Can Cashless Payments Spur Economic Growth?*

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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 economic outcomes, as measured by household income and small business activities, increased significantly in districts with higher intensity of cashless transactions. These effects are stronger for marginal households and financially less developed regions of the country. We achieve identification using two complementary empirical strategies. We first exploit the differences in the timing of participation on the UPI platform by different banks to obtain a quasi-random variation in the level of digital payments across districts. Second, we exploit 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. 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

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1 Introduction

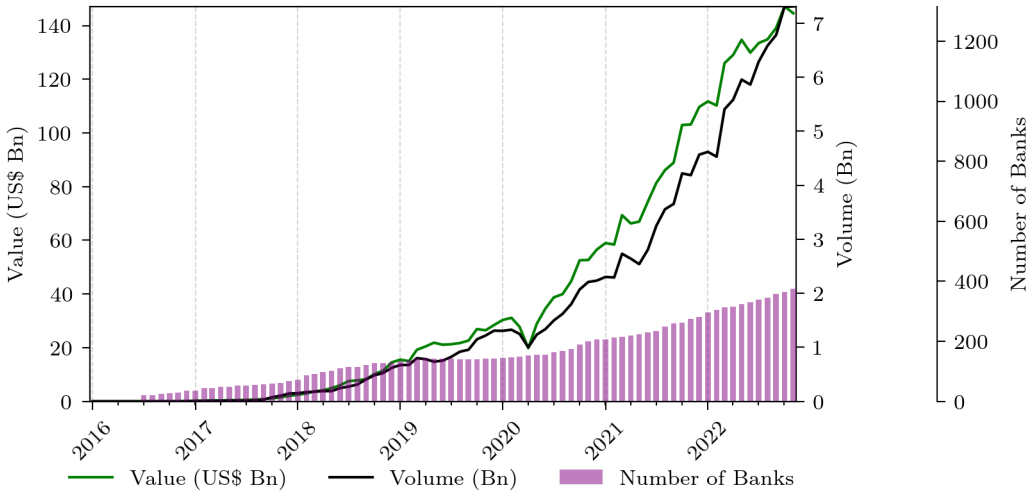
Can the means of payments affect economic growth? While the debate on whether monetary variables, such as cash, can affect economic outcomes is not new (Lucas and Stokey, 1987; Woodford, 2003), recent technological advancements in cashless payments has reinvigorated this debate. In a frictionless economy, 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. First, the economic magnitude of the adoption is large. 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. Second, the extent of cashless transactions in the early years varied greatly across districts depending on a host of factors, including whether the main public sector bank in the district was an early adopter of the UPI platform or not. We exploit these differences to estimate a causal effect. Finally, we are able to obtain a very high-frequency and granular household level panel data, which allows us to measure economic outcomes at a micro-level. The richness of our data facilitates a causal analysis. In

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

particular, we exploit variations in the benefits of 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.

Figure 1: Growth in Digital Transactions on the UPI Platform



Source: National Payments Council of India (NPCI)

Figure 1 shows the evolution of digital payments on the UPI platform over time on a monthly basis since its launch in late 2016. Average monthly volume of digital transactions increased rapidly from a level of less than $1 billion in early 2017 to almost $150 billion by the end of 2022. In the early months of its launch, less than 30 banks joined the platform, allowing their customers to use the UPI by linking their bank accounts to the UPI mobile Apps. The number of participating banks increased steadily over time, covering practically the entire banking sector by the end of 2022. Three 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 central government launched a universal banking program in 2014, called the Pradhan Mantri JanDhan Yojna (JDY), to provide a bank account to

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

every household in the country (Agarwal, Alok, Ghosh, Ghosh, Piskorski, and Seru, 2017; Chopra, Prabhala, and Tantri, 2017). Third, 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.

Our empirical work is motivated by 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 can be especially high in areas with lower availability of formal financial institutions. 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).

[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-inclusion.htm

We use a panel data covering 200,000 unique households spread across over 500 districts in India from 2014 to 2022 for our empirical work.[4] Our dataset has information on their overall income, income from business activities, credit market outcomes, and a host of characteristics such as their occupation and whether they reside in a rural or urban area. Our focus on household level outcomes is especially suited for the task at hand since the mass adoption of digital payments is more likely to alleviate the transaction cost and credit constraint frictions for these households and small businesses operated by them. 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. We measure the extent of digital payments in a district by the volume of transactions reported by PhonePe, the leading provider of UPI App in the country, on a district-quarter level. The UPI payments data starts in 2018, i.e., a year after the launch of UPI, when the transaction volume started to become significant.

In our first analysis, we relate the extent of digital payments in a district in a year to the next year's economic outcome of the households living in that district. Since our model includes household and year fixed effects, our estimates are not contaminated by time-specific shocks to the aggregate economy, or time-invariant district and household characteristics. We show that the level of digital payments forecasts next year's economic outcome in an economically and statistically significant manner. The elasticity of income to digital payments is 0.06. In terms of business activities, districts with twice the level of digital payment have 0.8% higher number of households engaged in business activities, which is economically large since only 22% of households in our sample are engaged in business activities. In line with these findings, the level of income from business activities increased considerably for households residing in high digital payment districts. Consistent with the idea that digital payments can alleviate frictions generated by the lack of access to brick-and-mortar banks,

[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.

we find that our effects are stronger for districts with fewer bank branches on a per capita basis. In terms of credit outcomes, we find that a significantly higher fraction of households borrow for business purposes in the year following an increase in digital payments in their district. Their overall borrowing goes up, but the borrowing from formal sources such as banks increase even more.

Our base case specification shows that the level of digital payments affect next year's economic outcome. Our results, therefore, are less susceptible to unobserved shocks that affect the adoption of digital payments and economic outcomes at the same time. Yet, there can be endogeneity concerns that can arise from a correlation between digital payment adoption and expectations of future economic outcome in an area. In general, the key threat to our identification comes from time-varying changes in unobserved factors that might affect the adoption of digital payments and economic growth in a district. We use two complementary identification strategies to establish a causal link from digital payments to economic outcome.

Our first empirical strategy exploits the difference in the timing of participation on the UPI platform by different banks, and its impact on the adoption of digital payments by consumers who reside in different districts of the country. To use the UPI system, a customer needs to link her bank account to an UPI App that can be provided by either the same bank or third parties. Therefore, whether a customer's bank participates in the UPI platform or not becomes a key driver of her willingness and ability to begin using digital payments. While practically the entire banking sector has joined the platform by now, in the initial months of the UPI's launch less than 30 banks participated on the platform. Consequently, the UPI adoption rate across districts varied by the timing of a bank's participation on the platform and the presence of the bank in a given district. We exploit an institutional setting that provides quasi-random variation in the bank's presence across districts to achieve a causal link between digital payments and economic outcomes.

The Government of India nationalized all the large private sector banks of the country in

two waves of nationalization in 1969 and 1980. Soon after the first wave of nationalization in 1969, the Reserve Bank of India (RBI) established a system of "lead bank", under which every district in the country was assigned a government owned bank as its main bank. The lead bank was primarily responsible for expanding access to financial services to underserved communities, especially in rural and semi-urban areas. While there have been several tweaks to the initial structure of the lead bank system over the decades, the basic structure has remained intact. Every district in the country still has a government owned lead bank. Due to a long historical nature of this system, the lead bank remains a dominant source of banking infrastructure in the district, especially in rural and semi-urban areas.

At the time of the launch of the UPI in August, 2016, 29 banks had indicated their interests in joining the platform. 21 of these banks joined the platform immediately, and the rest of them did so by the end of November, 2016. Within the set of government owned bank, some large banks were notably missing from this list, creating a significant hurdle for their customer's desire to switch to digital payments. We divide districts into two categories based on whether their lead bank was an early or a late adopter of the UPI, i.e., whether it was part of the first set of 29 banks or not.[5] The late adopter banks joined the platform by May, 2017. Since the adoption of digital payments rely heavily on the network effects of its users, a delay of 6-9 months can have a large impact on the use of cashless payments even in normal times. But, the month of November, 2016 has a special significance in the history of India's monetary policy. During the early part of this month, the country went through an unexpected demonetization shock, making the availability of digital means of payments especially valuable. While the customers of the early adopter banks could easily switch to digital payments, those of the late adopter banks could not, leaving a long lasting difference in the adoption of digital payments across these districts. The combination of the

[5]The late adopter lead banks are: Indian Bank, Indian Overseas Bank, Bank of India, Syndicate Bank, Corporation Bank, and Dena Bank. The early adopter lead banks are: Andhra Bank, Bank of Maharashtra, Canara Bank, Punjab National Bank, United Bank of India, UCO Bank, Union Bank of India, Vijaya Bank, Oriental Bank of Commerce, Allahabad Bank, State Bank of India, Bank of Baroda, and Central Bank of India.

difference in the timing of adoption, the history of the lead bank system in the country, and the occurrence of demonetization shock during this period present us with a quasi-exogenous variation in the adoption of digital payments across different districts of the country.

We create a matched sample of early and late adopter districts that are in the same state, have similar bank branch penetration in 2016, and have similar literacy rate as per the last census. Therefore, we obtain two sets of very similar districts that differ in terms of their lead bank's participation on the UPI system. We show that the usage of digital payments was almost 25% higher in the early adopter districts in 2018 and 2019, compared to late adopters.

We employ a standard difference-in-differences empirical design to compare economic outcomes for households who live in the early versus late adopter districts. We consider economic outcomes from three years before the UPI's launch to three years after launch (i.e., 2014 to 2019) for these households.[6] Both the groups exhibit parallel trend in their income before the UPI shock, but households in the early adopter district have 5.8% higher income in the post-UPI period. These households have 1.45% higher level of business ownership and 19% higher business income in the post-UPI period in the difference-in-difference specification.

Our specifications include fixed effects for $state \times year$ to alleviate concerns for time-varying state level policies from impacting our results. We also include fixed effects for the interaction between calander year and an indicator for whether the household lives in an urban or a rural area to soak away the differential effect of government policies that target rural areas. Finally, we obtain a measure of district-level demonetization shock from the study by Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020). We include fixed effects for the interaction between calender year and the level of demonetization shock to soak away the potential differential impact of demonetization shock on economic outcomes across districts.

Our second identification strategy relies on a different assumption, and in turn, provides some novel economic insights. We exploit differences across households within a district-year

[6]We take 2017 as the first year after the UPI's launch since the platform was rolled out at a large scale in the later part of 2016.

to soak away time-varying differences across districts. Specifically, we estimate the differential effect of digital payments on outcomes for self-employed versus other households. The key idea behind our identification strategy is that the self-employed households are more likely to benefit from the adoption of digital payments as it allows 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.

In a supplementary test, we focus exclusively on a smaller set of self-employed households: 'street vendors and hawkers'. This category of self-employed households often operate with little-to-no collateral, and therefore face large credit constraints. We show that this group of entrepreneurs experience a significant increase in income compared to the other self-employed households as the level of digital payments increase. Consistent with the relaxation of credit constraints for marginal agents of the economy, we document a significant increase in borrowing for business purposes by hawkers and small traders in areas with higher levels of digital payments. The richness of our dataset allows us to carefully pin down the sources of borrowing. We find that these marginal borrowers increase their borrowing from banks and other non-bank formal credit institutions, whereas they significantly decrease their borrowing from informal sources such as money lenders and family and friends.

Our main results are based on the panel of household survey by the CMIE. One may be concerned about some noise in our data, as is typical in most household panel survey data of this nature. Our empirical strategy, especially the one with a difference-in-differences design across early and late adopter districts, is unlikely to be affected by these concerns since these variations are unlikely to be correlated with the identity of lead banks in a district, and even less so in a time-varying manner. Another concern about our study could arise due to

a "reporting" bias. If digital payment adoption makes households more likely to accurately report their income, then our empirical design presents no challenge. Some households are likely to underreport in the absence of digital information, whereas some overreport, making it unlikely to affect our main results. However, if households in lower digital payment districts systematically underreport their income to avoid taxes, then a part of our effect can be attributed to the underreporting bias. Our collective findings make this channel unlikely to explain all our results since there is no incentive to underreport credit outcomes or the source of credit for tax-avoidance reasons. Further, our results show that marginal entrepreneurs exhibit higher income after the adoption of digital payments. In our sample, most of these households are below the tax exemption limit of annual income in India, which provides very little incentive to distort income reporting in a systematic manner. Yet, to address the issue more directly, we use the district-quarter level data on the amount of credit extended by all commercial banks in the country that the RBI reports on a quarterly basis. In a panel regression with district and quarter fixed effects, we show that the level of credit increases in a district in the year following an increase in digital payments. Since credit creation is correlated with economic growth, the finding helps us rule out the reporting bias channel.

In sum, we show that digital payments impact real economic outcomes, especially for marginal households and for households who live in financially less developed districts. The relaxation of credit constraints is a key mechanism behind our findings. 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 one of the first to tease out a causal link between digital means of payment and real activities at a national level. Our work complements the body of work on mobile money, most notably on M-Pesa in Kenya, that are used predominantly for remittances. Our work is of independent interest not only due to our focus on a different economy, but also due to some key differences in the operations of mobile money (M-Pesa) and a pure digital payments system (the UPI). These differences allow us to uncover the effect of means of payments on economic outcomes that is independent of the effect that

arise due to better access to a storage of value technology or the dependence on an agent based network that the mobile money relies on. We discuss these differences in detail in the literature review section.

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 several strands of literature in economics and finance. It 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 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.

Our work relates to an important literature on mobile money, most notably on M-Pesa in Kenya.[7] Jack and Suri (2014) show that the use of M-Pesa in Kenya allows households to smooth their consumption since they are able to receive payments through remittances from a wider network of family and friends. Further, Suri and Jack (2016) show that the use of M-Pesa improved the allocation of consumption and labor in the economy, which in turn resulted in a reduction in poverty. While there are several similarities between our setting and mobile money such as M-Pesa, there are fundamental differences across the two systems. The mobile money sits outside the banking system since the accounts are only linked to a phone number, and not to a bank account or credit card (Suri, 2017). Therefore, a consumer needs to store her money with the mobile company as she begins to use the system. As a result, mobile money combines means of payments and store of value, unlike the digital payment system such as UPI that is purely a means of payment system.

Related, the availability of mobile money in Kenya effectively provided previously unbanked population to banking services as they could deposit and withdraw cash using the mobile money system. Therefore, it is hard to separate financial inclusion effect from means of payments effect using the setting of M-Pesa. In addition, mobile money system such as M-Pesa works as an agent-based model, i.e., the consumer need to have access to a network of mobile phone agents to send or receive payments. The UPI system doesn't rely on a network of agents, and therefore it does not face any trust, agency, information, or transaction cost frictions that an agent based system can create. Though not exclusively, a mobile money system is predominantly a person-to-person system, where people receive remittances from their family and friends, whereas the UPI system covers both peer-to-peer transfers and person-to-merchant transfers. The distinction is economically important as it allows the creation of new businesses at a much lower transaction cost under the UPI system. In sum,

[7]See Suri (2017) provides an excellent survey of this literature.

while our study complements the literature on M-Pesa, our exercise provides a relatively cleaner setting to tease out the effect of cashless means of payments that is independent of the implications of changes in the store of value, availability of an agent network, or remittances from family and friends.

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 et al. (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.[8]

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 of nationally representative sample of over 170,000 households three times a year.[9] 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.[10] We scale the number of branches per district by its population to arrive at our measure of financial development across the country.

Descriptive Statistics: As shown earlier in the paper, Figure 1 presents a graphical summary of the evolution of digital payments in the country since 2016. 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

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

[9]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.

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

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 ₹4,900 (∼US$60). For our outcome variables from the CPHS 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. Depending on the specific test, we use different parts of this broad sample. 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'. 22.85% of households in our sample own business on average. Their monthly business income is slightly below ₹4,000 (∼US$50).

Table 1: Summary Statistics

Table 1 presents the descriptive statistics of key variables used in the analysis. Cashless Transaction (bil.) measures the average annual value of UPI transaction over the 2018-2022 period in billions of Indian Rupee. Cashless Transaction per Person measures the average quarterly value of digital payment transaction in a district. These variables are available only from 2018. Remaining variables are computed based on the entire sample of the CMIE data, i.e., over 2014-2022. Monthly Income and Monthly Business Income are computed at the household level, and are reported in local currency (Indian Rupee). Further details on variable construction are provided in the Appendix.

Full Sample

	Mean	SD	P25	P50	P75	N
Cashless Transaction (bil.)	20.36	65.21	1.05	3.93	13.21	798,046
Cashless Transaction/Person	3411.03	4986.06	1048.59	1853.88	3507.12	798,046
Monthly Income	20104.28	14837.07	10274.04	15520.62	24683.90	1,470,408
Monthly Business Income	3675.05	9282.82	0.00	0.00	0.00	1,470,408
% owns business	22.85	41.98	0.00	0.00	0.00	1,470,408
% with borrowing	30.25	40.94	0.00	0.00	66.67	1,454,362
% with bank borrowing	7.61	22.42	0.00	0.00	0.00	1,454,362
% with borrowing NBFC	1.73	10.74	0.00	0.00	0.00	1,454,362
% with borrowing informal	21.10	35.50	0.00	0.00	33.33	1,454,362
% borrowing for business	3.53	16.36	0.00	0.00	0.00	1,454,362
% entrepreneur	25.05	43.33	0.00	0.00	100.00	1,470,408
% hawkers	3.37	18.04	0.00	0.00	0.00	1,470,408
% farmers	13.16	33.80	0.00	0.00	0.00	1,470,408
% salaried	21.56	41.12	0.00	0.00	0.00	1,470,408

In terms of credit outcomes, 30% of the sample reports some form of borrowing, and 7.61% reports borrowing from a bank. 1.73% of observations have borrowings from the NBFC, i.e., Non-Bank Finance Companies. These are non-bank institutions in the formal lending market. Therefore, only over 9% of borrowers borrow from formal financial institutions in the sample. The remaining 21% of observations fall under the category of informal borrowings. These are borrowings from sources such as money lenders, family and friends, employers, or local businesses. In our empirical analysis, we analyze whether digital payments alter the level as well as the source of borrowings. Our database also has information on the purpose of borrowing. 3.53% of observations has some form of outstanding borrowing 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%). Within the category of entrepreneurs, 3.37% identify themselves as hawker and small traders. These households run businesses such as fruit stalls and street food out of push-carts, roadside stalls, or other similar arrangements. Compared to more established entrepreneurs, they lack formal collateral in the form of a brick-and-mortar shop. They are likely to be relatively more credit constrained and they are likely to face a higher transaction cost friction in accepting payments from their customers in the pre-digital payment economy. 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 to assess the impact of digital payments on economic outcomes across groups with varying degree of benefits from the adoption of digital payments.

5 Empirical Strategy & Results

5.1 Baseline Results

We begin our study by estimating the following panel regression model at the household-year level:

$$y_{i,t} = h_i + year_t + z_{u,t} + \beta \times log(digital)_{i,t-1} + \epsilon_{i,t} \quad (1)$$

$y_{i,t}$ measures three economic outcomes: log of annual household income, whether the household owns a business or not, and log of one plus annual income from business activities. Since several household do not have any business income, we take the log transform of business income after adding one to it. The key explanatory variable is the log of the annual digital payments volume in the district of the household in year $t-1$. Our model include household and year fixed effects. Hence we exploit the within household variation in these outcomes after soaking away the effect of aggregate economic shocks during the sample period. The inclusion of household fixed effects obviates the need for the inclusion of district fixed effects.[11] We also include a set of fixed effects, $z_{u,t}$, by interacting whether the household lives in an urban or rural area with the year dummies. We do so to account for time varying differences in government welfare schemes or COVID-19 shock that can potentially have different implications for these households over time.[12]

Our digital payments data starts in 2018. Therefore, we estimate the above regression model with economic outcomes measured from 2019 to 2022, as we need the first year of data for the construction of the lagged value of digital payments. Our empirical setting estimates the effect of digital payment on next year's economic outcomes. Therefore, our model does not suffer from any bias that my arise due to unobserved shocks to a district that

[11] Further, due to the inclusion of granular household fixed effects that is a unit within the district, our estimates are identical if we use population adjusted measure of digital payments since our population data does not vary over time for a district.

[12] Our results remain similar without the inclusion of $z_{u,t}$.

can simultaneously increase both digital transactions and economic activity. The real threat to our identification strategy in this model comes from any forward-looking, i.e., anticipated positive effects of higher digital transaction in a district in year t on economic outcomes in year $t+1$. We first present the result of this model to establish some baseline results before discussing alternative identification strategies that we employ later in the paper.

Table 2: Cashless Payments and Outcomes: Panel Data

Table 2 presents the regression estimate of equation 1. The model is estimated with district-year level observations. The dependent variable is the log of income in Column (1), whether the household owns a business or not in Column (2), and log of one plus business income in Column (3). Cashless Payment measures the log of the amount of cashless transaction in the previous year. All standard errors are clustered at the household level.

	(1) Income	(2) Owns Business	(3) Business Income
Lagged Cashless Payments	0.0615***	0.0119***	0.1412***
	(0.0025)	(0.0022)	(0.0203)
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Urban x Year Fixed Effects	Yes	Yes	Yes
Nobs	633,313	633,523	633,523
Adjusted R-squared	0.722	0.574	0.606
Number of Households	169,647	169,647	169,647

standard error in parentheses

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

Table 2 presents the regression results. Column (1) provides an elasticity estimate of 0.0615 for the effect of digital transaction on income. The estimate is statistically significant at the 1% level. The estimate is economically important as well: a doubling of digital payment can lead to 4.3% higher income based on these estimates.[13] The interpretation of the economic magnitude has two caveats. Absent a comparable detailed study of economy wide effect of digital payment adoption on household income, we are not in a position to comment on the relative economic magnitude of our estimate compared to other studies.

[13]Since we estimate the regression model in log-log transformed manner, the economic effect of an x% increase in digital payments on income is computed as $((1+x)^{\beta}-1)100\%$.

Second, our estimates come from a transition period as an economy moves from a cash based system to a cashless payment system. In the steady state, the effects are likely to be smaller.

Column (2) presents the estimation results for the ownership of business as the dependent variable. The model estimates the effect of digital payment on the extensive margin of business activities. We find a statistically significant coefficient of 0.0119 on the lagged cashless payment variable. Every one percent increase in digital payment is associated with a 0.0119% higher likelihood of business ownership. Based on these estimate, a doubling of cashless intensity translates into approximately 0.82% higher business ownership in the area. The unconditional mean of business ownership is 22% in our sample. Thus the economic effect is reasonably large: an increase of about 3.6% of the sample mean with a doubling of the digital payment volume.

Column (3) presents the results on the effect of digital payments on the intensive margin of business income. We find a significant increase in business income for households who reside in districts with higher volume of digital payments. The estimated coefficients approximately translates into an economic magnitude of 0.14% higher business income for every 1% increase in digital transaction. Overall, these findings establish our baseline results: digital payment in a district is related to next year's economic outcomes. We now analyze the effect of digital payments on the alleviation of two key economic frictions that motivate our study: transaction cost and credit constraints.

5.1.1 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 as of 2016, and create a variable "LowFinDev" that measures one minus the percentile ranking. In other words, "LowFinDev"

measures lower financial development on the dimension of traditional banking before the launch of UPI. We estimate the following regression model:

$$y_{i,t} = h_i + year_t + z_{u,t} + \beta log(digital)_{i,t-1} + \gamma log(digital)_{i,t-1} \times LowFinDev_i + \epsilon_{i,t} \quad (2)$$

The coefficient on the interaction term, γ, measures the incremental effect of digital payments on districts with lower financial development. Table 3 presents the results. Across three measures of economic outcome, we find a positive and significant coefficient on the interaction term. In other words, the impact of digital payment on household income and business activity is higher for financially less developed districts.

Table 3: Effects Across Financial Development Measures

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 log of income in Columns (1), a binary variable indicating whether the household owns a business or not in Columns (2), and the log of one plus average monthly business income in Columns (3). Cashless Payment measures the log of the amount of cashless transaction in the previous year. All standard errors are clustered at the household level.

	(1) Income	(2) Owns Business	(3) Business Income
Lagged Cashless Payment	0.051***	0.003	0.052**
	(0.003)	(0.002)	(0.022)
Lagged Cashless Payment x Lower Fin Dev	0.013***	0.021***	0.206***
	(0.002)	(0.002)	(0.015)
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Urban x Year Fixed Effects	Yes	Yes	Yes
Nobs	617,544	617,753	617,753
Adjusted R-squared	0.723	0.575	0.608
Number of Households	165,476	165,476	165,476

standard error in parentheses

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

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. In our next test, we directly investigate whether digital payments alleviate

credit constraints of the affected households.

5.1.2 Credit Constraints

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. Using the same regression specification as in our base model of equation 1, Column (1) shows that higher cashless payments is associated with higher borrowing for business purposes in the following year. In economic terms, a doubling of digital payments is associated with approximately 1.36% higher borrowing for business purposes. This is an economically meaningful impact since the unconditional mean of "borrowing for business purposes" in our sample is 3.53%. Combined with our earlier results that establishes a link between cashless payments and business activities, this finding shows that digital payments aid in economic growth through the relaxation of borrowing constraints.

Columns (2) and (3) focus on the source of borrowings. Households in our sample borrow from multiple sources, including banks, Non-Bank Finance Companies (NBFC), local money lenders, family and friends and others. In Column (2), we consider borrowing from all possible sources as the dependent variable. As shown in the Table, households in high digital payment districts are significantly more likely to borrow than others. Column (3) considers borrowing from banks alone and finds even stronger results. A household residing in a district with twice as high the digital payments as another district has a 0.85% higher probability of borrowing from any source and 1.62% higher probability of borrowing from a bank. The unconditional means of borrowing from any source and borrowing just from the banks are 30.25% and 7.61%, respectively. Therefore, our estimates suggest that the increase in borrowing comes mainly from formal sources of debt. We explore these issues in greater detail later in the paper.

Our empirical designs so far establish a strong association between cashless payments and

Table 4: Borrowings and Cashless Payments

Table 4 presents the regression estimate of the regression model in equation 1 with credit outcomes as the dependent variables. The model is estimated with household-year level observations. The dependent variable is a binary variable indicating whether the household borrowed for business purposes, whether the households has any borrowings outstanding, or whether the household has a bank borrowing outstanding. Cashless Payment measures the log of the amount of cashless transaction in the previous year. All standard errors are clustered at the household level.

	(1) Business	(2) All	(3) Bank
Lagged Cashless Payments	0.0197***	0.0123***	0.0235***
	(0.0013)	(0.0023)	(0.0017)
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Urban x Year Fixed Effects	Yes	Yes	Yes
Nobs	622,238	622,238	622,238
Adjusted R-squared	0.458	0.492	0.376
Number of Households	169,610	169,610	169,610

standard error in parentheses

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

next year's economic outcomes in a district. Therefore, our baseline empirical model is less susceptible to endogeneity concerns that arise from unobserved shocks that affect both the adoption of digital payment and economic activities in a district at the same time. The key threat to our identification come from the possibility of a forward looking expectation of growth and the adoption of digital payments. Since a majority of digital payments occur at a retail level and are geared towards consumption items, we expect the anticipation effect to be small. In order to establish a more concrete causal link between the variables, we use two complementary identification strategies, one exploits the difference in the timing of UPI participation by banks, and the other exploits within-district-year variation in outcomes across households. These empirical designs complement each other and they provide some novel insights into the underlying economic mechanism as well.

5.2 Identification using differential timing of UPI participation

Our first identification strategy makes use of an institution feature of the Indian banking system to achieve a quasi-random variation in the rate of adoption of cashless payments across different districts of the country. In two waves of nationalization in years 1969 and 1980, all the large private sector banks of the country were nationalized by the government of India. Soon after the first wave of nationalization, the government launched a system of "lead banks" in the country based on the recommendation of Gadgil committee formed by the Reserve Bank of India.[14] Under this system, one of the government owned banks (also called the PSU Banks or nationalized banks) was designated as the lead bank for each district. The lead bank had the primary responsibility for expanding access to banking and credit to underserved communities in the district. While there have been several tweaks to the roles and responsibilities of the lead banks since its inception, the basic structure remains intact. Every district in the country has a lead bank responsible for carrying out several government-led credit and banking schemes, and expanding access to banking services in general. Due to a long history of this system in the country, lead banks still have significant presence in their districts in terms of branch network and customer base.

Interestingly for our purposes, banks differed in the timing of their participation on the UPI platform, as shown earlier in Figure 1. A customer needs her bank to participate on the UPI platform before she can link it with an UPI App on her mobile phone. Therefore, customers of banks that participated earlier in the program have earlier access to cashless payment infrastructure, providing us with a reasonably exogenous variation in the adoption of cashless payments in the early years of the UPI's launch.

At the time of the UPI's launch, 21 banks participated in the program. Some of these banks were part of a pilot program that the RBI conducted before the launch of the UPI. A handful of other banks, 8 of them to be precise, had indicated their desire to join the

[14] See a brief history of this system at the Reserve Bank of India's website: https://m.rbi.org.in/scripts/PublicationDraftReports.aspx?ID=552

platform at the time of launch, but delayed the joining by a few months to sort out some technical glitches. Within the next few months all of these banks joined the platform and the number of participating banks increased to 30 by the end of November, 2016. Within the set of public sector banks, six banks were notably missing from this list: Indian Bank, Indian Overseas Bank, Bank of India, Syndicate Bank, Corporation Bank and Dena Bank. All other public sector banks that had lead bank responsibilities anywhere in the country were the early participants.[15] Banks that joined the UPI platform in the earlier phase (i.e., by November 2016) are defined as the "early adopter" banks, whereas the remaining ones are defined as "late adopters". We compare households who reside in early versus late adopter bank's districts to obtain a causal link from digital payments to economic outcomes in a difference-in-difference setting.

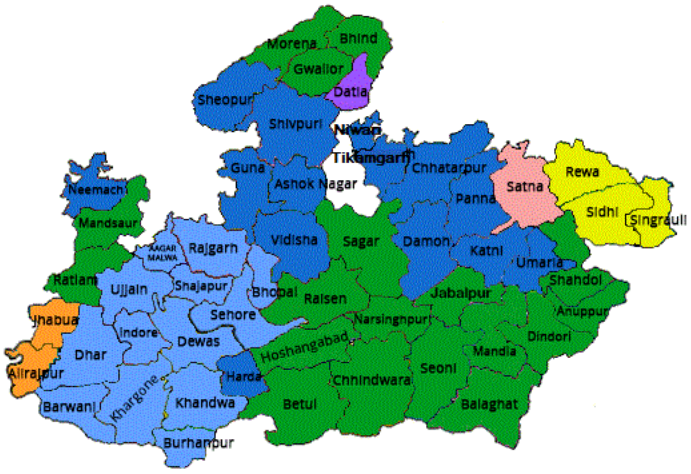
Since the lead bank assignment happened decades before the UPI shock and since we have a number of districts in the country that are otherwise identical on various socio-economic dimensions, our empirical setting is attractive. Further, the bank's decision to join the UPI platform is reasonably exogenous to the household's hidden characteristics, i.e., our unit of analysis. Since within a short period of time, all other banks joined the platform (see Figure 1), it is also unlikely to be correlated with any time-varying hidden differences across districts, especially on the matched sample of early versus late adopter districts. All these features of our setting make the timing of treatment reasonably exogenous for our analysis.

We illustrate this idea with an example of the state of Madhya Pradesh (MP) in Figure 2, obtained from the State Level Bankers' Committee (SLBC) of the state. Districts with different colors have different lead banks assigned to them. For example, the district of Rewa, colored in yellow, has Union Bank of India as its lead bank, whereas Satna, colored pink in the map, was led by Indian Bank. Union Bank of India was an early adopter of the UPI

[15]These banks are: Andhra Bank, Bank of Maharashtra, Canara Bank, Punjab National Bank, United Bank of India, UCO Bank, Union Bank of India, Vijaya Bank, Oriental Bank of Commerce, Allahabad Bank, State Bank of India, Bank of Baroda, and Central Bank of India. Punjab & Sind bank was also a late adopter, but we do not have any district in our sample where it was a lead bank.

platform, whereas Indian Bank joined it later. Such differences exist in several states of the country. Since the use of UPI requires the customer to link an UPI App to their bank account, customers in the early adopter districts are likely to join the platform at a faster rate in the initial years of the launch. Given the network externality involved in the payment system, even a small delay in the adoption can lead to large differences in the adoption rate in the immediate aftermath of the launch.

Figure 2: Lead Banks in MP



Source: Reproduced from http://www.slbcmadhyapradesh.in/lead-banks.aspx

As mentioned above, the lead bank role is assigned only to the government owned banks. Private banks, such as the ICICI Bank, also have branch networks across the country but they do not act as lead banks. Our identifying strategy exploits the variation in UPI adoption due to the incremental role played by the government owned lead banks. However, to avoid any potential bias due to differences in the presence of other banking institutions across districts with early versus late adopter banks, we conduct our matched sample analysis across districts with similar level of overall bank branch penetration based on the per capita number of brick-and-mortar bank branches in 2016.

With these institutional details and idea behind our identification strategy, we conduct a standard difference-in-difference test comparing households who reside in an early adopter

district with households who reside in a comparable late adopter district on a matched sample of early and late adopter districts. We have 404 unique districts in the sample that have coverage both on the CMIE database as of 2016, the year of our matching criteria, and the identity of the lead district. For our matched sample analysis, we begin with the sample of all the late adopter districts (92 districts in the sample) and find a comparable early adopter district in the same state. Our base case matching criteria is simple: we require the two districts to be in the same state and to be comparable in terms of per capita bank branches before the launch of UPI and the literacy rate. We pick these two dimensions of matching for our main specification to control for the supply of financial services and the customer's knowledge and willingness to use an electronic medium of payment.

We require the matched districts to be within one standard deviation on both measures. Within the set of all districts that meet these criteria, we pick the one with closest value of bank branch penetration. If an early adopter district gets matched with multiple late adopter districts, we keep all of them in the sample. Our results are not sensitive to these choices since we conduct our analysis at the household level. Our result remain similar if we match with or without replacement or whether we change the matching criteria by changing the bandwidth within which we find the matched districts. We obtain a sample of 77 early and 50 late adopter districts in the matched sample, spread across 10 large states in the country. Figure 5 plots the kernel densities of bank branch penetration, literacy rate, population and income across the early and late adopter districts. As expected the two densities have a nearly identical shape for the two dimensions that we match on: bank branch penetration and literacy rates. At the same time, they are also well balanced on the population and income as measured in 2016.

With the set of matched district, we first estimate the following cross-sectional regression model at the district level to establish the relevance of lead bank as an important driver of

digital payment adoption in the early years.

$$log(digital)_d = s_d + \beta \times log(population)_d + \theta \times log(findev)_d + \gamma \times early_d + \epsilon_d \quad (3)$$

The regression model estimates the effect of early adoption of the UPI by the lead bank of the district on the level of digital payments in the district after controlling for the effects of population and financial development measure (bank branch per capita) of the district. Results are provided in Table 5. We focus on differences in the early parts of the sample for the obvious reason that the effect of early adoption should mainly matter in the initial part of the sample. Column (1) uses digital payments in 2018Q1, i.e., the first quarter of our digital payment data, as the dependent variable. Column (2) uses the average value of digital payments during 2018Q1-2019Q4. We stop before the COVID-19 pandemic shock for two reasons. First, it allows us to focus on the early months of adoption. Second, it allows us to draw our inferences before the effect of COVID-19 on the adoption of digital payments and in turn its effect on outcomes. We find that the early adopter districts had 22%-27% higher cashless payments, depending on the model specification. The effects are large and statistically significant.

After establishing the importance of the lead bank's adoption of the UPI platform on the level of cashless payments in the district, we estimate the following model:

$$y_{i,t} = h_i + z_{u,t} + State \times Year + Demo \times Year + \sum_{\tau} (year = \tau) \times \beta_\tau \times EarlyAdopter_i + \epsilon_{i,t} \quad (4)$$

We estimate the model with yearly observations from 2014 to 2019, i.e., we focus on years before the COVID-19 shock for the reasons stated earlier. The regression model estimates the difference in economic outcomes for households in early versus late adopter districts on an annual basis, with the year of UPI's launch, 2016, as the base year. $y_{i,t}$ measures economic outcomes in the same manner as in the earlier models. We include the household fixed effects

Table 5: Cashless Payments Across Early vs. Late Adopters

Table 5 presents the regression estimate of the regression model in equation 3. The model is estimated with district level observations. The dependent variable is the log of cashless payments in a district in 2018Q1 in Column (1) and the log of the average value of this number over 2018Q1-2019Q2.

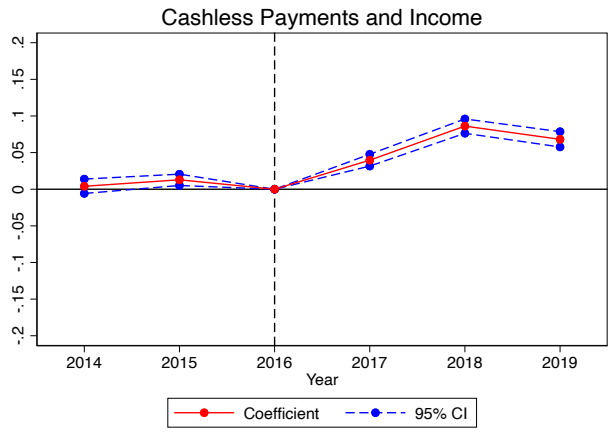
	(1) Cashless Payment 2018Q1	(2) Cashless Payment 2008Q1-2019Q4
Log Population	1.4721***	1.5035***
	(0.0853)	(0.1029)
Early Adopter	0.2297***	0.2699***
	(0.0751)	(0.0886)
Log Branch Density	1.3592***	1.3862***
	(0.1532)	(0.1928)
State Fixed Effects	Yes	Yes
Nobs	127	127
Adjusted R-squared	0.853	0.825
Number of Early Adopter Districts	50	50

standard error in parentheses

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

and $urban \times year(z_{u,t})$, fixed effects in the model, as in our earlier analysis. In addition, we include fixed effects for $State \times Year$ since we are conducting our analysis within the matched sample of states. Finally, following Chodorow-Reich et al. (2020), we sort districts based on their measure of the intensity of demonetization shocks across districts on a scale of 1 to 7. We include the interaction of the demonetization shock levels with years as fixed effects in the model to separate out the differential effects of demonetization across these districts. Results are graphically presented in Figure 3.

Figure 3: Effect of Digital Payment on Income



As shown in the figure, prior to the adoption of the UPI, households in early versus late adopter districts exhibited a parallel trend in their income. However, the coefficient becomes positive and significant in the early adopter districts soon after the launch. By 2018, households in the early adopter districts have 8.6% higher income. The difference begins to narrow in 2019, as the effect of early adoption advantage becomes less important. However, the difference remains economically and statistically significant even in 2019. We find similar result using business income as the outcome variable. We omit them from the paper for brevity.

We estimate the following model to estimate the average effect of early adoption on income across all the years from 2014-2019 in the sample:

$$y_{i,t} = h_i + z_{u,t} + State \times Year + Demo \times Year + \beta \times Post_t \times EarlyAdopter_i + \epsilon_{i,t} \quad (5)$$

$Post_t$ equals one for 2017-2019, and zero otherwise. The estimation results are provided in Table 6. Model 1 of the Table shows that households in the early adopter districts have significantly higher income of 5.8% per year in the post period. These households have 1.45%

higher business ownership rate, and their business income is approximately 19% higher. All these estimates are economically large and statistically significant.

Table 6: Cashless Payments and Outcomes: Early vs. Late Adopters

Table 6 presents the regression estimate of the regression model in equation 5. The model is estimated with household-year level observations from 2014-2019. The dependent variable is the log of average monthly income of a household in a given year in Column (1), business ownership in Column (2) and log of one plus business income in Column (3). All standard errors are clustered at the household level.

	(1) Income	(2) Owns Business	(3) Business Income
Early Adopter x Post 2016	0.0584***	0.0145***	0.1899***
	(0.0045)	(0.0040)	(0.0356)
Household Fixed Effects	Yes	Yes	Yes
State x Year Fixed Effects	Yes	Yes	Yes
Urban x Year Fixed Effects	Yes	Yes	Yes
Demonetization x Year Fixed Effects	Yes	Yes	Yes
Nobs	310,538	310,653	310,653
Adjusted R-squared	0.713	0.396	0.432
Number of Households	69,357	69,370	69,370

standard error in parentheses

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

5.3 Identification using within-district-year variation

As a complementary empirical strategy, we now exploit variation in outcomes across different types of households within the same district and same year to shed some further light on the economic channel behind our results. Motivated by the economic frictions that connects digital payments to growth, our identification strategy in this section rests on the assumption that the benefit of digital payments accrue at a disproportionately higher rate to self-employed households (such as shop-keepers, hawkers, entrepreneurs) compared to salaried households within the same district in the same year. While both groups are likely to benefit from overall economic improvement in an area, it is the group of self-employed households who are more likely to benefit from the relaxation of transaction costs and credit

constraints. On the other hand, it is unlikely that consumers increase their usage of digital payment in a district in year t in anticipation of a disproportionately better information, and hence expectation, of economic outcomes only for the self-employed group in year $t+1$. Therefore, the key endogeneity concern in our base empirical model that relates the lagged values of digital payments to economic outcome is unlikely to affect the within-district-year regression specification that estimates the effect of digital payments on economic outcomes across self-employed and salaried households.

Digital payments benefit self-employed households 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. And these economic forces are likely to be stronger for self-employed households.

We estimate the following regression model with the inclusion of district-year fixed effects

that soak away time-varying unobserved shocks across districts:

$$y_{i,d,t} = h_i + year_t + m_{d,t} + \beta \times self_{i,pre} + \theta \times self_{i,pre} \times log(digital)_{i,t-1} + \epsilon_{i,d,t} \quad (6)$$

$y_{i,d,t}$ measures the log income of household i in district d in year t. $m_{d,t}$ are district-year fixed effects. $self_{i,pre}$ measures whether the household is self-employed or not in the "pre" period, i.e., before we measure economic outcomes. We consider the following categories of occupation in the CPHS database as self-employed: Entrepreneurs, Self-employed Entrepreneurs, Self-employed Professionals, and Small Traders/Hawkers. We label them all as "Entrepreneurs" for expositional convenience. We compare their outcomes with households who are salaried employees and workers. The comparison groups cover both the government employees and private sector employees, for example a salaried employee at a doctor's office or local business falls under this category. We estimate the model on the same sample as our base case analysis with equation 1, i.e., on the sample from 2019-2022.

Results are presented in Table 7. In Columns (1) we classify a household under the self-employed group if it falls under the entrepreneur category in year $t-1$. For all other columns, we classify them under the self-employed category based on their occupation status as of 2016, 2017, and 2018, i.e., before we measure the economic outcomes. For these columns, the employment status of a household is fixed based on their characteristic before our estimation sample begins. While the time-varying classification of occupation status allows us to capture changes in occupation categories over time, we focus our discussions on the specifications in Columns (2)-(5) as they are less contaminated by the endogenous switching of occupation after the increase in digital payments.

Column (2) considers all the entrepreneurs as self-employed and compares them with salaried households. The elasticity of income to digital payments is higher by 0.0341 for the self-employed group compared to salaried households in this specification. When digital payments increase in a district, it leads to higher income for self-employed households

Table 7: Effects For Self-Employed Households

Table 7 presents the regression estimate of the regression model in equation 6. 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 Payment measures the log of the amount of cashless transaction in the previous year. All standard errors are clustered at the household level.

	(1) Income	(2) Income	(3) Income	(4) Income	(5) Income
Self-Employed	-0.3899***				
	(0.0239)				
Self-Employed X Lagged Cashless Payments	0.0167***	0.0341***	0.0526***	0.0352***	0.0169***
	(0.0011)	(0.0013)	(0.0028)	(0.0020)	(0.0024)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Self-Employed Group	Entrepre	Entrepre	Hawkers	Farmers	Hawkers
Comparison Group	Salaried	Salaried	Salaried	Salaried	Other Entrepre
Nobs	255,793	268,441	148,563	204,783	146,623
Adjusted R-squared	0.766	0.766	0.772	0.747	0.768
Number of Households	84,082	70,573	39,690	54,775	38,975

standard error in parentheses

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

compared to all the salaried households in the same district after accounting for unobserved district-year shocks. In Column (3), we compare a subset of entrepreneurs who are more likely to benefit from digital payment, namely the hawkers, to the salaried household. As discussed earlier, this sub-category of entrepreneurs are relatively poor and their business establishment is typically "unbankable". Often their business is run out of a fruit stall or a temporary location, with very limited availability of collateral. The effect of digital payments in especially higher for this sub-group: an increase in elasticity of 0.0526. In Column (4), we consider a different occupation category as self-employed: the farmers. The group of farmers are also likely to benefit more from the relaxation of credit constraints and transaction costs as is the case with the entrepreneurs. Our results show that farmers' income increases by more in response to an increased digital payment activity in a district.

Finally, in Column (5) of the Table, we compare hawkers to other entrepreneurs. Our motivation behind this specification is two-fold. First, it allows us to exploit the variation in

outcome across relatively marginal versus more established entrepreneurs. Second, one may be concerned that our estimates simply capture the "reporting" effect and not real economic effects. To be precise, if digital payments deter tax avoidance, then a move towards cashless society can result in higher reported income even if the actual income has not changed. Since salaried households are less likely to be affected by this channel, comparing them with entrepreneurs can lead to a bias due to tax avoidance incentives. When we compare income across hawkers and more established entrepreneurs, such a bias is likely to disappear for two reasons. First, both these group of households generate income from their own business. Second, the tax avoidance incentive should be lower for marginal entrepreneurs since they earn significantly lower income on average, compared to other entrepreneurs. In our sample, hawkers have about 35% lower annual income than other entrepreneurs. With an average annual income of less than ₹200,000, majority of hawkers in our sample fall under the tax exempt limit as per the Indian tax rule. Hence, they have little incentive to hide income in a systematic manner. Therefore, comparing hawkers with other entrepreneurs provides a setting when benefits of digital payments are higher for the hawkers but the tax avoidance incentives lower. Our results show that the income increased significantly more for hawkers compared to the other entrepreneurs.

The variation across occupation categories provides us with a useful setting to test whether digital payments alleviates credit market friction for households who face higher constraints such as hawkers compared to other self-employed households. Hawkers have very little collateral, and therefore they face relatively larger credit constraints. We use the same within-district-year empirical strategy as in the rest of this section and present the estimation results in Table 8. Column (1) shows that hawkers borrow for business purposes at a significantly higher rate than other self-employed households in districts with higher levels of digital payment.

Remaining columns of the Table analyze the sources of borrowing. Column (2) uses borrowing from any sources as the dependent variable. While the hawkers borrow at a

rate that is higher than the other self-employed category, the relation is not significant in statistical sense. However, overall borrowing masks an important variation in the type of credit that hawkers obtain after an increase in cashless payment. As shown in Column (3), their borrowings from traditional banks increased significantly with the adoption of digital payments. Column (4) uses borrowing from the Non-Bank Finance Companies (NBFC), another provider of formal credit. Again, hawkers' borrowing from the NBFC sector increased after digital payments. Column (5) only uses borrowing from non-formal sources, i.e., borrowings from sources other than banks or NBFC, and shows that hawkers decreased their lending from these sources. The overall message from this analysis is that not only did the credit for business purposes increase for marginal borrowers, the composition of credit also moved from informal sources such local money lenders to more formal sources such as banks or NBFC.

Table 8: Borrowings and Cashless Payments Across Occupation

Table 8 presents the regression estimate of the regression model in equation 6. 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 Payment measures the log of the amount of cashless transaction in the previous year. All standard errors are clustered at the household level.

	(1) Business	(2) All	(3) Bank	(4) NBFC	(5) Informal
Hawkers X Lagged Cashless Payments	0.0062***	0.0034	0.0062***	0.0021**	-0.0054**
	(0.0017)	(0.0024)	(0.0017)	(0.0010)	(0.0024)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
District x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Nobs	142,600	142,600	142,600	142,600	142,600
Adjusted R-squared	0.506	0.622	0.452	0.460	0.586
Number of Households	38,310	38,310	38,310	38,310	38,310

standard error in parentheses

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

5.4 Additional Analyses

We now present some additional analysis to support the main claim of the paper.

5.5 RBI Credit

As discussed earlier, a potential concern with our analysis is related to the issue of "reporting bias". If digital payment adoption allows households to keep a better record of their financial transactions, then the quality of their reporting is likely to improve. There are two related issues on this dimension. First, if digital payment simply improves the accuracy of information, then our empirical strategy remains valid. Some households are likely to underestimate their income in the absence of digital information, whereas some others overestimate. The noise creates measurement error without generating any bias in our estimates. The resulting measurement error should make it harder for us to find the results that we document in the paper. The second concern is more critical for us: are households hiding information in the CPHS survey, our data source, in a systematic manner to avoid taxes? Under this scenario, digital payments simply makes it hard to underreport income, and our findings can be attributed to a reduction in hiding behavior, rather than an improvement in economic outcomes.

There are several reasons that our analysis is unlikely to be driven by this effect. First, our information does not come from tax records, rather from a detailed survey by the CMIE. Therefore the underreporting incentive is less severe for our data. Second, we document improvement not only in income, but also on business activity and credit outcomes. These economic measures are less likely to be affected by a desire to avoid taxes. In fact, some form of credit can lower the tax burden. Therefore, underreporting of borrowings is not incentive-compatible with tax avoidance. Third, we show that even within the class of self-employed household, it is the set of hawkers who show higher improvement after the adoption of digital payments. These households' income is typically below the level of tax

exemption limit in the country. Therefore, the incentive to hide income is absent. Finally, our results documenting an increase in formal sources of credit by marginal entrepreneurs and a corresponding decrease in informal credit cannot be explained away by the hiding behavior.

Yet, we address this issue more directly by analyzing the level of credit creation in a district in a quarter based on the data provided by the Reserve Bank of India. The database is naturally free from any reporting bias. A disadvantage of the data is that we miss individual specific variation in this dataset as it is aggregated at the district-quarter level. We estimate a panel data regression with district and quarter fixed effects, and log of total credit as the dependent variable on the same sample of districts on which we estimate our base case panel regression model. The lagged value of the log quarterly cashless payments in the district is the explanatory variable.

Results are provided in Table 9. Column (1) uses the first lag of cashless payment in the quarter as the explanatory variable, and reports an elasticity of 0.0243. Columns (2), (3), and (4) use the second, third, and fourth lag of cashless payment as the explanatory variable. Across the specifications, we find a strong position relation between cashless payments and credit. In Column (5), we use a distributed lag model to jointly exploit the information in lagged values of cashless payments across all four quarters. The sum of the coefficients on all the lagged explanatory variables is 0.0396, and the the p-value for the relevant F-test for their joint significant is 0.005. Therefore, as districts see increased level of cashless payments, the level of credit creation increases.These findings corroborate the evidence from micro-level data supporting a real effect of cashless payments on economic outcomes.

5.5.1 Growth

We now extend our panel data analysis to a regression model with the growth rate in income and digital payment as the variables of interest. The model is estimates with the first differenced log values of household income and digital payments with the following

Table 9: Cashless Payments and RBI Credit: Panel Data

Table 9 presents the results of a panel regression model with district-quarter level data from 2018-2022. The dependent variable is the log of credit extended by all banks in a given district in a quarter as reported by the RBI. Cashless Payment measures the log of the amount of cashless transaction in the previous quarters. All standard errors are clustered at the district level.

	(1)	(2)	(3)	(4)	(5)
Cashless Payment.L1	0.0243***				0.0316***
	(0.0086)				(0.0059)
Cashless Payment.L2		0.0233***			-0.0100***
		(0.0083)			(0.0030)
Cashless Payment.L3			0.0233***		0.0024
			(0.0085)		(0.0031)
Cashless Payment.L4				0.0220***	0.0156***
				(0.0082)	(0.0060)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Nobs	8,064	7,560	7,056	6,552	6,552
Adjusted R-squared	0.9976	0.9977	0.9979	0.9980	0.9981
Number of Districts	504	504	504	504	504
p-value (F-test)					0.0005

standard error in parentheses

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

specification:

$$y_{i,t}^{i,t+1} = h_i + y_t + z_{u,t} + \beta \times log(digital)_{i,t-1}^{i,t} + \epsilon_{i,t} \tag{7}$$

The model estimates the effect of growth rate in digital payments from year $t-1$ to t on income growth rate from t to $t+1$, i.e., our regression estimates capture the effect of growth rate in UPI payments in a lagged year on the growth rate in outcome variables in the future year. We lose first two years of observation for this estimation exercise since we need the lagged value of growth variable as the explanatory variable. For household income and UPI volume, the growth measure is computed as the logged difference in their respective values over the successive years. We estimate the model both with and without household fixed effects since the first differenced model soaks away variation in person and district specific factors. Our results remain qualitatively similar for the two specifications. For brevity, we only report the results with the inclusion of fixed effects in Table 10.[16]

Table 10: Cashless Payments and Outcomes: Growth Regression

Table 10 presents the regression estimate of equation 7. The model is estimated with household-year level observations. The dependent variable is the difference in log of income from year $t-1$ to t in Column (1), difference in business ownership over the same time period in Column (2) and the difference in one plus log of business income in Column (3). Cashless Payment measures the log of the amount of cashless transaction in the previous year. All standard errors are clustered at the household level.

	(1) Income Growth	(2) Diff Owns Bus	(3) Business Income Growth
Lagged Growth Cashless Payments	0.0506***	0.0264***	0.1823***
	(0.0041)	(0.0037)	(0.0331)
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Urban x Year Fixed Effects	Yes	Yes	Yes
Nobs	439,720	440,019	440,019
Within R-squared	0.084	0.003	0.003
Number of Households	153,869	153,897	153,897

standard error in parentheses

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

[16]We lose some observations for this estimation compared to the model in Table 2 because we need an additional year of data to compute the lagged differenced variables.

Column (1) reports a strong positive effect of increase in digital payment in the past year on income of the household in the next year. Since the dependent variable for business ownership is a binary variable, we use the simple difference in this variable over the year as the dependent variable for this specification (labeled as 'Diff Owns Bus' in the Table). We find a statistically significant coefficient on both the change in the business ownership status and business income. The estimates of elasticities are remarkably similar to our base case regression estimates in Table 2. Overall, these findings show that economic outcomes improves significantly in districts with higher cashless payment intensity.

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.

We use the difference in the timing of participation by a bank on the UPI system and the variation in their presence across different districts of the country as a source of quasi-exogenous variation in the adoption of digital payments in the early years of UPI launch. Our empirical setting allows us to draw a causal inference by investigating economic outcomes for households who reside in districts of early adopter versus late adopter banks.

We provide several pieces of evidence to support the claim that credit constraints and transaction cost frictions are some of the key drivers of our findings. Economic outcomes are especially better in districts where traditional banking infrastructure is weak, suggesting

that digital payments alleviate frictions created by the lack of brick-and-mortar institutions. Within the occupation categories, results are stronger for marginal self-employed households such as hawkers and small traders. These agents face significant frictions in accessing traditional financial markets that the digital payment infrastructure alleviates. We show that marginal entrepreneurs' borrowing from formal sources of financing goes up with digital payments, whereas their borrowing from informal sources come down at the same time. These findings provide insights into economic mechanism behind our findings.

Countries around the world are considering a move towards digital payment in various forms. Our study provides valuable inputs to policymakers: a move towards digital payment system affects economic outcomes in a positive manner. Therefore, the impact of digital payments go beyond a simple change in the means of payment. It alleviates economic frictions that can benefit marginal agents of the economy in a meaningful way.

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Appendices

A Data Variables

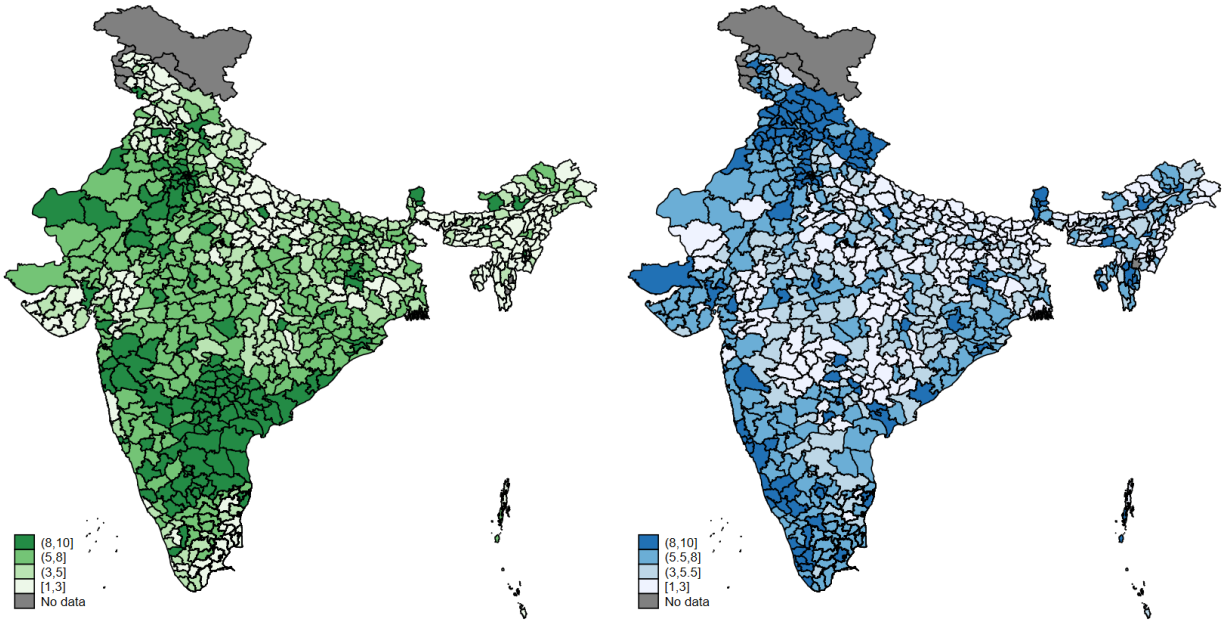
Variable	Data Source	Variable Construction
Household income	CMIE	`Total_Income` from the CMIE Income Pyramids which records total income reported by a household in Indian Rupees
Owns Business	CMIE	`Income_Of_Household_From_Business_Profit` from the CMIE Income Pyramids. We construct a binary variable 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

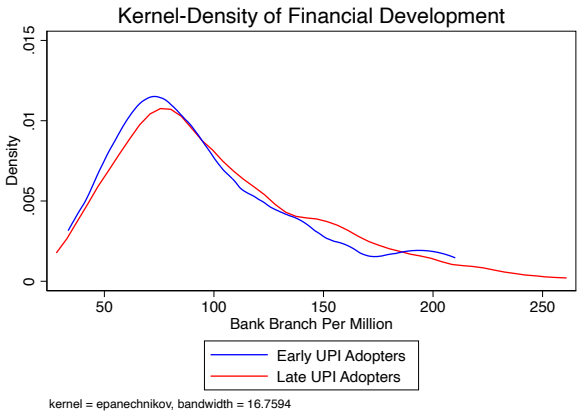
Figure 4: District-level Intensities



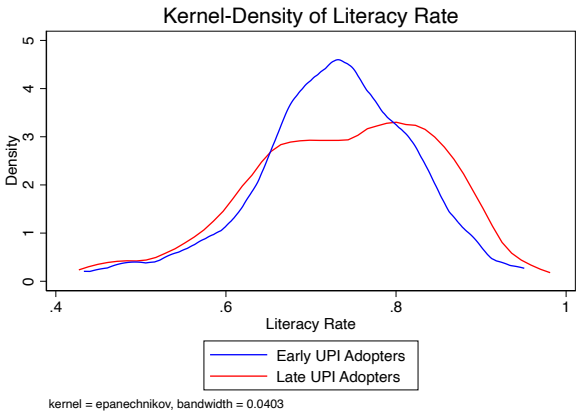
(a) Digital Payments Intensity

(b) Financial Development Intensity

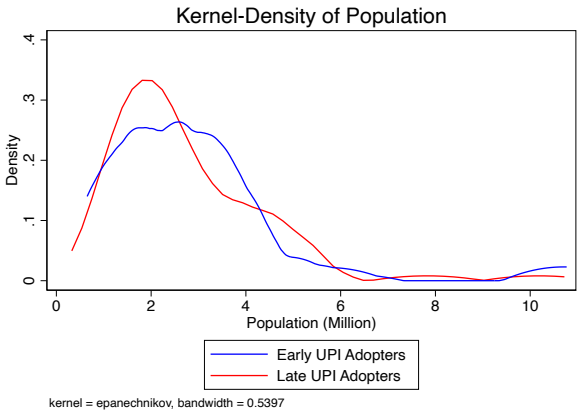
Figure 5: Kernel Densities Across Early and Late Adopter Matched Districts



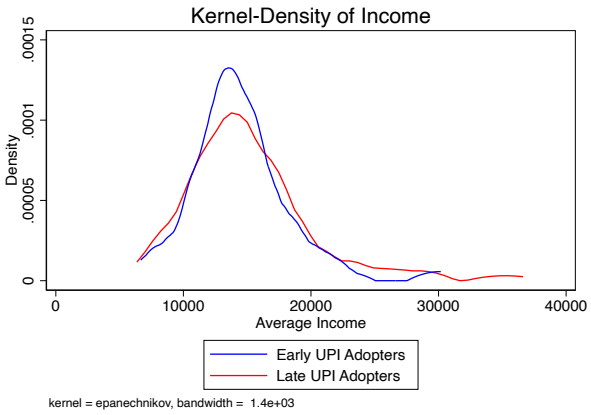
(a) Bank Branch Penetration



(b) Literacy Rates



(c) Population



(d) Average Income, 2016