Forecasting Africa’s Median Growth: A Marshallian Macroeconomic Model disaggregated by sectors and by countries

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ABSTRACT

The ability of Africa to produce insightful forecasting models will be determined by the expertise of African Macroeconomic Modellers to make use of update forecasting techniques. Existing models need to be periodically revitalised since they constitute guidance instruments for policy makers. The present research aims to bring improvement in the African project link with a different approach of forecasting median growth. The model provides useful information for policy makers regarding the past as well as the future of the continent using dynamic equations. As for any marshallian model, the research includes at least three types of equations: supply; demand; and entry/exit equations. Our modelling exercise is designed to incorporate a minimum of 10 development sectors for 25 African countries. Following the traditional principle of supply, demand and entry type of equation with always-extra functions for labour and capital required by the sector with additional functions for endogenous variables, a minimum of 2000 equations will be estimated in this model. The estimates make use of point or turning point forecasts with some restrictions. In order to obtain improved estimations and predictive precisions for both sectors and countries, the model combines Stein – like shrinkage techniques. The model also includes, level variables, leading indicator variables and time varying parameters to allow for possible structural breaks or any other factors causing time variance. The end results of our simulation experiments are meant to be used for African policy making process with higher reliability in terms of median growth forecasting that account for sectoral as well as country differentials.
INTRODUCTION

The progress and reliability of forecasting macro models for Africa has been noticed through several modelling workshops. The scarcity of sound forecasting frameworks weakens budgeting and planning processes in the continent. The lack of required expertise combined with the inexistence of a nurtured centralised database warehousing system, which both are associated with massive financial requirements, constitute and obstacle to the development of forecasting frameworks in Africa. The Economic Commission for Africa (ECA) depicted in one of its recent report the challenge faced by several African governments in their modelling exercises. They remain far behind in building full-fledged macroeconomic models and in providing accelerated training for qualified modellers and forecasters (ESPD – ECA, November 2005).

It is an historical fact that macroeconomic forecasting in Africa has been highly dependent on the developed world economic pattern. Due to the delay it had in modelling practices, Africa had to borrow westernised models, which were not true representation of local realities. The interest in proper African models has increased over the past years since thinkers as well as officials came to realise how forecasting models could be crucial for planning purposes.

With the Millennium Development Goals (MDGs), governments have been alerted to pursue and attain their macroeconomic objectives that are achievable through efficient macroeconomic models.

The main purpose of forecasting is to guide any policy-making unit to achieve its long-term goals. African government have set different goals aligned with the MDGs such as: long term economic growth (6 – 7%); poverty eradication; etc. Good projections are linked to sustainability of socio-economic policies. Therefore, in the early 90s (1992), the IMF (International Monetary Fund) and the World Bank alerted African policy makers on the importance of forecasting.

As it will be highlighted in the core of this study, several attempts have been made to build forecasting models in Africa. We can recall five traditional types of economy-wide models often discussed:

- the IMF financial programming framework;
- the World Bank RMSM models;
- the ‘three-gap’ models or the ‘two-gap’ models for Africa;
- the Computable General Equilibrium Models;
- the Dynamic, Large-Scale models.

We have noticed an extensive use of the two-gap model in African forecasting with regard to attraction of foreign direct investment needed for economic growth. Since this type of modelling process is money driven, the credit it can receive from purely academic analysts might be questionable. Nevertheless, the underpinning foundation of the two-gap model is that of Harrold Domar Growth model. It highlights the contribution of foreign resource inflows to enhance local economies.

**Outline of chapters**

We intend to have an introductive chapter where we explain how the all research idea is converted into the research question with reference to a specific research design and the description of the research process to be used. The research presentation will continue in the second chapter and we will include a broad discussion on the recent and related research outputs in the field. Chapter 3 will talk about Macroeconomic Modelling in Africa: A progress report (Cross country and regional analysis). The underlying theory of forecasting median growth and its use in the African context will be discussed in the 4th chapter while chapter 5 needs to provide full-fledged information on the role that Marshallian Macroeconomic Model are meant to play in regional forecasting. Chapter 5 will also highlight in details the variables to be considered in an African Marshallian Macroeconomic Model. A larger consideration to the all concept of Bayesian à la Stein forecasting techniques will be supplied in chapter 6 and chapter 7 is intended to fully describe the African data warehousing system and the data collection process for macroeconomic research. Before we conclude our research and supply policy implications and recommendations in the 9th chapter, the study results and comments will be included in chapter 8.
BACKGROUND

On the basis of the two-gap model, the ‘Bretton Woods’ Institutions have developed the ‘Revised Minimum Standard Model’. Fund’s related models are meant to address balance of payment deficit problems in member states.

Several attempts have been made to forecast African growth using the regressions approach. Although this approach has the weakness to require the supply of future values of the exogenous variables. Forecast values of exogenous series must be obtained from a univariate framework or its multivariate counterpart VAR (Vector Autoregressive). Countries like Kenya made use of VAR to obtain a period forecast for their exchange rate while the policy impact of the key variables was captured through impulse response functions. VAR models have been extensively used in many African macroeconomic models although their outcomes are more used for policy evaluation. AR (3) models including lagged leading indicators have been successfully used in point forecasting frameworks. Though, empirical results (Zellner & Tobias, 2000) have shown the improvement effects of disaggregating in both ARLI (Autoregressive Leading Indicators) as well as Marshallian Models (Competitive or Macroeconomic).

Our model is based on a sectoral and cross-country disaggregating including demand, supply and entry/exit relations. The use of disaggregating process in our marshallian model is sustained by sector differentials that prevail in African Economies. The output growth per sector presents disparate behaviour to such extends that using aggregate data entails loss of useful information (see figures).

**Figure 1: Example of the South African annual real output growth rates per development sectors**

![Graph of South African annual real output growth rates per development sectors](image)

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With:
- AFF: Agriculture, Fishing and Forestry
- **EGW**: Electricity, Gas and Water
- **FIRE**: Financial Intermediates and Real Estate
- **WRCA**: Wholesale, Retail trade, Catering and Accommodation

**Fig 2: Botswana Sectoral Growth**

**Fig 3: Namibia Sectoral Growth**

**Fig 4: Zambia Sectoral Growth**

**Fig 5: DRC Sectoral Growth**
The graphs presented in this proposal established clear evidence that sectors’ growth rates behave differently. Aggregate frameworks suffer from loss of crucial information and that lead to inaccurate policy recommendation without specific consideration of sectoral differentials. A major concern is then raised regarding the veracity or accuracy of the existing forecasts used for policy analysis. If sector differentials are not considered, the forecasting frameworks will remain questionable. Improvement effects of disaggregating have been captured through results obtained from ‘Mean Absolute Errors’ (MAEs) and ‘Root Mean Squared Errors’ (RMSEs). While using disaggregated frameworks, MAEs and RMSEs displayed smaller error figures compared to aggregate models and that is noticeable as improvement in forecasting performance. Few pilot studies on comparative analysis between ‘Aggregation and Disaggregation in terms of forecasting performance’ could be located. Zellner and Tobias (1999) published a
paper that focused on a comparative analysis between Aggregated Forecasting Model and Disaggregated Forecasting Model of median growth for eighteen industrialised countries. They made use of MAEs and RMSEs results to support the hypothesis that ‘disaggregation’ produces better forecasting outcomes. The aggregated approach used in their paper included median rate variables obtained from all eighteen countries1. In their alternative way to employ a disaggregated approach, Zellner and Tobias referred to the same AR(3)LI process while each of the estimates carried two subscripts: one for the country and the other one for the year considered. The disaggregated model increased the number of estimate equations and provides higher reliability to the panel data2. Outcomes of their research paper suggest that disaggregation is more likely to produce better forecast than ‘aggregation’, although their disaggregated equations included one aggregated variable: the annual median growth of Real GDP. Other evidence of improved forecasting results could be drawn from such comparative studies especially when we consider the fact that disaggregation provides more observations to estimate with reasonably better model specification.

Multiple equation forecasting models brought forward the use of: single information estimation technique (SEIE); limited information system methods (2 Stage Least Square, Instrumental Variable Estimation, Limited Information Maximum Likelihood); and full information system technique (3 Stage Least Square and FIML) in forecasting frameworks (Challen and Hagger, 1983) using VAR forecasting approach. The marshallian modelling approach relates to full information estimation methods to such extend that stochastic equations are estimated simultaneously.

In the forecasting literature of Africa, we need to incorporate “Excel-based model for forecasting (EBMF)” developed in 2004 by Huizinga et al (Huizinga and Alemayehu, 2004) an established on AD – AS framework. The EBMF also includes sectoral differentials using the CES function although the closing of the systems differ from the marshallian approach and the output growth is obtained from aggregation of investment consumption, exports, government expenditures, etc. Our model, though,

1 Zellner and Tobias modelled the median growth rate of GDP (aggregative) using an AR(3)LI process that includes three lagged variables of the median growth of GDP together with two other median growth variables: the median growth rate of Real Money; and the median growth rate of Real Stock Prices.
2 Alternatively, in their disaggregating model, Zellner and Tobias made use of ARLI relationships using the same variables as the one used in the aggregated model. They firstly allowed all coefficients to vary across countries, secondly they imposed all coefficients to be equal across countries and thirdly they imposed restriction only on leading indicators’ coefficients to be the same across countries.
allows a sectoral output growth that will facilitate obtaining countries median growth and the continent’s median growth while the forecasting part is based on Stein like shrinkage techniques using time varying parameters (Zellner, et al 2003).

**MODEL SPECIFICATION**

In order to formalize our forecasting, we have decided to include: level variables; leading indicator variables; and time varying parameters to allow for possible structural breaks or any other factors causing time variance (Zellner and Israilevich, 2003). The selected list of variables is as follows per country and per sector:

- $S_p$: Sector’s Total Production
- $S_d$: Sector’s Total Demand
- $w$: nominal wage
- $r$: user cost of capital (or nominal cost for capital services)
- $p$: product price
- $o$: oil price
- $A$: technology
- $l$: international price
- $n$: number of individuals or households
- $Y_d$: disposable income (individual or households)
- $G$: Gross fixed capital formation
- $t$: taxes on production
- $s$: subsidies on production
- $e$: educational level
- $d$: Company description
- $wex$: years of working experience
- $LU$: level of unionisation
- $UN$: level of unemployment
- $AP$: employer's ability to pay
- $i$: interest rate
- $dc$: economic depreciation rate of capital
- $ICC$: International Cost of Capital
In fact, our variables have been selected based on the role that they play in the production as well as demand structures of the African economy. Some variables might be very difficult to locate, although they remain crucial for the model development. In such situations, valid proxies may be introduced.

The present research targets the formulation of a complete 10 sectors MMM (Marshallian Macroeconomic Model) for a maximum of 25 African countries (see annex). Nevertheless priority has been given to countries with largest share in the African GDP (G 5 African countries) that account for more than 60% of the continent’s gross production. Data accessibility will unfortunately be another determinant in our country selection. Upon request of the World Bank as well as the IMF, several countries have introduced programs of data collection. Nevertheless, the data availability remains a major concern for any African related research.

Our marshallian approach includes supply, demand and entry/exit equations. Contrarily to the traditional competitive firm model, our entry/exit equations do not include the entrance and exit of new firms in the market but rather consider the price variables, which are the leading indicators of our closed marshallian macroeconomic model. Our supply equations operate under a Cobb-Douglas production specification. Sectoral factors demand functions for labour and capital services are aggregated over sectors to obtain market factor demand functions (Zellner et al, 2003). Considering: a dynamic supply equation; a dynamic demand equation; two dynamic price equations; two dynamic market demand equations; and two dynamic market supply equations; we have a MMA with 8 equations per sectors meaning 80 equations per country.

Supply equations:

\[ \frac{\dot{S}_{pai}}{S_{pai}} : \text{Time variable for change in sector's production} \]
\[ S_{pai} = AL^{\alpha/\theta} K^{\beta/\theta} G^{\phi/\theta} \]
\[ \text{with } \theta = \alpha + \beta + \phi \]

\[ \frac{\dot{S}_{pai}}{S_{pai}} = \dot{A}_{ni} / A_{ni} + (\alpha / \theta) \dot{L}_{ni} / L_{ni} + (\beta / \theta) \dot{K}_{ni} / K_{ni} + (\phi / \theta) \dot{G}_{ni} / G_{ni} \]

With ‘n’ sectors and ‘i’ countries

Demand equations:

\[ \frac{\dot{S}_{dai}}{S_{dai}} = \delta_1 \frac{\dot{P}_{dai}}{P_{dai}} + \delta_2 \frac{\dot{Y}_{dai}}{Y_{dai}} + \delta_3 \frac{\dot{n}_{ni}}{n_{ni}} \]
Entry equation:
\[
P_{ni}/P_{ni} = \sigma_0 + \sigma_1 I_{ni}/I_{ni} + \sigma_2 (S_{dni} - S_{pmi}) + \sigma_3 t_{ni}/t_{ni} + \sigma_4 s_{ni}/s_{ni}
\]
\[
I_{ni}/I_{ni} = \ell_1 o_n/o_n + \ell_2 w_n/w_n
\]

Factor market demand equation:
\[
L_{dni}/L_{dni} = \partial_1 S_{pmi}/S_{pmi} - \partial_2 w_{ni}/w_{ni} + \partial_3 I_{ni}/I_{ni}
\]
\[
K_{dni}/K_{dni} = \varphi_1 S_{pmi}/S_{pmi} - \varphi_2 r_{ni}/r_{ni} + \varphi_3 n_{ni}/n_{ni}
\]

Factor Supply equations:
\[
w_{ni}/w_{ni} = \beta_1 P_{ni}/P_{ni} + \beta_2 e_{ni}/e_{ni} + \beta_3 d_{ni}/d_{ni} + \beta_4 \text{wex}_{ni}/\text{wex}_{ni} + \beta_5 L^U_{ni}/L^U_{ni}
\]
+ \[
\beta_6 \text{UN}_{ni}/\text{UN}_{ni} + \beta_7 \text{AP}_{ni}/\text{AP}_{ni}
\]
\[
r_{ni}/r_{ni} = \zeta_1 i_{ni}/i_{ni} + \zeta_2 d_{ni}/d_{ni} + \zeta_3 \text{ICC}_{ni}/\text{ICC}_{ni}
\]

Forecasting using Bayesian à la Stein techniques

Stein shrinkage techniques constitute an appropriate way to improve forecasting of African median growth while accounting for sectoral as well as country differentials. The use of shrinkage techniques has produced better outcomes on country as well as regional forecasting. In addition to that, outcomes on different development sectors could be obtain through this framework, which is more insightful than the forecasts obtained from the aggregate GDP.

The Stein’s Mean approach consists of estimating the vector mean using a quadratic loss function including the goodness of fit. The model specifications of our balanced loss function as well as the squared error loss function (Dey et al, 1994) are as follows:

- Balanced loss function:
  \[
  L(\theta, \theta) = w(y - \theta)'(y - \theta) + (1 - w)(\hat{\theta} - \theta)'(\hat{\theta} - \theta)
  \]
- Squared error loss function:
  \[
  L_b = w(t' y - \hat{T})^2 + (1 - w)(\hat{T} - T)^2
  \]

With:
- \(\theta\): the vector of means
- \(y\): the series considered
- \( w \): a weigh imposed
- \( T \): total of the mean observation vectors

The shrinkage techniques make use of future vector of observations presented in quadratic loss functions (squared errors) to predict future total using the predictive means. For each sector and for each country we estimate specific mean vectors and compute their totals.

Considering the sectoral as well as the countries disparities, we need to generate our observation vectors using SUR (Seemingly Unrelated) models:

\[
y_{ni} = x_{ni}^\gamma_{ni} + \mu_{ni} \quad with \quad n = 1, \ldots, 10 \]
\[
i = 1, \ldots, 25
\]

The shrinkage estimation of the \( \gamma_{ni} \) will affect prediction of a future observation vector and the total. For our \( ni \) means we shall add an informative prior (Leonard et al, 2001) when we consider both the prior and a normal likelihood. The shrinkage estimators we use for our \( ni \) problems are accepted under lemma conditions for quadratic loss functions. Since we have disaggregated our model by countries and by sectors, we have made the consideration of national as well as sectoral shrinkage assumptions regarding the estimates of our vectors of means.

To evaluate the predictive performance of our shrinkage estimates, we consider running comparative analysis with existing forecasting models looking at criteria like; the MAEs; the RMSEs; and the Akaike or Schwarz criteria.

**DATA COLLECTION**

The data to be used in our analysis is secondary and collected from 1970 on a yearly basis. Our intended source of data collection has been all the official sources as well as the link forecasting models established all over the continent. It is expected that link-forecasting units are most likely to provide clean and appropriate information. Aggregate output figures are the easiest to locate. Although data regarding input components as: Investment; Employment; Wages; etc; are much more difficult to locate especially in countries without proper data warehousing systems. Generic sources like: the IMF (International Monetary Fund); the World Bank; or the African Development Bank will be more reliable for regional data. However the location of sectoral data
including: sectoral production or demand; sectoral input utilisation; sectoral prices remain the biggest challenge to collect. Very little data warehousing systems are implemented to provide such information necessary though. We have targeted 25 African countries with priority on the African ‘G5’ that account for closely 60 % of the African GDP. Regarding the development sectors we have targeted a maximum of 10 sectors with ‘Transport’ and ‘Telecommunication’ most likely to be combined into one. Some participating countries are willing to provide annual data as far back as 1970 or earlier. Generally, though, above-mentioned sources provide data with some missing sectoral information making the model synchronisation process more difficult to achieve. To address the missing data problem, our analysis considers the option of solving for reduced form equations for output and uses the outcome for forecasts (Zellner and Israilevich, 2003). As can be garnered from the number of participating countries or forecasting links, the interest for our modelling exercise is very high although the disaggregated or sectoral data problem constitutes one of the major obstacles the present research has to face.

**CONCLUSION AND STUDY LIMITATION**

The present research mainly focuses on the improvement of forecasting process through disaggregating and use of Bayesian shrinkage estimations (à la Stein). Countries as well as sectoral disparities clearly support the fact that aggregate forecasts carry information inconsistencies. The inexistence of an African data warehousing system disaggregated by sectors and by countries put restrictions to our sample size. The empirical approach used in this research in terms of the Marshallian macroeconomic techniques and the shrinkage estimations is not without flaws. Despite those flaws, MMA when carefully used with shrinkage estimation techniques can be valuably introduced to guide output growth forecasting in multiple output sectoral units, as long as the data used in the analysis and the vector means is representative of the production process and can be compared to appropriate peer production units. This study will open new horizons for further researches in forecasting models including more detailed leading indicators and probably more countries.
REFERENCES


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Annex: Country list

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