Sources of Macroeconomic Fluctuations in Sub-Saharan Africa: A Bayesian DSGE Approach

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First version: April 13, 2025
This version: March 26, 2026

Abstract

This paper examines the sources of macroeconomic fluctuations in Sub-Saharan Africa using a structurally estimated small open economy real business cycle model with financial frictions applied to annual data from 23 countries over 1960-2019. Using Bayesian methods, we decompose volatility into permanent and transitory productivity shocks, country risk premium shocks, and other disturbances. We find that stationary productivity shocks explain a larger share of output volatility than nonstationary trend shocks, while financial shocks dominate investment and external balance fluctuations. These results challenge the view that African business cycles are primarily driven by trend shocks and highlight the central role of financial frictions in shaping macroeconomic instability.

Keywords: Trend productivity shocks; Financial frictions; Macroeconomic volatility; Small open economy; Sub-Saharan Africa
JEL Classification Numbers: E13; E32; E44; F43; O11; O16

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1 Introduction

Sub-Saharan Africa is home to some of the most volatile macroeconomic environments in the world, yet our understanding of the sources of this volatility remains remarkably limited. This gap is not merely academic. It speaks to the broader question of whether the macroeconomic tools and theories developed for advanced or emerging economies can help us understand — and perhaps improve — the economic trajectories of developing economies. A substantial body of work in international macroeconomics has examined the underlying sources of differences between emerging markets and developed economies in several key dimensions of business cycle behavior. The literature has proposed two leading approaches to account for macroeconomic fluctuations in emerging economies.

The first, more traditional approach, attributes macroeconomic fluctuations in emerging economies primarily to permanent (non-stationary) productivity shocks. It suggests that a standard neoclassical model with no distortions and driven by trend shocks can adequately capture the observed macroeconomic dynamics in these countries. In contrast, a second and more recent strand of research emphasizes the role of financial frictions, particularly in conjunction with foreign interest rate shocks. This view argues that models must incorporate such frictions to accurately capture the behavior of emerging markets.

Most of the existing research following these approaches has focused on countries in Asia and Latin America. Sub-Saharan Africa, by comparison, remains understudied. These theories have shaped our understanding of macroeconomic instability in Latin America and Asia. But do they travel to Africa? This question forms the starting point of our inquiry. This paper addresses these questions using a Bayesian estimation of a simple small open economy model with financial frictions, applied to a compiled dataset from 23 Sub-Saharan African countries.

A striking feature of Sub-Saharan African economies is the exceptionally high volatility of consumption and investment relative to output. As documented by Melina and Portillo (2018), consumption growth is substantially more volatile than output growth, and the trade balance exhibits weak or acyclical behavior over the business cycle. This pattern emerges consistently across countries and time periods and is robust to alternative detrending methods. It is this empirical regularity that serves as the starting point of our analysis.

Understanding whether macroeconomic fluctuations are primarily driven by permanent (trend) shocks or transitory disturbances is not merely an academic exercise. If the cycle is indeed the trendas argued by influential studies on emerging marketsthen countercyclical policies such as fiscal stimulus or monetary interventions may be ineffective or even destabilizing. Conversely, if fluctuations are mainly transitory, then policy can play a more active and stabilizing role.

Moreover, international institutions such as the IMF and World Bank frequently condition debt relief, aid disbursement, and macroeconomic forecasts on long-run growth assumptions. These assumptions often rest—implicitly or explicitly—on views about the nature of productivity shocks. Thus, clarifying the empirical relevance of trend shocks is essential for both theoretical and policy considerations.

African economies are uniquely vulnerable to external and domestic disturbances. Unlike other emerging markets that have gradually strengthened macroeconomic frameworks, many Sub-Saharan African countries operate with narrow policy buffers, shallow capital markets, and fragile debt positions. These features raise fundamental questions about the sources and persistence of business cycle shocks in the region and about the mechanisms through which shocks are transmitted and amplified.

We approach these questions by estimating a small open economy RBC model with both permanent and transitory productivity shocks using Bayesian methods. Our model is applied to annual macroeconomic data from 1960 to 2019 for 23 Sub-Saharan African economies. We find that in most countries permanent productivity shocks explain only a small fraction of the volatility of output, consumption, and investment. Moreover, the benchmark RBC model systematically fails to replicate key features of African business cycles, including the excess volatility of consumption and the weak cyclicality of the trade balance.

We obtain a substantially better fit by extending the model to include country-specific interest rate premium shocks that capture financial frictions. These shocks play a dominant role in explaining macroeconomic volatility and significantly reduce the importance attributed to trend shocks. Our results suggest that standard RBC models driven primarily by permanent productivity shocks are insufficient for capturing the macroeconomic reality of African economies and that incorporating financial market imperfections is crucial.

This paper contributes to the literature on the role of trend shocks and financial frictions in emerging and developing economies. Aguiar and Gopinath (2007) emphasize the dominance of trend productivity shocks in emerging markets, a view that has motivated several applications to African economies. **?** and Naoussi and Tripier (2013) provide early evidence suggesting an important role for trend shocks in Sub-Saharan Africa. However, these studies rely on calibration or GMM estimation and abstract from financial frictions or fix the debt elasticity of interest rates at arbitrary values.

By contrast, our approach follows Garcia-Cicco et al. (2010) in using Bayesian methods to estimate key structural parameters directly from country-level data. We integrate financial frictions by introducing shocks to the interest rate premium, in the spirit of Neumeyer and Perri (2005) and Uribe and Yue (2006). Recent work by Germaschewski et al. (2024) shows that when the debt elasticity of the interest rate is estimated rather than fixed, the contribution of trend shocks to output volatility declines sharply. We build on this insight and extend the analysis to 23 Sub-Saharan African economies, providing new evidence on the joint role of trend shocks and financial frictions in low-income countries.

The remainder of the paper is organized as follows. Section 2 documents key business cycle facts for Sub-Saharan African economies. Section 3 presents the theoretical model. Section 4 describes the data and estimation strategy. Section 5 reports the results and evaluates the models performance. Section 6 concludes.

2 Empirical Regularities of Business Cycles in Sub-Saharan African Countries: 1960-2019

This section documents the empirical regularities of economic fluctuations of Sub-Saharan African countries with emphasis on the contrast with Asian and Latin American emerging economies. The sample covers economies with at least 40 years of annual data from 1960 to 2019, drawn from the World Banks World Development Indicators (WDI). Details on country coverage and sources are provided in the Appendix.

Table 1 reports key business cycle moments—standard deviations, persistence, and contemporaneous cross-correlations—for real GDP, consumption, investment (all per capita), and the trade balance (exports minus imports scaled by GDP) in Sub-Saharan Africa. As is typical for real business cycles in emerging economies reported in Aguiar and Gopinath (2007) and Garcia-Cicco, Pancrazi, and Uribe (2010), per-capita consumption growth in Sub-Saharan Africa is significantly more volatile than per-capita output growth. The excess volatility of consumption relative to output is more than three percentage points. However, the trade balance is not strongly countercyclical in Sub-Saharan Africa.

Table 2 documents substantial regional differences in business cycle volatility across EMDEs. Sub-Saharan Africa exhibits consistently higher volatility than Asia and Latin America for all macroeconomic variables considered. For example, the standard deviation of output growth in Sub-Saharan Africa is 5.25, compared with 3.48 in Asia and 4.10 in Latin America. A similar pattern holds for consumption and investment, whose volatilities in Sub-Saharan Africa are roughly twice as large as those observed in Asia. Fluctuations in the trade balance relative to output are also more pronounced in Sub-Saharan Africa than in the other regions.

Taken together, Tables 1 and 2 reveal that business cycle fluctuations in Sub-Saharan Africa are more volatile than in other emerging regions. These facts raise a central question: what are the underlying sources of this excess volatility? In the canonical real business cycle literature on emerging economies, beginning with Aguiar and Gopinath (2007), high macroeconomic volatility is primarily attributed to large and persistent non-stationary technology shocks rather than to stationary productivity fluctuations. More recent studies, however, emphasize the role of financial frictions and imperfect access to international capital markets as key amplification mechanisms of business cycle fluctuations. Distinguishing between these channels is crucial for understanding the nature of macroeconomic instability in African economies.

This observation motivates the structural analysis conducted in the following section, where we estimate a DSGE model using Bayesian methods and decompose the observed volatility into contributions from different structural shocks.

Table 1: Business Cycle Features in African Economies: 1960–2019

	ΔY	ΔC	ΔI	TB/Y
Standard Deviation	5.25	8.80	23.65	7.94
	(2.08)	(4.31)	(9.05)	(5.02)
Correlation with ΔY	-	0.43	0.37	-0.05
	-	(0.28)	(0.22)	(0.23)
Correlation with TB/Y	-	-0.21	-0.12	-
	-	(0.17)	(0.17)	-
Serial Correlation	0.10	-0.08	-0.13	0.73
	(0.24)	(0.18)	(0.17)	(0.12)

Notes: ΔY, ΔC, and ΔI denote the growth rates of real output per capita, real consumption per capita, and real investment per capita, respectively, and TB/Y denotes the trade balance-to-output ratio. Standard deviations are reported in percentage points. Standard errors are shown in parentheses. The data are annual, and the sources are listed in the Appendix.

Table 2: Differences in Business Cycle Volatility across EMDEs

	Sub-Saharan Africa	Asia	Latin America
ΔY	5.25	3.48	4.10
	(2.08)	(0.41)	(1.18)
ΔC	8.80	3.95	5.99
	(4.31)	(0.90)	(2.34)
ΔI	23.65	14.99	16.89
	(9.05)	(2.03)	(6.97)
TB/Y	7.94	6.95	3.98
	(5.02)	(4.23)	(1.90)

Notes: ΔY, ΔC, and ΔI denote the growth rates of real output per capita, real consumption per capita, and real investment per capita, respectively, and TB/Y denotes the trade balance-to-output ratio. Standard deviations are reported in percentage points. Standard errors are shown in parentheses. The data are annual, and the sources are listed in the Appendix.

3 RBC Model with Financial Frictions

This section introduces the RBC model to analyze the characteristics of economic fluctuations in Sub-Saharan African countries. Our theoretical framework follows Garcia-Cicco et al. (2010). The model is a standard, single-good, single-asset, small-open economy model that incorporates transitory and trend shocks to productivity, as well as financial frictions, preference shocks, and spending shocks. Their model extends the canonical small open economy RBC model of Schmitt-Grohe and Uribe (2003) by introducing permanent productivity shocks as in Aguiar and Gopinath (2007) and a simple financial friction to explain the characteristics of macroeconomic fluctuations in emerging economies.

We begin by describing the technology. Specifically, output Y_t is produced using capital K_t and labor H_t according to a Cobb-Douglas production function:

$$Y_t = a_t K_t^{\alpha} (X_t H_t)^{1-\alpha}.$$

$\alpha \in (0,1)$ represents the share of capital in output. a_t and X_t represent productivity processes. a_t is the stationary (transitory) productivity component and X_t is the non-stationary level of labor-augmenting technology component, in other words, the cumulative product of "growth" shocks. Interpretations of these two sources of aggregate volatility are not limited to exogenous technological variations. Still, it includes other disturbances affecting total factor productivity, such as terms-of-trade shocks. Different stochastic properties characterize the two productivity processes. Specifically, a_t follows a first-order autoregressive (AR(1)) process in logarithms:

$$\ln a_{t+1} = \rho_z \ln a_t + \epsilon^a_{t+1};\ \epsilon^a_t \overset{iid}{\sim} N(0, \sigma^2_a).$$

Let the gross growth rate of the non-stationary technology be $g_t := \frac{X_t}{X_{t-1}}$. It follows an AR(1) process given by

$$\ln(\frac{g_{t+1}}{g}) = \rho_g \ln(\frac{g_t}{g}) + \epsilon^g_{t+1};\ \epsilon^g_t \overset{iid}{\sim} N(0, \sigma^2_g).$$

The term g represents the productivity rate in the long term. The economy is inhabited by a representative household that seeks to maximize [1],

$$\sum_{t=0}^{\infty} \nu_t \beta^t \frac{[C_t - \theta\omega^{-1} X_{t-1} H_t^{\omega}]^{1-\gamma} - 1}{1-\gamma}$$

subject to a sequence of budget constraints of the form [2]

$$C_t + K_{t+1} + S_t + D_t = Y_t + (1-\delta)K_t - \frac{\phi}{2}\left(\frac{K_{t+1}}{K_t} - g\right)K_t + \frac{D_{t+1}}{1+r_t}$$

where C_t is a consumption, D_{t+1} denotes the stock of debt acquired in period, I_t denotes gross investment, S_t represent government spending, and the parameter ϕ introduces quadratic capital adjustment costs. The parameter $\gamma > 0$ is the relative risk aversion, β is the discount factor, ω is the Frisch elasticity of labor supply, and θ governs the weight on the relative disutility of labor. ν_t captures shocks to preferences and follows

$$\ln \nu_{t+1} = \rho_\nu \ln \nu_t + \epsilon^\nu_{t+1};\ \epsilon^\nu_t \overset{iid}{\sim} N(0, \sigma^2_\nu)$$

Capital depreciates at rate $\delta \in [0,1]$ and is accumulated through investment I_t which gives

$$K_{t+1} = (1-\delta)K_t + I_t.$$

We assume that international financial transactions are restricted to one period,

[1]The period utility function features Greenwood et al. (1988) preferences to eliminate the wealth effect on labor supply. These preferences have been used to generate large responses of consumption and labor to productivity shocks. This results from the high degree of substitutability between leisure and consumption in the utility, eliminating the income effect on labor supply. Note that X_{t-1} ensures a constant labor supply along the non-stochastic balanced growth path.

[2]And also the no-Ponzi game constraint, taking as given the processes z_t, X_t, r_t, and the initial conditions k_0 and D_0.

risk-free bonds. The level of debt due in period t is denoted D_t. Based on the small open economy assumption, the steady-state real interest rate $r^* > 0$ is exogenously given. The price of debt is sensitive to the level of outstanding debt, taking the form:

$$r_t = r^* + \psi(e^{\tilde{D}_{t+1}/X_t - \bar{d}} - 1) + e^{\mu_t - 1} - 1. \tag{3.1}$$

The first component of the spread in Eq. (3.1) follows Schmitt-Grohe and Uribe (2003) by assuming that the risk premium increases with aggregate per capita external debt, which ensures stationarity after detrending. The second component captures a country risk premium shock as in Garcia-Cicco, Pancrazi, and Uribe (2010), which can alternatively be interpreted as innovations in the global interest rate but has equivalent effects on the domestic interest rate from the perspective of the home economy.The debt elasticity of the interest rate, ψ, measures financial frictions and is quantitatively important, since setting $\psi = 0.001$ as in Aguiar and Gopinath (2007) more than doubles the contribution of trend shocks to output fluctuations (Germaschewski, Horvath, and Rubini, 2024). The interest rate premium shock μ_t evolves according to the following AR(1) process

$$\ln \mu_{t+1} = \rho_\mu \ln \mu_t + \epsilon^\mu_{t+1};\ \epsilon^\mu_t \overset{iid}{\sim} N(0, \sigma^2_\mu).$$

An exogenous domestic spending shock following the AR(1) processes

$$\ln(\frac{s_{t+1}}{s}) = \rho_s \ln(\frac{s_t}{s}) + \epsilon^s_{t+1};\ \epsilon^s_t \overset{iid}{\sim} N(0, \sigma^2_s) \tag{3.2}$$

where $s_t = S_t/X_{t-1}$.

4 Estimation of the RBC Model

In this section, we quantify the contribution of different structural shocks to aggregate fluctuations in Sub-Saharan African economies, with particular emphasis on the role played by trend shocks. To do so, we bring the model to data from 23 Sub-Saharan African countries and structurally estimate it to conduct a formal comparison of the relative importance of different shocks in driving business-cycle fluctuations. Estimation is conducted within a Bayesian framework, which allows us to coherently combine prior information with the likelihood derived from the model. In estimating the model, we fix a subset of structural parameters through calibration, while estimating the remaining parameters using Bayesian methods to match country-specific data. In particular, we focus on estimating the parameters governing the stochastic structure of shocks as well as key parameters shaping the transmission mechanism of the model. We use the estimated DSGE model to decompose macroeconomic volatility into contributions from nonstationary and stationary productivity shocks, country risk premium shocks, preference shocks, and domestic spending shocks.

4.1 Data

The model presented in the previous section is estimated with Bayesian estimation techniques using four key macroeconomic annual time series as observable variables: the log difference of real GDP, real consumption, real investment and trade balance to output ratio (exports minus imports scaled by GDP). Our dataset features annual national accounts data for 23 countries in Sub-Saharan Africa. We refer to the World Development Indicators. A full description of the data used is given in the Data Appendix. The sample period is 1960-2019. The following countries' sample periods are different because of the data availability:

4.2 Calibrated Parameters

We calibrate the parameters γ, δ, α, ω, θ, and β as well as parameter values that are common in related business-cycle studies. These parameters are assumed to be common across all sample countries. Table 3 summarizes our baseline calibration. Many of the parameter values are standard in business cycle research, but several are worth highlighting. The parameter $\bar{d}$ in Eq. (3.1) is calibrated to match each countrys average trade balance to GDP ratio in the data. We calibrate the mean of the exogenous spending process s in Eq (3.2) to match each countrys average government spending to GDP ratio observed in the data

We estimate the remaining parameters of the model using Bayesian methods and data from sample African countries on output growth, consumption growth, investment growth, and the trade balanceto-output ratio over the period 1960-2019.

Table 3: Calibrated Parameters

Parameter	Value	Description	Source
γ	2.0	Intertemporal elasticity of substitution	Naoussi and Tripier (2013)
δ	0.2155	Depreciation rate	Naoussi and Tripier (2013)
α	0.32	Capital share in production function	Naoussi and Tripier (2013)
ω	1.6	Exponent on labor in utility function	Garcia-Cicco et al. (2010)
θ	2.24	Weight on dis-utility of labor	Garcia-Cicco et al. (2010)
β	0.9231	Discount factor	Naoussi and Tripier (2013)

Table 5: Government Expenditure and Trade Balance Ratios

Country	G/Y	TB/Y
Burundi	0.141	-0.121
Benin	0.109	-0.096
Burkina Faso	0.140	-0.134
Botswana	0.247	-0.044
Central African Rep.	0.150	-0.103
Cameroon	0.114	-0.006
Congo, Rep.	0.171	-0.029
Comoros	0.109	-0.183
Gabon	0.143	0.179
Gambia	0.155	-0.110
Kenya	0.156	-0.055
Madagascar	0.146	-0.060
Mauritania	0.255	-0.058
Mauritius	0.136	-0.051
Namibia	0.235	-0.072
Niger	0.141	-0.086
Rwanda	0.131	-0.115
Sudan	0.108	-0.058
Senegal	0.138	-0.128
Seychelles	0.302	-0.267
Togo	0.127	-0.095
South Africa	0.150	0.020
Zimbabwe	0.153	-0.055

Table 6: Calibrated Values of $\bar{d}$ and s

Country	$\bar{d}$	s
Burundi	-0.180	0.019
Benin	-0.150	0.015
Burkina Faso	-0.195	0.019
Botswana	-0.060	0.034
Central African Rep.	-0.150	0.020
Cameroon	-0.015	0.015
Congo, Rep.	-0.045	0.023
Comoros	-0.271	0.015
Gabon	0.631	0.025
Gambia	-0.165	0.022
Kenya	-0.075	0.022
Madagascar	-0.090	0.020
Mauritania	-0.090	0.036
Mauritius	-0.075	0.019
Namibia	-0.105	0.033
Niger	-0.135	0.019
Rwanda	-0.180	0.018
Sudan	-0.090	0.015
Senegal	-0.195	0.019
Seychelles	-0.406	0.041
Togo	-0.135	0.018
South Africa	0.030	0.020
Zimbabwe	-0.090	0.020

4.3 Estimation specification

We carry out a Bayesian estimation defining standard priors on the estimated parameters. We run a Markov Chain Monte Carlo (MCMC) algorithm to obtain draws from the marginal posterior distributions of the parameters[3]. Our methodology draws on recent theoretical and computational advances in Bayesian estimation of structural macroeconomic models[4]. We then compute forecast error variance decompositions of the observables at the estimated posterior modes. The model is specified at an annual frequency. For the estimation of the model, we specify the following measurement equations:

$$\begin{aligned}
\Delta \ln Y_t^{obs} &= \ln Y_t - \ln Y_{t-1} \\
\Delta \ln C_t^{obs} &= \ln C_t - \ln C_{t-1} \\
\Delta \ln I_t^{obs} &= \ln I_t - \ln I_{t-1} \\
TB_t^{obs}/Y_t^{obs} &= TB_t/Y_t
\end{aligned} \tag{4.1}$$

where $\Delta \ln Y_t^{obs}, \Delta \ln C_t^{obs}, \Delta \ln I_t^{obs}$ and TB_t^{obs}/Y_t^{obs} correspond to the empirically observed time series which we analyzed in Section 2. The variables on the right hand side of Eqs. (4.1) are model concepts defined in Section 3 [5]. As explained above, we estimate the parameters governing the stochastic processes of all shocks, as well as other key structural parameters. Table 7 summarizes the priors imposed on the parameters. They were based, to the extent possible, on earlier studies on emerging markets business cycles. While Garcia-Cicco et al. (2010), Hwang and Kim (2022), and Germaschewski et al. (2024) mainly employ uniform distributions as priors, we found that uniform priors led to poor convergence in our estimation. Therefore, following Chang and Fernández (2013) and Miyamoto and Nguyen (2017), we specify beta and gamma distributions as priors for the structural parameters. To address stochastic singularity, we introduce measurement error shocks for all observed variables. This approach completes the probability space of the model and ensures that the implied covariance matrix of observables is non-singular. The use of measurement errors is particularly warranted given

[3]For each country, we run two independent MCMC chains with 30 million draws each. We discard the first one-third of the draws and retain the remaining draws for inference. The acceptance ratios for each countrys estimation are reported in the Appendix. We conduct Bayesian estimation using Dynare. See Adjemian et al. (2024) for details.

[4]See , for example, An and Schorfheide (2007), Canova (2011), Herbst and Schorfheide (2016), or Fernández-Villaverde et al. (2016) for detail.

[5]Note that while we solve the (linearized) model in variables that are normalized by X_{t-1}, we here use growth rates in the original non-normalized variables. This is possible, as the implied nonstationary variables can be recomputed from the model solution.

the well-documented data quality issues in macroeconomic statistics from African economies[6] and the fact that some of the restricted models feature fewer structural shocks than the encompassing model.

To sample from the posterior distribution, we implemented a Random Walk Metropolis algorithm, described in An and Schorfheide (2007) and elsewhere, to generate draws from the posterior distribution. This procedure constructs a Gaussian approximation around the posterior mode, which we found via a numerical optimization, and uses a scaled version of the inverse of the Hessian computed at the posterior mode to efficiently explore the posterior distribution in the neighborhood of the mode.

Table 7: Estimated Parameters and Priors

Parameter	**Description**	**Distribution**	**Mean**	**Std. Dev.**	**5%**	**95%**
ρ_g	AR(1) coef. permanent tech. process	Beta	0.45	0.07	0.34	0.57
ρ_z	AR(1) coef. transitory tech. process	Beta	0.85	0.05	0.77	0.93
ρ_μ	AR(1) coef. premium shock	Beta	0.70	0.03	0.65	0.75
ρ_ν	AR(1) coef. preference shock	Beta	0.85	0.03	0.80	0.90
ρ_s	AR(1) coef. spending shock	Beta	0.45	0.03	0.40	0.50
σ_g	Std. dev. of permanent TFP shock	Gamma	0.02	0.005	0.013	0.029
σ_z	Std. dev. of transitory TFP shock	Gamma	0.02	0.005	0.013	0.029

Continued on next page

[6]African Development Bank (2013) reports that limitations in institutional capacity and data collection infrastructure have led many African economies to rely on outdated base years and infrequent surveys and to face persistent difficulties in measuring informal and non-monetary production, thereby constraining the reliability of macroeconomic statistics, including GDP.

Table 7 (continued): Estimated Parameters and Priors

Parameter	Description	Distribution	Mean	Std. Dev.	5%	95%
σ_v	Std. dev. of preference shock	Gamma	0.30	0.005	0.292	0.308
σ_μ	Std. dev. of premium shock	Gamma	0.02	0.005	0.013	0.029
σ_s	Std. dev. of spending shock	Gamma	0.05	0.005	0.042	0.058
g	Steady-state growth rate	Gamma	1.50	0.50	0.78	2.40
ϕ	Investment adjustment cost	Gamma	2.00	1.00	0.55	3.88
ψ	Debt elasticity of interest rate	Gamma	2.00	0.75	1.19	2.97
σ_Y^{me}	Std. dev. of measurement error in Y	Gamma	0.013	0.005	0.005	0.025
σ_C^{me}	Std. dev. of measurement error in C	Gamma	0.024	0.005	0.015	0.035
σ_I^{me}	Std. dev. of measurement error in I	Gamma	0.063	0.005	0.054	0.073
$\sigma_{TB/Y}^{me}$	Std. dev. of measurement error in TB/Y	Gamma	0.019	0.005	0.011	0.030

4.4 Results

In summary, the estimation results across the 23 countries reveal a coherent and theoretically consistent identification structure: the data are highly informative about short-run volatility and measurement components, moderately informative about deep structural parameters, and only weakly informative about persistence. This pattern underscores both the strengths and limitations of the model, highlighting where inference is robust and where it remains sensitive to prior specification.

The cross-country evidence from the prior-posterior comparisons reveals a highly structured and remarkably consistent pattern of parameter identification. A first and robust finding is that the variance parameters associated with exogenous shocks—namely $\sigma_g, \sigma_z,$ and σ_μ are strongly and systematically identified in virtually all countries. In each case, posterior distributions are sharply concentrated and clearly shifted away from their corresponding priors, indicating that the likelihood function provides substantial information about these parameters. This pattern aligns closely with the diagnostic role of prior-posterior comparisons that tight posterior distributions relative to priors are indicative of strong data informativeness (An and Schorfheide, 2007). The stability of these results across heterogeneous economies suggests that shock variances are among the most reliably estimated components of the model.

A similarly strong, though more nuanced, pattern emerges for measurement error parameters. Across almost all countries, the posterior distributions of $\sigma_Y^{me}, \sigma_C^{me}, \sigma_I^{me},$ and $\sigma_{TB/Y}^{me}$ exhibit substantial updating relative to their priors, often becoming highly concentrated. This indicates that the model relies heavily on these parameters to reconcile the data with the theoretical structure. However, in several cases, the posterior distributions become extremely sharp—approaching near—degenerate (spike-like) shapes. Such behavior raises concerns about overfitting or model misspecification, as the likelihood may be forcing measurement errors to absorb discrepancies between the model and the data. This interpretation is consistent with the broader Bayesian workflow perspective articulated by Gelman et al. (2013), who emphasize that overly concentrated posteriors can signal model inadequacy rather than genuine identification.

Turning to structural parameters, such as ϕ, and ψ, the results indicate intermediate but heterogeneous identification strength. In most countries, these parameters are clearly updated relative to their priors, implying that the data contain meaningful information about deeper structural features of the model. However, the shape of the posterior distributions reveals important irregularities. In particular, these parameters frequently display pronounced asymmetry and skewness, suggesting nonlinear identification and uneven curvature of the likelihood function. Moreover, the degree of updating varies substantially across countries, ranging from weak shifts (indicating partial prior dependence) to very strong movements (suggesting near-complete data dominance). This cross-country heterogeneity highlights that identification of deep structural parameters is sensitive to the informational content of the data and the specific economic environment.

In contrast, the persistence parameters—especially ρ_s—exhibit systematic weak identification. Across nearly all countries, the posterior distributions of these parameters closely resemble their priors, indicating that the data provide little additional information. This lack of updating is a textbook case of weak identification in Bayesian DSGE models and reflects the well-known difficulty of pinning down persistence parameters when model dynamics and observables do not provide sufficient independent variation. As discussed in Herbst and Schorfheide (2016), such weak identification often manifests as posterior distributions that are nearly indistinguishable from priors, implying that inference for these parameters is largely driven by prior assumptions rather than data.

The overall shape of the posterior distributions further reinforces these conclusions. On the positive side, the absence of multimodality across all countries suggests that the estimation is numerically stable and that the posterior surface does not exhibit severe global identification problems. However, the pervasive presence of asymmetry and, in some cases, extreme concentration or boundary solutions (e.g., persistence parameters approaching unity) indicates that local identification issues and nonlinearities remain important. These features are consistent with the broader literature on DSGE estimation, which emphasizes that identification is often parameter-specific and may vary significantly even within a single model (An and Schorfheide, 2007; Herbst and Schorfheide, 2016).

Taken together, the results point to a clear hierarchy of identification strength. Shock variances and, to a slightly lesser extent, measurement error parameters are strongly identified and largely data-driven. Structural parameters are moderately identified but exhibit substantial cross-country heterogeneity and non-Gaussian posterior shapes. Persistence parameters, by contrast, are systematically weakly identified, with posterior distributions often dominated by prior assumptions. This hierarchy is highly consistent with the canonical identification patterns documented in the Bayesian DSGE literature.

Table 8 reports the summary statistics for posterior estimates across all countries. It is noteworthy that the estimated value of ψ differs from the value of 0.001 assumed in Naoussi and Tripier (2013). The debt elasticity of the interest rate, ψ, captures the severity of financial frictions and plays a quantitatively important role, as imposing $\psi = 0.001$ following Aguiar and Gopinath (2007) more than doubles the contribution of trend shocks to output fluctuations (Germaschewski et al., 2024). Our estimated value of ψ, however, departs significantly from this benchmark. This suggests that Naoussi and Tripier (2013) may have overestimated the contribution of trend shocks to business-cycle fluctuations in Africa.

Another noteworthy point is that the mean estimated value of ρ_g across Sub-Saharan African countries is lower than those for Asia and Latin America reported in Hwang and Kim (2022). This suggests that permanent growth regime shifts are less persistent in Africa, consistent with more frequent policy reversals, institutional instability, and recurrent crises. In this sense, Africa appears as an extreme case of low trend-shock persistence among emerging economies.

Table 9 compares key second moments in the data with those generated by the model. Overall, the model provides a good quantitative match to the empirical volatility and comovement patterns. In particular, it successfully reproduces the relative volatility of output and investment as well as their positive correlation with aggregate output growth. The model also captures the weak contemporaneous correlation between the trade balancetooutput ratio and output growth observed in the data, together with the high persistence of the trade balance. These features are important stylized facts of business cycles in Sub-Saharan African economies and are well reflected in the model. While the model slightly overestimates the volatility of the trade balance and the cyclicality of consumption, the overall fit across second moments is satisfactory. Taken together, these results indicate that the model is able to replicate the main empirical regularities in the data and provides a reliable quantitative framework for analyzing the transmission of structural shocks.

5 How important are trend shocks in African business cycles?

This section studies the role of estimating the non-stationary technology shocks in assessing the contribution of trend shocks to macroeconomic volatility. To do so, we compare the variance decomposition of output growth, consumption growth, investment growth, and trade balance to the output ratio for the model with estimated parameters. We then contrast the model performance in terms of the business cycle moments.

5.1 Baseline FEVD (without measurement error)

Table 10 report the forecast error variance decomposition implied by the estimated model. Output fluctuations are primarily driven by productivity shocks. Stationary technology shocks account for about 55 percent of output growth volatility,

Table 8: Summary of posterior medians across countries

Parameter	Min	Max	Mean
ρ_g	0.444	0.818	0.496
ρ_z	0.655	0.930	0.837
ρ_μ	0.697	0.782	0.718
ρ_ν	0.665	0.957	0.803
ρ_s	0.450	0.451	0.450
100*σ_g	1.401	4.187	2.457
100*σ_z	0.908	4.787	2.386
100*σ_ν	29.797	30.968	30.261
100*σ_μ	1.509	4.500	2.757
100*σ_s	4.801	5.061	4.964
g	0.972	1.035	1.003
ϕ	0.589	2.848	1.176
ψ	0.094	2.122	1.262
100*σ_Y^{me}	0.503	6.598	1.645
100*σ_C^{me}	1.089	6.996	3.574
100*σ_I^{me}	5.746	8.397	6.979
100*$\sigma_{TB/Y}^{me}$	0.697	5.875	2.185

Notes: Min and Max denote the minimum and maximum values of the posterior median values across countries. Mean represents the average cross-country value of posterior medians.

Table 9: Comparing model and data: Second Moments

	ΔY	ΔC	ΔI	TB/Y
Standard deviation (%)				
Data	5.25	8.80	23.65	7.94
	(2.08)	(4.31)	(9.05)	(5.02)
Model	5.80	7.14	21.09	15.45
Correlation with ΔY				
Data	–	0.43	0.37	-0.05
	–	(0.28)	(0.22)	(0.23)
Model	–	0.76	0.33	-0.03
Correlation with TB/Y				
Data	–	-0.21	-0.12	–
	–	(0.17)	(0.17)	–
Model	–	-0.15	-0.35	–
Serial correlation				
Data	0.10	-0.08	-0.13	0.73
	(0.24)	(0.18)	(0.17)	(0.12)
Model	0.15	0.03	-0.24	0.62

Notes: Standard deviations are reported in percentage points. Standard errors of sample moment estimates are shown in parentheses. Each figure represents the average values of the countries. Posterior distributions are simulated using 30 million draws per chain. Model moments are computed as the median based on a subsample of 1,200 posterior draws (Dynare default).

while nonstationary (trend) technology shocks explain an additional 31 percent. Country premium shocks contribute roughly 10 percent, whereas preference and domestic spending shocks play only a minor role. This pattern indicates that aggregate output dynamics in Sub-Saharan African economies are largely governed by real productivity disturbances rather than by demand-side or fiscal shocks.

Consumption growth exhibits a different composition. Preference shocks emerge as the dominant source of consumption volatility, accounting for about 43 percent, followed by stationary and nonstationary technology shocks, which together explain slightly more than half of total variation. In contrast, country premium shocks contribute less than 3 percent. This finding suggests that consumption dynamics are mainly shaped by household-side disturbances and real shocks, with a limited direct role for financial shocks.

Investment growth, by contrast, is overwhelmingly driven by financial shocks. Country premium shocks explain approximately 60 percent of investment volatility, far exceeding the contribution of both stationary and nonstationary technology shocks. This result highlights the central role of external financing conditions and sovereign risk in shaping investment dynamics in these economies, consistent with the view that investment responds strongly to fluctuations in borrowing costs and risk premia.

The trade balance-to-output ratio is also primarily influenced by country premium shocks and preference shocks, which together account for more than 70 percent of its volatility. Technology shocks play a secondary role. This pattern reflects the importance of financial conditions and intertemporal substitution in determining external adjustment dynamics.

5.2 FEVD including measurement error

Table 11 presents the variance decomposition when measurement errors are explicitly incorporated. Measurement error accounts for a non-negligible share of fluctuations, particularly for consumption and investment, where it explains about 22 and 16 percent of the variance, respectively. This result is consistent with concerns regarding data quality in national accounts for low-income countries.

Importantly, the qualitative ranking of shocks remains largely unchanged. Output growth continues to be primarily driven by stationary and nonstationary technology shocks, while investment and trade balance fluctuations remain dominated by country premium shocks. Preference shocks continue to play a central role in explaining consumption volatility. Hence, the main conclusions of the baseline variance decomposition are robust to allowing for measurement error.

5.3 Interpretation of measurement error

When measurement errors are incorporated, they account for a non-negligible fraction of the variance of consumption and investment growth. While this result is consistent with concerns about data quality in national accounts for low-income countries, an alternative interpretation is that measurement errors may partly capture model misspecification. As emphasized by An and Schorfheide (2007) (Section 3.1), introducing measurement error can be viewed as a reduced-form device that absorbs discrepancies between the data-generating process and the structural model when relevant economic mechanisms are omitted.

In the context of Sub-Saharan African economies, several important structural features are abstracted from in the baseline model and may contribute to this residual variation. These include the presence of a large informal sector, highly concentrated export structures dominated by primary commodities, strong dependence on imported consumption and intermediate goods, and institutional factors affecting sovereign risk and external borrowing conditions. Moreover, fluctuations in world commodity prices and external financial conditions may transmit to domestic activity through channels that are not fully captured by the representative-agent small open economy framework.

From this perspective, the estimated measurement error should not be interpreted solely as statistical noise, but rather as an indicator of economically meaningful forces that are not explicitly modeled. This observation points to promising directions for future research. Extending the model to incorporate informal production, sectoral heterogeneity between tradable and non-tradable goods, import dependence in consumption and investment, and richer sovereign risk mechanisms may help account for a larger share of observed macroeconomic fluctuations and improve the structural interpretation of the variance decomposition results.

Such extensions would allow the model to better reflect the distinctive features of African economies and provide a more structural explanation for the components of volatility that are currently attributed to measurement error.

Table 10: Variance Decomposition Predicted by the Model

Shock	Output growth	Consumption growth	Investment growth	Trade balance to GDP ratio
Nonstationary tech.	31.17	19.51	7.62	8.53
	(12.36)	(14.29)	(6.76)	(15.39)
Stationary tech.	54.96	33.83	24.93	17.83
	(14.33)	(12.35)	(14.17)	(15.04)
Preference	3.14	42.97	6.22	27.36
	(2.37)	(15.58)	(5.77)	(18.85)
Country premium	10.19	2.81	60.33	44.08
	(8.17)	(3.84)	(17.00)	(23.10)
Domestic spending	0.06	0.14	0.17	0.99
	(0.05)	(0.15)	(0.15)	(0.89)

Notes: Posterior distributions are simulated using 30 million draws per chain. Model moments are computed as the median based on a subsample of 1,200 posterior draws(Dynare default). This table lists average values of sample countries. Standard deviations are in parentheses.

Table 11: Variance Decomposition Predicted by the Model (including measurement error)

Shock	Output growth	Consumption growth	Investment growth	Trade balance / GDP
Nonstationary tech.	28.70	15.62	6.34	8.01
	(11.25)	(13.79)	(5.91)	(15.35)
Stationary tech.	50.35	25.79	20.54	15.93
	(13.62)	(10.20)	(11.87)	(14.22)
Preference	2.94	33.51	4.64	24.99
	(2.22)	(14.70)	(3.70)	(18.42)
Country premium	9.30	1.97	51.53	38.45
	(7.66)	(2.76)	(18.18)	(19.80)
Domestic spending	0.05	0.10	0.13	0.88
	(0.04)	(0.11)	(0.11)	(0.79)
Measurement error	7.39	21.99	15.89	9.96
	(7.98)	(16.36)	(13.11)	(8.31)

6 Conclusion

This paper has examined the sources of macroeconomic fluctuations in Sub-Saharan African economies through the lens of a structurally estimated small open economy real business cycle model. Using annual data for 23 countries over the period 1960-2019 and Bayesian estimation methods, we assessed the quantitative importance of permanent (trend) productivity shocks relative to transitory productivity shocks and financial disturbances.

Our results yield three main findings. First, contrary to the influential view that the cycle is the trend, permanent productivity shocks play minor role in explaining business cycle fluctuations in Sub-Saharan Africa than stationary technology shocks. While productivity shocks remain important drivers of output dynamics, stationary disturbances account for a larger share of volatility than nonstationary ones in most countries. This suggests that growth regime shifts are less persistent in African economies than in other emerging market regions.

Second, introducing financial frictions in the form of country-specific interest rate premium shocks substantially improves the models ability to replicate key features of African business cycles. In particular, investment and external balance fluctuations are dominated by financial shocks rather than by technology shocks. This finding highlights the central role of external financing conditions and sovereign risk in shaping macroeconomic dynamics in low-income economies.

Third, allowing for measurement error does not overturn the qualitative ranking of shocks but reveals that a non-negligible fraction of consumption and investment volatility cannot be fully accounted for by the baseline model. This result likely reflects both data limitations and the omission of important structural features of African economies, such as informality, sectoral heterogeneity, and strong dependence on imported consumption and intermediate goods.

Taken together, these findings challenge the applicability of standard frictionless RBC models to Sub-Saharan Africa and underscore the importance of financial market imperfections in understanding macroeconomic instability in low-income countries. Models that attribute volatility primarily to trend productivity shocks risk overstating the role of long-run growth disturbances while neglecting the amplification mechanisms arising from borrowing constraints and risk premia.

This study also points to several directions for future research. Extending the model to incorporate informal production, sectoral distinctions between tradable and non-tradable goods, and explicit commodity price channels would provide a richer account of African macroeconomic dynamics. Likewise, embedding sovereign risk and default mechanisms into the framework may help explain the strong role of interest rate premia uncovered in the empirical results. Finally, the use of higher-frequency data and multi-country panel estimation techniques may further improve identification and allow for a more precise comparison across regions.

Overall, this paper provides new evidence that financial frictions, rather than trend shocks alone, are central to understanding business cycle fluctuations in Sub-Saharan Africa. Recognizing this distinction is crucial both for advancing macroeconomic theory and for designing effective stabilization policies in developing economies.

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Appendix

A Optimality Conditions of the Households Problem

Letting $\lambda_t X_{t-1}^{-\gamma}$ denote the Lagrange multiplier associated with the sequential budget constraint, the optimality conditions associated with this problem are

$$\left[\frac{C_t}{X_{t-1}} - \theta\omega^{-1}H_t^{\omega}\right]^{-\gamma} = \lambda_t,$$

$$\left[\frac{C_t}{X_{t-1}} - \theta\omega^{-1}H_t^{\omega}\right]^{-\gamma} \theta H_t^{\omega-1} = (1-\alpha)a_t\left(\frac{K_t}{X_{t-1}H_t}\right)^{\alpha}\left(\frac{X_t}{X_{t-1}}\right)^{1-\alpha}\lambda_t,$$

$$\lambda_t = \beta\frac{1+r_t}{g_t^{\gamma}}E_t\lambda_{t+1}$$

$$\left[1+\phi\left(\frac{K_{t+1}}{K_t}-g\right)\right]\lambda_t = \frac{\beta}{g_t^{\gamma}}E_t\lambda_{t+1}\left[1-\delta+\alpha a_{t+1}\left(\frac{X_{t+1}H_{t+1}}{K_{t+1}}\right)^{1-\alpha}\right.$$
$$\left. +\phi\left(\frac{K_{t+2}}{K_{t+1}}\right)\left(\frac{K_{t+2}}{K_{t+1}}-g\right)-\frac{\phi}{2}\left(\frac{K_{t+2}}{K_{t+1}}-g\right)^2\right].$$

B Description of Data Sources

Unless noted otherwise the data source is the World Bank's WDI database. The raw data from this source consists of the following annual time series.

- GDP per capita in constant local currency units
- Household final consumption expenditure, etc. (% of GDP),
- Gross capital formation (% of GDP)
- Imports of goods and services (% of GDP)
- Exports of goods and services (% of GDP)

Our sample for Latin America consists of Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela, while the Asian sample includes Indonesia, the Republic of Korea, Malaysia, the Philippines, Singapore, and Thailand.