Can Cashless Payments Spur Economic Growth?*

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First Draft: February, 2023
This Draft: February, 2023

Abstract

After the introduction of a nationwide Unified Payment Interface (UPI) in 2016, India has become one of the world's leading economies for cashless transactions. We exploit the heterogeneity in the intensity of the adoption of digital payments across districts to show that the household income increased significantly in districts with higher intensity of cashless transactions after the launch of UPI. These households started a significantly higher number of new businesses and earned higher business income after the launch of UPI. We achieve identification by exploiting the within-district-year variation in the effect of cashless payments on economic outcomes across households who are differentially impacted by the adoption of digital payment. Specifically, we show that the impact of digital payments is stronger for self-employed households, such as hawkers and traders, compared to others. Relaxation of borrowing constraints and reduction in the transaction cost of payments are two principal mechanisms behind our findings.

Keywords: Cashless, FinTech, Digital Payments, UPI
JEL Classification: G21, G28

*We are grateful to Andrey Malenko, Puneet Manchanda, and Uday Rajan for comments on the paper. We thank the Mitsui Life Financial Research Center for providing financial support for this research.

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1 Introduction

Can the means of payments affect economic growth? While the debate on whether monetary variables, such as cash, can affect economic outcomes is not new (Lucas and Stokey, 1987; Woodford, 2003), recent technological advancements in cashless payments has reinvigorated this debate. In a frictionless economy, the means of payments act simply as a medium to settle claims across transacting parties, leaving no role for it to directly influence real economic outcomes. However, in the presence of transaction costs and information asymmetry between transacting parties, some forms of payments can be more effective than others in minimizing these frictions. As a result, the medium of payment can affect real outcomes and economic growth. As countries around the world are experimenting with digital payments, a careful empirical examination of the effect of cashless payments on economic outcome can help shape the policy debates as well as shed light on economic frictions at play. Our paper provides one of the first empirical evidence on this question using the large scale adoption of cashless payments across India in the past few years.

The adoption of digital payments in India presents a unique and attractive empirical setting for three principal reasons. Firstly, the economic magnitude of the adoption is large. Specifically, digital payments in India accelerated after the nationwide launch of the Unified Payments Interface (UPI) on August 25, 2016[1], an initiative of the Government of India, that facilitated a quick and seamless settlement of payments across the entire banking network in the country without any cost to the consumers and merchants. Secondly, the extent of cashless transactions varies greatly across districts in the country, allowing us to carry out a difference-in-difference analysis with the intensity of treatment measured in terms of per person digital transactions as the main explanatory variable. Finally, we are able to obtain a very high-frequency and granular household level panel data, which allows us to identify the effect causally. In particular, our approach allows us to exploit variations in the benefits of

[1] https://www.npci.org.in/what-we-do/upi/product-overview

cashless payments within a specific district and time-period across different households based on the likely benefit of digital transactions to them. Such a within-district-year empirical approach minimizes concerns about omitted time-varying latent characteristics of districts from affecting our results.

Two critical factors were responsible for the successful launch and adoption of the UPI platform. First, every Indian resident was provided with a unique identification card, called the Aadhaar Card, through a nationwide initiative that started in 2010.[2] Second, the government and private sector firms invested significant resources in developing the digital infrastructure needed for such a secure and fast payments architecture that operates across platforms; for example, users only need a mobile phone, not necessarily a smartphone, to access the UPI platform. Importantly, the digital and biometric-based Aadhaar card made the verification of a banking transaction instant and secured. After the launch, several government sponsored incentive schemes and promotional campaigns were launched across the nation. Furthermore, two additional factors - the demonetization of high denomination currency notes in November 2016, and the COVID-19 pandemic - provided additional boost to the adoption of digital payments in the country. Consequently, the UPI adoption rate across districts was not driven by one dominant factor, rather it varied based on a host of factors such as the availability of formal banking institutions, the percentage of population that linked their Aadhaar card to bank accounts, the rate of mobile phone penetration, the impact of demonetization, any variation in local government policies, and others.

There are two principal economic frictions that a mass adoption of digital payment system can alleviate to foster economic growth. First, it can minimize transaction costs of payments, which in turn can facilitate higher level of economic activities. For example, street vendors and small shopkeepers can easily accept payments for their goods and services through a digital wallet after the launch of the UPI system.[3] The benefits of lower transaction cost

[2]Aadhaar is a Hindi word for 'foundation'.

[3]For example, see the IMF's report on India's digital stack: https://www.imf.org/external/pubs/ft/fandd/2021/07/india-stack-financial-access-and-digital-

can be especially high in areas with lower availability of formal financial institutions or higher possibility of theft and crime faced by businesses. Second, a digital payments economy can alleviate financing frictions by improving the flow of information to the lenders for credit decisions (Berg, Burg, Gombović, and Puri, 2020; Balyuk, 2023; Parlour, Rajan, and Walden, 2022), improving the processing time for credit decisions (Fuster, Plosser, Schnabl, and Vickery, 2019), or increasing the ability of lenders to enforce the repayment contracts (Brunnermeier and Payne, 2022; Dai, Han, Shi, and Zhang, 2022). Indeed, several FinTech firms around the globe use digital payments information to provide financing, especially to small businesses who face greater limitations in gaining access to financing opportunities (Ghosh, Vallee, and Zeng, 2021). These frictions are likely to be more binding for self-employed household such as small shop owners and street vendors.

We use a detailed household level panel dataset that is available at a very high frequency to empirically examine the effect of digital payment adoption on real economic outcomes. Our dataset covers more than 200,000 households spread across over 500 districts in India from 2014 to 2022.[4] We focus on three key measures of real economic activities: (a) overall income of these households, (b) creation of new businesses by them, and (c) their business income. The level of digital payments is measured by the amount of digital transactions per person in each district in our sample in the post-UPI period.

In our first analysis, we use a difference-in-difference research design with the intensity of digital payments adoption as the treatment variable and the year 2016 as the year of digital payments shock. Our model includes household fixed effects to soak away the effects of time-invariant characteristics of these households on economic outcomes. We first show that the outcomes across districts followed a parallel trend before the shock, i.e., there was no difference in the path of income, business creation, or business income before 2016 across

inclusion.htm

[4]The dataset comes from the Center for Monitoring Indian Economy (CMIE). It provides a representative sample of households across the country covering various income, age, education, and occupation group. See Gupta, Malani, and Woda (2021) for a detailed discussion of the database.

districts with different levels of digital payment adoption. After the shock, however, there is a remarkable change in the evolution of each of these economic outcomes across districts. Soon after the launch of UPI, households in high digital payments districts started new businesses at a significantly higher rate compared to their counterparts in low digital payments district. As expected, these households also experienced a commensurate increase in their business income after the shock. The total household income increased steadily over time, with a noticeable jump during the COVID-19 year. In economic terms, districts with ten percentile higher digital payments had 0.17% higher income in the post-shock period in our base case specification. The corresponding increase in the number of new businesses by households in these districts is 0.88%. These are economically large estimates, but are they causal in nature?

Our base case specification shows that districts with varying intensity of digital payments adoption exhibited parallel trend in their economic outcomes before the UPI shock. Hence, the threat to our identification comes from time-varying changes in unobserved factors that correlate both with the adoption of digital payments and economic growth in a district. We exploit differences across households within a district-year to soak away such time-varying differences across districts. Specifically, we estimate the differential effect of digital payments on self-employed versus other households to tease out our main effect. The key idea behind our identification strategy is that the self-employed households are more likely to benefit from the adoption of digital payments compared to salaried households. The assumption is in line with the economic idea that digital payments allow entrepreneurs to start their own businesses or expand the scale of their business due to lower transactions costs and improved access to business credit. While other households also benefit from faster and cheaper payments processing, by definition they are relatively less likely to benefit from the channels that underpin business growth. Using a within-district-year variation, we show that self-employed households experience a significantly higher increase in their income compared to other households in higher digital payments districts after the UPI shock. In a supplementary test, we focus exclusively on a smaller set of self-employed households: 'street vendors and hawkers'. We show that this group experienced a significant increase in its income compared to the non-self-employed group. Our empirical design alleviates concerns that omitted time-varying characteristics of a district could be driving our main finding.

In our next set of tests, we focus on the economic channel behind our results. These analyses shed light on the frictions that digital payments alleviate, and provide further boost to the causal interpretation of our results. A principal benefit of a mobile phone-based digital payments system is that it reduces the cost of accessing banking services at a local bank branch. Areas with fewer bank branches on a per capita basis face both higher transactions cost in making payments, as well as potentially lower access to credit (Petersen and Rajan, 2002). We show that the effect of digital payments on economic outcomes is concentrated predominantly in districts with lower levels of financial development, measured using the number of bank branches per capita. In this empirical specification, a triple-difference regression model, we separate out the standalone effects of financial development and digital payments intensity on the economic growth in a district after the UPI shock. It is within the set of financially less developed districts that we find the positive effect of digital payments on economic growth. Therefore to invalidate our causal interpretation, any omitted variable of concern must affect high digital payments district only in the less financially developed areas after the shock.

In a supplementary test, we exploit the variation in crime rate across districts to assess whether digital payments aid business growth, especially in high crime districts. The motivation for using district crime rate is related to the transactions cost of cash that small entrepreneurs face. In high crime areas, the cost of carrying cash is higher due to the possibility of theft and burglary. This translates to a higher cost of cash transactions in high crime districts. We find that the effect of digital payments on income and business growth is higher in high crime districts. These tests show that digital payments boost economic growth through the alleviation of transactions cost of cash. Combined with our results on within-district-year variation, these results provide further support to a causal link from digital payments to economic growth through business creation.

In our final test, we analyze the borrowing outcomes of households to shed light on the second mechanism: the alleviation of financing constraints through digital payments. Our database allows us to observe both the source and use of debt. Using this information, we show that households in districts in the highest percentile of digital payments are 3.64% more likely to borrow from a bank in the post-UPI period compared to households in districts with the lowest digital payments intensity. In terms of the use of funds, these households are 3.17% more likely to borrow for their business. Building on our earlier results linking measures of financial development to economic growth, we also estimate a triple-difference model for household borrowing outcomes. We find that the effect of digital payments on borrowings is considerably higher in districts that are financially less developed. These findings provide support for the claim that the relaxation of borrowing constraint is a key mechanism behind our results.

In sum, we show that digital payments impact real economic outcomes through the relaxation of borrowing constraints and reduction in transactions cost. While there is a large and growing literature on the role of digital payments on borrowing outcomes, to the best of our knowledge our paper is the first to document its impact on real activities. Our paper also relates to an old literature on the role of financial development on economic growth, with the adoption of digital payments as the measure of financial development in our context. In Section 2, we discuss the contribution of our work to the existing literature. Section 3 discusses the institutional setting of the UPI platform in more detail. Section 4 describes the data that we use and presents descriptive statistics. In Section 5, we discuss our empirical strategy and show our results, before we conclude in Section 6.

2 Literature Review

Our paper contributes to three strands of literature in economics and finance: (a) financial development and economic growth, (b) effect of cashless payments on borrowing constraints, and (c) drivers of economic growth in India.

Our work is most closely related to the growing literature that studies the effect of cashless payments on borrowing constraints faced by various agents in an economy. The main idea here is that digital payments can alleviate credit rationing due to information frictions in an economy (Stiglitz and Weiss, 1981). Recent studies such as Ghosh et al. (2021) and Brunnermeier and Payne (2022) indicate that electronic payments generate a verifiable digital transactions history which help reduce information asymmetry between lenders and borrowers. Furthermore when used for online retail purchases, cashless payments enhance the digital footprint of consumers in an economy. This improves the access to credit for potential borrowers as suggested by Berg et al. (2020) and Agarwal, Alok, Ghosh, and Gupta (2021), as well as increase the repayment likelihood of borrowers as shown by Dai et al. (2022). Moreover, improved digital footprint also helps lenders to price their loans better, as suggested by Di Maggio and Yao (2021). In general, there is a fast growing literature on the effect of FinTech on credit outcomes (Chava, Ganduri, Paradkar, and Zhang, 2021). While we build on this literature, our paper is distinct on a key dimension – it provides one of the first pieces of evidence on the impact of digital payments on real economic output. It is not clear ex ante whether and to what extent a switch to cashless payment can impact real economic activities. For example, if FinTech lenders simply substitute traditional forms of credit (Gopal and Schnabl, 2022), then it may not have any meaningful impact of real output.

At a broader level, our work relates to the literature on the role of financial development on economic growth, an idea first made prominent by Schumpeter (1911). Using data from over 80 countries, King and Levine (1993) show that high level of financial development is positively related to improvement in economic efficiency, capital accumulation and increase in present and future rates of economic growth. Rajan and Zingales (1998) and Demirgüç-Kunt and Maksimovic (1998) show that financial development promotes economic growth by reducing the cost of external financing for firms. Beck, Demirgüç-Kunt, and Maksimovic (2008) use survey data in 48 countries to show that financial development is significantly correlated with availability of external financing for firms, especially smaller firms who may find it more difficult to access financial services. Claessens and Laeven (2003) also find increase in economic growth with financial development due to improved access to financing. Cetorelli and Strahan (2006) also explore the role of financial development on real economic activity and show that concentrated local US banking markets result in increased difficulties in access to credit for newer, smaller firms. Using data from Italy, Guiso, Sapienza, and Zingales (2004) report that financial development facilitates economic growth by increasing business creation. In the Indian context, there is a rich literature on the role of rural banks and micro-financial institutions on economic growth and consumer welfare (Burgess and Pande, 2005; Banerjee, Duflo, Glennerster, and Kinnan, 2015). Our work adds to this literature as we highlight the role of digital payments in facilitating economic growth by relaxing financing constraints for entrepreneurs and improving business creation.

Lastly, we contribute to the literature that captures drivers of economic growth in India. Using the demonetization shock in India, Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020) study the role of cash crunch on economic output across districts that were hit differentially by the shock. They document a decline in the output in the affected districts in the immediate aftermath of the demonetization shock. Gupta et al. (2021) study the impact of the COVID-19 pandemic on income and consumption. Balakrishnan and Parameswaran (2007) identify the various growth regimes in India and find that in the last two decades, services have led economic growth. Basu and Maertens (2007) also study the trends and patterns of economic growth in India and conclude that structural drawbacks such as paucity of infrastructure are a main hinderance to economic growth. Our paper contributes to this literature by emphasizing the role of cashless payments via the Unified Payments Interface in driving economic growth in India.

3 Institutional Details

The Unified Payments Interface or UPI is a real-time payment solution that aims to serve as a one-stop-shop to unite, standardize and automate India's multiple traditional payment platforms. It facilitates instant fund transfer between bank accounts via mobile phones. Using a set of Application Programming Interfaces (APIs), UPI currently facilitates 'peer-to-peer' and 'peer-to-merchant' pay and collection requests for in-person, online and in-app purchases. The system allows users to set up recurring payments of up to ₹2,000 (∼US$25) at any frequency, using RuPay debit and credit cards, for their utility bill payments. The pilot program was launched on April 11, 2016 with 21 participating banks and UPI-enabled applications were available to download on Google Play store starting August 25, 2016.

The participants of the UPI ecosystem include payer and payee Payment Service Providers (PSPs), remitter bank, beneficiary bank, the National Payments Corporation of India (NPCI), bank account holders and merchants. As of February 2023, the UPI platform hosts 385 banks in India, of which 60 are PSPs and have their own applications on the UPI platform, whereas the remaining 325 banks are Issuers alone, i.e., they do not have their own applications on the UPI platform. However, account holders in these Issuer banks can access the platform through any UPI-enabled application they are registered on. UPI-enabled applications are provided by either banks directly, as discussed above, or by Third Party Application Providers (TPAPs) such as PhonePe, Google Pay and Amazon Pay. The UPI platform allows for full interoperability across all UPI-based payment applications and participating institutions.

In the UPI ecosystem, the mobile phone is the primary device for payment authorization. A bank account holder who banks with any UPI member bank can register themselves on a

UPI-enabled application using their AADHAR ID, a 12-digit individual identification number issued by the Unique Identification Authority of India (UIDAI) on behalf of Government of India, and generate their UPI ID, also known as a Virtual Address (VA). Registered UPI users who have access to a smartphone and internet can then use the user-friendly, one-click, two-factor authentication based UPI platform that allows for push and pull payment requests. Moreover, the platform provides unlimited flexibility to merchants and developers to customize their UPI-based applications to their business requirements. Registered UPI users who do not have a smartphone or internet connection can also access UPI via the UPI PIN option. Leveraging the Unstructured Supplementary Services Data (USSD) channel, bank account holders who use feature phones can avail instant and secure UPI payment services.

4 Data & Descriptive Statistics

We obtain data from multiple sources. The data on the measure of digital payment adoption at the district-level comes from PhonePe, one of the leading firms in the industry. We obtain district-level UPI transaction amount data available at quarterly frequency from 2018 Q1 to 2022 Q1. Founded in December 2015, PhonePe is a leading digital payments and financial technology company in India that facilitates e-commerce payments, utility bill payments, mobile recharge and offline payments. It also provides investment services. PhonePe is owned by the Flipkart Group (87% holding in PhonePe), a subsidiary of Walmart Inc. In 2022, PhonePe had a market share of about 50% by value.[5]

Our main data for measuring economic outcomes comes from a survey data of a large panel of households covering approximately 500 districts of the country: the Consumer Pyramids Household Survey (CPHS) by the Centre for Monitoring Indian Economy (CMIE). The CMIE is a private organization that conducts CPHS, a continuous survey administered on a panel

[5]See https://www.npci.org.in/what-we-do/upi/upi-ecosystem-statistics#innerTabTwoJan23.

of nationally representative sample of over 170,000 households three times a year.[6] We use the household-level income, business activity, borrowings, and a host of other characteristics of the households from the CPHS database for our analyses. For our analysis, we collapse the data at the annual level to remove the effect of seasonality. More information on this survey data, including the variables used in the study, is provided in the Appendix.

In order to develop a metric of financial development in a district, we use the data on the number of bank branches at district-level provided by the Reserve Bank of India (RBI) for the end of year 2016. We also use the district-level bank credit data provided by the RBI in order to analyze the impact of cashless payments on aggregate credit in a district. This data is available at quarterly frequency. We use population estimates for 736 districts in India in 2020 provided by Wang, Kim, and Subramanian (2021). These estimates were arrived at by summing the population count using the WorldPop raster data.[7] We scale the number of branches per district by its population to arrive at our measure of financial development across the country.

We use the district-level crime data in India provided by the National Crime Records Bureau (NCRB) as a proxy for the cost of carrying cash in a district. The NCRB's 'Crime in India' report is released at an annual frequency and provides a comprehensive account of cases registered and persons arrested in each district under various crime-heads. We look at violent crimes and economic crimes in each district in India during the year 2016. Relevant violent crimes that we look at include murder, attempt to murder, culpable homicide that did not lead to murder, rape, attempt to rape, and kidnapping and abduction. Related economic crimes that we consider include dacoity, robbery, burglary, theft, cheating, forgery, counterfeiting and extortion. We use the total number of crime scaled by the population of the district as a measure of crime intensity.

Descriptive Statistics: Figure 3 presents a graphical summary of the evolution of

[6]Each cohort of survey is called a "wave" by the CMIE. Each wave has about 170,000 households. The number of unique households across the entire sample period is over 200,000.

[7]https://hub.worldpop.org/geodata/summary?id=6527

digital payments in the country since 2016. As shown in the Figure, the amount of digital transaction increased from a negligible amount in 2016 to over $140 billion per month in 2022. The number of transaction reached a level of 7 billion transactions per month. Figure 4 shows the geographical dispersion in the adoption rate across districts. We compute the average amount of digital transaction per person over all the quarters in the post-UPI period for each district and report these averages graphically in the map. We also present the geographical dispersion in financial development measure, i.e., per capita bank branches, alongside the digital payment adoption map. As we can see, there is a rich heterogeneity across the country on both these measures. We exploit these differences across the districts in our empirical work.

Table 1 presents the summary statistics of the main variables used in our study. On average, a district has ₹3,400 (∼US$42.50) of digital payment transaction per person per quarter in our sample. We compute this measure as the average value across all the quarter (2018Q1-2022Q1) and then report the cross-sectional average across districts. There is a wide cross-sectional variation in this measure across districts as indicated by the standard deviation of ₹4,000 (∼US$50). For our tests, we create a percentile ranking of districts based on the average digital transaction per person, and use these rankings to sort districts on the intensity of digital payment adoption.

For our outcome variables from the CHPS database, we first aggregate the information for each household at the yearly level to remove the effect of seasonal variation in income. Thus, our analysis is based on about 200,000 unique households over a 9-year period, providing us with over 1.4 million observations. As shown in Table 1, households in the sample have an average monthly income of ₹20,000 (∼US$250), representing an annual income of ₹2,40,000 (∼US$3000). These numbers are representative of the entire population of the country since the CPHS sampling is a reasonable representation of the country's population.

We focus on two variables for business activities: (a) the number households who are engaged in business activities in the district, and (b) the value of business income earned during the year. We aggregate both variables at the annual level. If a household reports positive income from business activities in a given year, we count that as a household who 'owns business'. 22.77% of households in our sample own business on average. Their monthly business income is slightly below ₹4,000 (∼US$50).

In terms of credit outcomes, 39.48% of the sample reports some form of borrowing, and 12.14% reports borrowing from a bank. Our database also has information on the purpose of borrowing. 5.14% of households borrowed for businesses purposes in our sample. Finally, the Table provides the breakdown of occupation across households: entrepreneurs (25%), farmers (13%), salaried employees (21%), and retirees (7%). Other occupation categories include unemployed, social workers, wage earners, laborers, and miscellaneous. In our empirical test, we exploit variation across self-employed versus other categories. As discussed later, in our definition of self-employed households we include both entrepreneurs and farmers in the base case. We later analyze them separately.

Table 1: Summary Statistics

Table 1 presents the descriptive statistics of key variables used in the analysis. Cashless Transaction measures the average value of digital payments per person in a district. Monthly Income and Monthly Business Income are computed at the household level. Further details on variable construction are provided in the Appendix.

Full Sample

	Mean	SD	P25	P50	P75	N
Cashless Transaction	3416.57	4963.61	1075.04	1865.86	3507.12	1,426,159
Monthly Income	20363.63	18000.55	10225.00	15487.50	24666.67	1,426,159
Monthly Business Income	3958.27	11526.75	0.00	0.00	0.00	1,426,159
% owns business	22.77	41.93	0.00	0.00	0.00	1,426,159
% with borrowing	39.48	48.88	0.00	0.00	100.00	1,446,045
% with bank borrowing	12.14	32.66	0.00	0.00	0.00	1,446,045
% with borrowing for business	5.14	22.09	0.00	0.00	0.00	1,446,045
% entreprenuers	25.07	43.34	0.00	0.00	100.00	1,426,159
% farmers	13.15	33.79	0.00	0.00	0.00	1,426,159
% salaried	21.46	41.05	0.00	0.00	0.00	1,426,159
% retired	7.20	25.84	0.00	0.00	0.00	1,426,159

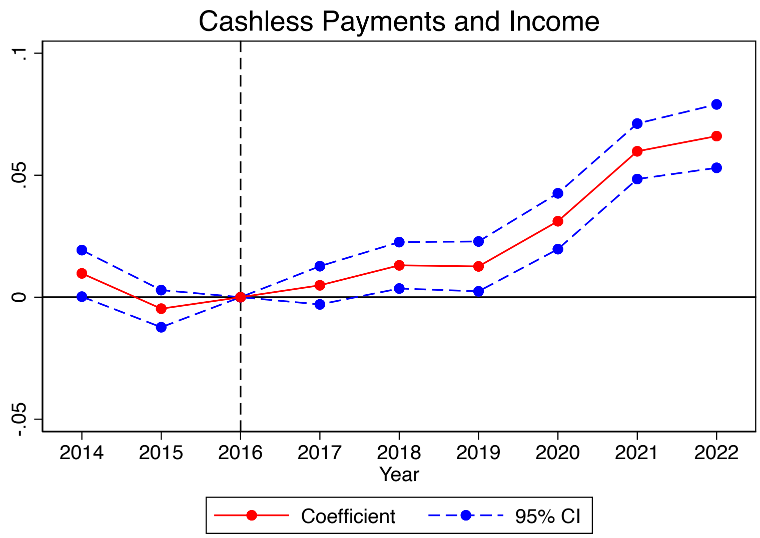
5 Empirical Strategy & Results

We estimate the following difference-in-difference model to obtain the effect of digital payment on economic outcomes on a yearly basis:

$$y_{i,t} = h_i + y_t + \sum_{\tau} (year = \tau) \times \beta_\tau \times CashlessIntensity_i + \epsilon_{i,t} \tag{1}$$

$y_{i,t}$ measures economic outcome of household i in year t: (a) log of household income, (b) whether the households reports business income in the year, and (c) log of one plus business income. $CashlessIntensity$ measures the percentile ranking of districts based on the amount of digital transactions on a per person basis for districts d, which is the same number for all households in one particular district. The model includes household fixed effects, and therefore also accounts for district fixed effects since households reside in the same district except for a very tiny percentage of movers. τ measures the year relative to 2016, i.e., the year of the adoption of the UPI by the country. All standard errors are clustered at the household level. We first present the results for overall income of the household as the dependent variable. The model is estimated with 2016 as the omitted category. Figure 1 presents both the estimated coefficients (β_τ) of the regression model and the 95% confidence interval around the estimate.

Figure 1: Effect of Digital Payment on Income



β_τ estimates the effect of cashless intensity, a district-specific variation, on household income over time. As shown in the figure, prior to the adoption of the UPI districts with varying intensity of cashless payments exhibited a parallel trend in their income: the coefficient is statistically indistinguishable from zero in 2014 and 2015. However, the coefficient becomes positive and increases steadily over time. By 2018, districts with higher intensity of digital payments have significantly higher household income. The income increases at a sharp rate in 2020, coinciding with the COVID-19 pandemic that gave a further boost of cashless payments all over the world. However, the positive effect of cashless payment on income began before the COVID-19 shock hit the country.

We estimate the following model to estimate the average effect of cashless payments on income across all the years in the sample:

$$y_{i,t} = h_i + y_t + \beta \times Post_t \times CashlessIntensity_i + \epsilon_{i,t} \tag{2}$$

$Post_t$ equals one for 2017-2022 and zero otherwise. Our model separates out differences in outcomes due to district specific characteristics, household characteristics, and aggregate time trends. Estimation results are provided in Table 2. Model 1 of the Table shows that districts with higher cashless intensity have significantly higher income in the post period. Since we measure cashless intensity in percentile terms, the coefficient estimates show that districts at two extreme ends of cashless intensity experienced a difference of 1.65% in income over this time period.

In Model 2, we further control for the differential rate of growth across urban and rural districts of the country. We do so for two main reasons: (a) the effect of COVID-19 crisis was felt disproportionately across these two groups, and (b) government programs such as the Mahatma Gandhi National Rural Employment Guarantee Act, a benefit scheme for unemployed population, are likely to have differential impact across the rural and urban parts of the country. Our main result becomes stronger. We find a 2.77% difference in average income of households at the extreme percentiles of digital payment intensity. The negative coefficient on the interaction term $Post \times UrbanDistricts$ shows that the rural part of the country performed relatively better during our sample period.

Finally, Model 3 of the paper includes the interaction of cashless intensity with an indicator variable post-COVID-19 that equals one for years 2020-2022, and zero otherwise. We find a much stronger effect of cashless intensity in the post-COVID-19 period. Yet, the coefficient on the base interaction term remains positive and significant, indicating that our results are not entirely driven by the COVID-19 shock. The coefficient estimates show that the average effect of digital transaction across districts in the extreme percentiles is 1.58%, and after the COVID-19 shock it increased by a further amount of 2.54%.

We now assess the impact of digital payments on the creation of new businesses and the level of business income earned by these households using the same empirical strategy. Our measure of business creation is simple: a binary variable that represents whether the

Table 2: Cashless Payments and Average Income

Table 2 presents the regression estimate of the regression model in equation 2. The model is estimated with household-year level observations. The dependent variable is the log of average monthly income of a household in a given year. Cashless Intensity measures the percentile ranking of a district based on their digital payment amount per person. All standard errors are clustered at the household level.

	(1)	(2)	(3)
Post X Cashless Intensity	0.0165***	0.0277***	0.0158***
	(0.0044)	(0.0044)	(0.0043)
Post X Urban Districts		-0.0516***	-0.0517***
		(0.0027)	(0.0027)
PostCovid X Cashless Intensity			0.0254***
			(0.0044)
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Nobs	1,425,548	1,425,548	1,425,548
Adjusted R-squared	0.650	0.651	0.651
Number of Households	209,098	209,098	209,098

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

households reports some income from business activity during a year or not. The yearly estimates are presented below:

Figure 2: New Business and Cashless Intensity

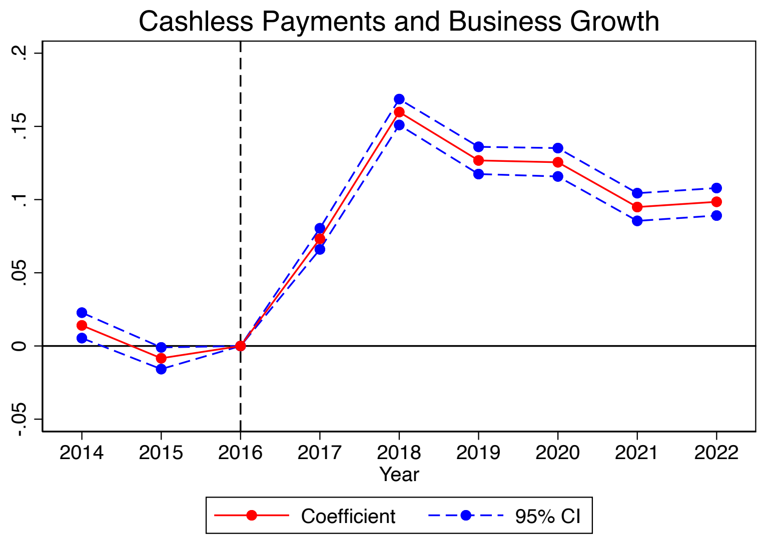


Figure 2 shows a remarkable increase in the number of new businesses started by households in the high intensity districts. Before 2016, districts followed a parallel trend. We find a similar pattern for the level of business income reported by these households, hence we do not present it for brevity. Overall, our results show that while districts with varying intensity of cashless payments had similar trend in business growth in the pre-2016 period, those with higher digital payments saw a remarkable increase in business creation.

We present the difference-in-difference regression results with business creation and business income as dependent variables in Table 3. The dependent variable in Columns (1) and (2) is a binary variable that equals one if a household owns business, zero otherwise. Therefore, the regression coefficient represents change in probability of starting a business by a household in a high cashless intensity district after the shock compared to before the shock, compared to the corresponding effect for low intensity districts. Households residing in the highest percentile district have 8.79% higher probability of starting a business compared to the lowest percentile district households. The effect becomes stronger when we separate out the effect of urban versus rural districts. Columns (3) and (4) use log of one plus business income as the dependent variable. We add one to the business income to include households who have zero business income in our estimation. As shown in the Table, business incomes is substantially higher in high intensity districts. Together, these results show that the increase in digital payments had an impact on both the extensive margin, i.e., the probability of starting a business, and the intensive margin, i.e., the level of income that a household earns from business activities.

Table 3: Business Creation and Business Income

Table 3 presents the regression estimate of the regression model in equation 2. The model is estimated with household-year level observations. The dependent variable is either a binary variable indicating whether the household owns a business or not, or the log of one plus average monthly business income of a household in a given year. Cashless Intensity measures the percentile ranking of a district based on their digital payment amount per person. All standard errors are clustered at the household level.

	(1) Owns Bus	(2) Owns Bus	(3) Bus Inc	(4) Bus Inc
Post X Cashless Intensity	0.0879***	0.1108***	0.8688***	1.0905***
	(0.0037)	(0.0037)	(0.0342)	(0.0341)
Post X Urban Districts		-0.1058***		-1.0244***
		(0.0023)		(0.0211)
Household Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Nobs	1,426,159	1,426,159	1,426,159	1,426,159
Adjusted R-squared	0.388	0.391	0.419	0.423
Number of Households	209,118	209,118	209,118	209,118

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

5.1 Within-district-year variation

Our empirical design in the baseline model already accounts for district-specific time-invariant characteristics and macroeconomic effects that may impact economic outcomes across the country. The main threat to our difference-in-difference identification strategy comes from the concern that districts with higher intensity of digital payments experience an unobserved shock that correlates positively both with the adoption of cashless payments and economic growth. A potential such channel could be large government spending or program in certain districts that improves its overall economic condition.

We now exploit variation across different types of households within the same district to address this concern. Motivated by the economic channel that connects digital payments to growth, our identification strategy rests on the assumption that the benefit of digital payments accrue at a disproportionately higher rate to entrepreneurs and self-employed households compared to other categories such as salaried households within the same district in the same year. Entrepreneurs and self-employed households earn their income through small businesses, often in informal economy. Digital payments benefit such businesses on counts of both the key economic channels we have in mind: (a) lower transaction costs help them with higher volume of business transactions, and (b) better information availability via digital transactions improves their access to external financing.

Our empirical setting is especially powerful because these households often have very limited access to financing from traditional institutions. On the other hand, in recent years there has been significant growth in Fintech companies that use information contained in digital payments to lend to these small borrowers. FinTech companies use a variety of tools of expand access to credit for such households. Our discussion with some of the industry leaders suggest at least three such potential channels: (a) improvement in information availability due to digital footprints, (b) the ability to tailor a borrower's repayment schedule based on the pattern of their cashflows, and (c) enhanced ability to collect the repayments. For examples, some FinTech lenders are able to obtain their repayments from small shopkeepers by directly accessing their payments through the digital platform. In addition, some small business owners prefer a tailored repayment contract. Collectively, these channels improve a borrower's access to financing, which in turn with their ability to start or expand their business.

The richness of our data allows us to estimate the effect of cashless intensity across these households while including district-year fixed effects in the model. The inclusion of district-year fixed effects soak away time-varying unobserved variation across districts. Our model is as follows:

$$
\begin{aligned}
y_{i,d,t} \;=\;& h_i + y_t + I_{d,t} + \beta \times Post_t \times SE_{i,t} + \theta \times Post_t \times CashlessIntensity_i + \\
& \gamma \times Post_t \times CashlessIntensity_i \times SE_{i,t} + \epsilon_{i,d,t}
\end{aligned} \tag{3}
$$

$y_{i,d,t}$ measures the log income of household i in district d in year t. $SE_{i,t}$ equals one for self-employed households, based on the occupation of the head of household in year t. There are several occupation categories in the CHPS dataset. We consider the following categories of occupation as self-employed: Entrepreneurs, Self-employed Entrepreneurs, Self-employed Professionals, Small Traders/Hawkers, Organized Farmers, and Small/Marginal Farmers. In later specifications, we separate out the first four categories from the later two between "entrepreneurs" and "farmers". Our results remain similar. We consider farmers in the self-employed group since most farmers in India are entrepreneurs who are likely to benefit from higher access to credit due to digital payment adoption in the same manner as those who explicitly identify themselves as entrepreneurs. All other occupation categories form the control group. These categories include white-collar salaried household, wage earners, workers, and retired household. $I_{d,t}$ are the district-year fixed effects.

Results are presented in Table 4. Columns (1) and (2) of the Table presents the results for the entire sample, where "entrepreneurs" and "farmers" are treated as self-employed and all other occupation categories are in the control group. The triple-interaction term γ measures the differential effect of cashless payments on income for the self-employed group compared to the rest of the households. We find a statistically significant 3.92%-4.09% higher earnings for self-employed households if they happen to be in the highest percentile digital payment district. In Columns (3) and (4) we change the definition of self-employed households and restrict the control group to only salaried and retired households. In Column (3), only entrepreneurs are defined as self-employed, whereas in Column (4) only the farmers are. Our results remain similar. Finally, in Column (5), we compare the group of small traders and hawkers to the salaried and retired households. Hawkers experienced a significantly higher income in high digital payments districts after the shock. Overall, we find that the effect of digital payments on income is significantly higher for the group of households who are likely to benefit more from better business opportunities that arises from the reduction in transactions costs and alleviation of financial constraints due to digital payments.

Table 4: Effects For Self-Employed Households

Table 4 presents the regression estimate of the regression model in equation 3. The model is estimated with household-year level observations. The dependent variable is the log of average monthly income of a household in a given year. Cashless Intensity measures the percentile ranking of a district based on their digital payment amount per person. All models include district-year fixed effects. All standard errors are clustered at the household level.

	(1) Income	(2) Income	(3) Income	(4) Income	(5) Income
Self-Employed	0.0040	0.0061	-0.1165***	-0.2359***	-0.1674***
	(0.0042)	(0.0042)	(0.0065)	(0.0121)	(0.0132)
Self-Employed X Cashless Intensity	0.0006	0.0014	0.0339***	0.1320***	-0.0225
	(0.0064)	(0.0064)	(0.0095)	(0.0182)	(0.0195)
Post X Self-employed	-0.0169***	-0.0201***	0.0185***	0.0531***	0.0476***
	(0.0046)	(0.0046)	(0.0067)	(0.0109)	(0.0135)
Post X Cashless Intensity X Self-employed	0.0409***	0.0392***	0.0341***	0.0571***	0.0541***
	(0.0069)	(0.0069)	(0.0099)	(0.0163)	(0.0204)
Post X Urban Districts		-0.0455***	-0.0315***	-0.0000	-0.0110
		(0.0028)	(0.0055)	(0.0060)	(0.0076)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Self-Employed	Ent+Farmer	Ent+Farmer	Ent	Farmer	Hawkers
Comparison Group	All	All	Salaried/Rtd	Salaried/Rtd	Salaried/Rtd
Nobs	1,409,330	1,409,330	737,900	562,293	420,549
Adjusted R-squared	0.698	0.698	0.721	0.699	0.751
Number of Households	192,882	192,882	138,864	121,862	99,170

standard error in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

We now tease out the underlying economic channel behind our results.

5.2 Financial Development

The benefit of a mobile-based digital payment system should be especially high in districts where physical bank branches are scarce. In these areas, both the transaction costs of payments and the borrowing frictions are likely to be higher. We sort districts into percentiles based on the number of bank branches on a per capita basis, and create a variable "LowFinPctl" that measures one minus the percentile ranking. In other words, "LowFinPctl" measures lower financial development. We also use a binary variable "LowFin" that equals one if a district falls in the bottom 33-percentile of the financial development measure. With these definitions are financial development, we estimate the following regression model:

$$\begin{aligned} y_{i,t} \;\; = \;\; & h_i + y_t + \beta \times Post_t \times CashlessIntensity_i + \theta \times Post_t \times LowFinPctl_i + \\ & \gamma \times Post_t \times CashlessIntensity_i \times LowFinPctl_i + \epsilon_{i,t} \end{aligned} \quad (4)$$

The coefficient on the triple interaction term, γ, measures the incremental effect of digital payments on districts with lower financial development. Table 5 presents the results. Column (1) and (3) use the log of household income as the dependent variable. Across both specifications, we find a positive and significant coefficient on the triple interaction term. In other words, the impact of digital payment on household income comes predominantly from financially less developed districts. Columns (2) and (4) estimate the corresponding models for the probability of owing a business. Again the effects are concentrated in districts with lower financial development. We obtain similar results for business income, as documented in Columns (3) and (6) of the Table.

The level of financial development affects both the transactions cost of payments, for example by increasing the distance between an average household and a bank branch, and the access to credit. We supplement this analysis by estimating the effect of digital transaction on economic growth across districts with varying level of crime. Areas with higher level of

Table 5: Effects Across Financial Development Measures

Table 5 presents the regression estimate of the regression model in equation 4. The model is estimated with household-year level observations. The dependent variable is log of income in Columns (1) and (4), a binary variable indicating whether the household owns a business or not in Columns (2) and (5), or the log of one plus average monthly business income in Columns (3) and (6). Cashless Intensity measures the percentile ranking of a district based on their digital payment amount per person. All standard errors are clustered at the household level.

	(1) Income	(2) Owns Bus	(3) Bus Inc	(4) Income	(5) Owns Bus	(6) Bus Inc
Post X Cashless Intensity	-0.011	-0.042***	-0.329***	-0.001	0.064***	0.658***
	(0.009)	(0.007)	(0.067)	(0.005)	(0.004)	(0.041)
Post X LowFinPctl	-0.085***	-0.246***	-2.279***			
	(0.011)	(0.009)	(0.082)			
Post X Cashless Intensity X LowFinPctl	0.032*	0.320***	2.967***			
	(0.017)	(0.014)	(0.132)			
Post X Urban Districts	-0.053***	-0.105***	-1.013***	-0.051***	-0.105***	-1.016***
	(0.003)	(0.002)	(0.021)	(0.003)	(0.002)	(0.021)
Post X LowFin				-0.066***	-0.117***	-1.075***
				(0.006)	(0.005)	(0.049)
Post X Cashless Intensity X LowFin				0.092***	0.139***	1.255***
				(0.013)	(0.011)	(0.097)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	1,390,244	1,390,851	1,390,851	1,390,244	1,390,851	1,390,851
Adjusted R-squared	0.651	0.395	0.426	0.651	0.395	0.426
Number of Households	204,302	204,322	204,322	204,302	204,322	204,322

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

crime should likely have higher transaction cost for cash-based business. A move towards digital payments can alleviate the risk of theft and robbery, and allow small businesses to grow. Results are provided in Table 6. The model includes the triple-interaction term of $Post$, $Cashless$ and $HighCrime$, measured as the log of total crime per capita in the district. We find that the effect of digital payments on economic outcome is significantly higher for households who reside in relatively higher crime districts.

Table 6: Crime Rates and Effect of Cashless Payment

Table 6 presents the regression estimate of the regression model in equation 4 augmented with an interaction term between $Post$ and $HighCrime$. The model is estimated with household-year level observations. The dependent variable is log of household income, either a binary variable indicating whether the household owns a business or not, or the log of one plus average monthly business income of a household in a given year. Cashless Intensity measures the percentile ranking of a district based on their digital payment amount per person. All standard errors are clustered at the household level.

	(1) Income	(2) Owns Bus	(3) Bus Inc
Post X Cashless Intensity	-0.1960***	-0.1828***	-1.8519***
	(0.0182)	(0.0153)	(0.1421)
Post X HighCrime	0.0139**	0.0416***	0.4075***
	(0.0058)	(0.0050)	(0.0458)
Post X Cashless Intensity X HighCrime	0.0532***	0.0256***	0.2984***
	(0.0075)	(0.0066)	(0.0609)
Post X LowFinPctl	-0.1193***	-0.2620***	-2.4705***
	(0.0116)	(0.0098)	(0.0902)
Post X Cashless Intensity X LowFinPctl	0.1535***	0.4157***	3.9992***
	(0.0198)	(0.0165)	(0.1529)
Post X Urban Districts	-0.0530***	-0.1059***	-1.0243***
	(0.0028)	(0.0023)	(0.0212)
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Nobs	1,390,244	1,390,851	1,390,851
Adjusted R-squared	0.652	0.396	0.428
Number of Households	204,302	204,322	204,322

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

5.3 Borrowing Constraints

In our final analysis, we analyze whether households have better access to credit in districts with high digital payments. Our database allows us to observe both the source and the use of borrowing. In our first model, we use as dependent variable whether the household has borrowed from any source for any use during the year or not. The regression results are documented under Column (1) of Table 7. Households in high digital payment intensity districts are significantly more likely to borrow than others. A household residing in the highest percentile district has a 1.66% higher probability of obtaining borrowings. Column (2) only focuses on borrowings from banks, and the corresponding estimate is an even higher 3.64%. Finally, consistent with our earlier findings, the borrowing for business purposes are higher by 3.17% in these districts.

Table 7: Borrowings and Cashless Payments

Table 7 presents the regression estimate of the regression model in equation 2. The model is estimated with household-year level observations. The dependent variable is a binary variable indicating whether the households has borrowings outstanding, whether the household has a bank borrowing outstanding, or whether the household borrowed for business purposes. Cashless Intensity measures the percentile ranking of a district based on their digital payment amount per person. All standard errors are clustered at the household level.

	(1) All	(2) Bank	(3) Business
Post X Cashless Intensity	0.0166***	0.0364***	0.0317***
	(0.0038)	(0.0025)	(0.0015)
Post X Urban Districts	-0.0404***	-0.0313***	-0.0265***
	(0.0023)	(0.0016)	(0.0011)
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Y-Variable	1,398,696	1,398,696	1,398,696
Nobs	0.336	0.208	0.232
Adjusted R-squared	209,027	209,027	209,027

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Our earlier findings show that our main effect is stronger in districts with relatively lower levels of financial development. We now estimate whether the extent of borrowing also increases in such districts. Results are provided in Table 8. Consistent with our earlier results that document stronger effects of digital payment on economic growth in financially less developed districts, we find that the level of borrowing increases in these districts as well. Overall, these findings support the view that a relaxation in credit constraint drives the relation between digital payment adoption and economic growth.

Table 8: Borrowing Across Financial Development

Table 8 presents the regression estimate of the regression model in equation 2. The model is estimated with household-year level observations. The dependent variable is a binary variable indicating whether the household has a bank borrowing outstanding, or whether the household borrowed for business purposes. Cashless Intensity measures the percentile ranking of a district based on their digital payment amount per person. All standard errors are clustered at the household level.

	(1) Bank	(2) Business	(3) Bank	(4) Business
Post X Cashless Intensity	-0.0668***	-0.0055	-0.0040	0.0235***
	(0.0057)	(0.0034)	(0.0033)	(0.0020)
Post X LowFinPctl	-0.1491***	-0.0327***		
	(0.0064)	(0.0039)		
Post X Cashless Intensity X LowFinPctl	0.1929***	0.1406***		
	(0.0098)	(0.0062)		
Post X Urban Districts	-0.0347***	-0.0249***	-0.0343***	-0.0260***
	(0.0016)	(0.0011)	(0.0016)	(0.0011)
Post X LowFin			-0.0793***	-0.0341***
			(0.0032)	(0.0021)
Post X Cashless Intensity X LowFin			0.1254***	0.1089***
			(0.0065)	(0.0049)
Household Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Nobs	1,364,370	1,364,370	1,364,370	1,364,370
Adjusted R-squared	0.211	0.235	0.211	0.234
Number of Households	204,231	204,231	204,231	204,231

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

6 Conclusion

We document strong evidence in support of a positive impact of digital payments on economic growth as measured by household income and business activities. Our empirical setting from India is especially attractive since the country has become one of the leading economies of the world in adopting digital payments at mass scale. Further, we study the economic outcomes at the household level. Since these economic agents face significant frictions in accessing traditional credit markets and payment systems, the adoption of digital payments is especially valuable to them. Our findings that self-employed households benefit more from the adoption of cashless payments and they are able to do so in financially underdeveloped districts show that digital payments can be an important driver of economic growth.

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Appendices

A Data Variables

Variable	Data Source	Variable Construction
Household income	CMIE	`Total_Income` from the CMIE Income Pyramids which records total income reported by a household in Indian Rupees
Owns Business	CMIE	`Income_Of_Household_From_Business_Profit` from the CMIE Income Pyramids. We construct a binary variable which is 1 if a household reports business income and 0 otherwise
Business income	CMIE	`Income_Of_Household_From_Business_Profit` from the CMIE Income Pyramids. It reports the total business income reported by a household in Indian Rupees
Cashless intensity	PhonePe, WKS	We first use the amount of cashless transactions in a district in a year provided by PhonePe and divide it by the population estimate of that district as provided by WKS. We then estimate the percentile ranking of this value to arrive at cashless intensity of a district in a year
Post		This is a binary variable which is 1 for all years after 2016 and is 0 for all years before and including 2016. Since UPI was launched in India in the third quarter of 2016, this variable helps to record the nationwide shock to cashless payments
PostCovid		This is a binary variable which is 1 for all years after and including 2020 and is 0 for all years before 2020. Since India saw its first pandemic lockdown in the first quarter of 2020, this variable helps to record the COVID-19 pandemic shock
Urban District	CMIE	We use the indicator `Region_Type` from the CMIE database and construct this binary variable which is 1 for all urban districts and is 0 for all rural districts
SE	CMIE	SE refers to 'Self-employed'. We use the indicator `Nature_Of_Occupation` from the CMIE Income Pyramids and construct this binary variable which is 1 if occupation is reported as Entrepreneurs, Self-employed Entrepreneurs, Self-employed Professionals, Small Traders/Hawkers, Organized Farmers, and Small/Marginal Farmers and is 0 otherwise
LowFinPctl	RBI, WKS	We use district-level bank branches data provided by the Reserve Bank of India (RBI) for December 2016 and district-level India population estimates provided by WKS. We construct this variable by dividing number of bank branches in a district by its population, estimating its percentile rank, or `Dist_FinDev_Percentile` and finally arriving at LowFinPctl = 1 - `Dist_FinDev_Percentile`, a measure of low financial development in a district

Note: WKS refers to India district-level population estimates provided by Wang et al. (2021) for the year 2020

Variable	Data Source	Variable Construction
LowFin	RBI, WKS	This is a binary variable which is 1 if a district falls in bottom 33 percentile of `Dist_FinDev_Percentile` calculated above, and 0 otherwise
HighCrime	NCRB, WKS	We use crime data provided by the National Crime Records Bureau (NCRB) and estimate the total number of violent and economic crimes reported in all districts in 2016. We then divide total number of crimes in a district by its population estimate, as provided by WKS, and multiply it with $10,000$ to arrive at the total number of crimes reported per ten thousand people in a district. We use the log of this value to construct our HighCrime variable
Bank Borrowing Outstanding	CMIE	`Has_Outstanding_Borrowing` from CMIE's Aspirational dataset. It is a binary variable which is 1 if a household has an outstanding borrowing and is 0 otherwise
Borrowing for Business	CMIE	`Borrowed_For_Business` from CMIE's Aspirational dataset. It is a binary variable which is 1 if a household has an outstanding borrowing for business and is 0 otherwise

Note: WKS refers to India district-level population estimates provided by Wang et al. (2021) for the year 2020

Figure 3: Growth in Digital Transactions on the UPI Platform

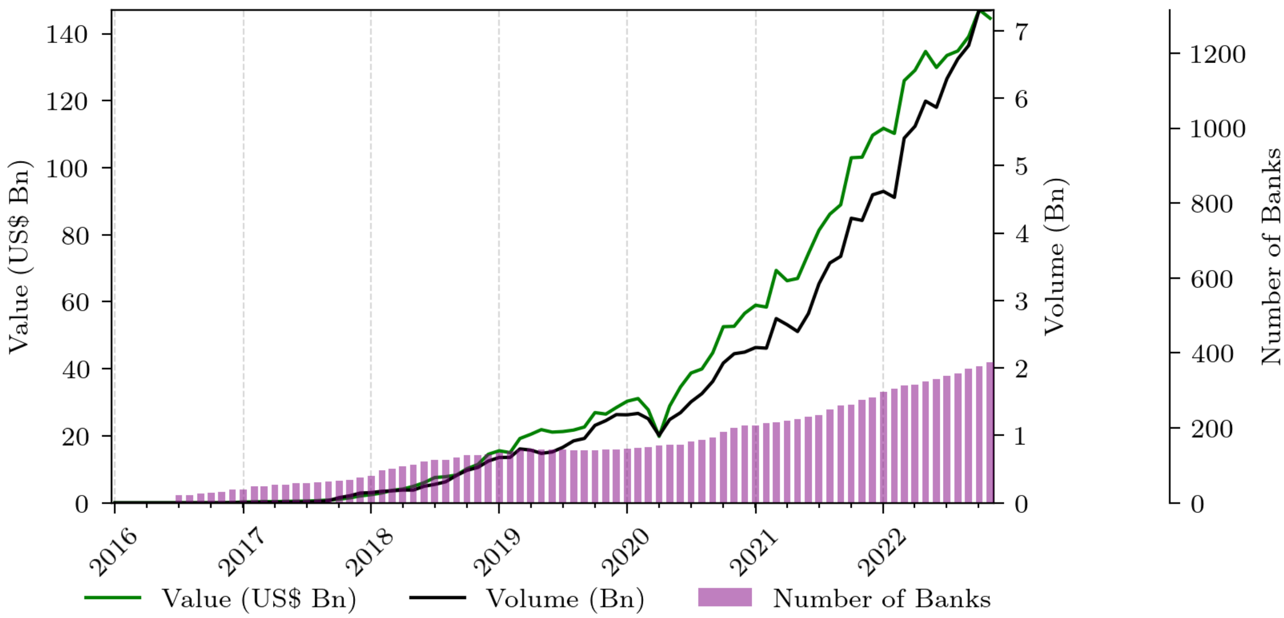
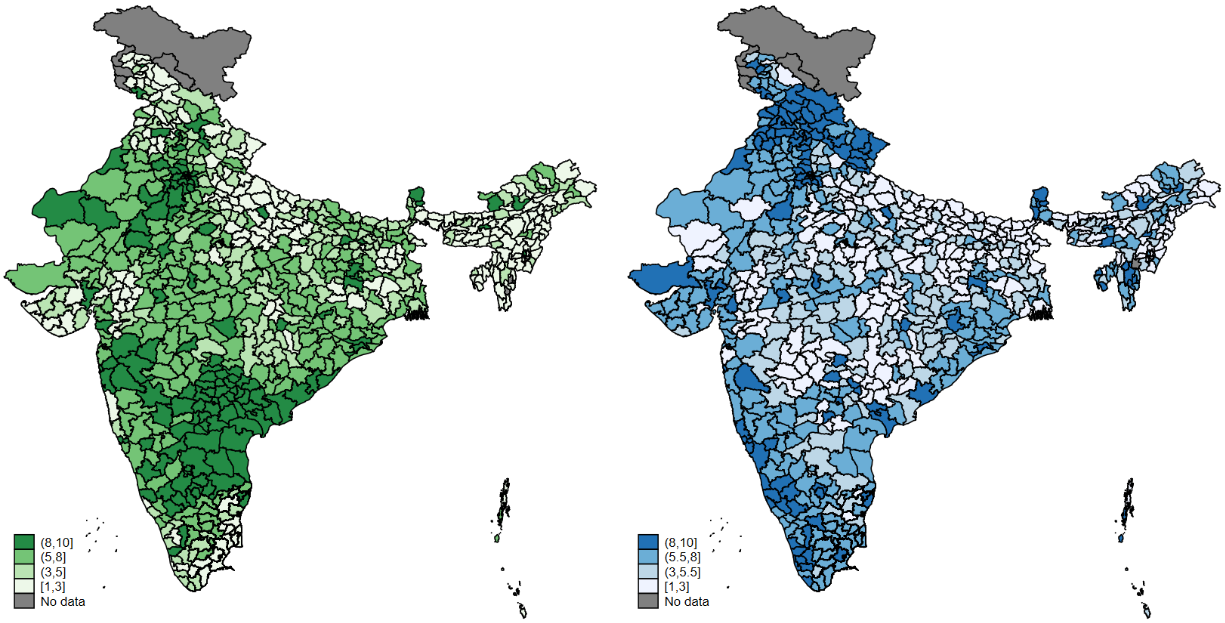


Figure 4: District-level Intensities



(a) Digital Payments Intensity **(b)** Financial Development Intensity