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

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

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February 2024

Abstract

This paper develops a prototype macroeconomic model for assessing monetary and fiscal policy in the Philippines. We make use of Bayesian estimation as well as calibration of a Dynamic Stochastic General Equilibrium model with data spanning 2005 to 2022. The model incorporates heterogeneous agents. There are Ricardian and non-Ricardian households, and entrepreneurial and working-capital firms. Optimal policies are set for both monetary policy and fiscal transfers targeting non-Ricardian consumption and loans to working-capital firms. The performance of these policies is assessed relative to the simulated base paths. We demonstrate that the base paths are closer to the optimal paths for fiscal transfers, compared to non-intervention policies for fiscal transfers and a pure inflation-targeting rule, during crisis periods.

JEL classification: F34, E44, E52, G28, G32, P52

Keywords: DSGE, monetary policy, fiscal policy, Bayesian estimation, Philippines

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Abbreviations

BCR	Banco Central de Reservas of Chile
BSP	Bangko Sentral ng Pilipinas
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 paper makes use of a small open economy model to assess policy performance of the monetary and fiscal authorities in the Republic of the Philippines 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 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). Previously, McNelis et al. (2009) developed a DGSE model for the Philippines which was estimated by Bayesian methods for data leading up to the GFC. While the model incorporated a banking sector, it did not specify the financial frictions characterizing post-GFC DGSE models, such as Gertler and Karadi (2011). The model compared a policy-rate reduction with an expansionary fiscal policy. Consistent with the framework of Dornbusch (1976), the fiscal effects were muted relative to the policy-rate reductions, due to capital mobility and flexible exchange rates.

More recently Alarcon et al. (2020) developed a semi-structural gap (not DSGE) model entitled PAMPh (Policy Analysis Model Philippines), in which they evaluated the response of key variables to once-over shocks to demand, policy-rates and remittances. This model excluded both the fiscal and the external sectors.

The model used in this analysis is much more extensive, with heterogeneity in both consumers and firms. It has a banking sector with financial frictions (in the form of an incentive-compatibility constraint for lenders to the banking system). Our focus is on policy targets not normally part of standard DSGE analysis, namely, stabilizing the consumption of non-Ricardian households and lending to non-entrepreneurial firms in need of working capital. Our focus is on these targets since they become especially important in times of crisis.

A detailed discussion of the model and a description of the Bayesian estimation methods may be found in McNelis (2023) and are not repeated here.

While extensive, we provide tractable policy analysis by comparing the paths of key variables under a no-intervention policy regime, with the of key variables under the optimal policy regime, which targets non-Ricardian consumption and working-capital lending with fiscal and monetary instruments. As in the case

of Malaysia, we found that the actual paths were closer to the paths under the optimal policies than to the paths with the no-intervention regime. The key policy result is that the transfers have stronger effects than the traditional Taylor-rule interest-rate instruments, particularly during times of crisis.

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.¹

2 Overview of Philippine Data

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

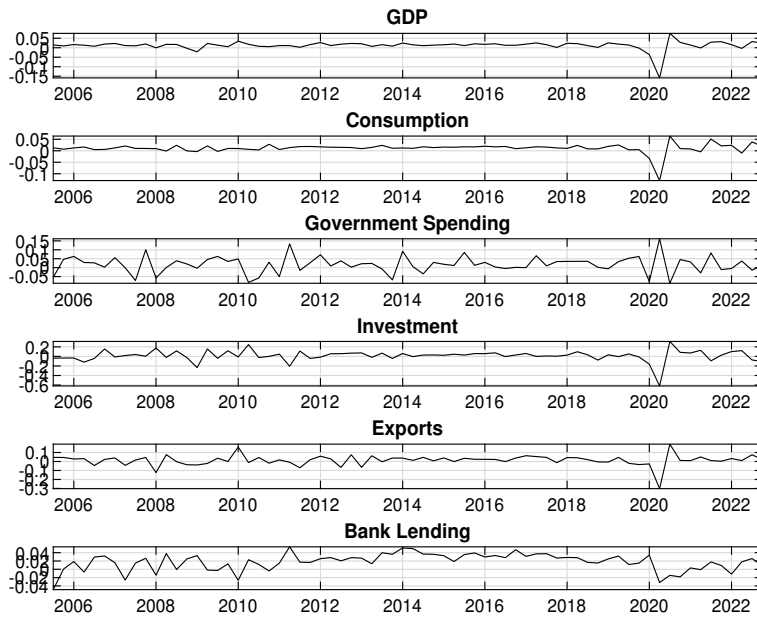
2.1 Aggregate macro indicators

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.

¹The 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 package.

Figure 1. Aggregate Macro Indicators

(Quarterly growth rate)

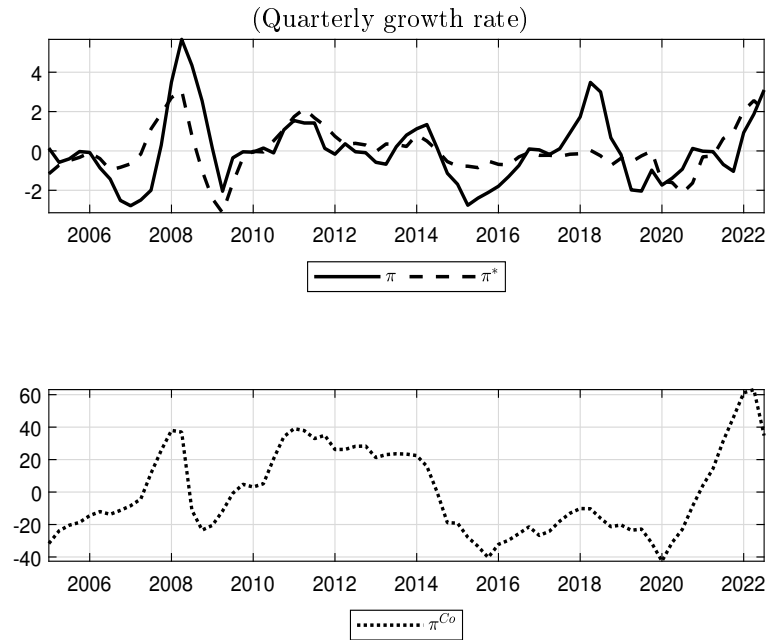


Source: Haver Analytics.

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 volatility as global commodity price inflation, π^{Co} .

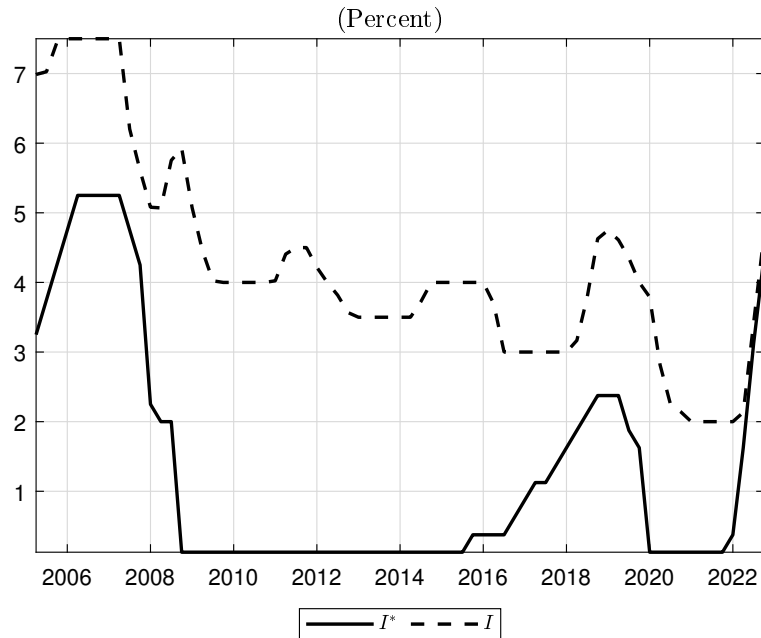
Figure 2. Domestic, World and Commodity Price Inflation Rates



Source: Haver Analytics.

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

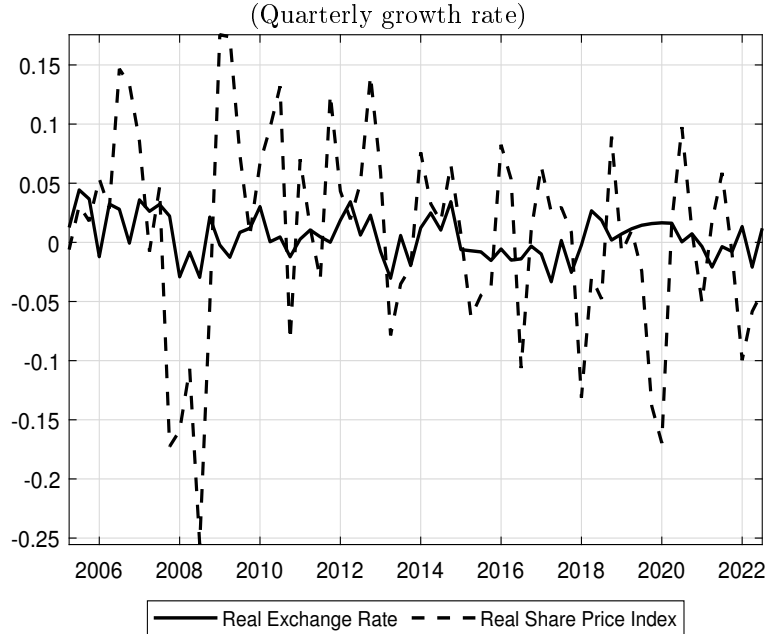
Figure 3. Interest Rates



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. The greater volatility of the share price change is likely due to the relatively thin market in the Philippines relative to the turnover of foreign exchange.

Figure 4. Real Market Indices



Source: Haver Analytics.

Summarizing recent macroeconomic developments in the Philippines, Tsang et al. (2021) note that the recovery has remained on track. They point out that the rebound was closely related to upturns in investment and exports. With the increase of world interest rates, they also warn of the risks of capital flow volatility.

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 2022 with quarterly data. GDP, investment, loans, foreign demand, exports, and government spending are in logarithms and were subjected to first-differencing. The nominal variables were detrended.

Table 1. Bayesian Estimates

<i>Coefficients</i>	<u>Priors</u>			<u>Posteriors</u>		
	Mean	Std Dev	Dist	Mean	Inf	Sup
ρ^{y^*}	0.5	0.2	Binomial	0.254	0.136	0.374
ρ^{π^*}	0.5	0.2	Binomial	0.670	0.628	0.716
ρ^{ν^L}	0.5	0.2	Binomial	0.813	0.759	0.873
ρ^{R^*}	0.5	0.2	Binomial	0.666	0.616	0.720
ρ^R	0.5	0.2	Binomial	0.494	0.434	0.555
ρ^g	0.5	0.2	Binomial	0.975	0.956	0.994
ρ^{gy}	0.5	0.2	Binomial	0.788	0.639	0.942
ρ^{gb}	0.5	0.2	Normal	0.009	0.002	0.016
ρ^z	0.5	0.2	Binomial	0.529	0.471	0.579
ρ^{ν^C}	0.5	0.2	Binomial	0.419	0.292	0.541
ρ^μ	0.5	0.2	Binomial	0.560	0.482	0.636
α^π	1.5	0.2	Normal	1.134	1.099	1.166
α^y	0.5	0.2	Binomial	0.869	0.834	0.900
<i>Std Deviations</i>						
σ^{y^*}	0.05	0.5	Inv Gamma	0.066	0.058	0.073
σ^g	0.05	0.5	Inv Gamma	0.000	0.000	0.001
σ^{ν^L}	0.05	0.5	Inv Gamma	0.029	0.024	0.034
σ^μ	0.05	0.5	Inv Gamma	0.035	0.034	0.036
σ^{ν^C}	0.05	0.5	Inv Gamma	0.055	0.054	0.056
σ^{R^*}	0.05	0.5	Inv Gamma	0.083	0.082	0.084
σ^R	0.05	0.5	Inv Gamma	0.010	0.008	0.011
σ^{π^*}	0.05	0.5	Inv Gamma	0.134	0.115	0.153
σ^z	0.05	0.5	Inv Gamma	0.023	0.019	0.026

Source: Author estimation.

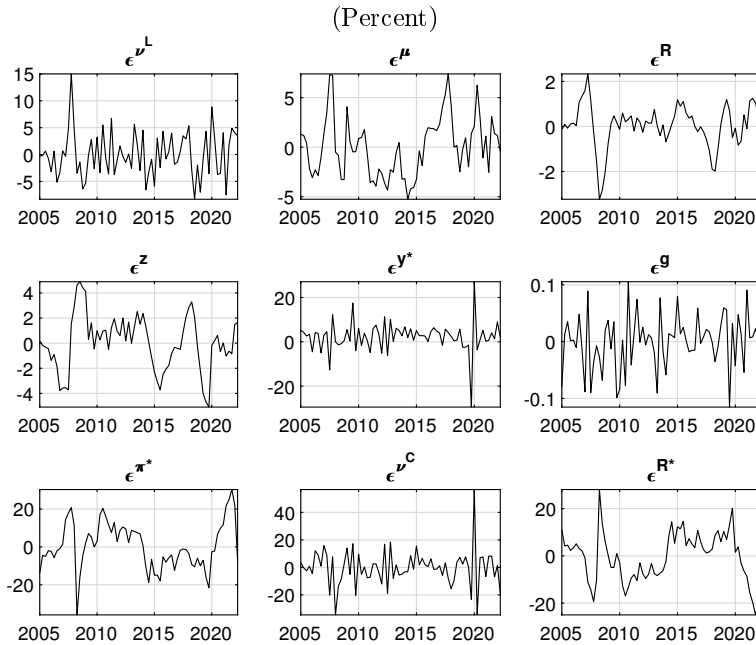
We note that the critical Taylor rule coefficients for inflation and output growth, given by α^π and α^y have values which ensure determinacy, as noted by Lubik and Schorfheide (2004). Such Taylor-rule estimated coefficients are known to vary quite a bit with the sample period, as noted by Orphanides (2001) in his analysis of US monetary policy. So it should not be surprising if these estimates are different from estimates based on different samples.

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^*} , followed by a rebound.

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



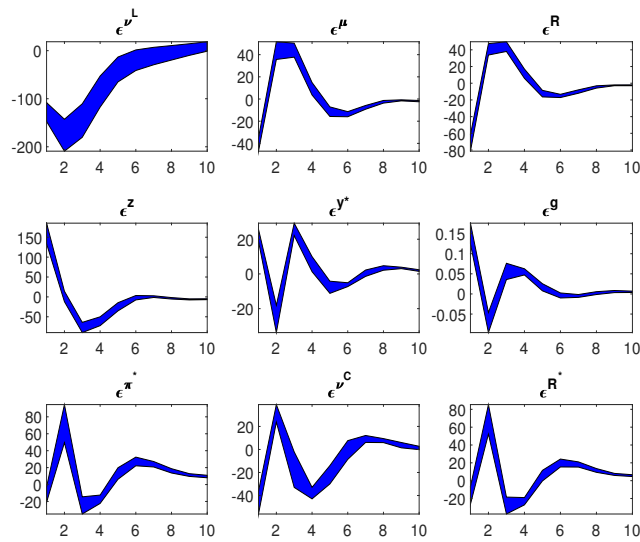
Source: Author calculations.

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, represented by ϵ^{y^*} , ϵ^g , ϵ^z , have initial positive effects on GDP growth. 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.

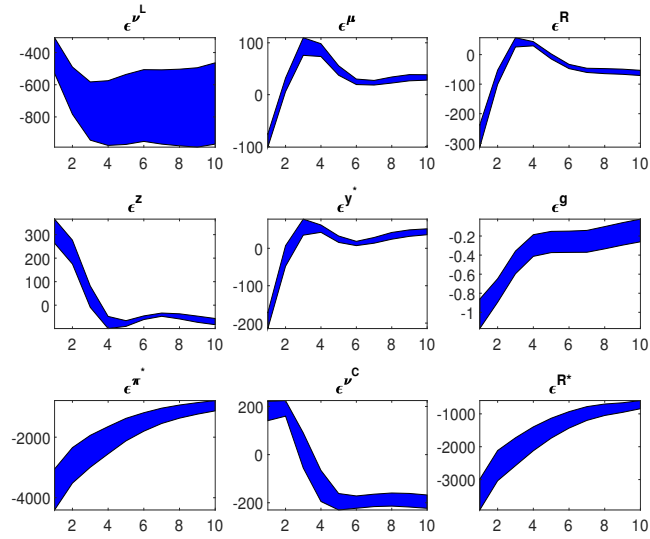
Figure 6. GDP: Impulse Response Paths
(Percentage deviation from the steady state)



Source: Author calculations.

Figure 7 shows that an increase in TFP leads to a real exchange-rate 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, which last a few quarters more.

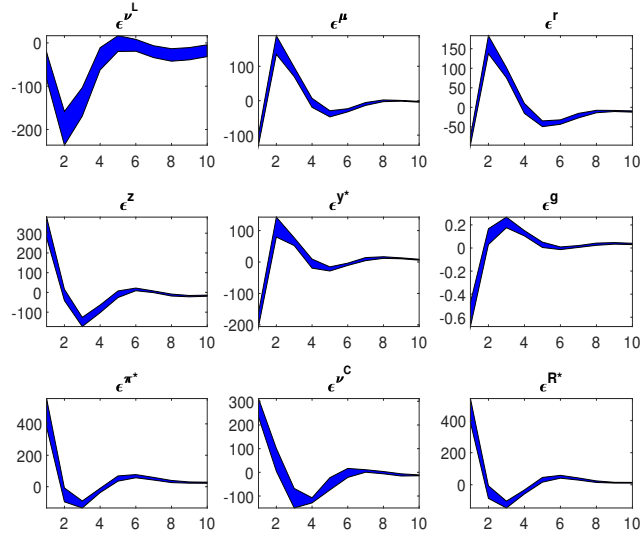
Figure 7. Real Exchange Rate: Impulse Response Paths
(Percentage deviation from the steady state)



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 the 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, TFP and the disutility of labor. While foreign factors do not show up, the cumulative influence of foreign inflation and the foreign interest rate shocks is only slightly above 10 percent.

Table 2. FEVD for GDP Growth

(Unit)

Quarterly horizon:

	1	4	8	12	16
ϵ^{ν^L}	0.314	0.513	0.505	0.505	0.513
ϵ^{μ}	0.035	0.041	0.041	0.041	0.040
ϵ^R	0.102	0.062	0.062	0.062	0.061
ϵ^z	0.486	0.243	0.235	0.233	0.229
ϵ^{y^*}	0.010	0.013	0.014	0.014	0.013
ϵ^g	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.003	0.044	0.054	0.055	0.055
ϵ^{ν^C}	0.043	0.036	0.038	0.038	0.038
ϵ^{R^*}	0.006	0.047	0.051	0.052	0.051

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
ϵ^{ν^L}	0.007	0.030	0.054	0.074	0.088
ϵ^{μ}	0.000	0.000	0.000	0.000	0.000
ϵ^R	0.003	0.001	0.001	0.001	0.002
ϵ^z	0.004	0.003	0.002	0.002	0.003
ϵ^{y^*}	0.001	0.001	0.001	0.001	0.001
ϵ^g	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.518	0.525	0.522	0.514	0.507
ϵ^{ν^C}	0.001	0.002	0.003	0.005	0.006
ϵ^{R^*}	0.465	0.437	0.417	0.403	0.393

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, ϵ^{ν^C} , and domestic interest rates, ϵ^R , explain about 30 percent of total variation of bank lending in the short run, while foreign interest rates and foreign inflation explain about 50 percent.

Table 4. FEVD for Bank Lending

	(Unit)				
	Quarterly horizon:				
	1	4	8	12	16
$\epsilon^{\nu L}$	0.004	0.070	0.070	0.071	0.071
ϵ^{μ}	0.020	0.053	0.054	0.054	0.054
ϵ^R	0.011	0.047	0.050	0.050	0.050
ϵ^z	0.166	0.154	0.150	0.150	0.150
ϵ^{θ^*}	0.049	0.054	0.053	0.053	0.053
ϵ^g	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.324	0.255	0.259	0.259	0.260
$\epsilon^{\nu C}$	0.104	0.110	0.110	0.110	0.110
ϵ^{R^*}	0.322	0.257	0.255	0.254	0.253

Source: Author calculations.

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

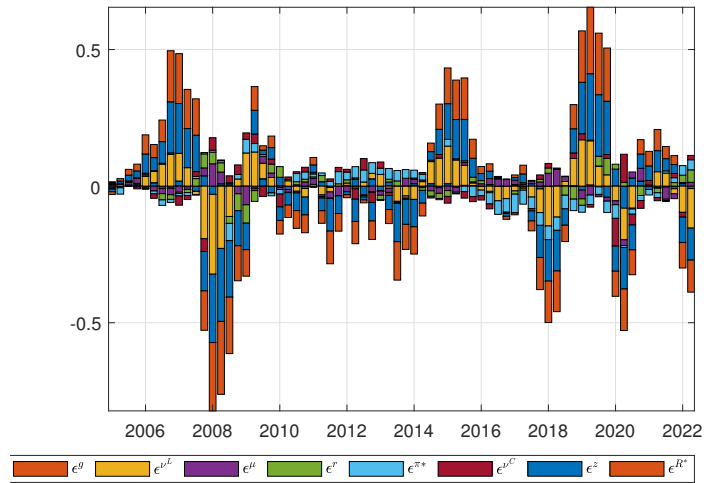
3.5 Historical Shock Decomposition

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, shocks to total factor productivity and the foreign interest rates 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 stronger play at the time of the GFC and at the time of the COVID-19 shocks.

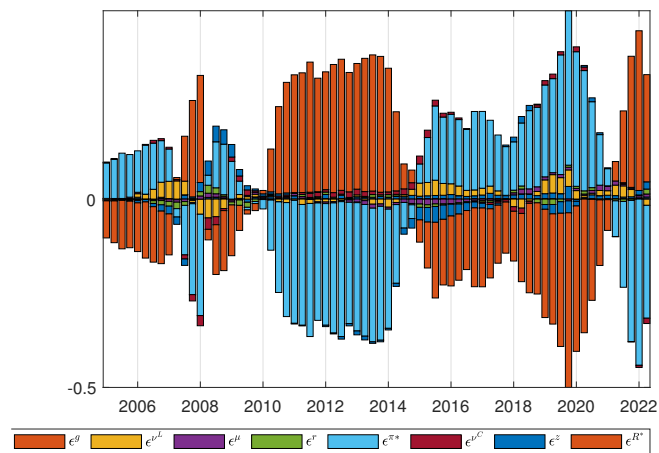
Figure 9. Historical Shock Decomposition: GDP Growth
(Unit contribution to quarterly growth rate)



Source: Author calculations.

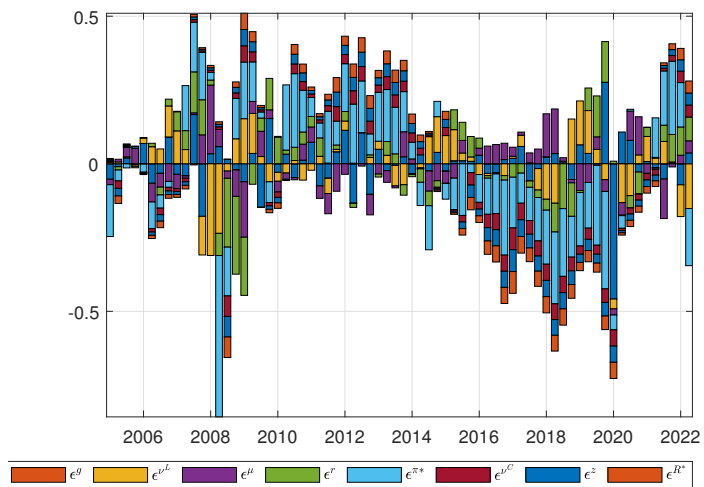
Figure 10 shows that the shocks to the foreign inflation and foreign interest rates are the key players for the movements of the real exchange rate throughout the sample.

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)

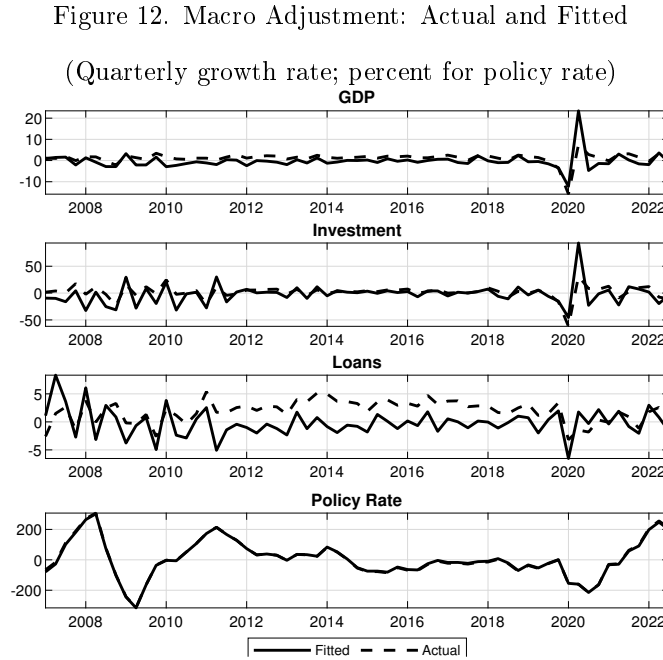


Source: Author calculations.

For bank lending, foreign inflation plays a strong role leading up to COVID-19 and afterwards. The other major factor comes from shocks to labor supply.

3.6 Historical simulations

Figure 12 pictures the evolution of the actual and model-simulated values for GDP, Investment, Lending, 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.

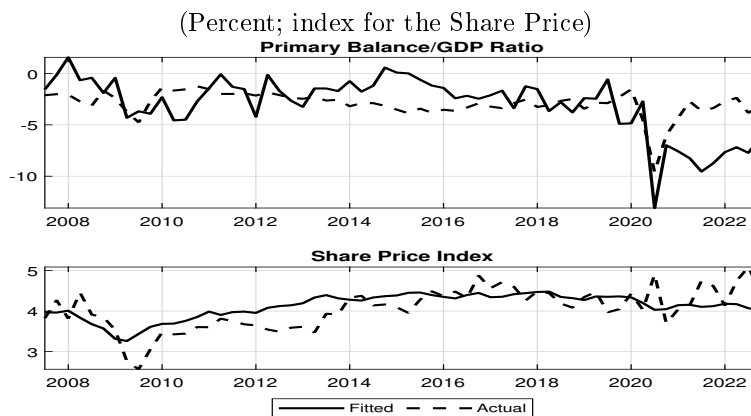


Source: Author calculations.

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 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,

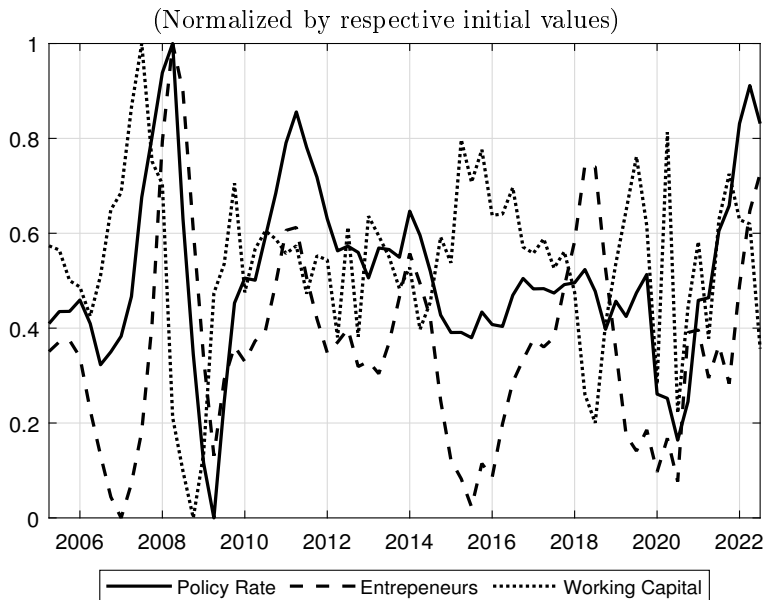
Figure 13. Primary Balance/GDP Ratio and Share Price Index



Source: Author calculations.

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



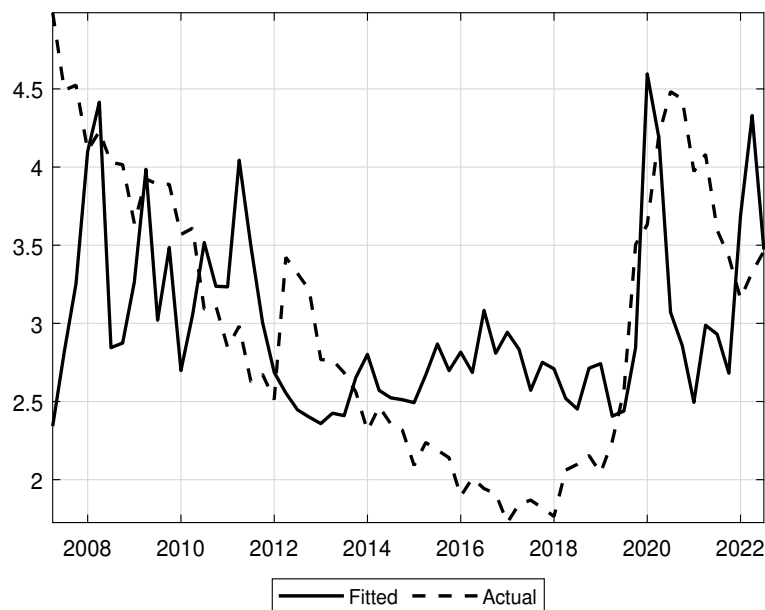
Source: Author calculations.

We fitted the non-performing loan (NPL) ratio with simulated values from

the model over the time period of 2008 to 2022. The actual and fitted paths appear in Figure 15. We see in Figure 15 that the fitted and actual ratios jumped at the time of GFC and COVID-19.

Figure 15. Non-Performing Loan Ratio

(Percent)



Source: Author calculations.

3.7 Dark corners: benchmark simulations

Following the methodology of Mendoza (2010) 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.²

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

²Fagan and McNelis (2020) applied this analysis to sudden stops in the Euro Area.

variables for all of the instances when GDP is two standard deviations below its stochastic mean.

We take 100,000 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.

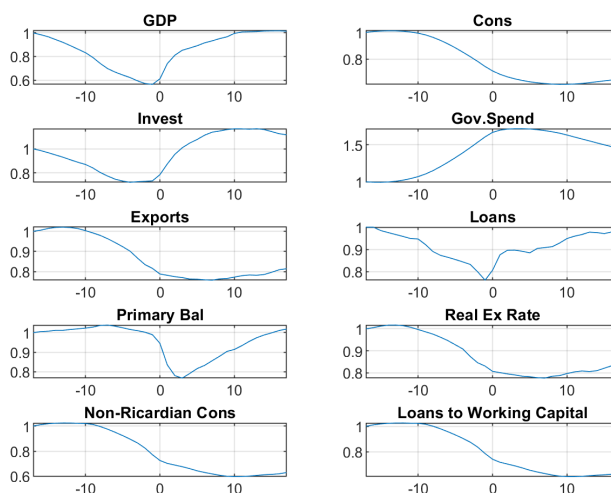
As noted by Mendoza (2010), pure welfare comparisons for alternative policy regimes often are not informative, since they span the whole sample and do not pick up key differences at shorter but severe crisis periods.

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 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 percent. As expected, the drops in non-Ricardian consumption and loans to working capital, as well as exports, are much slower and prolonged.

These results serve as a benchmark for evaluating how much, if at all, counterfactual policies make a difference in times of crisis.

Figure 16. Dark Corner Adjustment: Macro Indicators

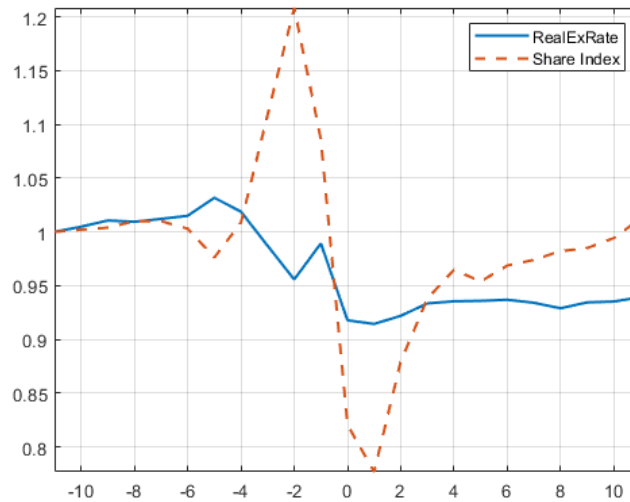
($t-16$ quarters = 1)



Source: Author calculations.

Figure 17 shows that the fall of the real exchange rate, relative to the share price index, is much less abrupt. This should not be surprising, since the share market is relatively limited relative to international currency flows.

Figure 17. Dark Corner Adjustment: Financial Indices
(t-16 quarters = 1)



Source: Author calculations.

3.8 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.

3.8.1 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 use of full-information Ramsey rules. However, we can approximate their behavior by evaluating how close the observed outcomes are 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:

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

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R} \right)^{\rho^R} \left[\left(\frac{\pi_t}{\bar{\pi}} \right)^{\alpha^\pi} \left(\frac{Y_t}{Y_{t-1}} \frac{1}{a_{t-1}} \right)^{\alpha^y} \right]^{1-\rho^R} \quad (2)$$

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. The coefficients for the rules are obtained through the solution of the Linear Quadratic Regulator problem, in which the volatility of the objective variables is minimized by the selection of these coefficients, given the dynamics of the model with its other estimated coefficients. Schmitt-Grohe and Uribe (2007) drew attention to the advantages of such rules, in contrast to Ramsey (1927) rules, in which the optimal policy rules depend on all of the state variables and specified shocks in the model.³

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}	.558	-
γ_1	C^{NR}	-6.895	-
γ_2	L^{wc}	-10.33	-
γ_3	π	.903	-
ρ^R	R_{t-1}	-	.983
α^π	$\frac{\pi_t}{\bar{\pi}}$	-	16.909
α^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 co-terms. However, one result is clear. The optimal transfer-rules

³A further discussion of the simple rules is given in McNelis (2023), equations 45 and 46, found on page 31.

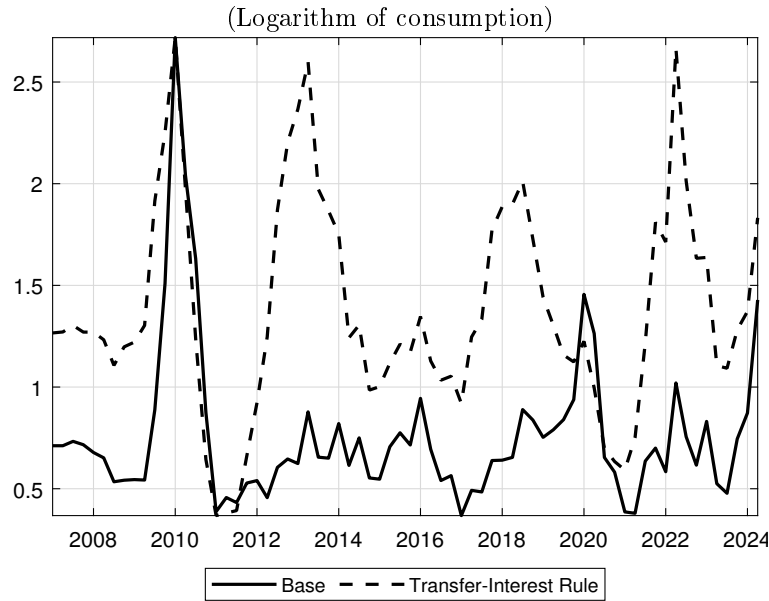
for the Non-Ricardian households and for working capital are counter-cyclical with respect to all three arguments. The Taylor rule coefficients change in the presence of the expansionary transfer rules, with positive weights on inflation as well as on the output gap.

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.

3.8.2 Historical simulations vs. counterfactual simple rules

Figure 18 pictures the evolution of the non-Ricardian consumption in the base case (with the historical policies in place) 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.

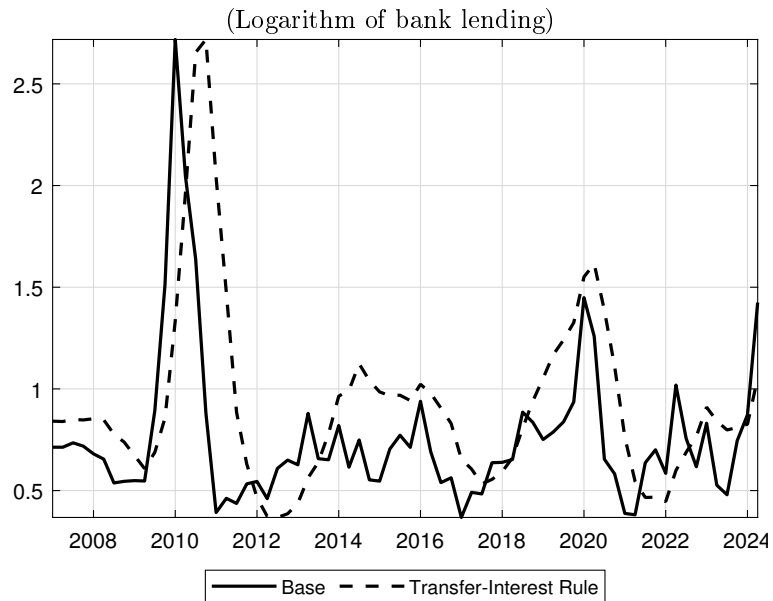
Figure 18. Non-Ricardian Consumption under Base Simulation and Simple Transfer-Interest Rule



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.

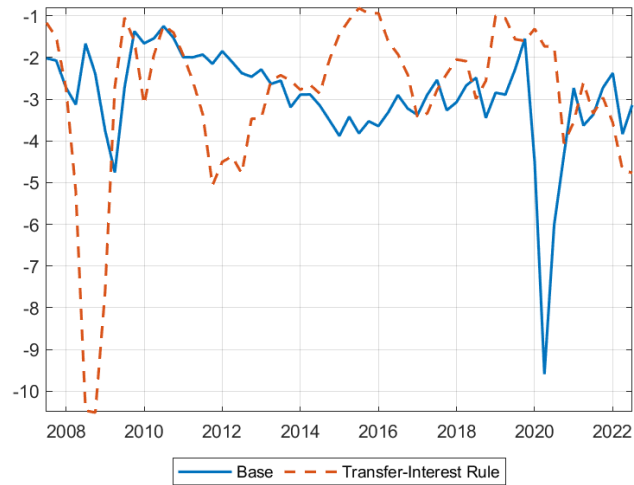
Figure 19. Working Capital Lending under Base Simulation and Transfer-Interest Rule



Source: Author calculations.

Figure 20 pictures the Primary Balance/GDP Ratio under the base and optimal simple rule scenarios. We see that the primary balance is much worse at the time of the GFC under the optimal rule, but much better at the time of the COVID-19 crisis. This result should not be surprising. The strong effects of the transfers on consumption and lending reduce negative pressures on the Primary Balance.

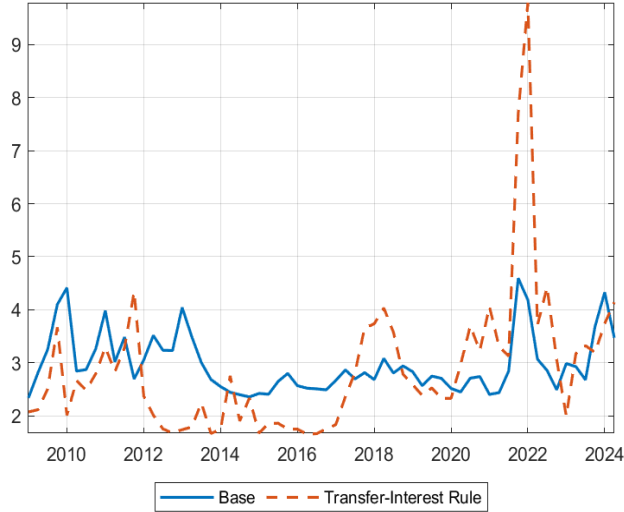
Figure 20. Primary Balance under Base Simulation and Simple Rules
(Percentage of GDP)



Source: Author calculations.

Figure 21 shows slightly greater fluctuations in the NPL ratio under the two rules. However we see that the rise in the NPL ratio is slightly muted following COVID-19 crisis, but not at the time of the GFC.

Figure 21. Non-Performing Loan Ratio under Base Simulation and Simple Rules
(Percentage)



Source: Author calculations.

3.8.3 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 a simple inflation-targeting rule with no transfers was not very different from the base regime. The 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. 2 , R: Table 5, Col. 3
Optimal Transfer/Inflation Target	TR: Table 5, Col. 2
	R: $\rho^R = .933, \alpha^\pi = 1.28, \alpha^y = 0$
No Support/Pure Inflation Target	TR: $\forall i \in [0, 3] : \gamma_i = 0$
	R: $\rho^R = .933, \alpha^\pi = 1.28, \alpha^y = 0$

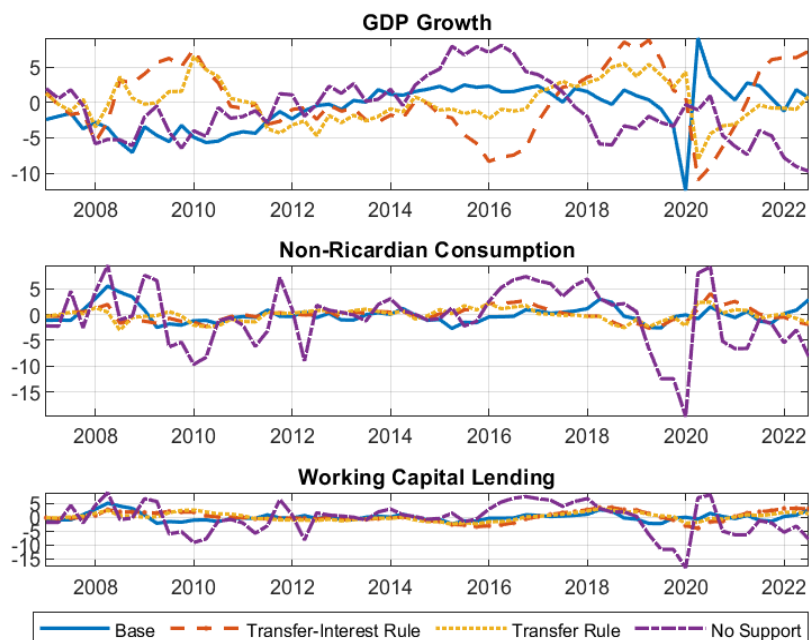
Source: Author estimates.

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 the four scenarios appear below, in Figure 22 for GDP growth, Non-Ricardian consumption, and working capital lending. 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, also appear.

We see that the base path, which track the actual paths, are closer to the optimal rules than the respective paths for the No Support regime, for Non-Ricardian consumption.

Figure 22. Macro Adjustment under Base and Alternative Regimes
(Percentage deviation from the steady-state)



Source: Author calculations.

Of course, optimal rules are heuristic devices. They tell us what can be done by a policymaker 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 in the preface, monetary policy can never be this type of computational science.

Figure 22 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 absolute differences between two paths. Under the assumption of no meaningful distance, we demean this vector and do bootstrap sampling and calculate the means. If the actual mean is outside the 95 percent confidence interval for the bootstrapped means, we can conclude that there is meaningful distance between the two paths.

Table 7 gives the Euclidean distance measures between the base path and the three paths. We see for the overall sample, there is little distance between the base path and the no support path with pure inflation targeting. However, for the crisis periods, during the GFC and COVID-19, we see that there is only a small difference between the base path and the pure transfer paths, while a significant difference emerges between the base path and the no support path, as well as the transfer/interest path.

The message of this result is that the base path, while not an official optimal path targeting non-Ricardian consumption and working-capital lending, is not significantly different from such an optimal transfer path during the periods of the crisis. During the other periods, of course, the base paths may be similar to paths generated by other types of optimal rules targeting other macroeconomic variables.

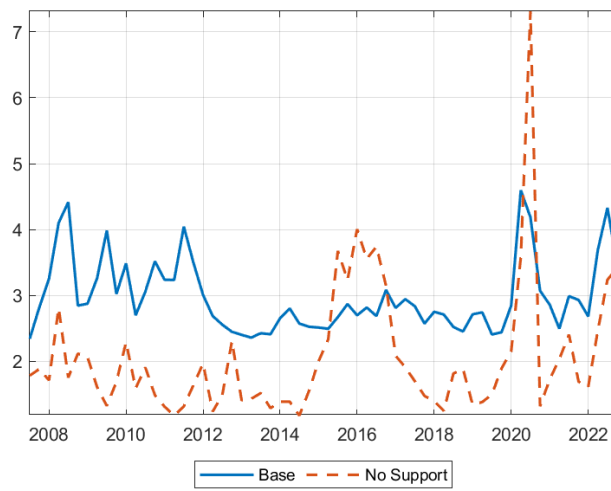
Table 7. Euclidean Distance Measures of Base & Policy Paths

		Full Sample	Crisis Periods
Policy Paths:			
Transfer+	Interest	5.024	4.969
Pure	Transfer	3.765	3.890
No	Support	3.481	4.888

Source: Author estimates.

To further illustrate the potential costs of a No-Support regime, Figure 23 pictures the Non-Performing Loan (NPL) ratios under the Base and the No-Support regimes. We see that the base path has a much lower NPL ratio at the time of the crisis but otherwise has a higher ratio for the rest of the sample periods.

Figure 23. NPL Ratio: Base and No-Support Regime
(Percent)

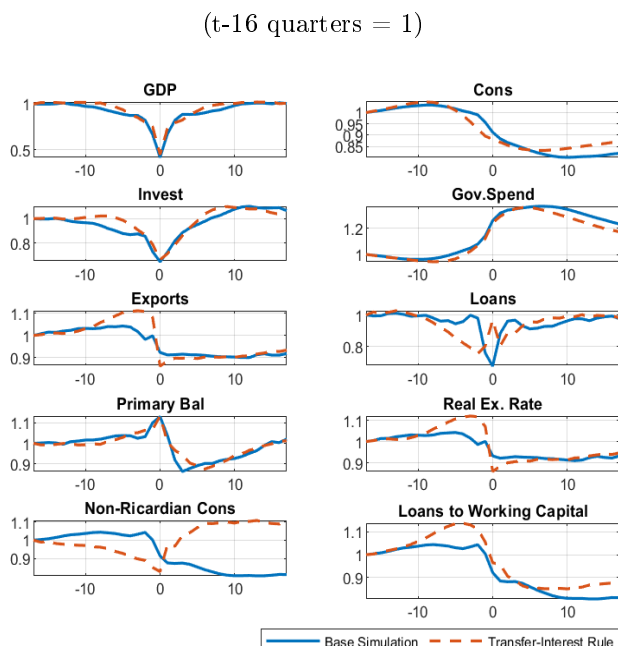


Source: Author calculations.

3.8.4 Dark corners under counter-factual policies

Figure 24 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 figure shows that at times of extreme crisis the optimal policies have their primary effects on stabilizing non-Ricardian consumption but not on other key macroeconomic indicators. This should not be surprising since our FEVD analysis shows that both government spending and interest-rate innovations only accounted for about six percent of the total variation of GDP growth (Table 2).

Figure 24. Dark Corner Dynamics under Base and Counterfactual Policy Rules



Source: Author calculations.

4 Conclusions

This paper employed a Bayesian DSGE model to assess the effectiveness of the monetary-fiscal policy mix implemented over the past two decades. The model incorporated domestic financial frictions as well as firm and household heterogeneity.

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, including the non-performing loan ratio. 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 only, in the periods of the GFC and COVID-19 episodes. Another insight emerging from the counterfactual policy analysis is that optimal fiscal transfer rules were more effective than optimal Taylor rules for achieving the policy objectives. This result is consistent with Gali et al. (2007), who found that fiscal multipliers increase when we incorporate rule-of-thumb consumers into dynamic models.

Another result which stands out in our estimation is the strong relative importance of shocks to the disutility of labor, especially for explaining the historical shock decomposition of GDP growth, during the times of the GFC and COVID-19. This result also showed up in our study of Korea, Thailand, and Malaysia. In one sense it should not be surprising. The threat of contracting COVID-19 would surely increase the disutility of going to work rather than staying home. However, a deeper analysis of the transmission of this shock would involve further specification of labor-market search and matching frictions, as seen Gomes et al. (2010).

As noted by Box (1979), "all models are wrong but some are useful", we present our results in this spirit. The model is limited in many respects. In particular, it is a linear model and thus does not take up nonlinear factors in the adjustment. The advantage of the linear specification, of course, is that it is amenable to Bayesian estimation and that the solution of the model is quick.

There are also, of course, a myriad of optimal rule configurations we could study. But we chose to focus on simple fiscal transfer and monetary-policy rules with a focus on the consumption of non-Ricardian households and working-capital of small firms (not investment in productive capital), to capture the welfare of more vulnerable groups at the time of the crisis events.

We also did not take up rules for optimal inflation targeting. To be sure, this is an important topic for central bank policy-rule formulation and for monetary-fiscal coordination. However this paper is one of a series of four papers (on Malaysia, Thailand and Korea) using a common small open-economy DSGE framework to assess the relative effectiveness of monetary and fiscal policy rules, in a common time frame, encompassing both the Global Financial Crisis and the COVID-19 pandemic. At these crisis times, it is safe to say that inflation targeting was not at the center of the stage for policy formulation.

We also did not assess the model for its predictive accuracy relative to simpler or alternative models. As Diebold (2015) noted, tests of predictive accuracy, such as the Diebold-Mariano statistic (Diebold and Mariano (1995)), were never meant to assess the overall performance of a model. Predictive accuracy of one model relative to simpler or more complex models is only one measure of the usefulness of a model. Our focus was on comparative policy analysis with counter-factual policy simulations in a structural model, not subject to the criticism of Lucas (1976). In particular, Vector Autoregressive Models may be able to forecast with greater accuracy than any DSGE model, as noted by

Sims (1980), but they would not be useful for counter-factual policy simulation, as emphasized by Lucas (1976).

We restricted the model estimation to eight observables with eight stochastic shocks or exogenous forcing variables. There are, of course, more complex DSGE models with many more observables, such as Smets and Wouters (2007). However, for each observable, for identification, we need a corresponding exogenous shock. For the sake of parsimony we decided to limit the number of shocks so that we can better interpret the relative importance of the different forcing variables. But more to the point, as noted by Chari et al. (2009), with an increasing number of shocks, models such as ours become less and less useful for counterfactual policy analysis. For this reason we decided to err on the side of caution and limit the number of shocks and observables to eight variables.

While this model has one specific focus, it can be adapted, changed, and restructured to investigate alternative policy issues such as alternative inflation-targeting or exchange-rate rules, using different sets of observables and different selections of shocks, which would depend on the issue under investigation. Just as we have developed an ensemble of models with a similar structure across a set of countries, for comparing monetary and fiscal transfer rules, an important extension would be to develop an *ensemble* of models for one country with a focus on alternative policy objectives, such as inflation targeting, or over macroeconomic stability.

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