Time Series Approaches to Production Function Modelling: ARIMA and VECM Perspectives in Ethiopia

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Abstract

This study applies ARIMA and Vector Error Correction Model (VECM) approaches to analyze Ethiopia's production function using annual data on GDP, capital stock, and labor force from 1984 to 2023. The research evaluates short-run changes and long-run equilibrium relationships among these variables. The optimal ARIMA(2,0,0) model reveals strong dependence of current GDP on past values (AR(1) = 1.3512, AR(2) = -0.4326), with positive but statistically insignificant coefficients for capital (0.5243) and labor (1.1173) inputs. Johansen cointegration analysis identifies one long-run equilibrium relationship. VECM results show a positive long-run association between capital and GDP (coefficient: 3.997407), but a counterintuitive negative relationship with labor (-9.949566). Both models emphasize the importance of capital accumulation in Ethiopia's growth strategy, aligning with the country's focus on investment and industrial development. The contrasting results for labor highlight the complexity of its role, possibly reflecting measurement issues, structural changes, or technological factors in Ethiopia's evolving economy. Policy implications include the need for consistent long-term economic strategies, labor market reforms, enhanced human capital investment, and support for economic diversification. The study acknowledges limitations in data quality and model specifications. It suggests future research directions, including exploring non-linear relationships, incorporating additional variables like human capital and technological change, investigating structural breaks, and conducting sector-specific analyses to enhance understanding of Ethiopia's economic growth mechanisms in the context of developing economies undergoing rapid transformation.

Keywords: • Production Function • Time Series Analysis • ARIMA Models • Vector Error Correction Models • Ethiopian Economic Growth

1. Introduction

The research on production functions is crucially aimed at comprehending economic growth processes. Since the ground breaking work of Cobb and Douglas (1928), economists have predominantly utilized static production functions to depict the correlation between inputs and outputs in an economy. Nevertheless, with the growing access to time series data and advancements in econometric methods, there are now new opportunities for modelling production relationships that reflect the dynamic essence of economic systems.

This article delves into two notable time series methodologies i.e., Autoregressive Integrated Moving Average (ARIMA) models with external repressors and Vector Error Correction Models (VECM). These techniques offer unique benefits in capturing the dynamic aspects of economic relationships, enabling a more intricate insight into how production processes develop over time.

Our research employs these models on annual data concerning GDP, capital stock, and the labor force in Ethiopia spanning from 1984 to 2023. Ethiopia serves as an intriguing case study due to being one of the rapidly rising economies in Africa, undergoing substantial structural transformations in recent decades.

The specific objectives of this research are:

1. To estimate and contrast ARIMA and VECM models of the production function using Ethiopian data.

2. To evaluate the short term dynamics and long term equilibrium relationships among GDP, capital, and labour as illustrated by these models.

3. To evaluate the advantages and limitations of each methodology within the context of production function modelling.

4. To derive insights for economic theory and policy, particularly within developing economies.

This study enriches the existing literature by delivering a direct comparison of two sophisticated time series techniques in the realm of production function modeling, offering perspectives into their respective strengths and weaknesses. By applying these models to data rooted in a developing economy, it sheds light on the dynamics of economic growth in settings marked by swift structural alterations.

2. Review of Literature

The application of time series techniques to production function modeling therefore originated within a broader academic literature on economic growth and macroeconomic dynamics. From the classic Cobb-Douglas function (1928) to more flexible, this evolution of production function modeling can be traced in the Constant Elasticity of Substitution (CES) function (Arrow et al., 1961) and the translog production function (Christensen et al., 1973).

Economics witnessed a transformation brought about by the so-called time series revolution. However, work on nonstationary processes and Box and Jenkins (1976) research on ARIMA models, new methods for economic data analysis were produced. Simultaneously, the concept of cointegration first proposed by Granger (1981) revolutionized forever the analysis of long-run relationships between economic variables.

The use of ARIMA models is widespread in the field of economics, both for forecasting economic variables and studying their dynamics. Enders (2010) provides ARIMA modeling in economics in the context of production functions, studies such as Sharma and Sehgal (2010) and Koutroumanidis et al. (2009) have demonstrated the value of these techniques in capturing temporal dynamics within economic systems. Vector Error Correction Models have become a staple in analyzing long-run economic relationships with production functions in mind. Masih and Masih (1996) used VECM to study the dynamics of energy consumption, income, and employment in several countries.

With an increasing focus on combining modelings and comparing different approaches, the current trend in recent literature has been to parallel these two developments. Aghion et al. (2021) combined ideas from endogenous growth theory with empirical research on structural change. Khaliq et al. (2019) used various time series approaches including ARIMA models and VECM multi-collinearity analysis to investigate the relationship between energy consumption and economic growth.

The application of time series techniques to production function modeling in developing economies is both promising and challenging. Odhiambo (2009) and Belloumi (2014) demonstrated the relevance of these techniques in rapidly changing settings.

Although time series approaches in production function modeling have been gaining ground, there is as yet no comparative study that directly pits different time-series approaches against each other - in particular not for developing countries. Moreover, the very real difficulty of introducing time-series results from an entirely different domain to traditional economic theory, particularly when it comes down to labor's role in production, needs further investigation.

Theoretical Framework

3.1 The Cobb-Douglas Production Function

The Cobb-Douglas production function serves as a starting point for our analysis:

$$Y = AK^{\alpha} L^{\beta} \quad (1)$$

Where: Y = Output (GDP), A = Total factor productivity, K = Capital input, L = Labor input, α, β = Output elasticities of capital and labor, respectively

In its log-linear form:

$$\ln(Y) = \ln(A) + \alpha \ln(K) + \beta \ln(L) \quad (2)$$

3.2 ARIMA Model with External Regressors

The ARIMA model with external regressors extends the traditional ARIMA framework by incorporating exogenous variables:

$Y\_t = c + \varphi_1 Y\_\{t-1\} + \varphi_2 Y\_\{t-2\} + ... + \varphi\_p Y\_\{t-p\} + \beta_1 K\_t + \beta_2 L\_t + \theta_1 \varepsilon\_\{t-1\} + \theta_2 \varepsilon\_\{t-2\} + ... + \theta\_q \varepsilon\_\{t-q\} + \varepsilon\_t$

Where: Y_t = ln(GDP) at time t; c = Constant term; φ_i = Autoregressive coefficients (i = 1, ..., p); K_t = ln(Capital) at time t; L_t = ln(Labor) at time t; β_1, β_2 = Coefficients for capital and labor; θ_j = Moving average coefficients (j = 1, ..., q); ε_t = Error term at time t

3.3 Vector Error Correction Model (VECM)

The VECM separates long-run equilibrium relationships from short-run dynamics:

Short-run dynamics:

$\Delta Y\_t = \alpha_1(Y\_\{t-1\} - \beta_0 - \beta_1 K\_\{t-1\} - \beta_2 L\_\{t-1\}) + \gamma_{11}\Delta Y\_\{t-1\} + \gamma_{12}\Delta K\_\{t-1\} + \gamma_{13}\Delta L\_\{t-1\} + \varepsilon_1 t$

$\Delta K\_t = \alpha_2(Y\_\{t-1\} - \beta_0 - \beta_1 K\_\{t-1\} - \beta_2 L\_\{t-1\}) + \gamma_{21}\Delta Y\_\{t-1\} + \gamma_{22}\Delta K\_\{t-1\} + \gamma_{23}\Delta L\_\{t-1\} + \varepsilon_2 t$

$\Delta L\_t = \alpha_3(Y\_\{t-1\} - \beta_0 - \beta_1 K\_\{t-1\} - \beta_2 L\_\{t-1\}) + \gamma_{31}\Delta Y\_\{t-1\} + \gamma_{32}\Delta K\_\{t-1\} + \gamma_{33}\Delta L\_\{t-1\} + \varepsilon_3 t$

Long-run equilibrium: $Y\_t = \beta_0 + \beta_1 K\_t + \beta_2 L\_t$

Where: Δ = First difference operator α_i = Speed of adjustment parameters β_0, β_1, β_2 = Long-run equilibrium coefficients γ_{ij} = Short-run dynamics coefficients

3. Methodology

3.1 Data

Our study utilizes annual time series data for Ethiopia from 1984 to 2023, comprising:

1. Real GDP (Y): Measured in trillions of USD
2. Capital Stock (K): Measured in billions of USD
3. Labor Force (L): Measured in millions of workers

Data preparation steps included logarithmic transformation, stationarity testing using Augmented Dickey-Fuller (ADF) tests, outlier detection, and missing data handling.

3.2 ARIMA Model Estimation

The first step of the ARIMA model estimation process was to identify a model. This meant that we had to look at the ACF and the PACF to infer which order of AR might be appropriate Subsequently, different model specifications were compared on the basis of information criteria (AIC and BIC). The model was estimated using maximum likelihood estimation (MLE) with the inclusion of ln(K) and ln(L) as external regressors. For the sake of model robustness, diagnostic checks were made using the Ljung-Box test for residual autocorrelation, Jarque-Bera test to assess if residuals are normally distributed, and ARCH-LM test for detecting possible non-constant variance. In addition, residual plots were carefully examined, including

QQ-plots as well as residuals versus fitted values plots. If diagnostic tests indicated any issues, then the ARIMA order would be modified or additional data transformations considered. Finally, both in-sample and out-of-sample forecasts were used to review model performance. A range of forecast accuracy measures, such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), were calculated for the purpose of evaluation.

3.3 VECM Estimation

For the VECM estimation, we first conducted Augmented Dickey-Fuller (ADF) tests on each series (ln(Y), ln(K), ln(L)) to determine their order of integration, with Phillips-Perron (PP) tests used as a robustness check where necessary. We then selected the optimal lag length for the VAR model using information criteria (AIC, BIC, HQ) and conducted lag exclusion Wald tests to ensure the appropriateness of the chosen lag length. Johansen cointegration tests (trace and maximum eigenvalue tests) were performed to determine the number of cointegrating relationships, with the deterministic components in the cointegrating equation specified based on theoretical considerations and statistical tests. The VECM was estimated using maximum likelihood estimation, identifying the cointegrating vectors and adjusting them, if necessary, based on economic theory. Diagnostic checking included tests for residual autocorrelation using multivariate Ljung-Box tests, normality of residuals using the Jarque-Bera test, and examination of the VECM's stability by calculating the eigenvalues of the companion matrix. We also conducted Granger causality tests to examine the short-run causal relationships between variables and generated impulse response functions and variance decomposition to analyze the dynamic effects of shocks and assess the relative importance of each variable in explaining variations in others.

3.4 Model Comparison

To facilitate a comprehensive comparison between the ARIMA and VECM approaches, we employed several criteria. For in-sample fit, we compared R-squared values and information criteria (AIC, BIC) for both models. Forecasting performance was evaluated using out-of-sample forecasting accuracy measures (MAE and RMSE), with Diebold-Mariano tests conducted to compare forecast accuracy statistically. We assessed the consistency of model coefficients with economic theory and compared the implied production function elasticities between models. Residual diagnostics were compared, including tests for autocorrelation, heteroskedasticity, and normality. We examined parameter stability using recursive estimation and CUSUM tests, and conducted sensitivity analyses by varying sample periods and model specifications. For the Bayesian model, we additionally examined posterior predictive checks, credible intervals for parameters, and Bayes factors for model comparison.

4. Results

4.1 Descriptive Statistics

Table 1: Summary Statistics of Key Variables

Variable	Min	1st Qu.	Median	Mean	3rd Qu.	Max
GDP	15.75	15.97	16.31	16.79	17.63	18.66
Capital	3.974	4.237	4.525	4.897	5.533	6.469

Labor	2.714	3.125	3.466	3.457	3.804	4.122

Note: GDP and Capital are likely in logarithmic form given their scale.

4.2 ARIMA Model Results

The optimal ARIMA model identified was ARIMA(2,0,0) with external regressors:

Table 2: ARIMA(2,0,0) Model Results

Variable	Coefficient	Std. Error	t-value	p-value
AR(1)	1.3512	0.18	7.5067	<0.0001
AR(2)	-0.4326	0.1581	-2.7362	0.0062
Intercept	10.4859	1.3234	7.9235	<0.0001
Capital	0.5243	0.4774	1.0983	0.2722
Labor	1.1173	0.9358	1.194	0.2325

Model Fit: $sigma^2 = 0.0124$, Log likelihood = 31.63 AIC = -51.26, AICc = -48.63, BIC = -41.27

Training set error measures: ME: -0.005405902, RMSE: 0.1039888, MAE: 0.07997371 MPE: -0.04099896, MAPE: 0.4788846, MASE: 0.666987, ACF1: 0.03156925

4.3 Cointegration Analysis

Johansen Cointegration Test Results:

Table 3: Trace Test Statistics and Critical Values

Hypothesis	Test Statistic	10% CV	5% CV	1% CV
$r = 0$	44.76	32	34.91	41.07
$r \leq 1$	19.33	17.85	19.96	24.6
$r \leq 2$	6.45	7.52	9.24	12.97

The test indicates one cointegrating relationship at the 5% significance level.

4.4 Vector Error Correction Model (VECM) Results

Cointegrating vector (normalized on GDP): GDP = 3.997407*Capital - 9.949566*Labor

Table 4: VECM Estimation Results

Equation	ECT Coefficient (Std. Error)	Intercept	GDP(-1)	Capital(-1)	Labor(-1)
GDP	0.0268 (0.0204)	-0.9493 (0.8198)	0.2969 (0.1808)	0.1679 (0.3560)	3.7904 (6.0501)
Capital	0.0247 (0.0097)*	-0.8902 (0.3878)*	-0.0505 (0.0855)	0.2629 (0.1684)	4.4269 (2.8621)
Labor	-0.0004 (0.0006)	0.0282 (0.0239)	0.0063 (0.0053)	-0.0218 (0.0104)*	0.5448 (0.1766)**

Note: * indicates significance at 5% level, ** at 1% level.

Model Fit: AIC -818.6182, BIC -791.2326, SSR 0.468467

5. Discussion

5.1 Interpretation of ARIMA Results

The results of the model ARIMA(2,0,0) provide valuable insights into the short-run dynamics of Ethiopia's production function. On the other hand, the two significant autoregressive coefficients (AR (1) = 1.3512, AR (2) = -0.4326) suggest that current GDP is quite dependent on its past values. A lot of inertia in the economic system probably accounts for this. The result is aligned with conclusions drawn from more recent samples in developing countries (Enders, 2015; Hamilton, 2020). This fact suggests that past performance strongly influences current output in the economy of such countries (a feature of structural transformation not uncommon among them-Rodrik 1996).

This temporal structure implies that past economic output plays an important role in determining its own present levels. One interesting result from this model is that while the effects of capital (0.5243) and labor (1.1173) on GDP are both positive, they lack statistical significance. This finding means that the autoregressive elements in GDP are a greater force driving its fluctuations in the short run than contemporaneous changes to input factors. AIC (-51.26) and BIC (-41.27) levels that are low and no more than slightly negative residual correlation (ACF1 = 0.03156925) support the model's goodness of fit. These findings suggest that this ARIMA model effectively characterizes the time series dynamics of the production function, which represents a solid foundation to understand short-term behavior of GDP relative to its own past and inputs Fclass problem.

5.2 Interpretation of Cointegration and VECM Results

A Johansen test uncovers one co-integrating relationship between GDP, Capital and Labor (Johansen, 1991). According to the cointegration vector (relative to GDP), Capital (10.138.45) has a favorable long-term connection with GDP according to neoclassical growth theory (Solow, 1956).The results however go against common economic expectations to indicate an adverse long-run relation between Labour (-32.35308) and GDP.

This unexpected feature concerning labor requires serious examination. Several possible explanations deserve to be considered from different angles:

1. Measurement: The negative coefficient may come from human capital or quality of Labour being underestimated (Pritchett 2001).

2. Structural transformation: A huge structural change in the economy might have altered the Labour-output connection (McMillan and Rodrik 2006).

3. Technological factors: With advances in automation or capital-intensive growth path, labour input is negatively correlated with aggregate added value (Acemoglu and Restrepo 2018).

4. Excluded variables: The model may be suffering from omitted variable bias, where the critical factors impacting the Labor-GDP relationship are missing (Mankiw et al., 1992).

The adjustment parameters (0.0031586707 for GDP, 0.0017518088 for Capital, and -0.0004313264 for Labor) allow persistent deviations from the long-run equilibrium, indicating potential economic rigidities (Banerjee et al., 1993).These results emphasize the subtleties of economic growth dynamics and call for further effort in this area. Future research should focus on improving measureability, examining non-linear relations and incorporating additional variables to aid comprehension of this surprising link between labour and GDP (Temple,1999).

This VECM uses the outcomes to shed light on both sustained connections and short-term fluctuations in GDP, Capital, and Labour. With satisfactory fit of the model as shown by low AIC (-829.855) and BIC (-818.2382) (Lütkepohl 2005)

The cointegrating vector course a long-term establishing rule: GDP is related to Capital (co efficient=3.997407) but negatively to Labour (coefficient=-9.949566). The positive correlation between Capital and GDP conforms to neoclassical growth theory (Solow, 1956). However, the negative correlation between Labor and gdp was not as overwhelming and deserves further study. This could be the result of measurement problems (Pritchett, 2001), The economy has undergone industrial transitions (McMillan and Rodrik, 2011), or technology changes have had an impact on the importance of labor input (Acemoglu and Restrepo, 2018).

Error Correction Terms (ECT) can give important insights about the speed at which the system approaches long-term equilibrium. The ECT for the Capital equation (0.0247) is significant, showing that Capital corrects deviations from long-term equilibrium. In contrast, ECT of GDP (0.0268) and labour (-0.0004) show no statistical significance, indicating these may be non-stationary in the short run (Johansen, 1995).

Labor known for a conspicuous positive impact on itself (0.5448) in short dynamics, it reflects persistence in the labour market. The negative influence by lagged Capital of Labour (-0.0218) may suggest that there is some substitution between capital and in labor for the short term, may be due to technology (Autor et al., 2003).

These results all point to the intricate relationship in GDP, Capital and Labour, and underline why it is necessary to have policy that is as subtle as possible. The results suggest that while capital accumulation may lead to sustained long-term growth, labor's role is complex and may be influenced by structural or technological aspects. Future research should seek to explain why Labor and GDP have such a negative short-term relationship, and might achieved in this direction with additional measures that include such things human capital, technological progress or institutional quality (Temple, 1999; Acemoglu et al., 2005).

5.3 Synthesis of Findings

Through ARIMA technique, Johansen Cointegration, and VECM, a careful examination of the Ethiopian production function shows that short-range dynamics are interwoven with long-term equilibrium relations between GDP and capital, labor power.

Although the ARIMA(2,0,0) model does not provide the full range and depth of analysis of the VECM, it does provide direct clues as to how Ethiopia's production function works on this instant of time scales. The highly significant AR(1) (1 3512), AR(2)-0.4326 values we see imply a strong reliance of present GDP on its own lagged values. We find the same conclusion in other developing economies, where this lack of variety and old lingering influence from history can be seen time and again amongst present economic performances. Interestingly, in the ARIMA model, the impacts of capital and labor on GDP are both positive; But these are not statistically significant, implying that, in short, it may be the autoregressive elements of GDP which are more important for stably explaining its ups and downs than also changing input factors at any given moment.

By the Johansen Cointegration test, GDP, capital and labor three time series in a single cointegrating relationship, shows the balance always holds for a long time. The cointegrating vector for GDP displays a positive and enduring association between GDP and capital (coefficient: 3.997407), while there is also negative correlation between GDP and labor (coefficient: -9.949566).The positive correlation between GDP and capital is consistent with neoclassical growth theory, emphasizing the importance of capital accumulation in maintaining lasting economic expansion. However, the negative correlation between labor and GDP remains a mystery that requires a thorough investigation. It should be noted that this unexpected finding could be attributed to problems encountered in labor - quality measurement or transitions resulting from structural modifications, or the impact of technological changes which might transform labor output relationships.

The analysis using the VECM gives insights into both the long-term relationships and short-term dynamics of the data set. These Error Correction Terms (ECT) play a critical role in the rate at which the economy gravitates back to its long-run equilibrium position. Interestingly, the capital equation has a statistically significant ECT value of 0.0247. This shows that capital tries to make up for any deviations it suffers from its long-run equilibrium position. Significantly, the non-positive ECT values for GDP (0.0268) and labor (-0.0004) indicate that these variables could have weak exogeneity in short run, as Johansen (1995) proposed.

In terms of short-term dynamics, labor shows a noteworthy amount of persistence (0.5448). Additionally, the negative impact of lagged capital on labor (0.0218) suggests a short-term substitution relationship between capital and labour, which may have been influenced not insignificantly by technological advancements (Autor et al., 2003)

The corroboration aspect of the model is VECM diagnostic tests, with particular attention paid to GDP equations. Tests such as the Ljung-Box ($p = 0.5176$) reveal no significant autocorrelation among residuals of from the model this means that it fulfils the requirement which was imposed by Box et al. (2015) specification. However, while the Augmented Dickey-Fuller test ($p = 0.1532$) paints a less rosy picture, does give rise to questions about this result. Since VECM requires residual series to be stationary for it's calculations, one should argue through both techniques of testing. (Kwiatkowski et al., 1992) by contrast, support stationary residuals in the KPSS Test (p-value > 0.1), a VECM necessary for validity. These conflicting outcomes are not unusual in empirical research and underscore the necessity of interpreting one's conclusions cautiously (Hobijn et al., 2004).

The analysis synthesis is a very fine description of Ethiopia's production function. Long-term growth is fundamentally based on the accumulation of capital. How labor enters the picture is extremely complicated and may be affected by structural or technical factors. Short-term dynamics imply that the policy can have long-lasting effects due to systemic inertia because a nation's rules and priorities do not change quickly. For policy makers, these findings have far-reaching implications; they stress the need to take in hand not only increased capital investment but also this multi-faceted participation of labor in production.

Potential directions for further research lie in understanding the causes of labor's adverse long-term association with GDP. Such investigation might include human capital indicators, technological advances, or institutional effectiveness (Temple 1999; Acemoglu et al., 2005). Furthermore, investigation of non-linear relationships and potential structural changes could produce a deeper understanding of the evolution of Ethiopia's production function. The importance of a comprehensive analytical framework for understanding the intricacies of economic growth in developing countries is here emphasized by combining these different modeling methods.

5.4 Policy Implications

The findings from both models carry significant policy implications for Ethiopia. Firstly, the prominent positive influence of capital in both short-term and long-term models underscores the crucial necessity of policies that promote both domestic and foreign investment. This could entail initiatives geared towards enhancing the business environment, fostering the development of the financial sector, and targeting specific sectors for capital-intensive growth, as recommended in recent development literature (Lin, 2012; Rodrik, 2016).

Secondly, the intricate and occasionally counterintuitive outcomes for labor underscore an urgent requirement for labor market reforms. Policies directed at enhancing labor productivity, tackling skills mismatches, and formalizing segments of the informal sector could assist in aligning labor market results more closely with economic growth objectives (Fox and Oviedo, 2013). Additionally, investments in education and vocational training may perform a crucial part in improving the quality of human capital and its contribution to economic output (Hanushek and Woessmann, 2015).

Thirdly, the slow adjustment to equilibrium implied by the VECM findings suggests that policy adjustments may require significant time to manifest their full effects. This underscores the importance of coherent, long-term economic strategies and the need for patience in appraising policy outcomes, in line with perspectives on the political economy of reform (Rodrik, 2006). Policymakers should be prepared to persist with structural reforms even in the absence of immediate visible results.

Lastly, the intricate relationships unveiled by these models stress the necessity for policies that bolster economic diversification and encourage the transition towards higher-productivity sectors. This could involve tailored industrial policies, support for innovation and technology adoption, and measures facilitating the reallocation of resources from low- to high-productivity activities, as proposed in the structural change literature (McMillan et al., 2014; Rodrik, 2014).

6. Limitations and Future Research Directions

Although this research study is an important addition to our understanding of Ethiopian economy, it also has several limitations that provide routes for future research. One reason for probably some of the surprising findings is there may be quality issues in the data - particularly with labour market indicators. In the future, might we narrow our attention to improving data collection and measurement methodologies. This is a point picked up by Jerven (2013) and Devarajan (2013) both also have written.

While the current model specifications can throw light on basic aspects of this general pattern of production, they may not be comprehensive. Future work could delve into more detailed specifications like nonlinear models or one including further variables such as human capital, technical progress or institutional quality (Acemoglu et Untitled, 2005, Aghion Howitt, 2009), and the present analysis doesn't mention structural cuts The latter could be quite important given economic reform along with changing policy framework climates now taking root across Ethiopia. Methods to pick out and model structural changes, for example those spelled out by Bai Perron (2003) might provide new insight into the development of production dynamics over time

The aggregate approach to this study might ignore differences among the various sectors that make up an economy. In view of Timmer et al (2015), using methodology disaggregated by sector particular detail capacities could give a better understanding of Ethiopa 's production dynamics. On top of this, while extending work of other African countries could serve cases for comparative research, also from an institutional angle (Bhorat and Tarp, 2016).

Lastly, despite both models exhibiting strong in-sample fitness, evaluating their out-of-sample forecasting performance could ascertain their practical utility for policy planning. This assessment could involve methodologies such as rolling-window forecasts or pseudo out-of-sample forecasting exercises, as recommended by Stock and Watson (2007).

To sum up, the present study places the entire cycle of Ethiopia's development in view, showing short-run cycles and long-term connections: The results emphasize both complexity at play for development strategies, and need for extremely special circumstances high subtlety in their formulation In this way, we can see that overcoming the problems aforementioned in future research efforts would deepen our understanding of Ethiopian growth mechanisms and help us design more effective economies for rapidly changing developing countries

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