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

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

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Abstract

This paper estimates and simulates a small open economy model for assessing Korea's monetary and fiscal policy performance between 2005 and 2022. 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. In particular, we find that both foreign and domestic factors played key roles for adjustment of GDP growth, real bank lending and the real exchange rate. We assess the adjustment of key variables under optimally-designed policy rules. We find that the optimal Taylor rule policy is very similar to the estimated Taylor rule over the sample period. We find that the base paths are closer to the optimal paths than they are to the non-intervention policies for fiscal transfers and a pure inflation-targeting rule for the Taylor rule, without an output-growth response, for the whole sample period.

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

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

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Abbreviations

BCR	Banco Central de Reservas of Chile
BOK	Bank of Korea
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 dynamic stochastic general-equilibrium model to assess policy performance of the monetary and fiscal authorities in the Republic of Korea since 2005, a span of time 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 later 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.

Extensive discussion of the model used for this analysis and a description of the Bayesian estimation methods may be found in McNelis (2023) and are not repeated here.

In previous work on Korea, Kim (2014) made use of a DSGE model estimated with Bayesian methods with data from 2000 to 2012 for the Korean economy. This study found limited effectiveness for fiscal policies. However, the author cautioned that the results may change if financial frictions were included in the model. Using post-GFC data, Kang and Suh (2017) found with Bayesian DSGE analysis that the slowdown in growth is due to lower technological growth while the lower inflation rates are due to a fall in the power of mark-up price setting. Finally, for a similar Korean time span of data, An and Kang (2011) found a low pass-through effect of world oil shocks to domestic inflation.

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 time periods or episodes.[1]

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

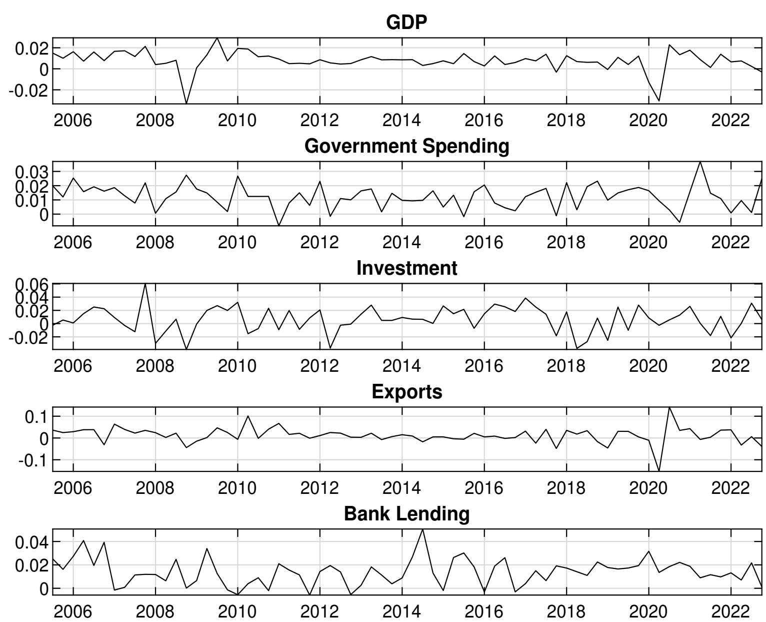
2 Overview of Korean Data

2.1 Aggregate macro indicators

Figure 1 pictures the log first-differences of real GDP, 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 exports was particularly sharp at the end of the period but its drop was followed by a strong rebound. By contrast, bank lending remained stable during the COVID-19 period.

Figure 1. Aggregate Macro Indicators

(Quarterly growth rate)



Source: Haver Analytics.

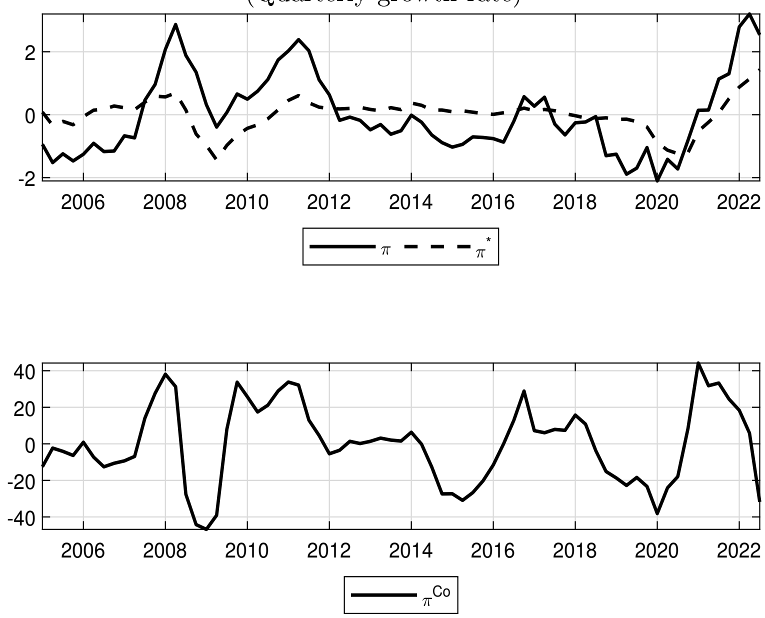
[1] Not surprisingly, we found that labor disutility comes into play during the COVID-19 period.

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^* and that commodity price inflation, π^{Co}, is a key driving force.

Figure 2. Domestic, World and Commodity Price Inflation Rates

(Quarterly growth rate)

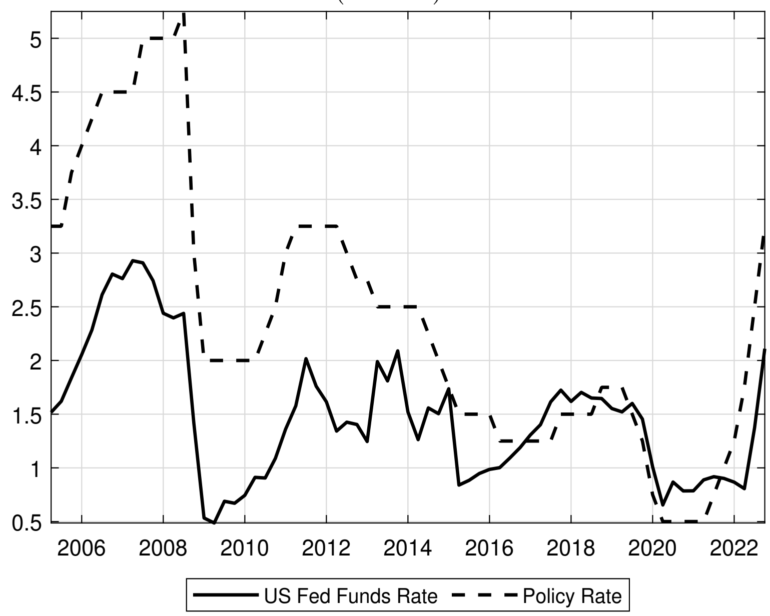


Source: Haver Analytics.

The interest rates appear in Figure 3. We see that the domestic policy rate was generally below the federal funds rate during the sample period.

Figure 3. Interest Rates

(Percent)

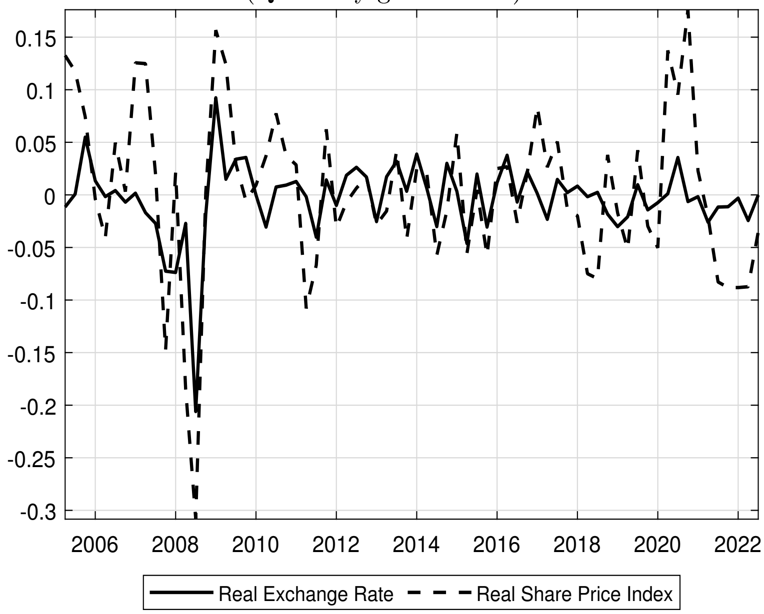


Source: Haver Analytics.

Figure 4 pictures the quarterly adjustment of the real exchange rate and real share price. We see that the real share price is more volatile 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 2022 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	0.996	0.993	0.999
$\rho^{\pi*}$	0.5	0.2	Binomial	0.044	0.006	0.080
ρ^{ν^L}	0.5	0.2	Binomial	0.834	0.780	0.889
ρ^{R^*}	0.5	0.2	Binomial	0.961	0.937	0.987
ρ^{R}	0.5	0.2	Binomial	0.724	0.673	0.775
ρ^{g}	0.5	0.2	Binomial	0.837	0.725	0.948
ρ^{gy}	0.5	0.2	Binomial	0.173	0.051	0.303
ρ^{gb}	0.5	0.2	Normal	0.003	0.001	0.005
ρ^{z}	0.5	0.2	Binomial	0.999	0.997	1.000
ρ^{ν^C}	0.5	0.2	Binomial	0.679	0.563	0.780
ρ^{μ}	0.5	0.2	Binomial	0.701	0.640	0.761
α^{π}	1.5	0.2	Normal	1.214	1.156	1.277
α^{y}	0.5	0.2	Binomial	0.830	0.764	0.900
Std Deviations						
σ^{y*}	0.05	0.5	Inv Gamma	0.059	0.051	0.068
σ^{g}	0.05	0.5	Inv Gamma	0.000	0.000	0.000
σ^{ν^L}	0.05	0.5	Inv Gamma	0.021	0.014	0.030
σ^{μ}	0.05	0.5	Inv Gamma	0.031	0.025	0.037
σ^{ν^C}	0.05	0.5	Inv Gamma	0.085	0.071	0.099
σ^{R*}	0.05	0.5	Inv Gamma	0.006	0.004	0.008
σ^{R}	0.05	0.5	Inv Gamma	0.004	0.003	0.004
$\sigma^{\pi*}$	0.05	0.5	Inv Gamma	0.206	0.179	0.234
σ^{z}	0.05	0.5	Inv Gamma	0.015	0.012	0.017

Source: Author estimation.

The Taylor rule is a widely used tool for assessing monetary policy performance across time for one country, as in Orphanides (2001). or for comparing countries for a given time period, as in Eschenhof (2009). To be sure, other variables may affect the adjustment of a policy rate at given times, as Taylor (1993) himself pointed out. This measure is specified for assessing the longer-term *policy stance* of the monetary authority, rather than capturing discretionary actions at particular times.

Our Taylor rule is a Taylor *growth* rule rather than a Taylor *gap* rule. In the latter rule, the output gap is defined as the difference between actual and potential output, usually in logarithmic units. Of course, this rule requires a specific functional form for the evolution of potential output. We use the Taylor growth rule rather than a Taylor gap rule, since the growth rate is one of our observable variables. Carlstrom and Fuerst (2012) note that the Taylor growth rules are almost as accurate as Taylor gap rules for explaining the evolution of the US policy rate.

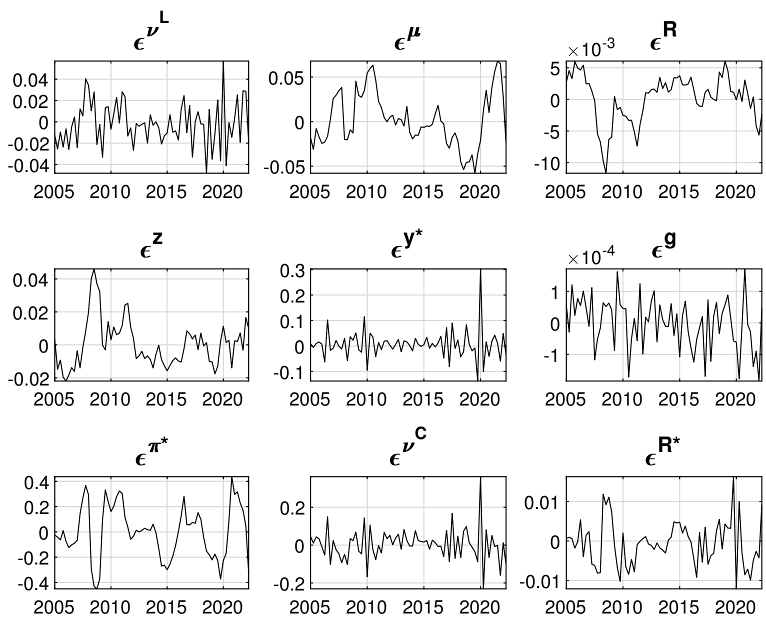
We note that the Taylor rule coefficient for inflation, α^{π} is greater than one while the Taylor rule for output growth, α^{y} is also positive. These estimates guarantee determinacy of inflation (and the price level).

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*}. We also see a jump in the banking uncertainty, given by ϵ^{μ}, both at the time of the GFC and at the time of COVID-19. The TFP index, given by ϵ^{z}, fell much more sharply at the time of the GFC than it did with the onset of the COVID-19 crisis. By themselves, the shocks do not convey much information in themselves. 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

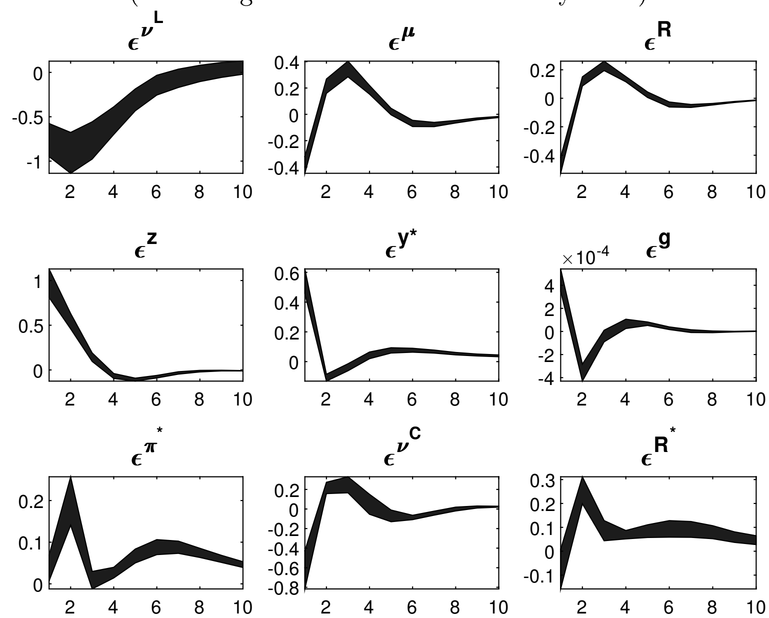
Figures 6 through 8 show the effects of a once-over *one-standard deviation* change in each of the forcing variables or exogenous shocks on GDP, the real exchange rate and on real bank lending. The paths also give the upper and lower values for each response for a 95 percent confidence interval.
One of the benefits of this analysis is to analyze the *qualitative* response of the endogenous variables to each shock. Do the responses make sense, at the time of impact of the shock? Secondly this analysis also shows us how long it takes for the propagation effects to dissipate and for the endogenous variable to return to the initial steady state.

Figure 6 shows that positive shocks to foreign GDP growth, government spending, and TFP , represented by $\epsilon^{y^*}, \epsilon^{g}, \epsilon^{z}$, all have initial positive effects. Increases in the domestic interest rates have an initial negative effect followed by a positive effect on GDP growth. Shocks to the disutility of labor and to the marginal utility of consumption, ϵ^{ν^L}, ϵ^{ν^c}, have the expected negative effects. We see, therefore, that the model is consistent with economic intuitions.[2]

[2]Shocks to the marginal utility of consumption have negative effects on consumption due our specification of a Constant Relative Risk Aversion (CRRA) utility function. If we specified the functional form of utility as quadratic, of course, shocks to the marginal utility would have positive effects. However, the marginal utility shock also affects investment decisions positively, so that in some cases the positive effects on investment may dominate the negative effects on consumpption, and thus increase GDP gowth.

Figure 6. GDP: Impulse Response Paths

(Percentage deviation from the steady state)

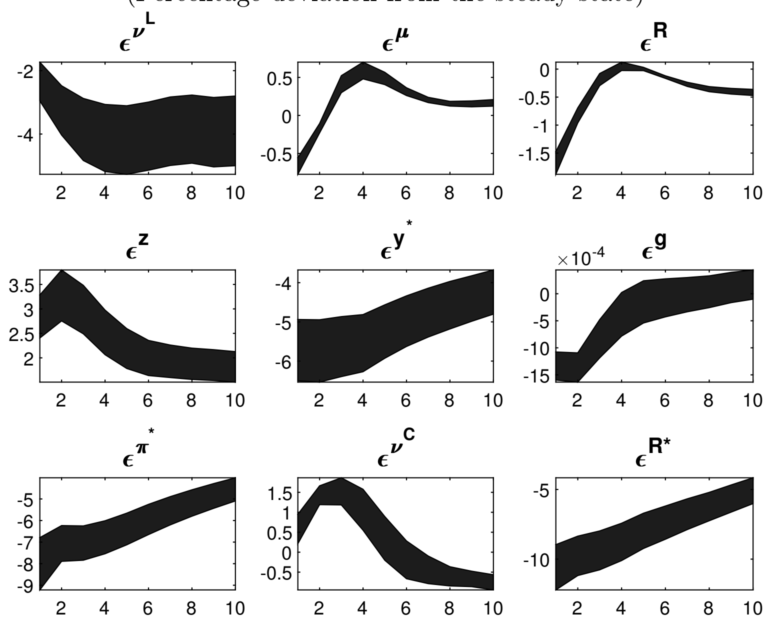


Source: Author calculations.

Figure 7 shows that an increase in TFP leads to a real appreciation. Similarly, A positive shock to the marginal utility of consumption leads to an appreciation in the real exchange rate, as it lowers consumption of domestic and imported goods and increases saving We also see that there is more persistence in the propagation of the shocks on the real exchange rate than on GDP growth.

Figure 7. Real Exchange Rate: Impulse Response Paths

(Percentage deviation from the steady state)

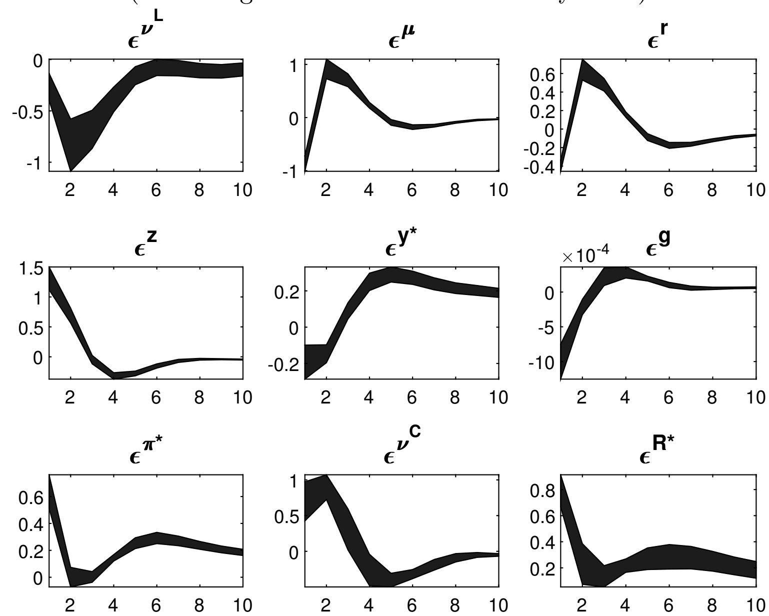


Source: Author calculations.

Figure 8 shows that shocks to the disutility of labor have strong negative effects on real bank lending, while shocks to TFP, as expected, have strong positive effects. Shocks to government spending, due to crowding out, have negative effects. Shocks to the marginal utility of consumption, foreign inflation and foreign interest rates also increase real bank lending, while a shock to banking uncertainty decrease real bank lending.

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, TFP, disutility of labor and the marginal utility of consumption. While foreign factors do show up, the cumulative influence of foreign inflation, foreign demand, and foreign interest rate shocks is less than ten percent. This result may be surprising, given the highly-open nature of the Korean economy However, the greatest fluctuations of GDP growth take place at the GFC and COVID-19 crisis periods, when the domestic shocks to TFP, labor disutility and consumption utility would dominate, in the midst of and in reaction to global uncertainty. The basic message is that these shocks are not purely exogenous but relate to global influences. As Chari et al. (2009) note, considerable care should guide our interpretation of what underlying behaviors the specific shock processes represent in these New Keynesian models, when we move beyond the usual

Total Factor Productivity shock.

Table 2. FEVD for GDP Growth

(Unit)

Quarterly horizon:	1	4	8	12	16
ϵ^{ν^L}	0.206	0.427	0.431	0.432	0.441
ϵ^{μ}	0.058	0.069	0.068	0.067	0.067
ϵ^{R}	0.084	0.059	0.057	0.057	0.056
ϵ^{z}	0.371	0.254	0.245	0.243	0.239
ϵ^{y^*}	0.106	0.057	0.058	0.058	0.057
ϵ^{g}	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.001	0.008	0.012	0.014	0.013
ϵ^{ν^C}	0.171	0.110	0.108	0.107	0.106
ϵ^{R^*}	0.003	0.016	0.021	0.023	0.022

Source: Author calculations.

Table 3 shows, not surprisingly, that foreign inflation, foreign demand, and 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}	0.026	0.064	0.092	0.112	0.126
ϵ^{R}	0.013	0.004	0.003	0.003	0.003
ϵ^{z}	0.036	0.045	0.041	0.042	0.044
ϵ^{y^*}	0.147	0.162	0.169	0.177	0.185
ϵ^{g}	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.293	0.266	0.266	0.264	0.261
ϵ^{ν^C}	0.001	0.008	0.006	0.006	0.007
ϵ^{R^*}	0.482	0.449	0.422	0.396	0.374

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 uncertainty, given by ϵ^{μ}, the marginal utility of consumption, ϵ^{ν^C}, and domestic interest rates, ϵ^{R}, explain most of total variation of bank lending, while foreign interest rates, foreign demand, and foreign inflation explain less than 25 percent of total variation after 16 quarters. This result indicates a highly open financial sector in the Korean economy. The foreign factors, of course, will affect other variables, such as consumption and investment, through this bank-lending channel.

Table 4. FEVD for Bank Lending

(Unit)

	Quarterly horizon: 1	4	8	12	16
ϵ^{ν^L}	0.018	0.150	0.137	0.135	0.134
ϵ^{μ}	0.182	0.230	0.205	0.198	0.196
ϵ^{R}	0.038	0.084	0.080	0.078	0.077
ϵ^{z}	0.398	0.239	0.217	0.209	0.207
ϵ^{y^*}	0.010	0.014	0.035	0.045	0.049
ϵ^{g}	0.000	0.000	0.000	0.000	0.000
ϵ^{π^*}	0.098	0.045	0.064	0.072	0.074
ϵ^{ν^C}	0.112	0.161	0.169	0.163	0.162
ϵ^{R^*}	0.143	0.076	0.093	0.100	0.100

Source: Author calculations.

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

3.5 Historical Shock Decomposition

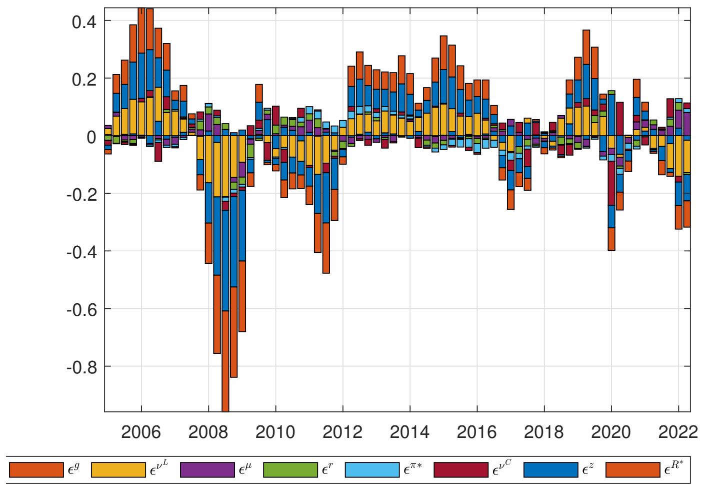
While the FEVD tells us which forcing variables are more important and which are less important over the entire sample, Historical Shock Decomposition (HSD) tells us which forcing variables are more important, and which are less important, at particular times in the sample. We acknowledge that with eight shocks, the variation in the color codings of the shocks becomes somewhat diminished. However, these charts show when certain shocks have little or no influence.

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

For GDP growth in Figure 9, varieties of shocks play key roles at the time of the GFC and the COVID-19 episodes. We also see that the disutility of labor, shown in yellow, comes into noticeable play at the time of the GFC and at the time of the COVID-19 shocks. Again,this make eminent sense. When the economy is in sharp decline and when there are threats of health, leisue has greater value than work.

Figure 9. Historical Shock Decomposition: GDP Growth

(Unit contribution to quarterly growth rate)

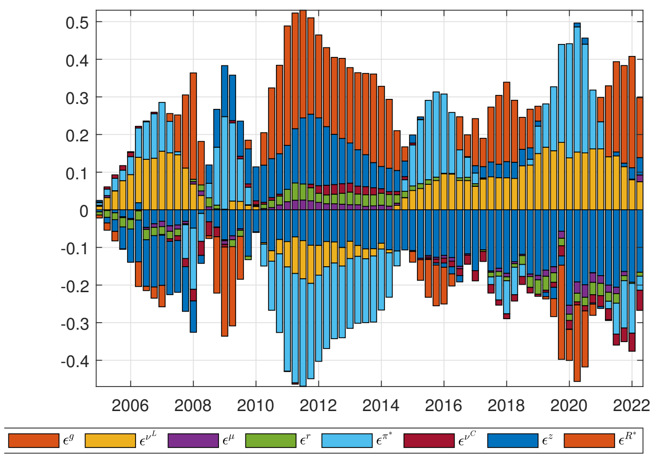


Source: Author calculations.

Figure 10 shows that the shocks to the foreign inflation, given by the light blue bars, comes into play at the time of the two crises. Again this makes sense for the real exchange rate.

Figure 10. Historical Shock Decomposition: Real Exchange Rate

(Unit contribution to quarterly growth rate)

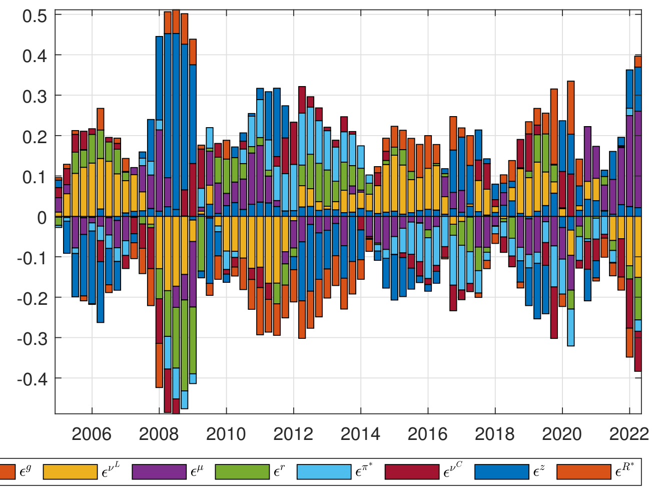


Source: Author calculations.

Figure 11 shows again that a mix of domestic and foreign factors play key roles for real bank lending throughout the sample. Shocks to banking sector uncertainty show up at the time of the GFC and the COVID-10 periods.

Figure 11. Historical Shock Decomposition: Bank Lending

(Unit contribution to quarterly growth rate)



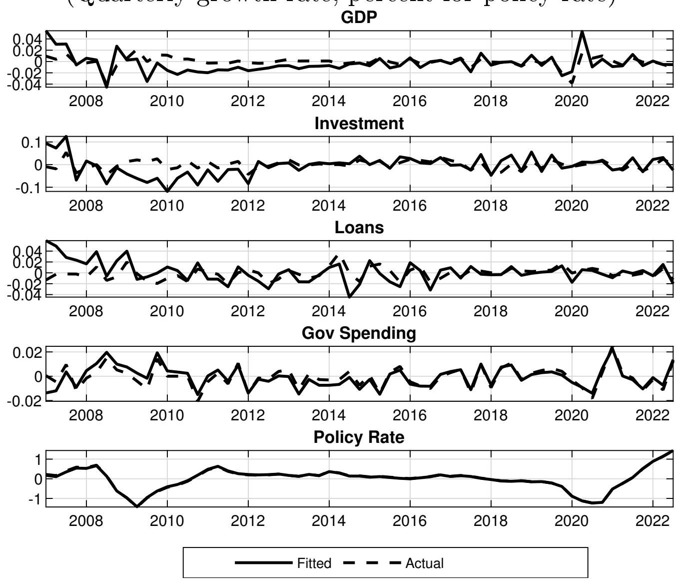
Source: Author calculations.

3.6 Historical simulations

Figure 12 pictures the evolution of the actual and model-simulated values for GDP, 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)

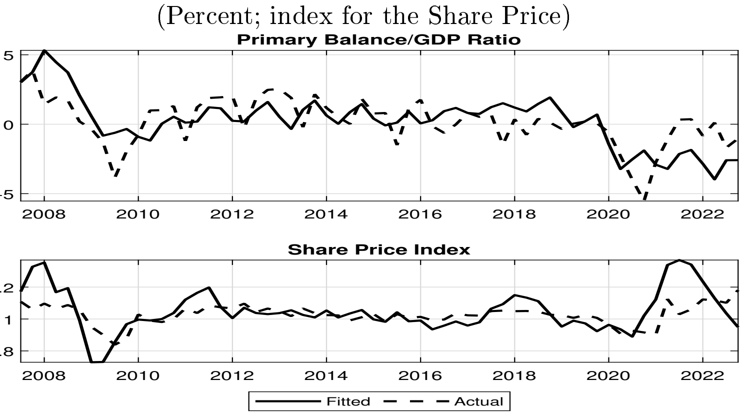


Source: Author calculations.

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 13. Primary Balance/GDP Ratio and Share Price Index

(Percent; index for the Share Price)

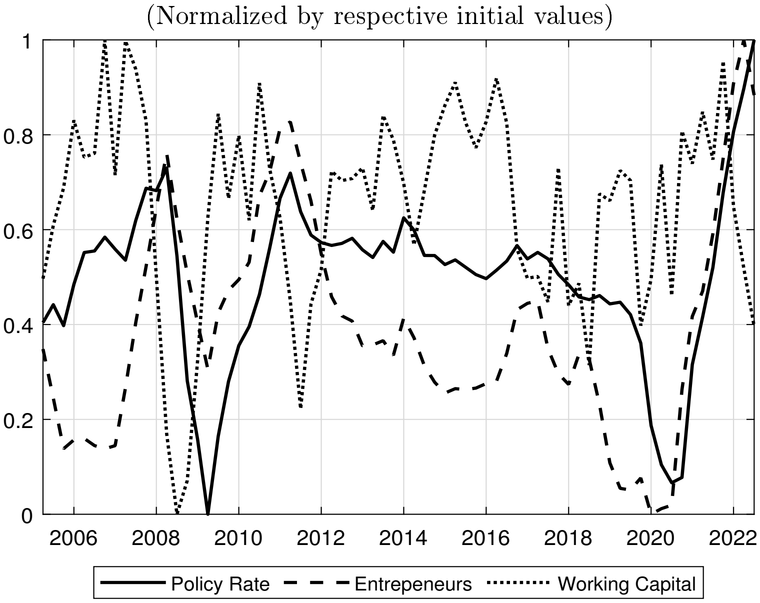


Source: Author calculations.

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, 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)

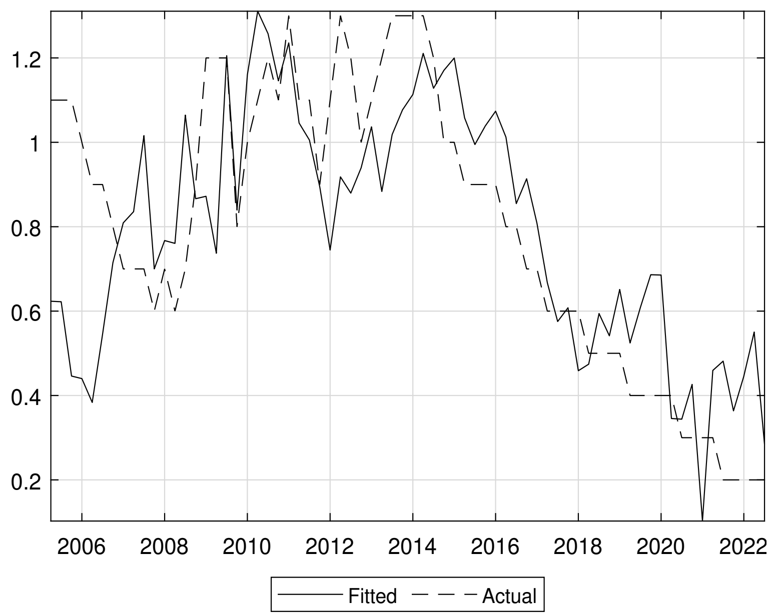


Source: Author calculations.

Figure 15 pictures the movement of the Non-Performing Loan Ratio over the sample period. We see a decline after 2014 for both the actual and fitted, with the fitted ratio showing a slight upturn at the end of the sample.

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.

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 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.

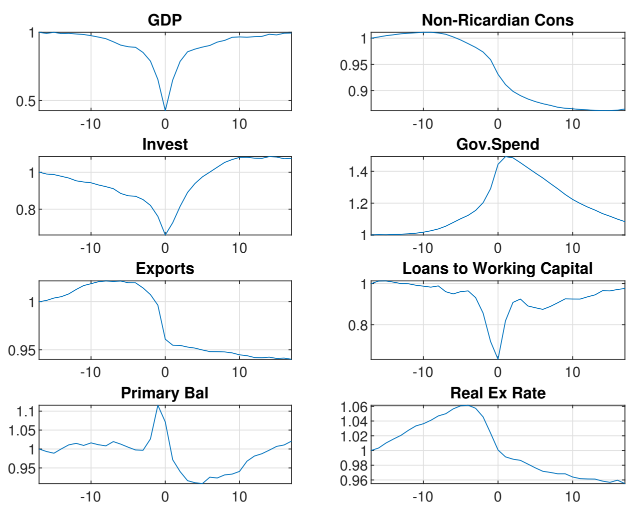
As noted by Mendoza (2010), looking at welfare measures over the full period of simulation, based on averages, will not help us see how these rules perform when things get bad, as they do, for all economies, some of the time.

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 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 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 difference in times of crisis. GDP, Exports, Investment and the Primary Balance fall quickly, while non-Ricardian consumption falls slowly.

Figure 16. Dark Corner Adjustment: Macro Indicators

(t-16 quarters = 1)

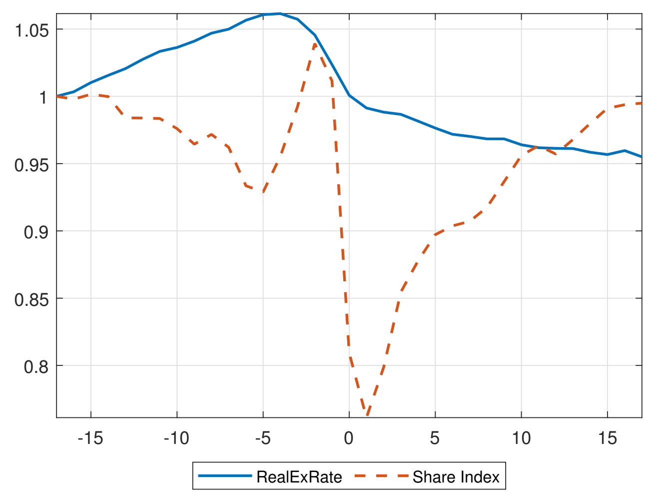


Source: Author calculations.

Figure 17 shows that the fall of the real exchange rate, relative to the share market index, is much slower.

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 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 has the following form:

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

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

Note that the functional form for the interest-rate rule is the same as the one used in the estimated model but now, for the optimal rule, there is no stochastic term.

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}	.569	–
γ_1	c^{NR}	-6.90	–
γ_2	l^{wc}	-10.31	–
γ_3	π	.894	–
ρ_R	R_{t-1}	–	.918
ρ_π	$\frac{\pi_t}{(\pi}$	–	1.27
ρ_y	$\frac{Y_t}{Y_{t-1}}$	–	.905

Source: Author estimates.

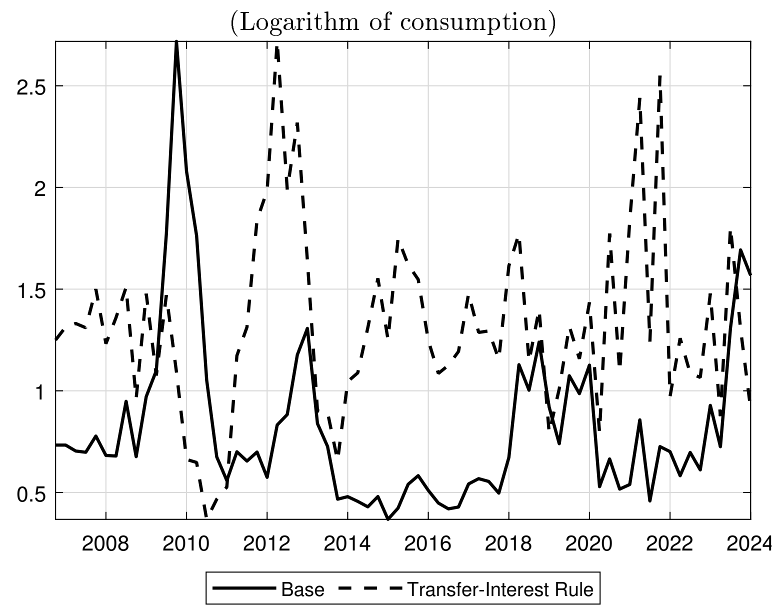
The relative size of the coefficients depend, of course, on the units of measurement of the co-terms. However, one result is clear. The optimal transfer-rules for the Non-Ricardian households and for working capital are counter-cyclical with respect to all three arguments. The Taylor rule coefficients change in the presence of the expansionary transfer rules, with positive weights on inflation as well as on output growth. We note, however, that these optimal Taylor rules are not markedly different from the Taylor rule parameters coming from Bayesian estimation.

In the next two sub-sections we evaluation 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 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. For most of the sample, this consumption index is higher under the transfer-interest rule.

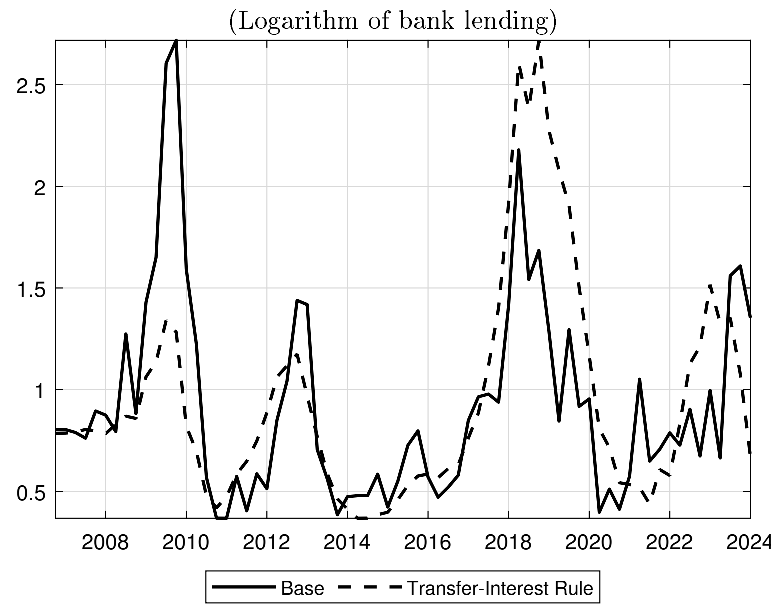
Figure 18. Non-Ricardian Consumption under Base Simulation and Simple Transfer-Interest Rule



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 COVID-19 episode than the GFC period.

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

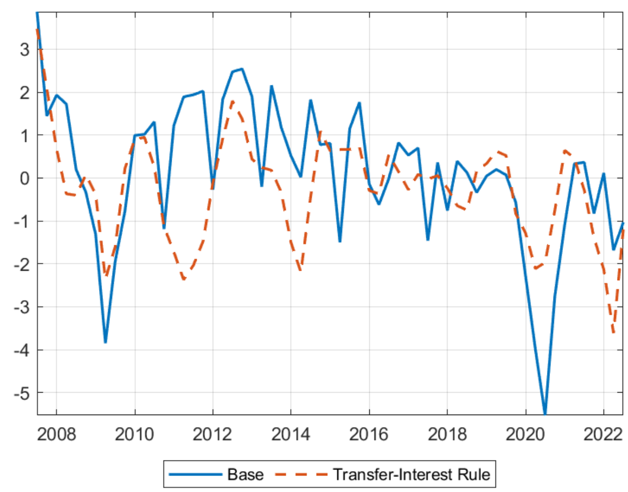


Source: Author calculations.

Figure 20 pictures the Primary Balance/GDP Ratio under the base and optimal simple rule scenarios. We see that the primary balance fall less at the time of the GFC and COVID-19 under the optimal rule, but during the recovery period after the GFC, it is worse. 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)

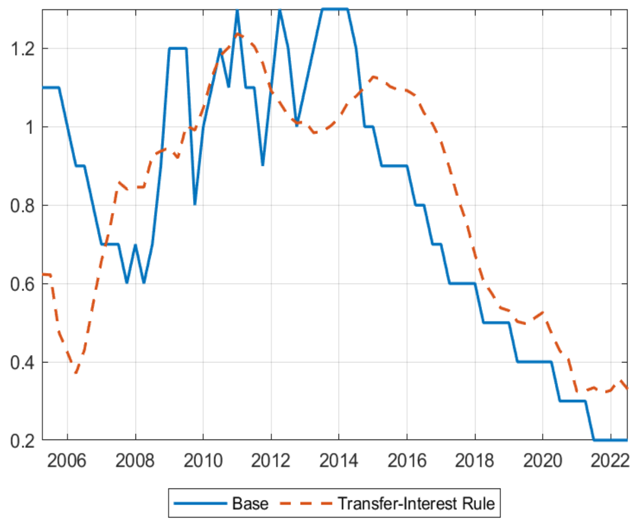


Source: Author calculations.

Figure 21 shows slightly greater fluctuations in the NPL ratio under the two rules. We see that the rise and fall of the NPL ratio is smoother under the optimal rules.

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 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 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: $\rho^R = .918, \alpha^\pi = 1.27, \alpha^y = 0$
No Support	TR: $\forall i \in [0,3] : \gamma_i = 0$
	R: $\rho^R = .724, \alpha^\pi = 1.21, \alpha^y = 0$

Source: Author estimates.

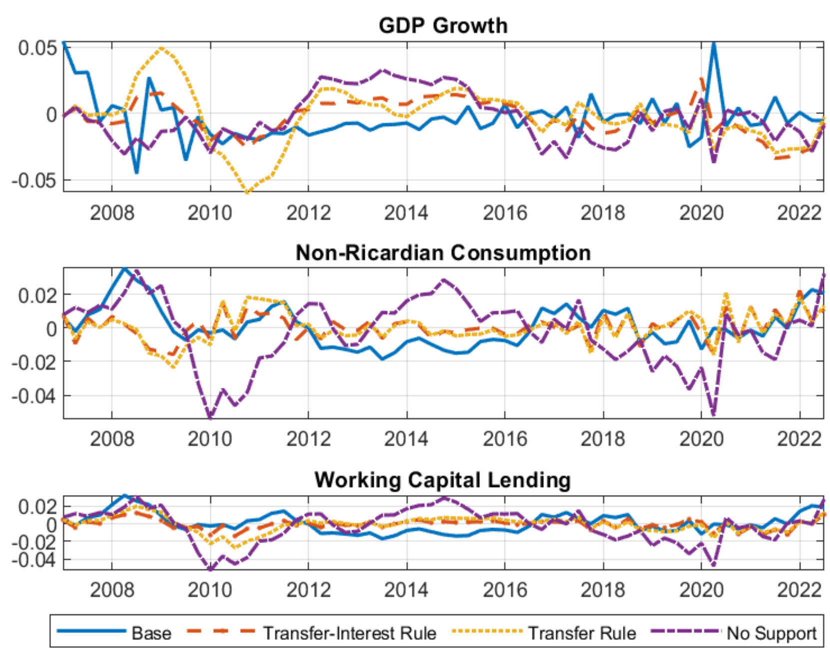
The reason why we compare these rules with the model-simulated actual path is that we realize that the actual policy framework guiding the actual path incorporated, to a greater or lesser extent at various points of time, included fiscal and monetary supports. The question we pose: is the actual path 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 22, 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 path, which track the actual paths, are 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 22. 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 Niehans (1978) 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 differences between two the paths, we take the mean and divide it by the square root of the Heteroskedastic and Autocorrelation Consistent (HAC) variance estimator, due to White (1980). 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 closer to the optimal paths under both rules than it is to the path generated by the no-support regime.

Using the sample for the past five years, we see another story. The base path is not significantly different from the optimal policy paths but is different from the No Support policy path. Again, the optimal policy paths are also different from the No Support paths but are not different from each other.

Table 7. Euclidean Distance Measures of Base & Policy Paths

		Policy Paths: Full Sample			
		Base	Transfer+	Pure	No
Policy Paths:		Path	Interest	Transfer	Support
Base	Path	0.000	–	–	– –
Transfer+	Interest	7.105	0.000	–	– –
Pure	Transfer	7.192	2.366	0.000	– –
No	Support	**14.265**	**13.881**	**12.306**	0.000

Source: Author estimates.

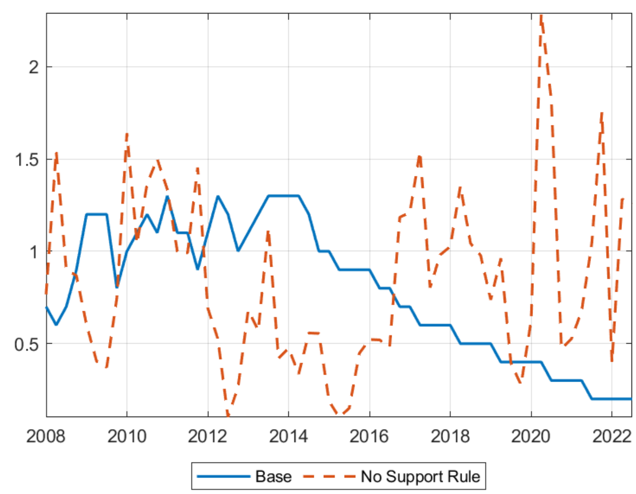
To further illustrate the potential costs of a No-Support regime, Figure 23 pictures the Non-Performing Loan (NPL) ratios under the Base and the No-Support regimes. We see that the no-support regime leads to a marked jump in the NPL ratio at the time of the COVID-19 period.

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. We see that the optimal rule moderates the fall in

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

(Percent)

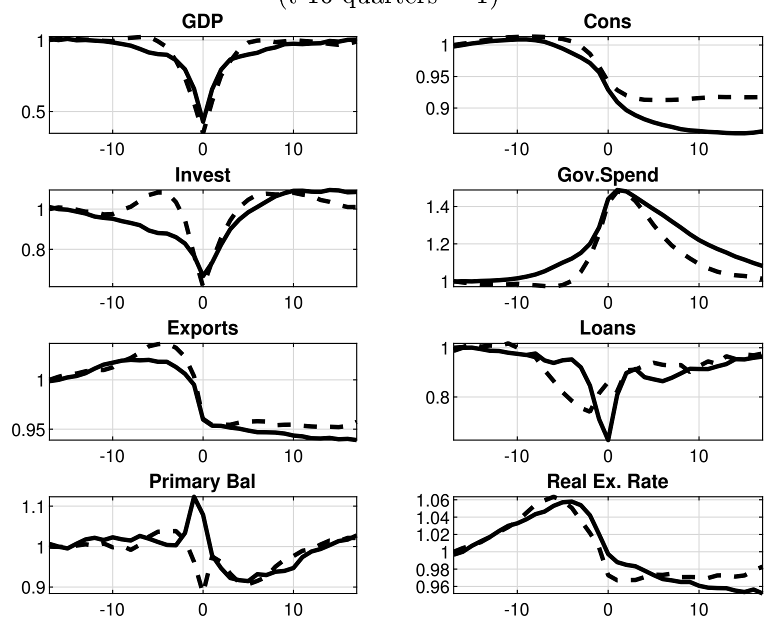


Source: Author calculations.

investment, lending and real lending, but it has only slight effects on GDP, exports and the real exchange rate.

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

(t-16 quarters = 1)



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. 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 fiscal transfers, as opposed to a No Support regime, during the past five years. The shocks with have guided key macroeconomic indicators come from a mix of both foreign and domestic sources.

Overall policy variables such as government spending have had much less influence than external forces, or shocks to the disutility of labor. This does not mean that fiscal policy has little or no effect. The government spending observable is for government consumption and investment, not fiscal transfers. In fact, such transfers, supported by monetary expansion, represent a quasi-monetary fiscal policy or a quasi-fiscal monetary policy, as noted by Sims (1994). But our results show that actual policy mix of quasi-fiscal or quasi-monetary policy, has become more closely aligned with optimal policy paths during the past five years.

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