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Digitalization and Financial Inclusion: Welfare Implications for India's Tech-Averse Population

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Biswajit Nag

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WPS No. EC-25-78

Digitalization and Financial Inclusion: Welfare Implications for India's Tech-Averse Population *

Vishal Parija[(1)], Biswajit Nag [(2)]

Abstract

India's rapid transition toward digital payment mechanisms, particularly post-demonetization, has significantly altered the country's transactional landscape. While platforms like UPI have made financial exchanges more seamless for the digitally literate (DL) population, a growing divide has emerged, leaving the digitally illiterate (DI) population- especially the elderly, low-income earners, and rural consumers at a potential disadvantage.

The primary objective of this study is to design a dynamic framework which aims to evaluate the overall welfare impact of digital transactions in India, offering a comparative analysis between DL and DI cohorts. The secondary objective, as an extension of the study introduces a denomination- specific, ***velocity-based approach*** *to better understand shifts in cash transaction behavior particularly in the context of rising digitalization and declining physical currency usage.*

The research is based on a combination of primary and secondary data analysis. A short survey was conducted in order to capture real-world transaction preferences, which were then translated into weights for welfare computation. However, the core methodological innovation lies in a dynamic, denomination-wise velocity-based model that incorporates soiled note shares as a proxy for cash transaction preference. At a later stage, the study employs Autoregressive Distributed Lag (ARDL) models, alongside the Bounds testing approach to determine the long -run causality

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of various macroeconomic variable influencing denomination wise cash transaction. Further, the Error Correction Model (ECM) is used to capture short-run dynamics and the speed of adjustment toward equilibrium.

While the overall preference for cash is declining, currency in circulation continues to rise, reflecting a reduction in the velocity of money. This has profound welfare implications, particularly for those excluded from the digital ecosystem. The welfare analysis reveals that DI individuals, who depend solely on cash and lower denominations (majorly) for daily transactions, increasingly face challenges due to the scarcity of small change, compromising their ability to transact and thereby reducing their welfare. In contrast, DL individuals enjoy smoother transitions, leveraging digital tools to maintain their consumption patterns. Furthermore, the denomination-wise velocity framework reveals that post 2022, low-value transactions are being increasingly digitized, whereas high-value transactions have been rapidly getting non-digitized through rising usage of higher denomination cash (Rs 500 and above), often linked to informal sector activity and tax-avoidance motives.

JEL Codes: E41, E42, G21, O33, D63, C22

Keywords- Welfare, Digital Divide, Currency in Circulation, Velocity, Cash Transactions, ARDL

1. Introduction

1.1 Background

India's payment landscape has undergone a paradigm structural transformation with the advent of digital transaction mechanisms such as UPI. This technological revolution has gradually altered consumers transactional preferences with rising substitution of cash with UPI.
It appears to have brought a significant decline in the preference for cash transactions as evident from the declining trend of Cash Withdrawal-to-Currency in Circulation ratio.
Although digital payments have seen rapid growth in recent years, the amount of currency circulating in the economy has also continued to rise. In fact, the currency-in-circulation (CiC) as a share of GDP reached a peak of 14.4% in 2020–21. Given that cash and digital payments are often considered substitutes, this concurrent increase in both forms of transactions appears puzzling, leading to what has been termed the "currency demand paradox" (*RBI, Occasional Papers*).
Considering both the afore-mentioned statement, it can be argued that although the cash transactions in overall has fallen, the cash holding is rising as evident from the rising CiC trend.
As far as the denomination wise cash trend is concerned, pre-demonetization the cash transactions in medium (Rs 50 to 200) and lower denominations (Rs. 20 and below) were relatively higher than that of in higher denominations (Rs 500 & above).
This structural arrangement suddenly changed following the demonetization shock. Cash transactions in higher denominations became quite rampant and as people tend to make panic buying of gold & jewelleries in order to convert their demonetized notes into assets.
Following demonetization, a sustained decline in the high denomination's transaction is observed suggesting a potential loss of people's trust on it. This behavioural shift appears to stem from the heightened perception of risk associated with policy-induced shocks, where high-denomination notes are viewed as more vulnerable to sudden regulatory invalidation.
Subsequently, GST rollout in July 2017 forced many businesses into formal tax net. Now, businesses registered under GST must have to issue proper tax invoices and digital or bank-based payments are preferred.
As a result, many individuals and businesses shifted their reliance from high to medium or low-level denominations for their day-day transactions. This process was further accelerated with rising UPI adoption.

During the COVID aftermath, cash transactions across all denomination categories rose as restrictions eased. However, a distinctive shift was observed with the onset of Russia- Ukraine War- which had led dreadful socio-economic implications on the world economy. The war triggered global economic disruptions and inflationary pressures.
During this period, the cash transactions in higher denomination spiked significantly eventually surpassing the declining lower denomination curve.
While making a comparative analysis of denomination wise cash transaction and velocity chart for the period of post Russo-Ukraine war, it was observed that for lower denomination the velocity and cash transactions both have declined- indicating that people that substituted their low valued transactions with UPI.
On the other hand, for higher denomination, the velocity has remained stagnant whereas the cash transaction has significantly increased- indicating an increase in overall higher denomination CiC as people are preferring to hold higher denomination for high valued transactions.

The declining tendency of velocity of lower denominations marks a decline in demand for lower value denominations like Rs.10, Rs.20, Rs.50 inter alia. On the contrast, there has been a rising trend in the demand for higher value denominations like Rs.100, Rs.200, and Rs.500 due to their higher purchasing power and store of value.
Over the coming years, the disparity between the availability of both types of denominations seems to be widening, indicating a shift towards currency hoarding behavior of high value denomination. The economic implications of reduced circulation of low-value denominations can be many and impact various stakeholders, from individuals to businesses.
There can be several problems associated to reduced circulation of low-value denominations due to the increasing adoption of digital payment systems.

1. Small vendors and businesses may struggle to provide change for transactions, especially in rural or semi-urban areas where digital adoption is lower.
2. Low-income groups or Tech-averse population may face challenges while making transactions due to the reduced availability of smaller denominations. These groups often rely on cash for daily transactions and may be disproportionately affected.
3. Those consumers who are not adapted to digital transactions may be forced to round off amounts, potentially leading to overpayment or underpayment. Overpayment might lead to perceived inflation which can affect their welfare.

While this digital revolution has enhanced financial inclusion and efficiency, its welfare implications on this critical segment of the population i.e. digitally illiterates remain un-explored. The tech-averse population, often concentrated in rural areas, low-income households, or among the elderly who face significant barriers in adopting digital financial tools due to limited digital literacy, infrastructural inadequacies and conservative mindset.
As the economy becomes increasingly digitized, these individuals may find themselves excluded from the benefits of speed, convenience, and transparency and may experience increased transaction costs, reduced bargaining power, or even a decline in their ability to participate effectively in the modern economy.
This dissertation seeks to examine the welfare impact of digital transactions on India's tech-averse population, with a focus on how structural shifts in the payment ecosystem have influenced their real transaction behaviour.

Using both **primary survey data and official secondary data**, the study attempts to draw a distinction between the welfare of Digital Literates (DL) and Digitally Illiterates (DI), and track their evolving patterns of real cash usage.

At the later stage, the paper employs ARDL approach to determine the factors influencing denomination wise currency demand in the economy.

1.2 Literature Review

The dynamics of currency demand in India have been the subject of extensive empirical research, especially in the context of evolving payment systems and macroeconomic uncertainties.

Singh (2016) investigates the stability of India's currency demand function over the period Q1 1996 to Q4 2014. Employing a seasonal cointegration framework and drawing upon the Gurley and Shaw (1960) hypothesis, the study incorporates private consumption, the tax-to-GDP ratio, and the deposit rate as explanatory variables. The findings indicate no long-run cointegration at zero or annual frequencies, though a significant relationship emerges at the biannual frequency. Importantly, since 2010, financial sector innovations—particularly in payment technologies—have increased the responsiveness of currency demand to changes in deposit rates, hinting at signs of endogenous financial innovation.

Awasthy, Misra, and Dhal (2023) examine the seeming paradox of a concurrent rise in both digital payments and currency in circulation in India. The empirical analysis concludes that this increase in currency demand is largely precautionary in nature and driven by the store-of-value function of money rather than its use as a medium of exchange. While digital payment systems are increasingly replacing cash for everyday transactions, the underlying demand for currency persists due to its role as a secure and liquid asset during times of uncertainty.

Chaudhari, Dhal, and Adiki (2019) analyze the interplay between income effects and substitution effects resulting from digital payment innovations. Their study highlights that while digital payments exert a long-term negative correlation with currency demand, the substitution effect remains relatively weak in comparison to the dominant income effect. Quantitatively, a 1% increase in digital retail transactions offsets only one-tenth of the income effect, suggesting that a substantial increase in digital usage would be necessary to significantly reduce overall currency demand.

Raj et al. (2020) adopt a heterodox approach using diverse time series and econometric techniques to model and forecast currency demand in India. The study finds that currency in circulation displays significant weekly and monthly seasonality, influenced by events such as festivals and elections. Furthermore, an increase in digital transactions (especially card-based) is associated with a short-term reduction in currency demand. However, the long-run income elasticity of currency demand is found to be unity, reaffirming the role of economic activity in driving currency usage.

Murad, Salim, and Kibria (2021) introduce the dimension of Economic Policy Uncertainty (EPU) into the Indian money demand framework. Applying both linear ARDL and asymmetric nonlinear models, the study reveals that policy uncertainty significantly impacts narrow money demand in the short run, with asymmetric effects observed across narrow and broad money aggregates. Despite these short-run dynamics, the stability of money demand in India is affirmed in both model specifications.

Collectively, these studies underscore the complex and evolving nature of currency demand in India, influenced by macroeconomic variables, technological innovation in payment systems, and policy-driven uncertainty. They suggest that while digitalization exerts downward pressure on cash usage for transactions, structural and behavioral factors continue to uphold the relevance of currency as a store of value.

2. Research Objectives

While most of the existing literature has primarily focused on analysing Currency in circulation and its determinants, often using it as a proxy for cash transactions due to the convenience and accessibility of data, very few have delved into the actual behavioural patterns of cash usage across denominations.
This study seeks to address this underexplored dimension by moving beyond conventional currency demand models and focusing on how shifts in cash usage patterns affect real transaction behaviour.
Primary objective - conduct a comparative welfare analysis between the digitally literate (DL) and digitally illiterate (DI) cohorts in the context of India's evolving payment landscape. The analysis aims to understand how differential access to and adoption of digital transaction systems influence economic well-being, financial participation, and transactional efficiency across these groups.
Secondary Objective- Introduce a novel methodology to examine economy-wide cash transaction behaviour, particularly through a denomination-wise lens. This approach, to the best of our knowledge, remains largely unexplored in existing literature and contributes a new dimension to understanding the behavioural shifts in currency usage.

3. Data, Sources & Methodology

3.1 Description of Study

This study investigates the welfare implications of India's accelerating shift toward digital payment systems, with a specific focus on the tech-averse population, which include digitally illiterate, older, rural, and financially marginalized groups.
It dives into actual transaction behaviour across currency denominations to understand the nuanced impact of digitalization on cash usage.
The research undertakes a time series analysis of denomination-wise real cash transactions and velocity trends from 2011 to 2024. By categorizing transactions into low (₹1–₹20), medium (₹50–₹250), and high (₹500+) denominations, the study captures evolving behavioral patterns in response to key economic events such as demonetization, the COVID-19 pandemic, and the Russia-Ukraine war.

3.2 Methodology

This study is primarily focused on analysing the welfare impact of digitalization on India's Tech-averse population.
The model is completely dynamic as it incorporates various time varying parameters affecting the dependent variables (Welfare Levels, Real Transactions, Denomination wise transactions).
The time horizon of the study is from 2011 Q1 to 2024 Q2.
As a part of secondary study, this study also explores the trend of denomination wise cash transactions in India from 2011 Q1 to 2024 Q2.
The Methodology Section is further divided into 2 sub sections: -
1.1. Welfare Analysis
1.2. Denomination wise Cash Transactions.

Both the subsections involve different methodology for their respective computations.

Model

The country's population has been segregated into two categories: -

1. Digitally Literate (DL)
2. Digitally Illiterate (DI)

Assumption: -

1. Digitally Literate (DL) cohort uses both **Cash & UPI** as a medium of transaction.
2. Digitally Illiterate (DI) cohort use only **Cash** as a medium of transaction.
3. Q2 2016 (Demonetization period) marks the beginning of UPI revolution.
4. Pre- Digitalization (Q2 2016), all individuals are assumed to be DIs.

Let,
$\boldsymbol{D_t}$ denotes the Value of total transaction made by the DLs at time pd. t
$\boldsymbol{U_t}$ denotes the Value of UPI transactions made by the DLs at time pd. t
$\boldsymbol{V_t}$ denotes Aggregate value of Cash transactions made in the economy by the DL's & DI' s in aggregate at time pd. t, where,

$$V_t = v_t . C_t;$$

$v_t = Velocity\ of\ money\ in\ period\ t$
$C_t = Value\ of\ currency\ in\ circulation\ (CiC)$

Product of Velocity & Value of currency in circulation will give us the Aggregate value of cash transactions made in the economy.

Velocity of Money computation

We know,

$$Velocity\ of\ Money(v_t) = \frac{Nominal\ GDP}{Broad\ Money(M_3)}$$

However, for our purpose, we will consider a slightly different version of Broad money i.e Adjusted Broad Money ($M_3^{'}$) which equals: -

$$M_3' = M_3 - Sum\ of\ small\ coins\ and\ notes$$

The logic behind deducting the small coins and notes from the broad money is the redundant nature of these small notes and coins (Rs 50 paise coins, Rs 1 note, Rs 2 notes) which are still part of CiC, however, doesn't contribute anything to cash transactions, considering the time frame of the study.

Hence, we modify the velocity equation into adjusted velocity equation: -

$$\boldsymbol{Adjusted\ Velocity}\ (\boldsymbol{v'}) = \frac{\boldsymbol{Nominal\ GDP}}{\boldsymbol{M_3'}}$$

Depiction

<table>
<tr><td>$D_t - U_t$
(Value of transactions made by Digitally Literate in cash)</td><td rowspan="2">U_t

(Value of UPI transactions made by Digitally Literate)</td></tr>
<tr><td>$V_t - (D_t - U_t)$

(Value of transactions made by digitally Illiterate in cash)</td></tr>
</table>

Determination of Value of Cash Transaction made by the DL's and DI's

Taking into consideration the assumption made earlier, total transaction by the DL's can be classified into two categories: -

1. $Cash\ Transaction\ (C_t^L)$
2. $UPI\ transaction\ (U_t)$

Total Transaction made by the DL's ($\boldsymbol{D_t}$) can be mathematically written as: -

$$D_t = U_t + C_t^L$$
$$= U_t + \alpha_t . D_t$$

$$\boldsymbol{D_t = \frac{U_t}{1 - \alpha_t}} \qquad \textbf{…..(1)}$$

α_t : $DL's\ cash\ transaction\ pref.out\ of\ D_t$ (%)

However, one important point to note is that, the above-mentioned formula for D_t is only applicable for large values of UPI transactions (U_t).
For instance,
U_t for Q2 2016 = Rs. 36 crores
α_t = 0.169
After incorporating the value of $\boldsymbol{\alpha_t}$ and U_t, we get D_t= Rs. 43.47 crore.
Intuitively, one can argue on this small value of D_t, which may not reflect the reality.

In order to resolve the problem Weighed Moving Average (WMA) method is used: -
3Qs, 5Qs, 7Qs, 8Qs, 9s, Weighted Moving average of Dt is taken into consideration.
The Dt is then determined based on the highest value among all the weighted MA's for a smooth transition.

$$\boldsymbol{D_t = max\{3QWMA, 5QWMA, 6QWMA, 7QWMA, 8QWMA, 9QWMA\}}$$

In the study,
The substitution of original D_t with the new D_t occurred till Q1 2017, following which the process stops and the original D_t is then taken into consideration.

Cash Transactions made by the DL,

$$C_t^L = \alpha_t . D_t$$

$$\boldsymbol{C_t^L = \frac{\alpha_t . U_t}{(1 - \alpha_t)}}$$

…..(2)

*Data pertaining to the value of UPI transactions are readily available at the UPI statistics tab of the NPCI web portal.

<u>Computation of α_t</u>

During the study, many efforts were made to find out a suitable proxy which can replicate the DL's Cash transaction behaviour post.

One of such likely proxy for $\boldsymbol{\alpha_t}$ could be: -

$$\boldsymbol{\alpha_t} = \frac{Cash\ Withdrawal\ (CW)}{Personal\ Disposable\ Income\ (PDI)}$$

Cash withdrawals as a share of Personal Disposable Income (PDI) can serve as a good proxy for cash preference because it reflects how much of a person's income is being withdrawn in cash form. A higher ratio suggests a stronger reliance on cash for spending, indicating preference for cash over digital modes.
Conversely, a declining ratio over time implies growing comfort with non-cash transactions like UPI or cards. This metric captures behavioural shifts in payment preferences at the macro level.

For the quarters before Q2 2016, $\boldsymbol{\alpha_t}$ **or** $\boldsymbol{\frac{CW}{PDI}}$ ratio is considered to be 1 as it has been assumed that before Q2 2016, cash is the only medium of transaction.
The divergence in the mode of transaction into UPI and Cash, came only after Q2 2016 (i.e post digitalization).
Once $\boldsymbol{\alpha_t}$ and U_t are determined and incorporated, the value for $\boldsymbol{C_t^L}$ can be readily obtained.
Cash Transactions made by the DI,

$$C_t^I = V_t - C_t^L$$

$$\boldsymbol{C_t^I = V_t - \frac{\alpha_t . U_t}{(1 - \alpha_t)}}$$

…..(3)

Welfare Function for DI's

The Welfare of the DI's are directly linked to purchase of commodities using real cash transactions. Higher real cash transactions => More amounts of goods purchased => Higher Welfare or Utility
In this Model, Weighted average of denomination wise real cash transactions made by the DI's has been chosen to serve as the proxy for the welfare function of the DI' s.
Presumably entire transaction born by the DI's will be incurred in cash. For the sake of convenience, we have classified the cash transactions by the DI' s into three categories.

1. *Lower Denomination Transactions (S^I_{1t})-* ***Rs. 1 to Rs. 20***
2. *Medium Denomination Transactions (S^I_{2t})-* ***Rs. 50 to Rs. 200***
3. *Higher Denomination Transactions (S^I_{3t})-* ***Rs. 500 and above***

The Welfare function for DI's can be deduced based on the weighted average of denomination wise real transaction, where the weights denote the preference for transaction using a particular denomination.
Thus, it can be mathematically written as the weighted average of log of denomination wise real cash transaction made by the DI's

$$W^I_t = z^I_{1t} . log\left(\frac{S^I_{1t}}{P_t}\right) + z^I_{2t} . log\left(\frac{S^I_{2t}}{P_t}\right) + z^I_{3t} . log\left(\frac{S^I_{3t}}{P_t}\right)$$

$$= \log\left[\left(\frac{S^I_{1t}}{P_t}\right)^{z^I_{1t}} . \left(\frac{S^I_{2t}}{P_t}\right)^{z^I_{2t}} . \left(\frac{S^I_{3t}}{P_t}\right)^{z^I_{3t}}\right]$$

$$\boldsymbol{W^I_t = log\left[\prod_k^3 \left(\frac{S^I_{kt}}{P_t}\right)^{z_{kt}}\right]}$$

…..(4)

; $\sum_k^3 z^I_{kt} = 1$

k = 1: Lower denomination
k = 2: Medium denomination
k = 3: -Higher denomination

z^I_{kt} – DI's Transaction Preference (%) using the kth denomination out of total cash transactions by them at time pd. t.

P_t – Consumer Price Index (CPI) at time pd. t

S^I_{kt} - Value of the kth Denomination Transactions made by the DI's at time pd.

Welfare Function for DL's

It has been assumed earlier, that DL's primarily make their transaction through Cash and UPI.

Thus, the Welfare function of DL's can be defined as the weighted average of log of real transactions made using UPI and cash respectively.
Furthermore, the cash transaction made by them can be then segmented into Lower, Medium and higher denomination transaction.

Mathematically,

$$W_t^L = x_{1t} . log \left(\frac{U_t}{Pt}\right) + x_{2t} \left[z_{1t}^L . log \left(\frac{S_{1t}^L}{P_t}\right) + z_{2t}^L . log \left(\frac{S_{2t}^L}{P_t}\right) + z_{3t}^L . log \left(\frac{S_{3t}^L}{Pt}\right)\right]$$

$$= \log \left[\left(\frac{U_t}{P_t}\right)^{x_{1t}} . \left(\frac{S_{1t}^L}{P_t}\right)^{x_{2t} z_{1t}^L} . \left(\frac{S_{2t}^L}{P_t}\right)^{x_{2t} z_{2t}^L} . \left(\frac{S_{3t}^L}{P_t}\right)^{x_{2t} z_{3t}^L}\right]$$

.

$$\boldsymbol{W_t^L = log \left[\left(\frac{U_t}{P_t}\right)^{x_{1t}} . \prod_k^3 \left(\frac{S_{kt}^L}{P_t}\right)^{x_{2t} z_{kt}^L}\right]}$$

…..(5)

$\sum_k^3 {z_{kt}}^L = 1$ & $\sum_m^2 x_{mt} = 1$

x_{1t} = Transaction Preference (%) using UPI by the DL's out their total transactions (Dt) at time t
x_{2t} = Transaction Preference (%) using Cash by the DL's out of Dt at time pd. t
*Note- $\frac{CW}{PDI}$ has been assumed to be the proxy for the DL's cash transaction preference.

z_{kt}^L = DL's Transaction Preference (%) using the k[th] denomination at time pd. t

P_t = Consumer Price Index (CPI) at time pd. t

S_{kt}^L= Value of the k[th] Denomination Transactions made by the DL's at time pd. t

U_t = Value of UPI transactions made at time pd. t

Generalized Welfare function for the *i[th]* cohort

The Welfare function can be further generalized for ith cohort as follows: -

$$\boldsymbol{W_t^i = log \left[\left(\frac{U_t}{P_t}\right)^{x_{1t}^i} . \prod_k^3 \left(\frac{S_{kt}^i}{P_t}\right)^{x_{2t}^i z_{kt}^i}\right]}$$

…..(6)

$\sum_k^3 {z_{kt}}^i = 1$ & $\sum_m^2 x_{mt} = 1$, for each 'i'

i= L => Digitally Literate's cohort

I => Digitally Illiterate's cohort

x_{1t}^{I} = DI's Transaction Preference (%) using UPI at time pd. t
*The value of $\boldsymbol{x_{1t}^{I} = 0}$, as it is assumed that DI's never uses UPI for transaction.

x_{2t}^{I} = DI's Transaction Preference (%) using Cash at time pd. t
(* The value of $\boldsymbol{x_{1t}^{I} = 1}$, as it is assumed that all transactions made by DI's are through Cash.)
x_{1t}^{L} = Transaction Preference (%) using UPI by the DL's at time pd. t

x_{2t}^{L} = Transaction Preference (%) using Cash by the DL's at time pd. t

U_t = Value of UPI transactions made at time pd. t

S_{kt}^{i} = Value of the kth Denomination Transactions made by the i[th] cohort at time pd. t

P_t = Consumer Price Index (CPI) at time pd. t
z_{kt}^{i} = i[th] cohort Transaction Preference (%) using the k[th] denomination at time pd. t

*Interestingly, equation (4), (5), (6) are the monotonic transformation of the Cobb Douglas Utility function- with denomination wise real cash transaction reflecting the commodities for the Utility Function.

Derivation of Value of denomination wise cash transaction ($\boldsymbol{S_{1t}^{i}, S_{2t}^{i}, S_{3t}^{i}}$) by the i[th] cohort.

The value of cash transaction made using a particular denomination in aggregate at time pd. t by the i[th] cohort can be calculated as product of velocity with Currency in circulation of that respective denomination.

$$\boldsymbol{S_{kt}^{i} = v_{kt}^{i} \cdot CiC_{kt}^{i}} \qquad \textbf{…..(7)}$$

v_{kt}^{i} = Velocity of the k[th] denomination held by the i[th] cohort

CiC_{kt}^{i} = Fraction of the k[th] denomination CiC held by the i[th] cohort

<u>Denomination wise velocity computation for the i[th] cohort</u>

v_{kt}^{i} can be defined as the ratio of total currency transactions made in the k[th] denomination by the i[th] cohort w.r.t the value of the k[th] denomination CiC held by them.

$$v_{kt}^{i} = \frac{Value\ of\ Cash\ Transaction\ in\ kth\ denomination\ made\ by\ the\ ith\ cohort\ at\ time\ 't'}{Value\ of\ kth\ denomination\ CiC\ held\ by\ the\ ith\ cohort\ at\ time\ 't'}$$

$$v_{kt}^{i} = \frac{\alpha_{kt}^{i} \cdot v_{kt} \cdot CiC_{kt}}{CiC_{kt}^{i}}$$

$$= \frac{\alpha_{kt}^{i} \cdot v_{kt}^{i} \cdot CiC_{kt}}{\mu_{kt}^{i} \cdot CiC_{kt}}$$

$$\boldsymbol{v_{kt}^{i} = \frac{\alpha_{kt}^{i} \cdot v_{kt}}{\mu_{kt}^{i}}}$$

….. (8)

v_{kt}^{i} = Velocity of k[th] denomination held by the i[th] cohort

α_{kt}^{i} = Proportion/Percentage of k[th] denomination transaction made by the i[th] cohort at time 't'

v_{kt} = Velocity of k[th] denomination

μ_{kt}^{i} = k[th] denomination holding preference by i[th] cohort.

Computation of $\boldsymbol{\alpha_{kt}^{i}}$

From the above explanation, α_{kt}^{i} can be defined as Ratio of the value of cash transaction made in k[th] denomination by the i[th] cohort out of the total transactions made in k[th] denomination at time pd.t.

$$\boldsymbol{\alpha_{kt}^{i}} = \frac{Value\ of\ cash\ transaction\ made\ in\ kth\ denomination\ by\ the\ ith\ cohort}{Total\ transactions\ made\ in\ kth\ denomination\ at\ time\ pd.t}$$

Mathematically,

$$\boldsymbol{\alpha_{kt}^{i} = \frac{z_{kt}^{i} \cdot C_{t}^{i}}{v_{kt} \cdot CiC_{kt}}}$$

….. (9)

z_{kt}^{i} = k[th] denomination transaction pref. by the ith cohort

C_{t}^{i} = Total Cash Transaction made by the ith cohort.

$z_{kt}^{i} \cdot C_{t}^{i}$ = Value of cash transaction made in k[th] denomination by the i[th] cohort at time 't'

$v_{kt} \cdot CiC_{kt}$ = Value of total transactions made in k[th] denomination at time pd. t.

From (8) & (9), we have

$$\boldsymbol{v_{kt}^{i} = \frac{z_{kt}^{i} \cdot C_{t}^{i}}{\mu_{kt}^{i} \cdot CiC_{kt}}}$$

…..(10)

$\sum_i \mu_{kt}^i = 1$ for i= I, L , for each k (i.e., $\mu_{kt}^I + \mu_{kt}^L = 1$) & $\sum_k^3 z_{kt}^i = 1$, for each i

Thus, the value of cash transaction made in k[th] denomination by the i[th] cohort at time 't' is given as: -

$$\boldsymbol{S_{kt}^i = v_{kt}^i . \mu_{kt}^i . CiC_{kt}}$$

…..(11)

or

$$\boldsymbol{S_{kt}^i = z_{kt}^i . C_t^i}$$

…..(12)

Equation (11) or (12) is applicable for the post digitalization time horizon. To depict the pre-digitalization denomination wise cash transaction scenario, we have to make slight modifications in the equation.

Considering the pre digitalization scenario (i.e. **pre Q2 2016**), since we have assumed all individuals to be DI's, the denomination wise velocity equation which varied with kth cohort can now be consolidated into one equation, reflecting denomination wise velocity of the economy irrespective of the cohort concerned.

So, Eqn. 10 can be transformed to,

$$\boldsymbol{v_{kt} = \frac{\beta_{kt} . v_t . CiC_t}{CiC_{kt}}}$$

…..(13)

where,

β_{kt} = Economy wide Cash Transaction Preference (%) in kth denomination

v_t = Velocity of money

CiC_t = Total currency in circulation

CiC_{kt} = kth denomination CiC

Computation of β_{kt}

The study identifies many proxy that can imitate the β_{kt} , out which the **Soiled Ratio-** the ratio of the amount kth denomination Soiled notes / Total amount of Soiled notes has been appropriated to be a better proxy that can truly reflect the denomination wise cash transaction behaviour prevailing in the economy.

Mathematically, Soiled Ratio can be defined as

$$\boldsymbol{\beta_{kt}} = \textbf{Soiled Ratio} = \frac{Soiled\ notes\ of\ kth\ denomination}{Total\ Soiled\ Notes}$$

Notes become soiled through repeated handling—so, denominations used more often in daily transactions tend to get soiled faster.
A higher share of soiled notes in a particular denomination likely indicates greater usage in cash transactions. While not perfect, this method offers an indirect but practical measure of denomination-wise cash usage.

*Note: - The weights for the computation are mentioned in the **Annexure.**

Aggregate Welfare

Aggregate Welfare can be determined from the weighted average of the Welfare of DI's and DL's respectively keeping population percentages of each cohort as respective weights.

$$\boldsymbol{AW_t = w_{1t}.\ W_t^L + w_{2t}.W_t^I}$$

….. (14)

s.t $\sum_i W_{it} = 1$, for i= I& L respectively

w_{1t} – Population % of the DL's at time period 't'

w_{2t} – Population % of the DI's at time period 't'

3.2 Variables under consideration and data sources

The study was based on both primary and secondary data analysis. Data has been collected from the online publication of Reserve Bank of India, Ministry of Statistics and Program implementation (MOSPI) and other official sources.

The list of secondary data along with their sources has been mentioned below: -

Variables	Notation	Data Source
Inflation	INF	Trading Economics
Currency in Circulation	CiC	Weekly Currency in Circulation, Reserve Bank of India
Lower Denomination Currency in Circulation	CiC_L	
Medium Deno. Currency in Circulation	CiC_M	
Higher Denomination Currency in Circulation	CiC_H	
Soiled Notes (High den. Medium den. & Low den.)	-	Monthly disposal of Soiled Banknotes, Reserve Bank of India
Cash Withdrawal	CW	Bankwise ATM/POS/Card Statistics, RBI

Personal Disposable Income	PDI	India Total Disposable Personal Income, Trading Economics
Nominal GDP at current prices	GDP	Annual and Quarterly Estimates of GDP at current prices, 2011-12 series, MoSPI
Broad Money	M3	Fortnightly data on money supply, RBI
UPI Transactions	UPI	UPI Statistics, NPCI
Consumer Price Index	CPI	Consumer Price Indices Warehouse, MoSPI
Total ATMs	ATM	State wise and Region wise Deployment of ATMs, RBI
Personal Tax Rate	P.Tax	Tax Rates - Central Board of Direct Taxes, incometaxindia.gov.in
Sales Tax Rate	S.Tax	India Sales Tax Rate – GST, Trading Economics
Savings Rate	Sav_Rate	Year wise Saving Deposits of Scheduled Commercial Banks, Dataful.in

Table 1

Apart from that the study has also conducted a short primary survey of 30 individuals of 30 + age group in order to determine their transaction preference- which is used for weight computation.

The demographic statistics has been shown below in **Table 2**: -

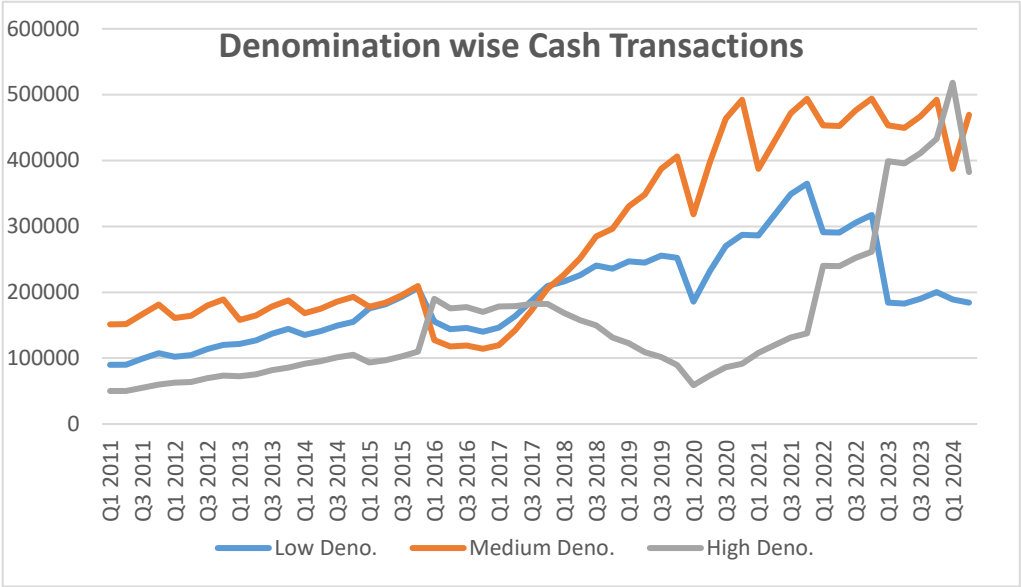
Classification on the basis of gender		
Gender	**Frequency**	**Percentage**
Male	20	66.66
Female	10	33.33
Total	30	100
Classification on the basis of Age		
Age	**Frequency**	**Percentage**
30-40	11	36.66
40-50	3	10
50-60	8	26.66
60-70	1	3.33
70 &above	1	3.33
Total	30	100
Classification on the basis of education		
Education/Qualification level	**Frequency**	**Percentage**
Illiterate	0	0
Matriculation	1	3.33
Graduation	8	26.66
Post Graduation and above	21	70
Total	30	
Classification on the basis of location status		
Location	**Frequency**	**Percentage**
Urban	25	83.33
Semi-Urban	4	13.33
Rural	1	3.33
Total	30	100
Classification on the basis of occupational category		

Occupational Category	Frequency	Percentage
Daily wage workers	0	0
Business Owners	1	3.33
Salaried Employee	23	76.66
Retired	2	6.66
Homemaker	2	6.66
Students	0	0
Others	2	6.66
Total	30	100
Classification on the basis of annual income level		
Annual Income Level	**Frequency**	**Percentage**
Upto Rs. 2.5 Lakhs	1	3.33
Rs. 2.5 - 3 Lakh	1	3.33
Rs. 3 - 5 Lakh	2	6.66
Rs. 5 - 10 Lakh	5	16.66
Above 10 Lakh	19	63.33
Currently Not earning	2	6.66
Total	30	100
Classification on the basis of Digital literacy		
Digital Literacy	**Frequency**	**Percentage**
Digitally Literate	25	83.33
Digitally Illiterate	5	16.66
Total	30	100
Classification on the basis of States		
States	**Frequency**	**Percentage**
Uttarakhand	1	3.33
Delhi	8	26.66
Haryana	4	13.33
Jharkhand	3	10
Maharashtra	1	3.33
Uttar Pradesh	2	6.66
Odisha	7	23.3
Telangana	2	6.66
West Bengal	2	6.66
Total	30	100

(*Source- Online Survey)* **Table 2**

4. Economy wide Cash Transaction

4.1 Denomination wise cash transactions



(Source – Author's Calculation) **Fig.1**

The figure depicts the quarterly trend of denomination wise cash transactions occurring in India. The deduction of the valuation of denomination wise cash transactions is **based on the methodology designed by the study** which has been described in ***Section 3.2.***

As evident from the Graph,
Pre Demonetization period was marked by high volume cash transaction in Medium Denomination followed by Lower denomination and then higher denomination.
This is indicative of the fact that people during the pre-demonetization period were incurring transactions primarily through lower and medium denominations. And transactions incurred in higher denominations were infrequent due to its high store of value function.

The Demonetization period caused a significant structural shift in people's cash transaction pattern. The cash transactions in higher denominations suddenly spiked following the announcement of withdrawal as people rushed towards panic buying of gold and jewelries. Following the government's announcement on November 8, 2016, invalidating ₹500 and ₹1,000 notes, there was a significant rush to buy gold. Jewelers sold approximately 15 tons of gold, worth around ₹5,000 crore, between 8 PM on November 8 and the early hours of November 9. Notably, nearly half of these sales occurred in Delhi, Uttar Pradesh, and Punjab (Source- Economics Times).

In Hyderabad alone, gold worth ₹2,700 crore was purchased using the demonetized notes between **November 8 and 30**. The Enforcement Directorate reported that approximately 8,000 kg of gold was imported into the city during this period (Source- Times of India).

Following the demonetization period, the pattern of cash transaction returned to its original level. The cash transactions in medium denomination again took the lead followed by the low and high denomination cash transactions respectively.

Intuitively, it can be argued, that the demonetization shocked the system especially for cash heavy sectors like real estate, informal retail agriculture and this led to loss of trust in high denomination currency as a reliable store of value among people.

Moreover, KYC norms were made stricter- PAN was mandatory for transactions over 2 Lakh under Section 269ST (Post 2017 Income Tax amendment) and other black money sectors came under scrutiny. These events subsequently led to rise in risk in high denomination cash dealing.

In addition to that,

1. Digital literacy campaign, Merchant QR code adoption, promotion of payment platforms like Google Pay, PhonePe etc. reduced dependency on cash.
2. GST rollout in July 2017 forced many businesses into formal tax net.
   Businesses registered under GST must have to issue proper tax invoices and digital or bank based payments are preferred.
3. Cash invoices for high-value transactions were accepted only to a limited extent due to stricter regulatory norms and compliance requirements.

Overall, these events made people risk averse with high denomination cash holding as a result precautionary savings got channelized into formal financial instruments like bank deposits.

During COVID, there was a sudden drop in all kind of transactions (dip could be visible at Q1 2020) as nation lockdowns and all economic activity halted.
The transactions in lower and medium denominations declined as people movements and consumption choices got restricted.
As restrictions eased, people began to make transactions in cash- shown by the rising trend of all three curves.

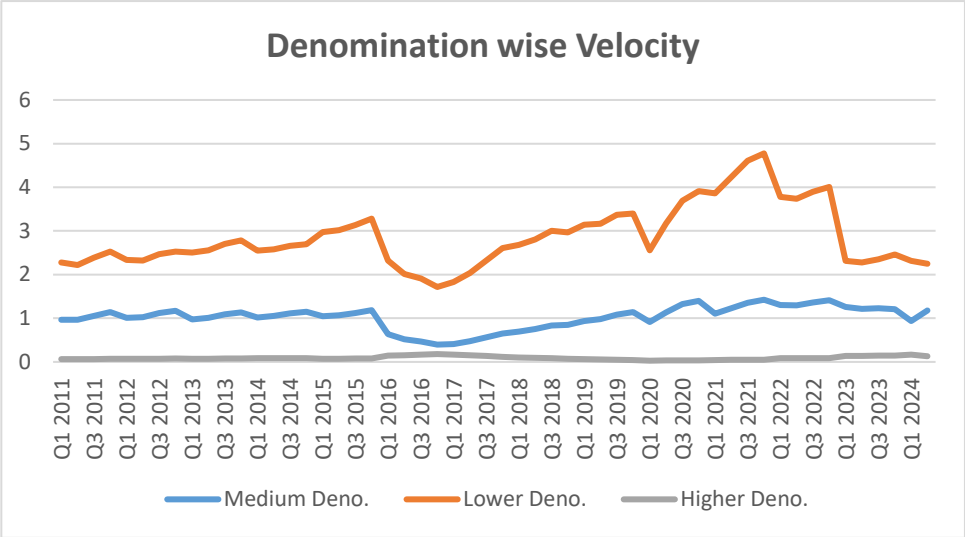
Post COVID Recovery occurred till Q1 2022, led to simultaneous resumption of consumption demand and all types transactions. Medium transactions being the highest reflects cash being used for day-day purchases.
Post 2022 was marked by the infamous Russia- Ukraine War, which had a dreadful socio-economic impact on the world economy.
The War triggered global inflation, supply shocks- made people hedge their asset with gold, real estate. The war led inflation caused the people to incur more expense irrespective of denominations on the same good purchased – could be one of the causes of rising cash transactions.

Moreover, the increasing trend in the Cash payments can also be accrued to rise in the informal economy. As COVID restrictions eased, many small businesses reopened without re-registering

formally and many informal workers returned to work. These workers and businesses prefer cash as there was no GST, no digital compliance, no trail.
Finally, after having a look over the overall cash transaction trend (Fig.8), It can be critically argued that with the rising digitalization, high valued transactions are gradually getting non-digitized, as people tend prefer cash transactions using higher or medium denominations in order to avoid having digital footprints which have tax implications. On the other hand, the low valued transactions are getting digitized with rising substitution by the UPI payment mechanisms- which provides a convenience to the people.

This result aligns with one of the propositions made in this research which reflect the actual scenario.

4.2 Denomination wise currency velocity



(Source- Author's Calculation) **Fig.2**

A key observation is that, among all the currency velocity of lower denominations is the highest among all denominations due to its high usage in exchange purposes. Velocity of currency experienced a dip around demonetization period, showing decline in the currency exchange, which is then followed by a recovery phase till COVID period.

Post-COVID (after Q2 2020), the velocity of low denominations rebounded briefly, reflecting increased use, but it has since declined drastically following the Russia-Ukraine conflict (Q1 2022), possibly indicating substitution by digital payments for small-value transactions.
In contrast, the velocity of medium denomination currency has shown moderate volatility but a steady upward trend after the initial shock of demonetization, implying growing utility in everyday transactions.

The velocity of high denomination currency, while consistently low throughout the period, remains remarkably stable—even during periods of economic shock—suggesting its role as a store of value rather than a medium of frequent exchange.

5. Cash Withdrawal & Currency in Circulation

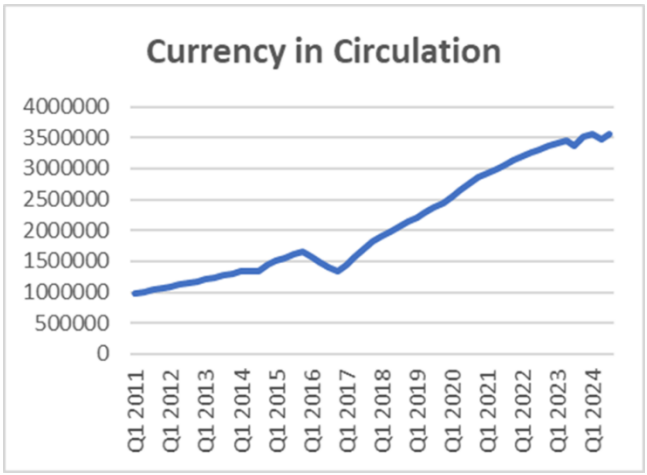


Fig.4

Fig.3

Fig.5

(Source- Author's Calculation)

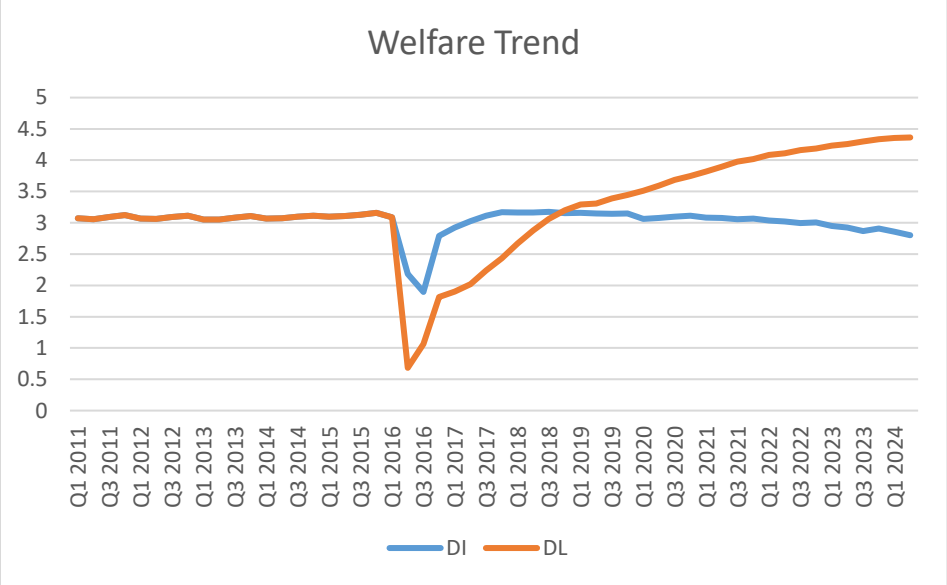
In India, the pref. for cash transaction is on a decline as evident from the declining trend of Cash Withdrawal- CiC ratio (Fig.5).

However, despite surge in the digital transaction's growth, CiC continues to rise (Fig.3). So, taking both the afore-mentioned statements into consideration, it can be critically argued although overall Cash transaction has fallen but the cash holding is rising. This is indicative of fact the Currency is staying in people's wallet and not circulating i.e. velocity of currency is declining- this causes a problem of unavailability of change while making transactions.

This phenomenon has mostly affected those who are not digitally sound (including senior citizens, low-income group etc.)- termed as Digitally Illiterate. These people mostly rely on low and medium denomination cash (Rs. 10, 20, 50, 100, 200) for daily expenses. If cash is not able to get exchanged with goods due to unavailability of change it perhaps leads to a compromise of transaction- which might have welfare consequences. So, at the local shop or vendor, **"CHUTE NAHI HAI"** becomes common, which hurts these people's ability to transact. Reasons for Welfare loss: - (i). **Reduced Consumption**, (ii). **Overpay due to rounding off**. On the other hand, the transaction process seems to be **convenient for the DL's** due to their access to multiple payment options (UPI), thus barring them from compromising transaction.

6. Welfare Analysis

6.1 Comparative Analysis of Welfare of DL vis-à-vis DI



(Source- Author's Calculation) **Fig.6**

The detailed methodology involving the computation of Welfare function for DI's and DL's has been explicated separately in the Section 3.2. The welfare function has been appropriated to be the weighted average of all real transactions involving high, medium, lower denominations and real UPI transactions.

The weights are nothing, but the transaction and holding preference of denominations by DI's and DL's respectively which has been computed based on primary survey of 30 individuals of 30+ age group.

According to the study, the entire population has been categorized into Digitally Literates (DL's)- those who have knowledge regarding UPI transactions, and Digitally Illiterate (DI's)- those who don't know about functioning of UPI.

DL's primarily uses both UPI and cash for transaction purposes whereas DI's uses cash only for transaction purposes.

Prior to Digitalization reforms, both cohorts are assumed to be DI's. The segregation between the 2 cohorts accentuated post digitalization i.e. (2016), with DL's transitioning themselves towards digital payments whereas unwillingness of DIs to adapt to new technology confined them to use only cash as a medium of transaction. This behavior of DI's not only restricted their choices of payment but also the consumption opportunities.

Demonetization significantly impacted cash transactions of both the cohorts leading to a dip in their respective welfare function.

It can be seen from the figure that the dip in the welfare of DL's is more than that of DI's, which seems quite counter-intuitive as DI's are expected to get more affected than DL's.

One probable intuition that arises in this regard could be as follows: -

Demonetization primary targeted higher denomination notes. Most of the digitally literate people hail from High or Middle-Income background where cash transactions were primary incurred in higher denominations. So, it's plausible that the extent of demonetization impact would had been higher on DLs vis-à-vis DI's where the transactions might have been focused on smaller and everyday cash exchanges.

Post recovery, the welfare of DI's shows a slow and consistent downward trend reflecting a less to no impact on DI's. However, as people are tending towards preferring UPI over cash transactions this has led to situation of unavailability of small coins and notes especially in retail stores due to which a Digitally illiterate individual has to compromise on the transaction due to lack of change.

On the other hand,

Strong upward rise in welfare of DL's is more significant and robust, surpassing the DI's. This growth in welfare reflects their increasing adoption of digital payments method which has contributed primarily to boost their welfare.

The transaction process seems to be convenient for the DL's due to their access to multiple payment opportunities, thus barring them from compromising transaction. In the event of failure of cash transaction, they have the privilege to switch over to UPI payments for completing their transactions, which is not the case for DI's.

Afterwards, the gap between both the welfare functions diverges significantly. This suggests that increasing digital literacy and the adoption of digital payments have a positive impact on the overall economic well-being on those who can utilize them, while those limited to cash transaction may be fall relatively.

7. Empirical Modelling of Denomination wise Cash Transactions

This study attempts to investigate the main driver of denomination wise cash transactions which include Cash Withdrawal/Personal Disp. Income, High denomination CiC, Per Capita Net

National Income, Inflation, UPI transactions, velocity of denomination, Savings Rate, Personal Tax rate, No. of ATMs.

To explore the nature of the relationship—whether short-run or long-run—between the variables, we employ the Autoregressive Distributed Lag (ARDL) model.

Given the relatively small sample size of 50 observations, more complex time series models like Vector Autoregression (VAR) or Vector Error Correction Model (VECM), which involve multiple equations, are not appropriate. The ARDL approach is well-suited for small samples as it conserves degrees of freedom and yields reliable estimates of both short-term dynamics and long-term equilibrium relationships.

A key advantage of the ARDL method is its flexibility with regard to the order of integration. Unlike traditional cointegration techniques proposed by Engle and Granger (1987) or Johansen (1995), ARDL can accommodate a combination of stationary and non-stationary variables.

However, it cannot be used if any variable is integrated of order two or higher. Therefore, we begin by applying the Augmented Dickey-Fuller (ADF) unit root test to verify the stationarity of the variables, with the results confirming their suitability for ARDL estimation.

Unit Root Test Results (ADF)

Variable	**Notations**	**Level Test Statistic**	**p-value**	**1st Difference Statistic**	**p-value**	**Order of Integration**
Log of High Deno. Transactions	**LHD.Trans**	1.72	0.97	-6.31	0.00	I(1)
Log of Medium Deno. Transactions	**LMD.Trans**	-.78	.81	-6.92	0.00	I(1)
Log of Lower Deno. Transactions	**LLD.TRANS**	-2.03	.27	-6.78	0.00	I(1)
Cash Withdrwal/ Personal Disposable Income Ratio	CW/PDI	-2.77	0.06	-6.87	0.00	I(1)
1st difference of High Deno.CiC	ΔLCiCh	-2.31	0.17	-6.60	0.00	I(1)
1st difference of Medium Deno.CiC	ΔLCiCm	-2.79	0.06	-6.64	0.00	I(1)
1st difference of Lower Deno.CiC	ΔLCiCl	-2.50	0.12	-5.95	0.00	I(1)
1st diff. of per capita net national income	ΔL(PCNNI)	-2.60	0.09	-15.61	0.00	I(1)
Inflation	INF	-1.92	.31	-5.04	0.00	I(1)
Savings rate	Sav.Rate	-0.13	.93	-5.74	0.00	I(1)
Personal Tax rate	P.Tax	-1.03	0.73	-7.4	0.00	I(1)
Sales Tax rate	S.Tax	-1.08	.71	-7.38	0.00	I(1)
1st difference of log of UPI transactions	**Δ**LUPI	-3.27	0.08	-6.45	0.00	I(1)
Velocity of high deno.	v_h	-1.39	0.57	-6.01	0.00	I(1)
Velocity of medium deno.	v_m	-1.81	0.36	-7.20	0.00	I(1)
Velocity of lower deno.	v_l	-1.98	0.29	-6.83	0.00	

						I(1)
Log ATMS	LATMs	-2.17	0.49	-9.54	0.00	I(1)

(Source- Author's Calculation) **Table 3**

ADF 5% critical values-
i. At Intercept-= -2.92
ii. At Trend and Intercept = -3.50
iii. At None = -1.94

Model

I. $$\boldsymbol{LHD.Trans_t} = \delta_0 + \delta_1 \left(\frac{CW}{PDI}\right)_t + \delta_2\, \Delta LCiCh_t + \delta_3\, \Delta L(PCNNI)_t + \delta_4\, INF_t + \delta_5\, Sav.Rate_t + \delta_6\, P.Tax_t + \delta_7\, S.Tax_t + \delta_8 \Delta LUPI_t + \delta_9\, v\_h_t + \delta_{10}\, LATMS_t + \delta_{11}\, Demonetization\ dummy + \delta_{12}\, Election\ dummy + \varepsilon_t$$

II. $$\boldsymbol{LMD.Transt} = \delta_0 + \delta_1 \left(\frac{CW}{PDI}\right)_t + \delta_2\, \Delta LCiCm_t + \delta_3\, \Delta L(PCNNI)_t + \delta_4\, INF_t + \delta_5\, Sav.Rate_t + \delta_6\, P.Tax_t + \delta_7\, S.Tax_t + \delta_8 \Delta LUPI_t + \delta_9\, v\_m_t + \delta_{10}\, LATMs_t + \delta_{11}\, Demonetization\ dummy + \delta_{12}\, Election\ dummy + \varepsilon_t$$

III. $$\boldsymbol{LLD.Transt} = \delta_0 + \delta_1 \left(\frac{CW}{PDI}\right)_t + \delta_2\, \Delta LCiCl_t + \delta_3\, \Delta L(PCNNI)_t + \delta_4\, INF_t + \delta_5\, Sav.Rate_t + \delta_6\, P.Tax_t + \delta_7\, S.Tax_t + \delta_8 \Delta LUPI_t + \delta_9\, v\_l_t + \delta_{10}\, LATMs_t + \delta_{11}\, Demonetization\ dummy + \delta_{12}\, Election\ dummy + \varepsilon_t$$

Empirical Results

Selected Model :-

	LHD.Trans	**LMD.Trans**	**LLD.TRANS**
Model type (ARDL)	(1,0,0,0,1,2,2,0,1,1,0,1,1)	(1,0,2,2,1,2,2,2,2,1,1,0,2)	(1,2,0,0,0,1,0,0,0,0,0,1,1)
CW/PDI	0.04 (0.13)	0.02 (0.01)	-0.00 (0.00)
ΔLCiCh	45.97 (68.82)	-	-
ΔLCiCm	-	-5.11 (5.01)	-
ΔLCiCl	-	-	-2.91** (1.37)
ΔL(PCNNI)	9.24 (12.02)	-5.80* (2.94)	0.27 (0.24)
INF	-0.00 (0.02)	0.00 (0.00)	0.00 (0.00)
Sav.Rate	0.57 (2.13)	-0.04 (0.24)	-0.02 (0.13)
P.Tax	29.51 (41.94)	5.17* (2.95)	-1.43 (1.50)
S.Tax	-6.01 (32.3)	14.11*** (4.28)	0.23 (2.30)
ΔLUPI	-2.81 (3.64)	0.34 (0.22)	0.04* (0.02)
v_h	14.01**	-	-

	(5.88)		
v_m	-	1.01*** (0.25)	-
v_l	-	-	0.29*** (0.01)
LATMs	-1.28 (5.07)	-1.81* (0.92)	1.42*** (0.36)
Election Dummy	-0.74 (1.08)	0.29** (0.10)	-0.03 (0.03)
Demonetization Dummy	9.21 (14.04)	-1.08** (0.42)	0.06 0.05
Intercept	4.44 (15.64)	16.72*** (3.22)	4.38*** (0.00)
Error Correction	-0.04*** (0.003)	0.19*** (0.11)	-0.27*** (0.02)
Bounds Test: F statistic	10.65	11.99	6.00
Model Test			
Adjusted R-squared	0.99	0.99	0.99
Durbin Watson Stat.	1.94	2.24	1.88

Table-4

Note: The Standard errors are in parenthesis
*p < 10% , **p < 5%, ***p < 1%
#Critical values for F-statistic at 5% around 3.0 and 4.0 for I(0) and I(1)assumptions respectively.
(Source-** Author's Calculation**)

8. Conclusion

The transition towards a digital payment ecosystem in India has undoubtedly transformed the transactional landscape, bringing with it greater convenience, transparency, and traceability. However, this study reveals that such a shift is not uniformly experienced across all sections of the population. While digitally literate individuals have adapted by adopting digital modes of payment and minimizing their reliance on cash, the digitally illiterate or tech-averse segment continues to face considerable frictions in adapting to this evolving financial environment.

Empirical analysis of denomination-wise transaction patterns and currency velocity suggests a nuanced behavioral shift. Despite the overall decline in cash dependency, there has been a notable and consistent rise in high-denomination cash transactions post-2022 — coinciding with geopolitical disruptions and increasing informal economic activity. Simultaneously, a sharp decline in lower-denomination transactions and their velocity indicates growing challenges for those reliant on small-value cash exchanges — particularly the digitally excluded.

This divergence not only underscores the persistence of informal economic channels among the digitally literate — who may be circumventing digital modes for privacy or tax-related reasons but also highlights the growing vulnerabilities of the tech-averse population. Reduced availability and circulation of low-value denominations, along with declining cash-to-income ratios, may

exacerbate financial exclusion and welfare loss for those unable to fully integrate into the digital payment framework.

In conclusion, while digital payments mark progress, they also risk creating a dual economy — one digitally included and thriving, and the other digitally excluded and struggling. Policymaking must recognize this divide and strive to make digital systems more inclusive, intuitive, and accessible, ensuring that the shift towards a cash-light economy does not come at the cost of widening the welfare gap.

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ANNEXURE

Quarters	High Deno. Trans. Pref		High Deno. Holding. Pref		Med. Deno. Trans. Pref		Med Deno. Holding. Pref		Low Deno. Trans. Pref		Low Deno. Holding. Pref	
	DL	DI	DL	DI	DL	DI	DL	DI	DL	DI	DL	DI
Q1 2011	0.172028	0.172028	0.492014	0.4925	0.51957	0.51957	0.520008	0.520278	0.308402	0.308402	0.355003	0.355019
Q2 2011	0.172028	0.172028	0.490162	0.490638	0.51957	0.51957	0.513554	0.51383	0.308402	0.308402	0.345868	0.345885
Q3 2011	0.172028	0.172028	0.488316	0.488783	0.51957	0.51957	0.507182	0.507463	0.308402	0.308402	0.33697	0.336987
Q4 2011	0.172028	0.172028	0.486478	0.486935	0.51957	0.51957	0.50089	0.501176	0.308402	0.308402	0.328302	0.328319
Q1 2012	0.192003	0.192003	0.484647	0.485093	0.494268	0.494268	0.494677	0.494969	0.31373	0.31373	0.319858	0.319876
Q2 2012	0.192003	0.192003	0.482925	0.483361	0.494268	0.494268	0.489743	0.490035	0.31373	0.31373	0.317388	0.317403
Q3 2012	0.192003	0.192003	0.481208	0.481635	0.494268	0.494268	0.484859	0.48515	0.31373	0.31373	0.31495	0.314962
Q4 2012	0.192003	0.192003	0.479498	0.479915	0.494268	0.494268	0.480023	0.480314	0.31373	0.31373	0.312546	0.312554
Q1 2013	0.20554	0.20554	0.477794	0.478201	0.449003	0.449003	0.475236	0.475526	0.345457	0.345457	0.310172	0.310178
Q2 2013	0.20554	0.20554	0.476197	0.476594	0.449003	0.449003	0.471342	0.471627	0.345457	0.345457	0.307496	0.307499
Q3 2013	0.20554	0.20554	0.474605	0.474992	0.449003	0.449003	0.46748	0.467761	0.345457	0.345457	0.304853	0.304853
Q4 2013	0.20554	0.20554	0.473019	0.473395	0.449003	0.449003	0.463649	0.463927	0.345457	0.345457	0.302244	0.302242
Q1 2014	0.231882	0.231882	0.471437	0.471804	0.425712	0.425712	0.459851	0.460124	0.342406	0.342406	0.299668	0.299663
Q2 2014	0.231882	0.231882	0.46996	0.470317	0.425712	0.425712	0.456678	0.456945	0.342406	0.342406	0.296909	0.296902
Q3 2014	0.231882	0.231882	0.468488	0.468834	0.425712	0.425712	0.453529	0.453789	0.342406	0.342406	0.294184	0.294175
Q4 2014	0.231882	0.231882	0.46702	0.467356	0.425712	0.425712	0.450401	0.450655	0.342406	0.342406	0.291494	0.291482
Q1 2015	0.20925	0.20925	0.465557	0.465883	0.398216	0.398216	0.447296	0.447543	0.392534	0.392534	0.288836	0.288823
Q2 2015	0.20925	0.20925	0.466839	0.467143	0.398216	0.398216	0.444634	0.444873	0.392534	0.392534	0.286125	0.286109
Q3 2015	0.20925	0.20925	0.468125	0.468406	0.398216	0.398216	0.441989	0.44222	0.392534	0.392534	0.283446	0.283429
Q4 2015	0.20925	0.20925	0.469414	0.469674	0.398216	0.398216	0.439361	0.439583	0.392534	0.392534	0.280801	0.280782
Q1 2016	0.401472	0.401472	0.470706	0.470944	0.269034	0.269034	0.444682	0.444861	0.329495	0.329495	0.272708	0.27269
Q2 2016	0.401472	0.444444	0.473244	0.526756	0.269034	0.37037	0.4778	0.5222	0.329495	0.185185	0.542005	0.457995
Q3 2016	0.381922	0.442226	0.46824	0.53176	0.31896	0.364843	0.474702	0.525298	0.299118	0.19293	0.540558	0.459442
Q4 2016	0.370728	0.439836	0.463243	0.536757	0.345637	0.359249	0.471606	0.528394	0.283635	0.200916	0.53911	0.46089
Q1 2017	0.358656	0.43727	0.458253	0.541747	0.373291	0.353588	0.468512	0.531488	0.268053	0.209142	0.537661	0.462339
Q2 2017	0.358284	0.434528	0.455116	0.544884	0.373631	0.347863	0.468393	0.531607	0.268085	0.217608	0.525247	0.474753
Q3 2017	0.357912	0.431608	0.451982	0.548018	0.37397	0.342077	0.468274	0.531726	0.268118	0.226315	0.512802	0.487198
Q4 2017	0.35754	0.428508	0.448853	0.551147	0.37431	0.33623	0.468154	0.531846	0.26815	0.235262	0.500341	0.499659
Q1 2018	0.357169	0.425229	0.445727	0.554273	0.374649	0.330326	0.468035	0.531965	0.268182	0.244445	0.48788	0.51212
Q2 2018	0.356816	0.421769	0.442629	0.557371	0.374919	0.324368	0.467966	0.532034	0.268265	0.253864	0.480935	0.519065
Q3 2018	0.356463	0.418128	0.439536	0.560464	0.375189	0.318358	0.467897	0.532103	0.268348	0.263514	0.473997	0.526003
Q4 2018	0.35611	0.414308	0.436448	0.563552	0.37546	0.312301	0.467828	0.532172	0.26843	0.273391	0.467069	0.532931
Q1 2019	0.355758	0.41031	0.433364	0.566636	0.37573	0.306199	0.467759	0.532241	0.268512	0.283491	0.460153	0.539847
Q2 2019	0.368405	0.406134	0.421501	0.578499	0.360969	0.300057	0.470879	0.529121	0.270627	0.293809	0.438624	0.561376
Q3 2019	0.381102	0.401783	0.409729	0.590271	0.346425	0.29388	0.474	0.526	0.272473	0.304337	0.417322	0.582678
Q4 2019	0.393829	0.39726	0.398058	0.601942	0.332123	0.287671	0.477124	0.522876	0.274047	0.315068	0.396325	0.603675
Q1 2020	0.393829	0.39726	0.398058	0.601942	0.332123	0.287671	0.477124	0.522876	0.274047	0.315068	0.396325	0.603675
Q2 2020	0.393829	0.39726	0.398058	0.601942	0.332123	0.287671	0.477124	0.522876	0.274047	0.315068	0.396325	0.603675
Q3 2020	0.393829	0.39726	0.398058	0.601942	0.332123	0.287671	0.477124	0.522876	0.274047	0.315068	0.396325	0.603675
Q4 2020	0.393829	0.39726	0.398058	0.601942	0.332123	0.287671	0.477124	0.522876	0.274047	0.315068	0.396325	0.603675
Q1 2021	0.393829	0.39726	0.398058	0.601942	0.332123	0.287671	0.477124	0.522876	0.274047	0.315068	0.396325	0.603675
Q2 2021	0.393829	0.39726	0.398058	0.601942	0.332123	0.287671	0.477124	0.522876	0.274047	0.315068	0.396325	0.603675
Q3 2021	0.393829	0.39726	0.398058	0.601942	0.332123	0.287671	0.477124	0.522876	0.274047	0.315068	0.396325	0.603675
Q4 2021	0.360265	0.387491	0.429539	0.570461	0.372007	0.29245	0.466535	0.533465	0.267728	0.320059	0.367465	0.632535
Q1 2022	0.356026	0.377811	0.436326	0.563674	0.371465	0.297189	0.46861	0.53139	0.272509	0.324999	0.401651	0.598349
Q2 2022	0.356968	0.368228	0.440573	0.559427	0.371026	0.301887	0.469528	0.530472	0.272006	0.329886	0.405353	0.594647
Q3 2022	0.357912	0.358747	0.444829	0.555171	0.370585	0.306538	0.470446	0.529554	0.271503	0.334715	0.409066	0.590934
Q4 2022	0.358856	0.349376	0.449092	0.550908	0.370144	0.311141	0.471364	0.528636	0.271	0.339483	0.41279	0.58721
Q1 2023	0.359802	0.340119	0.453364	0.546636	0.369702	0.315693	0.472282	0.527718	0.270497	0.344188	0.416523	0.583477
Q2 2023	0.356676	0.330983	0.468436	0.531564	0.372016	0.32019	0.472331	0.527669	0.271308	0.348826	0.427441	0.572559
Q3 2023	0.353561	0.321973	0.483566	0.516434	0.374329	0.324631	0.47238	0.52762	0.27211	0.353396	0.438431	0.561569
Q4 2023	0.350459	0.313093	0.498726	0.501274	0.376639	0.329013	0.472428	0.527572	0.272902	0.357894	0.449481	0.550519
Q1 2024	0.347368	0.304348	0.513889	0.486111	0.378947	0.333333	0.472477	0.527523	0.273684	0.362319	0.460581	0.539419
Q2 2024	0.347368	0.321429	0.513889	0.486111	0.378947	0.380952	0.472477	0.527523	0.273684	0.297619	0.460581	0.539419

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