Addendum

Essays on Transaction Technology and Payment System

debit card as we know it today was still some distance off, bur the creation of the world's first ATM seemed to hasten its arrival. According to the AU small finance bank, In the US by The Bank of Delaware first launch a pilot project involving Debit Cards in 1966. By the 1970s, many other banks started working on similar ideas. As per Wikipedia article (on "Cashless Society") Diners Club was the first to introduce credit cards in India.

In India in the year 1987 the first ATM was introduced in 1987 (Wikipedia Article*)*. Starting from 2014, the promotion of cashless transactions has been one of the policy priorities of the Government of India. In November 2013, electronic payments accounted for only about 13% of all transactions, while cash dominated the economy. Debit card transactions at POS terminals remained low, with most card usage focused on ATM withdrawals rather than cashless payments. (RBI 2019). After 2014 the total value of digital transactions exhibited steady growth, with moderate yearly increases. Kasana **(2023)** highlights the exponential growth of UPI transactions from 2017-18 to 2021-22, showing a 50-fold increase in volume and an 84-fold increase in transaction value. As per the annual report of RBI (2023) Debit and credit card transactions also grew, with the monetary value of card payments increasing 85% between 2017-18 and 2021-22.

According to the Press Information Bureau in December 2016, Government has adopted several measures for the promotion of digital and cashless transaction. One of the most controversial measure was demonetization policy[1] in November 2016 under this policy Govt. of India decided to ban two highest denominations of currency notes of Indian rupee. It was also believed that people would adopt the habit of cashless transaction Rekha (2019). Following demonetization, the Government of India launched the **Digital India program**, a flagship initiative aimed at

[1] Demonetization was motivated by the belief that the maximum portion of the black money was kept with those two highest currency notes.

transforming India into a digitally empowered society and knowledge-based economy. As part of this initiative, the **Cashless India Policy (Cash Mukt Bharat)** was introduced to promote cashless transactions and transition India toward a less-cash society. Under this programme, for promoting cashless transactions and converting India into less-cash society, various modes of digital payments were launched on 30th November 2016 by NPCI (National Payment Corporation of India), which included Unstructured Supplementary Service (USSD)[2], Aadhaar Enabled Payment System (AEPS)[3], the scheme of Digital Finance for Rural India[4], and others[5]. Examples of these initiatives include:

Petroleum PSUs offerd a 0.75% discount on the sale price on the purchase of petrol/diesel through digital means.

The Central Government extended financial support for the deployment of 2 POS devices each in 1 lakh villages with a population of less than 10,000 and issuing "Rupay Kisan Cards" to 4.32 crore Kisan Credit Card holders with the help of NABARD, enabling them to make digital transactions at POS machines/Micro ATMs/ATMs.

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[2]Govt. of India with the help of NPCI (National Payment Corporation of India) Launched on 30.11.2016 Unstructured Supplementary Service Data (USSD) . In this payment service Individual can perform mobile banking transactions using *99#, without Internet from basic mobile phone.

[3]In Aadhaar Enabled Payment System (AEPS) financial transaction can be performed at POS (Point of Sale / Micro ATM) using the Aadhaar authentication.

[4] Following the scheme titled 'Digital Finance for Rural India: Creating Awareness and access through CSCs', from December 2016. Govt. hosts awareness programs regarding policies and digital payment system for rural populations, besides enabling various mechanisms of digital financial services for example IMPS, UPI, Bank POS machines etc.

[5] Some examples are: the Petroleum PSUs offering 0.75% discount on the sale price on purchase of petrol/diesel through digital means; The Central Government extending financial support for deployment of 2 POS devices each in 1 Lakh villages with population of less than 10,000 and to issue "RupayKisan Cards" to 4.32 crore Kisan Credit Card with the help of NABARD to allow them to make digital transactions at POS machines/Micro ATMs /ATMs: Railway giving discount up to 0.5% through its sub urban railway network for monthly or seasonal tickets from January 1, 2017, on digital payments only. The Central Government ensured that transactions fee/MDR (Merchant Discount Rate, the cost paid by a merchant for accepting payment via credit or debit cards every time) charges shall not be passed on to the consumers and all such expenses shall be borne by them. No service tax will be charged on digital transaction charges/MDR for transactions up to Rs.2000 per transaction.

Against this backdrop, the present thesis seeks to explore the multifaceted nature of digital transactions, examining their technological foundations, socio-economic impacts, and regulatory implications. By synthesizing insights from literature, empirical studies, and industry reports, this study aims to elucidate the dynamics shaping the digital transaction landscape and identify opportunities and policy intervention of Indian economy. Through a comprehensive analysis of key trends, challenges, and future directions, this research aims to contribute to a deeper understanding of the transformative potential of digital transactions of Indian economy in an increasingly digitalized and interconnected world.

Now why India? Since 2014, promoting cashless transactions has been a key policy priority for the Government of India. The resource cost of a nation's payment system can account for up to 3% of its GDP (Humphrey, Pulley, and Vesala, 2000). Electronic payment systems offer two key advantages over cash-based or paper-based non-cash payment methods. First, since electronic payments generally cost only one-third to one-half of paper-based transactions (such as cheque payments), transitioning to electronic payment modes can significantly reduce the overall economic cost of the payment system. Second, cashless transactions ensure accurate and complete documentation of each transaction, minimizing the creation of untraceable money while enhancing transparency and tax compliance. Recognizing these economic benefits, the Government of India implemented several measures to promote digital and cashless transactions (Press Information Bureau, December 2016).

In November 2013, electronic payments accounted for only about 13% of all transactions, with cash still dominating the economy. Debit card usage at POS terminals remained low, as most cardholders primarily used them for ATM withdrawals rather than cashless payments (RBI, 2019). After 2014 the total value of digital transactions exhibited steady growth, with moderate yearly increases. **Kasana (2023)** highlights the exponential growth of UPI transactions from 2017-18 to 2021-22, showing a 50-fold increase in volume and an 84-fold increase in transaction value. As per the annual report of RBI (2023) Debit and credit card transactions also grew, with the monetary value of card payments increasing 85% between 2017-18 and 2021-22. One of the most rare and controversial measures was the demonetization policy in November 2016, which involved banning the two highest denominations of Indian currency notes. This policy was also expected to encourage people to adopt cashless transaction habits (Rekha, 2019).

Following demonetization, the Government of India launched the **Digital India programme**, a flagship initiative aimed at transforming India into a digitally empowered society and knowledge-based economy. As part of this initiative, the **Cashless India Policy (Cash Mukt Bharat)** was introduced to promote cashless transactions and transition India toward a less-cash society. Under this policy, the National Payments Corporation of India (NPCI) launched various digital payment modes on 30th November 2016, including Unstructured Supplementary Service Data (USSD), Aadhaar Enabled Payment System (AEPS), the Digital Finance for Rural India scheme, and several others. Due to these significant policy initiatives, combined with India's vast population, diverse demographics, and rapid fintech adoption, India serves as a crucial case for studying cashless digital transactions. Insights from India's experience can be applied to other emerging economies facing similar challenges. Understanding the Indian context allows policymakers and researchers to develop scalable and inclusive digital financial strategies.

Before going into the detailed analysis of those issues in the following chapters, the present chapter offers a succinct and concise overview of both the analytical and empirical literature concerning various themes related to cashless digital transaction for better understanding of the literature gap. We essentially investigate the studies on those issues we have explored in the upcoming chapters.

and interbank transactions. During the pandemic, cash and retail transactions saw a slight uptick, while the volume of intrabank and interbank transactions declined in comparison to the prior normal conditions. A notable increase of 2,117% was recorded in electronic money transactions using.

Bayero (2015) examines the relationship between the Cashless economy policy and financial inclusion in Kano, Nigeria. The research identifies key variables—awareness, customer value proposition, and payment infrastructure—as having significant positive relationships with financial inclusion, while the business model of financial service providers was found to have no substantial impact. The findings underscore the importance of awareness, infrastructure, and customer value in promoting financial inclusion, particularly in low-income settings like Kano, Nigeria. The study fills a gap in the literature by focusing on a sample of working-age adults in a developing country, providing empirical evidence that highlights the role of Cashless economy components in enhancing financial inclusion in this context.

Srouji (2020) explores the challenges faced by the United Arab Emirates (UAE) and Saudi Arabia in transitioning towards cashless economies despite significant efforts to expand digital payments. The study highlights the prevalence of cash in both countries, with cash still accounting for a large portion of total payments, and attributes this to factors such as infrastructure readiness, transaction costs, and security concerns. However, the paper argues that socio-economic inequality plays a crucial role in the continued reliance on cash, particularly in economies with large unbanked populations and informal financial systems. It cautions against viewing the shift from cash to digital payments as a linear or binary process, suggesting that, in emerging economies, cash and digital payments may serve complementary roles. The paper calls for inclusive financial policies to ensure equitable access to digital services and infrastructure, to prevent digital exclusion from exacerbating existing socio-economic disparities.

Zakari, M. (2023) investigates the impact of cashless policy measures, such as digital payment platforms, point-of-sale (POS) terminals, and debit/credit cards, on financial inclusion in Nigeria. Using a cross-sectional design and a sample of 400 respondents from Nigeria's commercial bank customers, the study found that digital payment platforms like electronic funds transfer (EFT) and debit/credit cards significantly contribute to financial inclusion by providing accessible, secure financial services. However, POS terminals were found to have no significant impact on financial inclusion. The study suggests that while POS terminals support cashless transactions, their direct effect on increasing financial inclusion is limited. The findings highlight the importance of policies and regulatory support for digital payment systems and recommend further incentivizing financial institutions to foster broader access to digital financial services. Additionally, government programs and initiatives have played a role in increasing formal financial inclusion, particularly in rural and underserved areas.

Osabutey, and Jackson (2024) examines the role of mobile money in promoting financial inclusion, highlighting both its benefits and the emerging challenges that have been underexplored in existing literature. While mobile money is seen as a tool for improving financial access, the study identifies three key issues that hinder its effectiveness: ensuring integrity, privacy, and security; addressing resource and infrastructure constraints; and aligning the interests of various stakeholders. Notably, the research suggests that merely addressing these challenges is insufficient for ensuring equitable benefits, especially for the poorest segments of society. Instead, the study argues that mobile money adoption has primarily benefited wealthier individuals, elites, and external stakeholders, with limited direct impact on local, lower-income communities. This raises concerns about the broader social and developmental implications of mobile money in driving meaningful, inclusive economic change.

Next, we consider studies pertaining to India mainly focused on the effects of PMJDY and Demonetisation on the digital transaction of the Indian economy.

Mukhopadhyay (2021) examines digital technology adoption for financial transactions in India after the launch of **Pradhan Mantri Jan Dhan Yojana (PMJDY) in 2014**, using microdata from 2013 and 2015. The study highlights a **digital divide** across income groups and urban-rural populations, with higher adoption among **men, the educated, salaried workers, and those with smartphones and mobile internet.** It emphasizes the need for **improved infrastructure, financial literacy, and regulatory frameworks** to enhance financial inclusion. Government initiatives like **UPI, AEPS, and POS expansion** are pivotal, but further research is needed to address existing gaps and enhance digital financial accessibility.

Podile & Rajesh (2017) underscores the significant shift towards electronic payments in India following demonetization period. It highlights the gradual transition from a cash-dependent economy to a cashless one, where transactions primarily occur through cards or digital means, minimizing the circulation of physical currency. The paper aims to investigate public perception in India regarding cashless transactions based on documentary and analytical method and a variety of secondary data sources, including books, journals, government publications, and online platforms, are actively consulted. A thorough literature research is part of the technique, when analyzing data, qualitative techniques are used to classify topics, identify patterns, and determine trends.

Balaji and Balaji (2017) examine the demonetization process in India initiated on November 8, 2016 and the study seeks to analyse the shift of the consumers towards digital payment types of the cashless transaction over the period of analysis. Our opinion is that the period of analysis is too short, (from January 2020 to June 2020,) to draw important conclusion.

The only study that uses an index to examine the growth of digital payment is The Digital Payments Index (DPI) introduce in January 2021 by The Reserve Bank of India (RBI). This index was created to track the adoption and usage of digital payment methods in India over time. The DPI covers various parameters to measure the extent of digitalization in the payment ecosystem, including payment enablers, payment infrastructure, payment infrastructure penetration, payment performance, and consumer centricity. As detailed analysis is not provided by the RBI, we couldn't comment on this study farther.

The above study makes us believe that COVID-19 pandemic could have sufficient impact on the payment mode behaviour of the individuals which could have larger impacts than the policies taken by the government, and that believe motivate us to incorporate COVID-19 period along with the study of the effectiveness of two major policy intervention by the govt. of India to promote cashless transaction of the India in to our study. As we have not come across any study that has used a comprehensive index in measuring the impact of PMJDY, Demonetization and post demonetization subsequent policies along with the impact of COVID-19 outbreak on the extent of cashless transaction of any economy. So, in the 3rd chapter we attempt to fill this literature gap.

2.2. Literatures on Acceptance of Cashless Transaction and Socio Economic Condition

In the 4th and 5th chapter our objective is to analyse the socio-economic determinants of the usage of the digital transactions theoretically and empirically validate the results. In other words in the 4th and 5th ascertaining how the socio-economic conditions of the buyer impact

3.1. Introduction:

Following RBI report[6] "Digital Transaction implies a payment transaction in a seamless system effected without the need for cash. This includes transactions made through digital / electronic modes wherein both the originator and the beneficiary use digital / electronic medium to send or receive money".

The resource cost of a nation's payment system can account for as much as 3 percent of its GDP (Humphrey, Pulley & Vesala, 2000). Electronic payment system has two clear advantages over the cash-based payment systems. First, since most electronic payments cost only around one-third to one-half of a paper-based non-cash payment (cheque payments), the economic cost of a payment system could be considerably reduced if it is shifted to electronic modes (Humphrey, Pulley & Vesala, 2000). Secondly, since under cashless transactions the documentation of each transaction is complete and accurate when compared to cash transactions, the possibility of creation of black money is less, thereby increasing transparency and improving tax compliance, because of these benefits associated with the digital transaction and payment system, the promotion of cashless transaction has been one of the policy priorities of the Indian government. Though it took time for Indians to switch from cash to card payments, but now debit cards have become one of the essential part of everyday life. Since 2014, promoting cashless transactions has been a key policy priority for the Government of India. In November 2013, electronic payments accounted for only about 13% of all transactions, with cash still dominating the economy. Debit card usage at POS terminals remained low, as most cardholders primarily used them for ATM withdrawals rather than cashless payments (RBI, 2019). After 2014 the total value of digital transactions exhibited steady growth,

[6] The report of the 'The High-level Committee on Deepening of Digital Payments' (2019)

with moderate yearly increases. **Kasana (2023)** highlights the exponential growth of UPI transactions from 2017-18 to 2021-22, showing a 50-fold increase in volume and an 84-fold increase in transaction value. As per the annual report of RBI (2023) Debit and credit card transactions also grew, with the monetary value of card payments increasing 85% between 2017-18 and 2021-22. Starting from 'Pradhan Mantri Jan Dhan Yojana' (PMJDY) in 2014, which was a national mission for Financial Inclusion for ensuring access to financial services to all Indians and transfer the benefits or subsidies directly to the beneficiaries' bank accounts, Government has adopted several measures for the promotion of digital and cashless transaction. One of the most controversial measure was demonetization policy[7] in November 2016 under this policy Govt. of India decided to ban two highest denominations of currency notes of Indian rupee. It was also believed that people would adopt the habit of cashless transaction Rekha (2019).

Following demonetization, the Government of India launched the **Digital India programme**, a flagship initiative aimed at transforming India into a digitally empowered society and knowledge-based economy. As part of this initiative, the **Cashless India Policy (Cash Mukt Bharat)** was introduced to promote cashless transactions and transition India toward a less-cash society. Under this policy, the National Payments Corporation of India (NPCI) launched various digital payment modes on 30th November 2016, which included Unstructured

[7] Demonetization was motivated by the belief that the maximum portion of the black money was kept with those two highest currency notes.

Where, $Index_t$ implies the value of the index at time point t, t denotes time trend, β_1 is the time coefficient, $\boldsymbol{\beta_2}$ is the non-linear time coefficient, x_t is adult population as one of the regressor because increase in the overall value of the cashless transaction can be the result of increase in the adult population growth, so changes in the a adult population is important to incorporate in the model, β_3 is coefficient of adult population, U_t is the error term.

The CUSUM chart of the value GDP index represented in the figure 3.31, says that post demonetization period has no impact on the overall value of the cashless transaction as a proportion of GDP (No structural break during post demonetization period), but during post pandemic period it has negative structural break, indicates negative impact of COVID-19 pandemic scenario on overall economic conditions, but the negative effect doesn't last long, during the end of 2022 it came back to the previous trend, indicates economic recovery as well as increment in the overall value of the cashless mode transaction.

Variable	Coefficient	p-Value
TIME	0.007284	0.0000
GDP_GCFDEF	-2.24E-06	0.3126
WORLD_GROWTH	0.112468	0.0000
Constant (C)	-0.012261	0.4925

Statistic	Value
R-squared	0.9837
Adjusted R-squared	0.9834
Standard Error of Regression	0.0361
Sum of Squared Residuals	0.1697

Table 3.5: Regression Results of Per Capita Volume Index
Source: Own

Variable	Coefficient	p-Value
TIME	0.003321	0.0000
GDP_GCFDEF	3.82E-05	0.0000
WORLD_GROWTH	0.058797	0.0001
Constant (C)	-0.350329	0.0000

Statistic	Value
R-squared	0.9784
Adjusted R-squared	0.9779
Standard Error of Regression	0.0393

Sum of Squared Residuals	0.2005

Table 3.6: Regression Results of Per Capita Value Index
Source: Own

Variable	Coefficient	p-Value
TIME	0.006927	0.2941
$TIME^2$	-3.65E-05	0.0001
ADULTPOPU	2.176765	0.6696
WORLD_GROWTH	-0.058613	0.0850
Constant (C)	-1.985938	0.6586

Statistic	Value
R-squared	0.8289
Adjusted R-squared	0.8236
Standard Error of Regression	0.0955
Sum of Squared Residuals	1.1771

Table 3.7: Regression Results of Value/ GDP Index
Source: Own

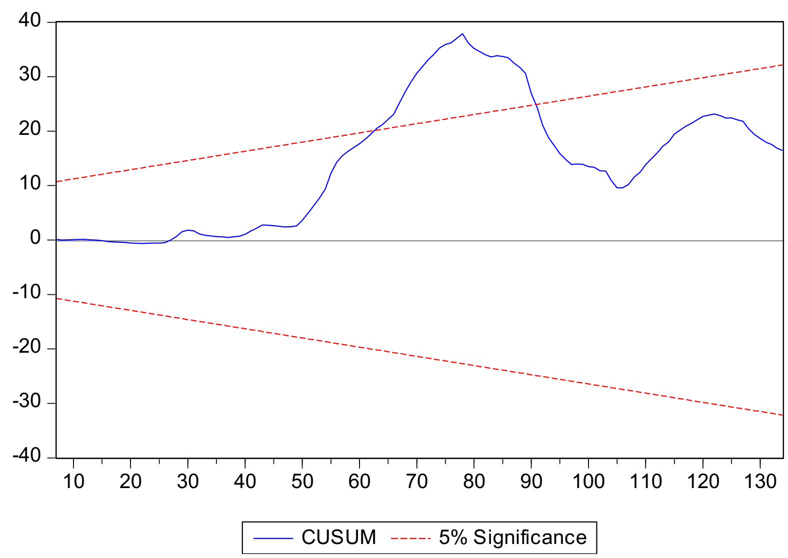

Figure 3.29: Cusum plot of Per Capita Volume Index
Source: Own.

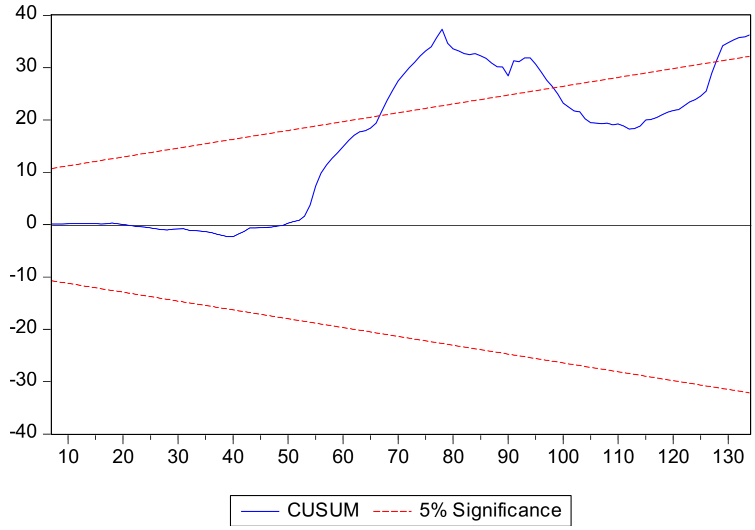

Figure 3.30: Cusum Plot of Per Capita Value Index

Source: Own.

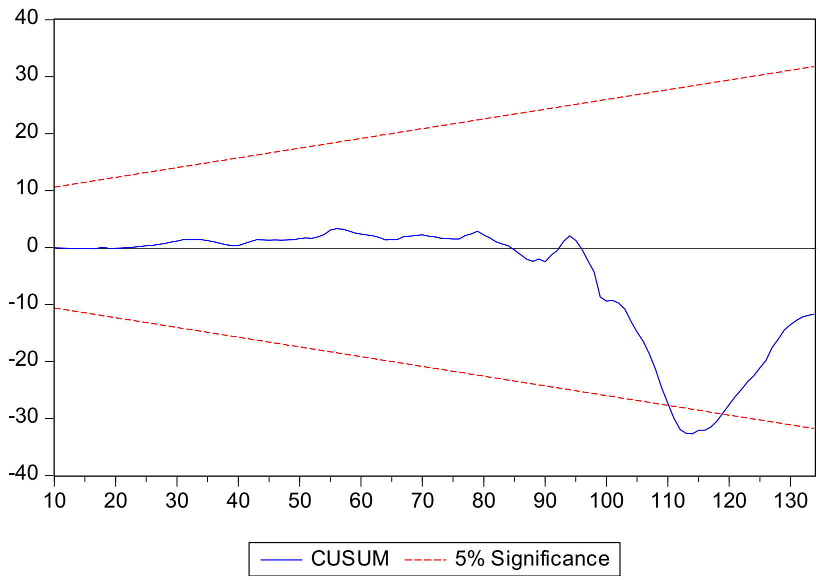

Figure 31: Cusum Plot of Value/ GDP Index

Source: Own

The following Table 3.8 summarizes the results[8].

	Impact of event: Nature of structural break		
Index	**After PMJDY**	**After Demonetization**	**After Pandemic**
Per capita volume index	Has started to increase rapidly but no structural break	Has Positive structural break,	Has Negative structural break
Per capita value index	Has started to increase rapidly but no structural break	Has Positive structural break	Has Positive structural break
Value-GDP index	Has No structural break	Has no structural break	Has temporary negative structural break

Table 3.8: Summary Table of the Indexes based on Structural Break Analysis
Source: Own

[8] The graphical plot of all the three indexes indicates an increase in the indices following the implementation of PMJDY. However, this increment was not substantial enough to create structural breaks in the data, especially when compared to the significant surges observed during the demonetization and COVID-19 periods. One key reason for this could be the relatively lower level of financial literacy in 2014, which may have limited the immediate impact of PMJDY on cashless transactions despite the increase in account penetration and secondly this was an indirect policy intervention not direct to increase the cashless transaction usage, but the main objective was to penetrate the access of cashless transaction into the economy.

In future, we could do further studies by including the UPI transactions in our analysis if more data will be available. The dimensions where demonetization has no impact are No. of Cards per 1000 Adults, Per Capita volume of NEFT, value of NEFT/ GDP, Per Capita Value of RTGS, value of RTGS/ GDP, value of ECS+NACH/ GDP.

The dimensions where only Covid-19 pandemic has positive impact are per capita volume as well as value of IMPS, Value of IMPS/ GDP, per capita volume of NEFT and per capita volume of RTGS. The impact of the Covid-19 pandemic on digital payment systems in India can be explained through changes in consumer behavior, economic activity, and policy interventions during the crisis. IMPS (Immediate Payment Service) is a real-time, instant fund transfer system that gained traction during the pandemic as people increasingly relied on digital transactions due to mobility restrictions and health concerns. The surge in online purchases and peer-to-peer (P2P) transfers contributed to higher per capita IMPS transactions. Government relief measures, such as direct benefit transfers (DBT) and financial aid, often utilized IMPS, further increasing its usage. NEFT (National Electronic Funds Transfer) and RTGS (Real-Time Gross Settlement) saw increased transaction volumes per capita as businesses and individuals moved away from cash and check-based transactions. Many businesses adopted digital payment modes for salaries, vendor payments, and utility bills, boosting these electronic fund transfer systems. Work-from-home policies led to greater use of digital banking services, further elevating transaction volumes.

The dimensions where Covid-19 pandemic has negative impact are No. of Cards/ 1000 Adults, all three measures of POS transactions, per capita value of NEFT, Value of NEFT/ GDP, per capita value of RTGS and Value of RTGS/ GDP. The decline in card issuance could be attributed to reduced consumer demand for credit due to economic uncertainty, job losses, and lower discretionary spending. Banks may have tightened credit card issuance policies due to heightened financial risks. POS transactions, which mainly involve in-store card payments, declined due to lockdowns, restrictions on physical shopping, and the closure of non-essential retail businesses. Consumers shifted towards e-commerce and online payment modes, reducing the reliance on POS transactions. The preference for contactless payments through UPI and QR codes further reduced the necessity of POS-based card transactions. While the volume of NEFT and RTGS transactions per capita increased, their overall value declined due to the economic slowdown. Business activities were disrupted, reducing high-value corporate transactions, which form a significant share of RTGS and NEFT payments. Lower investment and trade activities led to a decline in large-value interbank and business transactions, impacting the total transaction value. GDP contraction during the pandemic further contributed to the decline in these indicators when measured relative to economic output.

The trends of the indices as well as the individual dimensions establish that the cashless transaction of the Indian economy was already growing at a fast pace especially after the demonetization period. The individual dimension analysis as well as all three-index analysis suggests that in case of Per capita Volume index, the per capita volume of individual dimensions that have declined after Covid-19 outbreak, had more impact on the index than the per capita volume of individual dimensions that have increased after Covid-19 pandemic. Same in the case of Value/ GDP index. But in case of per capita value index, the dimensions that have positive impact after Covid-19 outbreak out way the negative impacts of some individual dimensions not right after the outbreak of Covid-19 but near the start of 2023.

4.1. Introduction:

RBI report[9] (2019) states that "Digital Transaction means a payment transaction in a seamless system effected without the need for cash at least in one of the two legs, if not in both." This includes transactions made through digital / electronic modes wherein both the originator and the beneficiary use digital / electronic medium to send or receive money".

In building the theoretical model, the focus on income and education level as key factors is driven by the need for simplification and analytical clarity. Income and education level are particularly significant because they directly affect an individual's access to and familiarity with digital technologies, financial tools, and banking systems (based on the empirical study mentioned below), which are critical for cashless transactions. Higher income often could correlates with greater affordability of digital devices and internet services, while higher education levels could tend to enhance digital literacy and awareness of financial innovations. While other variables such as age, gender, employment status, or place of residence (urban or rural) could influence the adoption of cashless payment modes which we incorporated in the empirical analysis in the 5th chapter following the theoretical model, other important variables are considered as constant or controlled for in the theoretical model. In the Indian context the report by National Payment Corporation of India (2020) studied the awareness, adoption and use of digital payment methods of households of India. The analysis is based on primary survey of 35000 households for the year of 2016. The key findings are, one third of Indian households are using it in some form or the other. It is heartening to note that almost a quarter of the households in the bottom 40% income group are using it as well and it has not remained rich or well-educated persons' precinct. 15%

[9] The report of the 'The High-level Committee on Deepening of Digital Payments' (2019)

households in bottom and middle category would like to adopt digital payments. Online banking is less well developed than payments, but has potential. Finally, the Direct Benefit Transfer system has worked very well and even better during lockdown. The paper emphasizes on the importance of education and income on the acceptance of cashless transaction, this study motivates us to incorporate the effects of socio economic conditions (especially education and income) as one of the objective of our research which we incorporated in this chapter and in the following chapter. As education and income is correlated with employment type and residence place so incorporating these two socio economic variables would be interesting as it could have policy implication. By isolating these two variables income and education, the model aims to specifically evaluate their impact without the confounding effects of other factors, thus providing a focused and manageable framework for analysis. This theoretical approach with income and education is not intended to diminish the importance of other variables but rather to ensure a clear understanding of the direct relationship between income, education, and the adoption of cashless payment modes.

The transaction cost of a certain amount of money depends on the type of transaction mode. For instance, the transaction cost of a cash transaction could vary from the transaction cost of a debit card or credit card transaction. Analysing the transaction costs associated with the particular mode of payment, the optimum type of transaction could be possible to identify, which ensures the fuller utilisation of resources. Now the question is, what are the factors which might have some influence over the total transaction cost associated with a particular type of payment mode? The motivation for the present chapter lies in identifying the differences in the transaction costs across individuals with different levels of income and education. For instance, individuals with lower incomes, the gain in interest by keeping income in a bank account might be outweighed by the annual charge of maintaining a debit card. Individuals with lower incomes may find that the fixed costs associated with maintaining a debit card—such as annual maintenance fees, minimum balance requirements, and possible penalties—are a significant burden relative to their financial resources. In contrast, high-income individuals may not be as sensitive to these fixed costs since they form a smaller proportion of their total income. While it is true that the interest earned from a savings account could outweigh the maintenance charge irrespective of income level, if income is distributed across many accounts. The impact on liquidity and immediate spending power is more pronounced for lower-income individuals. Therefore, lower-income individuals may avoid debit cards to minimize financial constraints, while high-income individuals may prioritize convenience over cost. Additionally, the skill required for executing digital payments is closely related to the level of education. Individuals with lower education levels may find it challenging to complete cashless transactions, as the potential for technical faults is higher, which may create a psychological barrier. In this chapter, our goal is to establish a theoretical relationship between an individual's choice of payment medium—cash or cashless—and its determinants mainly education & income. The chapter aims to establish, theoretically, the influence of education and income on the selection of transaction modes.

While existing literature discussed in chapter 2 has studied the relationship between education, age, and income with cashless transactions, many of these studies are limited to specific regions or states based on empirical data. While existing studies explore various aspects of payment systems and some socio economic conditions, mostly concerned with other issues like pricing of the cards, efficiency in card use etc. So we are trying to addressing an issue that has not been addressed before: namely the effect of interaction between education and income in adopting the cashless transaction. There is a gap in literature regarding the interaction issues between income and education, and the selection of payment modes. In this chapter, we attempt to fill this gap by mistakes associated with the transaction with debit card at the shop floor. This we name shop floor cost. Shop floor costs can vary depending on the mode of payment (such as between cash or debit card transactions). These differences arise from factors like remembering PINs, the fear of technical faults associated with debit card transactions, and the time loss and handling costs involved in cash transactions. The extent of these costs depends on the level of education and the amount of money transacted. A higher level of education may reduce the fear of technical faults in debit card usage. Conversely, while increased education can lower the time loss and handling costs of cash transactions, these costs tend to rise as the transaction amount increases.

Let $\emptyset$ **denote** the coefficient of inconvenience cost. As the representative individual withdraws c amount $\boldsymbol{f}$ times. So total inconvenience due cost will be $\emptyset \boldsymbol{c}.\boldsymbol{f}$, which we can write as $\emptyset \boldsymbol{Y}$ (by putting the value of $\boldsymbol{f}$ as $\frac{\boldsymbol{Y}}{\boldsymbol{C}}$**,** as the consumer spend all of his **Y** income by spending **C** amount each time over the period). Where **Y** is the total income of the buyer and buyer will spend his entire income over that period. So, here we consider inconvenience cost is an increasing function of income. The other component of the first type of cost is the banking cost of withdrawing money from the bank account, which is denoted as **b**, as we assume that buyer will get his entire income for that period in his bank account at the beginning of that period. This banking cost includes transportation cost as well as time loss and all other cost associated with withdrawing money from bank account and which is constant each time.

The second type of transaction cost of cash transaction at the shop floor is closely associated with the level of education. For zero level of education this cost is $\boldsymbol{\tau_R}$. This shop floor cost for each unit of money will reduced at the rate; $\mathbf{e_R}$ with the increase in level of education. In other words, $\mathbf{e_R}$ is

$$TC_B = \begin{cases} (\tau_R - e_R E)Y + \emptyset Y + \{y.i - g.Y\} + b.f & for\ E \le E_R \\ \overline{\tau_R}.Y + \emptyset Y + \{y.i - g.Y\} + b.f & for\ E > E_R \end{cases} \qquad \text{..........(4.ii)}$$

Now if he pays for goods and services each time with debit card every time directly, then the transaction costs are as follows:

τ_D is the shop floor cost per unit of money transacted using debit card transaction this cost includes time loss, the fear of technical fault[10] and fear of making mistakes associated with the debit card transaction at the shop floor. Total shop floor cost of debit card transaction will increase with the increase in the amount of money transacted each time. This could be a physiological cost or could be an actual cost if some mistakes could happen in real. This is the cost of fear of sending money to wrong account no. which will increase if the amount of transaction is much higher compare to the cost of fear in case of very little amount of transaction, this cost associated with handling a debit card transaction. This shop floor cost per unit of money also could reduce with the increase in the level of education because education affects an individual's **familiarity with technology**, **problem-solving skills**, and **confidence in handling unexpected issues**. Let's break this down in detail with examples: People with lower education levels often rely on others to help them with technical processes. This dependency increases handling costs, as the transaction requires additional time or external assistance. Education enhances cognitive abilities and problem-solving skills, which are crucial for resolving technical faults in debit card transactions. For less-educated individuals, encountering an error like "transaction declined" or "network error" may result in greater confusion and time loss as they struggle to identify the cause or solution. Higher education often correlates with greater confidence in handling errors or faults during a transaction. Conversely, lower education levels may amplify the psychological barrier, causing fear of

[10] cost of technical fault means if money will go to a different account due to mistake in typing the wrong account no. and so on or any type of technical miss lead.

"breaking the system" or making irreversible mistakes, even if the issue is minor. The effect of increase in the level of education in the reduction of shop floor cost could be divided into three stages, first when the level of education less than $\boldsymbol{E_{D1}}$ level, second when the level of education more than $\boldsymbol{E_{D1}}$ level but less than $\boldsymbol{E_{D2}}$ level and lastly when level of education more than $\boldsymbol{E_{D2}}$ level**.** Initially when level of education is less than $\boldsymbol{E_{D1}}$ then the marginal effect of education on the reduction of shop floor cost is $\boldsymbol{e_{D1}}$, which is less than the marginal effect of education on the reduction of shop floor cost when the level of education is more than $\boldsymbol{E_{D1}}$ but less than $\boldsymbol{E_{D2}}$ (marginal effect denoted as e_{D2}). This is because people in this group may not be well-versed in managing transactions. For example, while a class 3 student might be able to perform basic tasks like addition or counting, managing debit card transactions such as balance inquiries, remembering PINs, reading transaction messages, or maintaining account details is comparatively more challenging. This complexity often leads to errors, longer transaction times, and higher operational costs, making cash transactions simpler for them. When the education level surpasses $\boldsymbol{E_{D1}}$ but remains below $\boldsymbol{E_{D2}}$, individuals exhibit significant improvements in financial and technological literacy. The marginal effect of education, $\boldsymbol{e_{D2}}$, is higher at this stage compared to $\boldsymbol{e_{D1}}$, as individuals can perform debit card transactions more efficiently. This efficiency reduces transaction times, minimizes errors, and thus further lowers shop floor costs. The enhanced understanding of technology and financial systems allows this group to contribute more effectively to cost reduction. Lastly when level of education is more than $\boldsymbol{E_{D2}}$ then the shop floor cost will be lowest because after availing a certain level of education buyer can handle debit card transaction efficiently. **So, here** $\boldsymbol{e_{D1}}$, $\boldsymbol{e_{D2}}$ both are coefficients of education related to debit card transaction for the level of education less than $\boldsymbol{E_{D1}}$ and for the level of education more than $\boldsymbol{E_{D1}}$ but less than $\boldsymbol{E_{D2}}$. where $\mathbf{e_{D1}} < \mathbf{e_{D2}}$. We consider only two stages of education to reduce the complexity of the model, as dividing education into more stages could introduce unnecessary complications in this context.

prevailing empirical research on the relationship between education, age, earnings, and digital transactions in India are often limited to particular regions or states. Moreover, capturing the combined effect of education and earnings is absent in the literature. Our research seeks to address this space by examining the joint effect of level of education and income, along with other socio-economic situations, on the electronic transaction usage, utilizing available secondary data.

By addressing these objectives, this chapter aims to contribute to the existing literature by filling up the gap in our understanding of the relationship between the socio economic background and the adoption of cashless payment modes. Overall, the present research endeavours to shed light on the complex dynamics between education, income, and cashless payment adoption, paving the way for evidence-based policymaking and initiatives that foster financial inclusion and economic development. While this chapter aims to identify the determinants of cashless transactions, it is important to acknowledge that the results presented here indicate associations rather than causation. Due to potential endogeneity concerns, including reverse causality and omitted variable bias, the estimated relationships should be interpreted with caution. Although efforts have been made to minimize these biases, some degree of uncertainty remains.

The chapter is organised as follows: Section 2 discusses the existing literature gap, Section 3 describes the data and methodology employed, section 4 presents the empirical implications of the methodology, and finally, section 5 provides the conclusion.

One of the key limitations of this chapter lies in the time period of the data used for testing the model developed in Chapter 4. The analysis relies on two waves of the India Human Development Survey dataset, from 2004–05 and 2011–12. During this period, digital transactions and credit card usage were not as prevalent in India as they are today. The widespread adoption of digital financial systems, spurred by significant policy shifts and technological advancements after 2014, particularly under the new federal government, has fundamentally transformed the financial landscape. As a result, the findings and policy recommendations based on data over a decade old may not fully capture the dynamics of the current financial system in India. However, this study provides valuable insights into the baseline conditions of India's financial behaviours and system prior to the digital revolution. Despite its limitations, the study makes an important contribution to understanding the evolution of financial behaviours in India and underscores the necessity of adapting policies to a rapidly transforming economic environment.

Another limitation of this study is that credit card ownership is inherently dependent on income and asset thresholds, as financial institutions issue credit cards based on an individual's ability to meet specific income and debt criteria. This means that lower-income individuals or those without stable employment may not qualify for a credit card, regardless of their preference for cashless transactions. Additionally, the decision to own a credit card is not solely influenced by income and education but also by individual risk perceptions. Some individuals, even with high education levels, may avoid credit cards due to concerns about debt accumulation. These factors were not explicitly modelled in the empirical analysis, and their exclusion may impact the interpretation of the findings.

Here significant limitation of this study is the lack of data on computer knowledge and smartphone operation for digital transactions in the 2004-05 wave, which restricts the ability to test the theoretical model across both time periods. Digital literacy cannot be appropriately compared between the two waves, as the necessary data is only available for the 2011-12 wave. Additionally, mobile phone ownership is used as a proxy for digital knowledge and computer access. However, in 2011-12, smartphones were not widely used for digital transactions, and mobile banking apps were still in their infancy. This discrepancy limits the applicability of the dataset for addressing the research question effectively, and this limitation has been acknowledged in the study.

d. Education - In Chapter 4, theoretical analysis suggests that level of education influences the selection of payment modes between cash and cashless transactions. To support that theoretical analysis, it is important to include education variable in this empirical analysis. Here the highest level of adult education in the household is considered, it is denoted as the no. of years of schooling/Education, ranging from 1 to 16 (where 16 denotes education level above graduation)

e. Log Age - Sharma (2011) stated that "In order to make e-Banking more popular, banks must separate their customers based on demographic priority and customize e-Banking services as per their needs and requirements". Younger individuals are more likely to adopt modern technologies, including cashless transactions, compared to the elderly, regardless of income and education levels. Here in our study, the log of the age of the male head of the household is considered to reduce the variability of the data.

f. Economic Class - This data is based on the household's perception of their social class, three categories were considered in the survey: poor, middle, and comfortable. It is important to examine whether the individuals who consider themselves to belong to comfortable class are availing credit cards and doing cashless transactions more than the other two classes, as there is a societal notion that credit cards symbolize luxury.

g. Interaction between Education and Income

Education and income have been **segregated into four categories based on quartiles**:

- **Education Categories**: Very Low Education, Low Education, Mid Education, High Education
- **Income Categories**: Very Low Income, Low Income, Mid Income, High Income

In the case of the **interaction term**, we have performed two separate multiplications:

1. **Each of the four education categories is multiplied with log income separately.**
2. **Log income is also multiplied with each of the four education categories separately.**

These interaction terms capture the combined effect of education and income on the likelihood of owning a credit card. According to the theoretical model in Chapter 4, the effect of income on the usage of cashless transactions depends on the education level of the household, and vice versa. To test this empirically, it is crucial to incorporate this interaction term into the analysis. This allows us to observe whether higher education amplifies or dampens the effect of income on credit card ownership and similarly whether higher income strengthens or weakens the effect of education on adopting cashless transactions.

By combining the dimensions according to the principal component analysis we got the each socio economic indexes.

5.2.2. Detailed Methodology

In the present study, we employed two logistic regression analysis. Two separate logistic regression model are estimated to examine the effects of education and income separately, on the usage of cashless transactions including all data, the points covering the two time periods. Two separate models were estimated to address the problem of multicolinearity between years of education and income level, discussed below. These two models capture the effects of some independent socioeconomic variables (except "Economic class belongs" as this data is not available for the year 2004-05) believed to influence individuals' use of cashless transactions, peroxide by credit card ownership.

Four separate logistic regressions were conducted – two for 2004-05 and another two for 2011-12 – to examine the effects of education and income on the usage of cashless transactions. In Table A5.1 (Appendix), a strong association between education level and household income (correlation coefficient: 0.728) was observed. Furthermore, Table A5.2 highlighted very high Variance Inflation Factor (VIF) values for income and education variables, suggesting potential multicollinearity. To address this, two separate logistic regressions were performed for each time point. In both the equations seven independent variables were included as stated below. The economic logic behind the inclusion of each variable has already been discussed in section 3.1.

In this analysis, we examine the **effect of income on the probability of owning a credit card** separately for **2004-05 and 2011-12**, incorporating a **threshold regression framework**. The regression equation is specified as:

$$\boldsymbol{Log(odds\ of\ owning\ credit\ card)_i = \beta_0 + \beta_1 log\ income_i + \beta_2 Age_i}$$

$$\boldsymbol{+ \beta_3(computer\ knowledge\ and\ access)_i + \beta_4(financial\ inclusion\ status)_i}$$

$$+ \boldsymbol{\beta_5}(\boldsymbol{household\ status})_i + \ \boldsymbol{\beta_6}(\boldsymbol{very\ low\ education} * \ \boldsymbol{log\ income})_i$$

$$+\boldsymbol{\beta_7}(\boldsymbol{low\ education} * \ \boldsymbol{log\ income})_i + \boldsymbol{\beta_8}(\boldsymbol{Mid\ education} * \ \boldsymbol{log\ income})_i$$

$$+\boldsymbol{\beta_9}\boldsymbol{Ecoclass2} + \boldsymbol{\beta_{10}}\boldsymbol{Ecoclass3} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(5.i)}$$

The **coefficients represent the estimated effects** of the independent variables on the **log odds of owning a credit card**. **Exponentiation of these coefficients yields odds ratios**, which indicate the **multiplicative effect on the likelihood of credit card ownership**.

A threshold effect is introduced through the interaction terms between education and income**,** allowing us to examine how the effect of income on credit card ownership varies across different education levels**.** The education variable is categorized into four groups based on endogenous threshold regression **:**

- Very Low Education
- Low Education
- Mid Education
- High Education

To capture the interaction effect, we introduce threshold interactions by multiplying each education category with log income separately**.** This allows us to assess whether there exists a threshold income level beyond which the effect of education becomes more significant in predicting credit card ownership.

The significance of the interaction term between education and income lies in capturing their joint effect on the log of odds of credit card ownership. In other words, the marginal effect of income on credit card ownership depends on the highest education level attained within a household**.**

From the **theoretical model in Chapter 4**, we expect that:

- For households with similar income levels, those with higher education levels are more likely to own a credit card than those with lower education levels.
- The overall effect of a change in income on the log odds of owning a credit card is given by:

$$\boldsymbol{\beta_1 + \beta_6(very\ low\ education * \ log\ income)_i + \beta_7(low\ education * \ log\ income)_i + \beta_8(Mid\ education * \ log\ income)_i}$$

- The effect of **income when education is at the higher threshold (above graduation level of education)** is captured **solely by $\boldsymbol{\beta_1}$**

Thus**,** threshold regression allows us to determine whether the relationship between income and credit card ownership is education level depended or not**.** If a threshold is present, this suggests that income effects are stronger or weaker depending on whether a household's education level surpasses a specific threshold**,** reinforcing the importance of financial literacy in promoting cashless transactions.

In the second regression, the effect of education on the probability of owning a credit card was analysed, including an interaction term between education and income. The regression equation is:

$$\boldsymbol{Log(odds\ of\ owning\ credit\ card)_i = \beta_0 + \beta_1 Education_i + \beta_2 Age_i}$$

$$\boldsymbol{+ \beta_3(computer\ knowledge\ and\ access)_i + \beta_4(financial\ inclusion\ parameter)_i}$$

$$\boldsymbol{+ \beta_5(household\ status)_i + \beta_6(very\ low\ income * education)_i}$$

$$\boldsymbol{+\beta_7(low\ income * education)_i + \beta_8(Mid\ income * education)_i}$$

$$\boldsymbol{+\beta_9 Ecoclass2 + \beta_{10} Ecoclass3} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ \textbf{(5.ii)}$$

As established in Chapter 4’s theoretical analysis, the effect of education on the selection of cashless payment modes depends on the household’s income level. To empirically validate this relationship, we incorporate an interaction term between education and income in the regression equation.

Income is divided into four quartiles to account for potential threshold effects:

- **Income Categories**: Very Low, Low, Mid, High

To **capture the interaction effect**, we multiply education with different income categories, allowing us to examine **whether education influences credit card ownership differently across income groups**.

The **overall effect of education on the log odds of owning a credit card** is given by:

$$\boldsymbol{\beta_1 + \beta_6(very\ low\ income * education)_i}$$

$$\boldsymbol{+\beta_7(low\ income * education)_i + \beta_8(Mid\ income * education)_i}$$

This formulation ensures that the impact of education on credit card ownership is not uniform but rather depends on the income threshold of the household. The interaction term captures the extent to which higher income strengthens or weakens the effect of education on credit card ownership**.**

This separate regression enables us to examine the independent effects of education and income. Explore their interaction effect to identify possible threshold effects. Account for the influence of other socio-economic variables on credit card ownership.

The model was estimated using **STATA**, and its validity was tested using the Hosmer-Lemeshow goodness-of-fit test**,** confirming the model's robustness.

5.2. Results:

In the present section we report the regression results. We start with providing an empirical justification behind using ownership of credit card as a proxy for usage of cashless transaction in section 4.1. Section 4.2 reports the results of logistic regression.

5.3.1. Justification behind Credit Card Ownership as a Proxy for the Usage of Cashless Transaction:

As has already been mentioned, non-availability of household level data on usage of cashless transaction was a major hurdle in our attempt to validate the theoretical results we developed in chapter 4. However, data on credit card ownership was available from India Human Development Survey datasets, we consider both 1st and 2nd round of the survey for the year 2004-05 and 2011-12. So we used this variable as a proxy for usage of cashless transaction. The present section provides empirical support to the use of this proxy.

Credit card ownership can be a useful proxy for the use of cashless transactions for several reasons: First Credit cards are a form of electronic payment, and their ownership indicates that individuals have access to a payment instrument that does not rely on physical cash. When people own credit cards, they have the means to make other types of electronic transactions as well. Secondly, Reserve Bank of India provides extensive data on credit card use as well as the usage of other types of cashless transactions. If we can establish a statistically significant positive relationship between the credit card ownership and the value and volume index of the cashless transaction (constructed in the 3rd chapter of this thesis) overtime, this could be used as sufficient justification for using credit card ownership as a proper proxy of the usage of cashless transactions. For our analysis, we conducted a correlation coefficient test between the No. of Credit Cards Outstanding and usage of different types of cashless transactions (Monthly data from 2012-2021 provided by RBI) Table 5.2 shows a strong correlation between the no. of credit cards outstanding and usage of different types of cashless transactions (except with the value of RTGS).

	No of outstanding Credit cards
No of outstanding Credit cards	**1**
POS amount	**0.931639049**
NEFT NO.	**0.95818575**
NEFT amount	**0.929964545**
RTGS volume	**0.888565739**
RTGS Value	**0.163257681**
Mobile Banking Volume	**0.853829856**
Mobile Banking Value	**0.902603686**
ECS+NACH Volume	**0.748324897**
ECS+NACH Value	**0.969851559**
IMPS Volume	**0.969109083**
IMPS Value	**0.978358218**

Table 5.2: Correlation between Different Types of Cashless Transactions and No. of Credit Card Outstanding
Source: Own.

For the justification of proxy we also regressed the number of credit cards outstanding, obtained from monthly data across various banks, on the value and volume index of cashless transactions developed in chapter 3.

In chapter 3, we constructed three different indices, which aggregated the overall value and volume of the cashless transaction of the Indian economy over the period of time (from November 2012 to December 2018), those indices are Per Capita Number of Cashless Transaction Index, Per Capita Value of the Cashless Transaction Index and Value of Cashless Transaction as a Proportion of GDP Index.

We have regressed number of credit card outstanding on all the three indexes separately to avoid the multicollinearity problem.

In the first case we regressed the number of credit card outstanding on the per capita volume index, the regression equation is;

$$\boldsymbol{(CC)_t = \alpha + \beta(PCVo)_t + \epsilon_t} \text{………………….. } \textbf{(5.iii)}$$

Where $(CC)_t$ is the credit card outstanding over the months including all the banks in India and $(PCVo)_t$ denotes per capita volume index of cashless transaction of Indian economy over the months (all data points are from September 2012 to December 2023).

Variable	Coefficient	p-Value
PER CAPITA VOLUME INDEX	1.056965	0.0000
Constant (C)	0.173896	0.0000

R-squared	0.8892
Adjusted R-squared	0.8884
Standard Error of Regression	0.1049
Mean of Dependent Variable	0.6196

Table 5.3: Summary Output Table No. of credit card outstanding regressed on Per Capita No. of Cashless Transaction Index

Table 5.3 describes the summary output of the regression equation (5.iii), it reveals that there is a statistically significant (1% level of significance) positive relationship between the number of credit card outstanding and the per capita volume index.

Also, we regress no. of credit card outstanding on the per capita value index and also separately on the value GDP index. The regression equations are;

$(\boldsymbol{CC})_t = \boldsymbol{\alpha} + \boldsymbol{\beta}(\boldsymbol{PCVa})_t + \boldsymbol{\epsilon_t}$**………………… (5.iv) And**

$(\boldsymbol{CC})_t = \boldsymbol{\alpha} + \boldsymbol{\beta}(\boldsymbol{VGDP})_t + \boldsymbol{\epsilon_t}$**………………….. (5.v)**

Where $(CC)_t$ is the credit card outstanding over the months including all the banks in India and $(PCV)_t$ denotes per capita value index of the cashless transaction of Indian economy over the months and $(VGDP)_t$ denotes the value-GDP index of Indian economy over the months (both from September 2012 to December 2023).

Variable	Coefficient	p-Value
PER CAPITA VALUE INDEX	1.024654	0.0000
Constant (C)	0.271908	0.0000

R-squared	0.7435
Adjusted R-squared	0.7415
Standard Error of Regression	0.1597
Mean of Dependent Variable	0.6196

Table 5.4: Summary Output Table of No. of credit card outstanding regressed on Per Capita Value of Cashless Transaction Index

Table 5.4 also reveals significantly positive relationship between the number of credit card outstanding and the per capita value of the cashless transaction.

Variable	Coefficient	p-Value
VALUE_GDP_INDEX	1.266806	0.0000
Constant (C)	0.152676	0.0000

R-squared	0.8416
Adjusted R-squared	0.8404
Standard Error of Regression	0.1255
Mean of Dependent Variable	0.6196

Table 5.5: Summary Output Table of No. of credit card outstanding regressed on Value of Cashless Transaction as a Proportion of GDP Index

Table 5.5 also reveals a significantly positive relationship between the total number of credit card outstanding and the value of the cashless transaction as a proportion of GDP index. This significant relationship justified the use of the ownership of credit card as a proxy for the usage of the cashless transaction.

5.3.2. Results of logistic regression

In this section we present the analysis of logistic regression for the years 2011-12 and 2004-05. The logistic regression results reported in Table 5.6 reveals the estimated marginal effect for each predictor variable in the model respectively for the year 2011-12. These marginal effects allow us to interpret the impact of each predictor on the probability of the event "owning credit card" occurring.

Dependent Variable: Probability of Holding a Credit Card (cards12)

Variable	Odds Ratio	p-Value (OR)	Marginal Effect (dy/dx)	p-Value (ME)
Income (log)	1.5647	0.000	0.0125	0.000
Age (years)	0.0067	0.027	-0.0002	0.027
Computer Knowledge	6.7053	0.000	0.0531	0.000
Household Status	1.6119	0.065	0.0133	0.065
Financial Inclusion	7.1994	0.000	0.0551	0.000
Economic Class 2	2.0695	0.000	0.0203	0.000
Economic Class 3	4.3919	0.000	0.0413	0.000
Income * Education Very Low	1.0490	0.169	0.0013	0.169
Income * Education Low	0.8815	0.000	-0.0035	0.000
Income * Education Middle	0.8673	0.000	-0.0040	0.000
Constant	0.0004	0.000	-	-

Table 5.6: Logistic Regression 1 Result for the Year 2011-12

This table presents the results of a **logistic regression model**, where the dependent variable is likely a binary outcome (e.g., financial participation, financial literacy, or inclusion). The interpretation focuses on **odds ratios (OR)** and **marginal effects (ME)**, with particular emphasis on the interaction terms involving income and education levels.

Income (log): A 1% increase in income increases the odds of the outcome by **1.5647 times**. The effect is significant (*p-value = 0.000*). The marginal effect suggests a **positive incremental effect (0.0125)** on the probability of the outcome.

Age: Older individuals are **unlikely** to experience the outcome (*OR = 1.0067, p = 0.027*), but the effect is **small (dy/dx = 0.0002)**.

Computer Knowledge: Individuals with more computer knowledge are much more likely to achieve the outcome, as indicated by a strong odds ratio (*OR = 6.7053, p = 0.000*) and a notable marginal effect (*dy/dx = 0.0531*).

Household Status: This variable has a positive but **moderately significant effect** (*OR = 1.6119, p = 0.065*), meaning that individuals in a particular household category (e.g., household head) are **more likely** to experience the outcome.

Financial Inclusion: It has a very strong positive effect (*OR = 7.1994, p = 0.000*), showing that those with financial inclusion have much higher odds of achieving the outcome.

Economic Class (compared to the base category, the poor class):

- **Class 2 (Middle Class)**: Higher odds (*OR = 2.0695, p = 0.000*), meaning that moving to this class **doubles** the probability of the outcome.

- **Class 3 (Higher Class)**: Even stronger impact (*OR = 4.3919, p = 0.000*), meaning individuals in this class are **more than four times as likely** to experience the outcome compared to the base category.

Interaction Terms (Income × Education Levels): These represent **slope dummies**, modifying the effect of income across different education levels (compared to the base: **High Education**).

- **Income × Education Very Low** (*OR = 1.0490, p = 0.169*): The interaction term is **not significant**, meaning that for individuals with very low education, the effect of income **does not significantly differ** from those with high education.
- **Income × Education Low** (*OR = 0.8815, p = 0.000*): The negative effect (*OR < 1, dy/dx = -0.0035*) suggests that for individuals with low education, **the positive effect of income is weaker** compared to those with high education.
- **Income × Education Middle** (*OR = 0.8673, p = 0.000*): Similar to the low education group, individuals in the middle education category also experience **a reduced impact of income** (*dy/dx = -0.0040*).

Overall Income positively influences the outcome, but **its effect weakens as education level decreases** (seen in the interaction terms with negative coefficients for low and middle education). Financial knowledge and financial inclusion have **the strongest impact** on the outcome. **Higher economic class status significantly increases the likelihood** of achieving the outcome. **Household status and age play moderate roles**, while education level moderates the effect of income.

Variable	Odds Ratio	p-Value (OR)	Marginal Effect (dy/dx)	p-Value (ME)

Education	1.0507	0.001	0.001384	0.001
Age	0.0076	0.013	-0.000211	0.013
Computer Knowledge	7.3525	0.000	0.055801	0.000
Household Status	1.7208	0.036	0.015182	0.037
Financial Inclusion	7.2344	0.000	0.055348	0.000
Economic Class 2	2.0665	0.000	0.020302	0.000
Economic Class 3	4.6042	0.000	0.042709	0.000
Very Low Income & Education	1.0046	0.675	0.000129	0.675
Low Income & Education	0.9427	0.000	-0.001651	0.000
Mid Income & Education	0.9578	0.000	-0.001206	0.000
Constant	0.0017	0.000	-	-

Table 5.7: Logistic Regression 2 Result for the Year 2011-12

This logistic regression model examines the factors influencing a particular outcome, where the dependent variable is likely a binary choice (e.g., financial inclusion, digital adoption, or economic participation). Below is an interpretation of the key findings:

Interaction Terms (Income & Education Groups Compared to the Base: High Income & Education)

These slope dummy variables assess how income and education jointly influence the outcome:

- **Very Low Income & Education** (*OR = 1.0046, p = 0.675*): This term is statistically insignificant, indicating that there is no effect of education when level of income is very low.
- **Low Income & Education** (*OR = 0.9427, p = 0.000*): **Negative effect** (*OR < 1, dy/dx = -0.001651*). This suggests that individuals with low income, the effect of education will decrease compared to the base group (high income).
- **Mid Income & Education** (*OR = 0.9578, p = 0.000*): Also **negatively affects** the probability (*dy/dx = -0.001206*) compare to the base group “High income”, though the effect is weaker than the "Low" group.

Education variable represents the effect of education with high level of income (base line category for slope dummy) Odds Ratio (OR) 1.0507, p value 0.001 implies, each additional unit of education (e.g., years of schooling or level attained) increases the odds of achieving the outcome by **5.07%**. The marginal effect (*dy/dx = 0.001384*) indicates a significant increase in probability.

As income level decreases, the likelihood of achieving the outcome with the increase in education declines. The effect is strongest for the low-income & low-education group, reinforcing the importance of education & income in shaping economic opportunities.

Age

Odds ratio of 0.0076, with p value 0.013**.** Age has a small but significant negative effect each additional year slightly decreases the likelihood of achieving the outcome.

Computer Knowledge

Odds ratio of 7.3525, with p-value 0.000. Individuals with computer knowledge are **7.35 times more likely** to achieve the outcome compared to those without it. The marginal effect (*dy/dx = 0.055801*) suggests a strong positive impact on the probability.

Household Status

OR = 1.7208, p = 0.036. Household status (e.g., being the household head or a primary income earner) is associated with **a higher probability** of achieving the outcome. The marginal effect (*dy/dx = 0.015182*) confirms the **moderate significance** of this variable.

Financial Inclusion

OR = 7.2344, p = 0.000. Individuals who are financially included (e.g., have a bank account, access to credit, or financial services) are **over seven times more likely** to achieve the outcome. The marginal effect (*dy/dx = 0.055348*) indicates **a strong contribution** to the probability.

Economic Class Effects (Compared to the Base Category, the poor Class)

- **Class 2** (*OR = 2.0665, p = 0.000*): Individuals in this category **are twice as likely** to achieve the outcome.
- **Class 3** (*OR = 4.6042, p = 0.000*): Being in this class **significantly increases the odds (by over 4.6 times)**, indicating a strong economic advantage.
- Both economic classes have significant positive **marginal effects** on the probability.
- Constant Term has **Odds ratio = 0.0017, p = 0.000**, This suggests that, holding all variables constant, the baseline probability with poor class of achieving the outcome is **very low**, emphasizing the importance of the included explanatory variables.

Overall Education, financial inclusion, and computer knowledge are critical drivers of the outcome. Higher economic class significantly improves the likelihood of achieving the outcome. Household status and age have moderate positive effects but are not as influential as financial or technological factors. Lower-income & lower-education groups face significant disadvantages, reinforcing the need for policies that improve financial access, digital literacy, and education opportunities for these groups.

Table A5.11 and A5.12 in the appendix represents the Hosmer-Lemeshow test results corresponding to the logistic regression test 1 and 2 respectively.

The Hosmer-Lemeshow tests suggest that there is no significant evidence to conclude that the logistic regression models provides a poor fit to the data.

The logistic regression results for the year 2004-05 are included in the appendix section. As all the socio economic coefficients are statistically insignificant in the year 2004-05. This could be the result of lack of awareness about the digital transaction literacy in the year of 2004-05.

Variables	edu12	age12	comkno12	logincome	fininclu12	hhstatus12	eduincome
edu12	1.0000						
age12	0.0740*	1.0000					
comkno12	0.4440*	0.0520*	1.0000				
logincome	0.7289*	0.1244*	0.4130*	1.0000			
fininclu12	0.2391*	0.1068*	0.2668*	0.2499*	1.0000		
hhstatus12	0.3752*	0.0921*	0.3980*	0.3808*	0.1971*	1.0000	
eduincome	0.6528*	0.1051*	0.4718*	0.5437*	0.2643*	0.4042*	1.0000

Table A5.1: Correlation coefficient Test Result
Source: Own

Variable	VIF	1/VIF
eduincome	123.36	0.0081
edu12	78.80	0.0127
logincome	9.67	0.1035
comkno12	1.45	0.6888
ecoclass2	1.39	0.7208
hhstatus12	1.36	0.7351
ecoclass3	1.29	0.7752
fininclu12	1.14	0.8768
age12	1.05	0.9519
Mean VIF	24.39	-

Table A 5.2: VIF Test for Multicollinearity
Source: Own

Group	Mean Probability	Observed 1s	Expected 1s	Observed 0s	Expected 0s	Total Observations
1	0.0016	2	2.7	2520	2519.3	2522
2	0.0029	5	5.5	2516	2515.5	2521
3	0.0047	11	9.4	2510	2511.6	2521
4	0.0075	20	15.1	2502	2506.9	2522
5	0.0117	23	23.9	2498	2497.1	2521
6	0.0181	46	37.0	2475	2484.0	2521
7	0.0275	50	56.7	2472	2465.3	2522
8	0.0432	80	87.7	2441	2433.3	2521
9	0.0735	141	143.6	2380	2377.4	2521
10	0.4930	329	325.4	2192	2195.6	2521

- **Number of Observations** = 25,213
- **Number of Groups** = 10
- **Hosmer-Lemeshow χ^2 (8)** = 6.00
- **p-Value** = 0.6469

Table A5.3: Hosmer Lemeshow Test Result for logistic Regression 1 for 2011-12
Source: Own

Group	Mean Probability	Observed 1s	Expected 1s	Observed 0s	Expected 0s	Total Observations
1	0.0020	2	3.9	2520	2518.1	2522

2	0.0032	5	6.6	2516	2514.4	2521
3	0.0050	11	10.2	2510	2510.8	2521
4	0.0074	17	15.3	2505	2506.7	2522
5	0.0111	28	22.9	2493	2498.1	2521
6	0.0166	35	34.6	2486	2486.4	2521
7	0.0253	53	51.9	2469	2470.1	2522
8	0.0401	90	80.4	2431	2440.6	2521
9	0.0731	125	136.3	2396	2384.7	2521
10	0.5740	341	344.9	2180	2176.1	2521

- **Number of Observations** = 25,213
- **Number of Groups** = 10
- **Hosmer-Lemeshow χ^2 (8)** = 5.00
- **p-Value** = 0.7581

Table A5.4: Hosmer Lemeshow Test Result for logistic Regression 2 for 2011-12

Variable	Odds Ratio	P-Value	Marginal Effect	P-Value
edu05	**0.999**	**0.958**	**-0.00002**	**0.958**
age05	**1.004**	**0.432**	**0.00006**	**0.433**
comkno05	**1.237**	**0.728**	**0.00332**	**0.728**
fininclu05	**1.043**	**0.885**	**0.00065**	**0.885**
hhstatus05	**1.033**	**0.642**	**0.00050**	**0.642**
Edu*very low income	**1.007**	**0.742**	**0.00011**	**0.742**
Edu*low income	**1.169**	**0.084**	**0.00244**	**0.085**
Edu*mid income	**0.834**	**0.072**	**-0.00283**	**0.074**

Table A 5.5: Logistic Regression 1 for 2004-05 Reporting Odds Ratio (To Capture The Effect of Education)

Group	Mean Predicted Probability	Observed Events (1)	Expected Events (1)	Observed Non-Events (0)	Expected Non-Events (0)	Total Observations
1	0.0146	24	22.5	1,559	1,560.5	1,583
2	0.0149	25	23.3	1,557	1,558.7	1,582
3	0.0152	26	23.9	1,556	1,558.1	1,582
4	0.0155	29	24.3	1,553	1,557.7	1,582
5	0.0158	20	24.7	1,562	1,557.3	1,582
6	0.0160	20	25.1	1,562	1,556.9	1,582
7	0.0163	18	25.6	1,564	1,556.4	1,582
8	0.0167	33	26.1	1,549	1,555.9	1,582
9	0.0173	22	26.9	1,560	1,555.1	1,582
10	0.0224	34	28.5	1,548	1,553.5	1,582

Test Summary

- **Number of observations: 15,821**
- **Number of groups (deciles): 10**
- **Hosmer–Lemeshow χ² (df = 8): 9.40**
- **p-value: 0.3096**

Table A5.6: Hosmer Lemeshowof Logistic Regression 1 for 2004-05

Variable	Odds Ratio	P-Value	Marginal Effect	P-Value
logincome	0.894	0.541	-0.00174	0.541
age05	1.004	0.428	0.00006	0.429
comkno05	1.259	0.703	0.00359	0.703
fininclu05	1.096	0.757	0.00143	0.757
hhstatus05	1.045	0.538	0.00068	0.539
Edu*very low income	1.004	0.759	0.00006	0.759
Edu*low income	1.170	0.077	0.00245	0.078
Edu*mid income	0.836	0.071	-0.00280	0.073

Table A 5.7: Logistic Regression To Capture The Effect of Income for 2004-05 (Reporting Odds Ratio)

Group	Mean Predicted Probability	Observed Events (1)	Expected Events (1)	Observed Non-Events (0)	Expected Non-Events (0)	Total Observations
1	0.0143	26	21.9	1,557	1,561.1	1,583
2	0.0148	27	23.0	1,555	1,559.0	1,582
3	0.0151	16	23.7	1,566	1,558.3	1,582
4	0.0155	29	24.2	1,553	1,557.8	1,582
5	0.0158	24	24.7	1,558	1,557.3	1,582
6	0.0161	22	25.2	1,560	1,556.8	1,582
7	0.0164	24	25.7	1,558	1,556.3	1,582
8	0.0169	21	26.3	1,561	1,555.7	1,582
9	0.0175	32	27.2	1,550	1,554.8	1,582
10	0.0226	30	29.1	1,552	1,552.9	1,582

Test Summary:

- **Number of Observations: 15,821**
- **Number of Groups (Deciles): 10**
- **Hosmer–Lemeshow χ² (df = 8): 7.51**
- **p-value: 0.4831**

Table A5.8: Hosmer Lemeshow of Logistic Regression 2 for 2004-05.