Forecasting Using Different VAR models with different Economic Indicators

Niveen Ali Mohammed Elmor*

*Assistant Lecturer at Statistics, Mathematics and Insurance Department
Faculty of Commerce –Port Said University

Abstract

This study addressed the problem of prediction integration. Different weighting methods are applied to different VAR models. In this study, some economic time series such as unemployment rates, economic growth rates and the general government expenditure series are used to study their effect on each other through the use of VAR , VARX and SVAR models. In this study, an evaluation of the integration between predections is presented .

Keywords :

Vector Autoregressive (VAR) – VARX – SVAR

الملخص

يتناول هذا البحث التنبؤ باستخدام اساليب مختلفه لنموذج متجه الانحدار الذاتي VAR,VARX,SVAR وذلك من خلال مؤشرات اقتصادية .وتتمثل السلاسل الزمنية الاقتصاديه في معدلات البطالة ، معدلات النمو الاقتصادي والانفاق الحكومي العام لدراسة اثر كل متغير على الاخر . ثم بعد ذلك التنبؤ للنماذج المستخدمة وتقييم التنبؤات .

Introduction

Multiple forecasts of the same variable are often available to decision makers. It can reflect differences in forecasters' subjective judgments due to differences in modeling approaches. In this case, two forecasters may well arrive at very different views depending on the maintained assumptions underlying their forecasting models, for example, constant versus time-varying parameters and linear versus non-linear forecasting models, etc. Faced with multiple forecasts of the same variable, an issue that immediately arises is how best to invest information in the individual forecasts.

Specifically, should a single dominant forecast be identified or should a combination of the underlying forecasts be used to produce a pooled summary measure? From a theoretical perspective, unless one can identify in advance a particular forecasting model that generates smaller forecast errors than its competitors (and whose forecast errors cannot be covered by other models), forecast combinations offer diversification gains that make it attractive to combine individual forecasts rather than relying on forecasts from a single model. Even if the best model could be identified at each point in time, combination may still be an attractive strategy due to diversification gains, although its success will depend on how well the combination weights can be determined. Forecast combinations have been used successfully in empirical work in such diverse areas as forecasting gross national product, currency market volatility, inflation, money supply, stock prices and meteorological data.

Research Problem

The problem of the study is that the process of integration of predictions considered a complex statistical process; therefore, the study tries use different weight method to apply the integration process to the models resulting from use of the vector autoregressive approach in different techniques. Furthermore, this study shows some economic time series such as unemployment rates, economic growth rates, and the general government expenditure series . The previously mentioned series affect one another through using VAR and SVAR models.

Objectives of the study

The main objective of this study is Forecasting Using Different VAR models with different Economic Indicators related to the Egyptian economy. This objective is divided into several sub-objectives:

1. To use the VAR method to estimate a model that can be used to measure the relationship between unemployment rates, economic growth rates , and general government expenditure.

Delimitations of the study

1- This study used three variables to apply the practical study represented in three times series (unemployment rates, economic growth rates and general government expenditure).
2- The study was limited in the applied phase on the years from 1995 to 2016 because lack of data before this period.
3- The study was limited in calculating the economic growth rate on the income criterion, which is considered the main criterion in the calculation of the rate of economic , and the study did not address the

other criteria such as health, educational and social standards because of its difficulty .

4- The study was limited to use some methods of the vector autoregressive such as : SVAR , VAR ,VARX and Simulation of VAR.

Hypothesis of the study

1. The study assumes that the VARX method is the best statistical model used.

Literatures Review

This study tries to establish a causal relationship between the nominal exchange rate and foreign direct investment in India using a time series data between 1992 and 2010. It tries to understand whether the fluctuation in the exchange rate in turn causes the change in the quantum of foreign direct investments inflows and vice-versa , which is of enormous importance in the wake of unprecedented depreciation of Indian Rupee against US dollar. Unit root test and Johenson cointegration test are used to show whether the variables under consideration exhibit stationarity and a long run association respectively (Raju &Gokhale , 2012).

The test indicates absence of any long-term association between the two variables under consideration. In this context , it appears that the data is not stationary at level and is stationary at first difference . The

Vector Autoregression (VAR) model depicts that the coefficients do not have any long run association. The results they obtained show Chi square value with probability of 0.5246 and 0.4622 respectively indicating that the variables jointly cannot influence the dependent variable. Hence, they see that there is no statistical evidence for the quantum of FDI investments into India to be dictated by the trends in nominal Exchange rate. The exchange rate fluctuation essentially does not impair the quantum of foreign direct investment. It can

be assumed that inward flow of direct investment is independent of exchange rate volatility. However, the first lag and second lag of the foreign direct investment exhibits a significant relationship between the foreign direct investments indicating that the lagged FDI could be responsible for attracting FDI in the subsequent year (Raju & Gokhale, 2012).

Artis and zhang (1990) conducted forecasts, derived from Bayesian vector autoregressive models, for the output growth, inflation and balance of payments of the G-7 countries. In constructing the models, particular attention is paid to the determination of the prior and to the choice of lag length and vector content. The forecasts derived from the models are compared with those published by the International Monetary Fund on alternative assumptions about the information set available to the forecaster. The results indicate that BVAR methods can provide a highly effective standard of comparison for forecasts produced by more traditional methods. The work reported in this paper has been directed at constructing alternative Bayesian vector autoregressive (BVAR) models for forecasting variables of interest for the leading industrial economies (Artis & zhang , 1990).

Two six-equation models were developed, differing in respect of vector content, and were set to produce ex ante forecasts for 1980-1987, using Kalman filtering techniques to update the estimation with the passage of time. Comparison of Theil statistics demonstrated the superiority of the BVAR model over univariate AR and unrestricted VAR models. However, the BVAR models must be 'tuned' correctly to achieve such results; inappropriate priors could yield less clear cut conclusions (Artis & zhang , 1990).

The forecasting performance of the BVAR models was then compared with that of the forecasts produced by the International Monetary Fund and published in the *World Economic Outlook* (WEO). These forecasts appear to be comparable in quality with the general run of economic predictions so that the relative performance of the BVAR models against the WEO can be taken to be broadly representative.

The comparisons indicate that in overall terms the BVAR models set a tough standard of comparison for forecasts produced by more traditional methods. Tuning the comparison to achieve exact equivalence in information sets is not feasible with the data available, and it is apparent that 'small' changes in the information assumption can change the ranking of the forecasts. Forecasts derived from BVAR models appear to provide an impressively high and comparatively cheap standard of comparison for international by more traditional methods (Artis & zhang , 1990).

The researchers concluded with a note concerning the sensitivity of our forecasting results to their prior. Given the close correspondence of their prior and posterior estimates of the parameters of the theoretical model, the potential sensitivity of their predictive densities to the adoption of alternative priors is nontrivial. But as the close correspondence between the posterior and likelihood quantiles depicted illustrates, the prior does not exert undo influence on the predictive densities in this case. In particular, the relatively tight prior the researchers specified over the parameters of the theoretical model induced very little shrinkage beyond that induced by the adoption of the theoretical model (Dejong et al.,2002).

They have proposed the use of a coherent statistical framework for formally bringing to bear theoretical models of dynamic macroeconomic activity in addressing empirical issues of interest to policy makers, forecasters, and practitioners interested in explaining the behavior of observed data. The framework is Bayesian for a given theoretical model ; it involves combining the likelihood function induced by the model with a prior distribution specified over the model's parameters, and using the resulting posterior distribution to address empirical questions of interest. Of interest to Dejong et al. (2002) in this application was the ability of a neoclassical business cycle model to generate accurate forecasts of the cyclical behavior of output and investment. Ability has been demonstrated in this case ; the performance of the model is comparable to that of a Bayesian VAR, a result we find to be impressive. Measurement with theory appears to have its merits.

From the previous presentation of the studies related to the subject of the study, there is a lack of studies to study all the static and dynamic approaches of the VAR models together, and therefore there is a clear lack of studies. Accordingly, the study will adopt this important research point (i.e. the static and dynamic methods of time series using the Vector Auto Regressive method).

Multivariate time series methods are widely used by empirical economists and econometricians. The methods highly contributed to refining and extending these techniques so that they are well suited for answering economic questions. Multivariate time-series analysis extends many of the ideas of univariate time-series analysis to systems of equations. The primary model in multivariate time-series analysis is the vector autoregression (VAR) a direct and natural extension of the univariate autoregression. Most results that apply to univariate time – series can be directly ported to multivariate time-series with a slight change in notation and the use of linear algebra , including (VAR analysis , cointegration and spurious regression). This chapter discusses the properties of vector time-series models , estimation and identification as well as Granger causality and Impulse Response Functions. Vector autoregressions are remarkably similar to univariate autoregressions ; too similar that the intuition behind most results carries over by simply replacing scalars with matrices and scalar operations with matrix operations.

Vector Autoregressive processes

The vector autoregression (VAR) model is one of the most successful, flexible, and easy to use models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. The VAR model has proven to be useful especially for describing the dynamic

behavior of economic and financial time series and forecasting. It often provides superior forecasts to those from univariate time series models and elaborate theory-based simultaneous equations models. Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model. Vector autoregressions (VARs) were introduced into empirical economics by Sims (1980), who demonstrated that VARs provide a flexible and tractable frame- work for analyzing economic time series. Cointegration was introduced in a series of paper by Engle and Granger (1987). These papers developed a very useful probability structure for analyzing both long run and short-run economic relations.

Since the critique of Sims (1980) in the early eighties of the last century, multivariate data analysis in the context of vector autoregressive models (henceforth: VAR) has evolved as a standard instrument in econometrics. As considering the frequent use of statistical tests in determining inter-dependencies and dynamic relationships between variables, this methodology was soon enriched by incorporating non-statistical a priori information. VAR models explain the endogenous variables solely by their own history, apart from deterministic regressors.

In contrast, structural vector autoregressive model(SVAR) allows the explicit modeling of contemporaneous interdependence between the left-hand side variables. Hence, these types of models try to bypass the shortcomings of VAR models. Just as Sims jeopardized the paradigm of multiple structural equation models laid out by the Cowles Foundation in the 1940s and 1950s, Engle and Granger (1987) endowed econometricians with a powerful tool for modeling and testing economic relationships, namely, the concept of cointegration. Nowadays these branches of research are unified in the form of

Vector Error Correction (VECM) and Structural Vector Error Correction Models (SVEC).

In addition to data description and forecasting, the VAR model is also used for structural inference and policy analysis. In structural analysis, certain assumptions about the causal structure of the data under investigation are imposed, as well as the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized.

These causal impacts are usually summarized with impulse response functions and forecast error variance decompositions.
This chapter doesn't just focus on the analysis of covariance stationary multivariate time series using VAR models, but it also studies the various dynamic multivariate forecasting models.

The fact that linear functions are relatively easy to deal with, it makes sense to begin with forecasts that are linear functions of past observations. Let us consider a univariate time series Y_t and a forecast $h = 1$ period into the future.

$$\hat{y}\,T + 1 = v + \propto_1 yT + \propto_2 yT - 1 + \cdots \ldots\ldots\ldots \quad (1)$$

The VAR system is based on empirical regularities embedded in the data. The VAR model may be viewed as a system of reduced form equations in which each of the endogenous variables is regressed on its own lagged values and the lagged values of all other variables in the system. In its basic form, a VAR consists of a set of K endogenous variables y_t= (y_{1t};……;y_{kt};… ;yk_t) for k = 1,… K. The VAR(p)-process is then defined as :

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \qquad (2)$$

Structural Vector Autoregressive Models (SVAR):

Needless to say that the major shortcoming of the VAR approach is its lack of theoretical substance. In response to this

criticism, Bernanke (1986) developed procedures ,called the structural vector autoregression (SVAR) approach ,which combines the features of the traditional structural modelling with those of the VAR methodology. The major advantage of using SVAR comes from the fact that standard VAR disturbances are generally characterized by contemporaneous correlations.

From the previous section, the definition of a VAR(p)-process, in particular the equation (2.4). A VAR(p) can be interpreted as a reduced form model. A SVAR model is its structural form and is defined as:

$$Ay_t = A_1^* y_{t-1} + \cdots + A_p^* y_{t-p} + B\varepsilon_t \qquad (3)$$

Types of SVAR depending on the imposed restrictions, three types of SVAR models can be distinguished:

***A* Model**: B is set to I_K
(Minimum number of restrictions for identification is $K(K-1)/2$).
***B* Model**: A is set to I_K
(Minimum number of restrictions to be imposed for identification is the same as for A model).
***AB* Model**: restrictions can be placed on both matrices (Minimum number of restrictions for identification is $K^2 + K(K-1)/2$).

The parameters are estimated by minimizing the negative of the concentrated log-likelihood function.

Vector Error Correction Models (VEC)

Dickey and Fuller (1979) have emphasized the necessity of analyzing the time-series properties of the variables before their relationship can be established .This is necessary in case variables in question are nonstationary **.**Then the estimated equations will yield spurious and misleading regression results. However , if the variables

in a relationship are stationary, thus it is generally true that any linear combination of these variables is said to be cointegrated .
Reconsider the VAR from:

$$y_t = A_1 y_{t-1} + \cdots A_p y_{t-p} + u_t \qquad (4)$$

Vector Autoregressive Moving-Average (VARMA)

A more flexible and perhaps more realistic class of processes is obtained by allowing an infinite VAR order. In case of , having only a finite string of time series data, the infinite VAR coefficients cannot be estimated without further assumptions. Two competing approaches have been used in practice in order to overcome this problem. In the first approach, it is assumed that the infinite number of VAR coefficients depend on finitely many parameters. Vector autoregressive moving average (VARMA) processes are introduced that may be viewed as finite parameterizations of potentially infinite order VAR processes. Operator is truncated at some finite lag and the resulting finite order VAR model is estimated , Whereby it is assumed that the truncation point depends on the time series length available for estimation. A suitable asymptotic theory for the resulting estimators is discussed both for stationary and cointegrated processes.

VAR Models with Exogenous Variables (VARX)

Consider a VAR model with exogenous variables:

$$Y_t = a_0 + A_1 y_{t-1} + \cdots A_p y_{t-p} + B_1 X_{t-1} + \cdots B_q X_{t-q} + U_t \qquad (5)$$

Where:
$Y_t \in R^k$, $X_t \in R^m$ is a vector of exogenous variables, $a_0 \in R^k$ is a vector of intercepts, the $A_j's$ are $K \times K$ coefficient matrices, the $B_i's$ are $K \times m$ coefficient matrices, and $U_t \in R_k$ is the vector of errors. This is a VARX model. The crucial condition for the correctness of this model is that:

$$E\left[U_t|\{Y_{t-j}\}_{j=1}^{\infty} \ ,\{X_{t-i}\}_{i=1}^{\infty} \ \right] = 0(\in R^k) \qquad (6)$$

With probability 1 .

Next, assuming a VAR model for X_t , it say:

$$X_t = C_0 + C_1X_{t-1} + \cdots + C_TX_{t-T} + V_t \ ,$$
$$E\left[V_t|\{Y_{t-j}\}_{j=1}^{\infty} \ ,\{X_{t-i}\}_{i=1}^{\infty} \ \right] = 0(\in R^m) \qquad (7)$$

Note that model (7) implies that Y_t does not Granger-cause, X_t which is a weak form of exogeneity.

In this study unemployment is the most important and the most serious problem facing most of the economic systems of the world and leads to negative results in the economic field. Governments are working to lower their rates and mitigation. It became a field test of the ability of the economic system to grow fast enough to provide jobs and restart idle units in the least amount of time possible.

Unemployment is a global phenomenon with economic and social effects. Developed and developing countries are working to address these, which occur in developing countries as a result of inadequate economic growth for the prosecution of population growth, and the result of the inability of domestic savings for financing the investments needed to provide jobs. Unemployment is increasing wishing to work in human resources, which are looking for job opportunities.

Unemployment occurs as a result of lower investments or landing in the course of economic activity as a result of a recession or a change in technology or changes in consumer demand or disqualification employment commensurate with changes in the labor market. Usually it produces the unemployment of the labor market imbalance of

considerations relating to the supply-side and demand.

This study aims to shed light on the effectiveness of the financial assessment of tackling unemployment. Furthermore, it aims at testing the ability of statistical models to explain the economic relationship between public spending stability (of government) and unemployment and economic growth rate.

The concept of unemployment

Unemployment is the lack of fit job opportunities thus we can know that unemployment is a lack of exercise per capita of any action either mental or intramuscular.

The concept of public spending (government)

Public spending refers to the amounts of money spent by the state. In other Words , it denotes government expenditure .

The concept of economic growth

Economic growth is concerned with the increase in the gross domestic output (GDP), or gross national income in order to achieve an increase in per capita income. Therefore , the concept of economic growth does not only mean an increase in GDP, but also must entails an increase in personal income, so the economic growth rate to be higher than the population growth rate. In the case of increasing the population growth at a higher rate, it prevents the increase in the average per capita income. Despite the increase in GDP in this dimension, but it does not achieve economic growth. Moreover, from here, there are several basic criteria for measuring economic growth: a. Income criteria , b. Social standards **,** and c. Educational standards **.**

Income criteria is considered the main indicator that the standards used to measure the degree of economic progress with the necessity of taking into account the weakness of statistical agencies

in developing countries and the difficulty of spending on items that are calculated within the GNP and the different countries with each other for the treatment of income items. Income criteria includes all of the total national income and total national income is expected.

Health standards:

As there are several criteria used to measure the progress and health, including:

1. The number of deaths per thousand of the population, the number of deaths per thousand children, the mortality rate of children under five years of age, mortality of infants (less than one year), inadequate health services, and inadequate food and malnutrition.

2. Life expectancy: the more pointed on economic growth on economic progress.
3. Number of people per doctor and number of individuals per bed hospitals.

Educational standards:

Education leads to increased knowledge and helps to acquire new skills. These things lead to increased productivity on the one hand and to rationalize spending on the other hand. It means that education increases income , investment , and savings.

This study is limited in use to the rate of economic growth on the main index and the benchmark and is the standard due to the difficulty of availability of data and other standards.

Data

This study has established on special human data rates of unemployment sourced from the monthly statistical bulletin of the Central Bank of Egypt and the time series of public spending the government source Central Agency for Public Mobilization and Statistics and the Egyptian Ministry of Finance. The study also relies on the other time series represented in the annual rates of economic growth and the source of the Egyptian Ministry of Finance.

Variables

This study is going to invistigate three basic variables are:

1. Unemployment rate:

Theoretically, it is the ratio of unemployed to the total labor force. This variable rate of unemployment emerged from a series of monthly statistical bulletin of the Central Bank of Egypt, and that of the year 1990up to 2016.

2. Public spending (government)

It is the state sector expenditures on goods and services (and is worth billions of pounds) and this standard at its source is the annual series of annual publications of the Ministry of Finance, especially the state budget. It is also used from 1990 to 2016.

3. Economic growth rate

It is on the accounts are held by certain equations from which the economic **growth rate** is calculated on each of:

- GNP rate.

- Personal income for individuals.

- Investment rates.

This variable is the time series of annual source (Ministry of Finance annual report used from 1990 to 2016) .

Descriptive Analysis of Temporal Sequences

Stationarty test (Stability test series)

Often characterized by time-series describing macroeconomic variables instability. This is because most of them change and grow over time, making it an average and variability unstable and linked in time, and it is necessary to the stability of the time series and processed test in case of instability, and to know the degree of integration. In addition, to test the stability of the time series, The researchers will rely on the Dickey Fuller tests ADF .

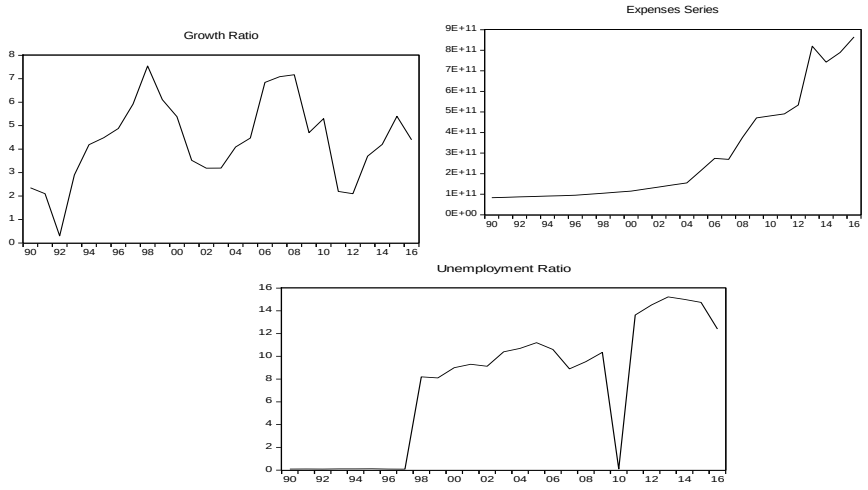

Figure (1) Descriptive analysis of temporal sequences graph

After the display the previous graphic formats temporal sequences used in the study was found initially instability of time-series cross-user time.

Outliers test

Outliers, as defined earlier, are patterns in data that do not conform to a well-defined notion of normal behavior, or conform to a well-defined notion of outlying behavior, though it is typically easier to define the normal behavior.

It has been found the lack of existence of outliers values for raw data in the Unemployment Ratio , Economic Growth Ratio and the Expenses Series from the draw shape Boxpolt of the three chains.

Dickey fuller unit root test :

We have been conducted Dicky Fuller unit root test on the three time series used in study. The results show that the three time series are not subject to stationarity property and have unit root and that is obvious from the following results :

Table (1) Dickey fuller unit root test

	Expenses Series			Growth Series			Unemployment Series		
	With constant	With trend & intercept	None	With constant	With trend & intercept	None	With constant	With trend & intercept	None
t-Statistic	1.1840	0.7983	1.6918	-4.1402	-3.9807	-0.4329	-1.9079	-3.4364	-0.6009
t-Statistic with 5%	-3.0206	-3.6584	-1.959	-2.9918	-3.6121	-1.9544	-2.9810	-3.5950	-1.9544
Prob.	0.9967	0.9994	0.9734	0.0040	0.0239	0.5168	0.3236	0.0683	0.4472

Depending on the previous results that the three time series are not subject to stationarity property, The researcher has taken the first differences for the three series and the results were like what is demonstrated on the following table.

It was obvious from displaying the second differences of Governmental Public Spending that the series has not been subjected to stationarity property, then the researchers will take the third differences for this series and the researcher will display the results in the following table.

After taking the third and the last differences for this series (Governmental Public Spending series) has been shown from the previous table results the series stability and its' subjecting to stationarity property.

Granger Causality test

The Granger causality test is a statistical hypothesis test for determining whether one time series is useful in forecasting another, first proposed in 1969 . Ordinarily , regressions reflect mere correlations , but Clive Granger argued that causality in economics could be tested for by measuring the ability to predict the future values of a time series using prior values of another time series. Since the question of true causality is deeply philosophical , and because of the post hoc ergo propter hoc fallacy of assuming that one thing preceding another can be used as a proof of causation , econometricians assert that the Granger test finds only predictive causality. Null hypothesis = Growth Ratio **not cause** Unemployment series Alternate hypothesis = Growth Ratio **cause** Unemployment Series P-Value of Growth =60% more than 5%. Therefore, this mean not reject null hypothesis and mean Growth ratio not cause Unemployment Ratio . When P-Value more than 5% this is, mean not reject null hypothesis and accept null hypothesis. Similarly, hypothesis test applies to all time series used in this study.

Optimal Lag Selection (Lag test)

There are few ways to determine the optimum lag and we use the ways Akaike Information Criterion (AIC) , Schwartz Criterion (SC) , Hannam-Quinn Criterion (HQC) and Final Prediction Error (FPE) . The study shows the results of each criterion for optimum lags. Here we can determine one of them based on the diagnostic tests' results. the lowest (AIC) and (HQ) values are chosen .The lower the values are better the model has four lags .

Estimation of VAR Models

VARX Model (1)

In this model, the public government's spending series and the unemployment series are introduced as endogenous variables of the model otherwise economic growth rate was introduced as exogenous of the model also results of this model two estimation equations for both government's spending and unemployment rate are shown as :

$$Expenses = -2.021716 * exp.(-1) - 3.408203 * exp.(-2) - 2.636960 * exp.(-3) - 1.964599 * exp.(-4) + 1.24E + 09 * unemployment(-1) + 7.35E + 08 * unemployment(-2) + 1.69E + 09 * unemployment(-3) - 6.05E + 08 * unemployment(-4) + 4.96E + 09 + 8.56E + 09 * growth$$

$$Unemployment = -1.18E - 10 * exp.(-1) - 1.39E - 10 * exp.(-2) - 2.13E - 10 * exp.(-3) + 2.69E - 10 * exp.(4 -) + 0.775503 * unemployment(-1) + 0.656231 * unemployment(-2) + 0.801495 * unemployment(-3) + 0.388370 * unemployment(-4) - 1.870496 + 3.400268 * growth$$

This model is significant and this through the values of T-statistic and P-value**.**

VARX Model (2)

The government's spending series and economic growth rate series have been used in this model as endogenous variables and the unemployment rates as exogenous variable of the model results from this model two estimation equations for both government's spending and economic growth rate as shown as follows:

$$Expenses = -1.870110 * exp.(-1) - 3.699471 * exp.(-2) - 2.769268 * exp.(-3) - 3.717200 * exp.(-4) + 4.08E + 09 * growth(-1) + 5.19E + 08 * growth(-2) + 3.51E + 09 * growth(-3) - 9.78E + 09 * growth(-4) + 1.10E + 10 - 4.76E + 08 * unemployment$$

$$Growth = 2.33E - 11 * exp.(-1) + 1.79E - 11 * exp.(-2) + 2.62E - 11 * exp.(-3) - 8.23E - 11 * exp.(-4) + 0.215752 * growth(-1) + 0.269853 * growth(-2) - 0.222683 * growth(-3) - 0.186784 * growth(* 4) + 0.093794 + 0.132771 * unemployment$$

After significance test, it is clearly obvious that model is significant and this through the values T-statistic and P-value.

SVAR Model

It has been inserted in the model the three variables to estimate the suggested model and also it has been inserted the two matrices (A,B) with the same number of used variables and entered in the model , so the model has been estimated and it has been shown the following results :

Table (2) SVAR Model

Structural VAR Estimates
Date: 12/30/17 Time: 20:52
Sample (adjusted): 1997 2010
Included observations: 14 after adjustments
Estimation method: method of scoring (analytic derivatives)
Failure to improve after 1 iterations
Structural VAR is over-identified (1 degrees of freedom)

Model: Ae = Bu where E[uu']=I
Restriction Type: short-run pattern matrix

A =

1	0	0
-1	1	C(2)
C(1)	0	1

B =

C(3)	0	0
0	C(4)	0
0	0	C(5)

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.937286	0.129022	7.264568	0.0000
C(2)	0.788261	0.270552	2.913531	0.0036
C(3)	0.653569	0.123513	5.291503	0.0000
C(4)	0.697545	0.131824	5.291503	0.0000
C(5)	0.315514	0.059626	5.291503	0.0000

Log likelihood	-1.25E+22		
LR test for over-identification:			
Chi-square(1)	2.51E+22	Probability	0.0000

Estimated A matrix:

1.000000	0.000000	0.000000
-1.000000	1.000000	0.788261
0.937286	0.000000	1.000000

Estimated B matrix:

0.653569	0.000000	0.000000
0.000000	0.697545	0.000000
0.000000	0.000000	0.315514

Forecast VAR Models

The researcher will evaluate forecasting within divided the used data in this study to two parts from 1990 to 2010 used for estimation and the data from 2011 to 2016 used to forecasting. We will be taking few methods to evaluate forecasting, Root Mean Error and Theil Inequality Coefficient.

VARX (1) model

***** (Expenses series-Unemployment ratios) **Endogenous var.**

***(**Growth ratios**)** **Exogenous var.**

Table (3) Dynamic forecast with VARX model (1)

Dynamic forecast			
Variable	**Obs.**	**RMSE**	**Theil**
Expenses series	6	5.68E+11	0.766037
Unemployment ratios	6	98.84880	0.950487

Table (4) Static forecast with VARX model (1)

Static forecast			
Variable	**Obs.**	**RMSE**	**Theil**
Expenses series	6	2.54E+11	0.380881
Unemployment ratios	6	55.44638	0.939888

VARX (2) model

***** (Expenses series- Growth ratios) **Endogenous var.**

***(** Unemployment ratios**)** **Exogenous var.**

Table (5) Dynamic forecast with VARX model (2)

Dynamic forecast			
Variable	**Obs.**	**RMSE**	**Theil**
Expenses series	6	2.26E+12	0.938205
Unemployment ratios	6	12.37008	0.941051

Table (6) Static forecast with VARX model (3)

Static forecast			
Variable	**Obs.**	**RMSE**	**Theil**
Expenses series	6	4.00E+11	0.551675
Unemployment ratios	6	12.58026	0.911387

SVAR model

Table (7) Dynamic forecast with SVAR Model

Dynamic forecast			
Variable	**Obs.**	**RMSE**	**Theil**
Expenses series	6	2.91E+12	0.937909
Growth ratios	6	31.54737	0.968261
Unemployment ratios	6	85.00070	0.925191

Table (8) Static forecast with SVAR Model

Static forecast			
Variable	**Obs.**	**RMSE**	**Theil**
Expenses series	6	4.90E+11	0.584725
Growth ratios	6	25.31017	0.957704
Unemployment ratios	6	53.22765	0.897163

RESULTS AND RECOMMENDATIONS

This study has reached a number of results, which should be introduced in the economic and statistical fields. These findings and recommendations will be presented as follows :

I. Results

(1) The study has shown statistically that government public expenditure is an endogenous of statistical analysis since it has had an impact on the statistical model. The more government spending on the development of the small system, as well as the concern for the health of individuals, the greater the development of society and hence economic growth rates and declining unemployment rates.

(2) The study has shown that using the VAR model with all variables of study as an endogenous variable is a statistically insignificant model.

(3) The significance of the VARX models has been clarified from the study by using two different models: The first model uses the government public spending series and economic growth rates as endogenous variables and consider variable unemployment rates as an exogenous variable. Model Two it is the use of the government public spending series and the unemployment rate series as endogenous variables and the consideration of economic growth rates as an exogenous variable but through the use of the two models have proven the statistical significant models.

II. RECOMMENDATIONS

(1) The study recommends that the Egyptian economy grow attention to the rates of economic growth and investment and increase

the values of public expenditure in the above-mentioned areas, as this will in turn lead to a decline in unemployment rates.

References

1. Akaike, H., (1973), Information theory and an extension of the maximum likelihood principle. In: **International Symposium on Information Theory**, 2 ND, Tsahkadsor, Armenian SSR. pp. 267-281.
2. Andersson ,M.K. , Karlsson , S., (2007) **Bayesian forecast combination for VAR models** .
3. Artis , M.J & Zhang ,W.(1990) BVAR forecasts for the G-7 , **International Journal of Forecasting ,** 6.
4. Asteriou, D. and Stephen G.Hall (2007) , **Applied Ecnometrics,** Revised Edition.
5. Bahgat M. Thabet , (1995) , Forecasting in time series (improving forecasts by means of combination) **A survey International ISSR** ,Cairo University.
6. Bates, J., and C. Granger (1969), The Combination of Forecasts, **Operations Research Quarterly**, 20, 451-468.
7. Bernanke, B.S. (1986): Alternative explanations of the Money-Income Correlation, Carnegie-Rochester Conference Series on Public Policy, 25, 49-99.
8. BRATU ,M.(2012) , COMBINING FORECASTS BASED ON ECONOMETRIC MODELS FOR SHORT RUN MACROECONOMIC PREDICTIONS WITH HIGH DEGREE OF ACCURACY , **The USV Annals of Economics and Public Administration** , Volume 12, Issue 2(16).
9. Casals, J. , Garca-Hiernauxy , A. & Jerez , M. (2010), From general State-Space to VARMAX models.
10. David N. DeJong , Beth F. Ingram , Charles H. Whiteman (2002) , A Bayesian approach to dynamic Macroeconomics , **Journal of Econometrics** .
11. DICKEY, D. A., AND W. A. FULLER , (1979) , "Distribution of the Estimators for Autoregressive Time Series With a Unit Root," Journal of the American Statistical Association, 74, 366, 427-431.
12. Doan, T., Robert Litterman , and C. Sims (1984), "Forecasting and conditional projection using realistic prior distributions," Econometric Reviews.
13. Eklund, J., Karlsson, S., (2007), Forecast combination and model averaging using predictive measures. **Econometric Reviews** 26.
14. Eliot, G., Rothenberg, T.J. & Stock, J.H. (1996) ,Efficient Test for an Autoregressive unit root. Econometrica, 64 (4):813 -836.

15. Eltony , M. , Al-Awadi , M. (2001) " Oil price fluctuations and their impact on the macroeconomic variables of Kuwait: a case study using a VAR model", **INTERNATIONAL JOURNAL OF ENERGY RESEARCH ,** Int. J. Energy Res, 25:939-959 .
16. Engle, R.F., Granger, C.W.J., (1987), Co-integration and Error Correction. Representation, Estimation and Testing. Econometrica 55, 251]276.
17. Pfaff , B. , (2008), VAR, SVAR and SVEC Models: **Implementation Within R Package vars** .
18. Sandu , C.& Ghiba , N. (2011), THE RELATIONSHIP BETWEEN EXCHANGE RATE AND EXPORTS IN ROMANIA USING A VECTOR AUTOREGRESSIVE MODEL , **Annales Universitatis Apulensis Series Oeconomica, 13(2)** .
19. Spencer , D. (1993), Developing a Bayesian vector autoregression forecasting model , **International Journal of Forecasting** , 9 .
20. Helmut Lutkepohl (2005), **New introduction to multiple time series analysis ,** ,Springer.
21. Sharifi-Renani , H. (2010) , Vector Autoregressive Analysis of Economic Growth, International Trade and Environment in Iran , **International Conference on Economics, Business and Management**
22. Ryšánek , J. (2010), COMBINING VAR FORECAST DENSITIES USING FAST FOURIER TRANSFORM.
23. Jonathan H. Wright , (2008), Bayesian Model Averaging and exchange rate forecasts , **Journal of Econometrics**,146 (2008) 329 341.
24. J.V. Raman Raju & Mayuresh S. Gokhale (2012) , Empirical Analysis of the Causal Relationship between Nominal Exchange Rate and Foreign Direct Investment in India using VAR (Vector Autoregression Model) , **Global Journal of Management and Business Research , VOL 17 Issue 22 .**
25. Kalliovirta , L. , Meitz , M. , Saikkonen , P. (2014) , **Gaussian mixture vector autoregression** , Helsinki center of Economic Research .
26. Ooms , M. (1994) , **Empirical Vector Autoregressive Modeling**, Springer-Verlag.
27. Po-Hsuan Hsu , Wang , C. , Joseph Z. Shyu , Hsiao-Cheng Yu , A Litterman (2002), BVAR approach for production forecasting of technology industries , **Technological Forecasting & Social Change** .
28. Schwarz, G., (1978) , Estimating the dimension of a model. **The Annals of Statistics 2** .

29. Simkins , S. (1995), Forecasting with vector autoregressive (VAR) models subject to business cycle restrictions, **International Journal of Forecasting 11**.

30. Sims, C.A. (1980) , "Macroeconomics and Reality," **Econometrica**.

31. SONALI DAS , GUPTA , R. , & KABUNDI , A. (2011) , Forecasting Regional House Price Inflation: A Comparison between Dynamic Factor Models and Vector Autoregressive Models , **Journal of Forecasting.**

32. Taiwo .A .I , Olatayo T.O (2013) , Measuring Forecasting Performance of Vector Autoregressive and Time Series Regression Models , **AMERICAN JOURNAL OF SCIENTIFIC AND INDUSTRIAL .**