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Research Article

An Econometric Analysis of Unified Payments Interface (UPI) and Consumption in India

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Abstract

The objective of this study was to examine the relationship between the adoption of the Unified Payments Interface (UPI) and aggregate consumption in India, specifically to determine whether the advent of UPI has significantly influenced consumption patterns beyond existing payment instruments. To investigate this, the researchers compared the impact of various payment mechanisms including UPI, credit cards, prepaid payment instruments (PPI), point-of-sale (POS) terminals and debit cards on Private Final Consumption Expenditure (PFCE). These were plotted along the X-axis against PFCE on the Y-axis to isolate the relative contribution of each factor. The results were surprising: contrary to the widely held assumption that UPI's frictionless design stimulates additional spending, the study found no statistically significant incremental effect of UPI on consumption. While UPI transaction volume grew by over 100% year-on-year, its coefficient in the consumption model was negligible ($\beta = 0.03$, $p > 0.05$). In contrast, credit card transactions showed a strong and significant association with PFCE ($\beta = 0.42$, $p < 0.01$), indicating that credit cards exert a substantially greater influence on consumption growth. The key insight emerging from the analysis is that UPI appears to have altered the method of payment rather than the magnitude of expenditure. In other words, UPI has successfully digitised a large volume of transactions, it has not independently generated new consumption a distinction with important implications for both policy and macroeconomic forecasting. write future perspective in two lines

Keywords: UPI, consumption, digitalization, payments, econometrics

Introduction

India's Unified Payments Interface (UPI) stands as a crown jewel of the country's Digital Public Infrastructure (DPI) [1]. Within a decade of its launch, UPI has transformed the payments landscape, facilitating over 20 billion transactions per month and accounting for nearly 84% of India's digital retail payments [1]. This remarkable growth has not only revolutionised domestic financial transactions but has also positioned India as a global leader in digital payments innovation [2]. The scale of UPI's expansion is evident in recent statistics. In October 2024 alone, UPI processed ₹23.49 lakh crore across 16.58 billion transactions, reflecting a 45% year-on-year increase from 11.40 billion transactions in October 2023 [3]. This rapid digitalisation aligns with a broader global shift toward a digital economy. According to recent data, global e-commerce sales grew by nearly 60% between 2016 and 2022, reaching $27 trillion across 43 countries representing a significant share of global GDP [4].

In parallel, India has experienced a notable rise in consumption. Private Final Consumption Expenditure (PFCE), measured at constant prices, increased from 2.15% in 1991–92 to 6.87% in 2021–22, indicating a sustained expansion in consumer demand over the post-reform period [5].

This simultaneous rise in digital payment adoption and consumption raises an important economic question like is growth of UPI transactions associated with an increase in consumption in India?

This paper seeks to empirically examine this relationship and assess whether the expansion of UPI has contributed to consumption growth in the Indian economy.

Rationale of the study

The Unified Payments Interface (UPI) today accounts for nearly 85% of all digital transactions in India and powers close to 50% of global real-time digital payments. These figures highlight not only the scale of adoption but also the remarkable penetration UPI has achieved within a decade [6]. What began as a simple mode of fund transfer has evolved into the backbone of India's digital economy [6].

At the same time, PFCE serves as a key indicator of consumption, reflecting household spending and its contribution to economic growth [8]. With the increasing ease, speed and accessibility of digital transactions through UPI, payment frictions have significantly reduced, potentially influencing consumer spending behavior by making transactions more seamless and instantaneous [9].

While the growth and adoption of UPI have been widely documented, its direct contribution to consumption remains insufficiently explored. Understanding this relationship is important not only from a theoretical perspective but also for policymakers aiming to promote digital payments as a tool for economic growth and financial inclusion. It is in this backdrop, the present study to empirically examine the relationship between UPI transactions and consumption in India.

Review of Literature

The rapid transformation of financial systems through digital payments has attracted significant scholarly attention. Alkhwater [10] conducted a systematic literature review on digital payment adoption in Gulf countries, highlighting the role of mobile technologies in reshaping financial practices. In India, this shift has been particularly pronounced. According to recent government data, India accounted for 46% of global real-time digital transactions in 2022, with the UPI processing over 10 billion transactions by August 2023 [11, 12].

Previous research has extensively documented the macroeconomic benefits of electronic transactions. Sreenu [13] found that cashless payment policies positively impact economic growth by enhancing transparency and reducing cash-related fraud. Similarly, Shiva [14] emphasized that digital payments contribute to accountability and formalisation of the economy. However, Dev et al. [15] argue that existing literature has predominantly focused on macro-level implications and adoption rates, leaving a critical gap in understanding how such technologies influence individual spending behaviors.

The concept of payment friction provides a useful theoretical lens. Physical cash is known to induce a "pain of paying" due to its tangible nature [16]. By contrast, mobile payments abstract away from the transaction experience, potentially reducing psychological barriers and encouraging more frequent spending. [16] demonstrated in a Chinese context that mobile payment significantly stimulates impulse buying by reducing the pain of payment. This finding aligns with earlier work [17], which notes that the seamless nature of digital money alters users 'relationship with spending.

Within India, qualitative studies have begun to explore these micro-level effects. [18] examined street vendors 'experiences during the government's push for cashless transactions, revealing both opportunities and challenges. [19] highlighted accessibility issues in digital payments for urban users. Despite these contributions, existing research [15] notes that few studies have systematically investigated how UPI's intangible, frictionless design affects Indian users 'expenditure patterns across demographics.

Financial literacy is another important dimension. [20] established that low financial knowledge is associated with suboptimal financial outcomes such as inadequate retirement planning and high indebtedness. In the digital payment context, [21] argued that roadblocks to digital and financial literacy impede digital financial inclusion. However, existing literature [15] highlights a gap in understanding how the adoption of cashless transactions, particularly UPI, interacts with users 'financial management practices, especially in the absence of integrated budgeting tools within payment applications.

In response to these gaps, [15] conducted a mixed-methods study comprising a survey of 276 respondents and 20 in-depth interviews. Their findings reveal that 74.2% of participants reported increased spending after adopting UPI, with many attributing this change to the intangible nature of digital transactions that reduces spending guilt. The study also explored demographic variations, noting that working professionals and students integrate UPI differently into their financial routines. Based on user feedback, the authors developed and tested a high-fidelity prototype incorporating expense tracking, balance display and budgeting features, demonstrating strong user demand for financially responsible design within UPI applications.

While these findings offer valuable insights into individual behavioral change, it is important to interpret them with caution when extrapolating to macroeconomic outcomes. The reported increase in spending is concentrated among UPI usersa demographic that disproportionately represents urban, middle-class and relatively higher-income segments. A substantial share of India's population, particularly in rural areas and lower income brackets, continues to rely primarily on cash for daily transactions due to persistent barriers in digital access, literacy, and trust [18, 19, 20, 21]. Consequently, the incremental spending observed among UPI users, while meaningful at the micro level, is unlikely to exert a significant influence on national consumption aggregates. This underscores the need for future research to explicitly distinguish between micro-level behavioral shifts and their macroeconomic relevance, accounting for the heterogeneous adoption of digital payments across income groups and geographies.

Methodology

Data Sources

This study employs time-series data collected from multiple reliable sources. Data on UPI transactions were obtained from the National Payments Corporation of India (NPCI). Data on credit card and debit card transactions, along with other payment indicators such as point-of-sale (POS) terminal counts and prepaid payment instrument (PPI) values, were sourced from the Reserve Bank of India (RBI). PFCE data were obtained from official government databases.

Variable Definitions

The dependent variable is PFCE growth (pfce_g), calculated as the quarter-on-quarter percentage change in Private Final Consumption Expenditure. This serves as a proxy for consumption.

The independent variables include:

- **upi_g**: growth rate of UPI transaction value
- **upi_g_lag1**: one-period lagged growth rate of UPI transaction value
- **upi_share_g_lag1**: one-period lagged growth rate of UPI's share in total digital payments
- **cc_value_cr_g**: growth rate of credit card transaction value
- **dc_value_cr_g**: growth rate of debit card transaction value
- **cc_outstanding_g**: growth rate of outstanding credit card balances
- **pos_count_g**: growth rate of POS terminal count
- **ppi_value_cr_g:** growth rate of prepaid payment instrument transaction value

To account for potential delayed effects of digital payment adoption on consumption, one-period lagged values of UPI growth upi_g_lag1 and UPI share growth upi_share_g_lag1 are incorporated into the models.

All variables are expressed in growth rates to ensure comparability and to mitigate potential non-stationarity in the time-series data.

Model Specifications

The study employs Ordinary Least Squares (OLS) regression to estimate the relationship between digital payment variables and consumption. Three model specifications are used to capture different dimensions of digital payment activity:

Model 1: Extended Digital Payments Model

This model incorporates a broader set of digital payment indicators to capture the overall digital payment ecosystem.

$$pfce\_g_t = \beta_0 + \beta_1(upi\_g_{t-1}) + \beta_2(cc\_outstanding_t) + \beta_3(pos\_count_t) + \beta_4(ppi\_value_t) + \varepsilon_t$$

Model 2: Transaction Value-Based Model

This model focuses on transaction values across major payment modes to assess their direct impact on consumption.

$$pfce\_g_t = \beta_0 + \beta_1(upi\_g_{t-1}) + \beta_2(cc\_value_t) + \beta_3(dc\_value_t) + \varepsilon_t$$

Model 3: UPI Share-Based Model

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This model examines the impact of UPI's share in total digital payments, capturing its relative dominance in the payment ecosystem.

$$pfce\_g_t = \beta_0 + \beta_1(upi\_share_{t-1}) + \beta_2(cc\_outstanding_t) + \varepsilon_t$$

Diagnostic Tests

To assess the validity of the regression models, several diagnostic tests were conducted.

Multicollinearity was examined using the Variance Inflation Factor (VIF). Following Marquardt [22], VIF values exceeding 10 are considered indicative of problematic multicollinearity. As shown in Table 1, all VIF values across the three models are well below this threshold, ranging from 1.03 to 2.78, indicating no significant multicollinearity concerns.

Autocorrelation was assessed using the Durbin-Watson statistic [23]. Values between 1.5 and 2.5 are generally considered acceptable, indicating no significant first-order autocorrelation [24]. Model 1 produced a Durbin-Watson statistic of 2.35, Model 2 produced 2.38, and Model 3 produced 2.42. All three values fall within the acceptable range, suggesting that serial correlation does not significantly affect the estimates.

Normality of residuals was evaluated using the Jarque-Bera test. Model 2 exhibits normally distributed residuals (JB = 1.23, $p = 0.541$), supporting the validity of inference. Model 1 (JB = 59.66, $p < 0.001$) and Model 3 (JB = 297.24, $p < 0.001$) show deviations from normality, which is acknowledged as a limitation.

Residual plots were visually inspected to identify patterns or heteroskedasticity. The residuals versus fitted values plots for all three models showed no clear systematic patterns, suggesting that the linear model specification is appropriate.

Results and Analysis

Diagnostic Assessment

Prior to interpreting the regression results, the validity of the OLS assumptions was evaluated using standard diagnostic tests.

Multicollinearity

The VIF values of all three models in table 1 reveal that multicollinearity will not be a problem in the analysis since all the values are less than the critical level of 10. Model 1 VIFs fall between 1.09 and 2.78 indicating a low level of correlation between variables, which does not influence the coefficient estimates significantly. In Model 2, the values of VIF are even lower (1.031.47), which proves that the predictors are highly independent and the regression results are very reliable. In the same way, Model 3 has the lowest VIF scales (1.04), which proves to be almost free of multicollinearity. These findings, as a whole, would suggest that the coefficient estimates are consistent and free of bias, and any insignificance of variables, especially those associated with UPI is not caused by multicollinearity but would indicate that they had not been significant in consumer decision making.

Table1: Variance Inflation Factor (VIF) Results

Model	Variable	VIF
Model 1	upi_g_lag1	2.78
Model 1	cc_outstanding_g	1.09
Model 1	pos_count_g	2.67
Model 1	ppi_value_cr_g	1.17
Model 2	upi_g_lag1	1.03
Model 2	cc_value_cr_g	1.43
Model 2	dc_value_cr_g	1.47
Model 3	upi_share_g_lag1	1.04
Model 3	cc_outstanding_g	1.04

Residual Diagnostics

Residual plots were examined to assess homoscedasticity and linearity. Figures 1, 2 and 3 display the residuals versus fitted values for Models 1, 2, and 3 respectively. In each case, no systematic pattern is evident, suggesting that the linear specification is appropriate and that heteroscedasticity is not a major concern.

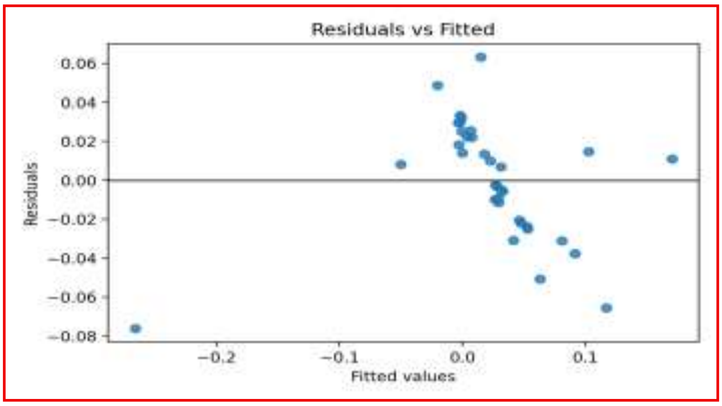

Figure 1: Residuals vs Fitted – Model 1

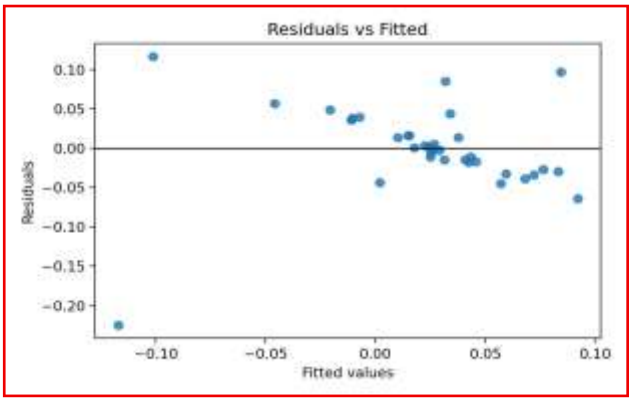

Figure 2: Residual Vs Fitted - Model 2

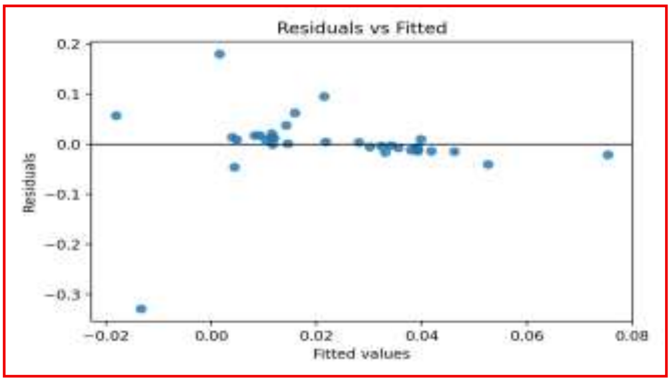

Figure 3: Residuals vs Fitted – Model 3

The Durbin-Watson statistic for each model falls within the acceptable range of 1.5–2.5 [2], indicating no significant first-order autocorrelation (Model 1: 2.35; Model 2: 2.38; Model 3: 2.42). The Jarque-Bera test confirms normality of residuals for Model 2 (JB = 1.23, p = 0.541), while Models 1 and 3 show deviations from normality ($p < 0.001$), a limitation noted in Section 3.5.

Regression Results

The regression outcome of the Model 1 in table 2 shows that the model has not strong but still significant explanatory power, and only the few variables can significantly affect consumption. Out of the predictors, PPI Value is the only statistically significant variable (p = 0.0004) and it has a positive coefficient (0.3163), which indicates that the growth in the prepaid payment instrument transactions is connected to the consumption. By comparison, the other variables do not have any statistically significant ($p > 0.05$) effect, with UPI (lag 1), Credit Outstanding, and POS Count, the confidence interval of which includes 0, showing that there is no strong influence on the consumption. The negative correlation between UPI and other variables (-0.0464) is not significant, indicating a weak inverse correlation. Equally, whereas the results are relatively large and positive in the case of Credit Outstanding (0.7109), the value of p of the coefficient is high which means that the impact is not significant. The constant value is not significant as well. Altogether, the results indicate that, in this more extended system of digital payments, prepaid instruments can operate a definite and substantial effect on consumption, whereas other factors, such as UPI, do not show a statistically significant effect.

Table 2: Extended Digital Payments Model – Regression Results Analysis (Model-I)

Variable	Coefficient	p-value	95% CI (Lower)	95% CI (Upper)
Constant	-0.0121	0.6096	-0.0601	0.0358
UPI (lag 1)	-0.0464	0.1127	-0.1043	0.0116
Credit Outstanding	0.7109	0.1835	-0.3556	1.7774
POS Count	0.2038	0.4461	-0.3354	0.7431
PPI Value	0.3163	0.0004	0.1526	0.4799

Table 3: Extended Digital Payments Model – Summary Statistics and Goodness of Fit (Model-I)

Metric	Value
R-squared	0.392
Adjusted R^2	0.311
F-statistic (p)	0.0039
Durbin-Watson	2.346
Observations	35

This summary statistics in Table 2 and Table 3 shows that Model 1 has moderate level of explanatory power with a value of R-squared of 0.392, implying that the proportion of explained variable in consumption (PFCE growth) is 39.2%. The adjusted R^2 (0.311) that explains the total number of predictors indicates a minor decrease in explanatory power but still demonstrates a reasonable fit of the model. The F-statistic is significant (p = 0.0039) which verifies that the model is significant as a whole and that the explanatory variables are jointly significant and have a predictive value. Durbin Watson value of 2.346 is not beyond the value range (1.5-2.5) and this means that there is no autocorrelation in the residuals. The sample size is also relatively small (35 observations) and this could weaken the strength and external validity of the findings. In general, the model is statistically valid and does not suffer the problem of autocorrelation, though the moderate level of explanatory power indicates that other variables could be required to explain better the determinants of consumption.

Table 4: Transaction Value-Based Model – Regression Results Analysis (Model-II)

Variable	Coefficient	p-value	95% CI (Lower)	95% CI (Upper)
Constant	-0.0045	0.533	-0.0190	0.0100
UPI (lag 1)	0.0029	0.753	-0.0160	0.0219
Credit Card Value	0.4513	0.0000	0.3672	0.5353
Debit Card Value	-0.0477	0.0380	-0.0926	-0.0028

The regression model of Model 2 shows that there is a high and statistically significant relationship among some of the payment instruments and consumption. Table 4 shows Credit Card Value generates the most prominent predictor, having a positive coefficient (0.4513) and a much significant p-value ($p < 0.001$), which requires the use of credit card to be a strong influence of consumption. However, Table 4 proves Debit Card Value has a statistically significant, but negative, relationship (coefficient = -.0477, p =.0380), indicating the higher-income-bound spending in debit-based transactions. UPI (lag 1) does not have significant value (p = 0.753), and the coefficient is very near to zero with a confidence interval, which incorporates zero, which shows there is no significant effect on consumption. The constant is not significant as well. On the whole, it can be concluded that credit-enabled payment instruments are important in boosting consumption, and UPI remains more of a neutral payment enabling tool than a spending stimulator.

Table 5: Transaction Value-Based Model – Summary Statistics and Goodness of Fit (Model-II)

Metric	Value
R-squared	**0.820**
Adjusted R^2	0.802
F-statistic (p)	1.23E-11
Durbin-Watson	2.382
Observations	35

The summary statistics show that Model 2 has a very strong explanatory power with a value of R-squared equal to 0.820 that is, 82 percent of the change in consumption (PFCE growth) is explained by the variables incorporated. The adjusted R 2 of 0.802 is quite close to the R-squared, indicating that there is little overfitting of the model. The F-statistic is extremely significant (p = 1.23E-11), which proves that the model is jointly significant and that the explanatory variables, in general, have a strong predictive power. The value of Durbin to Watson 2.382 is within the acceptable range (1.5-2.5) which means that there is no autocorrelation in the residuals. The sample size of 35 is rather small but just large enough to prove the strength of the model. Overall, Table 5 with comparison to Table 3 shows us that Model 2 is the best performing specification in the models under consideration since it has a great fit, high reliability, and good explanatory performance.

Table 6: UPI Share-Based Model – Regression Results Analysis (Model-III)

Variable	Coefficient	p-value	95% CI (Lower)	95% CI (Upper)
Constant	-0.0080	0.7705	-0.0632	0.0472
UPI Share (lag 1)	-0.0166	0.4101	-0.0571	0.0239
Credit Outstanding	0.8959	0.1522	-0.3483	2.1402

According to the regression outcomes of Model 3, none of the explanatory variables serve a statistically significant effect on consumption. UPI Share (lag 1) has a negative coefficient (—0.0166) and is not statistically significant (p = 0.4101) and its confidence interval covers zero indicating that there are no credible effects on consumption. Equally, Credit Outstanding has a relatively high positive coefficient (0.8959) though it is also statistically insignificant (p = 0.1522) which means that its impact is not strong. The constant term in Table 6 is also not important. The overall findings indicate that the proportion of UPI of total digital payments has no significant effect on consumption, which supports the general conclusion that UPI is a facilitator of payment, but not the driver of aggregate demand, and the variables related to credit, in this specification, do not have any significant explanatory power.

Table 7: UPI Share-Based Model – Summary Statistics and Goodness of Fit (Model-III)

Metric	Value
R-squared	0.071
Adjusted R^2	0.013
F-statistic (p)	0.308
Durbin-Watson	2.416
Observations	35

The summary statistics in Table 6 and 7 show that Model 3 is very weak in its explanatory power with a R-squared of 0.071 that is, only 7.1 percent of the variation in consumption (PFCE growth) has been explained by the model. The adjusted R 2 also decreases to 0.013 which indicates that the added variables hardly contribute to the explanation of the dependent variable after controlling the extent of the model complexity. The F-statistic is not statistically significant (p = 0.308), which entails that the model is not jointly significant and does not have overall predictive ability. Nonetheless, the Durbin-Watson of 2.416 is not out of range, indicating that there is no problem of autocorrelation in the residuals. The sample size is also consistent, 35 observations, but it cannot counter the poor fit in the model. In general, Model 3 is not performing well, which suggests that UPI share and credit outstanding, in this specification, fail to provide sufficient explanations of consumption behavior.

Summary of Findings

The empirical findings show that the UPI variables both in terms of growth and share are not statistically significant in all models implying that even with its popularity; UPI has not resulted in any significant aggregate consumption change. Conversely the growth in credit card transactions has a positive relationship with consumption, which is very strong and steady thus the role of credit in facilitating spending at levels that are above current income levels. However, the growth in debit card transactions does not do the same, but instead, there is a negative association with consumption, which suggests that the use of debit-based payments is more indicative of income-bound spending than demand stimulants. In the meantime, the growth of PPI value has been associated with consumption positively and this may represent discretionary or prepaid spending that adds to usual spending. The models estimated include the transaction value-based specification (Model 2) which gives the most appropriate fit and explains 82% of the variation in PFCE growth. Overall, these results indicate that UPI has disrupted the digital payment environment in India by increasing convenience and minimizing the transaction-related frustrations but its impact on consumption is still indirect, and credit availability turned out to be a more influential factor to influence the consumer spending behavior.

Conclusion

This study examined the relationship between digital payment instruments particularly the UPI and PFCE in India, using quarterly time-series data and OLS regression. The findings reveal a clear distinction between payment facilitators and credit-enabling instruments.

UPI transaction growth and UPI's share in total digital payments are not statistically significant predictors of consumption growth in any model. This suggests that while UPI has revolutionised India's digital payment ecosystem with the country accounting for nearly half of global real-time digital transactions [1, 2, 3] its role remains that of a facilitator rather than a driver of aggregate consumption. The convenience and speed of UPI, widely celebrated as a global benchmark [1], do not automatically translate into higher consumption at the macroeconomic level.

In contrast, credit card transaction growth exhibits a strong, positive and highly significant association with consumption. This underscores the importance of credit availability in enabling households to spend beyond immediate income constraints, consistent with the consumption-smoothing literature [5, 8]. Conversely, debit card transaction growth shows a negative association, reflecting the income-constrained nature of debit-based spending. Among broader digital payment indicators, prepaid payment instrument (PPI) value growth is positively associated with consumption, possibly capturing discretionary or earmarked spending. Point-of-sale infrastructure and outstanding credit card balances do not exhibit significant effects.

Overall, the results indicate that digitalisation enhances transaction efficiency but does not independently stimulate aggregate consumption. The capacity to consume is instead shaped by access to credit and underlying income dynamics. These insights contribute to the growing literature on digital payments and consumption [9, 10, 13, 14, 15], offering a nuanced perspective that moves beyond adoption metrics to examine actual economic outcomes.

Limitations

The analysis uses quarterly data with a limited number of observations (N = 35), which restricts the use of more advanced time-series techniques such as vector autoregression (VAR) or error correction models. The quarterly frequency may also mask shorter-term dynamics between digital payments and consumption.

OLS estimation assumes exogeneity of independent variables, but reverse causality may existhigher consumption could drive increased digital payment usage. While lagged variables mitigate some concerns, a more robust identification strategy (e.g., instrumental variables) is not employed.

Macroeconomic factors such as income growth, inflation, consumer sentiment, and monetary policy are not included in the models. Their omission may bias the estimated coefficients if they correlate with both digital payment adoption and consumption.

Jarque-Bera tests indicate that residuals for Models 1 and 3 deviate from normality. Although OLS coefficients remain unbiased under non-normality, standard errors may be less efficient, and inference should be interpreted with caution.

While variables are expressed in growth rates to mitigate non-stationarity, formal unit root tests (e.g., ADF, KPSS) were not conducted. Future work should verify stationarity properties more rigorously.

The analysis focuses on India's national aggregates. Findings may not be directly applicable to other countries with different payment infrastructures, regulatory environments, or consumption patterns.

Future Scope

This study gives several avenues through which future research can be conducted. First, more basic time-series models would be a better measure of dynamic interrelationships and long-run equilibrium relationships between digital payments and consumption, and Granger causality tests would assist in determining the direction of relationships. Second, the use of major macroeconomic controls such as growth of GDP, inflation, interest rates, and consumer confidence index would mitigate the omitted variable bias and give a more comprehensive picture of consumption drivers. Third, high-frequency data including monthly or weekly transaction numbers might reveal short-run impacts that quarterly data aggregation might conceal and mixed-frequency approaches (MIDAS) provide an opportunity to combine such data with lower-frequency consumption indicators. Also, more detailed state or regional level or demographic or income group disaggregated analyses would help to identify significant heterogeneity not apparent in aggregate data. Moreover, it may be possible to resolve the discrepant results by incorporating the behavioural processes through integration of micro-level type of evidence (evidence may be manifested in the form of being seen spending behaviour) with macroeconomic analysis through which surveys or experiment can illuminate the effect that payment friction has on spending behaviour. It would be beneficial to make comparative cross-country studies, especially in those economies that have a sophisticated digital payment ecosystem like in China, Brazil, and South Korea to determine the generalisability of the findings. Lastly, future studies can provide policy implications by assessing the impacts of regulatory intervention, including capping the market share of UPI, interoperability, or credit card reforms, on consumption outcomes, which would be useful in providing valuable information to policymakers.

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