasting procedure. The general result of Chow-Choy's (2008) study: iterative forecasts from the FAVAR model have more efficient predictive ability than the direct forecasts from simple AR and VAR autoregressive models. By using the iterative method, the model becomes more robust to misspesification.

On the other hand, Chevillon (2005) presents a literature review which includes papers of some exceptional researchers. The main task of these papers is, generally, the multi-step forecasting process, using either the direct or the iterated method. Moreover, this study reports the main results of the literature. Particularly, the author analyzes the forecast errors and seeks which of the two above-mentioned forecasting methods is more effective in terms of forecasting accuracy.

Johnston, Klein, and Shinjo (1974) analyze and compare one-step ahead and multi-step ahead forecasting techniques -by comparing their asymptotic properties- for AR(1) models. Their results indicate that the iterated method is more efficient than the direct counterpart and only if one of the four assumptions below exists, direct method is significant and well-fitted in the data and model. These assumptions are the following: i) model misspecification ii) different models used for iterated and direct methods iii) small samples.

On the other hand, Stoica and Nehorai (1989) stress the significance of model misspecification, using the direct forecasting method instead of the iterated method, and they fail to specify the relationship between model parameters and their powered-up multi-step counterparts. Using a sample of 200 observations and performing a Monte Carlo experiment, they find that when an ARMA (2,2) model is proxied by an AR(1) model the direct forecasts are more accurate than the iterated ones. This result is justified from the fact that under-parameterization may benefit the direct method.

Madrikakis (1982), Weis and Andersen (1984) use ARIMA (p,d,q) models to generate forecasts using either the iterated or the direct method. They argue that the accuracy of the forecasting procedure depends on the loss function (MSFE).

Ericsson and Marquez (1998) generate forecasts of various horizons using the two methods (direct and iterated). They observe that any interdependence between the estimation and forecasting procedure leads to a forecast error taxonomy. Clements and Hendry (1998), based on this result, assess the advantages of multi-step estimation. Hence, the authors show how direct multi-step estimation is beneficial for forecasting when model misspecification exists.

As a general result of Chevillon's (2005) paper, benefits from using iterated or direct approach change over time and depend on the forecasting horizon and the stochastic properties of the data. It was shown that the direct forecasting technique can asymptotically outweigh the iterated one. When the model is misspecified, the sample is finite and non-stationarity exists, the direct forecasting method may be the most suitable in order to approximate the actual values of models' variables.

Furthermore, McElroy (2010) focus his research on investigating the conditions that make the two competing forecasting methods identical. McElroy (2010), using ARIMA models find that both methods are identical when semi-infinite information set is utilized. In the case of finite past, the direct and iterated forecast methods are not identical. Generally, it has been shown that differences between the two methods come from three reasons: i) different models being used ii) different fitting methods being used and iii) different forecasting functions being used.

Cox (1961) and Klein (1968) have a prominent role in theoretical and empirical studies of this literature. The former author suggested that exponential smoothing models may be more accurate in forecasting if the exponential smoothing parameter is chosen as a function of the forecast horizon by using autoregressive models. After a few years, the latter author suggested direct multi-period estimation of dynamic forecasting models via minimizing the sum of squares of multi-period forecast errors. In contrast to other studies, both Cox (1961) and Klein (1968) inferred that direct forecasts are more efficient than iterated counterparts.

In addition to Cox (1961) and Klein (1968), Shibata (1980), Findley (1983, 1985), and Bhansali (1996, 1997, and 1999) find similar results and mention that a covariance stationary process is not degenerate to a finite lag order. Particularly, Findley (1983, 1985) claims that the multi-period ahead forecasts, generated from a separate multi-period forecasting model for each horizon, can improve forecasting ability by using the Root Mean Squared Error (RMSE) measure and the multi-period forecasts generated from iterated forecasting method can significantly enhance forecasting accuracy by using the loss function of Mean Absolute Error (MAE). These results were drawn by employing univariate models in two of Box's and Jenkin's time series variables (chemical process temperature and sunspots).

Furthermore, Bhansali (1997) observed that when a stochastic (autoregressive) process is unknown, the direct method produces asymptotically efficient forecasts whereas the iterated or the alternatively "plugged in" method does not. However, Bhansali (1999a) argues that if an autoregressive process has finite and known order (k), estimations and forecasts of parameters are asymptotically inefficient by using the direct approach. However, only the iterated method is advisable. As a general comment, Bhansali (1999) emphasized that multi-period ahead forecasting accuracy depends on the method of model selection and parameter estimation.

Ang, Piazzesi, and Wei (2005) compare the iterated and direct forecasting methods regarding the U.S. GDP growth using interest rates and term spreads as predictors. They use quarterly data spanning the period of 1952:2 to 2001:4 fitted in a VAR model. Yield curves include parameters and variables which follow this VAR model. Thus, they find that the yield-curve model has better forecasting out-of-sample results than the unrestricted OLS regressions. Hence, the one-step ahead process (yield curve) is more precise on forecasting performance than the direct approach (OLS regression).

Stock and Watson (2004) focus on the predictive content, ability and power that asset prices (house price index, interest rates, term premia, dividend price index, prices of gold and silver) may add to the real economic activity. The research was based on measurements and predictions which were made for the output growth of 7 OECD countries (Canada, France, Germany, Italy, Japan, the UK and the US). Data were obtained in quarterly form and covered the period from 1959:1 to 1999:4. One univariate AR model was used as a benchmark model and many bivariate VAR models were estimated for each country. Therefore, these VAR forecasting models produced recursively forecasts based on individual predictors. The comparison between the VAR models and the benchmark AR model –via the MFSE measure - leads to the essential result that asset prices, as indicators of output growth, have little predictive content in economic activity at 2, 4 and 8 quarter forecast horizon.

Moreover, Jiranyakul (2013) attempts to investigate the ability of stock market return to predict industrial production growth or real activity in Thailand which is an emerging market economy. Using monthly data from January 1993 to December 2011, Jiranyakul (2013) find that the AR model augmented with stock market return outperforms the single benchmark AR model in the forecast horizon of two months. Thus, the results seem to support the notion that stock market return is an efficient predictor of industrial output growth in the short run. As he argues, a change in stock market return is a signal for revising investment decisions by investors and portfolio managers.

Flavin, Panopoulou and Pantelidis (2008) have a useful contribution in this strand of literature as well. Using monthly data spanning the period from January 1995 to April 2006, they focus on forecasting output growth of the EU countries (EU12, EU15, EU25). More specifically, they compare different forecasting autoregressive models (single univariate benchmark model and nested-alternative AR models) either in country specific level or in aggregate level, in order to find which of the employed economic and financial indicators add predictive content to the estimation of output growth. They test if there is statistical evidence of superiority of the augmented model over the benchmark model. They find that none of the economic and financial variables (stock market returns, interest rates, money supply and exchange rates) improves the forecasting accuracy while forecasts of individual country specific models outperform those of the aggregated variables. They also find that adding stock market returns to the single benchmark model improves the forecast accuracy of output growth for the EU12 and EU15 aggregates at all time horizons. Likewise to Jiranyakul's (2013) study, they pint point how important indicator is the stock market return for output growth forecasts.

Finally, Kang (2003) reports puzzling outcomes in his study. Particularly, he uses univariate autoregressive models of nine U.S. economic time series and the results of predictions which took place at long horizon were proved ambiguous due to the fact that the direct method may or may not have improved their models' forecasting accuracy.

3. METHODOLOGY

We now briefly analyze the theoretical framework for our empirical analysis. Particularly, we use univariate and bivariate AutoRegressive (AR) models. In addition, several out-of-sample forecasts of U.S. output growth are generated in our study using either the single benchmark AR model or AR models augmented by individual economic and financial variables. In other words, our out-of-sample forecasting exercise is organized so that our benchmark AR model is always nested within the other estimated augmented models. These out-of-sample forecasts are recursively estimated using either the one-step ahead forecasting model or the multi-step ahead counterpart.

Furthermore, after estimating the autoregressive forecasting models, we compare their predictive power. Comparing different pairs of models each time, different results emerged. Our main outcomes can be summarized as follows. Firstly, comparisons between single multi-step forecasting AR model and each augmented benchmark AR model take place. Results of this comparison help us decide which of the individual candidate predictors improve the forecasts for the U.S. output growth. Secondly, we compare the single direct benchmark AR model with the one-step (iterated) benchmark counterpart. This kind of comparison helps us show which of the two forecasting methods (iterated or direct approach) achieves better results in forecasting the U.S. output growth rate.

This part of research is separated into sub-sections so that the structure of the empirical analysis is more easily understandable. So, in Sub-section 3.1, we examine the predictive power of different output growth indicators. Sub-section 3.2 briefly summarizes and compares the two forecasting methods. The last Sub-section 3.3 includes the general MSFE equation which is the basic tool for evaluating the predictive accuracy of each autoregressive model.

3.1. EVALUATION OF THE PREDICTIVE POWER OF CANDIDATE PREDICTORS

As we have already said in the introduction, the purposes of the present study are mainly two. Initially, our first goal is to examine whether a number of candidate economic or financial variables can help us predict the U.S. output growth. In other words, we investigate the existence of reasonable correlations between candidate predictors and GDP growth rate. We do this based on the following procedure. We first specify the equation of the general model of our methodology given as follows:

$$Y_{t+h} = c + a(L)Y_t + B(L)Z_t + u_{t+h} \quad (1)$$

where Y_{t+h} represents the h-step forecast of output growth (GDP) using information up to time t, c is a constant term, a(L) is a scalar lag polynomial of dependent variable used as a determinant, $B(L)$ is a vector of lag polynomial, Z_t is a vector of financial and economic variables as predictors and u_{t+h} is the pseudo out-of-sample multi-period forecast error of the regression.

The process we follow is as follows: When $B(L)$ is equal to zero, the model in equation (1) becomes the simple autoregressive (AR) model which can be used as a benchmark. So, by setting $B(L)=0$, we initially estimate the simple benchmark AR model. Afterwards, we augment this model by lags of a candidate predictor as in equation (1) $(B(L)\neq 0)$. To make it easy, let's assume a simple form of two variables. The model in equation (1) is specified as the following equation:

$$Y_{t+h}=c+\sum_{i=0}^{p-1}a_iY_{t-i}+\sum_{j=0}^{q-1}b_jR_{t-j}+u_{t+h}\quad(2)$$

where Y is the output growth and R is a candidate economic or financial predictor. The optimal lags of output growth and the candidate predictor are p and q. However, we can add more than one candidate predictors in equation (2) without changing its econometric form. When this case exists, R denotes a group of economic and financial variables. It is important to say that before entering both explanatory and dependent variables in the model, we should test them for stationarity either in levels or in first differences. Nevertheless, the benchmark AR (p) model is specified by the following equation:

$$Y_{t+h}=c+\sum_{i=0}^{p-1}a_iY_{t-i}+u_{t+h}\quad(3)$$

Both equations (2) and (3) are estimated recursively until the out-of-sample observations are exhausted. The model in equation (2) is tested against the model in equation (3) by comparing their MSFEs. Equations (2) and (3) are nested models. The order q in equation (2) is the number of parameters that exceeds the parameters of the benchmark model of equation (3). Taking the expected values of both equations (2) and (3) we can compare their forecasts $(\hat{Y}_{t+h})$ with the actual values (Y_{t+h}). Thus, we are able to define the out-of-sample forecast error $(\hat{u}_{t+h})$ as follows:

$$\hat{u}_{t+h} = Y_{t+h} - \hat{Y}_{t+h} \quad (4)$$

Estimations of equations (2) and (3) are obtained for multi-period horizon. Specifically, our forecasting horizon (h) ranges between 1 to 4 quarters. After making all the estimations, we obtain useful results about whether each candidate explanatory variable is an efficient predictor of U.S. output growth.

As we said above, the MSFE function is the basic tool for making model comparisons. Thus, the forecasting accuracy of each nested AR model is evaluated by estimating the ratio of the MSFE of the benchmark to the MSFE of the augmented model. Needless to say, a ratio greater than one means that the MSFE of the augmented AR model is less than this of the benchmark. Thus, the candidate predictor improves the predictive power of the benchmark.

3.2. DIRECT VS ITERATED METHOD

As mentioned above, our second goal is to compare the direct forecasts with the iterated ones. We should test the superiority of both forecasting approaches through comparing their MSFE values. We examine which of the aforementioned forecasting methods outweighs the other and achieves better results in forecasting the U.S. output growth rate.

The direct forecasting approach is based on equation (3). Contrary to the direct forecasting approach, the iterated forecasting method is a more complicated forecasting procedure, based on step-by-step estimation from which multi-step forecasts are obtained. In this case, the structure of one-period ahead AR model is the same as in the direct approach (see equation (3)). The main discrepancy between the two approaches is the way we obtain the forecasts. The iterated approach is based on the following model:

$$Y_{t+1}^{I} = d + b(L)Y_t + u_{t+1}^{I} (5)$$

or alternatively,

$$Y_{t+1}^{I} = d + \sum_{i=0}^{p-1} b_i Y_{t-i} + u_{t+1}^{I} (6)$$

where $Y^{I}{}_{t+1}$, d, $b(L)$, $u^{I}{}_{t+1}$ represent the one-step forecast of output growth (GDP) using information up to time t, the constant term, the scalar lag polynomial of Y_t and the out-of-sample forecast error respectively.

Based on model (5), we can describe the iterated process by making iterated estimations of output growth Y_t^{I}. To simplify the procedure and to be more understandable, let's assume a simple AR (1) model as follows:

$$Y_{t+1}^{I} = d + b_0 Y_t + u_{t+1}^{I} (7)$$

Assuming length horizon h>1 and taking expectations of equation (7), we generate the first forecast as follows:

$$\hat{Y}_{t+1}^{I} = \hat{d} + \hat{b}_0 \hat{Y}_t (7.1)$$

Equation (7.1) is estimated by using in-sample observations of Y (GDP). Based on this equation (7.1), we are able to generate the second forecast $\hat{Y}_{t+2}^{I}$:

$$\hat{Y}_{t+2}^{I} = \hat{d} + \hat{b}_0 \hat{Y}_{t+1} (7.2)$$

Based on equation (7.2) we generate the third forecasting estimation $\hat{Y}_{t+3}^{I}$ and so on. This forecasting procedure is continued until the length horizon is exhausted given h>1. Thus, in the final forecasting estimation we have:

$$\hat{Y}_{t+h}^{I} = \hat{d} + \hat{b}_0 \hat{Y}_{t+h-1} (7.3)$$

This forecasting procedure recurs recursively in each length horizon computing the MSFE of the estimated model. Looking the above equations (7-7.3), we can define the out-of-sample forecast error (u^I_{t+h}) as the difference between the actual value (Y_{t+h}) of the fitted variable minus the out-of-sample forecast ($\hat{Y}^I_{t+h}$) of it. In particular, the out-of-sample forecast error term is expressed as:

$$\hat{u}^I_{t+h} = Y_{t+h} - \hat{Y}^I_{t+h} \quad (8)$$

Thus, we observe that if the forecast error is equal to zero then the forecasting estimation of the dependent model variable coincides with the actual value.

In general, for each forecast horizon h>1, the evaluation of each forecasting method is conducted by means of the MSFE function.

After estimating the above benchmark AR model using the iterated approach, results of this method ought to be compared with those of the direct method.

At this point of the study, we may compare the two foresaid forecasting approaches. When it comes to which approach is more efficient and suitable for making multi-step forecasts, asymptotic theory and some empirical studies argue that the selection between iterated and direct forecasts depends on a tradeoff between bias and estimation variance. Marcellino, Stock and Watson (2006) argue that:

- The iterated procedure generates more efficient parameter estimates than the direct method when the one-step ahead model is well specified; otherwise it is prone to bias. Thus, when the model is mis-specified, direct forecasts have better forecasting performance and are more accurate than the iterated ones.
- If both direct and iterated autoregressive models have finite order, particularly k lags but the true lag order exceeds k, the asymptotic MSFE of direct method is less than the MSFE of the iterated method under the assumption of ignoring estimation uncertainty.
- If the true lag order is k or less then the corresponding MSFEs between the two forecasting approaches are equal if we ignore the estimation uncertainty.

- The MSFE, taking into account estimation uncertainty, is less for the iterated method when the lag order is correctly specified.
- Generally, the theoretical literature argues that the robustness of the direct forecasts to model misspecification makes it a more appealing process than the bias-prone iterated forecasts.

In general, we observe discrepancies between asymptotic theory and empirical results. However, it is still controversial which of the two, direct or iterated forecasting method outweighs in efficiency and accuracy. Many researchers argue that the approach which performs better is an empirical issue.

3.3. ESTIMATION OF MSFE

Let P_1 denote the date at which the first out-of-sample forecast is made and P_2 denote the date at which the final pseudo out-of-sample forecast is made. Then we are able to express the sample MSFE[2] equation as follows:

$$MSFE = \frac{1}{P_2 - P_1 + 1} \sum_{t=P_1}^{P_2} \hat{u}_{t+h}^2 (9)$$

where u_{t+h}^2 represents the square of the out-of-sample forecast error. Moreover, the sample MSFE is estimated for model, for each forecasting approach (direct or iterated method) and for each forecasting horizon (1 to 4 quarters ahead).

[2] Computations of MSFE were carried out using a code written in Eviews program.

4. EMPIRICAL RESULTS

This section is the most essential part of the whole study. We present and discuss our main results of the employed techniques and forecasting methods. These help us find the empirical forecasting relationship between output growth and economic-financial variables in case of the U.S. They also help us examine which of the two forecasting methods (direct or iterated) implemented in simple AR models provides superior forecasting accuracy.

4.1. DATA

The main aim of this study is to make out-of-sample forecasts on the U.S. output growth employing direct and iterated forecasting methods. To measure the output growth, we use the U.S. GDP index as a proxy of its economic development. However, many authors usually approximate the concept of output growth by using other relevant variables such as the industrial production (Marcellino, Stock and Watson (2006)).

It is noticeable that the economic and financial variables which used in this study as leading predictors of U.S. output, are categorized into five main groups: i) stock market returns ii) commodity prices-indices iii) asset prices, iv) monetary aggregates, and v) other macroeconomic variables. Particularly, the first category includes data from the S&P 500 composite index which constitutes the second largest capitalization index in the U.S. financial markets. Moreover, gold prices and the agriculture index belong to the second category. The third category consists of exchange rates (trade weighted U.S. dollar exchange rate) and the fourth category includes the M1 monetary stock supply. The last general category includes the Consumer Price Index (CPI). Some of the variables used in the models are seasonally adjusted.

Moreover, we use quarterly data spanning from 1973:Q1 to 2013:Q4. The reason why we use time series data until the last quarter of 2013 is that some candidate explanatory variables are not available for 2014. The data sources are three: The Federal Reserve Economic Data of St. Louis Fed (FRED), the Quandl database and the Yahoo Finance (see Data Appendix).

Before estimating the autoregressive model, the time series undertake some transformations and modifications. Initially we transform all explanatory and dependent variables of the model into the logarithmic form in order to downsize their scales and variances. Then, the data are tested for stationarity using three Unit Root tests namely as Augmented Dickey-Fuller (ADF) test, the Phillips-Perron test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test which are available in Eviews. When we test the stationarity of variables using the above Unit Root tests, we use both an intercept and a trend in the specification. The aforementioned economic and financial variables are integrated of order one, I(1), according to unit root tests employed (see Tables 3 and 4). Thus, the first differences of time series which represent the returns of the variables are stationary and the Ordinary Least Squared (OLS) method can be used for estimating our models.

Furthermore, descriptive statistics of our economic and financial variables (see Data Appendix-Table 2) such as mean, median, standard deviation, skewness, kurtosis and the J-B normality test help us conduct a more constructive analysis of the empirical results which are reported in the next sections of the study. Particularly, looking at Table 2, we observe that all first differences of time series (Δlog), except for these of trade weighted U.S. dollar index, are not normally distributed according to the Jarque-Bera test results. Moreover, skewness is a measure of symmetry. The majority of first differences of time series (apart from these of S&P 500 and the agriculture indices) have positive skewness following an asymmetrical distribution with a long tail to the right. Results of kurtosis show that only trade weighted U.S. dollar variable follows the normal distribution as its kurtosis approximates 3. The remaining variables tend to follow a leptokurtic distribution because they have kurtosis higher than three.

4.2. RECURSIVE SCHEME

In this study all (pseudo) out-of sample forecasts are generated recursively. To be more specific, before initiating the recursive process, the sample is splitted into two parts. The first one, with R observations, represents the in-sample observations used for the estimation of the models whilst the second one, with P observations, includes the observations used for the out-of-sample forecast exercise. Adding these two parts of our sample, the total number of observations (T) is produced (T=R+P). So, the recursive scheme generates the first forecast based on a model estimated by using R observations. Afterwards, the model is re-estimated using the R+1 observations and the second one-step ahead forecast is generated. The last one-step ahead forecast is produced based on a model estimated by using R+P-1 observations. This procedure is repeated until the sample observations are exhausted. Moreover, the start of the estimation period is fixed whereas the end of the in-sample period expands to include all the available information. Thus, in each step the estimation sample increases by one observation. This process is known as expanding window forecasting.

4.3. ECONOMETRIC MODELS AND FORECASTING EVALUATION

As we have already said in Sub-section 4.2, our out-of-sample forecasting methodology and procedure are based on the recursive scheme. Initially, the data are divided into two periods: the data for the in-sample and the out-of-sample periods. The in-sample period (R) spans from the initial observation 1973:Q1 to 1999:Q4 (108 observations). The out-of-sample (P) covers the rest of our sample, i.e. 2000:Q1 to 2013:Q4 (56 observations). The ratio of out-of-sample observations over the in-sample observations is approximately equal to 0.52. Both direct and iterated forecasts are generated for horizon 1 to 4 quarters and MSFEs are calculated in each case. However, we have to organize and classify our forecasting models as follows:

Direct forecasting models

- Model (2): General augmented AR model.
    - Model (2a): AR benchmark model + stock market returns (S&P500).
    - Model (2b): AR benchmark model + gold prices.
    - Model (2c): AR benchmark model + exchange rate (trade weighted U.S. dollar).
    - Model (2d): AR benchmark model + monetary aggregate stock (M1).
    - Model (2e): AR benchmark model + agriculture index.
    - Model (2f): AR benchmark + consumer price index (CPI)
- Model (3) is referred as the multi-step benchmark AR model.

Iterated forecasting models

- Model (6) is referred as the one-step benchmark AR model.

In the following step, we discuss and compare our final results from the above forecasting models. Particularly, in the next Sub-section 4.4 we compare each model's results (Models 2a-2f) with those of the initial benchmark AR Model (3). In this way, we test the predictive role of different indicators on the real U.S. economic activity. In Sub-section 4.5 we compare the empirical results from Model (2) and Model (3) for all forecast horizons. In this way, we compare the direct and iterated approaches.

4.4. OUTPUT GROWTH FORECASTS: THE PREDICTIVE ROLE OF CANDIDATE INDICATORS ON THE U.S. ECONOMIC ACTIVITY.

In this sub-section, we analyze the empirical results regarding the single multi-step autoregressive (AR) model and the augmented benchmark AR models. All forecasting models have the same number of lags (maximum lag length 12) and the forecasts are based on the same method of lag selection (Schwartz Information Criterion), for different forecast horizons. We compare model (3) with each alternative model (2a-2f). Results for all forecast horizons are reported in Table 5. Table 5 tabulates the ratios of the MSFE of the AR benchmark to that of the alternative models for all forecast horizons. Thus, we test if there is statistical evidence of alternative model superiority over the benchmark. A ratio greater than 1 suggests that the MSFE of the alternative model is lower than the MSFE of the benchmark model. In this case, the individual economic or financial variable improves the forecast accuracy of future U.S. output growth. Looking across Table 5, gold price has nothing to add to the benchmark AR model at all forecast horizons (h). Indeed, as the forecast horizon increases, the benchmark model becomes more desirable because it has lower MSFE than the augmented model. Moreover, the relative ratio of the MSFE of the benchmark model to the MSFE of the benchmark augmented with the stock market returns (S&P 500 index) marginally exceeds 1 for h=1, 2 and 3 quarters. This means that the S&P 500 index makes a slight forecasting improvement over the benchmark model at these forecast horizons. However, the ratio for h=4 is equal to 0.992 which is smaller than one. In other words, this variable has no predictive value over the benchmark model for h=4.

According to Table 5, the exchange rate (trade weighted U.S. dollar) tends to enhance the forecasting ability of the benchmark model only for h=2. A slight increase in benchmark's model forecasting power exists as the relative MSFE ratio is equal to 1.008. For forecast horizons h=1, h=3 and h=4, the variable of exchange rate does not add any predictive content to the estimation of U.S. GDP growth rate since the benchmark model has lower MSFE than the alternative model. Furthermore, we observe that the alternative model which includes the agriculture index produces lower MSFE only for h=3 quarters. For the other forecast horizons, the agriculture index is an inefficient predictor of U.S. output growth as the relative MSFE ratio is smaller than one. Contrary to many studies (Marcellino, Stock and Watson (2006)), our results indicate that the M1 monetary money stock variable is not an efficient predictor of U.S. output growth for the forecast horizons of 1,2 and 3 quarters. However, the M1 aggregate variable offers little forecasting improvements over the benchmark model at forecast horizon h=4. The relative MSFE ratio marginally exceeds one (1.019) and the alternative model is more suitable for accurate forecasts than the benchmark. In addition to the previous results, the last candidate predictor, Consumer Price Index (CPI) improves the forecasting performance of the benchmark model at short forecast horizons (1 and 2 quarters). As the forecast horizon increases (h=3 to 4), CPI becomes an inefficient predictor of U.S. output growth.

Generally, five out of six variables are proved inefficient predictors of U.S. output growth at least for three forecast horizons. Only the stock market index improves the forecast accuracy of future U.S output growth for h=1, 2 and 3 quarters. In general, the benchmark model outperforms the alternative models for most forecast horizons.

4.5. OUTPUT GROWTH FORECASTS: DIRECT VS. ITERATED BENCHMARKS

This sub-section analyzes and compares the empirical results of direct univariate model (3) against the iterated benchmark AR model (6). Particularly, Table 6 (see Tables in Empirical Results) summarizes the ratios of the MSFE of the direct forecast to the MSFE of the iterated forecast where the forecasts are based on the same method of lag selection (Schwartz Information Criterion), for different forecast horizons (1 to 4 quarters). We set the maximum lag order (p) in both cases equal to 12 lags.

Table 6 reveals the superiority of the direct method over the iterated approach at all forecast horizons except for the case of h=1. Needless to say, when h=1 the MSFE of direct forecast is equal to the MSFE of iterated forecast. For h>1, the direct method outperforms the iterated method because the former has smaller MSFE than the latter. The relative MSFE ratio is smaller than 1 at h=2 to 4. Indeed, the iterated forecasts can be markedly worse than the direct forecasts as the forecast horizon increases. The direct forecasts are more robust and accurate than the iterated forecasts.

5. CONCLUSIONS

We compare various forecasting models for the U.S. output growth rate. We have two main goals. Initially, we focus on a range of nested models using a simple AR model as our benchmark. We augment this with a battery of economic and financial variables and we test if they improve the forecast accuracy of the benchmark. Our second goal is to examine which of the two forecasting methods, direct or iterated, generates better forecasts for the U.S. GDP growth rate.

We find that none of the individual economic and financial variables systematically outperforms the benchmark. Indeed, most variables manage to improve forecast accuracy for some forecast horizons. Moreover, their performance is not robust to the forecast horizons. In most cases, the benchmark model is preferred to its alternative models.

Furthermore, regarding to our second goal, we find that the direct forecasting approach is more suitable and efficient for making accurate forecasts for the U.S. GDP growth than the iterated method at all time horizons (h=2 to 4). However, it is obvious that when the forecast horizon is equal to one, direct forecasts are equivalent to the iterated forecasts.

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DATA APPENDIX (Tables1-4)

This appendix lists the time series used in the empirical analysis. The series were downloaded from three economic sources i.e. Federal Reserve Economic Database, Yahoo Finance, and the Quandl database. All series are used in logarithms. We observe that all economic and financial variables are stationary in first differences. Moreover, the following abbreviations appear in the data descriptions: SA=seasonally adjusted; NSA=not seasonally adjusted. Thus, the data sources and the descriptive statistics of economic and financial variables which were used in this study are listed in Table 1 and Table 2 respectively. The unit root tests in levels and in first differences are listed in Tables 3 and 4 respectively.

Table 1: Data Sources

Source Name	General Category	Variables	Series	Transformation	Available Data
Federal Reserve Economic Data (FRED)	Output Growth	Gross Domestic Product (GDP) (SA)	GDP	Δlog	1973:Q1-2013:Q4
Federal Reserve Economic Data (FRED)	Asset Prices (Exchange Rates)	Trade Weighted U.S. Dollar Index: Major Currencies (NSA)	TRWUSD	Δlog	1973:Q1-2013:Q4
Federal Reserve Economic Data (FRED)	Monetary Aggregates	M1 money supply (NSA)	M1	Δlog	1973:Q1-2013:Q4
Yahoo Finance	Stock Market Returns	S&P 500 Stock Market Index (NSA)	S&P500	Δlog	1973:Q1-2013:Q4
Federal Reserve Economic Data (FRED)	Commodity Prices	Gold Prices (NSA)	GOLD	Δlog	1973:Q1-2013:Q4
Quandl Database	Commodity Index	Agriculture Index (NSA)	AGRIN	Δlog	1973:Q1-2013:Q4
Federal Reserve Economic Data (FRED)	Macroeconomic variables	Consumer Price Index (CPI) (SA)	CPI	Δlog	1973:Q1-2013:Q4

Table 2: Descriptive Statistics in first differences

Variables	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B*
ΔlogGDP	0.015	0.014	0.056	-0.020	0.010	0.511	6.168	75.246
ΔlogGOLD	0.017	0.003	0.437	-0.194	0.089	1.436	7.738	208.480
ΔlogS&P500	0.017	0.024	0.195	-0.303	0.085	-0.876	4.440	34.929
ΔlogTRWUSD	-0.002	0.001	0.106	-0.065	0.029	0.133	3.123	0.582
ΔlogAGRIN	0.006	0.004	0.239	-0.248	0.065	-0.146	5.541	44.438
ΔlogM1	0.014	0.013	0.077	-0.018	0.014	0.800	5.166	49.220
ΔlogCPI	0.010	0.008	0.039	-0.022	0.008	0.749	5.312	51.537

Note: *J-B denotes the Jarque-Bera normality test with the null hypothesis that the data are normally distributed.

Table 3: Unit Root Tests in levels

Variables	Aug. Dickey-Fuller* t-stat(p-value)	KPSS** LM-stat	Phillips-Perron* t-stat(p-value)
logGDP	-1.466(0.837)	0.364	-1.460(0.839)
logGOLD	-1.892(0.654)	0.184	-2.372(0.393)
logS&P500	-2.128(0.526)	0.235	-2.242(0.463)
logTRWUSD	-2.572(0.294)	0.101	-2.246(0.461)
logAGRIN	-2.258(0.454)	0.210	-2.370(0.394)
logM1	-1.797(0.702)	0.288	-1.499(0.826)
logCPI	-3.013(0.132)	0.352	-3.113(0.107)

Notes: * Augmented Dickey-Fuller test and Phillips-Perron test denote the null hypothesis that the time series has unit roots.

** KPSS test examines the null hypothesis that the time series is stationary. (Critical values:1% level:0.216, 5% level:0.146, 10% level:0.119)

Table 4: Unit Root Tests in first differences

Variables	Aug. Dickey-Fuller* t-stat(p-value)	KPSS** LM-stat	Phillips-Perron* t-stat(p-value)
ΔlogGDP	-9.274(0.000)	0.072	-9.423(0.000)
ΔlogGOLD	-10.709(0.000)	0.133	-10.942(0.000)
ΔlogS&P500	-11.543(0.000)	0.099	-11.509(0.000)
ΔlogTRWUSD	-9.073(0.000)	0.049	-9.032(0.000)
ΔlogAGRIN	-11.180(0.000)	0.074	-11.150(0.000)
ΔlogM1	-4.327(0.004)	0.155	-5.767(0.000)
ΔlogCPI	-6.267(0.000)	0.168	-6.209(0.000)

Notes: * Aug. Dickey-Fuller test and Phillips-Perron test denote the null hypothesis that the time series has unit roots.
** KPSS test examines the null hypothesis that the time series is stationary. (Critical values:1% level:0.216, 5% level:0.146, 10% level:0.119).

EMPIRICAL RESULTS (Tables 5-6)

Table 5: Relative MSFE ratios of benchmark AR vs. Augmented benchmark AR

	Forecast Horizon (quarters)			
Predictors	**h=1**	**h=2**	**h=3**	**h=4**
ΔlogGOLD	0.984	0.985	0.946	0.868
ΔlogS&P500	1.057	1.075	1.047	0.992
ΔlogTRWUSD	0.989	1.008	0.991	0.978
ΔlogAGRIN	0.975	0.939	1.034	0.987
ΔlogM1	0.926	0.960	0.984	1.019
ΔlogCPI	1.030	1.002	0.992	0.955

Note: MSFE ratio is the ratio of the MSFE of Model (3) over the MSFE of Models (2a-2f).

Table 6: Relative MSFE ratios of direct over iterated univariate forecasts

	Forecast Horizon (quarters)			
	h=1	**h=2**	**h=3**	**h=4**
MSFE Ratio	1.000	0.791	0.851	0.796

Note: MSFE ratio is the ratio of the MSFE of Model (3) over the MSFE of Model (6).