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KP Prabheesh

*Indian institute of technology Hyderabad, India, prabheeshkp@gmail.com*

R Eki Rahman

*Bank Indonesia, Indonesia, ki.r@bi.go.id*

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## MONETARY POLICY TRANSMISSION AND CREDIT CARDS: EVIDENCE FROM INDONESIA

K.P. Prabheesh<sup>1</sup>, R. Eki Rahman<sup>2</sup>

<sup>1</sup> Indian Institute of Technology Hyderabad, Hyderabad, India.

Email: prabheeshkp@gmail.com

<sup>2</sup> Bank Indonesia Institute, Bank Indonesia. Email: eki.r@bi.go.id

### ABSTRACT

This paper empirically tests the dynamics of credit cards and monetary policy in the context of Indonesia. Using monthly data from 2006 to 2018 and a structural vector autoregressive model, our findings indicate that credit card usage is mainly driven by Indonesia's fast economic growth over the last decade, which indeed reflects the role of credit cards in consumption smoothing. The study also finds that monetary policy transmission through the lending channel is weak, with a more prevalent role for exchange rates and global oil prices in the transmission process.

*Keywords:* Monetary policy; Structural vector autoregression; Credit cards.

**JEL Classification:** E44; E50.

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## I. INTRODUCTION

Technology has digitized monetary transactions across the world, including payment mechanisms such as debit and credit cards and online payments. These payment mechanisms have various benefits, such as their smoothness, transparency, speed, and efficiency. However, digitized transactions also pose many challenges to policymakers. One such challenge is the smooth implementation of monetary policy. In this paper, we explore possible interactions between credit card usage and monetary policy in the Indonesian context.

Indonesia, one of the growing emerging economies in the world, has experienced a considerable rise in credit card usage over the past decade.<sup>1</sup> Figure 1 shows that the volume of credit card transactions increased significantly, from 113 million to 338 million during 2006–2018. The growth in both volume and transactions was also found to be high during 2006–2010, with annual compound average growths in volume and the value of transactions of 12.5% and 24.5%, compared to 6% and 7.5% for 2011–2018 (Figure 2). Although credit cards can be used to withdraw cash, as well as for purchases, their use for cash withdrawals in terms of the total value of transactions is very low, around 3% in 2018, with the remaining 97% used for purchases (see Figure 3). These observations are a clear indication of an upsurge in credit card usage in the overall consumer credit market. Indonesia experienced a high growth trajectory during these periods. The excessive use of credit cards seems to indicate the possession of less money, since the individual uses less money for transactions. However, it is also argued that the excessive use of credit cards leads to more spending and, thus, higher prices. Bank Indonesia (BI) has adopted an inflation-targeting framework as the primary objective of its monetary policy, and the extensive use of credit cards will thus have significant implications on its effectiveness. This study is therefore warranted, given the present context of high credit card usage in Indonesia.

The remainder of the paper is organized as follows. Section II reviews the literature and presents the hypotheses and methodology. Sections III and IV discuss the econometric framework and data, respectively. Section V presents the empirical findings and Section VI concludes the paper.

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<sup>1</sup> Credit card ownership is low in Indonesia compared to other emerging economies. According to the Global Findex database (World Bank, 2017), credit card ownership in Indonesia among people above the age of 15 was around 2% in 2017 compared to India (3%), China (31%), Brazil (21%), and Malaysia (21%).

Figure 1. Usage of Credit Card

The figure presents trends in credit card transactions in Indonesia. Value of transactions are reported in IDR trillion, whereas volume of transactions are reported in millions. The data come from CEIC and Bank Indonesia website.

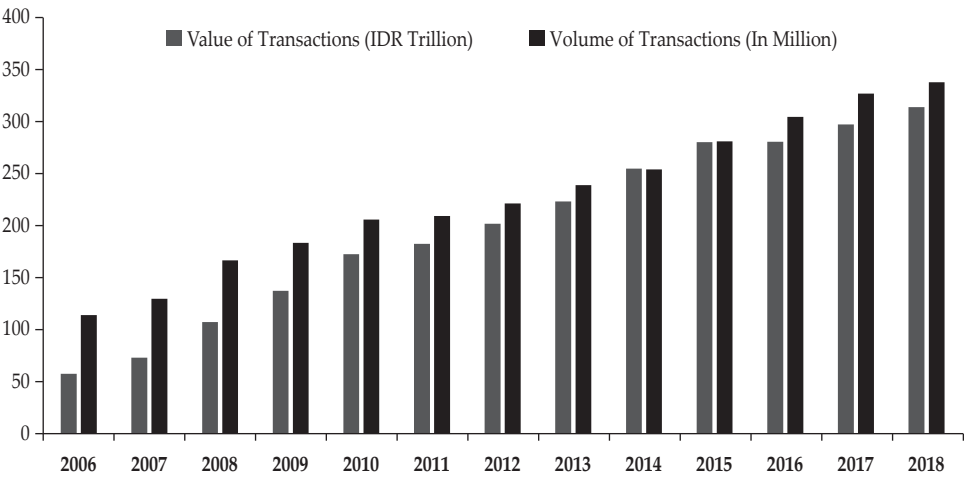
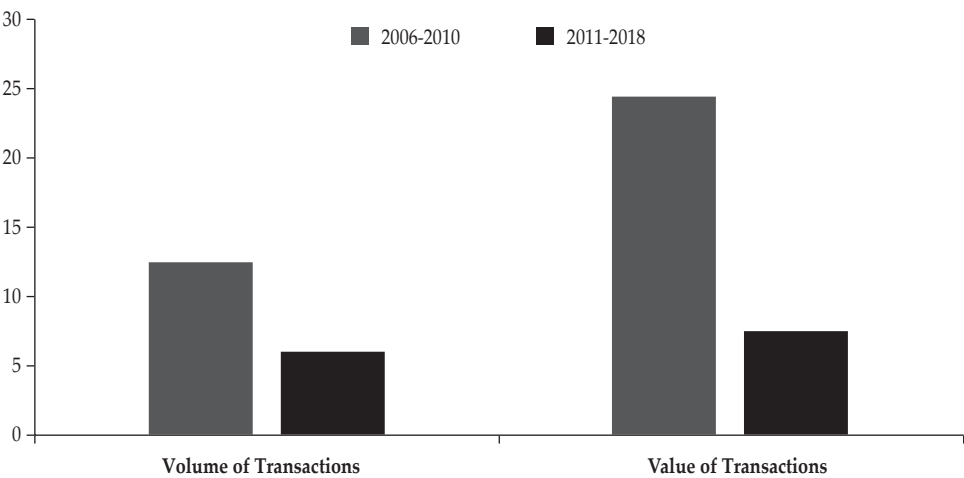


Figure 2. Growth of Credit Card transactions (CAGR, in percentages)

The figure represents the compound annual growth of volume and value of credit card transactions in Indonesia for two sub-periods 2006-2010 and 2011-2018. The values are represented in percentages, and data come from CEIC and Bank Indonesia website.



**Figure 3. Usage of Credit Card for Purchase and Cash Withdrawal**

The figure represents the proportion of credit card usage (value of transactions) in terms of purchase and cash withdrawal. The values are represented in percentages for two years, i.e., 2006 and 2018, and data come from CEIC and Bank Indonesia website.



## II. LITERATURE REVIEW, HYPOTHESES, AND METHODOLOGY

According to Fulford and Schuh (2018), the availability of credit cards helps individuals make three important decisions: First, credit cards help smooth their consumption when their income drops; hence, it is considered as an instrument to meet the precautionary and liquidity needs. Second, they can be used to revolve debt over the short and long term, and credit cards are thus a way of allocating life cycle consumption. Finally, as a means of payment, the amount spent with credit cards comprises part of consumer expenditures. Therefore, the economic implications of credit cards become more broader as their usage increases.

The literature on credit cards, especially related to monetary policy, generally focuses on the following: 1) the role of central banks in digital money and their independence in terms of monetary policy and 2) the implications of credit cards on monetary policy transmission. Regarding the first focus, studies suggest that the substitution of money with any alternative payment option, such as credit cards, debit cards, and digital currencies, reduces the overall demand for money in the economy (Akhand and Milbourne, 1986; Yilmazkuday and Yazgan, 2011). The usage of credit cards reduces the demand for money for transaction purposes, since they can be used as a medium of exchange in the transactions (Mandell, 1972). Hence, the traditional approach of implementing a monetary policy based on changing the monetary base might not be effective; for instance, the possibilities of raising seigniorage (income from printing money) using monetary policy would be limited. Therefore, central banks could be forced to depend on governmental financial support for their operational needs, thus affecting the independence of their monetary policy (Friedman, 1999; Freedman, 2000; Goodhart, 2000; Woodford, 2000).

Regarding the second focus, credit cards and monetary transmission, various challenges are posed by credit cards in the implementation of monetary policy. The usage of credit cards doubles the velocity of money, since the cash proceeds

from the sale of goods can be reused to pay the debt on credit card purchases. Theoretically, the velocity of money is inversely proportional to the demand for money, and hence lower demand for money due to credit card usage increases the velocity of money (Geanakoplos and Dubey, 2010). A high level of money velocity increases inflation, which can deviate from the central bank's inflation target. Similarly, the lower demand for money reduces the demand for central bank's reserves, which in turn shrinks the central bank's balance sheet. The lower demand thus reduces the central bank's ability to influence the short-term interest rate through open market operations (Friedman, 1999, 2000). Moreover, the evidence suggests that the central bank's balance sheet is potentially reduced through the increased use of electronic money, with serious implications on the bank's ability to effectively manage monetary policy and carry out its functions as lender of last resort (Bank for International Settlements, 2015).

It is also argued that inflation in the United States in the 1970s and early 1980s coincided with the introduction of credit cards (Geanakoplos and Dubey, 2010). Credit card usage can stimulate spending, since consumers underestimate or forget credit card purchases, because the act of paying by credit card is less painful than paying by cash or check (Soman, 2001). Moreover, the interest rates charged on credit cards are sticky and do not change with monetary policy, which complicates the implications of monetary policy through the credit card channel (Calem and Mester, 1995). If credit card interest rates were elastic in response to changes in the policy rate, monetary policy would have a multiplier effect on the consumption level through the availability of credit card funds. Further, Yilmazkuday (2011) argues that a contractionary monetary policy forces commercial banks to restrict lending through credit cards, and the credit (or lending) channel of monetary policy transmission would therefore be more effective in the presence of credit cards, compared to other channels of monetary transmission, such as the interest and exchange rates. Moreover, external risk factors, such as fluctuations in oil price and exchange rates, further complicate the mechanism of monetary transmission. Hence, it would be interesting to analyze the role of credit cards in monetary policy transmission, along with other global risk factors, such as exchange rates and oil price shocks.

Given this background, this paper examines the following questions in the context of Indonesia: 1) Does credit card usage play any role in the transmission of monetary policy? 2) Is the prevalence of the lending channel in the transmission of monetary policy due to credit card usage, as compared to other channels? 3) Does credit card play a consumption-smoothing role in monetary policy dynamics? Since studies related to the impact of credit cards on monetary transmission are relatively scarce, our paper marks an essential contribution to the literature in the following ways: 1) It is the first study that examines monetary policy transmission by taking into account global risk factors such as oil price shocks in the presence of credit card usage; 2) it is one of the first attempts to examine the empirical relation between credit card usage and monetary policy transmission, using a structural vector autoregressive (SVAR) approach; and 3) it is the first attempt to understand the dynamics of monetary policy in the presence of credit card usage in the context of Indonesia.

In this paper, we hypothesize the following: 1) Credit card usage reduces the effectiveness of monetary policy transmission because it raises price levels due to the high velocity of money (Friedman, 1999, 2000), and 2) credit card usage is positively affected by income levels, since higher income or output encourages consumers to spend more on consumption with credit cards and hence supports the consumption-smoothing role of credit cards Yazgan and Yilmazkuday (2011) Fulford and Schuh, (2017).<sup>2</sup> Similarly, credit card usage is negatively affected by interest rates, since they represent the opportunity cost of credit card usage, especially when credit card debt is not paid on time Yilmazkuday (2011). In addition, exchange rates and global oil prices affect domestic price levels through international trade, as we assume Indonesia to be a small open economy (Basnet and Upadhyaya, 2015). Finally, the central bank alters the policy rate to curb inflation, since BI has officially adopted an inflation-targeting framework.

Our approach to testing the above interlinkage is as follows. We use monthly data from 2006 to 2018 and an SVAR model. We use impulse response function analysis and forecast error variance to analyze monetary transmission. Further, the analysis includes commercial bank lending, to account for the lending channel of monetary policy. Accordingly, monetary policy actions affect the lending capacity of commercial banks and thus affect monetary policy targets. Similarly, we also incorporate exchange rates and global oil prices into the analysis to account for external shocks. Our empirical findings suggest the following. First, credit card usage is significantly explained by output, indicating the consumption-smoothing role of credit cards. Second, credit card usage is not affected by the interest rates, indicating the stickiness of interest rate charged on credit card. Fourth, variations in policy rates are significantly determined by variations in inflation, supporting the inflation-targeting objective of BI's monetary policy. Fifth, global oil prices play a significant role in explaining domestic inflation, indicating that external shocks pass through to domestic inflation. Finally, the impact of policy rates on inflation through the lending channel is not strong; however, the role of exchange rates in the transmission process is more prevalent, because exchange rate variations affect the liquidity conditions of commercial banks.

### III. ECONOMETRIC FRAMEWORK

This paper employs an SVAR model to analyze the dynamics of credit card usage and monetary policy.<sup>3</sup> The SVAR model is an alternative to the simultaneous equation models originally proposed by Sims (1980). A standard SVAR model can be written as

$$A_0 X_t = A_1(L)X_t + B_t \quad (1)$$

<sup>2</sup> The level of income is an important indicator of consumers' repayment patterns. Households with highly liquid assets or income are more likely to use credit cards for transactions and pay their credit card debt on time (Canner and Cynrak, 1985; Zhang and DeVaney, 1999).

<sup>3</sup> Most of the studies that analyze the monetary policy transmission mechanism use SVAR models, due to their dynamic nature, compared to other econometric techniques. For a survey on the use of SVAR models of the monetary transmission mechanism, see Christiano et al. (1999).

where  $X_t$  is an  $n \times 1$  vector of variables at time  $t$ ,  $A_0$  and  $B$  are  $n \times n$  matrixes of coefficients,  $A_1(L) = \sum_{i=1}^p A_{1i}L^i$  indicates the matrix polynomial in the lag operator, the matrix  $B$  contains the structural form parameter of the model, and  $\varepsilon_t$  is an  $n \times 1$  vector of serially uncorrelated and zero-mean structural shocks with an identity covariance matrix  $\sum \varepsilon = (\varepsilon_t \varepsilon_t') = I$ . The reduced form of the model can be expressed as

$$X_t = C(L)X_t + u_t \tag{2}$$

where  $C(L)X_t = A_0^{-1}A_1(L)$ , with  $A_0 u_t = B_t$ . The residuals  $u_t$  from the reduced vector autoregressive model are also assumed to be white noise, but can be correlated with each other due to the contemporaneous effect of the variables across equations. Therefore, to identify structural shocks, we must impose restrictions in the equation. We employ an identification strategy applying short-run restrictions on the contemporaneous coefficients in  $A_0$ . More precisely, to exactly identify the structural shocks, we need to impose  $n(n-1)/2$  restrictions.

To address the research issue, we estimate three separate SVAR models.<sup>4</sup> In model 1, we include four variables in the SVAR system, that is, output, inflation, credit card transactions, and the domestic policy interest rate.

The identification strategies for model 1 are as follows:  
 $X_t = (\text{Output, Inflation, Credit, Interest rate})$

$$\begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ 0 & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} u_t^{Output} \\ u_t^{Inflation} \\ u_t^{Credit} \\ u_t^{Interest\ rate} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ 0 & b_{21} & 0 & 0 \\ 0 & 0 & b_{31} & 0 \\ 0 & 0 & 0 & b_{41} \end{bmatrix} \begin{bmatrix} e_t^{Output} \\ e_t^{Inflation} \\ e_t^{Credit} \\ e_t^{Interest\ rate} \end{bmatrix} \tag{3}$$

where output is assumed to be contemporaneously exogenous to the other variables in the system, since the SVAR literature on monetary policy indicates that real variables, such as output, respond with a lag to the exogenous shocks of monetary variables (Sims, 2007; Abouwafia and Chambers, 2015). Similarly, inflation is also assumed to be contemporaneously exogenous to credit card transactions and interest rates, due to the delay in changes in prices (Friedman, 1961). We also assume that credit card transactions (credit) do not respond contemporaneously to changes in the interest rate, due to the sticky nature of interest rate charged on credit card (Calem and Mester, 1995). Finally, the policy rate (interest rate) is contemporaneously exogenous to output, since information related to output would not be available to the policy makers the same month, and the interest rate is therefore only set after the output information from the previous month has been observed (Leigh, 2005).

<sup>4</sup> We closely follow the SVAR approach of Prabheesh and Vidya (2018).

In model 2, we expand the above model by including information related to commercial banks' lending and exchange rates.<sup>5</sup> The inclusion of these variables will help us to identify the interaction of the credit card effect on monetary policy transmission through lending and the exchange rate channel.

The identification strategies for model 2 are as follows:

$X_t = (\text{Output, Inflation, Credit, Lending, Interest rate, Exchange rate})$

$$\begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ 0 & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{bmatrix} u_t^{\text{Output}} \\ u_t^{\text{Inflation}} \\ u_t^{\text{Credit}} \\ u_t^{\text{Lending}} \\ u_t^{\text{Interest rate}} \\ u_t^{\text{Exchange rate}} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{21} & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{31} & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{41} & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{51} & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{61} \end{bmatrix} \begin{bmatrix} e_t^{\text{Output}} \\ e_t^{\text{Inflation}} \\ e_t^{\text{Credit}} \\ e_t^{\text{Lending}} \\ e_t^{\text{Interest rate}} \\ e_t^{\text{Exchange rate}} \end{bmatrix} \quad (4)$$

where we assume commercial bank lending does not respond contemporaneously to the interest rate, since they do not change lending rates quickly in response to monetary policy changes, and lending thus changes with a lag. However, exchange rate is contemporaneously endogenous to all the other variables in the system, since they respond quickly to changes in real variables as well as monetary variables in the system.

Finally, in model 3, we incorporate global oil prices to account for global supply shocks, since increases in oil prices can increase the cost of production and thus lead to higher price levels (Narayan et al., 2014; Besnet and Upadhyaya, 2015). Hence, the central bank is assumed to react to global oil price movements by changing the policy rate. In this case, we assume oil prices are contemporaneously exogenous to all the other factors in the system. The identification strategies for model 3 are as follows:

$X_t = (\text{Oil, Output, Inflation, Credit, Interest rate, Exchange rate})$ <sup>6</sup>

$$\begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ 0 & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{bmatrix} u_t^{\text{Oil}} \\ u_t^{\text{Output}} \\ u_t^{\text{Inflation}} \\ u_t^{\text{Credit}} \\ u_t^{\text{Interest rate}} \\ u_t^{\text{Exchange rate}} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{21} & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{31} & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{41} & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{51} & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{61} \end{bmatrix} \begin{bmatrix} e_t^{\text{Oil}} \\ e_t^{\text{Output}} \\ e_t^{\text{Inflation}} \\ e_t^{\text{Credit}} \\ e_t^{\text{Interest rate}} \\ e_t^{\text{Exchange rate}} \end{bmatrix} \quad (5)$$

<sup>5</sup> The incorporation of inflation and exchange rate also helps address well-known price and exchange rate puzzles whereby inflation increases and the exchange rate depreciates, given a contractionary monetary policy (Sims, 1992; Cushman and Zha, 1997). A similar approach is adopted by Juhro and Iyke (2019) to address the effect of monetary transmission on financial conditions in Indonesia.

<sup>6</sup> To maintain degrees of freedom, we do not include commercial bank lending in model 3.

We use structural variance decomposition and structural impulse response functions to examine the dynamics of the variables in the SVAR system. Impulse response functions are helpful for analyzing the response of one variable to a shock to the other variables in the system. Variance decomposition assesses the percentage of forecast error explained by the innovation of each variable in the system.

IV. DATA

The study utilizes monthly data from January 2006 to December 2018, collected from various BI reports. The beginning period is attributed to the availability of data related to credit card transactions in Indonesia. The policy interest rate is proxied by the BI rate, which is an indicator of the monetary policy stance. The industrial production index is taken as a measure of output, due to the unavailability of monthly output data. Credit card usage is measured in real terms (i.e., the total value of credit card transactions divided by the Consumer Price Index), and inflation is measured as the percentage change in the Consumer Price Index corresponding to its previous year same month. Moreover, the industrial production index, credit card transactions, and bank lending are measured in percentage changes, seasonally adjusted using the Census Bureau’s X-12 method.<sup>7</sup> The exchange rate is measured as the number of Indonesian rupiahs in US dollars. Oil prices are proxied for by the percentage changes in Cushing, Oklahoma, and West Texas Intermediate crude oil prices, taken from the US Energy Information Administration.<sup>8</sup> Table 1 reports the descriptive statistics, such as the mean, standard deviation, skewness, kurtosis, and Jarque–Bera statistics, of the variables considered for the analysis. It is interesting to note that credit card usage has a high standard deviation (14), indicating large fluctuations during the study period. The Jarque–Bera statistics show a non-normal credit card usage distribution.

Table 1.  
Descriptive Statistics

This table presents descriptive statistics for the period 2007-2018. The mean, standard deviation (SD), skewness, Jarque–Bera (JB) test coefficient and its respective *p*-value are presented in parenthesis. The JB test examines the null hypothesis of a normal distribution. The variables, noted in column 1, namely output, credit, lending and oil denote the growth rate of the index of industrial production, credit card transactions, commercial banks’ lending and oil prices, respectively.

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Output	4.15	3.95	-0.44	4.98	28.40(0.00)
Inflation	5.48	2.25	0.99	3.60	25.76 (0.00)
Credit	15.90	14.60	1.11	3.86	34.17 (0.00)
Lending	11.50	6.29	0.13	1.62	11.71(0.00)
Interest Rate	6.70	1.32	-0.008	2.40	2.10 (0.34)
Exchange Rate	11136.5	2023.2	0.28	1.50	15.32 (0.00)
Oil	6.57	36.50	0.32	2.91	2.56 (0.276)

<sup>7</sup> We follow an approach similar to that of Yilmazkuday (2011).

<sup>8</sup> See <https://www.eia.gov>.

## V. EMPIRICAL RESULTS

As a first step, we examined the stationarity properties of the variables. Since standard unit root tests, such as the augmented Dickey–Fuller test and Phillip–Peron tests, do not take into account possible structural breaks in the data series, this study employs the unit root test proposed by Narayan and Popp (2010; hereafter NP) that accounts for two endogenous structural breaks. The main highlight of this test, compared to other structural break tests, such as those of Lumsdaine and Papell (1997) and Lee and Strazicich (2003), is that it uses a Dickey–Fuller-type test approach and the break date is determined by maximizing the significance of the break date coefficient. The NP test has good size and stable power and identifies the structural breaks accurately in finite samples. The NP test suggests two models, M1 and M2, that permit two breaks in levels and two breaks in level and trend, respectively. The test statistics reported in Table 2 shows that the null of the unit root can be rejected in all cases except the exchange rate, as for model M1 (intercept). Moreover, the break dates are found to be in various months during 2009–2011 for most of the variables. For instance, credit card growth experienced a break in the first month of 2010 and in the sixth month of 2011. Our empirical findings for the structural break test are in line with those of Sharma et al. (2018), who find that most of the macroeconomic data of Indonesia suffer from structural breaks.

**Table 2.**  
**Structural Break Unit Root Test**

This table shows the Narayan and Popp (2010) unit root test results for monthly data. We refer to Table 3 of Narayan and Popp (2010) for critical values for unknown break dates. Models 1 and 2 are two models for testing unit root. Model 1 (see Column 2, denoted M1) allows for two breaks in intercept and the Model 2 allows for two breaks in intercept as well as trend (see Column 2, denoted M2). The true break dates are denoted by TB1 and TB2;  $k$  represents the optimal lag length; and \*\*\*, \*\*, and \* indicate that the unit root null hypothesis is rejected at the 1%, 5%, and 10% levels of significance, respectively. In in the break date, for example 2011M8 denotes month. Similarly, output, credit, lending and oil denote growth rate of the index of industrial production, credit card transactions, commercial banks' lending, and oil prices, respectively.

M1: Two Breaks in Intercept					M2: Two Breaks in Intercept and Trend			
Variables	k	t-stat	TB1	TB2	Lag	t-stat	TB1	TB2
Output	0	-0.579 (-6.704)*	2011M8	2012M1	0	-0.537 (-6.156)*	2011M8	2012M2
Inflation	4	-0.122 (-4.202)**	2013M6	2014M12	4	-0.120 (-4.290)	2013M6	2014M12
Credit	2	-0.400 (-4.210)**	2010M1	2011M6	3	-0.487 (-4.523)***	2010M1	2010M6
Lending	4	-0.083 (-3.859)***	2009M8	2011M11	2	-0.030 (-1.153)	2011M11	2010M6
Interest Rate	4	-0.783 (-6.741)*	2009M9	2009M11	4	-0.810 (-6.821)*	2009M9	2009M11
Exchange Rate	4	-0.072 (-1.622)	2013M10	2015M9	4	-0.132 (-2.805)	2013M10	2015M9
Oil	4	-0.780 (-6.741)*	2009M9	2010M9	4	-0.810 (-6.821)*	2009M9	2010M9
Critical Values for Unit root test			1%		5%		10%	
Model M1 (Break in Intercept only)			-4.731		-4.136		-3.825	
Model M2 (Break in Intercept and Trend)			-5.318		-4.741		-4.430	

To perform the SVAR test, we convert the exchange rate into first differences to ensure stationary variable levels. The optional lag length for vector autoregression is then determined through the Schwarz–Bayesian and likelihood ratio criteria, which, respectively, find three to be the optimal number of lags for model 1 and two for models 2 and 3. The models fulfill the criteria for diagnostic tests of, for example, autocorrelation, normality, and heteroskedasticity. Apart from that, the intercept dummy variables are included, are considered exogenous in the SVAR system, and correspond to the break dates suggested by the NP test.

#### *A. Estimation of Model 1*

The impulse response function for the SVAR system is depicted in Figure 4. The dashed lines correspond to plus or minus two standard errors around the impulse responses. It is evident from Figure 4 that the interest rate significantly and positively responds to a positive shock on inflation, and the response is statistically significant for up to four months. This finding is not surprising, since BI adheres to an inflation-targeting policy and thus changes the policy rate when inflation deviates from its target, a monetary policy strategy popularly known as the Taylor rule. It is also important to note that interest rate does not respond to output and credit card transactions, which further underlines BI's preference for inflation over output. However, the response of inflation to changes in the interest rate is found to be negative, but the effect is not statistically significant, signaling weak monetary policy transmission through the lending channel.

It is also interesting to note that inflation responds positively to increase in credit card transactions. The rise in inflation can be attributed to the higher velocity of money with the use of credit cards. Similarly, the response of credit cards to output is positive and significant. The significant effect of output on credit card usage indicates that consumers use credit cards for transactions or purchases when their incomes increase. This finding underscores the role of credit cards in consumption smoothing among high-income consumers. It is also evident that the policy rate does not have any significant effect on credit card usage. This finding could be attributed to the sticky interest rates charged on credit cards. This inelasticity of credit card usage to the policy rate could weaken monetary transmission through the credit card channel.

Table 3 reports the variance decomposition results. It reveals that variations in output are largely driven by variation in the output itself (94% in the 10th month). Similarly, variations in inflation are largely explained by inflation's own variations, that is, around 84% in the 10th month, whereas the contributions of output and the interest rate to inflation are found to be 0.8% and 9.6%, respectively. Importantly, output explains around 38% of the variation in credit card transactions in the 10th month, further shedding light on the role of the rapid economic growth in Indonesia over the last decade on credit card usage. Similarly, around 15% of the variation in interest rates is explained by inflation.

The key findings of the analysis can be summarized as follows:

1. Inflation significantly explains the variations in interest rate, reflecting the central bank's monetary policy response to price stability.
2. Credit card transactions marginally explain variations in inflation.

3. Output significantly explains variations in credit card transactions, indicating the role of credit cards in consumption smoothing.
4. The impact of the policy rate on inflation is not statistically significant, indicating the weak transmission of monetary policy through the lending channel.

**Table 3.**  
**Variance Decomposition of Forecasted Variables (Model 1)**

This table shows the variance decomposition of Model 1 estimated using the SVAR methodology. These decompositions show the proportion of the variance in the forecast error of a variable that can be attributable to its own innovations and innovations in other variable in the VAR system. Here, output and credit denote growth rate of the index of industrial production and credit card transactions, respectively.

Period	Output	Inflation	Credit	Interest Rate
<b>Panel A: Variance Decomposition of Output</b>				
1	99.99	0.00	0.00	0.01
5	94.38	4.31	0.79	0.52
10	93.89	4.68	0.90	0.53
<b>Panel B: Variance Decomposition of Inflation</b>				
1	0.01	92.25	0.23	7.51
5	0.77	83.82	5.84	9.57
10	0.83	83.68	5.86	9.63
<b>Panel C: Variance Decomposition of Credit</b>				
1	0.72	0.00	99.26	0.02
5	36.50	1.56	60.27	1.67
10	38.04	1.98	58.34	1.64
<b>Panel D: Variance Decomposition of Interest Rate</b>				
1	0.00	0.00	0.00	100.00
5	0.50	14.76	0.90	83.84
10	0.67	15.06	0.92	83.34

**Figure 4. Impulse Response Function (Model 1)**

This figure represents the impulse response functions derived from the SVAR model (Model 1). The impulse response function traces the effect of a one standard deviation shock to one of the variables on current and future values of all the endogenous variables in the VAR system. Dashed lines represent the intervals of two standard deviations, while the solid lines represent the impulse function.

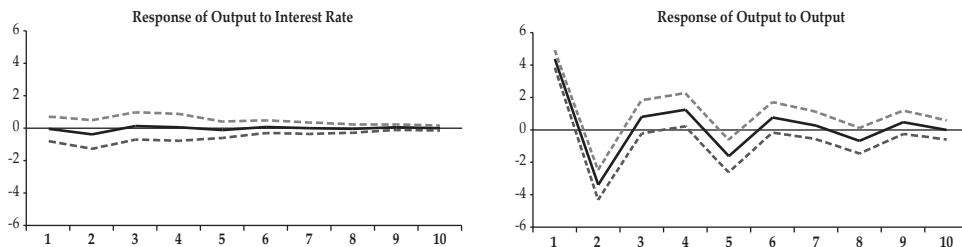
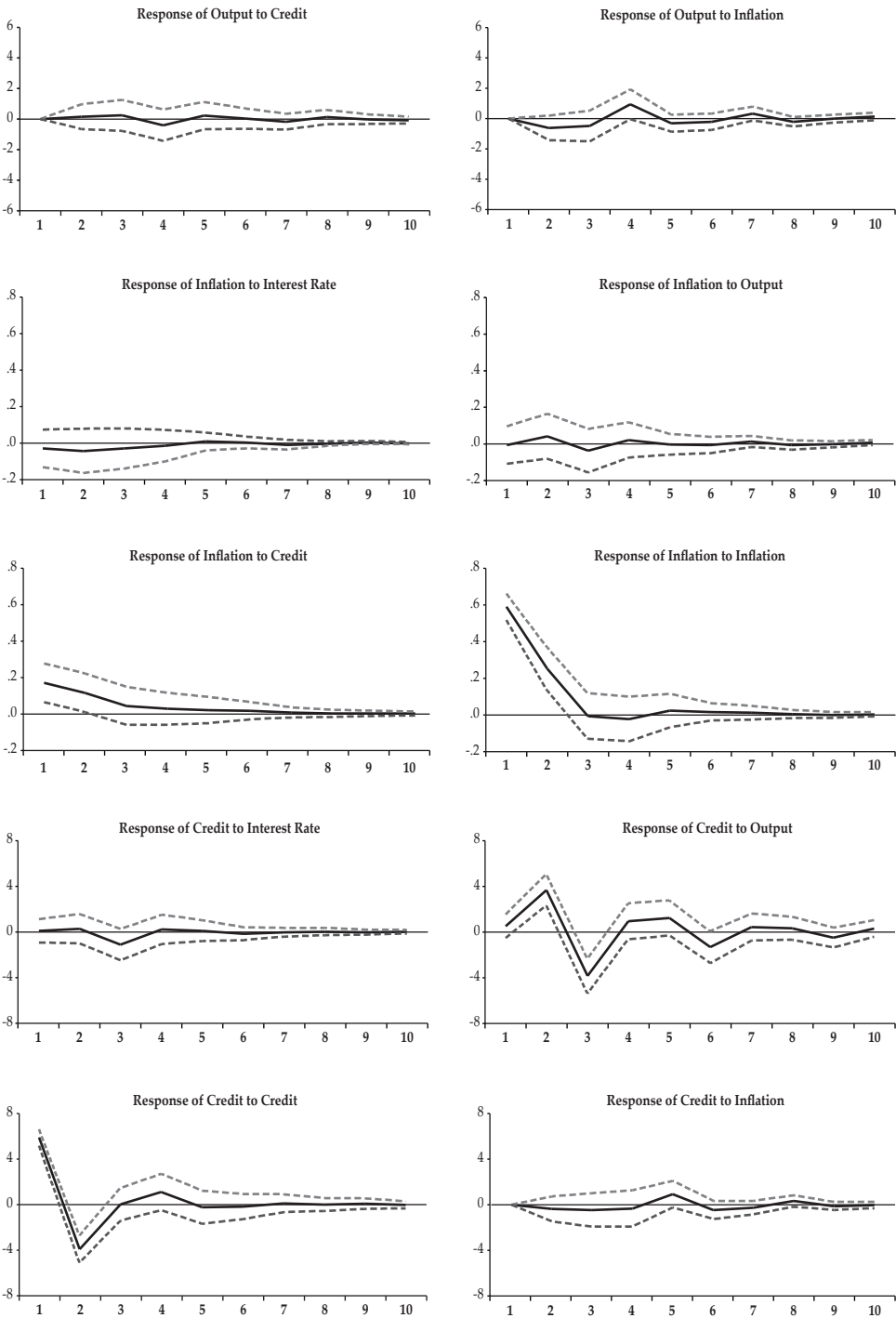


Figure 4. Impulse Response Function (Model 1) (Continued)



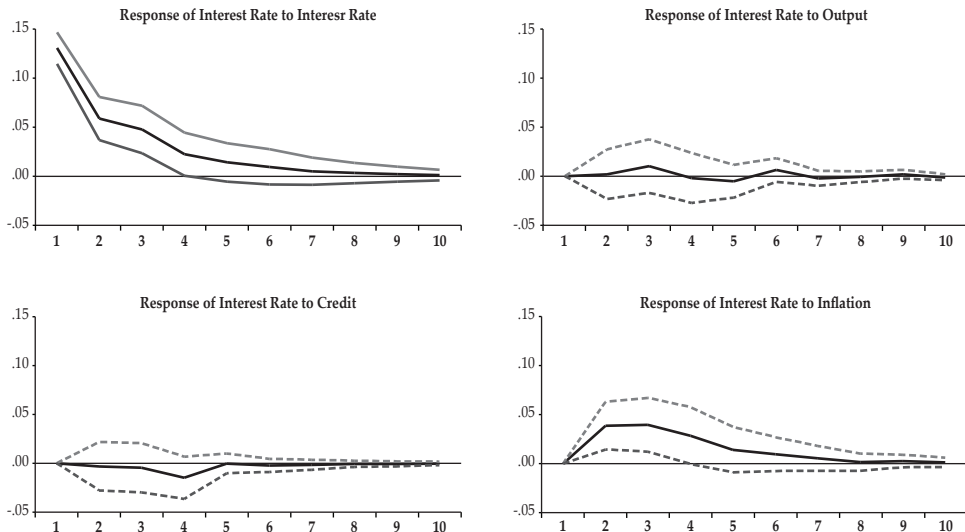
**Figure 4. Impulse Response Function (Model 1) (Continued)***B. Estimation of Model 2*

Figure 5 shows additional insights on the dynamics of monetary policy and credit card usage when taking into account exchange rates and commercial bank lending. It is interesting to note that the response of the interest rate to inflation is positive and statistically significant. This finding again indicates the central bank's reactions to inflation, which is consistent with BI's inflation-targeting policies. However, the response of lending to the interest rate is not found to be significant, providing evidence of weak monetary transmission through the lending channel. This result could be attributed to a delay in commercial banks adjusting their lending rate in response to the central bank's policy actions. More importantly, bank lending responds positively to credit card usage, which could reflect the pro-lending behavior of commercial banks toward credit card holders. In other words, credit card usage boosts commercial banks' lending activities in Indonesia. Figure 5 also shows that commercial banks' lending responds to exchange rates. Exchange rate depreciation leads to a significant decline in lending in the third month, reflecting the liquidity crunch faced by commercial banks during domestic currency depreciation.

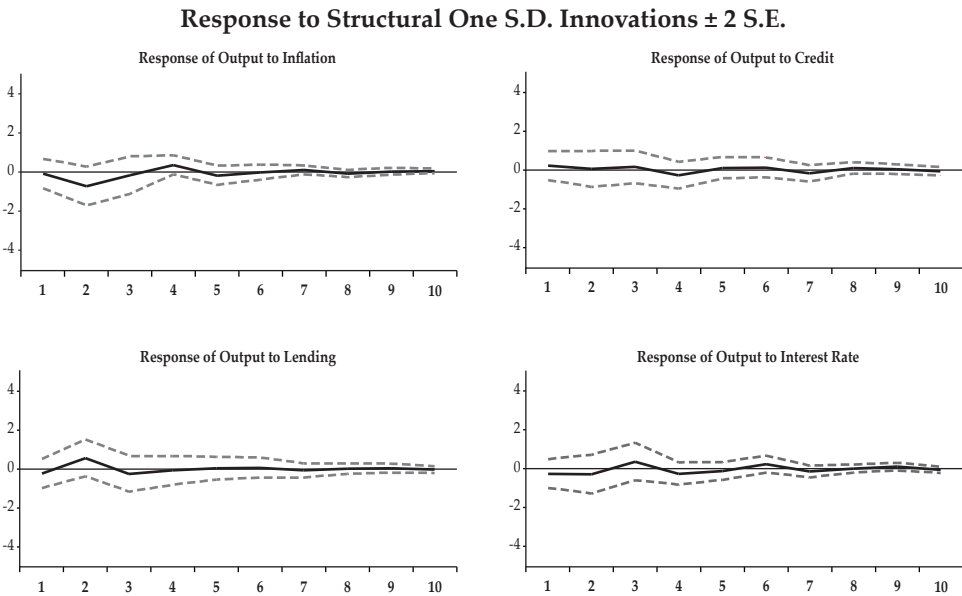
The impulse response functions of credit cards show that credit card usage is positively and significantly affected by output and lending. These findings reiterate the role of income and commercial bank lending in determining credit card usage. Inflation responds positively and significantly to variations in the exchange rate, indicating that the depreciation of domestic currency leads to higher inflation. This result underscores the role of external shocks in determining inflation in Indonesia. Unlike in the previous section, the response of inflation to credit card usage is not found to be significant here. However, the response of inflation to the interest rate is also insignificant, which is consistent with the findings in the previous section. Output is again found to not be responsive to any of the variables in the system, except its own variations.

The variance decomposition results reported in Table 4 further show that the exchange rate explains around 15% of the variations in inflation and 17% of the variations in bank lending. Output and lending explain 36% and 10% variations in credit card usage, respectively. Similarly, inflation explains 12.9% of the change in interest rate, but the interest rate explains only 4.5% of the variation in inflation. Similarly, variations in output are largely explained by their own variations, suggesting stable output during the study period.

- The key results can be summarized as follows:
1. The exchange rate significantly explains variations in inflation, indicating international shocks pass through to domestic inflation.
  2. Taking into account the exchange rate, the effect of credit card usage on inflation is found to be nonsignificant.
  3. The exchange rate significantly explains commercial banks' lending, indicating the liquidity stress banks face during exchange rate depreciation.
  4. Output significantly explains variations in credit card usage, indicating the consumption-smoothing role of credit cards at higher income levels.
  5. Monetary policy transmission is found to be more prevalent through the exchange rate than through the lending channel.

**Figure 5.**  
**Impulse Response Function (Model 2)**

This figure represents the impulse response functions derived from the SVAR model (Model 2). The impulse response function traces the effect of a one standard deviation shock to one of the variables on current and future values of all the endogenous variables in the VAR system. Dashed lines represent the intervals of two standard deviations, while the solid lines represent the impulse function.



**Figure 5.**  
**Impulse Response Function (Model 2) (Continued)**

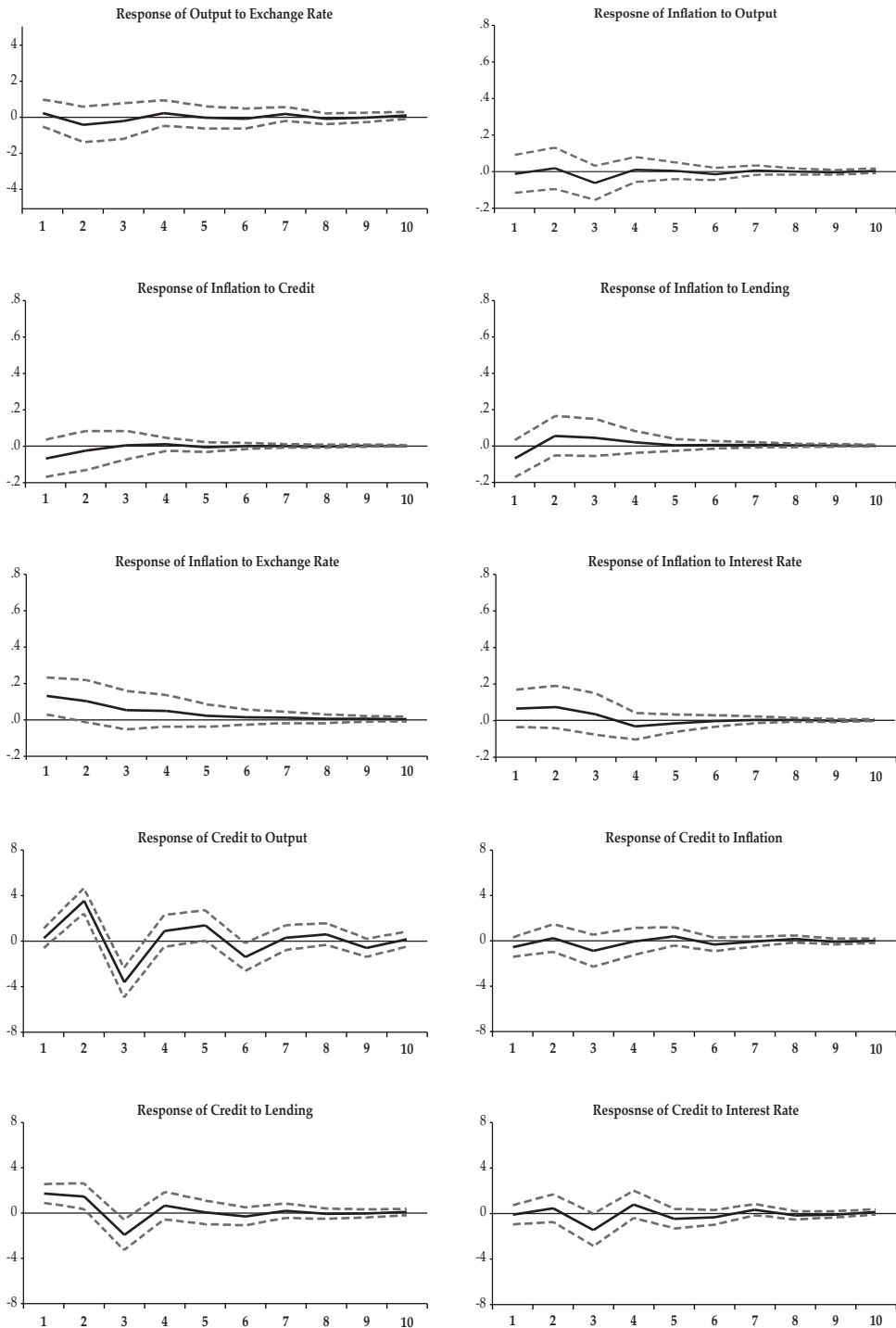
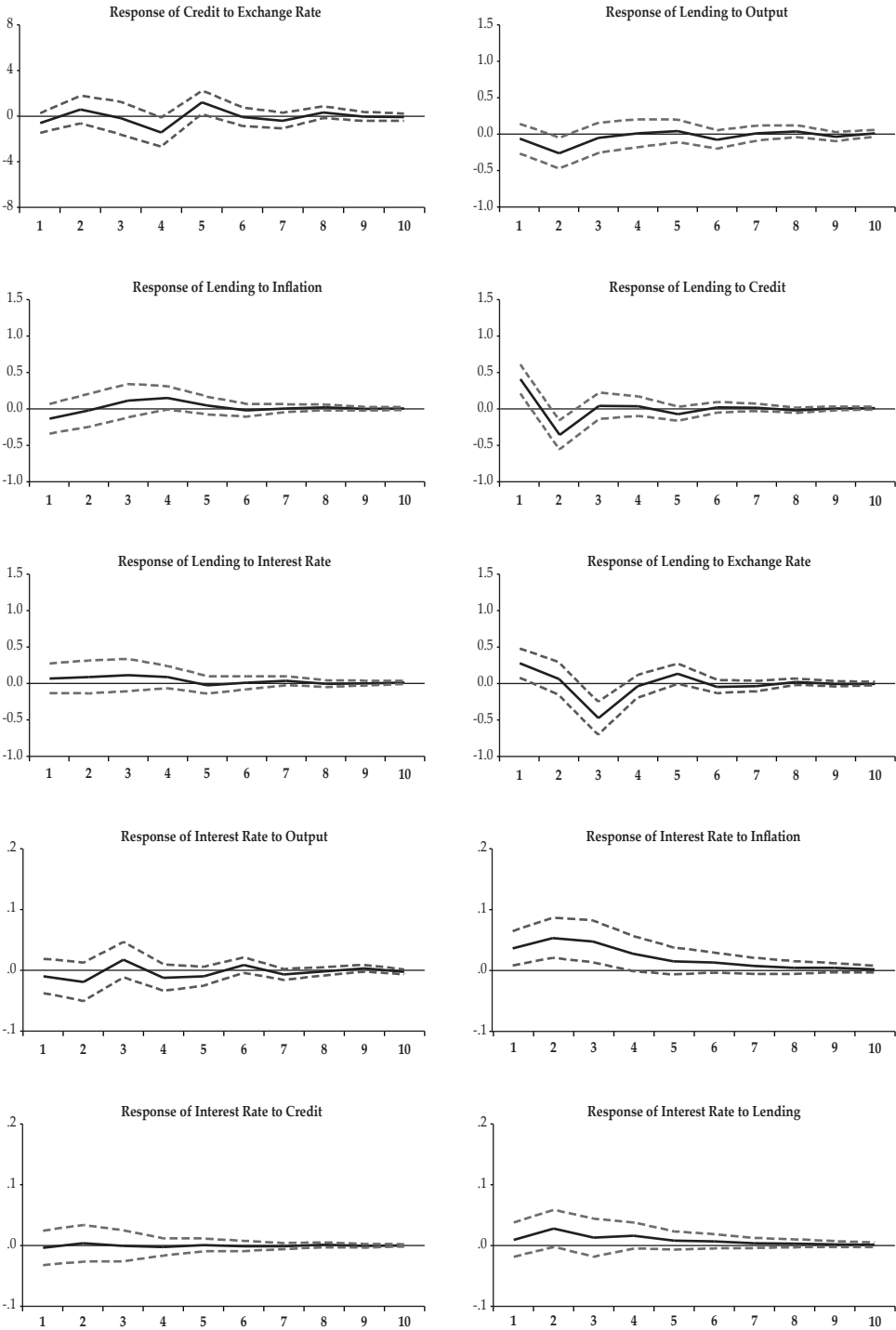


Figure 5.  
Impulse Response Function (Model 2) (Continued)



**Figure 5.**  
**Impulse Response Function (Model 2) (Continued)**

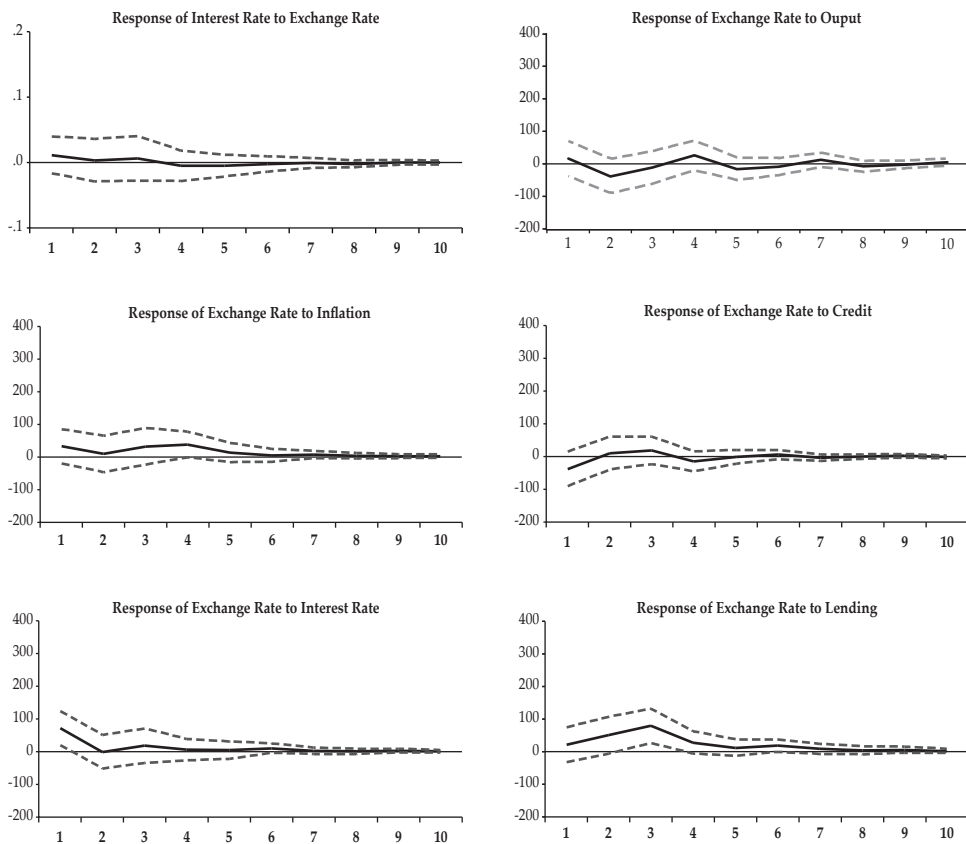


Table 4.  
Variance Decomposition of Forecasted Variables (Model 2)

This table shows the variance decomposition of Model 2 estimated using the SVAR methodology. These decompositions show the proportion of the variance in the forecast error of a variable that can be attributable to its own innovations and innovations in other variable in the VAR system. The variables, namely output, credit, lending and oil denote the growth rate of the index of industrial production, credit card transactions, commercial banks' lending and oil prices, respectively.

Period	Output	Inflation	Credit	Lending	Interest Rate	Exchange Rate
Panel A: Variance Decomposition of Output						
1	98.07	0.00	0.00	0.69	1.22	0.00
5	90.07	2.81	1.06	2.40	1.89	1.73
10	85.96	3.23	2.34	2.56	2.92	2.95
Panel B: Variance Decomposition of Inflation						
1	0.05	93.10	1.15	2.25	3.42	0.00
5	2.64	81.31	2.02	1.86	3.93	8.21
10	2.76	75.42	2.10	1.98	4.59	15.12
Panel C: Variance Decomposition of Credit						
1	0.18	0.00	94.87	4.94	0.00	0.00
5	36.96	2.04	43.54	9.21	4.530	3.68
10	36.52	1.99	40.95	10.44	5.78	4.28
Panel D: Variance Decomposition of Lending						
1	0.00	0.00	0.00	99.97	0.02	0.00
5	2.77	5.33	13.50	61.02	3.36	13.99
10	4.32	5.12	13.43	53.79	5.93	17.38
Panel E: Variance Decomposition of Interest Rate						
1	0.00	0.00	0.00	0.00	100.00	0.00
5	3.13	11.47	0.73	1.49	80.52	2.63
10	4.93	12.99	0.79	1.48	75.36	4.43
Panel F: Variance Decomposition of Exchange Rate						
1	0.01	0.65	6.16	2.75	0.02	90.38
5	5.53	3.92	5.36	3.91	5.48	75.77
10	6.80	5.52	5.18	3.69	7.04	71.75

C. Estimation of Model 3

Since we have seen, in the previous section, the greater role of international shock pass-through to domestic inflation through the exchange rate, in this section we include world oil prices in the analysis. Figure 6 exhibits the impulse response function of the SVAR model 3. The response of inflation to oil price is positive and statistically significant from the second to the seventh months, a clear indication of global oil price pass-through to domestic inflation. This could be due to Indonesia's high oil import levels in recent years. Although Indonesia is one of the members of the Organization of the Petroleum Exporting Countries (OPEC), after 2004 it became a net importer of oil due to increased consumption, along with a decline in oil production (US Energy Information Administration, 2015).<sup>9</sup> Similarly, it is

<sup>9</sup> Due to the decline in oil production, Indonesia suspended its OPEC membership in 2008. It reactivated it in 2016 but suspended it again in 2018 (OPEC, 2019).

interesting to see that the response of the exchange rate to oil prices is also positive and statistically significant, which implies that an increase in oil prices in the world market depreciates the domestic currency. Since Indonesia is a net importer of oil, an increase in oil prices in the international market would induce a high current account deficit, leading to high demand for foreign currency and depreciation of the domestic currency.

The response of inflation to the exchange rate is also found to be positive and significant, indicating that depreciation of the domestic currency leads to inflation, again emphasizing the relevance of the exchange rate channel in monetary policy transmission. The domestic interest rate can also be seen to respond positively to oil prices, indicating that the central bank accounts for oil price dynamics when framing monetary policy. Moreover, oil prices are found to be unaffected by any of the domestic variables in the system, underscoring their exogeneity. The remainder of the findings, especially related to credit cards, is consistent with those in the previous section.

The variance decomposition results shown in Table 5 reveal that around 14% of the variation in inflation is explained by oil prices, emphasizing the role of global oil price pass-through to prices, while the exchange rate contributes around 8% of the variation in inflation, which is lower than in model 2 (15%), as reported in Table 4. This finding shows that the inclusion of oil prices in the model decreases the role of the exchange rate in explaining inflation. In other words, once the source of external shock is accommodated for in the model through oil prices, the role of the mediator variable, that is, the exchange rate, is moderated. We can also see that oil prices explain around 7% of the variation in the exchange rate.

The key findings from this section can be summarized as follows:

1. Oil prices significantly explain variations in inflation, indicating the international shock pass-through to domestic inflation.
2. The inclusion of oil prices in the model moderates the effect of the exchange rate on inflation.
3. Oil prices significantly explain the policy rate, indicating that the central bank accommodates oil price-related information when framing monetary policy.

**Figure 6.**  
**Impulse Response Function (Model 3)**

This figure represents the impulse response functions derived from the SVAR model (Model 3). The impulse response function traces the effect of a one standard deviation shock to one of the variables on current and future values of all the endogenous variables in the VAR system. Dashed lines represent the intervals of two standard deviations, while the solid lines represent the impulse function.

#### Response to Structural One S.D. Innovations $\pm 2$ S.E.

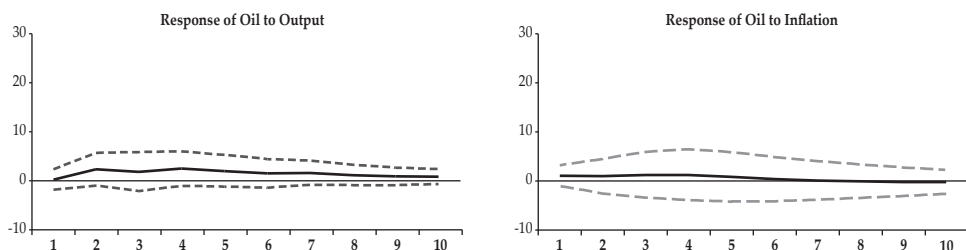
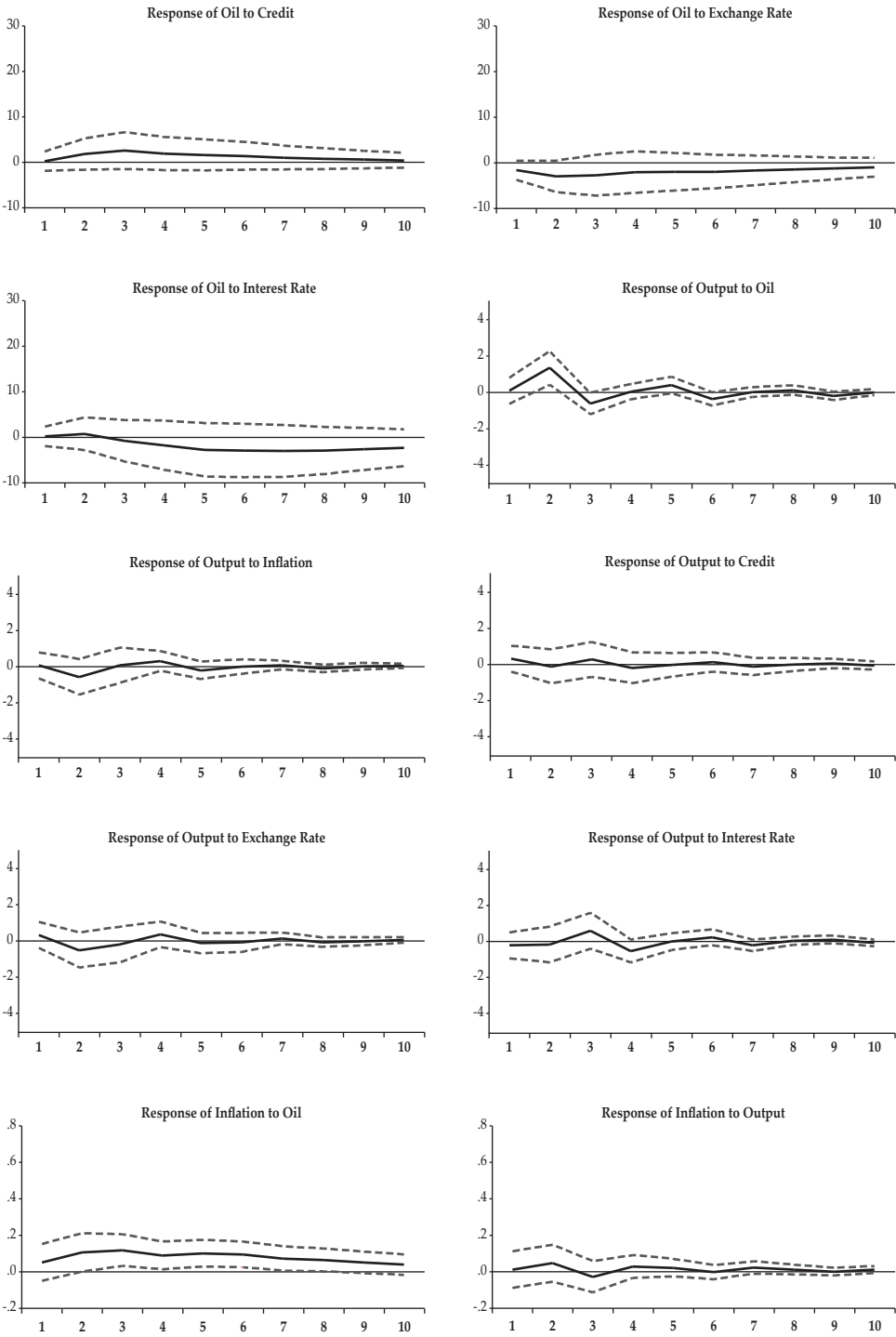


Figure 6.  
Impulse Response Function (Model 3) (Continued)



**Figure 6.**  
**Impulse Response Function (Model 3) (Continued)**

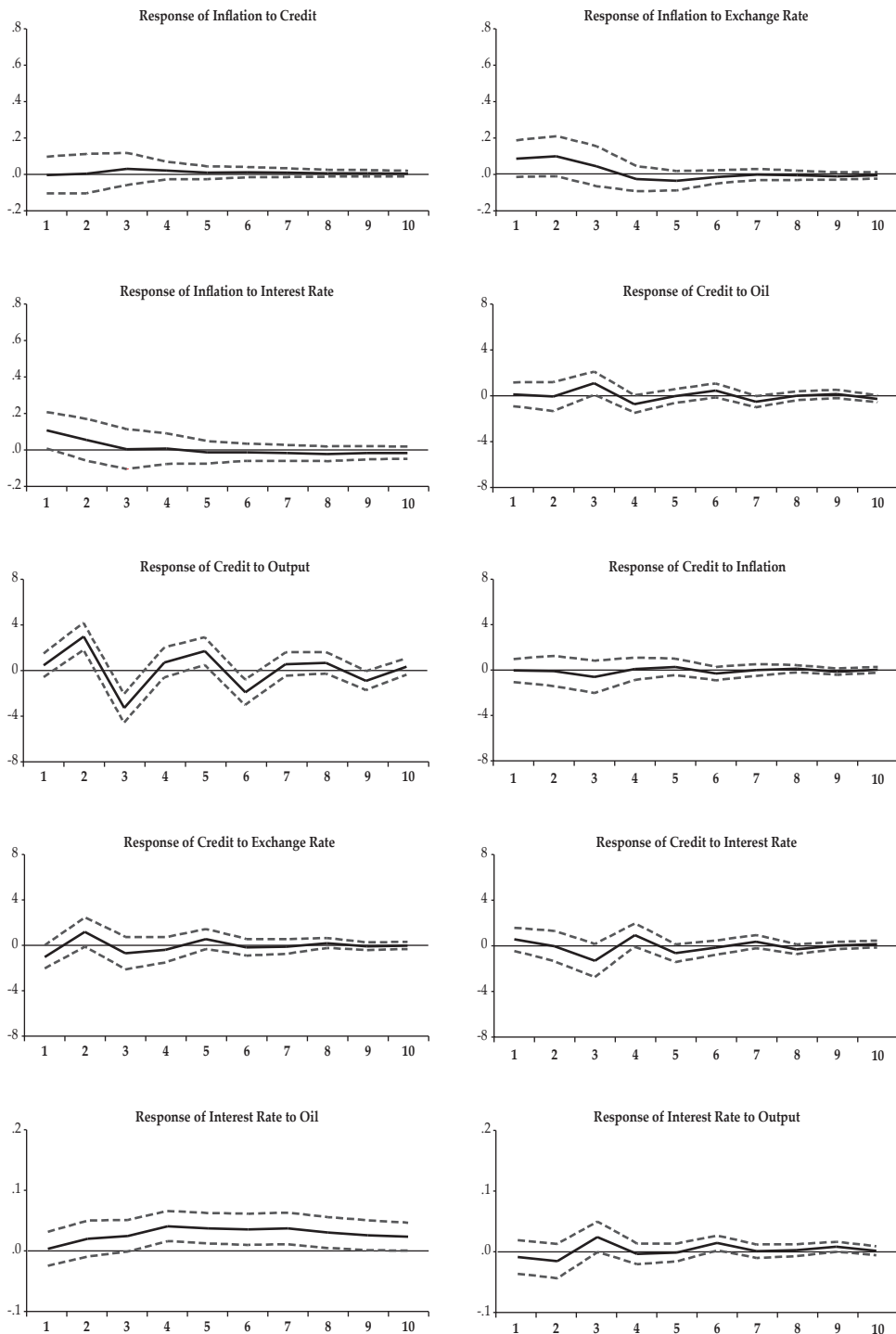
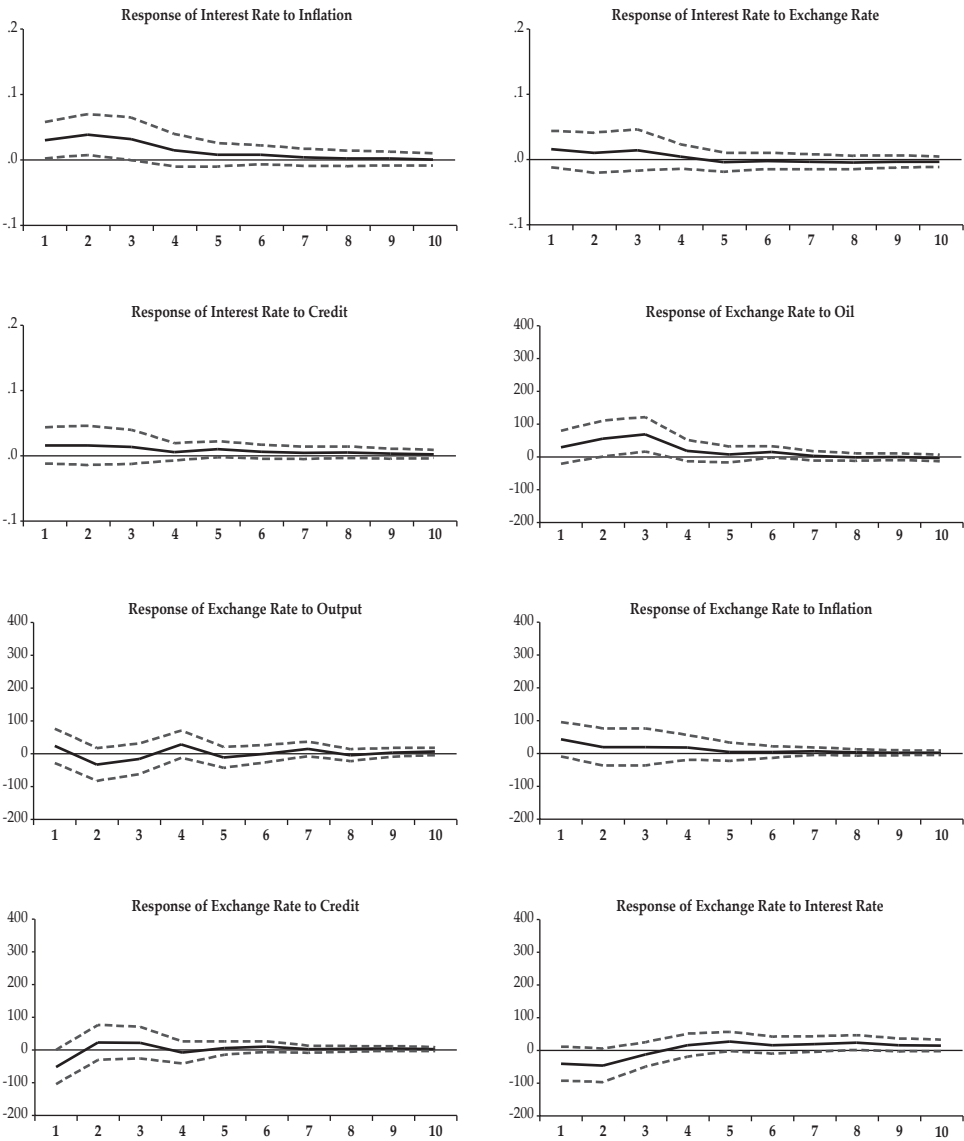


Figure 6.  
Impulse Response Function (Model 3) (Continued)



**Table 5.**  
**Variance Decomposition of Forecasted Variables (Model 3)**

This table shows the variance decomposition of Model 3 estimated using the SVAR methodology. These decompositions show the proportion of the variance in the forecast error of a variable that can be attributable to its own innovations and innovations in other variable in the VAR system. The variables, namely output, credit, lending and oil denote the growth rate of the index of industrial production, credit card transactions, commercial banks' lending and oil prices, respectively.

Period	Oil	Output	Inflation	Credit	Interest Rate	Exchange Rate
<b>Panel A: Variance Decomposition of Oil</b>						
1	100	0	0	0	0	0
5	96.44	1.24	0.04	0.87	1.34	0.07
10	94	1.3	0.21	0.79	3.64	0.06
<b>Panel B: Variance Decomposition of Output</b>						
1	0.04	99.96	0	0	0	0
5	6.3	89.35	1.45	0.44	1.88	0.59
10	6.55	88.67	1.44	0.54	2.11	0.69
<b>Panel C: Variance Decomposition of Inflation</b>						
1	0.75	0.03	99.22	0	0	0
5	10.05	0.9	81.03	0.26	0.14	7.61
10	14.23	1	75.5	0.28	0.51	8.48
<b>Panel D: Variance Decomposition of Credit</b>						
1	0.04	0.59	0.01	99.36	0	0
5	2.23	30.06	0.68	62.08	4.38	0.57
10	2.72	34.01	0.79	57.43	4.4	0.65
<b>Panel E: Variance Decomposition of Interest rate</b>						
1	0.03	0.31	3.37	1.02	95.26	0
5	9.93	2.33	8.23	2	77.05	0.46
10	14.03	2.62	12.36	1.9	68.68	0.42
<b>Panel F: Variance Decomposition of Exchange rate</b>						
1	0.93	0.66	2.3	3.09	1.74	91.28
5	7.15	2.52	2.93	3.69	4.22	79.5
10	7.2	2.69	2.89	3.7	5.59	77.93

## VI. CONCLUSION

This paper investigates monetary policy transmission in the presence of credit card usage in the context of Indonesia. Since Indonesia has adopted an inflation-targeting policy, excessive credit card usage is expected to have important implications for monetary policy. Using monthly data from 2006 to 2018 and an SVAR framework, we find that credit card usage marginally affects domestic inflation. However, taking into account the exchange rate, we find credit card usage has an insignificant effect on domestic inflation. Interestingly, our results show that credit card usage in Indonesia is mainly driven by the country's rapid economic growth over the last decade, which indeed reflects the role of credit cards in consumption smoothing. However, credit card usage is not found to be sensitive to policy rates, indicating that sticky interest rates prevail in the credit card market. Our empirical findings also provide evidence of commercial banks' proactive lending to credit card users. Finally, monetary policy transmission through the lending channel is found to be weak, since neither commercial bank lending nor

credit card transactions respond to changes in the policy rate. However, the role of external factors, such as global oil price movements and exchange rates, is more prevalent in the transmission process, stressing the need to account for global risk factors while framing monetary policies.

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