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Economic Commission for Africa

A Primer on Macroeconomic Forecasting and Policy Evaluation Models

Patrick N. Osakwe

December 2002

ESPD Discussion Paper No. 1

Economic Commission for Africa

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Patrick N. Osakwe
Economic and Social Policy Division
Economic Commission for Africa
P.O. Box 3005
Addis Ababa, Ethiopia

E-mail: posakwe@uneca.org

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Abstract

This paper is prompted by renewed interests in the development of a regional forecasting and policy evaluation model at the Economic Commission for Africa (ECA). It highlights the various phases of model-building, offers a critical assessment of the principal approaches to macroeconometric forecasting and policy evaluation in the literature, and discusses important issues that should be taken into account in the design and development of a macroeconomic model for Africa. Finally, it presents two plausible theoretical frameworks that could serve as the initial basis for policy evaluation and forecasting exercises at ECA.

Keywords: Model building; Forecasting; Policy evaluation; Africa

JEL classification: C51; C52; C53

Acknowledgements

I would like to thank Patrick Asea for helpful discussions, and Chantal Dupasquier and Malick Sy Oumar for comments on an earlier version of this paper. I am also grateful to participants at the ECA Methodological Workshop on "Model Building and Forecasting of Economic Growth in Africa" held in Yaounde, Cameroon, June 3-6, 2002, for useful suggestions. The views expressed in this paper are those of the author. No responsibility for them should be attributed to the Economic Commission for Africa.

Introduction

The design and development of a macroeconometric model for Africa that could be used for policy analyses and forecasting is a research priority for the Economic and Social Policy Analysis Division of the Economic Commission for Africa (ECA).[1] The successful development of a model will provide a formal framework for analysing economic developments in African economies, permit the division to trace the transmission mechanisms of various economic and social policy actions on macroeconomic variables in the region, and make explanations for policy advice easier.[2]

As a first step towards the achievement of this objective, this paper provides some background information on the process and methods of macroeconometric model building. I must emphasize at the outset that it does not attempt to provide a comprehensive review of the literature on macroeconometric models.[3] Rather, it outlines the major methodologies that have been adopted in forecasting and policy evaluation exercises so as to inform researchers at ECA about the frameworks that may be feasible. Furthermore, it is intended to elicit responses and provoke discussion among colleagues at ECA and it is my hope that it will also be useful to researchers in other institutions, faced with the responsibility of developing a model for forecasting economic growth in African economies.

The paper is organized as follows. Section 1 describes the process of model building and forecasting while section 2 presents the basic elements of successful forecasting. Section 3 reviews the principal approaches to forecasting and policy analyses adopted by economists in the last four decades, paying particular attention to the strengths and weaknesses of each method. In section 4, I highlight important issues, some of which are specific to developing economies and should be taken into account in the development of a model for the region. Section 5 presents two pragmatic models that could be used for forecasting economic growth in African economies. The last section of the paper deals with concluding remarks.

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1. This is clearly not the first attempt to develop a forecasting model at ECA. Various models have been used in the past but were abandoned in 1996 due in part to resource constraints. See, for example, the Social Accounting Matrix (SAM) based short-term forecasting model in Thisen (1998).
2. Note that although macroeconomic models improve our understanding of how economies function, they cannot be substitutes for sound economic analysis and judgement. Models are best seen as complements rather than substitutes for sound economic analyses.
3. For an exhaustive and historical review of the literature on large-scale macroeconometric models, see Bodkin et al. (1991). For methods of macroeconomic modelling and forecasting, see Whitley (1994).

1. The process of model-building

There are five stages in building a macroeconometric model for forecasting and policy evaluation. The first stage is model specification, which is generally based on a researcher's view of how an economy functions. Model specification involves writing down a set of behavioural equations and, in some cases, identities. The variables used in these equations are either endogenous or exogenous depending on whether or not they are explained within the model. Endogenous variables are explained by the equations in the model while exogenous variables are taken as given. As an illustration, consider the following simple model of a closed economy.

$$y_t = c_t + i_t \tag{1}$$

$$c_t = \beta_1 + \beta_2 y_t + \varepsilon_{ct} \tag{2}$$

$$i_t = \beta_3 + \beta_4 r_t + \varepsilon_{it} \tag{3}$$

Equation (1) is the national income identity for a closed economy with no government expenditure. It states that aggregate income y_t is made up of consumption c_t and investment i_t. In equation (2), consumption depends on aggregate income and an error term ε_{ct}. Investment, in equation (3), depends on the real interest rate r_t and an error term ε_{it}. In the simple framework presented above, consumption, investment and aggregate income are endogenous variables while the real interest rate is an exogenous variable. Also, the consumption and investment equations are stochastic because they have an error term which captures the effects of explanatory variables not included in the model. In general, the choice of explanatory variables is based on economic theory.

The second stage of macroeconometric modelling is estimation. After a model is specified, it has to be estimated using historical data and an appropriate econometric technique in order to obtain values for the parameters in the equations --- that is, the β 's in equations (1) to (3). The estimation technique used could be ordinary least squares, two-stage least squares, and full or limited information maximum likelihood. However, system estimation is preferred if it is feasible.

The third stage of model building is the solution of the model. After specifying and estimating a model, it has to be solved for the endogenous variables given the values of the exogenous variables. The method of solution adopted depends on the structure of the model. For example, the

structure represented by equations (1) to (3) is a simultaneous system but can be solved simply by substituting equations (2) and (3) into (1) and solving for y_t. With y_t known, we can compute c_t from equation (2) by substitution and i_t can be computed easily because it depends only on an exogenous variable. The method described above is appropriate for simple systems such as the one in the example above. For much more complicated systems, a general solution method is the use of the Gauss-Seidel technique. To solve our system of equation using the Gauss-Siedel procedure, we would start by guessing an initial value for y_t, and then compute c_t from equation (2) and i_t from equation (3). These computed values will then be used in equation (1) to obtain a new value for y_t which would then be used to obtain new values for the other endogenous variables. This process of replacing the previous value of y_t with a new value is repeated until the difference between the new value and the previous value is within a tolerance level (that is, until convergence is achieved). Once the model converges, the right hand side values are consistent with the left hand side values.

The fourth stage of model-building is testing. Historical data on the exogenous variables are used to obtain predicted values of endogenous variables in the model. These predicted values are then compared with actual values of the variables. If the predicted and actual values are close, then the model is said to perform well and can be used for policy evaluation exercises. This stage of the model-building process also requires an analysis of other properties of the model to see whether they are consistent with the actual properties of an economy.

The final stage of model-building is forecasting. Once a model has passed the testing stage, it can be reliably used for forecasting future values of the endogenous variables. This requires choosing or making assumptions about the future values of the exogenous variables in the model. For example, in our simple model, if in period t we want to forecast the value of aggregate income in period $t+4$ we would need assumptions on the future path of the real interest rate. One way of doing this is to assume that interest rates will remain unchanged, or change by a certain percentage, in the next four years. Given this expected path for the real interest rate we can forecast values of aggregate income, consumption, and investment. Because the forecasts obtained through this process are based on expected future values of the exogenous variables, they are often referred to as ex-ante simulation or forecasts.

2. Elements of successful forecasting

For any forecasting exercise to be successful, it is important for the forecaster to recognize that forecasts are made to guide decisions and that good forecasts enable policy makers to produce good decisions. In general, the basic elements of successful forecasting include:

(a) *Definition of the forecast object*: The object to be forecasted must be stated. That is, we need to know whether the object is a time series or an event. Having identified the object, a researcher must ascertain the length of the data as well as whether or not there are missing or unusual observations. These issues are important because the quantity and quality of available data affect the construction of forecasting models.

(b) *Statement of forecast*: Here we have to indicate whether the forecast will be a single number (point forecast), a range of values in which we expect the future value of the object to fall with some probability (interval forecast), or a probability distribution for the future value of the object (density forecast).

(c) *Forecast horizon*: The forecast horizon is the time period between today and the date of the forecast. It is important to state whether the forecast horizon is, for example, one month, one year, or ten years. This is necessary because the best modelling and forecasting strategy depends on the horizon of interest.

(d) *Information set*: Forecasts are made conditional on an information set. It is important to consider what information is available for the forecasts as well as its reliability.

(e) *Method and complexity of model*: A researcher has to choose among different models with varied degrees of complexity. The specific type of model chosen will depend on the nature of the problem the researcher is investigating. However, in economics, experience has shown that simple, parsimonious models perform better than complicated ones in out-of-sample forecasts.

(f) *Evaluation of forecasts*: A forecaster must have clear criteria for determining whether or not a forecast is good or optimal. He or she must also have a criterion for comparing forecasts from alternative models. Three common ways of evaluating the performance of forecasting models are: the Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE); and the Root Mean Squared Percent Error (RMSPE). For example, suppose y_{t+h} is the realization of a variable, $y_{t+h,t}$ is the forecast of the same variable, and N is the number of observations, then;

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |y_{t+h} - y_{t+h,t}| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N} (y_{t+h} - y_{t+h,t})^2} \tag{5}$$

$$RMSPE = \sqrt{\frac{1}{N}\sum_{t=1}^{N} \left(\frac{y_{t+h} - y_{t+h,t}}{y_{t+h}}\right)^2} \tag{6}$$

A model with a lower MAE, RMSE, or RMSPE is said to have better forecasting performance than an alternative model.

3. Approaches to macroeconometric model-building

Various kinds of models have been employed in macroeconometric research. To ease exposition, the models will be classified under four groups: traditional structural models; vector autoregression models; rational expectations structural models; and general equilibrium business cycle models.

Traditional structural models

This class comprises a wide variety of macroeconometric models used in policy evaluation up until the late 1970s. Popular models in this category include the 1950s Klein-Goldberger model of the US economy; the 1960s and 1970s RDX models of the Canadian economy; the 1960s Brookings and the MPS (MIT-Penn-SSRC) models of the US economy. Although there are differences among the models in this group in terms of specification, methods of disaggregation, and estimation, they generally have the following features:

They are large-scale models with high levels of disaggregation, assume adaptive expectations, and have short-run dynamics based on the Keynesian IS-LM paradigm.[4] Up until the early 1970s, these models also featured a long-run trade-off between inflation and unemployment.

Demand is disaggregated into consumption, investment, government expenditure, and net exports. Government expenditure is typically treated as an exogenous variable but the other components of aggregate demand are modelled as functions of the relevant macroeconomic variables. For example, in a representative model, consumption would be a function of income, investment would depend on the interest rate, and net exports would be a function of the real exchange rate and foreign domestic demand or output. Potential output is typically determined by supply factors.

In these models, the balance of payments is modelled using a structural portfolio-balance approach in which the nominal exchange rate is determined implicitly as the price that clears the balance of payments. A detailed description of the structure of these models can be found in Bodkin et. al. (1991).

Limitations

This approach to macroeconometric modelling came under serious criticisms beginning in the 1970s partly because it is inconsistent with optimization behaviour by households and firms.[5] In addition, structural parameters in these models are estimated without knowledge of the statistical model represented by the reduced form. Consequently, the statistical models implicit in traditional structural models are not accurate descriptions of the data.

In traditional models, identification is often achieved by arbitrarily assuming that some variables, for example the money supply, are exogenous. Sims (1980) argued that in an environment where agents are forward looking and solve intertemporal optimization problems, every variable is potentially endogenous. Furthermore, he argued that the restrictions needed to support exogeneity in traditional models are difficult to justify.

The treatment of expectations in traditional models has also been criticized. Lucas (1976) argued that because expectations are not taken into account explicitly in these models, the estimated structural parameters are a mixture of "deep parameters" describing tastes and technologies in the economy---which are invariant to policy regimes---and expectational parameters, which vary

4. As indicated earlier, there are relative differences between traditional models both in terms of size and levels of aggregation. For example, while the first version of the MPS model had about 60 behavioural equations, some versions of the Brookings model had 200 or more behavioural equations.
5. For more on this, see Lucas (1980).

across policy regimes. Therefore, the estimated structural parameters are likely to be unstable across policy regimes and, hence, are not useful for policy evaluation exercises.[6]

Another major problem with traditional large-scale macroeconomic models is that, because they are complicated and less transparent, it is difficult to know what feature of the model is responsible for the overall response of endogenous variables to shocks.

Vector autoregression models

This approach, popularized by Sims (1980), assumes that all macroeconomic variables are potentially endogenous. The models are essentially atheoretical and involve a small number of equations. They are used for forecasting and as a statistical framework to produce stylized facts for the evaluation of theoretical models.[7] In this setting, a theoretical model is considered a reasonable representation of an economy if its moments or responses to shocks match those of an empirical vector autoregression model.

The typical procedure involved in using a vector autoregression (VAR) model is as follows. Suppose we are interested in the relationship between output and inflation. We would set up a VAR model with two equations: one for inflation and one for output. The equation for each variable would have lags of that variable as well as lags of the other variables in the system. The lag length is chosen using a statistical criterion such as the Schwartz Bayesian Criterion (SBC) or the Akaike Information Criterion (AIC). The models are usually estimated by Seemingly Unrelated Regression (SUR) technique, which yields the same result as an OLS estimation of each equation if all equations have the same right-hand side variables. In the VAR literature there is some debate on whether non-stationary variables in a VAR system should be included in levels or in first differences. Some authors (Sims 1980) argue against differencing even if the variables are nonstationary. Their argument is that the aim of a VAR analysis is to uncover interrelationships among variables and not to determine the parameter estimates. Furthermore, they argue that differencing does not allow a researcher to capture the possibility of cointegrating (or long run) relationships.

A very important issue that a researcher using the VAR methodology must deal with is how to identify the model. To illustrate the identification problem, consider the following first-order VAR system for output y and inflation π.[8]

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6. This is generally referred to as the Lucas critique of econometric policy evaluation.
7. For a basic introduction to VAR models see Enders (1995). A less technical but intuitive exposition can be found in Stock and Watson (2001).

$$y_t = b_{10} - b_{12}\pi_t + \gamma_{11}y_{t-1} + \gamma_{12}\pi_{t-1} + \varepsilon_{yt} \tag{7}$$

$$\pi_t = b_{20} - b_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{22}\pi_{t-1} + \varepsilon_{\pi t} \tag{8}$$

As in the literature, we make the following assumptions

1. Output and inflation are stationary.
2. The shocks ε_{yt} and $\varepsilon_{\pi t}$ are white-noise with standard deviations σ_y and σ_π respectively.
3. ε_{yt} and $\varepsilon_{\pi t}$ are also uncorrelated.

The two-variable VAR system represented by equations (7) and (8) is of first order because the longest lag length is unity. However, it cannot be estimated directly because it is not a reduced - form system. Consequently, although we are interested in the original VAR system, the equations we actually estimate are those of the reduced form VAR system. It is not a reduced form system because y has a contemporaneous effect on π and π also has a contemporaneous effect on y. To transform the system into reduced form equations, rewrite equations (7) and (8) as:

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ \pi_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{\pi t} \end{bmatrix} \tag{9}$$

Let $B = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}$; $\Gamma_0 = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}$; $\Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}$; $x_t = \begin{bmatrix} y_t \\ \pi_t \end{bmatrix}$; and $\varepsilon_t = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{\pi t} \end{bmatrix}$.

If we multiply equation (9) by (B^{-1}) we can write the resulting equation in the form

$$x_t = A_0 + A_1 x_{t-1} + e_t \tag{10}$$

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8. A word of caution is important here. The relationship between output and inflation presented in equations (7) and (8) are for illustration only. It is not meant to capture the exact relationship between the two variables as suggested by economic theory.

where, $A_0 = B^{-1}\Gamma_0$; $A_1 = B^{-1}\Gamma_1$; and $e_t = B^{-1}\varepsilon_t$.

If a_{i0} is element i of the vector A_0; a_{ij} the element in row i and column j of the matrix A_1; and e_{it} the element i of the vector e_t, then we can rewrite equation (10) as:

$$y_t = a_{10} + a_{11}y_{t-1} + a_{12}\pi_{t-1} + e_{1t} \tag{11}$$

$$\pi_t = a_{20} + a_{21}y_{t-1} + a_{22}\pi_{t-1} + e_{2t} \tag{12}$$

The system represented by equations (11) and (12) is an example of a reduced-form VAR model. The identification question is whether we can recover all the parameters of the original VAR system, in equations (7) and (8), by estimating the reduced form system in equations (11) and (12). In general, this is not possible because the number of parameters in the estimated reduced form system is generally less than the number of parameters in the original VAR system. To illustrate this point, consider our two-variable VAR system. The original system has ten parameters: b_{10}, b_{20}, b_{12}, b_{21}, γ_{11}, γ_{12}, γ_{21}, γ_{22} and the standard deviations of the shocks σ_y and σ_π. However, the estimated reduced form system has nine parameters: a_{10}, a_{20}, a_{11}, a_{21}, a_{12}, a_{22}, the standard deviations of e_{1t} and e_{2t} and their covariance.

Various methods have been devised for identifying VAR models. One simple but popular identification procedure is the Choleski Decomposition technique, which achieves identification by imposing contemporaneous restrictions on some of the parameters in the original system. Following this approach, our original VAR system can be identified by setting b_{12} or b_{21} to zero.

Three very useful tools for presenting results of estimated VAR models are: Granger causality statistics, forecast error variance decompositions; and impulse response functions.

Granger causality

A very useful tool for VAR analysis is the Granger causality statistic. This is used to determine whether lagged values of one endogenous variable are important in predicting the values of another endogenous variable in the VAR system. For example, in our two-variable VAR system,

if lagged values of inflation are not useful in forecasting output, then one can conclude that inflation does not Granger-cause output.

Forecasting and variance decomposition

Once a reduced form VAR model has been estimated, it is possible to do forecasting and variance decomposition exercises. In VAR analysis, the forecast error variance decomposition is the proportion of the variance of the error in forecasting a given endogenous variable that is due to a specific shock in the system at a given horizon. To illustrate this, consider the reduced form VAR system in equation (10). If we are interested in forecasts of x_{t+n} given A_0, A_1 and the observed values of x_t, we would proceed as follows. First, we lead equation (10) by one period to obtain.

$$x_{t+1} = A_0 + A_1 x_t + e_{t+1} \tag{13}$$

Taking the conditional expectation of the above equation at time t yields;

$$E_t x_{t+1} = A_0 + A_1 x_t \tag{14}$$

The one-step ahead forecast error associated with this model is: $x_{t+1} - E_t x_{t+1} = e_{t+1}$. Similarly, the two-step ahead forecast of x_{t+2} is:

$$E_t x_{t+2} = [1 + A_1]A_0 + A_1^2 x_t \tag{15}$$

and the forecast error is: $x_{t+2} - E_t x_{t+2} = e_{t+2} + A_1 e_{t+1}$. Following the same procedure, we can show that the n-step ahead forecast is:

$$E_t x_{t+2} = [1 + A_1 + A_1^2 + \ldots + A_1^{n-1}]A_0 + A_1^n x_t \tag{16}$$

and the n-period ahead forecast error is: $e_{t+n} + A_1 e_{t+n-1} + A_1^2 e_{t+n-2} + \ldots + A_1^{n-1} e_{t+1}$.

These forecast errors can be rewritten in terms of the structural shocks using the relationship $e_t = B^{-1}\varepsilon_t$. They can then be used for forecast error variance decomposition analysis.

Impulse response functions

Another useful tool for VAR analyses is the impulse response function. It shows the response of each endogenous variable to a one-unit increase in the current value of one of the shocks. The assumption here is that there are no changes to other shocks and that the shock being varied returns to zero in subsequent periods. Note that for this experiment to be valid, the shocks must be uncorrelated across equations.

Limitations

There are a number of problems with the use of a VAR model. First, the results are very sensitive to the choice of lag lengths and, in most cases, data limitation forces researchers to use very short lag structures even though they may not be the optimal lag lengths. Second, it is difficult to give structural interpretations to the estimated parameters because these models have very little theoretical content. Third, they are vulnerable to the Lucas critique. Fourth, although they may produce relatively good short-term forecasts, their performance deteriorates rapidly as the forecast horizon increases. Finally, these models yield results that are highly sensitive to the number of variables included in the system as well as the identification scheme adopted. The once popular Cholesky Decomposition method used to identify VARs has been criticized because results from models using this identification scheme are sensitive to the ordering of the variables in the system and, unfortunately, economic theory sometimes does not provide information on the appropriate ordering.

Attempts have been made to identify VAR models using restrictions imposed by economic theory. This gave rise to the so-called Structural Vector Autoregression (SVAR) models. Four principal approaches have been used to identify SVAR models.

- A priori information (or economic theory) can be used to identify the structural parameters by imposing contemporaneous restrictions on the reduced form, as in Bernanke (1986).

- Identification of structural parameters can also be achieved by imposing zero restrictions on the long-run effect of structural shocks on the level of some endogenous variables in the model. For example, Blanchard and Quah (1989) identified the structural parameters in their model by imposing restrictions based on the widely held view that, in the long-run, demand shocks have no impact on output.

- There are also identification methods that combine both contemporaneous and long-run restrictions, as in Gali (1992).

The final approach to identification takes account of cointegrating relationships among non-stationary variables in the model. A vector error-correction framework is used to impose long-run restrictions in the model. This is the approach adopted by King, Plosser, Stock and Watson (1991).

Rational expectations structural models

These are generally forward-looking models with Classical and Keynesian features. In most of the models, there are no explicit optimization problems for agents. However, the equations used in these models are generally consistent with optimization behaviour by households and firms. Furthermore, they are consistent with the existence of nominal rigidities. These models can be classified into two groups---large or small scaled---based on the level of aggregation and size.

Large-scale rational expectations models

They have a fair degree of disaggregation. Consequently, there are a large number of behavioural equations and identities in these models.

They can be single-country, such as the FRB/US model developed in the 1990s, or multi-country as in Taylor (1993).[9] Since the Taylor model has most of the interesting features of models in this category, in the next few paragraphs, I describe the basic features of the model. Readers interested in more detailed descriptions of the structure of the model should read Taylor (1993). The model was developed for the G-7 countries: France, Canada, Italy, Japan, Germany, the United Kingdom, and the United States. It has around 100 behavioural equations and was estimated on quarterly data using single-equation techniques. The staggered wage-setting model of Taylor (1980) is used to generate sticky aggregate nominal wages and prices. Note that because nominal wages and prices are sticky, monetary shocks have real effects in the short-run in the model. Prices are set as a markup over wage costs and imported input costs. Because prices do not adjust instantaneously, the markup varies over time. Purchasing power parity does not hold in the short-run because:

(a) import and export prices adjust with a lag to changes in domestic prices and foreign prices (expressed in domestic currency); and

9. Note that the Federal Reserve Board also has a multi-country model called the FRB/MCM. For a detailed description of the structure of this model see Brayton et. al. (1997). A problem with the multi-country modelling approach is that researchers typically use the same framework for each country, thereby ignoring potential differences between countries.

(b) there is imperfect mobility of real goods and physical capital. Furthermore, there is long-run neutrality in the model: a change in the money supply has no effect on real variables in the long-run.

On the demand side, there are two levels of disaggregation. Total demand is disaggregated into consumption, investment, exports, imports, and government expenditure. Consumption is further disaggregated into durables, nondurables and services, while investment is subdivided into residential and nonresidential. The components of consumption depend on expected future income and the real interest rate. Investment depends on expected future sales and the real interest rate. Export and imports depend on relative price differentials between countries and income. Different lag structures are employed in these equations.

Financial capital is assumed to be perfectly mobile across countries. However, the interest rate differential between any two countries is equal to the expected rate of currency depreciation plus a risk premium term. Similarly, the long-term interest rate in any country is assumed to equal the expected average of future short-term interest rates plus a risk premium term. In addition, it is assumed that the instrument of monetary policy in each country is the short-term interest rate. Furthermore, in the monetary policy rule, the interest rate depends on prices, output, or exchange rates.

The model assumes rational expectations. However, it is not a perfect foresight model: shocks in the model are not fully anticipated. Consequently, there is the possibility of forecast errors, although the expected value of these errors in the long-run is zero.

Limitations

One problem with large-scale rational expectations models, which also applies to traditional structural models, is that they are expensive to maintain and the data requirements are enormous.

Another problem is that they are often estimated using single-equation methods--such as Two-Stage Least Squares (2SLS) or the Generalized Method of Moments (GMM)--whereas the rational expectations assumptions and the cross-equation restrictions imposed by the model require a system estimation method. Presumably, the size of these models makes it difficult to use a full-system estimation technique.[10]

Finally, as indicated earlier, the models are not derived explicitly from an intertemporal optimization problem although they are consistent with optimization behaviour by households and firms.

10. Note that although the estimates from the single-equation methods are consistent, they are not efficient.

Small-scale rational expectations models

These models are also called "Optimizing IS-LM models" because they can be developed from microfoundations, or "expectational IS-LM models" because they are based on rational expectations. For a survey of these models, see King (2000). McCallum and Nelson (1999) show how a forward-looking IS equation can be derived from an intertemporal optimization problem.

Models in this category are generally highly aggregated and focus on a few macroeconomic variables. A representative model in this group has a forward-looking aggregate demand equation consistent with intertemporal optimization, a forward-looking uncovered interest parity condition, a real money demand equation, a forward-looking inflation equation, and a monetary policy rule. There are also equations describing the evolution of exogenous variables or shocks in the model. For clarity and ease of comprehension, I outline the basic structure of models in this category below.

Specification of model

I begin the description of the model with the demand for domestic output. All variables, except interest rates, are in logs.

$$y_t - \bar{y} = \alpha_1(E_t y_{t+1} - \bar{y}) + \alpha_2(y_{t-1} - \bar{y}) - \alpha_3 r_{t-1} + \alpha_4 q_{t-1} + \alpha_5 z_{t-1} \tag{17}$$

The current output gap $(y_t - \bar{y})$ depends positively on expected future output gap and lagged output gap. The inclusion of the expected future value of the output gap as an explanatory variable makes the model forward-looking and consistent with intertemporal optimization behaviour by agents. The current output gap depends negatively on the lagged real interest rate r through investment channels. It also depends positively on the lagged real exchange rate q through trade channels. To capture other influences on demand or output, a vector of exogenous variables z is included as an argument in equation (17). Possible candidates for exogenous variables are the terms of trade, real oil price, growth rate of world GDP, etc. In the specification of equation (17) it is assumed that potential output is constant. Therefore one can consider output as effectively the same as the output gap by normalizing potential output to zero. In empirical applications, however, $(y_t - \bar{y})$ would be either detrended real output or other measures of the output gap.[11]

The next equation of the model describes aggregate supply or inflation. In equation (18), current Inflation π depends on expected future inflation, as well as the lagged output gap and the current change in the real exchange rate. If output in the previous year was above potential, the output gap widens resulting in an increase in current inflation. Also, a depreciation of the exchange rate

increases current inflation through its impact on import prices. The equation features price stickiness to be consistent with stylized facts on the monetary transmission mechanism. Furthermore, when $\lambda_1 = 1$, there is no long-run trade-off between inflation and output in the model. Note that equations (17) and (18) imply that it takes one year for a change in the real interest rate to affect output but it takes two years for this change in the interest rate to affect inflation. This reflects empirical evidence on the time lags associated with the transmission of monetary policy.

$$\pi_t = \lambda_1 E_t \pi_{t+1} + \lambda_2 (y_{t-1} - \bar{y}) + \lambda_3 \Delta q_t \tag{18}$$

The Fisher equation sets the nominal interest rate i_t equal to the sum of the real interest rate and the expected rate of inflation. That is,

$$i_t = r_t + E_t \pi_{t+1} \tag{19}$$

The exchange rate is endogenized using the uncovered interest parity (UIP) condition.[12] That is,

$$r_t = (r_t^* + E_t q_{t+1} - q_t) \tag{20}$$

The UIP condition sets the domestic real interest rate equal to the foreign real interest rate plus expected depreciation of the real exchange rate. This assumes that there is perfect capital mobility and can be modified to reflect the existence of capital market restrictions in developing economies.

The model is closed by specifying a money demand equation and a monetary policy rule. The demand for real money balances in equation (21) is positively related to income, and negatively related to the nominal interest rate.

$$m_t - p_t = \phi_1 y_t - \phi_2 i_t \tag{21}$$

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11. Note that if one is interested in knowing the impact of certain policies on trade, the output gap equation can be divided into two components: the domestic demand gap and the real net exports gap. In this case, the equation capturing the domestic demand gap will be the same as in equation (17) and the real net exports gap will be determined by changes in the real exchange rate, the foreign domestic demand gap etc. It is also possible to endogenize potential output using a production function approach.
12. Another way to capture capital market activities in an open economy is to assume that the real exchange rate depends on the real interest rate and a shock. In this setting, a rise in the domestic interest rate makes domestic assets attractive resulting in a real exchange rate appreciation.

In equation (22), the monetary authority is assumed to increase the interest rate when there is an increase in expected inflation, when output is above potential, or when there is a real exchange rate depreciation. The monetary policy rule specified here assumes that the instrument of monetary policy is the interest rate. It is also possible to use a money supply, as opposed to an interest rate, policy rule for countries in which the monetary base captures more accurately the instrument of monetary policy.

$$r_t = r_{t-1} + \rho_1 E_t \pi_{t+1} + \rho_2 (y_t - \bar{y}) + \rho_3 \Delta q_t \tag{22}$$

The model outlined above is typically estimated using an appropriate econometric technique or calibrated based on parameters from results of existing studies. In the estimation stage, some of the variables included in the model may be excluded if there is some evidence that they are not important. For example, if the output gap is insignificant in the monetary policy rule or reaction function estimated for an economy, it would be necessary to exclude that variable from equation (22). It is also standard practice to try different lags of the included variables to ascertain the relevant time lags. After the model has been estimated, it is solved. Because the equations in the system have expected future values of endogenous variables, finding the solution involves solving a linear rational-expectations difference equation. This is challenging but can be done using a numerical technique. After the model has been solved it is used to perform policy simulation experiments. The approach described above is a convenient framework for policy analyses. However, for forecasting purposes, it is sometimes necessary to simplify the model by assuming that the nominal interest rate as well as the nominal exchange rate are exogenous.

Small-scale rational expectations models are becoming increasingly fashionable because they are small, tractable, and can be employed to provide very interesting insights into the effects of economic policies on macroeconomic variables. They are preferred to large-scale models in environments where the focus of analyses is on the response of highly aggregated variables, such as the growth rate of output or the inflation rate, to policy actions. These models are also easier to estimate or calibrate because they have fewer parameters and equations. In addition, because they focus on highly aggregated variables, it is straightforward to impose cross-equation restrictions suggested by economic theory. For example the vertical long-run Phillips curve property can be easily imposed in small-scale models by constraining the relevant coefficients in the equation. This is much more difficult in large-scale models---these generally do not have an explicit aggregate supply or Phillips curve implying that one would have to restrict parameters of different equations to ensure that the model satisfies this specific long-run property.

Limitations

Because of the high degree of aggregation, these models generally have nothing to say about the behaviour of variables related to trade or the balance of payments. They may also miss important dynamics of an economy. In addition, although they are useful for policy analyses, they are not better than large-scale rational expectations models in terms of forecasting performance. Finally, they are also not derived explicitly from an intertemporal optimization problem.

General equilibrium business cycle models

This is made up of two classes of models: the real business cycle models and the monetary general equilibrium models.[13] The main difference between the two is that the former assumes that productivity shocks drive business cycles while the later assumes that they are predominantly caused by monetary or financial disturbances. These models generally assume rational expectations and are based on explicit optimization behaviour by both households and firms. They also assume that labour and goods markets are always in equilibrium.

In a typical general equilibrium business cycle model, a theoretical model with optimizing consumers, firms, and sometimes the government, is set up. Uncertainty is introduced into the model in the form of productivity shocks, as in Kydland and Prescott (1982), or monetary and financial shocks, as in Christiano and Eichenbaum (1992). The model is either calibrated using parameters from existing empirical studies, or estimated by the generalized method of moments (GMM), and then solved using a numerical technique. A major econometric limitation of estimating parameters of general equilibrium models by GMM is that the estimates are generally unstable. This is worrisome because the estimated parameters are typically "deep parameters" describing tastes and technologies and should be constant.

After calibration or estimation, the moments and impulse responses from the model are then compared to those obtained from an empirical vector autoregression model to ascertain whether or not the model is a good reflection of the data. If the model passes this testing or validation phase, then it is used for policy evaluation and forecasting exercises.

13. The term business cycles refers to the alternating pattern of boom and bust observed in market-oriented economies.

Limitations

Although these models are popular in academic research, they have not been widely used in practical policy evaluation and forecasting exercises because they are technically challenging, require enormous resources to maintain, and are often designed to answer questions that are of more academic than practical interest.[14] Furthermore, they sacrifice theoretical coherence in order to enhance their ability to match selected properties of the data. Consequently, they are unlikely to be robust to policy regime changes and are, therefore, subject to the Lucas critique.

4. Other important issues to consider

There are at least four issues to take into account in designing a macroeconomic model. First, a model builder has to make a decision on whether he/she is interested in forecasts of a few macro variables or a large number of variables? This would determine whether he/she should focus on a large-scale or a small-scale model. It would also indicate whether he/she should focus on a highly aggregated or a disaggregated model. For example, if the model builder is interested in the behaviour of highly aggregated variables---such as real output or inflation---this would suggest that an aggregate model is better. However, if he/she is interested in variables such as consumption, investment etc., a more disaggregated model would be more appropriate.

Second, a model builder has to decide whether a multi-country or a regional model is more appropriate given his/her objectives. This depends, partly, on whether he/she is interested in country forecasts or forecasts for a group of countries in a region. Regional models are good because they require less resources to maintain and conduct simulation experiments. The disadvantages are: aggregate data has to be constructed; there is the possibility of aggregation bias; there might not be much variability in the data; and aggregation masks differences in behaviour across countries.

Third, a model builder has to be clear on whether he/she is interested in a forecasting model, a projection model, or both. There is a difference between forecasting and projection exercises. A forecast is based on expected values of policy variables, treated as if they are exogenously fixed. A projection on the other hand involves searching for settings of the policy variables to achieve specific objectives. Unlike forecasting tasks that can be successfully accomplished using simple

14. This is not to say that they are not used in practical policy evaluation exercises. For example, the quarterly projection model (QPM) used for policy analyses and projection exercises at the Bank of Canada is a general equilibrium model. For a description of this model, see Coletti et al. (1996).

models, credible projection exercises require elaborate models with very good transmission mechanisms.

Finally, a researcher designing a model for Africa must recognize that the lack of data as well as the poor quality of African data impose a limit on the scale of the model. Smaller models are easier to maintain and implement and the resource requirements are also more reasonable. He/she also has to decide whether it is best to calibrate or estimate the model.

5. Forecasting economic growth in Africa

In this section, I describe the structure of two models that could be adapted and used by ECA for forecasting economic growth in African economies. The approach adopted here represents my initial thoughts on how to develop a reasonable but simple model for policy analyses and forecasting for developing economies in Africa. I have chosen very simple but insightful models because a larger and much more rigorous macroeconomic model will be less useful in practice due to data limitations.

A multi-sector forecasting model for Africa

The first model that I am proposing for forecasting and simulation exercises at ECA is a small open-economy model that incorporates both monetary and real sectors of an economy. The framework captures the interactions among most macroeconomic variables of interest to policy makers and is general enough to be applied to any African economy. To allow the data to determine the relevant functional form for each relationship, and the lags in the transmission mechanism, the equations of the model are specified in general terms. Letting Y denote real output; C consumption; I investment; $\overline{G}$ government expenditure; X exports; IM imports; Y_{oecd} real output of the Organisation for Economic Cooperation and Development (OECD); S the nominal exchange rate; P the domestic price level; P^* the foreign price level; RP_{oil} the real price of oil; CR country risk; T taxes; $YGAP$ the output gap; r the real interest rate; M the stock of money; i the nominal interest rate; and Y_p a measure of potential output, the basic structure of the model can be described as follows:

The national income (or output) identity for an open economy is:

$$Y \equiv C + I + \overline{G} + X - IM \tag{23}$$

Real exports depend on the real ouput of OECD countries, the real exchange rate, real oil price, and its own lags.

$$X = X\left(Y_{oecd}, \frac{SP^*}{P}, RP_{oil}, X_{lags}\right) \tag{24}$$

Real imports depend on domestic real output, the real exchange rate, and lags of real imports.

$$IM = IM\left(Y, \frac{SP^*}{P}, IM_{lags}\right) \tag{25}$$

Consumption depends on disposable income, the output gap, and lags of consumption.

$$C = C(Y - T, YGAP, C_{lags}) \tag{26}$$

Investment is a function of income, the real interest rate, the degree of financial sector development which affects the mobilization of savings, a measure of country risk, and lags of investment.

$$I = I\left(Y, r, \frac{M}{Y}, CR, I_{lags}\right) \tag{27}$$

The output gap is defined as actual output minus potential output. Potential output is assumed to be exogenous and can be obtained using the Hodrick Prescott filter.

$$YGAP \equiv Y - Y_p \tag{28}$$

On the monetary side, monetary equilibrium requires that real money supply must equal real money demand. Furthermore, real money demand is assumed to depend on income, the nominal interest rate, and expected rate of inflation.

$$\frac{M}{P} = M(Y, i, \Delta P) \tag{29}$$

The Fisher identity states that the real interest rate is equal to the nominal interest rate minus expected inflation.

$$r \equiv i - \Delta P \tag{30}$$

The change in domestic prices depends on the output gap, the change in the money supply, the change in the nominal exchange rate, and lags of the change in domestic prices.

$$\Delta P = P(YGAP, \Delta M, \Delta S, \Delta P_{lags}) \tag{31}$$

The model described above can be estimated for each African country and the forecasts obtained aggregated across countries using the share of each country in total African GDP as weights. This country-approach to forecasting economic growth in Africa will be useful if the relevant time series data are readily available. However, some African countries may not have long and consistent time series data on the relevant variables. Consequently, I would suggest focusing on the ten largest economies in Africa. Together they account for roughly 80 per cent of total African GDP and, historically, the average output growth rate of these countries approximates that of the region as a whole. Therefore, not much is lost by basing the forecasts for the region on data for a sub-set of countries. Table 1 contains a list of the 10 large economies in Africa. Note, however, that if a large number of countries do not have data on the key macroeconomic variables in the model, a framework that has much lower data requirements than the one described above would be more appropriate. In the next sub-section, I outline the structure of one framework that has fewer data requirements.

A VAR forecasting model for Africa

The second model that I am proposing for forecasting economic growth in Africa is based on a VAR framework and is highly aggregated. Its virtue is that it can be constructed based on a few variables and is therefore useful in environments where it is difficult to obtain data on certain macroeconomic variables. The proposed VAR model will have four endogenous variables: real GDP growth rate, real export growth rate, real investment growth rate, and the inflation rate. The growth rate of real exports is included as an endogenous variable to capture the importance of trade and competitiveness in the growth process. The real investment rate is included to reflect the fact that investment is necessary for sustained growth in an economy. A nominal variable, the inflation rate, is included to emphasize the importance of price stability in the growth process.

The rate of growth real output in OECD (Organization for Economic Cooperation and Development) countries and the real price of oil will be used as exogenous variables in the VAR

system. The real price of oil is an important exogenous variable because most African countries are either exporters or importers of oil. The OECD output growth rate is used as a proxy for external demand.

The empirical implementation of the model is relatively straightforward. The four-variable VAR model will be estimated for each of the ten large economies in Table 1 and the forecasts for output growth obtained. These forecasts will then be aggregated across countries based on the contribution of each country to the total GDP of the ten large economies in Africa.

6. Concluding remarks

In this paper, I provided an overview of the model-building process as well as the different approaches to macroeconometric research. I also proposed two plausible models that can be used for policy analyses and forecasting of economic growth in African economies. The models have been kept simple, and small-scale, to reduce data as well as other resource requirements and make them easier to maintain and implement. Furthermore, the proposed models are not perfect and can be revised to capture more accurately the transmission mechanisms of policy actions in African countries and improve their forecasting performance. The forecasting performance of the two models outlined in this paper will be explored in detail in a forthcoming working paper.

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Table 1: The Ten Large Economies in Africa[a]

Country	GDP growth rates		Share of Total African GDP	
	2000	2001	2000	2001
South Africa	2.8	2.5	21.1	20.7
Algeria	3.8	5.0	12.3	12.4
Egypt	4.1	5.8	11.6	11.8
Nigeria	3.1	4.0	8.0	7.9
Morocco	2.0	6.5	5.5	5.6
Libya	7.0	5.6	5.0	5.1
Tunisia	2.8	5.1	3.4	3.4
Cameroon	5.5	5.5	2.7	2.7
Sudan	6.8	9.0	2.4	2.5
Côte d'Ivoire	2.0	-0.9	2.2	2.1
Ten Large Economies	**3.6**	**4.4**	**74.1**	**74.2**
Africa	**3.5**	**4.3**	**100**	**100**

a. **Source:** Economic Commission for Africa

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