Systemic Effects on Intersectoral Linkages: Framework and Analysis

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Abstract

The existence of heterogeneity in size and response in each sector cannot be neglected. Moreover, there is an interaction between sectors in the form of trade between intermediate input and intermediate output. This research offers a framework to mathematically and empirically prove the existence of systemic effects on intersectoral linkages in the economy. This research is the first to interpolate data by scaling and updating the IO table using the RAS procedure to obtain quarterly IO datasets from 2001 to 2022 timeframe. Mathematically, on simple deductive proofs that combine Cobb–Douglas and Leontief's production function, research has revealed the propagation of systemic risk. Furthermore, by utilizing a previous literature model with data from Indonesia, empirical approaches simulate *shocks,* namely, crude oil prices and business confidence, by using the SVAR procedure. In this regard, the empirical results indicate that systemic effects on intersectoral linkages in Indonesia do exist.

Keywords: Systemic Effect, Intersectoral Linkages, Input–Output¸ SVAR

JEL Classification: D57, C67, C53, L16

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I. Introduction

The global financial crisis in 2008 successfully altered economic research focus due to the potential danger that emerged from systemic effects, thus shifting modern economic policy practices. However, most research on the topic of systemic effects is limited to the banking and financial sectors, whereas there is a high likelihood of systemic effects occurring on a broader scope, such as a country's intersectoral activities. Park & Chan (1989) argue that each of the sectors is connected asymmetrically, creating intersectoral dependencies that occur dynamically, might change over time, and are triggered by diverse shocks which lead to systemic effects.

In this article, the term "systemic effect" refers to the definition of systemic risk by Kaufman & Scott (2003), which is defined as all types of effects in the system caused by shock(s) occurring in a component or individual, and the impact is proven to be propagated across other parts or components of the system. This article tries to introduce simple approaches to prove, mathematically and empirically, the existence of systemic effects on intersectoral linkages in Indonesia, which might also constitute a breakthrough in examining firms' behaviors in Indonesia, from how each of them is interconnected and how the shocks are transmitted from one to another. This article mainly focuses on aggregated sectors, namely, primary, secondary, and tertiary sectors, which are sourced from a category in Statistics Indonesia (BPS) to accommodate different sector classifications before and after 2010, as shown in Appendix 1.

Research on the use of intersectoral linkages to determine interdependency in production structures have been ongoing for a long time, and intersectoral linkages or economic "connectedness" were quantified as backward and forward linkage equations by Rasmussen (1956). Su & Yao (2016) found that particular sectors might become an "engine" for economic growth, as they are capable of driving the growth of other sectors. Moreover, many studies on intersectoral linkages have focused on utilizing the input–output (IO) table, as it provides trades between sectors in a country for a given time and, most importantly, is able to determine propagated effects from a shock (Contreras & Fagiolo, 2014; Roson & Sartori, 2016).

Currently, there is a consensus among economists that economic activities always rely on economic agents' access to energy, as evidenced by studies showing that there is a long-term and two-way relationship between energy consumption and economic growth (Sachs & Warner, 1995; Belke et al., 2011; Tang et al., 2016). As a result, a shock in energy prices would have a significant negative impact on economic conditions (Basnet & Upadhyaya, 2015). On the other hand, if we look through sectoral production activities, an increase in crude oil price will change the composition of the production input of the manufacturing sector (Hudson & Jorgensen, 1978). The price-sensitive firm then responds by increasing capital investment, which might result in systemic effects in intersectoral trade, creating sectoral shifts (Berndt & Wood, 1986).

On the other hand, economic agents' perceptions, especially for businesspersons, also play an important role in economic activities. If a country is being treated or experiencing uncertainty, these conditions might affect people's sentiment, therefore altering their consumption pattern, which is explained in buffer-stock theory by Carroll (1992). Empirical results also suggest significant changes in economic agents' confidence and expectations in regard to economic growth and fluctuation (Guo & He, 2020; Leduc & Sill, 2013). Therefore, it is important to analyse the impact of business perception on intersectoral trade dynamics because it is possible to (1) measure aggregate business owners' confidence when organizing their business's productivity, (2) capture non-economic movements that cannot be captured when using only 1 economic indicator, and (3) be a predictor of future economic conditions.

Based on the explanation of the two variables above and their influence on the economy, the following question arises: do these two shocks have the same effect when transmitted through intersectoral relations? The limited empirical and theoretical findings related to systemic effects in intersectoral relations are the motivations for this research to offer an empirical evidence framework by examining two types of shocks, crude oil prices and business perception indices, that impact intersectoral linkages based on research by Baek (2021) and Alves (2019).

II. Literature Review

In brief, the IO model assumes n sectors in an economy where z_i represents the intermediate input consumed between sectors n, x_n denotes the total output of sector n, and f_n is the final demand, which is composed of household consumption (c_n), investment (i_n), government expenditure (g_n), exports (e_n), and imports (m_n), with the following equation:

$$x_i = z_{i1} + \cdots + z_{ij} + \cdots + z_{in} + f_i = \sum_{j=1}^{n} z_{ij} + f_i \tag{1}$$

Hence, we know that the intersectoral relationship to produce 1 unit of output can be written as:

$$\alpha_{ij} = \frac{z_{ij}}{x_j} \tag{2}$$

α_{ij} is a technology coefficient matrix that can be explained as the share of output z_i from sector i used as an input for sector j, which captures interactions between sectors. Therefore, it is possible that if key sectors increase (decrease), production will result in a mass increase (decrease) in other sectors' productivity due to multiplier effects (Miller, 1985).

In defining the existence of heterogeneous shock, Johann von Thünen in 1980 (Humphrey, 1997) introduced the concept of a production function:

$$P = f(x_1, x_2, \dots, x_n) \tag{3}$$

Firms always maximize production given their input function. Furthermore, the production function is a detailed neoclassical economics paradigm with the following function:

$$P = f(L, C, T \dots) \tag{4}$$

The production function is a component of labor (L), capital (C), and land (T). Firms in different sectors have divergent input compositions and might respond differently when receiving exogenous shocks or shocks from other sectors, which is the reason why heterogeneous shocks occurred.

Previous empirical studies have examined intersectoral linkages in many countries. Das et al. (2022), using intercountry data to prove spillover shocks from TFP, government expenditures, and COVID-19 to sectoral interdependency, found upstream and downstream network effects or spillovers. A study of India's growth structure by Sastry et al. (2003) using interperiod IO data and simple econometric methods revealed that agriculture acted as a key sector (between 1960 and approximately 1990) for pushing economic growth. Research on South Africa using the SVAR method revealed that manufacturing sectors have become major actors in driving economic growth in this country (Wild & Schwank, 2008). The Cobb–Douglas function is also utilized to define the impact of network-based shocks, where it contributes significantly more than direct shocks (Acemoglu et al., 2015). Finally, using the SVAR method, Barauskaite & Nguyen (2021) argue that positive idiosyncratic shocks might lead to both direct and network shocks affecting sectoral growth. Unfortunately, this study in

Indonesia is limited only to sector/subsector performance and the cocoa value chain (Putri et al., 2015) or to other aspects, such as the environment (Resosudarmo, 2003) and energy (Imansyah et al., 2017). The simulation of shock is only inspected in short time period (see Sajid & Gonzales (2021)).

Since long ago, numerous shocks and their impact on the economy have been researched, especially at a disaggregated scope, for instance, at the sectoral level, from the perspectives of agriculture (Hanson et al., 1991) and construction and manufacturing (Shaari et al., 2013) responses to crude oil price increases. However, studies on the impact of crude oil prices on sectoral performance are still unavailable. On the other hand, dynamic changes in economic agents' sentiment and their impact on economic activity have recently been explored. For example, Yunita (2021) utilized business confidence index (BCI) data to clarify its impact on conventional and Islamic finance during the pandemic and its impact on household consumption (Juhro & Iyke, 2020).

III. Data and Methodology

3.1. Methodology

3.1.1. Defining the Intersectoral Linkage Variable

This research considers the multisector model of Acemoglu et al. (2012), in which every good and service in an economy is produced by sectors, with the output being consumed or becoming input for the production process of other sectors. This interaction is described through a static economic model and perfect competition with n sectors, where each sector $i = 1,2, \dots, n$ behaves like a Cobb–Douglas production function:

$$y_i = e^{h_i} l_i^{\alpha_i^l} \prod_{j=1}^{n} x_{ij}^{a_{ij}} \tag{5}$$

$$x_{ij} = y_{i1}, y_{i2}, \dots, y_{ij} \tag{6}$$

In equation (13), y_i is defined as sectoral output i influenced by x_{ij}, the quantity of goods and services produced by sector j, which are used as sector inputs i, l_i is the primary input, and h_i is the Hicks-neutral productivity shock (representing other factors affecting productivity). In detail, equation (5) shows that the input from sector i also follows the Cobb–Douglas function. Next, we assume that every i, $\alpha_i^l > 0$, and $a_{ij} \geq 0$ for every j; therefore, the production function for every sector fulfils constant returns to scale conditions.

$$\alpha_i^l + \sum_{j=1}^{n} \alpha_{ij} = 1 \tag{7}$$

Equation (7) explains that 1 unit of output produced from sector i needs a certain proportion of the input from sector j. Because each of the outputs can be used as an intermediate input for their own production or other sectors, the market clearing condition for sector i is:

$$y_i = \sum_{i=1}^{n} z_i + f_i \tag{8}$$

where f_i depicts final demand or GDP for sector i and z_i denotes the output of sector i, which returns intermediate input (Miller, 1985). Therefore, we can combine equations (6) and (8) below:

$$l_i + \sum_{j=1}^{n} x_{ij} = \sum_{i=1}^{n} z_i + f_i \tag{9}$$

Equation (9) above represents the proportion of the output from sector j that contributes to the GDP of sector i. Hence, under the condition of market clearing, a negative shock of the output sector j implies a contraction of the intermediate input of sector i, therefore affecting sector i's GDP. The abovementioned discussion argues that, theoretically, this approach allows for intersectoral relationships as well as potential systemic effects. However, in this research, y will be aggregated into all sectors to produce the following equation:

$$\alpha^l + \sum_{i=1}^{n} \alpha^{x_i} = \sum_{i=1}^{n} \beta^z + \beta^f \tag{10}$$

where $x_i = y_1, y_2, \ldots, y_j, y_i$ with $y_i \neq y_i$. By transforming equation (7), we can derive the following equation:

$$\alpha^l + \sum_{i=1}^{n} \alpha^{x_i} = \sum_{i=1}^{n} \beta^z + \beta^f \tag{11}$$

$\alpha^{x_i} = \alpha y_1, \alpha y_2, \ldots, \alpha y_j, \alpha y_i$ is the proportion of input used to produce 1 unit of output, while β is the proportion of total output consumed, either as input in other sectors (z) or in final demand (f). Thus, in the empirical proof in Model 1 and Model 2 (explained in the section below), α^{x_i} acted as the weighting variable of intersectoral linkage, the contribution proportion for final demand, or, in this research, GDP. This approach is similar to that created by Wild & Schwank (2008), who used intermediate input weighting of mineral mining to sectoral output.

In modelling the systemic effect of a shock, we can revisit equation (5), which was constructed by Acemoglu et al. (2012) and further developed by Acemoglu et al. (2015), in which h acts as a productivity factor that cannot be captured by any stated production factor. Hence, we can conclude that h_j fluctuates sector j's productivity and has implications for sector i's output. In addition, other factors might affect input productivity, such as an increase in crude oil price, and socioeconomic turmoil influences business perceptions, thereby affecting the total output productivity of each company.

3.1.2. Proofing the Linkage: SVAR Approach

For empirical estimation, both models employ the structural vector autoregressive (SVAR) approach because of its ability to take short-term restrictions into account. For Model 1, the SVAR is appropriate for small open economy countries, one of which is Indonesia, which plays only a small role in determining oil prices and is thus considered an exogenous shock. On the other hand, the SVAR approach is also utilized in Model 2 because this approach is able to capture the existence of contemporaneous shocks transmitted from one variable to another. Furthermore, Alves (2019) exploits results from Christiano et al. (1998), where economic activity shocks are transmitted through output and inflation to monetary policy consecutively.

The SVAR model is derived from the reduced-form VAR model and can impose restrictions based on theory. To understand the SVAR approach, we can revisit the reduced-form VAR model:

$$x_t = \sum_{i=1}^{\rho} C_i X_{t-1} + u_t, \qquad u_t \sim N(0, \sum u\,), \tag{12}$$

where x_t is an (4×1) vector of endogenous variables, C_i is an (4×4) parameter matrix to be estimated, and u_t is an error vector $E(u_t u_t') = I_n$, where u_t consists of the white noise errors of every endogenous variable. However, the reduced-form VAR has failed to impose restrictions based on theory. Therefore, we formulate the SVAR approach by giving the structural shock below:

$$x_t = \sum_{i=1}^{\rho} A_0^{-1} A_i X_{t-1} + A_0^{-1} B \varepsilon_t. \tag{13}$$

where ϵ_t is the (4×1) orthogonalized structural shock vector

$$u_t = A_0^{-1} B_{\varepsilon_t} \tag{14}$$

Equation (14) shows the relation between u_t and equation (12) with structural shock ϵ_t, which gives $A_0^{-1}B = S$ and $u_t = S_{\epsilon_t}$. S is estimated using contemporaneous restrictions. After we obtain $\sum u$ through the reduced-form VAR and utilize equation (14),

$$\sum u = E[u_t ut'] = E[Su_t ut'S'] = SE[u_t ut']S' = SI_n S' = SS' \tag{15}$$

For Model 1, the construction of the SVAR model follows Basnet & Upadhyaya (2015) with error decomposition (u_t) constructed below:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ \theta_{21} & 1 & 0 & 0 \\ \theta_{31} & \theta_{32} & 1 & 0 \\ \theta_{41} & \theta_{42} & \theta_{43} & 1 \end{bmatrix} \begin{bmatrix} u_t^p \\ u_t^{y_s} \\ u_t^{\pi} \\ u_t^e \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon^p \\ \varepsilon^{y_{lp}} \\ \varepsilon^{\pi} \\ \varepsilon^e \end{bmatrix} \tag{16}$$

0 means no contemporaneous shocks on given matrix elements, and θ_{ij} specifies response parameter i from contemporaneous structural shock j. On the other hand, Model 2 is constructed as follows:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ \gamma_{21} & 1 & 0 & 0 \\ \gamma_{31} & \gamma_{32} & 1 & 0 \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & 1 \end{bmatrix} \begin{bmatrix} u_t^{bci} \\ u_t^{y_s} \\ u_t^{\pi} \\ u_t^{ir} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon^{bci} \\ \varepsilon^{y_{lp}} \\ \varepsilon^{\pi} \\ \varepsilon^{ir} \end{bmatrix} \tag{17}$$

γ_{ij} will act similarly to θ_{ij}. We should note that the construction of bci is based on a survey taken on period n, where respondents' knowledge about macroeconomic conditions is lagged on $n-1$. Hence, it is appropriate to place bci on top of the recursive lower triangular matrix, following the identification strategy of Leduc & Sill (2013) and Mendicino & Punzi (2013).

Those SVAR estimations will carry out several diagnostic tests, namely, (1) a stationarity test to avoid the risk of spurious regression problems (Granger & Newbold, 1974) using the augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests; (2) optimal lag selection using the SIC as the goodness-of-fit in accordance with Ivanov & Kilian (2005), who found that the SIC metric performs better with quarterly data and sample sizes below 120; and (3) a model stability test with roots of characteristic polynomial.

3.2. Data

3.2.1. Interpolating IO Data

Intersectoral linkages are obtained from IO data for 2005, 2010, and 2016 sourced from the BPS. Since time-series econometric analysis will be performed to obtain empirical evidence from Baek's (2021) and Alves's (2019) approaches, these data cannot be obtained due to the short study period. Therefore, the non-survey interpolation method is used to update or backdate and scale the time frequency, so we have quarterly data. To perform non-survey interpolation, we use the RAS approach because it provides the best estimation among other alternatives, such as GRAS or sign preserving squared differences (Jackson & Murray, 2004). However, the RAS procedure iterating the technology coefficient matrix does not directly calculate intermediate trade among sectors (Jackson & Murray, 2004), hence making this procedure more "conservative" compared to other approaches. The RAS procedure interpolates IO data via the following process:

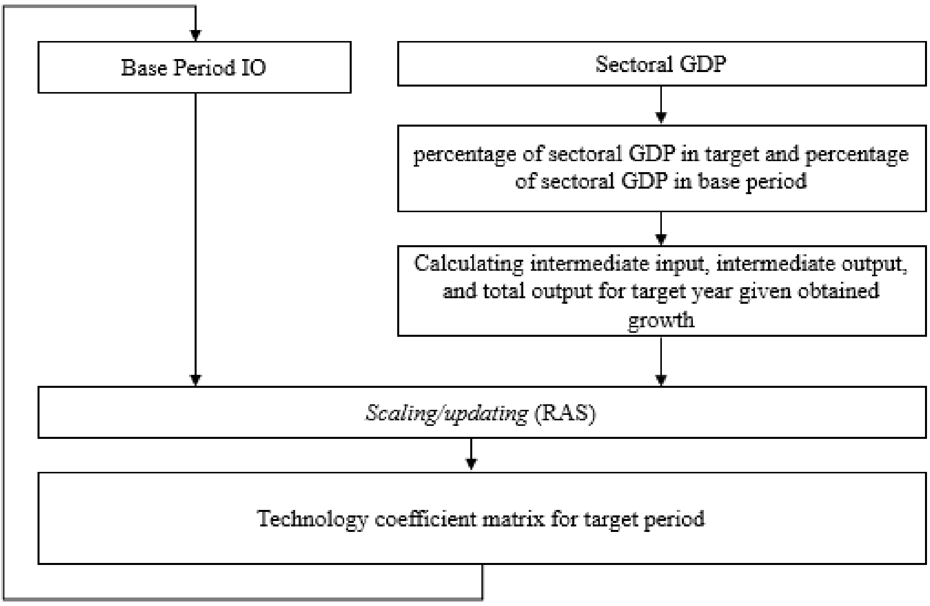


Fig 3.1 RAS Procedure Iteration on IO Data

Figure 3.1 shows that every updated/scaled IO result is used as a base IO to calculate the next period of the IO. This process will continue until we obtain the desired period. Sectoral GDP will be used as supplementary data for updating/scaling IO data because it can adjust intermediate input, intermediate output, and total output in accordance with sectoral GDP proportions and growth in the target year. Therefore, the interpolation process shown in Figure 3.1 is used to produce IO data, as shown in Figure 3.2.

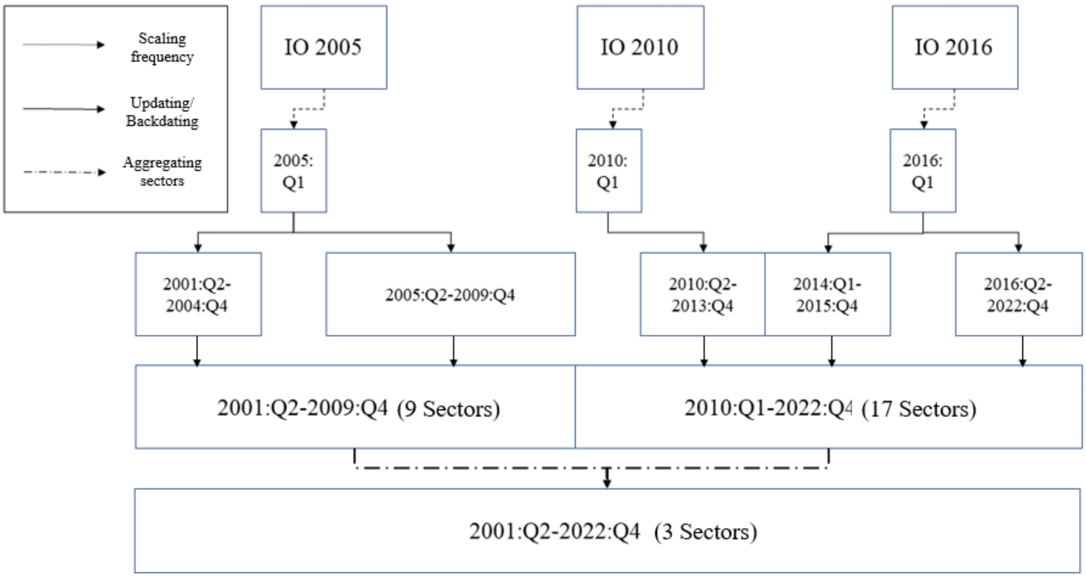


Fig 3.2 IO Table Interpolation Process Chart

Figure 3.2 shows a flowchart of IO table interpolation to obtain a set of IO data. As shown in the figure, the first step is to scale IO data from yearly to quarterly. This approach is similar to administrative scaling, such as from the provincial level to the municipal level (see Mumtaz & Sukarsih (2022); Yanti (2015)). After that, the data will be updated/backdated and aggregated to 3 major sectors to accommodate changes in classification before and after 2009. This aggregation adapts BPS classification, which includes primary, secondary, and tertiary methods (details are provided in **Appendix 1**). Finally, we use Indonesia's current price of GDP because available IO data output is also calculated in terms of the market price.

3.2.2. Confidence of Crude Oil Prices and Economic Agents

In general, this research follows the model specifications of Baek (2021) and Alves (2019), which use quarterly time series data and several secondary data. Baek (2021) attempted to define the impact of increases in crude oil prices on Indonesia's macroeconomic activity. However, since Indonesia has experienced different oil production regimes, he separates its period sample into two periods: when Indonesia acted as a net oil exporter country before 2004 and when it became a net oil importer from 2004 onwards. This sample division was carried out because there were differences in impact (Benhmad, 2012; Jahangard et al., 2017). Therefore, due to the limited data available, only the period during which Indonesia became a net oil importer, which is between 2004:Q4 and 2022:Q4, was acceptable.

In this model (referred to as Model 1), we use West Texas International (WTI) prices (p), which represent crude oil prices since they are often used as a benchmark for global crude oil prices (Basnet & Upadhayaya, 2015). Furthermore, we follow Baek (2021) to adjust WTI prices to a constant price of USD. Next, for the *output* data, we use our intersectoral linkage variable in equation (11), denoted by y_s, which consists of 3 sectors, namely, y_{prim} (primary), y_{sec} (secondary), and y_{ter} (tertiary). This variable will then be transformed into a constant price using Indonesia's CPI. Indonesia's inflation rate (π) is also included in the model to capture the transmitted impact of a given shock. Finally, we use the constant-price Indonesia Rupiah (IDR) exchange rate to USD or RER (e) using the approach proposed in Baek (2021):

$$e = CPI_{US} \times \left(\frac{e_{nom}}{CPI_{ID}}\right) \tag{18}$$

In addition to Model 1, we also replicate another model from Alves (2019) (referred to as Model 2). Alves (2019) used business confidence index (BCI) data (bci) because of its ability to describe economic agents' perceptions, specifically those of businessowners. The timeframe of this model is between 2002:Q1-2022:Q4, adjusted to data availability. Alongside bci, we utilize other data, such as the inflation rate (π) and three-month money market rates (ir). Finally, y_s will be added to capture the intersectoral linkages and their heterogeneous impacts.

IV. Results

4.1. Interpolation Results

Figure 4.1 below visualizes interpolation results from the IO table for 2005, 2010, and 2016 using the RAS procedure:

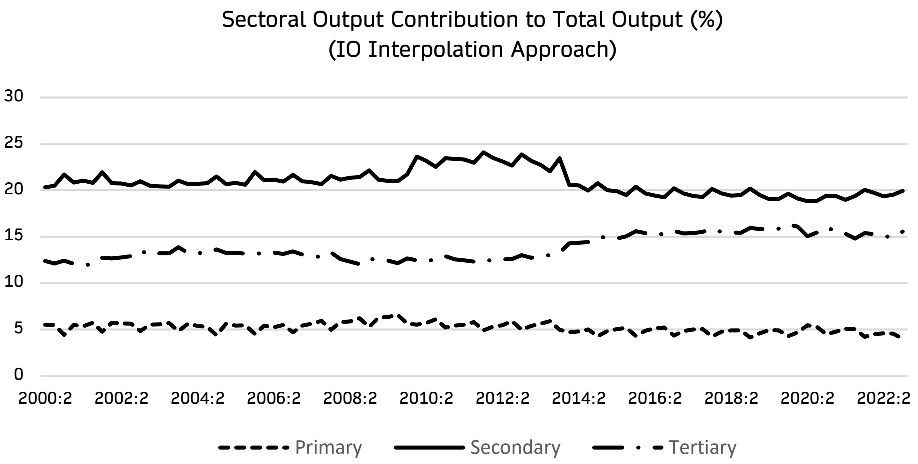


Figure 4.1 Percentage Contribution of Intermediate Output to Total Output in an Economy (%)

Figure 4.1 shows that the secondary sector consistently has the greatest contribution, followed by the tertiary and primary sectors. This result is relevant to findings from Haraguchi et al. (2017) and Naudé & Szirmai (2012) that argue that the manufacturing sector might act as an engine for economic growth because of its relatively large value added. This result contradicts Figure 4.2, which indicates that the tertiary sector, on the side of final demand, exceeded the secondary sector, whereas we see a similar increasing trend in the tertiary sector's proportion eroding the primary sector's proportion.

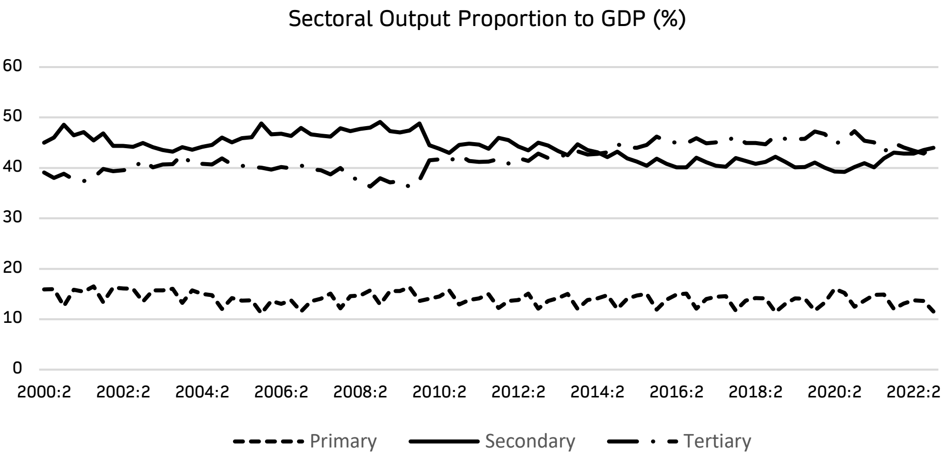


Figure 4.2 Sectoral GDP proportion (%)

Source: BPS

4.2. Model 1: Crude Oil Price Shock

First, we show the unit root test results obtained using the PP and ADF methods in Table 4.1.

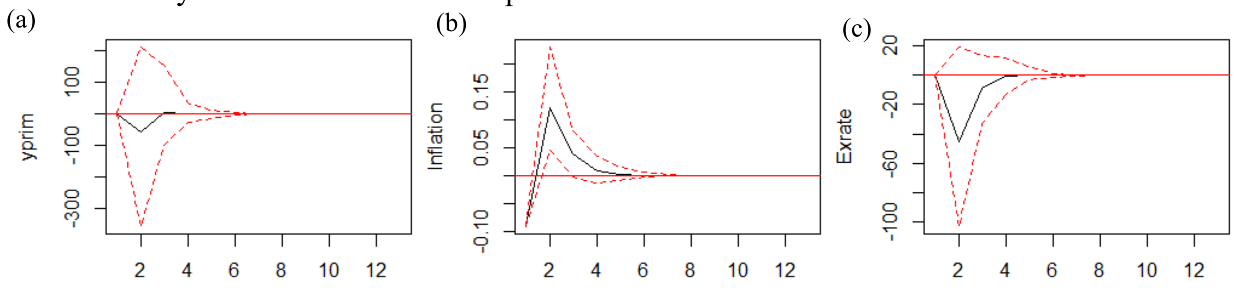
Table 4.1 Unit Root Test for Model 1

Variabel	PP		ADF	
	Level	First Difference	Level	First Difference
p	0.50	0.01***	0.44	0.01***
y_{prim}	0.01***	0.01***	0.64	0.07**
y_{sec}	0.78	0.01***	0.47	0.20
y_{ter}	0.45	0.01***	0.39	0.15
π	0.01***	0.01***	0.07*	0.01***
e	0.40	0.01***	0.74	0.01***

Notes: *** denotes rejection of the unit root hypothesis at a significance level of 1%, ** denotes rejection of the unit root hypothesis at a significance level of 5%, * denotes rejection of the unit root hypothesis at a significance level of 10%.

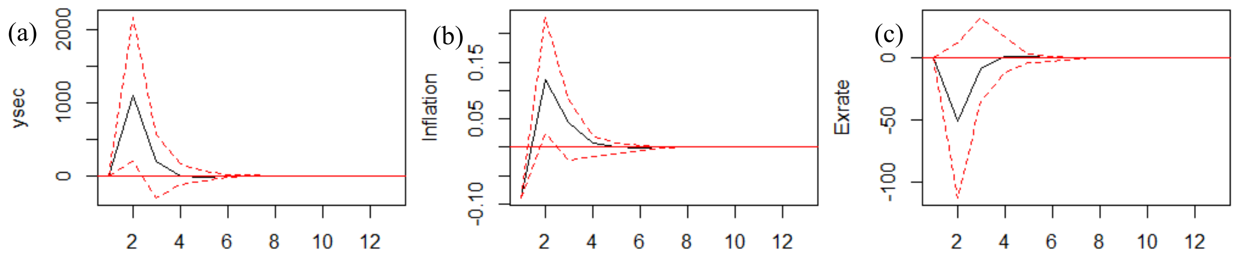
In the PP test, the majority of variables except y_{prim} and π reject the null hypothesis on the first difference. The ADF test also yields similar results with only y_{sec} and y_{ter}, which cannot reject the null hypothesis on both levels. Based on those unit findings, we conclude that SVAR estimations will first differ (stationary in $I(1)$). Furthermore, optimal lag selection with SIC suggests that the optimal lag is 1, in accordance with (Ivanov & Kilian, 2005). Finally, the model stability test revealed that Model 1 has a modulus less than 1 (stable).

The SVAR estimations for Model 1 will focus on the response of each sector to a shock caused by an increase in crude oil prices.



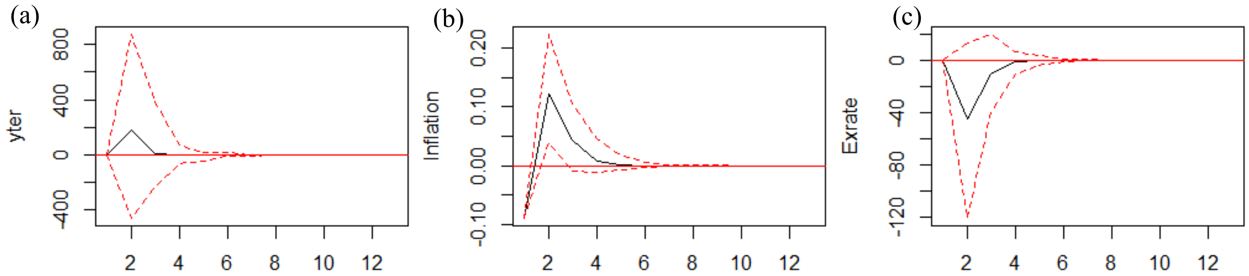
Note: 95% CI.

Figure 4.3 IRF of Crude Oil *Price Shocks* to (a) Primary Output Contribution, (b) Inflation, and (c) Real Exchange Rate



Note: 95% CI.

Figure 4.4 IRF of Crude Oil Price *Shock* to (a) Secondary Output Contribution, (b) Inflation, and (c) Real Exchange Rate



Note: 95% CI.

Figure 5.4 IRF of Crude Oil *Price Shocks* to (a) Tertiary Output Contribution, (b) Inflation, and (c) Real Exchange Rate

Our findings showed opposite results compared to those of Baek (2021) and Jiménez-Rodríguez & Sánchez (2005), who found that positive changes in crude oil prices actually had positive influences on secondary and tertiary sector productivity. In fact, those findings are linear to the "porter hypothesis", which argues that the presence of environmental regulation or barriers to accessing non-renewable energy sources might effectively push "innovation" and competition among firms (Porter, 1991; Porter & van der Linde, 1995). Complete IRF results in **Appendix 2.**

"Innovation" and the existence of systemic effects might be explained by Amann et al.'s (2021) firm-level research. They argue that oil prices increase in response to two types of investment: production machines and information technology and communication (ICT). According to Malik & Al-Zubaedi (2006), outdated machinery tends to be less energy efficient and more oil-fueled. Thus, unaffordable oil fuel forces firms to modernize their machinery to become more productive and electric-based, which shifts their main fuel to coal (Newell dkk., 1999; Steinbuks & Neuhoff, 2014). This fuel substitution has attracted growth in another sector, especially mining and quarrying (categorized in the secondary sector). Machinery investment also creates intermediate output demand for the manufacturing sector. Therefore, reciprocal trade relationships inside the secondary sector are shaped.

Second, transmission through ICT development will automate and computerize the production process (Ley et al., 2016). More importantly, development is negatively correlated with energy demand (Schulte et al., 2016). On the other hand, ICT development from firms will generate more demand for output from information and telecommunication services (in the tertiary sector). Form of investment involving the use of financial products will eventually initiate demand for financial services (Holmberg, 2013). Finally, this condition will encourage more demand for patents from professional research services (Crepon et al., 1998). Unfortunately, the transportation sector experiences negative productivity due to an increase in crude oil prices, which explains why the tertiary sector's IRF response is not as strong as that of the secondary sector.

The aforementioned discussion concludes that both the secondary and tertiary sectors provide positive feedback from an increase in the global crude oil price. This condition does not apply to the primary sector, which experiences the opposite response, which is in line with the findings of Binuomote & Odeniyi (2013). Although insignificant, a decrease in primary productivity might be proportionally associated with a reduction in primary contribution due to increased productivity in other sectors. Moreover, one of the promising factors is the increase in labor productivity in secondary and tertiary sectors (Amann et al., 2021), which can be positive and significant (Katovich & Maia, 2018), thus attracting migration from the primary sector (Ramsey et al., 2023). The increase in crude oil prices has directly responded to the inflation rate, as supported by several findings (see Akhmad et al., 2019; Basnet & Upadhyaya, 2015; Husaini & Lean, 2021). Finally, the negative effect of the RER or, in other words, the exchange rate is supported by some evidence (Chinn, 1997; Turhan dkk., 2013; Wang & Dunne, 2003).

Table 4.2 ***Response of the*** FEVD Sectoral Output Contribution to Shock: Model 1

Horizons	Primary Output Contribution			
	p	y_{prim}	inf	e
2	92.097%	0.065%	7.835%	0.002%
4	92.089%	0.065%	7.844%	0.002%
8	92.086%	0.065%	7.846%	0.002%
Horizons	Secondary Output Contribution			
	p	y_{sec}	inf	e
2	99.890%	0.000%	0.110%	0.000%
4	95.952%	0.001%	4.047%	0.000%
8	95.949%	0.001%	4.050%	0.000%
Horizons	Tertiary Output Contribution			
	p	y_{ter}	inf	e
2	89.970%	0.024%	10.003%	0.002%
4	89.822%	0.025%	10.152%	0.002%
8	89.820%	0.025%	10.153%	0.002%

The FEVD results reveal the significant role of crude oil prices in leading the dynamics of other variables. Narayan et al. (2014) also found similar results in which global crude oil prices made massive contributions to other forecast variables. However, among other sectors, the tertiary sector has relatively less influence. The complete FEVD results are shown in **Appendix 3**.

4.3. Model 2: Economic Agent Perception Shock

In this section, we describe the results of bci shocks to the macroeconomy starting from the pre-analysis below:

Table 4.3 Unit Root Test for Model 2

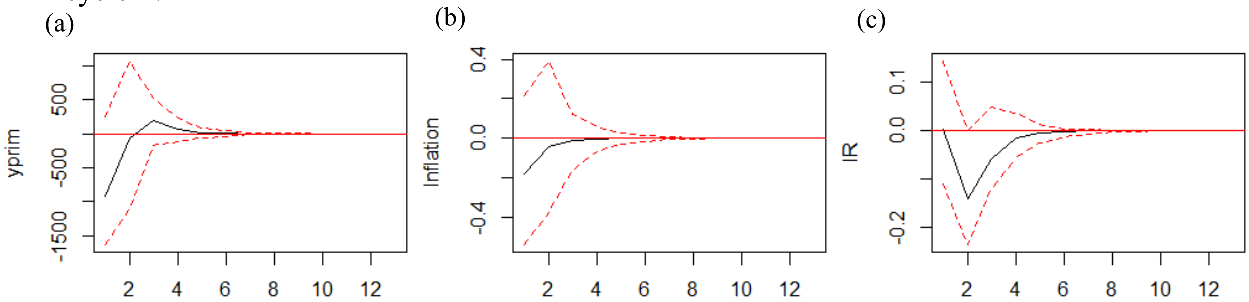
Variabel	PP		ADF	
	Level	First Difference	Level	First Difference
bci	0.216	0.01***	0.108	0.01***
y_{prim}	0.01***	0.01***	0.647	0.070*

y_{sec}	0.811	0.01***	0.484	0.207
y_{ter}	0.395	0.01***	0.333	0.169
π	0.01***	0.01***	0.090*	0.01***
ir	0.078	0.01***	0.01***	0.01***

Notes: *** denotes rejection of the unit root hypothesis at a significance level of 1%, ** denotes rejection of the unit root hypothesis at a significance level of 5%, and * denotes rejection of the unit root hypothesis at a significance level of 10%.

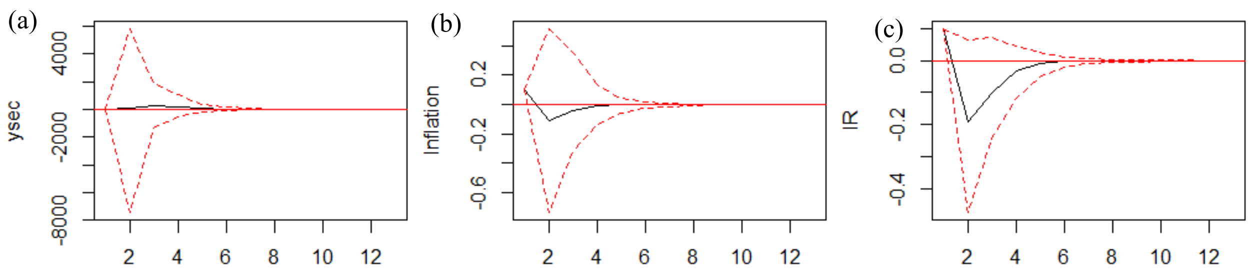
The unit root test using PP shows that y_{prim} and inflation are stationary in level and that the other variables are $I(1)$. For the ADF tests, π and ir show significant results, whereas π is only significant at the 10% level. According to the first difference test, y_{sec} and y_{ter} are not significantly related to bci, π, ir, or y_{prim}, while y_{prim} is only significantly related to 10%. Based on these results, we decided to list first difference of all variables in Model 2. Furthermore, optimal lag selection is achieved using a 1-year lag, and the root polynomials indicate that this model is stable.

Next, we present the SVAR estimation results from bci shocks to the variables in the system.



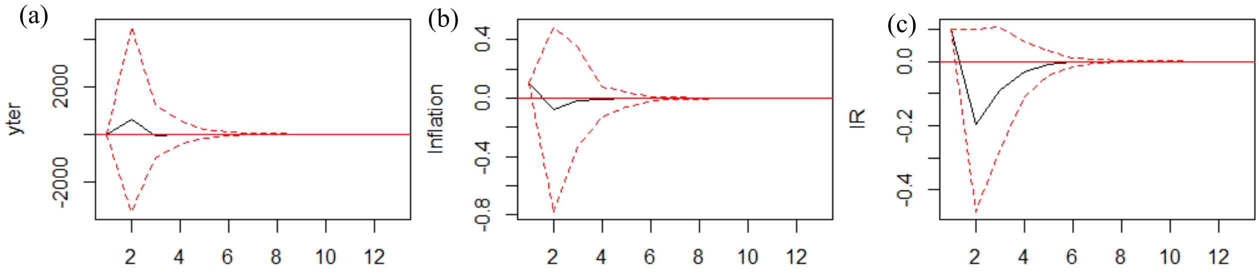
Note: 95% CI.

Figure 4.6 IRF of BCI to (a) Primary Output Contribution, (b) Inflation, and (c) Three-month Money Market Rates



Note: 95% CI.

Figure 4.7 IRF of BCI to (a) Secondary Output Contribution, (b) Inflation, and (c) Three-Month Money Market Rates



Note: 95% CI.

Figure 4.8 IRF of BCI to (a) Tertiary Output Contribution, (b) Inflation, and (c) Three-month Money Market Rates

First, the IRF results show that bci shocks increase the contributions of the secondary and tertiary sectors, which is consistent with the findings of Alves (2019) that an increase in bci positively affects firms' output (complete IRF results in **Appendix 4**). However, why does this phenomenon occur, and how are systemic effects transmitted?

This phenomenon might be caused by strong correlations between economic agents' perceptions of investment (Khan & Upadhayaya, 2020), as Evans & Timberlake (1980) argue that the majority of investment sources (especially FDI) go to developing countries, specifically in tertiary sectors, increasing their productivity. Fortunately, growth in the tertiary sector generates a spillover effect on other sectors, with a large proportion of this effect being received by the secondary sector (Sastry et al, 2003). These arguments are also supported by Murshed (1991), who reported that many tertiary sector outputs are becoming intermediate outputs for other industries. In contrast, positive BCI leads to investment in both the primary and secondary sectors, increasing demand for ICT or financial services (Singh, 2006)[1]. However, this effect might not be significant, as shown in the FEVD (Table 4.3) results, as the bci contribution to their variations appears to be large only in the tertiary sector. The complete FEVD results are shown in **Appendix 5.**

Table 4.4 Response of the FEVD Sectoral Output Contribution to Shock: Model 1

Horizons	Kontribusi *Output* Sektor Primer			
	bci	y_{prim}	inf	ir
2	2.903%	94.607%	0.057%	2.433%
4	3.014%	93.862%	0.681%	2.443%
8	3.015%	93.859%	0.683%	2.443%
12	3.015%	93.859%	0.683%	2.443%
Horizons	Kontribusi *Output* Sektor Sekunder			
	bci	y_{sec}	inf	ir
2	0.048%	14.420%	17.805%	67.726%

[1] Khan & Upadhayaya (2020) found type of investment who receives largest response was structured investment. This investment is closely related to financial service which surging intermediate demand for tertiary sector

4	2.030%	15.576%	19.232%	63.162%
8	2.084%	15.567%	19.221%	63.127%
12	2.084%	15.567%	19.221%	63.127%
Horizons	Kontribusi *Output* Sektor Tersier			
	bci	y_{ter}	inf	ir
2	27.949%	19.192%	23.683%	29.176%
4	27.655%	19.484%	24.044%	28.817%
8	27.658%	19.484%	24.044%	28.814%
12	27.658%	19.484%	24.044%	28.814%

The findings of this research can be extended further to see potential structural shifts as a result of systemic effects from BCI shock. Evans & Timberlake (1980) and Jaumotte & Spatafora (2007) argue that investment in the tertiary sector pulls labor migration from the primary sector. This phenomenon attracts intersectoral trade and encourages an increase in added value from the secondary sector, known as the downstream process (Arnold et al., 2011). Downstream shifts production input from the primary sector to tertiary or secondary sectors, which decreases sectoral dependency on the primary sector. In other words, this condition could be interpreted as a technical change (Cusumano et al., 2015). Therefore, as seen in the IRF results, the primary sector contribution is experiencing a negative impact from BCI shock.

Another interesting aspect of this finding is how inflation actually decreases in response to BCI shock. There are two arguments writers believe could help explain this phenomenon: declining aggregate labor wages and increased sectoral productivity. Worker migration to the tertiary sector has been found to decrease real aggregate wages (Beqiraj et al., 2019), which are positively correlated with the inflation rate (Taylor & Barbosa-Filho, 2021). However, their empirical findings in other countries indicate weak or even insignificant correlations between these two variables (Bobeica et al., 2019; Campos-Vazquez & Esquivel, 2020). The second argument refers to (Jarrett & Selody, 1982; Kendrick, 1973; Lydall, 1968). However, intriguing research from Jarret & Selody (1982) revealed a bidirectional relationship between productivity and inflation where a contraction in productivity will alter the output in the economy, creating cost-push inflation, while in contrast, an inflation shock will push down workers' willingness to work (seen on man-hours).

V. Conclusion

This paper tries to pursue the evidence of systemic effects on intersectoral linkages in Indonesia. This paper constructs a framework for this purpose. The framework first use a deductive approach by combining the Cobb–Douglas production function with the Leontief equation, which mathematically proves that a systemic effect on intersectoral relations might exist. Furthermore, we utilize that variable to empirically determine its existence by simulating two models from Baek (2021) and Alves (2019), and the results are as follows:

1. Crude oil price shocks cause firms to invest in their machinery to be more efficient and coal-based fuel. These responses affect intermediate demand for the manufacturing and mining industries. On the other hand, demand for investment will increase the productivity of financial service industry. This shock also surged any form of capital, such as ICT or intellectual property. This productivity boom would then attract intersectoral migration, causing a loss in the primary sector's productivity.
2. A positive shock to business perception significantly floods the economy through investment, especially for the tertiary sector. This results in pushing, either supply or demand, to enliven intersectoral trades, which ultimately leads to structural shifts and downstream phenomena. The downstream process shifts sectoral contributions, which decreases sectoral dependency on the primary sector.

From the two points above, we conclude that empirically, the existence of systemic effects on intersectoral linkages in Indonesia is proven.

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Appendix

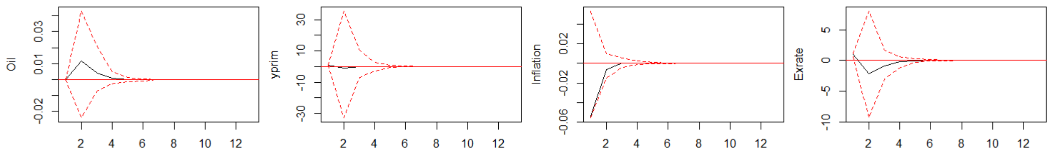
Appendix 1: BPS sectoral classification (2000-2009), BPS sectoral classification (2010-2022), and BPS sectoral classification (aggregate)

BPS Sectoral Classification (2000-2009)	**BPS Sectoral Classification (2010-2022)**	**BPS Sectoral Classification (Aggregate)**
Agriculture, Forestry, and Fisheries	Agriculture, Forestry, and Fisheries	Primary
Mining & Quarrying; Manufacturing Industry; Electricity, Gas, and Water Supply; Construction	Mining & Quarrying: Manufacturing Industry; Electricity & Gas Supply; Water Supply, Sewerage, Waste & Recycling Management; Construction	Secondary
Trade, Hotel and Restaurant; Transport and Communication; Financial, Ownership and Business; Services	Wholesales and Retail Trade, Repair of Motor Vehicles and Motorcycles; Transportation & Storage; Accommodation & Food Beverages Activity; Financial & Insurance Activity; Information & Communication; Real Estate; Business Services; Public Administration, Defense & Compulsory Social Security; Education Services; Human Health & Social Work Activity; Other Services	Tertiary

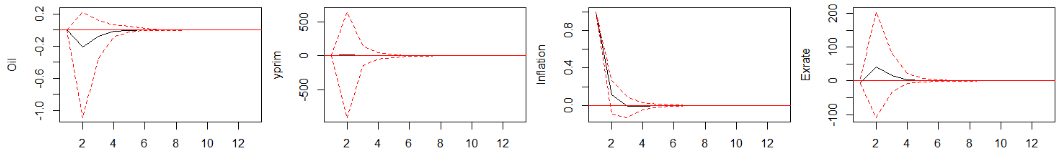
Appendix 2: IRF Model 1

y_{prim}

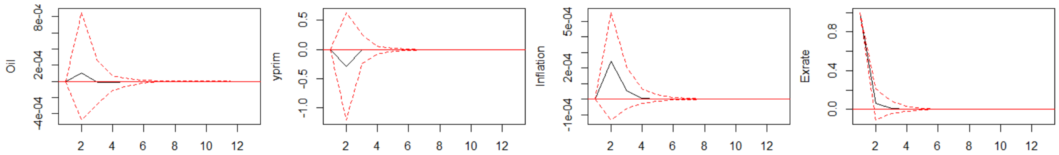
Impulse $= y_{prim}$



Impulse $= \pi$

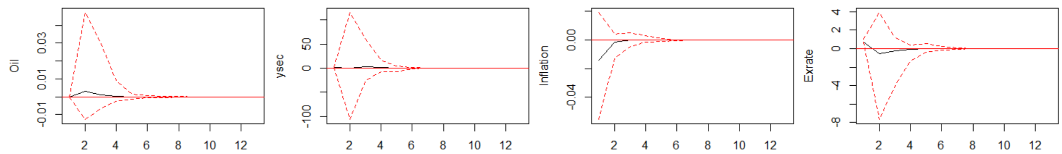


Impulse $= e$

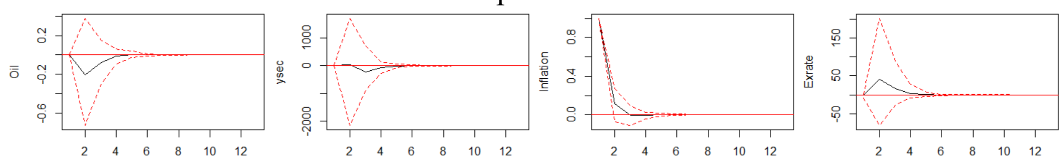


y_{sec}

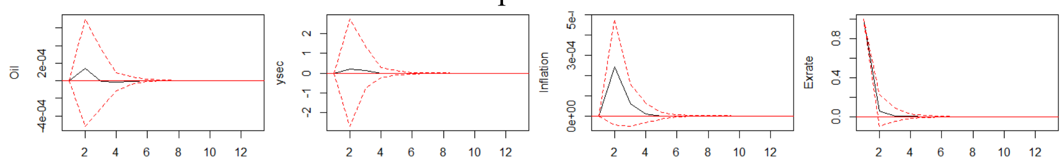
Impulse $= y_{sec}$



Impulse $= \pi$

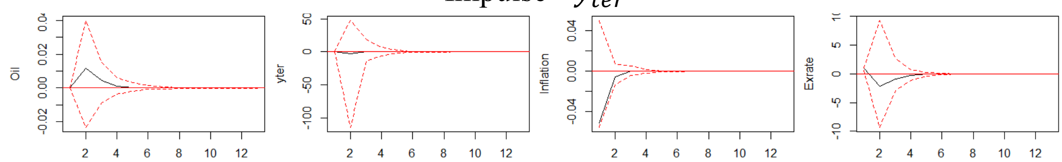


Impulse $= e$

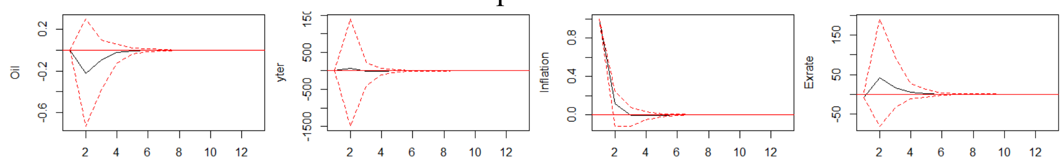


y_{ter}

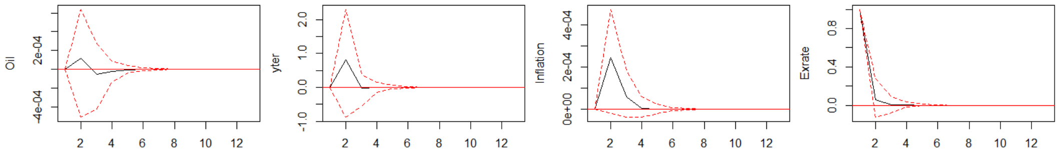
Impulse $= y_{ter}$



Impulse $= \pi$



Impulse $= e$



Oil
yter
Inflation
Exrate

Appendix 3: FEVD Model 1

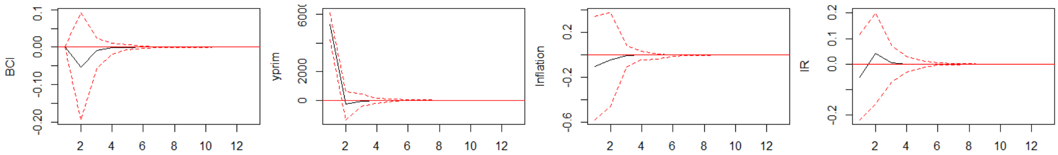
Horizons	p	y_{prim}	inf	e
Variance decompositions of p				
2	95.895%	0.012%	4.093%	0.000%
4	95.394%	0.013%	4.592%	0.000%
8	95.394%	0.013%	4.593%	0.000%
Variance decompositions of y_{prim}				
2	92.097%	0.065%	7.835%	0.002%
4	92.089%	0.065%	7.844%	0.002%
8	92.086%	0.065%	7.846%	0.002%
Variance decompositions of inf				
2	2.184%	0.283%	97.534%	0.000%
4	2.332%	0.282%	97.386%	0.000%
8	2.332%	0.282%	97.386%	0.000%
Variance decompositions of e				
2	53.464%	0.154%	46.356%	0.026%
4	50.795%	0.160%	49.022%	0.024%
8	50.790%	0.160%	49.027%	0.024%
Horizons	p	y_{sec}	inf	e
Variance decompositions of p				
2	96.311%	0.001%	3.688%	0.000%
4	95.734%	0.001%	4.265%	0.000%
8	95.734%	0.001%	4.265%	0.000%
Variance decompositions ofy_{sec}				
2	99.890%	0.000%	0.110%	0.000%
4	95.952%	0.001%	4.047%	0.000%
8	95.949%	0.001%	4.050%	0.000%
Variance decompositions of inf				
2	2.168%	0.020%	97.812%	0.000%
4	2.357%	0.020%	97.623%	0.000%
8	2.357%	0.020%	97.623%	0.000%
Variance decompositions of e				
2	60.053%	0.019%	39.905%	0.023%
4	56.763%	0.018%	43.197%	0.021%
8	56.768%	0.018%	43.192%	0.021%
Horizons	p	y_{ter}	inf	e
Variance decompositions of p				
2	95.572%	0.012%	4.416%	0.000%
4	94.901%	0.013%	5.085%	0.000%
8	94.900%	0.013%	5.086%	0.000%
Variance decompositions of y_{ter}				
2	89.970%	0.024%	10.003%	0.002%
4	89.822%	0.025%	10.152%	0.002%
8	89.820%	0.025%	10.153%	0.002%
Variance decompositions of inf				

2	2.206%	0.259%	97.536%	0.000%
4	2.389%	0.258%	97.353%	0.000%
8	2.389%	0.258%	97.353%	0.000%
Variance decompositions of e				
2	52.723%	0.139%	47.111%	0.026%
4	50.239%	0.144%	49.593%	0.023%
8	50.233%	0.144%	49.600%	0.023%

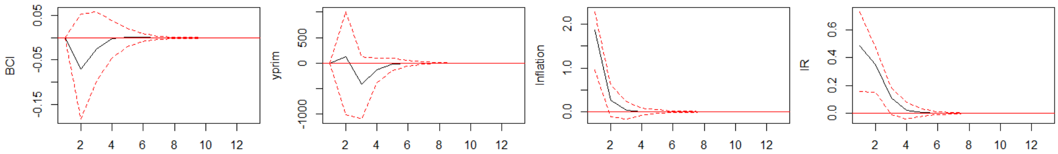
Appendix 4: IRF Model 2

y_{prim}

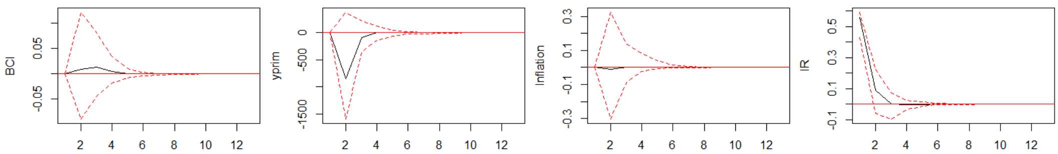
Impulse $= y_{prim}$



Impulse $= \pi$

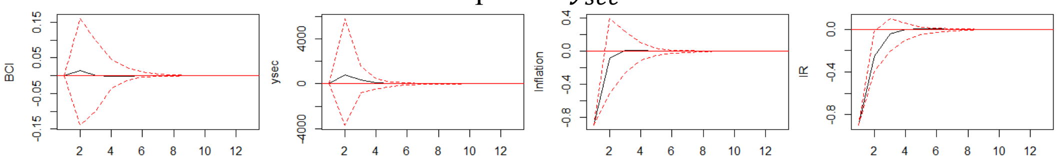


Impulse $= ir$

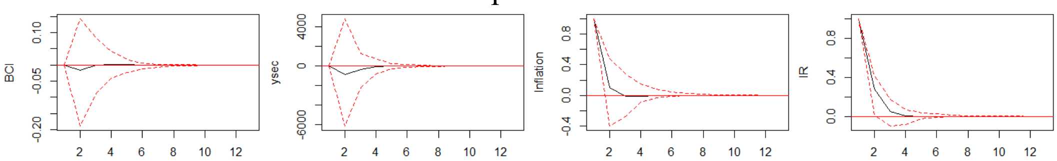


y_{sec}

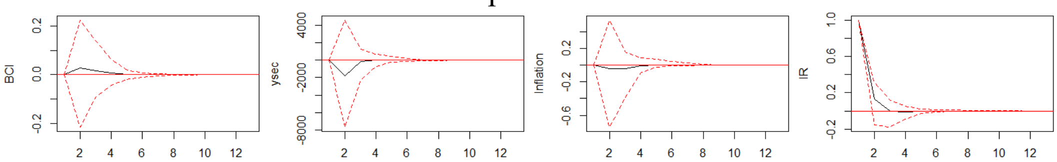
Impulse $= y_{sec}$



Impulse $= \pi$

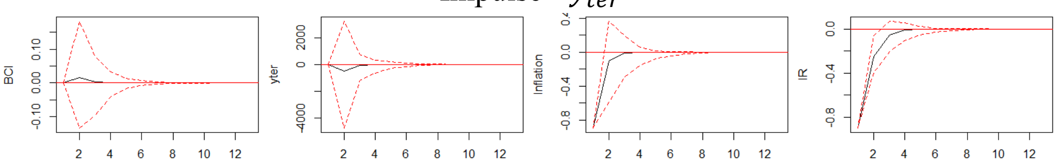


Impulse $= ir$

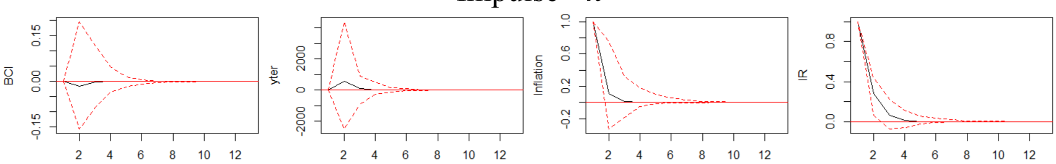


y_{ter}

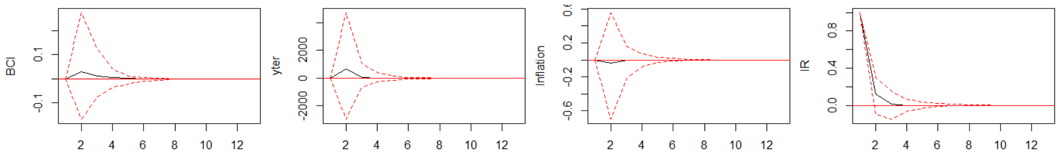
Impulse $= y_{ter}$



Impulse $= \pi$



Impulse $= ir$


BCI
yter
Inflation
IR

Appendix 5: FEVD Model 2

Horizons	bci	y_{prim}	inf	ir
Variance decompositions of bci				
2	98.204%	0.627%	1.151%	0.018%
4	98.009%	0.638%	1.291%	0.061%
8	98.009%	0.638%	1.291%	0.061%
Variance decompositions of y_{prim}				
2	2.903%	94.607%	0.057%	2.433%
4	3.014%	93.862%	0.681%	2.443%
8	3.015%	93.859%	0.683%	2.443%
Variance decompositions of inf				
2	0.949%	0.329%	98.718%	0.003%
4	0.952%	0.330%	98.716%	0.003%
8	0.952%	0.330%	98.716%	0.003%
Variance decompositions of ir				
2	2.776%	0.650%	50.993%	45.581%
4	3.227%	0.640%	51.552%	44.580%
8	3.229%	0.640%	51.552%	44.579%
Horizons	bci	y_{sec}	inf	ir
Variance decompositions of bci				
2	99.884%	0.020%	0.024%	0.072%
4	99.858%	0.020%	0.025%	0.097%
8	99.858%	0.020%	0.025%	0.098%
Variance decompositions of y_{sec}				
2	0.048%	14.420%	17.805%	67.726%
4	2.030%	15.576%	19.232%	63.162%
8	2.084%	15.567%	19.221%	63.127%
Variance decompositions of inf				
2	1.159%	44.184%	54.551%	0.106%
4	1.241%	44.107%	54.455%	0.197%
8	1.241%	44.107%	54.455%	0.197%
Variance decompositions of ir				
2	1.539%	28.966%	35.762%	33.734%
4	1.908%	28.877%	35.652%	33.562%
8	1.911%	28.876%	35.651%	33.562%
Horizons	bci	y_{ter}	inf	ir
Variance decompositions of bci				
2	99.878%	0.020%	0.025%	0.076%
4	99.863%	0.021%	0.026%	0.091%
8	99.863%	0.021%	0.026%	0.091%
12	99.863%	0.021%	0.026%	0.091%
Variance decompositions of y_{ter}				
2	27.949%	19.192%	23.683%	29.176%
4	27.655%	19.484%	24.044%	28.817%
8	27.658%	19.484%	24.044%	28.814%

Horizons	bci	y_{prim}	inf	ir
12	27.658%	19.484%	24.044%	28.814%
Variance decompositions of inf				
2	0.863%	44.329%	54.727%	0.082%
4	0.887%	44.317%	54.712%	0.083%
8	0.887%	44.317%	54.712%	0.083%
12	0.887%	44.317%	54.712%	0.083%
Variance decompositions of ir				
2	1.619%	28.958%	35.751%	33.672%
4	1.925%	28.904%	35.685%	33.486%
8	1.928%	28.903%	35.684%	33.485%
12	1.928%	28.903%	35.684%	33.485%