Action Report

I sincerely appreciate the time and effort the reviewer has taken to provide a detailed and thoughtful assessment of my thesis, "Essays on Transaction Technology and Payment System." *The comprehensive feedback on each chapter and the constructive comments on the theoretical and empirical contributions will be immensely valuable in refining my research. I am particularly grateful for the insights regarding the strengths of the theoretical model and the empirical validation of the proposed research. Additionally, the suggestions for improving certain aspects of the thesis will guide me in enhancing the clarity and robustness of my arguments.*

The following is the full answer report, corresponding to comments on each chapter, provided one by one:

1. **Statements were made in Chapter 1 without proper citations or references. For example, Section 1.1 (pages 2–4), starting with the sentence, "The notion of using ..." (second paragraph), provides the evolution and historical context of cashless transactions without a single reference. Where did the author get all this information? For example: "The U.S. Diner's Club card was one of the first such cards, and their use became widespread throughout the 1950s." "The Bank of Delaware first launched a pilot project involving debit cards in 1966. By the 1970s, many other banks started working on similar ideas." "In India, in the year 1987, the first ATM was introduced." I would recommend revisiting pages 2–4 and including additional citations where required. Also, please correct any spelling and grammatical errors**

Actions: I have reviewed the comment and added the necessary references in pages 2–4 of Chapter 1 to support the historical context of cashless transactions.

2. **The same trend of missing references continues in Chapter 2. For example, on page 14 (second paragraph): "The rise of digital transactions has been driven by a convergence of factors, including advancements in information and communication technologies (ICTs), the ubiquity of internet connectivity, and the growing demand for convenient and secure payment solutions in an increasingly digitalized world (Reference??)." Again, on page 14 (third paragraph): "Concerns regarding data privacy, cybersecurity, regulatory compliance, and equitable access underscore the need for robust governance frameworks, technological safeguards, and user-centric design principles to ensure the integrity, security, and inclusivity of digital transaction ecosystems (Reference??)." I am not sure whether the author is presenting these claims independently (if yes, on what basis?) or if they are drawn from previous literature. There are many similar instances throughout the chapter. I recommend thoroughly reviewing Chapter 2 and adding missing references where needed**

Actions:. I have reviewed Chapter 2 thoroughly and included all the necessary references to support the claims made..

3. **One missing feature in Chapter 2 is how this topic is relevant in the Indian context compared to other developing countries. In other words, why is India special? For example, on page 16 (last paragraph), the author states: "This study highlights the pivotal role of government initiatives and emerging digital payment platforms in driving India's transition towards a digitally empowered society." But why was the government initiative needed in the first place? What is the background information, i.e., the transaction level in India before PMJDY and the evolution of financial inclusion strategies since then? This is not clear from the current text. I recommend adding a brief section in Chapter 2 that cites relevant literature, provides some statistics/evidence, and highlights the importance of cashless transactions and financial inclusion policies in India thus far. This would justify why the research in this thesis is focused on India**

Actions: I have added a section in Chapter 2 that discusses the Indian context, including relevant literature, statistics. The paragraph is mentioned below(page 16-17):

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 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 program**, 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.

4. **Pages 17 and 18 lack a proper literature review. Only two international studies were presented to showcase the effectiveness of financial inclusion policies on cashless transactions—one World Bank report and another study on Indonesia (Trisnowati et al., 2020). Additionally, the Indonesian study was incorrectly depicted as a developed country study on page 17 (last paragraph), whereas Indonesia is a developing country.**

Many other international studies have been conducted in this context but have not been cited. Below is a small list (though not a comprehensive one):

- **Bayero, M. A. (2015).** ***Effects of cashless economy policy on financial inclusion in Nigeria: An exploratory study.*** **Procedia-Social and Behavioral Sciences, 172, 49–56.**

- **Srouji, J. (2020).** ***Digital payments, the cashless economy, and financial inclusion in the United Arab Emirates: Why is everyone still transacting in cash?*** **Journal of Risk and Financial Management, 13(11), 260.**
- **Zakari, M. (2023).** ***Impact of Cashless Policy Measures on Financial Inclusion in Nigeria.*** **Journal of Finance and Accounting Research, 5(2), 101–118.**
- **Osabutey, E. L., & Jackson, T. (2024).** ***Mobile money and financial inclusion in Africa: Emerging themes, challenges, and policy implications.*** **Technological Forecasting and Social Change, 202, 123339.**
- **Ong, H. B., Wasiuzzaman, S., Chong, L. L., & Choon, S. W. (2023).** ***Digitalisation and financial inclusion of lower middle-income ASEAN.*** **Heliyon, 9(2).**

Can the candidate include relevant references and rewrite this section accordingly?

Actions: We have incorporated the studies mentioned above into our thesis. We mentioned the following into the 2nd chapter of our thesis (page 20-21).

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 in African region, 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.

5. **The literature review, particularly the section on Indian studies on pages 21–22, is written in a way that criticizes almost every study or emphasizes how it differs from the present thesis. There is no need to highlight how the thesis differs from every cited study. Instead, the review should focus on how this study builds upon existing research and then identify gaps in the literature in a holistic manner to frame the research questions effectively.**

Actions: I have revised the literature review section, particularly the part on Indian studies, to focus on how this study builds upon existing research rather than merely differentiating it. The literature gap is now presented in a more holistic manner to effectively frame the research questions.

6. **Page 23 — The authors state, "We have not come across any theoretical literature that addresses the issue relating to the impact of interaction between income and education on the adoption of non-cash transactions." However, the author needs to argue why these two factors are important or were chosen in the first place to build the theoretical model. Why not consider other factors such as age, gender, employment, or place of residence (urban vs. rural)? This rationale is currently missing from the thesis. The previous literature on financial inclusion and financial development would help frame that argument.**

Actions: The rationale behind selecting income and education over other factors has now been incorporated (in page 77) into the thesis, which is also mentioned below:

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 correlates with greater affordability of digital devices and internet services, while higher education levels tend to make acquisition of digital literacy and awareness of financial innovations easier. While other variables such as age, gender, employment status, or place of residence (urban or rural)may 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. 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.

Chapter 3

7. **On page 34, the author makes the following claim in the last paragraph: *"We have not come across any study that has measured the impact of PMJDY, Demonetization, post-demonetization policies, and the COVID-19 outbreak together or the extent of cashless transactions in any economy..."* In this context, an important study is missing (both in Chapters 3 and 2):**
   Mukhopadhyay, J. P. (2021). Determinants of Digital Technology Adoption and Financial Inclusion in India: Some Empirical Evidence. Economic and Political Weekly, 56(26-27).

   Findings from many studies listed in this paper (see its reference list) are also not cited or discussed in Chapters 2 and 3. A more comprehensive literature review is needed.

Actions: we have incorporated this into our thesis as mentioned below (page 22)

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."*

8. **On page 35, the author states in the second paragraph: *"Therefore, our primary objective is to assess the impact of two major policy interventions on the growth of both the volume and value of different types of cashless transactions in the Indian economy."* While it is commendable that these policy interventions are studied in this thesis, there is not enough background information provided to readers about why the government introduced these policies and how they were implemented. Except for one sentence in the introduction (*"...the promotion of cashless transactions has been one of the policy priorities of the Indian government"*), no substantial explanation is given. Similarly, on page 39, the author refers to the *"Cash Mukt Bharat"* objective of the Indian government but never explains this term. A dedicated section in Chapter 2 titled "Why India?" would help avoid confusion, especially for international readers who may not be familiar with Indian government policy interventions and their impact on the domestic economy.**

*Actions: I have taken the reviewer's suggestion into account and have added a dedicated section in Chapter 2 titled 'Why India?' In this section, I provide a more comprehensive background on the rationale behind the government's focus on promoting cashless transactions, including the key objectives and the implementation strategies of major policy interventions such as **demonetization** and the **Cash Mukt Bharat** initiative. This additional content aims to provide clearer context, especially for international readers unfamiliar with Indian policies and their impact on the economy. (page 38)*

9. **COVID-19 was an economic shock, while the other two events were government policy interventions. Why are these three events treated similarly? It is also important to note that the first two policy interventions were India-specific, whereas COVID-19 had a global impact. How does the study control for international effects in the case of COVID-19?**

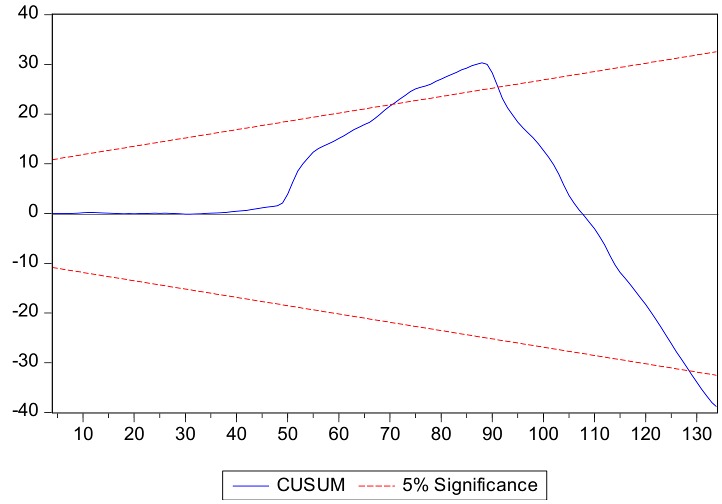
Actions: To account for international effects in the case of COVID-19, I have incorporated the world real GDP growth rate as a control variable in the analysis. I have re-estimated all the results with this additional control *and included the updated analysis in my thesis. However, the key findings and conclusions remain unchanged, indicating that the initial results are robust to international economic conditions.*

Regression Results for CARDS_1000

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.011387	0.0000
GDP_GCFDEF	5.58E-05	0.0000
WORLD_GROWTH	0.130868	0.0027
C	0.590235	0.0000

Statistic	Value
R-squared	0.847950
Adjusted R-squared	0.844441
Standard Error of Regression	0.117093
Sum of Squared Residuals	1.782392

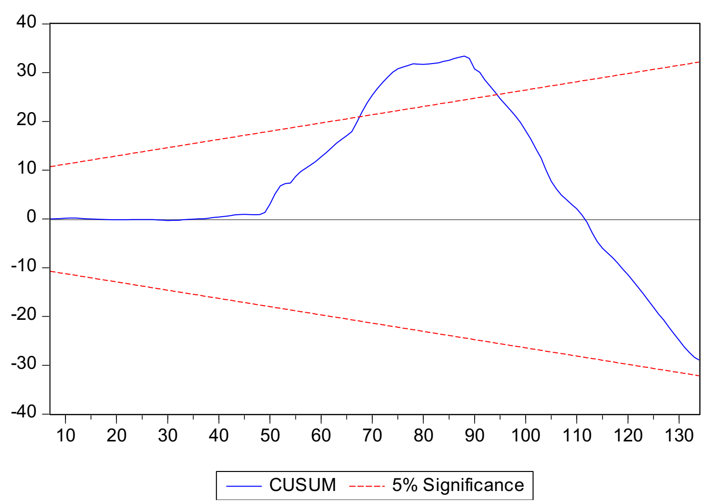


Regression Results for PERCAPNOPOS

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.012075	0.0000
GDP_GCFDEF	-6.22E-05	0.0000
WORLD_GROWTH	-0.400956	0.0000
Constant (C)	0.574685	0.0000

Statistic	Value
R-squared	0.838001
Adjusted R-squared	0.834263
Standard Error of Regression	0.130471
Sum of Squared Residuals	2.212939

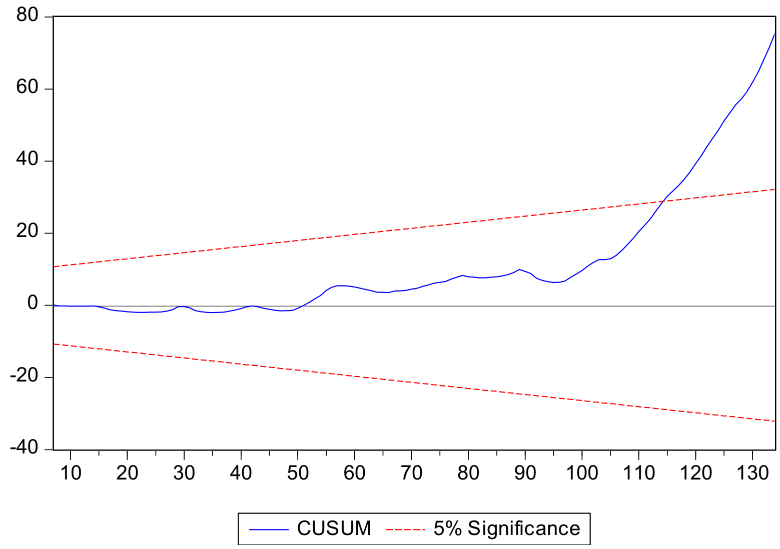


Regression Results for PERCAPNONEFT

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.003006	0.0000
GDP_GCFDEF	3.49E-05	0.0000
WORLD_GROWTH	0.036568	0.0551
Constant (C)	-0.342377	0.0000

Statistic	Value
R-squared	0.955091
Adjusted R-squared	0.954054
Standard Error of Regression	0.051660
Sum of Squared Residuals	0.346936

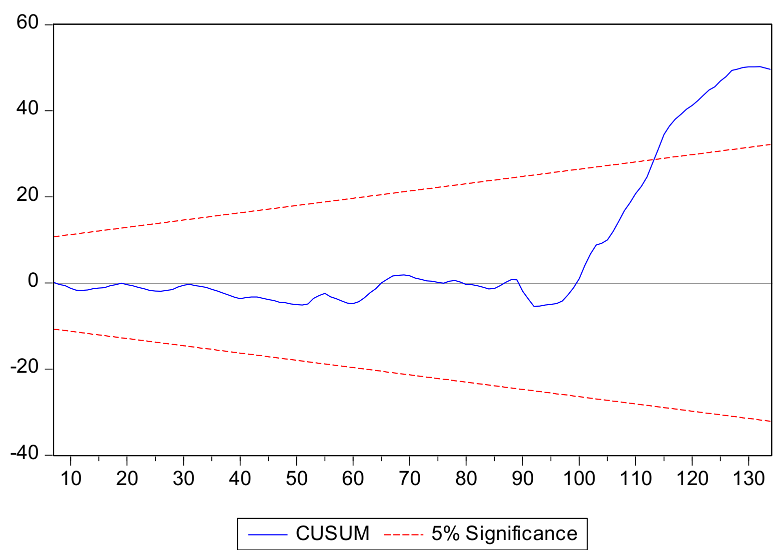


Regression Results for PERCAPNORTGS

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.003189	0.0000
GDP_GCFDEF	4.44E-05	0.0000
WORLD_GROWTH	-0.040818	0.1329
Constant (C)	-0.366574	0.0000

Statistic	Value
R-squared	0.935379
Adjusted R-squared	0.933888
Standard Error of Regression	0.073817
Sum of Squared Residuals	0.708355

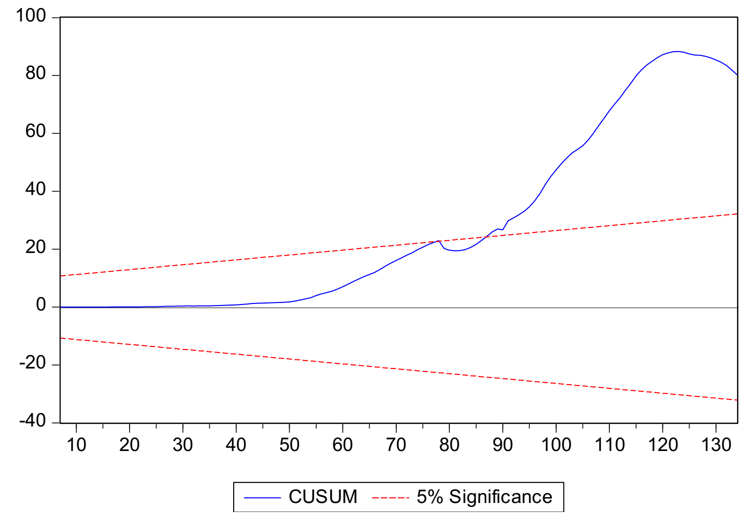


Regression Results for PERCAPNOIMPS

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.005430	0.0000
GDP_GCFDEF	3.98E-05	0.0000
WORLD_GROWTH	0.003382	0.9177
Constant (C)	-0.501938	0.0000

Statistic	Value
R-squared	0.938757
Adjusted R-squared	0.937344
Standard Error of Regression	0.089287
Sum of Squared Residuals	1.036388

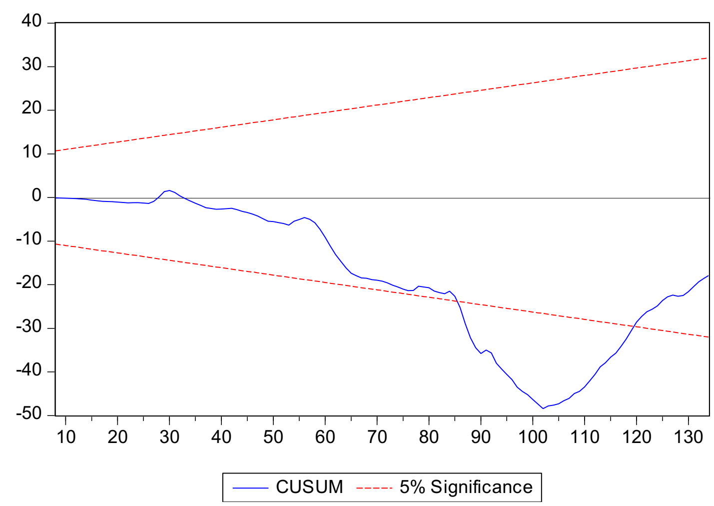


Regression Results for PERCAPNOECS_NACH

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.017632	0.0000
$TIME^2$	-8.00E-05	0.0000
GDP_GCFDEF	-6.51E-06	0.4379
WORLD_GROWTH	0.104628	0.0093
Constant (C)	-0.060709	0.4810

Statistic	Value
R-squared	0.879884
Adjusted R-squared	0.876159
Standard Error of Regression	0.101991
Sum of Squared Residuals	1.341892

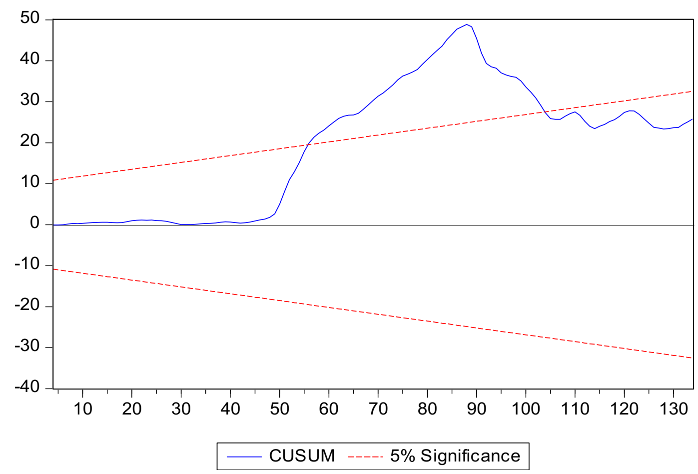


Regression Results for PERCAPVALUEPOS

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.003456	0.0000
GDP_GCFDEF	3.97E-05	0.0000
WORLD_GROWTH	0.095982	0.0000
Constant (C)	-0.352301	0.0000

Statistic	Value
R-squared	0.973110
Adjusted R-squared	0.972489
Standard Error of Regression	0.045965
Sum of Squared Residuals	0.274657

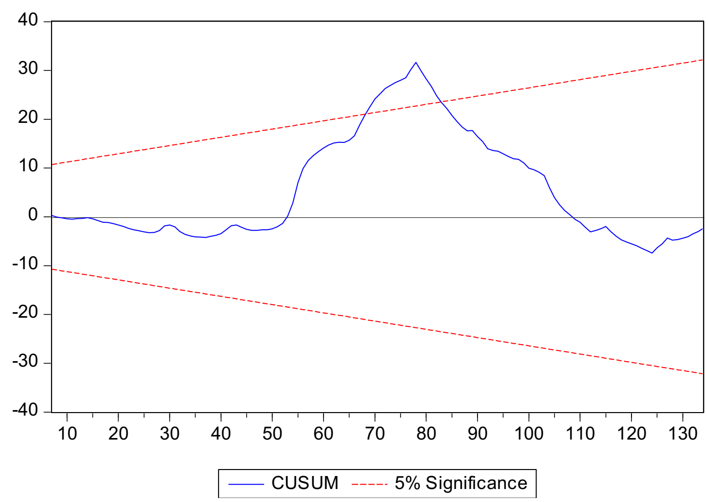


Regression Results for PERCAPVALUENEFT

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.005698	0.0000
GDP_GCFDEF	1.76E-05	0.0000
WORLD_GROWTH	0.065245	0.0003
Constant (C)	-0.160087	0.0000

Statistic	Value
R-squared	0.972866
Adjusted R-squared	0.972240
Standard Error of Regression	0.047526
Sum of Squared Residuals	0.293628

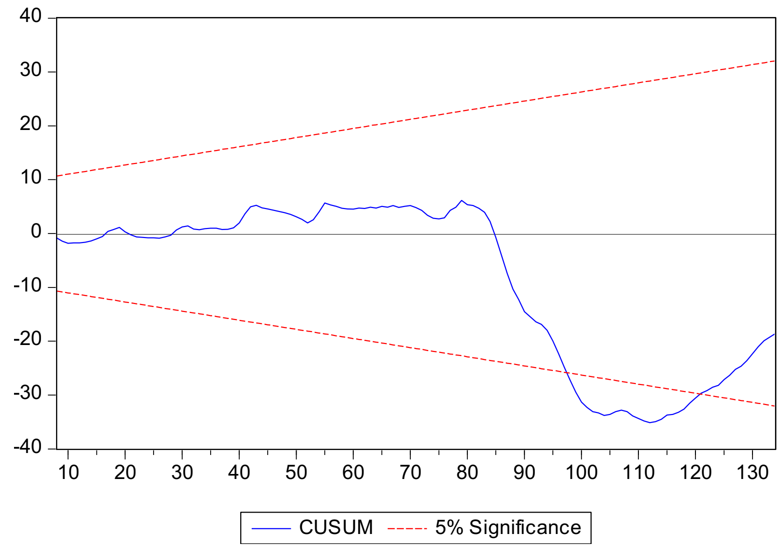


Regression Results for PERCAPVALUERTGS

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.003525	0.0008
$TIME^2$	5.30E-05	0.0000
GDP_GCFDEF	9.84E-05	0.0000
WORLD_GROWTH	0.094774	0.0324
Constant (C)	-0.700921	0.0000

Statistic	Value
R-squared	0.798121
Adjusted R-squared	0.791861
Standard Error of Regression	0.112770
Sum of Squared Residuals	1.640501

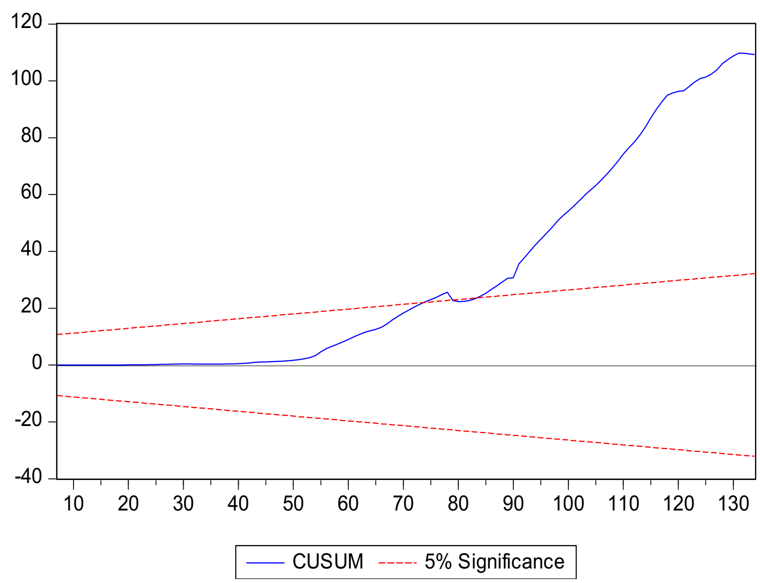


Regression Results for PERCAPVALUEIMPS

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Variable	Coefficient	p-Value
TIME	0.003367	0.0000
GDP_GCFDEF	5.22E-05	0.0000
WORLD_GROWTH	0.045949	0.0772
Constant (C)	-0.585693	0.0000

Statistic	Value
R-squared	0.951716
Adjusted R-squared	0.950602
Standard Error of Regression	0.070548
Sum of Squared Residuals	0.647007



Regression Results for PERCAPVALUEECS_NACH

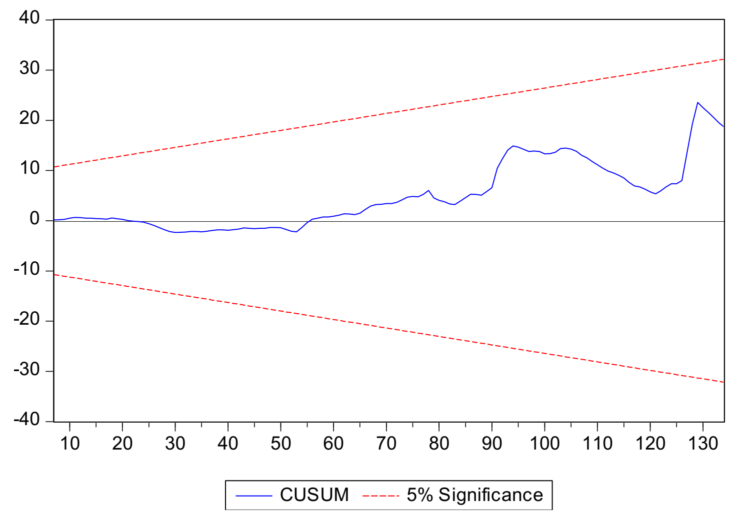
Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

Variable	Coefficient	p-Value
TIME	0.002664	0.0000
GDP_GCFDEF	2.97E-05	0.0000
WORLD_GROWTH	0.027735	0.2555
Constant (C)	-0.285610	0.0000

Panel B: Model Fit Statistics

Statistic	Value
R-squared	0.9064
Adjusted R-squared	0.9043
Standard Error of Regression	0.0664
Sum of Squared Residuals	0.5733
Log-Likelihood	175.2929



Regression Results for POS_GDP

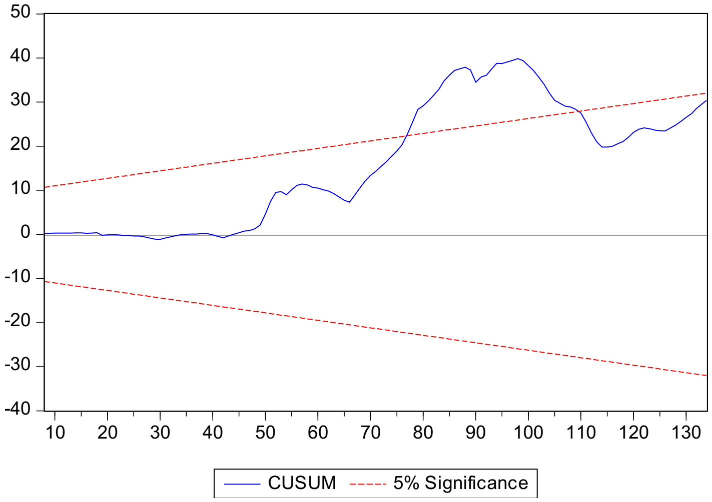
Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

Variable	Coefficient	p-Value
TIME	0.025381	0.0000
ADULTPOPU	11.86786	0.0001
WORLD_GROWTH	0.171386	0.0000
Constant (C)	10.40222	0.0001

Panel B: Model Fit Statistics

Statistic	Value
R-squared	0.9389
Adjusted R-squared	0.9375
Standard Error of Regression	0.0826
Sum of Squared Residuals	0.8866
Log-Likelihood	146.0829



Regression Results for NEFT_GDP

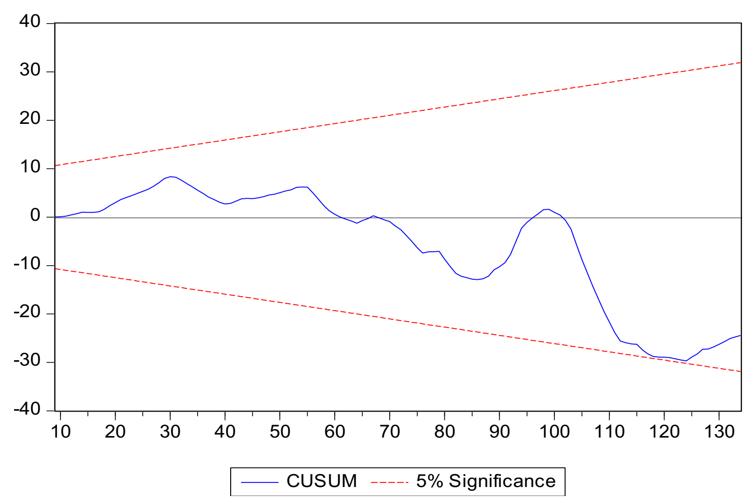
Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

Variable	Coefficient	p-Value
TIME	0.047879	0.0000
ADULTPOPU	27.51797	0.0000
WORLD_GROWTH	-0.003521	0.9218
Constant (C)	24.19110	0.0000

Panel B: Model Fit Statistics

Statistic	Value
R-squared	0.9051
Adjusted R-squared	0.9029
Standard Error of Regression	0.1013
Sum of Squared Residuals	1.3349
Log-Likelihood	118.6647

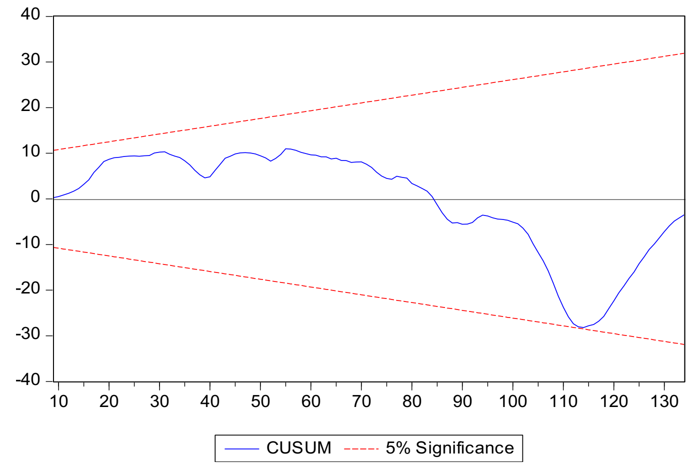


Regression Results for RTGS_GDP

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

Variable	Coefficient	p-Value
TIME	-0.005324	0.6794
$TIME^2$	5.96E-05	0.0010
ADULTPOPU	7.504102	0.4521
WORLD_GROWTH	0.170992	0.0107
Constant (C)	-6.163327	0.4833



Panel B: Model Fit Statistics

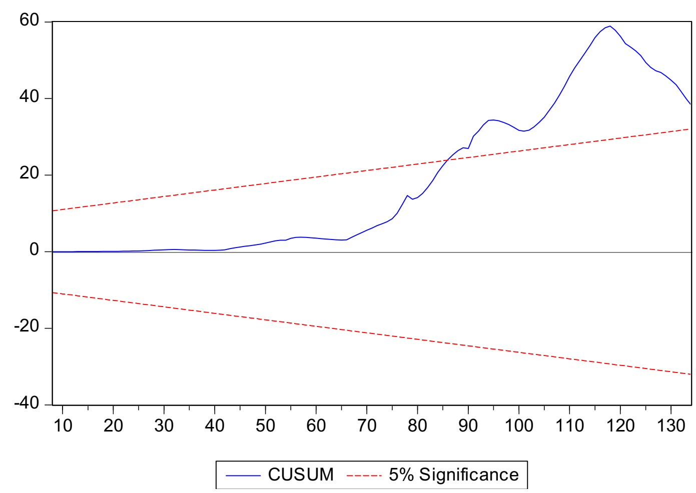
Statistic	Value
R-squared	0.3133
Adjusted R-squared	0.2920
Standard Error of Regression	0.1867
Sum of Squared Residuals	4.4986
Log-Likelihood	37.2648

Regression Results for IMPS_GDP

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

Variable	Coefficient	p-Value
TIME	-0.004405	0.2660
ADULTPOPU	8.948191	0.0012
WORLD_GROWTH	-0.009402	0.7215
Constant (C)	-8.042378	0.0009



Panel B: Model Fit Statistics

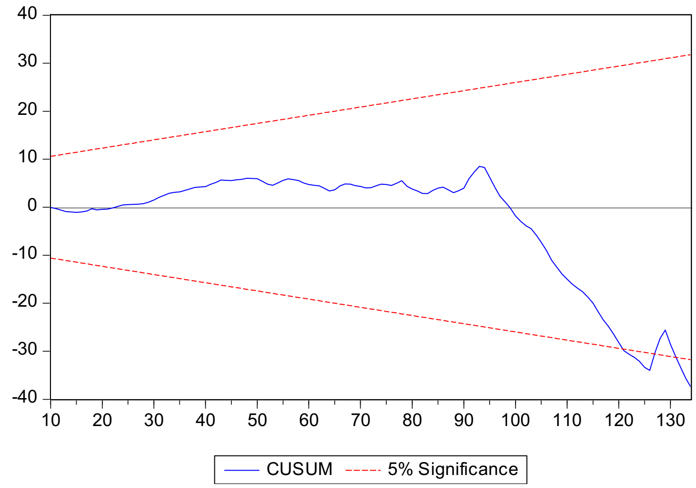
Statistic	Value
R-squared	0.9542
Adjusted R-squared	0.9531
Standard Error of Regression	0.0745
Sum of Squared Residuals	0.7209
Log-Likelihood	159.9369

Regression Results for ECS_NACH_GDP

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

Variable	Coefficient	p-Value
TIME	-0.004223	0.4773
$TIME^2$	-1.54E-05	0.0628
ADULTPOPU	7.957175	0.0852
WORLD_GROWTH	0.062142	0.0432
Constant (C)	-7.062399	0.0829



Panel B: Model Fit Statistics

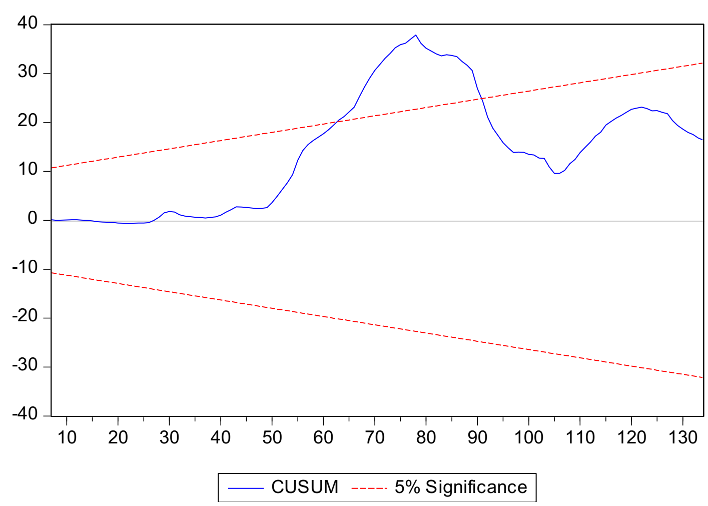
Statistic	Value
R-squared	0.8553
Adjusted R-squared	0.8509
Standard Error of Regression	0.0861
Sum of Squared Residuals	0.9558
Log-Likelihood	141.0440

Regression Results for PERCAPNOINDEX

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

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



Panel B: Model Fit Statistics

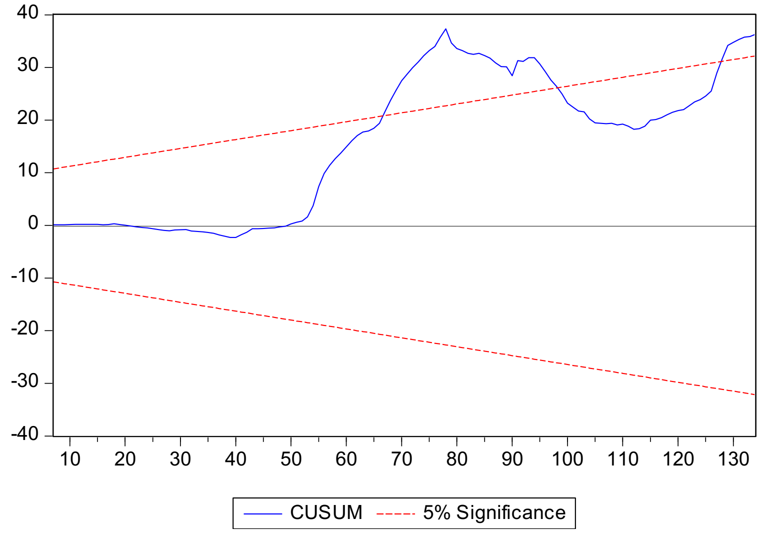
Statistic	Value
R-squared	0.9837
Adjusted R-squared	0.9834
Standard Error of Regression	0.0361
Sum of Squared Residuals	0.1697
Log-Likelihood	256.8669

Regression Results for PER_CAPVALUEINDEX

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

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



Panel B: Model Fit Statistics

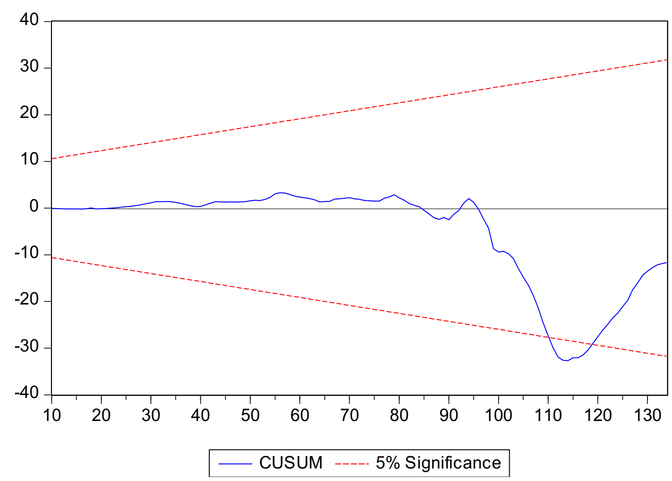
Statistic	Value
R-squared	0.9784
Adjusted R-squared	0.9779
Standard Error of Regression	0.0393
Sum of Squared Residuals	0.2005
Log-Likelihood	245.6727

Regression Results for VALUEGDPINDEX

Method: Least Squares
Sample: 1 to 134 (Included Observations: 134)

Panel A: Estimated Coefficients

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



Panel B: Model Fit Statistics

Statistic	Value
R-squared	0.8289
Adjusted R-squared	0.8236
Standard Error of Regression	0.0955
Sum of Squared Residuals	1.1771
Log-Likelihood	127.0944

10. **Table 3.1 (Per Capita Volume Index) – Why were the number of credit cards and debit cards combined? Anyone with a bank account is generally eligible for a debit card, but credit card eligibility is income- and debt-dependent. This distinction makes the analysis more complex. It would be advisable to analyze them separately.**

Actions: The primary objective of this analysis is to evaluate the overall accessibility of cashless transaction tools by assessing the number of cards in circulation per 1,000 adults. Both debit and credit cards serve as key instruments for digital transactions, contributing to the broader financial inclusion agenda.

- *Debit cards are issued automatically to most bank account holders, while credit cards are subject to eligibility criteria. However, both types of cards facilitate cashless transactions and represent access to digital payment infrastructure. And as our main motive is to segregate card usage and bank transfer (such as NEFT, RTGS, IMPS etc.)*
- *By combining them, we provide a holistic measure of how widely card-based transaction tools are available, irrespective of their specific access patterns.*
- *Many individuals possess both credit and debit cards, using them interchangeably for different types of transactions.*
- *The total number of cards per 1,000 adults helps assess the overall penetration of card-based payment systems in the economy, irrespective of card type.*
- *While credit and debit cards have different eligibility requirements and spending patterns, our focus is not so much on eligibility criterion but on evaluating the expansion of cashless transaction tools. So for as cashless transaction is concerned the end use of credit card and debit card are the same, though credit card allows for a delayed payment and can potentially create a debt trap.*
- *A higher combined figure indicates an increase in access to formal financial instruments, which aligns with the broader goal of digital financial inclusion.*
- *By combining credit and debit cards, this index effectively captures the expansion of digital payment tools among the consumers and provides a clearer picture of the overall accessibility of cashless transactions per 1000 adult consumers in the economy.*

11. **I am surprised that the PCA results show identical weightings for each dimension of the three indices (page 40, second paragraph). Since PCA is a data-driven technique, it rarely produces exactly the same weightings across different dimensions. This raises concerns about whether the PCA analysis was conducted properly.**

    Tables A3.4, A3.7, and A3.10 show that the first principal component explains most of the variations, but the factor loadings are not provided. Can the author verify if the PCA results were interpreted correctly? A scree plot would also be useful to include.

Actions: I have re-run the PCA analysis to verify the results, and once again, the weights across different dimensions remain very close to each other (except only RTGS/GDP). Given this, I have decided to adopt an equal-weighting approach for simplicity and consistency.

Regarding your concern about factor loadings, I would like to clarify that all factor loadings are provided in the following. Additionally, I have now included scree plots to further illustrate the variance explained by each component.
I appreciate your suggestions, as they have helped enhance the clarity and robustness of the analysis.

Table: PCA Analysis of Per Capita Number of Transactions

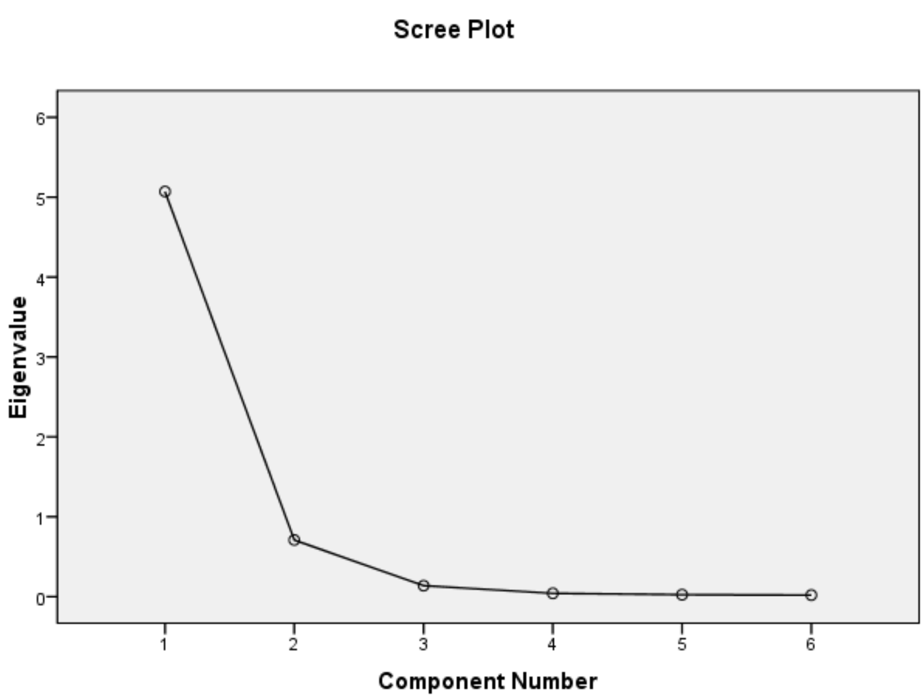
Variable	Card/1000	Per capita no. POS	Per capita no of NEFT	Per capita no. of RTGS	Per capita no. of IMPS	Per capita no. of ECS+NACH
Card/1000	**1.000**	**0.908***	**0.773***	**0.742***	**0.735***	**0.957***
Per capita no. POS	**0.908***	**1.000**	**0.711***	**0.703***	**0.738***	**0.890***
Per capita no of NEFT	**0.773***	**0.711***	**1.000**	**0.974***	**0.961***	**0.741***
Per capita no. of RTGS	**0.742***	**0.703***	**0.974***	**1.000**	**0.975***	**0.703***
Per capita no. of IMPS	**0.735***	**0.738***	**0.961***	**0.975***	**1.000**	**0.699***
Per capita no. of ECS+NACH	**0.957***	**0.890***	**0.741***	**0.703***	**0.699***	**1.000**

Notes: Significance Level: *** indicates **p < 0.01 (highly significant)**.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.071	84.511	84.511	5.071	84.511	84.511
2	.708	11.806	96.317			
3	.137	2.283	98.600			
4	.041	.683	99.283			
5	.024	.404	99.687			
6	.019	.313	100.000			

Extraction Method: Principal Component Analysis.



Variable	Factor Loading (Component 1)
card1000	0.926
percapnopos	0.896
percapnoneft	0.937
percapnortgs	0.926
percapnoimps	0.927
percapnoecsnach	0.903

Table: PCA Analysis of Per Capita Transaction Values

Variable	Per capita value POS	Per capita value of NEFT	Per capita value of RTGS	Per capita value of IMPS	Per capita value of ECS&NACH
Per capita value POS	**1.000**	**0.977***	**0.840***	**0.964***	**0.934***
Per capita value of NEFT	**0.977***	**1.000**	**0.825***	**0.947***	**0.938***
Per capita value of RTGS	**0.840***	**0.825***	**1.000**	**0.741***	**0.770***
Per capita value of IMPS	**0.964***	**0.947***	**0.741***	**1.000**	**0.949***
Per capita value of ECS&NACH	**0.934***	**0.938***	**0.770***	**0.949***	**1.000**

Notes: Significance Level: *** indicates **$p < 0.01$ (highly significant)**.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.563	91.252	91.252	4.563	91.252	91.252
2	.311	6.229	97.481			
3	.072	1.432	98.913			
4	.041	.814	99.727			
5	.014	.273	100.000			

Extraction Method: Principal Component Analysis.

Variable	Factor Loading (Component 1)
percapvaluepos	0.989
percapvalueneft	0.983
percapvaluertgs	0.870
percapvalueimps	0.966
percapvalueecsnach	0.963

Table: PCA Analysis of Value GDP Transactions

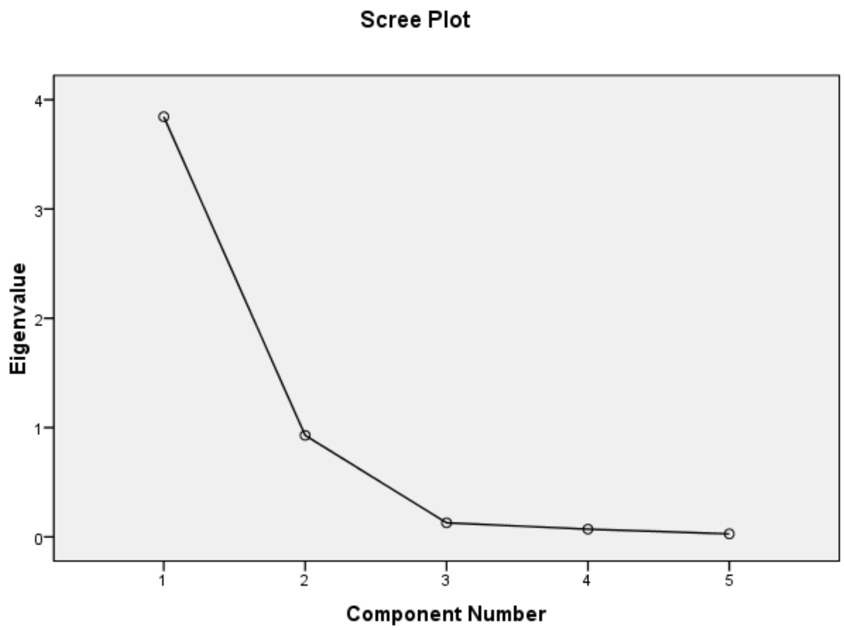
Variable	POS/GDP	NEFT/GDP	RTGS/GDP	IMPS/GDP	ECS&NACH/GDP
POS/GDP	**1.000**	**0.947***	**-0.255**	**0.929***	**0.876***
NEFT/GDP	**0.947***	**1.000**	**-0.165**	**0.875***	**0.888***
RTGS/GDP	**-0.255**	**-0.165**	**1.000**	**-0.465***	**-0.333***
IMPS/GDP	**0.929***	**0.875***	**-0.465***	**1.000**	**0.914***
ECS&NACH/GDP	**0.876***	**0.888***	**-0.333***	**0.914***	**1.000**

Significance Levels: *** $p < 0.01$ **(highly significant)**

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.845	76.897	76.897	3.845	76.897	76.897
2	.929	18.574	95.471			
3	.129	2.572	98.043			
4	.070	1.409	99.453			
5	.027	.547	100.000			

Extraction Method: Principal Component Analysis.



Variable	Factor Loading (Component 1)
posgdp	0.962
neftgdp	0.942
rtgsgdp	0.412
impsgdp	0.977
ecsnachgdp	0.952

12. To analyze the impact of the three major events (?) on cashless transactions, the author used the CUSUM test for structural breaks. However, this test is quite old and has been criticized in the literature. What are the advantages of using this test over more recent structural break tests such as:

a. Zivot-Andrews test (allows for intercept or trend breaks in unit root processes)

b. Bai-Perron (BP) test (identifies multiple structural breaks in an ADF test framework)

c. Clemente-Montañés-Reyes test (also used for structural breaks)

Were unit root tests conducted on the data? If not, why? The CUSUM test can be slow in detecting large shifts in the process mean, and CUSUM charts can be difficult to interpret because they are correlated. It would be beneficial to check the robustness of the results using an alternative structural break test.

Actions: ***Justification for Using the CUSUM Test Over Other Structural Break Tests***

*The **CUSUM (Cumulative Sum) test** was chosen instead of other structural break tests because our primary objective is to **identify whether the breaks in the cashless transaction trend were positive or negative**, indicating the **directional impact of policy interventions**. Unlike other structural break tests that focus primarily on the presence or timing of breaks, the CUSUM test allows us to visualize the **cumulative effect of shocks** over time and assess whether they led to an **upward (positive) or downward (negative) shift** in cashless transactions.*

1. Advantages of the CUSUM Test for Our Research Objective

- ***Tracks the evolution of policy effects***:
  - *The CUSUM test provides a **graphical representation of deviations from the mean**, helping us track how policies affected the **trend** of cashless transactions.*
  - *Unlike tests that only detect breakpoints, the **CUSUM chart shows the gradual accumulation of deviations**, which is crucial when policies have **progressive or lagged effects**.*
- ***Distinguishes positive and negative breaks***:
  - *Our goal is not just to detect breaks but also to understand **whether they are positive or negative**, which is **not explicitly provided by other structural break tests**.*
  - *The **CUSUM plot's movement above or below the control limits** helps us determine whether policies had an **increasing or decreasing effect** on cashless transactions.*
- ***Applicable to unknown breakpoints***:
  - *Some tests, such as the **Zivot-Andrews test**, assume a single break and require specifying break types (intercept/trend), which might not capture **multiple policy impacts occurring over time**.*
  - *CUSUM dynamically detects deviations from the expected trend **without requiring prior assumptions about break locations**.*
- ***Useful for policy analysis with time-series trends***:
  - *Since our study examines **policy-driven changes** in cashless transactions, CUSUM is more effective because it helps visualize the **gradual or abrupt shifts** induced by government interventions.*
  - *Structural break tests like Bai-Perron focus on **formal breakpoints but do not provide an intuitive trend assessment** of how cashless transactions evolved over time.*

2. Why Not Other Structural Break Tests?

Test	***Why It's Not Ideal for This Study***
Zivot-Andrews Test	*Designed for **unit root processes**, primarily used to test for **stationarity with a single endogenous break** (in trend or intercept). However, cashless transactions may have **multiple structural changes due to multiple policies**, making it **less suitable**.*
Bai-Perron (BP) Test	*Identifies **multiple structural breaks** but focuses on **break timing rather than the direction of the impact** (whether positive or negative). Additionally, it assumes an **ADF framework**, which may not align with the evolving nature of policy effects.*
Clemente-Montañés-Reyes Test	*Useful for **stationary processes** with **structural breaks**, but mainly **tests for the presence of breaks rather than analyzing their effects on trend direction**. Not suitable for policy impact assessment where the focus is on the **cumulative impact over time**.*

3. Consideration of Unit Root Tests

- ***Were unit root tests conducted?***
  - *If unit root tests (such as ADF, PP, or KPSS) were not performed, it could be because our **focus is on identifying policy-induced structural changes rather than testing for stationarity**.*
  - *Many economic time series (especially transaction trends) may be **non-stationary due to growth effects**, but **CUSUM remains useful in analyzing trend deviations even in non-stationary series**.*
- ***Why CUSUM without unit root tests?***
  - ***CUSUM is designed for detecting process shifts** rather than testing stationarity.*

- *Even if the series has a unit root, the* ***CUSUM test can still effectively track whether policy interventions altered the trajectory of cashless transactions****.*

The ***CUSUM test was chosen because it directly aligns with our research objective****—analyzing whether policy interventions caused a* ***positive or negative shift*** *in cashless transactions. Unlike other structural break tests, which focus on detecting the presence and timing of breaks, CUSUM provides a* ***visual and quantitative assessment*** *of how these breaks affected the overall trend, making it a more* ***intuitive and policy-relevant approach****.*

Though I have done the Bai perron tests which are mentioned below, but there could be discripency between CUSUM and Bai Perron breaks. The discrepancy between CUSUM and Bai-Perron breakpoints arises due to differences in their methodologies, sensitivities, and statistical criteria. CUSUM detects gradual shifts in parameters by tracking cumulative deviations of recursive residuals, making it more sensitive to progressive changes. In contrast, Bai-Perron identifies abrupt structural breaks by minimizing residual sum of squares (RSS) and selecting breakpoints based on statistical criteria like AIC or BIC. As a result, CUSUM may indicate instability over a broader period, while Bai-Perron pinpoints sharp break dates. Additionally, Bai-Perron requires predefined parameters, such as the maximum number of breaks and minimum segment length, which can influence results. If the structural change is smooth or occurs over time, CUSUM may detect it earlier, whereas Bai-Perron only captures distinct, statistically significant shifts. Variations in noise, sample size, or model assumptions can further contribute to differences in detected breakpoints.

Table: Bai-Perron Multiple Breakpoint Test Results of Cards per 1000 Adults

Sample Size: 134 observations
Break Test Options: Trimming = 0.15, Max Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significance
0 vs. 1	414.7018	1658.807	16.19	**Yes**
1 vs. 2	23.12404	92.49617	18.11	**Yes**
2 vs. 3	3.405364	13.62145	18.93	No

Break Dates Identified:

Break	Sequential Break Date	Repartition Break Date
1	80 June 2019	27
2	27 January 2015	80

Bai-Perron Multiple Breakpoint Test Results of Per Capita No. of POS

Sample Size: 134 observations
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significance
0 vs. 1	194.1183	388.2365	11.47	**Yes**
1 vs. 2	102.1270	204.2540	12.95	**Yes**
2 vs. 3	21.79510	43.59021	14.03	**Yes**
3 vs. 4	5.792198	11.58440	14.85	No

Break Dates Identified:

Break	Sequential Break Date
1	90 April 2020
2	50 December 2016
3	111 January 2022

Bai-Perron Multiple Breakpoint Test Results of Per Capita No. of NEFT

Sample Size: 134 observations
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significance
0 vs. 1	154.5424	618.1695	16.19	**Yes**
1 vs. 2	12.71458	50.85833	18.11	**Yes**
2 vs. 3	2.809957	11.23983	18.93	No

Break Dates Identified:

Break	Sequential Break Date
1	98 December 2020
2	29 March 2015

Bai-Perron Multiple Breakpoint Test Results of Per Capita No. of RTGS

Sample Size: 134 observations
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significance
0 vs. 1	153.1121	306.2241	11.47	**Yes**
1 vs. 2	8.670670	17.34134	12.95	**Yes**
2 vs. 3	3.287008	6.574017	14.03	No

Break Dates Identified:

Break	Sequential Break Date
1	98 March 2015
2	77 March 2019

Bai-Perron Multiple Breakpoint Test Results of Per capita No. of IMPS

Sample Size: 134 observations
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significance
0 vs. 1	205.3966	410.7931	11.47	**Yes**
1 vs. 2	54.64097	109.2819	12.95	**Yes**
2 vs. 3	12.98670	25.97340	14.03	**Yes**
3 vs. 4	3.810198	7.620396	14.85	No

Break Dates Identified:

Break	Sequential Break Date
1	54 April 2017
2	108 October 2021
3	88 **February 2020**.

Bai-Perron Multiple Breakpoint Test Results of Per capita No. of ECS+NACH

Sample Size: 134 observations
Breaking Variables: TIME, $TIME^2$, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	66.56132	199.6840	13.98	**Yes**
1 vs. 2	39.99810	119.9943	15.72	**Yes**
2 vs. 3	5.528601	16.58580	16.83	No

Break Dates Identified:

Break	Sequential Break Date
1	86 December 2019
2	28 February 2015

Bai-Perron Multiple Breakpoint Test Results of Per capita Value of POS

Sample Size: 134 observations
Breaking Variables: TIME, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	57.16203	114.3241	11.47	**Yes**
1 vs. 2	46.13677	92.27354	12.95	**Yes**
2 vs. 3	27.66254	55.32508	14.03	**Yes**
3 vs. 4	2.922298	5.844596	14.85	No

Break Dates Identified:

Break	Sequential Break Date
1	90 April 2020
2	50 December 2016
3	70 August 2018

Bai-Perron Multiple Breakpoint Test Results of Per capita Value of NEFT

Sample Size: 134 observations
Breaking Variables: TIME, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	19.94974	39.89947	11.47	**Yes**
1 vs. 2	25.59256	51.18512	12.95	**Yes**
2 vs. 3	3.426412	6.852823	14.03	No

Break Dates Identified:

Break	Sequential Break Date
1	91 May 2020
2	53 March 2017

Bai-Perron Multiple Breakpoint Test Results Per Capita Value of RTGS

Sample Size: 134 observations
Breaking Variables: TIME, $TIME^2$, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	46.70450	140.1135	13.98	**Yes**
1 vs. 2	38.62102	115.8631	15.72	**Yes**
2 vs. 3	4.342249	13.02675	16.83	No

Break Dates Identified:

Break	Sequential Break Date
1	89 March 2020
2	50 December 2016

Bai-Perron Multiple Breakpoint Test Results Per Capita Value of IMPS

Sample Size: 134 observations
Breaking Variables: TIME, GDP_GCFDEF, WORLD_GROWTH, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	254.9618	1019.847	16.19	**Yes**
1 vs. 2	14.09713	56.38851	18.11	**Yes**
2 vs. 3	2.760369	11.04148	18.93	No

Break Dates Identified:

Break	Sequential Break Date
1	54 April 2017
2	110 December 2021

Bai-Perron Multiple Breakpoint Test Results Per Capita Value of ECS+NACH

Sample Size: 134 observations
Breaking Variables: TIME, $TIME^2$, GDP_GCFDEF, WORLD_GROWTH, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Sequential F-Statistic Determined Breaks

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	35.18340	175.9170	18.23	**Yes**
1 vs. 2	21.83642	109.1821	19.91	**Yes**
2 vs. 3	1.168619	5.843095	20.99	No

Break Dates Identified

Break	Sequential Break Date
1	115 May 2022
2	91 May 2020

Bai-Perron Multiple Breakpoint Test Results of Value of POS/ GDP

Sample Size: 134 observations
Breaking Variables: TIME, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Panel A: Sequential F-Statistic Determined Breaks

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	82.05509	164.1102	11.47	**Yes**
1 vs. 2	43.66423	87.32846	12.95	**Yes**
2 vs. 3	6.826157	13.65231	14.03	No

Panel B: Estimated Break Dates

Break	Sequential Break Date
1	50 December 2016
2	90 April 2020

Bai-Perron Multiple Breakpoint Test Results of Value of NEFT/GDP

Sample Size: 134 observations
Breaking Variables: TIME, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Panel A: Sequential F-Statistic Determined Breaks

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	82.16288	328.6515	16.19	**Yes**
1 vs. 2	9.167654	36.67062	18.11	**Yes**
2 vs. 3	11.24378	44.97512	18.93	**Yes**
3 vs. 4	2.983093	11.93237	19.64	No

Panel B: Estimated Break Dates

Break	Sequential Break Date
1	65 March 2018
2	29 March 2015
3	93 July 2020

Bai-Perron Multiple Breakpoint Test Results of Value of RTGS/ GDP

Sample Size: 134 observations
Breaking Variables: TIME, $TIME^2$, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Panel A: Sequential F-Statistic Determined Breaks

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	53.39884	266.9942	18.23	**Yes**
1 vs. 2	6.376057	31.88029	19.91	**No**
2 vs. 3	8.186385	40.93192	20.99	**No**
3 vs. 4	2.909138	14.54569	21.71	No

Panel B: Estimated Break Dates

Break	Sequential Break Date
1	77 March 2019
2	36 October 2015
3	99 January 2021

Bai-Perron Multiple Breakpoint Test Results of Value of IMPS/ GDP

Sample Size: 134 observations
Breaking Variables: TIME, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Panel A: Sequential F-Statistic Determined Breaks

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	15.24271	30.48542	11.47	**Yes**
1 vs. 2	8.97154	17.94231	12.95	**Yes**
2 vs. 3	3.052881	6.105763	14.03	No

Panel B: Estimated Break Dates

Break	Sequential Break Date
1	77 March 2019
2	107 September 2021

Bai-Perron Multiple Breakpoint Test Results of Value of ECS+NACH / GDP

Sample Size: 134 observations
Breaking Variables: TIME, C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Panel A: Sequential F-Statistic Determined Breaks

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	15.24271	30.48542	11.47	**Yes**
1 vs. 2	8.97154	17.94231	12.95	**Yes**
2 vs. 3	3.052881	6.105763	14.03	No

Panel B: Estimated Break Dates

Break	Sequential Break Date
1	77 March 2019
2	107 September 2021

Bai-Perron Multiple Breakpoint Test Results of Value of ECS+NACH / GDP

Sample Size: 134 observations
Breaking Variables: TIME, TIME², C
Break Test Options: Trimming = 0.15, Maximum Breaks = 5, Significance Level = 0.05

Panel A: Sequential F-Statistic Determined Breaks

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Significant at 5%?
0 vs. 1	23.18915	69.56745	13.98	**Yes**
1 vs. 2	7.843951	23.53185	15.72	**Yes**
2 vs. 3	3.930889	11.79267	16.83	No

Panel B: Estimated Break Dates

Break	Sequential Break Date
1	95 September 2020
2	115 May 2022

13. **Table 3.8 (Page 66) – The results show that PMJDY had no significant impact on any of the three indices. In other words, the PMJDY policy intervention was ineffective for cashless transactions. How does the author justify this result?**

Actions: 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. (page 71 footnote)

14. **The conclusion on page 66 states: *"Nominal GDP has a significantly positive impact on the per capita value index only, indicating that the people who were doing cashless transactions before are still using cashless transactions for more valued goods and services than before, which reveals that not more people have started using cashless transactions than before."***

    How was this conclusion reached? It is strongly advised not to make concluding statements without clear supporting evidence.

Actions: I have carefully reviewed the conclusion on page 72 and have eliminated the statement in question. I have revised the section to ensure that all conclusions are strictly based on clear supporting evidence

15. **Similarly, on page 67, the conclusion states: *"So, we can conclude that while demonetization and post-demonetization policies had a definitive positive impact on both the per capita volume and per capita value indices, the pandemic period had a permanent positive impact on the per capita value index only."***

It is too early to claim that COVID-19 had a permanent effect on per capita values at an aggregate level, given that the data ends in 2023. Statements like this should be removed from the chapter.

Actions: I have removed the claim about the permanent impact of COVID-19 on per capita value indices and have rewritten the conclusion to reflect a more cautious and evidence-based interpretation of the results.

16. **It would be beneficial if the author explained some of the results in Chapter 3. For example:**
    a. **Why did COVID-19 positively impact some per capita volume index indicators but negatively impact others (e.g., *Number of Cards/1000 Adults* and all three measures of *POS transactions*)?**
    b. **How can these findings be explained? This has practical policy implications.**

    Once again, it is important to note that COVID-19 had an international effect (economic slowdown), which must be accounted for, unlike the other two policy interventions that were specific to India.

Actions: I have included the following paragraph in the text (page 74).

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 very possibly 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 may have 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.

17. **It would be good if the author could add a paragraph or two connecting the discussion with previous literature, showing the importance of income and education in cashless transactions before setting up the**

theoretical model. At present, it's not very clear why these variables were chosen to build the theoretical model compared to other determinants, e.g., age, gender, employment, or place of residence (urban vs. rural).

Actions: The rationale behind selecting income and education over other factors has now been incorporated (in page 77 -78) into the thesis, which is also mentioned as followed:

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. 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.

18. **The introduction on page 71 states: "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, for 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." I didn't understand the motivation, particularly with the example given. Even for high-income individuals, the gain in interest from keeping income in a bank account could outweigh the annual charge of maintaining a debit card if income is distributed across many accounts. The cost (annual charge) versus benefit (return in interest) of keeping a debit card is not strictly dependent on income level.**

Actions: I have included the following paragraph in page 79

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. Number of accounts and no. of debit cards for an individual with high income is his choice variable. So he is likely to optimize the choice 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.

19. Section 4.2.1 (page 73) states one of the assumptions of the model: "The period is divided into f equal intervals, and the buyer will make transactions f times over the period. Here 'f' is constant for every level of income and education." Keeping the number of transactions constant for every income and education level is too strong and unrealistic!

Actions: Incorporating varying transaction frequencies based on income and education levels would indeed be a more realistic assumption. However, implementing this change would require deeper analysis, as we need to establish the relationship between f and level of income and education then we need to do the farther analysis. Also allowing transaction frequency to vary across individuals may not fundamentally alter the conclusions of the model. The primary insights regarding the role of income and education in influencing transaction costs and cashless adoption are expected to hold even with this modification.

Nevertheless, I acknowledge the importance of this refinement, and I plan to explore this aspect in future research to enhance the model's applicability

20. Pages 73-74: Three cases of buyers are presented—Types A and B: cash transactions, and Type C: debit card transactions. What about a fourth case (Type D): a mixed case where the buyer sometimes uses cash and other times a debit card? Can the model incorporate this kind of buyer?

Actions: The introduction of a fourth type of buyer (Type D), who uses a mix of cash and debit card transactions, requires deeper analysis and some modifications to the existing model. In this case, the inconvenience cost of carrying cash would become an increasing function of the proportion of money held in cash. Which we have tried to do below.

However, it is important to note that if cashless debit card transactions are always available and the individual has a sufficient level of financial status and education, then the optimal choice would always be to keep money in the bank and exclusively use debit card transactions. This would not alter the final conclusion of this research I believe.

One of the primary reason individuals in developing countries still hold cash is the limited acceptance of cashless transactions in many retail shops and informal markets. This constraint forces consumers to keep some portion of their money in cash form despite the higher efficiency of digital payments, but in our model we consider that both cash mode and debit card payment mode is always available in the shops.

Below is the detailed analysis.

$$TC_{DC} = \begin{cases} \boldsymbol{\alpha[(\tau_R - e_R E)Y + (\emptyset\alpha Y) + i.Y] + b + (1-\alpha)[(\tau_D - e_{D1}E)Y + i.Y - g.Y] + F_a} & \boldsymbol{for\ E < E_{D1}} \\ \boldsymbol{\alpha[(\tau_R - e_R E)Y + (\emptyset\alpha Y) + i.Y] + b + (1-\alpha)[(\tau_D - e_{D2}E)Y + i.Y - g.Y] + F_a} & \boldsymbol{for\ E_{D1} \le E \le E_R} \\ \boldsymbol{\alpha[\overline{\tau_R}.Y + (\emptyset\alpha Y) + i.Y] + b + (1-\alpha)[(\tau_D - e_{D2}E)Y + i.Y - g.Y] + F_a} & \boldsymbol{for\ E_R \le E \le E_{D2}} \\ \boldsymbol{\alpha[\overline{\tau_R}.Y + (\emptyset\alpha Y) + i.Y] + b + (1-\alpha)[\overline{\tau_D}Y + i.Y - g.Y] + F_a} & \boldsymbol{for\ E > E_{D2}} \end{cases}$$

Where $(\boldsymbol{\emptyset\alpha Y})$ ***is the inconvenient cost of carrying cash it is a function of proportion of money carried***

Now when education level is between $\boldsymbol{E_{D1}}$ ***to*** $\boldsymbol{E_R}$ ***then F.O.C of*** TC_{DC} *minimization will give the optimum* α *as,*

$$\widehat{\boldsymbol{\alpha}} = \frac{(\boldsymbol{\tau_D} - \boldsymbol{e_{D2}E}) - (\boldsymbol{\tau_R} - \boldsymbol{e_R E}) - \boldsymbol{g}}{\boldsymbol{2\emptyset}}$$

Now, $\widehat{\boldsymbol{\alpha}}$ ***will exists when*** $\{(\boldsymbol{\tau_D} - \boldsymbol{e_{D2}E}) - (\boldsymbol{\tau_R} - \boldsymbol{e_R E}) - \boldsymbol{g}\} > \mathbf{0}$***,***

Or when $\boldsymbol{E} < \frac{(\tau_D - \tau_R) - g}{(e_{D2} - e_R)} (= \widehat{\boldsymbol{E_{\alpha 1}}} > \mathbf{0})$

$\boldsymbol{E} > \widehat{\boldsymbol{E_{\alpha 1}}}$***,*** $\boldsymbol{\theta}$ ***will be zero, then buyer will always prefer cashless transaction***

Now when education level is between $\boldsymbol{E_R}$ ***to*** $\boldsymbol{E_{D2}}$ ***then F.O.C of*** TC_{DC} *minimization will give the optimum* θ *as,*

$$\widehat{\boldsymbol{\alpha}} = \frac{(\boldsymbol{\tau_D} - \boldsymbol{e_{D2}E}) - \overline{\boldsymbol{\tau_R}} - \boldsymbol{g}}{\boldsymbol{2\emptyset}}$$

Now, $\widehat{\boldsymbol{\alpha}}$ ***will exists when*** $\{(\boldsymbol{\tau_D} - \boldsymbol{e_{D2}E}) - \overline{\boldsymbol{\tau_R}} - \boldsymbol{g}\} > \mathbf{0}$***,***

Or when $\boldsymbol{E} < \frac{(\tau_D - \overline{\tau_R}) - g}{e_{D2}} (= \widehat{\boldsymbol{E_{\alpha 2}}} > \mathbf{0})$

$\boldsymbol{E} > \widehat{\boldsymbol{E_{\alpha 2}}}$***,*** $\boldsymbol{\theta}$ ***will be zero, then buyer will always prefer cashless transaction***

When, education level is greater than $\boldsymbol{E_{D2}}$ ***then*** $\boldsymbol{\alpha}$ ***will not exists.***

21. **Page 74, second paragraph, last line—"For debit card transactions, shop floor cost includes the time loss, and handling cost includes the cost of technical faults and mistakes associated with the transaction with a debit card at the shop floor. This we name transaction cost." However, other fixed costs are associated with debit cards, e.g., learning how to use a debit card, remembering PINs, etc. So, when answering which transaction cost is higher—cash or debit card—doesn't this depend on whether the technical cost associated with using a debit card is higher than the value of time loss associated with cash? No distinction is made on this aspect—why?**

Actions: I acknowledge the importance of considering additional fixed costs associated with debit card usage, such as learning how to use a debit card and remembering PINs. However, I have already attempted to incorporate this aspect into the discussion on page 77, where I address the role of education in reducing transaction costs.

On page 81, I mention that "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."

22. **Page 77—"τ_D is the time loss and handling cost, which includes the fear of technical faults and mistakes associated with the transaction of one unit of money with a debit card at the shop floor when the level of education is zero." Why are time loss and handling costs, which include the fear of technical faults, dependent on the level of education? Explain in detail with examples.**

Actions: I have already provided a justification for this in the thesis, where I discuss the relationship between education and transaction costs.

On page 85, I mention that "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 "breaking the system" or making irreversible mistakes, even if the issue is minor." *This highlights that individuals with lower education levels may experience higher transaction costs due to a lack of familiarity with digital payment systems, leading to delays, errors, or hesitancy in using debit cards.*

23. **Page 78—"The effect of an increase in the level of education in the reduction of shop floor cost could be divided into three stages, ..." What is the rationale for using a three-stage education level? Why not two or four stages?**

Actions: The choice of a three-stage education level is primarily for clarity and simplicity in presenting the model. While it is possible to consider four or five stages instead, doing so would not alter the fundamental conclusions of the model.

Introducing more stages could create unnecessary confusion and make the model more complex without adding significant new insights. The three-stage framework strikes a balance between capturing the impact of education on transaction costs and maintaining the model's interpretability. Thus, for ease of understanding, I have adopted this approach.

24. **Figure 4.1 on page 85—What if Ex falls sharply before ER, i.e., EAD < ER? Also, can ER = EAD = EDI? Also, not sure why the slope of TCD is changing sharply at EDI. Why do we need a kink both at EDI and ED2? Can't it fall monotonically all the way to ED and then form a flat line (kink)? Similarly, in Figure 4.2 on page 86: what if ER' = EBD' = ED1?**

Actions: I have included the following.(page 92, footnote)

1. ***E_{AD} can be less than E_R**: E_{AD} represents the equilibrium level of education where the transaction cost of debit card transactions equals the transaction cost of cash transactions. E_{AD} Could be less than E_R, depending on the other variables, As the equilibrium will exists between the level E_{D1} and E_{D2} and E_R also lies between E_{D1} and E_{D2} . But E_R = E_{AD} = E_{D1} can't happen by definition, which contradicts the model's assumptions.*
2. ***Regarding the kink at E_{D1} and E_{D2}**: The reason for the kink is that the marginal effect of education on transaction cost reduction is not uniform across the entire range of education levels. At lower levels of*

education, the impact of education on reducing transaction costs is less significant. However, as education increases, the effect becomes more pronounced, leading to a steeper slope. Beyond a certain threshold, the transaction costs cannot be reduced further, which results in the curve flattening. After reaching the minimum threshold, the transaction costs level out, which justifies the kink at ***EDI*** *and* ***ED2****. The model needs to reflect this non-linear relationship, which wouldn't be captured by a monotonic decrease.*

25. **Page 92—An assumption was made as follows: "Let's consider two types of individuals—one with zero understated income and the other concealing all income to evade taxes." However, the probability of evading tax can increase with increasing income. Why does it have to be discrete at two extreme points?**

Actions: In response to the assumption made about two extreme types of individuals—one with zero understated income and the other concealing all income to evade taxes. we have conducted a separate analysis to determine the optimal proportion of understated income in the following section, but we have not incorporated that the probability of evading tax can increase with the increase in income, which needs farther deeper analysis. While the initial model used extreme points for simplicity and clarity, we acknowledge the importance of considering the probability of evading tax can increase with increasing income. We plan to explore the suggested analysis in future work to further refine our understanding of tax evasion behavior across different income levels.

26. **Overall, the theoretical chapter is well-written. Most of the comments made above in this chapter are clarificatory, and some of them could be incorporated for future work purposes**

Chapter 5

27. **Chapter 5 tests the model developed in Chapter 4 and considers two waves of data (2004-05 and 2011-12) from the India Human Development Survey datasets. The main limitation of this chapter is that it considers a period to test this model when digital transactions were not very popular in India. Digital transactions became more common after 2014 with the new federal government in place (also stated in Chapter 2). So, the time period 2004-05 and 2011-12 is not appropriate to examine this research question. Credit card use was not common in 2012 (the fee structure was also different). This limitation needs to be acknowledged upfront in the chapter, as it has enormous implications for policy directions. We are now in 2024, and this chapter is prescribing policies based on more than 10-year-old data. India's financial system has changed enormously since then. Unfortunately, this limits the scope and publication possibilities of this chapter in the future. Can this be added as a limitation to the study?**

Actions: I have acknowledged this limitation in my thesis. The discussion explicitly mentions that (page 115) "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 transaction pattern and system prior to the digital revolution. Despite its limitations, the study makes an important contribution to understanding the evolution of financial behaviors in India and underscores the necessity of adapting policies to a rapidly transforming economic environment."

28. **The other main comment is on the empirical modeling. There are four related points:**

a. **Firstly, it is important to note that credit cards are issued based on passing income/asset and debt tests. Not everyone gets a credit card. So, by default, credit cards are dependent on income thresholds. If a low-income earner with no fixed job wants a credit card, they will not be issued one by the bank because of failing the income test. Similarly, the preference for owning a credit card can vary with different levels of education; for example, owning a credit card can be viewed as a risk/debt, which many people may not prefer, irrespective of education or income level. These aspects were not considered in the empirical modeling. Can these be again added as a limitation to the study for thesis purposes?**

Actions: I mentioned the following in page 115

"One important 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 modeled in the empirical analysis, and their exclusion may impact the interpretation of the findings."

b. **Secondly, the interpretation of the interaction term between education and income is hard to explain. Education was found to have a negative impact on credit card ownership (Section 5.3.2). However, this does not mean income is zero in this case. Since income is not included in the specification, income is an omitted variable and is included in the error term. In this case, the interaction term cannot be interpreted as a joint effect as it may capture the effect from just one variable, as the other one is omitted from the specification. Thus, ideally, a threshold regression modeling technique needs to be used, where the effect of education on credit card ownership can be examined separately for low, mid, and high levels of income. This is also reflected on Page 104 of the introduction, where the author states: *"The theoretical analysis establishes that the level of income and level of education jointly influence the preference for cashless transactions. Higher income levels beyond a certain threshold lead to an increased likelihood of choosing cashless payment. Higher education levels beyond a certain threshold lead to an increased likelihood of choosing cashless payment."* These statements clearly indicate that the appropriate modeling technique for testing this theory is a threshold modeling approach. There are many ways to employ a threshold model: static and dynamic, as well as exogenous and endogenous threshold modeling. Can the author implement a simple threshold model as a robustness test?**

Actions: ***Following is the simple threshold model analysis***

- **Logistic Regression Results (Model 1) (where we consider 4 threshold levels of income (Based on endogenous threshold regression analysis) to find out the effect of education along with other socio economics variables)**

Model Statistics:
Number of Observations: 25,213
Log Likelihood: -2987.11
LR Chi2(10): 900.83
Pseudo R2: 0.1310

Variable	Odds Ratio	p-Value (OR)	Marginal Effect (dy/dx)	p-Value (ME)
Education	1.0740	0.001	0.001984	0.001
Age	0.0067	0.013	-0.000185	0.013
Computer Knowledge	6.4090	0.000	0.051596	0.000
Household Status	1.7294	0.036	0.015215	0.036
Financial Inclusion	7.0437	0.000	0.054219	0.000
Economic Class 2	2.0630	0.000	0.020114	0.000
Economic Class 3	4.2100	0.000	0.039924	0.000
Very Low Income & Education	1.0222	0.079	0.000610	0.079
Low Income & Education	0.9303	0.000	-0.002004	0.000
Mid Income & Education	0.9507	0.000	-0.002004	0.000
Constant	0.0018	0.000	-	-

- **Table 3: Logistic Regression 2 Results** (where we consider 4 threshold level of education (based on quartiles) to find out the effect of income along with other socio economics variables)

Dependent Variable: Probability of Holding a Card (cards12)

Model Statistics:

- Number of Observations: **25,213**
- Likelihood Ratio (LR) Chi-Square: **928.70**
- p-value for LR Chi-Square: **0.0000**
- Log-Likelihood: **-2973.17**
- Pseudo R^2: **0.1351**

Variable	Odds Ratio	p-Value (OR)	Marginal Effect (dy/dx)	p-Value (ME)
Income (log)	1.9006	0.000	0.0178	0.000
Age (years)	0.0057	0.027	-0.0001	0.027
Financial Knowledge	7.1894	0.000	0.0548	0.000
Household Status	1.7912	0.065	0.0162	0.065
Financial Inclusion	7.2828	0.000	0.0552	0.000
Economic Class 2	2.1512	0.000	0.0213	0.000
Economic Class 3	4.3644	0.000	0.0409	0.000
Income * Education Very Low	1.2910	0.169	0.0071	0.169
Income * Education Low	0.9494	0.000	-0.0014	0.000
Income * Education Middle	0.8773	0.000	-0.0036	0.000
Constant	0.0001	0.000	-	-

c. **definition, is intrinsically income-dependent, a more flexible model is required as a robustness test instead of just the logit model. It may be worth trying the linear probability model (LPM) or the conditional logit model.**

Actions: We have tried the linear probability model the results are mentioned below, which are not creating any contrudictions with the logistic regression results.

The logit model is a well-suited approach for analyzing credit card ownership because of the following reasons:

1. **Binary Dependent Variable Handling**: Credit card ownership is a binary choice (own or not own), making a binary choice model like logit appropriate. The logit model ensures that predicted probabilities lie strictly between 0 and 1, unlike a linear probability model (LPM), which may generate probabilities outside this range.
2. **Non-Linearity and S-Shaped Relationship**: The relationship between income and the probability of owning a credit card is unlikely to be linear. The logit model captures this by assuming an S-shaped (sigmoid) relationship, which reflects how the probability of credit card ownership increases at a decreasing rate as income rises.
3. **Better Interpretation through Odds Ratios**: The logit model provides an intuitive interpretation through odds ratios, which explain how changes in explanatory variables affect the odds of owning a credit card rather than just probabilities. This is particularly useful in understanding income-dependent decision-making.
4. **Robustness to Heteroskedasticity**: Unlike LPM, which suffers from heteroskedasticity (non-constant variance of errors), the logit model naturally accounts for varying variances in probability estimation, making statistical inferences more reliable.
5. **Flexibility in Functional Form**: While the conditional logit model is useful for choice-based settings with multiple alternatives, the standard logit model remains appropriate for single binary choices, such as whether an individual owns a credit card.

Thus, the logit model remains a strong choice for analyzing credit card ownership due to its theoretical justification, statistical properties, and practical interpretability. But for the robustness below are the results of LPM, after addressing the heteroscedasticity.

```
. regress cards12 edu12 age12 comkno12 hhstatus12 fininclu12 ecoclass2 ecoclass3
eduincverylow eduincomelow eduinc
> omemid, robust

Linear regression                               Number of obs     =     25,213
                                                F(10, 25202)      =      50.78
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0422
                                                Root MSE          =     .16822

-------------------------------------------------------------------------------
              |               Robust
      cards12 | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------+----------------------------------------------------------------
        edu12 |   .0016596   .0003014     5.51   0.000     .0010687    .0022504
        age12 |   .0001843     .00008     2.31   0.021     .0000276    .0003411
     comkno12 |   .0620914   .0076111     8.16   0.000     .0471731    .0770097
   hhstatus12 |   .0040932   .0046463     0.88   0.378    -.0050139    .0132003
   fininclu12 |   .0612048   .0064844     9.44   0.000      .048495    .0739145
    ecoclass2 |    .008596   .0018833     4.56   0.000     .0049045    .0122874
    ecoclass3 |   .0769443   .0086281     8.92   0.000     .0600328    .0938559
eduincverylow |  -.0009495   .0003104    -3.06   0.002     -.001558    -.000341
 eduincomelow |  -.0021649   .0002638    -8.21   0.000     -.002682   -.0016478
 eduincomemid |  -.0021252   .0002654    -8.01   0.000    -.0026455   -.0016049
        _cons |  -.0245545   .0048438    -5.07   0.000    -.0340486   -.0150605
-------------------------------------------------------------------------------
```

```
. . regress cards12 logincome age12 comkno12 hhstatus12 fininclu12 ecoclass2 ecoclass3
inceduverylow incedulow in
> cedumid, robust

Linear regression                               Number of obs     =     25,213
                                                F(10, 25202)      =      52.94
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0437
                                                Root MSE          =     .16809

------------------------------------------------------------------------------
             |               Robust
     cards12 | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
   logincome |   .0206393   .0041209     5.01   0.000     .0125621    .0287166
       age12 |   .0001677   .0000792     2.12   0.034     .0000125    .0003229
    comkno12 |    .057151   .0074942     7.63   0.000     .0424618    .0718401
  hhstatus12 |   .0011681   .0046606     0.25   0.802    -.0079669    .0103032
  fininclu12 |   .0615883   .0065097     9.46   0.000     .0488289    .0743478
   ecoclass2 |    .008547   .0018982     4.50   0.000     .0048265    .0122675
   ecoclass3 |   .0754698   .0085142     8.86   0.000     .0587815    .0921581
inceduverylow |  .0001644   .0008434     0.19   0.845    -.0014888    .0018176
   incedulow |  -.0035946   .0006178    -5.82   0.000    -.0048055   -.0023837
   incedumid |  -.0057201   .0006431    -8.89   0.000    -.0069806   -.0044596
       _cons |  -.1062264   .0205186    -5.18   0.000    -.1464441   -.0660088
------------------------------------------------------------------------------
```

d. Finally, although the author states that the aim of this chapter is to find the determinants of cashless transactions, the results presented here are all associations, not causation. In other words, endogeneity biases, including reverse causality and omitted variable biases, can exist in the estimates. It would be helpful if the introduction and conclusion of the chapter mention that some degree of caution is required in interpreting these results.

Actions: This limitation has been highlighted in both the introduction and conclusion of the chapter to ensure a careful interpretation of the findings. I have mentioned in page 113 "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."

29. Another limitation of this study is that data on computer knowledge and smartphone operation for digital transactions is only available for the 2011-12 wave and not for 2004-05. This makes it difficult to test the theoretical model when digital literacy cannot be compared appropriately between the two waves. On the same note, mobile phone ownership is taken as a substitute for computers and digital knowledge. However, in 2011-12, in reality, people hardly used smartphones for digital transactions! Smartphones and banking apps were developed much later. This again goes back to my first point that this dataset is not very informative for testing this kind of research question. It may be worth mentioning this as a limitation of the study.

Actions: This limitation has been acknowledged in the study. In page 118 we mentioned "Another 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."

30. **All the tables in the results section need to be presented professionally. Currently, the results appear to be directly copied and pasted from EViews software. Additionally, when represented in a table (e.g., Table 5.6, 5.7, etc.), several key statistics are missing (e.g., R-squared, standard errors, number of observations, etc.). It is advised that the candidate follows the style of a professional journal paper to format empirical tables properly.**

Actions: Done

31. **To check the variation over time (2004-05 vs. 2011-12), the ideal approach would be to run two separate regressions for the two waves and compare the coefficients of the key independent variables. Pooling the data and adding a time variable in the regression (e.g., Table 5.6) is not very useful.**

Actions: Based on your suggestion, we have decided to remove the panel data analysis from the thesis. Instead, we have conducted separate analyses for the two time periods (2004-05 and 2011-12) to allow for a clearer comparison of the coefficients of key independent variables and to derive better inferences.