ICRIER PROSUS
CENTRE FOR INTERNET AND DIGITAL ECONOMY

DIFFUSION OF DIGITAL PAYMENTS IN INDIA - INSIGHTS BASED ON DATA FROM PHONEPE PULSE

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Abstract

Digitalisation of payments is a global trend, with the COVID-19 pandemic having triggered accelerated adoption. While India has been at the forefront of this transition, there is little understanding of how the Unified Payments Interface (UPI), India's real-time digital payment system, has diffused and the extent of its inclusive scaling within the country. The paper relies on state and district level data from PhonePe, the largest digital payments platform in India, to better understand the heterogeneity in patterns of diffusion across states and districts of India. Data from various other sources are used to examine how socio-economic factors correlate with diffusion.

The initial periods beginning 2018 are marked with a few early-adopter districts that have high levels of user penetration. The COVID-19 pandemic appears to have catalysed large-scale adoption that resulted in lower variation in user penetration across districts and states. Regions that started off well, continue to lead, with little reordering in the ranking of district or states. For aspirational districts user penetration continues to remain relatively lower. Findings from cross-sectional regressions suggest that socio-economic indicators such as certain levels of income, poverty, education, digital literacy, and financial access are necessary but not sufficient for widespread adoption. Policy efforts therefore require a deeper understanding of the costs and benefits of digital payments to different users, and a multi-pronged approach to promote its adoption in way that is beneficial.

Keywords: Digital Payments, Financial Inclusion, Financial Institutions and Services

JEL classification: G20, O16, O13

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CONTENTS

List of Tables

List of Figures

Diffusion of Digital Payments in India - Insights based on data from PhonePe Pulse

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1. The Global Surge in Use of Digital Payments

Digitalisation of payments is a global trend. According to the World Bank's Findex, the share of adults making or receiving digital payments in developing countries increased from 35 percent in 2014 to 57 percent in 2021[1]. The COVID-19 pandemic was one of the key drivers of accelerated digital adoption. However, the Bank for International Settlements (BIS) stated in its recent publication that despite strong growth in the volume and value of real-time digital payments, they have not replaced cash[2].

Shifting payments from cash to digital, has the potential to lower the costs of transactions, and improve transparency, traceability, security, and financial inclusion. Digital payments are particularly helpful in enabling transactions in contexts like the pandemic when limiting physical interaction was essential. They have also transformed the nature of transactions between buyers and sellers, and the disbursement of wages, welfare payments, pensions, and social protection benefits. They have also resulted in higher cost efficiencies for the banking sector[3]. In the long run, infrastructure for digital payments can also facilitate digital provisioning of other important services such as credit, savings, remittances, and insurance, which are important attributes of the quality of financial inclusion[4].

On the flip side, digital payments come with the risk of security breaches and loss of privacy, uncertainty driven by network failures and technical glitches, and therefore, can potentially deepen financial divides. Inadequate focus on these aspects can lower benefits for the ecosystem and result in counterproductive outcomes.

Fast Payments Systems are driving the growth of digital payments across the world. These are systems in which the transmission of the payment messages and availability of final funds to the payee occur in real time or near-real time, and as near to 24 hours a day, seven days a week (24/7). The technology underlying many fast systems enable new and innovative functionalities for end users which have been key in driving their rapid adoption[5]. Many Central Banks have invested in a fast payments system that is integrated with their national payments system. This includes India's Immediate Payment Service (IMPS), China's Internet Banking Payment System (IBPS), and Singapore's Fast and Secure Transfers (FAST). Over a period of time, countries have built interoperable payment networks atop these fast (real-time) payment networks to also facilitate retail digital payments. These are now commonly referred to as Digital Public Infrastructure for Payments[6]. Examples include India's Unified Payments Interface (UPI), Thailand's PromptPay, Brazil's PiX, Philippine's' Instapay, and Singapore's PayNow.

1 https://www.worldbank.org/en/publication/globalfindex/Report

2 https://www.bis.org/statistics/payment_stats/commentary2301.htm.

3 Saroy et al. (2023)

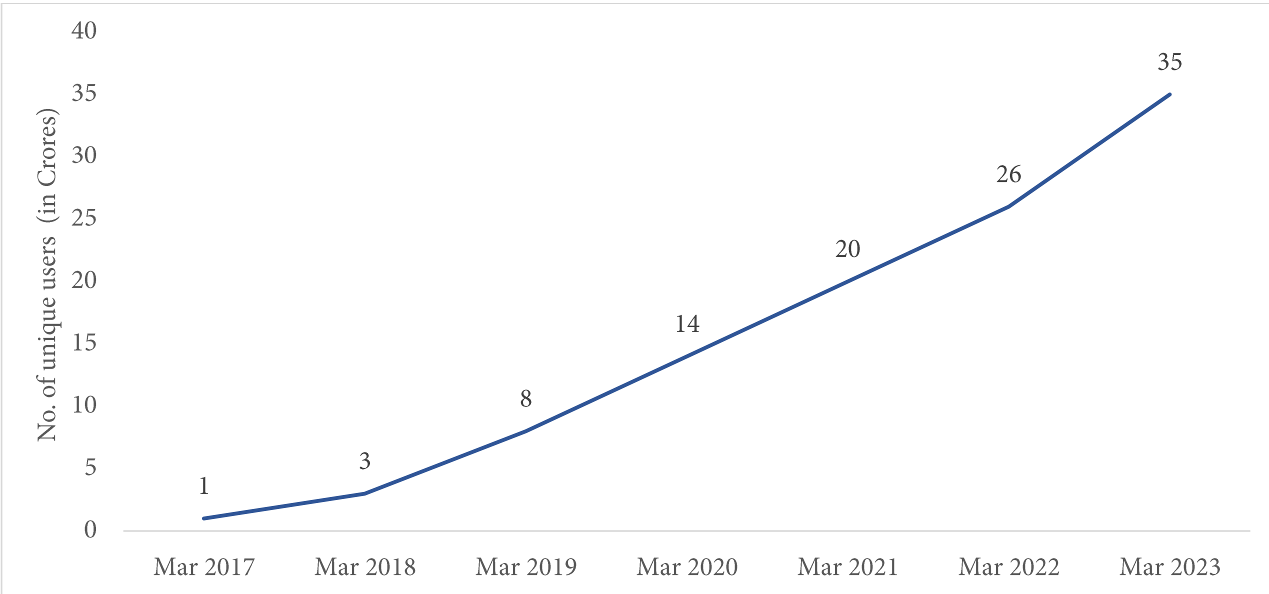
4 https://www.researchgate.net/profile/Rajesh-Kumar-122/publication/333369877_DIGITAL_FINANCIAL_SERVICES_IN_INDIA_AN_ANALYSIS_OF_TRENDS_IN_DIGITAL_PAYMENT/links/5eb654fca6fdcc1f1dcafcd8/DIGITAL-FINANCIAL-SERVICES-IN-INDIA-AN-ANALYSIS-OF-TRENDS-IN-DIGITAL-PAYMENT.pdf

5 https://www.bis.org/cpmi/publ/d154.pdf; https://fastpayments.worldbank.org/sites/default/files/2021-11/Fast%20Payment%20Flagship_Final_Nov%201.pdf

6 https://icrier.org/pdf/State_of_India_Digital_Economy_Report_2023.pdf; https://documents1.worldbank.org/curated/en/099755004072288910/pdf/P1715920edb5990d60b83e037f756213782.pdf

India is at the forefront of this transformation, with the highest volume of digital payments in the world. Over 45% of all global real-time digital transactions are now in India (ACI, 2023). The Unified Payments Interface (UPI), introduced by the National Payments Corporation of India (NPCI) in 2016, is among the fundamental drivers of this growth. UPI has seen rapid growth from approximately 3 crore unique customers in 2017 to over 33 crores according to the latest reported data – which amounts to approximately 24% of the Indian population (Figure 1). Starting with only 21 banks in 2016, it has now expanded to include over 550 banks and 22 third party apps[7]. The UPI network is currently driven by non-bank digital payment companies, which account for more than 80 percent of transactions[8].

Figure 1: Growth in Number of Unique UPI users



Source: Rise of New Era of Digital Payments Report (Ministry of I&B) and https://pib.gov.in/FeaturesDeatils.aspx?NoteId=151350&ModuleId%20=%202

UPI is a subset of digital payments that includes other retail instruments such as cards, bank transfers, and mobile money. While UPI transactions comprised only 3% of the value of digital payments in 2020-21, it accounted for more than half the number of transactions (Figure 2)[9]. It enables the digital processing of small value transactions without incurring the high costs of alternative methods such as debit cards and bank transfers. Critics often point towards this as a negative – i.e., overloading a network with too many low ticket-sized transactions, that could have been cleared in cash at a lower cost to the network.

7 https://www.npci.org.in/what-we-do/upi/product-statistics; https://inc42.com/features/record-breaking-numbers-upi-2022-hint-india-maturing-digital-payments-ecosystem/

8 UPI Ecosystem Statistics (June 2022), NPCI. https://www.npci.org.in/what-we-do/upi/upi-ecosystem-statistics

9 Ministry of Information and Broadcasting, Government of India (2022). Rise of a New Era of Digital Payments. Retrieved on February 10, 2023 from https://static.pib.gov.in/WriteReadData/specificdocs/documents/2022/nov/doc20221116125801.pdf

Figure 2: UPI vis-a-vis digital payments

Figure 2a: Value of transactions

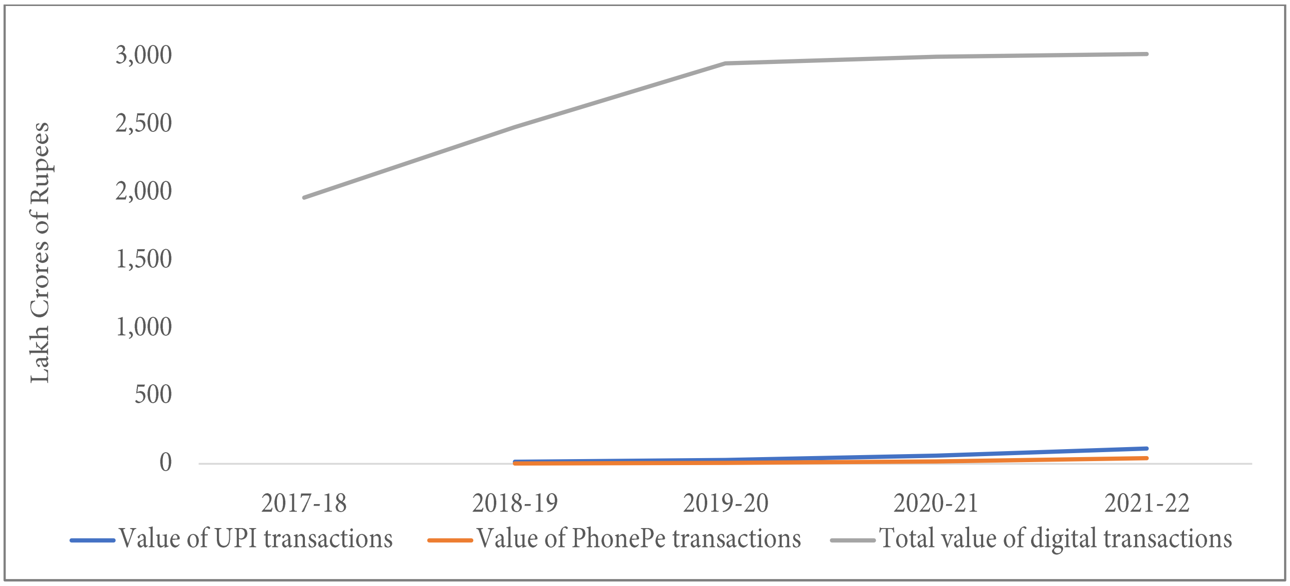
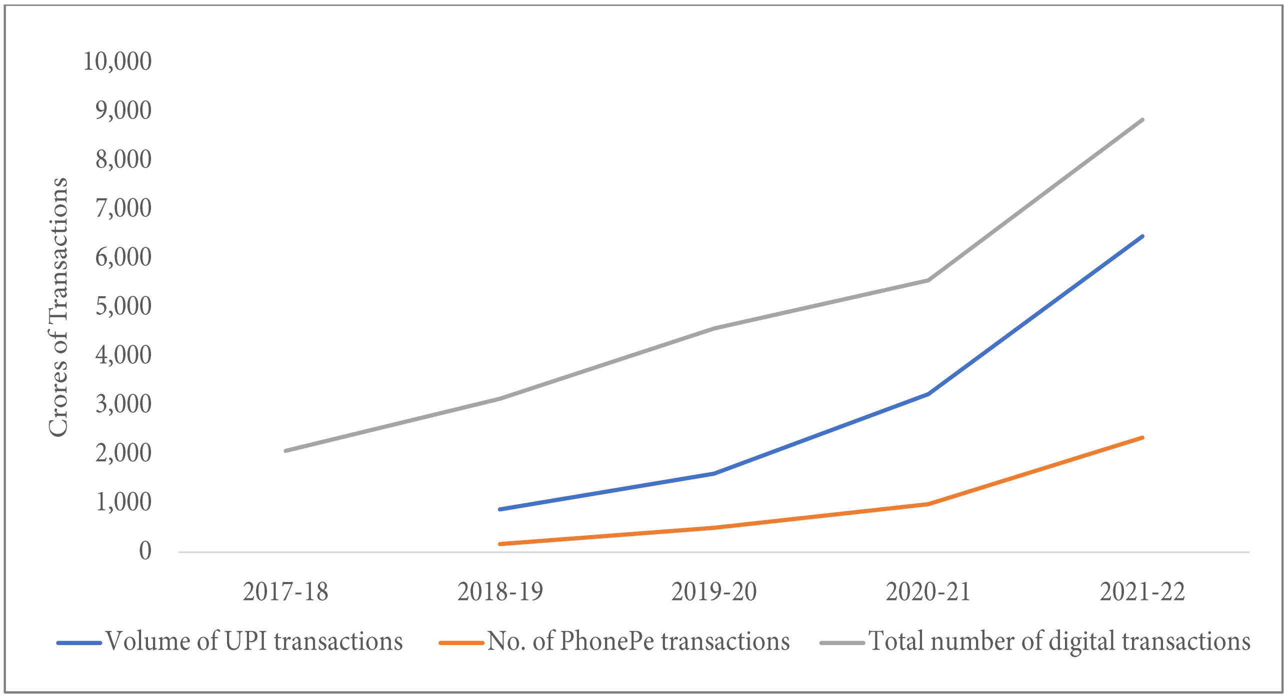


Figure 2b: Number of transactions



Source: PIB (from RBI, NPCI and Banks)[10], NCPI and PhonePe Pulse.

A number of studies have documented the rapid adoption of digital payments in India and across the world, though few focus on how it was distributed and how inclusive it is. Most studies examine the adoption of digital payments during and after the demonetisation of 2016 and the COVID-19 pandemic (Singh et al., 2022; Kumar et al., 2019; Bhasin et al., 2018). Chodorow-Reich et al. (2020) found that districts experiencing more severe demonetization were

10 https://pib.gov.in/PressReleasePage.aspx?PRID=1897272

also ones with reduced economic activity and lower bank credit growth, but relatively faster adoption of alternative payment technologies. Lahiri (2020) found that areas that were informal and not very integrated with the formal financial network were unlikely to adopt digitization in response to a shock like demonetization, suggesting a non-inclusive pattern of adoption. While the findings regarding the effect of demonetization on adoption has been mixed, studies have found that the pandemic generally accelerated adoption. The lack of empirical work is partly because data reported by NPCI on UPI is for transactions (by volume, value, entity) and not adequately available for users. While UPI has reportedly gained traction in Tier 2 and 3 cities[11], the poorer are found to be less likely to use it than the richer. A survey by NPCI finds that the bottom 40 per cent of the population is half as likely as the top 20 per cent to use digital payments[12]. Low-income households that do use digital payments, however, are more likely to use apps such as Paytm and PhonePe than credit cards, debit cards, and bank apps, compared to higher income households. A 2022 Oxfam report based on CMIE data, reports a much wider gap - with the richest 60 per cent being four times more likely to make a digital payment than the poorest 40 per cent[13].

A systematic and macro understanding of the patterns of diffusion at the sub-national level is missing. While promoting digital transactions is not a goal in itself, its potential benefits have made it an intermediate indicator of interest. Further, understanding its diffusion patterns is essential to prevent exclusion of marginalized groups as digital payments become the norm and start replacing non-digital alternatives. This paper presents an analysis of UPI diffusion in India with the purpose of understanding how inclusive it has been. The next section describes the data used and the methodology for the overall analysis. Section III present a descriptive analysis of trends over time, and across states and districts. This is followed by a convergence analysis of diffusion using the sigma measure of dispersion and the gamma measure of ranking in Section IV. Section V discusses the results of cross-sectional regressions that explain drivers of digital payments in India and some reasons for non-inclusive diffusion. Section VI concludes.
push towards digitalization has led to a dramatic rise in internet penetration in India.

2. Data and Methodology

The paper relies on data from PhonePe, the largest digital payments platform in India, with almost 50 percent market share in terms of volume and value of transactions (Figure 17, Appendix 1). The data covers adoption by individual as well as merchant users. It provides number of users, number of app opens, volume (number of transactions), and value of transactions for each quarter between the first quarter of 2018 and the fourth quarter of 2022.

The number of users refers to 'registered users', defined as unique mobile phone numbers that have downloaded the PhonePe app and accepted the Terms and Conditions displayed during the onboarding process. While this is a measure of adoption, it does not imply active usage of the app. The number of transactions per person provides a better measure of active usage. In the paper we assess diffusion using four different indicators 1) user penetration (number of registered users

11 BCG and PhonePe Pulse (2022). Digital Payments in India: A US$10 Trillion Opportunity. Retrieved on February 10, 2023 from https://www.phonepe.com/pulse-static-api/v1/static/docs/PhonePe_Pulse_BCG_report.pdf

12 NPCI (2020). Digital Payments Adoption in India. Retrieved on Janurary 26 2023 from: https://www.npci.org.in/PDF/npci/knowledge-center/Digital-Payment-Adoption-in-India-2020.pdf

13 Oxfam (2022). India Inequality Report 2022: Digital Divide. Retrieved on January 26 2023 from: https://www.oxfamindia. org/knowledgehub/workingpaper/india-inequality-report-2022-digital-divide

per capita) 2) average number of transactions per capita 3) average value of transactions per capita and 4) ticket size (average value of each transaction). While the value of transactions per capita and ticket size are not necessarily measures of how actively digital payments are being used, however, they can be informative in understanding the types of transactions a system like this is facilitating, and its impacts on efficiency and overall economic activity. Data on the actual distribution of transaction values and socio-economic indicators rather than averages would provide more insights on how different groups of the population are leveraging digital payments.

According to NPCI the latest reported number of unique UPI users was over 33 crores in March 2023[14] while PhonePe reported over 49.14 crore registered users in September 2023[15].The corresponding number for March 2023 is 45.38 crore. Most UPI users have accounts on multiple payment apps, so the number of active PhonePe users would likely be close to the NPCI estimate of active UPI users even though PhonePe's market share in terms of volume and value is about 50%. While the NPCI estimate serves as a benchmark, their numbers are also estimates and are subject to some degree of uncertainty. There may also be differences in how users are defined by UPI and PhonePe, giving rise to different estimates. Given the scale of PhonePe's network, we present our findings assuming that trends for PhonePe adoption are representative of trends in UPI as a whole. There may, however, be unique users for other payment apps such as Paytm or BHIM, that can limit the generalizability of these findings, especially in the early years of our data set (the market share of PhonePe was ~30% in 2018-19 – see Appendix 1). But we don't expect it to systematically affect the broader findings.

The analysis has been carried out both at the state and district levels. Table 1 shows the other sources of data used to examine how regional, demographic, and socio-economic factors correlate with adoption. Indicators used include population, income, wealth, poverty rate, literacy rate, access to mobile phones and the internet, digital literacy, and measures of financial inclusion. Density of bank branches is used as a proxy to examine how physical financial infrastructure mediates the adoption of digital payments (especially consequential in rural areas), and whether digital payment apps saw greater uptake in areas that were hard to reach for the traditional banking system. While data on smartphone ownership was not available, it is expected to be an important predictor. Table A1, Appendix 2 provides descriptive statistics for the variables used.

In order to compare indicators like the number of registered users, number of transactions, and transaction amount, we normalise the data by population. Where unavailable, the population data is linearly interpolated to obtain quarterly data. At the state level, the population data is sourced from the Ministry of Family Health and Welfare's 2019 projections for the years 2018 to 2022. At the district level, we use the population projections by the US Census Bureau till 2019 and extrapolate for 2021 and 2022.

14 doc20221116125801.pdf (pib.gov.in)

15 https://www.phonepe.com/pulse/explore/user/2022/3/

Table 1: Data Sources other than PhonePe Pulse

Indicator	State level	District level
Population	Annual projections by MoHFW (2019) based on 2011 census	Annual US Census projections based on 2011 census. Extrapolated by authors of this paper for 2021 and 2022.
Income	Net State Domestic Product (NSDP) (2018, 2022) (at 2011-12 constant prices) (RBI)	
GDP Composition	Sectoral shares of gross value added (2018, 2022) (RBI Handbook of Statistics)	
Internet Penetration	Individual Internet Penetration (2020) (IMRB Kantar)	Household internet penetration (2015-16) (2019-21) (NFHS)
Education and Literacy	Literacy Rate (Age 15-49) (2015-16) (2019-21) (NFHS)[16]	Literacy Rate (Age 15-49) (2015-16) (NFHS) Literacy Rate and Secondary Education Rate (2020-21) (NSS MIS)
Digital Skills	Percent of population able browse the internet, to send emails with attachments (2020) (IMRB Kantar)	Percent of population able to send emails with attachments (2020-21) (NSS MIS)
Consumption	Mean household consumption expenditure per capita (2019) (AIDIS)	Mean household consumption expenditure per capita (2019, AIDIS) (2014, NSS HCS)
Wealth		Wealth Index (2015-16) (2019-21) (NFHS)
Poverty	Multidimensional Poverty Headcount Ratio (NITI Aayog based on 2015-16 NFHS)	Multidimensional Poverty Headcount Ratio (NITI Aayog based on 2015-16 NFHS)
Financial Inclusion	Percent of households with bank account (2015-16) (2019-21) (NFHS)	Percent of households with bank account (2015-16) (2019-21) (NFHS)
Financial Infrastructure	Number of bank branches (Garg & Gupta, 2020) (SHRUG database)	Number of bank branches (Garg & Gupta, 2020) (SHRUG database)

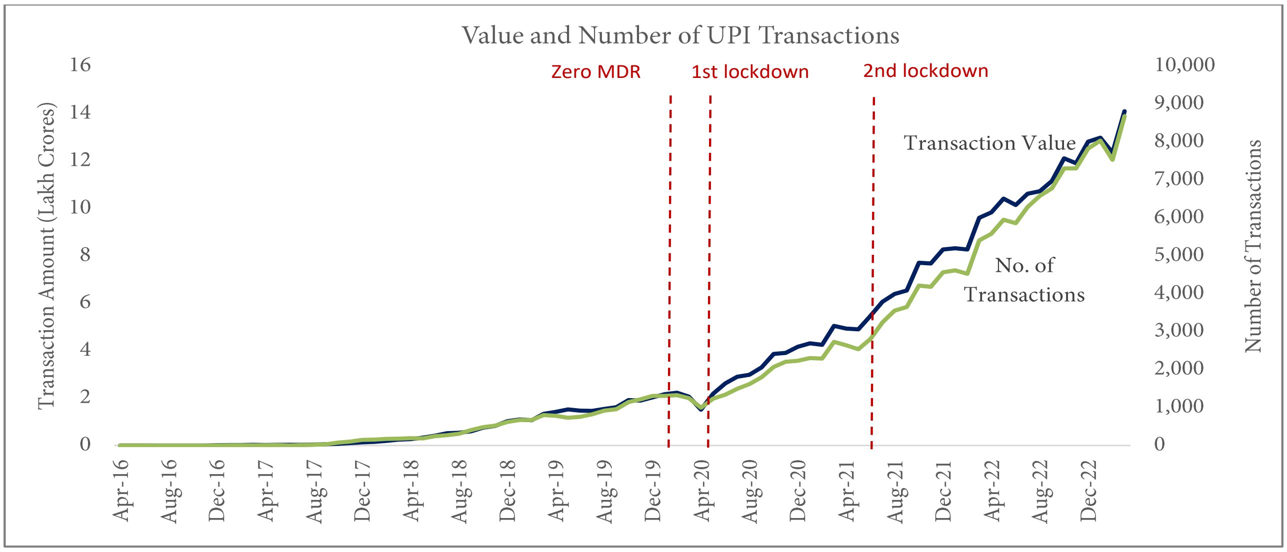
Note: NSS MIS: National Sample Survey – Multiple Indicator Survey; NSS HCES: Household Consumer Expenditure; NFHS: National Family Health Survey; AIDIS: All India Debt & Investment Survey; MoHFW: Ministry of Health & Family.

3. Stylised Facts on Diffusion of Digital Payments

a. While UPI has been gaining traction since late 2018, the acceleration following the first COVID-19 lockdown in early 2020 is noticeable. Both transaction values and transaction volumes have increased steadily since April 2020 (Figure 3). Structural break tests identify significant shifts after the first and second lockdown (Appendix 3).

16 Overall literacy rates for states are calculated as the weighted average of male and female literacy rates, using male and female population shares as weights respectively. Male and female population are taken from 2019 MoHFW Census population projections. For the district level, overall literacy rates are calculated as weighted average using the sex ratio of the entire population as provided by the NHFS, downloaded from Hindustan Times' Github extract (https://github.com/HindustanTimesLabs/nfhs-data). Both these weighted averages incur a margin of error due to weighting based on male-female ratios of the entire population, while the literacy rates are based on population aged 15-49.

Figure 3: Growth in UPI Transactions



Source: NPCI

b. **The growth for PhonePe mirrors that of UPI.** Growth in users is slower than growth in value and volume of transactions, implying an increase in intensity of use by the existing set of users (Figure 4). While the number of users tripled between 2018 and 2022, the number and value of transactions increased by more than 8 times.

Figure 4: Transaction Volume and Value for PhonePe have been growing at a steeper rate than registered users

Figure 4a: Value of PhonePe Transactions

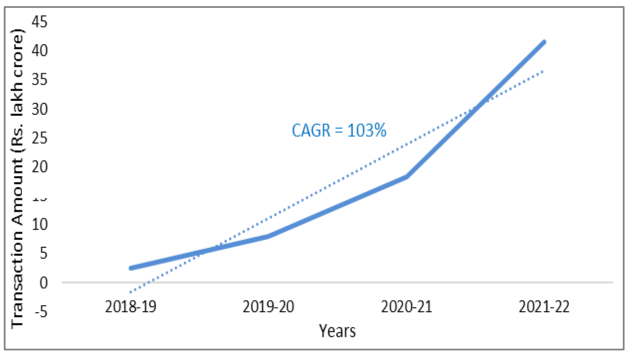


Figure 4b: Number of PhonePe Transactions

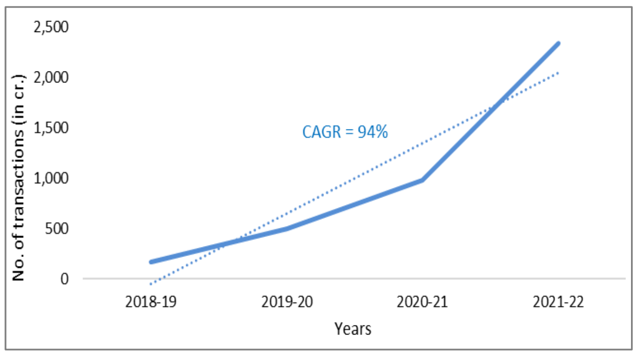
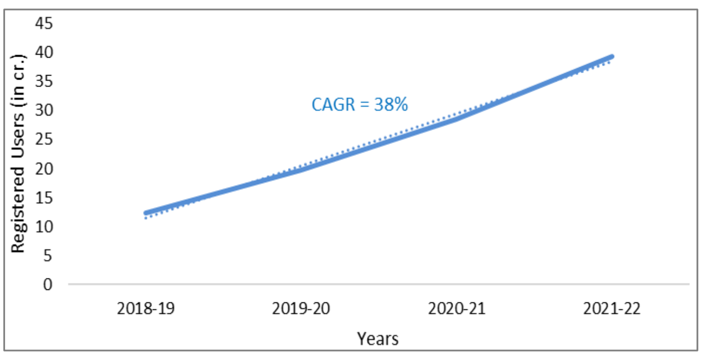


Figure 4c: Number of Registered PhonePe Users



Note: PhonePe reports the number of 'Registered Users', which is the number of unique users (identified by unique mobile phone number) who have downloaded the PhonePe app and accepted the Terms and Conditions displayed during the onboarding process. Only a subset of these would be active users.

c. **Leadership positions acquired by states from the time of launch, have remained unchanged in the adoption and use of UPI.** Among the states, Delhi and Telangana have maintained their top positions in user penetration, transactions per capita, transactions value per person, from the beginning of the assessment period (Figure 5b, 5d and 5f). Appendix 4 provides a comparison of diffusion at the state-level between 2018 and 2022 using choropleth maps. Current usage is also seen to be concentrated in the top few states. The top ten states accounted for 80% of total number of transactions, and the top five states accounted for 62%, while constituting only 64% and 29% of the population respectively. The distribution for value of transactions and number of users is slightly less concentrated – in Q4 2022, the top ten states accounted for 78% of transaction value and the top five states accounted for 60%, while constituting only 67% and 40% of the total population respectively. For registered users, the top ten states accounted for 72% and the top five states accounted for 44%, while constituting 68% and 41% of the total population respectively. The Northeast region as a whole has the poorest outcomes for diffusion, with Arunachal Pradesh showing some signs of catch up.

Figure 5: States with high initial value tend to remain on top

Figure 5a: Number of Registered Users

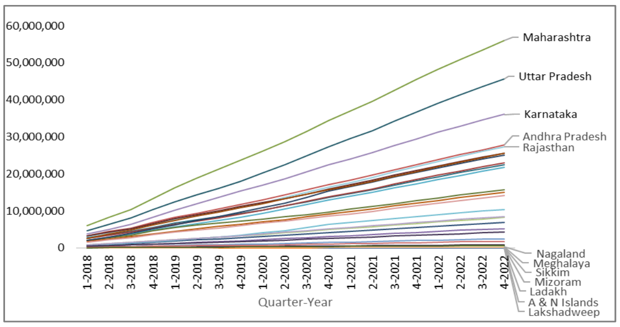


Figure 5b: Registered User Penetration

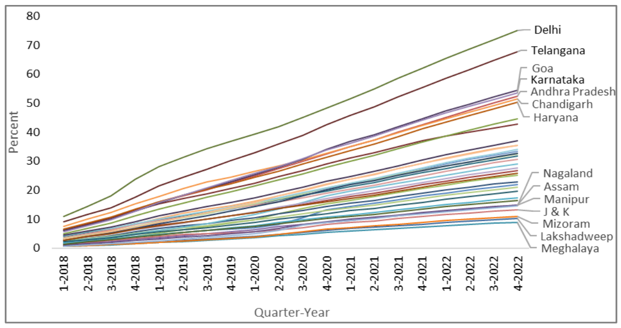


Figure 5c: Number of Transactions

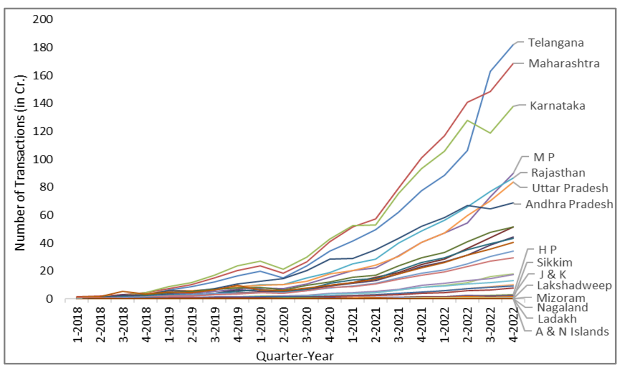


Figure 5d: Transactions per capita

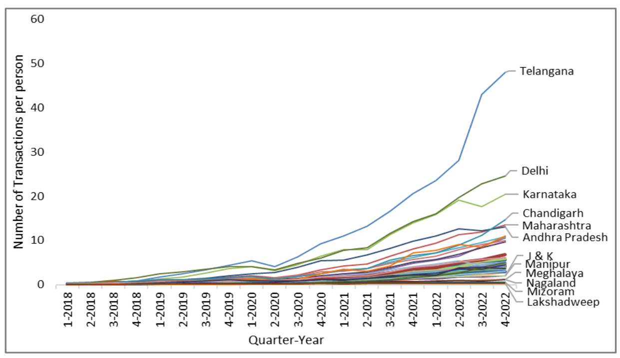


Figure 5e: Transaction Amount

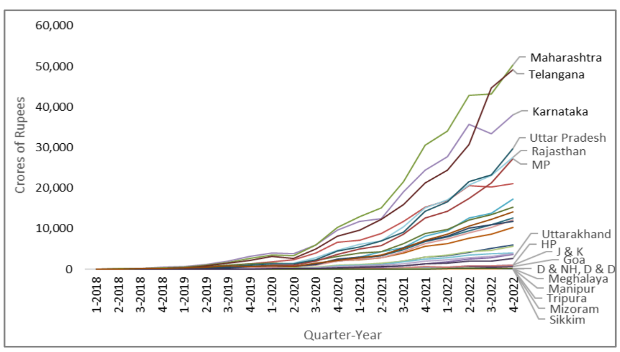
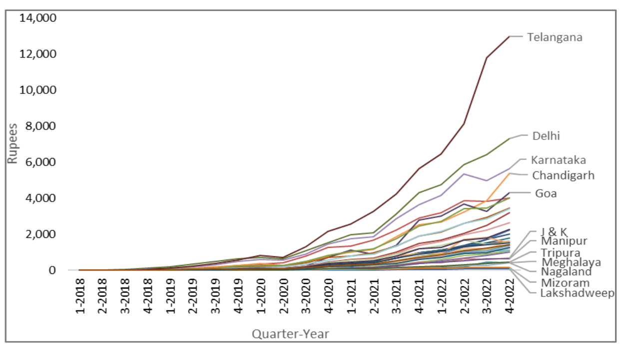


Figure 5f: Transaction Amount per person

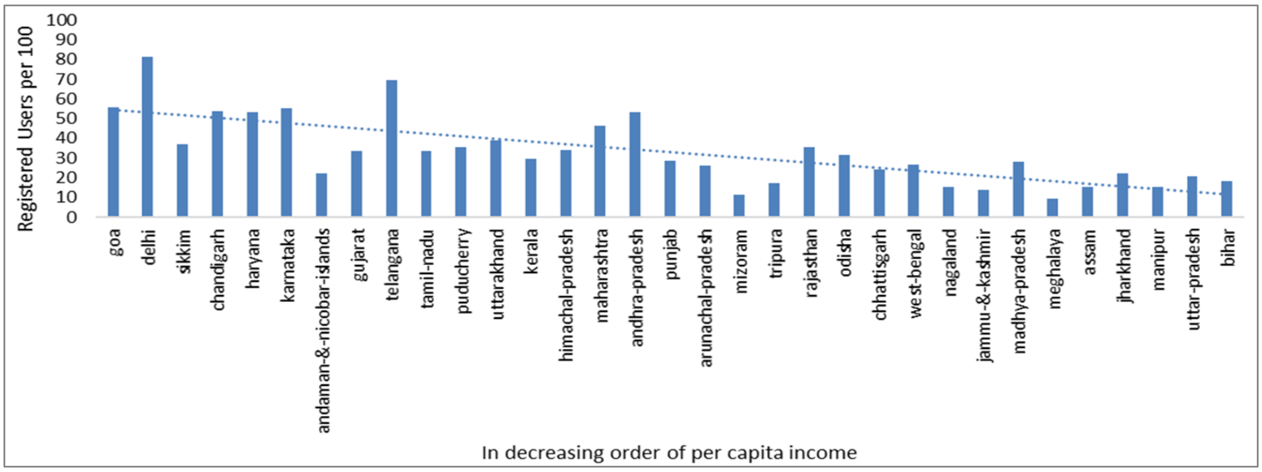


Source: PhonePe Pulse and population projections from Ministry of Family Health and Welfare.

d. **While economic prosperity matters, it does not fully explain diffusion.** Not all states with high average income per capita, and not all districts with high average household wealth index, have high PhonePe user penetration (Figure 6). While there is a general tendency for states with lower income per capita and districts on the lower end of the wealth index to have lower user penetration, beyond a threshold-level of income, penetration rates differ despite similar levels of average income/ wealth. In Figure 6b, the lowest 10 districts with respect to wealth index have a more uniform distribution of user penetration as compared to the top districts.

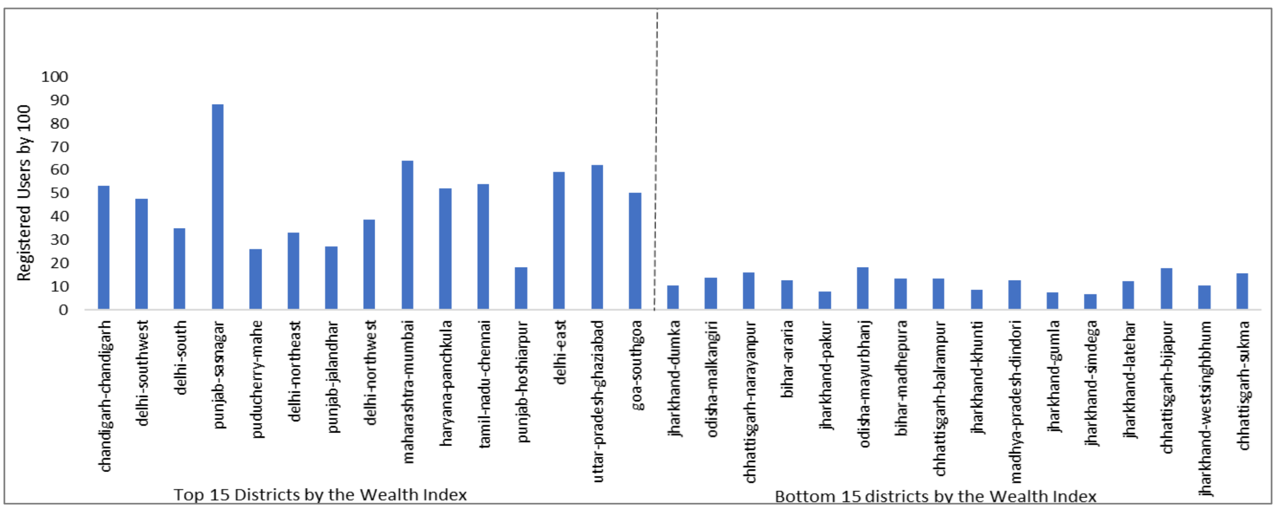
Figure 6: User penetration and economic prosperity

Figure 6a: User penetration and income per capita by state



Note: Ordered from left to right in decreasing order of average income per capita

Figure 6b: User penetration of top and bottom districts by wealth index



Note: Ordered from left to right in decreasing order of wealth index

Source: PhonePe Pulse (2022), NFHS (2019-2021) and NSS AIDIS (2019)

e. **Aspirational districts, as identified by the government's program of 2018, lag behind other districts in diffusion**[17]. Aspirational districts started off slow and continue to lag behind non-aspirational districts both in percentage of registered users as well as average number of transactions per capita. Non-aspirational districts had recorded over 1.6 times the number of users and over double the number of transactions as aspirational districts in 2018 (Figure 7). By 2022, the gap declined slightly for user penetration, and increased slightly for transactions per capita. In terms of transaction value per person, aspirational districts had an average of Rs. 251 in Q4 of 2018 while non-aspirational districts had an average of Rs 490. While this is consistent with lower intensity of use indicated by number of transactions, it could be a reflection of consumption expenditure, lower economic activity and differences in price levels. This difference of close to a hundred percent continues to exist in Q4 of 2022, with an average transaction value per person of Rs. 5,893 in aspirational districts, compared to Rs. 11,161 in non-aspirational districts (Appendix 5). Mean ticket size (value per transaction) declined in aspirational districts but increased in non-aspirational districts.

There is, however, significant variation even within aspirational districts. Existing research suggests that aspirational districts in South India usually fare better. From our data we find that within the aspirational districts, early adopters in Q4 of 2018 experienced a stronger growth in volume and value of transactions per person. These aspects are further explored in the convergence analysis provided in the next section of the paper.

Figure 7: Aspirational districts continue to lag behind in UPI adoption

Figure 7a: Registered PhonePe User Penetration Rates (Average)

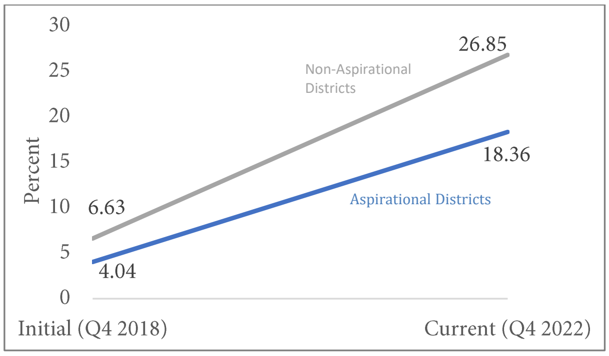
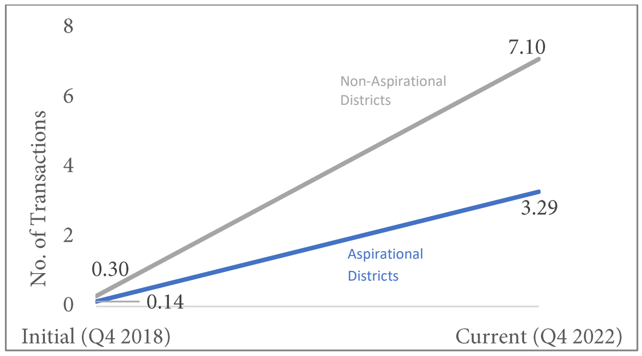


Figure 7b: Number of Transactions Per Capita (Average)



Source: PhonePe Pulse

4. Are States and Districts Converging in Adoption of UPI?

In this section, we estimate simple measures of convergence, σ (sigma) convergence and γ (gamma) convergence, to better understand the degree of variation in the diffusion of UPI. We do this at both the state and the district levels, for quarters between 2018 and 2022[18]. Details of these measures and their interpretation are provided in Table 2 below. We assess convergence for three indicators – user penetration (number of registered users normalised by population), number of transactions per capita and value of transactions per capita. This analysis assumes that PhonePe's trends represent those of all UPI payments within each state and district.

Table 2: Understanding σ (sigma) and γ (gamma) convergence

	σ (sigma)	**γ (gamma)**
Type of convergence measured	Estimates the year-on-year change in variation within a group	Estimates the variation in intertemporal ranking within a group
Value at the initial time period	1	1 (The value can never exceed 1)
Interpretation	An increasing value of σ indicates increasing dispersion within the group, and vice versa	A decreasing value of γ indicates larger shuffling within the ranks of the group

17 The Aspirational District Program, launched in 2018, aims to spur rapid transformation and development in the least developed districts across the country. The aspirational districts are selected by the Ministry of Home Affairs, other central ministries and NITI Aayog based on indicators for poverty, health, nutrition, education, and infrastructure. While the programme identifies 112 districts, our analysis includes 108 of them for which population projections were available.

18 Since σ convergence is a sufficient condition for β convergence, the results showing σ convergence also imply β convergence. β convergence is based on an assumption of a constant rate of convergence between the initial and final period. σ convergence can provide a better understanding of the path taken towards convergence within this period, since it considers the change in variation within the group at each time point between the initial and final period. Preliminary graphs of outcome variables suggest that the path taken was not a case of constant convergence. Discussion of both measures may be found in Appendix 3.

User penetration for UPI is converging at the state-level, but usage shows diverging trends. As reflected in Figure 8a, the falling value of the σ (sigma) measure suggests reduced dispersion in user penetration at the state-level. However, dispersion in number and value of transactions per capita has increased over the years (Figure 8b, 8c). The first COVID-19 lockdown in 2020 marks a significant fall in dispersion for registered user penetration, suggestive of the time when many people were forced to shift to digital payments. However, there was no significant change after this initial shock, and level of dispersion remain the same at the state-level. With respect to usage, there was some convergence initially, followed by divergence. There is no significant γ (gamma) convergence, suggesting that states don't significantly change in ranking for any of these parameters, over these years. This is also aligned with the discussion in the previous section (Figure 5).

Figure 8: Convergence analysis at the state-level

Figure 8a: User Penetration

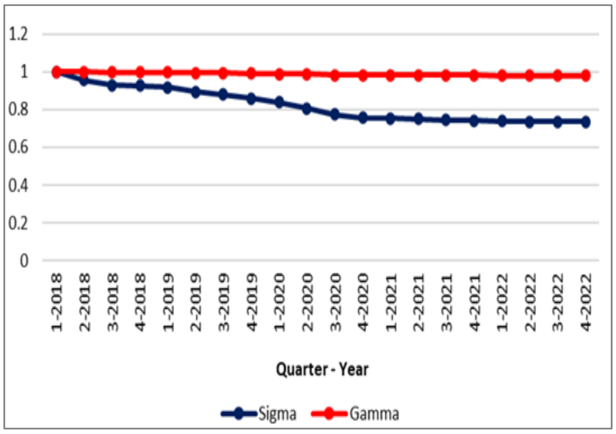


Figure 8b: Number of transactions per capita

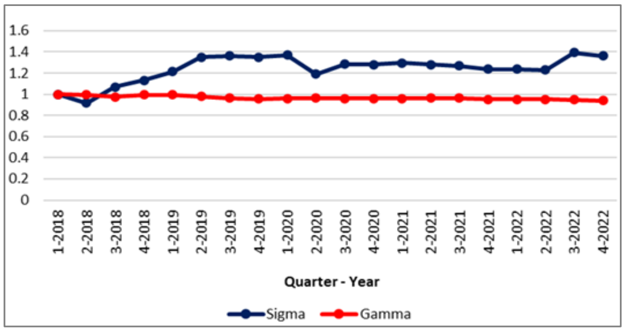
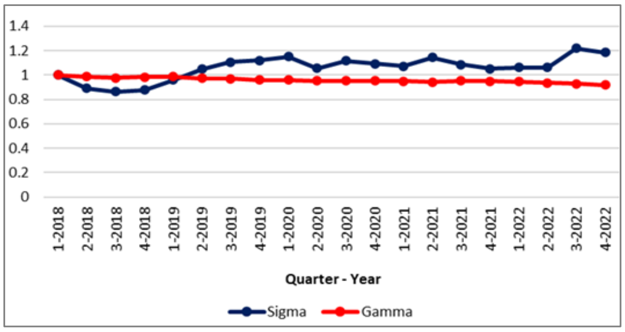


Figure 8c: Value of transactions per capita



Unlike states, districts recover from initial divergence and show signs of convergence. As was the case with states, there is convergence amongst districts in terms of user penetration, as indicated by the drop in the σ measure (Figure 9a). In terms of intensity of use, there is rising divergence in the initial quarters, which declines to the initial levels by the end of the period.(Figure 9b). Value of transaction per capita also shares a similar trend but eventually dispersion falls below the initial level (Figure 9c). The lack of σ convergence does not rule out the presence of β convergence, which measures whether districts with low initial levels grew at a faster rate than districts with high initial levels (See Appendix 6). Testing for this reveals that districts that had lower per capita value of transactions did show greater growth rates than those that had higher initial levels, signifying that there was β convergence. This also holds for number of transactions per capita. In terms of ranking, there is no significant change in the γ (gamma) measure, implying that districts have by and large maintained their rankings over the period of analysis.

Figure 9: Convergence analysis at the district level

Figure 9a: User Penetration

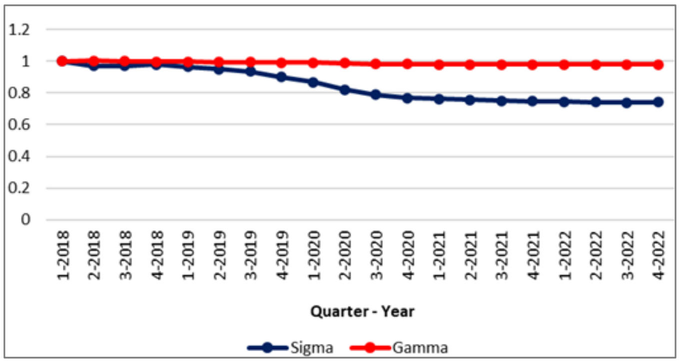


Figure 9b: Number of transactions per capita

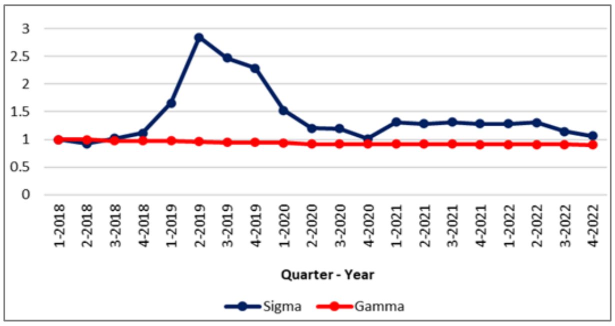
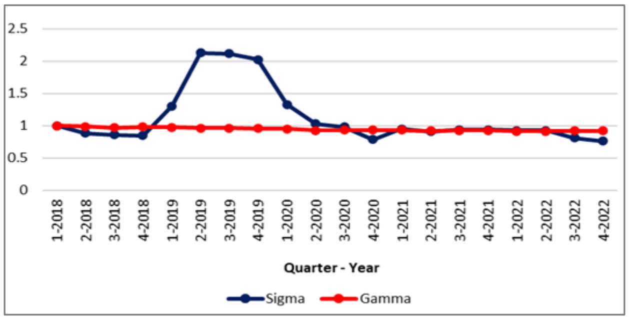


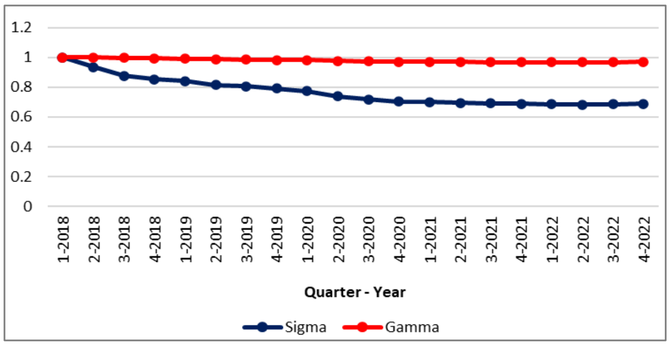
Figure 9c: Value of transactions per capita



Aspirational districts, when analysed as a separate group, follow the similar trends as the group of all districts[19]. While aspirational districts lag in terms of UPI diffusion, patterns for measures of dispersion are similar to that for other districts (Figure 10). User penetration shows a fall in dispersion. Number of transactions per capita and transaction amount per capita diverge, and then drop to the initial levels. There is no evidence of significant gamma convergence i.e., change in rankings across time. As expected, analysis of the group of non-aspirational districts also yields similar results. However, non-aspirational districts diverge by a larger amount than aspirational districts, and then converge to initial levels much faster (See Appendix 7 for graphs on convergence analysis for non-aspirational districts).

Figure 10: Convergence analysis for aspirational districts

Figure 10a: User Penetration



19 Washim district, Maharashtra appears to be an outlier and significantly affects the results so we restrict our study to 112 aspirational districts, excluding Washim district. Further understanding of what is driving high values in Washim would be interesting.

Figure 10b: Number of transactions per capita

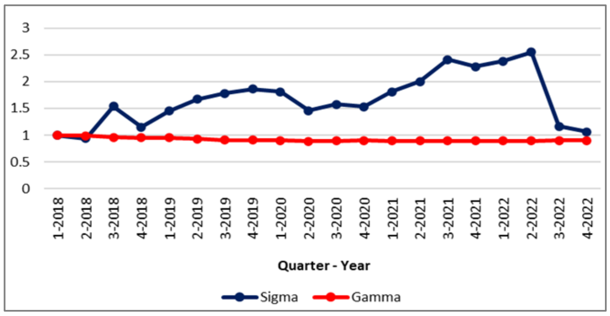
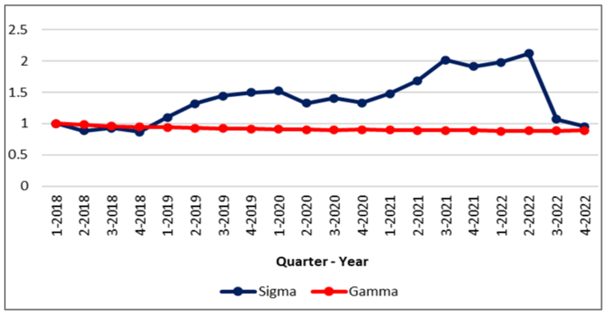


Figure 10c: Value of transactions per capita



5. Socio-economic factors driving UPI diffusion

It is no surprise that economically advanced regions are the ones to first adopt digital payments. Areas that are more market driven and rely on monetary transactions are also more likely to adopt digital payments than areas where home production is the norm and market transactions are limited (e.g., urban vs. rural areas). Other socio-economic factors such as literacy levels, internet access, and informality rates that are bundled with levels of prosperity, also impact how quickly new technologies diffuse into the ecosystem. On digital payments specifically, the quality of internet, transaction failure, security concerns and overall trust in the digital system also impact adoption. These causalities have been explored in the existing literature by Baghla, 2018; Pandey & Rathore, 2018; Amarnani & Amarnani, 2019; KPMG, 2020; MeitY, 2021; Muthukumaran & Haridasan, 2022. Studies related to small businesses find that lack of awareness, skill gaps, lack of access to the internet and devices, high costs, network issues, tax liability concerns, and customer demand affect adoption of digital payments.

In this paper, we examine the role of a few socio-economic factors in determining the level of UPI adoption in India using a cross-sectional regression analysis. The analysis has been carried out using PhonePe data at the district level and complemented by additional insights from a state level analysis.

The cross-sectional regressions are of the following form:

$$y_i=\alpha+\beta x_i+\varepsilon_i$$

where y_i is one of the three outcome variables (user penetration, transactions per capita, ticket size) for each district i, and x_i is a vector of explanatory and control variables. We divide our analysis into the following sub-sections:

(i) Cross-sectional regressions for the latest period (Q4 2022) to identify socio-economics factors that explain current levels of diffusion using user penetration.

(ii) Cross-sectional regressions with the same specifications as i) to explain diffusion using two other indicators – transactions per person and ticket size

(iii) A repeat of the analysis in i) and ii) for the initial period (Q4 2018), to identify factors that mattered for initial adoption and compare results with the latest period

While our regression estimates are not necessarily causal, they provide insights on the magnitude of these factors. Standard errors are adjusted for heteroskedasticity using the Huber-White method[20].

20 Stata command reg with the robust option was used.

District level internet penetration, secondary education rates, digital literacy rates, and measures of household economic status (consumption expenditure, wealth index) are positively correlated with PhonePe user penetration. Districts with Poverty rates are negatively correlated, as expected. Amongst the measures used as proxies for financial inclusion, bank branches per person is positively correlated with user penetration while percent of households with bank accounts has a weak negative correlation with user penetration[21](See Figure 11). These findings remain generally consistent across various specifications and hold even after controlling for median consumption expenditure levels (See Appendix 8).

Interpreting the magnitude of the coefficients provides an idea of the scale of association. Every additional 1000 rupees in median monthly per capita consumption expenditure is on average associated with an additional 3.8 PhonePe users per hundred population[22]. Districts with an additional 10 percentage points of households with internet have an additional 2 percentage point PhonePe user penetration. Every additional bank per 10,000 population is associated with an additional 8.5 percentage point PhonePe user penetration.

Figure 11: Regression Results for User Penetration (2022 Q4)

Figure 11a: Specification 1

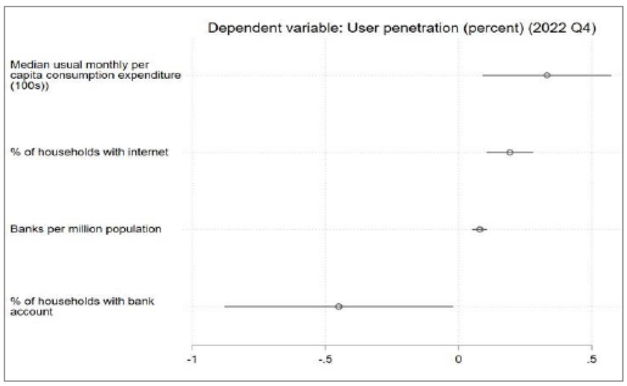
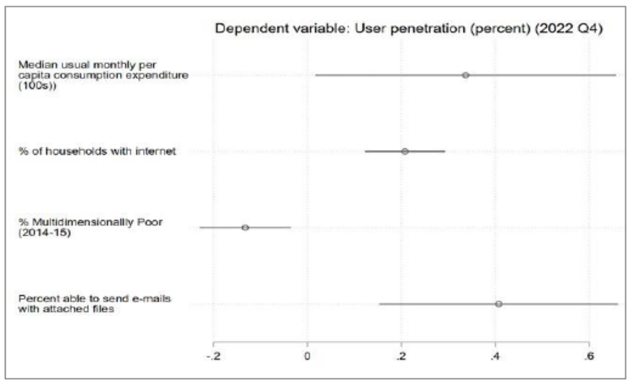


Figure 11b: Specification 2



Specification 1:

$$\textit{user penetration}_i = \alpha + \beta_1 \textit{median MPCE}_i + \beta_2 \textit{ internet penetration}_i + \beta_3 \textit{ banks per million}_i + \beta_4 \textit{ bank account penetration}_i + \varepsilon_i$$

Specification 2:

$$\textit{user penetration}_i = \alpha + \beta_1 \textit{median MPCE}_i + \beta_2 \textit{ internet penetration}_i + \beta_3 \textit{ multidimensionl poverty rate}_i + \beta_4 \textit{ digital literacy rate}_i + \varepsilon_i$$

where i represents each district

Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate. Results from other specifications are in Appendix 8.

21 The recent boost in bank account creation may dilute the ability of bank holding status to serve as a proxy for bank account usage. A measure of bank account holding time may perhaps provide useful insights.

22 The interpretations have been scaled for comprehensibility - the coefficient of 0.38 in Figure 11 for median usual monthly per capita consumption expenditure (MPCE) can be interpreted as an additional 0.38 Phonepe users associated with every additional hundred rupees of median MPCE, or an additional 3.8 Phonepe users associated with every additional thousand rupees of median MPCE. The mean MPCE across districts is 2105 rupees, with a minimum of 816 and maximum of 6000.

The regressions also provide insights on the relative importance of different factors. For example, the coefficients for variables that are in percentages can be compared to provide further insights on their relative magnitudes. Digital literacy rate has greater explanatory power and a larger magnitude of association than poverty rate, when no other controls are included (See Box 1). This is consistent with the idea that exiting poverty is not sufficient for individuals to adopt UPI, but that having a relatively high level of digital literacy is likely to enable adoption. It is notable, however, that even the coefficient for high digital literacy is less than 1, suggesting that every additional digitally literate individual is not a PhonePe adopter.

Examining scatterplots for determinants that are used in the regressions, we find additional insights into the how socio-economic indicators might be affecting adoption. The patterns suggest that many determinants may be necessary but not sufficient for adoption of digital payments. For example, districts with low literacy and low internet penetration have very low UPI penetration, but there is significant variation in user penetration amongst districts with high literacy and high internet penetration. (See Figure 12). This also holds true for percentage of households with bank accounts – although it is not significant in the regression analysis, the scatterplots indicate that a certain level of bank account penetration is necessary but not sufficient for adoption Other factors such as preferences, trust, and security concerns which are not accounted for in this analysis are also likely to be important. In cases where socio-economic barriers are not pertinent, the lack of adoption could reflect that the net costs of digital payments outweigh the net benefits for certain user groups. For some individuals, however, perceptions and awareness of the costs vs. benefits are misaligned, and strengthening this could boost adoption and its subsequent benefits.

Figure 12: Socio-economic conditions that may be necessary but are not sufficient for diffusion (District level scatterplots of PhonePe User Penetration and socio-economic factors - 2022 Q4)

Figure 12a: Literacy

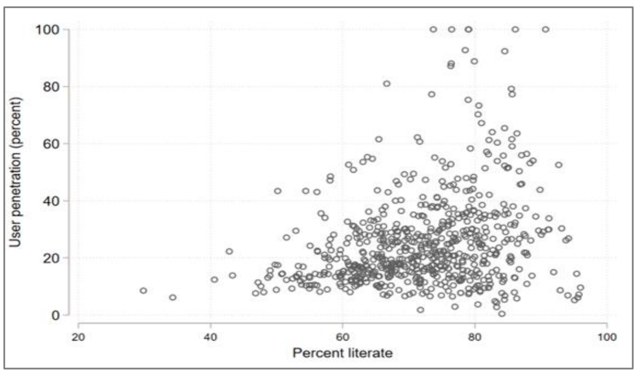


Figure 12b: Internet penetration

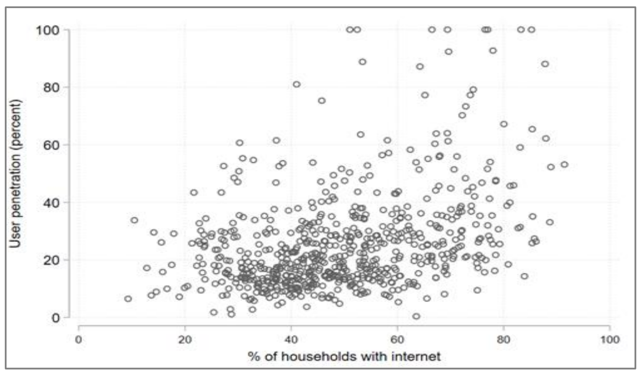


Figure 12c: Median Consumption

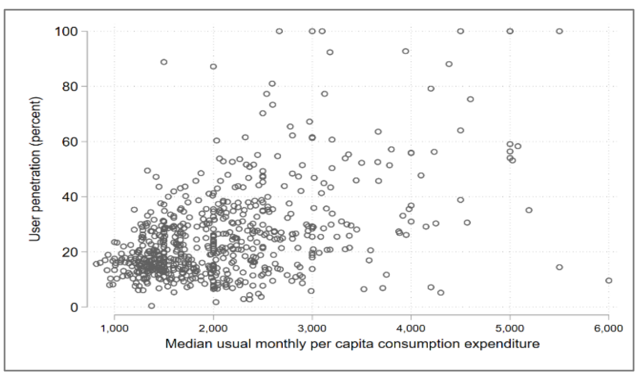


Figure 12d: Mean Consumption

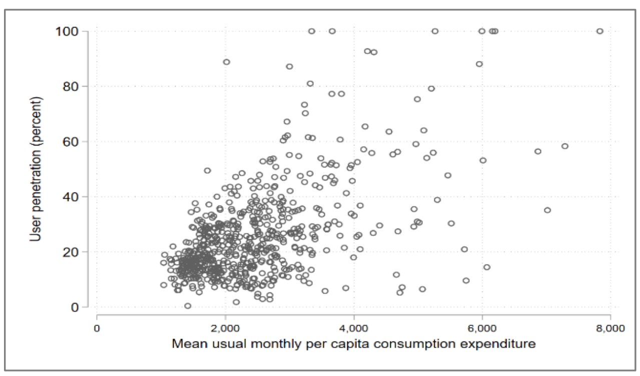


Figure 12e: Wealth Index

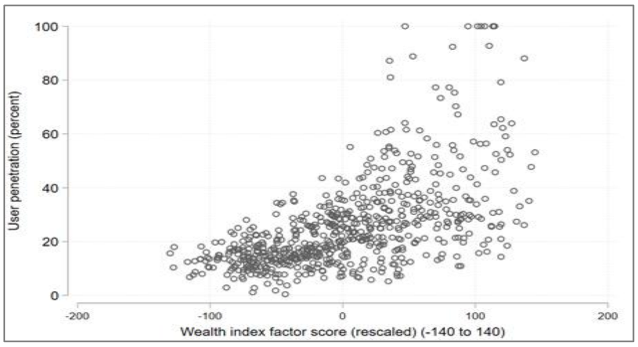


Figure 12f: Poverty

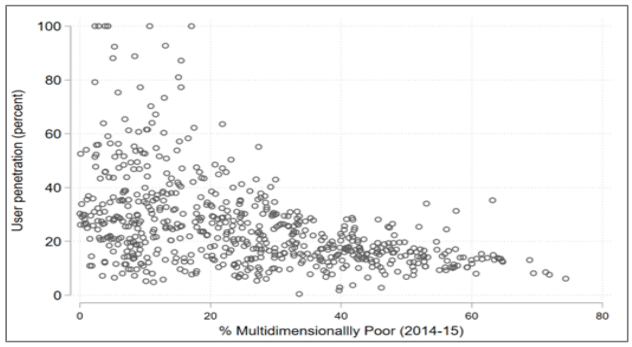


Figure 12e: Wealth Index

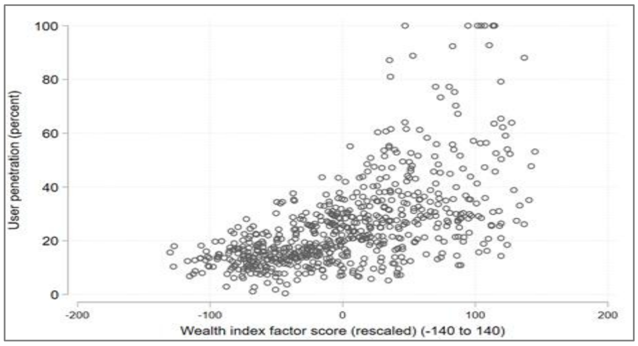


Figure 12f: Poverty

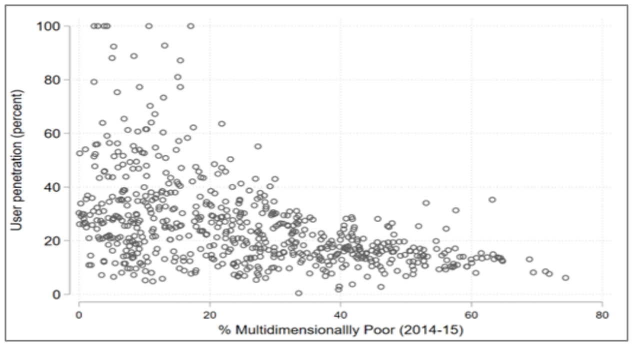


Figure 12i: Bank Account Penetration

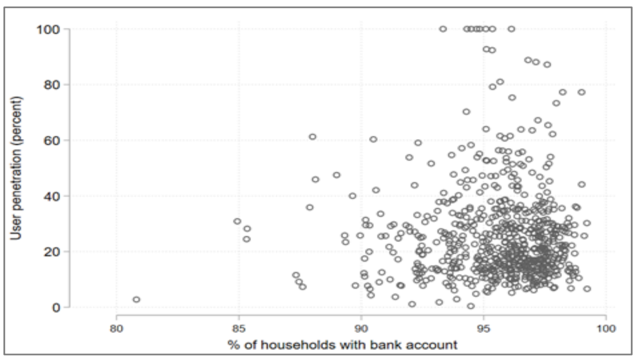
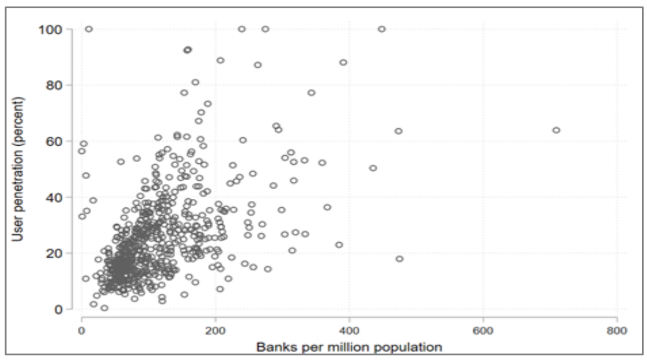


Figure 12j: Bank Density



Box 1: Relative Importance of Some Socio-Economic Indicators in Driving Diffusion

Digital literacy has greater explanatory power than poverty when no other controls are included (R^2 = 0.224 vs. 0.217). Since both these variables are in percentages, their coefficients can also be compared to provide insights on their relative importance. Digital literacy has a larger magnitude of association than poverty - for every additional percentage point of the population that can send an email with attachment, we observe a ~ 9 percentage point greater user penetration. Whereas for every additional percentage point of population that is poor, we see a ~5ppt lower user penetration. For both variables, their association (and impact, to the extent that they are causal) are less than proportionate – i.e., for every additional 100 people that are not poor, only 50 are expected to be PhonePe users, and for every additional 100 that have relatively high digital literacy, about 90 are expected to be PhonePe users. Controlling for differences in median household consumption expenditure per capita reduces these magnitudes (Figure 13).

Similarly, digital literacy has greater explanatory power and larger magnitude of association than internet penetration – the correlation of user penetration with percent of population able to send emails with attachment is about twice the magnitude of user penetration correlation with percent of households having internet. So *a single individual* having a medium level of digital literacy is associated with twice as much user penetration than *an entire household* having access to the internet.

It is important to note that these estimates are based on a linear model and at the current adoption levels – while in reality, the correlations/effects would be expected to be non-linear and to change with adoption levels due to network effects. While our regression estimates are not necessarily causal, it provides insights on the relative magnitude of these factors.

Figure 13: Comparison of Regression Results for Various Socio-Economic Indicators (2022 Q4)

Figure 13a: Digital literacy vs Poverty, without controls (separate regressions)

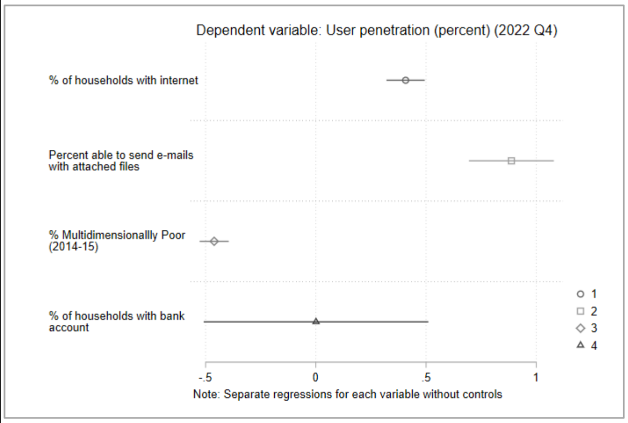


Figure 13b: Digital literacy vs Poverty, controlling for consumption expenditure (separate regressions)

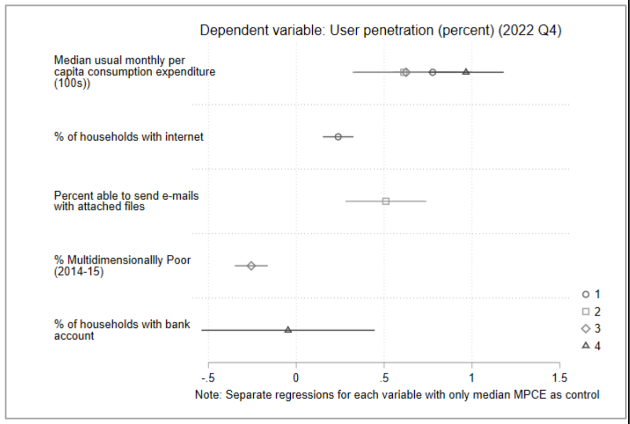


Figure 13a:

Regression 1: $user\ penetration_i = \alpha + \beta_1 internet\ penetration_i + \varepsilon_i$

Regression 2: $user\ penetration_i = \alpha + \beta_1 digital\ literacy_i + \varepsilon_i$

Regression 3: $user\ penetration_i = \alpha + \beta_1 multidimensional\ poverty\ rate_i + \varepsilon_i$

Regression 4: $user\ penetration_i = \alpha + \beta_1 bank\ account\ penetration_i + \varepsilon_i$

Figure 13b:

Regression 1: $user\ penetration_i = \alpha + \beta_1 median\ MPCE_i + \ \beta_2 internet\ penetration_i + \varepsilon_i$

Regression 2: $user\ penetration_i = \alpha + \beta_1 median\ MPCE_i + \beta_2 digital\ literacy_i + \varepsilon_i$

Regression 3: $user\ penetration_i = \alpha + \beta_1 median\ MPCE_i + \beta_2 multidimensionl\ poverty\ rate_i + \varepsilon_i$

Note: The markers show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate.

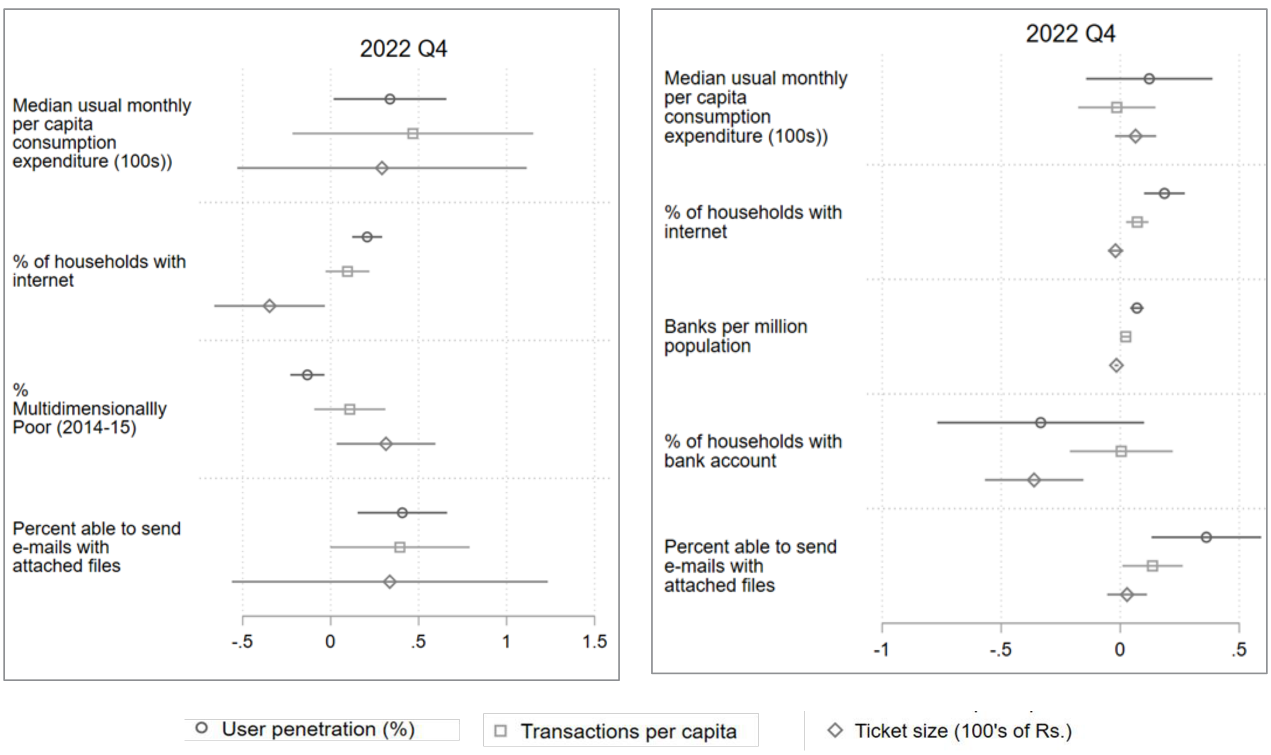
Other indicators of diffusion such as transactions per person and ticket size are also correlated with socio-economic factors, but individual preferences are likely to be important drivers. The results for transactions per capita, a more intensive measure of adoption, is qualitatively similar to results for user penetration. Transactions per person is positively correlated with internet penetration, secondary education rates, digital literacy rates, and household level measures of economic status (consumption expenditure, wealth index). The coefficients, however, tend to be more significant for user penetration than for transactions per population – i.e., these factors seem to be more significant in determining the rate of adoption than in determining the intensity of use (Figure 14). The magnitudes of the coefficients cannot be used for a direct comparison since the units of the two dependent variables are different. Poverty rate, which is significantly negatively correlated with user penetration is not significant for transactions per capita. While socio-economic factors do appear to matter for how frequently individuals use UPI, behavioural traits and preferences would also play an important role and can be captured through primary surveys.

The results for average ticket size (transaction value divided by number of transactions) are slightly different. Median consumption expenditure is not significantly correlated with ticket size, even though it is significant for adoption and intensity of use (user penetration and transactions per person). Average wealth index, percent of households with bank accounts, and banks per million are significantly negatively correlated with ticket size, and poverty levels are positively corelated – even when other variables are not included. Intuitively, this could imply that the more accessible UPI is to a wider portion of the population, the smaller the ticket size. A deeper look at the distributions of household wealth, income and poverty would be necessary to better understand how socio-economic factors affect ticket size.

Changes in ticket size are also driven by changes in what people use UPI for – if more people use it for smaller everyday transactions, then ticket size would be lower. Data shows that average ticket size began plateauing since early 2021 perhaps reflecting the greater ubiquity of UPI and its increasing use for smaller everyday transactions (Appendix 10). Further analysis on two aspects that are not captured in these regressions – consumer preferences for types of transactions done through UPI, and the impact of regulatory caps on the size of UPI transactions – would be insightful.

Figure 14: Comparison of Regression Results for Various Measures of Adoption (2022 Q4)

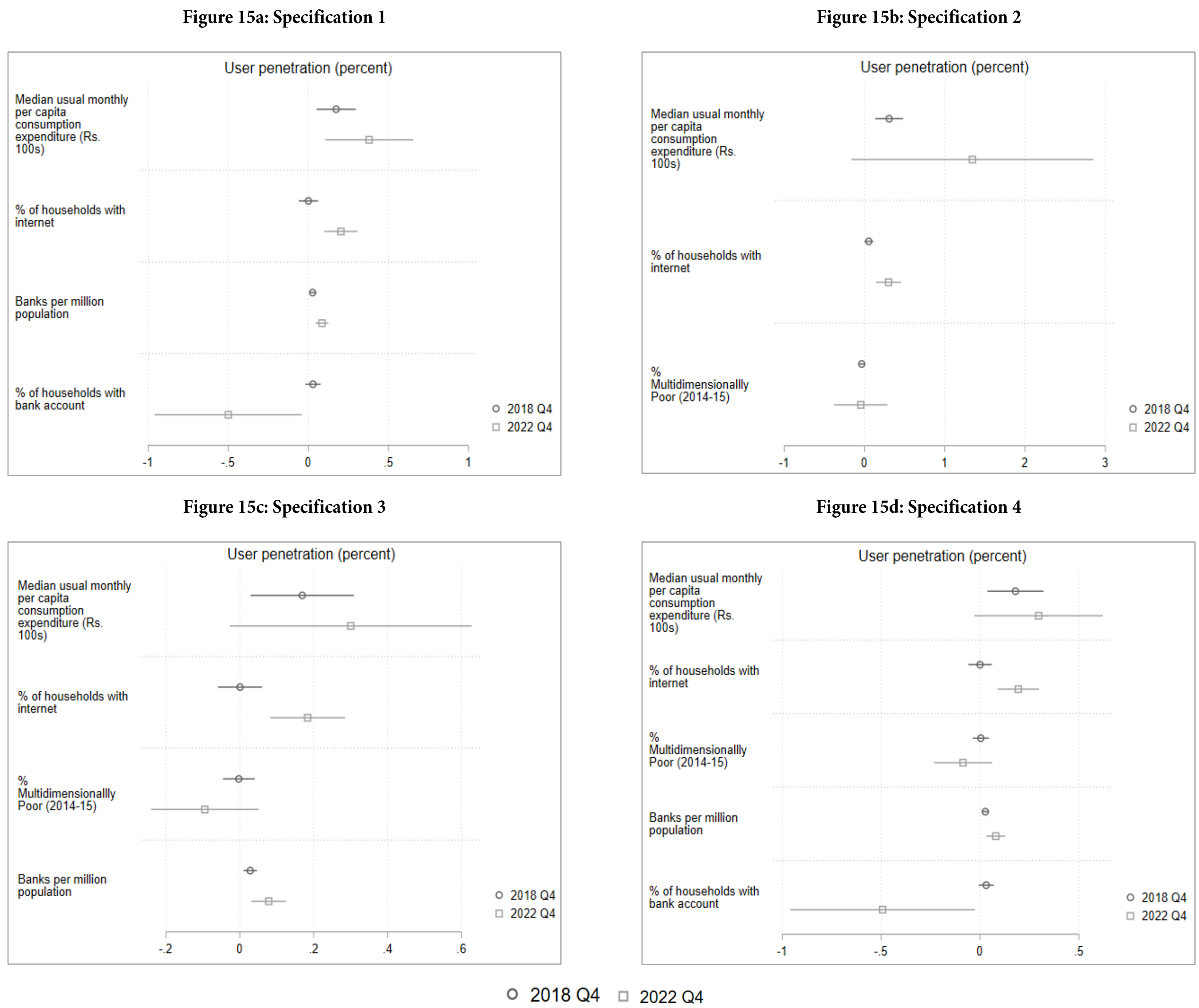
Figure 14a: Specification 1 **Figure 14b: Specification 2**



Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate. Results for alternate specifications are in Appendix 9.

Socio-economic factors appear to matter more over time for user penetration and transactions per person. Figure 15 shows that both the magnitudes and significance levels of the determinants are greater in Quarter 4 of 2022 compared to Quarter 4 of 2018. Individuals who are likely to be early adopters often possess behavioural traits associated with the propensity to try out and use new technologies (such as tolerance of ambiguity, intellectual ability, motivation, values, learning style)[23] which are not measured here – rather than have, or reside in regions with, a specific socio-economic profile. Institutional factors or other unobserved factors at the regional level may have also influenced early adoption. Adoption of new technologies by the rest of the population, however, depends on socio-economic characteristics and economic performance of the region. Further, as the technology becomes more mainstream and gains wider acceptance, these socio-economic factors are likely to determine which areas and individuals lag behind.

Figure 15: Comparison of Regression Results Over Time (2022 Q4 vs. 2018 Q4)



Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate. See Appendix 11 for a comparison over time of regressions results for number of transactions and ticket size. For the period 2018 Q4, median usual monthly per capita consumption expenditure is from NSS HCS (2014), percent of household with internet and percent of household with bank accounts are from NFHS-4 (2015-16), banks per million from Garg & Gupta (2020) is calculated as bank branches open as of 2015 normalized by estimated 2015 population. For the 2022 Q4 regression, usual monthly per capita consumption expenditure is from AIDIS (2019), percent of household with internet and percent of household with bank accounts are from NFHS-5 (2019-21), and banks per million is as of 2019 from Garg & Gupta (2020). Percent multidimensionally poor for both period regressions is from NITI Aayog's report on Multidimensional Poverty based on NFHS-4 (2015-16).

23 https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2690184/

The scatterplot below (Figure 16) helps understand these results in the context of the findings from the convergence analysis. In the initial period, there were a few districts with high user penetration rates while the majority were at low levels, below 20%. Socio-economic indicators mattered less in determining initial adoption. Over time, other districts began to adopt, and their relative performance was determined partly by socio-economic factors such as levels of income, poverty, education, digital literacy, and financial access. As adoption progressed, the distribution of user penetration spread out more evenly, reflected in a decrease in the sigma measure of convergence.

Figure 16: Comparison of Scatter plots over time (2022 Q4 vs. 2018 Q4)

Figure 16a: User penetration vs. Internet penetration (2018 Q4)

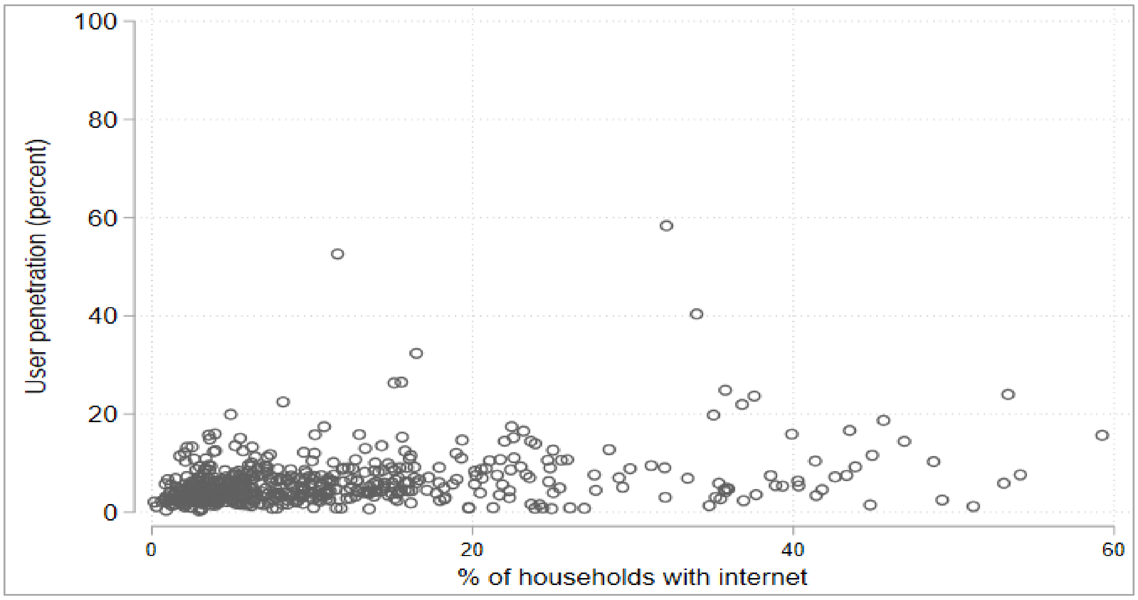
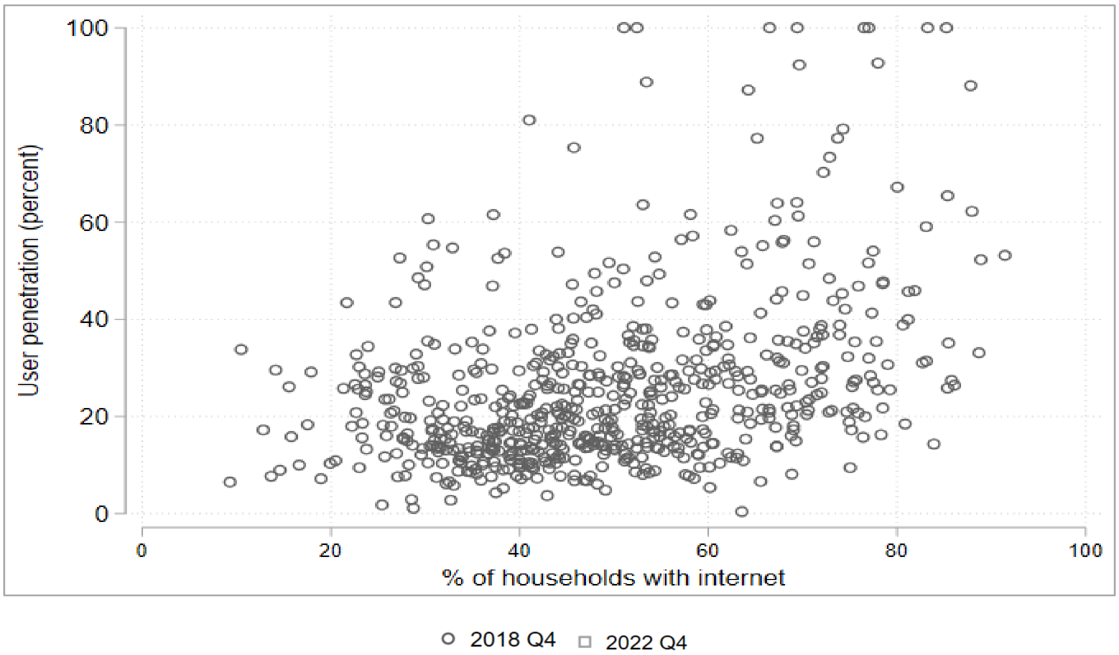


Figure 16b: User penetration vs. Internet penetration (2022 Q4)



Note: Scatterplots for many of the other variables show a similar pattern of change over time. The left panel presents a scatterplot of PhonePe user penetration rates for 2018 Q4 on the y axis against the percent of households with internet in 2015-16 from the NFHS-4. The right panel presents a scatterplot of PhonePe user penetration rates for 2022 Q4 on the y axis against the percent of households with internet in 2019-21 from the NFHS-5.

For ticket size, however, some factors seem to matter more initially, while others matter more later (Figure 29,). Average household consumption expenditure has a stronger positive correlation with ticket size in the initial period than the latest period. On the other hand, bank density, bank account penetration and higher education rates were more negatively and significantly correlated with ticket size in the latest period compared to initial. Over time, districts with greater financial access and secondary education had smaller ticket sizes. As discussed in the regression analysis, this could be the result of wider adoption over time, with more frequent use for everyday transactions and therefore lower average transaction value.

State level patterns are consistent with district level patterns. The results of the analysis at the state level are broadly consistent with those at the district level. User penetration and transactions per person is positively correlated with net domestic product per capita, household consumption expenditure per capita, internet penetration and digital literacy, but not literacy rate (Appendix 13). Digital literacy (% of population able to send an email with attachments) has a slightly larger coefficient than internet penetration (% of population using the internet) as one may expect.

Poverty rates are negatively correlated with user penetration and transactions per capita, but once controlling for overall economic performance (NSDP), the correlation becomes positive. The high correlation between NSDP and poverty rates might explain the change in signs when both are included. Again, looking at scatterplots supports the idea that poverty reduction appears to be necessary but not sufficient for adoption – i.e. states with high poverty have low user penetration and transactions per capita, but there is significant variation in user penetration for states with low poverty (Figure 30a, Appendix 12).

National accounting statistics was used for the state-level analysis, which is not available at the district level, to examine the relationship between economic structures and PhonePe adoption. We find that the share of value added in agriculture is negatively correlated with user penetration, but positively correlated with ticket size. This could simply reflect differences in economic activity which tend to be correlated with economic structure – share of value added in agriculture is no longer significant once controlling for state domestic product. Other sectors, manufacturing and services, were not significantly correlated with either indicator of diffusion. (Figure 30b, Appendix 12). As was the case for the district level analysis, the estimated correlations were stronger for user penetration than transactions per person.

Internet penetration rates and digital literacy seem to matter less in aspirational districts. While there doesn't appear to be significant differences between aspirational and non-aspirational districts in the relationship between adoption and socio-economic factors (consumption expenditure, literacy rate, secondary education rate, bank account penetration and bank branch density), internet penetration and digital literacy appear to matter less (see Appendix 14). Since aspirational districts are spread across the country, even those districts that are lagging behind, may have higher adoption due to regional spill overs. Poverty rates also seem to matter less – while aspirational districts with lower poverty rates do have higher user penetration, it is lower than in non-aspirational districts. This difference between aspirational and non-aspirational states is no longer significant once conditioning for median household consumption expenditure.

6. Conclusion

The analysis in this paper is informed by PhonePe data on individual users over the period Q4 2018 to Q4 2022. The data shows that while the number of users has significantly increased over time, many districts, especially the aspirational districts are lagging behind. There is clear indication of a positive shock triggered by the COVID-19 lockdown that led to large scale adoption of PhonePe (UPI) across the country, lowering the dispersion in user penetration both at the state and district levels. We must also acknowledge the important role of user-friendly interfaces or apps like Paytm, PhonePe and Google Pay, that drove rapid adoption and ensured the continued use of digital payments. Digital innovations like UPI123 and QR codes have also helped in wider diffusion, though these aspects are not captured in the data.

The diffusion has led to convergence in user penetration at both the district and state level. With regards to intensity of use, there is some convergence at the district level but divergence at the aggregated state-level. Moreover, states and districts that started off with high adoption continue to lead, with little reordering in the ranking of district or states. The regression analysis identifies socio-economic indicators such as income, access to internet, digital literacy and financial infrastructure that drive the adoption of digital payments. The analysis also suggests that these factors are necessary but not sufficient for adoption. Demographic data, user preferences, behavioural traits and regulatory interventions can complement this analysis to further explain the drivers of adoption. Disaggregating the analysis by urban and rural areas, when such data becomes available, would provide more robust and nuanced insights.

Key policy takeaways

Policy efforts to promote inclusive adoption of digital payments in a beneficial way cannot focus on one lever at a time – it would require a multi-pronged approach that improves internet penetration, digital literacy, affordability of devices, as well as addressing issues of trust, security, and reliability. Individually, these factors are necessary, but not sufficient.

Understanding behavioural factors and consumer preferences are key to understanding the potential benefits and costs of digital payments to heterogenous users. This would also bring to focus both digital and non-digital alternatives to UPI, and an acknowledgement of the benefits of a multi-modal payments system including sustaining cash as a payment mode – Concerns of privacy, security, and reliability, especially in situations of network/power outages and emergencies – perhaps warrants putting in place measures to actively preserve the option of cash-as-an-alternative. Effective policy efforts would need to comprise targeted, region-specific incentives and strategies.

Assessment of the role of key policy changes (such as Zero MDR) in driving adoption would provide valuable insights to the policy process. Better data collection and measurement of UPI usage would allow for a deeper understanding of its contributions to financial inclusion, barriers to adoption and use, and areas for improvement as the ecosystem continues to evolve. For instance, due to the lack of disaggregated data, this analysis does not cover divides by gender, urban/rural areas. In addition to quantitative analysis, qualitative evidence on attitudes, use, barriers, and risks is important for evidence-based policy-making.

Finally, it is important to reiterate that digital payments are not a goal in itself but a means to facilitate smoother functioning of markets and societies, contributing to greater wellbeing and standards of living. A better understanding of the extent to which digital payments contribute to these ultimate goals, and the distribution of its costs and benefits to various stakeholders, is essential.

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Appendices

Appendix 1: UPI market shares

Figure 17: Share of PhonePe in the UPI Market (March 2023)

Figure 17a - Number of Transactions (Millions)

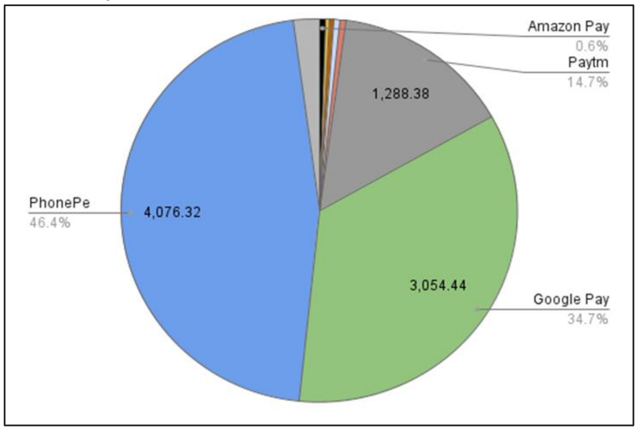
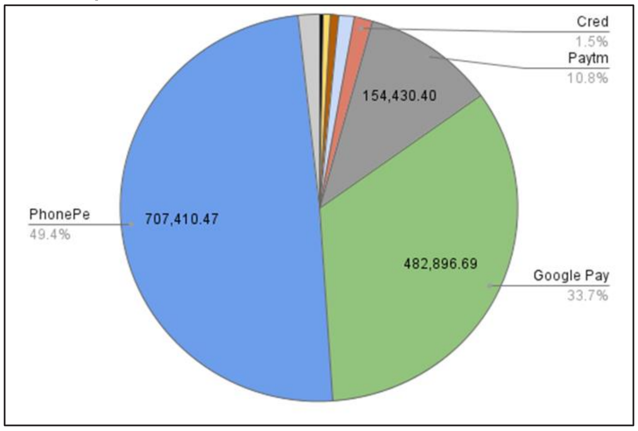


Figure 17b - Value of Transactions (Crores of Rs.)



Source: NPCI

Figure 18: Share of PhonePe in the UPI Market (2017-2022)

Figure 18a - Number of Transactions

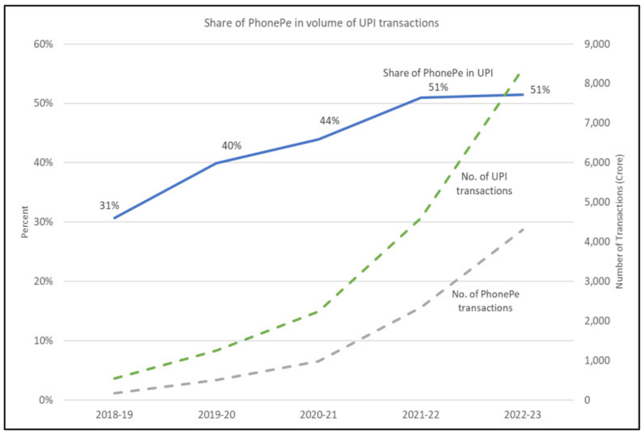
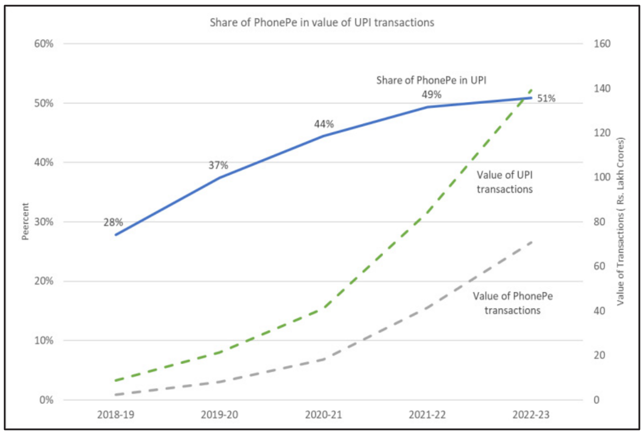


Figure 18b - Value of Transactions



Source: NPCI and PhonePe Pulse

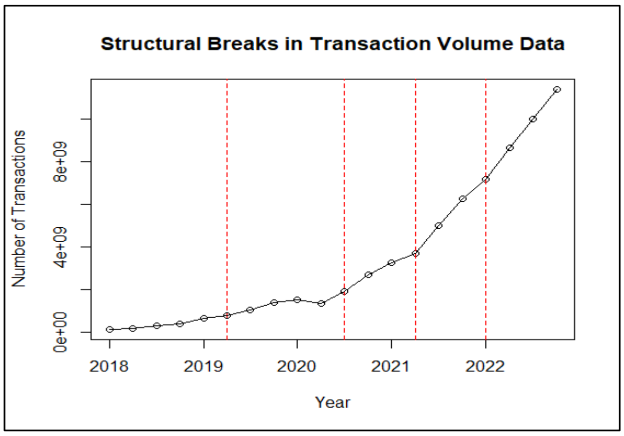
Appendix 2: Descriptive statistics

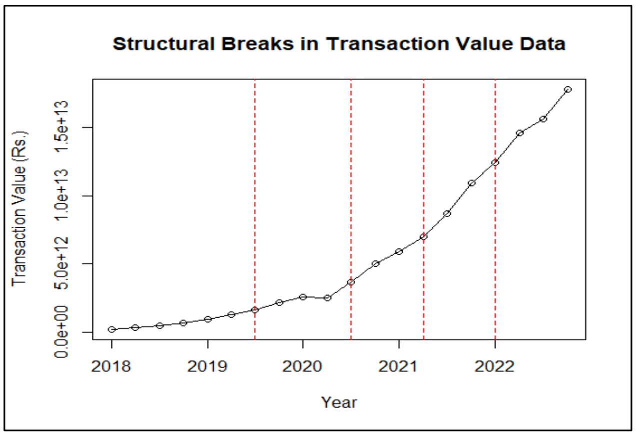
Table A1: District Level Descriptive Statistics

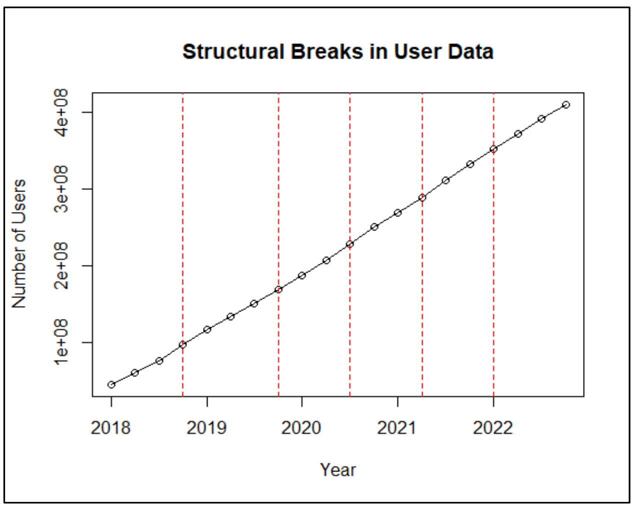
Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Outcome Variables					
Q4 2018					
PhonePe User Penetration (%)	668	6.21	6.97	0.0594	100
PhonePe Transactions per capita	668	0.2706	1.0155	0.0042	20.59
PhonePe Ticket Size	732	1890	596	478	5814
Q4 2022					
PhonePe User Penetration (%)	668	25.48	16.97	0.4126	100
PhonePe Transactions per capita	668	6.49	23.09	0.0791	413.89
PhonePe Ticket Size	732	1901	492	1084	6897
Independent Variables					
Mean Household Consumption Expenditure per capita (2019)	683	2439.76	1016.4	1037.01	7829.51
Wealth Index Factor Score (-14 to 14) (2019-21)	701	0.28	5.93	-13.02	14.50
Multidimensional Poverty Headcount Ratio (2015-16)	651	25.31	17.14	0	74.38
% of households with internet (2019-21)	701	48.74	16.65	9.29	91.44
Literacy rate (2020-21)	684	71.76	10.4	29.84	95.98
Secondary education rate (2020-21)	684	29.59	11.29	5.07	73.25
% of population able to send emails with attachments (2020-21)	684	11.82	8.92	0.2017	48.96
% of households with bank accounts (2019-21)	701	95.60	2.39	78.47	99.23
Banks per lakh population (2019)	618	11.35	7.43	0.01	70.91

Appendix 3: Structural break in Number of Users, and Transaction Volume and Value

Figure 19: Structural Breaks following the first and second COVID-19 lockdowns







Structural breaks identify points in a time series where the slope or mean abruptly shifts. We use the strucchange package in R to identify structural breaks in PhonePe's transaction and user data. Four structural breakpoints are identified in transaction data and five in user data. Both value and volume experience structural breaks at Q3 in 2020, Q2 in 2021 and Q1 in 2022. While transaction volume experiences a break at Q2 in 2019, transaction value has one in Q3 in 2019. The user data has structural breaks in Q4 of 2018, Q4 of 2019, Q3 of 2020, Q2 of 2021 and Q1-2022. The early structural breaks in user data precede those in transaction data and as expected, COVID significantly increased usage of PhonePe. One drawback of this methodology is the low frequency of Phone Pe's data as accurately determining structural breaks in a time series does require high frequency data.

Appendix 4: Choropleth maps of PhonePe Diffusion across Indian States

Figure 20: Delhi, Karnataka and Telangana show high user penetration and transactions per person

Figure 20a: User penetration (2018 Q4)

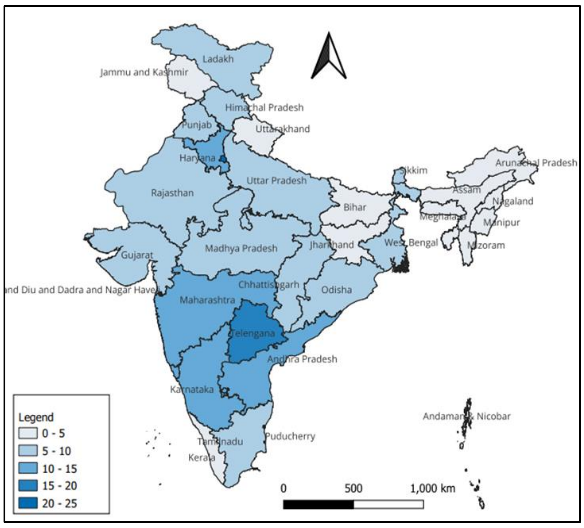


Figure 20b: User penetration (2022 Q4)

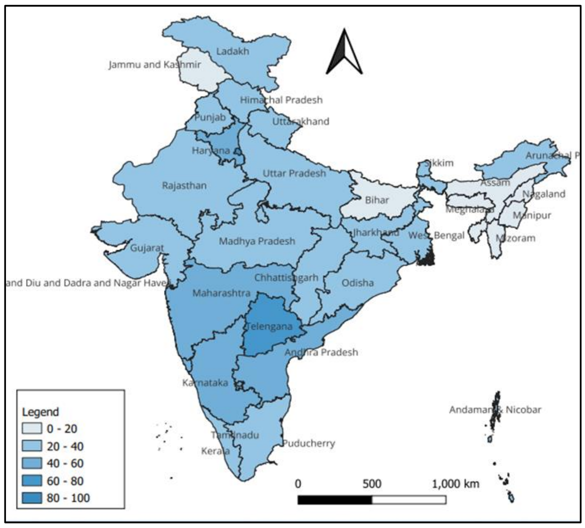


Figure 20c: Transactions per person (2018 Q4)

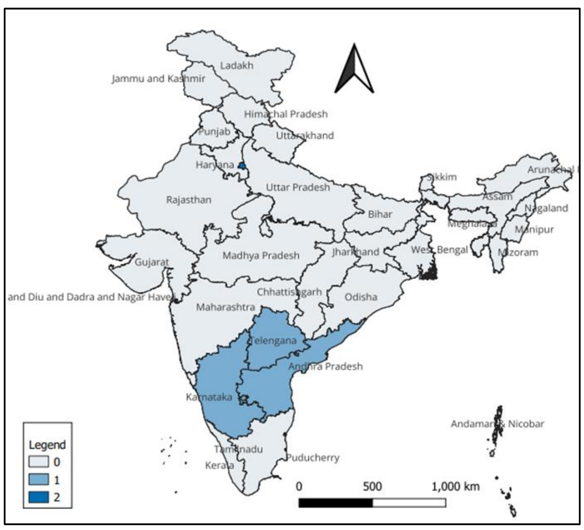
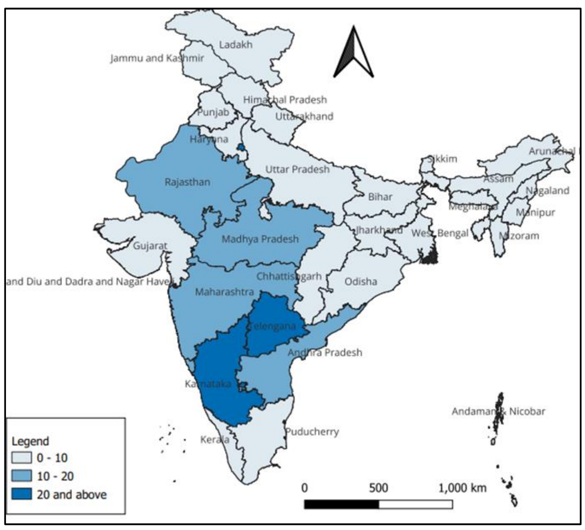


Figure 20d: Transactions per person (2022 Q4)



Source: PhonePe Pulse and population projections from Ministry of Family Health and Welfare. Note: The colour gradient scales differ between the two time periods, in order to enable an understanding of the performance of states with respect to each other, as opposed to comparing them between the two time periods.

Appendix 5: Aspirational vs. Non-aspirational districts

Figure 21: Aspirational vs. Non-aspirational districts

Figure 21a – Transaction Amount per capita (Average)

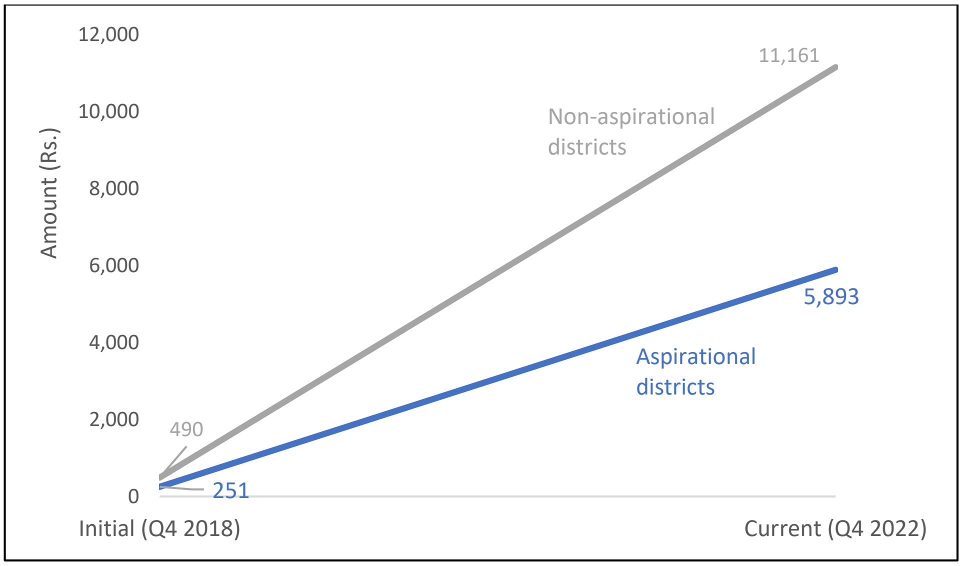
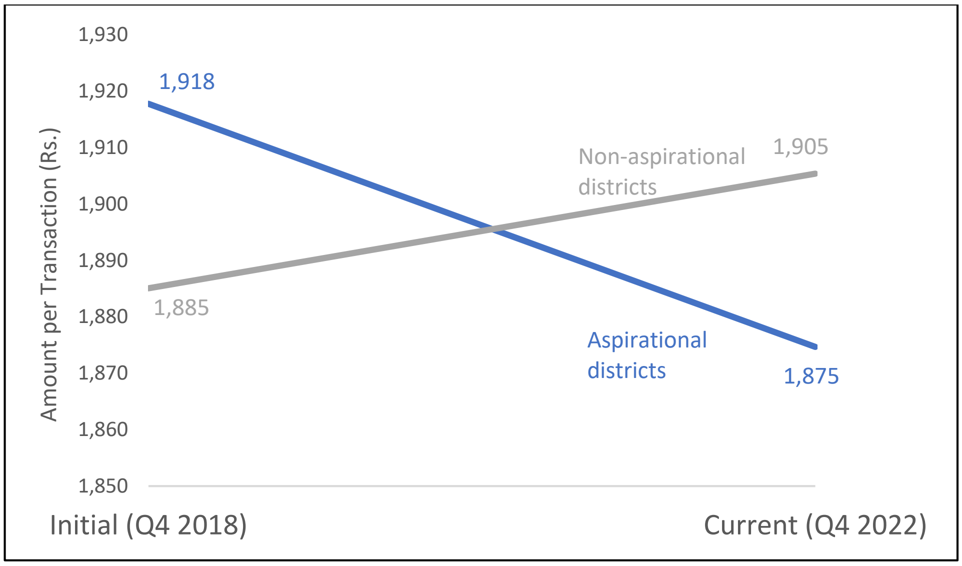


Figure 21b – Ticket size (Amount per transaction) (Average)



Appendix 6: Convergence Analysis

Boyle et al. (1997) offer a measure of a β convergence, which is an alternative to Barro's regression method.[24] The measure is presented below:

$$RC_t = \frac{Var(\sum_{t=0}^{T} AR(t)_{it})}{Var((T+1) * AR(Y)_{t0})}$$

24 They utilise Kendall's rank concordance (RC_t) to measure inter-temporal changes in distribution across multiple years. Supported by empirical evidence, they state that the rank concordance measure is a more appropriate measure of convergence compared to the conventional Barro regressions.

Boyle et al. (1999) applies simple measures of convergence, σ convergence and γ convergence, using GDP per capita to test for the presence of convergence among OECD countries. Their analysis supports the theory that the rate of convergence is not constant, lending credence to their hypothesis that σ convergence and γ convergence are better measures than β convergence. We extend use of these simple measures to indicators related to PhonePe's number of registered users, transactions value and volume.

σ convergence compares the initial coefficient of variation with the coefficient of variation at time t. If σ convergence is above 1, then the coefficient of variation is larger compared to initial level and therefore, the dispersion has increased between time o and time t. If σ convergence falls below 1, then we can say that dispersion within the group has decreased.

$$\sigma\ Convergence\ = \frac{\frac{\sigma_t}{x_t}}{\frac{\sigma_t}{x_o}}$$

γ convergence compares the initial ranking within the group with the ranking at time t. The denominator represents the maximum variation possible given the ranking at time o, occurring when the ranking remains the same. If there is a change in the ranking or distribution of the group, then the numerator will be smaller than the denominator and γ convergence falls below 1. By construction, γ convergence can never be greater than 1.

$$\gamma\ Convergence\ = \frac{Var(R(x_t)\ +\ R(x_o))}{Var(2 * R(x_o))}$$

Furceri (2005) shows that the existence of σ convergence is only a sufficient (but not necessary) condition for the existence of β convergence. We test for β convergence at the district level using a simple Barro regression after observing the presence of σ convergence. We account for variation across states by including a dummy variable for states. The simple OLS regression equation for measuring convergence is given below -

$$\frac{log(\frac{y_{iT}}{y_{io}})}{T}\ =\ \alpha\ +\ \beta * log(y_{io})\ +\ D(State_i)\ +\ u_{io,T}$$

Our initial period 'o' is quarter 1 of 2018 and final period 'T' is quarter 4 of 2022. We observe beta convergence if the coefficient β is negative and significant. Since the coefficient β is negative and significant for indicators (see Table A1), we can conclude that there does appear to be convergence between initial period and final period. It should be noted that the assumption under which the Barro regression is run is that the rate of convergence is constant and therefore it gives no indication of the path taken to achieve convergence.

Table A2: Results of Beta Convergence Analysis

Transaction Amount per capita				
Coefficient	Estimate	Std. Error	t value	p value
α	0.321637	0.012995	24.751	< 2e-16 ***
β	-0.017026	0.001082	-15.739	< 2e-16 ***
No. of Transactions per capita				
Coefficient	Estimate	Std. Error	t value	p value
α	0.225637	0.014510	15.550	< 2e-16 ***
β	-0.008522	0.001286	-6.626	7.40e-11 ***
Registered Users per capita				
Coefficient	Estimate	Std. Error	t value	p value
α	7.414e-02	4.007e-03	18.505	< 2e-16 ***
β	-0.01185	4.105e-04	-28.858	< 2e-16 ***

Appendix 7: Convergence analysis for non-aspirational districts

Figure 22: Convergence analysis for non-aspirational districts

Figure 22a: Value of transactions per capita

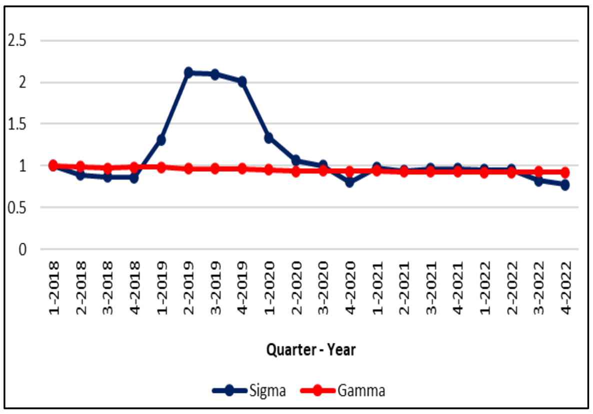


Figure 22b: Number of transactions per capita

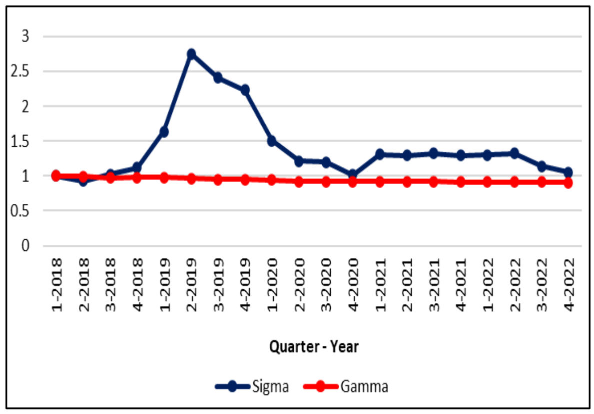
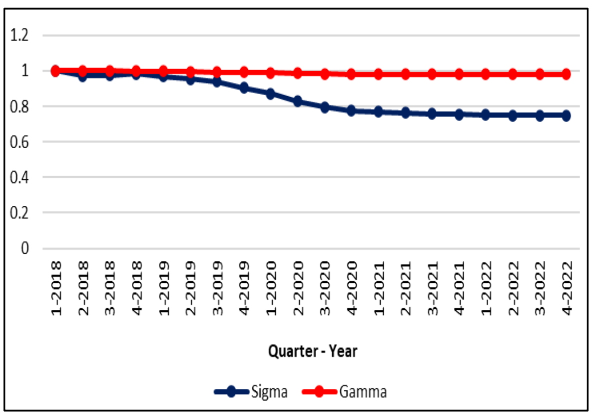


Figure 22c: User Penetration



Appendix 8: Sensitivity of regression results to various specifications

Figure 23: Regression Results for User Penetration (2022 Q4) - Alternate Specifications

Figure 23a: Specification 1

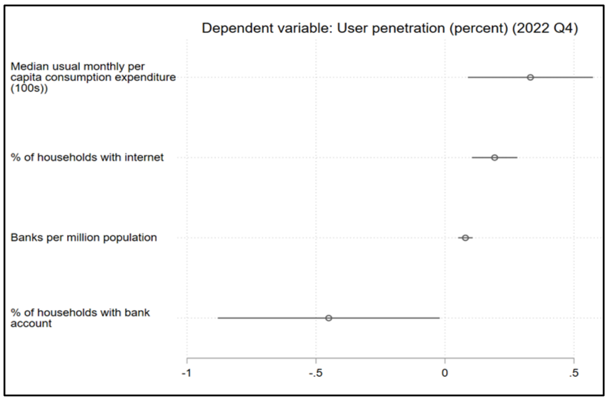


Figure 23b: Specification 2

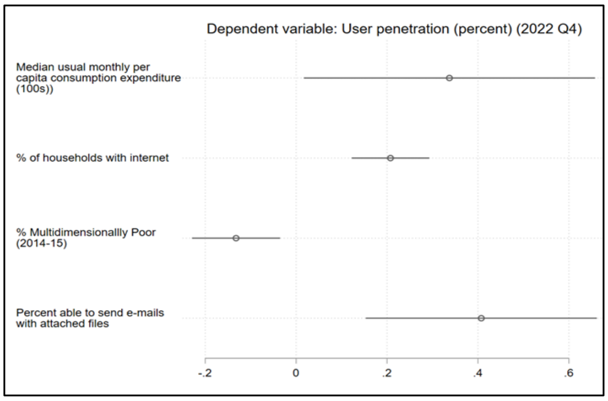


Figure 23c: Specification 3

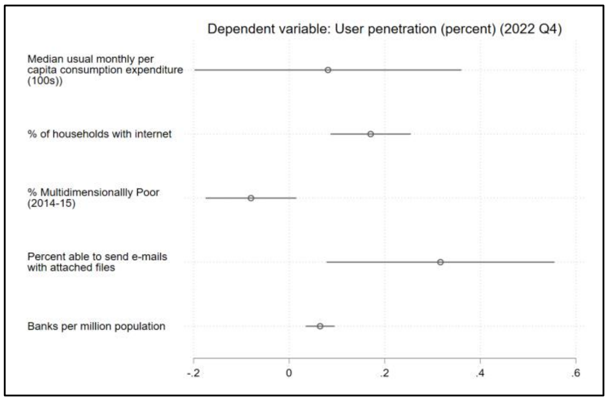


Figure 23d: Specification 4

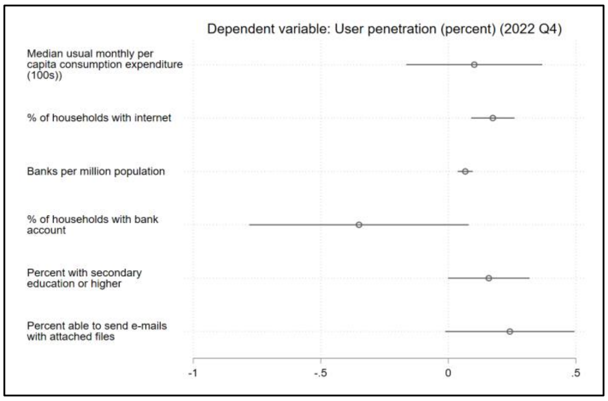


Figure 23e: Specification 5

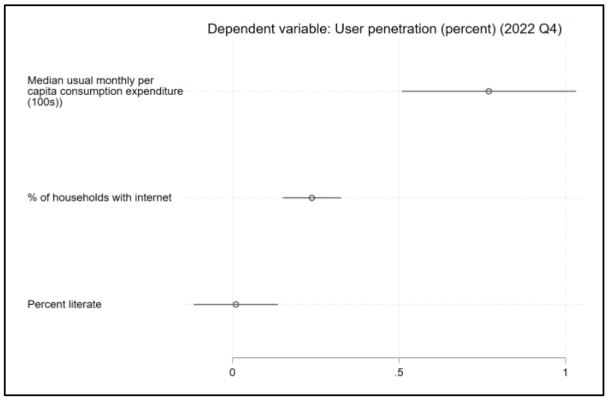
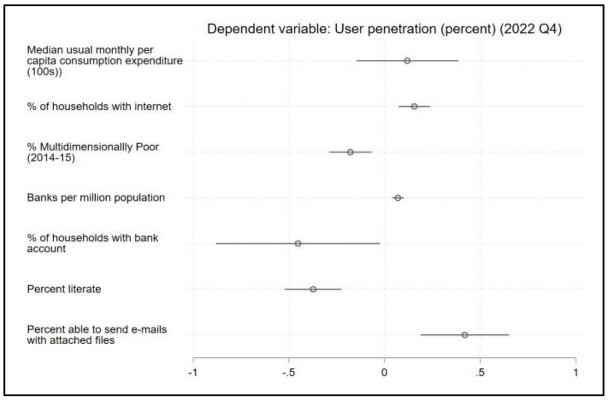


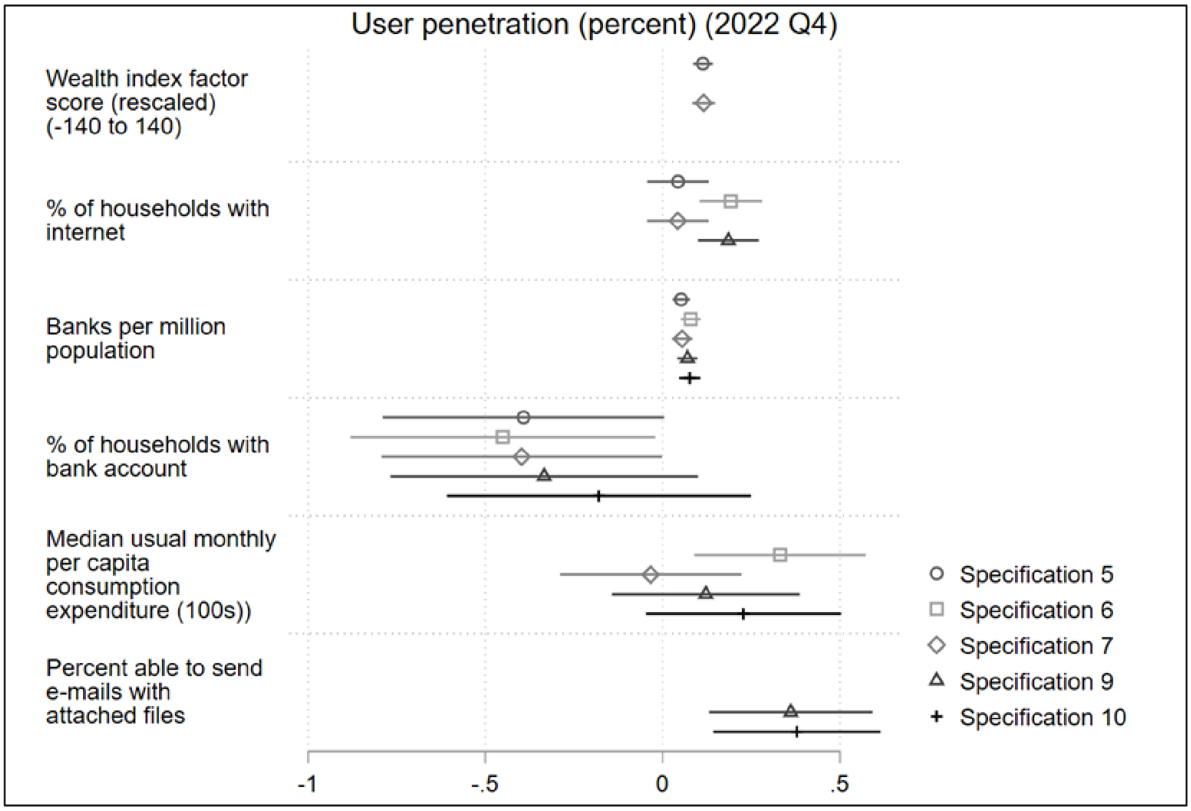
Figure 23f: Specification 6



Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate.

Since consumption expenditure, poverty rate, literacy rate, percent able to send email, and banks per million are highly correlated, including multiple of these variables together results in their estimated coefficients fluctuating.

Figure 24: Regression Results for User Penetration across Specifications (2022 Q4)



Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate.

Appendix 9: Comparison of regression results for various measures of adoption

Figure 25: Comparison of Regression Results for Various Measures of Adoption (2022 Q4) - Alternate Specifications

Figure 25a: Specification 1

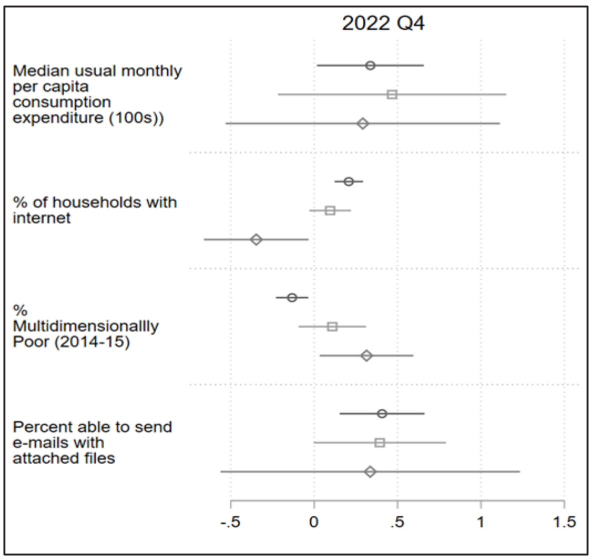
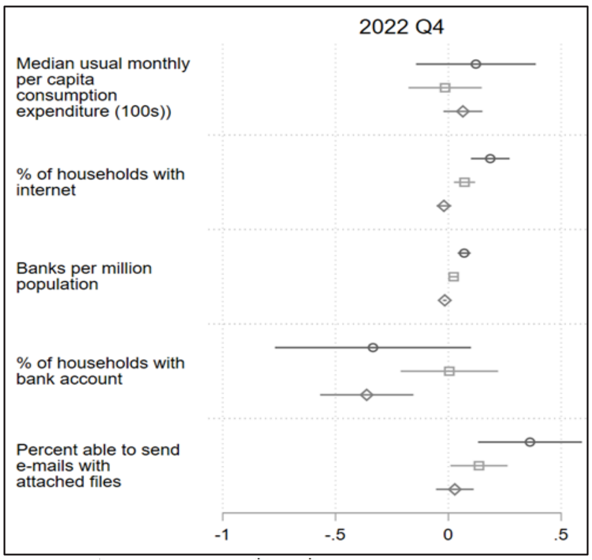


Figure 25b: Specification 2



User penetration (%) Transactions per capita Ticket size (100's of Rs.)

Figure 25c: Specification 3

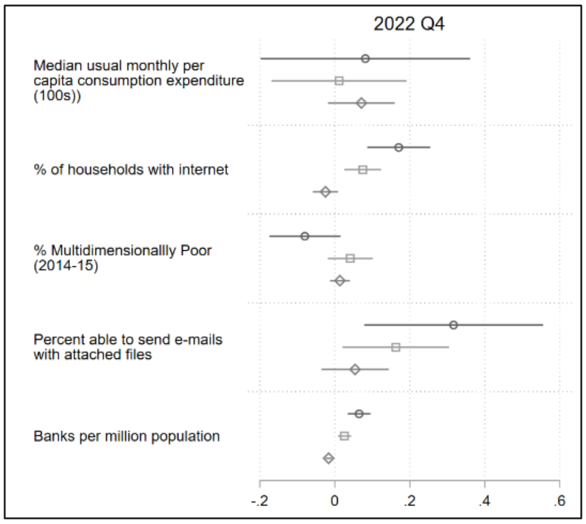


Figure 25d: Specification 4

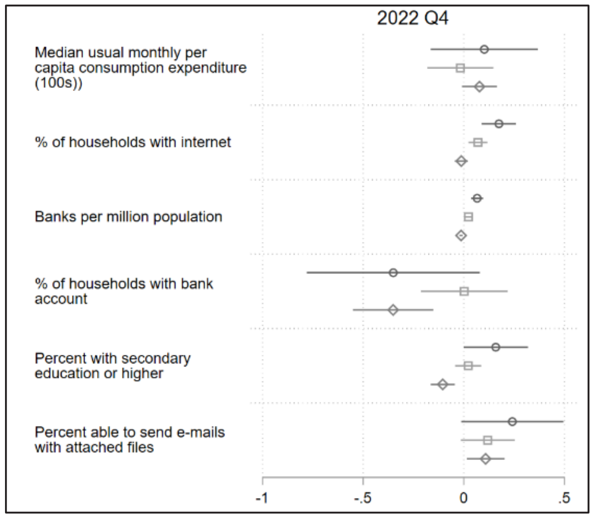


Figure 25e: Specification 5

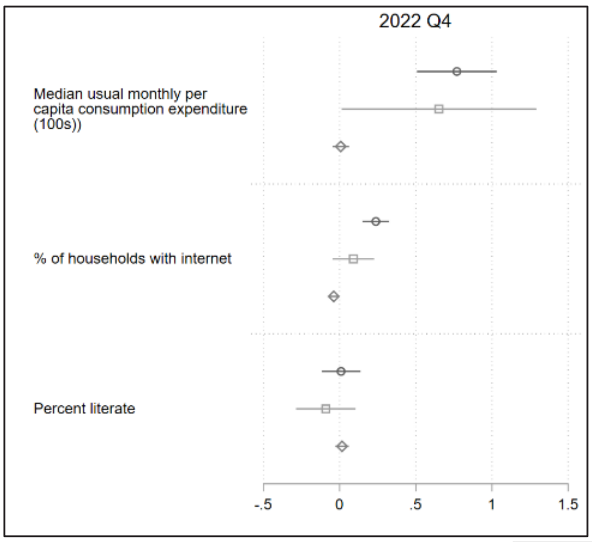
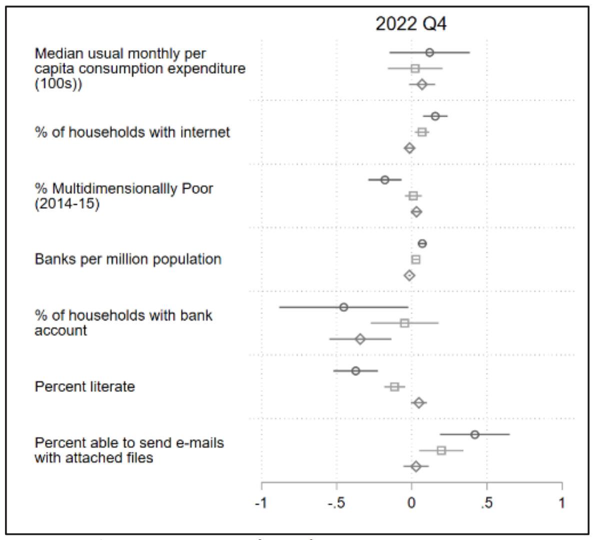


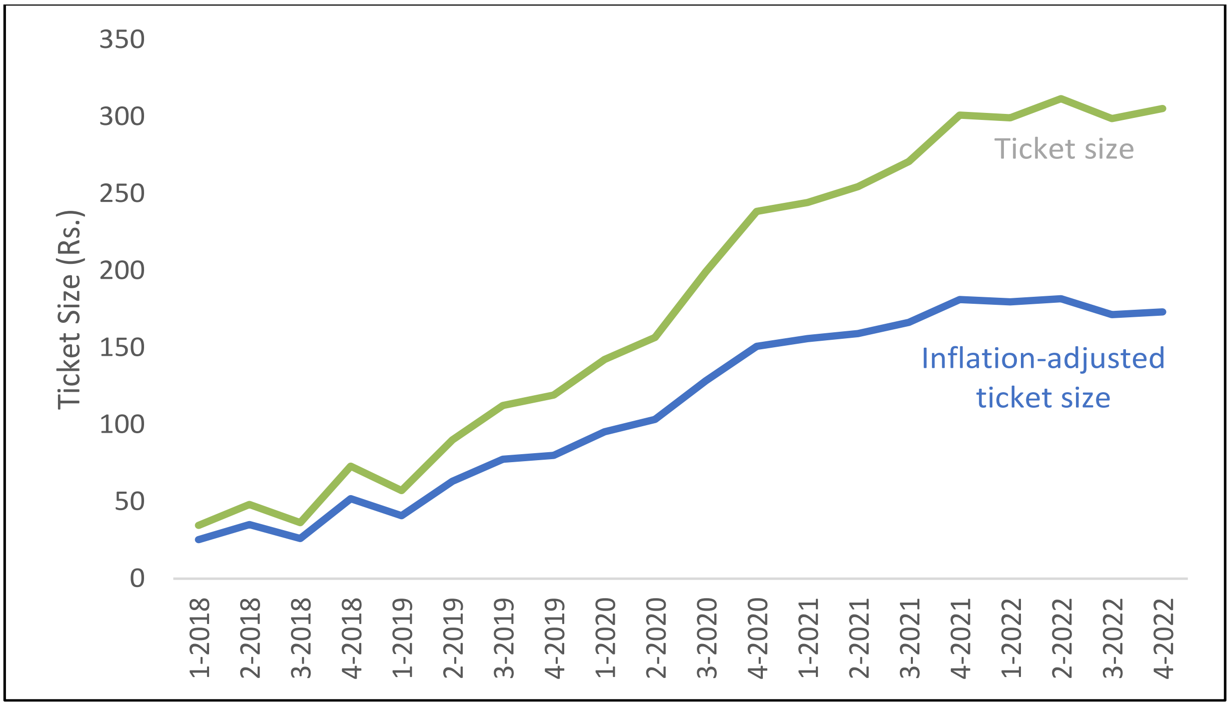
Figure 25f: Specification 6



Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate.

Appendix 10: Average ticket size over time

Figure 26: Average ticket size over time



Note: Ticket size has been adjusted for inflation using the CPI.
Source: PhonePe Pulse and DBIE RBI

Appendix 11: Comparison of regression results over time

Figure 27: Comparison of Regression Results over time – Transaction Volume (2022 Q4 vs. 2018 Q4)

Figure 27a: Specification 1

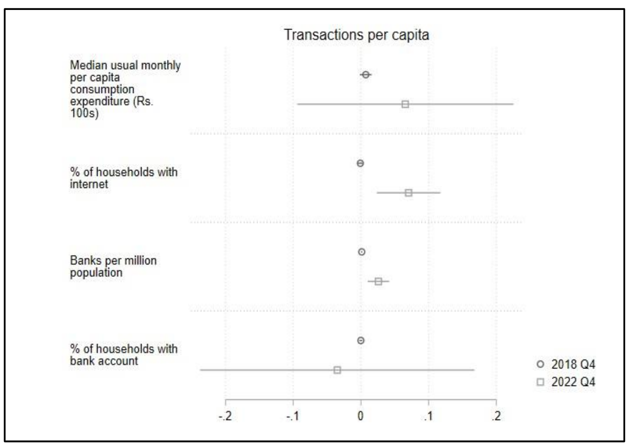
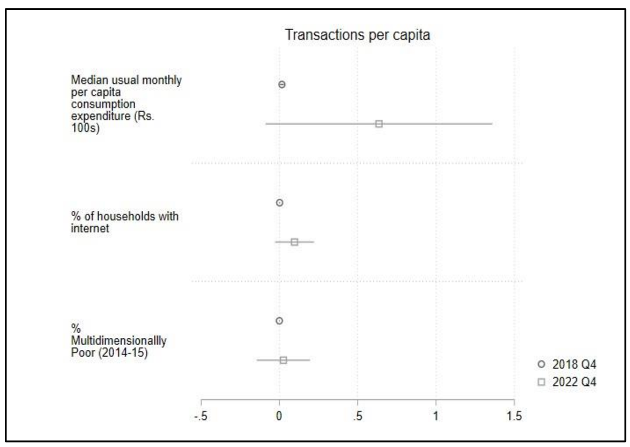


Figure 27b: Specification 2



○ 2018 Q4 □ 2022 Q4

Figure 27c: Specification 3

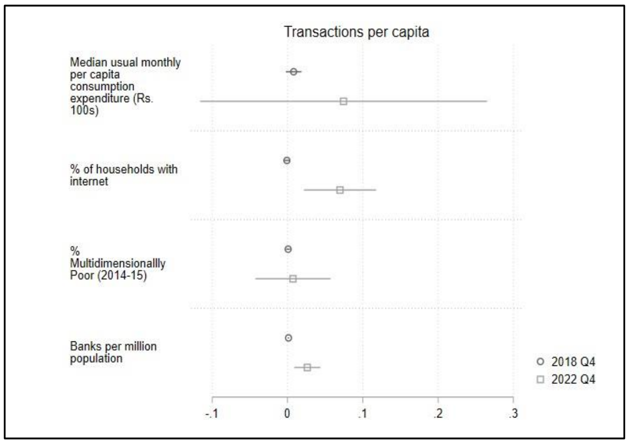
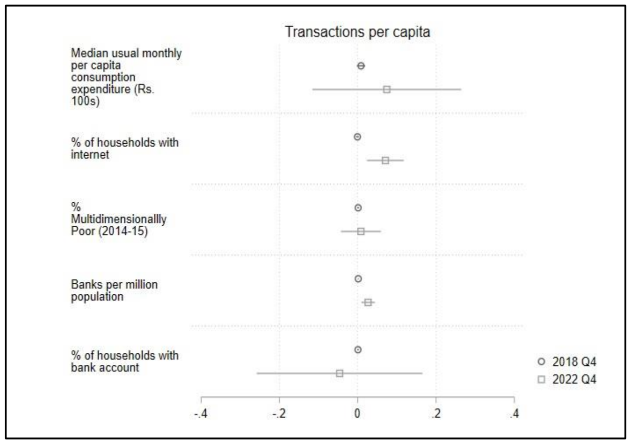


Figure 27d: Specification 4



○ 2018 Q4 □ 2022 Q4

Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate. For the period 2018 Q4, median usual monthly per capita consumption expenditure is from NSS HCS (2014), percent of household with internet and percent of household with bank accounts are from NFHS-4 (2015-16), banks per million from Garg & Gupta (2020) is calculated as bank branches open as of 2015 normalized by estimated 2015 population. For the 2022 Q4 regression, usual monthly per capita consumption expenditure is from AIDIS (2019), percent of household with internet and percent of household with bank accounts are from NFHS-5 (2019-21), and banks per million is as of 2019 from Garg & Gupta (2020). Percent multidimensionally poor for both period regressions is from NITI Aayog's report on Multidimensional Poverty based on NFHS-4 (2015-16).

Figure 28: Comparison of Regression Results over time – Ticket Size (2022 Q4 vs. 2018 Q4)

Figure 28a: Specification 1

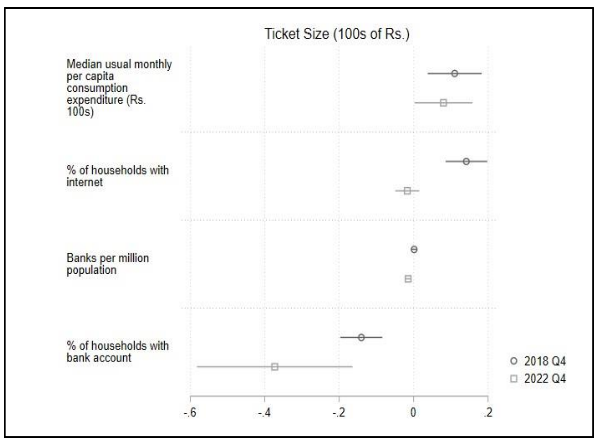
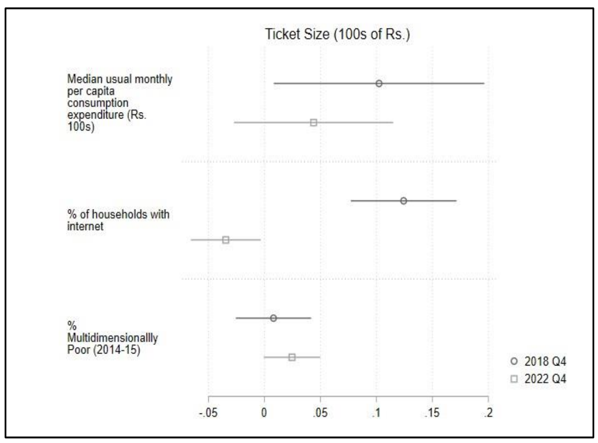


Figure 28b: Specification 2



○ 2018 Q4 □ 2022 Q4

Figure 28c: Specification 3

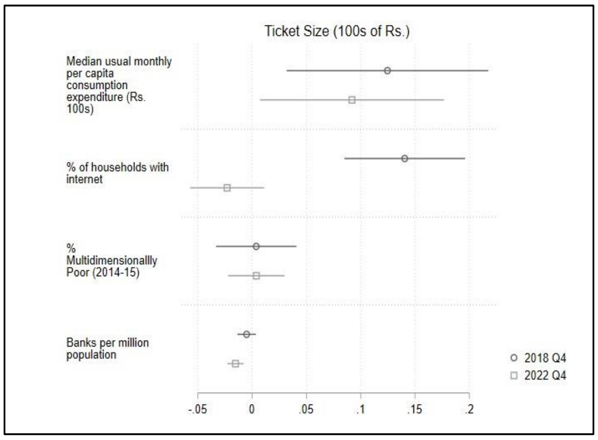
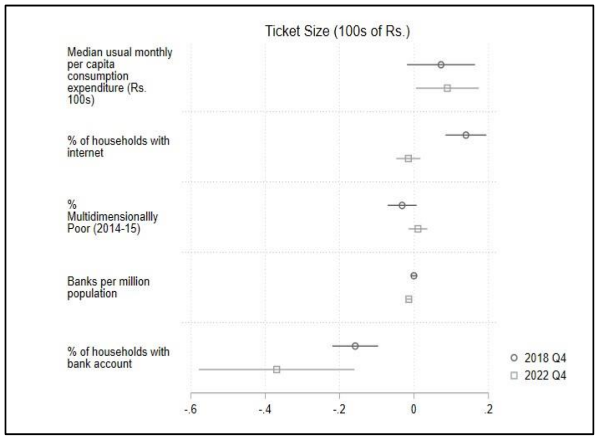


Figure 28d: Specification 4



○ 2018 Q4 □ 2022 Q4

Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate. For the period 2018 Q4, median usual monthly per capita consumption expenditure is from NSS HCS (2014), percent of household with internet and percent of household with bank accounts are from NFHS-4 (2015-16), banks per million from Garg & Gupta (2020) is calculated as bank branches open as of 2015 normalized by estimated 2015 population. For the 2022 Q4 regression, usual monthly per capita consumption expenditure is from AIDIS (2019), percent of household with internet and percent of household with bank accounts are from NFHS-5 (2019-21), and banks per million is as of 2019 from Garg & Gupta (2020). Percent multidimensionally poor for both period regressions is from NITI Aayog's report on Multidimensional Poverty based on NFHS-4 (2015-16).

Appendix 12: State level scatterplots

Figure 29: State level scatterplots of PhonePe User Penetration and Socio-economic factors (2022 Q4)

Figure 29a: Poverty

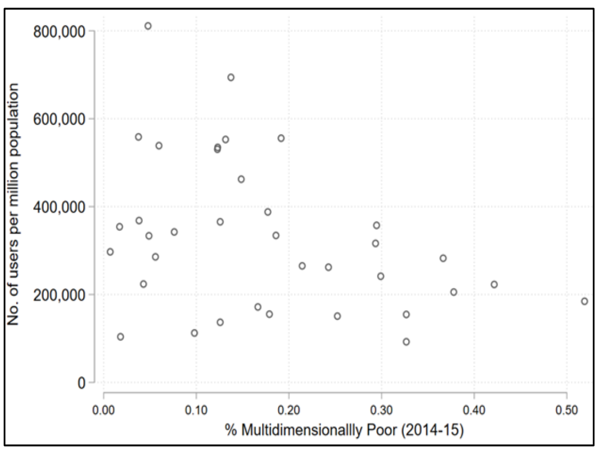


Figure 29b: Share of gross value added in agriculture

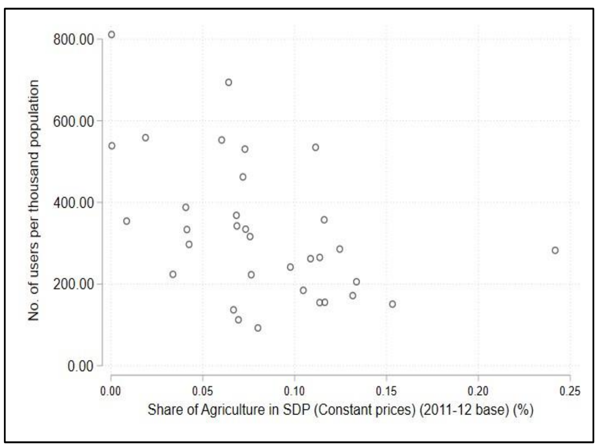


Figure 29c: Share of gross value added in manufacturing

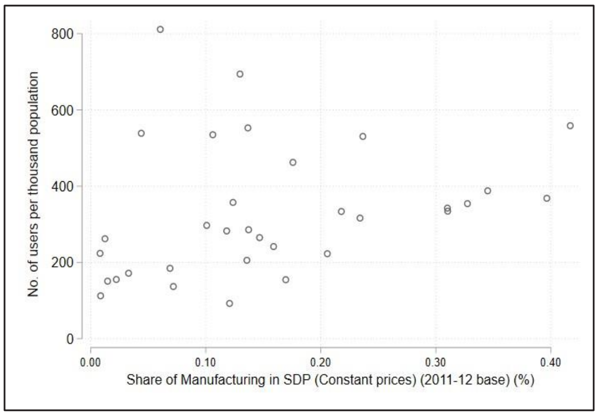


Figure 29d: Share of gross value added in services

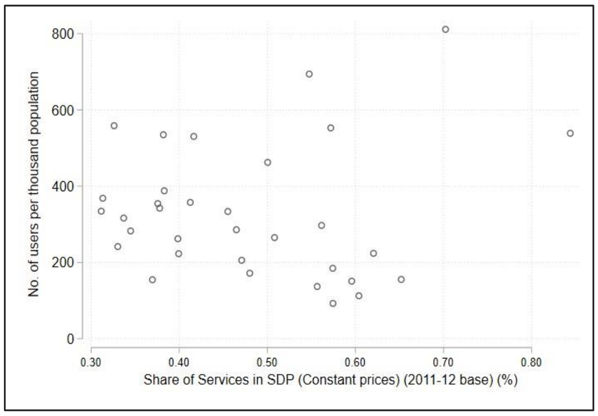


Figure 29e: Mean Household Consumption Expenditure per capita

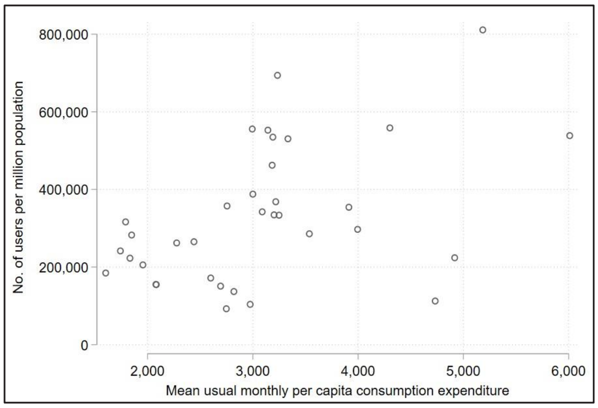


Figure 29f: Median Household Consumption Expenditure per capita

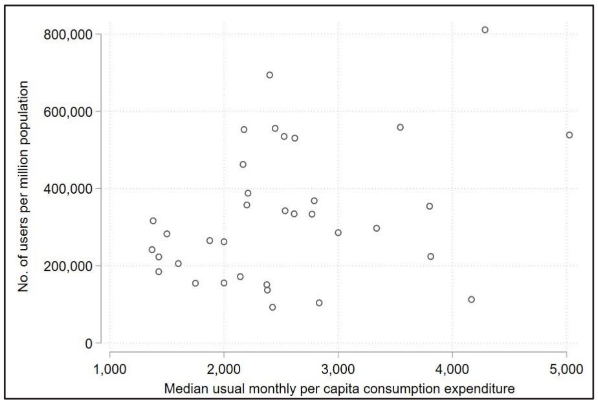


Figure 29g: Internet Penetration

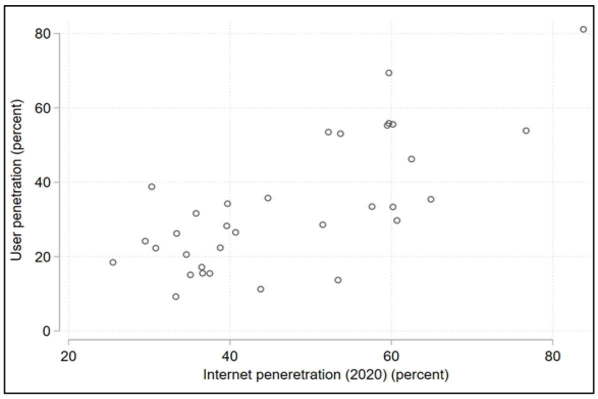


Figure 29h: Net State Domestic Product per capita

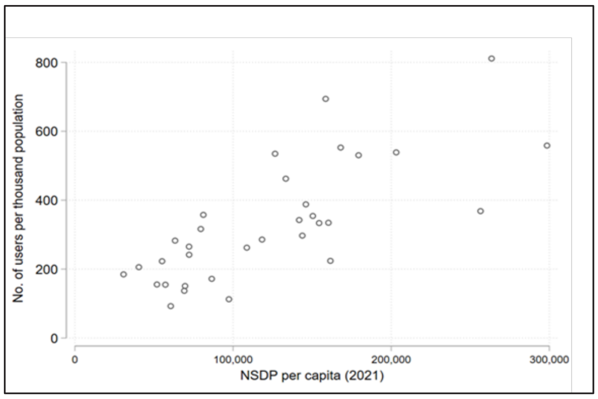


Figure 29i: Literacy Rate

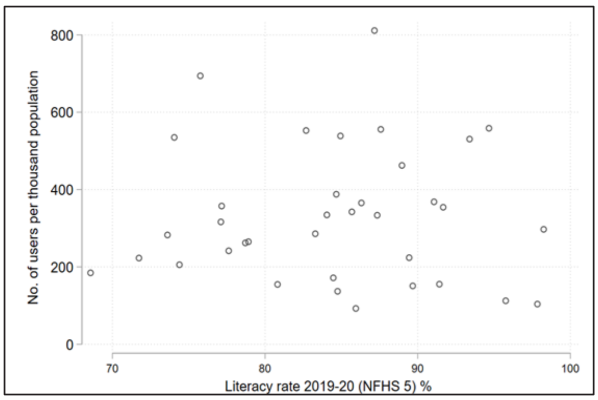
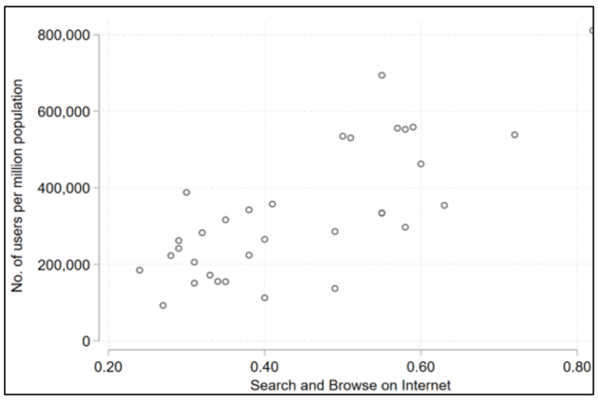


Figure 29j: Digital Literacy Rate



Appendix 13: Regression results for state level analysis

Figure 30: State-wise Regression Results

Figure 30a: Specification 1

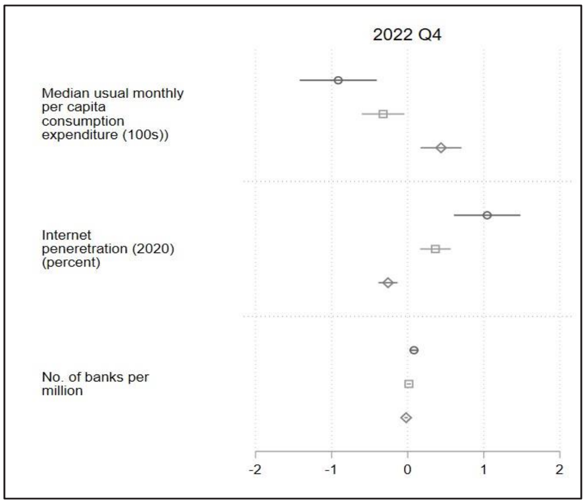
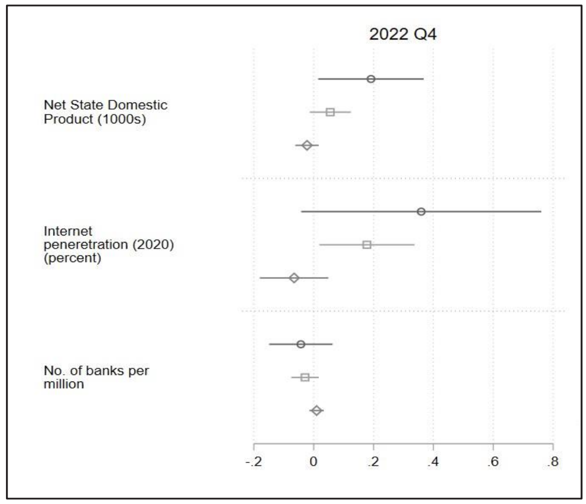


Figure 30b: Specification 2



○ User penetration (%)   □ Transactions per capita   ◇ Ticket size (100's of Rs.)

Figure 30c: Specification 3

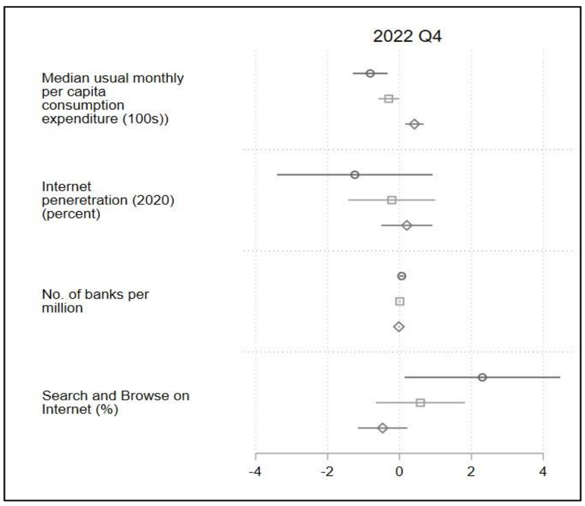


Figure 30d: Specification 4

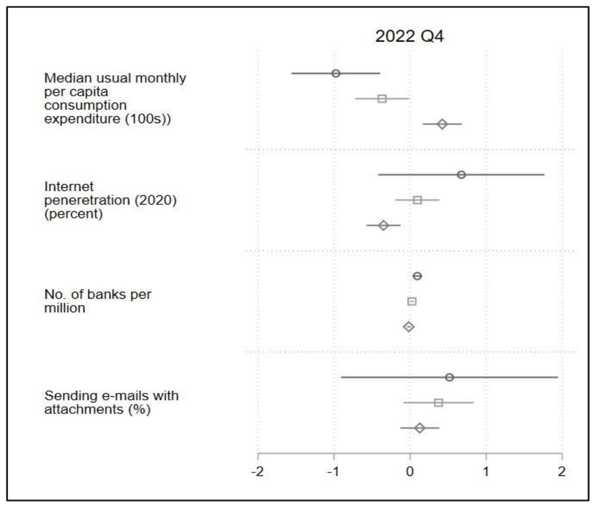


Figure 30e: Specification 5

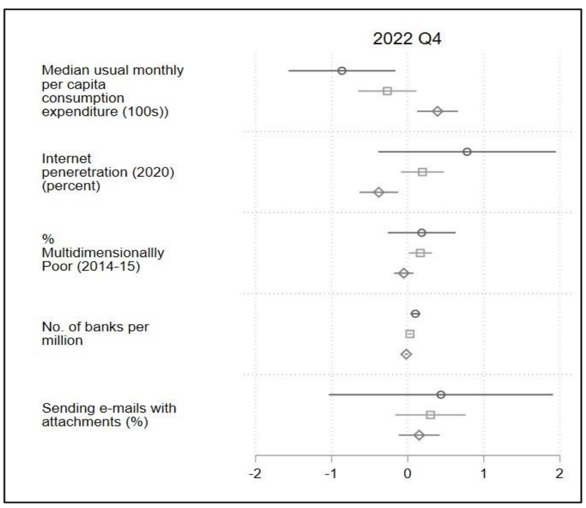
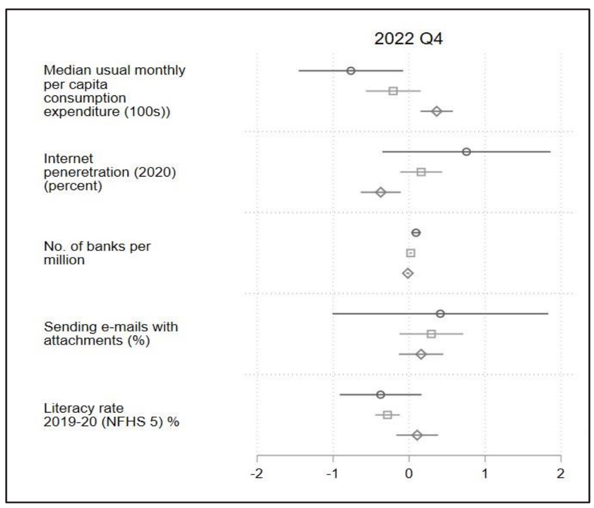


Figure 30f: Specification 6



○ User penetration (%)   □ Transactions per capita   ◇ Ticket size (100's of Rs.)

Figure 30g: Specification 7

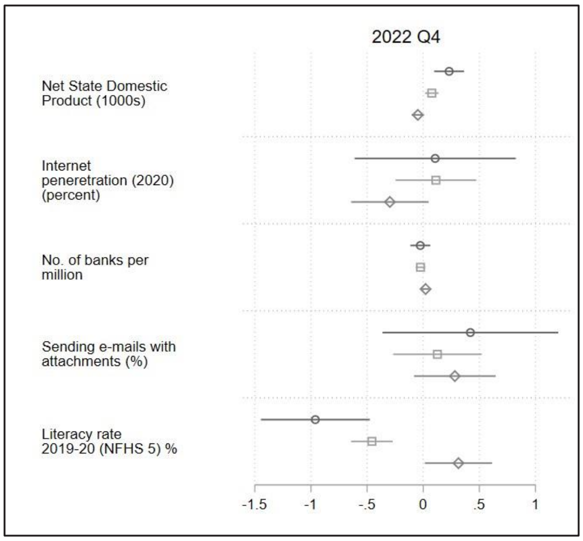
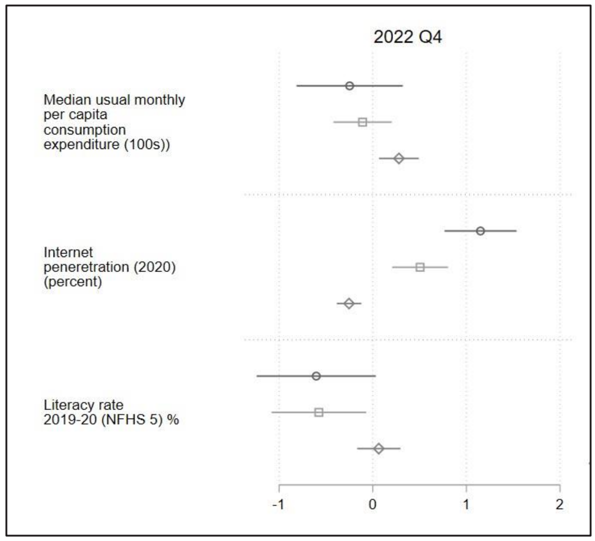


Figure 30h: Specification 8



○ User penetration (%) □ Transactions per capita ◇ Ticket size (100's of Rs.)

Figure 30i: Specification 9

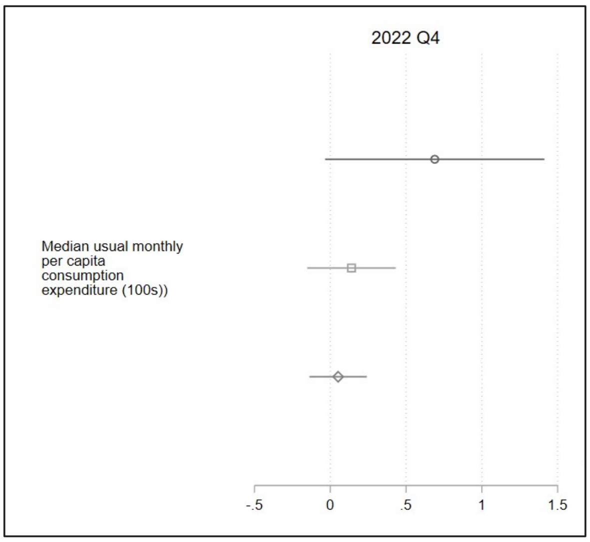
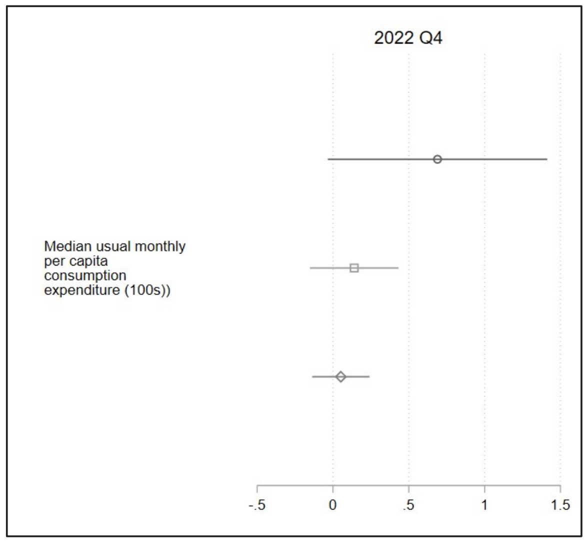


Figure 30j: Specification 10



○ User penetration (%) □ Transactions per capita ◇ Ticket size (100's of Rs.)

Note: The dots show the estimated value of the coefficient and the lines/whiskers show the confidence interval of the estimate.

Appendix 14: Interaction effects for aspirational districts

Figure 31: State-wise Regression Results

Figure 31a: Internet access

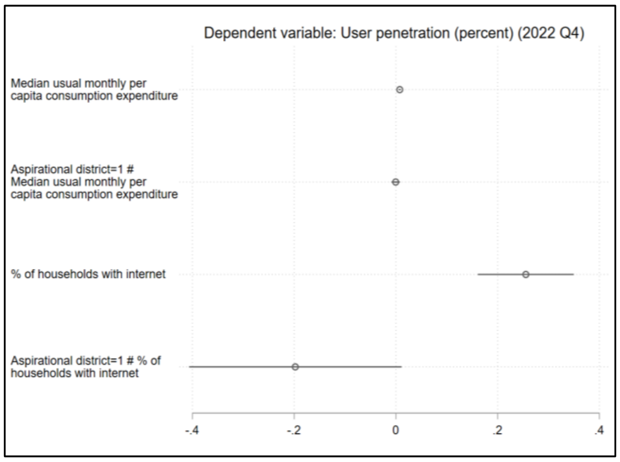


Figure 31b: Digital literacy

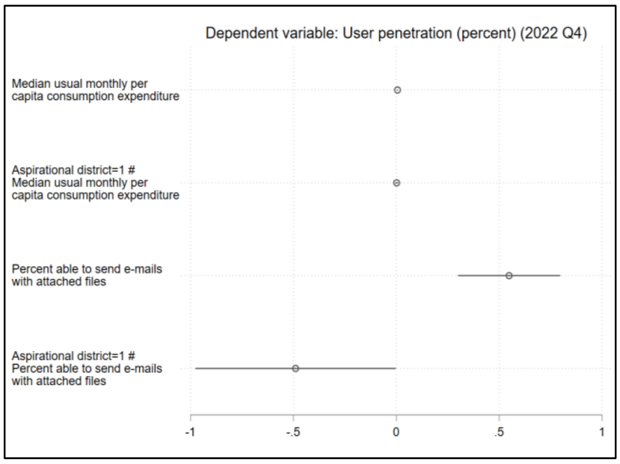


Figure 31c: Bank branch density

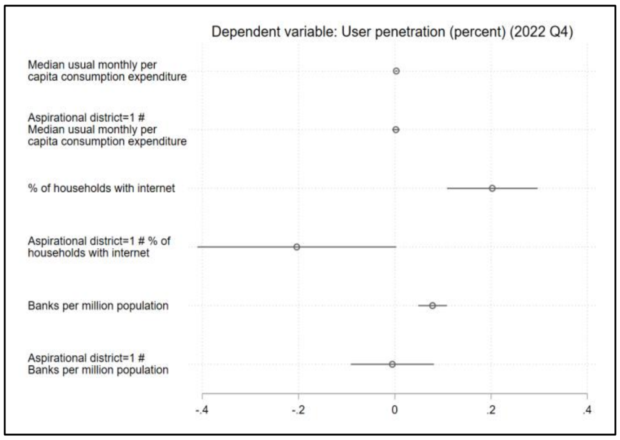


Figure 31c: Bank account penetration

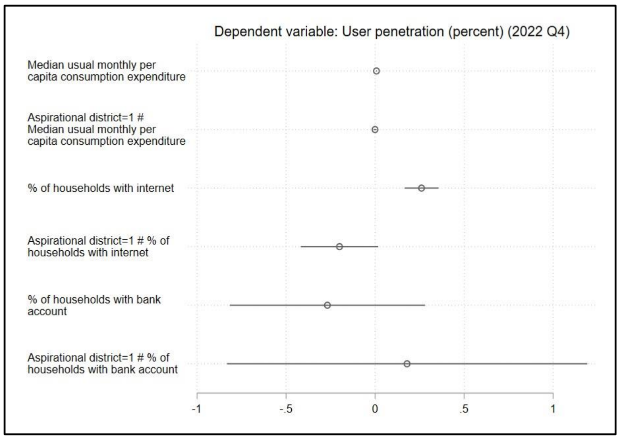


Figure 31e: Poverty rates

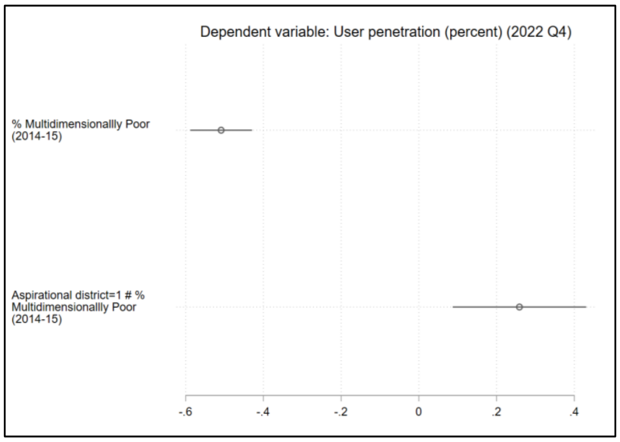
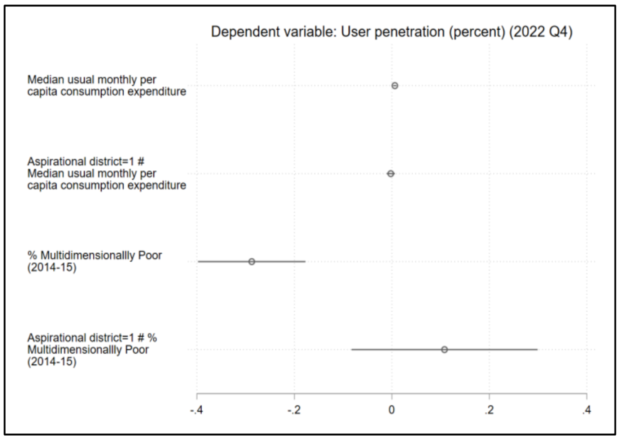


Figure 31f: Poverty rates, controlling for median consumption expenditure



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