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Mobile Banking Transactions in India: The Role of Income and Interest Rate

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Abstract

Purpose: To examine how income and interest rate affect mobile banking transactions in India's financial system during the digital era from January 2016 to December 2022. ***Design/Methodology/Approach*:** The authors first test the stationarity of variables using ADF and PP tests, followed by a residual-based Granger and Johansen cointegration tests. The dynamic ordinary least squares (DOLS) method is used to estimate the long-run coefficients whereas the short-run coefficients are examined through the ECM. Additionally, FMOLS, CCR, IRF and diagnostic tests are applied to ensure the robustness of the results. ***Findings*:** The stationarity tests indicate that all selected variables are integrated at their first differences. Furthermore, the Engle-Granger and Johansen cointegration tests confirm a long-term relationship. The DOLS results show that income (Y) and short-term interest rate (SR) significantly influence money demand through mobile banking in the long run. In the short run, the coefficients of income and interest rate are not statistically significant; however, the negative and significant error correction term (ECT) indicates adjustment toward long-run equilibrium. Additionally, the FMOLS, CCR, and IRF models support the robustness of the long-run results, and diagnostic tests confirm the accuracy of the findings. ***Originality/value*:** This study makes a unique contribution by examining the effects of income and interest rate on mobile banking in the digital era, as the dependent variable instead of the traditional measure of money demand—an area with minimal empirical research. It provides a deeper perspective on how these factors shape mobile banking transactions in an evolving financial sector. By bridging traditional economic theory with modern financial practices, this study enhances our understanding of liquidity preference in the digital age and demonstrates the ongoing relevance of Keynesian concepts in today's digital finance environment.

Keywords: Digital Finance; Mobile Banking; India's Financial Sector.

1. INTRODUCTION

The concept of money has undergone significant changes in recent decades, driven by rapid technological advancements and the increasing role of digital financial systems (Jaiswal & Singh, 2023; Shaikh *et al*., 2023). Traditional forms of money, such as physical coins and banknotes, have been supplemented by digital currencies, electronic payment platforms, and financial technologies. These developments have reshaped how we use money in daily transactions and understand its broader economic functions, challenging long-standing theories about monetary systems and their impact on key financial variables, particularly interest rate.

In economic theory, money has historically been understood through two main perspectives: the classical and the Keynesian views. The classical theory of money emphasizes its role as a neutral medium of exchange and store of value, with interest rates being determined by the interaction of savings and investment. In this framework, changes in the money supply only affect price levels (Niehans, 1987). On the other hand, the Keynesian theory introduces a more dynamic role for money, mainly through its liquidity preference approach, which emphasizes the role of money in determining interest rates.

However, the emergence of digital currencies, such as cryptocurrencies, central bank digital currencies (CBDCs), fintech platforms, and cashless payment systems, is disrupting traditional monetary theories (Nawaz *et al*., 2024). The modern concept of money has expanded beyond traditional ideas, incorporating decentralized digital currencies that are independent of physical cash (Kim & Park, 2023). Historically, money was defined by its core functions: a medium of exchange, a unit of account, a store of value, and a standard of deferred payment (Brunnermeier *et al*., 2019). Physical money, such as coins and banknotes, was the dominant instrument for facilitating economic transactions. In this conventional framework, money was tangible, controlled by central banks, and closely tied to the country's monetary system. However, Modern money advances have expanded its scope far beyond these traditional definitions. Digital currencies, electronic payment platforms, cryptocurrencies, and CBDCs have redefined how money is used and what constitutes money itself. These developments challenge the established roles of money in several important ways: As a medium of exchange, digital currencies and electronic payment systems have introduced faster, more efficient methods for conducting transactions.

However, with the advent of cryptocurrencies and decentralized finance (DeFi), the ability of central banks to control the money supply and influence interest rates is being fundamentally challenged. Cryptocurrencies, for example, operate independently of central bank policies, offering individuals an alternative store of value and medium of exchange not directly tied to interest-bearing financial products. This undermines Keynes's speculative motive for holding money, as people can now invest in digital assets outside the traditional interest rate framework.

Moreover, the demand for fiat money may decline in a world where people can hold and transact with digital currencies without relying on traditional banking systems. This could weaken central banks' ability to manage economic cycles through interest rate adjustments, as the effectiveness of liquidity management diminishes in a decentralized financial system.

The expansion of electronic payment systems and fintech platforms has also altered how people hold and use money, further complicating monetary policy transmission. Traditionally, money was mainly held physically or in bank deposits and central banks could influence liquidity through traditional banking mechanisms. Today, however, individuals can store and transfer wealth through digital wallets, mobile payment platforms, and fintech systems, which may not be tied to traditional banks or interest-bearing accounts.

This diversification of money holdings dilutes the ability of central banks to influence speculative behaviour, as individuals now have multiple alternatives to bank accounts and interest-based savings. As a result, the connection between liquidity preference and interest rates needs to be more apparent. For instance, individuals can easily switch between fiat currency and digital assets through fintech platforms, making it harder for central banks to manage liquidity and stabilize interest rates in response to changing economic conditions.

2. LITERATURE REVIEW

The rise of digital financial transactions has become a significant topic of discussion in academic and policy circles. A key focus in the literature is how decentralization, security, and technological advancements shape modern financial system. Blockchain's decentralized structure improves operational efficiency and holds the potential to reshape industries far beyond finance, offering applications in areas such as supply chain management, healthcare, and public administration (Zhang & Huang, 2022). Further, Sharma (2022) used a SWOT analysis to explore India's growing interest in cryptocurrency. The study highlighted the country's increasing attraction to digital assets and warns of risks, such as regulatory uncertainty and market instability. Moreover, widespread use of digital currency could help modernize the economy (Lal, 2022). On the other hand, Priyadarshini & Kar (2021) examined the role Central Bank Digital Currencies (CBDCs) and highlighted about national control over currency and the technology required for implementation. Bhowmik (2022) added to the discussion by arguing that CBDCs could reduce the reliance on physical cash, improving transaction efficiency and helping the government better oversee financial operations. In contrast, Shah (2018) stressed the need for a robust public awareness campaign, warning that a lack of understanding about digital currencies could harm public trust and slow adoption. Treleaven *et al*., (2017) examined blockchain's role in finance, showing its potential to enhance transparency, security, and trust while preventing fraud and increasing accountability. Additionally, Scott *et al*., (2017) found that digital finance can improve long-term profitability for smaller financial institutions by incorporating digital tools into their operations. Manyika *et al*., (2016) demonstrated that digital financial inclusion expands access to financial services and supports national economic growth by increasing tax revenue through reduced reliance on cash. Gomber *et al*., (2018) argued that digital finance increases economic participation and boosts GDP by integrating advanced technologies into financial system. On the other hand Berentsen (1998) and Muli (2019) pointed out that digital finance could significantly affect money demand and supply, potentially weakening traditional monetary policies. Moreover, Bordo & Levin (2017) suggested that digital currencies could enhance monetary policy by giving central banks more control over financial transactions, enabling more precise and effective economic interventions.

Existing literature on digital finance extensively explores technological advancements, regulatory challenges, and the impact of digital payments on money supply. However, it largely overlooks the influence of income and interest rate on money demand (mobile banking) in the digital era. This gap emphasize the need to examine how income and interest rate affect money demand through digital payment channels in India, particularly mobile banking.

3. DATA AND METHODOLOGY

This study explores India's transition from a traditional to a digital financial system between January 2016 and December 2022**,** focusing on how income and interest rate impact money demand through digital payments, especially mobile banking. The present study tries to analysis the influence of income and interest rate on Mobile banking (MB) serves as a proxy for money demand and assessing whether these theoretical relationships persist in a digital context. Moreover, information on the selected variables includes income, represented by Gross National Product (GNP) due to its broad capture of economic activity (Starleaf & Reimer, 1967), and sourced from the Macro trends database. Whereas, the short-term interest rate, represented by the 91-day Treasury Bill Rate (91-TBR) and payment through mobile banking (includes individual payments and corporate payments) used as a proxy for money demand, are sourced from the Reserve Bank of India.

3.1 MODEL SELECTION

The impact of income and interest rate on mobile banking transaction is represented in the following equation:

$$MB = L_1(Y) + L_2(SR) \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

Where, MB represents the payments through mobile banking, Y are income, SR is the rate of interest, L_1 and L_2 is the liquidity function. To achieve our stated objective, we transform equation (1) into a log-linear form for further econometric analysis.

$$LNMB = \beta_0 + \beta_1 LNY + \beta_2(SR) + \varepsilon_t \;\ldots\ldots\ldots\ldots\ldots\ldots 2$$

However, selecting an appropriate econometric model for time series analysis depends entirely on the stationarity order of the variables. To assess this, the stationarity of the variables was tested using the Augmented Dickey-Fuller (ADF) as proposed by Dickey & Fuller (1979), based on the following equation:

$$\Delta \mathrm{Y_t} = \beta \mathrm{Y_{t-1}} + \sum_{i=1}^{k} \varphi_i \Delta \mathrm{Y_{t-1}} + \varepsilon_t \;\ldots\ldots\ldots\ldots\ldots\ldots 3$$

Additionally, the study used the Phillips-Perron (PP) as proposed by Phillips & Perron (1988) to verify the reliability of the ADF findings. The results from both stationarity tests provide a basis for identifying the long-run relationship between the variables, for which the Engle-Granger (EG) test and the Johansen test are applied. The EG test originates from Engle & Granger (1987), while the Johansen test comes from Johansen (1988) and Johansen & Juselius (1990). The EG test examines the stationarity of residuals. If the residuals are stationary at level, it suggests that the variables are cointegrated. The EG test assumes a single cointegrating vector in systems with more than two variables and imposes an arbitrary normalization on this vector (Idowu, 2005). Additionally, the EG test is less powerful and robust compared to the Johansen cointegration test. Therefore, it is essential to complement the EG test with the Johansen test. However, both test revealed a long run relationship. Based on the cointegration results , the long-run coefficients analyze using the dynamic ordinary least squares (DOLS) method, as recommended by Stock & Watson (1993) because DOLS is a single-equation approach that addresses endogeneity and autocorrelation by incorporating leads and lags of the first differences of the explanatory variables (Aigheyisi, 2020). This makes it a robust method for estimating long-run relationships in co-integrated time series data. These advantages compel us to use the DOLS approach to get correct findings under the premise that the income and interest rate are the two determinants of money demand (here payments via mobile banking) where income establishes a positive relationship with money demand, and the interest rate establishes a negative relationship with money demand. The long-run DOLS models are specified as follows:

$$LNMB_{t=} = \beta_0 + \beta_1 Y_t + \beta_2 SR_t + \sum_{i=-p}^{p} \delta_{ti}\, \Delta Y_{t-i} + \sum_{i=-p}^{p} \delta_{2i}\, \Delta SR_{t-i} + \varepsilon_t \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$

However, Engle & Granger (1987) demonstrated that when variables are cointegrated, an error-correction representation must exist. This implies that changes in the dependent variable are influenced by the level of disequilibrium in the cointegrating relationship, which is captured by the error correction term (ECT), along with other explanatory variables. In this context, the sign of the ECT becomes important: a negative ECT indicates convergence, while a positive ECT indicates divergence. To test the ECT, previous studied suggest two approaches: the vector error correction model (VECM) or the two-step error correction model (ECM). The key difference between the two is that VECM is suitable when there are multiple cointegration relationships in a time series equation, whereas ECM is appropriate when only a single cointegrating relationship exists. In the present study, the Johansen test, which is suited for analyzing multivariate cointegration equations, indicates the presence of a single cointegration equation, as presented in Table 4 of Panel (B). Therefore, the ECM method is used to examine the short-run dynamics and long-run adjustments through correction mechanism as follows.

$$\Delta LNMB_t = \beta + \sum_{i=1}^{p} \beta_1 \Delta LNMB_t + \sum_{i=1}^{p} \beta_2 \Delta Y_t + \sum_{i=1}^{p} \beta_3 \Delta SR_t + \lambda ECT_{t-1} + \varepsilon_t \;\ldots\ldots\ldots\ldots\ldots\ldots 5$$

This approach provides valuable understanding into the short-term behavior of the variables. The estimation of short-run coefficients with ECM framework and long-run coefficients with DOLS method are employed in previous studies by Hawdon & Al-Azzam (1997), Alimi (2014), and Ola (2017). Furthermore, to validate the findings obtained from the DOLS model, the study used Fully Modified Ordinary Least Square (Philips & Hansen, 1990) and Canonical Cointegration Regression (Park, 1992) because both have the power to tackle challenges such as serial correlation, small sample bias, and endogeneity. Due to the strengths of these estimators, their results are employed as benchmarks for gauging the robustness of the DOLS results. To ensure the robustness of the short-run dynamics derived from the two-stage Granger procedure, diagnostic tests were conducted. The results of these diagnostic tests are summarized in Panel (B) of Table 6.

4. RESULTS AND ANALYSIS

Panel (A) of Table 2 displays the results of the ADF test. At their levels, the variables LNMB, LNY, and SR are non-stationary. However, after taking first differences, all variables become stationary with p-values below 0.05, indicating they are integrated of order one, I(1).

Table 2: Stationarity Results

Panel (A): Augmented Dickey Fuller					
	Level (Constant Form)		First Difference (Constant Form)		
	t-Statistic	Prob.	t-Statistic	Prob.	Order of Stationary
LNMB	-1.032	0.7385	-9.941	0.0000	I (1)
LNY	-0.918	0.7779	-9.289	0.0000	I (1)
SR-91	-1.065	0.7261	-8.075	0.0000	I (1)
Panel (B): Phillip Perron					
LNMB	-0.999	0.7506	-10.047	0.0000	I (1)
LNY	-0.892	0.7864	-9.302	0.0000	I (1)
SR-91	-1.131	0.7002	-8.052	0.0000	I (1)

Source: Author Calculation Based on Data obtained from the RBI and Macrotrends database

Panel (B) of Table 2 presents the PP test result, showing that the variables are non-stationary at their levels but become stationary after taking the first difference, consistent with the ADF test findings. The stationarity results provide the framework for analyzing the long-run relationship. To confirm this, cointegration tests were conducted, and the results are presented in Table 4. Additionally, the appropriate lag length was determined using the VAR Lag Order Selection Criteria, with outcomes detailed in Table 3.

Table 3: Lag Order Selection Criteria

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-82.85024	NA	0.001866	2.229876	2.321193	2.266402
1	177.8888	494.3882*	2.70e-06*	-4.308799*	-3.943531*	-4.162695*
2	182.3122	8.042647	3.04e-06	-4.189928	-3.550708	-3.934246
3	186.3399	7.009211	3.47e-06	-4.060777	-3.147606	-3.695516
4	189.3636	5.026425	4.08e-06	-3.905548	-2.718426	-3.430710

Source: Author Calculation Based on Data obtained from the RBI and Macrotrends database

The determination of the appropriate lag length in econometric modeling is crucial to accurately capture how past values influence current behavior. Table 3 presents the results from five different criteria used to identify the optimal lag length: Log-Likelihood (LogL), Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HQ). Each of these criteria suggests that Lag 1 is the most suitable for the current dataset, indicating that data from one previous period provides the best balance between model complexity and accuracy. As a result, the subsequent analysis is based on Lag 1.

Table 4: Cointegration Results

Panel (A): Cointegration Result via Residual			
	Critical Value	**t-Statistics**	**Prob.**
Residual	-3.511262 @ 1 %	-4.028286	**0.0021**

Panel (B): Johansen Cointegration				
Hypothesized No. of CE(s)	Trace Statistic	0.05 Critical Value	Max-Eigen Statistic	0.05 Critical Value
None*	40.08527	42.91525	**26.21505**	**25.82321**
At most 1	13.87023	25.87211	9.840618	19.38704
At most 2	4.029610	12.51798	4.029610	12.51798

Source: Author Calculation Based on Data obtained from the RBI and Macrotrends database
*Indicate one cointegrating equation suggested by Max-Eigen statistic

Table 4 in Panel (A) presents the residual-based cointegration approach from the static OLS regression, which shows that the residuals are stationary at the level, or I(0) at 1 % significance level, confirming the presence of a long-term relationship between the variables (Granger, 1987). Furthermore, the Johansen cointegration approach was also employed to detect cointegration among the selected variables, providing a more robust alternative to the EG test. Moreover, panel (B) of table 4 presents the Johansen cointegration results which show that the trace statistic indicates the no cointegrating equation, whereas, the maximum eigenvalue statistic suggests one cointegrating equation. Based on the maximum eigenvalue statistic the study concludes that the Johansen cointegration approach confirms the presence of one cointegrating equation, indicating a long-term relationship. Both tests provide evidence of a long-run relationship, justifying the use of DOLS for estimating the long-term relationship (Ola, 2017).

Table 5: Long-Run Estimation Results

Panel (A): Summary Statistic for Equation 4						
	DOLS		**FMOLS**		**CCR**	
Variable	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
LNY	5.478646	0.0000	5.505306	0.0000	5.508451	0.0000
SR-91	-0.359106	0.0000	-0.357469	0.0000	-0.357711	0.0000
Constant	-28.67478	0.0000	-28.91132	0.0000	-28.93408	0.0000
R-Squared	0.94		0.92		0.92	

Source: Author Calculation Based on Data obtained from the RBI and Macrotrends database

The empirical analysis of Equation 4, shown in panel (B) of Table 5 presents long-run coefficients where income (Y) and short-term interest rate (SR-91), are the independent variables, with payments through mobile banking (MB) serve as the dependent variable. To validate the results obtained from the DOLS model, the analysis is extended using FMOLS and CCR methods to ensure the robustness of the findings. The results show a positive and significant coefficient for income (LNY) across all models, implying that as income increases LNMB also increase significantly suggesting that people need more liquidity to facilitate greater economic activity as their income grows. Moreover, the negative and significant coefficient for short-term interest rates (SR) suggests that as short-term rate increases LNMB decrease this suggest that higher short-term interest rate reduce the need for holding liquid assets (in this case, mobile balance). When short-term interest rate rises, individuals prefer to invest in interest-bearing assets rather than holding non-interest-bearing liquid balances. In the digital era, particularly in India, this liquidity is increasingly managed through mobile banking rather than physical cash. The period 2016 witnessed for the digitalization where government start initiatives like demonetization (2016), which spurred digital adoption, and the rise of platforms such as Unified Payments Interface (UPI).

Table 6: Summary Statistics for Equation 5

Panel (A): Short-run dynamics			
Variable	**Coefficient**	**t-statistics**	**Prob.**
D(LNY)	0.357097	0.966042	0.3370
D(SR-91)	-0.005573	-0.142478	0.8871
ECT(-1)	**-0.162590**	**-2.669623**	**0.0092**
Panel (B): Diagnostic Test			
Test	Test Name	Prob.	
Serial Correlation	Breusch-Godfrey LM	0.6628	
Heteroscedasticity	Breusch-Pagan- Godfrey	0.5799	
Specification Error	Ramsey RESET	0.6906	

Source: Author Calculation Based on Data obtained from the RBI and Macrotrends database

The short-run results presented in panel (A) of Table 5 indicate that neither income nor interest rate are significant However, the error correction terms (ECT) is negative and significant, indicating that short-run disturbances adjust towards long-run equilibrium over time.

Moreover, to assess the accuracy of the results, several diagnostic tests were applied. The Breusch-Godfrey LM test indicates no serial correlation in the residuals, while the Breusch-Pagan-Godfrey test for heteroscedasticity confirms homoscedasticity, meaning that the residual variance is consistent. Additionally, the Ramsey RESET test suggests that the model is free from specification errors, ensuring its reliability in representing the relationships between the variables.

4.1 IMPULSE RESPONSE FUNCTION

The impulse response function analyzes how income and interest rates affect the future behavior of mobile banking money within the system. The results of this analysis are shown in Figure 1. According to Sims (1987), the extent to which the responses deviate from zero indicates the significance of the impulse response.

In Equation 2, LNMB is the dependent variable, while income (Y) and interest rate serve as independent variables. The average response of LNMB to Y is positive, indicating that Y has a significant positive impact on LNMB. Similarly, the response of LNMB to SR-91 is negative, showing that SR-91 has a significant negative impact on LNMB. These findings confirm that income and interest rate remain key determinants of money demand through mobile banking and align with the dynamic OLS results.

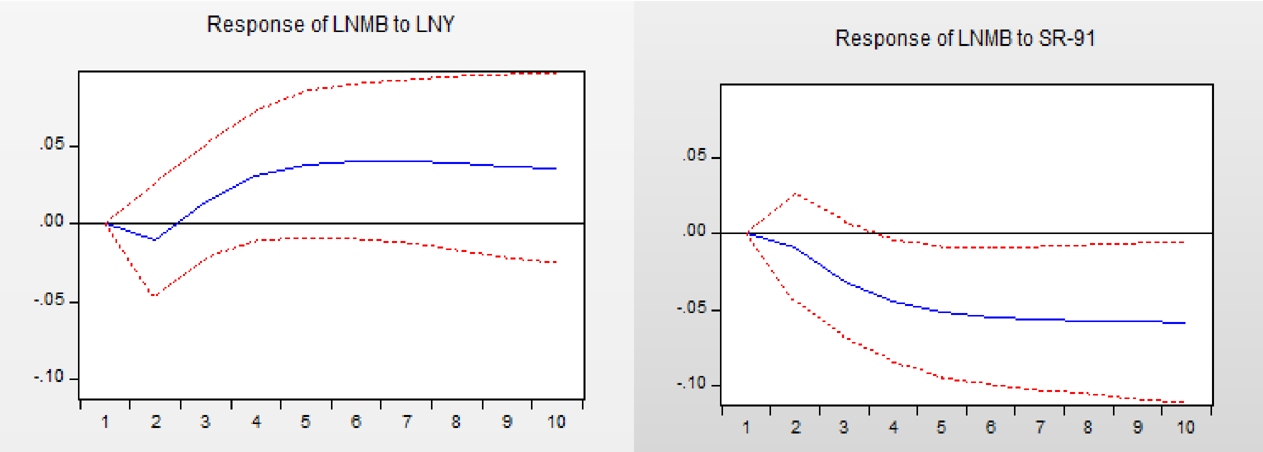

Figure 1: Impulse Response Function

Source: Author's Calculation based on data obtained from RBI and Macrotrends database

5. CONCLUSION

The dynamic OLS results show that income and short-term interest rate are both statistically significant, with income positively and interest rate negatively associated with payments through mobile banking money in India. These results are further supported by FMOLS, CCR, and IRF. In the short run, however, income and interest rate have an insignificant effect with payments through mobile banking in India, likely due to fluctuations from the COVID-19 pandemic, which disrupted relationships between income, interest rate, and money demand. Despite this, the negative and significant ECT confirms that any short-run imbalance can adjust back to equilibrium in the long run.

LIMITATIONS OF THE STUDY

The present study used mobile banking transactions as a proxy for money demand, but this may not fully capture the total demand for money. Additionally, the study relies on secondary data from January 2016 to December 2022, which may limit its ability to account for longer-term impacts of income and interest rates on mobile banking transactions. Furthermore, the study considers only two variables—income and interest rate—while including additional factors like internet access, digital skills, or age groups could provide a more comprehensive and accurate understanding of the overall impact.

Competing Interests: The authors have declared that no competing interests exist.

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