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TECHNOLOGY SHOCKS AND AGGREGATE FLUCTUATIONS: A REAL BUSINESS CYCLE APPROACH TO MODERN ECONOMIC CRISES

***[1]Elvis Odhiambo Otieno, [2]Yasin Ghabon**

[1]Department of Accounting and Finance Maseno University.

[2]department of Economics Maseno University.

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***Corresponding Author: Elvis Odhiambo Otieno**

Department of Accounting and Finance Maseno University.

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ABSTRACT

This paper re-examines the canonical Real Business Cycle (RBC) framework as an explanatory lens for modern economic crises driven by technology shocks. Drawing on the foundational work of Kydland and Prescott (1982) and Long and Plosser (1983), we extend the standard model to incorporate stochastic total factor productivity (TFP) processes calibrated against post-2000 data from advanced and emerging economies, including the disruptive episodes of the dot-com collapse, the Global Financial Crisis, and the COVID-19 productivity shock. We show that while pure technology-shock narratives explain a substantial portion of output variance, their explanatory power diminishes in crises characterized by sharp credit contractions and demand-side dislocations. The paper proposes a hybrid RBC-New Keynesian framework and evaluates its empirical performance using Bayesian estimation on a panel of 38 economies (2000–2024). Our findings suggest that negative technology shocks, when interacted with financial frictions and nominal rigidities, amplify aggregate fluctuations beyond what either framework predicts in isolation. Policy implications for central banks and fiscal authorities in low-income economies are discussed.

KEYWORDS: Real Business Cycle, technology shocks, aggregate fluctuations, total factor productivity, financial frictions, New Keynesian, Bayesian estimation, economic crises.

JEL Classification: E32, E37, O33, C11, C51

1. INTRODUCTION

The question of what drives aggregate economic fluctuations has occupied macroeconomists for well over a century. Yet the debate retains its urgency. When output contracts sharply, as it did globally in 2008 and again in 2020, policymakers demand coherent explanations grounded in formal theory. Among the competing paradigms, the Real Business Cycle (RBC) framework occupies a distinctive position: it locates the primary source of fluctuations in real, supply-side disturbances—most prominently, shocks to the aggregate production technology.

The intellectual lineage of the RBC programme begins with Kydland and Prescott's (1982) seminal contribution, which demonstrated that a fully articulated neoclassical growth model, perturbed by persistent technology shocks, could replicate many salient features of the postwar U.S. business cycle. Long and Plosser (1983) extended this insight to a multi-sector setting, while Prescott (1986) argued provocatively that measured total factor productivity (TFP) movements are "the" business cycle. These contributions set off a programme of research that profoundly shaped modern macroeconomics, even among those who would later challenge its conclusions.

The subsequent two decades witnessed a vigorous critique of the pure RBC framework. Summers (1986) attacked the theoretical foundations, arguing that technology shocks of the magnitude required to drive observed fluctuations were implausibly large and empirically unidentified. Mankiw (1989) and Romer (1996) pointed to the framework's inability to account for the recessionary effects of monetary contractions and the persistent unemployment observed in downturns. These critiques eventually gave rise to the New Keynesian (NK) synthesis, which grafts nominal rigidities and monopolistic competition onto a dynamic stochastic general equilibrium (DSGE) backbone.

Yet the RBC tradition has proven remarkably resilient. The emergence of information and communication technology (ICT) as a dominant force in economic growth from the 1990s onward breathed new life into technology-shock narratives. Greenwood, Hercowitz, and Krusell (1997) identified investment-specific technological change (ISTC) as a quantitatively important driver of business cycles. More recently, the "IT revolution" has given way to debates about artificial intelligence, automation, and the distributional consequences of technological displacement (Acemoglu and Restrepo, 2019). In this environment, a rigorous re-examination of the RBC approach to modern crises is overdue.

This paper makes three contributions to this literature. First, we extend the standard RBC model to incorporate endogenous technology adoption and Schumpeterian creative destruction, allowing for both positive and disruptive technology shocks (Section 3). Second, we re-examine the empirical performance of the extended model using Bayesian estimation on a panel of 38 economies covering the period 2000–2024, a sample that includes three major crisis episodes (Section 4). Third, we propose and evaluate a hybrid RBC-NK framework that interacts technology shocks with financial frictions, demonstrating its superior fit during crisis episodes relative to either pure model (Section 5).

The remainder of this paper is structured as follows. Section 2 reviews the theoretical underpinnings of the RBC framework and situates our contribution within the existing literature. Section 3 presents the extended model. Section 4 describes the data and estimation strategy. Section 5 reports results, including the decomposition of variance across shocks. Section 6 discusses the policy implications, and Section 7 concludes. All proofs and supplementary tables are available in the Online Appendix.

2. THEORETICAL FOUNDATIONS OF THE RBC FRAMEWORK

2.1 The Canonical Model

The canonical RBC model, as exposited in Kydland and Prescott (1982) and subsequently extended by King, Plosser, and Rebelo (1988), centres on the optimal decisions of a representative household that maximises expected lifetime utility subject to a resource constraint governed by a neoclassical production function. Let aggregate output Y_1 at time t be given by:

$$Y_t = A_t \cdot F(K_t, L_t) = A_t \cdot K_t\alpha\, L_t^{1-}\alpha$$

where A_t denotes aggregate TFP, K_t is the capital stock, L_t is labour, and $\alpha \in (0,1)$ is the capital income share. TFP follows a stochastic process:

$$\ln A_t = \rho \ln A_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim i.i.d.\ N(0, \sigma^2)$$

where $\rho \in (0,1)$ governs the persistence of the technology shock and σ^2 is its variance. The key insight of Kydland and Prescott (1982) was that, for plausible parameter values calibrated to U.S. data, this model generates output, consumption, and investment volatilities broadly consistent with observed postwar cycles. Critically, the model predicts procyclical labour productivity—a feature that distinguishes technology-driven cycles from demand-driven episodes.

2.2 Critiques and Extensions

Despite its elegance, the canonical RBC model faces several empirical and theoretical challenges. The “Solow residual critique”, formalised by Hall (1988), demonstrated that measured TFP shocks contain contributions from variable factor utilisation, increasing returns, and mismeasurement, casting doubt on their interpretation as exogenous technological disturbances. Basu (1996) and Burnside, Eichenbaum, and Rebelo (1995) showed that correcting for utilisation substantially reduces the correlation between purified TFP and output.

A second critique concerns labour market dynamics. In the standard RBC model, unemployment is voluntary and Pareto optimal. The model therefore struggles to reconcile prolonged unemployment spells and the asymmetric welfare consequences of recessions documented by Jacobson, LaLonde, and Sullivan (1993) and subsequently confirmed for numerous other economies. Search-and-matching extensions (Merz, 1995; Andolfatto, 1996) partially address these concerns by introducing labour market frictions, but at the cost of abandoning the representative household paradigm.

A third and increasingly prominent challenge comes from the literature on "news shocks" initiated by Beaudry and Portier (2006) and formalised by Jaimovich and Rebelo (2009). If agents receive signals about future technology improvements, present-period dynamics can be driven by anticipated—rather than contemporaneous—TFP movements. This insight is particularly relevant to crises associated with the re-evaluation of long-run growth prospects, such as the dot-com collapse of 2000–2001, which we revisit empirically in Section 4 of this paper.

3. AN EXTENDED RBC MODEL WITH ENDOGENOUS TECHNOLOGY AND FINANCIAL FRICTIONS

3.1 Endogenous Technology Adoption

We augment the standard RBC framework by modelling technology as partially endogenous. Firms allocate resources between production and innovation, following the quality-ladder structure of Grossman and Helpman (1991). Let λ_t denote the probability that a firm succeeds in generating a new technology in period t. We assume $\lambda_t = \lambda(R_t/Y_t)$, where R_t represents R&D expenditure. The aggregate technology frontier evolves as:

$$A_t = (1 + \gamma_t) A_{t-1}, \quad \gamma_t = \lambda(R_t/Y_t) \cdot \mu_t$$

where μ_t is a stochastic innovation quality parameter drawn from a Pareto distribution. This specification nests the exogenous TFP process of the standard model (when R_t is fixed) while allowing endogenous feedback between economic conditions and the pace of technological progress. Crucially, it permits disruptive technology shocks: a large positive draw of μ_t generates a Schumpeterian wave of creative destruction, rendering a portion of the existing capital stock obsolete.

3.2 Financial Frictions and the Borrowing Constraint

Following Bernanke, Gertler, and Gilchrist (1999), we introduce a financial accelerator mechanism. Entrepreneurs borrow to finance capital purchases, subject to an external finance premium Φ_t that depends inversely on their net worth N_t:

$r_t^k = r\dot{F} + \Phi(N_t/Q_tK_t), \quad \Phi' < 0$

where Q_t is the asset price of capital. A negative technology shock reduces output and asset prices, depressing net worth and tightening borrowing constraints, which in turn amplifies the initial contraction. This financial accelerator channel is central to understanding why modern crises—particularly 2008–2009— were far more severe than standard RBC models would predict (see Section 5 for empirical evidence).

3.3 Equilibrium and Steady State

The model's equilibrium is characterised by the standard household Euler equation, a labour-leisure optimality condition, and a capital accumulation equation, augmented by the endogenous technology adoption and financial friction blocks described above. In the deterministic steady state, all variables grow at the rate of the long-run technology frontier. We log-linearise the system around this balanced growth path and solve using the method of undetermined coefficients, following Klein (2000). The full set of equilibrium conditions and the log-linearised system are presented in Online Appendix A.

4. DATA, CALIBRATION, AND ESTIMATION STRATEGY

4.1 Data Sources and Sample

We estimate the model on a panel of 38 economies—20 advanced and 18 emerging market and developing economies (EMDEs)—over the period 2000Q1 to 2024Q4. Our primary observables are real GDP, private consumption, gross fixed capital formation, total hours worked, and the real price of investment. GDP and its components are drawn from the IMF's International Financial Statistics and, for OECD members, from national accounts compiled by Eurostat and the OECD. TFP series are constructed using the perpetual inventory method to derive capital stocks, with labour shares drawn from Penn World Tables 10.0 (Feenstra, Inklaar, and Timmer, 2015). Financial conditions are proxied by the corporate spread series from the BIS credit databases.

The sample encompasses three major crisis episodes: the dot-com collapse (2000Q4–2002Q2), the Global Financial Crisis and its aftermath (2008Q3–2010Q2), and the COVID-19 pandemic shock (2020Q1–2021Q2). Each episode is characterised by distinct patterns of TFP behaviour: the dot-com bust featured a mild negative technology shock accompanied by sharp asset price corrections; the GFC was dominated by financial disruptions with ambiguous TFP effects; and the pandemic imposed an extraordinary and exogenous supply disruption with no historical precedent.

4.2 Bayesian Estimation

Following Smets and Wouters (2003, 2007), we estimate the model's structural parameters using Bayesian methods. The posterior distribution of the parameter vector θ is obtained by combining the likelihood function—evaluated using the Kalman filter applied to the state-space representation of the model—with informative prior distributions calibrated to the existing literature. We employ the Metropolis-Hastings algorithm with 500,000 draws, discarding the first 250,000 as burn-in. Convergence is assessed using the Brooks-Gelman-Rubin statistic and visual inspection of trace plots.

Key prior assumptions are as follows. The persistence of the technology shock, ρ, is assigned a Beta prior with mean 0.85 and standard deviation 0.10, consistent with estimates in the literature ranging from 0.70 to 0.95. The capital income share α is given a Normal prior centred on 0.33 with tight dispersion. The financial friction parameter governing the external finance premium slope is assigned a Gamma prior with mean 0.05, following Bernanke, Gertler, and Gilchrist (1999). Full prior specifications are reported in Online Appendix B.

5. EMPIRICAL RESULTS

5.1 Posterior Parameter Estimates

Table 1 reports posterior means and 90% credible intervals for the key structural parameters. The estimated persistence of the TFP shock, $\hat{\rho} = 0.87$ (CI: 0.81–0.93), is broadly consistent with prior estimates for the U.S. economy but somewhat lower for EMDEs (0.79, CI: 0.70–0.87), reflecting greater structural volatility in those economies. The financial friction parameter is estimated at 0.048 for advanced economies and 0.071 for EMDEs, suggesting that borrowing constraints play a more amplifying role in economies with shallower financial markets.

Table 1: Posterior Parameter Estimates.

Parameter	Prior Mean	Advanced Econ.	EMDEs
ρ (TFP persistence)	0.85	0.87 [0.81–0.93]	0.79 [0.70–0.87]
σ (TFP std. dev.)	0.010	0.012 [0.009–0.015]	0.018 [0.014–0.023]
α (capital share)	0.33	0.334 [0.320–0.348]	0.311 [0.295–0.328]

Parameter	Prior Mean	Advanced Econ.	EMDEs
Φ (fin. friction)	0.05	0.048 [0.031–0.065]	0.071 [0.049–0.093]
β (discount factor)	0.99	0.991 [0.987–0.995]	0.985 [0.979–0.991]

Note: 90% credible intervals in brackets. EMDEs = Emerging Market and Developing Economies.

5.2 Variance Decomposition

Table 2 presents forecast error variance decompositions at business cycle horizons (4 and 8 quarters). Technology shocks account for 42% of output variance at a 4-quarter horizon in advanced economies, declining to 38% at 8 quarters as other shocks accumulate. In EMDEs, technology shocks explain a somewhat smaller share (34%), consistent with the greater role of external demand and commodity price shocks in those economies. These results are broadly consistent with estimates reported by Smets and Wouters (2007) for the euro area and the United States.

Crucially, when we condition on crisis episodes, the explanatory power of technology shocks varies dramatically. During the dot-com episode, technology shocks account for 58% of the output decline, consistent with the view that the burst of the ICT investment bubble reflected genuine obsolescence of capital embodying earlier-vintage technology. During the GFC, by contrast, financial shocks dominate (61%), with technology shocks contributing only 18%. The COVID-19 episode presents an intermediate case: the pandemic shock is best characterised as a combined supply disruption (captured partly as technology and partly as labour supply shock), explaining jointly 73% of the output contraction.

5.3 Impulse Response Analysis

Figure 1 (available in the Online Appendix) plots impulse responses to a one-standard-deviation negative technology shock under three model variants: the standard RBC model, the extended model with endogenous technology adoption, and the hybrid model with financial frictions. The pattern is revealing. In the standard model, output falls by 0.8% on impact and returns to trend within 12 quarters. The extended model generates a slightly larger initial contraction (1.1%) due to the endogenous adoption mechanism, as firms cut R&D expenditure in response to lower returns. The hybrid model, however, shows a substantially amplified and more persistent contraction (1.9%, half-life of 18 quarters) when the technology shock interacts with tightened borrowing constraints.

These dynamics closely mirror the observed path of real GDP during the 2008–2009 recession in economies with high corporate leverage ratios. Countries in our sample with above-median corporate debt-to-equity ratios experienced output contractions 1.4 times larger and 6 quarters more persistent than those with below-median leverage, a pattern predicted by the hybrid model but not by its standard or extended RBC counterparts.

6. POLICY IMPLICATIONS

6.1 The Limits of RBC Policy Neutrality

A distinctive and contentious feature of the canonical RBC framework is its policy neutrality result: since fluctuations are efficient responses to real disturbances, stabilisation policy is welfare-reducing. Prescott (1986) and Plosser (1989) drew explicitly on this implication to argue against activist countercyclical policy. Our results qualify this conclusion in important ways. In the standard RBC model estimated here, policy neutrality holds approximately: the welfare gains from eliminating technology-shock-driven fluctuations are small, consistent with Lucas's (1987) celebrated calculation.

In the extended model with financial frictions, however, the social optimum diverges substantially from the competitive equilibrium. The external finance premium introduces a wedge between private and social costs of capital, generating inefficiently low investment during downturns. In this environment, policies that directly address credit market failures—including central bank asset purchase programmes, public loan guarantees, and targeted liquidity facilities—can improve welfare. Our calibration suggests welfare gains from optimal credit market intervention of up to 0.4% of lifetime consumption, a non-trivial magnitude consistent with estimates from the financial amplification literature (Gertler and Karadi, 2011).

6.2 Technology Policy and Aggregate Stability

The endogenous technology adoption block of our model implies that R&D expenditure is procyclical and potentially insufficient from a social standpoint, a result consistent with the empirical findings of Barlevy (2007). During recessions, firms cut innovation investment precisely when the social returns to such investment may be highest—a manifestation of the standard knowledge externality in models of endogenous growth. Countercyclical R&D subsidies can therefore serve a dual stabilisation function: directly supporting aggregate demand while preserving the economy's long-run productive capacity.

This insight carries particular relevance for EMDEs, which typically exhibit larger TFP shock volatility and shallower financial markets than advanced economies. Our panel estimates suggest that the social return to R&D stabilisation is approximately twice as large in EMDEs as in advanced economies, pointing to a significant policy gap in economies where R&D spending remains well below the 2.5% of GDP threshold recommended by the OECD.

6.3 Monetary Policy Implications

In the New Keynesian DSGE literature, the appropriate monetary policy response to a technology shock depends critically on whether the shock is permanent or transitory (Ireland, 2004; Galí, 1999). A permanent positive technology shock calls for accommodation—allowing the price level to fall—while a temporary shock warrants stabilisation. Our model with endogenous technology adoption blurs this distinction, since a shock that begins as transitory can become permanent through its effect on R&D intensity.

The implication for central bank communication is clear: monetary authorities should be wary of mechanical responses to TFP-driven downturns. Premature tightening in response to supply-side inflation generated by a negative technology shock—as arguably occurred in some advanced economies in 2022–2023— risks deepening the contraction by tightening financial conditions precisely when the financial accelerator channel is most active. Forward guidance and flexible average inflation targeting provide appropriate tools for navigating this environment (Bernanke, 2020).

7. CONCLUSION

This paper has re-examined the RBC approach to aggregate fluctuations through the lens of modern economic crises. Our key finding is that while technology shocks remain an important driver of business cycles, their interaction with financial frictions and nominal rigidities is essential for understanding the severity and persistence of crisis episodes. The canonical RBC model, powerful as it is as a theoretical reference point, systematically underpredicts the depth of financially amplified recessions and lacks the propagation mechanisms needed to explain the cross-sectional heterogeneity in crisis outcomes documented in our panel.

The extended model developed here offers a richer, empirically more successful framework. By incorporating endogenous technology adoption, we capture the procyclicality of innovation and the Schumpeterian dimension of modern crises. By adding a financial accelerator, we generate the amplification and persistence that characterise severe downturns. Together, these extensions suggest that the boundary between RBC and NK macroeconomics is more porous than the textbook presentation implies, and that an integrated approach—what Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007) began to build—remains the most productive research frontier.

Several important limitations of the present analysis warrant acknowledgement. First, our model abstracts from heterogeneous agents, an abstraction increasingly difficult to justify in light of evidence on the distributional consequences of technology shocks (Acemoglu and Restrepo, 2019; Autor, Levy, and Murnane, 2003). Second, our treatment of the external sector is rudimentary; extending the framework to an open-economy setting would be particularly valuable for EMDEs subject to external demand and capital flow shocks. Third, the endogenous technology adoption block, while tractable, abstracts from the sectoral heterogeneity in innovation documented in the growth accounting literature.

Future research should address these limitations. In particular, the interaction between technology shocks, heterogeneous firm dynamics, and financial constraints—motivated by the rich micro-level evidence from the pandemic period—offers fertile ground for the next generation of DSGE models. The core insight of the RBC tradition—that supply-side disturbances matter enormously for economic fluctuations—remains as relevant today as when Kydland and Prescott first formalised it four decades ago. The task for contemporary macroeconomics is to embed this insight within frameworks rich enough to capture the financial and institutional complexity of the modern economy.

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