Credit Channel of Monetary Transmission Mechanism: New Insight from SVAR-DAG Approach

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Abstract

The credit channel of monetary transmission mechanism gains significant importance after global financial crises. The present study has investigated the credit channel for an emerging economy of Pakistan, which has an underdeveloped financial sector. The study has collected monthly data from June 2006 to June 2018 on credit to the private sector (CPRVS), interest rate, money supply, price level, and industrial production index. The study has contributed to the empirical literature by investigating the contemporaneous causal relationships among the variables. Further, the study has investigated the effectiveness of the credit channel of the monetary transmission mechanism. The study has employed the SVAR model along with direct acyclic graphs (DAG) to identify the covariance matrix.The study notes that the credit channel is ineffective in Pakistan, and it does not contemporaneously cause economic growth (EG).Further, EG causes credit supply to the private sector. Hence, when the economy grows, the financial sector develops, and commercial banks extend more credit to the private sector. The study also notes that the interest rate has no contemporaneous impact on the CPRVS. Moreover, for robustness check, we have estimated two SVAR models, one with a real discount rate as a measure of interest rate and the other is with the real lending rate, as it is more related to the credit supply. However, both proxies give the same results, which implies that our findings are robust. Hence, we can conclude that the credit channel is ineffective in Pakistan.
Key Words: Credit Channel, Direct Acyclic Graphs, Monetary policy, SVAR,
JEL Classification: C30, E40, E52, E58

Introduction

Global Financial Crises (GFC) of 2008 is the most critical event in the history of macroeconomics. It helps reshape macroeconomics and MP by looking at the new challenges that the world has been facing. It has raised several questions on modern macroeconomics and highlights the weakness within the old paradigm. For instance, the advanced texts in macroeconomic like Romar (2012) do not feature money and banks in their analysis, which is an integral part of recent economies. The financial activities were relatively unimportant in the economic discussions, and banks are considered intermediaries between buyers and sellers in the Dynamic Stochastic General Equilibrium (DSGE) models. For this reason, DSGE models could not read the pace and direction of the GFC. However, it is now widely believed that the GFC is, in fact, the banking crisis.

Bernanke and Gertler (1995) note that the traditional monetary and interest rate channels (IRC) do not capture all aspects of the real economy. On the other hand, the credit channel (CRC) better explains the transmission mechanism of monetary policy (TMMP) under information asymmetry. According to the credit channel, MP influences interest rate (the price of money) and credit (quantity of money) and hence loans demand.

CRC works through the *external finance premium (EFP)*. EFP shows market imperfections. The difference between the cost that banks faced when it generates funds internally and raised funds externally. When CB raises the interest rate, it increases EFP. As a result, it affects the cost of borrowing, real spending, and hence economic activity. Why the change in interest rate affect EFP? Two channels are discussed in the literature. First is the balance sheet channel (BSC), and second is the bank lending channel (BLC). BSC works through the balance sheets of borrowers, such as the impact of MP on their cash flows, net worth, and liquid assets.

In contrast, BLC focuses on the impact of MP on the supply of loans. BLC is more relevant for developing countries that face resource constraints, so any policy change directly affects borrowers. BLC assumes that the borrowers are resource constraint and can only finance their projects through borrowing. Hence, when CB changes policy, it influences bank loans supply, and thus investment and EG (Oliner & Rudebusch, 1996)

Similarly, the effectiveness of MTM is less explored in Pakistan. Further, there is no unanimous agreement on the channels through which MP affects the economy's real sector (Shaheen, 2020). Some studies have observed that IRC is effective (Agha et al., 2005; Munir & Qayyum, 2014), while other noticed price puzzle[1](Agha et al., 2005; Javid & Munir, 2010; Rashid & Jehan, 2014; Shaheen, 2020). Similarly,Hussain (2009) argues that the exchange rate channel is more effective in Pakistan than other channels. On the other hand, Agha et al. (2005); Chaudhry et al. (2012); Mukhtar and Younas (2019) observes that CRC is effective in Pakistan, whereasBaig (2011); Hussain (2014); Imran and Nishat (2013)argue that CRC is ineffective in Pakistan.Shaheen (2020) notice that broad money effectively enhances economic activity in the long run. In contrast, the reverse repo rate plays a significant role in controlling inflation in the long run and accelerating EG in the short run. Hence, there is still a debate in the literature about how MP affects the real sector of the economy.

The present study has contributed to resolving this controversy by employing the standard technique structural vector autoregressive (SVAR) model. Interestingly, the one possible reason for the differences in the literature is the use of different estimation methods. Even the studies that have employed the SVAR model couldn't reach the same conclusion. One of the possible reasons is the

[1]It is generally believed that tight MP (increase in interest rate) lowers inflation rate. However, when tight MP surge inflationary pressures in an economy this phenomenon is known as price puzzle.

differences in the identification restrictions imposed on the AB matrix. Traditionally, researchers either use Cholesky decomposition or economic theory to identify the covariance matrix. However, Cholesky decomposition is based on the whole idea, whereas the economic theory is relatively weak in causal relationships(Mizon, 1995). Usually, economists consider correlation as causation, which is not true.

For the effectiveness of MP, policymakers should understand the causal relationships among the policy variables and the response variables. Directed Acyclic Graphs (DAG) are extensively used in other disciplines, but economists rarely use them. Hence, by following Awokuse and Bessler (2003); Céspedes et al. (2008); Céspedes et al. (2015); Moneta (2004), we have used DAGs to identify the covariance matrix of SVAR. DAG is used to understand causal relationships based on conditional dependence.

Hence, the objectives of the present study are to investigate:

(i) the contemporaneous causal relationship among the policy variable and the response variables i.e., credit to the private sector (CPRVS),interest rate, economic growth (EG), inflation rate, and money supply,

(ii) the effectiveness of the CRC of MTM

The more specifically present study has investigated the impact of unanticipated interest rate shock on CPRVS. Moreover, how the output responds to the unanticipated increase in the CPRVS. The investigation of the effectiveness of the CRC helps the policymakers in different ways. Firstly, it helps to understand the contemporaneous causal relationship between the policy variable and the real variables. Secondly, it provides empirical evidence to understand the impact of MP in the real economy. Thirdly, it helps in assessing the role of banks in the modern financial era. Bernanke and Blinder (1992)note that loans, EG, unemployment, and other macroeconomic indicators are strongly correlated. If there are constraints on bank lending capacity, then it negatively affects investment and hence economic growth. However, the present study notes that CRC is ineffective in Pakistan. Further, the study note that the interest rate has no contemporaneous effects on CPRVS. It implies that there exist lags in transmitting the impact of policy. Secondly, the study notes that economic growth contemporaneously causes CPRVS, and CPRVS does not cause EG. It suggests serious policy implications for the SBP.

The present study is organized as follows. In section two, we have reviewed the empirical literature. In section three, model specifications, variables, and data sources are discussed. In section four, we have presented the estimation results. Discussion and policy implications are carried out in the section five, and the section six concludes the study.

Literature Review

Banks play an essential role in the MTM through interest rates and CRCs. The proponents of the bank lending channel assert that it helps in smoothing the fluctuations in output by affecting investment and consumer spending (Bernanke & Gertler, 1995). It is well documented in the literature that bank loans play an essential role in diverging the impact of MTM. The CPRVS helps in achieving economic development and stability. However, it is also true that most of the financial crises are due to abnormal fluctuations in credit. For instance, Japan and Scandinavia's financial crises in the early 1990s, Southeast Asian crises in 1997-98 are due to excessive foreign and domestic credit (Kaminsky & Reinhart, 1999).

A considerable amount of work has been done so far in advanced and emerging economies on the credit channel of MTM. However, empirical studies find mixed results. For instance, Bernanke and Blinder (1992) observe that CRC is effective by using the Granger causality test (GCT) and vector autoregressive (VAR) model. Similarly, Kashyap et al. (1996) note that tight MP affects firms' external financing. Hence decreases loan supply and shrinks investment activities. Lown et al. (2000) has used the VAR approach and observe that bank lending standards significantly affect loan supply and real output, and conclude that BLC is central to the MTM. Ekimova et al. (2017) observe that the policy rate effectively accelerates credit growth before GFC. However, it is ineffective after GFC. Further, the study notes that unconventional MP is more effective after GFC.

Traditionally, the central banks have monopoly power over the creation of the money supply (MS). The central bank increases MS or decreases MS to affect output and prices. Nowadays, MS is no more exogenous and in complete control of central banks. In advanced countries like England, 97% of MS is created by commercial banks. Similarly, SBP is no more targeting M2. The key policy variable is the policy rate, which SBP uses to control inflation and the real sectors of the economy.

The interest rate channel works well in a perfectly competitive environment. However, unfortunately, poor and developing economies have imperfect financial markets. In this scenario, the price and quantity of credit is an important policy tool (Kamin, 1997). However, the CRC is not independent. It enhances the IRC's impact on the economy (Bernanke & Gertler, 1995) through the external finance premium (EFP). EFP is the difference between internally and externally raised funds. The central bank can influence EFP through the bank lending channel (BLC) and the balance sheet channel (BSC) (Bernanke & Gertler, 1995). Bernanke and Gertler (1995) argue that BLC's focus is the impact of MP on the supply of bank lending. BLC is originated in the loanable fund theory and is the extension of the IS-LM model (Blinder & Stiglitz, 1983).

In Pakistan, MTMs are less explored in the literature. Moreover, whether MTM is effective in Pakistan is still inconclusive. Further, the channel through which MP affects the real sector of the economy is still under debate. Some studies observe that CRC (measure as a credit to the private sector) is effective in Pakistan in accelerating EG (Agha et al., 2005; Chaudhry et al., 2012; Mukhtar & Younas, 2019). In contrast, others observe that CRC is ineffective in Pakistan (Baig, 2011; Hussain, 2014).

Agha et al. (2005) examine the MTM in Pakistan by using the VAR model. The study has used data from 1996 to 2004 and observe that the bank lending channel is the most effective in Pakistan. Similarly, Alam and Waheed (2006) have employed the VAR model and argue that MP has real effects in the short run by using quarterly data from 1973 to 2003. The study notes that tight MP is more visible in the sectors with more reliance on bank loans. On the other hand, Hussain et al. (2009) note that the exchange rate channel effectively controls inflation and accelerates output than IRC and CRC. Javid and Munir (2010) have employed the SVAR model and note that tight MP leads to inflationary pressures in Pakistan. Further, the study notes that the contractionary MP initially accelerates output, which declines later on. Aftab et al. (2016) observe that a high-interest rate decreases CPRVS in the short-run and the long-run. The study has employed the ARDL model and used data from 1975-2011**.**

Mukhtar and Younas (2019) have observed that CRC effectively stimulates output and controls inflation in Pakistan. Similarly, Munir (2020) has used the FAVAR model to investigate the effectiveness of MP on money and credit. The study notes that the contractionary MP (increase in interest rate) has no significant impact on money (M0 and M1). However, it significantly decreases M2. Similarly, the positive interest rate shock significantly reduces CPRVS more than credit to the government sector and M2. Munir (2020) argues that the tight MP adversely affects CPRVS. It can be used as a tool to affect AD.

On the other hand, there are some studies which note that CRC is not effective in Pakistan. For instance, Imran and Nishat (2013) note that domestic deposits, EG, exchangerate, foreign liabilities, and monetary conditions are associated with CPRVS in Pakistan. In contrast, the inflation rate and interest rate are not associated with CPRVS. The study has employed the ARDL model using data from 1971 to 2010. Hence, there exists an exchange rate and price puzzle. However, Munir and Qayyum (2014) have used the FAVAR model and note that the tight MP plays a significant role in controlling inflation. Moreover, the study notes that the MP affects output in the short run, whereas it affects inflation and money in the long run.

Similarly, Hussain (2014) has investigated the effectiveness of IRC and CRC of MTM by using quarterly data from 1991 to 2012 and employed Variance decomposition and IRF and observe that both channels are ineffective in Pakistan. Further, the study has divided the sample into two parts, the first sample covers data from 1991 to 2000, and the second sample covers data from 2001 to 2012. The study notes that in the first sample, CRC is effective, while in the second sample, IRC effectively transmits the effects of MP to the economy. Hence, CRC is no more effective in Pakistan.Khan et al. (2016) note that a low policy rate couldn't increase CPRVS in Pakistan. Commercial banks are less willing to lend to the private sector. Hence the excessive government borrowing weakens the MTM

Similarly, Cheema and Naeem (2019) note that the CRC is not providing any additional leverage to the monetary authorities for conducting MP in Pakistan**.** The study has used monthly data from 2002-2012 and employed ARDL bound testing cointegration and ECM.

Hence, from the review of the literature, it is evident that the literature is inconclusive about the effectiveness of CRC. Hence to resolve this controversy, the present study has contributed to the empirical literature by investigating the effectiveness of CRC of MTM.

1. Model Specification and Variables

FollowingSims (1980), we have used the SVAR model, which can be represented as:

$A_0Y_t = A(L)Y_{t-1} + E_t$……………………………………. (1)

It is the nx1 vector of contemporaneous variables, wherediagonals contain ones and off-diagonals have non-zero elements. A(L) is lag operator polynomial, Et is the vector of error terms independent and identically distributed, and$E(EE')$ is diagonal. Moreover, Ao is a full-rank nxn matrix that shows causal relationships among variables. To identify this system n(n-1)/2 restrictions are imposed on the Ao matrix.

As in the empirical review of literature, we have observed that different studies lead to different conclusions, even using the same set of variables. The one possible reason is different identification restrictions imposed on the matrix structure, leading to different SVAR models, which may differ from the data generating process. To get the true causal relationship among the variables based on conditional independence, the graph-theoretic (GT) approach gains considerable attention in the mid of 1980s (Lauritzen, 2001; Pearl, 2000; Spirtes et al., 2000).However, these techniques have been extensively used in other fields, rare in the economic discipline (Céspedes et al., 2015).

In the GT approach, arrows are used to connect causal variables to their effects, which imply certain conditional independence or dependence among the variables. Moreover, we can represent the graph of the data generating process by imposing restrictions on the Ao matrix. To understand the GT approach, suppose we have three variables X, Y, and Z, where X and Y are dependent, but conditional on Y, it is independent. However, the intermediate variable Y can have a different role. For instance, If X→ Y→ Z (X causes Y causes Z) or X←Y←Z, in both cases, Y screen X from Z. Similarly, if X ←Y→ Z, then Y is the common cause of Z and X.

On the other hand, X and Y are independent, conditional on a set of variables that exclude Z or its descendant, if none of the variables that cause X or Y directly cause Z, i.e., X → Z ← Y. Hence conditional on Z, X and Y are dependent. Here Z is the unshielded collider on the path XZY[2]. In the GT approach, we have used directed acyclic graphs (DAG). It implies that if X→ Y→ Z, then it is not possible that Z→ X.

Conditional independence is based on the idea of d-separation presented by Pearl (1995). It states that Z d-separate X from Y (X⫫Y|Z)G, if and only if Z blocks every path from a vertex in X to a vertex in Y. Spirtes et al. (1993) have built a PC algorithm in TETRAD to incorporate the notion of d-separation to build DAG. PC algorithm starts with an unrestricted set of relationships among variables. Later on, it removes edges between variables based on zero or partial conditional correlations. Awokuse and Bessler (2003) argue that the DAG analysis's identification restrictions may yield theoretically consistent IRFs that can play anessential role in policy analysis.
The reduced form equation for model 1 is

$$X_{1t} = [LIPI\ LINF\ LCPRVS\ LM2\ RDR]' \qquad (2)$$

LIPI is the log of industrial production index, LINF is the inflation rate, measured as the annual change in the log of CPI. LCPRVS is the log of credit to the private sector. It includes both credits, i.e., credit extended to the firms and HH. Similarly, LM2 is the log of broad money supply, and RDR is the real

[2]On the other hand, shielded collider has direct link between X and Y.

discount rate used to measure the policy rate. The real discount rate is calculated by subtracting the inflation rate from the nominal discount rate.

Further, we have re-estimated the same model using the real lending rate (RLR) as commercial banks give loans on the lending rate. So, in this case, the reduced form equation becomes

$X_{2t} = [LIPI\ LINF\ LCPRVS\ LM2\ RLR]'$ (3)

We have collected data from June 2006 to June 2018 by using various national and international sources. For LIPI, we have collected data from Ejaz and Iqbal (2019). Previous studies rely on the large-scale manufacturing index as a proxy of the industrial production index. The data on RLR, LM2, and CPRVS have been collected from the SBP website. Moreover, the data on RDR is collected from IFS, and LINF is collected from PBS and SBP website. We have used Eviews 10 software to estimate the SVAR model and TETRAD V for DAG analysis.

Estimation Results

The present study has used monthly data from June 2006 to June 2018 and expressed all variables in the log form except interest rates. Further, we have introduced eleven seasonal dummies to capture the effect of seasonality. In addition to this, two dummies are also included to capture the oil price shocks of 2008 and 2016.

To check the stationary properties of all variables, we have employed ADF and PP unit root tests. The unit root result shows that all variables are the first difference stationary I(1) as shown in
Table **1**. It the necessary condition to proceed with the non-recursive SVAR model.

Table 1: Result of Unit Root Test

Variable	Level		First Difference		Order of Integration	
	ADF	PP	ADF	PP	ADF	PP
LIPI	0.92 (0.99)	-2.1 (0.30)	-4.88 (0.00)	-26 (0.00)	I (1)	I (1)
LINF	-1.67 (0.45)	-1.5 (0.50)	-10.1 (0.00)	-10 (0.00)	I (1)	I (1)
LM2	-0.97 (0.76)	-0.5 (0.90)	-4.79 (0.00)	-33.1 (0.00)	I (1)	I (1)
LCPRVS	1.23 (0.99)	-1 (0.94)	-6.46 (0.00)	-8.85 (0.00)	I (1)	I (1)
RDR	-1.68 (0.44)	-3.1 (0.10)	-6.47 (0.00)	-11.4 (0.00)	I (1)	I (1)
RLR	-1.47 (0.55)	-2.5 (0.10)	-6.92 (0.00)	-9.8 (0.00)	I (1)	I (1)

Note: P- values are available in the parenthesis

Next, to estimate the unrestricted VAR model and decides the lag length. Different criterion suggests different lag lengths for both models, as shown in

Table 2. SC and HQ indicate that we should include one lag, FPE suggests three lags, LR offers five lags, and AIC suggests six lags.

***Table 2**: Lag Order Selection Criteria*

Model 1					
Lag	LR	FPE	AIC	SC	HQ
0	NA	0.00	-6.15	-4.46	-5.46
1	1058.10	0.00	-14.84	-12.61*	-13.93*
2	46.70	0.00	-14.89	-12.13	-13.77
3	52.79	2.14e-13*	-15.02	-11.73	-13.68
4	32.38	0.00	-14.98	-11.16	-13.42
5	40.29*	0.00	-15.03	-10.68	-13.26
6	33.46	0.00	-15.03*	-10.15	-13.05
7	17.53	0.00	-14.87	-9.46	-12.67
Model 2					
Lag	LR	FPE	AIC	SC	HQ
0	NA	0.00	-6.32	-4.59	-5.62
1	1013.69	0.00	-14.92	-12.65*	-13.00*
2	51.08	0.00	-15.02	-12.21	-13.88
3	55.91	1.81e-13*	-15.19	-11.84	-13.83
4	28.43	0.00	-15.11	-11.22	-13.53
5	38.38*	0.00	-15.15	-10.71	-13.35
6	36.76	0.00	-15.19*	-10.22	-13.17
7	17.14	0.00	-15.03	-9.51	-12.78

Note: * indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

All diagnostics are satisfied with six lags; residuals are normally distributed with no heteroskedasticity and autocorrelation, as shown in

Table 3 and Table 7.

Table 3

: VAR Residual Normality and Heteroskedasticity test

	Model 1	**Model 2**
Normality Test		
Skewness	11.46 (0.06)	7.97 (0.16)
Kurtosis	3.98 (0.55)	3.60 (0.61)
Jarque-Bera	15.45 (0.12)	11.57 (0.31)
Heteroskedasticity Test		
	1180.62 (0.20)	1167.35 (0.28)

Table 4: *VAR Residual Serial Correlation LM Tests*

	Model 1		**Model 2**	
Lags	**LM-Stat**	**Prob**	**LM-Stat**	**Prob**
1	34.66	0.09	31.83	0.16
2	34.01	0.11	27.24	0.34
3	23.92	0.52	23.89	0.53
4	21.18	0.68	17.92	0.85
5	13.79	0.97	19.25	0.79
6	25.93	0.41	25.48	0.44

Moreover, the estimated models are stable; all roots are less than one, as shown in

Table 5: VAR Stability Condition

Model 1		**Model 2**	
Root	**Modulus**	**Root**	**Modulus**
0.989524	0.989524	0.987191	0.987191
0.963186	0.963186	0.965017	0.965017
0.914617 - 0.205225i	0.937358	0.901774 - 0.201828i	0.924084
0.914617 + 0.205225i	0.937358	0.901774 + 0.201828i	0.924084
0.790733 - 0.410693i	0.891026	0.788591 - 0.412444i	0.889936
0.790733 + 0.410693i	0.891026	0.788591 + 0.412444i	0.889936
-0.429207 + 0.774534i	0.885506	-0.428071 + 0.770797i	0.881687
-0.429207 - 0.774534i	0.885506	-0.428071 - 0.770797i	0.881687
0.674972 + 0.535115i	0.861357	0.674877 - 0.537572i	0.862811
0.674972 - 0.535115i	0.861357	0.674877 + 0.537572i	0.862811
0.820637	0.820637	0.239311 + 0.796300i	0.831483
0.524349 - 0.630745i	0.820233	0.239311 - 0.796300i	0.831483
0.524349 + 0.630745i	0.820233	0.541183 - 0.630499i	0.830908

0.212688 - 0.779059i	0.80757	0.541183 + 0.630499i	0.830908
0.212688 + 0.779059i	0.80757	0.820064	0.820064
-0.169306 + 0.773009i	0.791333	-0.195241 - 0.781084i	0.805115
-0.169306 - 0.773009i	0.791333	-0.195241 + 0.781084i	0.805115
-0.541866 + 0.526408i	0.755463	-0.527056 - 0.569789i	0.776175
-0.541866 - 0.526408i	0.755463	-0.527056 + 0.569789i	0.776175
-0.740129 - 0.029358i	0.740711	-0.72089	0.720886
-0.740129 + 0.029358i	0.740711	-0.497153 - 0.462783i	0.679212
-0.019373 - 0.722072i	0.722332	-0.497153 + 0.462783i	0.679212
-0.019373 + 0.722072i	0.722332	-0.674521 - 0.046703i	0.676136
-0.6485	0.648497	-0.674521 + 0.046703i	0.676136
-0.448880 - 0.464625i	0.646042	-0.017972 + 0.663691i	0.663934
-0.448880 + 0.464625i	0.646042	-0.017972 - 0.663691i	0.663934
0.62577	0.62577	0.646539	0.646539
-0.177923 + 0.456705i	0.490139	-0.125577 - 0.564086i	0.577895
-0.177923 - 0.456705i	0.490139	-0.125577 + 0.564086i	0.577895
0.193959	0.193959	0.249091	0.249091

Note: No root lies outside the unit circle.

Since all the variables are I(1), however, it is possible to use VAR in levels even with the I(1) series (Aslanidi, 2007; Kim & Roubini, 2000) to save the useful information available in the data. Hence, we have an estimated VAR in level. Further, to confirm the long-run relationship among the variables, we have employed the Johansen Cointegration (JC) test, which ensures that the long-run relationship exists among the variables. The result of the JC test is reported in

Table 6.

The trace and maximum eigenvalue test indicate that four cointegrating equations exist for model 1. Whereas for model 2, the trace test indicates that four cointegrating equations exist. In contrast, the maximum eigenvalue test shows that one cointegrating equation exists at a 0.05 level of significance. Hence overall, we can conclude that there exists a long-run relationship among the variables. So, we can estimate VAR in levels with the I (1) series.

Table 6: *Results of Johansen Cointegration Test*

Model 1							
No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
r=0	0.317	121.172	69.819	0.000	52.709	33.877	0.000
r≤1	0.190	68.463	47.856	0.000	29.163	27.584	0.031
r≤2	0.153	39.300	29.797	0.003	22.876	21.132	0.028
r≤3	0.112	16.424	15.495	0.036	16.401	14.265	0.023

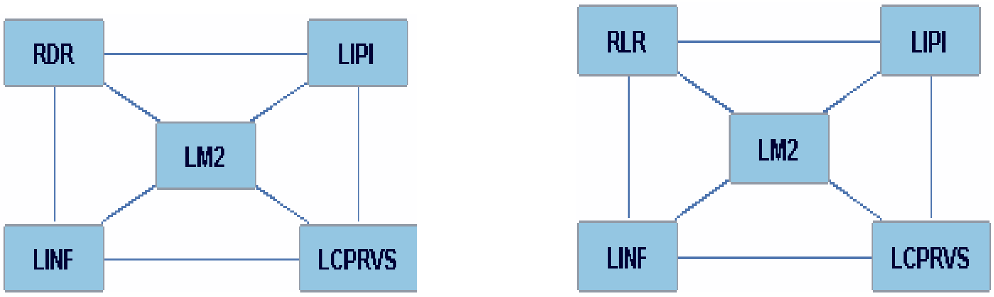
r≤4	0.000	0.022	3.841	0.882	0.022	3.841	0.882
Model 2							
No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
r=0	0.312	117.416	69.819	0.000	51.513	33.877	0.000
r≤1	0.175	65.903	47.856	0.000	26.546	27.584	0.067
r≤2	0.157	39.357	29.797	0.003	23.631	21.132	0.022
r≤3	0.108	15.726	15.495	0.046	15.725	14.265	0.029
r≤4	0.000	0.001	3.841	0.971	0.001	3.841	0.971

Note: Trace test indicates four cointegrating eqn(s) exists in both models, and the Max-Eigen test indicates four cointegrating eqn(s) exists for model 1A, and 1 cointegrating eqn exists for Model 1B at the 0.05 level

*MacKinnon et al. (1999) p-values

Contemporaneous Causal Relationship

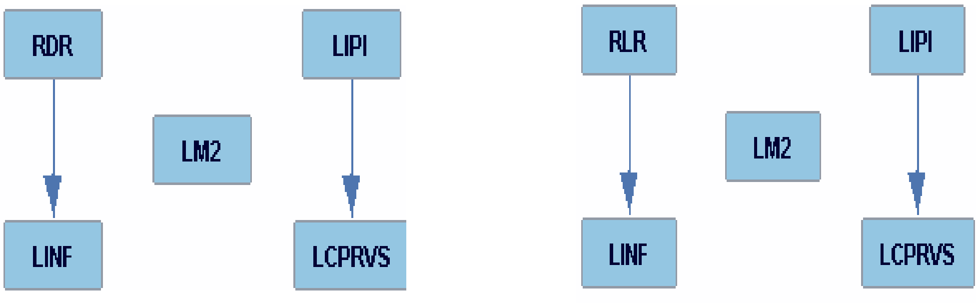
We have used the DAG analysis to investigate the causal relationship between the variables and identify the SVAR model. DAG starts with an undirected graph and connects all variables, as depicted in Figure 1**Error! Reference source not found.**



Model 1 Model 2

Figure 1: Undirected Graph: Model 1& 2

PC algorithm is used to remove edges based on conditional correlation. Finally, we get the following pattern, as shown in Graphs Figure. The DAG analysis for both models shows that interest rate causes inflation, and LIPI causes LCPRVS. Hence, when output increases, demand for credit also increases. Moreover, DAG analysis also suggests that none of the variables contemporaneously cause interest rate. This assumption is justified as the policymakers don't have complete information about output and prices within the same month. It is available with a lag (Alam, 2015; Cushman & Zha, 1995; Jones & Bowman, 2019; Kim & Roubini, 2000). Also, there is no direct contemporaneous causality running from RDR (RLR) to EG.



Model 1

Model 2

Figure 2 Direct Acyclic Graphs

The results of models 1 and 2 are summarized in equations 4 and 5.

$$B_1Y_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & \beta_{25} \\ \beta_{31} & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} LIPI \\ LINF \\ LCPRVS \\ LM2 \\ RDR \end{bmatrix} \quad (4)$$

$$B_2Y_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & \beta_{25} \\ \beta_{31} & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} LIPI \\ LINF \\ LCPRVS \\ LM2 \\ RLR \end{bmatrix} \quad (5)$$

We have used the identification restrictions proposed by the DAG analysis and estimate the over-identified SVAR model. The log-likelihood ratio test is available in

Table **7**, which shows that overidentifying restrictions are not rejected at a 10% level of significance for both models.

***Table 7**: LR test for Over-identification of Model 1 &2*

	Log-likelihood	Chi-square	Probability
Model 1	1133.712	5.507	0.702
Model 2	1147.182	5.515	0.701

Hence restrictions proposed by the DAG are consistent with the data. We have constructed structural impulse response functions (SIRF) and forecast variance decomposition (FVD) for dynamic analysis.

Structural Impulse Response Function

The SIRFs are used to observe domestic macroeconomic variables' response to one SD exogenous shock to the system's policy variables. We have also reported 95% confidence bands of the standard errors to see the response's significance. The study has estimated two models; the first model considers RDR as a measure of interest rate and the second model considers RLR as a measure of the interest rate. SIRF of model 1 is reported in the first panel, and model 2 is reported in the second panel of Figure 3

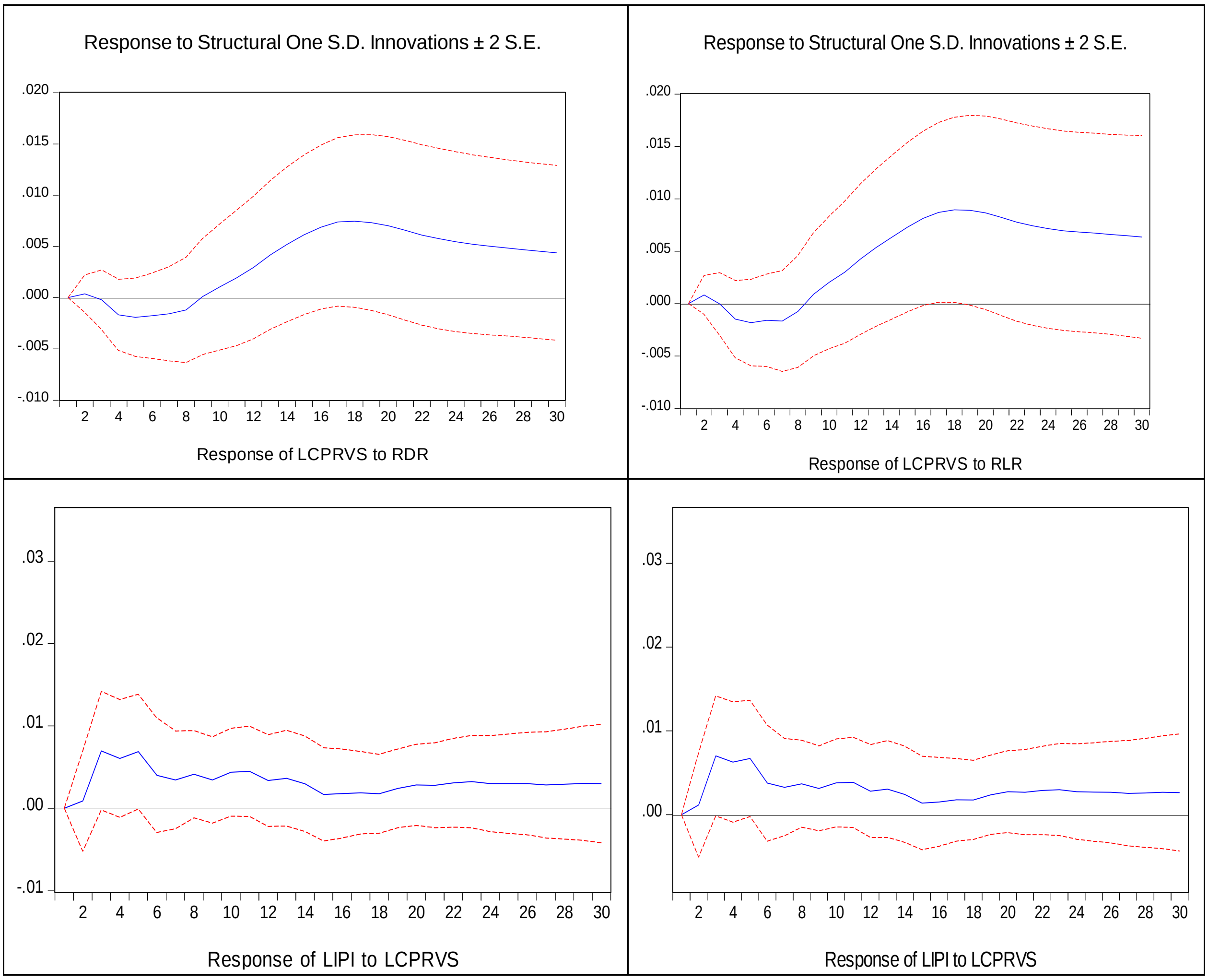


Figure 3: *Structural Impulse Response Functions of interest rate and credit shocks*

In response to unanticipated tight MP (increase in RDR), CPRVS respond after three periods. Initially, it decreases, and after eight months, it starts rising. However, the results are insignificant. The almost same pattern has been observed when we consider RLR. This implies that CPRVS does not significantly respond to interest rate movement.

Similarly, in response to the positive shock to LCPRVS, LIPI increases, but the results are insignificant. Hence, the CRC is ineffective. Our results are consistent with Baig (2011); Hussain (2014); Imran and Nishat (2013), who also observes that the CRC is not useful in Pakistan

Forecast Variance Decomposition

The FVD of model 1 and model 2 are reported in
Table **8**.
Similarly, Model 2 also depicts the same behavior. The main chunk of the variation in LIPI is explained by itself. In the first period, a 100% variation in LIPI is explained by itself. However, in the last period, 65% of the variation in LIPI is explained by itself. In contrast, LCPRVS explains 12% of the variation, RLR explains 13% of the variation, LINF explains 8% of the variation, and LM2 explains 2% of the variation. Hence in both models, the significant portion of the variation in LIPI is defined by itself. It also implies that some other factors affect output besides credit, interest rate, MS, and interest rate.

Table 9, respectively. In Model 1, the FVD of LIPI shows that a 100% variation in LIPI is explained by itself in the first period. However, in the fifth period, LIPI explains 90% of the variation, and LCPRVS explains almost 8% of the variation. In contrast, the remaining variation is elucidated by the other variables. Later on, over the horizon, the share of other variables increases a bit, and the share of LIPI decreases in explaining the variation in LIPI. However, still, the main chunk of variation in LIPI is explained by itself. In the last period, 64% of the variation in LIPI is explained by itself, LINF explains almost 11% of the variation, the LCPRVS explains 14%, the LM2 explains 2%, and the RDR shock explains 9%. Thus, the main chunk of variation in LIPI is explained by itself, whereas the other variables explain only minor variation.

Table 8: Forecast Variance Decomposition of Model 1

Period	LIPI Shock	LINF Shock	LCPRVS Shock	LM2 Shock	RDR Shock
Variance Decomposition of LIPI:					
1	100.000	0.000	0.000	0.000	0.000
2	99.392	0.004	0.060	0.408	0.136
5	90.025	0.344	8.392	0.809	0.430
10	75.076	4.005	10.561	2.137	8.221
15	70.552	5.839	11.431	2.042	10.136
20	67.747	8.595	11.871	2.085	9.702
25	65.280	10.594	12.970	1.976	9.178
30	64.224	11.168	13.873	1.887	8.848
Variance Decomposition of LCPRVS:					
1	3.597	0.000	96.403	0.000	0.000
2	10.562	6.E-06	89.074	0.299	0.065
5	22.686	0.194	74.634	1.425	1.061
10	51.504	0.083	46.380	1.091	0.942
15	48.657	0.872	45.213	1.568	3.690
20	48.185	3.007	39.916	1.222	7.670

25	46.905	5.898	37.906	0.920	8.371
30	44.814	9.425	36.948	0.737	8.076

Similarly, Model 2 also depicts the same behavior. The main chunk of the variation in LIPI is explained by itself. In the first period, a 100% variation in LIPI is explained by itself. However, in the last period, 65% of the variation in LIPI is explained by itself. In contrast, LCPRVS explains 12% of the variation, RLR explains 13% of the variation, LINF explains 8% of the variation, and LM2 explains 2% of the variation. Hence in both models, the significant portion of the variation in LIPI is defined by itself. It also implies that some other factors affect output besides credit, interest rate, MS, and interest rate.

Table 9: *Forecast Variance Decomposition of Model 2*

Period	LIPI Shock	LINF Shock	LCPRVS Shock	LM2 Shock	RLR Shock
Variance Decomposition of LIPI:					
1	100.000	0.000	0.000	0.000	0.000
2	99.044	0.122	0.098	0.347	0.390
5	89.867	0.243	8.415	0.662	0.812
10	74.796	2.645	9.832	2.417	10.310
15	70.300	3.707	10.017	2.175	13.801
20	67.628	6.285	10.459	2.188	13.440
25	65.583	7.851	11.471	2.090	13.005
30	64.725	8.250	12.237	2.009	12.779
Variance Decomposition of LCPRVS:					
1	3.2428	0.000	96.757	0.000	0.000
2	10.652	0.346	88.453	0.218	0.330
5	22.011	0.574	75.043	1.376	0.997
10	49.861	0.454	47.545	1.057	1.082
15	47.949	0.457	44.384	1.608	5.601
20	47.8777	1.428	38.058	1.296	11.340
25	46.684	3.524	35.806	1.006	12.979
30	44.874	6.152	34.904	0.820	13.251

The FVD of LCPRVS in Model 1 shows that 96% of the variation in LCPRVS is explained by itself, whereas the LIPI defines the remaining 4% variation. However, over time the share of LIPI increased. In the 10^{th} period, LIPI explains almost 52% of the variation, and LCPRVS explains 46% of the variation, whereas RDR explains nearly 4% of the variation. LINF explains less than 1% of the variation, and LM2 illustrates 2% variation. Similarly, in the 30^{th} period, LIPI explains 45% of the variation, and LCPRVS explains 37% of the variation. On the other hand, LINF explains 9% of the variation, and RDR explains 8% of the variation. Moreover, LM2 explains less than 1% of the variation.

Likewise, Model 2 also shows that 97% of the variation in LCPRVS is explained by itself, and the LIPI explains the remaining 3%. Over time, LIPI shock's role in defining the variation in LCPRVS increases, and the share of LCPRVS decreases. In the 30^{th} period, almost 45% of the variation in LCPRVS is explained by LIPI. Whereas LCPRVS explains 35% of the variation, RLR shock explains 13% of the variation, LINF explains 6% of the variation, and LM2 explains less than 1 % of the variation. Hence, we can conclude that the LIPI and LCPRVS explain the major chunk of variation in LCPRVS.

Discussion and Conclusion

The present study has reinvestigated the effectiveness of the CRC of MTM. The study has provided a novel contribution to the empirical literature by using DAG analysis to understand the causal relationship between the policy and the response variables. Further, the study has used the newly estimated data on the industrial production index (IPI), which was not available and used before in the empirical inquiry.

Stable prices and the increase in economic activities are the main goals of MP. To achieve these objectives, SBP formulates MP. Hence, it is the central concern of the policymakers to understand the MTM. After the GFC, CRC of MTM gains significant importance. It is considered the main cause of the financial crisis. In Pakistan, CRC is less explored, and its significance is inconclusive. The present study has investigated the contemporaneous causal relationship among the policy variables and the response variables to bridge the gap. Secondly, we have investigated the effectiveness of CRC of MTM by using monthly data from June 2006 to June 2018.

The study notes that the interest rate contemporaneously causes inflation. This implies that interest rates instantaneously affect inflation. Secondly, economic growth contemporaneously causes credit to the private sector. Hence, when the economy grows, the demand for credit from the private sector increases, and more credit is extended to the private sector. Further, the study notes that any variable in the system does not contemporaneously cause interest rate. Moreover, the interest rate has no contemporaneous impact on credit to the private sector.

The study also observes that the CRC is ineffective in transmitting the effects of MP in Pakistan. A positive shock to interest rate has no significant impact on credit to the private sector. Further, a shock to the credit to the private sector has no significant effect on output. It implies that CRC is ineffective in Pakistan. Our results are consistent with Baig (2011); Hussain (2014); Imran and Nishat (2013), who also observes that the CRC is not useful in Pakistan.

Imran and Nishat (2013)also note that interest rate has no significant affect on CPRVS and its monetary conditions which influence CPRVS in Pakistan. Our results are also in conformity with Hussain (2014) who note that before 2000 CRC is effective, and after 2000 IRC is effective in Pakistan. SimilarlyKhan et al. (2016)also reach to the same conclusion that the low policy rate couldn't increase CPRVS in Pakistan. The one possible reason behind the ineffectiveness of CRC is the underdeveloped financial sector. The private sector prefers to use other financing modes than the banking sector (Hasan, 2015).

Further, the major chunk of bank credit goes to the public sector compared to the private sector. According to SBP, in Dec 2018, almost 31% of commercial bank credit goes to the private sector, and the remaining 59% of the credit goes to the public sector. Hence, fewer resources are available for the private sector, which is the bone of any economy. Therefore, future studies can dig deeper to understand the actual reasons behind the ineffectiveness of CRC of MTM.

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