Can Ethiopia Reach a Lower-Middle-Income Status by 2025? A Framework of DSGE and VAR Models

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Abstract

Ethiopia has set the goal to be one of the Lower-Middle-Income (LMI) economies in the world by 2025. With that the target is to reach a GDP range of 147.5 to 578.4 bl. US$ and a GDP per capita range of 1,137 to 4,458 US$ by 2025. The present study asks whether Ethiopia is likely to reach these targets or not if the trends, dynamics, and volatility that have been experienced during the last decades persist. The out-of-sample forecast was analyzed using DSGE and VAR models, and the data set used in this study underwent a structural break test. Based on 1990-2018 data, the Nominal GDP of the Ethiopian economy is predicted to be 130.86 bl. US$ by the VAR model and 131.52 bl. US$ by the DSGE model in 2025. The 2004-2018 data gives a higher and above LMI margin predicted value of 164.84 bl. US$ and 169.69 bl. US$ for the VAR and DSGE models, respectively. Using the 2004-2018 data, the 2025 Nominal GDP in US$ is forecasted to be more than 164 bl, and the GDP per capita between 923 to 1,123 US$. Even though Ethiopia may surpass the target set in terms of Nominal GDP and come close to the GDP per capita target, still a lot necessity be done to make the goal of reaching the LMI status credible. Therefore, structural, financial and economic reforms, infrastructural investments and nurturing macro-economic balance, are among the policy measures that need to be taken to achieve a resilient LMI status by 2025.

Keywords: Ethiopia, LMI economy, 2025 forecast, DSGE, VAR
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1. Introduction

Ethiopia was the second poorest country in the world at the beginning of the century. However, the country has registered an encouraging continuous growth over the last decades, facing but standing various shocks and macroeconomic difficulties and moved to the 17th poorest in 2018 (WB, WDI, 2018). The country is one of the fastest growing economies in the world with an average growth rate of 10.5 percent from 2004-2018 (yet, the average growth rate was 6.9 percent from 1991-2018), registering a record growth rate of 13.6 percent in 2004 (WB, WDI, 2020).

On one hand, the economic growth rate of 6.9 percent (1991-2018) and 10.5 percent (2004-2018) in Ethiopia has been confirmed by Ethiopian government institutions, the World Bank (WB), the International Monetary Fund and many other independent international organizations. The massive public infrastructural investments (such as hydroelectric, green energy, railway, etc.) had been launched primarily following the 15th of May 2005 Ethiopian general election, which many agreed the event changed the behavior of Ethiopian government in the economic sector. Furthermore, the First Growth and Transformation Plan (GTP I) leads to a large inflow of foreign direct investment, foreign borrowing, remittance and grant/aid. The above two explanations amplified the real GDP figures of the Ethiopian economy from 18.7 billion US$ in 2003 to 89.6 billion US$ in 2019 (WB, WDI, 2020). However, the above remarkable growth of 3.8 folds accompanied by numerous hitches such as GDP's underline incapability of income/output/resource distribution, the incoming projects have longer gestation period, weak institutions, illegal outflow of loan, grants, and foreign reserves through embezzlement (poses double burden on the economy as debt and social opportunity cost).

On the other hand, the report of double-digit economic growth figure has been disproved by the known Ethiopian Economist Alemayehu Geda (2018) as reported in https://newbusinessethiopia.com on 28th of June 2018. On the basis of the already exaggerated 7 percent Total Factor Productivity (TFP)[3], the expert estimated

[3] Hungary, Peru, Ethiopia, and Indonesia have the greatest aggregate productivities out of the 80 developing nations examined throughout the same period across different regions—Eastern Europe and Central Asia, Latin America, Africa, and Asia. The highest values among the countries surveyed are found in Moldova, Nicaragua, Ethiopia, and Indonesia, according to a comparison of average productivities in each area (Saliola & Seker, 2011). Technical advancement, technical efficiency change, and scale effect are the three components of TFP growth. According to Melaku's (2013) study, there are significant inefficiencies that account for at least 14% of the production variation among Ethiopian firms. After 2001/02, TFP showed stronger advancement, and the rise is

the economic growth was only 6-7 percent, not 10+ percent. Furthermore, the expert at the IMF’s Finance and Development section based on the satellite images of the earth at night reveals economic growth in Ethiopia is exaggerated by 17 percent. However, the official data set of the IMF still confirms the double-digit economic growth in Ethiopia from 2004-2018 (IMF, 2018).

TFP's importance as a major source of growth in the last decade, compared to its negligible and sometimes negative contribution a decade before, demonstrates that the official GDP growth figure has a problem (Geda, 2008; Geda & Addis, 2014). This is due to the country's failure to implement meaningful technological and structural changes in its production methods, particularly in the agricultural sector, over the last decade, resulting in such unprecedented growth in factor productivity. It is also worth noting that TFP is calculated as a residual. Indeed, the jump in TFP from negative in 2002/03 to significant positive in 2003/04 (an unprecedented 14 percentage point jump) demonstrates the unrealistic nature of the officially reported growth figure. TFP in Ethiopia is more dependent on the vagaries of nature than on technology, and it has swung between negative and positive values. In the best of circumstances, it has historically remained below 1.5 percent (Geda & Addis, 2014).

Ethiopia's growth rate could not be accompanied by structural transformation. According to Table 1, the manufacturing and agriculture sectors contribute 6.8 percent and 32.5 percent, respectively, to the Gross Domestic Product (GDP) in 2020/21 (PDC, 2021; MoFED, 2012), and the agricultural sector employs approximately 75 percent of the population (World Bank, 2013). Indeed, the agricultural sector's contribution to GDP has declined from an average of 64.1 percent between 1991 and 2001 to 46.4 percent in 2011 and could fall to as low as 32.5 percent in 2020/2021, despite its contribution in terms of employment, foreign exchange earnings, and composition remaining largely unchanged. During this period, the contribution of the service sector and merchandise exports to GDP increased dramatically (World Bank, 2013). On the contrary, there was no discernible change in the industrial sector over the years.

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mostly attributed to technical change. Due to the time invariant efficiency of the majority of industrial groupings, the impact of efficiency change is quite minimal. Additionally, because most industrial groups have constant returns to scale or little deviance from constant returns to scale, the scale effect is nil or extremely minor. The TFP in Ethiopia and LDCs in general include technical advancements, climate shocks (such as rainfall, drought, and famine), inefficiencies in productivity and institutions, statistical inconsistencies, and external sector rather than only technology or technical advancement.

Table 1: Composition of the Ethiopian Economy (in GDP)

Sectors of Ethiopian Economy	1991-2001	2001-2011	2020/21
Agriculture	64.1	47.7	32.5
Industry	8.7	13.0	29
Manufacturing	3.0	5.7	6.8
Services	27.3	39.3	39.5
Export of goods and services	4.1	12	13.3

Source: MoFED (2012), PDC (2021).

Non-primary goods accounted for a small share of total exports, while primary goods such as coffee, oilseeds, chat, gold, and flowers accounted for three-fourths of total export value in 2010/11. (PDC, 2021; MoFED, 2012). The structural composition of the Ethiopian economy in the remaining sectors has remained essentially unchanged for many decades. It is obvious that sustainable economic growth and structural transformation cannot be achieved without strong sectoral interdependence and changes in sectoral composition, especially in the early stages of development.

In Ethiopia, several plans, strategies, and policies, including the Structural Adjustment Program (SAP, 1996), the Sustainable Development and Poverty Reduction Program (SDPRP, 2002), the Industrial Development Strategy (IDS, 2003), the Plan for Accelerated and Sustained Development to End Poverty (PASDEP, 2005/06-2009/10), the Agricultural Development Led Industrialization (ADLI, 1993), the Growth and Transformation Plan (GTP I, 2010/11-2014/15) and GTP II (2015/16-2019/20) have been implemented to bring sustainable economic growth, industrialization and structural transformation, yet they are unsuccessful to in bringing the standard desired changes. The government is currently developing a Homegrown Economic Reform Agenda (HGERA, 2019) and a Ten-Year Perspective Development Plan (TYPDP, 2020/21-2029/30), in the hopes of changing the economy's sluggish structural composition.

Several efforts to structurally change the Ethiopian economy have resulted in a shift from an agricultural to a service-based economy, skipping the intermediate and vital sector of the economy, namely the industrial sector. The transition from agriculture to the service sector is not typical for Ethiopia, and it is unlikely to result in either sustainable growth or structural change in the economy.

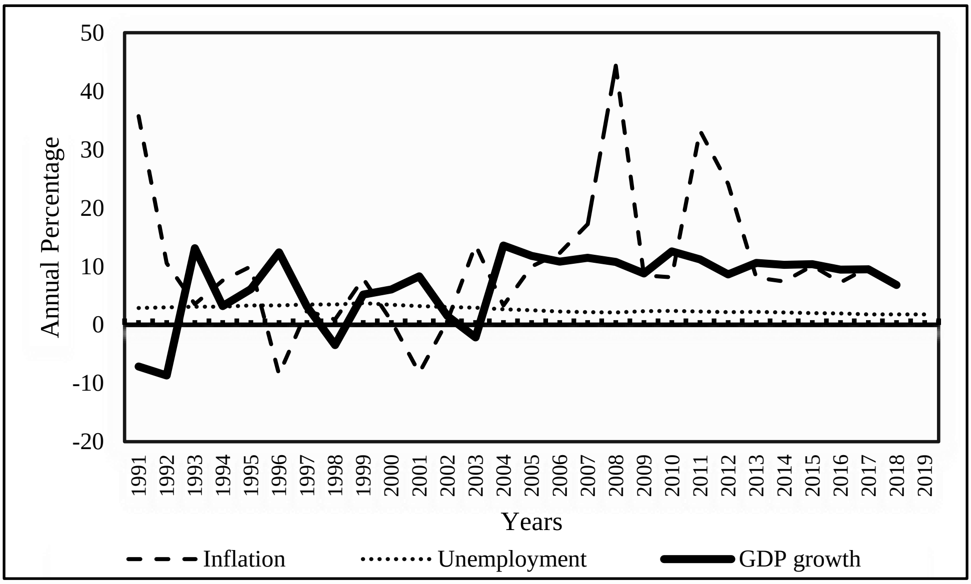
Figure 1 presents the inflation, unemployment and GDP growth trends in the economy. As reported in WB, WDI (2020) inflation reached an extremely high value of 44.4 percent in 2008, when the global economic downturn moderately hit the Ethiopian economy. After two years of single digit inflation, prices skyrocketed again to 33.3 percent in 2011, due to the Ethiopian currency devaluation of 2010. The unemployment level in Ethiopia remained high after the downfall of the Derg military regime in 1991 and increased further in the mid 1990's (WB, WDI, 2020). As Figure 1 presents, it showed a tendency to rise again in 2009-2010 may be due the global financial crisis. Since 2004, with the continuous achievement of double-digit economic growth, the employment rate slightly improved. The overall performance of the economy persuaded experts that Ethiopia could achieve the Lower-Middle-Income (LMI) economy status by 2025 as mentioned by MoFED (2010), WB (2013) and NPC (2016). According to UNDP (2018), the unprecedented sustained economic growth led some economists to assert that Ethiopia can achieve the aim to become LMI country by 2025.

Hence, upon the impressive performance of the economy relative to not only Africa at large, but also the world, Ethiopia has officially set the target to be listed in the LMI category by 2025 with a GDP in the range of 147.5 to 578.4 bl. US$ or 9.3 to 36.5 tr. ETB and a GDP per capita in the range of 1,137 to 4,458 US$[4]. By achieving this goal, Ethiopia is expected to pull millions of people out of poverty, improve life expectancy and reduce child and infant mortality.

It is worth reviewing studies that have been conducted on GDP forecasting to lay a foundational motivation for this study. Some of them are one-step ahead forecasts and did not emphasize dynamic forecasting. Also, most studies which grounded their forecasts on the Vector Autoregression (VAR) technique do not compare and evaluate their results against predictions by the Dynamic Stochastic General Equilibrium (DSGE) technique or other general equilibrium models.

[4] Own computation based on the GNI/GNP (Gross National Income/Gross National Product) per capita calculation of WB Atlas method data report from 1987 to 2018.

Figure 1: Trends of Macroeconomic Variables in Ethiopia



Source: NBE, 2022; WB, WDI, 2020

Abdul Razak, Khamis and Abdullah (2017) compare performance of Autoregressive Integrated Moving Average (ARIMA) and VAR models in the forecasting of Malaysian economic growth and suggest the best time series model from the two. The indicators used to measure economic growth are currency in circulation, exchange rate, external reserve, and reserve money. The forecast performances were appraised based on out-of-sample forecasts, using as error measurement the mean absolute percentage error. The study found out that the VAR model outperforms the ARIMA model based on the assessment of forecasting accuracy. The study by Bekana and Deressa (2017) has employed a VAR model to forecast the GDP of Ethiopia. However, their prediction is limited to a one-period-ahead forecast. In the study out-of-sample forecasts were produced for the Ethiopian GDP using the fitted model. The results for mean squared error, mean absolute error and Theils U statistic indicate that the estimated model is good enough to describe the data set. The paper by Trevor and Thorp (1988) presents three VAR models of the Australian economy. The forecasting performance of 1986-87 outcomes (on an ex-ante basis) is compared against three sets of private sector forecasts, the 1986-87 budget forecasts and the actual outcomes from the same period. The VAR forecasts perform at least as well or better than comparable forecasts of the private sector.

Among their conclusions, the detrending process is a key component of the quality of forecasting. The study objective of Patrick (2009) was to forecast GDP growth for the Baltic States Estonia, Latvia, and Lithuania. The forecasts were made based on a reduced VAR model which provided good results for horizons up to t+8 (Eight periods a head). Based on the findings it is possible to conclude that the model provided reliable estimates of future values of GDP for the assessed countries. The study suggests that the model should be appropriate to be applied to other countries of interest.

When trying to forecast Ethiopian GDP in 2025 from available data, we think it is appropriate to have more than one forecasting technique. Hence results from two or more methods should be evaluated for a more reliable and robust overall prediction. Due to limitation of resources, this study has employed a form of structural VAR and Small Open Economy (SOE) DSGE models to predict and evaluate the gross output level and income per capita projections of Ethiopia by 2025.

The first and second growth and transformation plans of Ethiopia from 2010 to 2020 (GTP I and GTP II) and the ensuing Homegrown Economic Reform Agenda all aim to transform the country from the low-income category to the next category of LMI by 2025. This study is meant to predict and evaluate the realization of the 2025 goal. More precisely, the present study inquires if Ethiopia is likely to meet its 2025 target if the trends, dynamics and volatility that have been experienced during the last decades endure. To the best of our knowledge, this question has not been investigated in detail. In fact, long run projections and estimations using DSGE and VAR models for Ethiopia are hardly available, but would seem to provide important guidance for policy interventions with appropriate measures. Recent outstanding, but potentially highly important events such as the expensive cost of living mainly caused by the climbing up of inflation to 20.16 percent in 2020 the first time since 2012, the COVID-19 crises, the unrest in different parts of the country and the disagreement with neighbouring countries may affect the prospects for Ethiopia’s development in ways that are obviously not incorporated in this study's forecasts.

2. Materials and Methods

2.1 Data and Variables

The analysis was based on the seasonally adjusted quarterly time series data set for different indicators of the economy. Two time periods of the Ethiopian economy, i.e., 1990q1[5]–2018q1 and 2004q1–2018q1, have been used for forecast analysis of the 2025 goal. The structural break test reveals that 2002q2 and 2003q2 mark structural changes in the economy. These structural break points have been taken care of by incorporating dummy variables. Even though the first data set contain more observations, the period is also accompanied by structural changes in 2002q2 and 2003q2. Thus, doing the projection based on the 2004-2018 data set might better reflect the economic growth dynamics in the upcoming period.

Data[6] for the variables were collected from the National Bank of Ethiopia, the World Bank's World Development Indicators (WDI), the International Monetary Fund, and the United Nations. The variables used in this study follow the definition given by Salvatore (2013), Mankiw (2013), Dornbusch, Fischer and Startz (2011) and Romer (2012) and are described as follows:

[5] 'q' is measurement of time/date in terms of quarters.

[6] In this study various sources of data were consulted to acquire facts. The data compiled by the datasets such as WB: WDI, IMF and UN contain most comprehensive set of data on national, regional, and global estimates/indicators. The data series by this organizations are coming primarily from official national sources (Such as the NBE, CSA of Ethiopia, MoF of Ethiopia, MPD of Ethiopia as they report to the international organizations). Following the acquisition of data from national/official sources, international data sources go through several standardized procedures before publishing the data/information. To this end, the study employs both the national and international data sources for analysis.

Table 2: Description of Variables Used to Forecast the 2025 LMI Target of Ethiopia

Variable	Description	Measurement Unit
Nominal GDP (NGDP, y)	Monetary value of economic output/income.	Currency[7]
GDP per capita	Mean income (output) averaged for the whole population of a country.	Currency
Nominal exchange rate (e)	Several units of the domestic currency that can purchase a unit of a given foreign currency.	Currency
Inflation (π)	A sustainable increase in the general (average) price level of goods and service over a period.	%
Nominal interest rate (r)	Amount of interest rate per period, as a proportion of the amount lent, deposited, or borrowed.	%
Terms of trade (TOT, q)[8]	Ratio between a country's export prices and its import prices.	%

2.2 Model Specification

A wide range of methods are available to predict macroeconomic variables. A popular classification of forecasts is into judgment-based (qualitative) forecasting methods and model-based (quantitative) forecasts. The first group of methods mainly relies on a specific forecaster’s ability to observe empirical regularities and irregularities in the economy which makes it difficult for an outsider to observe the model and data used (Robertson and Tallman, 1999). Such methods include executive opinions, Delphi methods, sales force estimates and consumer surveys. The second category relies on a statistical approach which paves the way to tracking sampling errors and to model performance evaluation. It includes VAR and DSGE

[7] Currency unit is measured in ETB and in the equivalent US$.
[8] In order to construct the terms of trade index, one must compare the export unit value indexes to the import unit value indexes relative to the base year 2000. Unit value indices are based on information provided by nations that meet UNCTAD's standards for data consistency, and they are augmented by UNCTAD's estimations, which are weighted using the previous year's trade values at the three-digit level of the Standard International Trade Classification. UNCTAD develops a set of average price indices at the three-digit product classification of the Standard International Trade Classification revision 3 using international and national sources, its commodity price statistics, and UNCTAD's secretariat estimates and calculates unit value indices at the country level using the current year's trade values as weights. This improves data coverage, especially for the most recent periods (WB, WDI, 2020).

models and many others like, exponential smoothing, trend projection, Autoregressive Moving Average (ARMA), ARIMA models, macroeconometric model and growth model. These quantitative forecasting methods are often classified into structural and non-structural ones, depending on how much 'structure' is provided by economic theory. These theoretical foundations may differ according to their view of the economy based on the assumptions they use and the components of the economy they emphasize. Some models focus only on the demand side of the economy, while others capture the supply constrained nature of developing economies, or are based on macroeconomic models such as the Real Business Cycle (RBC), New Keynesian (NK), Computable General Equilibrium, Global Macro, Applied General Equilibrium and Macroeconometric model.

The out-of-sample forecasts for 2025 in this study were analyzed and compared between DSGE and VAR models. On the theoretical grounds, VAR is a multivariate time series model, in which all the variables are considered as dependent. On the other hand, as Blanchard (2009) indicated the basic components of the standard open economy NK DSGE model comprises:

- the preferences of the households which capture intertemporal utility maximization,
- the technology capturing the relationship between different inputs and the output produced by profit maximizing monopolistically competitive firms,
- the monetary authority that employs different monetary policy instruments, and
- the economy's integration and interaction with international financial/asset markets.

2.2.1 VAR Model

VAR is a linear time-series technique that models the interrelationships between macroeconomic indicators assuming some variables as endogenous and others as exogeneous. One of the advantages of VAR modeling over DSGE is that, while a DSGE model provides an entire stochastic multivariate process, it places so many constraints on certain time series and are mostly rejected against less restrictive models such as VAR. VAR models became popular since their first use by Sims (1980) for macroeconomic analysis and are trying to achieve what Stock and Mark (2001) refers to as policy analysis, structural inference, forecasting and data description. Sims (1980, pp.16) identified the over-parameterization problem associated with large scale macro models when he argued that "if every variable is allowed to influence every other variable with a distributed lag of reasonable length, without restriction, the number of parameters grows with the square of the number of the variables and quickly exhausts degrees of freedom". Over-parameterization is severe when the model has many variables with short time dimension. As Koop and Korobilis (2010) explain, all the solutions developed so far to overcome the problem of over- parametrization have one thing in common; that is, they are all based on the idea of shrinkage, i.e., restricting some of the elements of the coefficient matrix of the VAR model and the associated variance-covariance matrix to zero.

Furthermore, as Sims (1980), VAR is a stochastic process technique that can be used to display the linear interdependence of multivariate time series variables. This model generalizes the univariate auto regressive model by permitting many evolving variables. If the time series variables data are stationary in a level, estimations of the models proceed using the variables in a level; otherwise, the level of integration changes depending on the unit root test results. Then, a VAR model is used to forecast each variable from the lagged values of its own and the lagged value of other variables. Therefore, VAR expresses each variable as a linear function of its own past values, the past values of all other variables being considered, and a serially uncorrelated error term. One application of VAR in time series forecast is to test whether the lags of included variable have useful predictive content above and beyond others variables in the model. The lag length for the VAR model is determined using model selection criteria (Akaike, 1973; Lütkepohl, 2005).

A comprehensive p-th order VAR model is given by equation (1) (Robertson & Tallman, 1999):

$$y_{i,t} = \alpha_i + \beta_1 y_{i,t-1} + \cdots + \beta_p y_{i,t-p} + \varepsilon_{i,t} \tag{1}$$

Where i is list of variables, α is constant, y at a given time depends on past values of y up to a lag length of p, β_ps' are coefficients of the lags and ε is an error term.

2.2.2 DSGE and The Small Open Economy Model

Until the mid-1970s the dominant paradigm in macroeconomics was Keynesian, in which short run fluctuations in economic activities are considered as caused by variations in aggregate demand. However, it was difficult to explain the stagflation that was closely linked to the oil price shock in the mid-1970s within the Keynesian paradigm, and thus contributed to the fading of this school and the rise of a new paradigm characterized by microeconomic foundations and supply side shocks.

The idea of DSGE was pioneered by Kydland and Prescott (1982) and Long and Plosser (1983) in their seminal contribution on the RBC model and it marks the rise of DSGE modeling. The typical RBC model is based on the neoclassical framework with 'microeconomic foundations' in the sense of optimization behavior of economic agents under flexible prices and the assumption of rational expectations. Being based on micro foundations has helped these models to overcome the criticism of Keynesian economics which does not have such foundations, whereas the rational expectations assumption enables them to address the Lucas critique, which says that estimated parameters may not be policy invariant such that using them for the future is invalid. The RBC models assume that markets always clear and economic fluctuations are the results of optimal inter-temporal decisions by economic agents and monetary variations cannot explain the fluctuations in aggregate variables. This has led to the conclusion that money is neutral and there is no need to use economic policy to correct the fluctuations (Snowdon & Vane, 2005). But the neutrality of money has faced serious challenges based on empirical evidence. The non-neutrality argument implies that prices and wages are not flexible, which led to the development in DSGE modeling that incorporate these issues.

Thus, New Keynesian short-run features were included into DSGE models. The new extended models have features of the RBC model, but include the NK assumption of imperfect competition and rigidities. In NK economics prices are rigid because of menu costs, aggregate demand externalities, coordination failure and staggered price contracts (Snowdon & Vane, 2005). Similarly, wages are also rigid because of efficiency wages, union power and staggered wage contracts. NK economists (such as Hicks) have thus given microeconomic foundations for rigidities introduced by J. M. Keynes (1936). Combining both households' and firms' optimization problems coming from the RBC approach with nominal and real rigidities, has provided a plausible explanation of short-run dynamic macroeconomic fluctuations and made macroeconomic models representative. The paper that first introduced this framework was Rotemberg and Woodford (1997). Remarkable changes have also been made in the specification and estimation of DSGE models (for example see, Goodfriend and King, 1997; Clarida, Gali and Gertler, 1999; Woodford, 2003; Mankiw, 2006; Goodfriend, 2007 and Gali and Gertler, 2007; Ohanian, Prescott and Stokey, 2009; Woodford, 2009; Tovar, 2009; Rochelle and Refet, 2010; Meeusen, 2011; Dotsey, 2013; Blanchard, 2016; 2017a; Nachane, 2017; Auclert, 2017; Christiano, Eichenbaum and Trabandt, 2018; Lindé, 2018; etc)

According to Tovar (2009, pp. 1) "DSGE models are powerful tools that provide a coherent framework for policy discussion and analysis. In principle, they can help to identify sources of fluctuations, answer questions about structural changes, forecast and predict the effect of policy changes, and perform counterfactual experiments". Tovar further states that "Central Banks (CBs) have become increasingly interested in their usefulness for policy analysis. Aside these rapid advances, the use of DSGE models remain in the periphery of the formal policy decision making process in most CBs. It remains in CBs to be seen whether these models will be adopted in the core process of forecasting and policy analysis frameworks, or whether they will only be employed as a supplementary tool outside the core framework".

Since the DSGE models that are estimated from actual data have performed well, they have become popular in developed countries where they become the dominant macroeconomic models used to analyze monetary policies (Sisay, 2011). There is a large literature that tries to improve DSGE models by incorporating new assumptions, by linking the model with data and by extending it to developing countries. The progress can also be seen from the aphorism quoted in Chari (2010, pp. 2) "If you have an interesting and coherent story to tell, you can tell it in a DSGE model. If you cannot, your story is incoherent". Even though advancement of conventional macroeconomics has been attained in the last thirty years, the proponents of these models do not seem to be convinced and shaken by the criticisms. The tone of dissatisfaction regarding the progress is shared by many (see for example, Chari and Patrick, 2006; Chari and Patrick, 2008; Woodford, 2009; Blanchard, 2016; 2017a; Nachane, 2017; Auclert, 2017; Christiano, Eichenbaum and Trabandt, 2018; Lindé, 2018). Simultaneously, a considerable progress has been made in the past two decades which addresses few of the criticisms on DSGE.

DSGE Models can be estimated using various methods: for instance, the Generalized Method of Moments (GMM) has been employed by Clarida, Gali and Gertler (2000) for analysis. This method controls for endogeneity, omitted variable bias, error in measurement and heterogeneity potential (Caselli, Esquivel & Lefort, 1996; Bond, Hoefler & Temple, 2001). It also improves the effectiveness and consistency of simulations by Monte Carlo methods (Blundell & Bond, 1998). Orphanides (2001) and Ball and Robert (2002) used Ordinary Least Squares methods and made implausible identification assumptions in order to avoid an endogeneity bias. Full-information Maximum Likelihood Estimation (FMLE) has been employed by Fuhrer and Moore (1995), Leeper and Sims (1994) and Kim (2000). One problem in estimating DSGE models by FMLE, however, is that estimates of FMLE structural parameters are often at odds with additional information or observations. Recently, DSGE has also been estimated by Bayesian Methods (BM) since, they fit 'the complete, solved DSGE model', avoid 'the dilemma of absurd parameter estimates,' and 'the weighting of the likelihood with the prior densities adds sufficient curvature in the posterior distribution to facilitate numerical maximization and identification' (Griffoli, 2010). Bayesian estimates of DSGE models based on likelihood have begun with the studies of Landon-Lane (1998), DeJong, Ingram and Whiteman (2000), Schorfheide (2000) and Otrok (2001). An and Schorfheide (2007) carried out analysis and estimation of a DSGE model by BM in a closed-economy framework. Lubik and Schorfheide (2007) used BM in a SOE framework to see the effects of exchange rate movement on CB's monetary policies, i.e., to investigate the hypothesis that CBs respond to exchange rates. de Walque and Wouters (2004), Lubik and Schorfheide (2006) and Rabanal and Tuesta (2006) used BM for multi-country DSGE estimates. The models can also be estimated using Moment Simulated Method (Francisco, 2011) and Indirect Inference Method (Le et al., 2012; Meenagh et al., 2019).

This study employed a NK SOE version of a DSGE model, that was developed by Gali and Monacelli (2005) and is increasingly used across the literature after its humble application by Lubik and Schorfheide (2007). The households, firms and CB decision-making processes that make up the DSGE model are listed as follows:

- The first order condition of the households' intertemporal utility maximization issue provides the economy's IS curve (demand or output gap Euler equation).
- The NK Phillips curve (or supply), which represents inflation dynamics, derived from the optimal price-setting decisions by profit maximizing monopolistically competitive firms.
- The Taylor-type interest rate rule is adopted from the target of monetary authority as a reaction function.

It's indeed possible to integrate the decision-making process and the optimal choices of these economic agents to provide the basic model framework that describes the economy. In this study, the SOE model used is as follows:

Households: the consumption Euler equation showing the supply side of the economy can be rewritten as an open economy IS-curve:

$$y_t = E_t y_{t+1} - (R_t - E_t \pi_{t+1} - z_t) \qquad \textbf{(2)}$$

Where y is aggregate output, R is the interest rate, π is the inflation rate measured by the Consumer Price Index (CPI), z is the growth rate of an underlying non-stationary world technology process, and E is the expected value operator.

Firms: optimal price setting of domestic firms leads to the following an open economy modified Phillips curve:

$$\pi_t = \beta E_t \pi_{t+1} + \kappa y_t \quad \textbf{(3)}$$

Where the coefficient κ is a function of underlying structural parameters, such as labor supply and demand elasticities and the parameters capturing the degree of price stickiness.

Central Bank: monetary policy is represented by a Taylor-type interest rate rule which says that the CB adjusts the interest rate in response to the inflation rate (Taylor, 1993).

$$R_t = \psi \pi_t + u_t \quad \textbf{(4)}$$

Where Ψ represents monetary policy coefficient and u_t is an error term.

Nominal Exchange Rate: the nominal exchange rate e is included in the model based on the definition of CPI by assuming that comparative Purchasing Power Parity holds:

$$e_t = \gamma \Delta e_t + \pi_t^* \quad \textbf{(5)}$$

Where π* is an unobserved world inflation shock, and may also be interpreted as the misspecification, or deviations from Purchasing Power Parity and Δ shows a change in the value of e.

Terms of Trade: q can be determined as the relative prices which clears the international goods market and Δq is a change in the value of q. It is as follows:

$$\Delta q_t = \sigma q_t + \varepsilon_t \quad \textbf{(6)}$$

The five equations (2) to (6) above form a linear rational expectations model. It can be solved by different methods and a linear approximation a very common one. The log-linearized DSGE model is set in a state-space form, so that the observed variables are connected to model variables by measurement equations. Simultaneously, the state equations provide the reduced form of the DSGE model by relating current variables to their lags and the independent and identically distributed (i.i.d.) shocks. Then, the DSGE model is completed by specifying the process how the state variables evolve. The standard specification is as shown from equation (7) to equation (10).

$$z_{t+1} = \rho_z z_t + \xi_{t+1} \quad \textbf{(7)}$$

$$u_{t+1} = \rho_u u_t + \phi_{t+1} \quad \textbf{(8)}$$

$$\pi^*_{t+1} = \rho_{\pi^*} \pi^*_t + \theta_{t+1} \quad \textbf{(9)}$$

$$\varepsilon_{t+1} = \rho_\varepsilon \varepsilon_t + \delta_{t+1} \quad \textbf{(10)}$$

Where, z_{t+1}, u_{t+1}, π^*_{t+1} and ε_{t+1} indicated as first-order autoregressive processes.

The reduced form was obtained by solving the expectation terms in the structural form of the model using a suitable numerical technique. The frequently used numerical technique include Anderson-Moore Algorithm (AiM)[9] and the Kalman filter method to compute the value of the log-likelihood function in case the solution shows a unique convergence[10].

2.3 Pre- and Post-Estimation Tests

The pre- and post-estimation tests applied in this study include the serial correlation test (Breusch 1978; Godfrey 1978) to observe the interdependence of adjacent items, the Jarque-Bera normality (Jarque & Bera, 1980) test to check the data distribution, the Chow breakpoint test: the structural break tests have been done to identify any break inside the data series (Chow, 1960), and the cumulative sum test for parameter stability (Brown, Durbin & Evans, 1975). The data series went through a stationarity test and optimal lag length determination (Dickey and Fuller, 1979, 1981; Phillips and Perron, 1988; Akaike, 1973).

3. Results and Discussion

To estimate DSGE model and make it computationally operational, a value must be assigned to the parameters. The calibrations of the parameters presented in Table 3 are standard assigned values in the DSGE literature.

DSGE introduces a check for linearity in the model equations and not reports any non-linearity. All the data series in DSGE and VAR models must contain zero mean and be weakly stationary to appropriately use them in the analysis.

[9] See for example, Anderson and Moore's (1985), Blanchard and Kahn (1980); Klein (2000); Sims (2002) and Christiano (2002).
[10] See for example, Kalman (1960).

Furthermore, to conduct the analysis, the optimal lag length has been determined for each model estimation.

Table 3: Calibration of Parameters

Parameters	Description	Value	Source of Calibration
β	Discount factor	0.97	Gibbs, Hambur and Nodari (2018)
ψ	Monetary policy coefficient	1.23	Author's calculation[11]
κ	Elasticity and degree of price stickiness	0.15	StataCorp. (2019)
σ	Coefficient of nominal exchange rate equation	0.25	Author's calculation
γ	Coefficient of terms of trade equation	0.24	Author's calculation

Column one in Table 4 shows the WB's income group classification of countries in the world as four groups and columns two, three and four the corresponding Ethiopia's goal measured by GDP. Ethiopia's target in 2025 is to be one of the LMI countries by achieving the income level between 1,138 US$ to 4,458 US$ (or 71,745 ETB to 281,300 ETB). In other way, the lower bound of LMI country in terms of nominal GDP is 147.53 bl. US$ or 9.31 tr. ETB.

[11] It is computed according to the instructions below: DSGE's solve option puts the model without estimating parameters in state-space form; it is like iterate (0) but faster because it does not calculate standard errors. The use of solve for a given model's different parameter values is a valuable way to explore the theoretical properties of the model (StataCorp., 2019).

Table 4: Classification by Income Group and Ethiopia's Expected Target by 2025

Income Group[12]	GNI per capita[13] (2025 - US$) (World Standard)	NGDP[14] (2025 – bl. US$) (In Ethiopia)	NGDP[15] (2025 – tr. ETB) (In Ethiopia)
Low Income	≤ 1,137	≤ 147.53	≤ 9.31
Lower-middle Income	1,138 – 4,458	147.54 – 578.42	9.32 – 36.5
Upper-middle Income	4,459 – 13,952	578.43 – 1,810.26	36.6 –114.23
High Income	> 13,952	> 1,810.26	> 114.23

Source: Own computation, 2020

3.1 Predicting Nominal Gross Domestic Product (NGDP)

The DSGE and VAR models were estimated and quarterly prediction results were attained. Table 5 shows the predicted values of the Ethiopian NGDP measured in local currency (ETB) and US$.

The two data sets used in this study were subjected to a structural break test. The structural break test for the period 1990-2018 reveals breaks on the dates 2002q2 and 2003q3. However, the specification, diagnostics and goodness-of-fit analysis for structural breaks show no breaks for the data runs from 2004 to 2018. The structural break test in Figure 2 reveals a data break on 2002q2 in the model where NGDP (ETB) considered as dependent variable. Therefore, during the analysis the structural break point date has been taken care of by incorporating dummy variables, i.e., an

[12] In terms of income, the WB divides the world's economies into four income groups, i.e., high, upper middle, lower-middle, and low. The income classification is based on a measure of national income per person, or GNI per capita, calculated using the Atlas method. In 1978, the first World Development Report (WDR) introduced groupings of 'low income' and 'middle income' countries using $250 GNI per capita as threshold between the groups. In the 1983 WDR, the 'middle income group' was split into 'lower middle' and 'upper middle' groups, and in 1989 a 'high income' country definition was introduced. Since then, the thresholds to distinguish between the income groups have been adjusted for prices over time and the classification is updated each year on July 1st (WB, WDI, 2019).

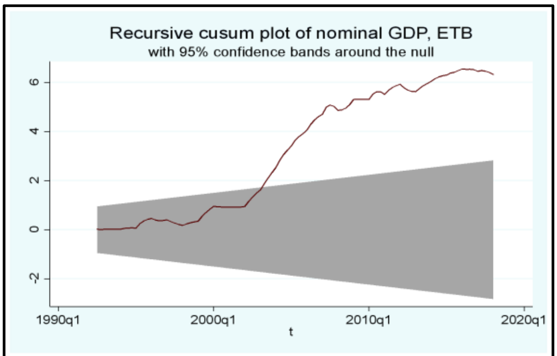
[13] Own computation and prediction based on the GNI per capita calculation of WB Atlas method data report from 1987 to 2018.

[14] The population of Ethiopia is projected to reach 129,749,455 in 2025 (United Nations, 2019).

[15] Exchange rate (/ETB per US$) was own prediction based on the VAR and DSGE analysis of this study. Accordingly, 1 US$ is expected to be exchanged by 63.10 ETB by end of 2025.

extra variable has been added in the right-hand side of the equation which contains a value of '0' before the break date and a value '1' after the break. The structural break test has also been conducted for the model of GDP per capita as dependent variable and the date 2003q3 was found as a breakpoint.

Figure 1: Structural Breakpoint Test for the Model NGDP (ETB) as Dependent Variable



Full sample: 1991q2 - 2018q1
Trimmed sample: 1995q3 - 2014q1
Estimated break date: 2002q2
Ho: No structural break

Test	Statistic	p-value
swald	120.6500	0.0000

Sample: 1991q2 - 2018q1 Number of obs = 108
Ho: No structural break

Statistic	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
recursive	2.3389	1.1430	0.9479	0.850

Table 5 shows that the NGDP of the Ethiopian economy is predicted to reach 8.36 tr. ETB for the VAR model and 7.78 tr. ETB for the DSGE model in the q4 of 2025. Furthermore, the uses of 2004-2018 data in Table 6 gives a higher predicted value of 8.52 tr. ETB and 12.14 tr. ETB for the VAR and DSGE models, respectively. For the 1990-2018 data, the values in US$ were 130.86 bl. and 131.52 bl. for VAR and DSGE models, respectively. Using the 2004-2018 data, the NGDP values in US$ increased to 164.84 bl. and 169.69 bl., respectively. The VAR and DSGE modeling are performing alike in terms of producing a robust predicting value of NGDP (ETB) against the 2025 targets of the country. Based on the prediction results for the period 1990-2018 and compared them against the Ethiopia's expected nominal GDP by 2025 in Table 5, all show the target of the country in 2025 will hardly to be fulfilled.

Table 5: NGDP Prediction Using 1990-2018 Data[16]

Model	VAR		DSGE	
Quarterly Date	NGDP (tr. ETB)	NGDP (bl. US$)	NGDP (tr. ETB)	NGDP (bl. US$)
2018q2	2.29	84.69	2.29	85.09
2018q3	2.38	84.99	2.39	85.90
2018q4	2.48	85.43	2.49	86.79
2019q1	2.59	86.08	2.60	87.74
2019q2	2.71	86.93	2.70	88.76
2019q3	2.83	87.96	2.82	89.84
2019q4	2.96	89.15	2.94	90.97
2020q1	3.10	90.46	3.06	92.16
2020q2	3.25	91.88	3.18	93.40
2020q3	3.40	93.37	3.32	94.69
2020q4	3.56	94.92	3.45	96.03
2021q1	3.73	96.51	3.60	97.41
2021q2	3.91	98.11	3.75	98.84
2021q3	4.09	99.72	3.90	100.31
2021q4	4.28	101.33	4.06	101.83
2022q1	4.48	102.94	4.23	103.38
2022q2	4.68	104.54	4.41	104.98
2022q3	4.88	106.15	4.59	106.62
2022q4	5.10	107.78	4.78	108.30
2023q1	5.32	109.43	4.98	110.02
2023q2	5.54	111.10	5.19	111.78
2023q3	5.78	112.82	5.40	113.57
2023q4	6.02	114.58	5.62	115.41
2024q1	6.27	116.40	5.86	117.29
2024q2	6.54	118.27	6.10	119.20
2024q3	6.81	120.20	6.35	121.16
2024q4	7.10	122.20	6.61	123.15
2025q1	7.39	124.26	6.89	125.18
2025q2	7.70	126.39	7.17	127.26
2025q3	8.02	128.59	7.47	129.37
2025q4	8.36	130.86	7.78	131.52

Source: Own computation, 2020

[16] All values are in the 95 percent confidence bound.

The results in Table 5 and Table 6 show that the target for Ethiopia to reach 9.31 tr. ETB by 2025 appears not to be achieved except for some scenario results using the 2004-2018 data. In those cases, it is expected that the NGDP measured in the ETB exceeds 12 tr. and the NGDP measured in the US$ to exceed 164 bl. The year 2004 marks the time when the Ethiopian economy has been turning around for more than a decade to take on the growth truck of double-digit economic growth. This could therefore be the reason why the data set for 2004-2018 provides better predictive values than other data sets, such as 1990-2018. If this sustainable economic growth has repeated itself in the Ethiopian economy in recent years, it guarantees the achievement of the 2025 target of the LMI group.

Table 6: GDP Prediction Using 2004-2018 Data[17]

Model	VAR		DSGE	
Quarterly Date	**NGDP (tr. ETB)**	**NGDP (bl. US$)**	**NGDP (tr. ETB)**	**NGDP (bl. US$)**
2018q2	2.29	84.94	2.30	85.37
2018q3	2.39	85.67	2.42	86.66
2018q4	2.50	86.69	2.55	88.18
2019q1	2.60	87.96	2.69	89.87
2019q2	2.72	89.38	2.83	91.70
2019q3	2.84	90.89	2.99	93.66
2019q4	2.97	92.48	3.16	95.72
2020q1	3.10	94.15	3.34	97.88
2020q2	3.23	95.93	3.53	100.13
2020q3	3.38	97.83	3.74	102.46
2020q4	3.54	99.87	3.95	104.87
2021q1	3.70	102.04	4.18	107.35
2021q2	3.87	104.35	4.42	109.91
2021q3	4.06	106.79	4.67	112.55
2021q4	4.25	109.34	4.94	115.25
2022q1	4.45	112.00	5.23	118.04
2022q2	4.65	114.76	5.53	120.89
2022q3	4.87	117.61	5.85	123.83
2022q4	5.09	120.55	6.19	126.84
2023q1	5.31	123.58	6.54	129.93
2023q2	5.55	126.71	6.92	133.10

[17] All values are in the 95 percent confidence bound.

Model	**VAR**		**DSGE**	
Quarterly Date	**NGDP (tr. ETB)**	**NGDP (bl. US$)**	**NGDP (tr. ETB)**	**NGDP (bl. US$)**
2023q3	5.79	129.95	7.32	136.35
2023q4	6.05	133.30	7.74	139.69
2024q1	6.31	136.77	8.19	143.12
2024q2	6.59	140.36	8.66	146.63
2024q3	6.88	144.09	9.16	150.23
2024q4	7.18	147.96	9.69	153.93
2025q1	7.49	151.96	10.25	157.72
2025q2	7.82	156.11	10.85	161.61
2025q3	8.16	160.40	11.47	165.60
2025q4	8.52	164.84	12.14	169.69

Source: Own computation, 2020

Figure 3: The VAR Model Prediction[18] Values of GDP (in ETB) in a 95 Percent CI

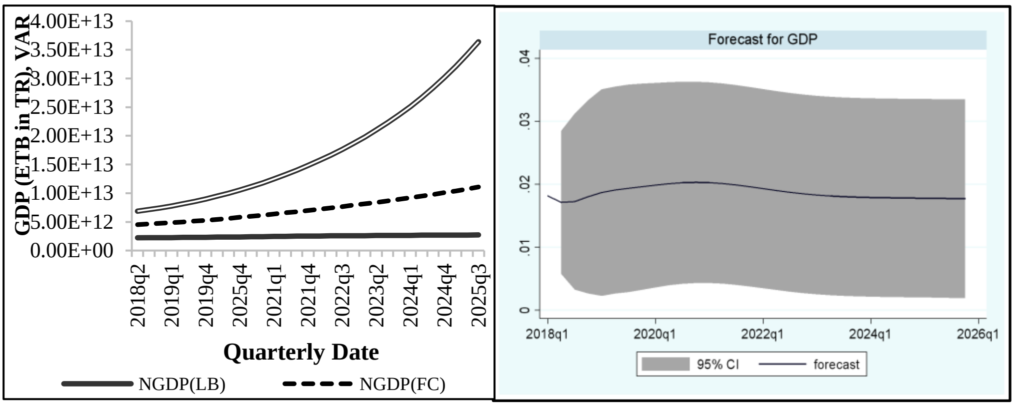
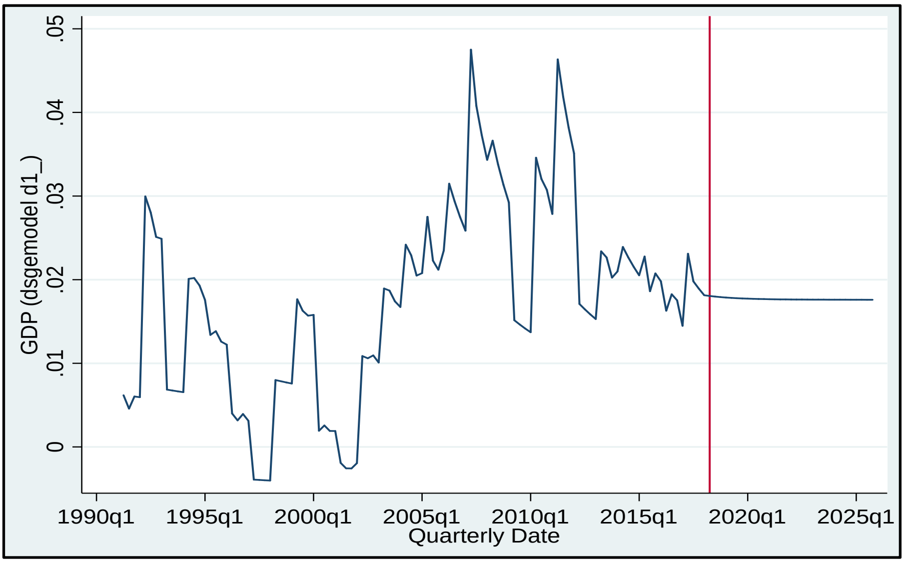


Figure 3 confirms that the out-off sample forecasts based on the VAR model entirely fall inside the 95 percent confidence interval. It indicates that the predicted results of GDP were in this interval with a 95 probability, if the assumptions of the model hold. The dynamic forecast in Figure 4 begins in the q2 of 2018. It shows the out-of-sample forecast for nominal GDP that employs a DSGE modeling.

[18] Based on 1990-2018 data series

Figure 4: The DSGE Model Forecast Values of GDP (ETB)



This study has also performed post-estimation diagnostics for the estimates. The autocorrelation, normality and stability test results are presented in Figure 5. The Lagrange-multiplier test revealed the absence of autocorrelation in the estimation process. Many of the Jarque-Bera test results confirm no normality in the data distribution except the pr(skewness)[19]. Regarding the stability of the VAR, all eigenvalues of the dynamic matrix lie inside the unit circle, which confirms the stability of the estimation procedures.

[19] Probability of skewness which is 0.2968 implying that skewness is asymptotically normally distributed (p-value of skewness > 0.05).

Figure 5: Autocorrelation, Normality, and Stability Diagnostics Tests for NGDP - US$

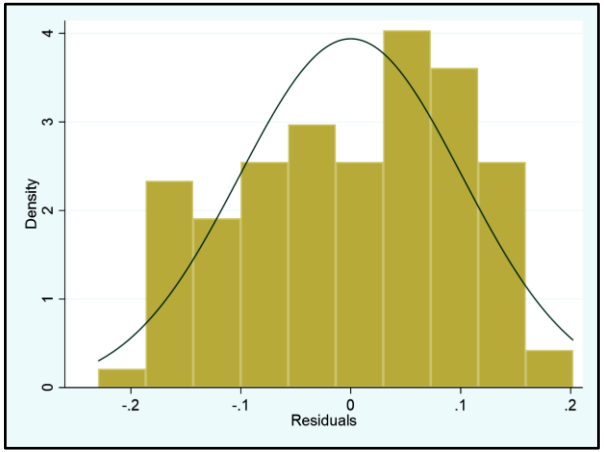
Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	15.5771	25	0.92684
2	7.6192	25	0.99967

H0: no autocorrelation at lag order

Jarque-Bera test

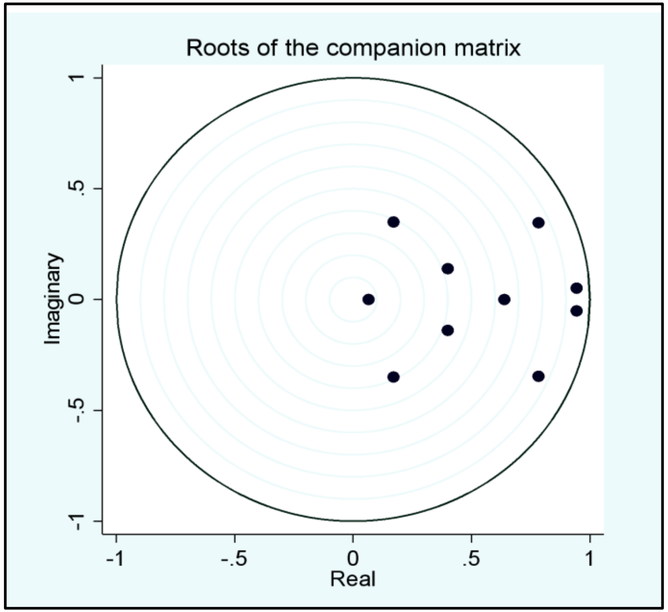
Equation	chi2	df	Prob > chi2
y1	8.979	2	0.01123
p	17.053	2	0.00020
R	47.950	2	0.00000
e	81.592	2	0.00000
q	25.994	2	0.00000
ALL	181.569	10	0.00000



Eigenvalue stability condition

Eigenvalue	Modulus
.94365 + .05127133*i*	.945042
.94365 - .05127133*i*	.945042
.782795 + .3464764*i*	.856046
.782795 - .3464764*i*	.856046
.6384549	.638455
.3994643 + .1392167*i*	.423028
.3994643 - .1392167*i*	.423028
.1702788 + .3497572*i*	.389005
.1702788 - .3497572*i*	.389005
.06497133	.064971

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.



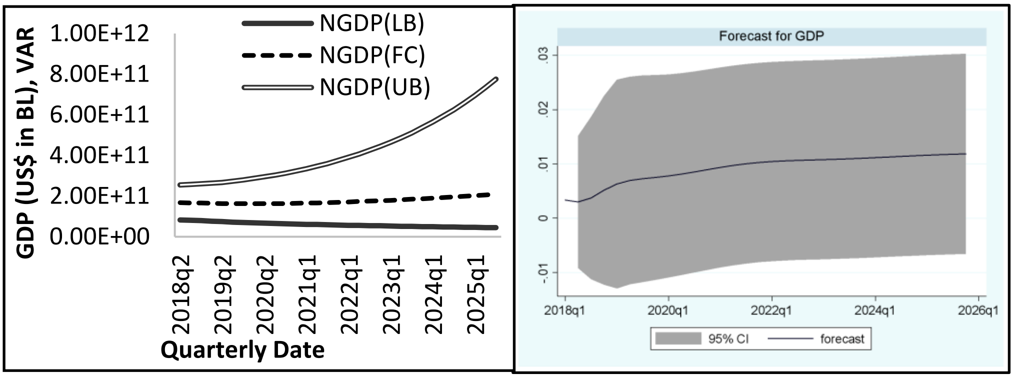

```
. sktest resid

                    Skewness/Kurtosis tests for Normality
                                                          ——— joint ———
    Variable        Obs  Pr(Skewness)  Pr(Kurtosis) adj chi2(2)   Prob>chi2
```

				joint	
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
resid	109	0.2960	0.0020	9.28	0.0097

Figure 6 confirms that out-off sample forecasts for the VAR estimation in 2018-2025 period entirely fall inside the 95 percent confidence bound. However, the results found are close to the lower margin of the LMI group. Thus, it requires a structural and sustainable growth in the economy to reliably apprehend the GDP range of the LMI category.

Figure 6: The VAR Model Prediction[20] Values of GDP (in US$) in a 95 Percent CI



3.2 Predicting GDP Per Capita for 2025

The predicted GDP per capita earning capacity of individuals for 2018-2025 in Ethiopia are presented in Table 7. Accordingly, the 2025 GDP per capita values using the 1990-2018 data series are 1072.3 and 923.2 US$ for the VAR and DSGE models, respectively. The 95 percent confidence band in the period 2004-2018 produces GDP per capita values of 1,122.57 and 1093.08 US$ for the VAR and DSGE models. The estimates based on the 2004-2018 period produced a better predicted value compared to the 1990-2018 period. Even though the GDP per capita value of 1,122.57 US$ was relatively close to the lower LMI margin of 1,138 US$, none of the predicted values confirms the country will achieve the goal of the LMI status before the end of 2025.

As the Ethiopian economy fails to reach even the bottom margin of the LMI range which is still quite low as compared with the upper margin of 4,458 US$, a strengthened growth and development are a head for Ethiopia to be in a reasonable interval of the LMI group.

[20] Based on 2004-2018 data series

Table 7: GDP Per Capita Prediction – US$[21]

Period	GDP per capita (1990-2018)		GDP per capita (2004-2018)	
Quarterly date	VAR model	DSGE model	VAR model	DSGE model
2018q2	773.6	773.86	773.97	775.81
2018q3	776.11	775.92	777.18	781.2
2018q4	780.56	778.44	782.76	788.03
2019q1	786.97	781.36	790.6	795.95
2019q2	794.94	784.64	800.17	804.7
2019q3	804.02	788.25	810.86	814.07
2019q4	813.8	792.13	822.19	823.93
2020q1	823.96	796.27	833.81	834.16
2020q2	834.33	800.64	845.53	844.67
2020q3	844.78	805.21	857.29	855.4
2020q4	855.29	809.96	869.09	866.29
2021q1	865.87	814.86	880.99	877.31
2021q2	876.54	819.91	893.04	888.43
2021q3	887.33	825.09	905.29	899.62
2021q4	898.24	830.38	917.75	910.87
2022q1	909.28	835.77	930.42	922.16
2022q2	920.4	841.25	943.25	933.49
2022q3	931.58	846.81	956.2	944.83
2022q4	942.75	852.44	969.21	956.2
2023q1	953.89	858.13	982.23	967.58
2023q2	964.95	863.88	995.22	978.97
2023q3	975.92	869.67	1,008.15	990.37
2023q4	986.78	875.51	1,021.02	1,001.78
2024q1	997.56	881.38	1,033.81	1,013.19
2024q2	1,008.27	887.29	1,046.55	1,024.60
2024q3	1,018.93	893.23	1,059.25	1,036.01
2024q4	1,029.58	899.19	1,071.92	1,047.42
2025q1	1,040.22	905.17	1,084.58	1,058.84
2025q2	1,050.89	911.17	1,097.24	1,070.25
2025q3	1,061.58	917.18	1,109.90	1,081.67
2025q4	1,072.30	923.21	1,122.57	1,093.08

Source: Own computation, 2020

[21] The values are presented in 95 percent confidence bound

As Figure 7 presents, the t-test for the forecast scenarios based on the 1991-2018 dataset for VAR and DSGE forecasting models show statistical differences value between the two forecasting models.

Figure 7: Significance Difference t-test Between DSGE and VAR (1990-2018)
ttest: varmodel – dsgemodel

	obs	Mean1	Mean2	dif	St Err	t value
varmodel - dsgemod~	31	912.298	839.942	72.355	8.689	8.35

However, in Figure 8 it has been presented, the t-test for the forecast scenario based on 2004-2018 data for VAR and DSGE forecasting models show no statistical differences between the two forecasting models. The t-test results reveals that the forecasting scenario based on the 2004-2018 dataset is producing more reliable and robust results over the forecasting scenario based on the 1991-2018 dataset.

Figure 8: Significance Difference t-test Between DSGE and VAR (2004-2018)
ttest : varmodel – dsgemodel

	obs	Mean1	Mean2	dif	St Err	t value
varmodel - dsgemod~	31	935.227	925.19	10.037	2.034	4.95

4. Conclusion and Policy Implications

Ethiopia has moved from the 2nd poorest country in the world at the beginning of this century to the 17th poorest in 2018[22], and the overall predictions of this study show that it will get closer to the goal of reaching the LMI status by 2025. DSGE & VAR models have been used, based on the quarterly time series data between 1990q1–2018q1, to evaluate, predict, & compare NGDP & per capita GDP values of the country by 2025. The prediction results in this study, particularly using the 1990-2018 prediction period, made clear that the 2025 goals of Ethiopia to reach a GDP of 147.5 US$ (or 9.3 tr. ETB) and a per capita GDP of 1,137 are not easily achievable with the current dynamics and trends of the economy. According to the predictions of this study Ethiopia's economy by 2025 will not reach even the lowest margin of the LMI range by many of estimation scenarios. The year 2004 is a reference point for the Ethiopian economy, as the average growth rate of the

[22] WB, WDI (2018)

economy was persistently more than 10 percent thereafter. In the case of prediction based on the 2004-2018 data set, the NGDP measured in the ETB become 12.14 tr. and the NGDP measured in the US$ reach 169.69 bl. But, even though the 2004-2018 data set produced exceeding above target predicted values than the 1990-2018 data set, the prospects of achieving a reasonable LMI value of GDP & GDP per capita (as a minimum an average US$ of 2797.5) by 2025 are not realizable.

To acquire lessons for the future, authorities and policymakers should focus on the driving factors behind the forecasting scenarios that reports higher values in this study. Ethiopian economy needs to improve its all-encompassing performance to realize the goal of LMI status by 2025. The measures to be taken embraces infrastructural investments, generating sustainable finance, structural reforms, nurturing macro-economic balance which all may certainly contribute to further growth of GDP and GDP per capita.

Singular, but potentially highly important events such as the peace accord with neighboring Eritrea and Sudan, but also the COVID-19 disasters and the 2020 state of Tigray crisis may also affect the prospects for Ethiopia’s development in ways that are obviously not incorporated in this study's forecast. It also must be recognized that GDP and GDP per capita are not be the sole and only measures of a country’s level of development. Other criteria such as those of the human development index, economic vulnerabilities (measured by a country’s initial macroeconomic fundamentals), the degree of a country’s integration into the global financial system, the distribution of wealth and income, and the ecological footprint all need to be considered for an overall assessment a country’s development. For instance, a reduction of poverty may be accomplished by a better distribution of income rather than a growth of GDP, and building a climate resilient green economy may not so much require growth of GDP, but rather a change of its composition. Such considerations and criteria, however, are beyond the scope of this study and it better be left to future to incorporate them.

Acronyms and Abbreviations

ARIMA	Autoregressive Integrated Moving Average
bl.	Billion
BM	Bayesian Methods
CB	Central Bank
CPI	Consumer Price Index
DSGE	Dynamic Stochastic General Equilibrium
ETB	Ethiopian Birr
FMLE	Full-information Maximum Likelihood Estimation
LMI	Lower-Middle-Income
NGDP	Nominal Gross Domestic Product
NK	New Keynesian
RBC	Real Business Cycle
SOE	Small Open Economy
TFP	Total Factor Productivity
tr.	Trillion
VAR	Vector Autoregression
WB	World Bank
WDI	World Development Indicator
WDR	World Development Report

References

Abdul Razak, N. A., Khamis, A., & Abdullah, M. A. A. (2017). ARIMA and VAR Modeling to Forecast Malaysian Economic Growth. *Journal of Science and Technology*, 9(3), 16-24.

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In B. N. Petrov & B. F. Csaki (Eds.), Second International Symposium on Information Theory, (pp. 267–281). Academiai Kiado: Budapest.

An, S. & Schorfheide, F. (2007). Bayesian analysis of DSGE models. Econometric Reviews, 26(2), 113-172.

Anderson, G. & Moore, G. (1985). A linear algebraic procedure for solving linear perfect foresight models. Economics Letters, 17, 247-252.

Ball, L. & Robert, T. (2002). The fed and the new economy. American Economic Review, 92(2), 108-114.

Bekana, G. & Deressa, W. (2017). Modelling and forecasts of GDP in Ethiopia: Multivariate time series Application. *International Journal of Current Advanced Research*, 6(2), 2121-2124.

Blanchard, O. (2009). The state of macro. The Annual Review of Economics, 1, 209–228.

________. (2016). Do DSGE Models Have a Future? Policy Brief PB16-11, Peterson Institute for International Economics.

________. (2017a). Further Thoughts on DSGE Models. Peterson Institute for International Economics. Available at https://piie.com/blogs/realtime-economic-issues-watch/further-thoughts-DSGE-models.

Blanchard, O.J. & Kahn, C. M. (1980). The solution of linear difference models under rational expectations. *Econometrica,* 48(5), 1305-1312.

Blundell, R. & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics,* 87(1), 115-143.

Bond, S., Hoefler, A. & Temple, J. R.W. (2001). *GMM estimation of empirical growth models.* Economics Papers No.2001-W21, Economics Group, Nuffield College: University of Oxford.

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. Australian Economic Papers, 17, 334–355.

Brown, R. L., Durbin, J. & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time (with discussion). *Journal of the Royal Statistical Society*, 37, 149-192.

Caselli, F., Esquivel, G. & Lefort, F. (1996). Reopening the convergence debate: a new look at cross-country growth empirics. *Journal of Economic Growth,* 1(3), 363–389.

Chari, V. V. & Patrick, J. K. (2006). Modern macroeconomics in practice: how theory is shaping policy. *Journal of Economic Perspectives*, 20(4), 3–28.

Chari, V. V. & Patrick, J. K. (2008). Response from V. V. Chari and Patrick J. Kehoe. *Journal of Economic Perspectives*, 22(1), 247–249.

________. (2010). Testimony before the committee on science and technology, subcommittee on investigations and oversight. U.S. House of Representatives. University of Minnesota and Federal Reserve Bank of Minneapolis.

Chow, G.C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica*, 28(3), 591-605.

Christiano, L. J. (2002). Solving dynamic equilibrium models by a method of undetermined coefficients. Computational Economics, 20(1-2), 21-55.

Christiano, L. J., Eichenbaum, M. S., Trabandt, M. (2018). On DSGE Models. NBER Working Papers 24811, National Bureau of Economic Research, Inc.

Clarida, R., Gali, J. & Gertler, M. (1999). The science of monetary policy: A New Keynesian perspective. *Journal of Economic Literature*, 37(4), 1661-1707.

________. (2000). Monetary policy rules and macroeconomic stability: evidence and some theory. *Quarterly Journal of Economics*, 115(1), 147-180.

de Walque, G. & Wouters, R. (2004). An Open Economy DSGE model linking the Euro Area and the U.S. Economy. Manuscript, National Bank of Belgium.

DeJong, D. N., Ingram, B. F. & Whiteman, C.H. (2000). A Bayesian approach to dynamic macroeconomics. *Journal of Econometrics*, 98(2), 203-223

Dickey D. A. & Fuller W. A. (1979). Distribution of estimators of autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74, 427-31.

________. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49(4), 1057-1072.

Dornbusch R., Fischer, S. & Startz, R. (2011). *Macroeconomics* (11th ed). New York, USA: McGraw-Hill.

Dotsey, M. (2013). DSGE Models and Their Use in Monetary Policy. Business Review, Federal Reserve Bank of Philadelphia, issue Q2, 10-16.

Francisco, J. R. (2011). Estimating Nonlinear DSGE Models by the Simulated Method of Moments. Meeting Papers 237, Society for Economic Dynamics.

Fuhrer, J. & Moore, G. (1995). Inflation persistence. *Quarterly Journal of Economics*, 110(1), 127-159.

Gali, J. & Gertler M. (2007). Macroeconomic modeling for monetary policy evaluation. *Journal of Economic Perspectives*, 21(1), 25–46.

Gali, J. & Monacelli, T. (2005). Monetary policy and exchange rate volatility in a small open economy. The Review of Economic Studies, 72(3), 707-734.

Geda, A. (2008). *The Political Economy of Growth in Ethiopia: Country Case Studies*. In Benno Ndulu, Stephen A. O‘connell, Jean_Paul Azam, Rober H. Bates, Augustin K. Fosu, Jan Willem Gunning and Dominique Njinkeu editors. Cambridge: Cambridge University Press.

Geda, A. (2018). Economics professor disproves double digit economic growth. Reported in https://newbusinessethiopia.com in June 28, 2018.

Geda, A. & Addis, Y. (2014). The Political Economy of Growth, Poverty and Inequality in Ethiopia, 2000–2013. Dessalegn Rahmato, Meheret Ayenew, Asnake Kefale, Birgit Habermann

Gibbs, C. G., Hambur, J. & Nodari, G. (2018). DSGE Reno: Adding a Housing Block to a Small Open Economy Model. Research Discussion Paper. RDP 2018-04. Sydney, Australia.

Godfrey L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica*. 46, 1293–1301.

Goodfriend, M. (2007). How the world achieved consensus on monetary policy. *Journal of Economic Perspectives*, 21(4), 47–68.

Goodfriend, M. & King R. (1997). The new neoclassical synthesis and the role of monetary policy, NBER Macroeconomics Annual, 231-283.

Griffoli, T. M. (2010). Dynare user guide: an introduction to the solution and estimation of DSGE models. GNU Free Documentation License

IMF (International Monetary Fund). (2018). National Statistics Office Latest actual data. World Economic Outlook Database. Washington DC. USA.

Jarque, C. M.; Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics Letters, 6 (3), pp. 255 259.

Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering*, 82, 35–45.

Keynes, J.M. (1936). *The general theory of employment, interest, and money*. London, Macmillan.

Kim, J. (2000). Constructing and estimating a realistic optimizing model of monetary policy. *Journal of Monetary Economics,* 45(2), 329-359.

Klein, P. (2000). Using the generalized Schur form to solve a multivariate linear rational expectations model. *Journal of Economic Dynamics and Control,* 24, 1405-1423.

Koop, G. & Korobilis D. (2010). Bayesian multivariate time series methods for empirical macroeconomics. Foundations and Trends in Econometrics, 3(4), 267–358.

Kydland, F. E. & Prescott, E. C. (1982). Time to build and aggregate fluctuations. *Econometrica*, 5(6).

Landon-Lane, J. (1998). Bayesian comparison of dynamic macroeconomic models. Ph.D. dissertation, University of Minnesota.

Le, V., Meenagh, D., Minford, P. & Wickens, M. (2012). Testing DSGE models by Indirect inference and other methods: some Monte Carlo experiments. Cardiff Economics Working Papers E2012/15, Cardiff University, Cardiff Business School, Economics Section.

Leeper, E. M. & Sims, C. A. (1994). *Toward a modern macroeconomic model usable for policy analysis*. In Stanley, F., Rotemberg, J. J., editors. NBER Macroeconomics Annual 1994. Cambridge, MA: MIT Press, 81-118.

Lindé, J. (2018). DSGE models: still useful in policy analysis? Oxford Review of Economic Policy, 34(1–2), pp. 269–286.

Long, J. & Plosser C. (1983). Real Business Cycles. *Journal of Political Economy*, 94, 39-69.

Lubik, T.A. & Schorfheide, F. (2006). A Bayesian look at new open economy macroeconomics. In: Mark, G., Rogoff, K., editors. NBER Macroeconomics Annual 2005. Cambridge, MA: MIT Press, 313-366.

________. (2007). Do central banks respond to exchange rate movements? A structural investigation. *Journal of Monetary Economics*, 54, 1069-1087.

Lütkepohl, H. (2005). Structural Vector Autoregressive Analysis for Cointegrated Variables. European University Institute Working Paper ECO, no. 2005/2.

Mankiw, N. G. (2006). The Macroeconomist as scientist and engineer. *Journal of Economic Perspectives*, 20(4), 29–46.

________. (2013). *Macroeconomics* (8th ed). New York, USA: Worth.

Meenagh, D., Minford, P., Wickens, M. & Xu, Y. (2019). Testing DSGE Models by Indirect Inference: A Survey of Recent Findings. Open Economies Review, 30, 593–620.

Meeusen, W. (2011). Whither the Microeconomic Foundations of Macroeconomic Theory? Brussels Economic Review, ULB - Universite Libre de Bruxelles, 54(1), 51-80.

MoFED (Ministry of Finance and Economic Development). (2010). FDER: GTP I (Federal Democratic Republic of Ethiopia: Growth and Transformation Plan I: 2010/11-2014/15). Addis Ababa, Ethiopia.

________. (2012). Ministry of Finance and Economic Development, Ethiopia's Progress Towards Eradicating Poverty: An Interim Report on Poverty Analysis Study.

Nachane, D. (2017). Dynamic stochastic general equilibrium (DSGE) modelling in practice: identification, estimation and evaluation. Macroeconomics and Finance in Emerging Market Economies, 10(2), pp. 107-134.

NBE (National Bank of Ethiopia). (2022). Statistical Data Series. Addis Ababa, Ethiopia.

NPC (National Planning Commission). (2016). FDRE: GTP II (Federal Democratic Republic of Ethiopia: Growth and Transformation Plan II: 2015/16-2019/20). 1, Addis Ababa, Ethiopia.

Ohanian, L. E., Prescott, E. C., & Stokey, N. L. (2009). Introduction to dynamic general equilibrium. *Journal of Economic Theory*, 144: 2235–2246.

Orphanides, A. (2001). Monetary policy rules based on real-time data. American Economic Review, 91(4), 964-985.

Otrok, C. (2001). On measuring the welfare cost of business cycles. *Journal of Monetary Economics*, 47(1), 61-92.

Patrick, P. (2009). Forecasting GDP growth: The case of the Baltic States. Jönköping International Business Scholl. Jönköping University.

PDC (Planning and Development Commission). (2021). Ten-year Development plan, Addis Ababa Ethiopia.

Phillips, P. C. B. & Perron P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-46.

Rabanal, P. & Tuesta, V. (2006). Euro-Dollar real exchange rate dynamics in an estimated two-country model: what is important and what is not. CEPR Discussion Paper No. 5957.

Robertson, J. C. & Tallman, E. W. (1999). Vector autoregressions: forecasting and reality. Federal Reserve Bank of Atlanta Economic Review, 84(4), 4-18.

Rochelle, M. E. & Refet S. G. (2010). How Useful Are Estimated DSGE Model Forecasts for Central Bankers? Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, 41(2), 209-259.

Romer, D. (2012). *Advanced Macroeconomics* (4th ed). New York, USA. McGraw-Hill.

Rotemberg, J. & Woodford, M. (1997). An optimization-based econometric framework for the evaluation of monetary policy, NBER Chapters, in: NBER Macroeconomics Annual 1997. National Bureau of Economic Research, Inc., 12, 297-361.

Salvatore D. (2013). *International Economics* (11th ed). Wiley & Sons, Inc

Schorfheide F. (2000). Loss function-based evaluation of DSGE models. *Journal of Applied Econometrics*, 15(6), 645-670.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48(1), 1-48.

________. (2002). Solving linear rational expectations models. Computational Economics, 20, 1-20.

Sisay, R. (2011). How applicable are the New Keynesian DSGE models to a typical Low-Income Economy? MPRA Paper. University of Antewerp. No. 30931.

Snowdon, B. & Vane, H. R. (2005). Modern Macroeconomics: Its Origins, Development and Current State, London: Edward Elgar, 294-344,

StataCorp. (2019). STATA dynamic stochastic general equilibrium reference manual: release 16. College Station, TX: StataCorp LLC.

Stock, J. H. & Mark W. (2001). Vector Autoregressions. *Journal of Economic Perspectives,* 15(4), 101–115.

Taylor, J. B. (1993). Discretion versus policy rules in practice. Carnegie-Rochester Conference Series on Public Policy, 39, 195–214.

Tovar, C. E. (2009). DSGE models and central banks. Bank for international settlements, Economics: The Open Access, *Open-Assessment E-Journal,* 3.

Trevor, R. G. & Thorp, S. J. (1988). VAR forecasting models of the Australian economy: A Preliminary Analysis. Reserve Bank of Australia Research Discussion Paper 8802.

UNDP (United Nation Development Program) Ethiopia. (2018). Ethiopia's progress towards eradicating poverty: paper to be presented to the inter-agency group meeting on the ‘implementation of the third united nations decade for the eradication of poverty (2018 – 2027)’. Addis Ababa, Ethiopia

United Nations, Department of Economic and Social Affairs, Population Division. (2019). World population prospects 2019. Online Edition. Rev. 1.

WB (World Bank). (2013). Ethiopia economic update II: laying the foundation for achieving middle income status. World Bank, Washington, DC.

WB, WDI (World Bank, World Development Indicators). (2018). Selecting all countries, GDP per capita (current US$). World Bank (Accessed on 1st of July 2019.): Washington DC. USA.

________. (2019). Classifying countries by income. Washington DC. USA.

________. (2020). Excel data base report on low-income Sub-Saharan Africa: Ethiopia. Washington DC. USA.

Woodford, M. (2003). *Interest and prices: foundations of a theory of monetary policy.* Princeton, NJ: Princeton University Press.

________. (2009). Convergence in macroeconomics: elements of the New Synthesis. *American Economic Journal*, 1(1), pp. 267-279.