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A Small Open Economy Model to Assess Macroeconomic Policy Performance: The Case of Malaysia

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A Small Open Economy Model to Assess Macroeconomic Policy Performance: The Case of Malaysia

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Abstract

This paper develops a prototype macroeconomic model for assessing monetary and fiscal policy in a small emerging-market open economy. We then use this model to evaluate the performance of monetary and fiscal policies in Malaysia between 2005 and 2021. The paper presents a discussion of key macroeconomic variables over this period. Bayesian estimation is applied to the model to obtain parameter values governing dynamic adjustments, and we identify which variables played pivotal roles in overall macroeconomic volatility during the sample period. Optimal policy designs for both monetary policy and fiscal transfers are determined, and their performance is assessed relative to the historical base paths. Additionally, we demonstrate that the base paths are closer to the optimal paths compared to non-intervention policies for fiscal transfers and a pure inflation- targeting rule for the Taylor rule, without an output-gap response.

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Abbreviations

BCR	Banco Central de Reservas of Chile
BNM	Bank Negara Malaysia
CES	Constant Elasticity of Substitution
ECB	European Central Bank
GFC	Global Financial Crisis
HSD	Historical Shock Decomposition
MCMC	Monte Carlo Markov Chain

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Economics should be under no illusion that central banking will ever become a science. — Jürg Niehans, *The Theory of Money,* 1978, p. 296

1 Introduction

This is the specification of the benchmark model to be implemented using Bayesian estimation and simulation for small open economies in AMRO, which act as price-takers in the world's export and import markets. Our detailed examination focuses on Malaysia. Analyzing Malaysian data serves as a template for applying this approach to other member countries of AMRO.

The model adheres to the specification outlined by Christiano et al. (2011), incorporating real and financial-sector frictions while omitting labor-market frictions. We also draw from the work of Garcia-Cicco et al. (2015). The former model was calibrated and estimated using data from Sweden, while the latter model was calibrated and estimated using data from Chile. The latter model additionally includes a natural-resource export sector, partially owned by the government, contributing to fiscal revenue. This model builds upon the earlier work of Lim and McNelis (2018), who employed a similar setup to account for banking-sector frictions in a two-country model with flexible prices. Chow et al. (2014) developed and estimated a small open-economy model for Singapore, excluding a banking sector, to assess alternative exchange-rate regimes.

Over the past two decades, a significant lesson learned is the critical role of financial frictions. As noted by Garcia-Cicco et al. (2015), previous studies on open economies explored frictions leading to external financing premia, measured by spreads between domestic and foreign interest rates. However, in the context of small open economies, these authors highlighted that internal financial frictions played a substantial role in amplifying the adverse effects of negative external shocks on the economy.

The past decade has delved into the role of such frictions in light of the Global Financial Crisis (GFC) that commenced in 2008. These models should prove valuable in examining the adjustment and recovery dynamics of the global COVID-19 pandemic. Nevertheless, it is imperative to acknowledge that models developed in the aftermath of the previous GFC crisis may not be entirely sufficient for analyzing the adjustment and recovery following the COVID-19 crisis. Crises share similarities but also exhibit differences.

The objective of this research is to adapt the prior generation of models to provide more accurate and useful analysis of the current adjustment challenges faced by the ASEAN+3 economies. This necessitates a starting point. Therefore, we will present a concise summary of the previous-generation modeling and apply this modeling to the data of the ASEAN+3 economies through Bayesian estimation. We subsequently assess counterfactual policy scenarios to facilitate comparative policy analysis of monetary and fiscal instruments.

In the subsequent section, we offer an overview of the primary features of the model. A more comprehensive exposition of the model, including appendices with full derivations, can be found in Christiano et al. (2011) and Garcia-Cicco et al. (2015), covering two versions of this model.

It is crucial to emphasize that this is a benchmark model that will undergo adaptation and extension in various ways to suit specific countries. The model will be applied to the data through calibration and Bayesian estimation, as demonstrated in Christiano et al. (2011) and Garcia-Cicco et al. (2015), as well as in Chow et al. (2014).

Following the model discussion, we delve into the Malaysian data used for Bayesian estimation of key parameters governing the model's dynamics. Subsequently, we discuss the estimation results, impulse response analysis, variance decomposition, and historical shock decomposition. Our aim is to spotlight the key factors driving the dynamics induced by the COVID-19 pandemic. We then proceed to counterfactual policy analysis to determine which policy combinations would have best mitigated the pandemic's effects.

2 The Model

The model is undoubtedly state-of-the-art for small open-economy analysis. For instance, Christiano et al. (2011) developed their model for the Riksbank, the central bank of Sweden, while Garcia-Cicco et al. (2015) adapted this model for the Banco Central de Reservas (BCR) of Chile. The former is specified for an advanced-country small open economy, while the latter applies to an emerging-market small open economy. The BCR of Chile is among the top three banks ranked for Europe and Latin America in terms of research productivity and relevance, following the European Central Bank (ECB) and the Federal Reserve Bank [see Sarmiento (2010)]. So, making use of this framework places one in esteemed company.

The model incorporates real frictions in the form of habit persistence in consumption and adjustment costs for investment. It also includes nominal frictions in the form of Calvo (1983) staggered wage-setting. These are the typical New Keynesian modeling assumptions for both closed and open economies. Finally, it encompasses financial frictions in terms of incentive constraints for bank lending, which indicates that the opportunity cost to the bank of diverting assets cannot be smaller than the gain from diverting assets.

The model produces both home goods and traded goods, in the form of products created by labor and productive capital made by entrepreneurs, as well as commodities. Banks extend loans to entrepreneurs for the production of productive capital and to domestic goods-producing firms for working capital to cover salaries and services from domestic capital, such as real estate.

The standard policy variables, such as government spending, household taxation, and the domestic interest rate (in the form of a Taylor rule), are embedded in the model. However, additional instruments, like liquidity support for the banking sector or transfers to domestic firms or households, can be easily incorporated into the model.

The exogenous variables driving the system include various shocks, such as those affecting household preferences, domestic labor supply, total factor productivity, labor-augmenting technology, risk premia for interest rates, shocks to banking-sector incentive-compatibility constraints, and policy instruments.

2.1 The household

The representative Ricardian household maximizes the expected discounted utility, which is driven by consumption goods, C_t and hours worked, h_t:

$$E_t \sum_{s=0}^{\infty} \beta^s [\nu^C_{t+s} log(C_{t+s} - hC_{t+s-1}) - \nu^L_{t+s} \kappa \frac{h^{1+\phi}_{t+s}}{1+\phi}] \tag{1}$$

The variable ν^C_t is an exogenous consumption preference shock, while β is the discount factor, h the habit persistence parameter, while κ is the disutility of labor and ϕ is the Frisch elasticity parameter. The variable ν^L_t is a shock to the disutility of labor supply.

Wage setting follows the Calvo (1983) framework, whereby each household or union can set its nominal wage optimally in a fraction of $1 - \theta_s$ randomly-chosen labor markets, while in the remaining markets the past wage is indexed to a weighted average of past and steady-state inflation rates.

The budget constraint of the household has the following expression:

$$C_t + B_t + rer_t B^*_t + L_t + T_t = \int_0^1 W_t(i) h_t(i) di + r_t B_{t-1} + rer_t r^*_t B^*_{t-1} + r^L_t L_{t-1} + \Sigma_t \tag{2}$$

The variables $C_t, B_t, B^*_t, L_t, T_t$on the expenditure left-hand side represent consumption, domestic bond and foreign bond purchases, liquid deposits, and tax payments at time t, while rer_t is the real exchange rate. The real exchange rate is simply the relative price of foreign assets or goods in domestic currency, so that $rer_t = P^*_t / P_t$.

On the income right-hand side, the variables W_t, h_t, r_t, r^*_t are the real wage level, the aggregate labor, the real domestic and real foreign interest rate at time t, while $B_{t-1}, B^*_{t-1}, L_{t-1}$ stand for government bonds, foreign assets and deposits held at time t-1, while Σ_t represents dividend payments from firms.

The nominal interest rates for domestic and foreign bonds are simply the gross nominal rates adjusted by the gross domestic inflation rate and the foreign gross inflation rates, π_t, π^*_t. The real lending rate at time t, r^L_t is simply the gross nominal lending rate adjusted for gross inflation:

$$r_t = R_{t-1}\pi_t^{-1} \tag{3}$$

$$r_t^* = R_{t-1}^*\xi_{t-1}(\pi_t^*)^{-1} \tag{4}$$

$$r_t^L = R_t^L\pi_t^{-1} \tag{5}$$

The gross foreign nominal interest rate R_t^* follows an exogenous process, as discussed in Section 2.8, while the gross domestic nominal interest rate R_t is set by the central bank, as presented in equation 21.

The model also includes representative non-Ricardian households, who consume their income and do not engage in saving or investment decisions. Following Garcia-Cicco et al. (2015), we specify the proportion of non-Ricardian household consumption to be 20 percent of total final consumption.

2.2 Final goods

The final consumption Y_t^C, investment I_t , and government expenditure goods G_t are produced as composites produced with home-produced and imported goods through a Constant Elasticity of Substitution (CES) bundling technology:

$$Y_t^C = [(1-o_C)^{1/\eta_C}(X_t^{C,H})^{(\eta_C-1)/\eta_C} + (o_C)^{1/\eta_C}(X_t^{C,F})^{(\eta_C-1)/\eta_C}]^{\eta_C/(\eta_C-1)} \tag{6}$$

$$I_t = [(1-o_I)^{1/\eta_I}(X_t^{I,H})^{(\eta_I-1)/\eta_I} + (o_I)^{1/\eta_I}(X_t^{I,F})^{(\eta_I-1)/\eta_I}]^{\eta_I/(\eta_I-1)} \tag{7}$$

$$G_t = [(1-o_G)^{1/\eta_G}(X_t^{G,H})^{(\eta_G-1)/\eta_G} + (o_G)^{1/\eta_G}(X_t^{G,F})^{(\eta_G-1)/\eta_G}]^{\eta_G/(\eta_G-1)} \tag{8}$$

The goods $X_t^{C,H}, X_t^{I,H}, X_t^{G,H}$ are the demands of home composite goods by each firm while $X_t^{C,F}, X_t^{I,F}, X_t^{G,F}$ represent the demand for foreign composite goods. Each firm takes the prices of each good as given. The parameters o_c, o_I, o_G are the shares of foreign and domestic produced goods for the composite consumption, investment and government spending good. The parameters η_C, η_I, η_G are the aggregation parameters for the CES bundling technologies for each final good.

2.3 Production, consumption and investment

Entrepeneurs We assume that entrepeneurs or investors need to finance a fraction α_L^K of their capital purchases by loans, L_t^K. Hence $L_t^K = \alpha_L^K q_t K_t$ holds each period. With r_t^K and q_t being the rental rate and relative price of capital, respectively, we have the following expression for the cash flow of a representative investor, given by the symbol Π_t^E. Note that the cash flow takes into account the rate of depreciation of productive capital, δ:

$$\Pi_t^E = \frac{r_t^K + q_t(1-\delta)}{\alpha_L^K q_{t-1}} - \frac{(1-\alpha_L^K)q_t K_t}{\alpha_L^K q_{t-1} K_{t-1}} \tag{9}$$

Given the zero profit condition implied by the perfect competition condition, with $\Pi_t^E = 0$, the return on lending has the following expression:

$$r_t^L = \frac{r_t^K + q_t(1-\delta)}{\alpha_L^K q_{t-1}} - \frac{(1-\alpha_L^K)q_t K_t}{\alpha_L^K q_{t-1} K_{t-1}} \tag{10}$$

The parameters α_L, α_K represent the standard shares of labor and capital in the production function.

Capital goods The law of motion for capital K_t has the following expression, driven by a convex adjustment cost function Γ as well as a stochastic shock $\bar{\omega}_t$ to the tranformation of investment goods into productive capital:

$$K_t = (1-\delta)K_{t-1} + [\Gamma(I_t/I_{t-1})]\bar{\omega}_t I_t \tag{11}$$

The convex adjustment cost function has the following form:

$$\Gamma(I_t/I_{t-1}) = \frac{\gamma}{2}(\frac{I_t}{I_{t-1}} - \bar{a})^2 \tag{12}$$

The symbols $\gamma, \bar{a}$ are parameters for the adjustment process for new investment goods. Note that the adjustment costs accelerate when the rate of growth increases. This is a standard assumption in the literature and puts a "break" on the accumulation of capital.

Final goods The following CES aggregator generates the final goods composite:

$$Y_t^C = [(1-o)^{1/\eta}(X_t^H)^{(\eta-1)/\eta} + o^{1/\eta}(X_t^F)^{(\eta-1)/\eta}]^{\eta/(\eta-1)} \tag{13}$$

The price of the two goods are p_t^H and p_t^F for the home and foreign-goods components of the aggregate consumer good.

Home composite goods Y_t^H The representative firm bundles goods of all varieties j into the composite home good:

$$Y_t^H = [\int_0^1 X_t^H(j)^{(\epsilon_H-1)/\epsilon_H} dj]^{\epsilon_H/(\epsilon_H-1)} \tag{14}$$

The parameter ϵ_H is the CES bundling-technology parameter for the home composite good Y_t^H.

Home goods production Each home-goods variety is produced according to the standard Cobb-Douglas technology:

$$Y_t^H(j) = z_t K_{t-1}(j)^{\alpha}(A_t h_t(j))^{1-\alpha} \tag{15}$$

The variable z_t is an exogenous stationary technology shock while A_t is a non-stationary technology shock. Both are common to all varieties of goods. The marginal cost, mc_t^H, of each good good j has the following expression:

$$mc_t^H(j) = \frac{1}{\alpha^{\alpha}(1-\alpha)^{(1-\alpha)}} \frac{(r_t^K)^{\alpha} W_t^{1-\alpha}(1+\alpha_L^{WC}(R_t^{L,WC}-1))}{p_t^H z_t A_t^{1-\alpha}} \tag{16}$$

The parameter α_L^{WC} is the fraction of the firm's costs to be financed by such lending to working-capital firms, financed by the rate $R_t^{L,WC}$.

Foreign composite goods The representative foreign firm bundles goods of all varities j into the composite foreign good:

$$Y_t^F = [\int_0^1 [X_t^F(j)^{(\epsilon_F-1)/\epsilon_F} dj]^{\epsilon_F/(\epsilon_F-1)} \tag{17}$$

Foreign goods The following relation shows that marginal costs of foreign goods in foreign currency adjust to the price of the foreign good in domestic currency through the nominal exchange rate S_t:

$$p_t^F mc_t^F(j) = p_t^F mc_t^F = S_t p_t^{F*} \tag{18}$$

Commodities A firm produces a commodity good Y_t^{Co}. The production follows an exogenous process cointegrated with the non-stationary TFP process for A_t. The entire production is sold internationally at a given price, P_t^{Co*}. This price is assumed to evolve exogenously. The government receives a share $\chi \in [0,1]$ and the rest is remitted abroad.

2.4 Fiscal and monetary policy

The government consumes an exogenous stream of goods G_t, levies taxes, issues bonds and receives a share of income generated by the commodity sector. The following equation gives the government budget constraint, with p_t^{Co} representing the relative price of commodities and Y_t^{Co} the amount of raw materials produced:

$$G_t + r_t B_{t-1} = T_t + B_t + \chi p_t^{Co} Y_t^{Co} \tag{19}$$

We describe the stochastic process for G_t, in Section 2.8. The tax rate is calibrated for a steady-state B_t/Y_t ratio of 60 percent. The tax rate adjusts partially to offset an increase in the debt, so that the debt/GDP ratio does not explode, but it does not balance the budget under the base simulations and under alternative counter-factural policy simulations. Monetary policy follows a Taylor rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho^R} \left(\frac{\pi_t}{\bar{\pi}}\right)^{\alpha^\pi} \left(\frac{Y_t/Y_{t-1}}{a_{t-1}}\right)^{\alpha^y} (1-\rho^R)\exp(\epsilon_t^R) \tag{20}$$

The parameters $\rho_R, \alpha_y, \alpha_\pi$ represent the smoothing, the output, and expected inflation effects on the interest-rate mechanism. The variable ϵ_t^R is a stochastic shock to the interest rate.

2.5 Banks

Banks make loans to home-goods producing firms for working capital as well as to entrepreneurs for new capital:

$$L_t^{WC} = \alpha_L^{WC}[W_t h_t(j) + r_t^K K_t(j)] \tag{21}$$

The parameter α_L^{WC} is the fraction of the firm's costs to be financed by such lending. The costs simply are the costs of hiring workers at the economy-wide rate W_t and paying the rental rates on its capital, given by the term R_t^K:

$$R_t^{L,e} L_t^K = \bar{\omega}_{t+1}^e [R_{t+1}^K u_{t+1} - \phi(u_{t+1}) + (1-\delta) q_{t+1}] K_t \pi_{t+1} \tag{22}$$

The variable $\bar{\omega}_{t+1}^e$ is the cut-off value for the source of heterogeneity among entrepeneurs. With higher heterogeneity among entrepeneurs, there are higher lending costs.
The variable u_t is the capital utilization rate, while $\phi(u_t)$ is the cost function for higher capital utilization rates:

$$\phi(u_t) = \frac{r^K}{\phi_u}\exp[\phi(u_{t-1}) - 1] \tag{23}$$

The balance sheet of the representative financial intermediary is given by the following identity:

$$L_t^{WC} + L_t^K = D_t + N_t \tag{24}$$

where D_t denotes deposits, L_t^{WC} and L_t^K are the stock of loans to home-goods producing firms and investors, while N_t is the net worth of the bank.
Net worth has the following law of motion:

$$\begin{aligned} N_{t+1} &= R_{t+1}^{L,WC} L_t^{WC} + R_{t+1}^{L,K} L_t^K - R_{t+1} D_t \\ &= (R_{t+1}^{L,WC} - R_{t+1}) L_t^{WC} + (R_{t+1}^{L,K} - R_{t+1}) L_t^K + R_{t+1} N_t \end{aligned} \tag{25}$$

The objective of the bank is to maximize terminal wealth, V_t:

$$V_t = E_t \sum_{s=0}^{\infty} (1-\omega)\omega^s \beta^{s+1} \Xi_{t,t+s+1} N_{t+s+1} \tag{26}$$

The variable Ξ_t is the households' stochastic discount rate for payoffs. The following incentive constraint applies:

$$V_t \geq \mu_t (L_t^{WC} + L_t^L) \tag{27}$$

The incentive constraint, due to Gertler and Karadi (2011), tells us that the opportunity cost to the bank of diverting assets cannot be smaller than the gain from diverting assets. Positive shocks to the parameter μ_t only make this constraint more severe.

Based on the method of undetermined coefficients, the terminal wealth can be written as a linear functions of the the two loan categories to working-capital and entrepreneurial firms, WC, and K, as well as the net worth of the bank:

$$V_t = \rho_t^{L,WC} L_t^{WC} + \rho_t^{L,K} L_t^K + \rho_t^N N_t \tag{28}$$

The *leverage ratio* is simply the ratio of total loans to net worth. Hence, $lev_t = (L_t^{WC} + L_t^K)/N_t$. This ratio can be simplified to the following expression:

$$lev_t = \frac{\rho_t^N}{\mu_t - \rho_t^L} \tag{29}$$

We see that a higher ratio of divertable funds, ${}_m u_t$, lowers the leverage ratio. The lending-deposit spread is given by the following expression:

$$spr_t = \frac{R_t^{L,WC} L_t^{WC} + R_t^{L,e} L_t^K}{L_t} \frac{1}{R_t} \tag{30}$$

Both the leverage ratio and the spread are important indicators of banking-sector fragility.

2.6 The rest of the world

The real exchange rate is given by the following expression:

$$rer_t = \frac{S_t P_t^*}{P_t} \tag{31}$$

The commodity price in terms of domestic consumption goods, P_t^{Co} is simply equal to the real exchange rate multiplied by the world price of commodities, $rer_t P_t^{Co*}$. Finally foreign demand for the home composite export good is given by the folowing expression:

$$X_t^{H*} = o^* (\frac{P_t^{H*}}{P_t^*})^{-\eta^*} Y_t^* \tag{32}$$

The variable Y_t^* denotes foreign aggregate demand.

2.7 Accounting identities

The following equations define the Trade Balance, GDP, the GDP deflator, and the evolution of the net foreign asset position:

$$TB_t = p_t^H X_t^{H*} + rer_t p_t^{Co} Y_t^{Co} - rer_t M_t \tag{33}$$

$$Y_t = C_t + I_t + G_t + X_t^{Y*} + Y_t^{Co} - M_t \tag{34}$$

$$p_t^Y Y_t = p_t C_t + p_t I_t + p_t G_t + TB_t \tag{35}$$

$$rer_t B_t^* = rer_t r_t^* B_{t-1}^* + TB_t - (1-\chi) rer_t p_t^{Co*} Y_t^{Co} \tag{36}$$

2.8 Forcing variables

The exogenous or forcing variables in the model are given in the following table:

Table 1. Forcing Variables

Symbol	*Name*
ν_t^C	Consumption references
ν_t^L	Disutility of labor
z_t	Total factor productivity
R_t^*	Foreign interest
R_t	Domestic interest
π_t^*	Foreign inflation
y_t^*	World demand
g_t	Government spending
μ_t	Banking incentive constraint

Source: Author.

Each of these variables follows a standard logarithmic autoregressive, with an autoregressive coefficeient and a standard deviation:

$$\log(x_t/\bar{x}) = \rho_x \log(x_{t-1}/\bar{x}) + \epsilon_t^x \sigma^x \tag{37}$$

with the constraints $\rho_x \in [0, 1]$ and $\bar{x} > 0$. The standard deviation for the random variable ϵ_t^x is given by a stochastic index, σ^x.
The stochastic term ϵ_t^x has a Normal distribution with mean zero and variance unity:

$$\epsilon_t^x \sim \mathcal{N}(0, 1) \tag{38}$$

3 Overview of Malaysian Data

Before proceeding to the Bayesian estimation and dynamic analysis of the model, we examine key features of Malaysian data since 2005.

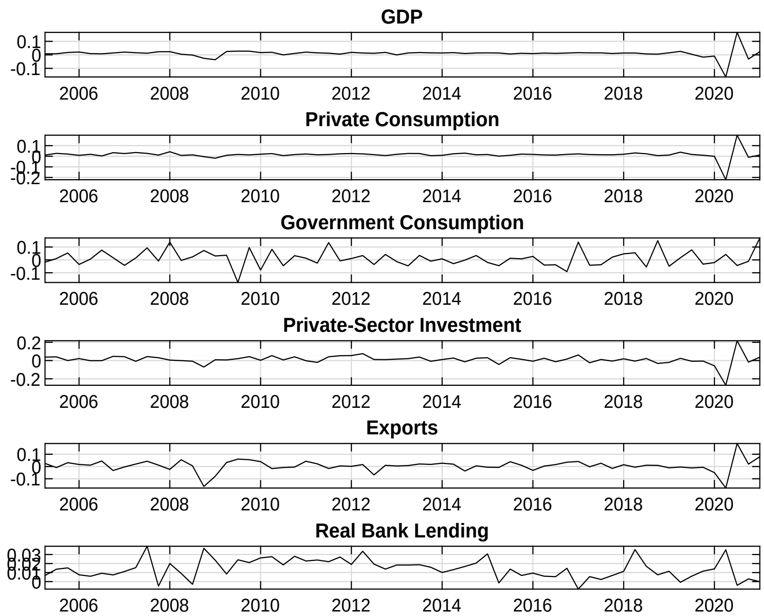
3.1 Aggregate macro indicators

Figure 1 pictures the quarterly rates of growth for GDP, private and government consumption, private investment, real exports and total bank loans.

This figure shows the collapse of investment at the time of the Global Financial Crisis in 2008 as well during the COVID-19 crisis. In both cases there were falls in GDP. We also see a major collapse of private consumption at the time of COVID-19. While real bank lending fell, this was due to an increase in inflation and not a fall in nominal lending.

Figure 1. Aggregate Macro Indicators: Quarterly Rates of Growth

(Quarter-on-quarter growth rate)



Source: Haver Analytics.

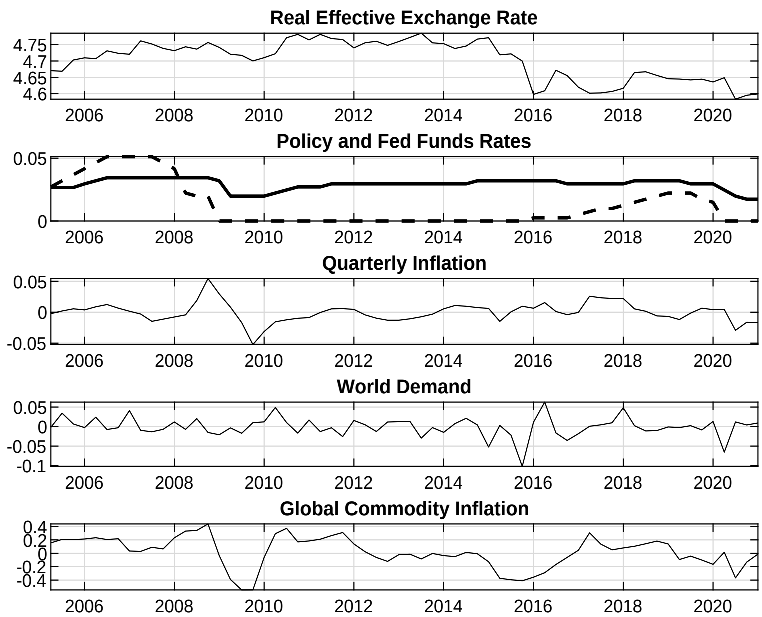
3.2 Financial indicators

Figure 2 pictures the evolution of the logarithm of the real exchange rate, the policy rate of the Bank Negara Malaysia (BNM), the US Federal Funds rate, quarterly inflation and the quarterly rate of change of commodity prices and an indicator for world demand. For the latter, we use a trade-weighted average of the HP-Filtered GDP of the US, Euro Area and China.

We note that there was a steady appreciation of the real exchange rate before 2015, but depreciated thereafter. The policy rate remained higher than the US Federal Funds rate throughout the sample, with the exception of the start of the sample after 2005 to 2008. We also see that the quarterly inflation rate remained low and stable and closely mirrored the patterns of the global commodity inflation rate.

Figure 2. Financial and Global Indicators

(Quarter-on-quarter growth rate; index for policy rates)



Source: Haver Analytics.

3.3 Overall assessment

del Rosario et al. (2022) note that the post-COVID-19 recovery has gained momentum and that the banking system remains sound. The fiscal deficit is now more than 6 percent. As debt continues to rise, to 63.4 percent of GDP, can have retarding effects. These authors note that the upsurge in commodity prices has pushed up inflation. They note that the policy rate of BNM has "scope to increase". Finally, the expected continued policy-tightening by the US Federal Reserve System presents financing challenges to the Malaysian economy.

4 Bayesian Estimation

4.1 Bayesian method with prior distributions

In brief, the Bayesian approach assumes specific distributions for the model's parameters, encompassing the autoregressive parameters, Taylor rule coefficients, and the standard deviations of the shock process.

With a parameter set $\mathbf{\Omega} = [\rho, \sigma]$, one finds the posterior distributions of key parameters via Bayes's Rule:

$$pr(\mathbf{\Omega}|y) \propto pr(y|\mathbf{\Omega})pr(\mathbf{\Omega}) \tag{39}$$

where the symbol $\propto$stands for "is proportional, $pr(y|\mathbf{\Omega})$ is the likelihood of the series y conditional on the parameters, and $pr(\mathbf{\Omega})$ is the prior probability distribution of the parameters. The parameter set includes both the autoregressive coefficients, Taylor rule coefficients, as well as the standard deviations of the key shocks.

Under Bayesian estimation, each parameter has a prior probability distribution with a prior mean and variance. For parameters which fall in the interval [0,1], the usual distribution is the beta distribution, whose parameters α, β are chosen to replicate the per-specified prior mean and variance:

$$pr(x) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)}\Gamma(\beta)x^{\alpha-1}(1-x)^{\beta-1} \tag{40}$$

The symbol Γ is the Gamma distribution:

$$\Gamma(z) = \int_0^\infty t^{z-1}\mathbf{e}^{-t}dt \tag{41}$$

For the Taylor rule inflation coefficient, we specify the usual normal distribution with the prior $\mu > 1$

$$pr(x) = (2\pi\sigma^2)^{-.5}\mathbf{e}^{-.5(\frac{x-\mu}{\sigma})^2} \tag{42}$$

The standard deviations are distributed with Inverse Gamma distributions, **IG**,

$$\mathbf{IG}(x;\alpha,\beta) = \frac{\beta^\alpha}{\Gamma(\alpha)}(1/x)^{\alpha+1}\mathbf{e}^{\frac{-\beta}{x}} \tag{43}$$

The parameter α is known as the shape parameters while β is the scale paremeter. Once the prior mean and standard deviation of the distribution is specifed, these parameters are solved to generate the pre-specified means and standard errors.

Under Bayesian estimation, the process involves the estimation of the likelihood function to obtain initial values. Subsequently, the process includes iteratively drawing parameters from Ω. Given the prior probabilities, the likelihood is recalculated, leading to the determination of posterior probabilities.

In the presence of prior distributions, we engage in repetitive sampling and posterior probability calculations. The common approach for sampling is through the Monte Carlo Markov Chain (MCMC), wherein an initial set of parameters is sampled. Subsequently, another draw is made, and a new posterior probability is computed. A comparison is then performed between the new and previous posterior probabilities. The decision to accept or reject this set of parameters is made based on a draw from a uniform distribution. If the draw from the uniform distribution is less than the ratio of the probabilities of the new draw relative to the previous one, the new draw is accepted; otherwise, it is rejected. The fundamental idea behind MCMC is to ensure that the parameter sampling covers not only the central region of the probability distribution but also its tails.

Once a large number of draws have been obtained, and the posterior probabilities have been calculated, we can derive statistical measures such as the mean, median, standard deviation, and upper and lower values at the 95% confidence level from the distribution. It's worth noting that Bayesian estimation of a model does not rely on classical (or frequentist) tests of significance using t-statistics or F statistics.

4.2 Parameter estimates

Table 2 and present the Bayesian estimates of the autoregressive and Taylor rule coefficients as well as the standard deviations of the shocks or forcing variables. Note that we have ten estimated standard deviations, for eight observables: $y_t, I_t, L_t, R_t, R*_t, G_t, y*_t, \pi*_t$, real GDP, real investment, real banking loans, the domestic policy rate, the Federal Funds rate, real government spending, foreign GDP, foreign inflation.

The estimation period begins in 2005 and ends in 2021 with quarterly data. GDP, investment, loans, foreign demand, and government spending are in logarithms and were subjected to first-differencing. The other nominal variables were detrended.

For the stochastic volatility parameters, we do not use Bayesian estimation. We estimate the autoregressive parameters as well as the standard deviations of these shocks with information from the smoothed shocks generated by the Bayesian estimation.

Table 2. Bayesian Estimates

Coefficients: Bayesiam Estimates

	Priors			Posteriors		
	Mean	Std Dev	Dist	Mean	Inf	Sup
ρ^{y*}	0.5	0.2	Binomial	0.189	0.060	0.310
$\rho^{\pi*}$	0.5	0.2	Binomial	0.626	0.561	0.689
ρ^{ν^L}	0.5	0.2	Binomial	0.945	0.923	0.966
ρ^{R*}	0.5	0.2	Binomial	0.997	0.993	1.000
ρ^R	0.5	0.2	Binomial	0.931	0.918	0.945
ρ^g	0.5	0.2	Binomial	0.933	0.882	0.988
ρ^{gy}	0.5	0.2	Binomial	0.118	0.030	0.198
ρ^{gb}	0.5	0.2	Normal	0.064	0.021	0.103
ρ^z	0.5	0.2	Binomial	0.544	0.212	0.853
ρ^{ν^C}	0.5	0.2	Binomial	0.979	0.964	0.995
ρ^μ	0.5	0.2	Binomial	0.566	0.263	0.896
α^π	1.5	0.2	Normal	1.284	1.211	1.360
α^y	0.5	0.2	Binomial	0.118	0.100	0.143

Std Deviations:Bayesian Estimates

	Priors			Posteriors		
	Mean	Std Dev	Dist	Mean	Inf	Sup
σ^{y*}	0.001	Inf	Inv Gamma	0.025	0.021	0.029
σ^g	0.001	Inf	Inv Gamma	0.066	0.056	0.077
σ^{ν^L}	0.001	Inf	Inv Gamma	0.064	0.044	0.081
σ^μ	0.001	Inf	Inv Gamma	0.010	0.004	0.016
σ^{ν^C}	0.001	Inf	Inv Gamma	0.445	0.281	0.601
σ^{R*}	0.001	Inf	Inv Gamma	0.022	0.017	0.026
σ^R	0.001	Inf	Inv Gamma	0.006	0.005	0.007
$\sigma^{\pi*}$	0.001	Inf	Inv Gamma	0.397	0.321	0.475
σ^z	0.001	Inf	Inv Gamma	0.007	0.004	0.011

Source: Author estimates.

Regarding the estimates, it is clear that there is evidence of learning from the data, as several of the posterior means of the coefficients differ from the prior means, with the exception of the foreign inflation and government spending autoregressive coefficients. Notably, both the Taylor rule inflation coefficient and the output-gap coefficient are positive and align with the Taylor-rule priors.

The standard deviation estimates, for the most part, deviate from the prior means. Values that are very small, extending more than three decimal places to the right, are essentially treated as zeros.

However, it's essential to recognize that we cannot interpret the economic significance of these estimations without further analysis, including impulse response path examination, forecast-error variance decomposition, and historical shock decomposition. Before delving into these analyses, we first examine the smoothed shocks or residuals, which enable the model to precisely track the eight observables.

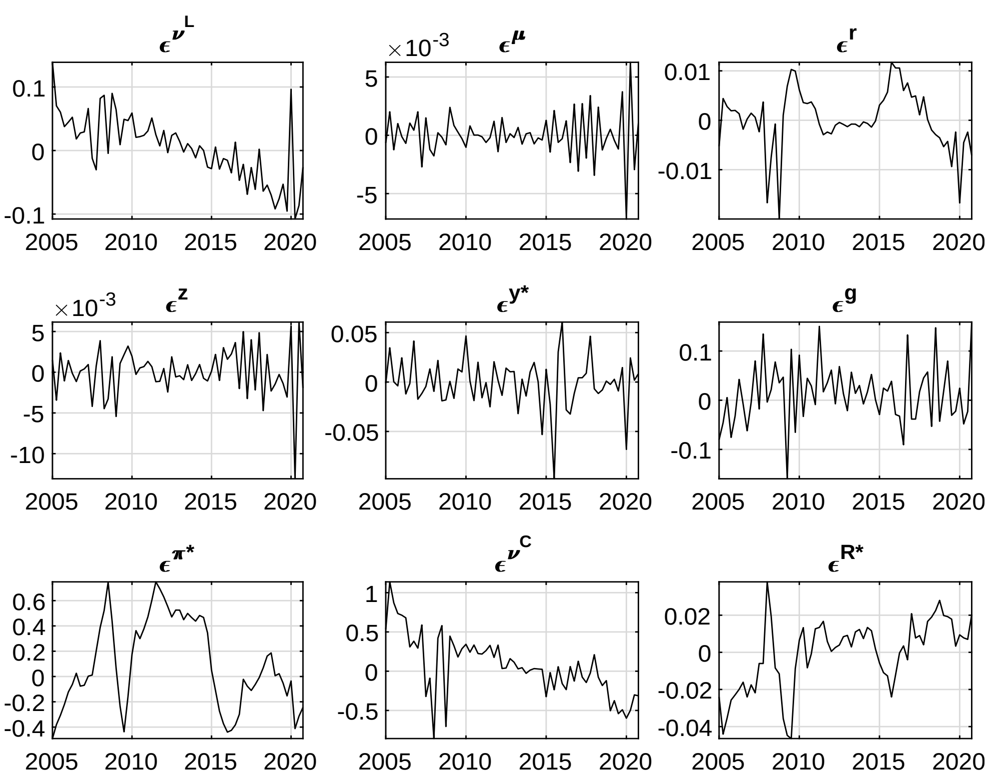
4.3 Smoothed shocks

The smoothed shocks appear in Figure 3. These residuals force the model to match the eight observables if they replace the stochastic shocks. The smoothed shocks, not surprisingly, show greater volatility at the time of the Global Financial Crisis as well as after the onset of COVID-19. The jump in ϵ^{ν^L} shows the marked increase in the disutility of labor during the COVID-19 period. There is also a negative shock to TFP, ϵ^z, at this time, as well as a negative innovation to world demand, ϵ^{y*}.

The key question, of course, is how these shocks affect the dynamics of the model and the interaction among key endogenous variables.

Figure 3. Smoothed Shocks

(Logarithm of variable)



Source: Author calculations.

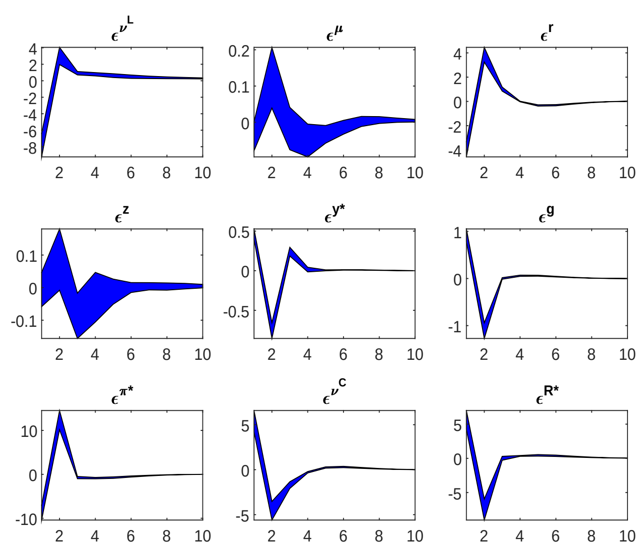
4.4 Impulse Response Analysis

Figures 4 through 6 show the effects of a once-over change in each of forcing variables on GDP, the real exchange rate and on real bank lending. The paths give the upper and lower values for each response for a 95 percent confidence interval. One of the benefits of this analysis is to analyze the qualitative response of the endogenous variables to each shock. Do the responses make sense, qualitatively? Secondly this analysis also shows us how long it takes for the propagation effects to dissipate.

Figure 4 shows that positive shocks to foreign GDP growth, government spending, and TFP all have initial positive effects. Increases in the domestic interest rates have an initial negative effect followed by a positive effect.

Figure 4. GDP: Impulse Response Paths

(Percent deviation from steady state)

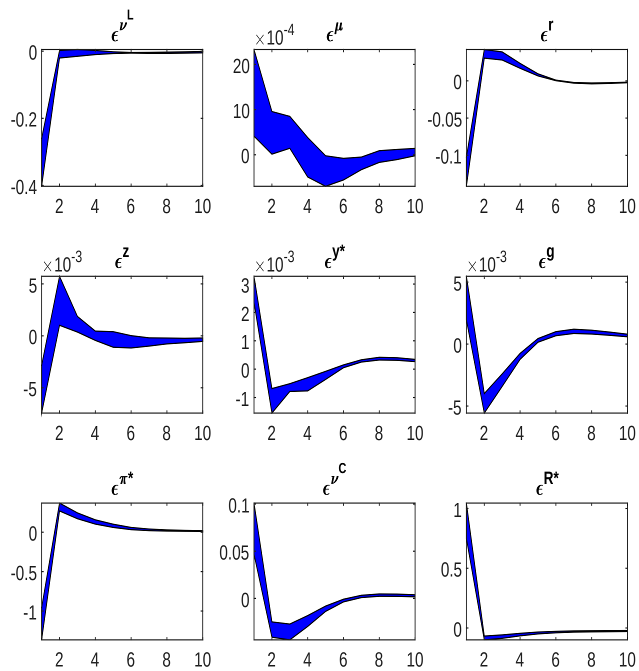


Source: Author calculations.

Figure 5 shows that an increase in foreign demand leads to an appreciation of the real exchange rate, as do TFP shocks. The disutility of labor leads to a depreciation of the real rate. We see all of the shocks dissipate within four quarters.

Figure 5. Real Exchange Rate: Impulse Response Paths

(Percent deviation from steady state)

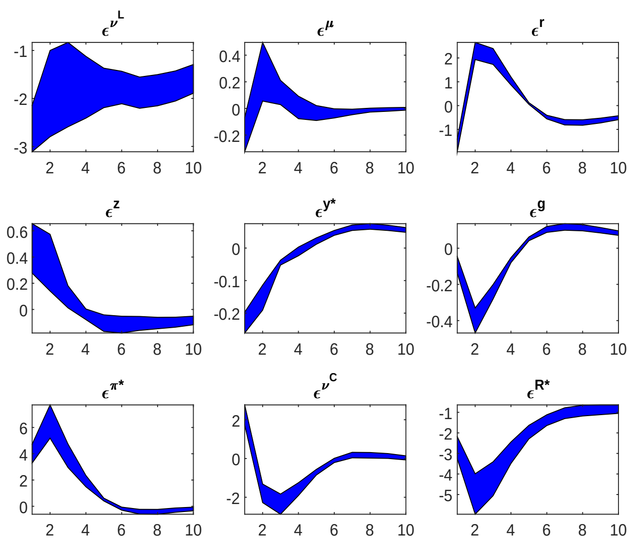


Source: Author calculations.

Figure 6 shows that shocks to the disutility of labor has a strong negative effect on real bank lending, while shocks to TFP have strong positive effects, while government spending, due to crowding out, has a negative effect.

Figure 6. Real Bank Lending: Impulse Response Paths

(Percent deviation from steady state)



Source: Author calculations.

4.5 Forecast Error Variance Decomposition

Tables 3, 4, and 5 show the Forecast Error Variance Decomposition statistics for GDP growth, the real exchange rate and the rate of growth of bank lending. While the impulse response figures show us the qualitative effects of shocks on key variables, as well as the duration of the adjustment process. FEVD analysis helps us assess the relative importance of the forcing variables at short and longer-term horizons.

Table 3 shows that the most important forcing variables for overall GDP growth after 20 quarters are foreign inflation, followed by the foreign interest rate, the disutility of labor, and the utility of consumption. These results are not surprising, given the high degree of openness of the economy, that foreign inflation and foreign rates would matter more than domestic factors such as disutility of labor or consumption utility.

Table 3. FEVD for GDP Growth

(Unit)

Quarterly horizon:

	1	4	8	12	16	20
$\epsilon_{\nu L}$	0.294	0.161	0.162	0.162	0.163	0.163
ϵ_{μ}	0.000	0.000	0.000	0.000	0.000	0.000
ϵ_{R}	0.072	0.067	0.067	0.067	0.067	0.067
ϵ_{z}	0.000	0.000	0.000	0.000	0.000	0.000
ϵ_{y*}	0.001	0.002	0.002	0.002	0.002	0.002
ϵ_{g}	0.004	0.004	0.004	0.004	0.004	0.004
$\epsilon_{\pi*}$	0.331	0.451	0.450	0.450	0.450	0.450
$\epsilon_{\nu C}$	0.149	0.124	0.123	0.123	0.123	0.123
ϵ_{R*}	0.149	0.191	0.191	0.191	0.191	0.191

Source: Author calculations.

Table 4 shows, not surprisingly, that foreign inflation as well as foreign interest rates play the dominant roles for the real exchange rate, both in the short and long term.

Table 4. FEVD for Real Exchange Rate

(Unit)

Quarterly horizon:

	1	4	8	12	16	20
$\epsilon_{\nu L}$	0.049	0.045	0.045	0.045	0.045	0.045
ϵ_{μ}	0.000	0.000	0.000	0.000	0.000	0.000
ϵ_{R}	0.007	0.007	0.007	0.007	0.007	0.007
ϵ_{z}	0.000	0.000	0.000	0.000	0.000	0.000
ϵ_{y*}	0.000	0.000	0.000	0.000	0.000	0.000
ϵ_{g}	0.000	0.000	0.000	0.000	0.000	0.000
$\epsilon_{\pi*}$	0.579	0.602	0.602	0.602	0.601	0.601
$\epsilon_{\nu C}$	0.003	0.004	0.004	0.004	0.004	0.004
ϵ_{R*}	0.362	0.341	0.341	0.342	0.342	0.342

Source: Author calculations.

Table 5 shows that both foreign inflation and foreign rates are the more important determinants of bank lending, with the disutility of labor and domestic interest rates playing observable but minor roles.

Table 5. FEVD for Bank Lending

(Unit)

	Quarterly horizon:					
	1	4	8	12	16	20
$\epsilon_{\nu L}$	0.178	0.089	0.144	0.178	0.187	0.188
ϵ_{μ}	0.001	0.001	0.001	0.001	0.001	0.001
ϵ_{R}	0.069	0.072	0.070	0.069	0.069	0.068
ϵ_{z}	0.006	0.003	0.002	0.002	0.002	0.002
ϵ_{y*}	0.001	0.000	0.000	0.000	0.000	0.000
ϵ_{g}	0.000	0.001	0.001	0.001	0.001	0.001
$\epsilon_{\pi*}$	0.398	0.406	0.362	0.341	0.335	0.334
$\epsilon_{\nu C}$	0.146	0.097	0.089	0.083	0.082	0.083
ϵ_{R*}	0.200	0.330	0.330	0.323	0.321	0.321

Source: Author calculations.

The analysis shows that foreign inflation and foreign interest rates are the key driving variables for GDP growth, the real exchange rate and real bank lending.

4.6 Historical Shock Decomposition

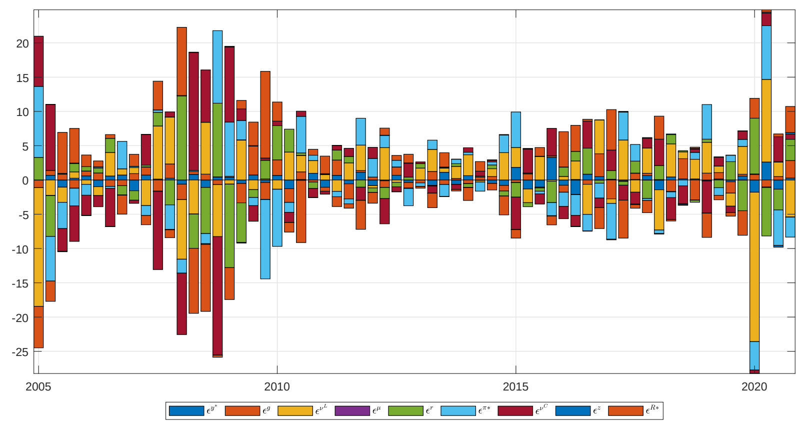
While the FEVD tells us which forcing variables are more important and which are less important over the entire sample, Historical Shock Decomposition (HSD) tells us which forcing variables are more important, and which are less important, at particular times in the sample.

Figures 7, 8 and 9 present the HSD for GDP growth, the real exchange rate, and bank lending.

For GDP growth in Figure 7, a mix of domestic and foreign shocks contributed similar amounts to GDP growth. The disutility of labor comes into noticeable play at the time of the GFC and at the time of the COVID-19 shocks.

Figure 7. Historical Shock Decomposition: GDP Growth

(Unit contribution to quarter-on-quarter growth rate)

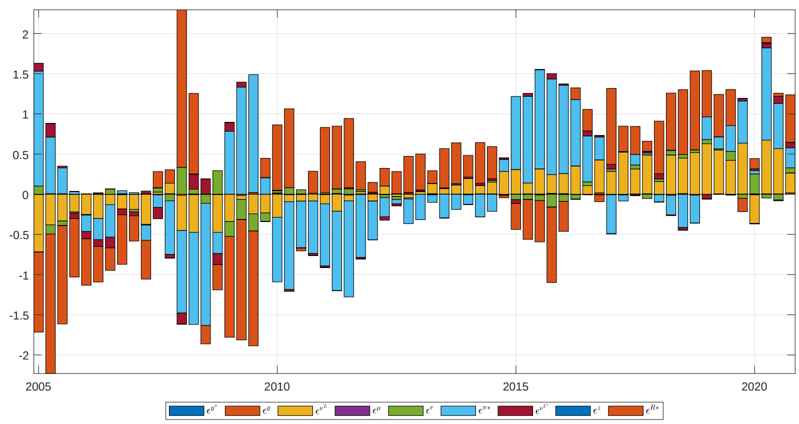


Source: Author calculations.

Figure 8 shows that the relative importance of shocks changes, with foreign inflation playing a major role over the course of the sample but the disutility of labor coming a stronger factor toward the end of the sample.

Figure 8. Historical Shock Decomposition: Real Exchange Rate

(Unit contribution to quarter-on-quarter growth rate)



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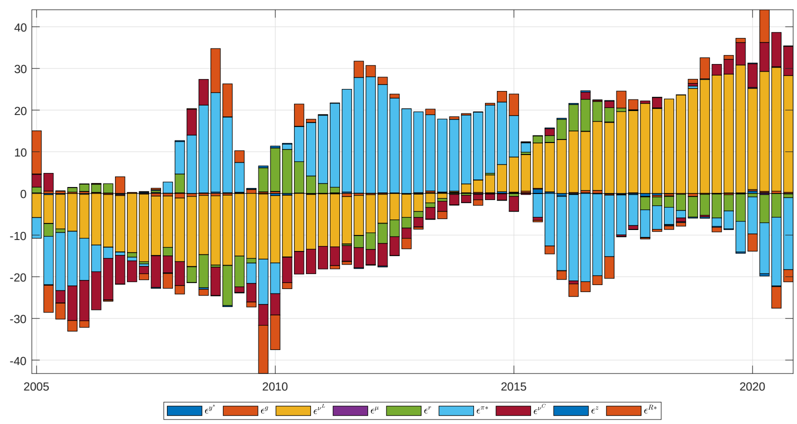
Source: Author calculations.

Figure 9 shows that foreign inflation rates play the key roles for bank lending, while an increase in the disutility of labor was associated with a fall in lending at the beginning of the sample with increased lending at the end of the sample, during COVID-19, likely due to pro-active and supportive macro-financial policies.

Figure 9. Historical Shock Decomposition: Bank Lending

(Unit contribution to quarter-on-quarter growth rate)



Source: Author calculations.

5 Simulations

In this section, we conduct simulations of the model using smoothed shocks, which are derived from accurately fitting the model to the eight observable variables. The objective is to ascertain the implications of these historical simulations for key variables that are not part of the observable list, such as interest-rate spreads, the trade balance, and the non-performing loan ratio. Subsequently, we will proceed to stochastic simulations based on the estimated standard deviations of the shocks or forcing variables. These stochastic simulations are carried out to calculate benchmark welfare measures and benchmark indicators of what are termed "dark corners" under the current policy settings. Blanchard (2014) introduced the concept of "dark corners" to describe periods when the economy begins to "function poorly." We interpret dark corners as intervals during which the output gap falls more than two standard deviations below its stochastic mean. We will then develop alternative policy regimes to assess how welfare can be improved and to evaluate how the depth and frequency of these dark corners change in response to such policy adjustments.

5.1 Historical simulations

Figure 10 pictures the evolution of the actual and model-simulated values for GDP, Exports, Investment , Lending, Government Spending, and the Policy Rate. We see that the model tracks well the turning points at the time of the

GFC as well as COVID-19.

Figure 10. Macro Adjustment: Actual and Fitted

(Quarter-on-quarter growth rate)

Source: Author calculations.

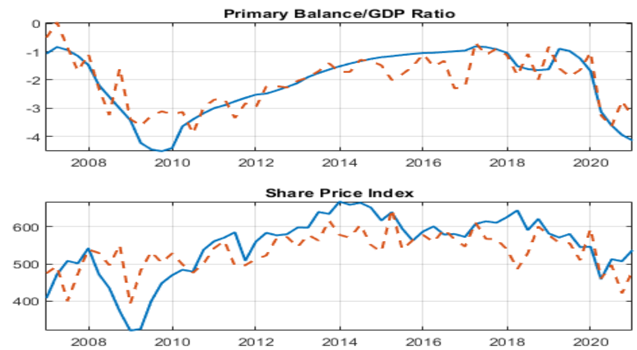
Figure 11 shows the actual and fitted values of the Primary Balance/GDP ratio and the Share price index. Since these variables are not observables or input variables in the estimation process, the fitted values of these variables are projections from the fitted values of the observables in the model.

Figure 12 pictures the policy rate and the model-simulated lending rates of the banking system to working capital and to entrepreneurs for the production of investment goods.

The chart illustrates that the policy rate and the lending rate to entrepreneurs exhibit a closer and more synchronized movement than the co-movement observed between the policy rate and the lending rate to working capital firms. However, during the times of the GFC and the COVID-19 crisis, we observe a significant co-movement of the three rates. This chart suggests a rapid transmission effect, particularly during times of crisis, from the policy rate to the lending rates for both entrepreneurs and working capital firms.

Figure 11. Primary Balance/GDP Ratio and Share Price Index

(Percent; index for share price)

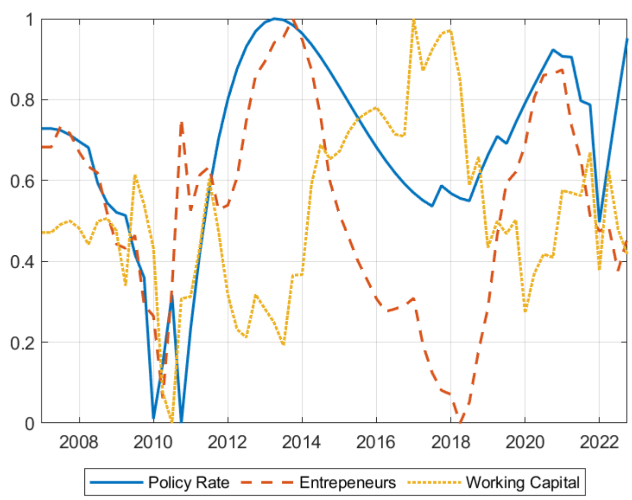


___________Fitted _ _ _ _ _ _ _ Actual

Source: Author calculations.

Figure 12. Policy Rate and Lending Rates

(Normalized by respective initial values)



Source: Author calculations.

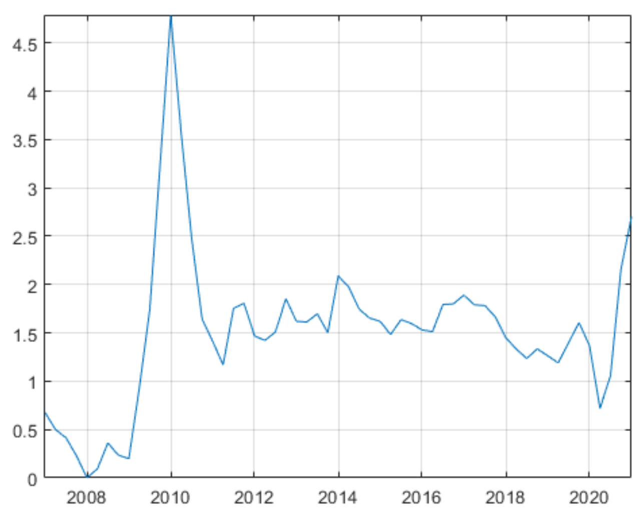
For the above simulations we can calculate the implied Non-performing Loan (NPL) ratio. The change in the NPL ratio is specified as a function of the GDP gap (relative to its steady state) as well as the logarithm of the share price (also relative to its steady-state value):

$$\Delta npl_t = \rho_{npl} \Delta npl_{t-1} + (1 - \rho_{npl})[\beta_y \Delta y_t + \beta_q \Delta q_t] \tag{44}$$

For values of $\rho = .5, \beta_y = -.5, \beta_q = -.025$, we simulated the path of the NPL ratio over the time period of the estimated model in Figure 13. It should be pointed out that the NPL ratio is a variable which requires nowcasting, since the reporting of the actual ratio is often delayed. We see in Figure 13 that this ratio reaches its largest values at the time of the Global Financial Crisis.

Figure 13. Non-Performing Loan Ratio

(Percent)

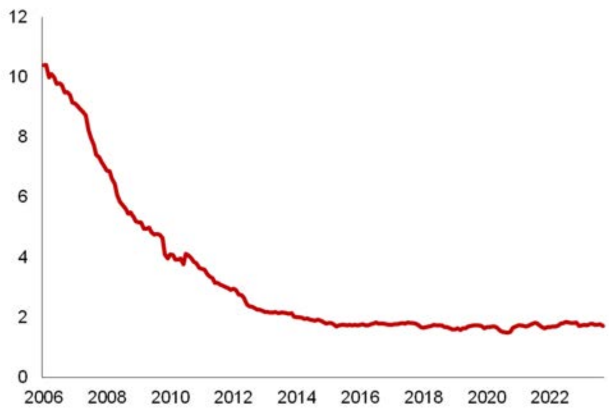


Source: Author calculations.

By contrast, Figure 14 pictures the reported values of the NPL ratio over the past two decades. The reported NPL ratio at the time of the GFC is close to the simulated values close to four percent, while the reported values of 2 percent are close to the simulated values at the time of the pandemic.

Figure 14. Reported Non-Performing Loan Ratios

(Percent)



Source: Bank Negara Malaysia via CEIC.

5.2 Dark corners: benchmark simulations

Following the methodology of Mendoza (2010) we then use a crisis-event analysis, since we are interested in the dynamic behavior of key variables, pre-, during and post- crisis events, where the crisis events have been generated by a sequence of adverse shocks in the home country. Following Kaminsky et al. (2005), we are interested in the adjustment process not just when it rains but when it pours.

Following this approach, we first examine the adjustment for two years (eight quarters) before and eight quarters after the worst crisis event in the long simulation, when GDP is at its absolute minimum value. We then examine the median values of key variables for all of the instances then GDP is two standard deviations below its stochastic mean.[1] An alternative approach would be based on the "sudden stop" episode. Following the definition provided by Calvo et al. (2004) we specify that the sudden stop be characterized by a large and unexpected reversal of capital flows and be associated with a contraction in output. We identify a sudden stop episode when the output gap is at 2.33 standard deviations below its stochastic mean during the episode. This is equivalent to a probability of two percent of the event taking place.

We take 100000 quarterly observations generated by our stochastic simulations and, emulating the empirical literature on crisis events or sudden stops, identify particular sudden stop episodes. We then go backward and forward by

[1] Note that the stochastic means are different from the steady state values of the endogenous variables, due to higher order approximation methods.

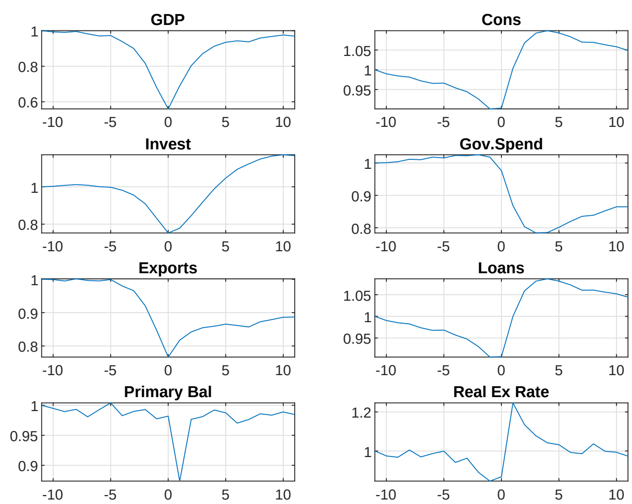
eight quarters and obtain the median values of key variables leading up to and following the crisis event. To understand the relative change in each variable, we normalize the value of each variable leading up to the crisis event or sudden stop at unity.

As noted by Mendoza (2010), looking at welfare measures over the full period of simulation, based on averages, will not help us see how these rules perform when things get bad, as they do, for all economies, some of the time.

Our interest is how key variables behave in down times or crisis periods, and how their adjustment changes when alternative monetary and fiscal supports are in place. The time scale as the "crisis event" or GDP bottoming out at time t=0. Figure 15 shows the adjustment of GDP, Consumption, Investment, and Exports. We see that the median drop in GDP at the crisis event t=0 is mor than 40 percent. As expected, the drop in consumption and exports is much lower. The collapse of investment is faster and harsher, but its recovery at the crisis event is also faster.

Figure 15. Dark Corner Adjustment: Macro Indicators

(t-12 quarters = 1*)

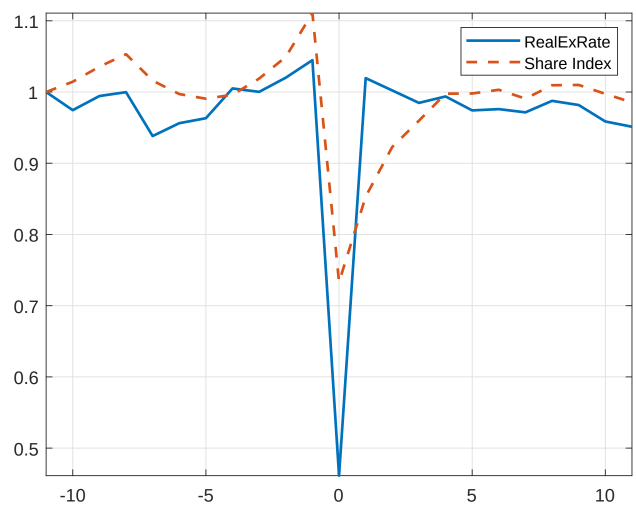


Source: Author calculations.
Note: *Normalized by the value at t-12 quarters, or 3 years, before a crisis event.

Figure 16 shows that the fall of the real exchange rate, relative to the share market index, is faster and steeper. This should not be surprising, since Malaysia is a highly open economy, and many export industries are not listed on the stock exchange.

Figure 16. Dark Corner Adjustment: Financial Indices

(t-12 quarters = 1*)



Source: Author calculations.
Note: *Normalized by the value at t-12 quarters, or 3 years, before a crisis event.

5.3 Counterfactual policy simulation

We make use of optimal simple rules for evaluating the effectiveness of transfers and lending forbearance policies on overall adjustment, both during the sample period and during dark corners.

5.3.1 The optimal rule

Schmitt-Grohe and Uribe (2007) drew attention to the use of such rules for the Taylor rule and for tax-rate adjustment in an economy with sticky prices. They found that such rules closely replicate the welfare effects of more complex Ramsey optimal-policy rules, in which the decision rule depends on all of the endogenous and exogenous state variables of the model.

While there are many simple rules, we specify the design of two rules, one for transfers to the non-Ricardian households and to the firms needing working-capital loans as well as an optimal Taylor rule, in conjunction with the transfer rules. The overall objective of the decision rule is to minimize the volatility of the consumption of non-Ricardian households, the loans to working capital, as well as the volatility of inflation and the interest rate. The simple rules for the combined monetary/fiscal intervention has the following form:

$$TR_t = \gamma_0 TR_{t-1} + \gamma_1(C_{t-1}^{NR} - C_{ss}^{NR}) + \gamma_2(L_{t-1}^{WC} - L_{ss}^{WC}) + \gamma_3(\pi_{t-1} - \pi_{ss}) \quad (45)$$

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\bar{\pi}}\right)^{\alpha_\pi} \left(\frac{Y_t}{Y_{t-1}} \frac{1}{a_{t-1}}\right)^{\alpha_y}\right]^{1-\rho_R} \quad (46)$$

Note that the function form for the interest-rate rule is the same as the one used in the estimated model but now there is no stochastic term. The variable C^{NR} is the consumption of non-Ricardian households, whileL^{WC} represents loans to working-capital firms. The subscript ss represents the steady-state values of the corresponding variables.

Using the above objectives, we obtained the following estimates for the simple-rule coefficients for the transfer rules and monetary policy:

Table 6. Coefficients for Optimal Simple Transfer Rules

Coefficient	Co-Term	TR	R
γ_0	TR_{t-1}	.558	–
γ_1	C^{NR}	-6.895	–
γ_2	L^{WC}	-10.330	–
γ_3	π	.963	–
ρ_R	R_{t-1}	–	.993
ρ_π	$\frac{\pi_t}{\bar{\pi}}$	–	16.909
ρ_y	$\frac{Y_t}{Y_{t-1}}$	–	5.740

Source: Author estimates.

The relative size of the coefficients depend, of course, on the units of measurement of the variables they multiply. However one result is clear. The optimal transfer rule coefficients for the non-Ricardian households and for working capital are counter-cyclical with respect to the levels of consumption and lending relative to their steady-state values. The transfer rule also calls for increased transfer during periods of inflation. The Taylor rule coefficients change in the presence of the expansionary transfer rules, with much stronger positive weights on inflation as well as on the output gap.

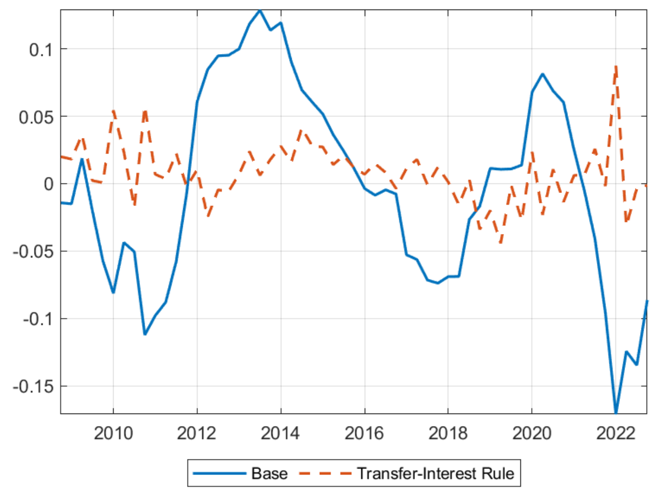
In the next two sub-sections, we evaluate how these rules perform in the historical simulation as well as in the dark-corner simulations, relative to the base path with no optimal transfer rules.

5.3.2 Historical simulations: counterfactual simple rules

Figure 17 pictures the evolution of the non-Ricardian consumption under the base simulation and with the optimal simple rule for transfers and the interest rate.

Figure 17. Non-Ricardian Consumption under Base Simulation and Simple Transfer-Interest Rule

(Logarithm of private consumption)

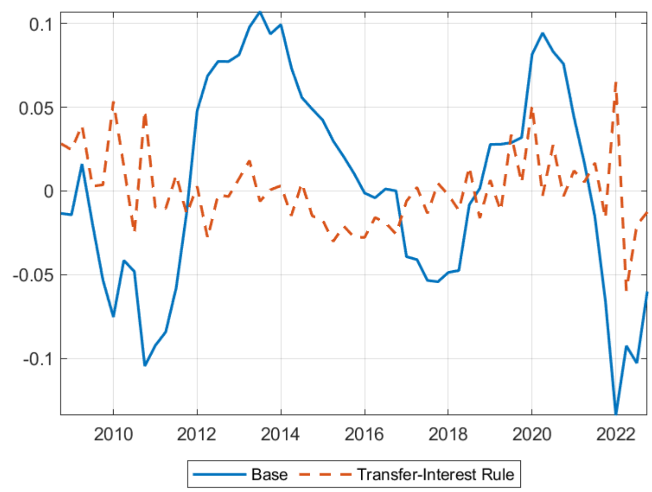


Source: Author calculations.

Figure 18 pictures working-capital lending under the base and under the simple-rule simulations. As in the case of the consumption of non-Ricardian households, we see that implementing the simple rules is an effective stabilizer.

Figure 18. Working Capital Lending under Base Simulation and Simple Rules

(Logarithm of working capital loan)



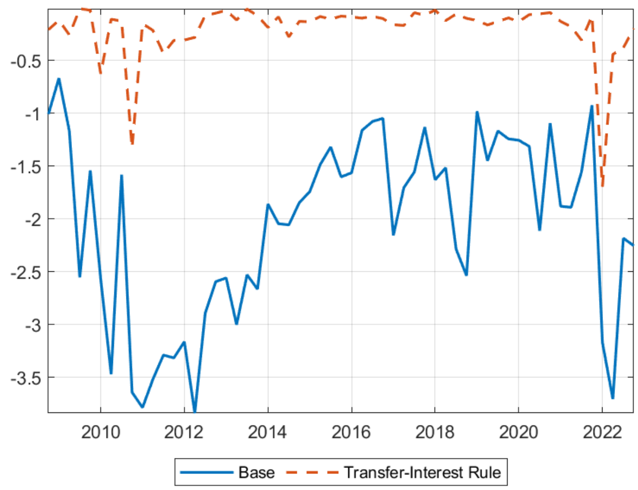
Source: Author calculations.

Figure 19 pictures the Primary Balance/GDP Ratio under the base and optimal simple rule scenarios. We see that the implementation of the simple rule actually improves the primary balance relative to the base simulation, which has a much deeper drop at the time of the GFC and the COVID-19 periods. However, even with the transfer rules, the primary balance remains negative. Both the base simulation and the simple-rules simulation show sharp drops in the primary balance at the time of the GFC and Pandemic, although the drops are not as sharp.

These results should not be surprising. The strong effects of the transfers on consumption and lending reduce negative pressures on the Primary Balance.

Figure 19. Primary Balance under Base Simulation and Simple Rules

(Percent of GDP)



Source: Author calculations.

5.3.3 Historical simulations: counterfactual transfer vs. interest-rate rule

To better explore the effect of alternative transfer vs. interest-rate support policies, we compare three scenarios with the estimated base path: one with both optimal transfer and optimal Taylor rules, as discussed in section 5.3.1, the optimal transfer rule with monetary policy only targeting inflation, and a no-support regime, in which the fiscal authority balances the budget and the monetary authority simply targets inflation. We found that an optimal Taylor rule with no transfers was not very different from the base. Our comparative policy regimes are described in Table 7.

Table 7. Policy Regime Comparison

Regime	**Parameters for Transfers (TR) and Taylor Rule (R)**
Base Regime	Table 2
Optimal Transfer/Taylor Rules	TR: Table 6: Col. 2 , R: Table 6, Col. 3
Optimal Transfer/Inflation Target	TR: Table 6, Col. 2
	R: $\rho^R = .933, \alpha^\pi = 1.28, \alpha^y = 0$
No Support	TR: $\forall i \in [0,3] : \gamma_i = 0$
	R: $\rho^R = .933, \alpha^\pi = 1.28, \alpha^y = 0$

Source: Author estimates.

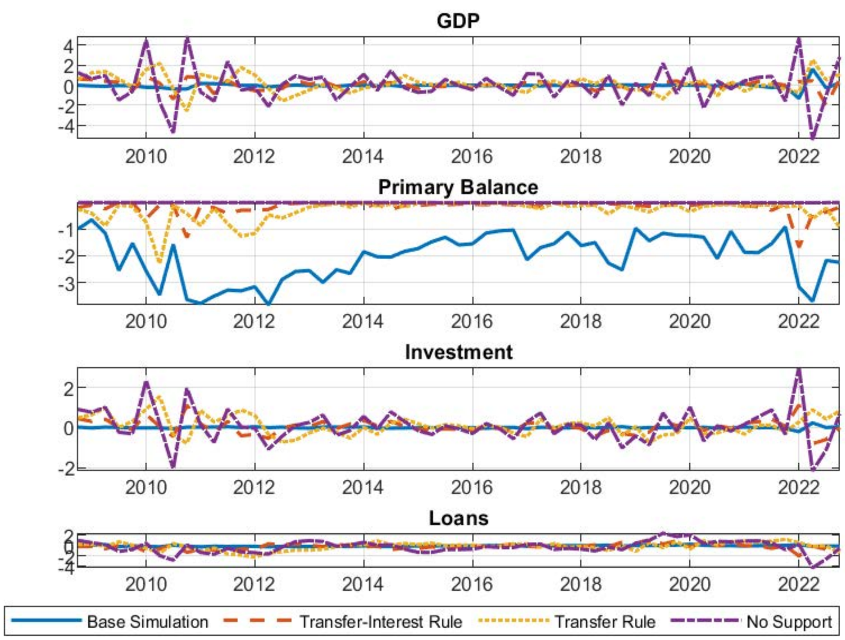
The reason why we compare these rules with the model-simulated actual path is that we realize that the actual policy framework guiding the actual path incorporated, to a greater or lesser extent at various points of time, fiscal and monetary supports. The question we pose: is the actual path closer to the path generated by a framework with no supports or closer to one with simple but *optimal* support rules.

The results for four scenarios rules appear below, in Figure 20 for GDP, the Primary Balance, Investment, and Real Lending, appear below, as well as the results for the base and the combined rule, and a No-Support scenario, with a balanced fiscal budget and pure inflation-targeting Taylor rule.

We see that the base line, which tracks the actual path, is closer to the optimal rules than the respective paths for the No Support regime, for GDP, Investment, and Lending, To be sure, the Primary Balance is much worse under the base than under the optimal rules and, of course, the balanced-budget rule.

Figure 20. Macro Adjustment under Base and Alternative Regimes

(Percent change deviation from steady state)



Source: Author calculations.

Of course, optimal rules are a heuristic device: they tell us what can be done by a policy maker if the model were true and if the policy maker knew all the details of the model, including the distribution of the stochastic shocks impinging on the system. As noted by Jurg Niehans about the preface, monetary policy can never be this type of computational science.

What Figure 20 tells us is that the paths of the actual path are close to those generated by the optimal rules than to the paths generated with no monetary/fiscal support, in the form of a balanced-budget rule and pure inflation-targeting.

To clarify this point, Table 8 gives the Euclidean distance measures or Indices of Dissimilarity between the paths in pairwise combinations. This table shows that the distance between the No Support paths and each of the other three (the base, transfer-interest, and pure transfer) is twice as large as the pairwise distances among the three paths. In fact, the distance measures of the three paths with each other is not significantly different from zero. However, in bold, we show that the distance measures of three paths with respect to the No Support paths are all significantly different at the five percent level.

The message of this result is that the base path, while not an official optimal path, is not significantly different from any of the hypothetical optimal paths, in comparison with respect to a path based on no policy support.

Table 8. Euclidean Distance Measures of Base & Policy Paths

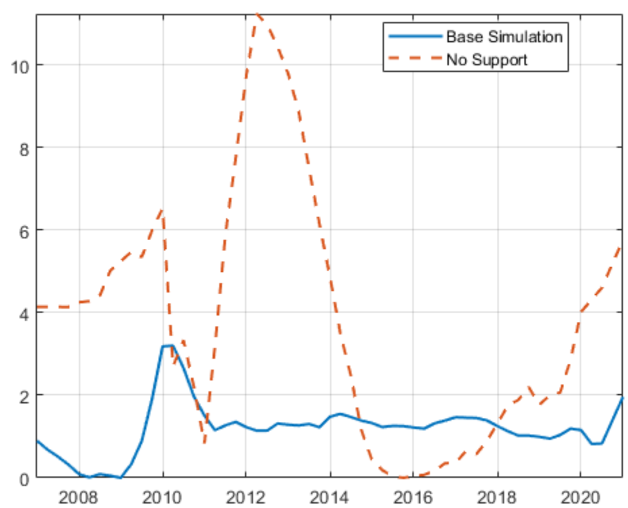
Policy Paths:		Policy Paths: Base Path	Transfer+ Interest	Pure Transfer	No Support
Base	Path	0.000	– –	– –	– –
Transfer+	Interest	4.035	0.000	– –	– –
Pure	Transfer	5.758	6.253	0.000	– –
No	Support	**13.334**	**11.256**	**15.345**	0.000

Source: Author estimates.

To further illustrate the potential costs of a No-Support regime, Figure 21 pictures the Non-Performing Loan (NPL) ratios under the Base and the No-Support regimes. We see, not surprisingly, that a pure fiscal and pure inflation-targeting rule would have led to higher NPL ratios. This was a period in which the primary deficits were at their low points in the sample period, so that stabilization rule would not have been as harsh as in other earlier periods. This result shows that the policy mix during the period, especially during the GFC and the COVID-19 episodes, enhanced the stability of the finance system, at least as measured by the NPL ratios.

Figure 21. NPL Ratio: Base and No-Support Regime

(Percent)



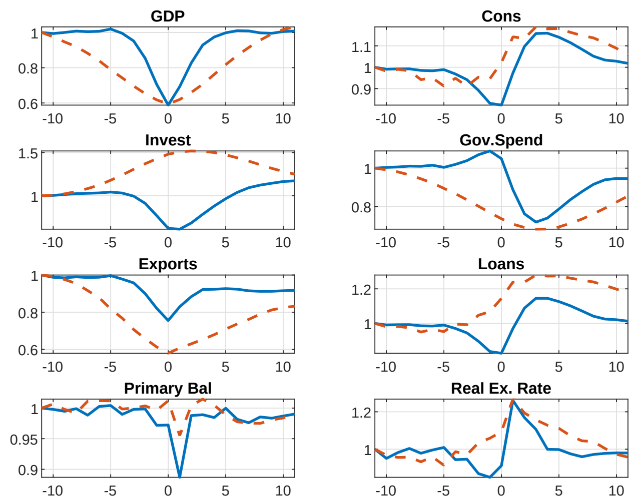
Source: Author calculations.

5.3.4 Dark corners under counter-factual policies

Figure 22 gives the dark-corner dynamics under the base and counter-factual transfer-interest-rate rule. For the sake of brevity we omit the pure transfer and pure interest-rate rules. This results shows interesting patterns of adjustment. With the use of policy supports, both consumption and investment are stabilized relative to the base path. The primary balances is also stabilized. However exports decline more so under the transfer-interest policy program. The reason is that the real exchange rate does not depreciate as much under the policy supports as it would under the base program.

Figure 22. Dark Corner Dynamics under Base and Counterfactual Policy Rules

(t-12 quarters = 1*)



______Base simulation - - - Counterfactual Transfer-Interest Rule

Source: Author calculations.
Note: *Normalized by the value at t-12 quarters, or 3 years, before a crisis event.

6 Conclusions

This paper employed a Bayesian DSGE model to assess the effectiveness of the monetary-fiscal policy mix implemented over the past two decades. It is important to note that the model serves as an approximation of the underlying dynamics of the macroeconomic system. Nonetheless, it closely approximates the evolution of key macroeconomic indicators during both normal periods and crisis periods, such as the GFC and the COVID-19 pandemic.

The primary insight gleaned from the analysis is that the dynamics generated by the actual policy framework were more aligned with the results produced by "optimal" rules for transfers and the base policy rate, as opposed to a No Support regime. In the latter, fiscal policy adheres to balanced-budget targets, and the monetary authority follows strict inflation targets, without considering the output gap. Our results also indicate that the actual framework, while not optimal in every aspect, significantly contributed to the stability of the financial system compared to a non-interventionist fiscal and monetary policy framework. Our results support the position that stabilization programs work best when monetary and fiscal sectors work in tandem.

It is worth noting that welfare optimization, which takes into account aggregate consumption and economy-wide disutility of labor, would yield different outcomes. This is because we are examining optimal simple rules designed to stabilize consumption for non-Ricardian households and investment by Working Capital firms. Nevertheless, the welfare generated by these simple rules consistently outperforms welfare relative to a no-intervention policy framework.

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