Bulletin of Monetary Economics and Banking

Volume 25
Number 0 *15th BMEB Call for Paper Special Issue*
Article 4

1-31-2022

THE IMPACT OF COVID-19 ON DIGITAL PAYMENT HABITS OF INDIAN HOUSEHOLDS

Rajas Saroy
Reserve Bank of India, India, rajassaroy@rbi.org.in

Sakshi Awasthy
Reserve Bank of India, India, sakshiawasthy@rbi.org.in

Naveen K. Singh
Reserve Bank of India, India, naveensingh@rbi.org.in

Sonali M. Adki
Reserve Bank of India

Sarat Dhal
Reserve Bank of India

Follow this and additional works at: https://bulletin.bmeb-bi.org/bmeb

Recommended Citation

Saroy, Rajas; Awasthy, Sakshi; Singh, Naveen K.; Adki, Sonali M.; and Dhal, Sarat (2022) "THE IMPACT OF COVID-19 ON DIGITAL PAYMENT HABITS OF INDIAN HOUSEHOLDS," *Bulletin of Monetary Economics and Banking*: Vol. 25: No. 0, Article 4.
DOI: https://doi.org/10.21098/bemp.v25i0.1823
Available at: https://bulletin.bmeb-bi.org/bmeb/vol25/iss0/4

This Article is brought to you for free and open access by Bulletin of Monetary Economics and Banking. It has been accepted for inclusion in Bulletin of Monetary Economics and Banking by an authorized editor of Bulletin of Monetary Economics and Banking. For more information, please contact bmebjournal@gmail.com.

Bulletin of Monetary Economics and Banking, Special Issue 2022, pp. 19 - 42
p-ISSN: 1410 8046, e-ISSN: 2460 9196

THE IMPACT OF COVID-19 ON DIGITAL PAYMENT HABITS OF INDIAN HOUSEHOLDS

Rajas Saroy*, Sakshi Awasthy**, Naveen K. Singh***, Sonali M. Adki****, and Sarat Dhal*****

* Corresponding author. Department of Economic and Policy Research, Reserve Bank of India, Mumbai. Email: rajassaroy@rbi.org.in
** Department of Economic and Policy Research, Reserve Bank of India, Mumbai. Email: sakshiawasthy@rbi.org.in
*** Department of Payment and Settlement Systems, Reserve Bank of India, Mumbai. Email: naveensingh@rbi.org.in
**** Department of Payment and Settlement Systems, Reserve Bank of India, Mumbai.
***** Department of Economic and Policy Research, Reserve Bank of India, Mumbai.

ABSTRACT

The COVID-19 induced lockdown in India was an inflection point for on-boarding of new users into digital payments. Using a large survey dataset, we examine the driving factors of this shift for those who used digital payments for the first time. Apart from demographic drivers of payment choice traditionally explored in the literature, we find that this shift was significantly shaped by the degree of awareness of digital modes, access to smartphones and debit cards, and pandemic-relief welfare transfers. Users who had abandoned digital payments due to prior bad experience switched back to such modes.

Keywords: Payment systems; Logistic regression; Digital economy.
JEL Classifications: E42; C25; G28.

Article history:
Received : October 05, 2021
Revised : December 01, 2021
Accepted : December 07, 2021
Available online : January 31, 2022

https://doi.org/10.21098/bemp.v25i0.1823

I. INTRODUCTION

As social distancing became the norm during the COVID-19 pandemic, India's 68-day lockdown was an inflection point for digitalisation across sectors, including education, healthcare, governance, and payments. Spurred by new users, the number of digital transactions in India jumped 28% in the fiscal year 2021 over the previous year. Safety concerns regarding viral transmission and, later, the impact of eventual "unlocking" on reinvigorating economic activity are likely to have led to a hastened migration to digital modes of payments.

We attempt to ascertain whether this behavioural shift in payment choice was merely a temporary response to the pandemic or was it in fact a permanent one. The answer lies in the underlying drivers of adoption at the micro-level, particularly for new users. We use data from a household survey conducted by *People Research on India's Consumer Economy and Citizen Environment* (*PRICE*), in collaboration with the *National Payments Corporation of India (NPCI)*, which reveals that 32% of surveyed households transacted digitally for the first time during the lockdown. Using a discrete-choice model, we evaluate the effect of socio-economic characteristics; awareness of digital modes; access to smartphones, debit cards, banking agents and mobile apps; physical proximity to banks; social security payments; and previous experience of using digital payments on this switch to digital payments. Building upon the characteristics and needs of new end-users, we suggest measures for an inclusive and sustainable digital transformation in payments. Our paper attempts to address the dearth of empirical research investigating the impact of COVID-19 induced changes in payment habits at the ground level in India. Moreover, we define digital transactions broadly to not only include card payments, but also transactions through mobile wallets, apps, and even biometric authentication.

Overall, five findings emerge. First, awareness of digital modes and educational achievement mattered significantly for new adoption. The likelihood of the middle-aged to have switched post-lockdown was particularly high, indicating a probable narrowing of the age-based digital divide. Second, access, particularly to smartphones and debit cards, played a key role in on-boarding of new customers. Third, those critically dependent on Direct Benefit Transfer (DBT)-based income support were compelled to go digital to access their entitlements. Fourth, many who had earlier abandoned digital payments due to underlying issues shifted back post-lockdown. Fifth, proximity to brick and mortar banking as well as bank employees mattered for digital financial inclusion.

The remainder of the paper is organized as follows: Section II encapsulates the literature and provides an overview of the Indian payment systems. Data and methodology are discussed in Section III, empirical perspectives in Section IV and Section V concludes with policy recommendations.

II. LITERATURE REVIEW

A.1. Drivers of Digital Payment Adoption

The evolution of the payments ecosystem has been at the core of central banking innovations in the past few decades, entailing the transition from paper-based methods of payment to a variety of digital solutions. The literature on choice of payment instrument encompasses a wide range of determinants: transaction characteristics (Wang and Wolman, 2016); socio-economic and demographic factors (Stavins, 2002; Mester, 2012); opportunity costs and interest elasticities (Klee, 2008); and rewards/incentives on cards' usage (Arango-Arango *et al*., 2018). Research also links consumers' perceptions of safety, acceptance, and convenience to payment behaviour (Shree *et al*., 2021).

On the demand side, demographic characteristics provide insights into inclusivity of behavioural change. The conventional wisdom of the pre-pandemic literature holds that the use of electronic modes of payments over traditional means like cash is associated with users that are relatively richer (Cohen and Rysman, 2013; Fujiki and Nakashima, 2019); younger (Bagnall *et al*., 2014; Greene *et al*., 2017) and better educated (Koulayev *et al*., 2012). Awareness of digital payments is another important factor as lower levels of financial literacy diminish the propensity to use digital mediums (Wyman, 2017). In the Indian context, Bhuyan *et al. (*2021) show that income, education, and access to bank accounts were statistically significant in determining awareness and usage of digital payments.

Our paper also includes measures of access to electronic payments. Previous research has recognised internet and smartphones as key facilitators of financial inclusion and electronic payments, especially in areas with rudimentary banking access (Suri and Jack, 2016). However, Ivatury and Mas (2008) demonstrate the importance of maintaining a balance between technological and human interfaces to improve awareness and perceptions regarding digital services. Kaur *et al.* (2021) suggest that personal contact leads to enhanced trust and confidence in digital banking platforms. There are mixed findings on government transfers providing a fillip to the usage of digital modes. While Klapper and Singer (2017) and Iazzolino (2018) note the furthering of financial and digital inclusion through such transfers, Bold *et al.* (2012) show that immediate cashing-out of these benefits by recipients limits the scope for digital payments.

A.2. Impact of COVID-19 on Digital Payments

Recent literature has revealed the ramifications of the pandemic on economic output (Barro *et al*., 2020); household liquidity and consumption levels (Li *et al*., 2020); financial markets (Narayan, 2020) and corporate performance (Shen *et al*., 2020). However, despite the overall negative economic consequences, the pandemic has provided impetus to digitalisation. De' *et al.* (2020) explore the surge in adoption of digital technologies owing to social distancing norms and other containment measures. Our paper focusses on identifying key drivers behind the rise in digital payment adoption amidst the lockdown. Exploring the socio-economic factors underpinning the pandemic-induced digital shift, Jonker *et al.* (2020) conclude that debit card usage increased at the expense of cash, and such a digital shift was more pronounced for older age groups. Liu *et al.* (2020) highlight the significance of mobile payment apps in mitigating the negative impact of disruptions in consumption spending during the pandemic. Alber and Dabour (2020) examine mobility and payments data from ten countries (including USA, UK, UAE, and India) and find a significant positive impact of social distancing norms on digital payments. This sudden shift towards cashless modes of payments can be attributed to the fear of viral transmission through bank notes and a broad alteration in the habits of customers towards adoption of digital modes (Wisniewski *et al*., 2021). Further, there is evidence of persistence of this pandemic-induced digital metamorphosis even after the initial outbreak subsided (Jonker *et al*., 2020; Ardizzi *et al*., 2020). Interestingly, even though the transactional demand for cash witnessed a fall during the pandemic owing to lockdown-induced disruptions, the currency in circulation rose, driven by precautionary hoarding of cash balances and lack of opportunities to spend (Auer *et al*., 2020; Chen *et al*., 2021).

The role of FinTechs is also explored in the post-pandemic literature, especially in bolstering financial inclusion (Sahay *et al*., 2020); easing financial constraints faced by corporates (Ling *et al*., 2021); and enhancing the efficiency of government welfare payments (Agur *et al*., 2020). COVID-19 led to governments around the world stepping up their social assistance programs. Nearly 17% of the world's population was covered by at least one COVID-related cash transfer scheme between 2020 and 2021 (Gentilini *et al*., 2020). Pandemic relief *via* cash transfers by governments is likely to induce more people to open bank accounts and boost digital adoption (Toh and Tran, 2020).

Overall, a growing number of studies are exploring the 'go digital' dynamics of the pandemic. However, the literature capturing the micro-level drivers behind the shifting of the populace to digital means, especially from the perspective of emerging economies, is still relatively scant. As Sha and Sharma (2020) also point out, there is need for a broader analysis encompassing emerging Asian economies to ascertain changes in household behaviour as an adaptive response to the pandemic.

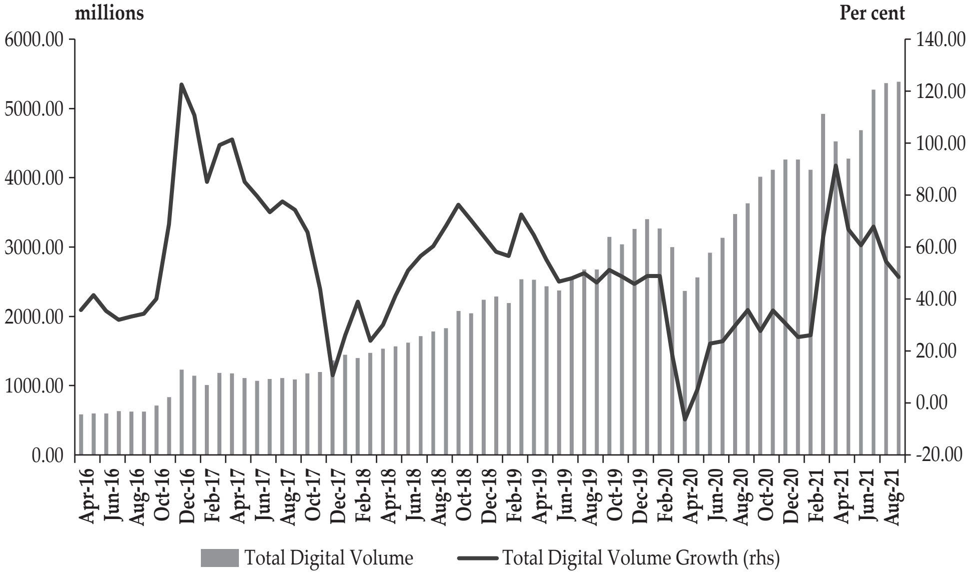
B. Payment Systems in India

High cash usage notwithstanding, India witnessed remarkable growth in digital transactions in the recent past (Figure 1), supported by policy, expansion of smartphones and internet coverage, and pro-active participation by the private sector. Compared to other countries, India's payments ecosystem has been fast-forwarded to reach the present stage in the shortest possible time (Chaudhari *et al*., 2019). Figure 2 presents the timeline of important regulatory developments since the enactment of payment system legislation in 2007.

Saroy et al.: THE IMPACT OF COVID-19 ON DIGITAL PAYMENT HABITS OF INDIAN HOUSEH

Figure 1.
Trends in Digital Transactions

The graphs illustrate the growth in India's digital payment transaction volume and value (in Indian rupees) since April 2016. The data is sourced from the Reserve Bank of India's Database on Indian Economy.



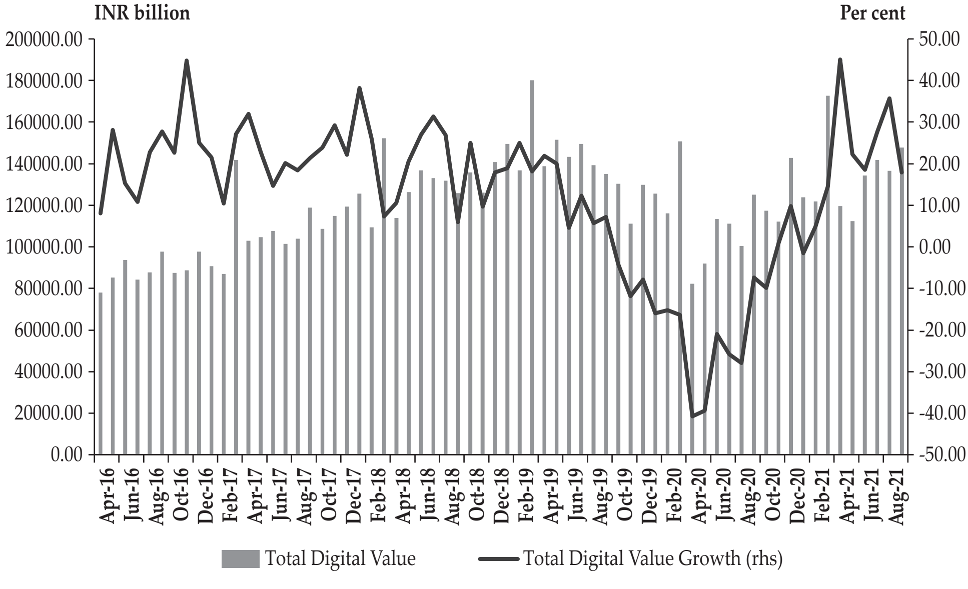
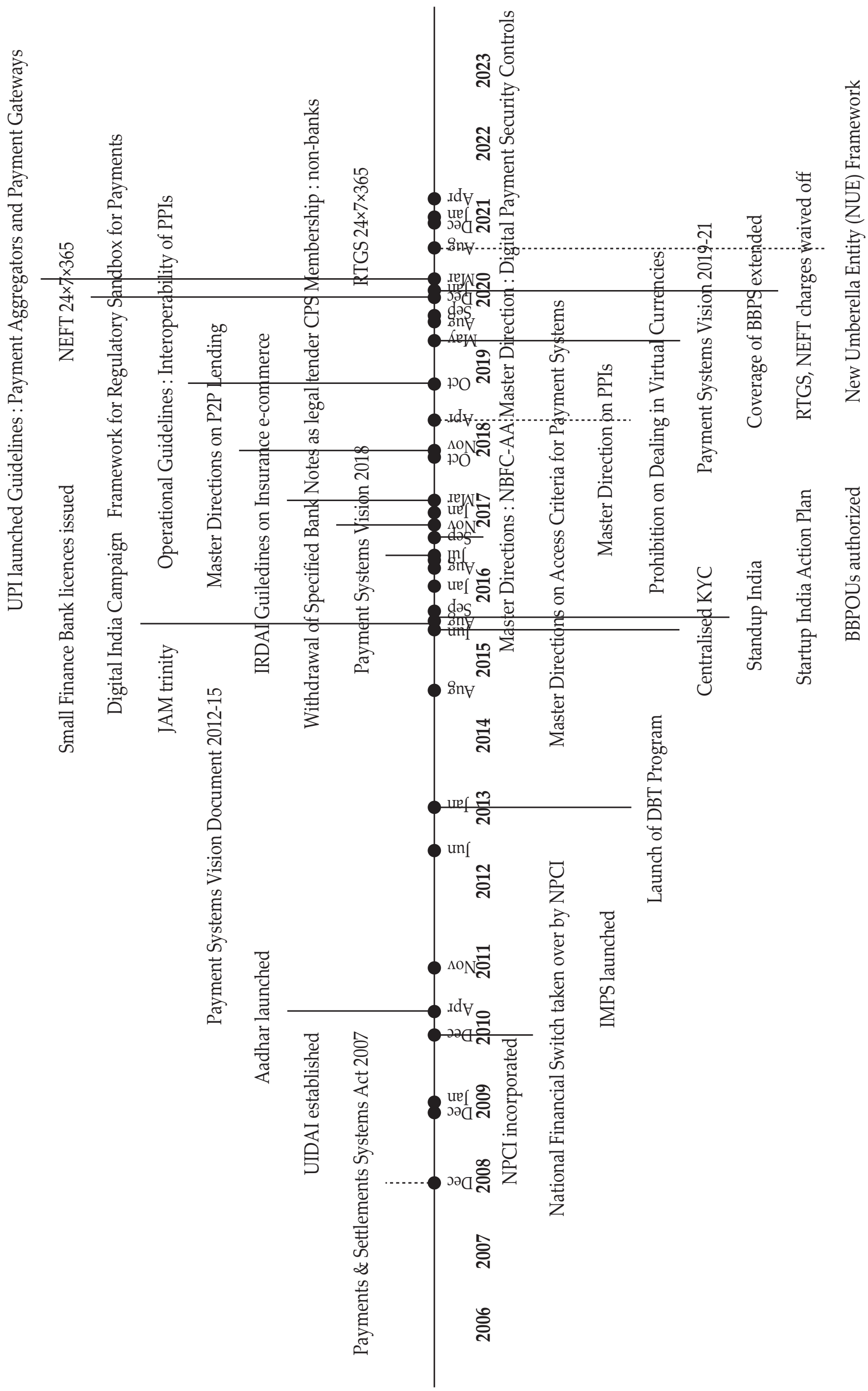


Figure 2.
Regulatory Timeline of Payment Systems in India

The figure presents the timeline of important regulatory developments pertaining to the payment ecosystem in India since the enactment of payment system legislation in 2007.



The Reserve Bank of India (RBI), as the regulator and supervisor of India's payment and settlement system, has been playing an active role in the digital transformation of the country through timely impetus to payments infrastructure and regulatory framework. Initially, the focus was on large-value payments and critical back-end infrastructure. The Payment and Settlement Systems Act, 2007 set the stage for a new era in the history of India's payment systems. Over the next decade, the Government of India stepped up its involvement in the digital revolution, creating a robust and highly scalable public infrastructure, popularly known as the India Stack, including the universal biometric authentication program, Aadhaar. The Pradhan Mantri Jan-Dhan Yojana (PMJDY) was launched in 2014 to ensure access to financial services through zero balance bank accounts for the financially excluded. Combined with Aadhaar, it paved the way for direct transfers of government subsidies. The Aadhaar Enabled Payments System (AePS) facilitates operations from Aadhaar seeded bank accounts using biometric authentication. The Digital India campaign was launched in 2015 to ensure that Government services are made available to citizens electronically through improved online infrastructure and internet connectivity. Since its launch in 2016, the Unified Payments Interface (UPI), a mobile-based 365x24x7 payment system for immediate money transfer, has become the mainstay of the retail digital ecosystem.

III. DATA AND METHODOLOGY

A. Data

We use the stratified sample survey 'Tracking Digital Payments Awareness, Adoption and Use Behaviour of Households' by PRICE and NPCI, comprising 5314 households across India (Table 1). The survey includes many rural respondents, making our results relevant even to payment habits in the hinterlands. The respondent was the person "mostly doing banking and payment related work for the household", who may or may not be the family's chief wage earner. The survey is unique in that it captures payment habits post the stringent lockdown in India from March 24 to June 2021, followed by a phased "unlock".

Table 1.
Sample Households

The table presents classification of the respondents into the Bottom 40%, Middle 40% and Top 20% categories based on their average household income levels (in Indian rupees). Further, the proportion of the respondents residing in the rural and urban areas is shown for each income bracket

Household Income Bracket	Rural/Urban Split		Average Household Income (INR)
	Rural	Urban	
Bottom 40%	80%	20%	110,000
Middle 40%	60%	40%	180,000
Top 20%	45%	55%	360,000

Table 2 presents the sample summary statistics. Most respondents are male (93%) and of the working-age group. Respondents were largely educated, and only 9% had no formal education. A third of the households surveyed undertook digital payments for the first time after the pandemic; a quarter of the households in the lowest income category, a third in the middle-income category, and nearly half in the top-income category. Questions allowing multiple responses reveal that digital payment modes in descending order of popularity were third-party mobile apps/wallets (80%), UPI (55%), bank's mobile apps (36%) and cards (34%).

Table 2.
Summary Statistics

The table reports the summary statistics for the sample. The total number of observations is 5314. All the variables in the sample are categorical with maximum being 1 (one) and minimum being 0 (zero).

Variable	Mean	Standard Deviation
Transacted digitally for the 1st time during the pandemic	0.323	0.468
Income		
Bottom 40%	0.446	0.497
Middle 40%	0.361	0.480
Top 20%	0.193	0.394
Age		
< 18 years	0.005	0.068
18-40 years	0.406	0.491
40-60 years	0.529	0.499
> 60 years	0.060	0.238
Gender		
Female	0.076	0.265
Male	0.924	0.265
Education		
Graduates	0.218	0.413
Matriculation (10th grade)	0.390	0.488
Primary	0.298	0.458
Uneducated	0.094	0.292
Access to Smartphones	0.685	0.465
Access to Feature Phones	0.311	0.463
No phones	0.001	0.031
Received DBT support post-lockdown	0.540	0.498
Distance to Bank		
< 1 Km.	0.245	0.429
1-2 Km	0.292	0.455
2-3 Km	0.271	0.445
3-5 Km	0.109	0.312
> 5 Km.	0.084	0.277
Access to Bank agent (Bank *mitra*)	0.559	0.497
Owns a Debit Card	0.760	0.427
Abandoned digital payments in the past	0.089	0.286

Table 3 confirms heterogeneous access to digital payment methods and access infrastructures (smartphones, internet, and debit cards) across income, gender, and age groups. The age profile shows the middle-aged and older populace catching

https://bulletin.bmeb-bi.org/bmeb/vol25/iss0/4
DOI: 10.21098/bemp.v25i0.1823

up to their younger counterparts in the adoption of digital methods during the pandemic. Consumer preferences for digital modes are not uniform across age cohorts, with mobile wallets and UPI being more popular with the middle-aged and those over 60 being the main customers for mobile banking apps and cards. As the younger population moves towards modern methods like mobile wallets and real-time payment modes, the older populace is seen adopting the "traditional" digital methods like cards during the pandemic.

The access to smartphones and debit cards rises with levels of income and education. Feature phones were more prevalent among the lowest income group at 43%, which declines to 10% for the most affluent households. Moreover, a significant proportion of the uneducated had a feature phone (64%). Smartphones were used mostly for social media-related activities and entertainment. Differences by income become less pronounced among new digital users for the usage of mobile apps and UPI, with greater use shown by the lower-income households. These differences, however, remain high for older digital payment modes like cards, suggesting that UPI-based third-party apps may be easier to use and adopt by new users. Most households had a debit card and nearly all had access to a bank account. However, cash-withdrawal remains the most popular use of debit cards.

As the distance to bank branches increases, the fraction of respondents using digital methods in that distance category falls- a finding explored later. There is evidence of DBT nudging people towards digital payments for the first time during the lockdown; 54% of the respondents received government support through DBT route after the lockdown in India[1]. Of them, 53% withdrew the entire amount in cash while the rest withdrew as per need, leaving some balance in their accounts. Respondents who had used digital payments earlier but discontinued later (9%) were highly likely to revert post-pandemic.

[1] Gentilini *et al*. (2020) report cash-based transfers in India were disbursed chiefly under the Pradhan Mantri Kisan Samman Nidhi (₹ 2000 each to 87 million farmer beneficiaries every 4 months), the Pradhan Mantri Jan-Dhan Yojana (₹ 500 each to 200 million women beneficiaries for three months) and the National Social Assistance Program (₹ 1000 each to 35 million pension beneficiaries).

Table 3.
Select Digital Payment Indicators by Socio-Economic Characteristics (in per cent)

The table shows the degree of penetration of digital payments by socio-economic characteristics like income, age, gender and educational levels (Column 1). Column 2 presents the percentage of respondents who used digital methods for transfers or payments for the first time during the pandemic-induced lockdown. These are calculated as the percentage of only those households that used digital payments for the first time in the demographic cohort. Digital payment modes include third-party apps or wallets; Unified Payments Interface (UPI); credit and debit cards; and the bank's own mobile app. The last column shows respondents' access to enablers like smart phones; feature phones; and debit cards across select demographics. These figures are as a percentage of the total sample.

Indicators	Transacted Digitally for the 1st Time During the Pandemic	Digital Payment Modes Used During the Pandemic				Access Variables		
		Third-party Apps/ Wallets	UPI	Credit & Debit Card	Bank's app	Smart Phones	Feature Phones	Debit Cards
Income								
Bottom 40%	24%	81%	61%	21%	19%	57%	43%	67%
Middle 40%	34%	80%	49%	41%	44%	72%	28%	78%
Top 20%	49%	79%	58%	40%	45%	90%	10%	93%
Age								
<18 years	40%	30%	70%	20%	60%	84%	16%	90%
18-40 years	27%	75%	50%	31%	30%	74%	25%	79%
40-60 years	37%	85%	60%	35%	37%	66%	34%	75%
>60 years	22%	66%	34%	60%	77%	52%	47%	64%
Gender								
Female	21%	67%	43%	37%	40%	56%	43%	59%
Male	33%	81%	56%	34%	36%	69%	30%	77%
Education								
Graduates	55%	84%	59%	33%	31%	94%	6%	95%
Matriculation	38%	82%	57%	29%	30%	78%	22%	87%
Primary	13%	66%	45%	43%	52%	49%	51%	61%
Uneducated	16%	72%	40%	69%	86%	34%	64%	42%
Total	32%	80%	55%	34%	36%	68%	31%	76%

B. Methodology

We estimate the likelihood of using digital means of payments post-pandemic using a logistic regression model, given that all data is collected as categorical variables. The dependent variable indicates *"first time users of digital methods for money transfer or payments after the lockdown happened"*. This variable is coded as 1 if the respondent did shift to digital payments post-lockdown *and* was not using them before. Note that it takes the value zero for both, respondents who did not transact digitally even during lockdown, *or* were already using digital payments. Thus, a positive sign on the explanatory variables may be interpreted straightforwardly, but a negative sign does not lead us to conclude that the associated variable hinders first-time adoption. To control for respondents already using digital payments pre-lockdown, we use the "awareness" variable, expecting that respondents characterized by high awareness of various digital payment modes, who answered "No" were perhaps already on board such platforms. Despite this, we take a conservative approach and restrict our interpretations to positive signed coefficients, which provide us adequate evidence.

We check how the adoption of digital payments varies by socioeconomic factors (income, age, and education); levels of awareness; access variables (smartphones, bank's app, debit cards, proximity to bank's branch and bank *mitra*) and entitlement to DBT (before and after the COVID induced lockdown). We also factor in respondents who had earlier used digital payments but stopped using them later. Therefore, we estimate the following baseline model:

$$In\left\{\frac{\Pr(Yi=1|Xi)}{\Pr(Yi=0|Xi)}\right\}$$

$$= \beta_0 + \beta_1 income_i + \beta_2 age_i + \beta_3 education_i + \beta_4 awareness_i$$

$$+ \beta_5 smartphones_i + \beta_6 mobilebankapp_i + \beta_7 distancetobranch_i$$

$$+ \beta_8 debitcard_i + \beta_9 bankmitra_i + \beta_{10} usedbeforeandabandoned_i$$

$$+ \beta_{11} DBTprelockdown_i + \beta_{12} DBTpostlockdown_i$$

$$+ \beta_{13}(DBTprelockdown_i * DBTpostlockdown_i) \quad (1)$$

We also report predicted probabilities of the dependent variable. Following Williams (2012), we report the Marginal Effect at Means (MEM) which is the marginal effect of a particular regressor with other regressors held at their mean values.

IV. EMPIRICAL PERSPECTIVES

We estimate two models. The baseline logit (Model 1) is presented in Table 5. This attempts to characterise the motivations of the respondents who switched to digital payments post-lockdown. Model 2 restricts the sample to users without smartphones (Table 6). After cleaning the data and removing "Don't Know" and "Not Applicable" responses, we arrive at a dataset of 4061 observations for our regression analysis.

A. Digital Awareness and Digital Literacy

The questionnaire asks respondents about their familiarity with four digital payment modes (RuPay cards, UPI, BHIM and AePS[2]), and we calculate the degree of awareness based on their responses (Table 4). Allowing for substitutability, a person is considered highly aware even if she only has high awareness of any one of the digital payment methods. All four are relatively new interventions, equally sophisticated, and rely on the same underlying infrastructure of an Aadhaar linked bank account. BHIM is an app built upon the UPI infrastructure, making them close substitutes.

[2] UPI is a highly popular account to account transfer mechanism using only a virtual ID, Bharat Interface for Money (BHIM) is a Government promoted app for enhancing adoption of the UPI platform, RuPay is an indigenous card network and the Aadhaar Enabled Payment System (AePS) allows for quick payments using only biometric authentication.

Table 4.
Calculating Level of Awareness

The table shows the derivation of the 'awareness' variable taken in the study. Column 1 presents the scores attached to the responses of the survey participants (Column 2). The last row of the table shows the formula used to calculate the Final Awareness Score awarded to the respondents.

Awareness Score	Responses
0 (Nil)	"Have not heard of it"
1 (Low)	"Heard of it, but don't have it", "Have it but don't use it", "Someone in my family knows how to use it"
2 (Medium)	"Use it occasionally"
3 (High)	"Use it regularly"

$$Final\ Awarness\ Score_{\ i} = \max_{j} Score_{ij},$$
$$for\ respondent\ i; \quad j \epsilon \{UPI, BHIM, AePS, RuPay\ Card\}$$

Marginal effects indicate that awareness is the second most important factor influencing the probability of the post-lockdown digital switch, after the "used before but abandoned later" variable. Further, the effect is the highest for the 'Medium' awareness group, which points to the fact that rather than intensive knowledge and usage experience, occasional use and familiarity with the modes was enough to trigger adoption. Nevertheless, the probability of adoption increases sharply as awareness increases from Low to Medium/High. As seen later, other regressors produce varying marginal effects at different levels of awareness, establishing it as a highly important driver of post-pandemic digital adoption.

Table 5.
Logistic Regression (Baseline): Model 1

This table presents regression results for the baseline logit model. The dependent variable is "*Did you use digital methods for the first time after the lockdown?*" In addition to the logit coefficients, the odds ratio and the marginal effect at means are also computed. The base case for 'Awareness' is 0 (Nil); for 'Distance from Branch' is more than 5 kilometres; and for 'Income Category' is Top 20%. The 'Level of Education' is on the scale: 1 (Illiterate- lowest), 2 (Primary School), 3 (High School), 4 (Graduates and above- Highest). The standard errors are reported in parentheses and the significance levels are denoted with asterisk: * p < 10%, ** p < 5%, and *** p < 1%.

	(1)	(2)	(3)
Variables	**Logit Coefficients**	**Odds Ratio**	**Marginal Effect at Means**
Level of Awareness = 1 (Low)	2.357***	10.56***	0.0334***
	(0.615)	(6.492)	(0.00544)
Level of Awareness = 2 (Medium)	4.676***	107.4***	0.277***
	(0.619)	(66.50)	(0.0293)
Level of Awareness = 3 (High)	4.608***	100.3***	0.264***
	(0.615)	(61.67)	(0.0228)
Received DBT before lockdown	-2.317***	0.0986***	-0.0639***
	(0.255)	(0.0252)	(0.0142)
Received DBT after lockdown	-0.265	0.767	0.0841***
	(0.206)	(0.158)	(0.0134)
Received DBT pre-lockdown*Received DBT post-lockdown	2.601***	13.47***	

Table 5.
Logistic Regression (Baseline): Model 1 (Continued)

	(1)	(2)	(3)
Variables	**Logit Coefficients**	**Odds Ratio**	**Marginal Effect at Means**
	(0.324)	(4.367)	
Distance from Branch (< 1 km)	0.860***	2.362***	0.0951***
	(0.226)	(0.533)	(0.0230)
Distance from Branch (1-2 km)	-0.379*	0.685*	-0.0252
	(0.226)	(0.155)	(0.0170)
Distance from Branch (2-3 km)	-0.822***	0.440***	-0.0458***
	(0.234)	(0.103)	(0.0173)
Distance from Branch (3-5 km)	-0.0897	0.914	-0.00673
	(0.266)	(0.244)	(0.0202)
Access to Smartphone	1.436***	4.205***	0.0860***
	(0.193)	(0.812)	(0.0122)
Access to Debit Card	2.171***	8.768***	0.106***
	(0.285)	(2.497)	(0.0128)
Access to Bank *Mitra*	0.474***	1.606***	0.0327***
	(0.113)	(0.182)	(0.00852)
Access to Mobile Banking App	0.407***	1.502***	0.0314***
	(0.115)	(0.173)	(0.0101)
Used Digital Payments earlier but discontinued later	2.826***	16.88***	0.458***
	(0.192)	(3.238)	(0.0484)
Income Category = Bottom 40%	0.170	1.185	0.0135
	(0.139)	(0.164)	(0.0108)
Income Category = Middle 40%	-0.321**	0.725**	-0.0208**
	(0.131)	(0.0954)	(0.00922)
Level of Education	0.169**	1.185**	0.0121**
	(0.0695)	(0.0823)	(0.00519)
Age	0.355***	1.426***	0.0255***
	(0.0914)	(0.130)	(0.00715)
Constant	-9.609***	6.71e-05***	
	(0.794)	(5.33e-05)	
McFadden's R^2	0.493		
McFadden's Adjusted R^2	0.481		
Observations	4,061	4,061	4,061

B. Access to Smartphones, Cards and Apps

Next, we consider variables important in determining the household's relative position in the continuum from financially excluded to digitally and financially included, through access to relevant infrastructure and services including smartphones, debit cards, bank *mitras*[3] and mobile-banking apps. Debit cards,

[3] Bank Mitras facilitate banking-related services, especially in unbanked areas of the country. They are tasked with facilitating account opening for the unbanked population, but they also play auxiliary roles such as accepting deposits and facilitating small value remittances.

followed by smartphones are the leading contributors to the switch to digital post-lockdown. The impacts of bank *mitras* and mobile banking apps are positive but dwarfed in contrast. Considering the differential impact of these variables by education and awareness (Figure 3), we see that more than attainment of formal education, general awareness about payment modes contributed to first-time adoption. While the plots for education have a mild but positive gradient, it is quite sharp for the role of digital awareness, especially in the lower levels of awareness. Also, the prominent intercept for the marginal effects at levels of education implies that even with the lowest educational attainment, there was a chance to adopt digital payments. Therefore, new users of digital payments may be on-boarded with focussed awareness and word-of-mouth campaigns, leading to higher adoption even in communities with low levels of education.

Ownership of a smartphone emerges as a very important determinant of the switch, since most popular payment modes in India are app-based. An increase in digitisation of payments may be brought about not only by enhancing smartphone and debit card penetration on the supply side but also complementing it by providing impetus to digital awareness, which leads to enhanced use of these instruments for payments.

Figure 3.
Access Variables, Awareness and Education

The figure illustrates the conditional marginal effects of the access variables (*i.e.,* debit cards, smartphones, bank *mitras* and mobile banking apps) on the probability of respondents to switch to digital payments post-lockdown by levels of awareness and educational achievement. These have been computed from Model 1 (Table 5).

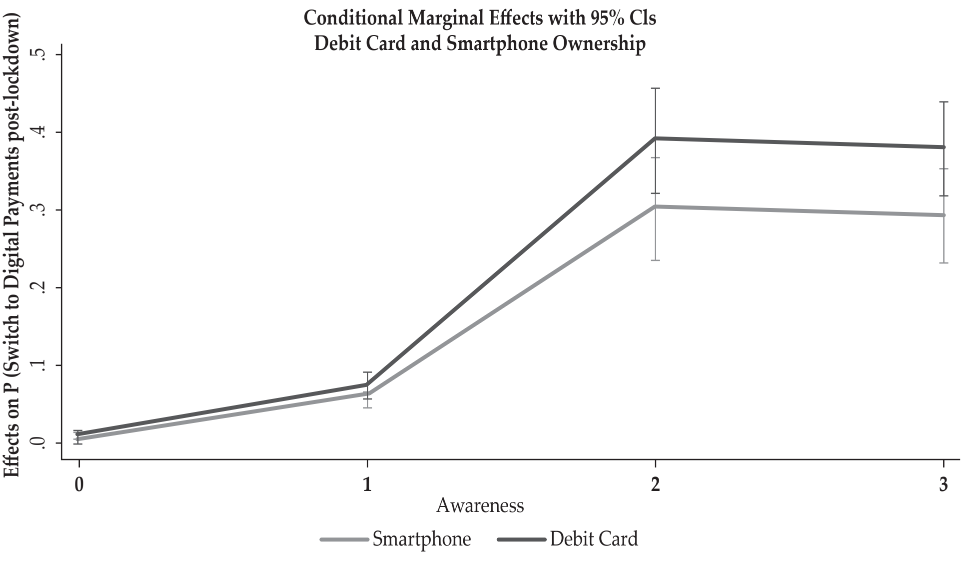
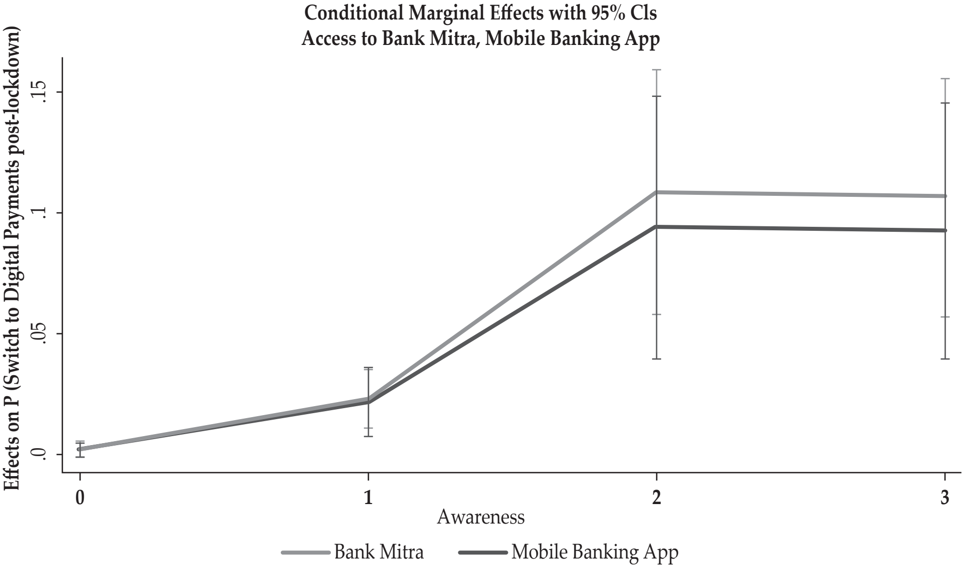


Figure 3.
Access Variables, Awareness and Education (Continued)



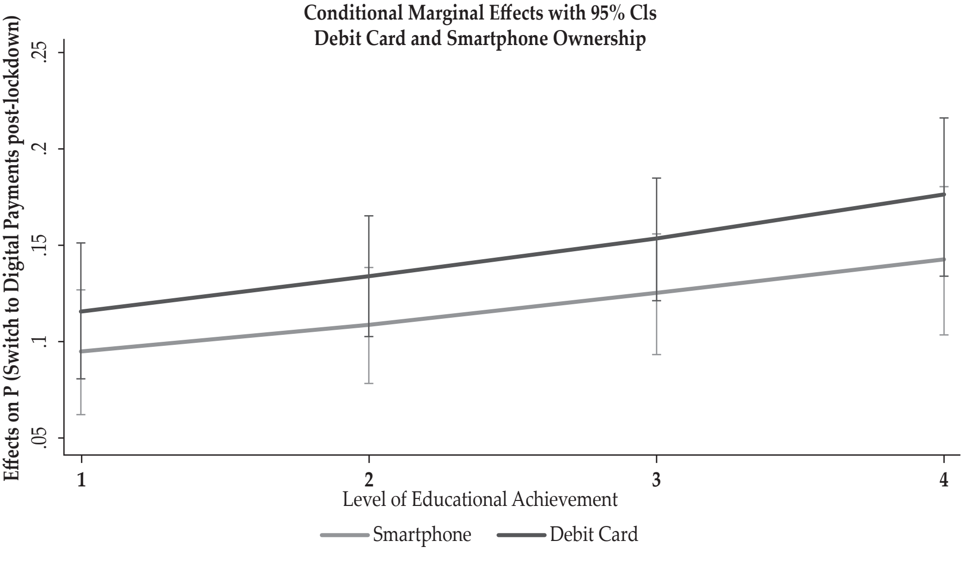
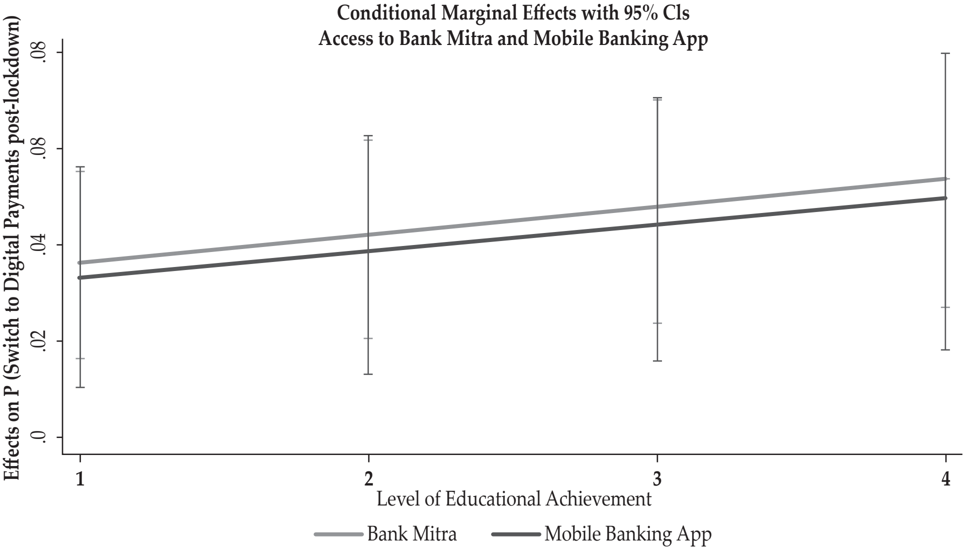


Figure 3.
Access Variables, Awareness and Education (Continued)



In Model 2 (Table 6), we restrict our sample to respondents without smartphones. We find that even if the respondent did not own a smartphone, having a family member with access to one led to an increased likelihood of switching. It is also interesting that the coefficient for access to a bank-*mitra* becomes statistically insignificant, hinting that perhaps the services rendered by a bank-*mitra* may be provided equally well by a family member who is digitally aware and empowered. Ozili (2018, p.333) states "Individuals in the informal sector and in poor communities often do not trust bankers or bank marketers who come to their homes to persuade them to use digital finance services, rather they are more likely to trust the recommendation they receive from friends and family members who are already users of digital finance platforms".

Table 6.
Logistic Regression: Model 2
(Sub-sample: Those Who Do not Own a Smartphone)

This table presents regression results for the model with the sample restricted to users without access to smartphones. The dependent variable is "*Did you use digital methods for the first time after the lockdown?*" In addition to the logit coefficients, the odds ratio and the marginal effect at means are also computed. The base case for 'Awareness' is 0 (Nil); for 'Distance from Branch' is more than 5 kilometres; and for 'Income Category' is Top 20%. The 'Level of Education' is on the scale: 1 (Illiterate- lowest), 2 (Primary School), 3 (High School), 4 (Graduates and above- Highest). The standard errors are reported in parentheses and the significance levels are denoted with asterisk: * p <10%, ** p <5%, and *** p <1%

	(1)	(2)	(3)
Variables	**Logit Coefficients**	**Odds Ratio**	**Marginal Effect at Means**
Level of Awareness = 1 (Low)	1.310	3.707	0.00608
	(1.096)	(4.064)	(0.00469)
Level of Awareness = 2 (Medium)	3.333***	28.02***	0.0155**
	(1.122)	(31.45)	(0.00691)

Table 6.
Logistic Regression: Model 2
(Sub-sample: Those Who Do not Own a Smartphone) (Continued)

	(1)	(2)	(3)
Variables	**Logit Coefficients**	**Odds Ratio**	**Marginal Effect at Means**
Level of Awareness = 3 (High)	3.136***	23.00***	0.0146**
	(1.092)	(25.12)	(0.00632)
Received DBT before lockdown	-0.298	0.742	-0.00187
	(0.915)	(0.679)	(0.00291)
Received DBT after lockdown	-0.471	0.624	-0.00260
	(0.804)	(0.502)	(0.00296)
Received DBT pre-lockdown*Received DBT post-lockdown	-0.190	0.827	
	(1.194)	(0.988)	
Distance from Branch (< 1 km)	-1.054	0.349	-0.00489
	(0.987)	(0.344)	(0.00510)
Distance from Branch (1-2 km)	-1.231	0.292	-0.00571
	(0.760)	(0.222)	(0.00422)
Distance from Branch (2-3 km)	-0.785	0.456	-0.00365
	(0.711)	(0.324)	(0.00358)
Distance from Branch (3-5 km)	-0.617	0.540	-0.00286
	(0.735)	(0.397)	(0.00363)
Access to Smartphone (sample selection criterion)	-	-	-
Someone in family has Access to Smartphone	1.912***	6.767***	0.00888**
	(0.587)	(3.972)	(0.00445)
Access to Debit Card	1.310**	3.707**	0.00608*
	(0.519)	(1.924)	(0.00351)
Access to Bank *Mitra*	-0.125	0.883	-0.000580
	(0.437)	(0.386)	(0.00203)
Access to Mobile Banking App	1.874***	6.515***	0.00870*
	(0.455)	(2.964)	(0.00461)
Used Digital Payments earlier but discontinued later	2.322***	10.20***	0.0108*
	(0.493)	(5.031)	(0.00595)
Income Category = Bottom 40%	0.506	1.659	0.00235
	(0.640)	(1.063)	(0.00317)
Income Category = Middle 40%	0.310	1.364	0.00144
	(0.606)	(0.827)	(0.00288)
Level of Education	-0.0575	0.944	-0.000267
	(0.249)	(0.235)	(0.00116)
Age	-0.617*	0.539*	-0.00287
	(0.354)	(0.191)	(0.00214)
Constant	-5.298***	0.00500***	
	(1.719)	(0.00860)	
McFadden's R^2	0.591		
McFadden's Adjusted R^2	0.463		
Observations	1,259	1,259	1,259

C. Direct Benefit Transfers (DBT)

We now consider another important enabler of the switch - DBT from the government for pandemic relief. These are credited into Aadhaar-authenticated beneficiaries' bank accounts. Over the past year, governments amped up cash transfers to help citizens cope with unemployment and dwindling incomes (Gelb and Mukherjee, 2020). In India, small and marginal farmers, senior citizens, widows, and women with Jan-Dhan accounts were eligible for income support.

Respondents were asked whether they were entitled to DBT cash support pre and post-lockdown. While the former had a negative marginal effect on the probability of switching, the latter emerges as an enabler for digital payment modes post the lockdown. The interaction of these two binary variables is positive and significant, which means that it is not only the recent COVID-related transfers that mattered for digital payments adoption, but a sustained flow of such transfers from earlier. Long-term recipients of government support may have switched to digital modes of payment spurred by social distancing, reduced functioning of banks due to pandemic protocols and a rise in digital payments acceptance even in less well-off communities. Since such recipients would be from the most vulnerable sections of society, they were more likely to be in dire need COVID-relief transfers and going digital may have been inevitable to secure access to their entitlements.

D. Those Earlier Disillusioned with Digital Payments Came Back

Nearly 9% of the respondents had earlier tried using digital payments but discontinued for various reasons. Our results show that many were forced to go back into the digital fold due to the exigencies created by the pandemic. In terms of the marginal effect on the probability of switching, this regressor has the highest impact, which is expected, since such respondents perhaps already had access to and know-how regarding digital modes of payments. These respondents were further probed to provide specific reasons which led them to discontinue such payments. Nearly half cited "Difficulty in use" as a reason. Other reasons listed are bad experience or were cheated, lack of internet access, digital payments leading to overspending, lack of merchant acceptance, and feeling that they didn't need such payment modes. Note that this finding may also indicate that factors like ease of use of apps, awareness, and merchant acceptance could have improved post-pandemic. This reasoning needs to be verified through further research.

E. Demographic Characteristics

Education has a beneficial impact on digital payments adoption, and those with higher educational attainment are shown more likely to have switched to digital payments after the lockdown. Gender does not seem to influence the switch in a statistically significant manner and has been left out of the analysis. Being middle-aged contributes significantly to the 'switch', supporting the finding that a majority of first-time users were from the middle-age category. This offers a different perspective from the prevailing knowledge that associates digital use to younger people. In this sense, the pandemic may have "force-bridged" the generation gap in digital payments. A recent report confirmed increasing adoption of digital payments among the older demographic in India[4].

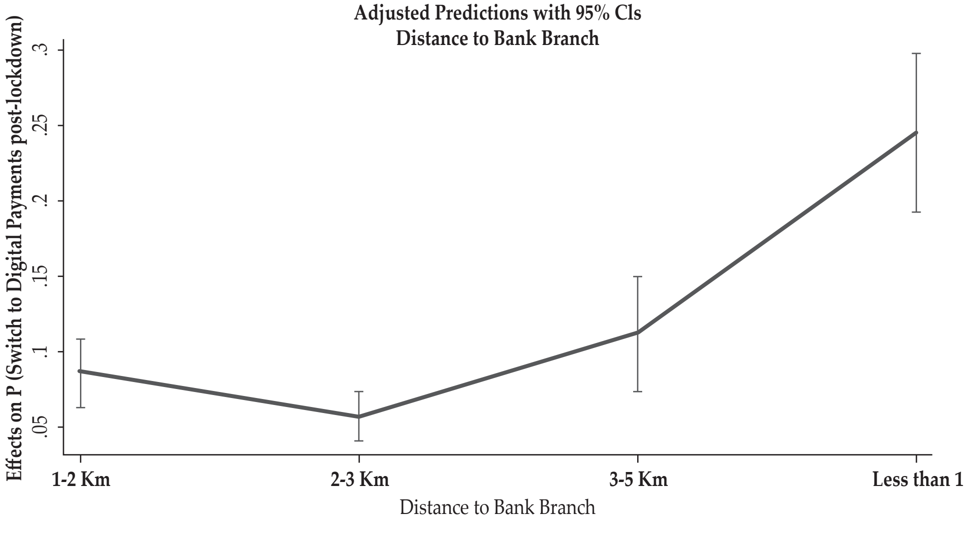
Compared to the base of the "Top 20%" income bracket, those in the middle-income category were significantly less likely to switch to digital payments post-pandemic. This is most likely due to the mixed base case of the dependent variable - people who were high/medium earners were perhaps already on board the digital payments bandwagon. The positive sign on the "Bottom 40%" income category coefficient could hint that this shift to digital payments was mostly undertaken by the poorest sections of society, but it is not statistically significant.

F. Proximity to Bank Branches

Compared to the base case of "more than 5 kilometres away", proximity to a physical bank branch is important factor impacting the switch. This regressor has a non-linear impact, as seen in Figure 4. The impact is positive and significant for those living within a kilometre of a bank branch, hinting that physical interaction with bank staff and access to banking facilities was important even during the pandemic as it provides trust and comfort to the first-time users. However, the effect turns negative with increasing distance from the branch, leading to a U-shaped curve. One explanation could be that while those near banks could easily get guidance which facilitated the switch, those furthest off may have switched on their own, as long-distance movement was discouraged by the authorities.

Figure 4.
Marginal Effects of Proximity to Bank Branch

The figure illustrates the marginal effects of proximity to bank branch on the probablity to switch to digital payments post-lockdown, computed from Model 1 (Table 5)



[4] KPMG, April 2021. *Me, My Life, My Wallet*. available at https://assets.kpmg/content/dam/kpmg/in/pdf/2021/05/me-my-life-my-wallet-3.pdf

Awareness played a positive role in the digital switch only for those living closest to a bank and had nearly no differential impact on those living far off in the 3-5-kilometre zone. Activation of payments apps, handholding, demonstration of the usage of apps, and troubleshooting are critical services that bank employees provide, especially to illiterate and digitally novice customers. More clarity regarding the features of the products leads to enhanced usage of payment instruments (Klapper and Singer, 2014). In the future, it may be difficult to replace physical banks completely with smartphones and banking apps, given these considerations. This argument is further bolstered by the coefficient of access to a bank *mitra*.

G. Robustness Checks

The survey design takes care of independent sampling of observations, which is a key assumption underlying logistic regression models. Further, the large sample size ensures precise estimates. While we provide McFadden's pseudo *R*-squared values as estimates of goodness of fit of our models, we also gauge the predictive accuracy of the baseline model by splitting our dataset into training and testing sets (80:20). The classification accuracy of the model stands at 87%, sensitivity (the model's ability to predict true positives) at 89% and specificity (the model's ability to predict true negatives) at 82%. We also compute the Cooks' distance (Cook, 1977) for influential outliers, concluding that there is a negligible number of such outliers in comparison to the sample size. To rule out multicollinearity of independent variables, we calculate the Generalised Variance Inflation Factors (Fox and Monette, 1992) instead of the usual Variance Inflation Factors (VIFs), since our model includes factor variables with multiple categories. The GVIFs are found to be below 3, when adjusted for the dimension of the confidence ellipsoid.

V. POLICY IMPLICATIONS AND CONCLUSION

Using a large survey dataset, we examine the shift to digital payment modes witnessed in India post-COVID-19. We characterise the drivers of this shift and, in doing so, arrive at some recommendations for future policy that may be crucial to future-proof the transition.

First, digital literacy and awareness matters the most in influencing the likelihood to shift to digital. Awareness also significantly increases digital adoption by complementing enablers of digital payments like debit cards and smartphones for availing financial services. Sustained investment in financial literacy, digital literacy/hygiene, and higher education is necessary to attain the goal of *Digital India*. Advertisements, demonstrations, word-of-mouth publicity, and integration into traditional financial literacy programmes could be the way forward for digitalisation.

Second, the penetration of mobile phones is not reason enough to obviate the expansion of the banking sector. As of now, banks and banking personnel appear to complement the penetration of digital payments in India. This role might also be carried out by those who are digitally aware and inspire confidence in digital modes among other members of their household. Older respondents were more likely to switch, indicating that the pandemic has nudged the middle-aged to 'get with the program'.

Third, post-pandemic government income support was a motivator for digitalisation, especially for those who relied on such payments prior to the pandemic. It remains up to these new and possibly vulnerable users to gauge whether they find digital payments worthy enough to change their payment habits in the long run. To retain their trust, matters such as authentication failures, transparency, trust in payment mode, removal of misconceptions, sensitisation of bank staff, and prompt redressal of customer grievances in the local language need to be addressed. Further, issues like frauds, overspending, poor merchant acceptance, etc. as reported by the erstwhile 'disillusioned' switchers need to be rapidly addressed to increase public faith in new payment systems and make this shift to digital a permanent one.

Our final argument deals with whether the post-COVID surge in digital payments is sustainable enough in the long run. In short, we need to address various underlying concerns which if left unattended may lead to cash remaining king. While individual and household characteristics, and access points matter for long-term sustainability, it is interesting to recall the evidence of 'reluctant switchers'- those who discontinued digital payments in the past but returned to the digital fold due to the pandemic. If the lockdown is to be treated as a random event, and there were significant changes in underlying drivers like an increase in acceptance infrastructure, merchant on-boarding, reduction in frauds, greater customer trust in digital payments with consumer protection, enhanced customer-friendliness of apps, etc. compared to the before-lockdown period, these users may have shifted 'voluntarily' and are likely to stay permanently digital. On the other hand, if there were no significant changes pre- and post-lockdown in the driving variables, the long-term sustainability of this shift may be questionable, as they may have been 'forced' to change, rather than 'incentivised'. Likely, such people would not have adopted digital means without the exogenous push under extraordinary circumstances of the pandemic. As long as problems they faced earlier regarding acceptance, fraud, overspending/overcharging, consumer protection, etc. persist, we can expect them to return to cash use once things normalise. The sustainability of this switch is further brought into question by the large impetus provided by post-lockdown DBT payments. What happens when such payments are discontinued as the pandemic subsides? For such agents, the digital payments 'revolution' may indeed just be a temporary hiccup in their normal comfort zone of cash payments.

There is immense scope for further research into the drivers of digital behaviour (including the pandemic) and the sustainability of such change, especially as better datasets emerge. Our findings may be affected by issues arising from survey design, the mixed base case of the switch variable, a relative dearth of questions on post-pandemic behaviour in the questionnaire, and the lack of geographical identifiers for respondents. Nevertheless, we hope this is a fruitful step towards exploring the rapid and unprecedented fusion of society, economy, and technology underway in India.

Acknowledgements: The authors are thankful for the feedback received from Yezhou Sha and other participants at the 15th Bulletin of Monetary Economics and Banking (BMEB) International Conference, organised by the Bank Indonesia Institute. The views expressed in the paper are those of the authors and do not reflect the views of the Reserve Bank of India.

REFERENCES

Agur, I., Peria, S. M., & Rochon, C. (2020). Digital Financial Services and the Pandemic: Opportunities and Risks for Emerging and Developing Economies. *International Monetary Fund Special Series on COVID-19, Transactions*, 1, 2-1.

Alber, N., & Dabour, M. (2020). The Dynamic Relationship between FinTech and Social Distancing under COVID-19 Pandemic: Digital Payments Evidence. *International Journal of Economics and Finance*, 12.

Arango-Arango, C. A., Bouhdaoui, Y., Bounie, D., Eschelbach, M., & Hernandez, L. (2018). Cash Remains Top-of-wallet! International evidence from Payment Diaries. *Economic Modelling*, 69, 38-48.

Ardizzi, G., Nobili, A., & Rocco, G. (2020). A Game Changer in Payment Habits: Evidence from Daily Data during a Pandemic. *Bank of Italy Occasional Paper*, 591.

Auer, R., Frost, J., Lammer, T., Rice, T., & Wadsworth, A. (2020). Inclusive Payments for the Post-pandemic World. *SUERF Policy Notes*, 193.

Bagnall, J., Bounie, D., Huynh, K. P., Kosse, A., Schmidt, T., Schuh, S. D., & Stix, H. (2014). Consumer Cash Usage: A Cross-country Comparison with Payment Diary Survey Data. *International Journal of Central Banking*, 12, 1–61.

Barro, R. J., Ursúa, J. F., & Weng, J. (2020). The Coronavirus and the Great Influenza Pandemic: Lessons from the "Spanish Flu" for the Coronavirus's Potential Effects on Mortality and Economic Activity (No. w26866). *National Bureau of Economic Research*.

Bhuyan, P., Roy J., & Priyadarshi R. R. (2021). Retail Payment Habits in India - Evidence from a Pilot Survey. *RBI Bulletin April 2021*. https://www.rbi.org.in/Scripts/BS_ViewBulletin.aspx?Id=20205

Bold, C., Porteous, D., & Rotman, S. (2012). Social Cash Transfers and Financial Inclusion: Evidence from Four Countries. *Consultative Group to Assist the Poor*, Focus Note 77/2012.

Chaudhari, D. R., Dhal, S., & Adki, S. M. (2019). Payment Systems Innovation and Currency Demand in India: Some Applied Perspectives. *Reserve Bank of India Occasional Papers*, 40, 33-63.

Chen, H., Engert, W., Huynh, K., Nicholls, G., & Zhu, J. (2021). Cash and COVID-19: The Effects of Lifting Containment Measures on Cash Demand and Use. *Staff Discussion Paper* (2021-3). Bank of Canada

Cohen, M. A., & Rysman, M. (2013). Payment Choice with Consumer Panel Data. *Working Papers* 13-6, Federal Reserve Bank of Boston.

Cook, R. (1977). Detection of Influential Observation in Linear Regression. *Technometrics*, 19, 15-18. doi:10.2307/1268249

De', R., Pandey, N., & Pal, A. (2020). Impact of Digital Surge during Covid-19 Pandemic: A Viewpoint on Research and Practice. *International Journal of Information Management*, 55, 102171.

Fox, J., & Monette, G. (1992). Generalized Collinearity Diagnostics. *Journal of the American Statistical Association*, 87, 178-183. doi:10.2307/2290467

Fujiki, H., & Nakashima, K. (2019). Cash Usage Trends in Japan: Evidence Using Aggregate and Household Survey Data. *TCER Working Paper Series*, E-131, 1-42. https://doi.org/10.2139/ssrn.3351429

Gelb, A., & Mukherjee, A. (2020). Digital Technology in Social Assistance Transfers for COVID-19 Relief: Lessons from Selected Cases. *CGD Policy Paper*, 181.

Gentilini, U., Almenfi, M., Orton, I., & Dale, P. (2020). Social Protection and Jobs Responses to COVID-19. World Bank.

Greene, C., O'Brien, S., & Schuh, S. D. (2017). US Consumer Cash Use, 2012 and 2015: An Introduction to the Diary of Consumer Payment Choice. *Research Data Reports Paper*, 17-6.

Iazzolino, G. (2018). Digitising Social Protection Payments: Progress and Prospects for Financial Inclusion (No. 57). *Bath Papers in International Development and Wellbeing*.

Ivatury, G., & Mas, I. (2008). The Early Experience with Branchless Banking. *CGAP Focus Note*, 46.

Jonker, N., van der Cruijsen, C., Bijlsma, M., & Bolt, W. (2020). Pandemic Payment Patterns. *DNB Working Paper* No. 701

Kaur, S. J., Ali, L., Hassan, M. K., & Al-Emran, M. (2021). Adoption of Digital Banking Channels in an Emerging Economy: Exploring the Role of in-branch Efforts. *Journal of Financial Services Marketing*, 26, 107-121.

Klapper, L., & Singer, D. (2014). *The Opportunities of Digitizing Payments.*

Klapper, L., & Singer, D. (2017). The Opportunities and Challenges of Digitizing Government- to-person Payments. *The World Bank Research Observer*, 32, 211-226.

Klee, E. (2008). How People Pay: Evidence from Grocery Store Data. *Journal of Monetary Economics*, 55, 526-541.

Koulayev, S., Rysman, M., Schuh, S., & Stavins, J. (2012). Explaining Adoption and Use of Payment Instruments by US consumers. Working Papers No. 12-14. Federal Reserve Bank of Boston.

Li, J., Song, Q., Peng, C., & Wu, Y. (2020). COVID-19 Pandemic and Household Liquidity Constraints: Evidence from Micro Data. *Emerging Markets Finance and Trade*, 56, 3626-3634.

Ling, S., Pei, T., Li, Z., & Zhang, Z. (2021). Impact of COVID-19 on Financial Constraints and the Moderating Effect of Financial Technology. *Emerging Markets Finance and Trade*, 57, 1675-1688.

Liu, T., Pan, B., & Yin, Z. (2020). Pandemic, Mobile Payment, and Household Consumption: Micro-evidence from China. *Emerging Markets Finance and Trade*, 56, 2378-2389.

Mester, L. J. (2012). Changes in the Use of Electronic Means of Payment: 1995-2010. *Federal Reserve Bank of Philadelphia Business Review Q*, *3*, 25-36.

Narayan, P. K. (2020). Did Bubble Activity Intensify during COVID-19? *Asian Economics Letters*, 1, 17654. https://doi.org/10.46557/001c.17654

Ozili, P. K. (2018). Impact of Digital Finance on Financial Inclusion and Stability. *Borsa Istanbul Review*, 18, 329-340.

Sahay, M. R., von Allmen, M. U. E., Lahreche, M. A., Khera, P., Ogawa, M. S., Bazarbash, M., & Beaton, M. K. (2020). The Promise of Fintech: Financial Inclusion in the Post COVID-19 Era. *International Monetary Fund*.

Sha, Y., & Sharma, S. S. (2020). Research on Pandemics Special Issue of the Journal Emerging Markets Finance and Trade. *Emerging Markets Finance and Trade*, 56, 2133-2137.

Shen, H., Fu, M., Pan, H., Yu, Z., & Chen, Y. (2020). The Impact of the COVID-19 Pandemic on Firm Performance. *Emerging Markets Finance and Trade,* 56, 2213-2230.

Shree, S., Pratap, B., Saroy, R., & Dhal, S. (2021). Digital Payments and Consumer Experience in India: A Survey based Empirical Study. *Journal of Banking and Financial Technology*, 1-20.

Stavins, J. (2002). Effect of Consumer Characteristics on the Use of Payment Instruments. *New England Economic Review· February*.

Suri, T., & Jack, W. (2016). The Long-run Poverty and Gender Impacts of Mobile Money. *Science*, 354, 1288-1292.

Toh, Y. L., & Tran, T. (2020). How the COVID-19 Pandemic May Reshape the Digital Payments Landscape. *Payments System Research Briefing*, 1-10.

Wang, Z., & Wolman, A. L. (2016). Payment Choice and Currency Use: Insights from Two Billion Retail Transactions. *Journal of Monetary Economics*, 84, 94-115.

Williams, R. (2012). Using the Margins Command to Estimate and Interpret Adjusted Predictions and Marginal Effects. *The Stata Journal*, 12, 308-331.

Wisniewski, T. P., Polasik, M., Kotkowski, R., & Moro, A. (2021). Switching from Cash to Cashless Payments during the COVID-19 Pandemic and Beyond. *NBP Working Paper* 337, Narodowy Bank Polski

Wyman, O. (2017). Accelerating Financial Inclusion in South-East Asia with Digital Finance. https://dx.doi.org/10.22617/RPT178622-2