Examining the Role of Digitization in the Transmission of Monetary Policy: An Empirical Analysis of India

Garima Gupta[1], Pabitra Kumar Jena[2]& D P Priyadarshi Joshi[3]

Abstract

The study aims to find the impact of digitalization on the dual objectives of the monetary policy: output growth and stable prices. The study collected data from Reserve Bnak of India (RBI), Economic ad Political Weekly Research Foundation (EPWRF) and Central Statistics Office(CSO) databases from April 2004 to November 2021. Structural Vector Auto Regressive (SVAR) technique has been employed to explore the transmission mechanism by introducing digitalization as one of the variables. The study results reveal that policy rate (call money rate) and digitalization have a significant contemporaneous relationship. This study also find a positive and significant relationship between digitalization and the index of industrial production both in the short and long run. This implies that as digitalization increases, industrial production also increases; hence the output increases. However, this study finds a negative and insignificant relationship between digitalization and the consumer price index, which becomes positive and significant in the long run. This short-run negative relationship can be attributed to the fact that with digitalization comes better transparency and flow of information, which helps form inflation expectations, thus, lowering its trend. In the long run, the upward pressure is attributed to the fact that economic growth increases the incomes of people, thus increasing their demand and ultimately leading to higher digital transactions. The study suggests that the growth of digital finance should be incorporated into the monetary policy framework in order to increase its effectiveness. In a word, central banks should modify their policy responses to the new realities of the digital world.

Keywords: Digitization, Monetary Policy, SVAR and India

JEL Classification: E02; E52; G280 & E310

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1. Introduction

Digitalization can be seen as a major technological shock that impacts macroeconomic variables such as economic growth and inflation, which are important for the monetary policy framework. In recent years, the world has seen rapid advancements that have altered the global economic environment. Such innovations include financial technologies in terms of digitalization of means of payment. Digital payments include transactions settled through several media of paper- and electronic-based payment systems such as Real Time Gross Settlement (RTGS), National Electronic Fund Transfer (NEFT), National Electronic Clearing Services (NECS Credit/Debit), Credit Cards, Immediate Payment Service (IMPS) among others. Traditional ways of cash payments are on the path to replacement by unconventional means since the internet came into existence in the 1990s. Internet penetration in India increased from 92.57 million users in 2010 to 825.30 millionn Q4 of FY21 (Manchanda, 2021). The Indian Government has recently attempted to digitalize a large portion of its economy to deliver inclusive and transparent services to its citizens. The success of financial inclusion in India is attributed to rapid digitalization and initiatives taken by the Government, such as Jan Dhan Yojana in 2014, the Digital India campaign in 2015, etc. All these initiatives aim at transforming India into a digitally empowered nation. The importance of digital payments has been recognized in today's world as it helps to reduce the printing cost of paper currency. Other advantages of digital payments are that they are transparent, help in financial inclusion, and are accountable as they can be easily recorded and tracked. Reserve Bank of India is the apex financial and regulatory institution. It has to ensure that the payment and settlement system evolves continuously and is as technologically sound as possible. The major initiative in the direction to strengthen the e-payments system was the Payment and Settlement Systems Act (PSS Act) 2007. All of these developments and advancements in digital technology have begun to influence monetary policymaking, potentially leading to a departure from the traditional policy framework.

Data shows a behavioural shift in Indian ways of transacting especially after the COVID-19 pandemic wherein the digital dependency increased much more than ever. As of Jan 2022, the total number of ATMs in India reached 251,000 and total credit and debit cards reached 101 crores (EPWRF India Time Series, n.d.). Within a span of two years, we can see a 275.64% increase in

the value of UPI (Unified Payments Interface) transactions in India from June 2020 to Apr 2022, as shown in Figure 1.

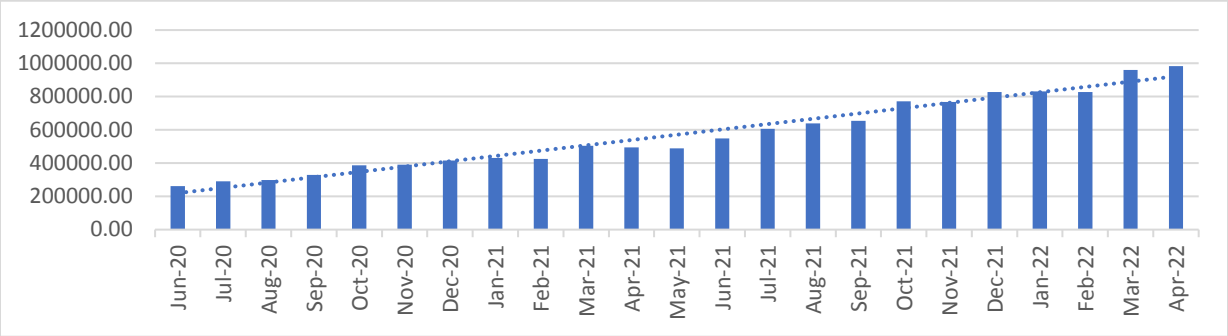

Figure 1: UPI (Value in Rs Crore) Source: RBI

Now, if we look at the total number of credit and debit cards, we'll witness a drastic increase from Apr 2006 to Jan 2022 as shown by the trend line in Figure 2.

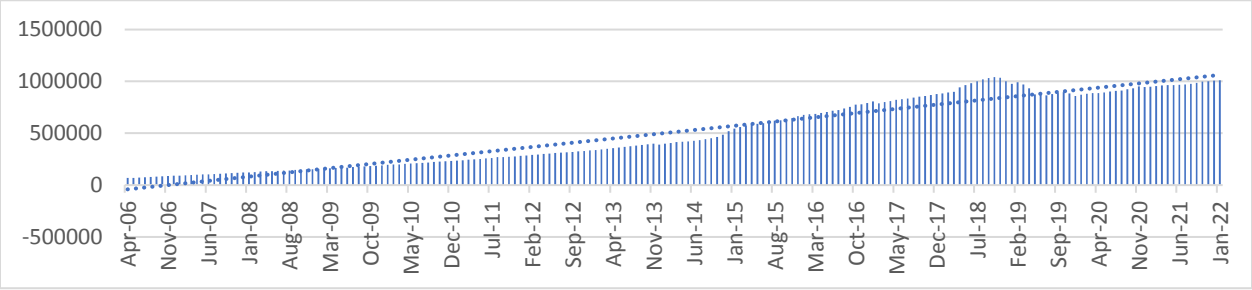

Figure 2: Total credit & debit cards (in thousand) Source: EPWITS

The graphs below show a huge increase in the number of ATMs, Point of Sale (POS) machines and value in mobile banking from Apr 2011 to Jan 2022. The trend line shows the increase in Figures 3, 4 and 5 respectively.

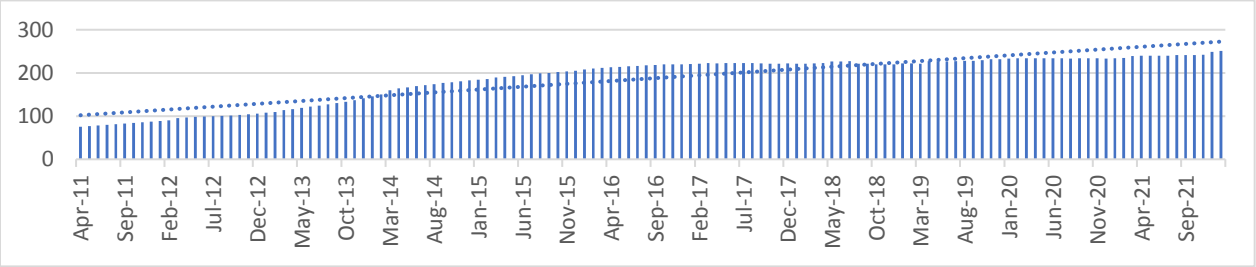

Figure 3: No. of ATMs (in thousand) Source: EPWITS

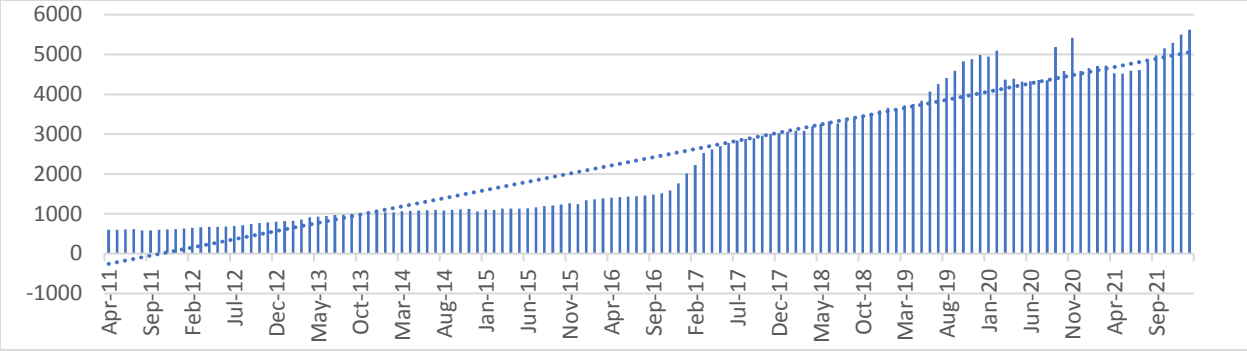

Figure 4: No. of POS Machines (in thousand) Source: EPWITS

Now, why are these numbers important? It is so because the progress in these digital transactions can have both positive and negative consequences. The increasing trend shows the possibility of the substitution of cash with digital payments. From the graphs obtained, it is evident that the digital revolution has already taken place in the country. This makes it an interesting yet important topic to study, particularly in the context of the monetary policy framework. A lot of research has been done to check the effectiveness of monetary policy transmission using various policy rates, whereas a minuscule study has been found in the context of digitalization. Therefore, the increasing value of digitalisation compels us to consider this important factor while analysing the effectiveness of monetary policy transmission. The process by which policy changes are converted into the ultimate twin objectives of price stability and sufficient credit to support aggregate demand and ensure strong and sustained growth is known as monetary transmission. (Mohan, Monetary policy transmission in India, 2007), (Mohanty, 2012)

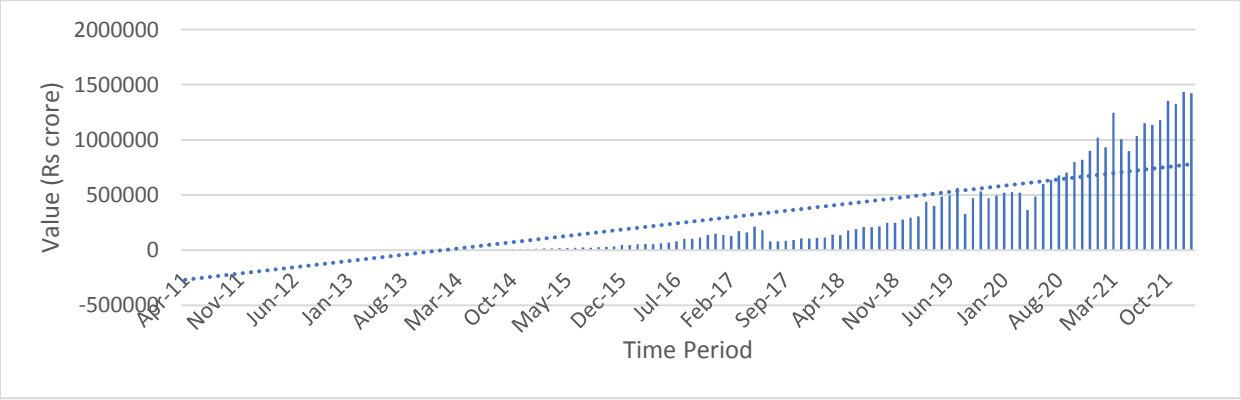

Figure 5: Value of Mobile banking transactions (Rs Crore) Source: EPWITS

Digitalization is a novel concept, however, it has tremendously transformed several aspects of the policy framework and will continue to do so in the near future. The advancements have altered central banks' ability to effectively execute monetary policy. Hence, there is a strong need to evaluate its impact on transmission mechanisms as it is ultimately related to inflation and the country's output. In this regard, this study propose applying SVAR and evaluating how digital currency would affect monetary policy transmission by identifying the purely exogenous shocks to the variables considered and catching sight of how macroeconomic variables react to it through impulse response. Overall, this study finds that digital payments significantly impact economic growth (both in the short and long run) and inflation (in the long run). Also, it has consequences for the effectiveness of the monetary policy. Soon the RBI is planning to launch Central Bank Digital Currency (CBDC) in 2022-23. Therefore, future payments in our country seem to centre around digital platforms rather than cash payments. Therefore, the central bank should evaluate the impacts of digitalization while framing monetary policy.

The study has been presented as follows. The second section describes the brief review of past literature. The data and methodology are presented in section 3. The empirical findings and discussions are presented in section 4. Section 5 presents the policy suggestions, followed by the conclusion.

2. Review of Literature

There is vast empirical literature on transmission channels of the monetary policy mechanism. (Mohan & Ray, Indian Monetary Policy in the Time of Inflation Targeting and Demonetisation, 2019) . They presented a chronicle of the history of Indian monetary policy in their paper focusing on the period 2008-2017. The studies have identified four traditional channels: the interest rate channel, asset price channel, credit channel, and exchange rate channel. The theoretical explanations of the conduct of monetary policy have evolved over the years. A fifth channel i.e., the expectations channel has also been given importance by many researchers like (Goyal & Parab, 2021) (Mohan, Monetary policy transmission in India, 2007) (Khundrakpam & Jain, 2012) (Mohanty, 2012) among others. Researchers have looked into the relative importance of numerous monetary policy transmission channels to inflation and growth, but the channels' ambiguity persists. The monetary transmission mechanism - the well-known "black box" - is still considered a challenging process, even after many years of intensive research, because several channels can

simultaneously act to reach the end policy objectives with no understanding of how precisely they do so. In short, there's no certainty about the uniqueness of each channel. (Mohanty, 2012) (Khundrakpam & Jain, 2012) . Talking about the effectiveness of the channels, the interest rate channel is considered to be the most dominant one in India with the central bank having a greater reliance on it. (Mohanty, 2012) used a quarterly SVAR framework and presented empirical evidence of the interest rate channel. He emphasised the importance of interest rates as a powerful monetary policy instrument based on his findings. (Mohan, Monetary policy transmission in India, 2007), in his paper, summed up that the interest rate pass-through has increased in recent years, with implications for transmission. (Kapur & Behera, 2012) used VAR-based studies to assess the monetary policy transmission using the nominal interest rate in India. They found that the magnitude of the impact of interest rate on growth and inflation is comparable to major advanced and emerging economies. The cross-country analysis also shows the importance of the interest rate channel. (Kelikume, 2014) studied the implications of the interest rate channel in Nigeria using cointegration and error correction modelling and found that the interest rates had the expected sign and were statistically significant in influencing the long-run output. (Ndubuisi, 2015) did an extensive review of literature on different countries like the US, Euro area countries and emerging and developing countries. He found that the interest rate channel remains operational in today's world and tends to be more pronounced as economies develop and their financial inclusion improves. However, some arguments go against the notion. (Al-Mashat & Billmeier, 2008) in their study on Egypt found that the interest rate channel is relatively insignificant in the monetary transmission mechanism.

A study by (Mishra, Montiel, & Sengupta, 2016) estimated a VAR using monthly data from April 2001 to December 2014. They concluded that the passthrough to bank lending rates from the policy rate is in the supposedly predicted direction, although the passthrough is incomplete. (Das, 2015) used a two-step vector error correction model and found that there is a significant, though slow, pass-through of changes in policy rates to bank interest rates in India. They also discovered an asymmetric monetary policy adjustment, in which the lending rate corrects faster to monetary contraction than to expansion. (Farajnezhad & Ramakrishnan, 2019) analysed the effectiveness of the monetary policy transmission mechanism procedure for commercial banks in Malaysia and found evidence in the credit channel leading to the conclusion that the fluctuations in monetary policy change in interest rate previous year would affect credit supply in recent years. Using an

SVAR model, (Khundrakpam & Jain, 2012) found that the credit channel and the asset price channel are the important channels in the Indian monetary policy framework in addition to the direct interest rate channel whereas the exchange rate channel to GDP growth is either absent or weak but has a non-negligible monetary policy dampening impact on inflation.

After reviewing the literature on transmission channels of monetary policy, it has been found that most of the researchers have been silent about digitalisation's impact on monetary policy transmission. Even though digitalisation has become a crucial part of today's world and has gained enormous importance during the outbreak of the COVID-19 pandemic. Only a few studies have been done recently in this regard both in India and abroad. In this concern, this paper aims to be an addition to the existing literature gap. Digitalisation has affected, and will continue to alter, the environment in which monetary policy works, according to a study by the European Central Bank (Anderton & Cette, 2021). Thus the way the monetary policy framework is conducted needs to be adapted. (Jiang, Qiu, & Zhou, 2021), in their paper, selected the data from 2011 to 2020 in China. Their empirical analyses revealed that the total index of digital finance had a considerably inverse influence on the growth of an economy. This implies that digital finance has harmed the effectiveness of the monetary policy. However, the interconnection of digital finance and monetary policy has a significant positive impact on economic growth, showing that the moderating effect of monetary policy benefits digital finance in terms of economic growth. (Meaning, Dyson, Barker, & Clayton, 2018) also argued that the monetary policy can have better operation through central bank digital currency transactions as a consequence of which the policy instruments could be strengthened. (Keister & Sanches, 2019) claimed that with the use of digital currency, monetary policy's flexibility and social welfare effect can be improved. Given the fact that central banks are exploring digital currency, they have highlighted a crucial policy trade-off between efficiency and investment. While a digital currency tends to promote efficiency in exchange, it can also crowd out bank deposits, raise banks' funding costs, and decrease investment. However, a central bank's digital currency can still raise welfare despite these consequences. Furthermore, (Hasan, Kwak, & Li, 2020) used the Interacted Panel VAR model and found that the adoption of financial technology mitigates the monetary policy transmission to real GDP, consumer prices, bank loans, and housing prices. (Bordo & Levin, 2017) claimed that digital currency is beneficial for strengthening the monetary policy framework and fostering true price stability. Using the Error Correction Model (ECM), (Wasiaturrahma & Wahyuningtyas, 2019),

discovered that credit cards have an inverse and significant influence on circulation of cash in the long run, but debit/ATM cards have a considerable direct effect. (Ugwuanyi, Efanga, & Anene, 2020) used data from Nigeria and applied the ARDL Model to discover that the money supply also increases as digital finance increases. (Muli, 2019), based on Friedman's quantity theory of money demand and Keynes Model, concluded that digital finance is a vital factor that negatively impacts the demand for money.

There is a solid theoretical foundation on digital finance and monetary policy effectiveness. (Rooj & Sengupta, 2020) utilised a Bayesian Vector Autoregression model and discovered that as RTGS increases, money supply and price level also increase. The more people will indulge in electronic transactions, the more will be the economic growth of the country. They also concluded that monetary policy has an insignificant effect on general price level or online system of payments. (Mumtaz, Smith, & Mahmood, 2020) employed GMM technique and discovered that following the start of fintech activities, income velocity and the money multiplier have no influence. Mobile technology, internet technology, and Bitcoin, on the other hand, have an impact on money demand, whilst the others have no impact. They discovered that Bitcoin, Ethereum, and Ripple are significant determinants of the output gap, whereas the monetary policy transmission may impact mobile and internet technology, Ethereum, and Ripple after accounting for fintech instruments and their interaction with real interest rates. On the other hand, (Tule & Oduh, 2017) indicated that financial innovation has an impact on the stability of the money multiplier, money velocity, and demand for money. (Xiang) applied the error correction mechanism and claimed that digital currency would generally affect the money supply indirectly by influencing the velocity of money. In their study, (Padha, Jena, Mishra, & Mahalik, 2021) used structural VAR to establish that monetary policy protects India's financial stability. On this note, some researchers also claim that digitalisation can contribute to uncertainty and complexity in the financial system of a country. Additionally, it may weaken the credit channel. (Anderton & Cette, 2021) Whereas (Tule & Oduh, 2017) stated that replacing cash with e-money will increase the financial system's efficiency and the interest rate channel of monetary policy transmission. However, it increases the output gap and adds an element of uncertainty to the monetary policy environment. (Jun, 2018) stressed that the expansion of fintech will increase competitiveness in the financial sector, resulting in the enhanced responsiveness of the market to interest rates, and thus affect the monetary policy transmission.

3. Data Description and Methodology

The study has collected data from RBI Database, EPWITS and CSO. The sample period is April 2004 to November 2021. The period and variables are chosen based on the available data. as shown in Table 1.

Table 1: Sources of Data

S. No.	Name of the variable	Unit of Measurement	Data Source
1.	Call money rate	Monthly average per cent	EPWITS
2.	IIP (monthly)	Spliced log-values based on Base Year: 2011-12 = 100	EPWITS
3.	CPI (monthly)	Monthly percentage change expressed as an annual rate	CSO
4.	An aggregate of digital payments (monthly)	Log-transformed values	EPWITS
5.	Money supply (M1)	Log-transformed values	EPWITS

Since we want to study the interaction between digitalisation and monetary policy tools taking the effect of various macroeconomic variables into account, this study will use the SVAR model. The majority of academics have utilised this methodology to estimate and investigate the effectiveness of the monetary policy transmission mechanism, as evidenced by past studies such as (Mohanty, 2012), (Mishra, Montiel, & Sengupta, 2016), (Khundrakpam & Jain, 2012), (Goyal & Parab, 2021) among others.

3.1 Theoretical Framework

Many pieces of literature fear that without any active rules and regulations, digitalisation may alter the ability of the central bank to regulate the economy and thereby hamper the monetary policy effectiveness (Tanaka, 1996; Berentsen, 1998; Woodford, 2001). Similarly, many studies concluded fintech adoption can increase monetary policy transmission as it alleviates financial frictions (Rajan 2006; Stein, 2013). Thus, it becomes imperative to study the impact of digitalisation on the effectiveness of the monetary policy. Monetary policy has dual objectives;

first, to regulate money supply in the economy to control inflation; second, to contribute to economic growth. In this section, we represent the theoretical framework for the implications of digitalisation on monetary policy effectiveness.

Digitalisation is a form of Fintech revolution and is delivered through mobile phones, different cards linked to bank accounts, the use of different payment apps and competing unified payment interfaces (UPI). Digitalisation has promoted social safety and economic relief; at the same time, it helps reduce corruption by abolishing the middle-man. Thus it has been instrumental in reducing financial exclusion and is causing changes in financial institutions. Digitalisation in the form of e-commerce, e-payments, monetary transfers has increased tremendously in recent years. These structural changes lead to changes in the composition of monetary bases. Digitalisation leads to a reduction in the cash in circulation while it will lead to more time deposits. Digital finance does not require money in hand; hence, transaction demand for money will be less. However, for digital payment, consumers and firms should have banking accounts and bank savings in the form of time deposits. Thus to locate the impact of digitalisation on monetary policy, we need to analyze the composition of monetary bases and their impact on money supply due to changes in these components.

We use the standard money supply formula to find the money multiplier. Here, we define narrow money (M_1) as the summation of cash in circulation (C) and demand deposits (D). The generalised money supply (M_2) has another component added to M_1, i.e., the time deposit (S). Similarly, the monetary base (H) is the addition of cash in circulation (C) and reserves with the commercial banks (R). These reserves can be divided into two components, one statutory deposit (R_L) and second excess deposits reserves (R_E). Thus, the money multipliers are represented by the following equation 1 and 2 for narrow money and generalised money supply, respectively.

$$m_1 = \frac{M_1}{H} = \frac{C + D}{C + R_L + R_E} = \frac{1 + c}{c + (r_L + r_E) \times (1 + s)} \qquad (1)$$

$$m_2 = \frac{M_2}{H} = \frac{C + D + S}{C + R_L + R_E} = \frac{1 + c + s}{c + (r_L + r_E) \times (1 + s)} \qquad (2)$$

From equation (1) and (2), c is the currency leakage ratio defined as the ratio of C to D; r_L is the required reserve ratio; r_E is the excess reserve ratio; and s is the time deposit ratio. The development of digital finance will have a negative impact on the money multiplier. To be more specific, digital finance has promoted the growth of e-commerce and the progressive transition of payment methods from traditional cash payments to electronic ones. Additionally, c keeps shrinking. People's financial conceptions have significantly improved in emerging market countries thanks to the growth of digital finance, which has caused a substantial decrease in the entry threshold for money market funds. This will cause D to decline and s to rise. In fact, developing nations may fully utilise digital finance to speed the process up of interest rate liberalisation, lower the cost of social funding, and end information asymmetry. As a result, r_L can be thought of as a short-term constant, and r_E will decrease.

If we take the paritial derivative of equation (1) and equation (2) with respect to c, r_E and s, then we get the set of impacts of these ratios on the narrow money and generalised money.

$$\frac{\partial m_1}{\partial c} = \frac{(r_L + r_E) \times (1 + s) - 1}{[c + (r_L + r_E) \times (1 + s)]^2} \tag{3}$$

$$\frac{\partial m_1}{\partial r_E} = -\frac{(1 + c) \times (1 + s)}{[c + (r_L + r_E) \times (1 + s)]^2} \tag{4}$$

$$\frac{\partial m_1}{\partial s} = -\frac{(1 + c) \times (r_L + r_E)}{[c + (r_L + r_E) \times (1 + s)]^2} \tag{5}$$

$$\frac{\partial m_2}{\partial c} = \frac{(r_L + r_E - 1) \times (1 + s)}{[c + (r_L + r_E) \times (1 + s)]^2} \tag{6}$$

$$\frac{\partial m_2}{\partial r_E} = -\frac{(1 + s + c) \times (1 + s)}{[c + (r_L + r_E) \times (1 + s)]^2} \tag{7}$$

$$\frac{\partial m_2}{\partial s} = -\frac{c \times [1 - (r_L + r_E)]}{[c + (r_L + r_E) \times (1 + s)]^2} \tag{8}$$

From these set of partial derivatives it is clear that the impact of c on narrow money is uncertain, while it is negative on generalised money. The excess reserve ratio has a negative impact on both narrow and generalised money supply. In addition, s has a negative impact on narrow money and

a positive impact on generalised money. Due to the increase in digitalisation, c will shrink and s will expand. Thus the impact of digitalization on money supply depends on the net effect of c and s on the generalised money (M_2).

3.2 Econometric Technique

In this section, this study shows the general approach for the SVAR model. In the subsequent sections, we implement it with data. (Gottschalk, 2001) gave an introduction to the SVAR methodology and showed that analyzing the monetary transmission mechanism is advantageous. (Sims, 1986) and (BERNANKE, 1986) proposed modelling the innovations using economic analysis. The idea is to estimate the relationships among the structural shocks using an economic model. An SVAR aims to use economic theory to add structural restrictions to the VAR model. Additionally, it allows for examining the causal relationships and helps to analyze the impact of individual shocks on other variables.

Let's consider a structural VAR (1) where Y_t depends on its lag and structural shock μ_t which is independent among all.

$$AY_t = \beta_0 + \beta_1 Y_{t-1} + \mu_t \quad \ldots (8)$$

Generalized form:

$$AY_t = \sum_{j=1}^{n} \beta_1 Y_{t-1} + \mu_t \quad \text{where } \mu_t \sim N(0, D)$$

Here,

$Y_t = (Y_{1t}, Y_{2t}, Y_{3t} \ldots Y_{kt})$ is a k*1 vector of endogenous variables.

$\beta_1, \beta_2, \beta_3 \ldots \beta_k$ is a k*k matrix of lag coefficients to be estimated on j^{th} lag.

μ_t is a k*1 vector of disturbances representing the structural shocks and has a covariance matrix (a diagonal matrix having the variances).

A is a matrix that reflects the contemporaneous interactions among the endogenous variables and is very important in the identification process.

In our model, Y_t contains five underlying variables, that is, Call Money Rate (CMR), log of an aggregate of digital payments (DIG), y-o-y growth rate of Consumer Price Index (CPI), natural

log of Index of Industrial Production (IIP) and log of money supply (MS). The system of equations is as follows.

$$\alpha_{11}CMR_t + \alpha_{12}DIG_t + \alpha_{13}CPI_t + \alpha_{14}IIP_t + \alpha_{15}MS_t = \beta_{10} + \beta_{11}CMR_{t-1} + \beta_{12}DIG_{t-1} + \beta_{13}CPI_{t-1} + \beta_{14}IIP_{t-1} + \beta_{15}MS_{t-1} + \mu_{CMRt} \ldots (9)$$

$$\alpha_{21}CMR_t + \alpha_{22}DIG_t + \alpha_{23}CPI_t + \alpha_{24}IIP_t + \alpha_{25}MS_{25} = \beta_{20} + \beta_{21}CMR_{t-1} + \beta_{22}DIG_{t-1} + \beta_{23}CPI_{t-1} + \beta_{24}IIP_{t-1} + \beta_{25}MS_{t-1} + \mu_{DIGt} \ldots (10)$$

$$\alpha_{31}CMR_t + \alpha_{32}DIG_t + \alpha_{33}CPI_t + \alpha_{34}IIP_t + \alpha_{35}MS_t = \beta_{30} + \beta_{31}CMR_{t-1} + \beta_{32}DIG_{t-1} + \beta_{33}CPI_{t-1} + \beta_{34}IIP_{t-1} + \beta_{35}MS_{t-1} + \mu_{CPIt} \ldots (11)$$

$$\alpha_{41}CMR_t + \alpha_{42}DIG_t + \alpha_{43}CPI_t + \alpha_{44}IIP_t + \alpha_{45}MS_t = \beta_{40} + \beta_{41}CMR_{t-1} + \beta_{42}DIG_{t-1} + \beta_{43}CPI_{t-1} + \beta_{44}IIP_{t-1} + \beta_{45}MS_{t-1} + \mu_{IIPt} \ldots (12)$$

$$\alpha_{51}CMR_t + \alpha_{52}DIG_t + \alpha_{53}CPI_t + \alpha_{54}IIP_t + \alpha_{55}MS_t = \beta_{50} + \beta_{51}CMR_{t-1} + \beta_{52}DIG_{t-1} + \beta_{53}CPI_{t-1} + \beta_{54}IIP_{t-1} + \beta_{55}MS_{t-1} + \mu_{MSt} \ldots (13)$$

It can be represented in matrix form as:

$$\begin{bmatrix} 1 & \alpha_{12} & \alpha_{13} & \alpha_{14} & \alpha_{15} \\ \alpha_{21} & 1 & \alpha_{23} & \alpha_{24} & \alpha_{25} \\ \alpha_{31} & \alpha_{32} & 1 & \alpha_{34} & \alpha_{35} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & 1 & \alpha_{45} \\ \alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & 1 \end{bmatrix} \begin{bmatrix} CMR_t \\ lnDig_t \\ CPI_t \\ IIP_t \\ MS_t \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \\ \beta_{40} \\ \beta_{50} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} & \beta_{25} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} & \beta_{45} \\ \beta_{51} & \beta_{52} & \beta_{53} & \beta_{54} & \beta_{55} \end{bmatrix} \begin{bmatrix} CMR_{t-1} \\ lnDig_{t-1} \\ CPI_{t-1} \\ IIP_{t-1} \\ MS_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{RRt} \\ \mu_{Digt} \\ \mu_{CPIt} \\ \mu_{IIPt} \\ \mu_{MSt} \end{bmatrix}$$

Now, we multiply eq. (8) by the inverse of matrix A i.e., A^{-1} to get the reduced-form VAR as:

$$A^{-1}AY_t = A^{-1}\beta_0 + A^{-1}\beta_1 Y_{t-1} + A^{-1}\mu_t \ldots (14)$$

Or $Y_t = G_0 + G_1 Y_{t-1} + e_t \ldots (15)$

where $AA^{-1} = I$ (identity matrix), G- coefficients and, e_t is the forecast error which is a linear combination of the structural shock μ.

$e_t = A^{-1}\mu_t$ … (16)

3.3 Identification

It starts from the estimation of the reduced-form VAR i.e., eq. (16) $Y_t = G_0 + G_1 Y_{t-1} + e_t$ where Y_t depends upon its own lagged values. Being a theoretical construct, SVAR is non-observable and therefore, cannot be estimated directly. Here, we have the time series of variables. When we use them to estimate a VAR, we estimate coefficients of each variable against its lag and the lag of the other variables contained in the VAR. With this, we obtain the coefficients G as well as the forecast errors or the reduced-form residuals.

The goal is to get a structural model that isolates exogenous shocks and measures how these shocks affect the variables in the model. For that purpose, we need to go for the identification process which is a challenge in itself. Now, for identification, we need to restrict matrix A. Multiply Equation (8) by matrix A to get the structural model, shocks, and contemporaneous interactions among variables.

$AY_t = \beta_0 + \beta_1 Y_{t-1} + \mu_t$ … (17)

Since the structural shocks are independent, therefore, the covariance is zero. After that one can see what happens to all variables once a structural shock hits the economy.

Let's estimate the reduced-form VAR.

$CMR_t = g_{10} + g_{11}CMR_{t-1} + g_{12}DIG_{t-1} + g_{13}CPI_{t-1} + g_{14}IIP_{t-1} + g_{15}MS_{t-1} + e_{CMRt}$ … (18)

$DIG_t = g_{20} + g_{21}CMR_{t-1} + g_{22}DIG_{t-1} + g_{23}CPI_{t-1} + g_{24}IIP_{t-1} + g_{25}MS_{t-1} + e_{Digt}$ … (19)

$CPI_t = g_{30} + g_{31}CMR_{t-1} + g_{32}DIG_{t-1} + g_{33}CPI_{t-1} + g_{34}IIP_{t-1} + g_{35}MS_{t-1} + e_{CPIt}$ … (20)

$IIP_t = g_{40} + g_{41}CMR_{t-1} + g_{42}DIG_{t-1} + g_{43}CPI_{t-1} + g_{44}IIP_{t-1} + g_{45}MS_{t-1} + e_{IIPt}$ … (21)

$MS_t = g_{50} + g_{51}CMR_{t-1} + g_{52}DIG_{t-1} + g_{53}CPI_{t-1} + g_{54}IIP_{t-1} + g_{55}MS_{t-1} + e_{MSt}$ … (22)

Matrix form of the above reduced-form VAR equations:

$$\begin{bmatrix} CMR_t \\ Dig_t \\ CPI_t \\ IIP_t \\ MS_t \end{bmatrix} = \begin{bmatrix} g_{10} \\ g_{20} \\ g_{30} \\ g_{40} \\ g_{50} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} & g_{13} & g_{14} & g_{15} \\ g_{21} & g_{22} & g_{23} & g_{24} & g_{25} \\ g_{31} & g_{32} & g_{33} & g_{34} & g_{35} \\ g_{41} & g_{42} & g_{43} & g_{44} & g_{45} \\ g_{51} & g_{52} & g_{53} & g_{54} & g_{55} \end{bmatrix} \begin{bmatrix} CMR_{t-1} \\ Dig_{t-1} \\ CPI_{t-1} \\ IIP_{t-1} \\ MS_{t-1} \end{bmatrix} + \begin{bmatrix} e_{CMRt} \\ e_{Digt} \\ e_{CPIt} \\ e_{IIPt} \\ MS_t \end{bmatrix}$$

We obtain 30 coefficients (g) and the (symmetric) variance-covariance matrix of residuals with the estimation. That is 45 parameters in total: 30 coefficients, 5 variances and 10 covariances. On the other hand, the SVAR has 50 unknowns: 45 parameters and 5 variances. Therefore, there are more unknowns in the structural model and all the information we have consists of fewer parameters estimated with reduced VAR. As a consequence, we need to impose restrictions which is the next crucial step of identification.

3.4 Imposition of Restrictions

Usually, the restriction is inculcated in matrix A. Imposing restrictions on the contemporaneous relations among the endogenous/dependent variables of the structural model backed by some economic theory/knowledge/intuition is all about identification. It is important to note that by imposing restrictions on matrix A, we also impose restrictions on the inverse of A in the reduced VAR. The unknown parameters in the structural model become equal to the number of equations obtained from the estimated VAR when employing reduced-form estimation to recover the structural shocks and structural parameters. Here, we employ the point zero approach for identification. The method is simple recursive ordering which is also known as Cholesky Decomposition. Based on the available literature, it is found that slower-moving variables are preferably ordered before faster-moving variables (Bruno & Shin, 2015). Previous empirical and theoretical studies also revealed that the ordering generally follows the pattern in the sequence of macroeconomic variables followed by monetary policy and financial variables. In our model, we assume that digitalisation impacts other variables contemporaneously but itself is impacted by the other variables with a lag. Thus, we place it at the beginning of the order, that is; before macroeconomic and monetary variables. Based on the above-mentioned facts, in our model, we also assume that the central bank considers current output and prices while planning the rates for the monetary policy so, we place policy rates after IIP and CPI.

These assumptions agree with (Debasis Rooj and Reshmi Sengupta, 2020) research work on the analysis of digital payment systems and economic growth. So, the final ordering of our variables goes like this: DIG followed by IIP, CPI, CMR and MS. Given that the central bank's monetary policy targets are pursued with short to medium-term horizons, we consider the short-run representation. The SVAR with recursive short-run restriction type (denoted by S in E-Views) in the pattern matrix form is as follows:

$\mathrm{Ae} = \mathrm{Bu}$ where $\mathrm{E[uu']} = \mathrm{I}$

$$A = \begin{bmatrix} C(1) & 0 & 0 & 0 & 0 \\ C(2) & C(6) & 0 & 0 & 0 \\ C(3) & C(7) & C(10) & 0 & 0 \\ C(4) & C(8) & C(11) & C(13) & 0 \\ C(5) & C(9) & C(12) & C(14) & C(15) \end{bmatrix}$$

Or

Table 2: Recursive Short-run restrictions

		DIG	IIP	CPI	CMR	MS
A =	DIG	C(1)	0	0	0	0
	IIP	C(2)	C(6)	0	0	0
	CPI	C(3)	C(7)	C(10)	0	0
	CMR	C(4)	C(8)	C(11)	C(13)	0
	MS	C(5)	C(9)	C(12)	C(14)	C(15)

4. Empirical Results and Discussion

Our empirical exercise seeks to address the monetary policy effectiveness in the presence of digitalization using an SVAR model of five variables: the aggregate of digital payments (DIG), output (IIP), inflation (CPI), and monetary policy (call money rate) and money supply (M1).

4.1 Unit Root Test

We first conduct the unit root test to examine the stationarity of the variables. For that, we applied the Augmented Dickey-Fuller (ADF) test. The unit root test for all of the variables considered is represented in Table 3.

Table 3: Augmented Dickey-Fuller Test

ADF: NULL- HAS A UNIT ROOT				
	Level		1st Difference	
Variables	Intercept	Intercept and Trend	Intercept	Intercept and Trend
DIG	0.0004***	0.0074***	0.0000***	0.0000***
IIP	0.0161**	0.0049***	0.0000***	0.0000***
CPI	0.0362**	0.1947	0.0000***	0.0000***
CMR	0.0106**	0.0365**	0.0000***	0.0000***
MS	0.6746	0.0209**	0.0000***	0.0000***

*, **, *** represents significance at 10%, 5%, and 1% level respectively.

The results from the ADF test show that DIG, IIP and CMR are stationary at level (both at intercept and trend). CPI is stationary at intercept (at level, 5% level of significance) and MS is stationary at intercept and trend (at level, 5% level of significance). Hence, every variable in the model has the same order of integration I (0). So, we would run our model by keeping all the variables in their level form.

4.2 VAR lag order selection criteria

The next step is to identify the suitable lag length for the estimation of the standard VAR model. With the help of the lag length selection criteria, available in E-Views, we decided on sufficient lags for our model. Based on the Hannan–Quinn information criterion, we finalize the optimal lag order as two, as shown in Table 4.

Table 4: VAR Lag Order Selection Criteria

Endogenous variables: IIP, CPI, CMR, D(TB), D(MS), DIG			
Lag	AIC[4]	SC[5]	HQ[6]
0	3.661231	3.742557	3.694129
1	-8.674884	-8.186926*	-8.477496
2	-8.941990	-8.047399	-8.580112*
3	-9.014707*	-7.713484	-8.488339
4	-9.004263	-7.296407	-8.313404
5	-8.993756	-6.879268	-8.138407
6	-8.865209	-6.344089	-7.845370
7	-8.817282	-5.889529	-7.632953
8	-8.805322	-5.470937	-7.456503

4.3 Short-Run Impulse Response

The coefficient output obtained and the corresponding matrix with recursive short-run impulse response (S triangular) mentioned in the methodology are as follows:

$$S = \begin{bmatrix} 0.071714 & 0 & 0 & 0 & 0 \\ 0.017113 & 0.027652 & 0 & 0 & 0 \\ -0.015221 & 0.092435 & 0.391416 & 0 & 0 \\ 0.155924 & 0.113689 & 0.092490 & 0.807442 & 0 \\ 0.003462 & 0.002126 & -0.000634 & -0.000255 & 0.013235 \end{bmatrix}$$

Estimated matrix with short-run restrictions where:

		DIG	IIP	CPI	CMR	MS
S =	DIG	C(1)	0	0	0	0
	IIP	C(2)	C(6)	0	0	0
	CPI	C(3)	C(7)	C(10)	0	0
	CMR	C(4)	C(8)	C(11)	C(13)	0
	MS	C(5)	C(9)	C(12)	C(14)	C(15)

Table 5: Coefficient Output obtained from the short-run impulse response

[4] AIC- Akaike information criterion
[5] SC- Schwarz information criterion
[6] HQ- Hannan–Quinn information criterion
*Lag order selected by the criterion.

	COEFFICIENT	SE	Z-STATISTIC	P VALUE
C(1)	0.071714	0.003499	20.49390	0.0000***
C(2)	0.017113	0.002083	8.216189	0.0000***
C(3)	−0.015221	0.027763	-0.548251	0.5835
C(4)	0.155924	0.057138	2.728910	0.0064**
C(5)	0.003462	0.000941	3.676840	0.0002***
C(6)	0.027652	0.001349	20.49390	0.0000***
C(7)	0.092435	0.027384	3.375483	0.0007***
C(8)	0.113689	0.056357	2.017305	0.0437**
C(9)	0.002126	0.000920	2.310454	0.0209**
C(10)	0.391416	0.019099	20.49390	0.0000***
C(11)	0.092490	0.055901	1.654518	0.0980*
C(12)	−0.000634	0.000914	-0.693784	0.4878
C(13)	0.807442	0.039399	20.49390	0.0000***
C(14)	−0.000255	0.000913	-0.279261	0.7800
C(15)	0.013235	0.000646	20.49390	0.0000***

*Significance at 10%, **significance at 5%, ***significance at 1% level

The impacts of the shock on DIG, IIP, CMR and MS from DIG are all significant, according to the aforementioned S matrix data. However, the impact of the shock on CPI from DIG is not significant. DIG has a maximum significant impact on CMR (15.5924%) followed by DIG (7.1714%), IIP (1.7113%) and MS (0.3462%). Additionally, it shows a positive relationship between DIG and IIP, DIG and CMR, DIG and MS while an inverse relationship between DIG and CPI. Moreover, the impacts of the shock on IIP, CPI, CMR and MS from IIP are all significant at 5% level of significance. Furthermore, a shock to CPI has a significant impact on CMR and an insignificant impact on MS. This can be explained by the fact that shocks in macro variables impact each other immediately in varying magnitude.

4.4 Long-run Impulse Response

Now, if we look at the long-run matrix (given by the F matrix in E-views), we obtain the following estimates (Table 6).

Table 6: Coefficient output obtained from Long-run Impulse Response

	COEFFICIENT	SE	Z-STATISTIC	P VALUE
C(1)	2.261164	0.110335	20.49362	0.0000***
C(2)	0.904179	0.045731	19.77149	0.0000***
C(3)	10.73541	1.483000	7.238979	0.0000***
C(4)	-3.116862	0.494912	-6.297811	0.0000***
C(5)	2.36841	0.124221	19.06791	0.0000***
C(6)	0.174371	0.008508	20.49389	0.0000***
C(7)	8.610287	1.322255	6.511818	0.0000***
C(8)	1.650117	0.464030	3.556059	0.0004***
C(9)	0.495009	0.038586	12.82872	0.0000***
C(10)	18.16829	0.886522	20.49390	0.0000***
C(11)	1.464679	0.451368	3.244980	0.0012***
C(12)	0.228620	0.027947	8.180551	0.0000***
C(13)	6.458422	0.315139	20.49390	0.0000***
C(14)	-0.332628	0.019828	-16.77578	0.0000***
C(15)	0.165044	0.008053	20.49390	0.0000***

Based on various macroeconomic theories, it has been highlighted that the monetary policy has real effects in the short-run and neutral effects in the long run. However, research conducted by (Jordà, Singh, & Taylor, 2020), strongly challenged this view and concluded that monetary policy has real effects even in the long run that can last for a decade or more. Our model also estimated the long-run estimates and found that the impact of a shock on DIG significantly impacts all the variables DIG, IIP, CPI, CMR and MS. DIG has a positive impact on both IIP and CPI in long run. Additionally, the impact of shocks to all the variables on other variables in the model is significant.Since we are primarily interested in determining the influence of digitalization on output and inflation variability in this study, the Impulse Response Functions for each model are examined.

4.5 Impulse Response Functions

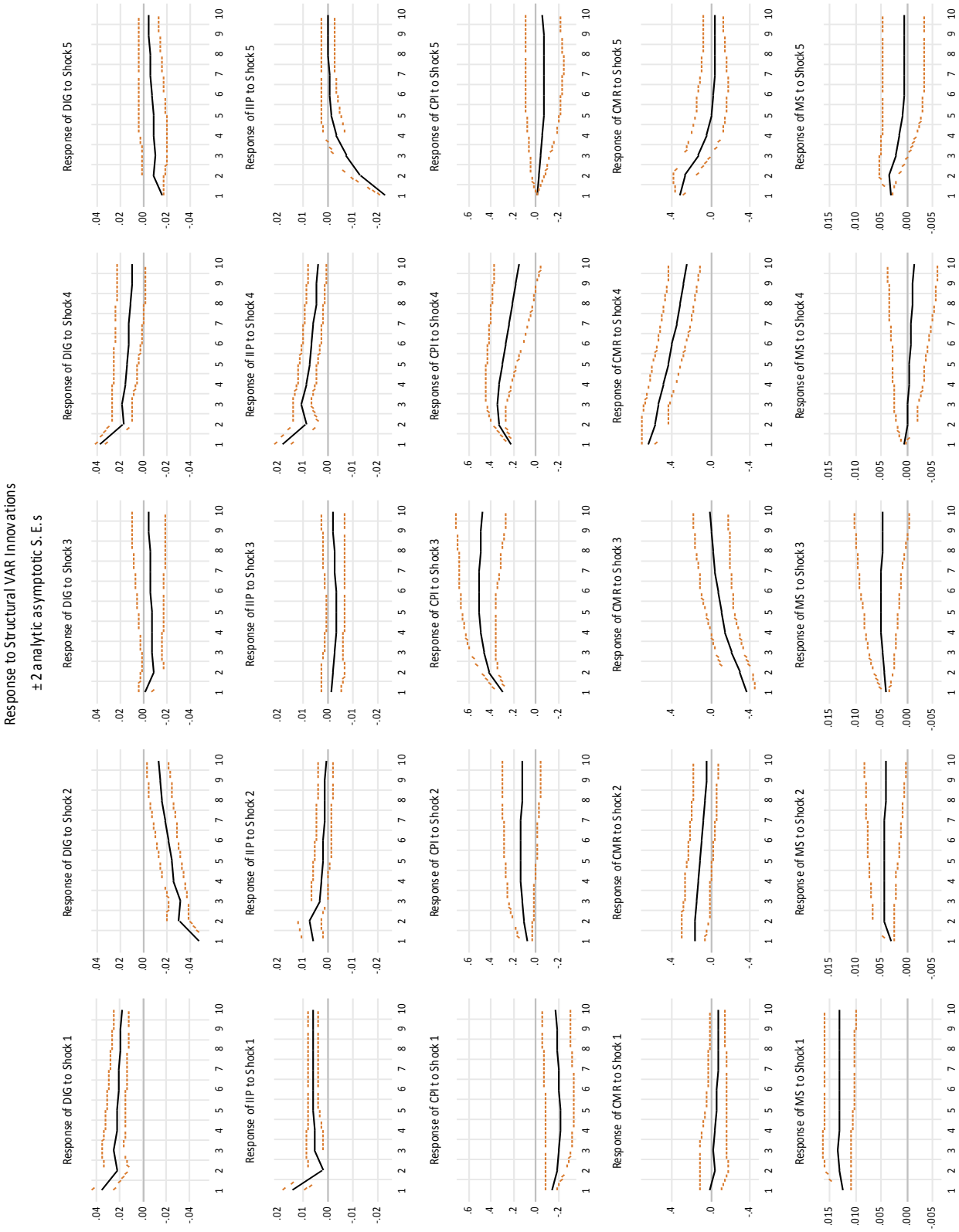

Figure 6: Impulse Response Functions: Response to Non-factorized One S.D. Innovations

Figure 13 shows the impulse response functions for the response of variables to structural VAR Innovations in all other variables of the model. In the first column, we present the responses to a shock to digitalization (DIG). A structural shock to DIG first decreases IIP up to the second period, increases it up to the third period, and stabilizes after the fifth period. Its initial decline can be attributed to the absence of the economic agent's abilities and skills to adapt to the changing technology in terms of digitalization. As the establishment of skills and adaptability increases, digitalization increases industrial production. This significant impact indicates that digitalization enhances the movement in the index of industrial production. This conclusion is akin to the impact of IIP on RTGS (Debasis Rooj and Reshmi Sengupta, 2020). The impact of digitalization on CPI is negative in the short run while it becomes positive in the long run. We find that an increase in the value of digitalization decreases CPI up to the fifth period. The negative relation between digitalization and CPI follows the conclusion of (Csonto, Huang, & Tovar, 2019) who concluded that digitalization is a key driver of lower trend inflation since digitalization brings transparency and flow of information and thus improves the expectations of economic agents, resulting in lowering the CPI trend. However, after the fifth period, we observed a slight increase in CPI after every period, which is significant and persistent until the tenth period.

The second column shows the impact of a shock to IIP on other variables. A shock to IIP produces a positive trend in DIG, CPI and MS while a negative trend in CMR. It demonstrates that the impact of industrial growth on high-value money transfers via digital platforms is on the rise. Next, as seen in the third column, we look at the impact of CPI on other variables. A shock to CPI has an immediate response on DIG with a negative trend up to the second period and starts increasing after this period up to the tenth period. However, IIP decreases up to the fourth period, remains constant up to the seventh period, and starts increasing after that. On CMR, it has a positive response throughout the horizon of ten periods while MS hovers around the zero-axis throughout the set period. A shock to CMR declines all the variables in the model with MS showing the minimal movement and sticks around the zero-axis up to the fifth period. The last column shows the impact of the money supply on other variables. A shock to MS increases DIG and IIP while it decreases CPI and MS. DIG increases in the whole horizon, IIP increases up to the sixth period and then stabilizes at zero-axis, CPI decreases up to the fifth period, remains stable up to the ninth period and slightly increases in the tenth period. CMR decreases up to the fifth period and then stabilizes around the zero-axis horizon.

4.6 Variance Decomposition

This section discusses the roles of DIG, IIP, and CPI shocks in explaining each other's variations. We explore variance decomposition using Cholesky (d.f. adjusted) factors to highlight the significance of each of the identified shocks in the fluctuations of the variables. For DIG, in the short-run (say the first period), we find that the maximum forecast error variance is explained by IIP followed by CMR, DIG, MS and CPI. In the long run (say the tenth period), the maximum variance is explained by IIP followed by DIG, CMR, MS and CPI. For IIP, we find that the maximum variance is explained by IIP itself followed by DIG in the short run. In the long run, the maximum variance in IIP is explained by CMR followed by MS, DIG, IIP and CPI. For CPI, we find that the maximum variance is explained by CPI itself followed by CMR, DIG, IIP and MS in the short run. The maximum variance is explained by CPI followed by CMR, DIG, IIP and MS in the long run.

Variance decompositions of DIG, IIP and CPI are summarized in Table 7.

Table 7: Variance Decomposition

Variance Decomposition						
Variance Decomposition of DIG						
Period	S.E.	DIG	IIP	CPI	CMR	MS
1	0.071714	24.12854	44.82441	0.058447	26.24082	4.747782
2	0.083714	24.50293	46.25107	1.060485	23.57662	4.608899
3	0.095812	25.88009	46.13535	1.433983	21.75306	4.797522
4	0.103894	26.96265	45.79457	1.780907	20.60465	4.857226
5	0.110466	28.03006	45.23872	1.996641	19.86882	4.865757
6	0.115624	29.02597	44.61615	2.154165	19.37005	4.833664
7	0.119832	29.98012	43.95739	2.260837	19.01657	4.785083
8	0.123288	30.89167	43.29519	2.333066	18.75014	4.729935
9	0.126169	31.76583	42.64423	2.379016	18.53746	4.673470
10	0.128596	32.60452	42.01445	2.405620	18.3564	4.617763
Variance Decomposition of IIP						
Period	S.E.	DIG	IIP	CPI	CMR	MS

1	0.032519	17.63066	3.003402	0.140411	30.53970	48.68582
2	0.036645	14.21369	6.323307	0.498059	29.26506	49.69988
3	0.039295	14.07346	6.135543	0.806799	32.29291	46.69129
4	0.040817	14.53913	6.215596	1.339810	34.08021	43.82525
5	0.042111	15.60167	6.069911	1.820832	35.22685	41.28073
6	0.043177	16.80428	5.930540	2.226566	35.75013	39.28848
7	0.044091	18.07881	5.785251	2.524876	35.92793	37.68313
8	0.044874	19.34047	5.653602	2.733580	35.89035	36.38200
9	0.045557	20.57106	5.534301	2.870824	35.72189	35.30193
10	0.046159	21.75948	5.427443	2.955333	35.46929	34.38845
Variance Decomposition of CPI						
Period	S.E.	DIG	IIP	CPI	CMR	MS
1	0.402470	11.56649	4.113851	54.37317	29.93224	0.014251
2	0.695959	10.68694	3.900953	53.15685	32.16170	0.093562
3	0.935906	10.69833	1.007577	53.99214	31.07362	0.228326
4	1.134163	10.69355	4.081977	55.40439	29.40662	0.413468
5	1.300229	10.71372	4.161186	56.94430	27.59361	0.587183
6	1.441470	10.71815	4.233470	58.46818	27.85472	0.725479
7	1.563208	10.70350	4.304383	59.91821	24.25008	0.823831
8	1.669390	10.66766	4.375379	61.27282	22.79543	0.888719
9	1.762958	10.61295	4.447900	62.52438	21.48633	0.928436
10	1.846133	10.54226	4.522410	63.67262	20.31248	0.950229

5. Conclusion and Policy Suggestions

The dynamics of the financial environment have altered dramatically as a result of global advances in financial technology. Digitalization is a novel concept that has the power to influence the monetary transmission mechanism. In this context, the role of digitization in India's monetary policy framework is empirically examined in this paper. First, we applied an ADF test and found that our variables are stationary at level. Then we applied the SVAR methodology and put recursive restrictions on both the short-run and long-run matrices. We observed that digitalization

has a significant contemporaneous relationship with the index of industrial production, call money rate and money supply while a negative non-significant relationship with the consumer price index in the short run. Additionally, in the long-run, digitalization has a significant relationship with all the variables at a 1% level of significance. The positive relation with IIP is attributed to the fact that digitalization brings economic growth as it is nothing but advancement in technology. The negative relationship between CPI and digitalization is attributed to the fact that digitalization brings more transparency and a greater flow of information thus leading to better expectations resulting in lowering the CPI trend. On the other hand, its upward pressure on CPI, in the long run, indicates that with economic growth, the incomes of the people rise to lead to an increased demand and digital transactions in the economy ultimately leading to inflation. Since digitalization has a positive effect on economic growth and a negative effect on inflation, at least in the short term, it helps fulfill the policy framework's dual objectives. Thus we can conclude that digitalization has many consequences for the transmission mechanism of the monetary policy shown by its varying interactions with policy rates and macroeconomic variables both in the short-run and long-run. We also analyzed the Impulse response functions and variance decompositions of variables of our model to identify the response and the explained forecast error variance on shocks to other variables.

Our results have revealed that digitalization has implications for the effectiveness of the monetary policy mechanism. It has affected the environment in which the monetary policy operates. Based on our findings, digitalization and IIP are strongly related to each other. They have a significant and positive relationship between them. Moreover, it has significant interactions with the monetary policy, therefore, the central bank should evaluate all the aspects of digitalization while framing the monetary policy. It is also evident from the results that there’s a negative association between inflation and digitalization in the short run. Though this is an insignificant relationship in the short-run it still implies that even though digitalization increases, there should be no fear of a direct increase in inflation. In this way, digitalization helps in fulfilling the twin objectives of the central bank that is, it promotes economic growth; on the other hand, it also lowers the trend of inflation. However, some studies have shown that digitalization may have upward pressure on inflation in the medium to long term. Our study also found a positive and significant relationship between digitalization and CPI. This makes it important for the central banks to closely monitor the impacts of digitalization on output gap and price dynamics while framing their country's monetary policy,

keeping in view its implications. They should also keep an eye on how digital adoption impacts the incidence of shocks and their transmission mechanism. They should also analyze whether digitalization is a permanent process or will saturate at some point in time. Additionally, the development of digital finance should be integrated with the monetary policy framework to enhance its effectiveness further. In a nutshell, central banks should recalibrate their policy response to the reality of the new era of the digital world.

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