Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Interconnectedness of Libyan Financial and Real Sectors[1]

Mohamed ELGNAIDI[2] 0009-0008-5149-0456
İstanbul Sabahattin Zaim University, elgnaidi.mohamed@std.izu.edu.tr , Türkiye

Metin TOPRAK 0000-0001-9217-6318

İstanbul Sabahattin Zaim University, metin.toprak@izu.edu.tr ,Türkiye

Article Type: Research Article *Received: 17.08.2023*
Vol 5 (Issue 2) 2023: 90-109 *Revised: 27.08.2023*
Accepted: 01.09.2023
10.5281/zenodo.10339729
Cite as: Elgnaidi, M. (2023). Interconnectedness of Libyan Financial and Real Sectors. Quantrade Journal of Complex Systems in Social Sciences, 5 (2) , 90-109. Doi: 10.5281/zenodo.10339729

Abstract
The Global Financial Crisis of 2008 has motivated modern economists to investigate the link between economies as well as between real and financial sectors. Thus, in last decade the existence of real and financial connectedness has become a corner stone in policy making when understanding how financial shocks impact real economy (Uluceviz & Yılmaz, 2018). Therefore, the aim of this chapter is to analyse the interconnectedness between the real and financial sectors of Libya. To accomplish the chapter's aim, firstly it discusses roles of real and financial sector. Secondly, this chapter shed light on a recent related empirical literature. Methods used in measuring the connectedness between financial and real sectors are drown thirdly. In the fourth section, this chapter illustrates the method used and the model for measuring the Libyan real and financial sectors dependency, in addition to variables selection. Fifthly, our empirical results are displayed. Finally, a conclusion will be highlighted.
Keywords: Interconnectedness, Libyan Real Sector, Libyan Financial Sector

1. Introduction : Role of the Real Sector in the Economy

According to Anyanwu (2010, p. 31) breaks down the real sector into activities of industry, agriculture, construction, building and services. Moreover, Mordi (2014, p. 5) thinks households and firms that participate in goods and services productions, are element of the real sector. However, a wider view is made by Greene (2018, p. 2), according to him, the real sector consists of expenditure and production in the economy, and that widely called national accounts. Thus, this sector fundamentally functions an important role in the economy. Indeed, Klimenko et al. (2021, p. 2) considers that the real sector as the soul creation of "a surplus production" in the economy that assures the financial sector functions. Therefore, it appears that the fact that the real sector is the basis for the derivation of value added in the economy.

Anyanwu (2010, p. 31) essentially highlights a number of reasons which makes the real sector strategic, i.e., satisfying the aggregate demand by the production of goods and services, measuring the macroeconomic policies effectiveness, releasing the pressure on the external sector, and finally generating income and employment. The point is that the real sector has played a crucial role affecting the living standard directly or indirectly, and also affecting the welfare as a result of applied macroeconomic policies. It is, therefore, that the real sector creates connections in the economy between the product market and factor market. In this regard, the real sector links the household, who receives income by selling their capital, i.e., labor and savings, with the firms, which buy. In another level the real sector is about linking in the product market where the households become the buyers of goods and services and the firms are the sellers.

2. Role of the Financial System in the Economy

The previous chapter has discussed the Libyan financial sector outlook without discussing its role in the economy. It might be necessary to shed some lights the financial sector's functions in the economy. It is well known that the major role of the financial system is to link lenders and borrowers (Ulusoy and Ugur,2020). In other words, its main role to provide the deficit units with the needed supply from surplus units. linking surplus units with deficit units may be efficient as it results low costs of information, transaction and enforcement (Mordi, 2014, p. 10; Zhuang et al., 2009, p. 3). This is also supported by Kaur (2017, p. 1868) who believed the efficient allocation of resources is the core function of financial sector and return maximization which all resulting economic growth. Thus, the financial sector throughout its institution

[1] Publication from Ph.D. Dissertation
[2] Corresponding Author elgnaidi.mohamed@std.izu.edu.tr

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

connects these units easily and efficiently. At this point, it may be useful to consider the concepts of company value and financial risk (Ulusoy,2008).

However, Krippner (2011, p. 11) referred to Giovanni Arriighi's theory where profits come from material expansion, the first phase and the late phase of financial channels. This indeed demonstrates the expanded role of financial sector. For example, banks as financial intermediations undertake a critical role in finance provision. A contractual relationship is the base of banks' function between the units of surplus and deficits. Similarly, other institutions like financial markets are channels funds flow through different types of instruments that also provide the units to pool their risks. Indeed, Levine (2004, pp. 5) provided an extensive literature on the functions of financial system and identified five key roles that enhance economic growth; "providing information on potential investments, monitoring investments and implementing corporate governance, facilitating trade, diversification and risk management, savings mobilization and pooling, and exchange of goods and services". Nonetheless, payment mechanism has not been taken into consideration by Levine (2004) even though he identified key points which could indirectly refer to payment mechanism. Governance has a key role in economic growth and linking firms (Ulusoy et al., 2022)

In sum, the financial sector has been playing a critical role to meet the needs of deficit units/ borrowers with surplus units/ lenders. Therefore, it seems to be the fact that financial sector via its institutions collects funds and direct these funds towards other economic activities which lead to economic growth.

3. Linkages Between Financial and Real Sectors: Related Literature

The literature generally believes the sectors are related in several ways, and thus development in one sector may have a direct or an indirect effect on the other. For instance, according to Greene (2018, p. 5-6) highlights that a change in a fiscal policy by increasing the desire to consume more leads to impact the financial sector by decreasing the amount of savings. Furthermore, if the monetary policy were relaxed, this would increase consumption and/or investment through higher lending. Hence, it may be said that the higher investment or consumption, the higher economic growth rate. Moreover, it has been suggested that the Global Financial Crises indicated the impact of the financial architecture on the systematic risk negatively or positively according to authorities policy (Acemoglu et al., 2015, p. 564; Ahelegbey et al., 2016, p. 371). This is because "When a bank experiences financial stress, its troubles could spill over to other banks and threaten to contaminate the broader financial system. This is what regulators refer to when they define and measure systemic risk." (Greenwood et al., 2015, p. 471). Therefore, measuring the interconnectedness between financial institutions has received significant attention for the last decade. This tendency of research could be reasoned to the lack of information about the network obligation between the financial institutions (Gai & Kapadia, 2010, p. 6; Glasserman & Young, 2016, p. 779).

To start our analysis with Eisenberg & Noe (2001) who questioned the independency of a firm's debt to other firms' debt. Thus, they developed a model of nodes representing the financial institutions vector payments to the other nodes. Simply, the model indicates which node was affected by a default of another node. Furthermore, Gai & Kapadia (2010) constructed an artificial statistical model to analyze the banks network and the effect of an idiosyncratic shock on the linkages between banks that compromised 80% external assets and also the banks were from developed countries. Recently, there has been many studies applied network models, which specified models for interconnectedness between financial institutions and liabilities. Studies of Gai et al. (2011) , Markose et al. (2012), Anand et al. (2013) and Acemoglu et al. (2015) and Glasserman & Young (2016) are examples of method based of nodes network. However, there may be some limitations such as the models did not account for what could have caused default nodes which perhaps could be due to a dynamic process of households or nonfinancial institutions.

Other studies endeavored to investigate the interconnectedness between the global financial institutions applying other approaches. For instance, evidence on measuring interlinkages between systematically banks and insurers of U.S, Asia and European Union using a vector autoregressive (VAR) model on daily equity returns (Malik & Xu, 2017). In addition, a similar study by Andrieş et al. (2022) investigated the interconnectedness between global systematically important institutions and banks and the global financial system. Their method was based on several approaches to assess the interconnectedness between these institutions and the global financial system. For example, Bayesian Graphical VAR model and Granger causality networks were among the methods applied in their study to account for the spillover effect. The two sets of data used were, on one hand, balance sheet data of market equity, total assets and book equity regarding systematically important institutions and banks, and on the other hand, market indices related to the global financial system. In another side, Abedifar et al. (2017) employed systemic risk measures and graphical network models to measure interlinkages between Islamic banks, conventional banks and conventional banks with Islamic windows in the GCC countries. It seems that the importance of the financial institutions' role has given space to literature to emerge characterizing the systematic risk of these institutions and an idiosyncratic shock on the other related financial institutions.

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

For more empirical analysis about the interdependency of institutions and markets employing network graphs see for example, Giudici et al. (2020), Battiston & Martinez-Jaramillo (2018) and Giudici & Spelta (2016).

Interconnectedness between cryptocurrencies has also attracted recent research. For instance, Paolo Giudici & Pagnottoni (2020) investigated the connectedness of major eight Bitcoin returns using vector error correction models. Another study applied a unit root testing approach to determine whether the cryptocurrencies explosive behaviors are interlinked (Agosto & Cafferata, 2020). While others like Paolo Giudici & Pagnottoni (2020) attempted to measure the interconnectedness between Bitcoin and gold, crude oil and 12 developed equities applying Bayesian time-varying parameter vector autoregressive and cross-quantilogram to detect the directional predictability and dependence between the variables. This suggests the importance of understanding the connection between the cryptocurrency markets and other assets (Kendirli et. al.,2022)(Kendirli and Şenol, 2021)(Konak and Özkahveci,2023).

However, research has also accounted for measuring interconnectedness with respect to the real economy. For example, Acemoglu et al. (2012) investigated the shocks of sectoral inputs on aggregate output in the U.S using a network approach. The sectoral inputs were captured by the value spent on commodity, which was considered as an input to another sector, and the aggregate output represented by total added value. Even though they attempted to measure the interlinkages between microlevel and macrolevel, they did not account for the financial sector. In contrast, Ahelegbey et al. (2016) endeavoured to measure the interconnectedness in the U.S between the real economy and the financial sector using Bayesian Graphical VAR model. The real sector was represented by a several response virials while the financial sector was determined by thirteen predictor variables. A unidirectional connectedness from financial sector to the real sector was captured during 2007-2009, and from 2010 to 2013 a bidirectional connectedness between the sector were suggested by their results. Later study used a similar approach but different model inputs. Uluceviz & Yılmaz, (2018) evaluated the connectedness between real and financial sectors using VAR model in U.S based on representative indices for the real economy, and data representing the financial side were the returns of the stock, bond, and foreign exchange markets. They conducted a real activity index (ARI) based on real GDP, employment, and initial claims. The other index representing real economy was the already published index of Aruoba-Diebold-Scotti (ADS). Their results appeared to be mixed where the ADS showed the real sector interconnected with the financial sector, while RAI showed a reserve connectedness. This may be due to the different deriving methods of ADS and RAI indices where the former contains financial observations and the later does not.

4. Tools of Interconnectedness Measurements

The literature provides a handful of approaches that are employed to detect the interconnectedness between the economic sectors. For example, Li et al. (2012, Table 1) summarized five methods for interconnectedness analysis such as correlation, cointegration analyses, panel analyses, VAR and dynamic factor analyses. Similarly, Bricco & Xu (2019, pp. 18-19) provided a summery of interconnectedness measurment approches and their applicaplity. And thus, a researcher should consider each method's limitations in undertaking interconnectedness measures. For instances, for more discussion on methodologies limitations see, Li et al. (2012, Table 1) and Andrieş et al. (2022, Table 1). Moreover, the availability of data plays a cruciel role in determining the measurment approach as was mentioned by Bricco & Xu (2019, p. 38).

5. Measuring Libyan Real-Financial sector interconnectedness

According to Li et al. (2012, pp. 138–139), measuring interlinkages among economies are accounted for different endogenous economic variables when VAR employed. They also add that impulse response functions (IRFs) and decompositions of variance are usually introduced by VAR, the former measures response of a variable to another variable's shocks and the later measure shocks' relative importance. More importantly, because of this chapter's purpose and considering each method limitations, VAR will be considered an optimal selection to measure interconnectedness between real and financial sector in Libya. This can evidenced by Bricco & Xu (2019, p. 38) when they argued the VAR is the selection if the purpose to analyze the interdependency between macro-financial variables . In addition, a recent research measuring the interconnectedness between macro-financial variables, VAR was widely adopted in empirical research (Acemoglu et al., 2015; Ahelegbey et al., 2016; Andrieş et al., 2022; Giudici & Pagnottoni, 2020; Uluceviz & Yılmaz, 2018).

5.1 Bayesian VAR Approach

In this section, Bayesian Theorem is mentioned briefly, according to Thomas Bayes the relationship of two random events is described under their conditional probabilities.

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

$$P\left(\frac{x}{y}\right) = \frac{P(y)P(y|x)}{P(x)} \qquad \text{Eq. 1}$$

Where $P(x)$ represents a random event probability of x, and $P(y)$ represents a random event probability of y. That is known as prior probability. The term $P(y|x)$ represents the occurrence of event y conditioned to the event x occurrence. Also, $P(x|y)$ represents the occurrence of event x conditioned to the event y occurrence. That is known as posterior probability. Thus, Bayesian Theorem can also be stated as

$$P_p = L_i \times p_p \qquad \text{Eq. 2}$$

Whare P_p and $p_p$stands for the posterior probability and prior probability, respectively.

Generally, the variables dynamic can be modelled in SVAR process (structural vector autoregressive process) as in Ahelegbey et al. (2016)

$$Y_t = \beta_0 Y_t + \sum_{i=1}^{\rho} \beta_i Y_{t-i} + \sum_{i=1}^{\rho} \mathrm{C}_i Z_{t-i} + \varepsilon_t \qquad \text{Eq. 3}$$

Where Z_t is a n_z predictor variables vector, β_0 is $n_y \times n_y$ coefficients matrix of structural contemporaneous, β_i and C_i are respectively $n_y \times n_y$ and $n_y \times n_z$ structural coefficients vector and ε_t is n_y structural error term vector, and t = 1,,,, T.

According to Ahelegbey et al. (2016) Andrieş et al. (2022), not only the applicability of estimating Eq. 3 and also over parameterized problem in SVAR model was considered. Thus, *to* solve these problems, Let X_t = (Y_t , Z_t)` be n_y+ n_z = n observed variables dimensional matrix at time t, and β_i^* = (β_i, C_i), $1 \leq i \leq \rho$, and $n_y \times n$ are unknown coefficients of response and predictor variables matrices. The equation 5 can be expressed in a reduced form of VAR as

$$Y_t = \sum_{i=1}^{\rho} A_i X_{t-i} + A_0^{-1} \varepsilon_t \qquad \text{Eq. 4}$$

For t = 1,,,, T, where A_0 = (I_{n_y} – β_0) is $n_y \times n_y$ matrix, I_{n_y} is the n_y dimensional identity vector, A_i (dimension of $n_y \times n$) = A_0^{-1} β_i^*, $1 \leq i \leq \rho$ are the coefficient matrices of the reduced form VAR model. u_t = A_0^{-1} ε_t is reduced form errors of n_y dimensional matrix and $u_t \overset{i.i.d}{\sim} N(0, \sum u)$.

The dynamic of the reduced Var model is given through variance decompositions or impulse response functions by estimating A_0 and $\sum \varepsilon$ from the following errors covariance matrix based on Eq. 6. First, following recent literature i.e. Ahelegbey et al., (2016) we assume the prior distribution of covariance is Minnesota, thus, $A_+ \sim N(A, V)$.

Conducting total index of interconnectedness (D-Y) is introduced by Diebold & Yilmaz (2009), to measure the spillover between returns and their volatility, developed later by Diebold & Yilmaz (2012) considering the impulse response functions and the forecast error variance decomposition. Therefore, we conduct the same measure for interconnectedness. However, the forecast error variance decomposition is influenced by variable ordering. Hence, this is dealt with according to Ankargren et al. (2017) and variable order becomes GDP, Gross Capital Formation, inflation, Government Debt, M1, m2, Un-official Exchange rate and Domestic Private Credit by Banks.

The main attention is on the h-stet error variance decomposition of variable i is caused by variable j shocks, that expressed mathematically as

$$\tilde{\varphi}_{\boldsymbol{ij,t}}^{\boldsymbol{g}}\,(\boldsymbol{h}) = \frac{\sum_{t=1}^{h-1} \Psi_{ij,t}^{2,g}}{\sum_{i=1}^{N} \sum_{t=1}^{h-1} \Psi_{ij,t}^{2,g}} \qquad \text{Eq. 5}$$

Where $\tilde{\varphi}_{\boldsymbol{ij,t}}^{\boldsymbol{g}}\,(\boldsymbol{h})$ indicates the h-step ahead forecast error variance decomposition, $\Psi_{ij,t}^{g} = S_{ij,t}^{\frac{-1}{2}} A_{h,t} \sum_t \varepsilon_{ij,t}$, $\sum_t$ the error term $\varepsilon_{ij,t}$ covariance matrix. Based on Eq. 5 total connectedness index is constructed as

$$C_{\boldsymbol{t}}^{\boldsymbol{g}}\,(\boldsymbol{h}) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\varphi}_{ij,t}^{g}(\boldsymbol{h})}{\sum_{j=1}^{N} \tilde{\varphi}_{\boldsymbol{ij,t}}^{\boldsymbol{g}}\,(\boldsymbol{h})} \times 100 \qquad \text{Eq. 6}$$

Firstly, the spillovers of variable i to all others j is calculated indicating the total directional connectedness to others as

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

$$C^{g}_{i\to j,t}\,(h) = \frac{\sum_{j=1,i\neq j}^{N}\tilde{\varphi}^{\,g}_{ji,t}(h)}{\sum_{j=1}^{N}\tilde{\varphi}^{g}_{ji,t}\,(h)} \times 100 \qquad \text{Eq. 7}$$

Secondly, the computation of the spillovers of all variables j to variable i, describing the total directional connectedness from others as

$$C^{\boldsymbol{g}}_{\boldsymbol{i\leftarrow j,t}}\,(\boldsymbol{h}) = \frac{\sum_{j=1,i\neq j}^{N}\tilde{\varphi}^{\,g}_{ij,t}(\boldsymbol{h})}{\sum_{i=1}^{N}\tilde{\varphi}^{\boldsymbol{g}}_{\boldsymbol{ij,t}}\,(\boldsymbol{h})} \times 100 \qquad \text{Eq. 8}$$

Thirdly, the differences between the total directional connectedness to others and from others to obtain the net total directional connectedness $C^{\boldsymbol{g}}_{\boldsymbol{i,t}}$ is calculated as

$$C^{g}_{i,t}\,(h) = C^{g}_{i\to j,t}\,(h) - C^{g}_{i\leftarrow j,t}\,(h) \qquad \text{Eq. 9}$$

The sign of the net total directional connectedness shows whether the variable i is driving or driven by the others.

The final step is the calculation of the net total directional connectedness to investigate the bidirectional connections by calculating the net pairwise directional connectedness (NPDC) as

$$NPDC_{ij}(h) = \frac{\tilde{\varphi}^{g}_{ji,t}(h) - \tilde{\varphi}^{g}_{ij,t}(h)}{N} \times 100 \qquad \text{Eq. 10}$$

5.2 Data and model variables selection

The research organized in this chapter depends on annually secondary data, perhaps from 1973 to 2020. Taking into account the authenticity of the results, the selection of the variable was in line with the literature i.e. Bricco & Xu (2019, p. 38). In the case of Libya in which a researcher could suffer some limitations in terms of data availability and data time horizon, the selected variables are; GDP (Ahelegbey et al., 2016; Ibadin et al., 2014; Uluceviz & Yılmaz, 2018), gross fixed capital formation (GCF) (Ibadin et al., 2014), M1, M2 (Ahelegbey et al., 2016), government debt (Andrieş et al., 2022), inflation (INF) (Ahelegbey et al., 2016) and Unofficial exchange rate (MBER) (Uluceviz & Yılmaz, 2018; Ahelegbey et al., 2016 who used effective exchange rate). Also, we capture the Libyan finacial sector by dmestic private credit by banks (DPCB).

Regarding data collection, there has been a use of different sources. For example, GDP and gross capital formation were obtained from United Nations National Accounts. M1, M2 and dmestic private credit by banks (DPCB) for the period from 1973 to 2017 were obtained from Monetary and Financial Statistics (1966-2017) (Central Bank of LIBYA, n.d., tab. 2) and from 2018 to 2020 was gathered from (Central Bank of LIBYA, 2021, tab. 3). Government debt and Inflation were obtained from IMF data sources. Finally, the unofficial exchange rate was surveyed through historical records of Al-Mushir Market- Tripoli-Libya.

5.3 Empirical Results and Diagnostics

Before proceeding further, it may be worth mentioning statistical results related to the empirical results.

5.3.1 Descriptive Statistics

Results of descriptive statistics are shown in Table 5.1 displaying the number of observations mean and standard deviation of the variables.

Table 5.1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GDP	48	35440.3	35684.685	2401.197	116721.42
Gross Capital Formation	48	7.864e+09	4.411e+09	2.274e+09	1.879e+10
Inflation Rate	48	6.263	7.754	-9.798	29.38
Government debt	48	25067.373	54121.758	152.476	201517.74
M1	48	24452.165	34927.761	514	122950.3

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

M2	48	26692.919	35452.781	810.9	125543
Un-official Exchange Rate	48	1.932	1.695	.31	7.2
Domestic Private Credit by Banks	48	7711.087	9552.493	212.617	40729.164

5.3.2 Correlation Test

Table 5.2 shows pairwise test results of correlation between the variables. According to the results GDP only is correlated positively with GCF and adversely government debt which also has same relation with GCF.

Table 5.2. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) gdp	1.000							
(2) GCF	0.568*	1.000						
(3) inflation	-0.370	-0.339	1.000					
(4) gov_debt	-0.444*	-0.378*	0.312	1.000				
(5) m1	0.255	0.096	0.242	0.123	1.000			
(6) m2	0.226	0.144	0.233	0.112	0.866*	1.000		
(7) bmer	-0.083	0.022	0.204	-0.156	0.125	0.037	1.000	
(8) pcbs	-0.027	0.052	0.018	0.352	0.291	0.407*	-0.114	1.000

**** p<0.01, ** p<0.05, * p<0.1*

5.3.3 Testing for Unit Root

The stationarity test is carried out in this section for all variables. As shown in Table 5.3, the null hypothesis of non-stationary is rejected at I (0). Yet, the null is not rejected at I (1), the Un-official exchange rate is still stationary and thus becomes stationary at I (2).

Table 5.3. Results of Augmented Dickey–Fuller Tests

Variables	I (0)			I (1)		
	Z	p-value	lags	Z	p-value	lags
GDP	-1.395	.585	1	-3.038	.032	1
Gross Capital Formation	-2.464	.124	1	-5.543	.000	1
Inflation	-3.724	.004	1	-6.411	.000	1
Gov.debt	-1.15	.695	1	-6.089	.000	1
M1	-.12	.947	1	-3.51	.008	1

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

M2	.073	.964	1	-3.61	.006	1
Black market exchange rate	-1.364	.599	1	-2.66	.081	1
Domestic_priva~a	-1.533	0.517	1	-4.185	.000	1

Black market exchange rate becomes stationary at I (2).

5.3.4 *Optimal lag number*

In all VAR(p) models, the selection of lag order is important. In this part we conduct the test of the lag order for BVAR(p). The results of the test in Table 5.4 confirms only the first lag may be included in the model and thus our model becomes BVAR (1).

Table 5.4 Bayesian model tests: Optimal Lag Selection

	log (ML)	P(M)	P(My)
lag1	-170.395	0.250	0.991
lag2	-175.078	0.250	0.009
lag3	-189.114	0.250	0.000
lag4	-182.815	0.250	0.000

5.3.5 *Stability Condition*

To process our model BVAR (1), the model must be stable, therefore, checking for the model stability is performed and the results are displayed in Table 5.5. The results confirm the condition of stability, that is, eigenvalues lie inside the unit circle meaning our model BVAR (1) satisfies the stability condition.

Table 5.5 Bayesian VAR (1) Stability Condition Test

Eigenvalue stability condition Companion matrix size = 8
MCMC sample size = 80000

Eigenvalue			Equal-tailed			
modulus	Mean	Std.	dev.	MCSE	Median	[95% cred. interval]
1	0.904	0.179	0.001	0.878	0.633	1.344
2	0.744	0.122	0.000	0.735	0.527	1.002
3	0.647	0.106	0.000	0.643	0.450	0.866
4	0.567	0.099	0.000	0.565	0.379	0.767
5	0.493	0.098	0.000	0.493	0.302	0.686
6	0.414	0.103	0.000	0.415	0.209	0.611
7	0.316	0.113	0.000	0.317	0.099	0.532
8	0.189	0.118	0.000	0.179	0.010	0.433

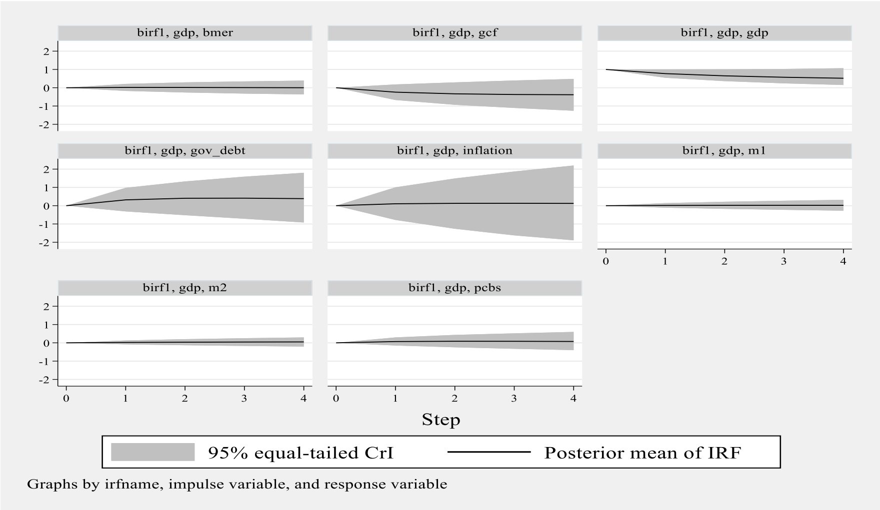
Pr(eigenvalues lie inside the unit circle) = 0.7605

5.3.6 Impulse Response Function

GDP Shocks

Figure 5.1 below which reports the impulse response results to GDP shocks. The results reveal that Inflation and government Debt are positively highly sensitive to GDP shocks while M1, M2, domestic private credits by banks and the un-official exchange rate seem to have less positive sensitivity to GDP shocks. In contrast, gross capital formation shows a negative response to the GDP shocks.

Figure 5.1 Impulse Response Functions to GDP shocks



Gross Capital Formation Shocks

Figure 5.2 reports the responses to changes in gross capital formation. As shown in the figure, homogenous responses from unofficial exchange rate, M1, M2 and domestic private credit by banks to changes in gross capital formation. However, inflation shows a high sensitivity to gross capital formation shocks even though the inflation response is just above zero. The noticeable responding can be seen from government debt, that is a positive respond is generated from a positive shock of gross capital formation. GDP, on the other hand, reveals negative respond to gross capital formation.

Inflation Shocks

From Figure 5.3 below, it is evident that one standard deviation shock of inflation has a positive impact on gross capital formation and negatively affects government debt. According to the other variables, a shock of inflation has no impact on them.

Government Debt Shocks

Figure 5.4 reports the impulse response functions to government shocks. Homogenous responses to the government debt shocks are from unofficial exchange rate, M1 and M2. Domestic private credit by banks shows a negative steady response reaching almost -1% in the fourth period to 1% change in government debt. Similar responses are recorded by GDP and gross capital formation to a shock in government debt, that is both recorded a positive response by 1% from almost the second period and upwards to the fourth period due to 1% change in government debt.

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Figure 5.2 Impulse Response Functions to Gross Capital Formation Shocks

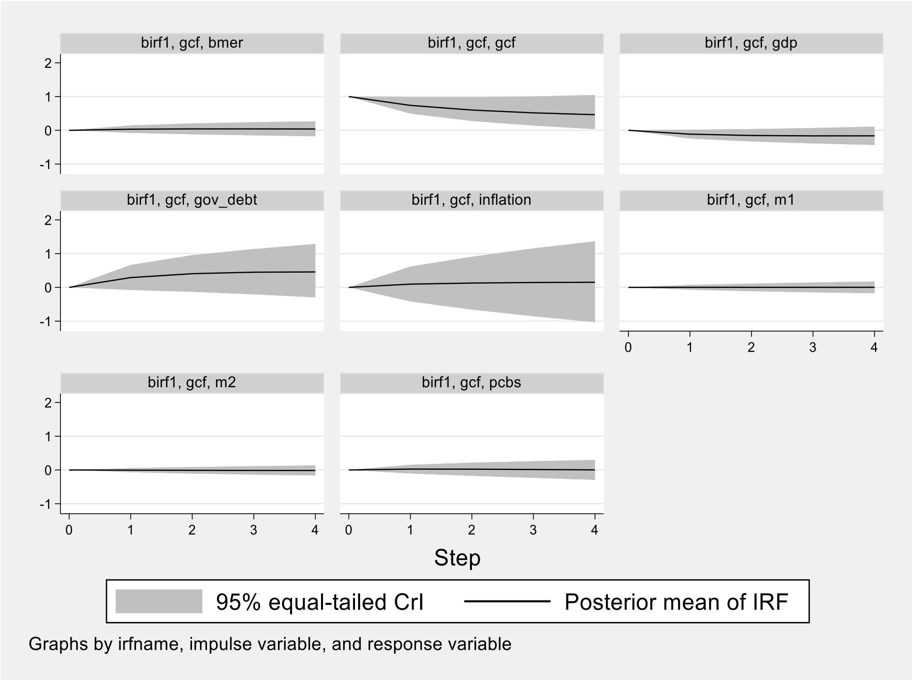
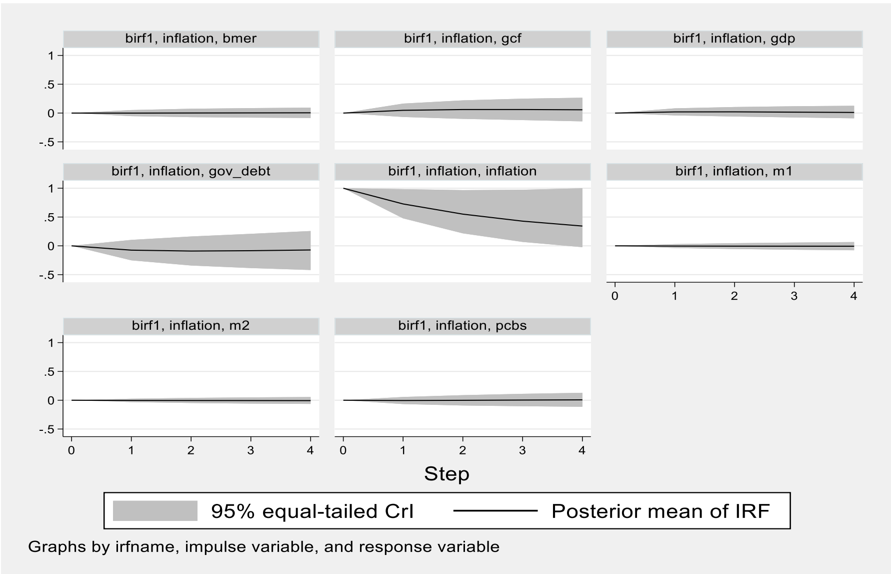
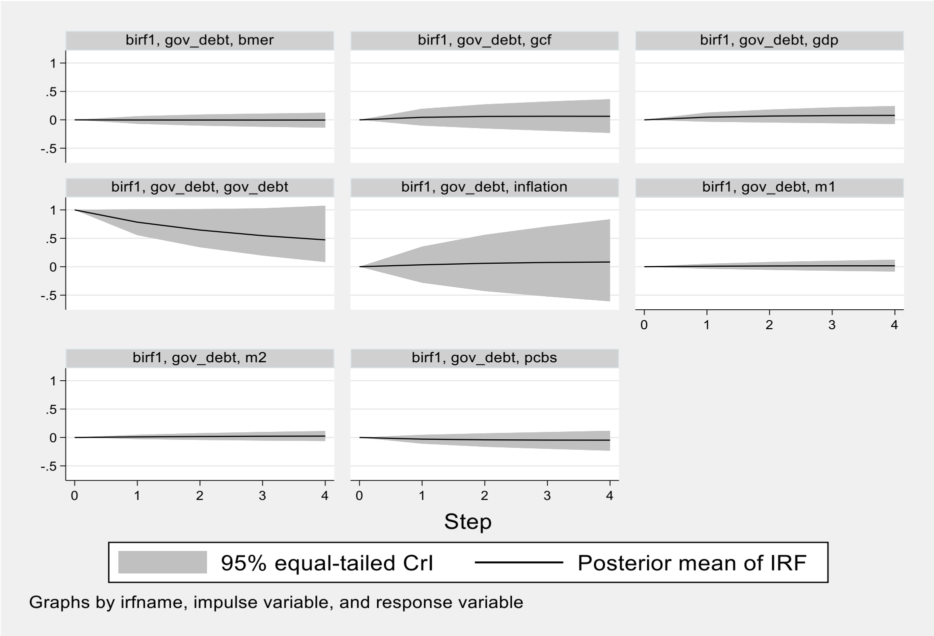


Figure 5.3 Impulse Response Functions to Inflation



Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Figure 5.4 Impulse Response Functions to Government Debt Shocks



M1 Shocks

Responds to M1 shocks somehow different as shown in Figure 5.5. For example, not only un-official exchange rate and M2 seems to be negatively responding to M1 shocks but also government debt can be seen highly negatively sensitive to M1 shock. Inflation also is recorded to have positive response to M1 shocks. Moreover, gross capital formation seems responding positively to M1 shocks. Similar low positive responses are recorded for GDP and domestic private credit by banks to M1 shocks.

M2 Shocks

Figure 5.6 reports impulse response functions to M2 shocks. Homogenous responses to M2 shocks are documented by unofficial exchange rate, GDP, and gross capital formation, while M1 and domestic private credit by banks recorded negative responses in the fourth period to M2 shocks. High sensitivity response to M2 shocks is recorded by government debt and even higher negative response by inflation.

Black Market Exchange Rate Shocks

Figure 5.7 displays standard deviation shock of inflation on the other variables. Significantly, one shock in unofficial exchange rate leads to decrease in inflation rate while government debt responds positively to inflation shock. Others, however, show undetectable reaction to a standard deviation shock in unofficial exchange rate.

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Figure 5.5 Impulse Response Functions to M1

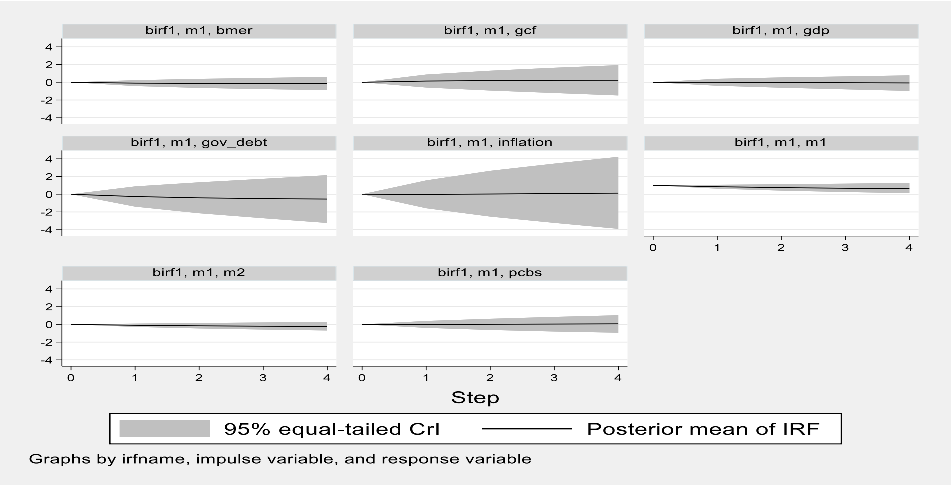
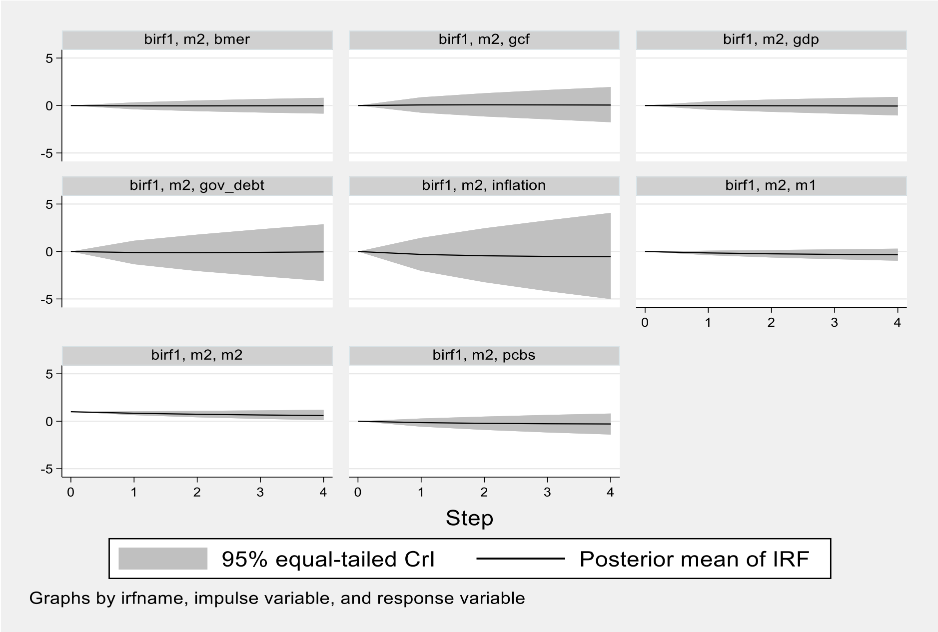
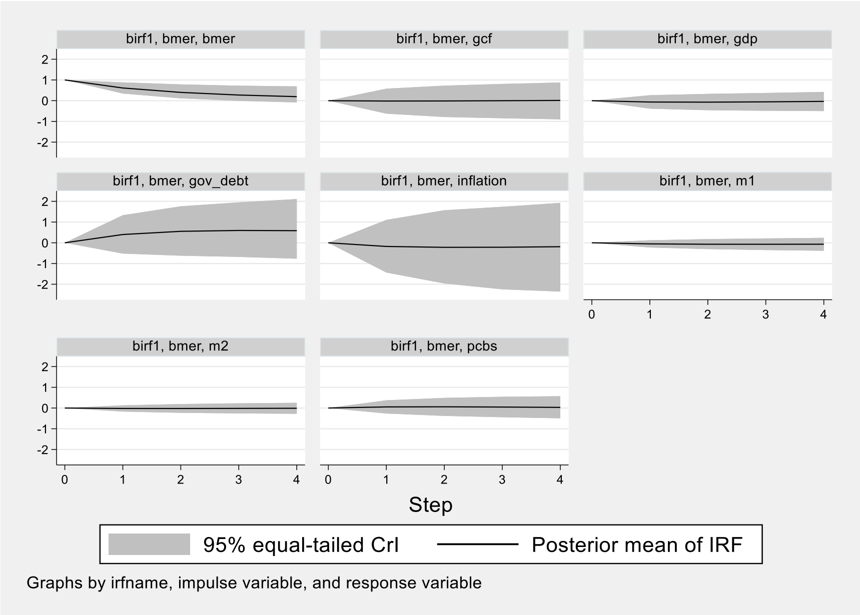


Figure 5.6 Impulse Response Functions to M2



Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

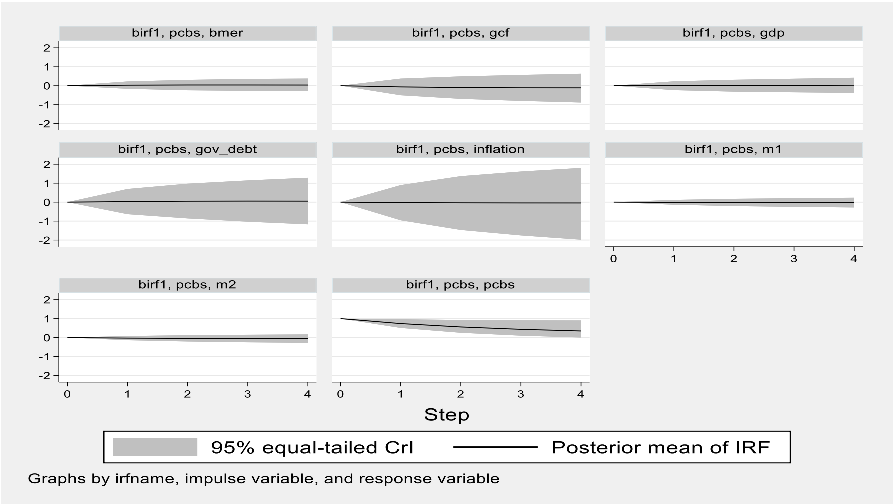
Figure 5.7 Impulse Response Functions to Inflation



Domestic Private Credit by Banks Shocks

The impulse response functions to shocks of domestic private credit by banks are reported in Figure 5.8. Noticeably, the mean of responses for unofficial exchange rate, GDP, M1 and M2 remains steady and almost zero. However, inflation shows being highly sensitive to domestic private credit by banks followed by government debt and gross capital formation, respectively, while the latter records a negative response in the fourth period.

Figure 5.8 Impulse Response Functions to Domestic Private Credit by Banks



5.3.7 Variance Decomposition Results

The dynamic analysis of variance decomposition is given in Table 5.6. With respect to GDP, it explains its prognostic standard deviation by 48% in the first year but for coming years other variables increasingly engage in explaining the error of GDP. Gross capital formation error is increasingly explained by other from about 40% in the first year to almost 55% in the fifth year. Inflation seems to be highly self-explaining its own variance by of 78% in the first year and gradually

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

decreased to 56% in the fifth year, and this also almost the same for government debt. However, M1 standard deviation appears to explain its own error by 52% and gradually decreases to explain 46% of its variance. In the case of M2, it explains 60% of its own prognostic error in the for the first and second years but slightly declines to explain 53% of its prognostic error in the fifth year. Unofficial exchange rate variance, on the other hand, explains 97% of its own error in the first year and this drops to account for 67% of its own error. Finally, domestic private credit by banks decreasingly interferes to explain its own prognostic error from 100% in the first year to nearly 71% in the fifth year.

Table 5.6 Cholesky Variance Decomposition

Step	GDP	GCF	Inf	Gov.d ebt	M1	M2	BMER	DPCB
1	48.8%	60.9%	78.3%	76.7%	54.2%	60.7%	97.6%	100.0%
2	48.1%	57.8%	73.0%	73.2%	52.7%	60.6%	83.2%	92.9%
3	46.0%	52.9%	66.6%	67.6%	50.7%	58.7%	75.6%	84.5%
4	43.6%	48.3%	61.4%	61.9%	48.6%	56.0%	70.9%	77.2%
5	41.5%	44.4%	56.9%	56.9%	46.5%	53.0%	67.6%	71.0%

Source: Author based on the BVAR (1) results.

Variance Decomposition – GDP

Table 5.7 declares the amount of information that the variables contribute to GDP. Apart from how much GDP explains its own error, higher contributions come from gross capital formation and government debt, however, their contribution decreases over time. Inflation, M1, M2, unofficial exchange rate and domestic private credit by banks have an increasing contribution to explain GDP error.

Table 5.7 Cholesky Variance Decomposition of GDP

Step	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB
1	48.8%	25.4%	3.3%	15.1%	1.5%	1.7%	1.6%	2.5%
2	48.1%	24.4%	3.8%	13.2%	2.2%	2.4%	2.8%	3.1%
3	46.0%	23.5%	4.4%	12.4%	3.0%	3.2%	3.5%	4.1%
4	43.6%	22.7%	5.0%	12.2%	3.7%	3.8%	4.0%	4.9%
5	41.5%	22.0%	5.5%	12.3%	4.2%	4.4%	4.4%	5.6%

Source: Author based on the BVAR (1) results.

Variance Decomposition of Gross Capital Formation

Table 5.8 confirms high contribution of GDP, M1, M2, unofficial exchange rate and domestic private credit by banks in explaining the error of gross capital formation. Inflation and government debt decreasing contribute to gross capital formation.

Variance Decomposition of Inflation

Increasingly contribution to inflation is found to be by all variables over time as in Table 5.9. The highest contribution to inflation error comes from M2 and M1 respectively.

Table 5.8 Cholesky Variance Decomposition of Gross Capital Formation

Step	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB
1	..	60.9%	9.3%	11.2%	5.2%	3.4%	6.5%	3.4%
2	4.2%	57.8%	8.5%	9.2%	5.6%	4.0%	6.7%	4.1%
3	8.7%	52.9%	8.1%	8.4%	6.0%	4.5%	6.8%	4.7%
4	11.9%	48.3%	8.2%	8.2%	6.4%	5.0%	6.9%	5.2%
5	13.9%	44.4%	8.2%	8.3%	6.9%	5.5%	7.0%	5.7%

Source: Author based on the BVAR (1) results.

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Table 5.9 Cholesky Variance Decomposition of Inflation

Step	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB
1	..	..	78.3%	2.2%	4.7%	9.7%	2.5%	2.7%
2	1.4%	1.8%	73.0%	3.0%	4.7%	9.5%	3.4%	3.3%
3	2.7%	3.7%	66.6%	4.0%	5.2%	9.5%	4.2%	4.1%
4	3.7%	5.1%	61.4%	4.8%	5.8%	9.7%	4.7%	4.9%
5	4.4%	6.2%	56.9%	5.5%	6.4%	9.9%	5.1%	5.6%

Source: Author based on the BVAR (1) results.

Variance Decomposition of Government Debt

Table 5.10 shows the results of government debt variance decomposition. Noticeably, the variables have a growth contribution to government debt error, except domestic private credit by banks which has 6.8% to 6.6% contribution to government debt error.

Table 5.10 Cholesky Variance Decomposition of Government Debt

Step	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB
1	..	..	..	76.7%	4.9%	3.1%	8.6%	6.8%
2	1.8%	1.1%	0.9%	73.2%	5.7%	3.4%	8.2%	5.7%
3	3.7%	2.2%	2.0%	67.6%	6.6%	4.2%	8.1%	5.8%
4	5.2%	3.3%	3.0%	61.9%	7.4%	4.9%	8.1%	6.1%
5	6.5%	4.2%	4.0%	56.9%	7.9%	5.6%	8.3%	6.6%

Source: Author based on the BVAR (1) results.

Variance Decomposition of M1

Table 5.11 below illustrates how much the variables contribute to M1. From around 0.5% in the first year to about 3% in the fifth year can be linked to GDP, GCF, inflation and government debt. M2, on the other hand, has a decreasing contribution to account for M1 error. Unofficial exchange rates and domestic private credit by banks increasingly contribute to M1 over time.

Table 5.11 Cholesky Variance Decomposition of M1

Step	GDP	GCF	Inf	Gov. debt	M1	M2	BMER	DPCB
1	..	..	..	..	54.2%	38.4%	4.9%	2.5%
2	0.6%	0.7%	0.7%	0.6%	52.7%	36.7%	5.2%	2.8%
3	1.3%	1.5%	1.5%	1.3%	50.7%	34.6%	5.7%	3.3%
4	2.0%	2.3%	2.3%	2.0%	48.6%	32.8%	6.2%	3.9%
5	2.7%	3.0%	3.0%	2.6%	46.5%	31.1%	6.5%	4.4%

Source: Author based on the BVAR (1) results.

Variance Decomposition of M2

Table 5.12 shows M2 variance decomposition. As can be seen in the first year, the contribution to M2 comes from domestic private credit by 31% followed by 8.3% from unofficial exchange rate. However, despite the steady contribution of unofficial exchange rate, domestic private credit by banks decreases over time to account only for 19% of M2 error. The other variables start in the second year contributing to M2, the highest contribution among them comes from M1.

Table 5.12 Cholesky Variance Decomposition of M2

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Step	GDP	GCF	Inf	Gov. debt	M1	M2	BMER	DPCB
1	..	..	..	..	..	60.7%	8.3%	31.0%
2	0.8%	0.8%	0.8%	0.8%	1.4%	60.6%	8.3%	26.5%
3	1.6%	1.6%	1.6%	1.9%	3.2%	58.7%	8.2%	23.3%
4	2.3%	2.5%	2.5%	2.5%	5.1%	56.0%	8.4%	20.8%
5	2.9%	3.2%	3.7%	3.2%	6.8%	53.0%	8.3%	19.0%

Source: Author based on the BVAR (1) results.

Variance Decomposition of Unofficial Exchange Rate

Table 5.13 shows un-official exchange rate variance decomposition. In the first year, only domestic private credit by banks contributes 2.4% of the unofficial exchange rate error. However, from the second year all variables, over time, increasingly contribute to unofficial exchange rate variance that their contribution in total is 32.4%.

Table 5.13 Cholesky Variance Decomposition of Unofficial Exchange Rate

Step	GDP	GCF	Inf	Gov. debt	M1	M2	BMER	DPCB
1	..	..	..	..	..	..	97.6%	2.4%
2	1.9%	1.9%	2.0%	3.1%	2.2%	1.7%	83.2%	4.1%
3	2.7%	2.7%	3.1%	4.9%	3.3%	2.7%	75.6%	4.9%
4	3.2%	3.3%	3.8%	6.1%	4.1%	3.3%	70.9%	5.4%
5	3.6%	3.7%	4.2%	6.9%	4.6%	3.7%	67.6%	5.7%

Source: Author based on the BVAR (1) results.

Variance Decomposition of Domestic Private Credit by Banks

The domestic variance decomposition of domestic private credit by banks is shown in Table 5.14. in the first year non-of the variables contributes to domestic private credit by banks. However, increasing contribution from all variables over time is recorded to account for 29%, in total, of the error of domestic private credit by banks.

Table 5.14 Cholesky Variance Decomposition of Domestic Private Credit by Banks

Step	GDP	GCF	Inf	Gov. debt	M1	M2	BMER	DPCB
1	..	..	..	..	..	..	..	100.00%
2	1.0%	1.0%	0.9%	1.0%	0.9%	1.3%	1.1%	92.9%
3	1.9%	2.2%	2.1%	2.1%	2.1%	3.0%	2.2%	84.5%
4	2.9%	3.2%	3.1%	2.9%	3.2%	4.5%	2.9%	77.2%
5	3.7%	4.1%	4.1%	3.8%	4.2%	5.9%	3.4%	71.0%

Source: Author based on the BVAR (1) results.

5.3.8 Uncertainty spillovers

The analysis now will shed light to examine the uncertainty spillovers between the variables. Panels A and B of Table 5.15 display the effect of uncertainty between the decomposed components. It can be observed from the panels the contribution originating FROM and TO any given variable increase as time horizons increases. Therefore, this indicates uncertainty spillovers between the variables seem to be significant with a lag. This finding of increasing uncertainty spillovers corporates with Antonakakis et al., (2018) and Biljanovska et al. (2017).

Panel C of Table 5.15 shows the net spillovers for the selected variables. The signs of the net spillovers indicate the transmission direction. For example, GDP and GDF net spillovers are being driven by other variables, while M2 and

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

domestic private credit by banks net spillovers signs indicating the two are driving variables. The total net directional connectedness lies between 22.9% and 21.9% implying the total net spillovers of the entire network.

Table 5.15 Decomposed Components - connectedness

Step	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB
				Panel A: Contribution FROM others				
1	51.2	39.1	21.7	23.3	45.8	39.3	2.4	-
2	51.9	42.3	27.1	26.8	47.3	39.4	16.8	7.1
3	54.1	47.1	33.4	32.4	49.3	41.3	24.4	15.5
4	56.4	51.7	38.7	38.1	51.5	44.1	29.1	22.8
5	58.5	55.6	43.1	43.1	53.5	47	32.4	29
				Panel B: Contribution TO others				
1	-	25.4	12.6	28.5	16.3	78.6	32.4	51.4
2	11.8	31.7	17.5	30.8	22.7	82.9	35.6	49.6
3	22.7	37.5	22.7	34.8	29.3	85.8	38.6	50.1
4	31.2	42.5	27.9	38.7	35.6	87.3	41.2	51.2
5	37.6	46.4	32.6	42.6	40.9	88.1	43.1	52.7
				Panel C: Net Spill Over				
1	-51.2	-13.6	-9.2	5.2	-29.5	39.3	29.9	51.4
2	-40.1	-10.5	-9.6	4	-24.6	43.5	18.8	42.5
3	-31.4	-9.6	-10.6	2.4	-20	44.5	14.2	34.6
4	-25.2	-9.2	-10.8	0.6	-15.8	43.2	12.1	28.3
5	-20.9	-9.2	-10.5	-0.5	-12.5	41.2	10.6	23.7

Note: All numbers are percentages.

5.3.9 Dynamic Connectedness results

To further compute the NPDC, now we turn dynamic connectedness calculation based on BVAR (1) model. Tables 5.16 to 5.20 illustrate the calculation steps using D-Y index. The index results are summarized in Table 5.21. From Table 5.21, we can see the system total connectedness increases over time, reaching up to 45% for the fifth component. This finding perhaps gives an indication that in the long run the economy adjusts over time to any potential domestic uncertainty sources. The analyses in Tables 5.16 to 5.20 reveal that longer spam changes in mostly M2, domestic private credit by banks and unofficial exchange rate tend to be important for GDP and GFC. Overall, it is found that uncertainty spillover tends to be decreasing over time except for M2, and also the transmission directions are constant (the sings of net spillovers) revealing aging the importance of M2, domestic private credit by banks and unofficial exchange rate, respectively.

Table 5.16 Uncertainty spillover connectedness for the 1st component

	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB	FROM
GDP	48,83	25,44	3,27	15,14	1,46	1,71	1,61	2,54	51,17
GCF	0,00	60,94	9,29	11,20	5,22	3,44	6,49	3,44	39,06
Inf	0,00	0,00	78,25	2,18	4,73	9,65	2,46	2,73	21,75
Gov.debt	0,00	0,00	0,00	76,66	4,91	3,05	8,62	6,76	23,34

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

M1	0,00	0,00	0,00	0,00	54,15	38,44	4,89	2,51	45,85
M2	0,00	0,00	0,00	0,00	0,00	60,74	8,31	30,95	39,26
BMER	0,00	0,00	0,00	0,00	0,00	0,00	97,55	2,45	2,45
DPCB	0,00	0,00	0,00	0,00	0,00	0,00	0,00	100	0,00
Contribution TO others	0,00	25,439	12,559	28,516	16,320	56,281	32,381	51,370	222,87
Contribution including own	48.83	111.82	103.37	133.69	86.79	173.31	162.32	202.74	
Net spillovers	-51.17	-13.62	-9.19	5.17	-29.53	17.03	29.93	51.37	**27.86**

Note: All numbers are percentages. The diagonal values indicate self-contribution, and the off-diagonal values indicate spillover rates. The bold number (bottom right corner) is the system total connectedness.

Table 5.17 Uncertainty spillover connectedness for the 2nd component

	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB	FROM
GDP	48.13	24.44	3.80	13.16	2.19	2.41	2.78	3.10	51.87
GCF	4.24	57.75	8.47	9.20	5.57	4.00	6.66	4.12	42.25
Inf	1.43	1.79	72.95	2.95	4.73	9.46	3.39	3.30	27.05
Gov.debt	1.83	1.10	0.85	73.20	5.72	3.41	8.16	5.72	26.80
M1	0.61	0.74	0.67	0.61	52.72	36.65	5.18	2.82	47.28
M2	0.83	0.83	0.83	0.83	1.38	60.61	8.26	26.45	39.39
BMER	1.85	1.85	1.98	3.09	2.22	1.73	83.19	4.08	16.81
DPCB	1.00	1.00	0.85	1.00	0.85	1.28	1.14	92.89	7.11
Contribution TO others	11.77	31.74	17.45	30.82	22.67	58.94	35.57	49.60	258.57
Contribution including own	59.90	121.22	107.85	134.84	98.07	178.48	154.34	192.08	
Net spillovers	-40.10	-10.52	-9.60	4.02	-24.60	19.54	18.76	42.48	**32.32**

Note: All numbers are percentages. The diagonal values indicate self-contribution, and the off-diagonal values indicate spillover rates. The bold number (bottom right corner) is the system total connectedness.

Table 5.18 Uncertainty spillover connectedness for the 3rd component

	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB	FROM
GDP	45.95	23.46	4.43	12.36	2.99	3.22	3.51	4.08	54.05
GCF	8.71	52.92	8.13	8.36	5.96	4.47	6.76	4.70	47.08
Inf	2.69	3.74	66.64	4.00	5.21	9.47	4.17	4.08	33.36
Gov.debt	3.70	2.19	1.96	67.55	6.58	4.16	8.08	5.77	32.45
M1	1.33	1.54	1.47	1.33	50.74	34.62	5.68	3.29	49.26
M2	1.59	1.59	1.59	1.85	3.17	58.73	8.20	23.28	41.27
BMER	2.74	2.74	3.10	4.89	3.34	2.74	75.57	4.89	24.43
DPCB	1.92	2.19	2.06	2.06	2.06	3.02	2.19	84.50	15.50

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Contribution TO others	22.67	37.46	22.74	34.85	29.31	61.69	38.59	50.10	297.41
Contribution including own	68.62	127.83	112.12	137.25	109.36	182.11	152.75	184.69	
Net spillovers	-31.38	-9.62	-10.62	2.40	-19.95	20.42	14.16	34.60	**37.18**

Note: All numbers are percentages. The diagonal values indicate self-contribution, and the off-diagonal values indicate spillover rates. The bold number (bottom right corner) is the system total connectedness.

Table 5.19 Uncertainty spillover connectedness for the 4th component

	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB	FROM
GDP	43.62	22.70	5.00	12.20	3.66	3.84	4.03	4.94	56.38
GCF	11.86	48.31	8.16	8.16	6.42	5.01	6.86	5.22	51.69
Inf	3.67	5.12	61.35	4.78	5.80	9.73	4.69	4.86	38.65
Gov.debt	5.23	3.34	3.01	61.92	7.35	4.90	8.13	6.12	38.08
M1	2.03	2.33	2.33	1.96	48.55	32.78	6.18	3.85	51.45
M2	2.28	2.53	2.53	2.53	5.06	55.95	8.35	20.76	44.05
BMER	3.17	3.29	3.76	6.10	4.11	3.29	70.89	5.40	29.11
DPCB	2.94	3.20	3.07	2.94	3.20	4.54	2.94	77.17	22.83
Contribution TO others	31.18	42.50	27.85	38.68	35.61	64.08	41.17	51.16	332.24
Contribution including own	74.81	133.32	117.06	139.27	119.76	184.11	153.24	179.50	
Net spillovers	- 25.19	-9.18	-10.80	0.59	-15.85	20.03	12.07	28.33	**41.53**

Note: All numbers are percentages. The diagonal values indicate self-contribution, and the off-diagonal values indicate spillover rates. The bold number (bottom right corner) is the system total connectedness.

Table 5.20 Uncertainty spillover connectedness for the 5th component

	GDP	GCF	Inf	Gov.debt	M1	M2	BMER	DPCB	FROM
GDP	41.50	21.99	5.50	12.34	4.22	4.41	4.41	5.63	58.50
GCF	13.87	44.42	8.24	8.34	6.88	5.53	6.99	5.74	55.58
Inf	4.37	6.22	56.89	5.46	6.39	9.92	5.13	5.63	43.11
Gov.debt	6.49	4.22	4.00	56.86	7.89	5.62	8.32	6.59	43.14
M1	2.71	3.01	3.01	2.63	46.54	31.13	6.54	4.44	53.46
M2	2.92	3.16	3.65	3.16	6.81	53.04	8.27	18.98	46.96
BMER	3.62	3.73	4.20	6.88	4.55	3.73	67.56	5.72	32.44
DPCB	3.66	4.05	4.05	3.79	4.18	5.87	3.39	71.02	28.98
Contribution TO others	37.62	46.38	32.64	42.61	40.92	66.21	43.06	52.72	362.16
Contribution including own	79.12	137.18	122.17	142.08	128.38	185.47	153.67	176.46	
Net spillovers	-20.88	-9.20	-10.47	-0.53	-12.54	19.25	10.62	23.74	**45.27**

Note: All numbers are percentages. The diagonal values indicate self-contribution, and the off-diagonal values indicate spillover rates. The bold number (bottom right corner) is the system total connectedness.

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Table 5.21 Total Connectedness Index

Component	Value
1	27.86
2	32.32
3	37.18
4	41.53
5	45.27

6. Conclusions

In this research, the spillovers existence in the Libyan economy was investigated using a Bayesian Vector Autoregressive model. To achieve the chapter purpose, D-Y index of Diebold & Yilmaz (2012) was followed to figure out the system interconnectedness of the Libyan economy. The empirical findings suggest the uncertainty spillovers between the variables seem to be a significant emphasizing transmission direction, and this finding corporates with Antonakakis et al., (2018) and Biljanovska et al. (2017). Moreover, the dynamic connectedness calculation reveals that the system total connectedness increases over time, reaching up to 45% for the fifth component. In addition, the transmission direction implies the importance of M2, domestic private credit by banks and unofficial exchange rate, respectively.

References

Abedifar, P., Giudici, P., & Hashem, S. Q. (2017). Heterogeneous market structure and systemic risk: Evidence from dual banking systems. *Journal of Financial Stability*, *33*, 96–119. https://doi.org/10.1016/j.jfs.2017.11.002

Acemoglu, D., Carvalho, M. C., Ozdaglar, A., & Tahbaz-Salehi, A. S. (2012). The Network Origins of Aggregate Fluctuations. *Econometrica*, *80*(5), 1977–2016. https://doi.org/10.3982/ecta9623

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, *105*(2), 564–608. https://doi.org/10.1257/aer.20130456

Agosto, A., & Cafferata, A. (2020). Financial bubbles: A study of co-explosivity in the cryptocurrency market. *Risks*, *8*(2), 1–14. https://doi.org/10.3390/risks8020034

Ahelegbey, D. F., Billio, M., & Casarin, R. (2016). Bayesian Graphical Models for STructural Vector Autoregressive Processes. *Journal of Applied Econometrics*, *31*(2), 357–386. https://doi.org/10.1002/jae.2443

Anand, K., Gai, P., Kapadia, S., Brennan, S., & Willison, M. (2013). A network model of financial system resilience. *Journal of Economic Behavior and Organization*, *85*(1), 219–235. https://doi.org/10.1016/j.jebo.2012.04.006

Andrieş, A. M., Ongena, S., Sprincean, N., & Tunaru, R. (2022). Risk spillovers and interconnectedness between systemically important institutions. *Journal of Financial Stability*, *58*. https://doi.org/10.1016/j.jfs.2021.100963

Ankargren, S., Bjellerup, M., & Shahnazarian, H. (2017). The importance of the financial system for the real economy. *Empirical Economics*, *53*(4), 1553–1586. https://doi.org/10.1007/s00181-016-1175-4

Antonakakis, N., Gabauer, D., Gupta, R., & Plakandaras, V. (2018). Dynamic connectedness of uncertainty across developed economies: A time-varying approach. *Economics Letters*, *166*(February), 63–75. https://doi.org/10.1016/j.econlet.2018.02.011

Anyanwu, C. M. (2010). An overview of current banking sector reforms and the real sector of the Nigerian economy. *Central Bank of Nigeria Economic and Financial Review*, *48*(4), 31–56.

Battiston, S., & Martinez-Jaramillo, S. (2018). Financial networks and stress testing: Challenges and new research avenues for systemic risk analysis and financial stability implications. *Journal of Financial Stability*, *35*, 6–16. https://doi.org/10.1016/j.jfs.2018.03.010

Biljanovska, N., Grigoli, F., & Hengge, M. (2017). *Fear thy neighbor: Spillovers from economic policy uncertainty* (2017/240; 240). https://doi.org/10.1111/roie.12531

Bricco, J., & Xu, T. (2019). Interconnectedness and Contagion Analysis: A Practical Framework. *International Monetary Fund*. https://doi.org/10.2139/ssrn.3491243

Central Bank of LIBYA. (n.d.). *Monetary and Financial Statistics (1966-2017).*

Diebold, F. X., & Yilmaz, K. (2009). Measuring Financial Asset Return and Volatility Spillovers, With Application To Global Equity Markets. *The Economic Journal*, *119*(534), 158–171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 5 (Issue 2) Fall 2023
https://dergipark.org.tr/en/pub/quantrade

Gai, P., Haldane, A., & Kapadia, S. (2011). Complexity, concentration and contagion. *Journal of Monetary Economics*, *58*(5), 453–470. https://doi.org/10.1016/j.jmoneco.2011.05.005

Gai, P., & Kapadia, S. (2010). Contagion in Financial Networks. In *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* (Issue 383). https://doi.org/10.2139/ssrn.1577043

Giudici, P., Sarlin, P., & Spelta, A. (2020). The interconnected nature of financial systems: Direct and common exposures. *Journal of Banking and Finance*, *112*, 105149. https://doi.org/10.1016/j.jbankfin.2017.05.010

Giudici, P., & Spelta, A. (2016). Graphical Network Models for International Financial Flows. *Journal of Business & Economic Statistics*, *34*(1), 128–138.

Giudici, Paolo, & Pagnottoni, P. (2020). Vector error correction models to measure connectedness of Bitcoin exchange markets. *Applied Stochastic Models in Business and Industry*, *36*(1), 95–109. https://doi.org/10.1002/asmb.2478

Glasserman, P., & Young, H. P. (2016). Contagion in financial networks. *Journal of Economic Literature*, *54*(3), 779–831. https://doi.org/10.1257/jel.20151228

Greene, J. E. (2018). Introduction To Macroeconomic Accounts, Analysis, And Related Policy Issues. In *World Scientific Book Chapters* (pp. 1–17).

Greenwood, R., Landier, A., & Thesmar, D. (2015). Vulnerable banks. *Journal of Financial Economics*, *115*(3), 471–485. https://doi.org/10.1016/j.jfineco.2014.11.006

Ibadin, L. A., Moni, O. M., Eikhmun, D. E., & Accounting. (2014). Real Sector , Gross Fixed Capital Formation and the Nigerian Stock Market. *European Journal of Business and Management*, *6*(33), 157–168.

Kaur, K. (2017). Financial Sector Reforms. *International Journal Of Business Management*, *3*(1).

Kendirli, S., & Şenol, F. Y. (2021). Crypto Currencies in the Framework of Chaos Theory and the Relationship of Crypto Currency with Big Exchanges. Quantrade Journal of Complex Systems in Social Sciences, 3(2), 15-23.

Kendirli, S., Şenol, F. Y., & Ergenoğlu, S. (2022). Analysis oF The Relationship Between Cryptocurrency Index (CCi30), BIST 100, and NASDAQ with Granger Causes Test. Quantrade Journal of Complex Systems in Social Sciences, 4(2), 35-43.

Klimenko, P., Sevryukova, L., Goncharenko, M., & Dmitriev, D. (2021). Financial mechanisms to stimulate the real economy in the global economic security system. *SHS Web of Conferences*, *92*, 08011. https://doi.org/10.1051/shsconf/20219208011

Konak, F., & Özkahveci, E. (2023). Blockchaın Üzerine Yeni Bir Halka: Non-Fungıble Token (Nft)'Nin Bilinirliği Üzerine Bir Araştırma. Düzce Üniversitesi Sosyal Bilimler Dergisi, 13(1), 97-115. Https://Doi.Org/10.55179/Dusbed.1193852

Krippner, G. (2011). *Capitalizing on crisis: The political origins of the rise of finance*. Harvard University Press.

Levine, R. (2004). Finance Growth Theory Evidence. *Nber Working Paper Series*, *10766*, 1–118.

Li, L., Zhang, N., & Willett, T. D. (2012). Measuring macroeconomic and financial market interdependence: a critical survey. *Journal of Financial Economic Policy*, *4*(2), 128–145. https://doi.org/10.1108/17576381211228989

Malik, S., & Xu, T. (2017). Interconnectedness of Global Systemically-Important Banks and Insurers. In *IMF Working Papers* (Vol. 17, Issue 210). https://doi.org/10.5089/9781484320716.001

Markose, S., Giansante, S., & Shaghaghi, A. R. (2012). Too interconnected to fail' financial network of US CDS market: Topological fragility and systemic risk. *Journal of Economic Behavior and Organization*, *83*(3), 627–646. https://doi.org/10.1016/j.jebo.2012.05.016

Mordi, C. N. (2014). The link between the financial (banking) sector and the real sector of the Nigerian economy. *Economic and Financial Review*, *84*(4), 205–214.

Research and Statistics Department. (2021). *Economic Bulletin Vol.No. 61 Fourth Quarter 2021*.

Ulusoy, T. (2008). Systematic Risk and Firm Financial Structure: Evidence on Istanbul Stock Exchange. The Business Review, Cambridge, 11(2), 226-231.

Uluceviz, E., & Yılmaz, K. (2018). *Measuring real-financial connectedness in the U . S . economy* (Issue 1812).

Ulusoy,T. and Ugur, S. O.(2020). "The Effect of Macroeconomic Factors on the Detection Value of the Firm: An Application in Istanbul Stock Exchange," International Journal of Economics, Business and Management Studies, Online Science Publishing, vol. 7(2), pages 224-233.

Ulusoy, T., Saeed, M.and Kaplan Dönmez,N.F. (2022). "The Mediating Role Of Innovation On The Relationship Between The Board Information Technology Governance And Firm Performance: Theoretical Approach:",International SocialMentality andResearcher ThinkersJournal, (Issn:2630-631X) 8(59): 841-848

Zhuang, J., Gunatilake, H., Niimi, Y., Khan, M. E., Jiang, Y., Hasan, R., Khor, N., Lagman-Martin, A. S., Bracey, P., & Huang, B. (2009). Financial sector development, economic growth, and poverty reduction: A literature review. *ADB Economics Working Paper Series*, *173*, 1–48.