

INDONESIA'S FINANCIAL STRESS EVENTS AND MACROECONOMIC DYNAMICS

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ABSTRACT

In this study, we use a Markov-Switching Bayesian Vector AutoRegression model to investigate the episodic relationship between financial stress and the key macroeconomic variables in the case of Indonesia. We find different nature of relationships among Indonesia's real sector variables (household consumption expenditure and consumer price index), financial sector variables (interbank money market rate) and the policy variable (broad money supply during the times of high and low financial stress). Regime changes occurred on several occasions, including during the 2008 global financial crisis period and at the beginning of the COVID-19 pandemic.

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I. INTRODUCTION

Many studies investigate the linkages between a country's financial system stability and macroeconomic condition (see, *inter alia*, Mishra and Narayan, 2015). Many researchers who examine the links between financial stress and macroeconomic variables use conventional econometrics or Dynamic Stochastic General Equilibrium (DSGE) models. Hubrich and Tetlow (2014) argue that many of these models could not capture the episodic relationship between financial stress and macroeconomic variables through the changes in economic agents' behavior. For example, in "normal times" (i.e., when the financial system works properly) firms consider the profitability of a project first and then seek financing. When the financial system is not working properly (i.e., the stress event), credit seems like the only thing that matters for firms. Hubrich and Tetlow (2014) suggest that the Markov-Switching Bayesian Vector Autoregression (MSBVAR) model would be suitable to capture the episodic links between financial stress and macroeconomic variables.

There is scant literature on the MSBVAR model to examine the episodic relationship between financial stress and macroeconomic variables. Among this literature is a study by Hartmann *et al.* (2013) that examines the dynamic relations between systemic financial stress and macroeconomic variables in the Euro Area. They develop an MSBVAR model with a two-state (low- and high-stress) coefficient and five endogenous variables: (1) industrial production growth, (2) the Consumer Product Index (CPI) inflation, (3) short-term interest rate, (4) the growth rate of nominal bank loans to the private sector, and (5) the Composite Indicator of Systemic Stress (CISS) developed by Holló *et al.* (2013). They find that financial shocks are larger and their effects on real activity are bigger during regimes with high systemic stress than during tranquil times.

Hubrich and Tetlow (2014) develop MSBVAR models with two-state (i.e., high- and low-stress states) and three-state (high-, medium, and low-stress states) combinations of the data's variance and coefficients for the US economy. They investigate the relations between the US Federal Reserve Financial Stress Index (FSI), personal consumption expenditure, core inflation, the nominal Fed funds rate, and the nominal broad money supply (M2) aggregate. They find that financial stress has different impacts on the output: Financial stress is of negligible importance in "normal times" but of critical importance in the high-stress regime.

Aboura and van Roye (2017) develop an FSI for France as a composite indicator of 17 financial variables and extract a financial stress component from the variables using a dynamic approximation model. They use the FSI, inflation, industrial production growth, and short-term interest rate (3-month PIBOR/EURIBOR) in their MSBVAR with a two-state (low- and high-stress) coefficient model. They find that financial stress transmits very strongly in a high-stress regime, whereas economic activities remain nearly unaltered in a low-stress regime.

Tezuka and Matsubayashi (2018) develop an MSBVAR model with a two-state (i.e., "unstable" and "stable" regimes) coefficient to examine how the widening credit spread in "unstable" periods affects primary markets, lending markets, and production activities, in comparison with the "stable" periods. They define a credit spread as the difference between the straight corporate bond and the Japanese government bond of the same maturity. They find that the widening credit spread

has different impacts in different regimes. During a stable period, the credit spread positively affects corporate bond issuance and industrial production, but negatively affects banks' average loan balances. During an unstable period, the widening credit spread is associated with unfavorable economic conditions and negatively affects corporate bond issuance, but positively affects lending.

Kuek *et al.* (2020) develop a Financial Vulnerability Index (FVI) for Malaysia using a composite indicator that comprises ten macroeconomic variables. They construct a two-state coefficient MSBVAR model that incorporates four variables: the FVI, the growth of industrial production (IPI), inflation rate, and the change in the short-term interest rate (represented by the 3-month KLIBOR). They find that financial vulnerability catalyzes considerable negative impacts on economic activity in high-vulnerability periods but has negligible impacts in low-vulnerability periods.

We find no study that investigate the episodic linkages between financial stress and Indonesia's macroeconomic condition. While some studies (Salim, 2019; Basri, 2017; Jayasuriya and Leu, 2017) have investigated the impacts of financial system shocks on Indonesia's real sector or *vice versa*, those studies do not account for episodic linkages between the two areas. We are particularly interested in Indonesia – the largest economy in Southeast Asia. Indonesia has undergone various reforms to strengthen its financial system in the aftermath of the 1997/1998 Asia financial crisis. Some of the key reforms include making its central bank independent in 1999, encouraging commercial banks to adopt the Basel Accords, and strengthening regulations on the capital market and the banking system.

We believe it is important to understand the different impacts of financial stress on Indonesia's macroeconomic variables under the different financial system conditions. Therefore, we are motivated to conduct this study to fill in the gap in the literature and to provide recommendations to policymakers.

Our study is different from previous studies on the relationship between Indonesia's financial sector and the country's macroeconomic condition because we use the MSBVAR model to reveal the episodic nature of relationships between the financial sector and the macroeconomic variables, which are often overlooked by conventional econometric and DSGE models.

The main question in our study is whether there is evidence of episodic relationships between financial stress and Indonesia's macroeconomic condition. To be more specific, we would like to know whether financial stress has different impacts on Indonesia's key macroeconomic variables under different financial system conditions.

We develop some MSBVAR model candidates and select the best model that can meet two objectives of our study: (1) it should be able to appropriately identify the relationship between financial stress and Indonesia's key macroeconomic indicators; and (2) it should be useful for policymakers for nowcasting and forecasting needs. Our MSBVAR model should be useful not only for intellectual exercises but for practical uses by policymakers. Thus, our study not only contributes to the academic literature but also provides an analytical tool for policymakers.

Our decision with these two objectives brings consequences to the model selection: instead of using only the Marginal Data Density (MDD) criteria for

model selection (such as in Hubrich and Tetlow, 2014), we use other three criteria that are related to the performance of the model in nowcasting the actual stress events. Hence, in this study we select an MSBVAR model that is not the best (but still performs very well) based on the MDD criteria but can meet all the four criteria with relatively superior performance than the other models. This will be explained further in Section II.

The outputs of our MSBVAR model show different nature of relationships among Indonesia's real sector financial, and policy variables (M2) during the times of high and low financial stress as shown by the regime changes in our MSBVAR model outputs. The regime changes affect all variables in the models and cause economic agents to change their behavior.

This paper proceeds in the following direction. Section II elaborates the methodology of this study, including the construction of the FSI, the MSBVAR model, and the criteria to select the best among the MSBVAR models. Section III discusses the selection of the MSBVAR model for Indonesia. Section IV discusses the episodic relationship between financial stress and Indonesia's macroeconomic variables using the FSI and the MSBVAR model. Section V provides some concluding remarks.

II. METHODOLOGY

This section elaborates three steps involved in developing the MSBVAR model. We first construct a FSI. We then develop the MSBVAR candidate models. Finally, we discuss the four criteria to select the best model among the MSBVAR models.

A. Construction of the FSI

The FSI is constructed to identify the occurrence of high-stress events in the financial system, although not every high-stress event will materialize into a crisis. This index is commonly used as a component of nowcasting and/or forecasting models. There are many studies related to the construction of the FSI (or similar indexes with different names) for the country, regional, or global level, including those by Hakkio and Keeton (2009) and Monin (2019) for the US economy, Juhro and Iyke (2019) for Indonesia, Holló *et al.* (2012) for the Euro area, Park and Mercado (2014) for 25 emerging economies, Stolbov and Shchepeleva (2016) for 14 emerging countries, and Poonpatpibul *et al.* (2021) for the ASEAN-5 + CJK (China, Japan, and Korea), Abdymomunov (2013) for the US financial market.

We use the Park and Mercado (P-M) FSI construction technique due to its comprehensiveness in covering the financial markets and banking sector, as well as its simplicity. The P-M FSI methodology is used by the Asian Development Bank (ADB) for its FSI. The P-M FSI comprises the following components: (1) banking sector stress, (2) foreign exchange market pressure; (3) the stock market volatility, (4) the stock market return, and (5) sovereign debt market stress. The P-M FSI is constructed using variance-equal weights for the five components, implying these components are equally important. The ADB uses the P-M FSI construction technique to build the cross-country Asia financial stress index as well as the FSI for selected Asian countries.

The FSI components and the calculation methods are elaborated as follows.

A.I. Banking Sector Stress Coefficient (β)

$$\beta = \frac{\text{cov}(r, m)}{\text{var}(m)} \quad (1)$$

where r and m are the returns of the banking sector stock price and the overall stock price returns, respectively. A higher banking sector β implies greater banking sector stress. If $\beta > 1$, the banking sector is relatively risky, because the volatility of returns on bank shares is greater than the volatility of returns for the overall stocks in the market. The JCI is used as a proxy for the overall stock price returns, while the finance sector composite index in the ISX is used for the banking sector price returns.

A.II. Foreign Exchange Market Stress (EMPI)

$$EMPI_t = \frac{(\Delta e_t - \mu_{\Delta e})}{\sigma_{\Delta e}} - \frac{(\Delta RES_t - \mu_{\Delta RES})}{\sigma_{\Delta RES}} \quad (2)$$

where Δe and ΔRES denote month-on-month percent changes in the foreign exchange rate of local currency per USD and foreign exchange reserves, respectively; μ and σ are the mean and standard deviation, respectively. The higher the value of the $EMPI$, the higher the foreign exchange market stress.

A.III. Stock Market Volatility (ϑ^2)

The stock market volatility is assumed to follow a generalized autoregressive conditional heteroskedasticity, GARCH (1,1) process as follows:

$$\vartheta_t^2 = \omega + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \sigma_{t-1}^2 \quad (3)$$

where ϑ^2 refers to the variance, and ε^2 error terms in the equation given by:

$$y_t = \alpha_t + \gamma y_{t-1} + \varepsilon_t \quad (4)$$

where y is the stock return, which is the JCI. The higher the value of ϑ , the higher the stress from the equity market volatility.

A.IV. Stock Market Returns (SRET_t)

$$SRET_t = \log(P_t) - \log(P_{t-1}) \quad (5)$$

where P is the price of stocks, which is the JCI. The lower the return, the higher the stress from the stock market.

A.V. Debt Market Pressure (DMP_t)

$$DMP_t = 10YIDGB_t - 10YUST_t \quad (6)$$

where $10YIDGB$ is the yield of Indonesia's benchmark 10-year government bond, and $10YUST$ is the yield of the benchmark 10-year US government bond.

Unlike the P-M FSI that uses equal weighted for the FSI components, we weigh each component based on its standard deviation. The higher the standard deviation, the bigger the weight of the respective component in the FSI. We find that using the equal-weighted method causes poor FSI performance in the case of Indonesia because the method fails to acknowledge the different impacts on Indonesia's financial system of shocks from different FSI components. For a better-scaled FSI, each component of the FSI is indexed where the highest value of the observation is set at 100, and other values of the component are adjusted accordingly.

The FSI is computed by summing up the weighted and indexed five components, according to the following equation:

$$FSI_t = \omega_1 \beta + \omega_2 EMPI_t + \omega_3 \vartheta_t^2 + \omega_4 SRET_t + \omega_5 DMP_t \quad (7)$$

where ω_i ($i = 1, 2, 3, 4, 5$) are the weight of each component, and t is the time index.

The means, standard deviations, and weights of each component are reported in Table 1.

Table 1.
Means, Standard Deviations, and Weights of the FSI Components.

This table displays the means, standard deviations, and weights of the FSI components.

	β	$EMPI$	ϑ^2	$SRET$	DMP	FSI
Mean	0.627	0.000	1.089	0.011	6.256	25.229
Standard deviation	0.652	1.677	0.403	0.059	1.817	11.208
Weight in the FSI	0.142	0.364	0.088	0.013	0.394	1.000

Source: Authors' calculations

We examine following three different FSI thresholds based on the mean and standard deviation (stdev) as depicted in Table 2: (1) $mean(FSI) + 1 * stdev(FSI)$; (2) $mean(FSI) + 1.5 * stdev(FSI)$; and (3) $mean(FSI) + 2 * stdev(FSI)$. We do not select the first threshold, as it is too low and causes difficulties in distinguishing impactful high financial stress (such as the 2008 GFC) from less impactful stress events. We also do not select the third threshold, as it is too high and caused the FSI to miss important high-stress events, such as the presidential election event in June 2004.

Therefore, we select the second threshold; that is, high financial stress is defined as any observation whose value is larger than the mean of the FSI plus 1.5 times the standard deviation of the FSI. With this threshold, the FSI can capture ten high financial stress events in Indonesia from January 2003 to September 2020. The FSI components are not independent and mutually exclusive as Indonesia's bond, stock, foreign exchange (FX), and credit markets affect each other (Sugandi, 2021).

Table 2.
Actual High-stress Events in the FSI with Different Thresholds

This table displays the three threshold candidates for the FSI to capture the actual high-stress events in Indonesia. We select the threshold that uses the mean(FSI) + 1.5 * stdev(FSI).

Mean(FSI) + 1*Stdev(FSI)	Mean(FSI) + 1.5*Stdev(FSI)	Mean(FSI) + 2*Stdev(FSI)
June 2004	June 2004	
May 2005		
July 2005		
August 2005	August 2005	August 2005
September 2005	September 2005	September 2005
November 2005		
June 2006	June 2006	June 2006
October 2006		
April 2008		
May 2008	May 2008	
September 2008		
October 2008	October 2008	October 2008
November 2008	November 2008	November 2008
February 2009	February 2009	February 2009
September 2011		
June 2013		
July 2013	July 2013	
August 2013		
September 2013		
March 2015		
September 2015		
January 2015		
January 2016		
September 2018		
May 2019		
March 2020	March 2020	March 2020
Number of high-stress events: 25 Number of high-stress events: 10 Number of high-stress events: 7		

Source: Authors' calculation

B. Development of the MSBVAR Candidate Models

The second stage is to develop an MSBVAR model that comprises five variables as in Hubrich and Tetlow (2014) but adjusted to Indonesia's case: (1) the FSI; (2) month-on-month growth of household consumption (PCE); (3) month-on-month headline inflation (CPI); (4) 3-month IDR money market rate; and (5) month-on-month growth in broad money (M2). The reduced form of the MSBVAR model follows Hubrich and Tetlow (2014) and is stated as follows:

$$y'_t = x'_t B (s_t^c) + u'_t (s_t^p, s_t^e) \quad ; \quad t = 1, 2, \dots, T \quad (8)$$

with

$$B(s_t^c) = A_+(s_t^c)A_0^{-1}(s_t^c)$$

$$u_t'(s_t^v, s_t^c) = A_0'^{-1}(s_t^c)e_t' \Xi^{-1}(s_t^c)$$

$$E(u_t(s_t)u_t'(s_t)) = (A_0(s_t^c)\Xi^2(s_t^v)A_0'(s_t^c))^{-1}$$

where y is an $n \times 1$ vector of endogenous variables; $s_t^m, m=\{v, c\}$ are unobservable (latent) state variables, one each for variances (v) and intercept and coefficients (c); A_0 is an $n \times n$ matrix of parameters describing contemporaneous relationships between the elements of y ; and A_+ is an $n \times n$ matrix of parameters of the endogenous variables. The values of s_t^m are elements of $\{1, 2, \dots, h^m\}$ and evolve according to the first-order Markov process.

C. Selection Criteria for the MSBVAR for Indonesia

We seek to find the most suitable MSBVAR model for Indonesia's economy. Unlike Hubrich and Tetlow (2014) who use only Marginal Data Density (MDD) criteria for model selection, we use four criteria to select the model: (1) The model can correctly call actual high-stress events by issuing "high probability of high-stress" signals, (2) the model has a relatively low ratio of adjusted "high probability of high-stress" signals to noises, (3) there is a relatively acceptable probability of actual high-stress occurrence when the model issues a signal of a "high probability of high-stress event," and (4) the model has the highest or relatively high MDD compared to other models.

Criteria (1), (2), and (3) are similar to indicators introduced by Kaminsky *et al.* (1998) for their leading indicator for a currency crisis. We set the signal issuance threshold at 90% probability of "high stress" occurrence; that is, when the MSBVAR produces an observation with a value equal to or higher than 90% probability of a "high stress" event, a signal is issued. For the fourth indicator, we use the MDD calculation technique developed by Waggoner and Zha (2012). We select a model that has the best or better performance in all of these indicators compared to other models. As shown in the next section, using the MDD as the only criterion may not produce the best model for high-stress event nowcasting.

The following are the formulas for the three indicators:

C.I. Indicator (I)

Correctly called actual "high stress" events by "high probability of high stress" signals = $\frac{\text{Number of correctly called high-stress events}}{\text{Number of actual high-stress events}}$

C.II. Indicator (II)

Ratio of adjusted "high probability of high stress" signals to noise = $\frac{B/(B+D)}{A/(A+C)}$

Where A represents number of correct signals, B and C denotes number of Type II and Type I errors, respectively, and D is number of observations when the model correctly does not issue "high-stress" signals.

C.III. Indicator (III)

Probability of actual "high stress" event when a "high probability of high stress" signal issued

$$= \frac{A}{(A+B)}$$

Where A and B represent number of correct signals and number of Type II errors, respectively.

Using all five variables, we construct the potential MSBVAR basic models based on the combination of the number of chain(s) for the variance (v) and the coefficient (c) as follows: (1) $v=1, c=1$; (2) $v=1, c=2$; (3) $v=2, c=1$; (4) $v=2, c=2$; (5) $v=1, c=3$; (6) $v=2, c=3$; (7) $v=3, c=1$; (8) $v=3, c=2$; and (9) $v=3, c=3$.

Combinations of the number of chains for the variance and the coefficient are used to distinguish between variance switching and coefficient switching. Coefficient switching suggests either economic agents change their behavior during episodes of high financial stress or that the environment they face is materially different. Variance switching suggests that financial crises are a matter of happenstance (Hubrich and Tetlow, 2014).

Following Hubrich and Tetlow (2014), we use two sets of priors for estimation of the models: the Minnesota prior for estimating the VAR parameters and the Dirichlet prior for estimating the state transition matrix.

We explore two types of MSBVAR models based on the number of states (regimes) of the financial conditions: (1) two-state models (comprise "high stress" and "low stress") and (2) three-state models (comprise "high stress", "medium stress", and "low stress"). Thus, we examine nine potential basic models for the two-state models and nine potential basic models for the three-state models and selects the best model for nowcasting.

After finding the best MSBVAR model that includes all five variables, we investigate models that use the same number of chain(s) for the variance and the coefficient but with a restricted number of equations. This examination is conducted to find which variable(s) in the model switch(es) when the regime changes, i.e., whether it is the FSI, the real sector variables (PCE and/or CPI), the monetary policy response variables (M2 and/or MMR), or combinations of these variables. The four criteria used for the basic models are also used to examine the restricted models.

We use monthly data from January 2003 to September 2020. The variables, data, and data sources are summarized in Table 3.

Table 3.
Variables, Data, and Data Sources

This table displays the variables, data, and data sources used in our study.

Variable	Data	Source
Returns to the banking sector stock	Finance sector composite index in the ISX	Bloomberg
Overall stock market returns	Indonesia Composite Index	Bloomberg
Month-on-month percent changes in the foreign exchange rate of local currency per USD	USD/IDR exchange rate	Bloomberg
Foreign exchange reserves	Indonesia foreign exchange reserves	Bank Indonesia
Overall price of stocks	Indonesia Composite Index	Bloomberg
Yield of domestic government bond	Yield of Indonesia's 5-year government bond	Bloomberg
Yield of foreign government bond	Yield of 5-year US Treasury security	Bloomberg
Month-on-month growth of household consumption	Nominal household consumption (interpolated from quarterly to monthly data)	CEIC
Month-on-month headline inflation	Consumer price index	CEIC
Interest rate	3-month IDR money market rate	Bloomberg
Month-on-month growth of broad money (M2)	Broad money (M2)	Bank Indonesia

III. SELECTION OF THE MSBVAR MODEL FOR INDONESIA

Table 4 displays the performance of the two-state basic models that incorporate all five FSI components. Among these basic models, Model 2s1v2c is the best model based on the four performance indicators. Model 2s1v2c has a 90% value for indicator (1). Although Models 2s2v1c, 2s2v2c, and 2s3v1c also have a value of 90% for indicator (1), Model 2s1v2c has better performance in indicators (2) and (3) than those models. The MDD value of Model 2s1v2c is higher compared to those of other models (except for Model 2s2v2c), but the overall indicators show that this model is still the best compared to the other models.

Table 5 displays the performance of the three-state basic models. Model 3s3v3c is the best model. However, the performance of the Model 3s3vc3c indicators is weaker than those of Model 2s1v2c. This result shows that it is difficult to differentiate between low- and medium-stress events, as well as between medium- and high-stress events. The result may also indicate that the change in Indonesia's financial system condition tends to happen abruptly rather than gradually.

Table 4.
Performance of the Two-state (2s) Models

This table displays the performance of the two-state models to select the best candidate model based on the four criteria set in our study. Model 2s1v2c is selected as the best model among the two-state models.

Criteria	2s1v1c	2s1v2c	2s1v3c	2s2v1c	2s2v2c	2s2v3c	2s3v1c	2s3v2c	2s3v3c
(1) Correctly called actual "high stress" events by "probability of high stress" signals (%)	80.0	90.0	80.0	90.0	10.0	70.0	90.0	90.0	60.0
(2) Ratio of adjusted "high probability of high stress" signals to noises (%)	21.0	15.5	55.3	19.8	413.3	60.5	17.9	19.4	32.4
(3) Probability of actual "high-stress" event when a "high probability of high-stress" signal issued (%)	16.3	21.4	4.7	17.0	0.7	4.5	18.8	17.3	10.9
(4) Waggoner-Zha marginal data density (MDD)	-3,074	-3,079	-3,011	-3,002	-3,117	-2,978	-3,006	-2,997	-3,071

Source: Authors' calculation

Table 5.
Performance of the Three-regime (3s) Models

This table displays the performance of the three-state models to select the best candidate model based on the four criteria set in our study. Model 3s3v3c is the best model among the three-state model, but has poorer performance than Model 2s1v2c (which is the best model among the two-state models).

	3s1v1c	3s1v2c	3s1v3c	3s2v1c	3s2v2c	3s2v3c	3s3v1c	3s3v2c	3s3v3c
(1) Correctly called actual "high-stress" events by "probability of high-stress" signals (%)	20.0	0.0	20.0	10.0	20.0	20.0	10.0	20.0	70.0
(2) Ratio of adjusted "high probability of high-stress" signals to noises (%)	23.5	0/0	58.7	101.8	50.9	21.2	0.0	80.6	31.7
(3) Probability of actual "high stress" event when a "high probability of high-stress" signal issued (%)	16.7	0/0	6.9	4.2	8.0	18.2	100.0	4.9	10.8
(4) Waggoner-Zha Marginal Data Density (MDD)	-2,950	-2,928	-2,878	-2,882	-2,916	-2,852	-2,925	-3,298	-2,941

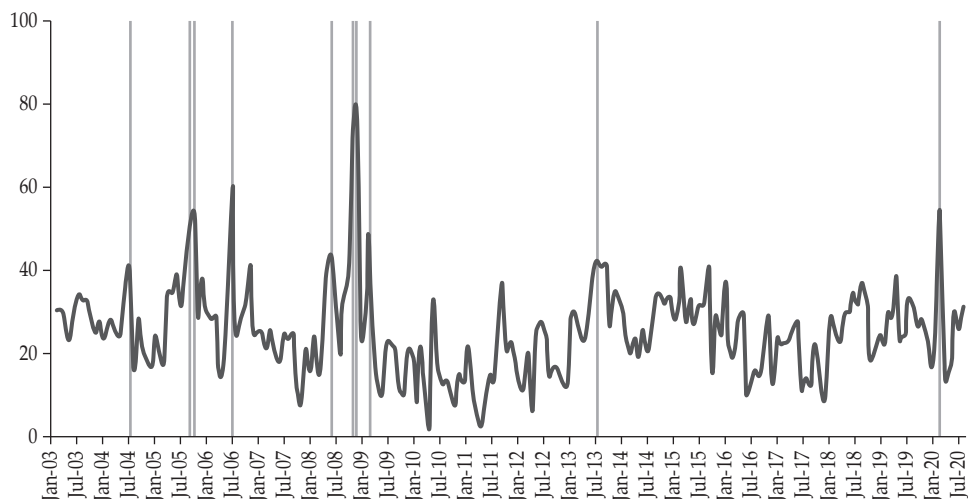
Source: Authors' calculation

Figures 2 and 3 display the high- and low-stress signals issued by the 2s2v1c MSBVAR model, respectively. The model has a good performance, as it can call 90% of the actual high-stress events. That said, not all of the high-stress signals issued by the model imply that the actual high-stress events really took place, as policymakers might have taken measures to prevent such a risk from taking place.

Table 6 shows that the unrestricted model 2s1v2c is the best model compared to 2s1v2c restricted models. While the unrestricted model 2s1v2c do not have the highest MDD value, the overall performance of this model based on the four criteria in our study are better than the restricted models. Therefore, we can use the unrestricted model 2s1v2c both for nowcasting/forecasting purposes and for explaining the episodic relationship between financial stress and Indonesia's macroeconomic condition.

Figure 1.
The FSI and High-stress Events in Indonesia's Financial System

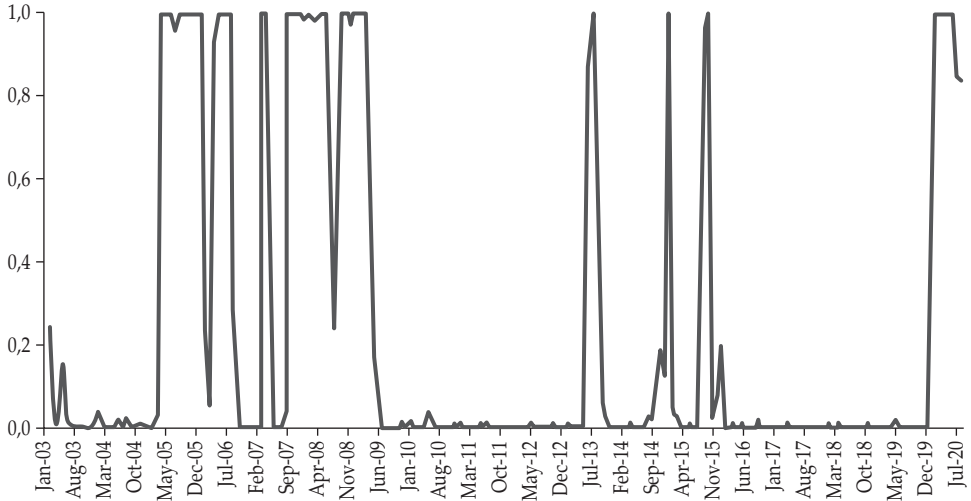
This figure shows the FSI in our study and the actual high-stress events in Indonesia's financial system. The FSI can capture major stress events, including the 2008 GFC and the beginning of the COVID-19 outbreak in Q1-2020.



Source: Authors' calculation

Figure 2.
The Probability of “High-stress Event” Signals Issued by the 2s1v2c MSBVAR Model

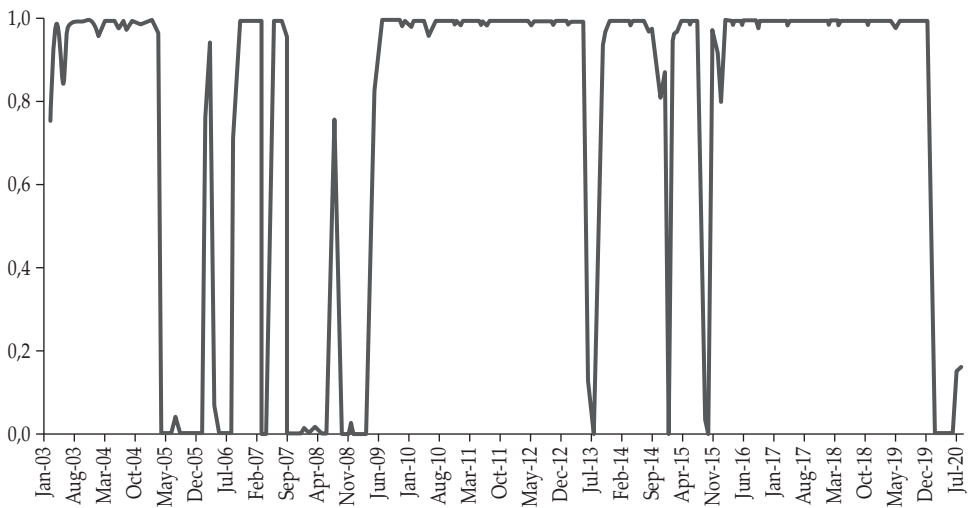
This figure displays the probability of “high-stress event” signals issued by the 2s1v2c MSBVAR model.



Source: Authors' calculation

Figure 3.
The Probability “Low-stress Event” Signals Issued by the 2s1v2c MSBVAR Model

This figure displays the probability of “low-stress event” signals issued by the 2s1v2c MSBVAR model.



Source: Authors' calculation

Table 6.
Performance of the Unrestricted and Restricted 2s1v2c Models

This table displays the performance of the unrestricted and restricted 2s1v2c models. The result shows that the unrestricted model has the best performance compared to the unrestricted models.

	Correctly called actual "high stress" events by "probability of high stress" signals (%)	Ratio of adjusted "probability of high stress" signal to noise (%)	Probability of actual "high stress" event when a "probability high stress event" signal issued (%)	Waggoner-Zha Marginal Data Density (MDD)
FSI	20.0	97.2	3.9	-2,988
FSI PCE	70.0	60.5	4.5	-2,983
FSI CPI	70.0	64.3	4.0	-2,984
FSI MMR	20.0	92.4	4.2	-2,991
FSI M2	20.0	95.6	4.0	-2,993
FSI PCE CPI	20.0	102.0	3.7	-2,997
FSI PCE MMR	20.0	97.2	3.9	-2,996
FSI PCE M2	70.0	59.0	4.7	-2,988
FSI CPI MMR	20.0	95.6	4.0	-2,985
FSI CPI M2	20.0	95.6	4.0	-2,990
FSI MMR M2	70.0	61.2	4.4	-2,991
FSI PCE CPI MMR	0.0	0/0	0/0	-2,984
FSI PCE CPI M2	70.0	60.7	4.5	-2,995
FSI PCE MMR M2	70.0	60.5	4.5	-2,994
FSI CPI MMR M2	70.0	59.5	4.6	-2,997
FSI PCE CPI MMR M2	90.0	19.8	17.0	-3,002
(unrestricted model)				

Source: Authors' calculation

IV. THE EPISODIC RELATIONSHIP BETWEEN FINANCIAL STRESS AND INDONESIA'S MACROECONOMY

A. The FSI and Actual High-Stress Events in Indonesia

Our FSI captures ten actual high-stress events in Indonesia's financial system during 2003 and Q3-2020 (Figure 1).

There was a high-stress event in June 2004, driven by the exchange market and debt market pressures. The high-stress event was related to Indonesia's first direct presidential election on 5 July 2004. The IDR weakened by 4.4% from 8,965 per USD at the end of May 2020 to 9,382 per USD at the end of June 2020, while the BI FX reserves fell from USD 36.5 billion to USD 34.9 billion. During the same period, the yield of Indonesia's 5-year SUN rose by 20 basis points (bps) from 11.4% to 11.6%. The JCI fell only marginally from 733 to 732, and the stock market was less volatile. The banking sector stress coefficient was well below 1.0, which is considered low stress. As the presidential election ran smoothly, pressures on Indonesia's financial system gradually receded in July 2004. Although a second-

round election on 20 September 2004 was needed to determine the winner, there was no spike in the FSI.

In August and September 2005, the government budget was under pressure due to the rising oil prices that led to capital outflows amid concerns about inflation risk. These outflows primarily came from the bond market, which caused a sharp depreciation in the IDR (known as the "IDR mini-crisis"). The IDR weakened from 9,799 per USD at the end of July 2005 to 10,233 per USD at the end of September 2005, while the BI FX reserves fell from USD 32.2 billion to USD 30.3 billion. During the same period, the yield of the 5-year SUN spiked by 300 bps to 14.7%, while the JCI fell by almost 9%. The banking sector stress coefficient was at 1.172, where a coefficient value higher than 1.0 is an indication of a risky condition for the banking sector. The IDR gradually strengthened, and the SUN yields fell in October 2005 as oil prices declined.

In June 2006, Indonesia's financial markets were under high stress amid concern among market participants about the country's spiking inflation due to rising food prices. The main driver of the high stress was the exchange market pressures due to capital outflows. The IDR weakened from 8,985 per USD at the end of May 2006 to 9,363 at the end of June 2020. BI heavily intervened in the FX market to defend the IDR, causing the BI FX reserves to fall from USD 44.3 billion to USD 40.1 billion in June 2006 alone. During the same period, the JCI fell marginally from 1,330 to 1,310, while the yield of Indonesia's 5-year SUN slightly rose from 12.1% to 12.3%. The banking sector coefficient was at 1.423, which indicated that the banking sector was at high risk. The pressures on Indonesia's financial markets gradually receded from July 2006 as the inflation pressures gradually eased.

There were high financial stress events related to the 2008 GFC and the 2009 global recessions; these events took place in May 2008, October 2008, November 2008, and February 2009. The events were caused by pressures in the FX market, the bond market, and the stock markets. The banking sector was relatively safe during these events, except in May 2008 when the banking stress coefficient was at 1.119. The financial stress gradually receded in March 2009, as many countries, particularly major economies, launched economic stimulus packages to revive their economies and created positive spillovers to the global economy.

A high financial stress event occurred in July 2013 caused by pressures in the FX market, the bond market, the stock market, and the banking sector. These pressures were triggered by concern from financial market participants about the risk of rising inflation due to subsidized fuel price hikes in June 2013. The IDR weakened from 9,882 per USD at the end of June 2013 to 10,073 at the end of July 2013, while the FX reserves dropped from USD 98.1 billion to USD 92.7 billion due to BI's heavy intervention in the FX market. The yield of the 5-year SUN spiked by 102 bps to 7.3%, while the JCI fell by 4.5%. The banking sector stress coefficient was at 1.193, indicating a risky situation for the banking sector. The pressures on Indonesia's financial market receded in Q3-2013 as inflation gradually decreased.

The outbreak of the COVID-19 pandemic in Indonesia put high stress on Indonesia's financial market. The pandemic triggered capital outflows from Indonesia's stock and bond markets and caused the IDR to depreciate sharply in March 2020. IDR underwent rapid depreciation from 14,318 per USD at the end of February 2020 to 16,310 per USD at the end of March. During the same period,

the yield of the 5-year SUN rose by 112 bps to 7.2%, while the JCI fell by 20%. Nonetheless, the banking sector coefficient was well below 1.0, indicating that the banking system was safe. Pressures on Indonesia's financial market receded in April 2020, as the condition of the global financial markets improved, and the Indonesian government announced the fiscal policy package on 31 March 2020.

B. Financial Stress and Its Episodic Relationship with Indonesia's Macroeconomy

We use our MSBVAR model to investigate three important aspects of the episodic relationship between the financial stress and Indonesia's key macroeconomic variables: (1) whether there are different relationship dynamics during the high-stress period and the normal times; (2) whether the regime-switching is confined to the coefficient switching (which implies the behavior change of economic agents and/or changes in the environment that the agents face) or variance switching (which implies that the financial stress does not alter agents' behavior); and (3) whether the regime-switching is confined to a specific variable equation in the model (which implies that the sole variable is responsible for the regime-switching) or all variables in the models (which implies that all variables in the model are responsible for the switching).

Figures 2 and 3 (see again Section III) display the probability of regime-switching from the low stress to high-stress events and vice versa, where actual regime-switching took place at some points in time. The regimes changed several times within the period of this study, including during the 2008 GFC and the beginning of the COVID-19 pandemic in Q1-2020. It implies that there is indeed different nature of relationships between financial stress and Indonesia's macroeconomic variables.

Our model shows that the high-stress period during the COVID-19 pandemic seems to be shorter than that of the 2008 GFC. While one can argue that the shorter high period of high stress is because our data ends in Q3-2020, Indonesia's financial markets quickly rebounded from late March 2020 when advanced economies' financial markets rebound and after government announce policy packages to restore the economy (Sugandi, 2021). Indonesia's bank credit growth slowed in Q2-2020 and Q3-2020 (Otoritas Jasa Keuangan, 2021), but there was no banking crisis. The COVID-19 pandemic has limited impacts on Indonesia's economy and financial system than the 2008 GFC.

The selected model 2s1v2c in our study shows that there is only one state of the variance (thus, no variance switching) and two states of the coefficients. The switching between the two states of the coefficient indicates economic agents have different behavior in the high financial stress period compared to in the low-stress period. The regime changes are confined to all variables in model 2s1v2c. It implies that the FSI, the real sector variables (PCE and CPI), the financial sector variable (MMR), and monetary policy (M2) variables all change when there is a regime switch in the financial system.

In Appendix, Section A.1. displays variance decomposition ergodic of the variables in model 2s1v2c, which shows the influence of each variable on a variable's dynamics. The FSI is almost entirely affected by its own past values. The PCE is affected mostly by its own past values and to a lesser extent by M2

past values. The CPI is influenced mostly by its own past values and to a lesser extent by M2 past values. The MMR is influenced mostly by its own past values and to a lesser extent by FSI past values. The M2 is influenced mostly by its own past value and to a lesser extent by the PCE past values. The outputs show that the high stress in the financial sector will have a substantial impact on the interbank money market rates, where the shock is transmitted by the banking system to the real sector of the economy.

In Appendix Section A.2, depicts the impulse responses ergodic of each variable in model 2s1v2c to a shock in a variable in the model. Figures A2.1 in Appendix 2 shows that a shock in the FSI increases household consumption and consumer price index in the short run. It implies that high stress in the financial system can prompt households to increase their spending due to panic buying, which causes inflation to increase. The FSI shock increases the interbank money market rates in the short run, as banks seek to secure the liquidity to meet cash withdrawal from their customers. Higher demand for cash from banks and households in the short run can dwindle the M2 liquidity in the banking system before the central bank increase the M2 supply.

Then, in Appendix, Section A.III shows the stability of MSBVAR forecasts by model 2s1v2c. The forecasts are not explosive and lie within the upper and lower bound. Hence the model is suitable for forecasting purposes.

The findings from our study imply that BI needs to issue different policies to address different conditions in the financial system. There is a higher risk of macroeconomic crisis when the financial system is under the high-stress regime than under the low-stress regime. Under the high-stress financial regime, monetary policies should be directed to financial system stabilization. For example, BI can increase M2 supply when there is a liquidity shortage in the financial system (as reflected by the rising MMR) and the banking system in the short run due to high stress in the financial system. Under the low-stress regime, BI can return from financial stabilization policies to normal policies, e.g., by reducing the M2 supply.

V. CONCLUSION

Our MSBVAR model performs well for the nowcasting/forecasting purpose. It can also explain the episodic types of relationships among Indonesia's key macroeconomic variables under different financial sector regimes. The relationship among these variables changes when the financial sector regime changes from the low-stress to the high-stress regime, and *vice versa*. The regime changes affect all variables in the model and cause economic agents in Indonesia's economy to change behavior.

The policy implication of our findings is that Bank Indonesia—Indonesia's central bank— needs to prepare different monetary policies to deal with different conditions of the financial system. Policies directed for financial system stabilization should be used during the high-stress regime, while “normal” policies can be implemented under the low-stress regime.

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Funding

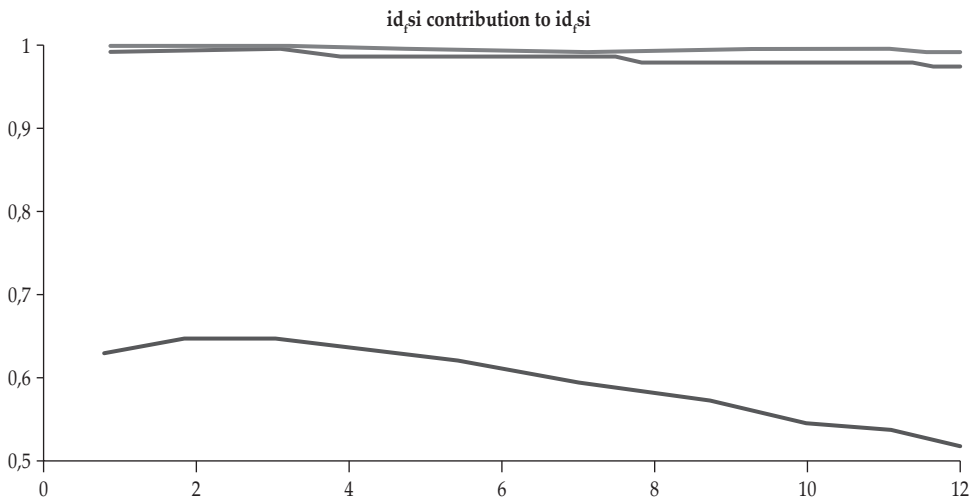
The authors received funds from The Ministry of Research, Technology and Higher Education of The Republic of Indonesia No. NKB-1756/UN2.R3.1/HKP.05.00/2019.

APPENDIX.

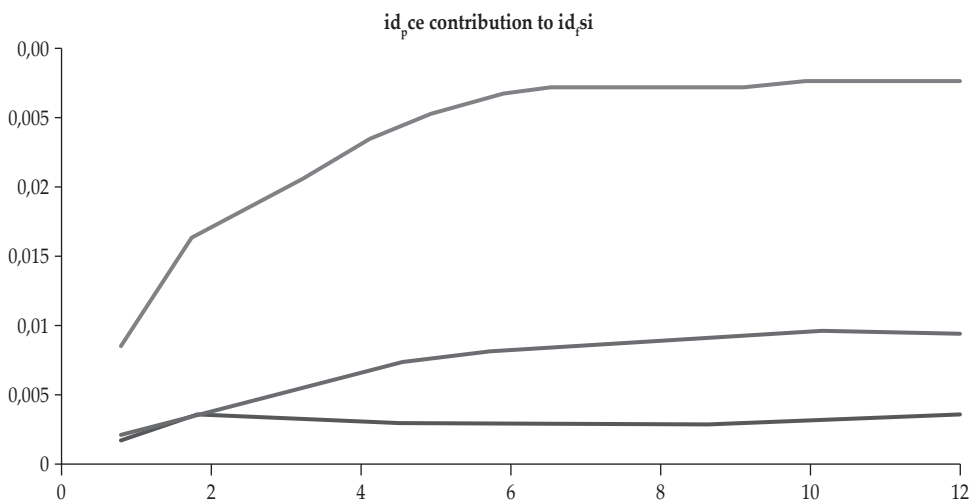
A.I. Variance Decomposition Ergodic

This section displays the variance decomposition ergodic of variables in Model 2s1v2c. The orange line in each graph is the estimate, while the yellow and the blue lines are the upper and the lower bounds, respectively.

Figure A.1.
Contributors to FSI Variance

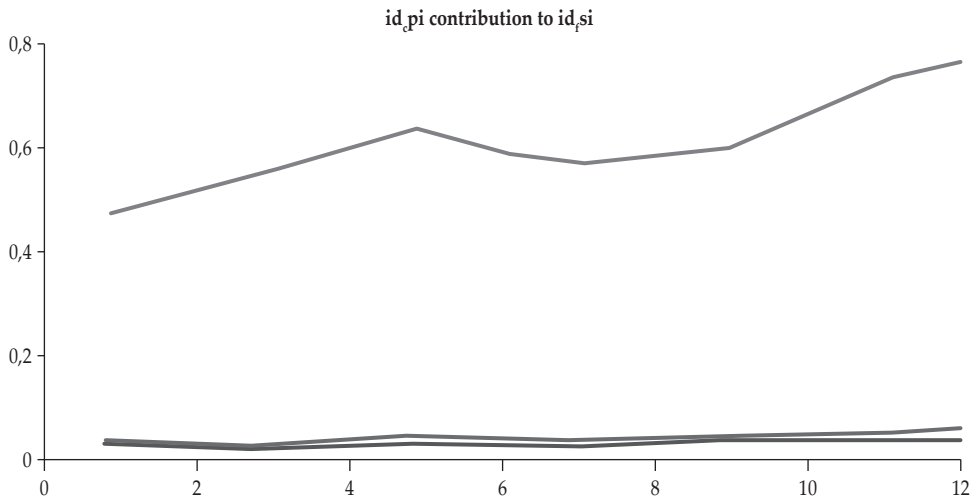


Source: Authors' calculation

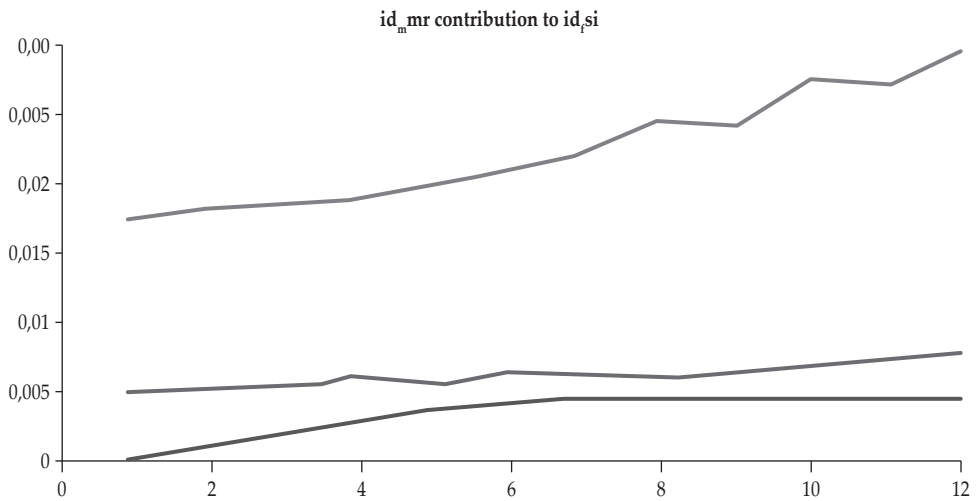


Source: Authors' calculation

Figure A.1.
Contributors to FSI Variance (Continued)

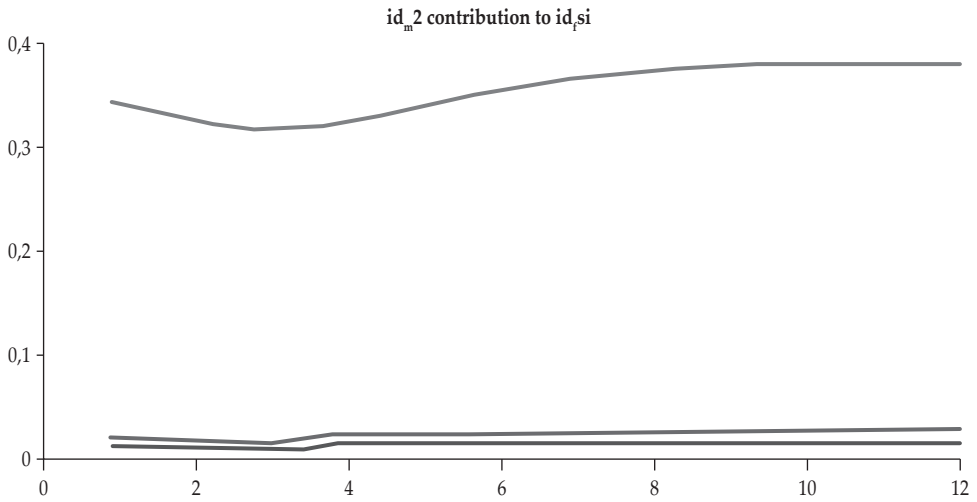


Source: Authors' calculation



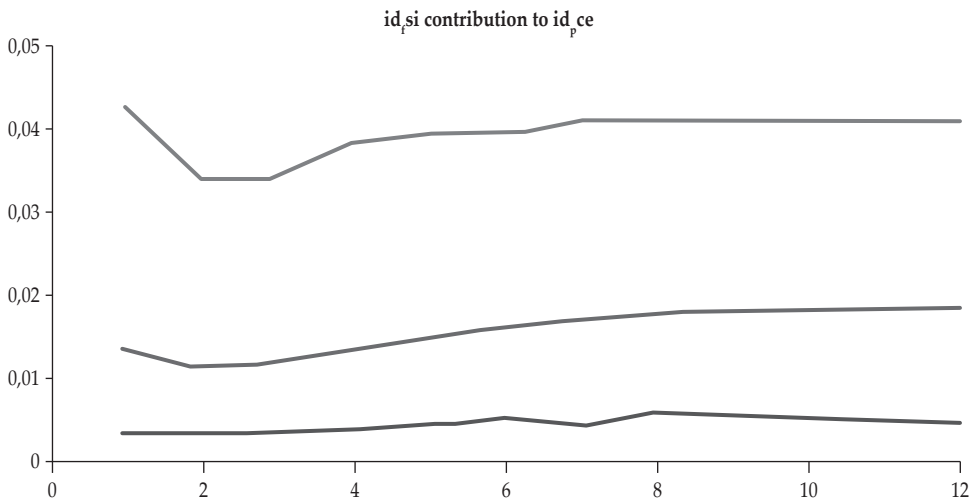
Source: Authors' calculation

Figure A.1.
Contributors to FSI Variance (Continued)



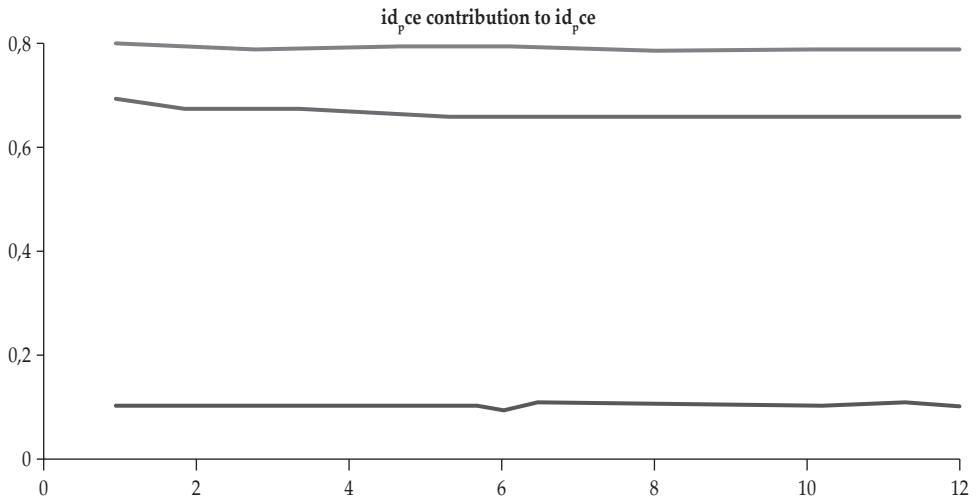
Source: Authors' calculation

Figure A.2.
Contributors to PCE Variance

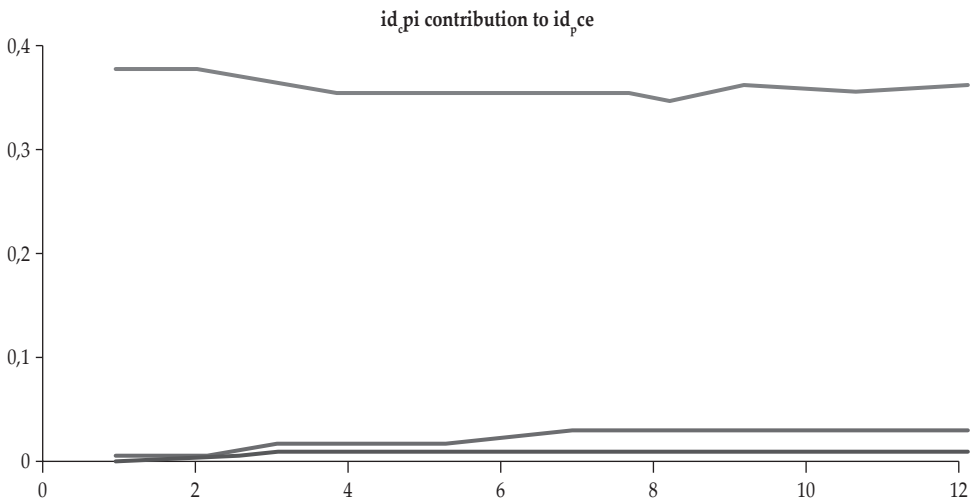


Source: Authors' calculation

Figure A.2.
Contributors to PCE Variance (Continued)

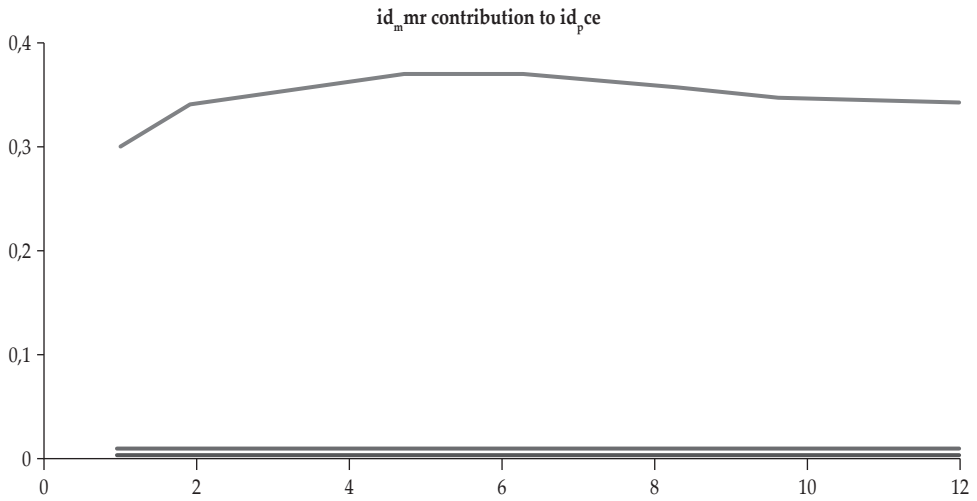


Source: Authors' calculation

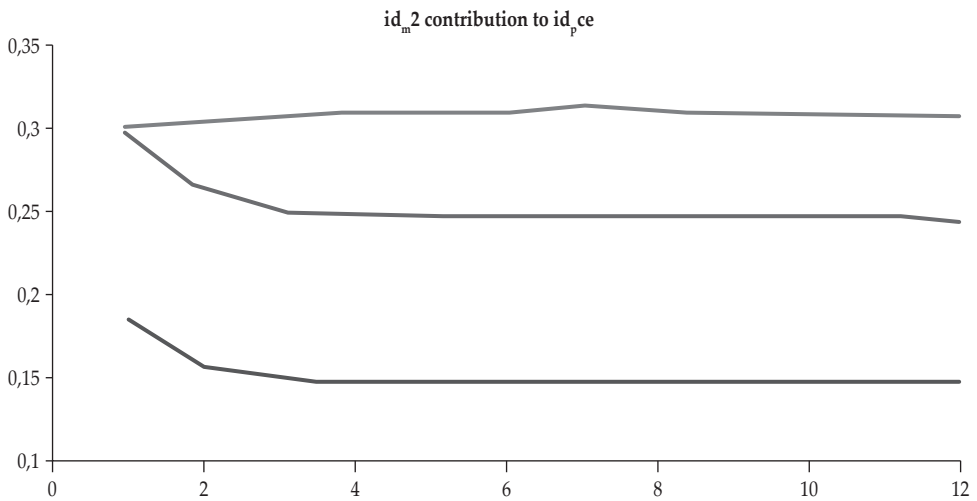


Source: Authors' calculation

Figure A.2.
Contributors to PCE Variance (Continued)

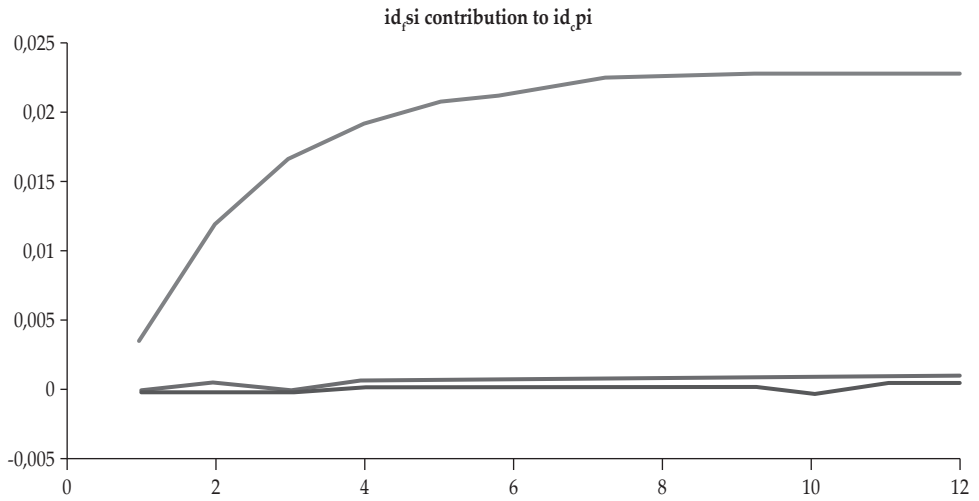


Source: Authors' calculation

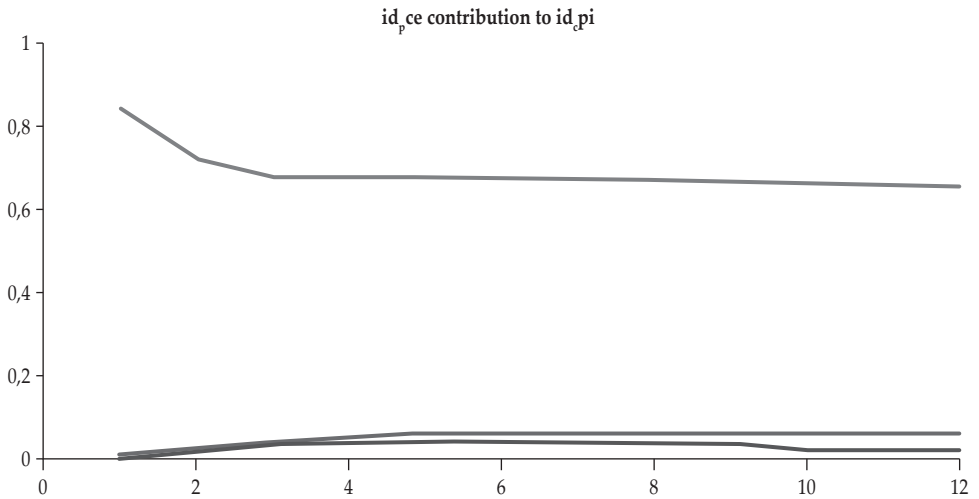


Source: Authors' calculation

Figure A.3.
Contributors to CPI Variance

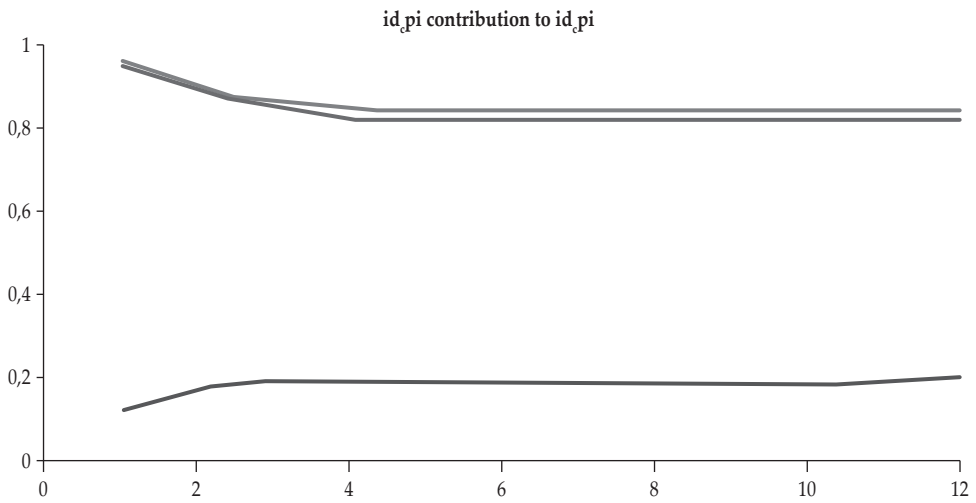


Source: Authors' calculation

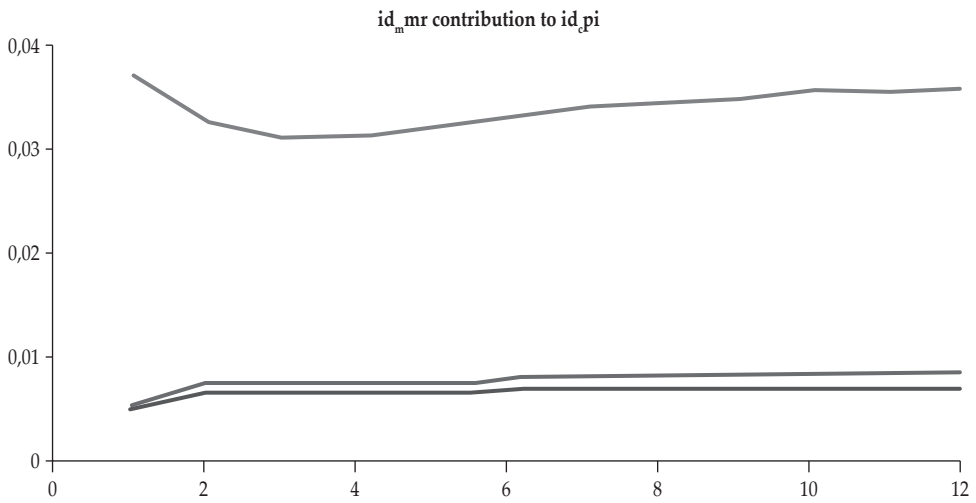


Source: Authors' calculation

Figure A.3.
Contributors to CPI Variance (Continued)

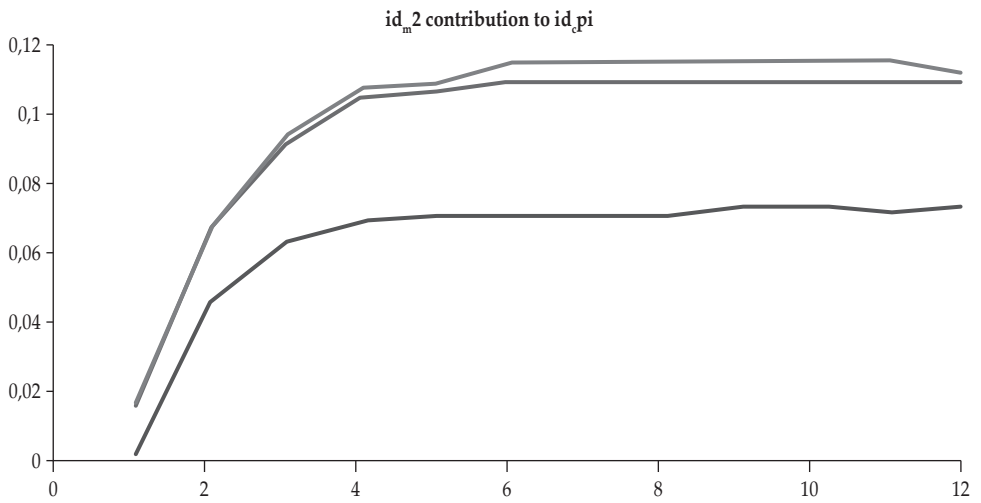


Source: Authors' calculation



Source: Authors' calculation

Figure A.3.
Contributors to CPI Variance (Continued)



Source: Authors' calculation

Figure A.4.
Contributors to MMR Variance

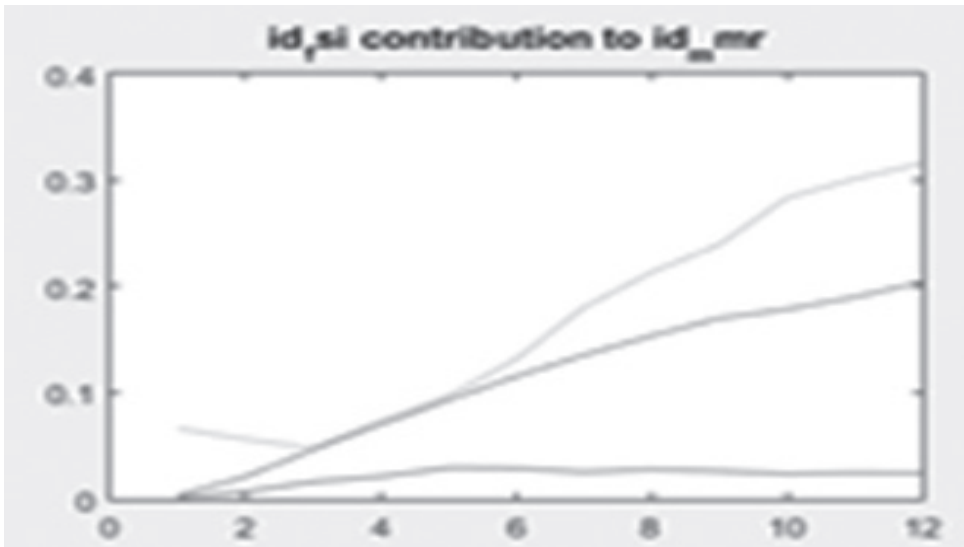


Figure A.4.
Contributors to MMR Variance (Continued)

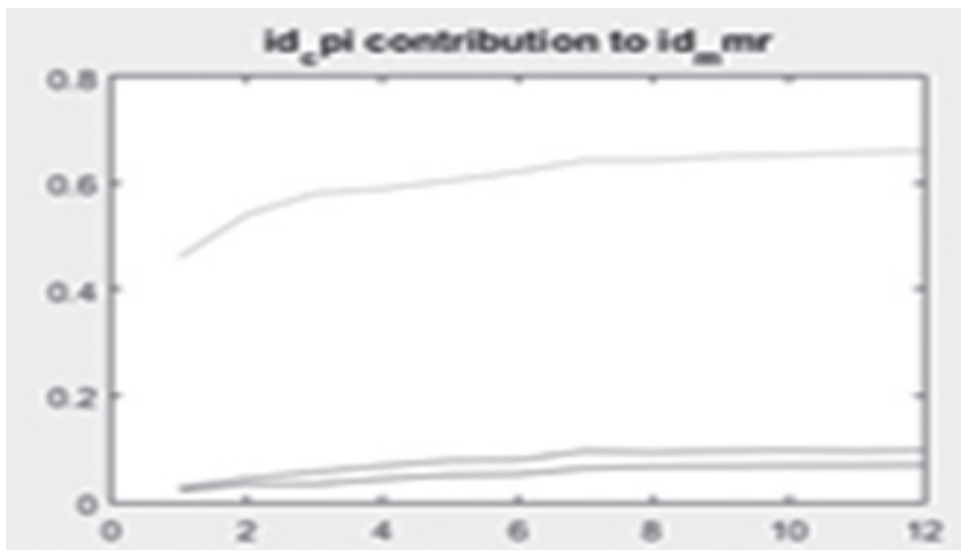
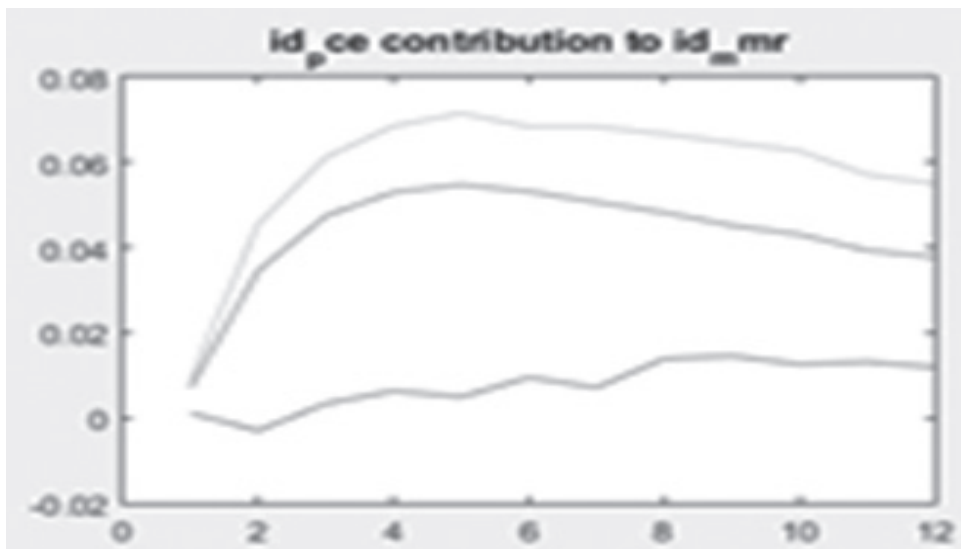


Figure A.4.
Contributors to MMR Variance (Continued)

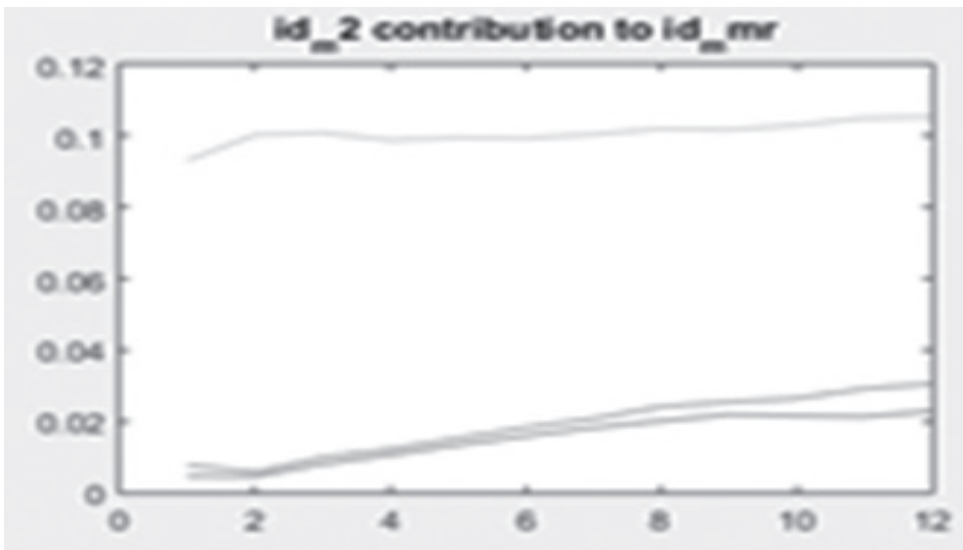
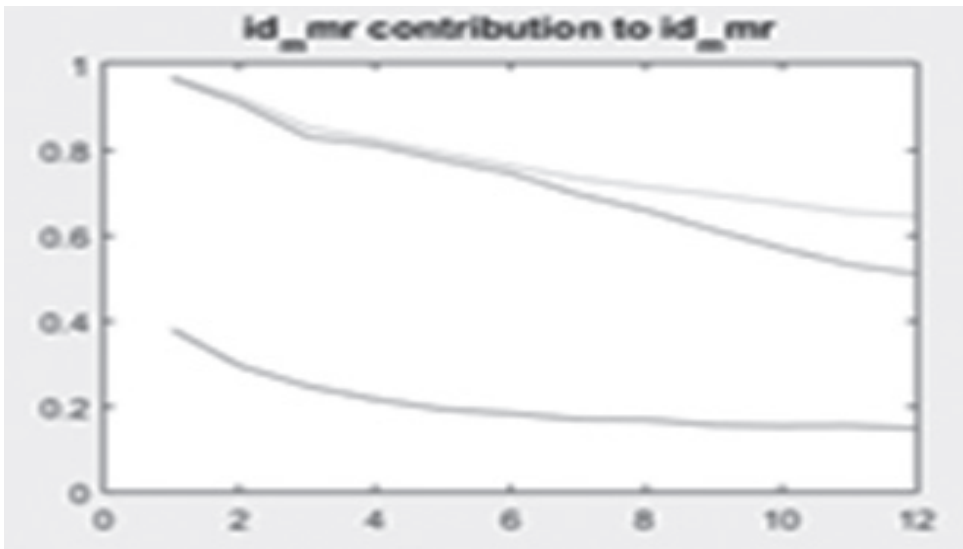


Figure A.5.
Contributors to M2 Variance

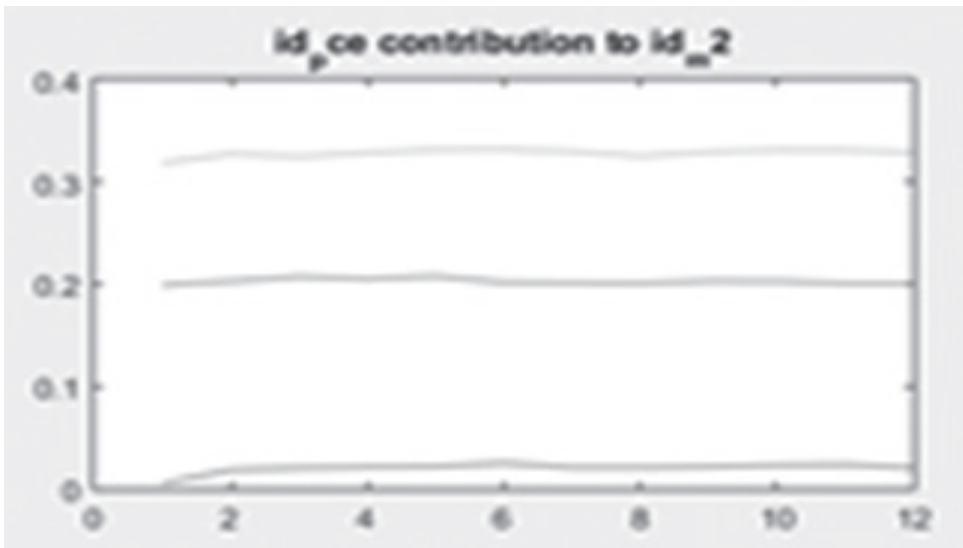
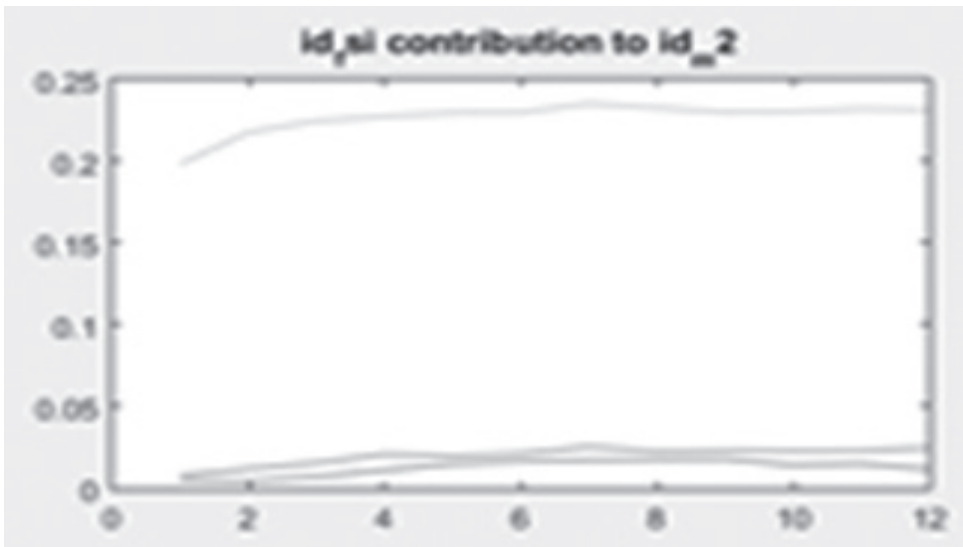


Figure A.5.
Contributors to M2 Variance (Continued)

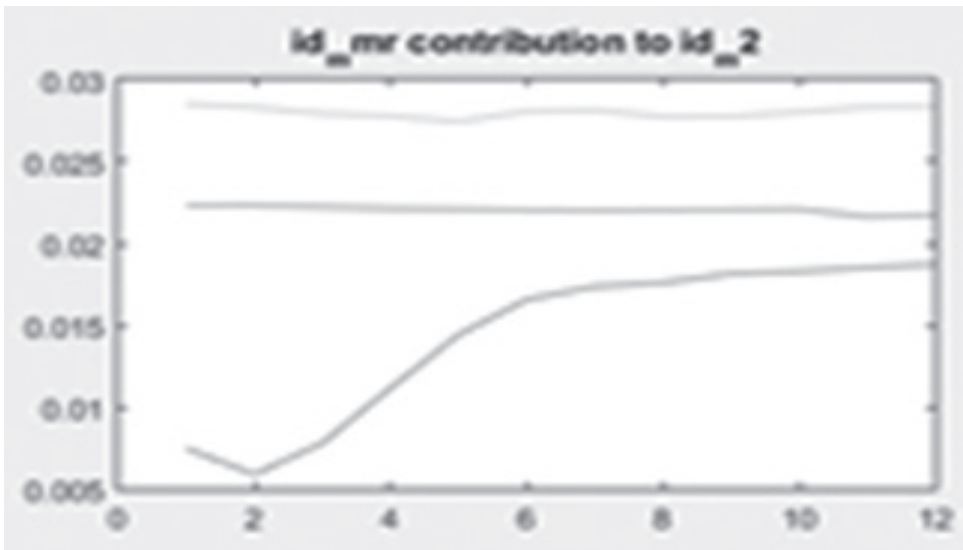
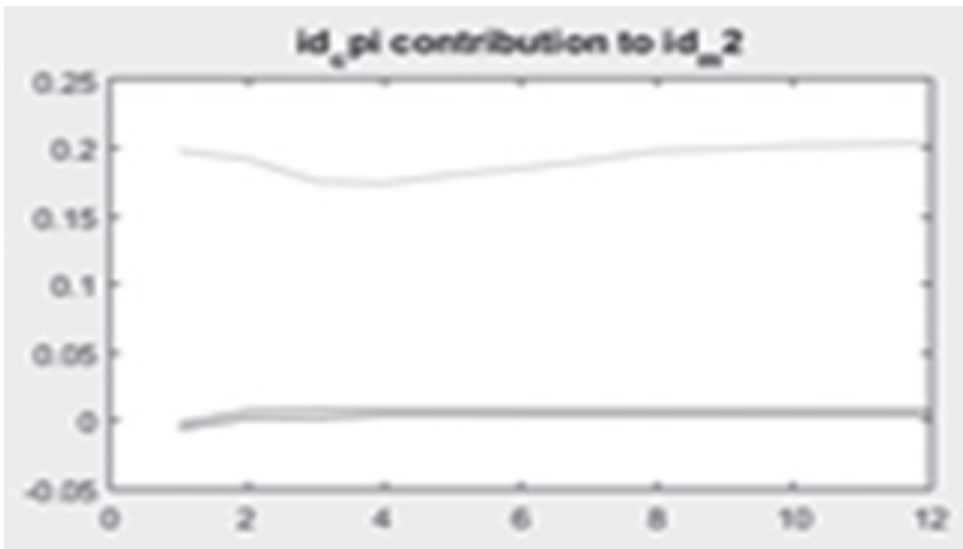
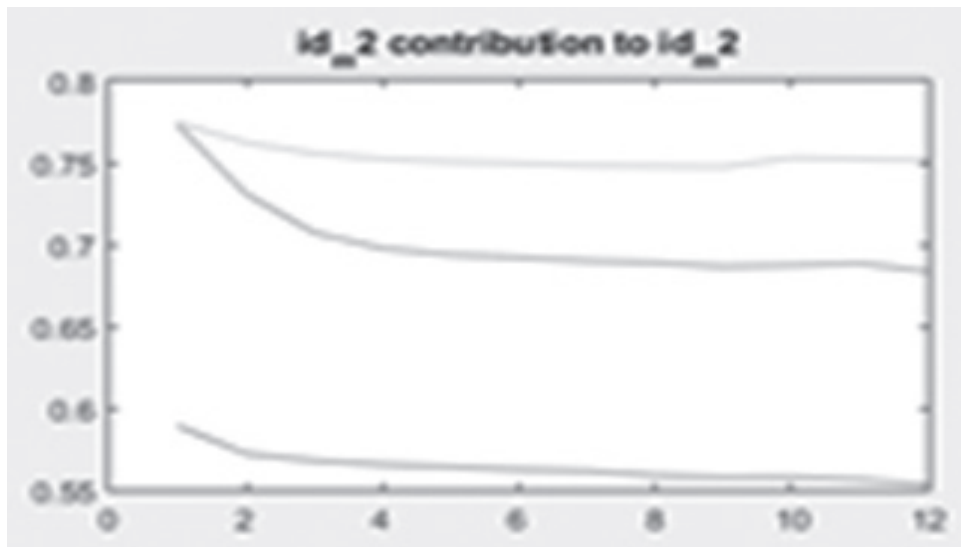


Figure A.5.
Contributors to M2 Variance (Continued)



A.II. Impulse Responses Ergodic

This section displays the impulse response ergodic of variables to a shock in a particular variable in Model 2s1v2c. The orange line in each graph is the estimate, while the yellow and the blue lines are the upper and the lower bounds, respectively.

Figure A.6.
Impulse Responses to Shock from FSI

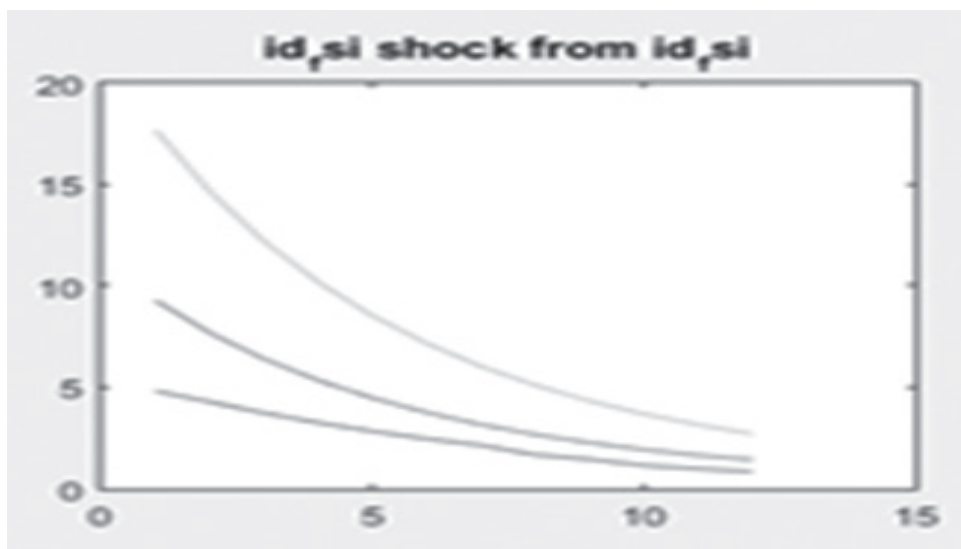


Figure A.6.
Impulse Responses to Shock from FSI (Continued)

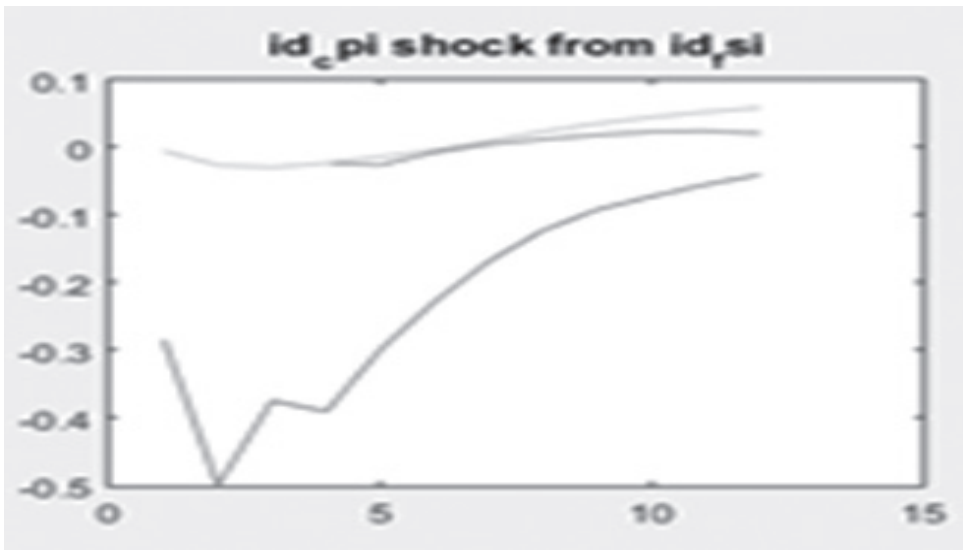
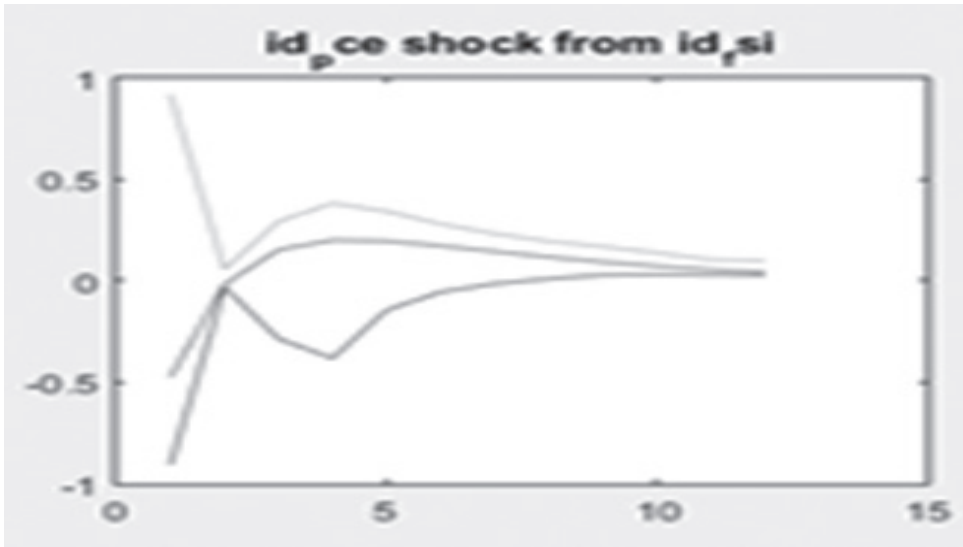


Figure A.6.
Impulse Responses to Shock from FSI (Continued)

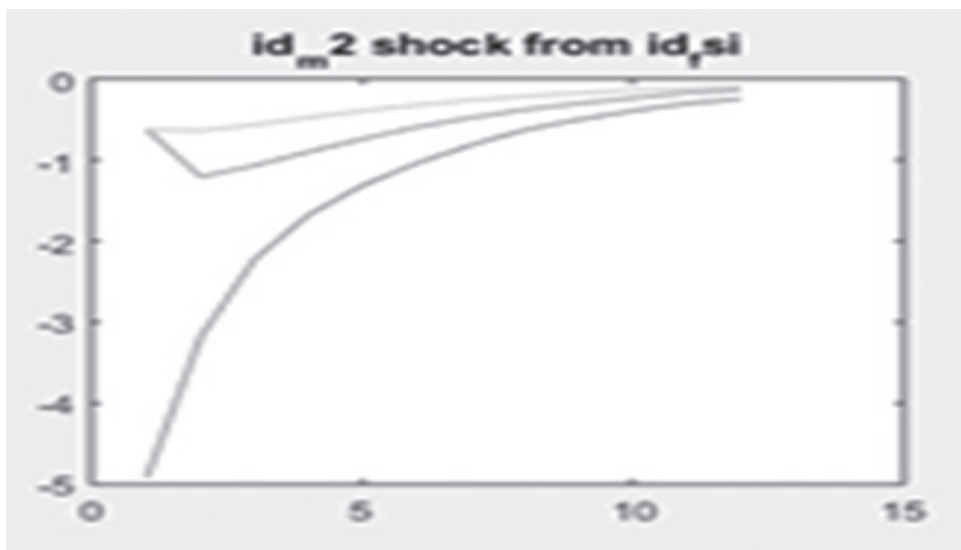
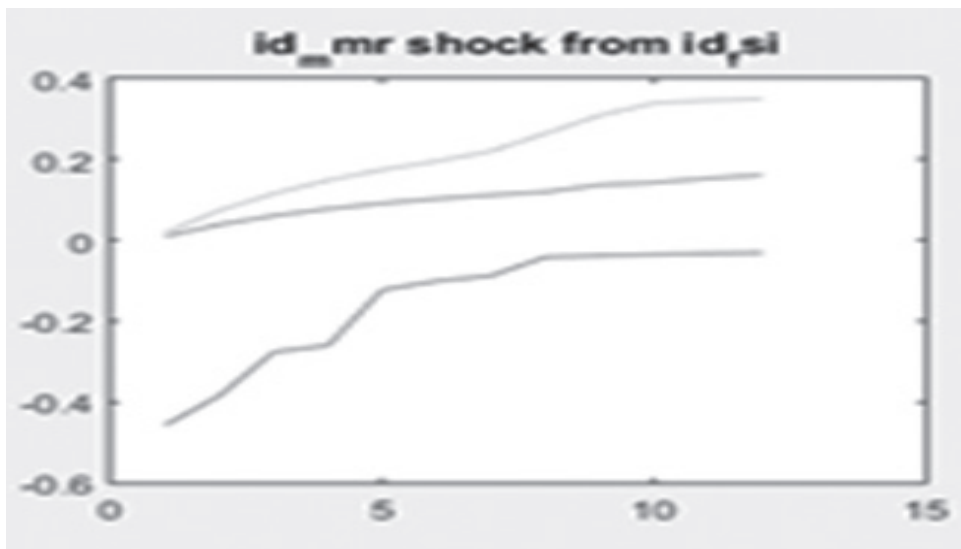


Figure A.7.
Impulse Responses to Shock from PCE

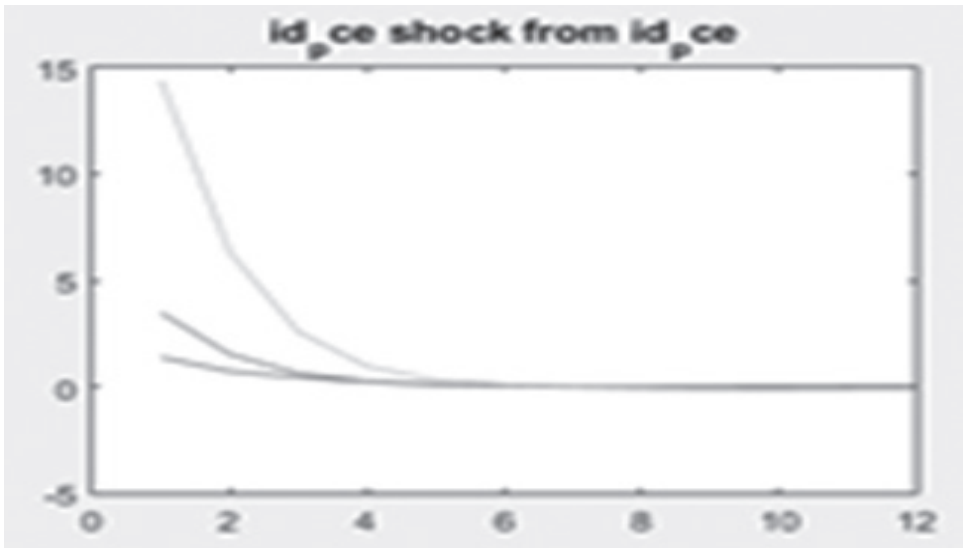
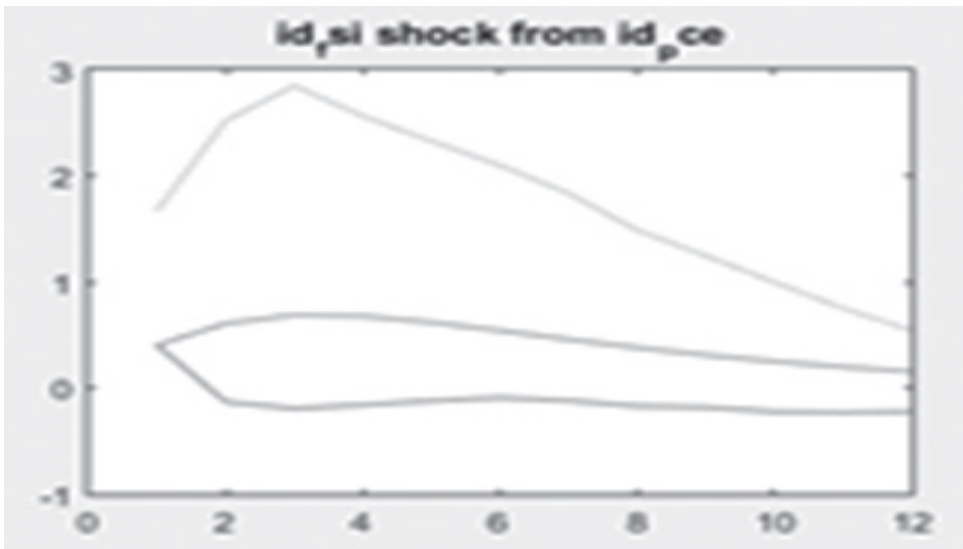


Figure A.7.
Impulse Responses to Shock from PCE (Continued)

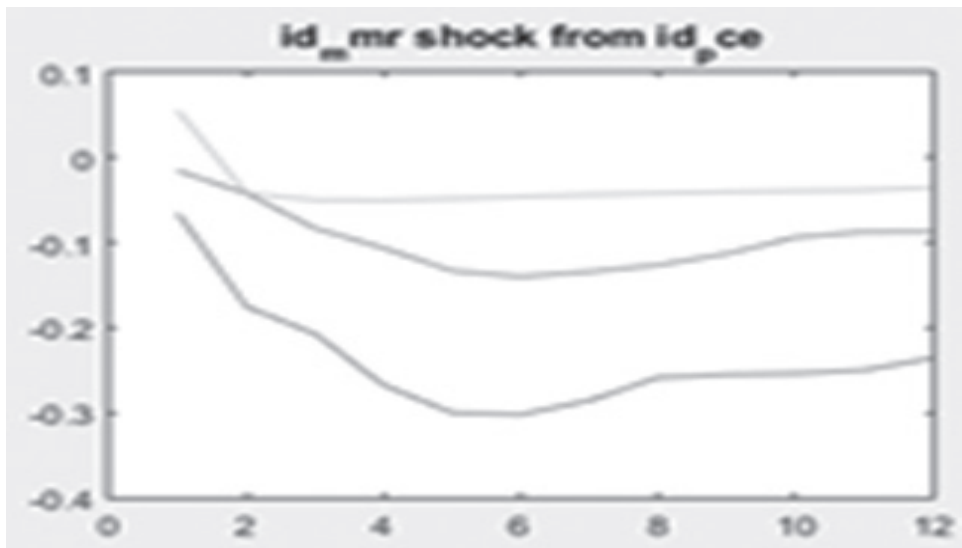
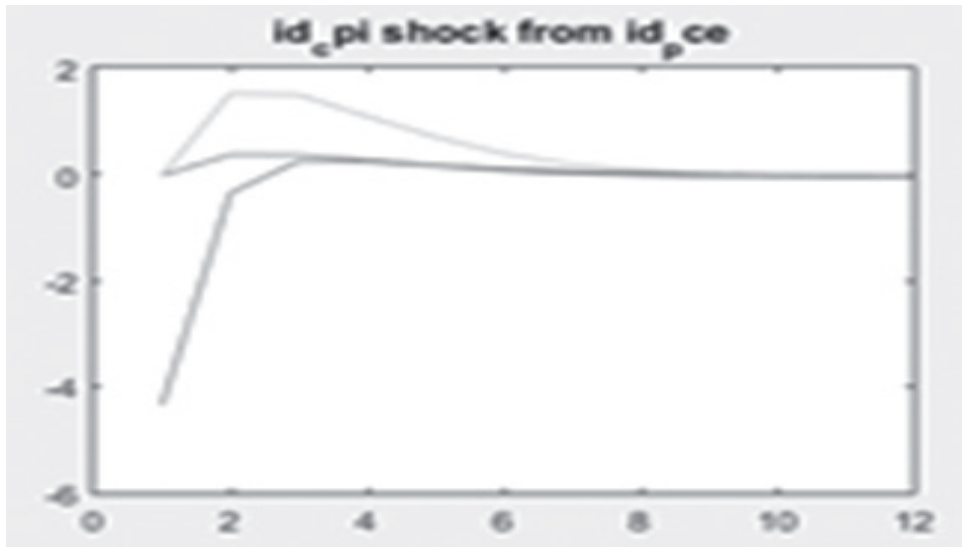


Figure A.7.
Impulse Responses to Shock from PCE (Continued)

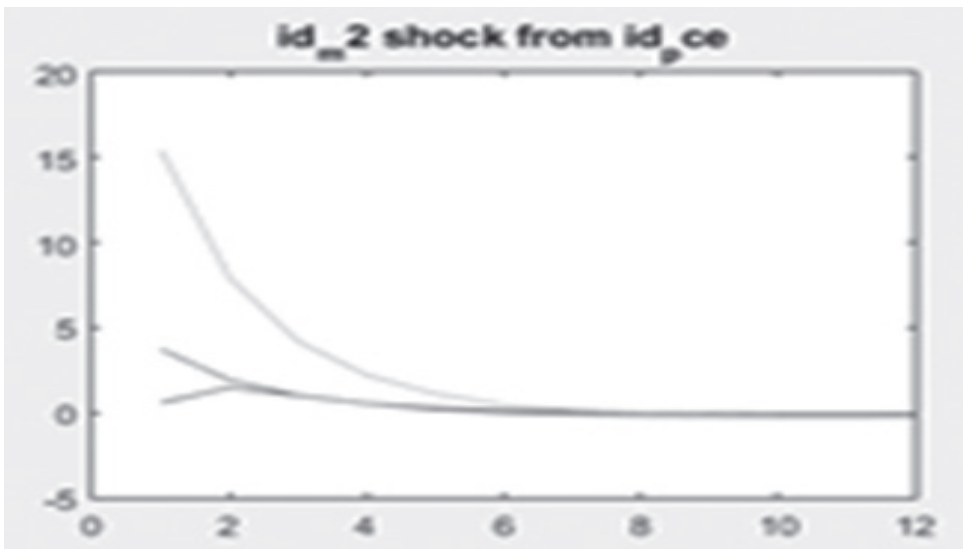


Figure A.8.
Impulse Responses to Shock from CPI

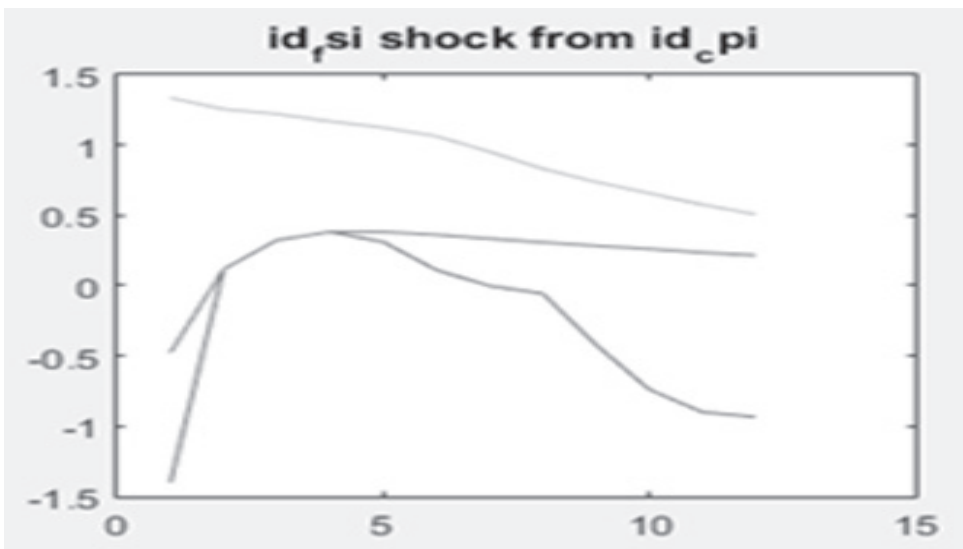


Figure A.8.
Impulse Responses to Shock from CPI (Continued)

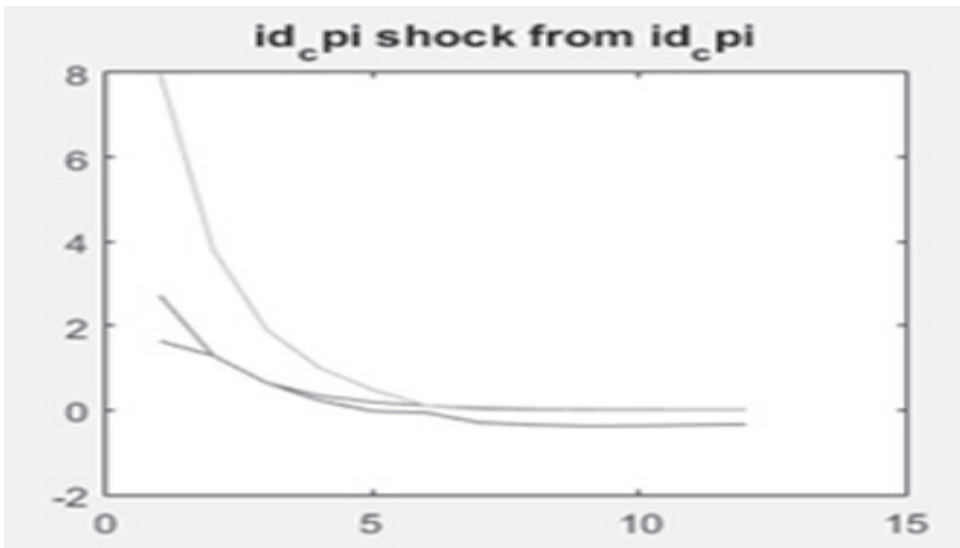
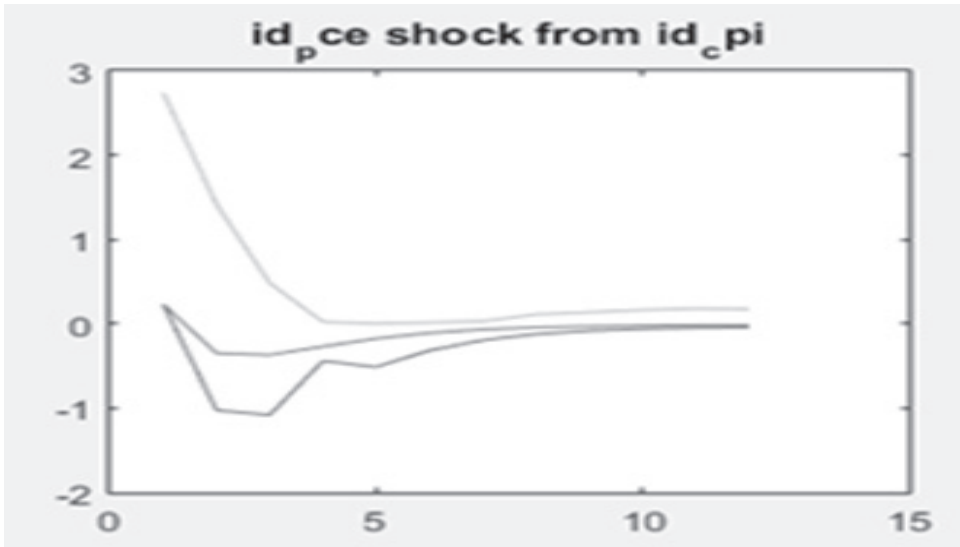


Figure A.8.
Impulse Responses to Shock from CPI (Continued)

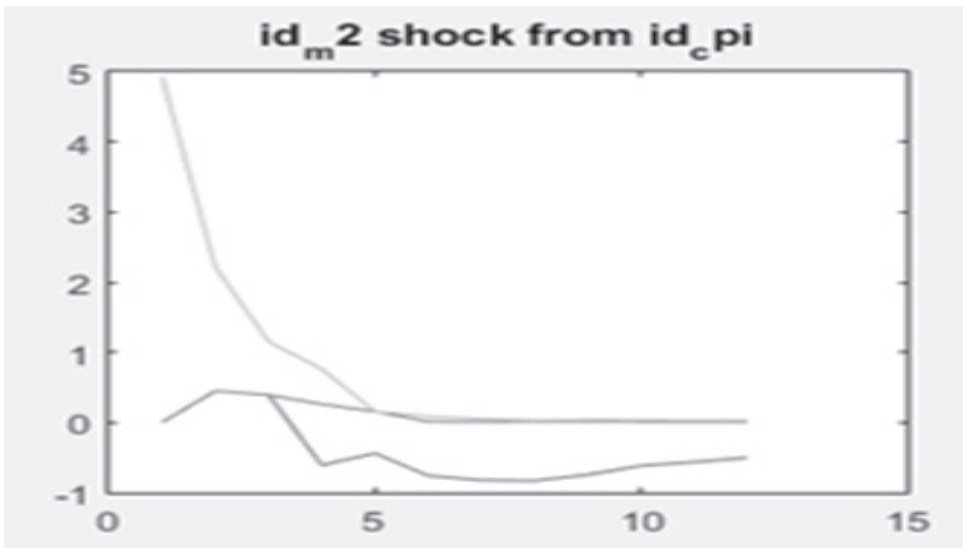
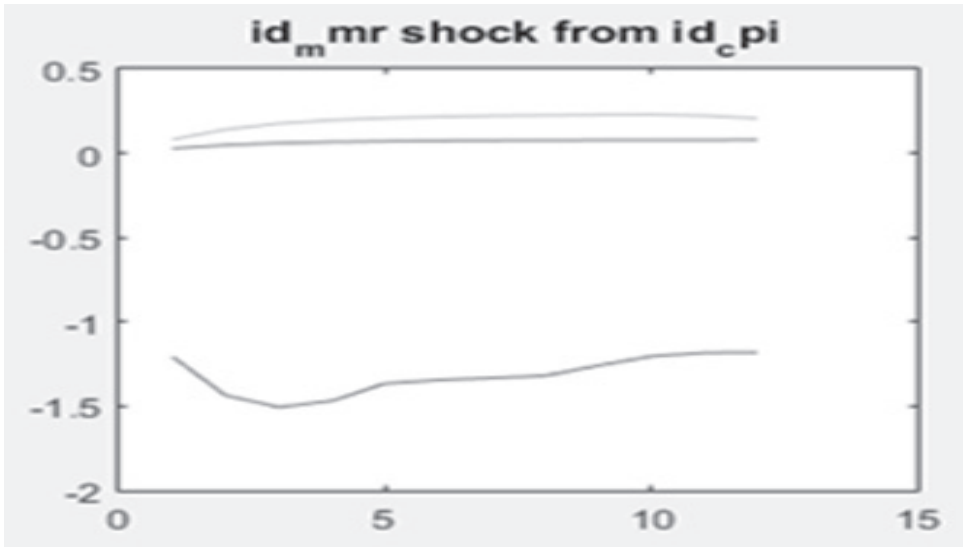


Figure A.9.
Impulse Responses to Shock from MMR

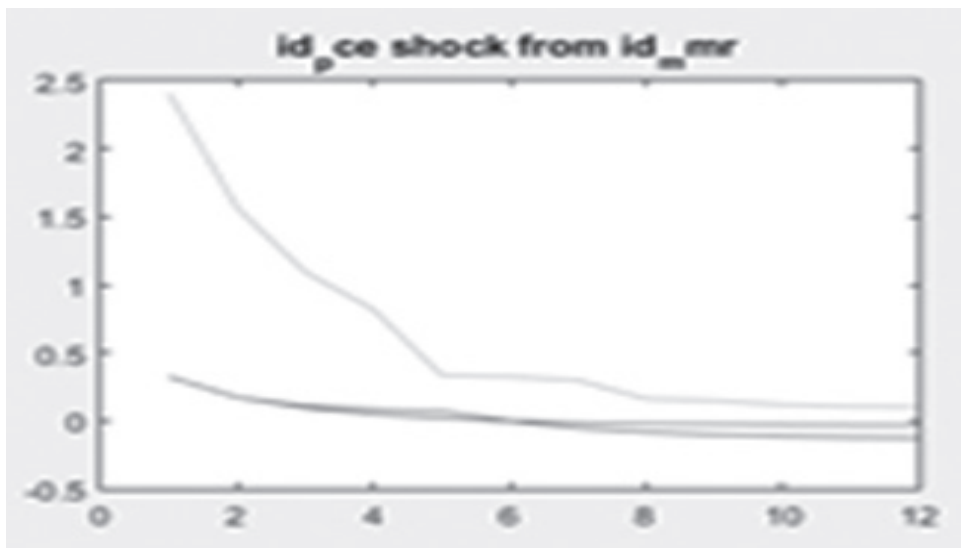
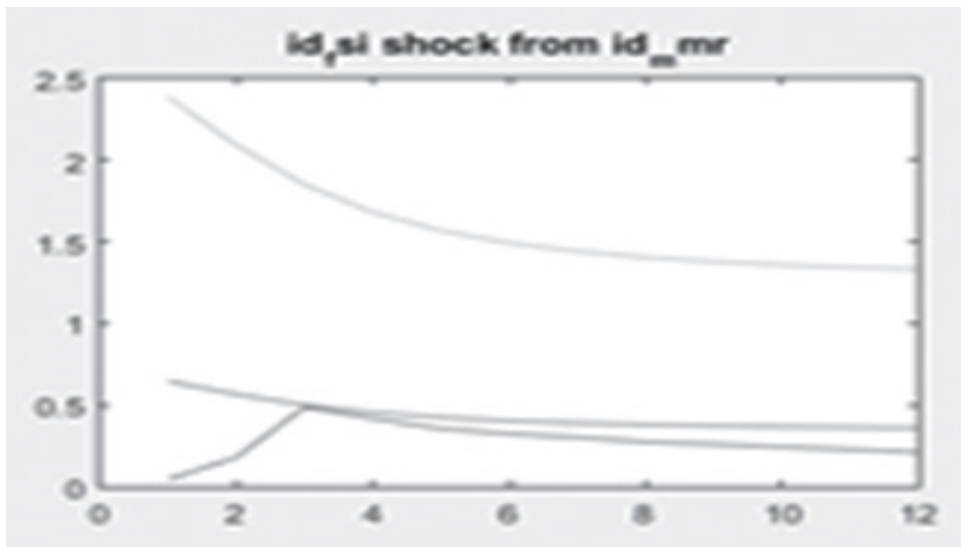


Figure A.9.
Impulse Responses to Shock from MMR (Continued)

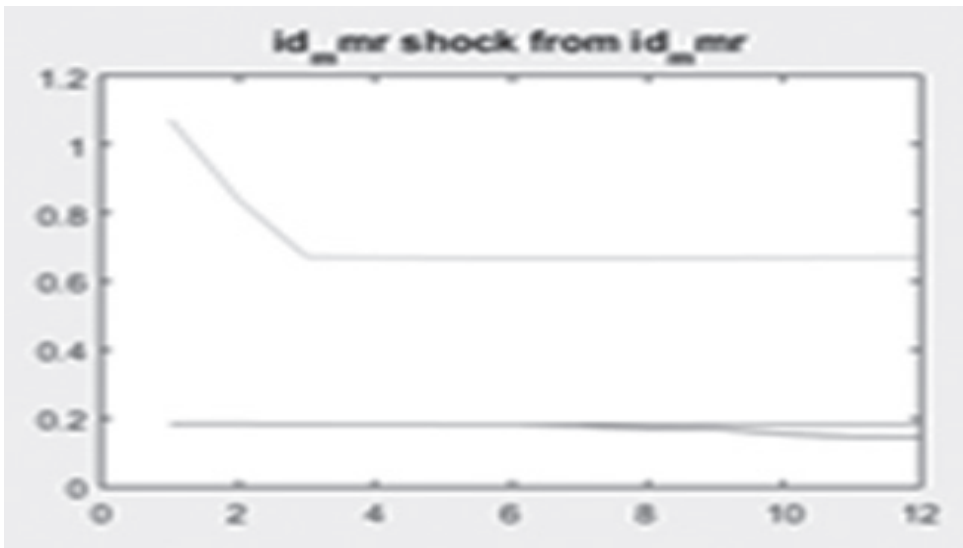
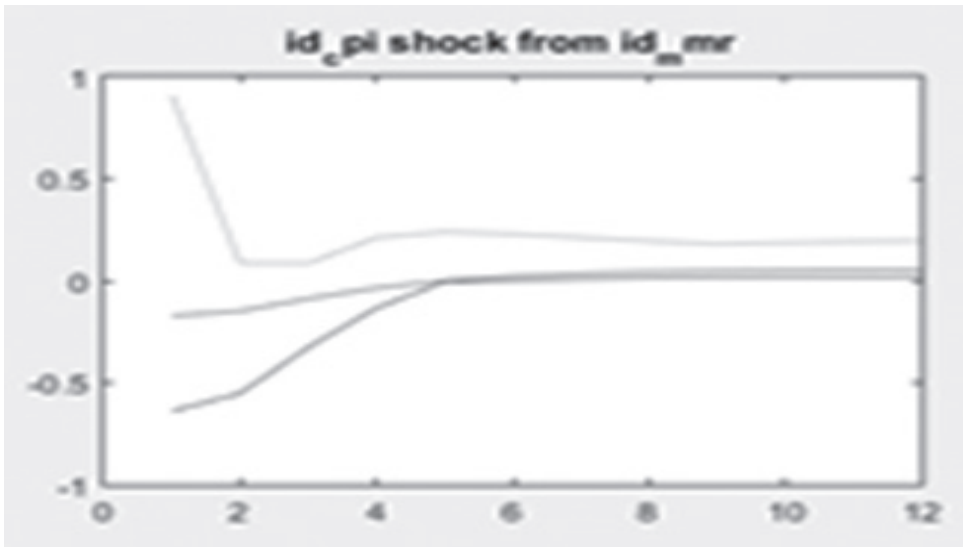


Figure A.9.
Impulse Responses to Shock from MMR (Continued)

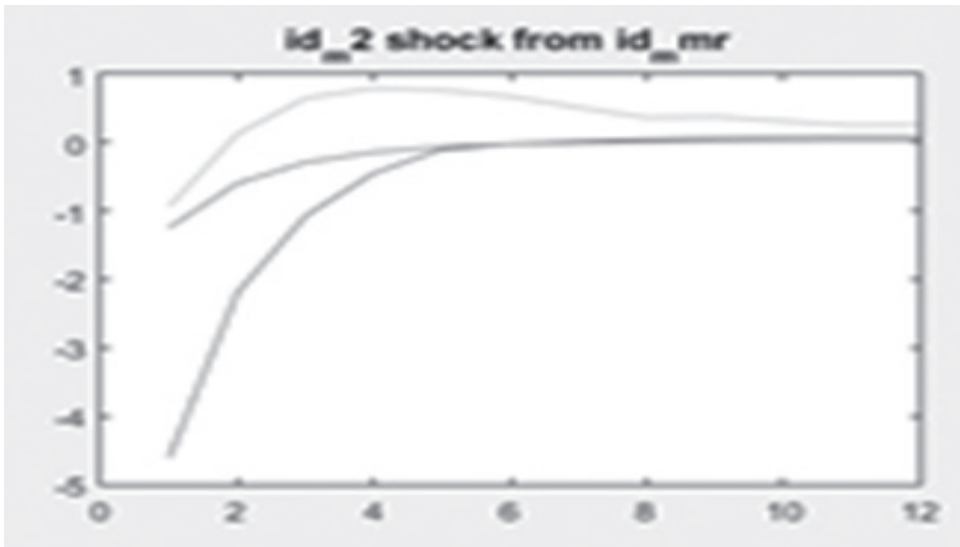


Figure A.10.
Impulse Responses to Shock from M2

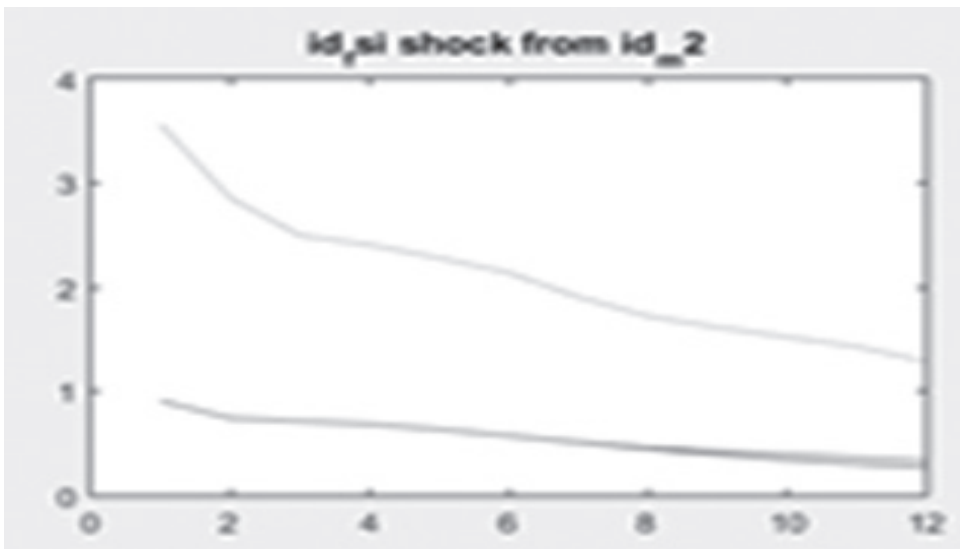


Figure A.10.
Impulse Responses to Shock from M2 (Continued)

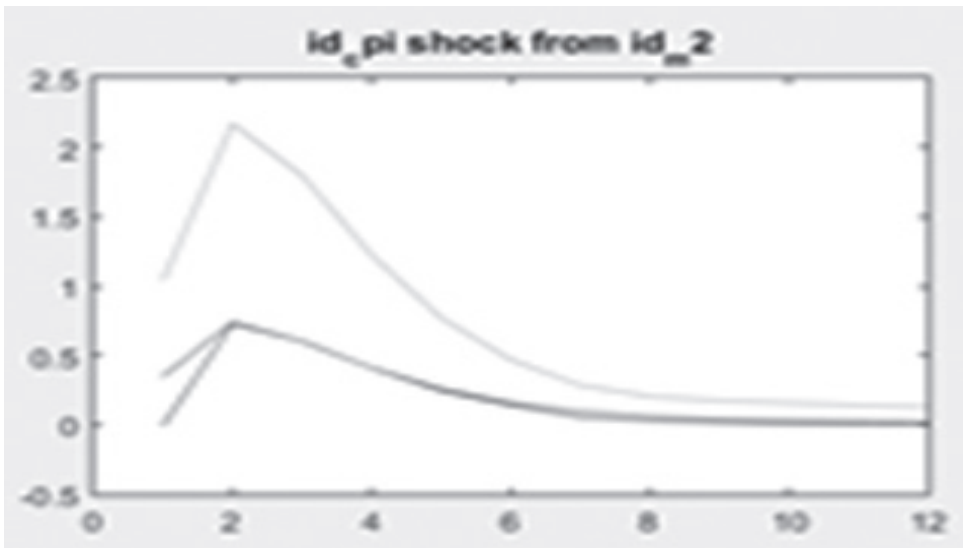
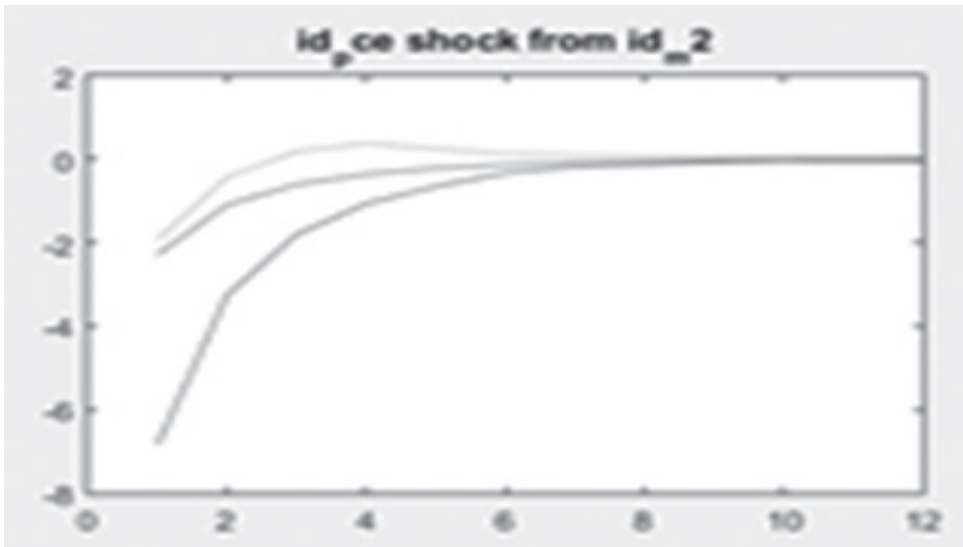
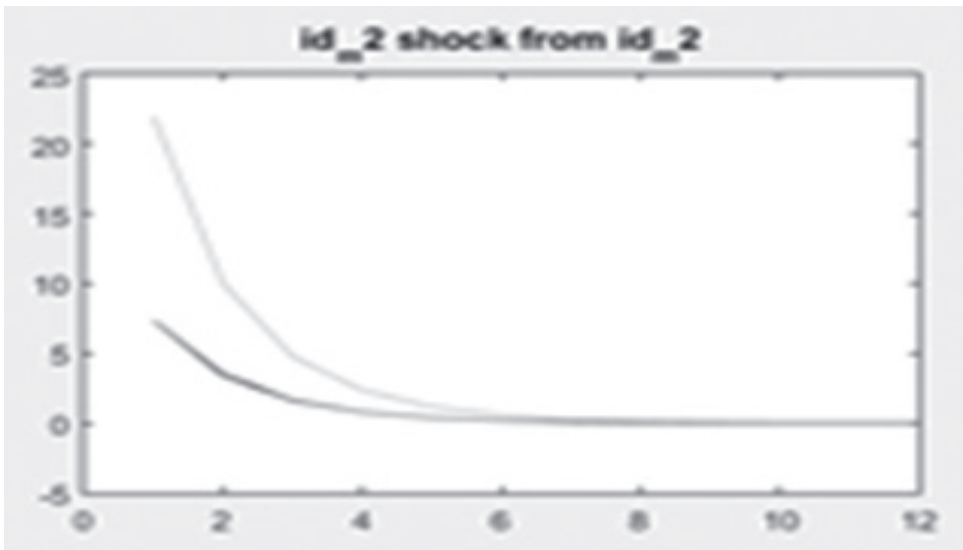
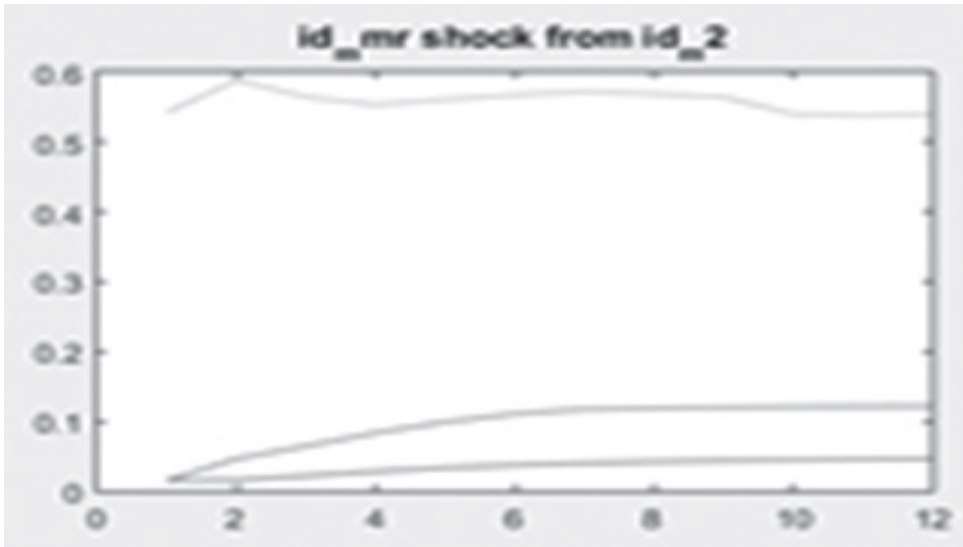


Figure A.10.
Impulse Responses to Shock from M2 (Continued)



A.III. MSBVAR Forecasts

Figure A.11.
MSBVAR Forecasts

This graph displays the forecasts by Model 2s1v2c. The orange line in each graph is the estimate, while the yellow and the blue lines are the upper and the lower bounds, respectively.

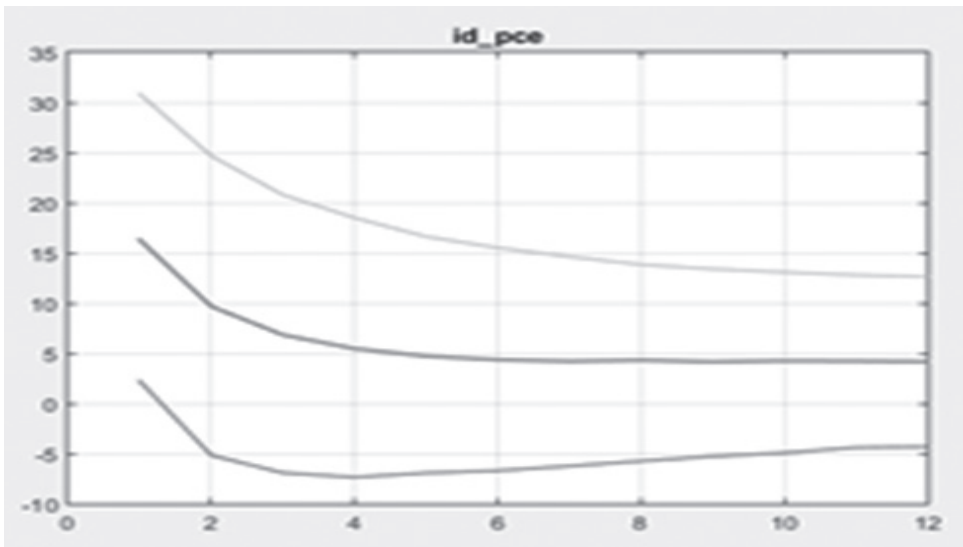
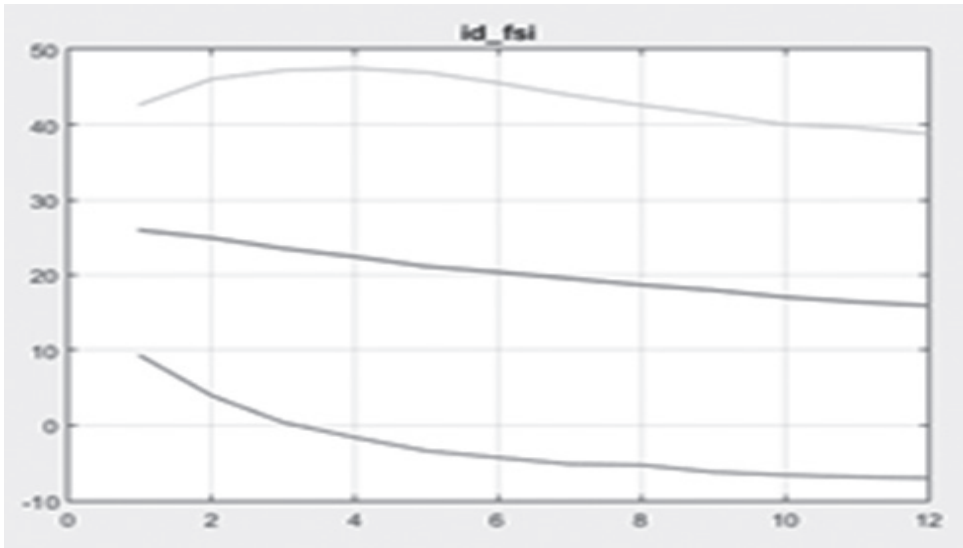


Figure A.11.
MSBVAR Forecasts (Continued)

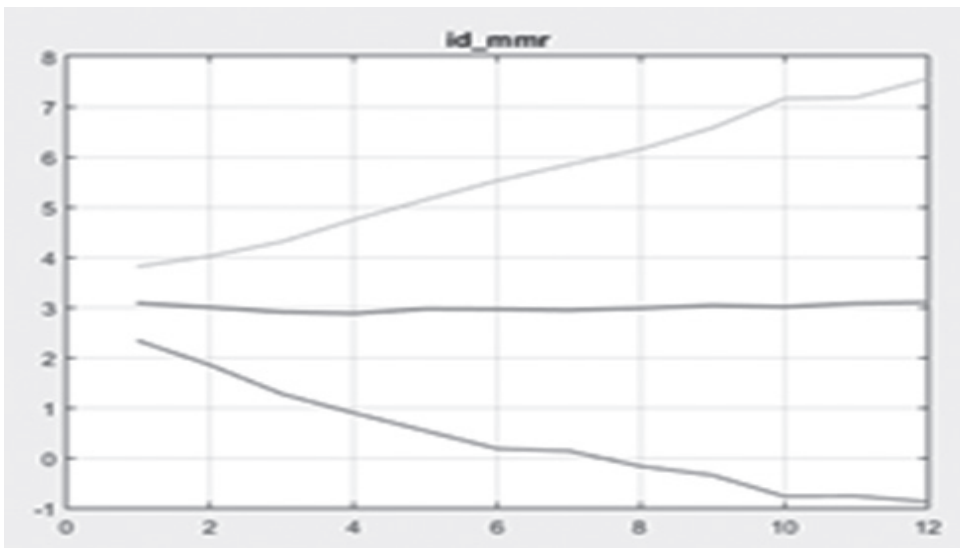
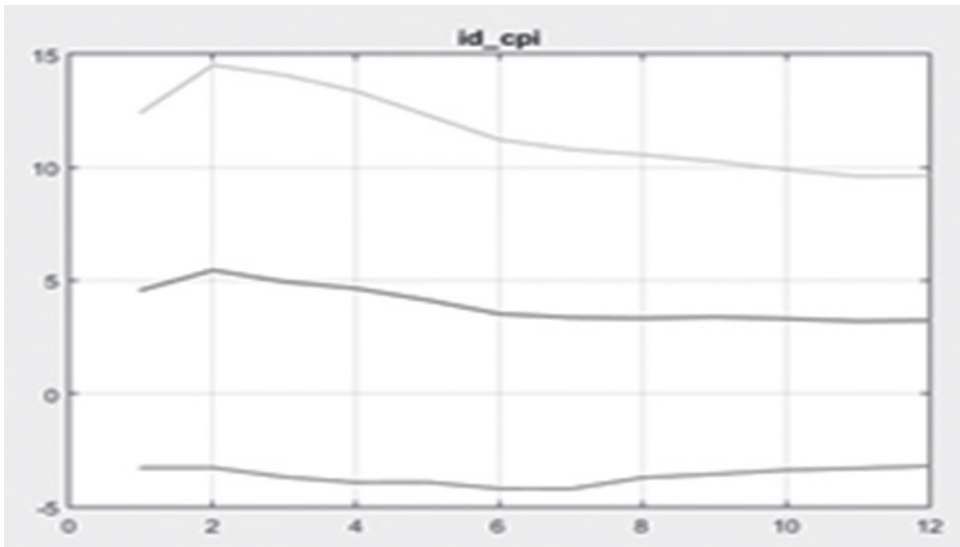
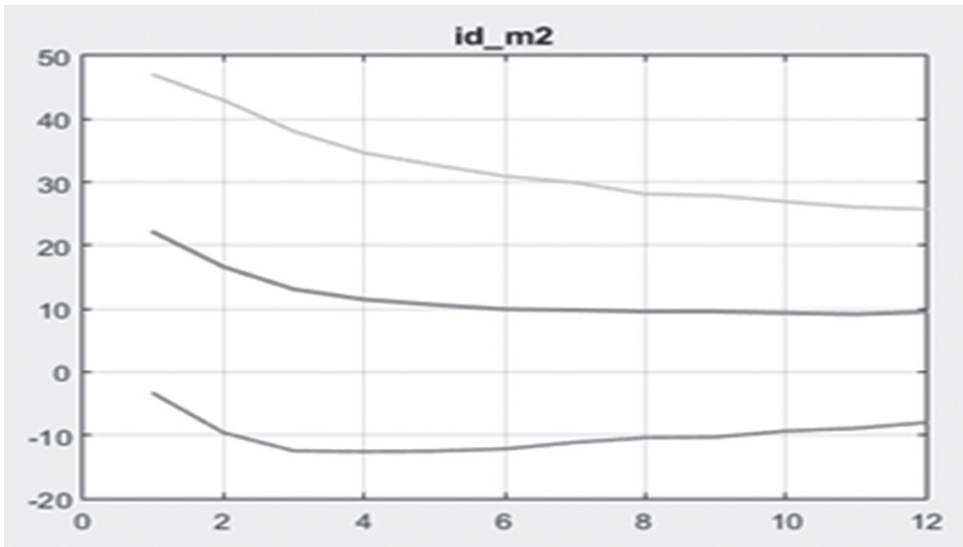


Figure A.11.
MSBVAR Forecasts (Continued)



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