Working Paper (WP/24-01)

Assessing Policy Performance in Thailand in a Dynamic Structural General Equilibrium Framework

Paul D. McNelis

January 2024

[This page is intentionally left blank]

Assessing Policy Performance in Thailand in a Dynamic Structural General Equilibrium Framework

Prepared by Paul D. McNelis [1] [2] [3]

Authorized by Li Lian Ong
January 2024

Abstract

This paper provides an analysis of policy performance coming from Bayesian estimation and simulation of a Dynamic Structural General Equilibrium (DSGE) model for Thailand. The model then examines the optimal counter-factual monetary and transfer policies directed to non-Ricardian "rule-of-thumb" consumers and to firms which borrow only for working capital. The results show throughout the sample period (2005-2021) that key macroeconomic variables were driven by a mix of internal and external real shocks. The dynamic adjustment paths from the actual policies are closer to those generated by optimal transfer and monetary policies during key crisis periods, than they were to paths generated by only a pure inflation-targeting policy with no other transfers.

---

[1] Author's e-mail: mcnelis@fordham.edu

[2] Paul D. McNelis is Professor Emeritus of Finance and Business Economics at Fordham University. He is currently an AMRO Research Fellow under the AMRO Collaboration Research Program funded by the Japan-AMRO Special Trust Fund. The views expressed in the paper are those of the author and not necessarily the views of Fordham University, which should not be held responsible for any consequence arising from the use of the information contained therein.

Abbreviations

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

Contents

List of Figures

List of Tables

[This page is intentionally left blank]

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 paper makes use of a small open economy to assess policy performance of the monetary and fiscal authorities in Thailand since 2005, a span of data which includes both the Global Financial Crisis (GFC) and the COVID-19 Pandemic, thus times of challenge for policy-makers. Our aim is to ask how the de-facto policies approximated optimal policies for stabilization of consumption and investment relative to no-intervention policies. This is the central question of this paper.

However. Bayesian estimation and simulation of the estimated model allow us to identify the major sources of real and financial-sector instability, both for the overall sample and for adjustment in particular time periods, since the sample is book-ended by the GFC and COVID-19 episodes.

Building on previous work on Malaysia [see McNelis (2023)], we make use of Bayesian estimation of a Dynamic Stochastic General Equilibrium (DSGE) model for a small open economy, based on previous work by Christiano et al. (2011) and Garcia-Cicco et al. (2015).

Extensive discussion of the model and a description of the Bayesian estimation methods can be found in McNelis (2023) and are not repeated here.[1]

The next section presents an overview of key macroeconomic time series we use for Bayesian estimation and evaluation of accuracy of our model. Following the data discussion there is a discussion of the Bayesian estimation and its implications for understanding implications of the model for impulse responses, forecast error decomposition and historical shock decomposition. In other words, the estimation allows us to assess which variables are more important at specific times.

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

2 Overview of Thai Data

2.1 Aggregate macro indicators

Figure 1 pictures the log first-differences of real GDP, Consumption, Government Spending, Investment, Exports and Bank Lending. We see the sharp drops of GDP, Consumption, Investment, Exports and Bank Lending at the COVID-19 period, while Government Spending actually rose as GDP dropped at the start of this period. The fall in investment was sharper than the fall in GDP and closely follows the drop in exports.

---

[1]The estimation, optimal policy calculations and simulations of the model were done with Dynare, Version 5.5. See Adjemian et al. (2014) for further documentation of this software.

Figure 1. Aggregate Macro Indicators

(Quarterly growth rate)
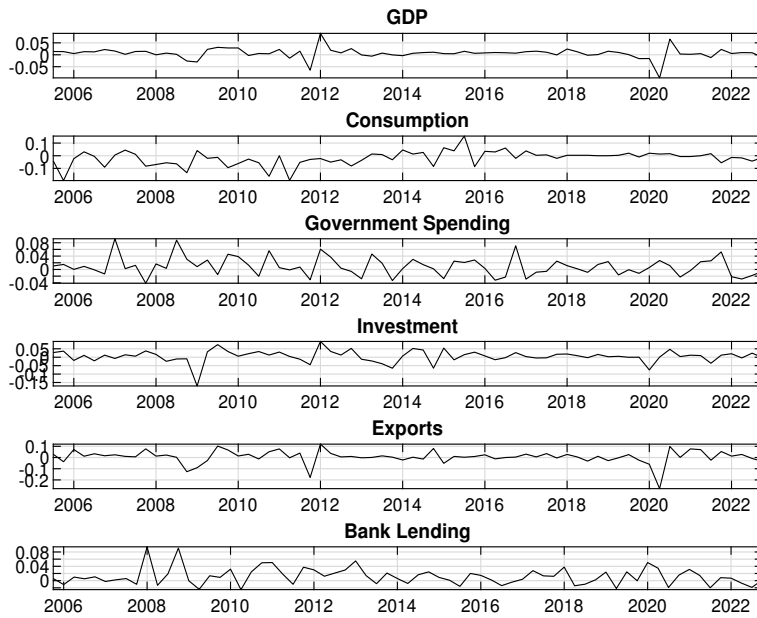
Source: Haver Analytics.

2.2 Financial Indicators

Figure 2 pictures domestic and foreign inflation as well as the rate of change of the global commodity price index. It is clear that domestic inflation π is more volatile than foreign inflation π^* but neither inflation rates are as volatile as global commodity price inflation, π^{Co}.

Figure 2. Inflation Rates

(Percent)

Detrended Domestic and Foreign Inflation

Detrended Global Commodity Price Inflation
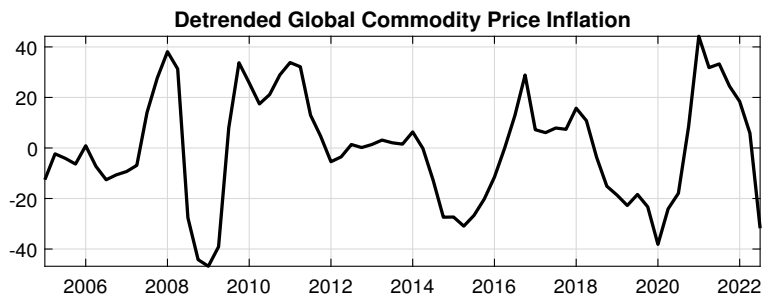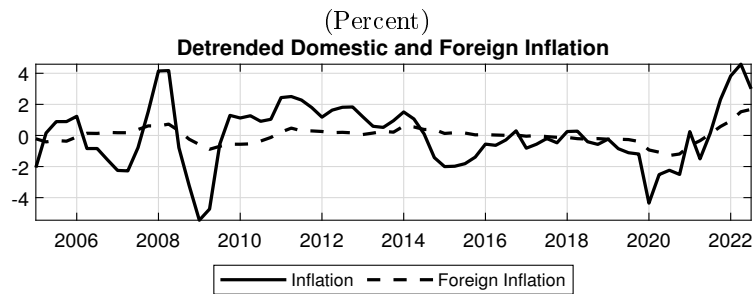
Source: Haver Analytics.

The interest rates appear in Figure 3. We see that the domestic policy rate was generally above the Global Federal Funds rate until the recent FED hikes in 2022.

Figure 3. Interest Rates

(Percent)

U.S. Federal Funds and Domestic Policy Rates
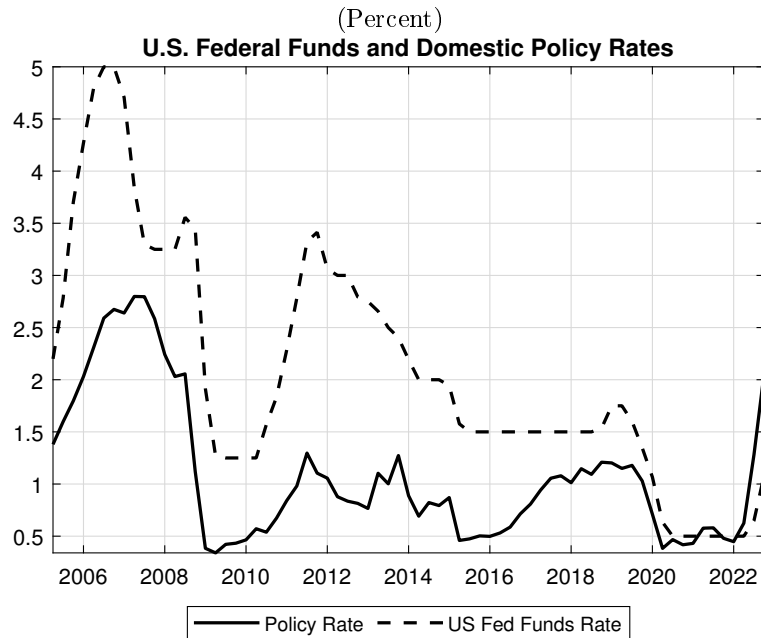
Source: Haver Analytics.

Figure 4 pictures the quarterly adjustment of the real exchange rate and real share price. We see that the real share price shows more volatility than the real exchange rate.

Figure 4. Real Market Indices

(Quarterly growth rate)
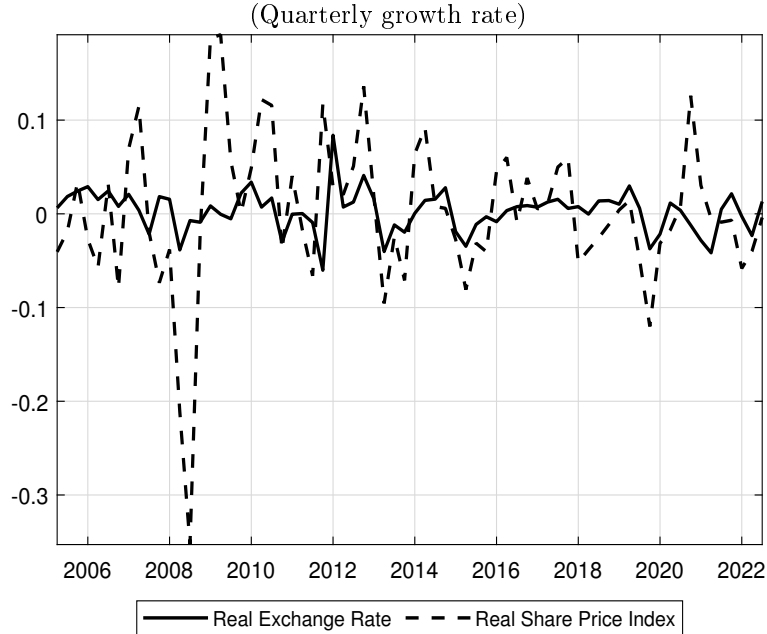
Source: Haver Analytics.

3   Empirical Estimation and Analysis

This section presents the Bayesian results as well as key information derived from the estimation of the model, to understand the economic message of this estimation.

3.1   Parameter estimates

Table 1 presents 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 nine estimated standard deviations, for eight observables: real GDP, real investment, real banking loans, the domestic policy rate, the Federal Funds rate, real government spending, foreign GDP, foreign inflation, represented by the symbols $y_t, I_t, L_t, R_t, R*_t, G_t, y*_t, \pi*_t,$

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 nominal variables were detrended.

Table 1. Bayesian Estimates

Coefficients	Priors			Posteriors		
	Mean	Std Dev	Dist	Mean	Inf	Sup
ρ^{y*}	0.5	0.2	Binomial	0.873	0.861	0.887
$\rho^{\pi*}$	0.5	0.2	Binomial	0.376	0.358	0.394
ρ^{ν^L}	0.5	0.2	Binomial	0.850	0.842	0.858
ρ^{R*}	0.5	0.2	Binomial	0.281	0.276	0.288
ρ^{R}	0.5	0.2	Binomial	0.616	0.596	0.633
ρ^{g}	0.5	0.2	Binomial	0.144	0.136	0.155
ρ^{gy}	0.5	0.2	Binomial	0.422	0.413	0.431
ρ^{gb}	0.5	0.2	Normal	0.106	0.105	0.107
ρ^{z}	0.5	0.2	Binomial	0.999	0.999	1.000
ρ^{ν^C}	0.5	0.2	Binomial	0.004	0.001	0.007
ρ^{μ}	0.5	0.2	Binomial	0.095	0.077	0.111
α^{π}	1.5	0.2	Normal	1.103	1.094	1.115
α^{y}	0.5	0.2	Binomial	0.753	0.745	0.763
Std Deviations						
σ^{y*}	0.05	0.5	Inv Gamma	0.0665	0.0655	0.0674
σ^{g}	0.05	0.5	Inv Gamma	0.0009	0.0009	0.0009
σ^{ν^L}	0.05	0.5	Inv Gamma	0.0363	0.0356	0.0369
σ^{μ}	0.05	0.5	Inv Gamma	0.0351	0.0346	0.0356
σ^{ν^C}	0.05	0.5	Inv Gamma	0.0550	0.0543	0.0556
σ^{R*}	0.05	0.5	Inv Gamma	0.0834	0.0823	0.0845
σ^{R}	0.05	0.5	Inv Gamma	0.0045	0.0043	0.0048
$\sigma^{\pi*}$	0.05	0.5	Inv Gamma	0.0575	0.0565	0.0581
σ^{z}	0.05	0.5	Inv Gamma	0.0327	0.0322	0.0331

Source: Author estimation.

3.2 Smoothed shocks

The smoothed shocks appear in Figure 5. 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 5. Smoothed Shocks

(Percent)
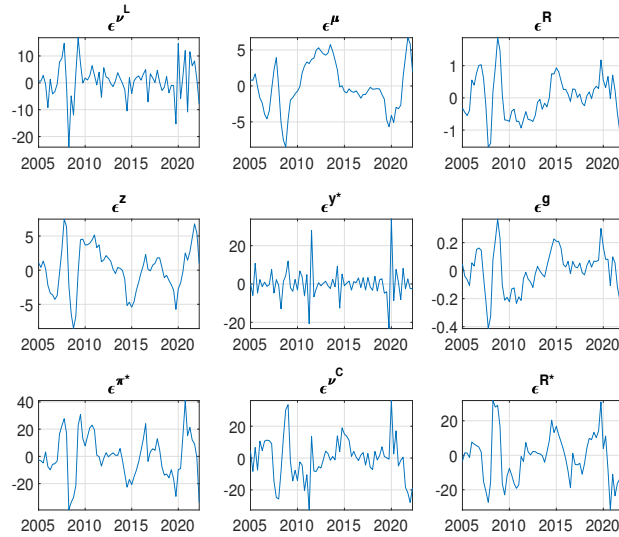
Source: Author calculations.

3.3 Impulse Response Analysis

Figures 6 through 8 show the effects of a once-over change in each of the 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 6 shows that positive shocks to foreign GDP growth, government spending, and TFP , $\epsilon^{y^*}, \epsilon^g, \epsilon^z$, all have initial positive effects. Increases in the domestic interest rates have an initial negative effect followed by a positive effect. Shocks to the disutility of labor, ϵ^{ν^L}, have the expected negative effects.

Figure 6. GDP: Impulse Response Paths

(Percentage deviation from the steady state)
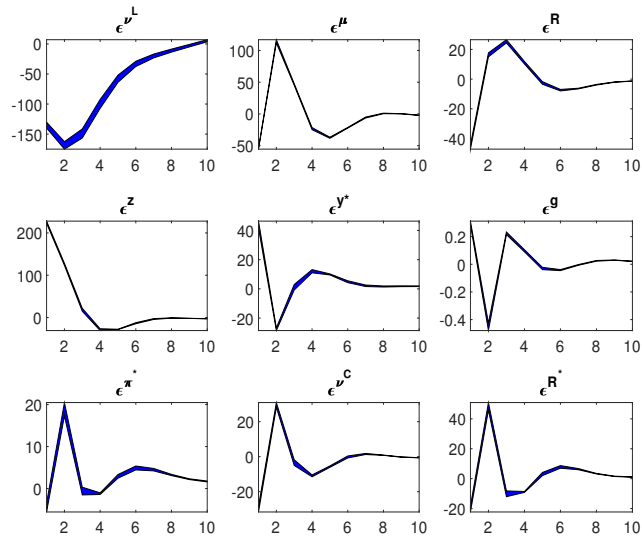
Source: Author calculations.

Figure 7 shows that an increase in TFP leads to a real appreciation. The disutility of labor leads to a depreciation of the real rate. We see all of the shocks dissipate within four quarters, with the exception of shocks to the disutility of labor.

Figure 7. Real Exchange Rate: Impulse Response Paths
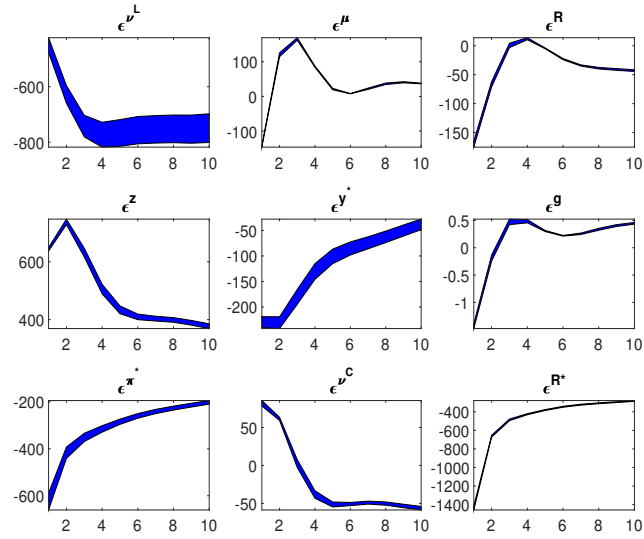
(Percentage deviation from the steady state)

Source: Author calculations.

Figure 8 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. Shocks to government spending, due to crowding out, have negative effects.

Figure 8. Real Bank Lending: Impulse Response Paths

(Percentage deviation from the steady state)
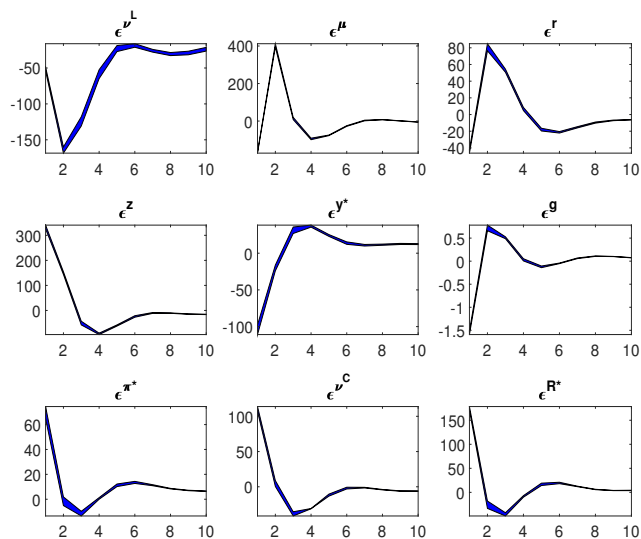
Source: Author calculations.

3.4   Forecast Error Variance Decomposition (FEVD)

Tables 2, 3, and 4 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 2 shows that the most important forcing variables for overall GDP growth after 16 quarters are domestic factors, namely TFP and the disutility of labor. While foreign factors do show up, the cumulative influence of foreign inflation and the foreign interest rate shocks is less than 2 percent.

Table 2. FEVD for GDP Growth

(Unit)

Quarterly horizon:

	1	4	8	12	16
$\epsilon^{\nu L}$	0.237	0.449	0.456	0.457	0.466
ϵ^{μ}	0.039	0.106	0.111	0.111	0.109
ϵ^{R}	0.028	0.018	0.018	0.018	0.017
ϵ^{z}	0.655	0.382	0.369	0.368	0.362
ϵ^{y^*}	0.025	0.016	0.016	0.016	0.016
ϵ^{g}	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.000	0.002	0.002	0.003	0.002
$\epsilon^{\nu C}$	0.012	0.011	0.010	0.010	0.010
ϵ^{R^*}	0.005	0.017	0.017	0.016	0.016

Source: Author calculations.

Table 3 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 3. FEVD for Real Exchange Rate

(Unit)

Quarterly horizon:

	1	4	8	12	16
$\epsilon^{\nu L}$	0.065	0.240	0.368	0.439	0.480
ϵ^{μ}	0.007	0.009	0.006	0.005	0.005
ϵ^{R}	0.009	0.005	0.003	0.003	0.003
ϵ^{z}	0.130	0.219	0.206	0.197	0.195
ϵ^{y^*}	0.016	0.021	0.016	0.013	0.011
ϵ^{g}	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.122	0.106	0.094	0.083	0.076
$\epsilon^{\nu C}$	0.002	0.002	0.002	0.002	0.003
ϵ^{R^*}	0.649	0.398	0.305	0.257	0.228

Source: Author calculations.

Table 4 shows that both domestic and foreign factors have about the same overall influence on bank lending. Shocks to total productivity, banking frictions, given by ϵ^{μ}, shocks to the marginal utility of consumption, $\epsilon^{\nu C}$, and domestic interest rates, ϵ^{R}, explain about 75 percent of the total variation of bank lending, while foreign interest rates and foreign inflation explain less than 10 percent.

Table 4. FEVD for Bank Lending

(Unit)

Quarterly horizon:

	1	4	8	12	16
ϵ^{ν^L}	0.013	0.103	0.105	0.108	0.108
ϵ^{μ}	0.140	0.425	0.423	0.420	0.420
ϵ^{R}	0.010	0.024	0.025	0.025	0.026
ϵ^{z}	0.550	0.307	0.305	0.304	0.304
ϵ^{y^*}	0.054	0.029	0.030	0.031	0.031
ϵ^{g}	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.023	0.010	0.011	0.011	0.011
ϵ^{ν^C}	0.060	0.031	0.030	0.030	0.030
ϵ^{R^*}	0.151	0.071	0.070	0.070	0.070

Source: Author calculations.

The analysis shows that both domestic and foreign factors have important roles for overall macroeconomic adjustment.

3.5   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 9, 10 and 11 present the HSD for GDP growth, the real exchange rate, and bank lending.

For GDP growth in Figure 9, a variety of shocks play the key roles at the time of the GFC and the COVID-19 episodes. We also see that the disutility of labor comes into noticeable play at the time of the GFC and at the time of the COVID-19 shocks.

Figure 9. Historical Shock Decomposition: GDP Growth

(Unit contribution to quarterly growth rate)
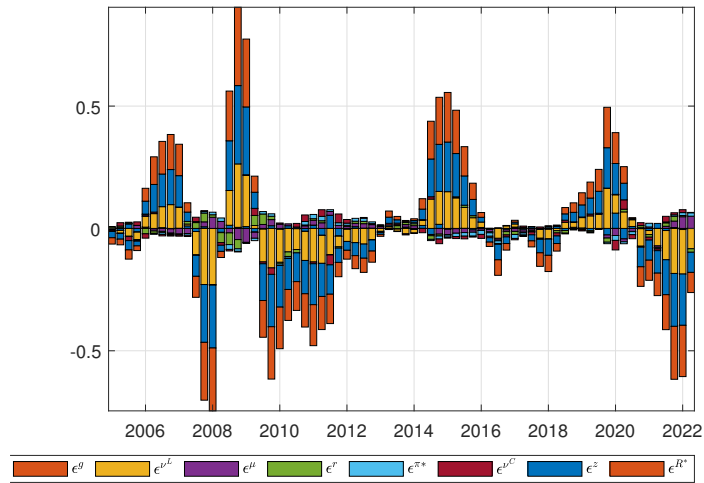
Source: Author calculations.

Figure 10 shows that the shocks to the foreign inflation and foreign interest rates are the key players for the movements of the real exchange rate throughout the sample. Foreign interest rates are especially important at the end of the sample period.
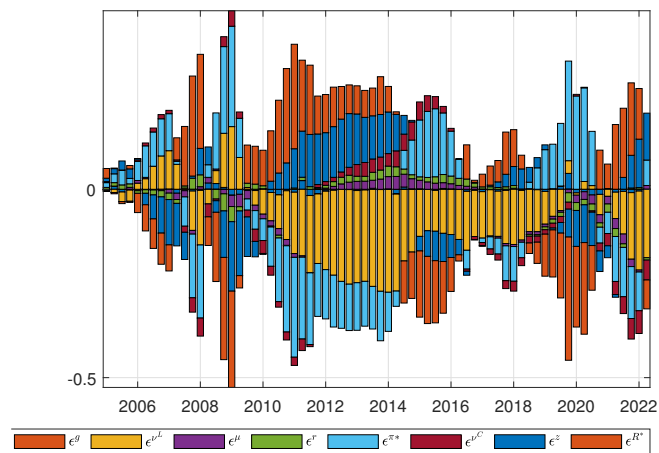
Figure 10. Historical Shock Decomposition: Real Exchange Rate

(Unit contribution to quarterly growth rate)

Source: Author calculations.

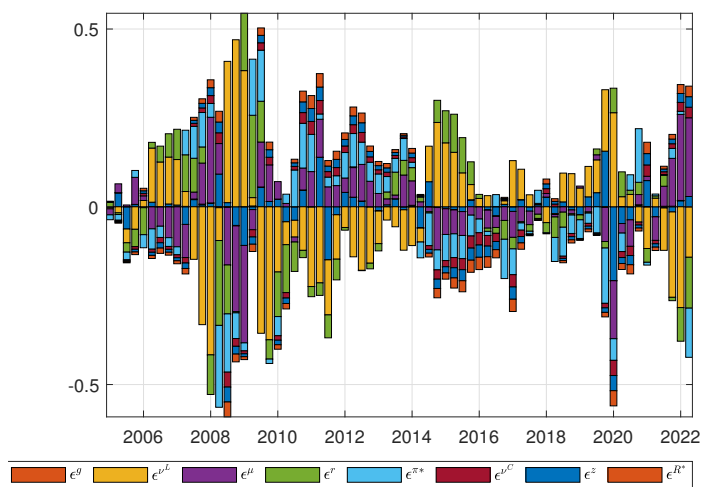Figure 11. Historical Shock Decomposition: Bank Lending

(Unit contribution to quarterly growth rate)

Source: Author calculations.

4 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.

4.1 Historical simulations

Figure 12 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 12. Macro Adjustment: Actual and Fitted

(Quarterly growth rate; percent for policy rate)
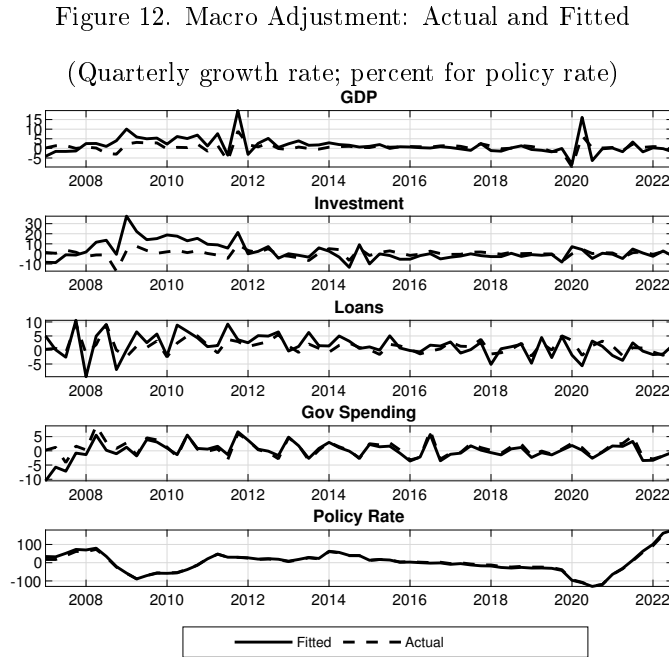
Source: Author calculations.

Figure 13 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 14 pictures the fitted policy rate and the model-simulated lending rates of the banking system to working capital and to entrepreneurs for the production of investment

Figure 13. Primary Balance/GDP Ratio and Share Price Index

(Percent; index for the Share Price)

_____Fitted _ _ _ _ _ _ _ Actual
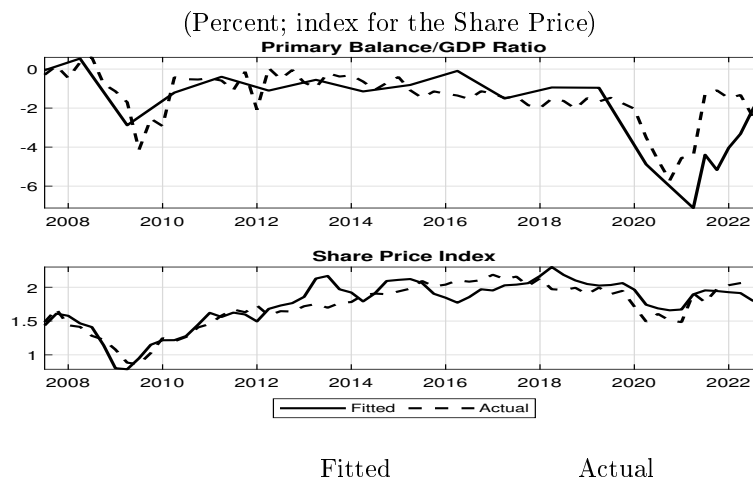
Source: Author calculations.

goods. To better capture the interrelated dynamics, we normalized the detrended series for all three rates. 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 Global Financial Crisis (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 14. Policy Rate and Lending Rates

(Normalized by respective initial values)
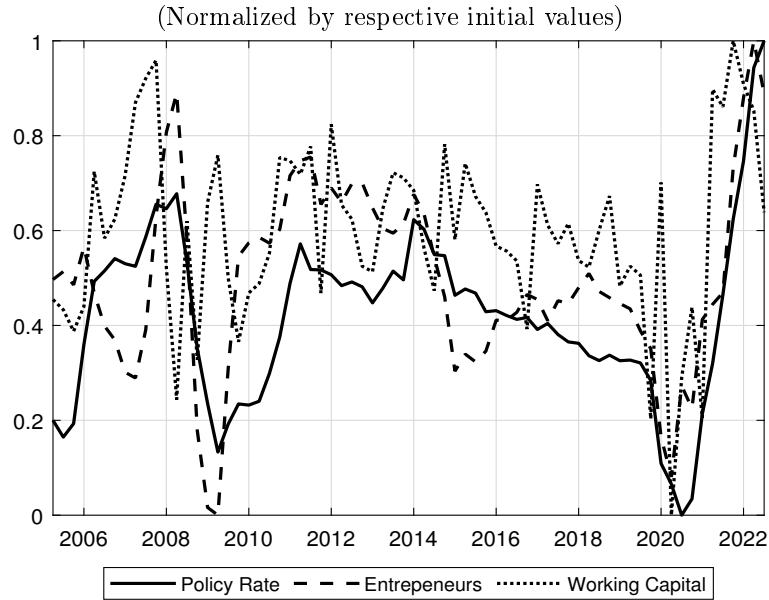
Source: Author calculations.

Figure 15 pictures the movement of the Non-Performing Loan Ratio over the sample period. We see that the model-predicted values closely track the actual values. We see a steady decline up to 2012 as the Thai financial sector recovered from the Asian Financial Crisis in the late 1990's. The twin crisis periods of 2008 and 2023, by comparison, had marginal effects on this ratio.

Figure 15. NPL Ratio
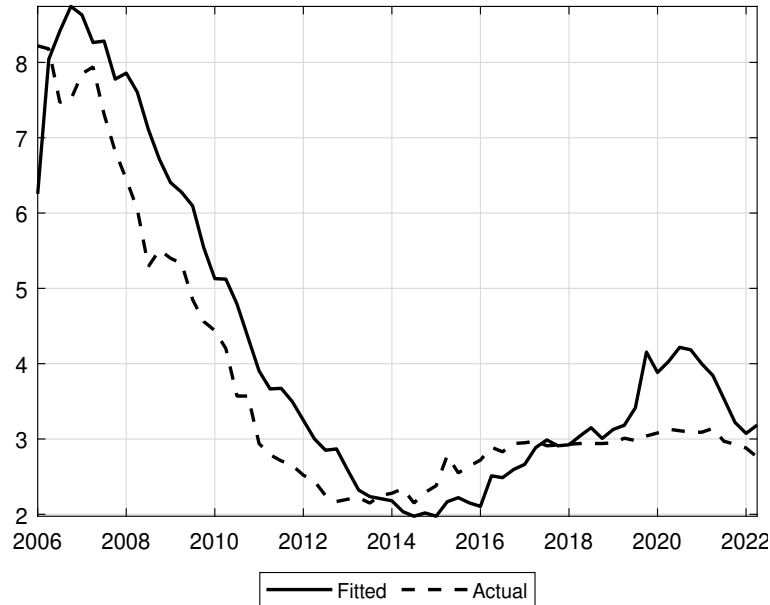
Source: Bank of Thailand and author calculations.

4.2 Dark corners: benchmark simulations

Following the methodology of Mendoza (2010) and implemented for the Euro Area by Fagan and McNelis (2020), we 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 four years before and four years after the worst crisis events in the long simulation, when GDP is at its absolute minimum value. We examine the median values of key variables for all of the instances when GDP is two standard deviations below its stochastic mean.

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 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 is the "crisis event" or GDP bottoming out at time t=0. We set each variable at an index of unity for four years before the crisis event. Figure 16 shows the adjustment of GDP, Consumption, Investment, and Exports. We see that the median drop in GDP at the crisis

event t=0 is almost 40%. As expected, the drop in consumption, non-Ricardian consumption and loans to working capital, as well as exports, is much slower and prolonged.

These results serve as a benchmark for evaluating how much, if at all, counterfactual policies make a different in dark corner periods.

Figure 16. Dark Corner Adjustment: Macro Indicators

(t-16 quarters = 1)
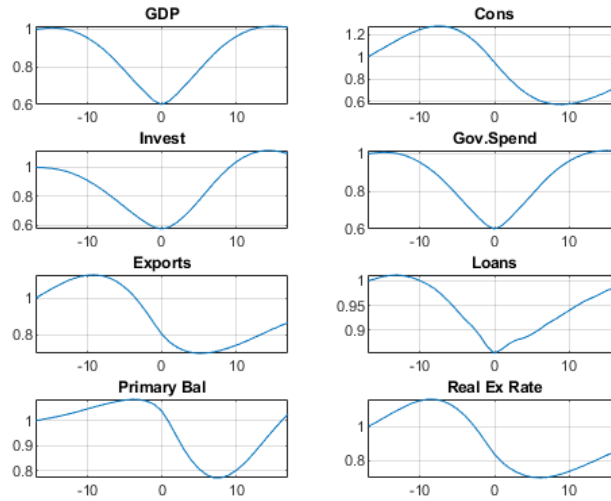
Source: Author calculations.

Figure 17 shows that the fall of the real exchange is sharper than that of the share market at the onset of the dark-corner crisis event. The dynamics of the variables are normalized in the same way as in Figure 16.

Figure 17. Dark Corner Adjustment: Financial Indices

(t-16 quarters = 1)
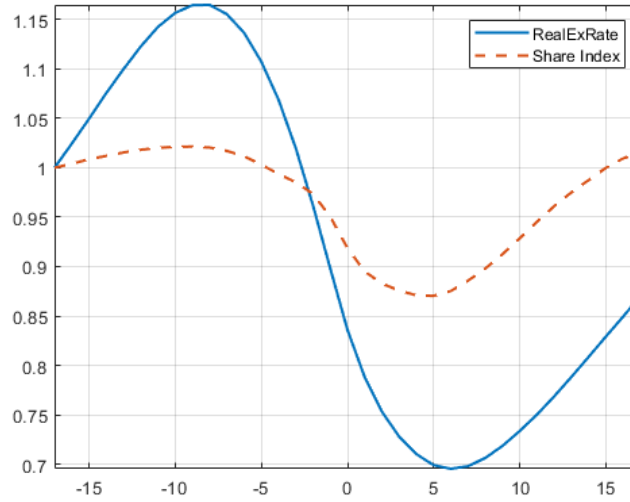
Source: Author calculations.

4.3 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 corner episodes.

4.3.1 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. Clearly, policy makers cannot make us of full-information Ramsey rules. However, we can approximate their behavior by evaluating how close observed outcomes come to outcomes driven by simple rules.

While there are many simple rules, we specify the design of two rules, one for transfers to the non-Ricardian households and the other for loan-forbearance measures 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 have the following form:

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

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\bar{\pi}}\right)^{\alpha_\pi} \left(\frac{Y_t}{Y_{t-1}} \frac{1}{a_{t-1}}\right)^{\alpha_y}\right]^{1-\rho_R} \tag{2}$$

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.[2]

Using the above objectives, we obtained the following estimates for the simple-rule coefficients for the transfer rules and monetary policy, as shown in Table 5.

Table 5. Coefficients for Optimal Simple Transfer Rules

Coefficient	Co-Term	TR	R
γ_0	TR_{t-1}	.624	–
γ_1	C^{NR}	-6.898	–
γ_2	L^{wc}	-10.31	–
γ_3	π	.893	–
ρ_R	R_{t-1}	–	.675
ρ_π	$\frac{\pi_t}{\bar{\pi}}$	–	1.022
ρ_y	$\frac{Y_t}{Y_{t-1}}$	–	4.013

Source: Author estimates.

The relative size of the coefficients depend, of course, on the units of measurement of the co-terms. However one result is clear. The optimal transfer-rules for the Non-Ricardian households and for working capital are counter-cyclical with respect to all three arguments. The Taylor rule coefficients change in the presence of the expansionary transfer rules, with 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.

4.3.2 Historical simulations vs. counterfactual simple rules

Figure 18 pictures the evolution of the non-Ricardian consumption under the base simulation and with the optimal simple rule for transfers and the interest rate. As expected we see that the optimal transfer rules do not prevent falls in non-Ricardian consumption at the time of the GFC and COVID-19 episodes, but they induce a quicker recovery.

---

[2] A further discussion of the simple rules is given in McNelis (2023), equations 45 and 46, on page 31/

Figure 18. Non-Ricardian Consumption under Base Simulation and Simple Transfer-Interest Rule

(Logarithm of consumption)
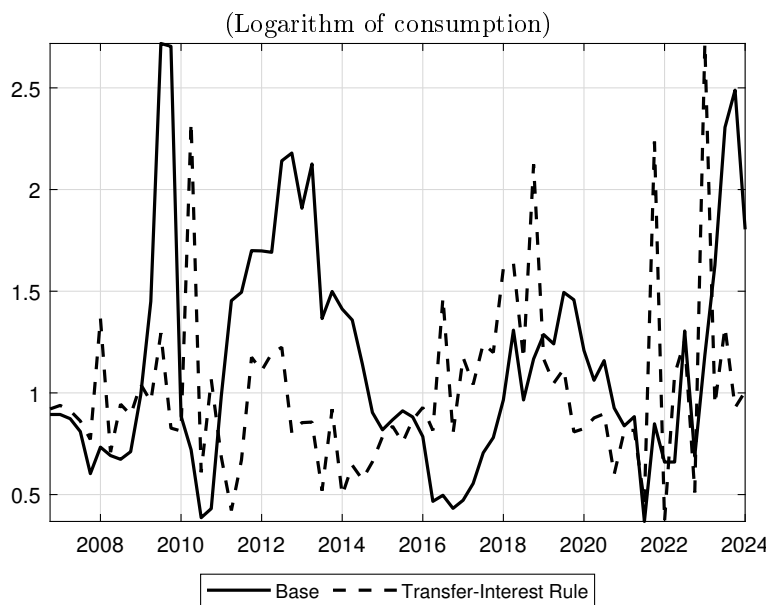
Source: Author calculations.

Figure 19 pictures working-capital lending under the base and under the simple-rule simulations. The difference between the optimal and actual base rules is not as strong as it is for non-Ricardian consumption. We do see a slightly faster recovery after the GFC and the COVID-19 episodes.

Figure 19. Working Capital Lending under Base Simulation and Transfer-Interest Rule

(Logarithm of bank lending)
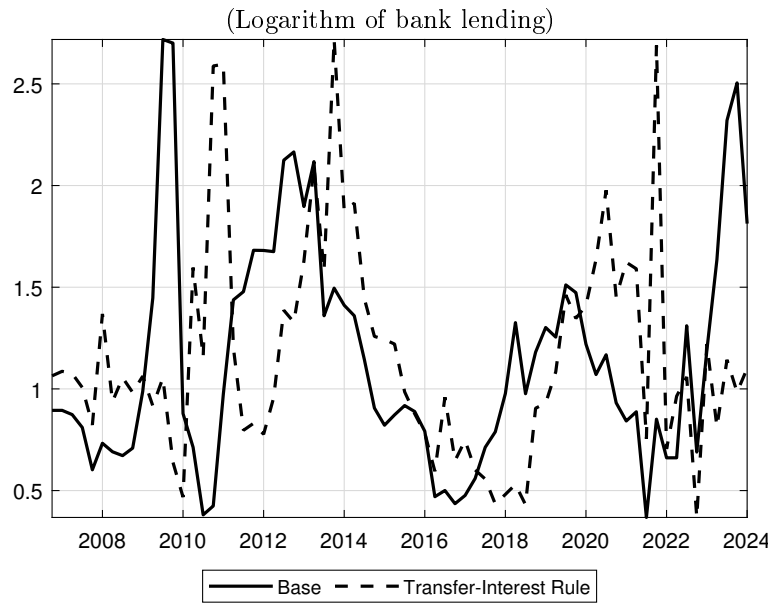
Source: Author calculations.

Figure 20 pictures the Primary Balance/GDP Ratio under the base and optimal simple rule scenarios. We see that the implementation of the simple rule does not markedly deviate from the primary balance under the base path.

Figure 20. Primary Balance under Base Simulation and Simple Rules

(Percentage of GDP)
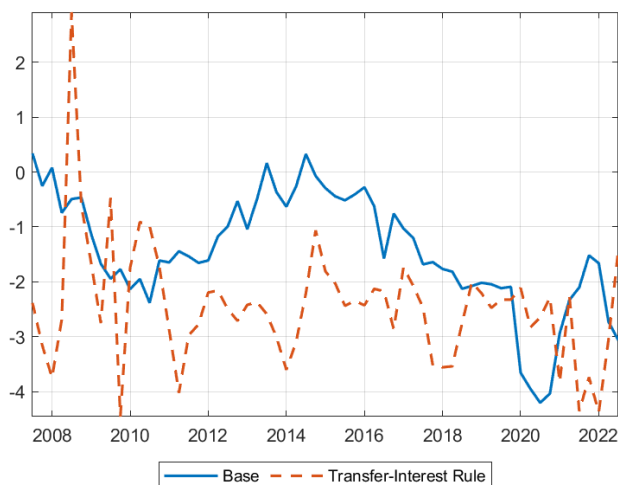
Source: Author calculations.

4.3.3 Historical simulations: counterfactual rules vs. no support

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 above, 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 6.

Table 6. Policy Regime Comparison

| Regime	Parameters for Transfers (TR) and Taylor Rule (R)
Base Regime	Table 1
Optimal Transfer/Taylor Rules	TR: Table 5: Col. 3 , R: Table 5, Col. 4
Optimal Transfer/Inflation Target	TR: Table 5, Col. 3
	R: $\rho^R = .616, \alpha^\pi = 1.03, \alpha^y = 0$
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 21, for GDP, Non-Ricardian Consumption and Working Capital Lending.

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 21. Macro Adjustment under Base and Alternative Regimes

(Percentage deviation from the steady-state)
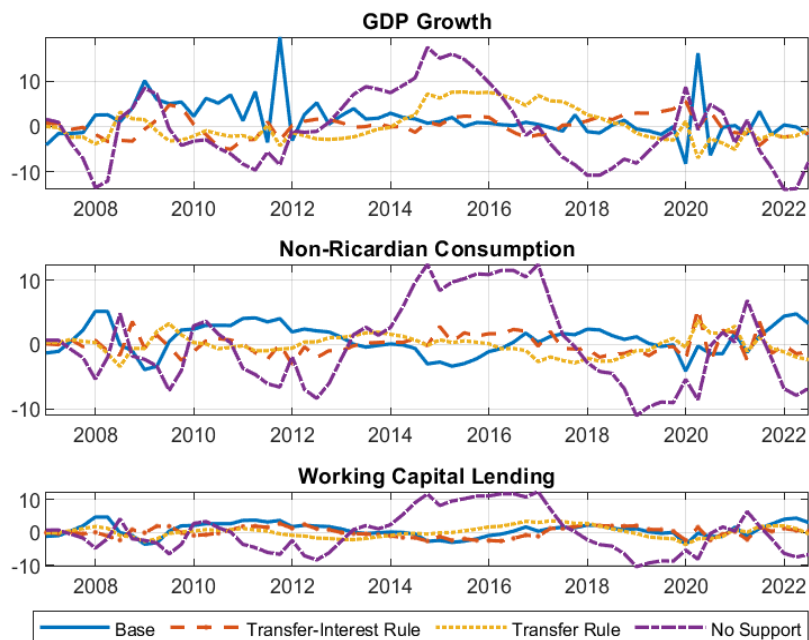
Source: Author calculations.

Of course, optimal rules are a heuristic device: they tell us what can be done by a policy make 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 Jürg Niehans in the preface, monetary policy can never be this type of computational science.

Figure 21 raises the question: are the base paths closer to any of the optimal paths or to the no-support paths? For GDP growth we use Indices of Dissimilarity based on pairwise Euclidean distance measures. We simply calculate the differences between two the paths, we take the mean and divide it by the square root of the Heteroskecastic and Autocorrelation Consistent (HAC) variance estimator, due to White (1992). Under the assumption of a zero mean, this statistic is normally distributed. For comparing forecast accuracy of two models

or methods, this statistic was developed by Diebold and Mariano (1995) but may be used to assess the significance of distance measures between any two random series, and, as noted by Diebold (2015), are not intended for overall model comparison.

Table 7 gives the Euclidean distance measures between the base path and the three paths for the overall sample and for the sample period covering the past five years. For the overall sample, the Base path is significantly different, or distant from both the optimal policy paths as well as the No Support paths. The optimal policy paths are also significantly different from the No Support path. This result suggests that for the overall sample the actual policy path was not related in any way to these specific policy rules nor to a no-support rule.

Using the sample for the past five years, we see another story. The base path is not significantly different from the optimal policy paths for our specific rules, but is different from the No Support policy path.

Table 7. Euclidean Distance Measures of Base & Policy Paths

| Policy Paths:		Policy Paths: Full Sample			
		Base Path	Transfer+ Interest	Pure Transfer	No Support
Base	Path	0.000	— —	— —	— —
Transfer+	Interest	**7.231**	0.000	— —	— —
Pure	Transfer	**6.305**	2.628	0.000	— —
No	Support	**4.286**	**7.281**	**6.131**	0.000
Policy Paths:		Policy Paths: 2018-2022			
		Base Path	Transfer+ Interest	Pure Transfer	No Support
Base	Path	0.000	— —	— —	— —
Transfer+	Interest	1.811	0.000	— —	— —
Pure	Transfer	1.235	0.768	0.000	— —
No	Support	**2.904**	**4.777**	**3.837**	0.000

Source: Author estimates.

4.3.4 Dark corners under counter-factual policies

Figure 22 gives the dark-corner dynamics under the base and counter-factual transfer-interest-rate rule We see that the optimal rule does reduce the fall in GDP, Consumption, Investment, Government Spending, and Exports, at the time of the crisis events. We also see that there is a steep fall in lending at the time of the crisis but the recovery is much quicker under the transfer-interest rule. Finally the both the primary balance and the real exchange rate are stabilized.

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

(t-16 quarters = 1)
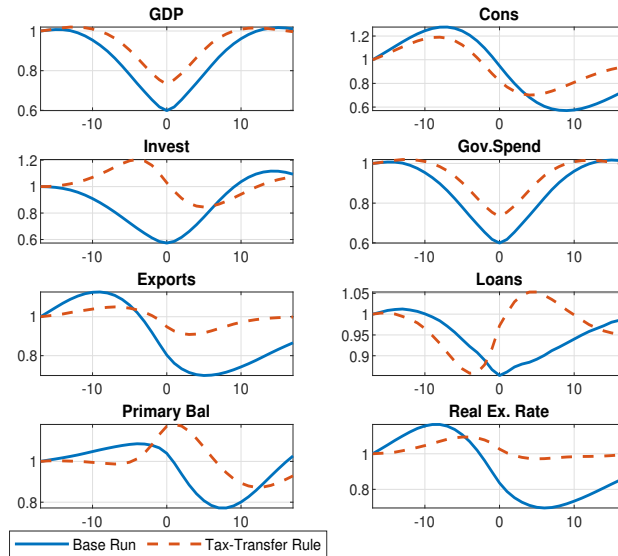
Source: Author calculations

5   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 Global Financial Crisis (GFC) and the COVID-19 pandemic. The analysis shows that throughout the sample, macroeconomic adjustment was driven by a mix of domestic and foreign shocks.

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, as opposed to a No Support regime, during the past five years. The shocks which have driven key macroeconomic indicators come from a mix of both foreign and domestic sources. Overall policy variables have had less influence than external forces, but our results show that actual policy has become more closely aligned with optimal policy paths during the past five years.

References

Adjemian, S., H. Bastani, F. Karame, M. Juillard, J. Maih, F. Mihoubi, G. Perendia, J. Pfeifer, M. Ratto, and S. Villemot (2014). Dynare: Reference manual version 4. Dynare Working Papers 1.

Blanchard, O. (2014). Where danger lurks. *Finance and Development*.

Christiano, L. J., M. Trabandt, and K. Walentin (2011). Introducing financial frictions and

unemployment into a small open economy model. *Journal of Economic Dynamics and Control 35*, 1999–2041.

Diebold, F. X. (2015, January). Comparing Predictive Accuracy, Twenty Years Later: A Personal Perspective on the Use and Abuse of Diebold-Mariano Tests. *Journal of Business & Economic Statistics 33*(1), 1–1.

Diebold, F. X. and R. S. Mariano (1995, July). Comparing Predictive Accuracy. *Journal of Business & Economic Statistics 13*(3), 253–263.

Fagan, G. and P. D. McNelis (2020). Sudden stops in the Euro Area: Does monetary union matter? *Journal of International Money and Finance 108*(C).

Garcia-Cicco, J., M. Kirchner, and S. Justel (2015, April). Domestic Financial Frictions and the Transmission of Foreign Shocks in Chile. In C. Raddatz, D. Saravia, and J. Ventura (Eds.), *Global Liquidity, Spillovers to Emerging Markets and Policy Responses*, Volume 20 of *Central Banking, Analysis, and Economic Policies Book Series*, Chapter 6, pp. 159–222. Central Bank of Chile.

Kaminsky, G., C. Reinhart, and C. Vegh (2005). When it rains, it pours: Procyclical capital flows and macroeconomic policies. In *NBER Macroeconomics Annual 2004, Volume 19*, pp. 11–82. National Bureau of Economic Research, Inc.

McNelis, P. D. (2023). A small open economy model to assess macroeconomic policy performance: The case of malaysia. Technical report, Asean+3 Macroecnomic Research Office.

Mendoza, E. G. (2010, December). Sudden stops, financial crises, and leverage. *American Economic Review 100*(5), 1941–66.

Schmitt-Grohe, S. and M. Uribe (2007, September). Optimal simple and implementable monetary and fiscal rules. *Journal of Monetary Economics 54*(6), 1702–1725.

White, H. (1992). Robust standard errors for the linear regression model. *Journal of the American Statistical Association*.

[This page is intentionally left blank]

AMRO

ASEAN +3 MACROECONOMIC RESEARCH OFFICE

Address: 10 Shenton Way, #15-08
MAS Building, Singapore 079117
Website: www.amro-asia.org
Tel: +65 6323 9844
Email: enquiry@amro-asia.org
LinkedIn | **Twitter** | **Facebook** | **YouTube**