



Promoting Financial Inclusion through Central Bank Digital Currency: An Evaluation of Payment System Viability in India

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Abstract

The Reserve Bank of India (RBI) is considering introducing a Central Bank Digital Currency (CBDC). According to studies, India's financial system plays a significant role in the execution of the CBDC. India is at the forefront of technological advancements in digital payment methods. The central banks that support CBDC's design concept are susceptible to adaptations to the evolution of economic and financial systems. This study will highlight the potential of CBDC to boost financial inclusion. Quantitative regression analysis is being used to quantify the potential drivers of financial sector efficiency and stability to measure the impact of CBDC implementation on financial inclusion. The central bank should build the CBDC utilizing the Structural Vector Auto-Regression model while considering payment system visibility. The proposed study can help to identify the lags in attaining financial inclusion in India and to design CBDC. The proposed study can also establish the policymakers' role in maximizing benefits to the consumers. The study establishes the potential role of RBI in the smooth functionality of implementing CBDC. The study brings out the trend of the payment system in India that opens up the possibility of positive implementation of CBDC and its welfare to percolate among consumers.

JEL Classification: D53, G53, E42

Keywords: Central Bank Digital Currency, Financial Inclusion, Payment System, India

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Introduction

The way the economy functions has transformed along with the evolution of the human race. The medium of exchange, which has evolved from the barter system, which relies heavily on the coincidence of desires, to include precious metals, fiat money, and now digital currencies, is critical for all economic transactions. Currency in digital form has been available for quite some time. Still, one of the most unusual effects of the Great Financial Crisis was the creation of a virtual currency known as Bitcoin that does not depend on financial mediators (Böhme et al., 2015; Nakamoto, 2008). Since Bitcoin's inception, there has been a consensus on whether or not it is a legitimate means of trade. However, the technology underlying it is considered groundbreaking, having applications in many fields, such as the execution of fiscal policies, budget management, public procurement systems, smart contracts, property rights, and so on (Legotin et al., 2018). In India's digital currency revolution, the RBI is designing a national digital currency (CBDC). CBDC design must be in line with the stated objectives of currency and payment system efficiency for monetary policy and financial stability. CBDC would be implemented in three stages: proof of concept, pilots, and eventually, widely. The RBI has researched CBDC's merits and cons. Financial stability, currency efficiency, and monetary policy must be considered when building the CBDC, according to new RBI research. Converting low-value cash transactions to digital, context-based retail payments, alternative authentication for digital payments, and a social media analytic monitoring tool help reduce CBDC implementation difficulties. CBDCs can benefit from these design features. India has never been a cryptocurrency or blockchain pioneer. The government has never demonstrated interest in legislating cryptocurrencies, despite many attempts. India just started taxing cryptocurrency gains at 30%.

The payment system is a crucial component in the endeavor to raise the percentage of people who are financially included in the economy. India's payment sector has made significant progress in the last three decades due to the RBI's systemic initiatives and roadmaps (Mahesh A. and Ganesh Bhat S., 2022). RBI says India's leadership in digital payments since 2017–2018 is behind the digital currency's implementation. Rising smartphone use and internet access in India are fueling the Indian digital payment market. Mobile wallets, prepaid cards, and telco-based payment systems (Airtel Money and Vodafone M-Pesa) have all emerged in recent years. In India, 11 persistent payment banks (Airtel Payment Banks, PayTm, etc.) are used as mobile wallets. The government's 2016 demonetization of the economy, which compelled residents in urban India to use digital payment systems, is another factor in the country's shift towards digital payment. Paytm's user base grew by 35% to 185 million three months after demonetization and reached 280 million by November 2017. (2017) The COVID-19 pandemic outbreak since 2020 has prompted people to use contactless digital payments instead of cash. (Singh,2022).

One definition of financial inclusion describes it as the process of enabling access to relevant financial goods and services for all segments of society, but especially for those with limited resources and income, at a price that is fair and open to the public, via established mainstream institutions that are held to high standards of accountability and transparency (Chakrabarty, 2011). Where financial inclusion is a major issue, transaction accounts are promoted. Throughout recent decades, there has been a shift toward a greater emphasis on having a significantly larger number of active holders of transaction accounts, specifically those associated with public and private commercial banks. In other words, the goal of financial inclusion is to increase the number of people who have accounts that are actively used for transaction purposes (Allen et al., 2016). A number of studies (Donovan, 2012; Lichtfous et al., 2018) propose that digital money may be used

to promote financial inclusion. But in a country like India, where the literacy rate is 74.04% (Literacy Rate of India 2022-List of States & Union Territories by Literacy Rate, n.d.), the hindrance towards the use of digital currency is that consumers really ought to commit passwords like Pin Code or One Time Password (OTP) to memory (Brunnermeier et al., 2019). If not, consumers may need to hire an agent, who may be unavailable or charge a fee. When there's a problem, the customer may have to wait hours to speak to someone. Under certain conditions, consumers may have to contribute to communication, making it expensive for those with financial problems. Cash has various advantages over digital money. Cash doesn't require passwords, it's easy to understand, and it's culturally related to people's lives. The number of persons in the country with a formal account rose from 35% in 2011 to 53% in 2014 to 80% in 2017, according to the World Bank's Findex 2017 Report. This rise occurred in the last five years (Global Finance 2017, 2021). This success is mostly due to PMJDY3, India's primary financial inclusion program. This program and India's financial sector authorities' favorable environment are largely responsible for the increase. Financial literacy will be key to ensuring that people use appropriate formal financial services to ensure their financial well-being and further the benefits of financial inclusion efforts. This is needed to advance the benefits of financial inclusion programs (Reserve Bank of India, Reports, n.d.). The importance of digital currency for the dependents of how financial transactions take place comes from how the benefits can be reaped by non-account holders. The government can keep control of digital money if the Central Bank Currency is implemented, it keeps criminals at bay, and there is a possibility of being anonymous to preserve the privacy of the users. But the idea of perfect anonymity, on the other hand, is implausible. Because of this, digital money should not only secure the privacy of its users, but also be able to help people avoid crimes.

If the Central Bank Digital Currency does not fulfil design requirements for anti-money laundering, countering terrorist funding, and tax avoidance, it will be rejected in general. Bank systems and digital wallets are all part of the project's overall development. Also included are identity identification and large data analysis systems, as well as security chips (Huang et al., 2022). The effectiveness of any payment system is reliant on its acceptance, the infrastructure required to sustain it, and the legislation around it, i.e., if it is cost-effective and craters to mass acceptance. The Indian economy's reliance on digital wallets like UPI may affect financial inclusion. This study explores how RTGS and Retail, prepaid payment instruments, and card payments (including debit and credit card transactions) would interact to determine the currency's overall value in securing financial inclusion. Time series analysis is employed. These measures improve digital transaction efficiency, acceptance, and infrastructure. By minimizing a general Euclidean Distance, linear programming can fit quantile regression models. Quantile regression is an effective research method. Social scientist software can easily fit quantile regression models (Yu, Lu, & Stander, 2003). Structural vector autoregressions (SVARs) are crucial for macroeconomic research (SVARs). Multivariate linear autoregressive equations describe economic dynamics. These correlations can be estimated using a limited set of limitations (so-called shock identification), and the variables can be represented as linear functions of current and previous structural shocks. Imperative response functions illustrate how model variables respond dynamically to system shocks. Short-term, long-term, and sign constraints are some ways to determine structural shocks (Gottschalk, 2001; Pfaff, 2008).

The regulatory framework is also examined in this research. The research has been divided up into six different sections. In addition to the introduction, there is a review of the previous research, a methodology section, an analysis section, a discussion section, and a conclusion section.

Review of Literature

Theoretical Issues

Based on LexisNexis News & Business's coverage of over 660 million news items from 2015–2021, Wang et al. (2022) developed two new indices to measure the uncertainty and interest in Central Bank Digital Currency (CBDC) (CBDCAI). Both indices rose in response to CBDC and digital currency news. MSCI World Banks Index, USEPU, and FTSE All-World Index have a negative relationship with CBDC volatility, while cryptocurrency, foreign exchange, bonds, VIX, and gold have positive relationships. CBDC uncertainty has a higher impact on the financial markets than CBDC attention.

In the paper, Bofinger and Haas (2020) examine central bank digital currencies from a systemic viewpoint (CBDC). An examination of how CBDC plans might fit into the current ecosystem of national, superregional, and worldwide payment systems is necessary from a systemic viewpoint. We use a price-theoretical banking model to examine the effects of CBDCs on private non-banks, allowing them to choose between holding bank deposits and CBDCs. A store-of-value CBDC option is available in addition to CBDC payment items. It's possible that central banks may build a payment system without introducing a new payment object, as is the case with most CBDC ideas.

Piazzesi, M., and Schneider, M. (2020), examine the economic benefits of implementing a digital currency issued by the central bank (CBDC). Because CBDC is a novel product, it might have challenges with both commercial banks in the context of deposits and credit lines used to make payments in the market for liquidity. A central bank offering CBDC but not offering credit lines would conflict with the current payment system's complementary relationship between credit lines and deposits. The introduction of CBDC may actually reduce well-being because it dilutes the benefits of new technology that makes deposits more affordable. Stable coins and other "deposit-only" types of liquidity supply face the same criticism.

In the study by Matsui and Perez, (2021), a number of machine learning methodologies are used to establish how much financial and strategic factors influence the development of Central Bank Digital Currencies (CBDC) in a nation. The CBDC project index (CBDCPI) is used as a measure of this development, as the authors established in this study. Our model's most essential element is a measure of the country's financial progress, followed by a measure of its GDP per capita and a measure of its people's capacity to speak out and hold government officials accountable. According to an earlier qualitative study, nations with a high level of financial development or digital infrastructure have more established CBDC programs. We also get good results when trying to forecast the CBDCPI over time.

Digital payments are now a standard feature of all financial transactions (Gupta, N. K., 2002). In a cashless world, digital money replaces banknotes and coins. ICICI Bank was the first to offer online banking in India, and Digi Bank is leading the way in digitalizing its transactional services.

In the context of a two-tiered monetary system, Niepelt (2020) evaluates the central bank's policy choices for reserves and retail CBDC, which are issued by banks not in direct competition but with one another. Currency costs and liquidity vary. The best policy rules are developed using a business cycle model with "pseudo wedges." Spreads must meet modified Friedman rules for taxing or subsidizing deposits. Our extension of Brunnermeier and Niepelt's (2019) work on

CBDC's macro irrelevance shows that a deposit payment system requires higher taxes. The model predicts that U.S. banks received implicit yearly subsidies of 0.8% of GDP during 1999–2017.

CBDC must have a well-defined niche in the payment environment to be embraced and used efficiently, according to Jiang, J. H. (2020). Consider CBDC as "better cash" that reduces the costs of carrying and storing currency and allows electronic transactions, but retains cash's benefits. Universal accessibility, low transaction costs, great privacy, and robust offline capabilities may be part of a CBDC's design. Due to network effects, CBDC as a P2B payment mechanism will only be embraced if consumers and merchants benefit from the switch. P2P may boost consumer P2B usage.

Digital payments have seized a major slice of the Indian payments pie in recent years, and this trend is projected to continue. The cash-to-paper changeover began. The Reserve Bank of India and its main institutions are working to realize the "Digital India" goal. With roughly a billion cards and more than two billion PPIs, India has one of the world's fastest-growing and largest digital payment infrastructures. E-commerce was driven by the rapid proliferation of internet infrastructure. UPI is a game-changing payment method for retail digital payments. This article focuses on India's digital payment business. According to a new study, the National Payment Corporation of India's (NPCI) 2016 UPI deployment boosted digital payments in India. Government rules, regulator intent, societal behavior, more smartphone use, decreased internet costs, and other factors have all led to the expansion of the digital payment industry by providing consumers and companies with safe, quick, cost-effective, and secure payment choices (Mahesh A. and Ganesh Bhat S., 2022).

The financial industry supports the economy. Through banking sector reforms, the government and central banks aim for economic and price stability. In 2016, the RBI began targeting inflation. The Reserve Bank of India may introduce Central Bank Digital Currency (CBDC) in stages (RBI). This article shows how policy and loan rates affect the RBI's operational objectives, namely monetary reserves (RBI). Using R's decision tree classification modelling and time series regression analysis, we can assess if current banking rates affect money growth and our monetary base projection. Introducing Central Bank Digital Currency into India's new currency would boost the country's economy (Bordo & Levin, 2017).

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Empirical Issues

Financial inclusion and exclusion research lacks consensus on the index or indices that assess financial inclusion and exclusion in different nations (Ozili, 2021). Financial inclusion measurement is crucial for financial planning goals. A thorough measure of financial inclusion and exclusion allows for country and regional comparisons, which are crucial for assessing investments and growth.

Many governments have adopted digital money as a tool to speed the deployment of inclusive financial systems to bridge financial disparities between the wealthy and the disadvantaged, as well as between rural and urban areas, and to handle financial settlement concerns. More than 80% of the countries in the world are looking into CBDCs as a way to use digital money.

Industrialized and rising economies are leading this trend. According to Benni and Clifford-Chance (2021), another concern about digital currency proliferation is COVID-19.

This trend boosts "central banks' digital currencies" (CBDCs). CBDCs are central bank-issued, government-backed cryptocurrencies. CBDCs can transact money. They reduce volatility risk by providing a digital platform for legally controlled financial transactions.

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Methodology

Model

We adopt a model similar to that developed by Demir et al. (2020) and Altunbas and Thornton (2019) to assess the influence of digital payment on financial inclusion in India. The model is defined as :

$$(FINANCIAL\ INCLUSION)_t = \beta_0 + \sum_{p=1}^n \beta_1 (DIGITAL\ PAYMENT)_{k,t} + \beta_2 X_{p,t} + \varepsilon_t \quad (1)$$

The equation refers to FINANCIAL INCLUSION at a time 't' where DIGITAL PAYMENT refers to the diversified practices engaged for financial transactions in India. $X_{p,t}$ are the various control variables that impact the payment system and hence indirectly relate to financial inclusion. ε_t is the disturbance term while β_0 , β_1 and β_2 are the regression coefficients. In India, digital payments are divided into four categories: RTGS, Retail, Card Payment, and Prepaid Payment Instruments. These make up the digital money equation (1). Several pieces of literature highlight population growth, GDP, inflation, and education as control variables (Demir et al., 2020; Shree et al., 2021; Okonkwo and Nwanna, 2021). Our study ignores how economic development affects digital payments. Thus, the model is explicitly arranged as

$$(FINANCIAL\ INCLUSION)_t = \beta_0 + \beta_1 Credit\ Payment - RTGS_t + \beta_2 Credit\ Payment - Retail_t + \beta_3 Card\ Payment + \beta_4 Prepaid\ Payment\ Transactions_t + \varepsilon_t \quad (2)$$

Equation (2) demonstrates the incorporation of digital financial systems in an economy that requires it to act as a composite for attaining inclusion.

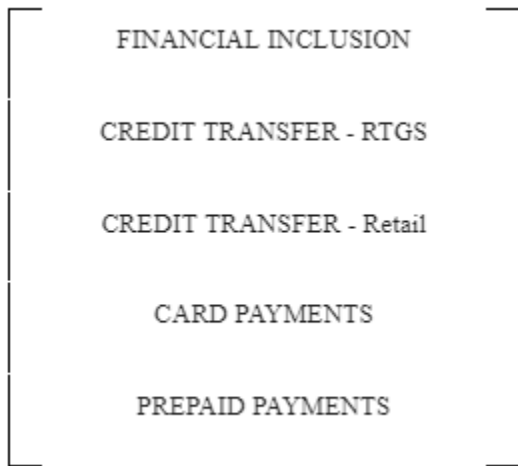
The contribution in the form of VAR in its reduced version does not have a straightforward explanation in economics. To decipher the simultaneous relationship that exists between the variables in the model, SVAR models rely on economic theory to do the basic functions. Shocks to levels in a series have no long-term influence if the data we're studying is level-stationary. We

need at least one variable to be non-stationary in levels for the model to be estimated, but after applying differences, the variables must be in a stationary form.

The challenge in the model is to identify purely exogenous shocks. Suppose we have the following SVAR(1) as

$$AX_t = \beta_0 + \beta_1 X_{t-1} + u_t; \text{ where structural shocks } u \text{ are independent. (3)}$$

X has 5 variables such that $X_t =$



The variance-covariance matrix must be examined in further aspects in order to fully comprehend SVAR models. Endogenous variables' variances and errors' covariances may be found on their diagonal and off-diagonal components. The covariances reveal the instantaneous interactions between the variables. When using normal VAR models, the covariance matrices are symmetric, which means that entries to the right and up the diagonal (the "upper triangular") mirror each other (the "lower triangular"). A correlation between endogenous variables only reveals correlations, not causative links, and this is reflected in this statement.

Impulse response analysis silhouette the dynamic effects of anatomical shocks on the endogenous variables. Shocks have an influence on one system variable at impact t, and then on t+1, and so on. Each response function takes the shock influence into account. All other variables prior to t are maintained constant in this model's Impulse Response function (Yaffee,2008). Grid graphs displaying the individual reactions of each variable to a shock administered over a predetermined time period are the most common means of interpreting impulse responses.

Decomposition of the prediction error variance into the contributions from distinct exogenous shocks is an aspect of structural analysis known as "FEVD" (forecast error variance decomposition). Shocks are essential because they explain a model's fluctuation in the variables, and thus show how important a shock is.

Forecast error variance decompositions are often shown as either a bar graph or an area graph, like impulse response functions. The graph shows the distribution of error variance across shocks to all of the variables at each point in time.

The best linear forecast of y_{t+i} based on information available at time t is

$$y_{t+i|t} = \mu + \Psi_i u_t + \Psi_{i+1} u_{t-1} + \dots \quad (4)$$

and the forecast error is

$$y_{t+i} - y_{t+i|t} = u_{t+i} + \Psi_{i-1} u_{t+i-1} + \dots + \Psi_{i-1} u_{t+1}. \quad (5)$$

Data

Ozil (2021) created a financial inclusion rate (RFI). The research separates the financial inclusion rates in urban and rural areas. The estimations are easily derived from financial data in most emerging nations. In this study, the technique served as the foundation for constructing the financial inclusion index. The size of the financial sector can be estimated using many indices, such as the ratio of financial system deposits to GDP, bank deposits to GDP, and M2 to GDP. We used M2/GDP to measure our banking sector. Because India is a cash-based economy, M2 more properly reflects the size of the financial system than deposits do because most people in the rural sector don't have bank accounts. Four distinct elements affect India's digital payment. Credit Transfer-RTGS includes customer and interbank transactions. Credit Transfer-Retail comprises AeTs, ECS, IMPS, NACH, NEFT, and UPI. Credit and debit cards can be used to buy cards. Debit cards have PoS. Prepaid payment tools include wallets, cards, and PoS-based devices. During data extraction, the volume of transactions is emphasized above their value because it better reflects people's inclination to use digital transfers. We use 2011-2012 (Q1) to 2021-2022 quarterly data (Q4). All data comes from the RBI (RBI). Q.R. and SVAR are used for analysis. Quantile Regression is an extension of Linear Regression utilized when its conditions aren't met. Vector Auto-Regressive (VAR) models multilinear time series. Such models can't express simultaneous variable connections by default. In impulse response analysis, it's important to recognize the simultaneous effects of economic disturbances. Cholesky decomposition errors determine their correlation. Organizing the model's variables is crucial. SVAN provides a more cohesive relationship between simultaneous variables (Pfaf, 2008). R software powers statistical programming (Tibshirani et al, 2013).

Analysis

This section explores the results of the influence that digital payment has had in India in bringing about financial inclusion. The financial inclusion in Figure (1), is witnessed to have increased throughout 2011. However, there is a fall in the growth in the Q3 and Q4 of the financial year 2016-2017 to 0.810 units. But thereafter, there is a steep positive rise, with its boom in the Q4 of the financial year 2019-2020 to 1.64 units.

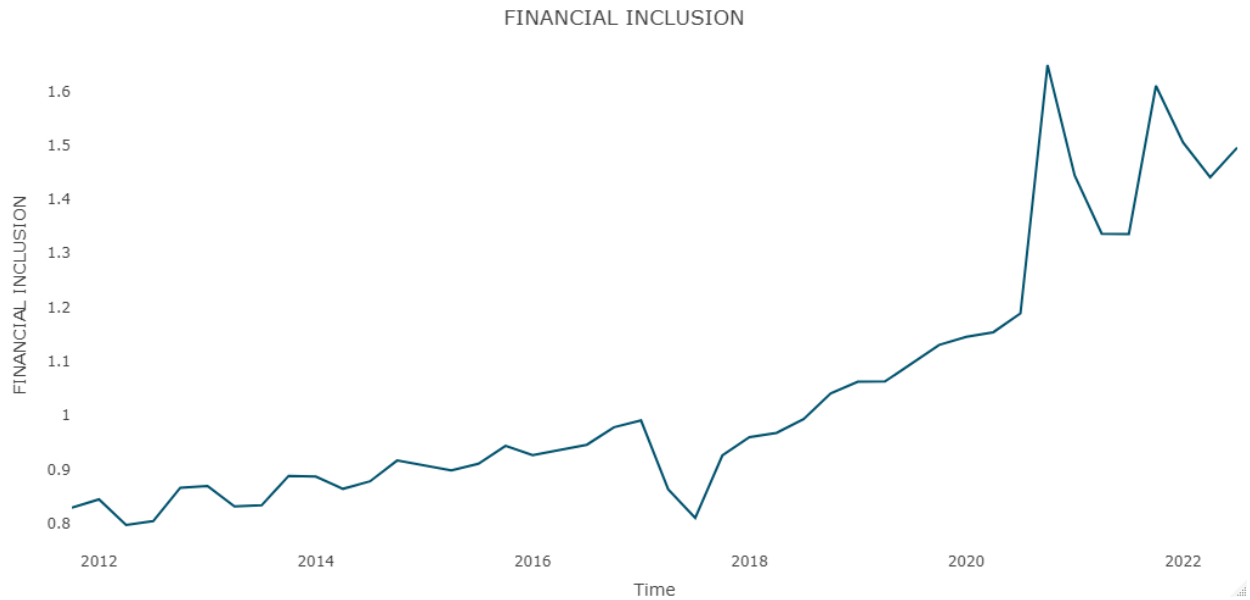


Figure 1: Growth of Financial Inclusion in India 2011: 1 - 2021:4
Source(S): Author's Calculation

Figure 2, Figure 3, and Figure 4 shows the exponential growth in the usage of digital payment throughout the relevant period of study, possibly to credit the development of financial inclusion in India.

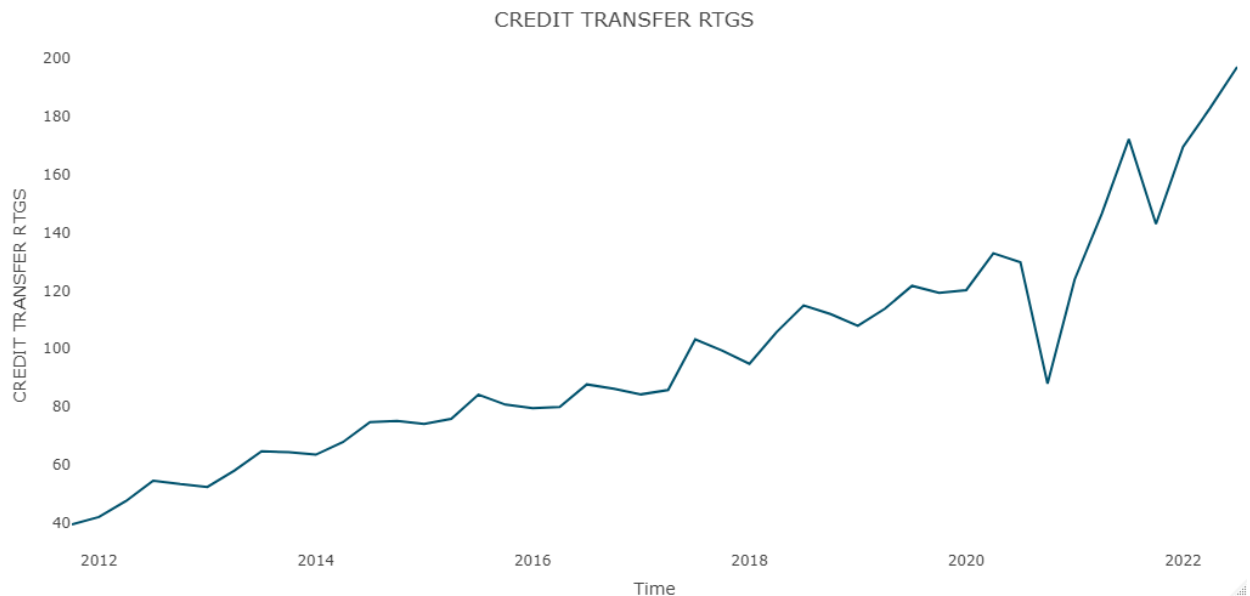


Figure 2: Growth Of Credit Transfers -Rtgs In India 2011: 1 - 2021:4
Source(S): Reserve Bank of India

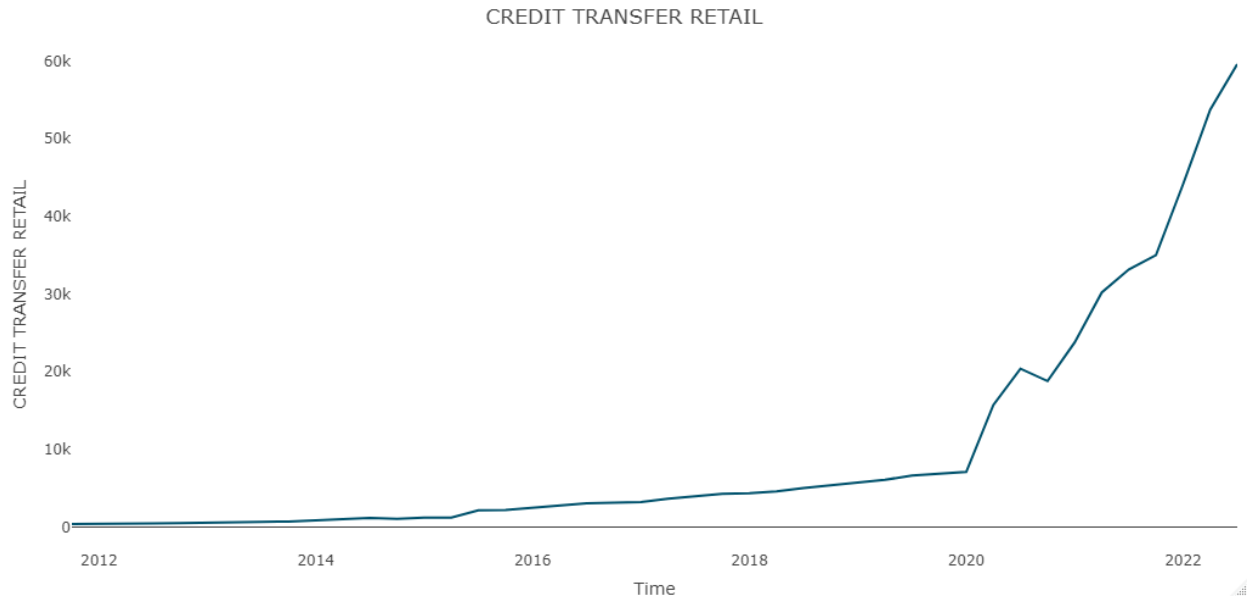


Figure 3: Growth Of Credit Transfers -Retail In India 2011: 1 - 2021:4

Source(S): Reserve Bank of India

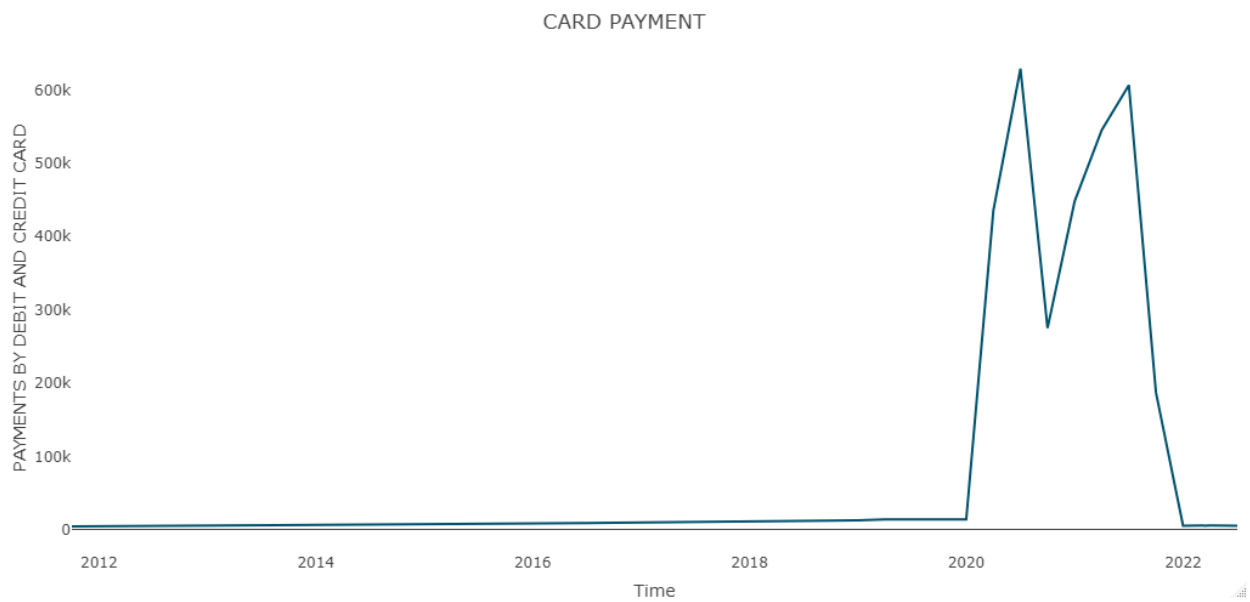


Figure 4: Growth Of Card Payment In India 2011: 1 - 2021:4

Source(S): Reserve Bank of India

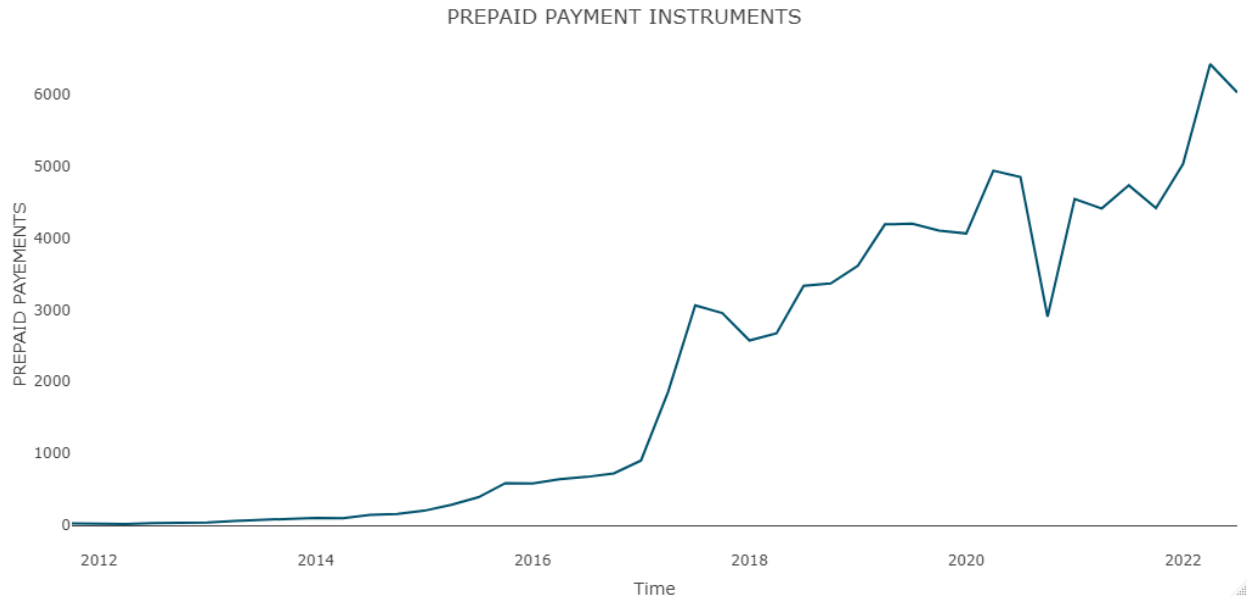


Figure 5: Growth Of Prepaid Payment Instruments In India 2011: 1 - 2021:4
Source(S): Reserve Bank of India

Descriptive Statistics

Table 1 presents the descriptive interpretations of the variables. The presence of outliers is prominent in the data as depicted in Figure 6 hence reducing the possibility of cratering the OLS regression.

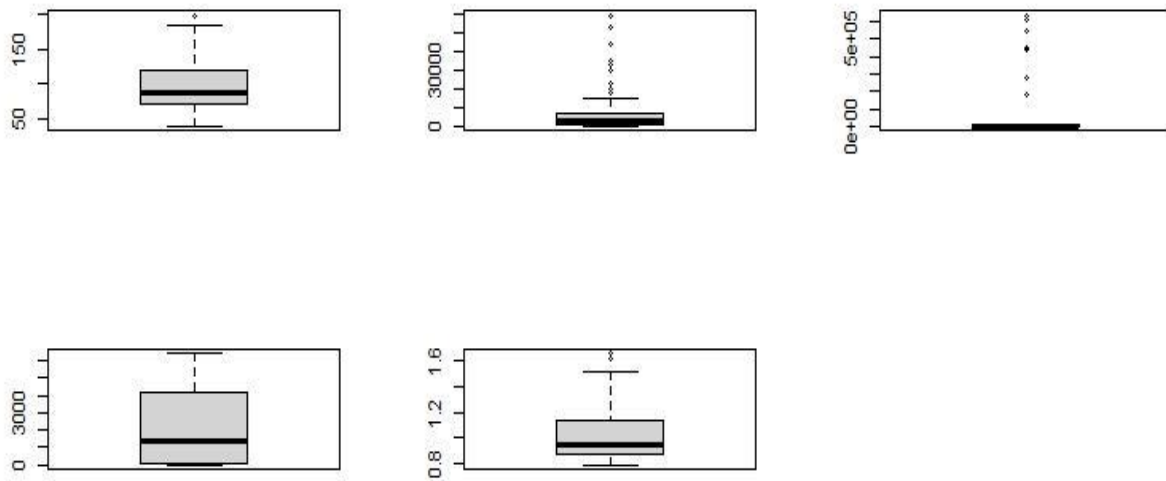


Figure 6: Box Plot representing the presence of the Outliers

The data remains skewed towards the left for all variables. The normality is checked through the Jarque- Bera test (Jarque and Bera; 1987). The null hypothesis states as (Ho:) data is normally distributed. We would reject the null hypothesis for financial inclusion, Credit Transfer -Retail,

and Card Payment. While in the case of Credit Payment - RTGS and Prepaid Payment Instruments fail to reject the null hypothesis.

	Financial Inclusion	Credit Transfer - RTGS	Credit Transfer - Retail	Card Payment	Prepaid Payment Instruments
Mean	1.0403	97.16	9734.7	78075	2139.5
Median	0.9449	86.97	3425.8	8785	1380.9
Maximum	1.6483	197.21	59639.5	629057	6415.5
Minimum	0.7974	39.43	371.8	4462	19.6
Std. Dev.	0.233	38.089	14831.46	173714.2	2056.282
Skewness	1.234	0.771	2.005	2.288	0.391
Kurtosis	3.37	3.098	6.106	6.681	1.665
Jarque- Bera	0.003	0.1116	5.565e ⁻¹¹	1.843e ⁻¹⁴	0.1115
Observations	44	44	44	44	44

Table 1: Descriptive Statistics

Source(s): Authors' extraction from the empirical data

Autocorrelation mapping and Unit Root Test

While analyzing time series, one may use the autocorrelation function (ACF) to find correlations between consecutive data. ACF is the average variance of each succeeding observation. As a result, the degree to which scores at one point in time are predictive of scores at a subsequent point in time is known as the "autocorrelation" of scores. The autocorrelation function uses "lags," which are often regarded as measurement intervals interpreted as time, to evaluate the correlation between data. Each correlation is a function of the shared variance between the variable's value at a certain moment in time and the value of the delayed variable (Taylor, 1990).

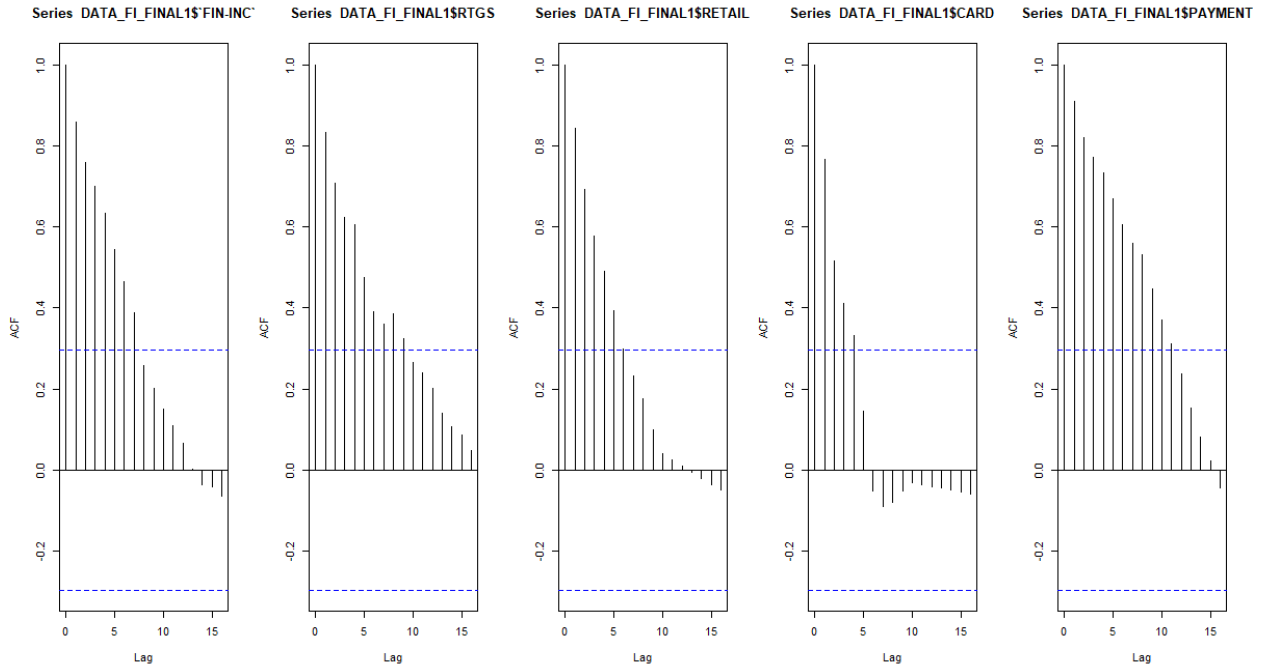


Figure 7: Autocorrelation Mapping
Source(s): Authors' extraction from the empirical data

From 2011 to 2021, we ran a unit root test on our quarterly data. The results are shown in Table 2. Augmented Dickey-Fuller (ADF) was utilized to answer empirical questions regarding spurious stationarity caused by weak and power size failures. Findings demonstrate variables are non-stationary at levels. Any policy or suggestion based on estimates of these variables will be prejudiced.

As outlined in theory, the autoregressive distributed lag technique in estimation can only be used if there are no stationary variables in a model that is greater than order 1 (Ekong and Mboho, 2021). Nonetheless, our primary goal is to examine the role of digital banking in India's financial inclusion, utilizing quantile regression in a stepwise forward approach developed in this experiment. Using this method, the study examines how each additional variable affects financial inclusion.

Variables	ADF (p-value)	Lag Order
Financial Inclusion	0.9775	3
Credit Transfer -RTGS	0.99	3
Credit Transfer -Retail	0.99	3
Card Payment	0.5033	3
Retail Payment Instruments	0.5664	3

Table 2: Unit Root Results
Source(s): Authors extraction from the empirical data

Quantile Regression Model

The Quantile Regression (Q.R.) approach is devised to examine the effect of digital payment on financial inclusion such that it can be a base for the implementation of CBDC. For the purpose of analyzing the simultaneous repercussions of the study, Q.R. is followed by the Structural Vector Auto-Regressive (SVAR) model.

The model is defined as

$$Q_{\tau}(Y_i) = \beta_0(\tau) + \beta_1(\tau)x_{i1} + \dots + \beta_p(\tau)x_{ip} ; \forall i = 1,2\dots n \text{ and } p = 1,2,\dots n$$

Here τ represents quantile. For our study, we consider the 1st and 3rd quantiles.

hence our equation becomes

$$\begin{aligned} (\text{Fin_Inc})_t(\text{Digital Payments})_t &= 7.471079e-01 (0.25) + 1.616902e-03 (0.25)RTGS_{i1} \\ &+ 6.365474e-06 (0.25)Retail_{i1} + 9.907315e-08 (0.25)CardPayments_{i1} \\ &+ 8.213177e-06 (0.25)Prepaid Payment Instruments_{i1} \end{aligned}$$

In this case, we can conclude that for an increase of every unit of RTGS, Retail, Card Payment and Prepaid payment Instruments, financial inclusion increased by 0.00162, 0.00001, 0.00000 and 0.00001, respectively Table 2. However, the question arises whether these variables are contributing significantly or not to express the financial inclusion depends on the p-value. In the specific study, no variables respond significantly to express financial inclusion. Thereupon, we perform our test for $\tau = 0.75$

$$\begin{aligned} (\text{Fin_Inc})_t(\text{Digital Payments})_t &= 7.926446e-01 (0.75) + 1.322526e-03 (0.75)RTGS_{i1} \\ &+ 8.732443e-06 (0.75)Retail_{i1} + 4.225839e-07 (0.75)CardPayments_{i1} \\ &+ 1.997543e-05 (0.75)Prepaid Payment Instruments_{i1} \end{aligned}$$

As can be seen in Table 3, there is an increase in the rate of financial inclusion of 0.00132, 0.00001, 0.00000, and 0.00002 per unit of RTGS, Retail, Card Payment, and Prepaid payment instruments, correspondingly. As for whether factors are significant, the p-value determines whether or not they contribute to financial inclusion, where no factors responded substantially. The quantile regression does not respond positively to finding the significant effect of financial inclusion. As a result, the study continues with more statistical research.

In Figure 7, the coefficients of the variables are shown by a black dotted line, while the shaded region indicates the lower and higher confidence intervals of the quantile regression results. The solid red line depicts the OLS estimator, while the dotted red line represents the estimations' 95% confidence interval.

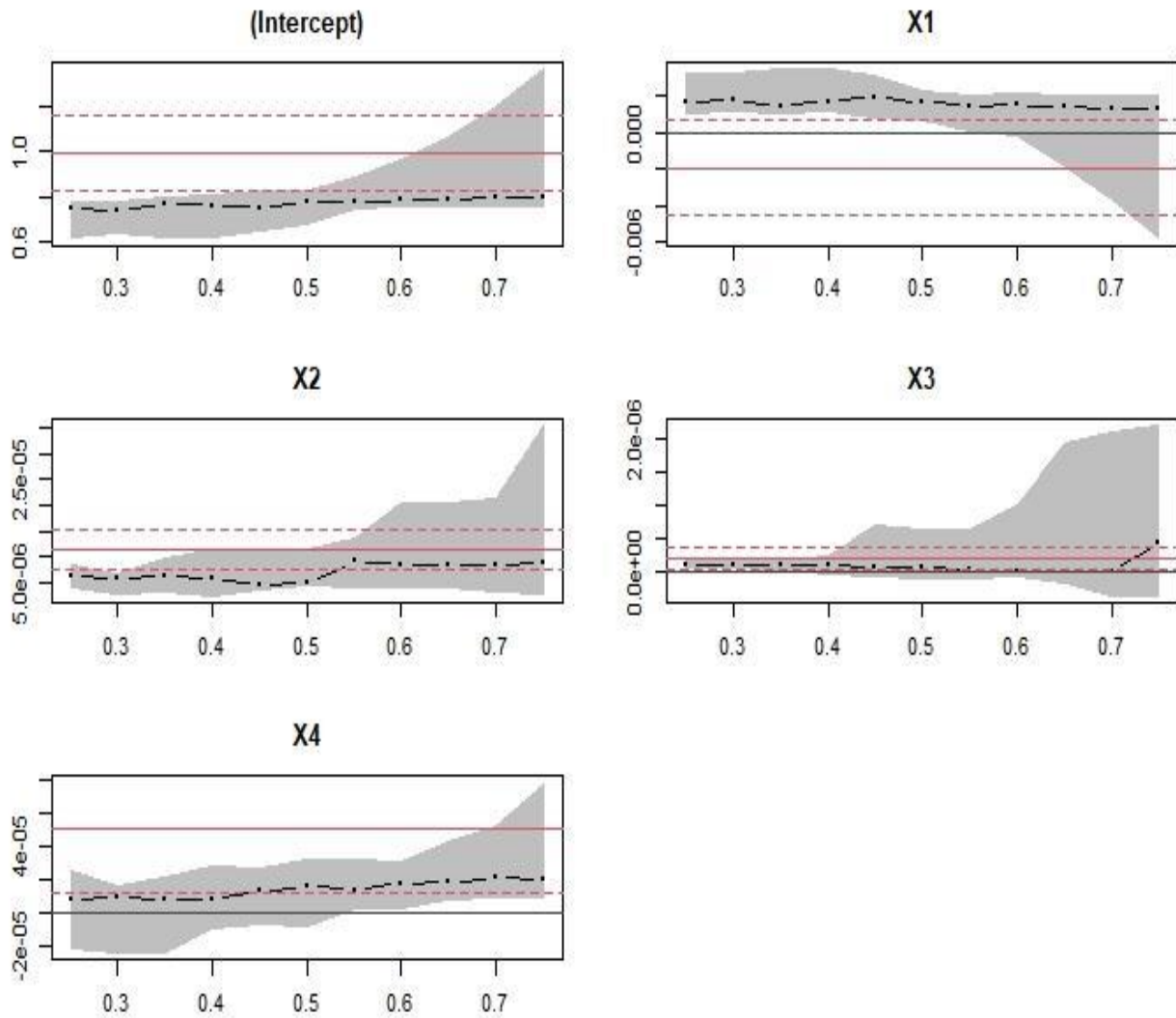


Figure 8: Graphical Representation of the Quantile Regression
 Source: Authors' extraction from the empirical data

Structural Vector Autoregression (SVAR) Model

We build up a model constraint in the form of a matrix that depicts the simultaneous correlations that affect the variables. We assume simultaneous effects in the VAR and identify the SVAR using matrix limitations. The 5×5 identity matrix has diagonal components representing parameter variance and off-diagonal elements representing variable covariance. The study's matrix is based on economic intuitions that the behavior of digital payment systems is linked to financial inclusion shocks and can be used to implement CBDC. The elements in the lower triangle of the matrix are now an ace in that they can be unconstrained regardless of the system's coefficients. The higher triangular zeros prevent the dependent variable from being impacted by the independent variables in the same period.

	[,1]	[,2]	[,3]	[,4]	[,5]
[,1]	1	0	0	0	0
[,2]	NA	1	0	0	0
[,3]	NA	NA	1	0	0
[,4]	NA	NA	NA	1	0
[,5]	NA	NA	NA	NA	1

Table 3: The Variance Covariance Matrix
 Source: Authors extraction from the empirical data from R software

The lag selection criteria are an important feature while deciding the model of SVAR. For the particular data, the lag is 7.

AIC(n)	HQ(n)	SC(n)
7	7	7

Table 4: The Lag Selection
 Source: Authors extraction from the empirical data from R software

	FIN_INC	Credit Transfer RTGS	Credit Transfer Retail	Card Payment	Prepaid Payment Instruments
FIN_INC	1.0000	0	0	0	0
Credit Transfer RTGS	0.10000	1.0000	0	0	0
Credit Transfer Retail	0.09996	0.09964	1.0000	0	0
Card Payment	-0.80789	-0.82343	-8.9622	1.0000	0
Prepaid Payment Instruments	0.14898	0.15008	0.7485	-8.9622	1.0000

Table 5 : SVAR Estimation Results:
 Source : Authors extraction from the empirical data from R software

FIN_INC	FIN_INC	Lower Band, CI= 0.95	Upper Band, CI= 0.95
[1,]	1	1	1
[2,]	-3.687055	-3.879782	-3.286692
[3,]	2.408254	1.065737	2.932908
[4,]	14.769527	12.772582	17.118067
[5,]	8.000838	6.397015	10.05254
[6,]	-2.059308	-3.937012	0.736139
[7,]	4.323681	2.540064	7.621122
[8,]	17.859756	12.785003	21.079224
[9,]	4.975305	2.722382	9.034246
[10,]	24.981088	18.165491	28.762238
[11,]	5.196459	1.710408	12.994393

Table 6: Impulse response coefficients of Financial Inclusion on Financial Inclusion
 Source: Authors extraction from the empirical data from R software

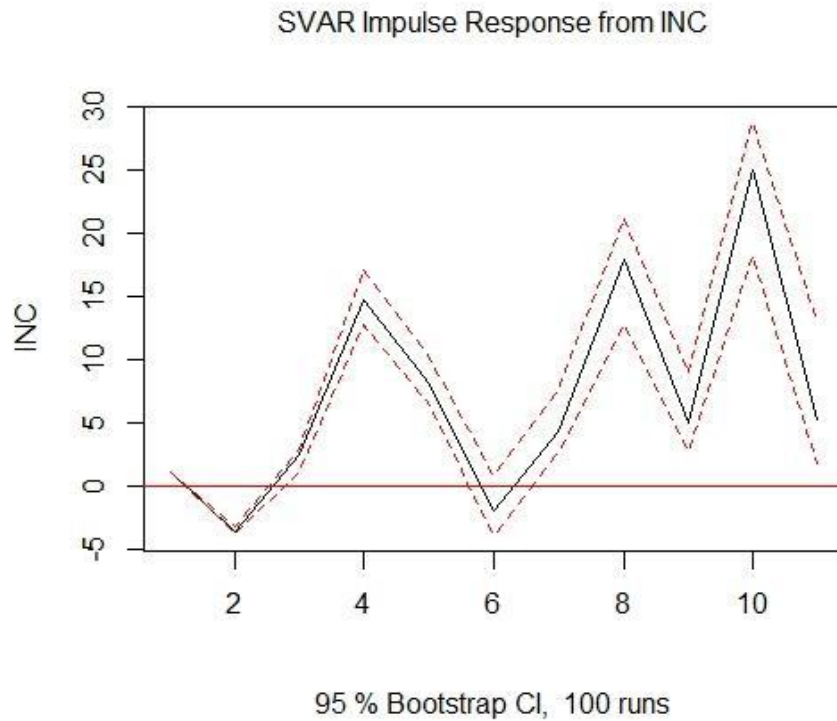


Figure 9: Graphical Representation of the Impulse Response of Financial Inclusion on Financial Inclusion
 Source: Authors' extraction from the empirical data

There are short downward oscillations in the trend, but overall, the long-term research shows an increasing trend, confirming that financial inclusion will rise. This is a favorable response to India's financial inclusion.

FIN_INC	Credit Transfer - RTGS	Lower Band, CI= 0.95	Upper Band, CI= 0.95
[1,]	0.000000000	0.000000000	0.000000000
[2,]	-0.010447591	-0.011164710	-0.007372756
[3,]	0.009401135	0.000050720	0.011596578
[4,]	0.067539330	0.048344430	0.073213360
[5,]	0.028841628	0.018572980	0.036855186
[6,]	-0.024586629	-0.036767740	-0.017553655
[7,]	0.003708424	-0.005808518	0.022851536
[8,]	0.054588328	0.023469880	0.065908127
[9,]	0.007542700	-0.006993262	0.040701757
[10,]	0.075540039	0.017677420	0.090542414
[11,]	-0.020962584	-0.042523660	0.051324723

Table 7: Impulse response coefficients of Credit Transfer - RTGS on Financial Inclusion
 Source: Authors extraction from the empirical data from R software

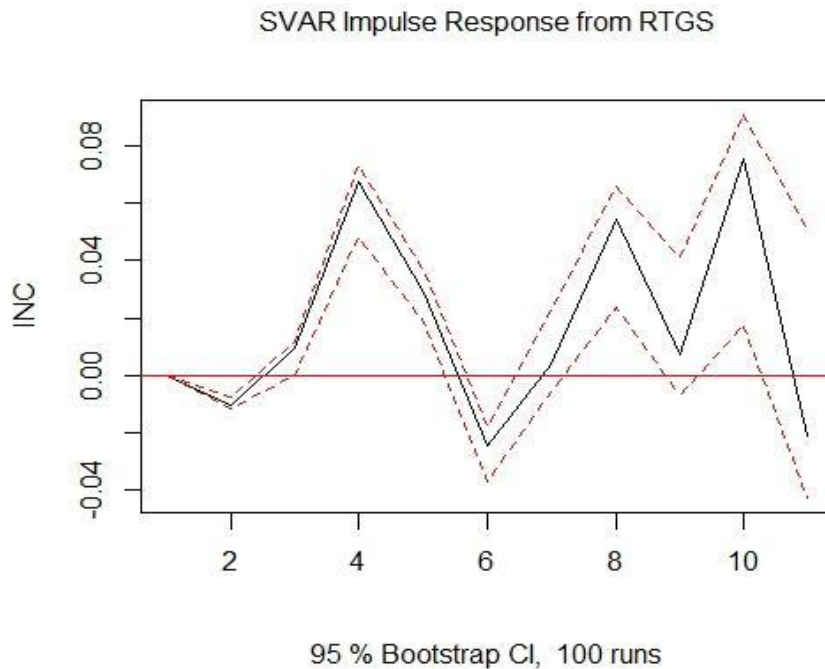


Figure 10: Graphical Representation of the Impulse Response of Credit Transfer - RTGS on Financial Inclusion
 Source: Authors' extraction from the empirical data

To find the effect of the impulse of Credit Transfer from RTGS, in response to attain financial inclusion, cyclically varies in trend, implying that over time the dependence on RTGS becomes difficult for achieving financial inclusion.

FIN_INC	Credit Transfer - Retail	Lower Band, CI= 0.95	Upper Band, CI= 0.95
[1,]	0.000000000	0.000000000	0.000000000
[2,]	0.000000000	0.000000000	0.000000000
[3,]	-0.000033682	-0.000038829	-0.000028519
[4,]	0.000096306	0.000082070	0.000112726
[5,]	0.000494645	0.000458216	0.000528947
[6,]	-0.000040211	-0.000074411	-0.000001024
[7,]	-0.000091798	-0.000137335	-0.000053457
[8,]	0.000033124	-0.000010925	0.000093865
[9,]	0.000190214	0.000135038	0.000263301
[10,]	0.000128331	0.000046245	0.000175066
[11,]	0.000051483	-0.000086561	0.000122190

Table 8: Impulse response coefficients of Credit Transfer - Retail on Financial Inclusion
 Source: Authors extraction from the empirical data from R software

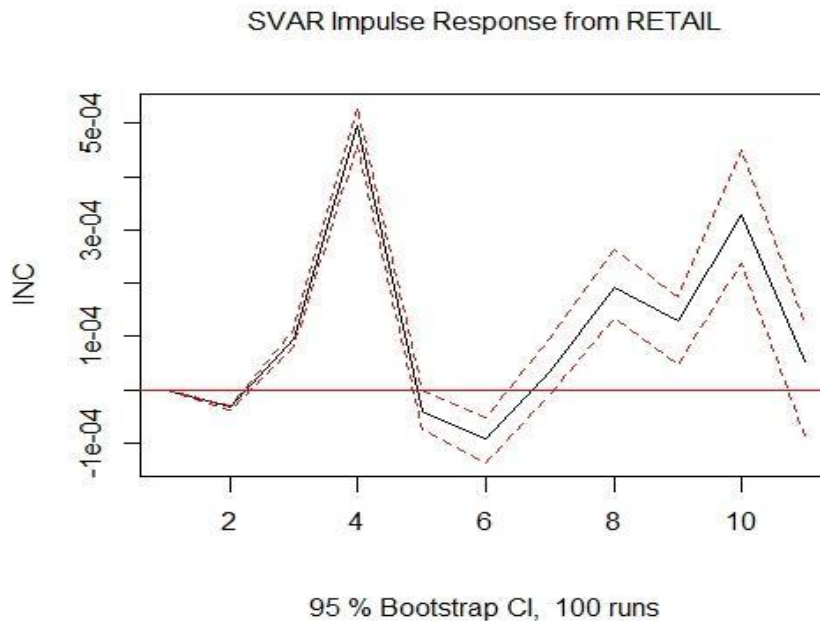


Figure 11: Graphical Representation of the Impulse Response of Credit Transfer - Retail on Financial Inclusion
 Source(s): Authors' extraction from the empirical data

Again, effective attention for drawing the conclusion of the impulse of Credit Transfer - Retail in attaining

Impulse response coefficients increase over time, but there is a downtrend in the foreseeable future.

FIN_INC	Card Payment	Lower Band, CI= 0.95	Upper Band, CI= 0.95
[1,]	0.000000000	0.000000000	0.000000000
[2,]	-0.000038514	-0.000040453	-0.000036298
[3,]	0.000023711	0.000017341	0.000029639
[4,]	0.000129877	0.000112113	0.000146533
[5,]	0.000080043	0.000064171	0.000094825
[6,]	0.000001312	-0.000017449	0.000021485
[7,]	0.000051958	0.000035196	0.000084246
[8,]	0.000185362	0.000156388	0.000211972
[9,]	0.000089874	0.000070545	0.000122132
[10,]	0.000262538	0.000223276	0.000295759
[11,]	0.000096646	0.000062104	0.000152833

Table 9: Impulse response coefficients of Card Payment on Financial Inclusion
 Source: Authors extraction from the empirical data from R software

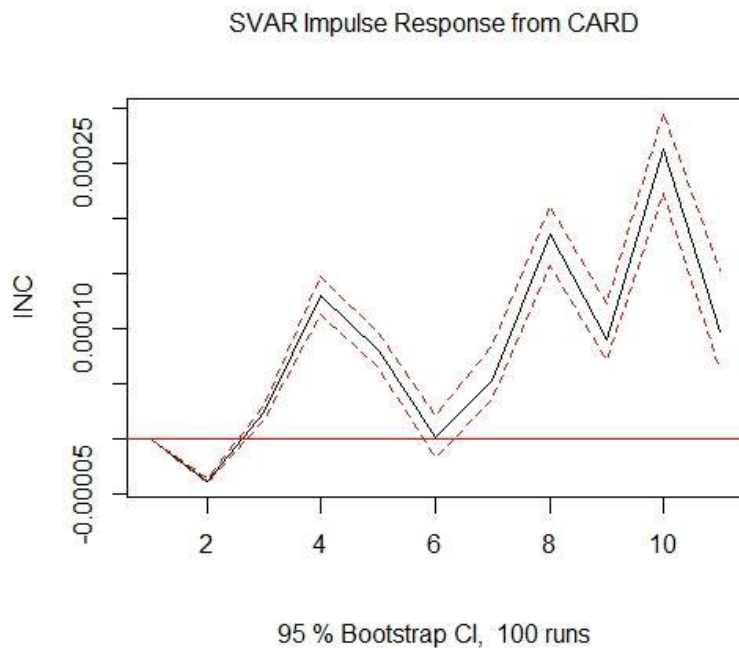


Figure 12: Graphical Representation of the Impulse Response of Card Payment on Financial Inclusion
 Source: Authors' extraction from the empirical data

To discuss the progress of card payment in accomplishing the financial inclusion target, card payment plays a crucial role with a generic upended movement establishing the dependency of the economy on both credit and debit cards.

FIN_INC	Prepaid Transfers	Payment	Lower Band, CI= 0.95	Upper Band, CI= 0.95
[1,]	0.000000000	0.000000000	0.000000000	0.000000000
[2,]	-0.000520760	-0.000540512	-0.000482052	-0.000482052
[3,]	0.000325350	0.000213098	0.000373433	0.000373433
[4,]	0.001855769	0.001586007	0.002041074	0.002041074
[5,]	0.001045298	0.000826071	0.001233377	0.001233377
[6,]	-0.000014172	-0.000302842	0.000149218	0.000149218
[7,]	0.000675947	0.000411133	0.001023420	0.001023420
[8,]	0.002492629	0.002084248	0.002751784	0.002751784
[9,]	0.001205232	0.000940876	0.001582261	0.001582261
[10,]	0.003553617	0.002954211	0.003913244	0.003913244
[11,]	0.001197750	0.000746046	0.001650759	0.001650759

Table 10: Impulse response coefficients of Prepaid Payment Instruments on Financial Inclusion
 Source: Authors extraction from the empirical data from R software

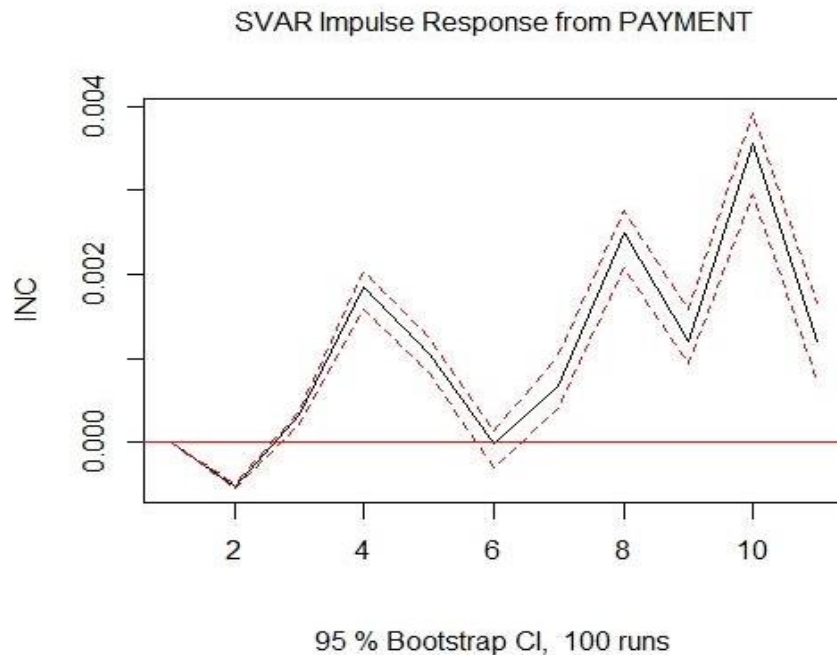


Figure 13: Graphical Representation of the Impulse Response of Prepaid Payment Instruments on Financial Inclusion
 Source: Authors extraction from the empirical data

Finally, the most crucial variables which directly link to the implementation of CBDC gradually move upwards in the forthcoming periods by attaining financial inclusion.

We plot the Forecast Error Variance Decompositions that determine the amount of the variability in the errors in predicting y_1 and y_2 at time $t + i$ based on the knowledge available at time t that is attributable to the variation in the structural shocks 1 and 2 between times t and $t + i$.

Discussion

Card and Prepaid Payments have positive effects. If the country maintains its present level of digital currency use until 2025, it may be able to deploy CBDC. The study is like the takeout and development needed to make digital money more stable to permit growth (Ekong & Ekong, 2022). With the payment system taking a jump, digital currency growth demands a dedicated effort to digitally smooth out finances to support sustainable growth. According to Ayuso and Conesa (2020), increasing monetary policy (M.P.) efficacy is not a major motivation for CBDCs, and the impact on M.P. transmission will depend greatly on CBDC design. Repercussions include bank reserve management and disintermediation. Physical cash and CBDC will likely coexist in the near future, regardless of design. Researchers advocate for efforts to avoid financial cybercrime, fix systemic network faults, and build pro-poor digital banking products (Wang et al., 2022). Substituting cash for CBDC offers up future study possibilities (Bofinger & Haas, 2020). Our study shows that digital currency outlets are extremely valuable for financial inclusion in India and other developing countries. All of these channels are related to India's payment system and have the potential to create the CBDC. It is critical to discuss the numerous analytic frameworks of central bank digital currency monetary policy paths developed by economists who have studied CBDC issuances, designs, and applications of unexplored areas in incorporating banking literacy rates and involving the non-account holder segment (Bhowmik, 2022).

As consumers grow more aware of digital money, consumer alignment shifts the percentage of digital financial solutions on the market. Increasing the quantity of digital currency-using goods in the financial system would promote financial inclusion. In this situation, the CBN's support of retail options for e-currency growth should be praised. This will make it easier for consumers to construct electronic wallets, easing digital transactions throughout the country.

The research findings included an in-sample projection of India's financial inclusion in the future. Users can quickly see uncertainty based on sequential distribution simulations or pre-calculated quartiles of distributions. Fanplot's straightforward design allows this. Net elicited features interactive chart visualizations. The R demo with the package forecast (RStudio and Inc., 2014; Guy, 2015) shows an increase in RTGS, Card Payments, and Prepaid Payment Transactions.

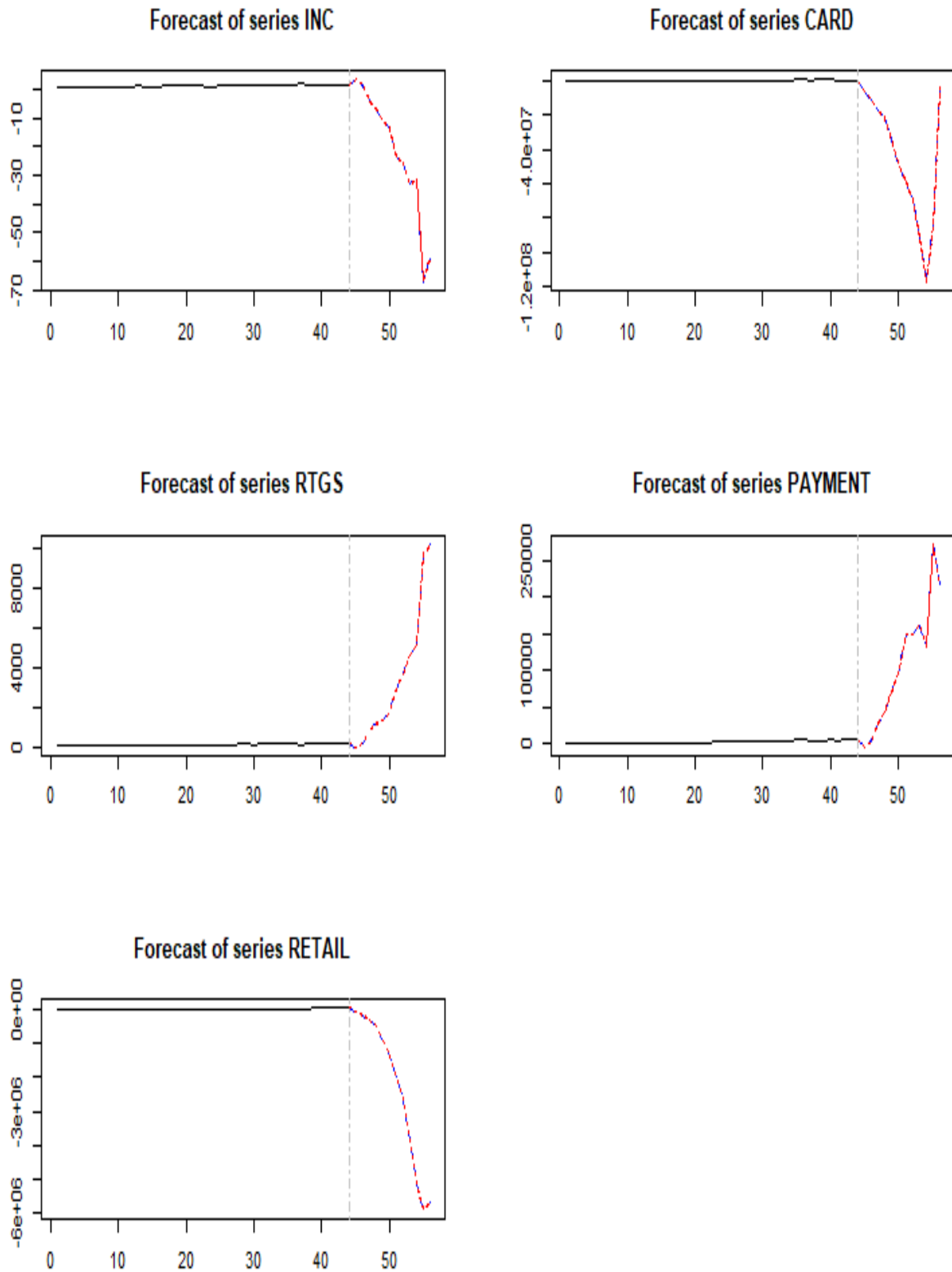


Figure 14: Forecast Analysis of the Payment System until 2025
 Source(s): Authors' extraction from the empirical data

Previous CBDC projects and pertinent research would also be considered. Two important design alternatives are:

(1) Whether the CBDC should be wholesale or retail, and (2) Whether an account-based or token-based CBDC is compatible with data usage and availability. It's important to visualize wholesale (including the central bank and external parties) and retail user cases (involving third parties and end users). This method needs to identify allowed third parties, which transactions will be recorded at the central bank, and who will handle user onboarding. Because direct model consumers have a direct claim on the central bank, no third-party CBDC distributors are needed (Usher et al., 2021).

Conclusion

This research evaluates the influence of digital currencies on India's financial inclusion between 2011 and 2020. Digital money, or digital finance, is gaining popularity in the fight for global financial inclusion. Emerging economies like India must capitalise on this trend. The CBDCs' monetary system's function, economic success, and social acceptance are all debatable. If CBDC indices are associated with higher stock market volatility, and worse financial statement performances in policy-sensitive industries like energy, technology, and real estate, it opens up new study areas. It would be interesting to investigate if CBDC indices and monetary policy are linked using the VAR, DCC-GARCH, or VAR spillover connection model. CBDC indicators can be made more predictive. Building infrastructures to support CBDC growth, issuing and controlling the CBDC market, and guaranteeing compliance with and overseeing financial institutions all need more research. Individual users are another study option. CBDCs offer benefits and drawbacks to a country's consumers. Can CBDC's research generate results if other digital payment mechanisms have a larger market share? Regression quantifies a dependent variable and its associated variables. Standard regression has been a popular statistical method for decades. Quantile regression is a common approach to analysis in labour economics and macroeconomics. Buchinsky (1995; Demir et al. Value at risk (VAR) refers to the daily risk assessment that banks are required by law to produce. VAR models are the most popular way to measure market risk in finance (Lauridsen,2000). SVAR models analyse structural correlations between variables, such as simultaneous correlation or instrumental variable models, by constraining the covariance matrix and adding additional coefficient matrices as needed. This strategy heavily relies on researcher preconceptions. Even when supported by legitimate economic theory, many researchers find this too subjective. They may be useful, so investigate further (Wang et al., 2022). The research uses digital finance channels for developing nations like India that are largely recognised in development literature and demonstrates that digital finance's influence on financial inclusion in India is positive overall. To attain the necessary results, policy for development must include the arrest and prevention of financial cybercrime, the correction of systemic network failures, and the creation of more digitally friendly financial goods that appeal to the pro-poor group in terms of financial inclusion

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