INTERNATIONAL MONETARY FUND

Integrating Fragmented Networks: The Value of Interoperability in Money and Payments

Alexander Copestake, Divya Kirti, Maria Soledad Martinez Peria and Yao Zeng

WP/25/126

IMF Working Papers **describe research in progress by the author(s) and are published to elicit comments and to encourage debate.**
The views expressed in IMF Working Papers are those of the author(s) and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

2025
JUN

WORKING PAPER

© 2025 International Monetary Fund WP/25/126

IMF Working Paper
Research Department

Integrating Fragmented Networks: The Value of Interoperability in Money and Payments

Prepared by Alexander Copestake, Divya Kirti, Maria Soledad Martinez Peria and Yao Zeng*

Authorized for distribution by Giovanni Dell'Ariccia

June 2025

***IMF Working Papers* describe research in progress by the author(s) and are published to elicit comments and to encourage debate.** The views expressed in IMF Working Papers are those of the author(s) and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

ABSTRACT: Payments technologies pose an economic dilemma: network effects can lead to a small number of dominant platforms, but efforts to increase choice can risk market fragmentation. We examine whether interoperability can help resolve this tension, using data from India's Unified Payments Interface—the world's largest fast payment system by volume—as well as from a major pre-existing fintech firm. When the two networks became interoperable, overall usage of digital payments rose. Consistent with a model of payment choice that we propose, this increase was driven by regions where digital payments were more fragmented across platforms ex ante. Our model implies that the unification of networks increased total usage of digital payments by more than 50% in the year after integration.

JEL Classification Numbers:	E42, G23, L14, O33
Keywords:	Payments, Interoperability, Networks, FinTech, UPI

Author's E-Mail Address:	acopestake@imf.org; dkirti@imf.org; mmartinezperia@imf.org; yaozeng@wharton.upenn.edu

* We are grateful to Ritesh Shukla, Nikita Agrawal, Kapil Patil, and Harshya Matthews at NPCI for sharing data and for many helpful conversations. We thank Tobias Adrian, Itai Agur, Tanuj Bhojwani, Daniel Björkegren, Luis Breuer, Markus Brunnermeier, Kamya Chandra, Nada Choueiri, Giovanni Dell'Ariccia, Harald Finger, Lukas Freund, Pierre-Olivier Gourinchas, Deepro Guha, Srinivas Gynedi, Vikram Haksar, Paavi Kulshreshth, Nikhil Kumar, Rohit Kumar, Nicola Limodio, Filippo Mezzanotti, Sudip Mohapatra, Divyanshu Pathak, Manasa Patnam, Nicola Pierri, Andrea Presbitero, Dinar Prihardini, Guillermo Galicia Rabadan, Karthik Raghupathy, Pallavi Rao, Saravana Ravindran, Edona Reshidi, Marco Reuter, Krishna Srinivasan, Nujin Suphaphiphat, Jay Surti, Ashutosh Thakur, and K Vijayakumar for helpful discussions, as well as seminar participants at the IMF and the Lee Kuan Yew School of Public Policy. Cage Englander and Ariadne Checo de los Santos provided excellent research assistance.

1 Introduction

Money is a fundamental economic technology characterized by network effects (Menger, 1892; Fisher, 1911; Krugman, 1984): its value rises with others' willingness to accept it. Modern digital payment technologies share this characteristic and could generate even stronger network benefits (Crouzet, Gupta, and Mezzanotti, 2023; Alvarez, Argente, Lippi, Méndez, and Patten, 2023), creating a dilemma for the optimal design of payment systems. On one hand, network effects can concentrate users on a few dominant platforms, limiting user choice and potentially raising concerns of rent extraction (Katz and Shapiro, 1985; Brunnermeier and Payne, 2022, 2023). On the other hand, introducing new platforms can fragment markets (Vayanos, 1999; Duffie, 2023), reducing the inherent network benefits of converging on leading platforms. This dilemma recurs in many contexts, from regulating card networks and fintech firms to introducing public payment options like FedNow or a Digital Euro (Brainard, 2019; Lagarde, 2025; Lane, 2025). Is there a way to avoid fragmentation without sacrificing user choice?

In this paper, we study payment interoperability, which offers a potential escape from the dilemma yet has not been widely studied academically. By enabling users to transact seamlessly across payment platforms, interoperability can unlock the benefits of network unification without requiring centralization on a single private platform provider—preserving choice for users. It could therefore allow users to reap the best of both worlds: the freedom to choose their favorite platform, alongside access to the full network of users. Despite its importance and anecdotal support, data constraints have made it difficult to study the role of interoperability in encouraging usage of digital payments.

We present a theoretical framework and tightly connected empirical evidence showing that interoperability can increase adoption and usage of digital payments by integrating fragmented networks. To do so, we leverage novel data covering *both* the universe of payments on India's Unified Payments Interface (UPI)—the world's largest fast payment system by volume—and all payments on a major pre-existing fintech platform.[1] Our data allow us to observe—at a granular

[1]The fintech firm requested to remain anonymous; we thus refer to it throughout as "the incumbent platform", or

geographical level—two large payment networks that initially operated separately and then integrated through interoperability. We also observe a proxy for the use of cash with the same level of geographical granularity. Together, these data allow us to directly examine users' choices of payment apps, how payments flowed *between* them, and the wider transition from cash to digital payments.

We begin with two new stylized facts—both drawing on our unique data—that suggest that interoperability accelerated the adoption of digital payments in India. First, cross-app transactions drove growth in UPI transaction volumes. Indeed, most UPI transactions occur between users of two different apps, directly utilizing interoperability. Second, after a common shock that increased demand for digital payments, users largely chose an interoperable option over a closed-loop payments platform. These telling patterns suggest that interoperability was an important part of the dramatic growth in digital payments in India.

Building on these stylized facts, we develop a formal conceptual framework that shows how interoperability makes digital payments more valuable by amplifying network effects. Users choose between two digital payments platforms and an outside option that is already universally accepted (e.g., cash). Users initially fragment across platforms due to exogenous differences in brand familiarity or personal preferences, limiting the network benefits associated with using digital payments. By allowing users to choose one platform yet transact directly with users on another, interoperability expands the set of accessible users. This, in turn, unlocks the full extent of network benefits, thereby maximizing digital payment usage and overall welfare.

A novel theoretical prediction of our framework is that the greater the initial fragmentation, the larger the gains from introducing interoperability. This is because markets that are more fragmented have greater unrealized network benefits across platforms. By stitching these previously more fragmented networks together, interoperability unlocks a larger share of potential new digital payment transactions. In contrast, in markets that are relatively unified ex ante—i.e., where there is minimal fragmentation—the gains from interoperability are only marginal, as network benefits

variations thereof, and describe relevant results in event time rather than chronological time.

are mostly already realized.

Informed by the conceptual framework, we empirically examine the heterogeneous implications of interoperability by exploiting a unique natural experiment: the integration with UPI of a large pre-existing payments platform. The incumbent fintech firm initially provided only closed-loop payment services—i.e., transactions could only take place when *both* counterparties used its digital wallet. This platform therefore initially competed with UPI for digital payments users, fragmenting the digital payments market. However, following a directive from the Reserve Bank of India (RBI) mandating interoperability, the incumbent connected its network to UPI, enabling transactions between users of the two platforms. Crucially, the extent of fragmentation of payments markets prior to integration varied significantly across districts—producing variation in the extent of unrealized cross-platform network benefits that were unlocked by interoperability. We exploit this variation in a heterogeneous adoption design (de Chaisemartin and D'Haultfœuille, 2023), comparing post-interoperability trends in districts whose digital payment markets were more fragmented ex ante than the median (hereafter, "more fragmented districts") to less fragmented districts.

To sharpen identification, we include granular fixed effects and control variables. We work at the district-month level and include district and state-month fixed effects in our baseline specification. We also control for differential trends resulting from differences in districts' *total* digital payments usage prior to integration, leveraging only district-wise differences in the *composition* of those payments—i.e., differences in the extent to which digital payments were initially unified on one platform versus fragmented between the two. Conditional on these controls, we do not see meaningful differential trends in digital payments usage prior to integration in districts with more ex-ante fragmentation.

We find substantial positive effects of network integration on total digital payments. Over the year after integration, differential growth in the total value of digital payments in more fragmented districts amounted to 88% of more fragmented districts' pre-interoperability mean and to 118% of less fragmented districts' post-interoperability mean. Total digital payments also differentially increased sharply relative to a proxy for cash usage based on ATM withdrawals. Consistent with our conceptual framework, the presence of cross-app network effects enabled by interoperability induced substitution away from cash.

Dis-aggregating the differential increase in total digital payments in more fragmented districts, we find that newly enabled transactions *between* the incumbent platform and other UPI apps took off after integration, providing direct evidence that users valued the cross-network payments capability created by interoperability. We also observe significant differential increases in transaction values *within* both the incumbent platform and other UPI apps after their integration—consistent with positive spillovers from the ability to reach more users that are also present in our conceptual framework. In addition, we show that the differential increase in the total value of digital payments in more fragmented districts was primarily driven by a larger increase in the number of users—with relative increases in the number of transactions per user and the average size of transactions also present but playing a quantitatively smaller role.

We present a battery of robustness checks that confirm these empirical findings and support a causal interpretation. We do not find any evidence of differential pre-trends in high-fragmentation districts in our main specification, and high-fragmentation districts are similar to low-fragmentation districts on many observables. Nevertheless, concerns may remain about the potential endogeneity of ex-ante fragmentation to subsequent trends in usage of digital payments. We show that our results are similar when using two additional estimation strategies to mitigate such concerns. First, we explicitly match districts with high ex-ante fragmentation to districts that differ only on ex-ante fragmentation, not on observables. Second, we use the incumbent's earlier choices of "hub" cities in which to launch to construct an instrument for the extent of fragmentation prior to integration.[2] Specifically, given that users in districts closer to hubs were more likely to encounter the incumbent platform, we use the distance of each district to one of these hubs as our instrument. We also conduct placebo tests and consider a wide range of alternative specifications.

[2] Importantly, these hubs were selected by the incumbent more than a year before integration, and before the demonetization shock radically changed the landscape of digital payments adoption in India (see, for instance, Chodorow-Reich, Gopinath, Mishra, and Narayanan, 2020; Lahiri, 2020), mitigating concerns about an interdependency between hub choice and the decision of the incumbent to integrate.

Finally, we explore the broader implications of our analysis in two dimensions. First, we combine our theory and empirics to derive a model-implied estimate of the aggregate impact of the two networks' integration on total nationwide usage of digital payments. While our results in the cross-section are well-identified, we cannot infer the aggregate impact of integration from such evidence alone due to a missing intercept problem (e.g., Wolf, 2023; Buera, Kaboski, and Townsend, 2023). However, our model implies that interoperability brings no additional gains in markets with no fragmentation prior to integration—enabling us to use districts with very little fragmentation as a "no-interoperability" counterfactual. Aggregating accordingly, we estimate that connecting the two networks increased total national usage of digital payments by more than 50% in the year after integration. Second, we trace the knock-on implications for the real economy of the increased uptake of digital payments. Using a similar specification to our baseline, we show that lending likely based on data generated from digital payments activity also accelerated in districts whose digital payments markets were more fragmented prior to integration. Again, interoperability had the largest benefits in places where network fragmentation was previously most severe.

Our results have important implications for policymakers across a wide range of both domestic and cross-border payment settings. Policymakers in many developing economies aim to increase adoption of digital payments as a stepping stone to broader financial inclusion (Berg, Fuster, and Puri, 2022; Dubey and Purnanandam, 2023; Alok, Ghosh, Kulkarni, and Puri, 2024). Our results highlight that integrating fragmented networks can substantially increase uptake of the combined platform. Conversely, our results warn that introducing a new, non-interoperable payment technology could exacerbate existing fragmentation. In other developing economies, payment systems are well developed but currently dominated by a small set of private providers operating distinct, non-interoperable networks (see, for instance, Yi, 2021). Concerns about market power, limited user choice, and fragmentation are also relevant for advanced economy payment systems (see, for instance, Brainard, 2019; Cunliffe, 2023; Lane, 2025). In the realm of cross-border payments, policymakers have discussed the potential benefits of interoperability between many different types of domestic systems (Financial Stability Board, 2024). Policymakers are also increasingly raising the possibility of a more multi-polar—and more fragmented—global currency paradigm (Lagarde, 2025; Pan, 2025). Our paper speaks to all of these settings, by presenting empirical evidence on the impact of integrating large payments networks.

Related literature. We contribute to several main areas of research. First, we contribute to the extensive literature on money and payments. The idea that money functions as a network good dates back to Menger (1892) and Fisher (1911), and has been formalized in modern economic models on the emergence of and competition between monies, such as Krugman (1984), Kiyotaki and Wright (1989), Matsuyama, Kiyotaki, and Matsui (1993), Farhi and Maggiori (2018), and Coppola, Krishnamurthy, and Xu (2023). Recent innovations in payment systems, including the rise of public and private fast payment platforms, cryptocurrencies, and central bank digital currencies (CBDCs), have further transformed the landscape (Duffie, 2019; Benigno, Schilling, and Uhlig, 2022; Cong and Mayer, 2025; Steinsson, 2025). However, alongside the realization of network benefits, concerns have also emerged about dominant private players in payments and their potential negative welfare implications (e.g., Brunnermeier and Payne, 2022; Goldstein, Yang, and Zeng, 2023).

We contribute to this evolving literature by examining the role of interoperability, an increasingly prominent yet understudied feature of payment systems, in shaping the trade-offs between network benefits and user choice in the evolution of money and payments. In doing so, we follow the recent literature on convenience yield (e.g., Krishnamurthy and Vissing-Jorgensen, 2012; Stein, 2012) by modeling the convenience users derive from a given payment method, while explicitly incorporating network externalities—i.e., that a user experiences higher convenience when more users adopt the same method, as modeled in, for example, Cong, Li, and Wang (2021) and Crouzet, Gupta, and Mezzanotti (2023). This combination of payment convenience and network effects allows us to analyze the role of interoperability in a transparent and tractable way, yielding new and sharp empirical implications.

More specifically, we contribute to the growing literature on the consequences of introducing interoperability between payment networks.[3] We contribute to this literature through both our conceptual focus and our empirical methodology. On the former, we offer a detailed examination of "demand-side" implications of interoperability, in a setting that allows us to abstract from "supply-side" considerations that have been the focus of recent work. Specifically, recent papers have highlighted a potential downside of interoperability that can emerge through the impact on network providers: increased competition can reduce their incentives to invest in expanding platform access (Ferrari, Verboven, and Degryse, 2010; Björkegren, 2022; Brunnermeier, Limodio, and Spadavecchia, 2023).[4] In contrast, in our context infrastructure provision is held fixed as part of a wider program of investment in digital public infrastructure (Reserve Bank of India, 2022; Alonso, Bhojwani, Hanedar, Prihardini, Una, and Zhabska, 2023), with low direct costs for private payment providers. We are therefore able to spotlight demand-side mechanisms. We use our clean setting to show that interoperability has quantitatively large implications for demand.

Turning to our methodological contribution to the empirical literature, our theory-informed empirical design allows us to relax a previous trade-off between imposing strong assumptions and drawing comparisons between relatively dissimilar units of observation. Specifically, a common challenge for assessing the impact of interoperability empirically is the lack of empirical variation within a given country, requiring the imposition of significant structural assumptions (as in, for example, Ferrari, Verboven, and Degryse, 2010; Björkegren, 2022), or the use of other countries as the counterfactual (as in, for example, Brunnermeier, Limodio, and Spadavecchia, 2023).[5] We therefore innovate by exploiting within-country variation in interoperability: while the integration of the incumbent platform with UPI occurred nationally, the *de facto* increase in interoperability varied across districts depending on their degree of ex-ante fragmentation. When estimating the

[3]See Bourreau and Valletti (2015) and Bianchi, Bouvard, Gomes, Rhodes, and Shreeti (2023) for recent surveys, focused on the implications of interoperability in mobile money markets. For recent theoretical work focused on the implications of strategic decisions taken by platform operators, see Brunnermeier and Payne (2022, 2023), Bourreau and Kraemer (2023) and Ekmekci, White, and Wu (2025).

[4]For instance, in Brunnermeier, Limodio, and Spadavecchia (2023) interoperability in the mobile money market—by lowering user fees—reduces the incentive for vertically integrated mobile network and mobile money operators to pay the variable costs associated with operating mobile towers, reducing network coverage.

[5]Brunnermeier, Limodio, and Spadavecchia (2023) do present some results using (cross-operator) within-country variation in interoperability, but note in their Section 3.1.4 that the vast majority of this variation is driven by country-level interoperability policies, since African telecoms operators very rarely deviate from national policy.

impact of interoperability on usage of digital payments, we are thus able to draw a tighter comparison than previous work.[6]

More broadly, a long literature addresses the adoption and diffusion of network technologies, including payments. Building on initial theoretical work (e.g., Katz and Shapiro, 1985; Weinberg, 1997; Rochet and Tirole, 2003, 2004), a more recent empirical literature leverages newly available microdata to test and deepen our understanding of the underlying mechanisms across various settings, for example, Björkegren (2019) on mobile phones, Higgins (2024) on debit cards and POS machines, and Wang (2024) on credit cards. Most closely related to our work are papers by Crouzet, Gupta, and Mezzanotti (2023) and Alvarez, Argente, Lippi, Méndez, and Patten (2023), which each examine the implications of strategic complementarities for the adoption of a digital payment platform. We build on their insights by considering the implications of network externalities when *multiple* such platforms co-exist. This multiplicity of providers introduces two new considerations: the potential for network fragmentation, and the amplification of strategic complementarities that support adoption in the presence of interoperability.

Finally, our paper relates to a growing literature on the downstream impacts of widespread use of digital payments, particularly in the context of India.[7] Reflecting the speed and scale of UPI's take-off, these impacts have been pervasive, affecting risk-sharing (Patnam and Yao, 2020), debt enforcement (Rishabh and Schäublin, 2021), lending (Rishabh, 2024; Ghosh, Vallee, and Zeng, 2022; Alok, Ghosh, Kulkarni, and Puri, 2024), bank deposits (Di Maggio, Ghosh, Ghosh, and Wu, 2024), consumption (Agarwal, Ghosh, Li, and Ruan, 2024) and growth (Dubey and Purnanandam, 2023), among other outcomes. This extensive literature—including some large estimated benefits of digital payments—raises an important question: What drove such a rapid take-off of digital payments in India? Several of these papers exploit the demonetization shock of November 2016, following which severe cash shortages prompted widespread substitution to digital alterna-

[6]Indeed, by including state-time fixed effects in our regressions, we in fact base our estimates on comparisons across districts within the same *state*, i.e., within a sub-national region.

[7]Beyond India, a series of recent papers also examine the impacts of Pix on the financial sector and monetary policy transmission in Brazil (Sarkisyan, 2023; Sampaio and Ornelas, 2024; Ding, Gonzalez, Ma, and Zeng, 2024; Liang, Sampaio, and Sarkisyan, 2024).

tives. However, this shock alone cannot explain longer-term adoption trends: Crouzet, Gupta, and Mezzanotti (2023) show that adoption of a closed-loop electronic wallet contracted once the cash crunch subsided, while Lahiri (2020) shows that aggregate digital payment transaction volumes in India declined in the first half of 2017, before suddenly re-accelerating. Crouzet, Ghosh, Gupta, and Mezzanotti (2024) offer another explanation for rapid adoption in India: a relatively young population, who prefer mobile payments and so in turn incentivize businesses to adopt the technology. In this paper, we contribute a third explanation: the creation of an interoperable retail digital payments system, UPI, allowed the unification of previously fragmented networks without sacrificing users' ability to choose their preferred payment app. This view can explain the rapid acceleration in digital payments volumes in late 2017, since two major platform operators joined UPI in that period, bringing with them their existing user bases.

The rest of this paper proceeds as follows. Section 2 summarizes the institutional setting and our data and presents descriptive evidence that users value interoperability. Section 3 presents our conceptual framework and highlights that ex-ante fragmentation shapes the benefits of the introduction of interoperability. Section 4 presents our empirical strategy, takes the model predictions in the cross-section to the data, and explores robustness. Section 5 considers the wider implications of our results, estimating the total national impact on digital payments usage and examining spillovers to credit markets. Section 6 concludes.

2 Setting and Descriptive Evidence

This section first provides background on the institutional context of our study, then describes our data and presents descriptive evidence that users value interoperability.

2.1 Institutional context

UPI is an instant payments platform built on top of the Immediate Payment Service (IMPS) infrastructure, India's pre-existing real-time interbank electronic fund transfer service. The National

Payments Corporation of India (NPCI, regulated by the Reserve Bank of India) provides payment rails. UPI apps are provided by both banks and non-bank third-party application providers (TPAPs), which are typically fintech firms. In the case of bank apps, the bank provides both a user-facing front-end application and executes transactions on the back end through IMPS. TPAPs provide the front-end application but partner with a payment service provider (PSP) bank that is connected to IMPS and executes the transaction.[8] Users of any UPI app are thus able to initiate payments from their accounts at any participating bank to accounts at other participating banks, as well as to receive notifications of payments received into their accounts.[9]

UPI enabled new types of transactions between clients of different banks and fintech payment providers. Prior to UPI, end users could make transfers between some of the participants that would later join UPI. For instance, users could (i) make bank-to-bank transfers via IMPS, (ii) transfer money between some bank accounts and electronic wallets issued by closed-loop e-money providers, and (iii) transfer money between electronic wallets hosted by the same closed-loop e-money provider. However, users could not initiate transactions between bank accounts using apps offered by third parties, nor could they transfer money between electronic wallets offered by different e-money providers. UPI increased interoperability on both these dimensions by allowing TPAPs—including both new fintech firms and existing e-wallet providers—to interact with NPCI's IMPS via a partner PSP.[10] End users gained tahe ability to choose their favorite UPI payments app without affecting either the location of their deposits (which stay in their bank) or the set of other UPI users with whom they can transact.

This interoperability contrasts with closed-loop digital payment apps, where both the payer and the payee must use the same payment app. In a typical closed-loop transaction, the payer first loads money into an electronic wallet hosted by the app provider. If and only if the payee also maintains a wallet with the same provider, they can then receive a transfer through the provider's

[8] Appendix Figure A.1 depicts the steps involved in a UPI transaction. See also Copestake, Kirti, and Martinez Peria (2025) for further details.

[9] Settlement for end users is immediate, while settlement among financial institutions is managed through deferred net settlement with ten daily cycles.

[10] The extent of this interoperability in practice grew over time as more banks and closed-loop e-money providers joined the system.

network. At this point, the payee can either keep the money in the provider's network for other payments, or withdraw the funds to their bank account, which may be subject to fees and/or delays. Crucially, the requirement for both counterparties to hold wallets with the same provider creates a network effect: the more users a provider has, the more attractive it is to new users, since it offers more possibilities for transactions. This is not the case with app providers under UPI, where interoperability means that network effects operate primarily at the platform level.

The UPI ecosystem has grown steadily, and now features several hundred participating apps and banks (Figure 1). Total transaction values on the platform have grown exponentially to more than 18 billion per month, with UPI now dominating other forms of electronic retail payments in India and proxies for cash beginning to decline (Figure 2). Indeed, thanks to UPI India now makes more fast payments than any other country (Figure 3; see also ACI Worldwide (2023)).

The spread of UPI was facilitated by earlier public and private investments that reduced potential barriers to widespread adoption. The Pradhan Mantri Jan Dhan Yojana (JDY) financial inclusion program opened hundreds of millions of new bank accounts (Agarwal, Alok, Ghosh, Ghosh, Piskorski, and Seru, 2017). The Aadhaar biometric ID scheme provided each individual with a unique, verifiable digital identity that could be used to speed up transaction authentication and Know Your Customer checks. Lastly, the cost of mobile data fell by roughly 96 percent during the mid-2010s, driven in part by the entry of Reliance Jio, a new 4G-only network operator (Alonso, Bhojwani, Hanedar, Prihardini, Una, and Zhabska, 2023).

2.2 Data

We draw on three key sources of data. First, we use data on the universe of UPI transactions, provided directly by NPCI and not previously used for academic research.[11] We received monthly totals of value and volume, split by the interaction of the payer's app and the payer's bank branch,

[11] In contrast to previous work on UPI (e.g., Dubey and Purnanandam, 2023; Alok, Ghosh, Kulkarni, and Puri, 2024), our dataset covers transactions from *all* apps and banks in the UPI ecosystem, allowing us to provide a comprehensive picture of UPI usage.

from the beginning of UPI's pilot phase in April 2016 through to September 2024.[12] For the largest three UPI apps, plus the publicly developed app BHIM (the "Bharat Interface for Money") and a consolidated "Other Apps" category, we also received the full matrix of payer and payee app choices—i.e., for the same period, we have monthly totals of value and volume, split by the interaction of the payer's bank branch, the payer's app and the payee's app. In both cases, transaction totals are dis-aggregated into peer-to-peer (P2P) and peer-to-merchant (P2M) transactions. We also observe the number of unique users—proxied by the number of unique phone numbers—per month at the IFSC level. Second, we use data from a major Indian fintech firm ('the incumbent'). This firm pre-dated UPI and offered a popular closed-loop wallet before subsequently integrating with UPI. We obtain monthly, district-level totals of value, volume and unique users, again split by P2P and P2M transactions. Third, we obtain data from NPCI on cross-bank cash withdrawals from automated teller machines (ATMs) across India between April 2016 and December 2023, split by bank and pincode, which we aggregate to the district level.

Taken together, this unique data allows us to observe two large payment networks that initially operated separately—and subsequently integrated via interoperability—at a granular geographical level. Combined with a proxy for cash, this allows us to present empirical evidence that is tightly connected with our conceptual framework.[13]

2.3 New stylized facts

In this section, we present two stylized facts that suggest interoperability supported adoption of digital payments in India. Both draw on our novel data and are new to the literature.

1. Cross-app transactions drove growth in UPI transaction volumes. Figure 4 plots the share of UPI transactions in which the payer and payee use different UPI apps. On both value and

[12]Bank branches are identified by Indian Financial System Codes (IFSC), from which we extract the bank name and pincode, which we use to attribute transactions to banks and districts.

[13]We also use survey data for a large panel of households covering most Indian districts. Specifically, we use the Consumer Pyramids Household Survey (CPHS) conducted by the Centre for Monitoring Indian Economy (CMIE). This provides comprehensive, granular, high-frequency panel data on borrowing at the household level. See Dubey and Purnanandam (2023) for a more detailed description.

volume, the share of cross-app transactions consistently tops 40%, with cross-app transactions playing an especially large role in the early years when the platform reached widespread adoption. In the absence of an interoperable platform, these transactions could not take place, demonstrating that users directly value and utilize the ability to make payments to users of different apps. The strong persistence of cross-app transactions also suggests that—consistent with our conceptual framework—preferences for payment apps vary across users.

2. Users' post-demonetization choices indicate a preference for interoperable over closed-loop payments. As noted above, a wide literature exploits the decline in cash availability after demonetization as a shock to demand for digital payments. A natural question is then: When forced to try digital payments, which type of platform did users prefer? The incumbent payments platform for which we have data still offered only a closed-loop digital wallet in the year after demonetization—i.e., it had not yet integrated with UPI—allowing us to compare the impacts of demonetization on usage of closed-loop versus interoperable payments. Figure 5 shows the results. In November and December 2016, when the cash shortage was most severe, transaction values increased sharply on both platforms. However, as cash availability returned to normal in early 2017, the trends diverge: growth in total usage of the non-interoperable, closed-loop incumbent payment platform plateaued, even as adoption of UPI continued to grow exponentially. The difference in trends is substantial: while adoption of the non-interoperable alternative was flat between March and October 2017, UPI grew roughly three-fold. Moreover, UPI's interoperability was central to this growth. Cross-app payments rose even more than within-app payments (Appendix Figure A.2), suggesting that the extra feature of UPI relative to the closed-loop incumbent—i.e., interoperability—was indeed valued by users.

Both stylized facts are telling and point to an important role for interoperability in driving the growth of digital payments. However, they do not allow for causal or quantitative inference about the role of interoperability. Did digital payments grow more than they would have in a counterfactual without interoperability? By how much? We next turn to tightly linked theoretical and empirical evidence that can speak to these questions.

3 Model

This section introduces a stylized model in which "users", representing both households and firms, choose a payment method between two digital payment platforms and an outside option that can be thought of as cash. After setting up the model in Section 3.1, in Section 3.2 we show how interoperability can increase usage of digital payments by unifying the platforms' otherwise fragmented networks, and that this increase is larger for more fragmented districts. In Section 3.3, we extend the framework to derive empirical predictions that we then test in Section 4. Section 3.4 discusses a few modeling choices and assumptions, highlighting how they help isolate the key economic channels on which we focus. All proofs are provided in Appendix B.

3.1 Setup

Environment. We build a model of payment method choice and competition inspired by the modern literature on currency competition (e.g., Farhi and Maggiori, 2018; Coppola, Krishnamurthy, and Xu, 2023). The model is static. Many districts $d \in \{1, ..., D\}$ each contain a closed unit square of users, and each user seeks to make a within-district payment. Three payment methods are available and mutually exclusive: digital payment platform a, digital payment platform b, and an outside option C, which we label as cash.[14] Users in each district are distributed uniformly along two dimensions, x and y, where $(x, y) \sim U([0, 1] \times [0, 1])$. These dimensions capture users' intrinsic preferences over the payment methods, as we elaborate shortly. All users choose their payment method $p_{d,x,y} \in \{a, b, C\}$ simultaneously. To focus on how interoperability affects competition between multiple networks, we abstract from dynamic considerations related to early versus late adoption decisions within any single payment network, a question that has been studied extensively in Crouzet, Gupta, and Mezzanotti (2023) and Alvarez, Argente, Lippi, Méndez, and

[14] Imposing mutual exclusion rules out multihoming in the model. In Appendix D, we discuss the potential implications of this assumption for our empirical estimates.

Patten (2023).

Preferences for digital payments. To focus on network effects in the use of money and payments, we follow the literature (e.g., Krishnamurthy and Vissing-Jorgensen, 2012; Stein, 2012) in modeling the convenience that users derive from a given payment method, explicitly incorporating network externalities—that is, a user enjoys higher convenience when more users adopt the same payment method, as similarly modeled in the recent literature on digital payment adoption (e.g., Cong, Li, and Wang, 2021; Crouzet, Gupta, and Mezzanotti, 2023).

Specifically, user (x, y) in district d perceives digital payments platform $i \in \{a, b\}$ to provide utility in terms of convenience:

$$u^a_{d,x,y} = \begin{cases} 1 + \kappa N^*_{d,a} & \text{if } x \le \hat{x}_d \\ 0 & \text{if } x > \hat{x}_d \end{cases} \qquad u^b_{d,x,y} = \begin{cases} 0 & \text{if } x \le \hat{x}_d \\ 1 + \kappa N^*_{d,b} & \text{if } x > \hat{x}_d \end{cases} \tag{1}$$

where $N^*_{d,i}$ is the number of digital payments users that can be *accessed* through platform i in district d. In the absence of interoperability, this is simply equal to the number of users of platform i in district d, which we denote by $N_{d,i}$. Intuitively, the inclusion of $N_{d,i}$ captures the network externalities: a user of digital payment method i in district d enjoys higher convenience when more users adopt the same payment method i. The parameter $\kappa > 0$ summarizes the intensity of network benefits that each accessible user generates for each (other) platform user.

Following the literature on payment competition and consumer affinity for different types of service (e.g., Parlour, Rajan, and Zhu, 2022), we assume that exogenous differences across users—e.g., brand familiarity, service attachment, or personal preferences—split potential users of the two digital payment methods a and b into two types along the x-dimension: those who consider using platform a versus cash, and those who consider using platform b versus cash. Specifically, the boundary $\hat{x}_d \in (0, \frac{1}{2})$ in equation (1) above denotes the share of users in each district that perceive benefits from platform a relative to platform b. We allow districts to differ in the level of this $\hat{x}_d$. The lower bound $\hat{x}_d > 0$ implies that all districts include some users who consider each platform. The upper bound $\hat{x}_d < \frac{1}{2}$ is without loss of generality and imposed purely for expositional convenience: it entails that platform b always ends up with more digital payments users in every district, allowing us to use higher values of $\hat{x}_d$ as a monotonic indicator of pre-interoperability network fragmentation. Aside from differences in $\hat{x}_d$, districts are assumed to be identical.

Preferences for cash. Similarly, using cash provides utility $u^C_{d,x,y} = \gamma y$ from its convenience, and we denote by $N_{d,C}$ the number of cash users in district d. As a benchmark, we assume that this cash convenience to a given user does not depend on other users' choices of payment method. Instead, users differ on a pure cash preference y, which could reflect pure idiosyncratic heterogeneity or differences in adoption costs, demographic preferences (Crouzet, Ghosh, Gupta, and Mezzanotti, 2024), or instrumental motives (e.g., informal merchants seeking to minimize taxable income). We impose the parameter restriction that $\gamma > 1 + \kappa$, which is sufficient to ensure that some users always choose cash.[15]

Expectations and equilibrium concept. Users have rational expectations over others' choices, and we focus on stable, rational equilibria in pure strategies. Specifically, any equilibrium consists of a collection $\{N_{d,a}, N_{d,b}, N_{d,C}\}$ such that $N_{d,a} + N_{d,b} + N_{d,C} = 1$ for all $d \in \{1, \ldots, D\}$. In equilibrium, users' expectations about the total number of users adopting their chosen payment method are correct. Moreover, following a deviation by a small but positive mass of users, choices revert to the same equilibrium, ensuring stability.[16]

Interoperability. When interoperability is imposed, it entails that each digital payments platform enables access to the combined user base of both: $N^*_{d,i}$ becomes $N^D_d := N_{d,a} + N_{d,b}$ for both $i \in \{a, b\}$.

[15]To see this, note that for the users with strongest preferences for cash ($y = 1$), even if all other users pooled on a given digital platform ($N_{d,i} \to 1$), the payoff from using i would still be less than that from using cash, since $\lim_{N_{d,i}\to 1} u^i_{d,x,y}(y = 1) = 1 + \kappa < \gamma = u^C_{d,x,y}(y = 1)$.

[16]We also impose the tie-breaking assumption that users who are indifferent between cash and a digital platform choose the digital platform. Given that each user has infinitesimal mass, this assumption is without loss of generality.

3.2 Equilibrium analysis

We first consider the implications of interoperability in a single district d and examine equilibria in the baseline and when interoperability is imposed. Users' problem is to choose the payment method that maximizes their utility, given their perceptions of the value of each option and their expectations of others' choices:

$$\max_{p_{d,x,y} \in \{a,b,C\}} U_{d,x,y} = \begin{cases} u^a_{d,x,y} & \text{if choosing digital payments platform } a, \\ u^b_{d,x,y} & \text{if choosing digital payments platform } b, \\ u^C_{d,x,y} & \text{if choosing cash.} \end{cases} \tag{2}$$

Since each user's valuation of cash never changes across scenarios, total welfare rises monotonically with the number of users choosing to make digital payments in equilibrium, allowing us to use total digital payments as a proxy for social welfare.[17]

We first construct a benchmark against which to measure the impact of interoperability by considering the simplified case in which all users value the two digital payments platforms identically. Specifically, when equation (1) is replaced with $u^i_{d,x,y} = 1 + \kappa N_{d,i}$ for $i \in \{a, b\}$ we derive the following lemma:

Lemma 1 (Homogeneous platform valuations)**.** *When users' valuations of the two digital platforms are homogeneous, the only stable equilibria are those in which all digital payments users pool on one platform. In these equilibria, total digital payments usage is* $N_d^{D,Homog} = \bar{y} = \frac{1}{\gamma - \kappa}$.

This outcome is depicted in Figure 6. Intuitively, when all users value the two digital payments platforms identically, all digital payments users—those for whom the utility of digital payments outweighs their preference for cash—prefer to be on the larger platform. Such users thus always choose the platform they expect to have a larger user base, so any outcome in which they end up

[17] Intuitively, cash is always available to every user, and always provides the same value to them, i.e., γy. Thus each inframarginal user choosing instead to use digital payments must receive value strictly greater than γy, implying a rise in total welfare.

on the smaller platform does not fulfill their expectations, violating our concept of equilibrium.[18] Ultimately, this leads to a single dominant platform, realizing the maximum possible network benefits.

Turning to the baseline, where preferences follow equation (1), the exogenous differences in familiarity or preferences lead digital payments users to split between the two platforms, leading to fragmentation and reducing total realized network benefits.

Lemma 2 (Baseline equilibrium)**.** *When users' valuations of the two digital platforms are heterogeneous, digital payments users fragment between platforms. Usage of platform a is $N_{d,a} = \hat{x}_d \hat{y}_{d,a} = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d}$ and usage of platform b is $N_{d,b} = (1 - \hat{x}_d)\hat{y}_{d,b} = \frac{1-\hat{x}_d}{\gamma - \kappa(1-\hat{x}_d)}$, resulting in total digital payments usage $N_d^{D,Baseline} = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} + \frac{1-\hat{x}_d}{\gamma - \kappa(1-\hat{x}_d)}$.*

This outcome is depicted in Figure 7a. Intuitively, the heterogeneous preferences among users on which digital payments platform is preferable leads them to fragment between the two. This, in turn, reduces the network benefits associated with each platform and lowers total usage of digital payments and total welfare relative to the pooling equilibria that result from homogeneous preferences in Lemma 1.

Lemma 3 (Interoperability equilibrium)**.** *When users' valuations of the two digital platforms are heterogeneous, interoperability raises total digital payments to the level that results when valuations are homogeneous. Usage of platform a is $N_{d,a} = \hat{x}_d \bar{y} = \frac{\hat{x}_d}{\gamma - \kappa}$ and usage of platform b is $N_{d,b} = (1 - \hat{x}_d)\bar{y} = \frac{1-\hat{x}_d}{\gamma - \kappa}$, resulting in total digital payments usage $N_d^{D,Interop} = \bar{y} = \frac{1}{\gamma - \kappa}$.*

This outcome is depicted in Figure 7b. Interoperability unlocks network benefits between users on different platforms, leading total usage of digital payments to rise to the level that results when users all pool on one platform. Combining Lemmas 1, 2 and 3, we have:

Proposition 1 (Interoperability and total digital payments)**.** *Interoperability resolves market fragmentation, increasing total usage of digital payments—and hence welfare—to the level that would*

[18] A third equilibrium does exist where usage of the two digital payments platforms is exactly equal, but this outcome is unstable: the deviation of an arbitrarily small but positive mass of users ϵ from platform j to platform i would lead all other digital payments users to also prefer i, implying a pooling equilibrium once again.

result in the absence of heterogeneous valuations of platforms across users.

Importantly, Proposition 1 highlights that interoperability delivers the network benefits and level of total adoption that would otherwise require a single, dominant platform while still respecting users' heterogeneous preferences across competing platforms. When user preferences are homogeneous, the two configurations—either connecting platforms through interoperability or pooling all users onto a single monopoly platform—lead to the same level of digital payment usage, denoted $\bar{y}$. However, when users have heterogeneous preferences over the competing platforms and do not naturally converge on one, only interoperability can unify them within a single connected network while respecting their heterogeneous preferences, thereby maximizing welfare. In this sense, interoperability helps realize the full network benefits of digital payments without sacrificing user choice.

Immediately, we note that by realizing previously unrealized cross-platform network effects, interoperability not only increases total adoption of digital payments but also makes *both* platforms more valuable to users:

Proposition 2 (Interoperability and usage per digital platform)**.** *When users' valuations of digital payments platforms are heterogeneous, interoperability increases usage of both platforms, relative to the baseline equilibrium without interoperability.*

This outcome is illustrated by the arrows in Figure 7b. Intuitively, the expanded user base accessible to each platform's users makes both platforms more attractive. This increased appeal attracts more users, regardless of their heterogeneous preferences over the two platforms, leading them to adopt their preferred digital payment method over cash.

An important question is: how do these benefits and improvements vary with the degree of pre-interoperability fragmentation? Recall that Proposition 1 characterizes the increase in digital payments usage unlocked by the introduction of interoperability. We examine the heterogeneous effects across districts by differentiating this quantity with respect to $\hat{x}_d$, which captures the degree of initial fragmentation. The next key result shows that, interestingly, the greater the initial fragmentation, the larger the gains from introducing interoperability.

Proposition 3 (Impact on total digital payments by initial fragmentation)**.** *The more fragmented users of digital payments are across platforms prior to interoperability, the larger the increase in total digital payments usage—and hence welfare—unlocked by interoperability.*

To help understand Proposition 3, Figure 8a illustrates this result by comparing equilibrium outcomes in two districts, District 0 and District 1, where the latter has a higher share of users that perceive benefits from platform a relative to platform b (i.e., $\hat{x}_1 > \hat{x}_0$). The blue and green areas respectively show the no-interoperability usage of platforms a and b in District 0, while the dotted lines trace the corresponding regions in District 1 (which are also the same as the shaded regions in Figure 7a). Total usage of digital payments in the no-interoperability equilibrium is lower in District 1 than in District 0: the lower usage of platform b in District 1 more than outweighs the higher usage of platform a. With interoperability, both districts converge to the same level of total usage of digital payments $\bar{y}$. Combining these two observations reveals that interoperability increases adoption of digital payments by more in District 1 than in District 0. The top arrow in Figure 8b shows the comparison being made: both districts see a rise in total digital payments under interoperability—or equivalently, a reduction in usage of cash—but this is largest in the district with higher $\hat{x}_d$ (recalling that $\hat{x}_d < \frac{1}{2}$, so both districts are to the left of the peak of the red line).

The key economic intuition underlying Proposition 3 is that more fragmented networks ex ante imply greater unrealized network benefits ex ante. In the model, greater fragmentation prior to interoperability, captured by a larger $\hat{x}_d$, implies that users are split more evenly across the two competing platforms due to differences in preferences or attachments. This fragmentation limits each platform's effective network size, leaving substantial network benefits unrealized. By enabling cross-platform transactions, interoperability effectively combines the disjoint user bases into a unified network, thereby realizing higher previously unrealized network benefits and unlocking a larger share of potential digital payment transactions over cash. In contrast, when $\hat{x}_d$ is small—i.e., when the district is already relatively integrated and users are concentrated on a single platform—the marginal gains from interoperability are limited, as most network benefits of digital payments over cash are already realized.

Finally, how are the larger gains from interoperability in more fragmented contexts distributed between platforms? Proposition 2 highlights that interoperability increases usage of each platform relative to the no-interoperability baseline. Differentiating the gain for each platform with respect to $\hat{x}_d$, we derive the following proposition:

Proposition 4 (Impact on usage per platform by initial fragmentation)**.** *When the no-interoperability level of fragmentation is relatively low, a marginally higher level of such fragmentation leads to a larger increase in usage of both digital payments platforms under interoperability. When the no-interoperability level of fragmentation is relatively high, a marginally higher level of such fragmentation can lead to either a larger or smaller increase in usage of a given digital payments platform under interoperability.*

To see these two cases intuitively, consider two districts again and let $\hat{x}_0 = \epsilon$ and $\hat{x}_1 = \epsilon + \zeta$. First, set $0 < \zeta < \frac{1}{2}$ and $\epsilon \to 0$. As ϵ approaches zero, District 0 approaches full unification (on platform b) even without interoperability—i.e., the no-interoperability level of fragmentation is very low. In such a case, introducing interoperability has a negligible impact on the utility of digital payments, since almost all digital payments users can transact with one another even without interoperability. In comparison, in District 1 the introduction of interoperability unlocks non-negligible cross-platform network effects, increasing usage of digital payments on both platforms. Thus interoperability increases usage on both platforms by more in the district where usage is initially more fragmented, as in the first case in Proposition 4. Second, let $\epsilon \to \frac{1}{2}$ and $\zeta \to 0$. As ϵ approaches one half, the impact of further fragmentation on total gains from interoperability levels off—since once fragmentation peaks at $\hat{x}_d = \frac{1}{2}$, further increases in $\hat{x}_d$ would imply a *reduction* in fragmentation. Thus, in the region of $\hat{x}_d \approx \frac{1}{2}$, a higher level of no-interoperability fragmentation $\hat{x}_d$ does not imply any increase in total digital payments in the interoperability equilibrium. Therefore if one platform is to nonetheless *gain* greater usage under interoperability when initial fragmentation rises, the other platform must *lose* such usage—producing the ambiguity in the second case in Proposition 4.[19]

[19] To see this in Figure 8b, we first highlight that the black curve need not be symmetrical around $\hat{x}_d = \frac{1}{2}$ (unlike

3.3 Empirical predictions

The simplest tests of our model would compare the observed usage of digital payments in a given district before and after the introduction of interoperability. However, such tests would require the strong assumption that all else remains equal over the same interval. In Appendix C, we extend the model to allow for external shocks ω that affect ΔN_d^D, the change between pre-interoperability and post-interoperability equilibria in total digital payments. We show that while ω precludes using ΔN_d^D (or the single-platform equivalents $\Delta N_{d,a}$ and $\Delta N_{d,b}$) in a single district to test Propositions 1 and 2, we can nonetheless derive unambiguous tests of the extended model, based on Propositions 3 and 4, by comparing similar districts. Specifically, the extended model implies predictions for how ΔN_d^D, $\Delta N_{d,a}$ and $\Delta N_{d,b}$ vary across districts with (i) common shocks ω and (ii) different levels of fragmentation in the pre-interoperability equilibrium. Since $\hat{x}_d$ is not observable, we derive predictions that measure (ii) by $F_d := \frac{N_{d,a,-1}}{N_{d,-1}^D}$, where $N_{d,a,-1}$ and $N_{d,-1}^D$ are respectively the (observable) usage of platform a and of both platforms combined in the pre-interoperability equilibrium. Our predictions, analogous to Propositions 3 and 4, are as follows:

Prediction 1 (Interoperability and total digital payments)**.** *Introducing interoperability increases total usage of digital payments by more in districts where digital payments usage is initially more fragmented across platforms—i.e.,* $\frac{\partial \Delta N_d^D}{\partial F_d} > 0$.

Prediction 2 (Interoperability and usage per platform)**.** *When districts' digital payments users are relatively unified ex ante, introducing interoperability increases usage on each platform by more in districts where digital payments usage is initially more fragmented across platforms—i.e.,* $\frac{\partial \Delta N_{d,a}}{\partial F_d} > 0$ *and* $\frac{\partial \Delta N_{d,b}}{\partial F_d} > 0$.

the red curve): for any given $\hat{x}_d$, the increase in usage of platform a (the blue region) could differ from the increase in usage of platform b (the green region), albeit subject to the constraints that (i) the two increases (regions) sum to the reduction in usage of cash (i.e., the area under the red curve), and (ii) the increase in usage of platform a for a given $\hat{x}_d$ is equal to the increase in usage of platform b for $1 - \hat{x}_d$, since the two platforms are mirror images of each other. The condition that "the no-interoperability level of fragmentation is low" in Proposition 4 then equates to the condition that the districts under consideration are to the left of the peaks of the black line and the equivalent curve for platform b.

3.4 Discussion of modeling choices

The baseline model is deliberately kept simple to highlight the key economic channels. Below, we discuss several modeling choices and assumptions, and assess the extent to which they affect the scope of our model's predictions.

Focus on adoption and number of users rather than transactions. In focusing on adoption decisions, our equilibrium concept is based solely on the equilibrium number of users for each payment method. Accordingly, the model implies that for each method the total number of transactions is proportional to the total number of users. This modeling choice is supported by the data. In particular, our empirical analysis disaggregates the effects across three margins: (i) the average value per transaction, (ii) the number of transactions per digital payment user, and (iii) the number of users per capita. We find that margin (iii) accounts for the majority of the observed variation, consistent with the model's emphasis on adoption as the key driver.

Focus on user rather than platform decisions. The model abstracts from the objectives and actions of the platform providers, simply assuming that two competing platforms exist and that interoperability may or may not be exogenously imposed. In this context, users always benefit from joining a platform with a larger user base and unification of users in a single network is always beneficial. Unification in a single integrated network through interoperability thus delivers the same total welfare as the unification on a single private provider that would occur in the absence of heterogeneous platform valuations. In reality, these two outcomes could have quite different implications. As discussed in Section 1, "winner-takes-all" private unification could lead to rent extraction from users or reduce incentives to innovate, leading policymakers to prefer the interoperability outcome even if rapid unification on a single private platform is feasible.[20] We abstract from these considerations in the model to focus on crystallizing the mechanisms in our main empirical results. We leave a detailed exploration of provider behavior to future work.

[20] Even unification on a single interoperable platform could have downsides, however, if doing so slows innovation on the underlying platform infrastructure. See, for instance, previous debates around introducing 'New Umbrella Entities' to compete with UPI, which ultimately did not proceed.

Within-district payments only. We focus on within-district payments to simplify the model by removing cross-district dependencies. We analyze the implications of cross-district payments in Appendix E. The core implication for our main empirical exercise is that the presence of cross-district transactions would attenuate our estimates of the impact of integration on digital payments usage, implying that our empirical results are likely to be a lower bound on the true effect.

Exogenous and discrete preference boundary $\hat{x}_d$. We assume an exogenous and discrete boundary $\hat{x}_d$ between the two digital payment platforms, which remains unaffected by the introduction of interoperability. This modeling choice significantly simplifies the derivation of the equilibrium, while still allowing the two platforms to compete for users who would otherwise rely on cash.[21] One downside is that this eliminates a "platform switcher" margin: for instance, a user might have an intrinsic preference for platform a yet choose platform b in the absence of interoperability because it provides access to a larger network; interoperability then unlocks an additional benefit for the user, since it frees them to switch to the platform that they intrinsically prefer. However, incorporating this channel would not affect our main empirical predictions, if the proportion of "potential switchers" is sufficiently small, and our empirical results align with this interpretation.[22]

4 Empirical Analysis

This section examines the integration of two large payment networks. We examine the heterogeneous implications of interoperability due to variation in ex-ante fragmentation in empirical tests that are tightly linked to the model's predictions. We consider growth in digital payments in absolute terms and relative to cash.

[21] Specifically, imposing the exogenous $\hat{x}_d$ boundary removes the need to solve a three-way indifference problem, in which the marginal user is perfectly balanced between the network benefits of platform a, the network benefits of platform b, and their own preferences for cash. This could be solved by introducing sufficiently strong platform preferences that vary continuously rather than discontinuously across users, but doing so would add little extra insight.

[22] Specifically, *both* platforms grow by more in ex-ante more fragmented districts after integration; we do not find evidence of overall substitution away from either platform. Of course, "gross switching" (where reallocating users swap platforms) could still be occurring, even without overall "net switching" (where many move in the same direction). However, we cannot observe such switching in our data. If it occurs, it simply layers an additional benefit of interoperability on top of our mechanisms.

4.1 Estimation strategy

Variation. To test our model predictions, we exploit the integration with UPI of a major incumbent fintech firm that previously offered only closed-loop payments. Founded before UPI, this firm's platform processed a larger total value of transactions than UPI in the month prior to their integration, but UPI was growing substantially faster (Figure 9). Moreover, UPI had a much wider geographical presence: in the median district, the incumbent platform had only a 7.4% share of total transaction value across the two platforms in the month before integration (Figure 10). Defining t_{-1} as the month before integration, we construct the following measure of the presence of the incumbent across districts d:

$$P_d := \frac{\text{Total value of transactions on the incumbent platform in district } d \text{ in } t_{-1}}{\text{Total value of transactions across both platforms in district } d \text{ in } t_{-1}}. \quad (3)$$

Values of P_d closer to 50% imply that users of the two platforms were more fragmented between platforms prior to the platforms' integration. Conversely, values closer to zero or 100% imply greater unification prior to the platforms' integration. In practice, 97% of districts have incumbent shares of less than 50% prior to integration (reflecting the skew in Figure 10a), so higher values of P_d almost always imply higher fragmentation. For our regressions below, we construct a dummy variable P_d^+ that takes value one only in districts with above-median values of P_d. The skew in P_d is such that even the highest value of P_d (87%) implies greater fragmentation than the median value of P_d (7.4%)—there is no district where the incumbent is so dominant that it reduces fragmentation to a level below the median. Thus, P_d^+ serves as an indicator for both (i) districts having an above-median *presence* of the incumbent platform prior to integration, and (ii) districts with an above-median *degree of fragmentation* between the two platforms prior to integration.[23] Consequently, we use both interpretations interchangeably when describing our results in this section.

[23]Put differently, P_d^+ is identical to F_d^+, where the latter is a dummy variable taking value one for above-median values of

$$F_d := \frac{\text{Total value of transactions on the smaller platform in district } d \text{ in } t_{-1}}{\text{Total value of transactions across both platforms in district } d \text{ in } t_{-1}} \quad (4)$$

which is the empirical analogue of F_d as defined in Section 3.3.

Specification. We adopt a heterogeneous adoption design (de Chaisemartin and D'Haultfœuille, 2023), comparing the average change in outcome variable y_{dt} after integration between districts d whose digital payments markets were more versus less fragmented ex ante. Specifically, we run the following specification at the district-month level

$$y_{dt} = \alpha_d + \alpha_{st} + \beta(P_d^+ \times 1_{\{t \geq t_0\}}) + \beta_Z(Z_d \times 1_{\{t \geq t_0\}}) + e_{dt}\,, \tag{5}$$

where: α_d and α_{st} are district and state-time fixed effects; $1_{\{t \geq t_0\}}$ is a dummy variable indicating post-integration periods; and Z_d is the total value of transactions across both platforms in period t_{-1} (i.e., the denominator in equation (3)). We include the Z_d term to account for the fact that districts with higher P_d also tend to have higher total pre-integration transaction values, making it important to distinguish the impact of integrating *more fragmented* networks from any differential impact that integration may have had in districts where digital payments usage *in general* was greater ex ante. We cluster standard errors at the district level (Bertrand, Duflo, and Mullainathan, 2003).

Our coefficient of interest, β, measures the monthly average increase in y_{dt} after integration in districts that were more fragmented than the median ex ante, relative to districts that were less fragmented, after controlling for district and state-time fixed effects and differential trends by total pre-integration transaction value. Put differently, we use the low fragmentation districts to directly observe a counterfactual in which *de facto* interoperability is relatively unaffected by the integration event—since most digital payments users in such districts could transact with each other even before interoperability was imposed nationally. To explore the dynamics of this increase, we also run the corresponding event-study specification:

$$y_{dt} = \alpha_d + \alpha_{st} + \sum_{\tau \neq t_{-1}} \beta_\tau(P_d^+ \times 1_{\{t=\tau\}}) + \sum_{\tau \neq t_{-1}} \alpha_\tau(Z_d \times 1_{\{t=\tau\}}) + v_{dt}\,, \tag{6}$$

where the succession of month-wise dummies $1_{\{t=\tau\}}$ allows us to estimate differences in y_{dt} between P_d^+-groups in each period relative to the difference in the pre-integration baseline period.

Our primary outcome variable is the total peer-to-merchant (P2M) transaction value, across both platforms, per capita. This reflects the total transaction value across both platforms, minus peer-to-peer (P2P) transactions. Excluding the latter provides a closer match to our model—which focuses on within-district payments—because it eliminates remittances, which can be very large, are not payments (i.e., transfers of money in exchange for a good or service), and frequently cross district boundaries.[24] In our baseline specification we winsorize the top 1% of y_{dt} to moderate the influence of a small number of districts with very high transaction values.

Identification: no anticipation. In the model, when users make their payment choices in the non-interoperability equilibrium they do so with the correct, certain belief that the two platforms are not in fact interoperable. In reality, users making payment decisions prior to integration may have anticipated that the two platforms would integrate in future. If users correctly predicted that digital payments would increase in usefulness by more in high P_d districts relative to low P_d districts, total digital payments y_{dt} may have increased by more in high P_d districts prior to integration. For instance, merchants in high P_d districts may have increased their acceptance of digital payments relative to those in low P_d districts. Such anticipation would bias our estimate of β, since it is estimated by comparing the average change in the value of digital payments after integration between the two groups.

Three considerations mitigate this concern. First, the incumbent's decision to integrate with UPI was immediately preceded by an RBI directive mandating that digital wallet providers make their wallets interoperable through UPI. Accurate anticipation would thus have required detailed knowledge of the regulatory landscape. We do not consider it plausible that such knowledge would have been sufficiently widespread among the general population to affect our results. Second, such widespread anticipation—if it did occur—would only bias down our estimate of β in equation (5), since higher usage of digital payments in above-median P_d districts ex ante would reduce an estimated increase in usage ex post. Thus this concern would only reduce the likelihood that we

[24] See Section 3.4 and Appendix E for further discussion of the potential implications of including cross-district transactions.

find evidence in favor of Prediction 1 of the model, making our conclusions relatively conservative. Finally, when we examine the dynamics of our estimated effects using equation (6), we do not see evidence of differential pre-trends between high- and low-P_d districts, suggesting that anticipation is not a significant concern for our results.

Identification: parallel trends. In the model, districts d differ only on the exogenous boundary $\hat{x}_d$, which in turn determines the market shares of each platform in the absence of interoperability between them. In reality, high- and low-P_d districts could differ in other ways, such that the observed evolution of outcomes y_{dt} in low-P_d districts does not provide an accurate proxy for the potential outcomes of the high-P_d districts in the counterfactual world in which they were less exposed to the platforms' integration.

We mitigate this concern in five ways. First, we include state-time fixed effects, such that we only compare high- and low-P_d districts within the same state. Second, we control for differential trends by total pre-integration transaction value. Thus we control for any factors that affect districts' propensity to use digital payments *overall*, leveraging only differences in the *composition* of that usage. Third, we find no statistical differences in pre-integration trends in y_{dt} between high- and low-P_d districts using equation (6). Fourth, we show that results remain similar when comparing high-P_d districts to a matched sample of low-P_d districts that are otherwise similar on observables. Fifth, we show that results also remain similar when instrumenting P_d with geographic decisions taken by the incumbent more than a year prior to integration—before the unexpected demonetization shock changed the landscape of digital payments in India. Further details and results from the matching and instrumental variable approaches are provided in Sections 4.3.1 and 4.3.2 respectively.

4.2 Estimation results

Our baseline estimation results for equation (5) are shown in Table 1. Column 1 shows that the total P2M transaction value per person increased by 8 Rupees per person per month more after integration in high-P_d districts than in low-P_d districts. This response is statistically highly significant and economically substantial: the increase is 88% of average P2M digital payments in high-P_d districts in the month prior to integration, and 118% of average monthly P2M digital payments in low-P_d districts across the year after integration. Consistent with our conceptual framework, digital payments grew not just in absolute terms but also relative to cash: Column 2 shows that total P2M digital payments relative to cash withdrawals similarly increased by substantially more in high-P_d districts than in low-P_d districts. Figure 11 shows the dynamics of these differences: low-P_d and high-P_d districts do not differ significantly prior to integration, then substantial and persistent differences emerge after integration.

What drove this relative increase in usage of digital payments? The final three columns of Table 1 break down the total increase in Column 1 across three different categories of transactions: transactions where both the payer and the payee used the incumbent's app (Column 3), transactions where both the payer and payee used an alternative UPI app (Column 5), and the newly enabled transactions where one of the payer and payee used the incumbent's app, and the other used another UPI app (Column 4). All three transaction categories show increases that are both statistically and economically significant. The coefficient on the increase in transactions between users of the incumbent's app and users of other UPI apps is smaller, since the total value of these transactions begins at zero, but the magnitude is substantial when compared to the average increase in low-P_d districts: the differential increase in such payments in high-P_d districts is more than 50% of the level reached in low-P_d districts. Turning to transactions between users of the incumbent's app, and transactions between users of other UPI apps, in both cases districts that were more fragmented ex ante see substantially larger increases in usage post-integration—implying that the greater increase in total network size encouraged users of all apps to use the combined platform more intensively, even for transaction types that were feasible pre-integration. Our results thus suggest that unifying fragmented networks was a "win-win" in this context: instead of leading to substitution away from one of the previously separate networks, integration increased usage of both.[25]

[25] Appendix Figure A.3 shows the dynamics of these estimates: again, low-P_d and high-P_d districts do not differ significantly prior to integration, then substantial and persistent differences emerge after integration.

To unpack the margins underlying the increase in total transaction value per capita, we next decompose our main estimate (Table 1 Column 1) into the impacts via (i) average value per transaction, (ii) transactions per user, and (iii) users per capita. In short, we take the total derivative of transaction value per capita around the post-interoperability low-P_d sample mean, giving us the shares of the total effect that are explained by changes in each of (i) to (iii).[26] We show the decomposition in Figure 12, and the constituent estimates in Appendix Table A.1. All three margins increased significantly more in high-P_d districts than in low-P_d districts, with (i), (ii) and (iii) increasing by 3.0%, 2.6% , and 16% respectively relative to the post-interoperability mean among low-P_d districts. Overall, growth in (iii), the number of users per capita, explained 72% of the total increase in digital payments per capita relative to this mean. While significant increases also occurred on the other two margins, the primary impact of integration was through an increase in the number of new users, in line with our focus on this margin in the model.

4.3 Robustness

In this section, we explore two complementary extensions of our main specification, both of which support a causal interpretation of our results. First, we repeat equation (5) when matching high-P_d districts to low-P_d districts with similar observables, and second, we instrument districts' P_d-status using pre-determined geographic decisions taken by the incumbent. Beyond these two approaches, in Appendix G we also check the robustness of our findings to a wide range of alternative specifications and run placebo tests for both the cross-sectional and temporal variation underlying our results. In all cases we find that our main results are qualitatively and quantitatively robust.

4.3.1 Matching on district characteristics

For our results to have a causal interpretation, we require that the low-P_d districts provide an accurate measure of the potential outcomes of the high-P_d districts in the counterfactual scenario in which they were less fragmented prior to integration. One potential concern is therefore that

[26] For a full description of our decomposition, see Appendix F.

the high-P_d districts differed from low-P_d districts in ways not accounted for by our controls and fixed effects. Appendix Figure A.4 shows the association between P_d^+ and a range of district-level observables. While high-P_d and low-P_d are similar on most dimensions, high-P_d districts have significantly larger populations.

To mitigate concerns that this observable difference in the evolution of digital payments usage between P_d^+-groups after interoperability, we construct a new sample in which we match each high-P_d district to similar low-P_d districts. We identify the three nearest low-P_d for each high-P_d district neighbor using Mahalanobis distance matching (with replacement) on the log of population. Additionally, we exclude 19 high-P_d districts for which no good match exists. This process of matching allows us to achieve balance across our high-P_d and low-P_d districts on all observables including population, while retaining 504 districts from our baseline sample.

We repeat our baseline from equation (5) using this matched sample. The results, shown in Table 2, are qualitatively and quantitatively similar to the baseline, as are the dynamics (Appendix Figure A.5). As in our baseline, we see no evidence of differential trends in payments prior to integration.

4.3.2 Instrumenting ex-ante fragmentation

Technologies diffuse through space (see, for instance, Comin, Dmitriev, and Rossi-Hansberg, 2012; Kalyani, Bloom, Carvalho, Hassan, Lerner, and Tahoun, 2025). Like many platform services, the incumbent firm's platform began in a small number of cities before spreading nationally, as a function of a marketing strategy decided well in advance of the subsequent—and unanticipated—integration with UPI. At any point in time, districts therefore varied in their proximity to the largest clusters of users. Adoption externalities could then imply that, following a shock that increased demand for digital payments, users closest to these clusters would be more likely to choose the incumbent's platform than an alternative, such as UPI (in the pre-integration world, where they were not yet interoperable).[27] We can exploit this variation to isolate variation

[27] Crouzet, Gupta, and Mezzanotti (2023) provide an extensive discussion of the possible sources of such adoption externalities in their Online Appendix F.

in P_d that is unlikely to be correlated with any remaining omitted factors that influence both P_d and the evolution of outcomes y_{dt}.

Building on Crouzet, Gupta, and Mezzanotti (2023), we identify eight "hub" districts in which at least 1000 merchants had adopted the platform by September 2016. These districts were outliers: 92% of districts had fewer than 100 merchants signed up, 85% had fewer than 10, and 42% had zero (Appendix Figure A.6a). However, the districts surrounding these hubs do not look significantly different from other districts (Appendix Figure A.6b): after all, they were not targeted by the incumbent firm, they simply happened to be located near a city that was.[28] To exploit this variation, we define a new proximity variable H_d: the negative of the distance in kilometers from the centroid of district d to the centroid of the nearest hub district. This measure is highly correlated with the presence of the incumbent in the last month before integration (Appendix Figure A.7a). This is unsurprising: when demonetization hit in November 2016, firms were more likely to adopt a given digital payments technology if they were close to other users (Crouzet, Gupta, and Mezzanotti, 2023). Moreover, the variation in P_d that can be explained by H_d is balanced on observable district characteristics (Appendix Figure A.7b).[29]

To implement this strategy, we first exclude the hub districts from the sample, then repeat equation (5) with the following first stage:

$$(P_d^+ \times 1_{\{t \geq t_0\}}) = \gamma_d + \gamma_{st} + \beta_H (H_d \times 1_{\{t \geq t_0\}}) + \gamma_Z (Z_d \times 1_{\{t \geq t_0\}}) + u_{dt} \,. \tag{7}$$

The results, shown in Table 3, are qualitatively similar, and quantitatively somewhat stronger than the baseline. The dynamics are also similar (Appendix Figure A.8).

[28] The one exception is that districts closer to hubs have a slightly lower agricultural share of workers, reflecting that they are more urban. However, given that income, literacy rates and bank and mobile phone coverage do not vary significantly with proximity to hubs, we do not consider this likely to be driving our results. Any residual concerns are mitigated by the fact that we find similar results when using our matched sample, described in the previous section, which is balanced on this variable.

[29] Again, the one exception is a marginally significant negative correlation with the agricultural share of workers, as discussed in the previous footnote.

5 Wider Implications

The analysis thus far focuses on the implications of interoperability for district-level usage of digital payments. We now widen our analysis in two dimensions. First, we combine our theory and empirics to derive a model-implied estimate of the aggregate national impact of the two networks' integration on usage of digital payments. Second, we examine the downstream consequences of districts' increased usage of digital payments, specifically the implications for credit markets.

5.1 Aggregate national impact

While the analysis in Section 4 validates our model's empirical predictions, it focuses on the *relative* impact of unifying fragmented networks, identified in the cross-section of districts.[30] Put differently, our well-identified estimates in the cross section do not directly imply an estimate of aggregate impact. Deriving such an impact requires us to solve a "missing intercept problem" (e.g., Wolf, 2023; Buera, Kaboski, and Townsend, 2023) to convert the cross-sectional estimates into aggregates. To solve this problem, we impose additional structure from our model, enabling us to derive estimates of the absolute impact of unification in each district, which we can then aggregate to the national level.

We define our object of interest in the model as $\Delta^I N^D$, the total national change in usage of digital payments that results from integrating fragmented networks. Building on the extended model in Appendix C, we derive the following result:

Proposition 5 (Aggregate impact)**.** *The aggregate impact of integrating the two platforms on total national usage of digital payments is equal to the sum of the observed changes in usage in each district, normalized by the observed change in usage in a district whose digital payments users are*

[30]Specifically, our estimates are informative on the differential increase in usage of digital payments after the introduction of interoperability, when comparing a district where digital payments are less fragmented ex ante, to one where digital payments are more fragmented ex ante.

already fully unified prior to interoperability. We have:

$$\Delta^I N^D = \sum_d \left[\Delta N_d^D - \Delta N_{d_0}^D\right] \ , \tag{8}$$

where $\Delta N_{d_0}^D$ is the post-interoperability change in usage of digital payments in a district whose digital payments users are already fully unified on one platform prior to interoperability.

Intuitively, we use the model's result that connecting the two networks has no impact on a district that is already fully unified on one platform ex ante: all digital payments users can already interact, so no new connections are enabled by interoperability. Thus $\Delta N_{d_0}^D = \omega$, so we can use the observed changes in d_0 to net out the impact of the unobserved shock in other districts.

Turning to the data, we proxy the "fully unified ex ante" districts d_0 with the first decile of the F_d distribution. Put differently, these districts allow us to directly observe a "no-interoperability" counterfactual. We can then estimate the impact in a given district d relative to that in d_0 by making the change in usage of digital payments in first-decile districts the baseline value in a version of equation (5). Specifically, we run:

$$y_{dt} = \alpha_d + \alpha_{st} + \sum_{n=2}^{10} \beta_n (F_d^n \times 1_{\{t \geq t_0\}}) + \beta_Z (Z_d \times 1_{\{t \geq t_0\}}) + e_{dt} \ , \tag{9}$$

where F_d^n is a dummy taking value one if district d is in the nth decile of the distribution of F_d. By omitting the interaction between F_d^1 and the post-interoperability dummy, each coefficient $\beta_2, ..., \beta_{10}$ is estimated relative to the baseline change in the most ex-ante unified districts—i.e., each coefficient β_n approximates $\Delta N_d^D - \Delta N_{d_0}^D$ within decile n of the F_d distribution. Thus under the assumptions of the model, and the identification assumptions discussed in Section 4.1 and Appendix C, this method recovers the absolute change in y_{dt} that results from integrating the two platforms' previously fragmented networks.

We define y_{dt} as the total P2M transaction value per capita, as in Section 4.1. Thus, each estimated coefficient $\hat{\beta}_n$ represents the monthly average increase in total P2M transaction value per capita after interoperability was introduced, across districts in decile n of the F_d distribution, relative to districts in the first decile, when controlling for district and state-time fixed effects and differential trends by total pre-integration transaction value. Appendix Figure A.9 plots the coefficients. As predicted by the model, we find a limited impact of interoperability in districts that are initially relatively unified, and an increasing impact in districts that are initially relatively fragmented.

Finally, we aggregate these estimates to the national level by calculating the empirical analogue of equation (8). Defining the total national increase in y that is attributable to interoperability as $\Delta^I y$, we calculate:

$$\Delta^I y = \frac{\sum_d \sum_{n=2}^{10} \hat{\beta}_n \times F_d^n \times \text{Population}_d}{\sum_d \text{Population}_d}\,, \tag{10}$$

i.e., we calculate the estimated impact $\hat{\beta}_n \times F_d^n$ in each district d in each decile n, aggregate these to the national level by applying population weights Population_d, then re-normalize using the national population. We find that connecting the two networks increased the total value of digital payments nationally by $\Delta^I y = 9.9$ Rupees per capita per month within the first year after integration. Comparing this to the average national P2M transaction value per capita in the month before integration, this equates to an increase of

$$\frac{\Delta^I y}{\left(\frac{\sum_d y_{d,t_{-1}} \times \text{Population}_d}{\sum_d \text{Population}_d}\right)} \times 100 = 160\%. \tag{11}$$

This large number partly reflects that overall digital payments grew substantially over the period. We therefore also compare $\Delta^I y$ to an estimate of the monthly average national P2M transaction value per capita in the month of the reform and over the following year, in the event that integration had not occurred. This counterfactual is simply the observed average national P2M transaction value per capita minus the part that we estimate results from interoperability, i.e., $\Delta^I y$. Thus we estimate that the two networks' integration raised the average national P2M transaction value per capita per month by

$$\frac{\Delta^I y}{\frac{1}{13}\sum_{t\geq t_0}\left(\frac{\sum_d y_{dt}\times \text{Population}_d}{\sum_d \text{Population}_d}\right) - \Delta^I y} \times 100 = 57\% \tag{12}$$

relative to the value that would have occurred in the absence of the integration event. Thus, our estimates from combining our model with cross-sectional evidence suggest that integrating fragmented networks can have a substantial aggregate impact on usage of a payments network. Considering that UPI ultimately integrated various other pre-existing networks—although none so large as the incumbent network that we study—our findings thus suggest that interoperability played a significant role in the take-off of the platform.

5.2 Downstream impact on lending

We primarily focus on how interoperability supports usage of digital payments in this paper. The conceptual framework and evidence we present shows that interoperability can increase usage of digital payments by integrating networks that would otherwise be fragmented. Here, we present evidence of a natural consequence of this increase in digital payments: increased activity in credit markets.[31]

We use a similar heterogeneous adoption design as in our baseline to examine whether higher usage after fragmented networks are integrated leads to more borrowing. We use the following specification at the household-survey wave level:

$$y_{ht} = \alpha_h + \alpha_{st} + \beta(P_d^+ \times 1_{\{t\geq t_0\}}) + \beta_Z(Z_d \times 1_{\{t\geq t_0\}}) + e_{dt}\,. \tag{13}$$

Our dependent variable here is the probability of borrowing from non-banks, as non-banks are more likely to be able to draw on the information generated by greater digital payments activity

[31] For surveys of the potential channels through which digital payments can facilitate credit provision, see Berg, Fuster, and Puri (2022) and Ouyang (2021, Section 3.2.1). For additional evidence in the Indian context, see Dubey and Purnanandam (2023).

(Ghosh et al., 2022). As in our baseline, this specification asks whether borrowing increased more in districts that were more fragmented ex ante, relative to districts that were less fragmented, after controls. In this case, we include household fixed effects α_h, as the data is at the household level, as well as state-time fixed effects α_{st}. We continue to cluster standard errors at the district level.

We find that borrowing does increase more in districts that benefited more from the integration of previously fragmented networks. Table 4 shows the results. After integration, in districts with above median fragmentation, the probability of borrowing increases by 1.1% relative to districts with below median fragmentation, which is economically large given the low baseline probability of borrowing. These increases were larger for households more likely to benefit from digital payments activities, specifically entrepreneurs or hawkers.[32]

Importantly, consistent with our conceptual framework and evidence on digital payments usage, we find that interoperability provides larger downstream benefits in districts with higher ex-ante fragmentation. As our measure of borrowing focuses exclusively on the extensive margin, these results show that more households are able to access credit after integration. These results therefore suggest that greater usage of retail digital payments reduces frictions in credit markets, allowing more households to borrow, consistent with prior work (Dubey and Purnanandam, 2023; Alok, Ghosh, Kulkarni, and Puri, 2024).

6 Conclusion

The presence of network effects in payment technologies leads to an important tradeoff in payment system design. On one hand, stronger network effects lead to concerns about the emergence of a few dominant platforms. On the other hand, disruption from new entrants—including public platforms—could lead to more fragmentation, undermining the inherent network benefits of payments.

[32]These households typically lack formal collateral, have significant credit constraints, and also face relatively high transaction frictions—each of which can be ameliorated by digital payments that create a verifiable record of revenues (Dubey and Purnanandam, 2023; Berg et al., 2022; Ghosh et al., 2022).

We use novel data to examine whether interoperability can help resolve this tension by reducing fragmentation without requiring all users to centralize on a single payments provider. Crucially, we observe activity on two large payment networks—and a proxy for cash—at a granular geographic level. This allows us to exploit the unique natural experiment created when the two networks became interoperable.

By comparing districts in which payments markets were more fragmented prior to integration—which effectively saw a larger integration shock—to districts with less initial fragmentation, we isolate the causal impact of interoperability. We estimate that integration roughly doubled the monthly value of digital payments in more fragmented districts. Importantly, newly enabled transactions between the two platforms rose significantly after integration, highlighting that users valued the additional options interoperability provided them. We also see positive spillovers within each network.

These estimates have important wider implications. Aggregating nationally, we estimate that integrating the two networks increased total nationwide usage of digital payments by more than 50% in the year after integration. Moreover, lending grew by more in districts in which interoperability brought larger gains to users of digital payments, consistent with greater uptake of digital payments reducing financial frictions.

Our empirical evidence on the impact of integrating large payment networks has important implications for policymakers focused on both domestic payments and cross-border payments. Where payment networks are poorly developed or fragmented, our results highlight that increasing interoperability can unlock substantial network benefits for users. Conversely, our results warn that promoting new, non-interoperable payment platforms risks significant costs by increasing fragmentation.

References

ACI WORLDWIDE (2023): "Prime Time for Real-Time Report 2023," .

AGARWAL, S., S. ALOK, P. GHOSH, S. GHOSH, T. PISKORSKI, AND A. SERU (2017): "Banking the Unbanked: What do 280 Million New Bank Accounts Reveal about Financial Access?" SSRN Scholarly Paper 2906523, Social Science Research Network, Rochester, NY.

AGARWAL, S., P. GHOSH, J. LI, AND T. RUAN (2024): "Digital Payments and Consumption: Evidence from the 2016 Demonetization in India," The Review of Financial Studies.

ALOK, S., P. GHOSH, N. KULKARNI, AND M. PURI (2024): "Does Open Banking Expand Credit Access?" NBER Working Papers.

ALONSO, C., T. BHOJWANI, E. HANEDAR, D. PRIHARDINI, G. UNA, AND K. ZHABSKA (2023): "Stacking Up the Benefits: Lessons from India's Digital Journey," Tech. rep., International Monetary Fund, Washington, D.C.

ALVAREZ, F. E., D. ARGENTE, F. LIPPI, E. MÉNDEZ, AND D. V. PATTEN (2023): "Strategic Complementarities in a Dynamic Model of Technology Adoption: P2P Digital Payments," NBER Working Papers, 31280 National Bureau of Economic Research, Inc.

BENIGNO, P., L. M. SCHILLING, AND H. UHLIG (2022): "Cryptocurrencies, Currency Competition, and the Impossible Trinity," Journal of International Economics, 136, 103601.

BERG, T., A. FUSTER, AND M. PURI (2022): "FinTech Lending," Annual Review of Financial Economics, 14, 187–207, annual Reviews.

BERTRAND, M., E. DUFLO, AND S. MULLAINATHAN (2003): "How Much Should We Trust Differences-In-Differences Estimates?" The Quarterly Journal of Economics, 119, pp. 249–275.

BIANCHI, M., M. BOUVARD, R. GOMES, A. RHODES, AND V. SHREETI (2023): "Mobile Payments and Interoperability: Insights From the Academic Literature," Information Economics and Policy, 65, 101068.

BJÖRKEGREN, D. (2019): "The Adoption of Network Goods: Evidence from the Spread of Mobile Phones in Rwanda," The Review of Economic Studies, 86, 1033–1060.

——— (2022): "Competition in Network Industries: Evidence From the Rwandan Mobile Phone Network," The RAND Journal of Economics, 53, 200–225.

BOURREAU, M. AND J. KRAEMER (2023): "Interoperability in Digital Markets: Boon or Bane for Market Contestability?" SSRN Scholarly Paper 4172255, Social Science Research Network, Rochester, NY.

BOURREAU, M. AND T. VALLETTI (2015): "Competition and Interoperability in Mobile Money Platform Markets: What Works and What Doesn't?" Communications & Strategies, 1, 11–32, iDATE, Com&Strat dept.

BRAINARD, L. (2019): "Delivering Fast Payments for All," Speech at the Federal Reserve Bank of Kansas City Town Hall, Kansas City, Missouri, August, 5, 2019.

BRUNNERMEIER, M. AND J. PAYNE (2022): "Platforms, Tokens, and Interoperability," Working Paper, Princeton University. Economics Department.

BRUNNERMEIER, M. K., N. LIMODIO, AND L. SPADAVECCHIA (2023): "Mobile Money, Interoperability, and Financial Inclusion," SSRN Scholarly Paper 4574641, Social Science Research Network, Rochester, NY.

BRUNNERMEIER, M. K. AND J. PAYNE (2023): "Strategic Money and Credit Ledgers," NBER Working Papers, 31561.

BUERA, F. J., J. P. KABOSKI, AND R. M. TOWNSEND (2023): "From Micro to Macro Development," Journal of Economic Literature, 61, 471–503.

CHODOROW-REICH, G., G. GOPINATH, P. MISHRA, AND A. NARAYANAN (2020): "Cash and the Economy: Evidence from India's Demonetization," The Quarterly Journal of Economics, 135, 57–103.

Comin, D. A., M. Dmitriev, and E. Rossi-Hansberg (2012): "The Spatial Diffusion of Technology," NBER Working Papers, 18534.

Cong, L. W., Y. Li, and N. Wang (2021): "Tokenomics: Dynamic Adoption and Valuation," The Review of Financial Studies, 34, 1105–1155.

Cong, L. W. and S. Mayer (2025): "Strategic Digitization in Currency and Payment Competition," Journal of Financial Economics, 168, 104055.

Copestake, A., D. Kirti, and M. S. Martinez Peria (2025): "Growing Retail Digital Payments: The Value of Interoperability," IMF Fintech Note 2025/004, International Monetary Fund, Washington, DC.

Coppola, A., A. Krishnamurthy, and C. Xu (2023): "Liquidity, Debt Denomination, and Currency Dominance," Tech. rep., National Bureau of Economic Research.

Crouzet, N., P. Ghosh, A. Gupta, and F. Mezzanotti (2024): "Demographics and Technology Diffusion: Evidence from Mobile Payments," SSRN Scholarly Paper 4778382, Social Science Research Network, Rochester, NY.

Crouzet, N., A. Gupta, and F. Mezzanotti (2023): "Shocks and Technology Adoption: Evidence from Electronic Payment Systems," Journal of Political Economy, 131.

Cunliffe, J. (2023): "The Digital Pound," Speech at UK Finance.

de Chaisemartin, C. and X. D'Haultfœuille (2023): "Credible Answers to Hard Questions: Differences-in-Differences for Natural Experiments," SSRN Scholarly Paper 4487202, Social Science Research Network, Rochester, NY.

Di Maggio, M., P. Ghosh, S. Ghosh, and A. Wu (2024): "Impact of Retail CBDC on Digital Payments, and Bank Deposits: Evidence from India," SSRN Scholarly Paper 4779520, Social Science Research Network, Rochester, NY.

DING, D., R. GONZALEZ, Y. MA, AND Y. ZENG (2024): "The Effect of Instant Payments on the Banking System: Liquidity Transformation and Risk-Taking," SSRN Scholarly Paper 5250569, Social Science Research Network, Rochester, NY.

DUBEY, T. S. AND A. PURNANANDAM (2023): "Can Cashless Payments Spur Economic Growth?" SSRN Scholarly Paper 4373602, Social Science Research Network, Rochester, NY.

DUFFIE, D. (2019): "Digital Currencies and Fast Payment Systems: Disruption Is Coming," in Asian Monetary Forum, May, mimeo.

——— (2023): "Fragmentation Risks to the Dollar-Dominated International Financial Order," Keynote Speech at Asian Bureau of Finance and Economic Research.

EKMEKCI, M., A. WHITE, AND L. WU (2025): "Platform Competition and Interoperability: The Net Fee Model," Management Science.

FARHI, E. AND M. MAGGIORI (2018): "A Model of the International Monetary System," The Quarterly Journal of Economics, 133, 295–355.

FERRARI, S., F. VERBOVEN, AND H. DEGRYSE (2010): "Investment and Usage of New Technologies: Evidence from a Shared ATM Network," The American Economic Review, 100, 1046–1079.

FINANCIAL STABILITY BOARD (2024): "G20 Roadmap for Enhancing Cross-border Payments," Tech. rep., Financial Stability Board, Basel, Switzerland.

FISHER, I. (1911): The Purchasing Power of Money. Its Determination and Relation to Credit, Interest and Crises, New York: The Macmillan Co.

FROST, J., P. K. WILKENS, A. KOSSE, V. SHREETI, AND C. VELASQUEZ (2024): "Fast Payments: Design and Adoption," BIS Quarterly Review.

GHOSH, P., B. VALLEE, AND Y. ZENG (2022): "FinTech Lending and Cashless Payments," SSRN Scholarly Paper 3766250, Social Science Research Network, Rochester, NY.

GOLDSTEIN, I., M. YANG, AND Y. ZENG (2023): "Payments, Reserves, and Financial Fragility," Available at SSRN, 4547329.

HIGGINS, S. (2024): "Financial Technology Adoption: Network Externalities of Cashless Payments in Mexico," American Economic Review, 114, 3469–3512.

KALYANI, A., N. BLOOM, M. CARVALHO, T. HASSAN, J. LERNER, AND A. TAHOUN (2025): "The Diffusion of New Technologies," The Quarterly Journal of Economics, 140, 1299–1365.

KATZ, M. L. AND C. SHAPIRO (1985): "Network Externalities, Competition, and Compatibility," The American Economic Review, 75, 424–440.

KIYOTAKI, N. AND R. WRIGHT (1989): "On Money as a Medium of Exchange," Journal of Political Economy, 97, 927–954.

KRISHNAMURTHY, A. AND A. VISSING-JORGENSEN (2012): "The Aggregate Demand for Treasury Debt," Journal of Political Economy, 120, 233–267.

KRUGMAN, P. (1984): "The International Role of the Dollar: Theory and Prospect," Exchange Rate: Theory and Practice, 1, 261–278.

LAGARDE, C. (2025): "This Is Europe's 'Global Euro' Moment," Op-ed in Financial Times.

LAHIRI, A. (2020): "The Great Indian Demonetization," Journal of Economic Perspectives, 34, 55–74.

LANE, P. (2025): "The Digital Euro: Maintaining the Autonomy of the Monetary System," .

LIANG, P., M. SAMPAIO, AND S. SARKISYAN (2024): "Digital Payments and Monetary Policy Transmission," SSRN Scholarly Paper 4933059, Social Science Research Network, Rochester, NY.

MATSUYAMA, K., N. KIYOTAKI, AND A. MATSUI (1993): "Toward a Theory of International Currency," The Review of Economic Studies, 60, 283–307.

MENGER, K. (1892): "On the Origin of Money," The Economic Journal, 2, 239–255, [Royal Economic Society, Wiley].

OUYANG, S. (2021): "Cashless Payment and Financial Inclusion," SSRN Scholarly Paper 3948925, Social Science Research Network, Rochester, NY.

PAN, G. (2025): "A Few Observations on Global Financial Governance," Speech at 2025 Lujiazui Forum.

PARLOUR, C. A., U. RAJAN, AND H. ZHU (2022): "When FinTech Competes for Payment Flows," The Review of Financial Studies, 35, 4985–5024.

PATNAM, M. AND W. YAO (2020): "The Real Effects of Mobile Money: Evidence from a Large-Scale Fintech Expansion," IMF Working Papers.

RESERVE BANK OF INDIA (2022): "Discussion Paper on Charges in Payment Systems," Reserve Bank of India, Department of Payment and Settlement Systems, Central Office, Mumbai.

RISHABH, K. (2024): "Beyond the Bureau: Interoperable Payment Data for Loan Screening and Monitoring," SSRN Scholarly Paper 4782597, Social Science Research Network, Rochester, NY.

RISHABH, K. AND J. SCHÄUBLIN (2021): "Payment Fintechs and Debt Enforcement," Working papers, 2021/02 Faculty of Business and Economics - University of Basel.

ROCHET, J. AND J. TIROLE (2004): "Two-Sided Markets: An Overview," Toulouse, France, The Economics of Two-Sided Markets.

ROCHET, J.-C. AND J. TIROLE (2003): "Platform Competition in Two-Sided Markets," Journal of the European Economic Association, 1, 990–1029, MIT Press.

SAMPAIO, M. AND J. R. H. ORNELAS (2024): "Payment Technology Complementarities and their Consequences on the Banking Sector," SSRN Scholarly Paper 5002235, Social Science Research Network, Rochester, NY.

SARKISYAN, S. (2023): "Instant Payment Systems and Competition for Deposits," SSRN Scholarly Paper 4176990, Social Science Research Network, Rochester, NY.

STEIN, J. C. (2012): "Monetary Policy As Financial Stability Regulation," The Quarterly Journal of Economics, 127, 57–95.

STEINSSON, J. (2025): "Money and Banking," in Lectures in Macroeconomics, chap. 14.

VAYANOS, D. (1999): "Strategic Trading and Welfare in a Dynamic Market," The Review of Economic Studies, 66, 219–254.

WANG, L. (2024): "Regulating Competing Payment Networks," working paper.

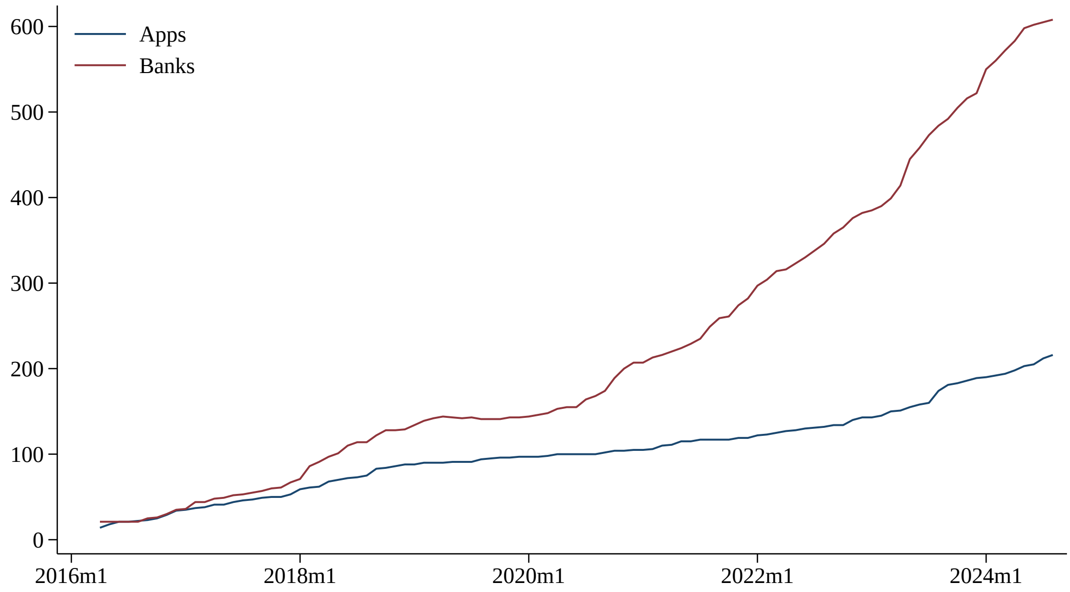
WEINBERG, J. A. (1997): "The Organization of Private Payment Networks," SSRN Scholarly Paper 2129857, Social Science Research Network, Rochester, NY.

WOLF, C. K. (2023): "The Missing Intercept: A Demand Equivalence Approach," American Economic Review, 113, 2232–2269.

YI, G. (2021): "China's Experience With Regulating Big Tech," Speech at 11th BIS Research Network meeting.

Figures and Tables

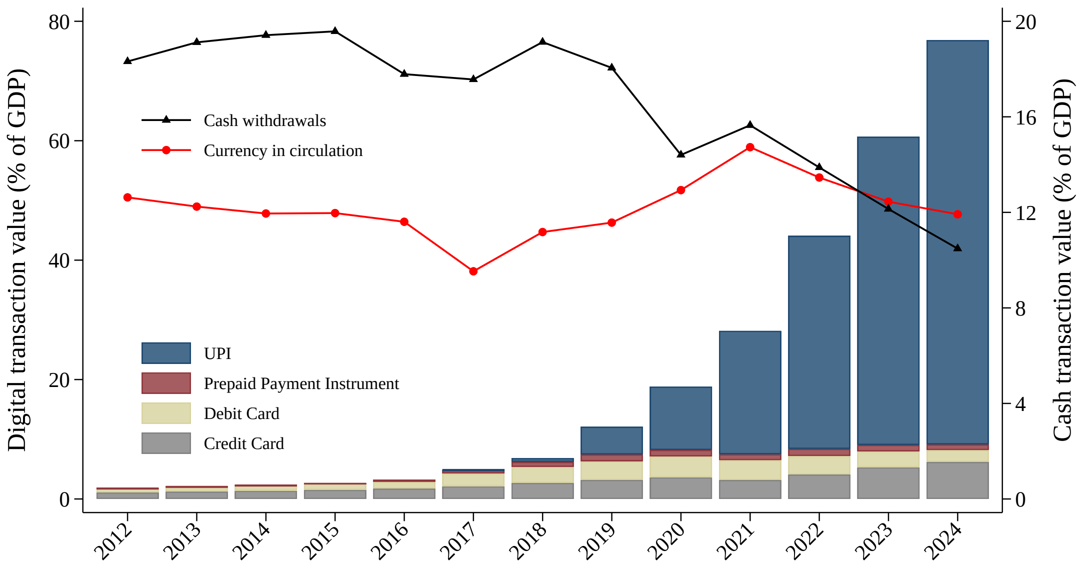
Figure 1: Number of apps and banks participating in UPI



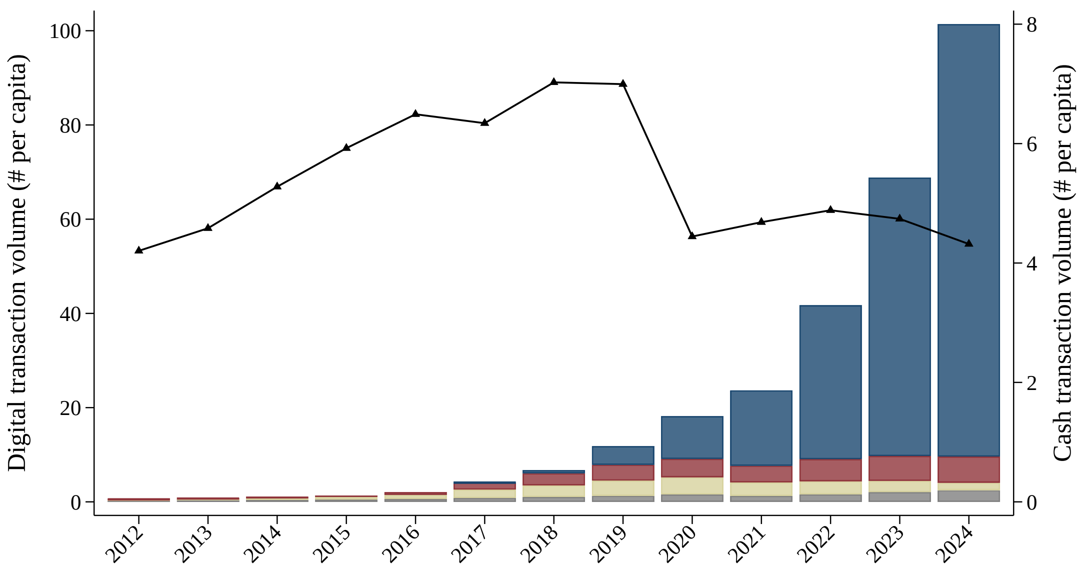
Notes: This graph shows the cumulative number of apps and banks participating in the UPI ecosystem over time. *Source:* NPCI.

Figure 2: Electronic retail payments in India

(a) Value (percent of GDP)

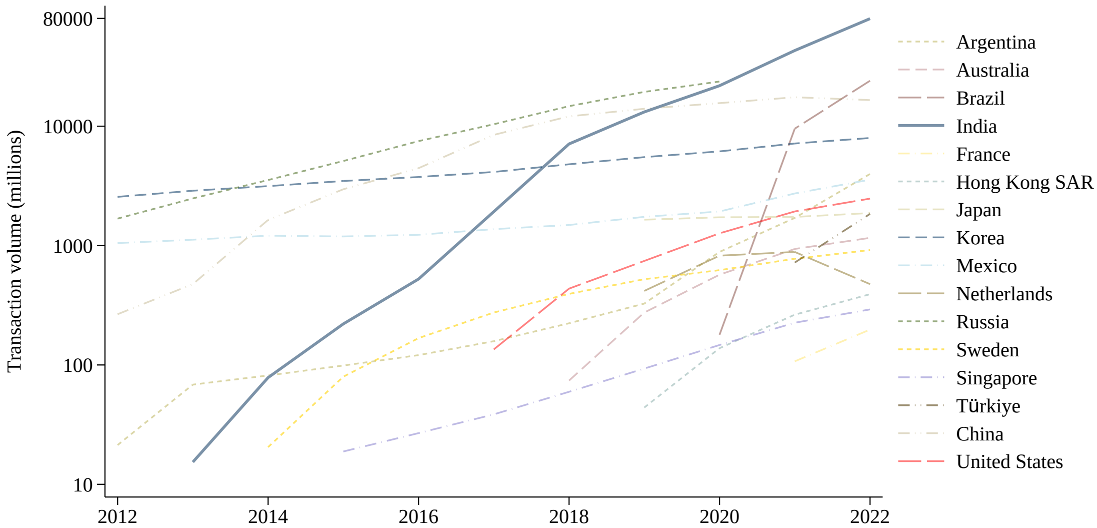


(b) Volume (transactions per capita)



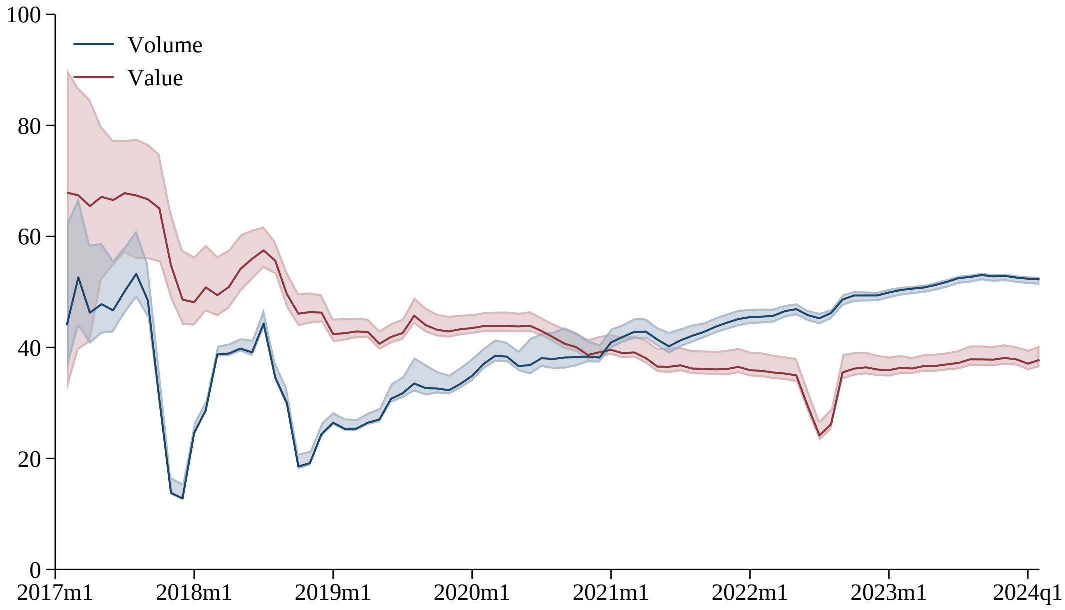
Notes: This graph shows the value and volume of UPI and other electronic retail payment methods in India. Pre-paid payment instruments include smart cards and mobile wallets that are pre-loaded with value using cash, card or other methods. *Source:* RBI, NPCI, Haver Analytics, WDI.

Figure 3: Volume of fast payment transactions (millions)



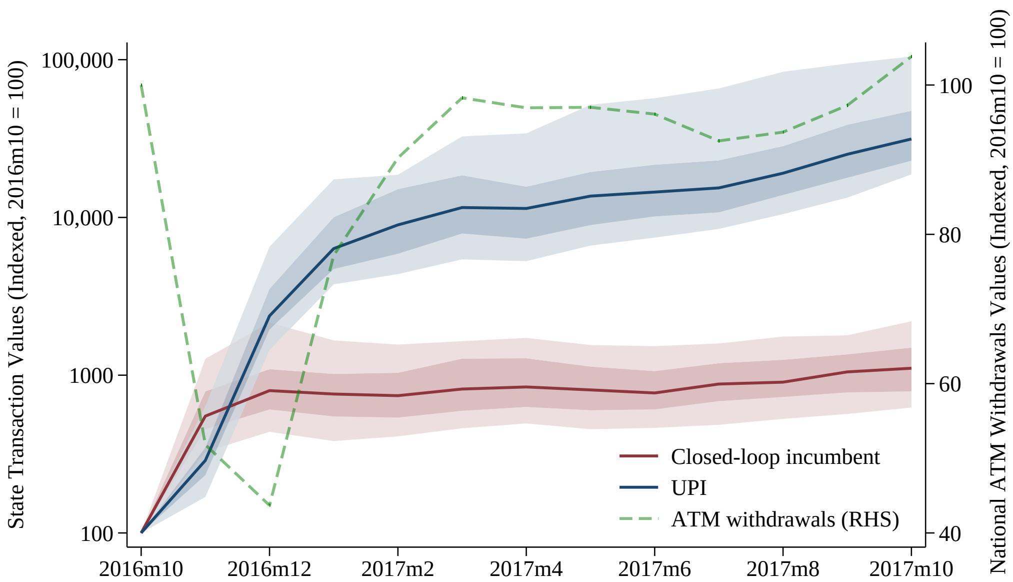
Notes: Fast payments: real-time or near real-time transfers of funds between accounts of end users as close to a 24/7 basis as possible (Frost, Wilkens, Kosse, Shreeti, and Velasquez, 2024). US comprises Zelle from 2017 and RTP from 2020. *Source:* BIS, Statista, The Clearing House.

Figure 4: Share of cross-app transactions on UPI (%)



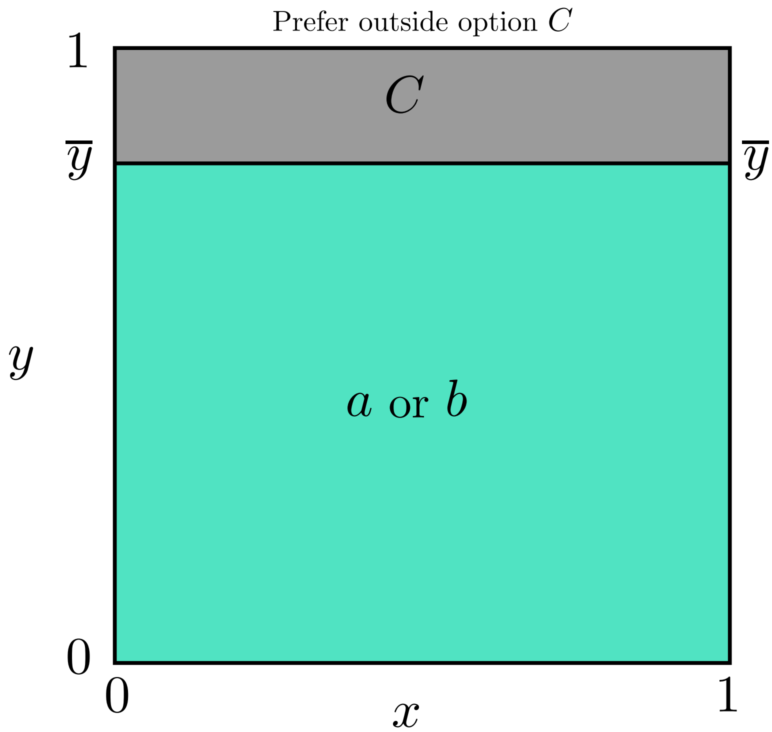
Notes: This graph plots the share of transactions on UPI that occur between two different apps, measured in turn using transaction value and transaction volume. Since we only observe the full payer app-payee app matrix for four major apps plus a consolidated “Other app” category, we estimate the share of cross-app payments in the “Other app” to “Other app” cell using the procedure described in Appendix H. The shaded areas show the range of possible values without using this procedure, with the maximum (minimum) values depicting the result when categorizing all (no) “Other app” to “Other app” transactions as cross-app transactions.

Figure 5: Closed-loop and interoperable digital payments after demonetization (indexed)



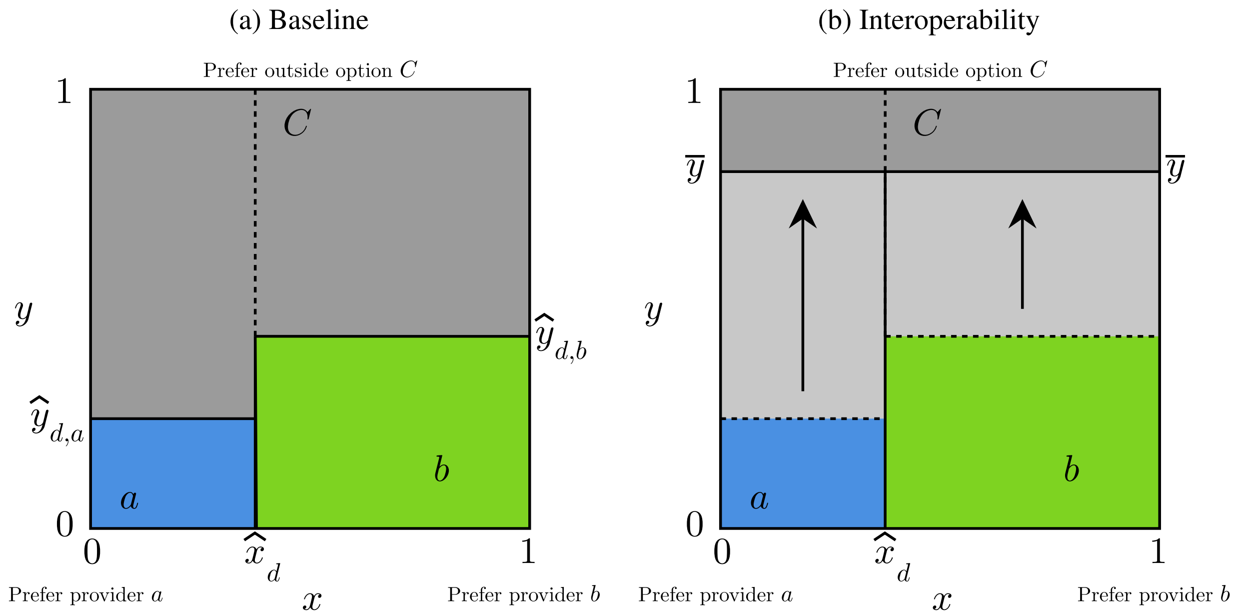
Notes: The green line shows national ATM withdrawals, by value, indexed to 100 in the month before demonetization (October 2016). The red line shows the total value of transactions on a major closed-loop incumbent digital payments platform in the median state, again indexed to 100 in October 2016. The blue line shows the same for transactions on UPI (which did not during this period include the closed-loop incumbent). The inner (outer) blue and red shaded regions show the 25-75th (10-90th) percentiles across states.

Figure 6: Equilibrium when all users value the digital platforms identically



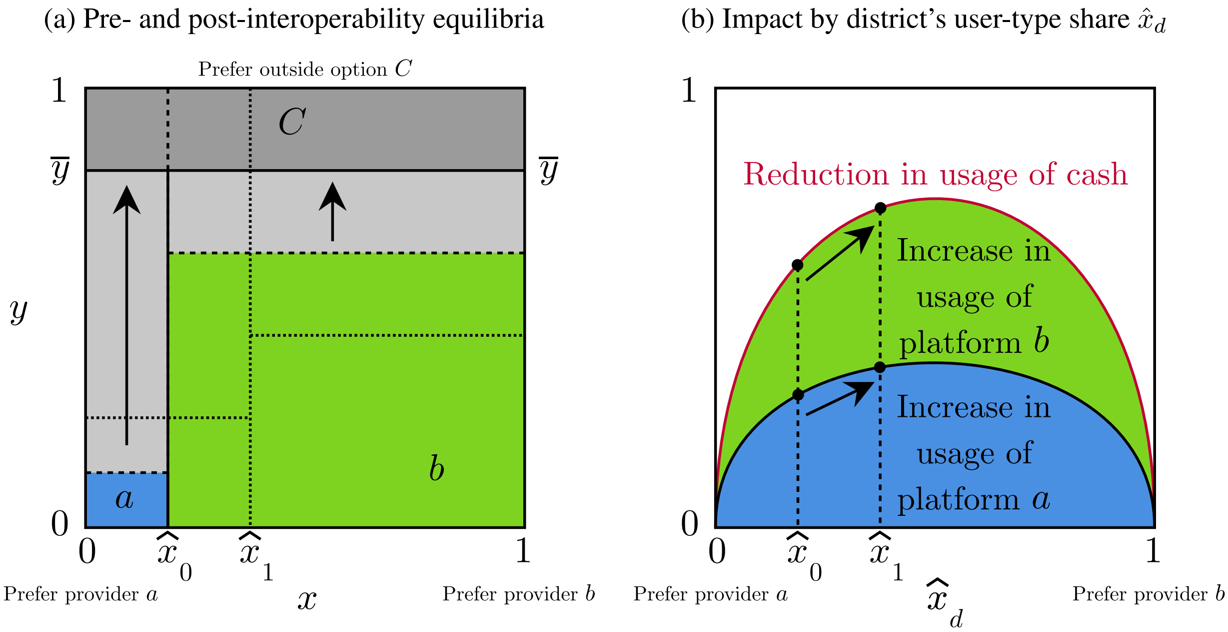
Notes: This figure depicts the outcome in Lemma 1, where users have homogeneous preferences across digital payments platforms so in equilibrium all pool on one. The resulting level of digital payments usage $\bar{y}$ represents the benchmark level achieved when network benefits are maximized, in this case by all digital payments users being unified on one dominant platform. Shaded regions indicate the equilibrium payment method choices of the users contained within them.

Figure 7: Equilibria for a given boundary $\hat{x}_d$



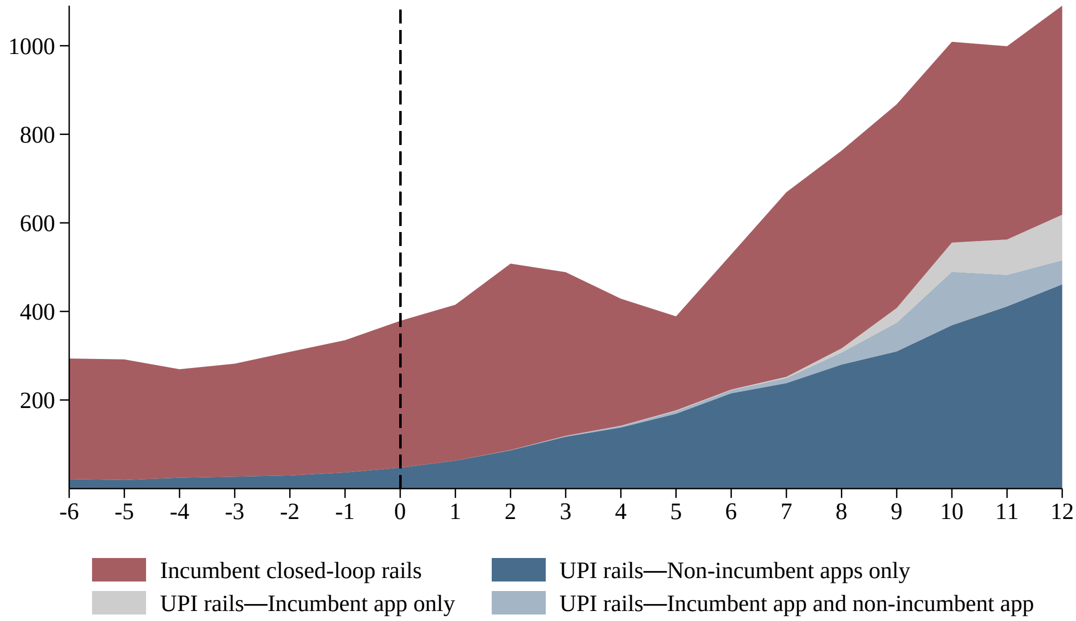
Notes: Panel (a) depicts the outcome in Lemma 2, in which users are fragmented across platforms and the number of transactions on platform b is larger, since $\hat{x}_d < \frac{1}{2}$ by assumption. Panel (b) depicts the outcome in Lemma 3, in which interoperability unifies the two fragmented networks, increasing total network benefits and restoring the benchmark level of adoption $\bar{y}$ in Figure 6. Shaded regions indicate the equilibrium choices of the users contained within them. Regions containing arrows indicate changes in these choices when comparing the baseline equilibrium to the equilibrium with interoperability.

Figure 8: Comparing the impact of interoperability across districts



Notes: Panel (a) compares the equilibrium outcomes of the district in Figure 7 (shown here as District 1) to those in another District 0 with $\hat{x}_0 < \hat{x}_1$. Without interoperability, total adoption of platform a is smaller and total adoption of platform b is larger in District 0, relative to District 1. Interoperability increases adoption of both platforms in both districts, but the increases are larger in District 1 than in District 0, as summarized in Panel (b). In Panel (a), shaded regions relate to District 0 and indicate the equilibrium choices of the users contained within them, while regions containing arrows indicate changes in these choices when comparing the baseline equilibrium to the equilibrium with interoperability. The dotted lines in Panel (a) indicate the corresponding regions for District 1, which are also the same as the shaded regions in Figure 7. In Panel (b), the red line plots the total reduction in usage of cash that results when interoperability is introduced, for a district with share $\hat{x}_d$ of users perceiving benefits from platform a relative to platform b. The blue and green areas then show how the users switching away from cash divide between platforms a and b. The arrows indicate the differences in the impact of interoperability between District 0 and District 1.

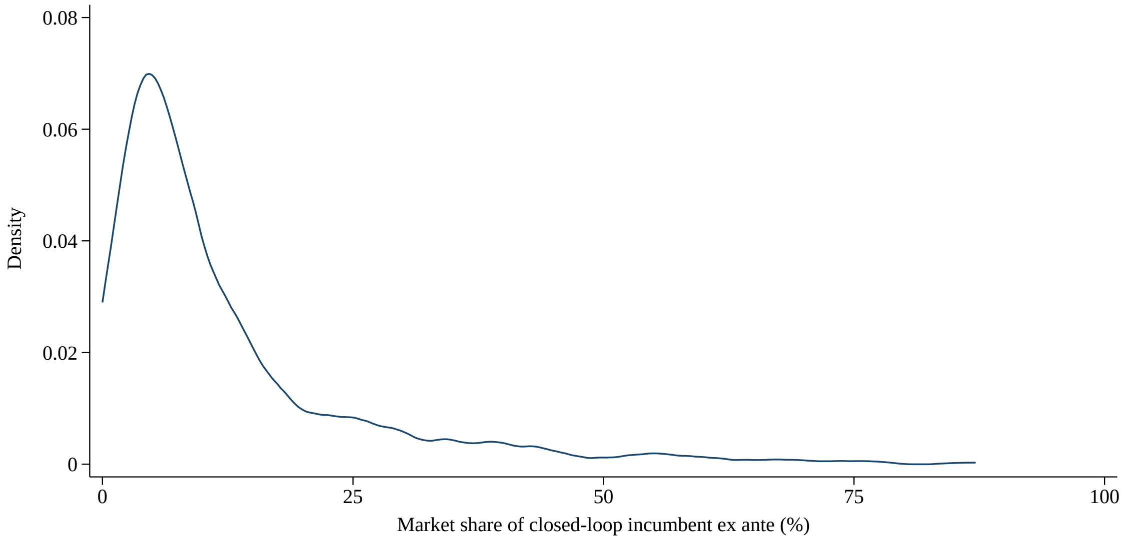
Figure 9: Aggregate value of transactions on UPI and incumbent platform (Rupees, billions)



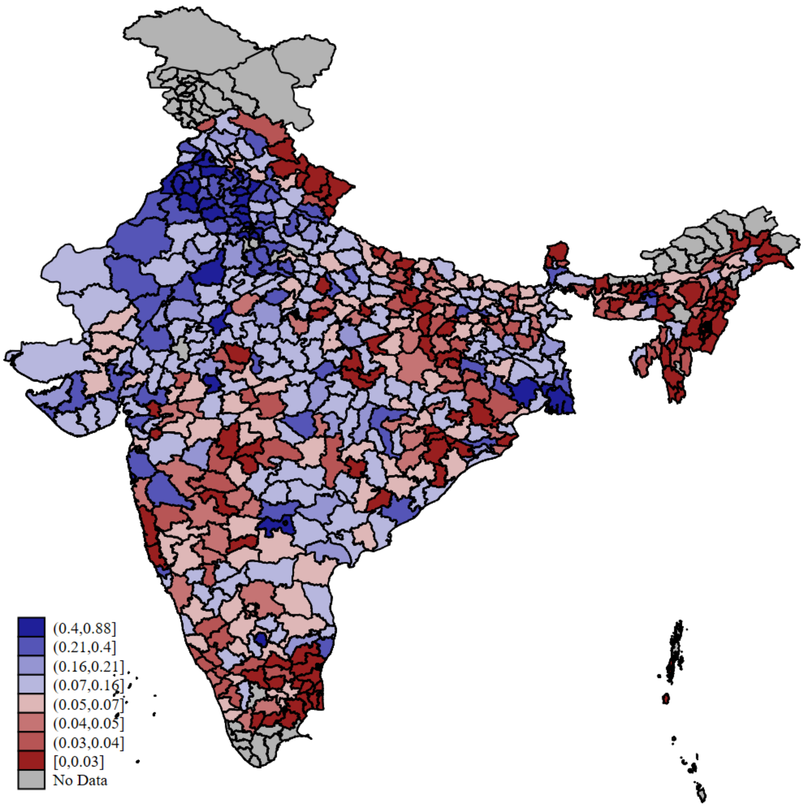
Notes: Each region shows the value of transactions by transaction type. The dark red shaded region shows transactions using the incumbent's closed-loop payments technology, which by definition required both the payer and payee to use the incumbent's app. The dark blue shaded region shows transactions made using UPI, excluding any transactions that were made using the incumbent platform's app on either the payer or payee side. The gray shaded region shows transactions made through UPI rails, yet where both the payer and payee used the incumbent's app. Finally, the light blue shaded region shows the newly enabled "cross-platform" transactions on UPI, where either the payer or the payee used the incumbent's app and their counter-party did not.

Figure 10: Variation in P_d

(a) Density distribution



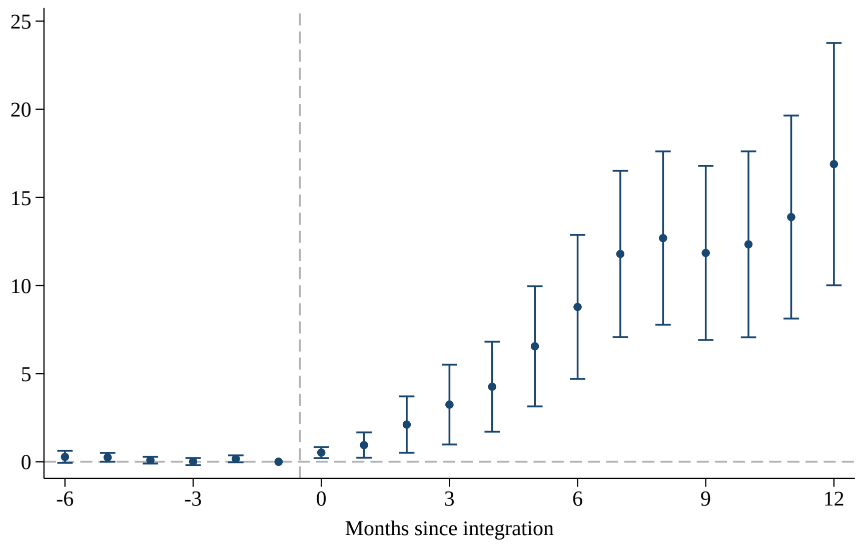
(b) Geographical distribution



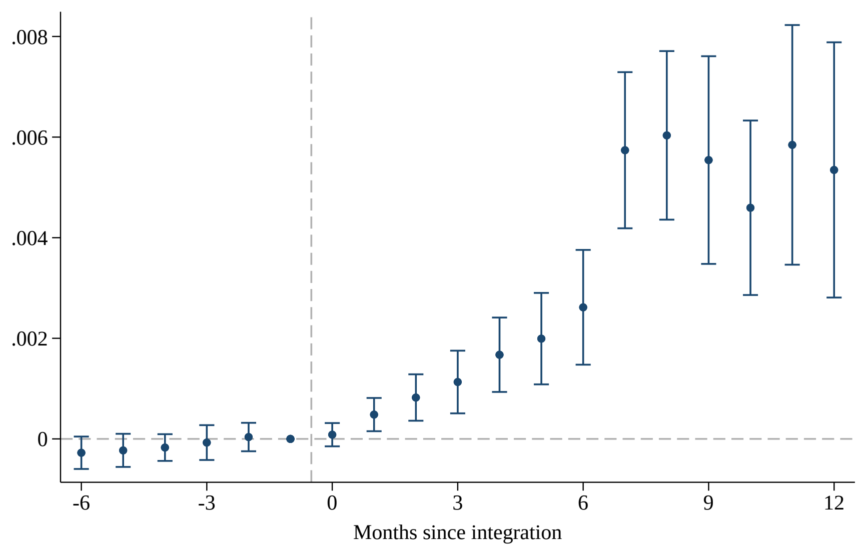
Notes: This figure plots the distribution of P_d, the market share of the incumbent in the month prior to integration. The first panel plots the estimated probability density distribution using an Epanechnikov kernel function. The second panel plots the values of P_d by district, with blue districts indicating an above-median presence of the incumbent and red districts indicating a below-median presence of the incumbent.

Figure 11: Response dynamics of total digital payments adoption to platform integration

(a) Total P2M transaction value per person (Rupees per capita)

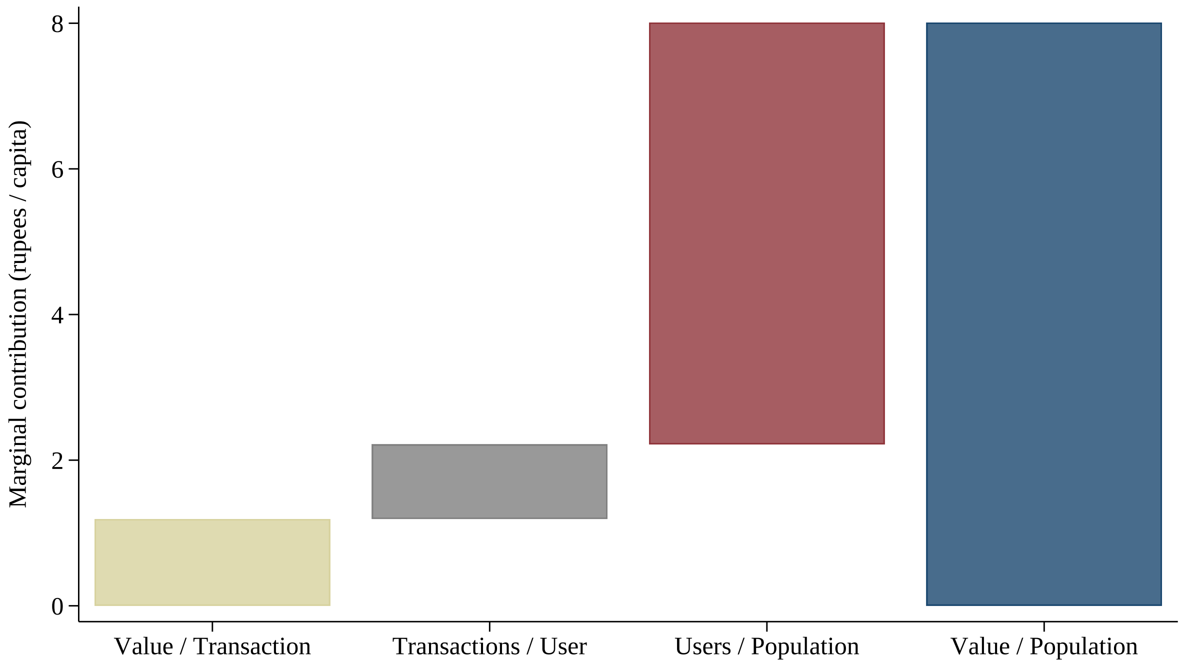


(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-P_d and low-P_d districts, based on equation (6). The first panel normalizes total P2M transaction values relative to population, and the second panel normalizes total P2M transaction values relative to cash withdrawals from ATMs. Vertical lines show 95% confidence intervals.

Figure 12: Decomposition of more fragmented districts' differential response to integration



Notes: This figure decomposes our main baseline estimate (Table 1 Column 1). That coefficient represents the monthly average increase after integration in the total P2M transaction value per head of population, in districts that were more fragmented than the median ex ante, relative to districts that were less fragmented, after controlling for district and state-time fixed effects and differential trends by total pre-integration transaction value. Here, we decompose that result into the portion attributable to corresponding increases in each of three margins: (i) the average value per transaction, (ii) the number of transactions per user, and (iii) the number of users per head of population. We perform this decomposition using the estimation procedure described in Appendix F. In short, we take the total derivative of transaction value per capita around the post-interoperability low-P_d sample mean, giving us the shares of the total effect that are explained by changes in each of (i) to (iii).

Table 1: Response of digital payments adoption to platform integration

	Total/pop (1)	Total/cash (2)	(Inc$\rightarrow$Inc)/pop (3)	(Inc$\leftrightarrow$Oth)/pop (4)	(Oth$\rightarrow$Oth)/pop (5)
$P_d^+ \times 1_{\{t>t_0\}}$	8.010***	0.00334***	11.75***	0.106***	1.989***
	(4.64)	(5.74)	(5.95)	(2.93)	(2.68)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	9.118	0.007	14.365	0	1.936
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	6.795	0.012	2.77	0.191	5.179

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts, based on specification (5). P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. Z_d is the total value of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. *t*-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table 2: Response of digital payments adoption to platform integration, matching districts based on log population size

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	6.777***	0.00336***	9.935***	0.0978***	1.644**
	(4.79)	(4.51)	(6.36)	(2.92)	(2.45)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts, based on specification (5), using a matched sample based on high-P_d districts' three nearest neighbors by log population size. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. Z_d is the total value of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. Standard errors are clustered at the district level. *t*-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table 3: Response of digital payments adoption to platform integration, instrumented with proximity to incumbent hub districts

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	17.11***	0.0117***	18.67***	0.299*	5.046*
	(2.71)	(3.30)	(3.03)	(1.78)	(1.90)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓	✓
K-P F-Stat	25.25	25.25	25.25	25.25	25.25
N	10,621	10,620	10,621	10,621	10,621
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	6.511	0.007	9.613	0	1.656
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	6.729	0.012	2.77	0.188	5.113

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts when instrumenting using proximity to incumbent hub districts H_d, using second-stage equation (5) and first-stage equation (7). Hub districts are dropped from the sample prior to estimation. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. Z_d is the total value of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. t-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table 4: Response of household level NBFC borrowing to platform integration

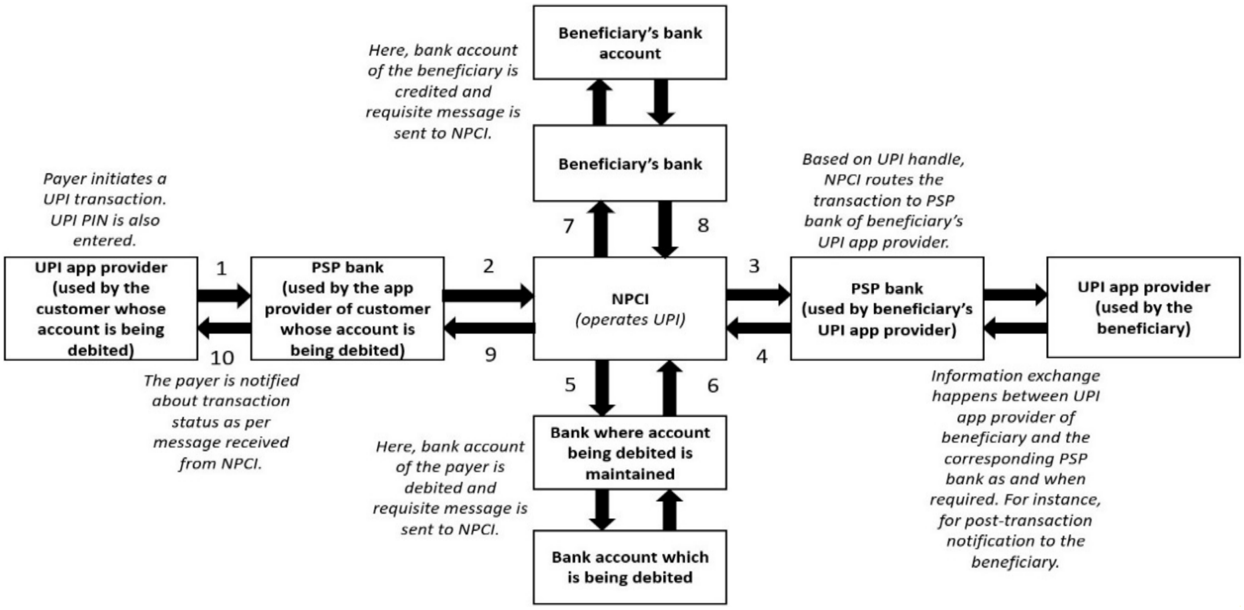
	NBFC Borrowing (Y/N)		
	(1)	(2)	(3)
$P_d^+ \times 1_{\{t>t_0\}}$	0.0113**	0.0192**	0.0136***
	(2.17)	(2.54)	(3.00)
Household FEs	✓	✓	✓
State-Wave FEs	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓
Sample	All	Entrepreneurs	Hawkers
N	898,412	54,161	22,387
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	0.0062	0.0118	0.0049
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	0.0137	0.0209	0.0153

Notes: This table shows how the response in household level borrowing from NBFCs (Non-Banking Financial Company) to integration differed between households in high-P_d and low-P_d districts. This is based on specification (5), using household level data at a wave frequency of every four months. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. The outcome variable in each case is an indicator for households that borrowed in a given wave. Column (1) uses the full sample of households. Column (2) restricts the sample to only households for which the primary occupation is 'entrepreneur'. Column (3) restricts the sample to only households for which the primary occupation is 'hawker'. Z_d is the total value of digital payments in the month before integration. We control for state-time and household fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from twelve months before integration to twelve months after integration. Standard errors are clustered at the district level. t-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Online Appendices

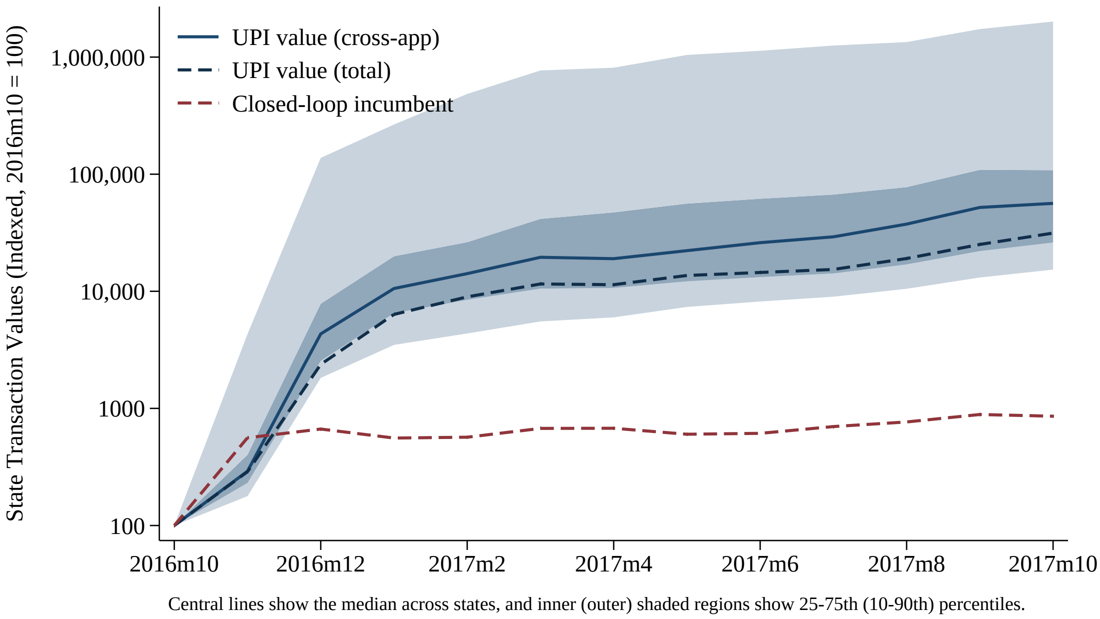
A Additional figures and tables

Figure A.1: Detailed UPI transaction flow (payer initiated)



Notes: This figure shows a detailed breakdown of the steps involved in a payer-initiated UPI transaction. An initial interaction between the payer and their app provider is conveyed to the app provider's payment service provider (PSP), who in turn informs NPCI. The payer's bank account is then debited, the payee's bank account is credited, and notifications are sent to the payer and payee via their app provider and its PSP. *Source:* Reserve Bank of India (2022).

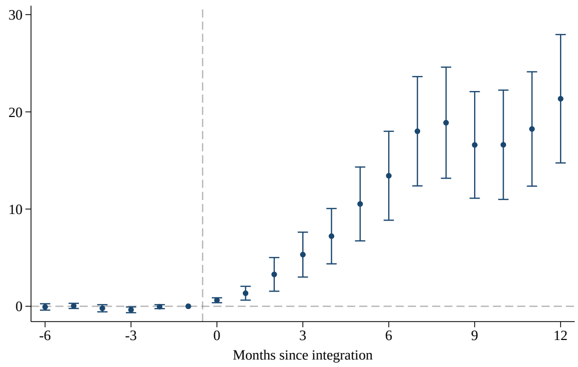
Figure A.2: Cross-app interoperable digital payments after demonetization (indexed)



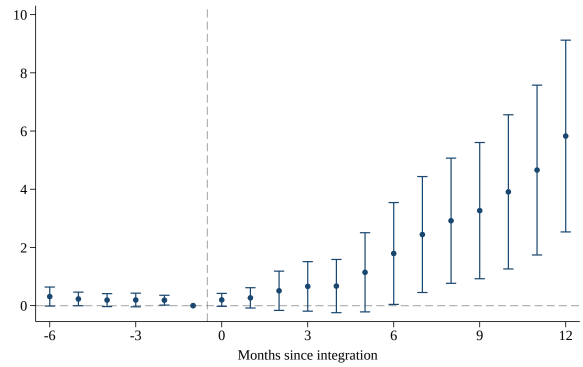
Notes: The blue and red dashed lines repeat those on Figure 5—i.e., they show the total value of transactions on UPI and a major closed-loop incumbent digital payments platform in the median state, indexed to 100 in the month before demonetization (October 2016). The solid blue line plots the same for cross-app UPI payments only. The inner (outer) blue shaded regions show the 25-75th (10-90th) percentiles across states.

Figure A.3: Response dynamics of digital payments adoption to platform integration, split by transaction participants' app choices

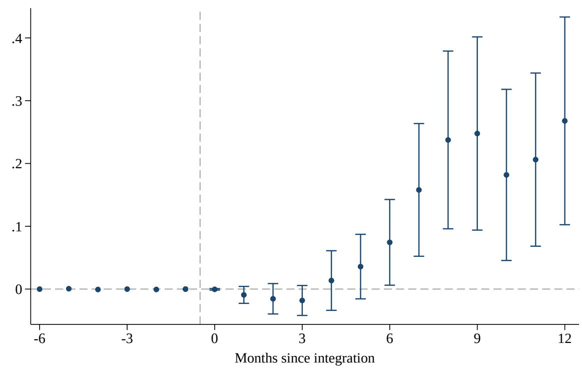
(a) Transactions between two users of the incumbent app (Rupees per capita)



(b) Transactions between two users of other UPI apps (Rupees per capita)

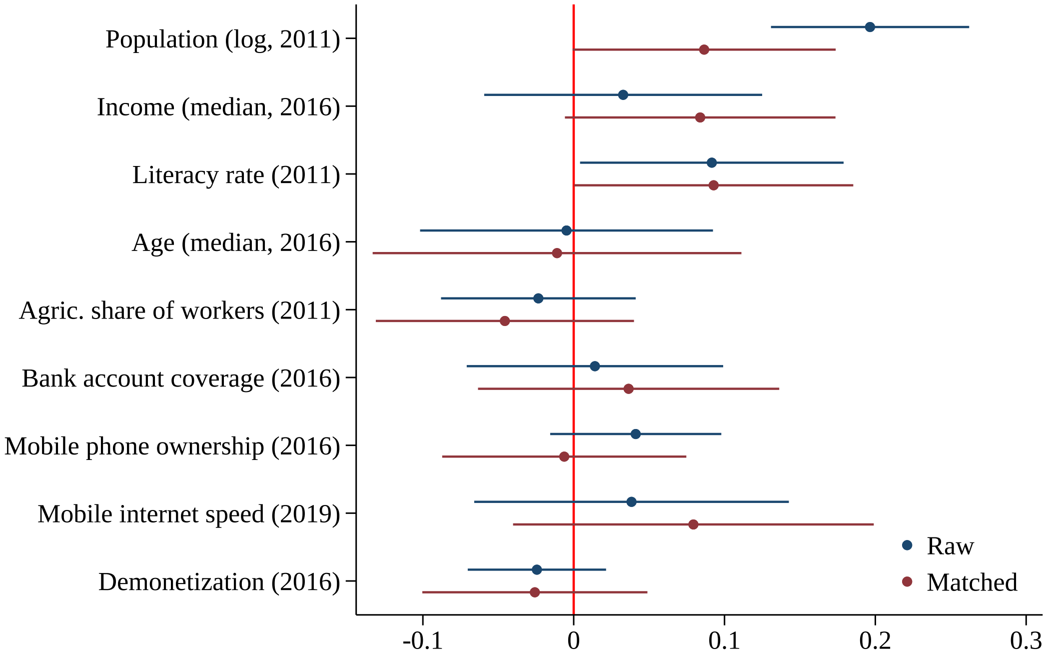


(c) Transactions between a user of the incumbent app and a user of another UPI app (Rupees per capita)



Notes: This figure plots the dynamics of the difference in P2M transaction values between high-P_d and low-P_d districts, based on equation (6), for different subsets of transactions based on the transaction participants' app choices. The first panel shows results when including only those transactions for which both counterparties used the incumbent firm's app. This includes both transactions that took place on its proprietary closed-loop rails, and transactions that took place through UPI. The second panel shows results when including only those transactions for which both counterparties used other UPI apps. The third panel shows results when including only those transactions for which one counterparty used the incumbent firm's app and the other counterparty used another UPI app. By definition, such transactions were impossible in all districts prior to integration, hence the zero estimates in pre-integration months. Vertical lines show 95% confidence intervals.

Figure A.4: Association of P_d^+, raw and matched

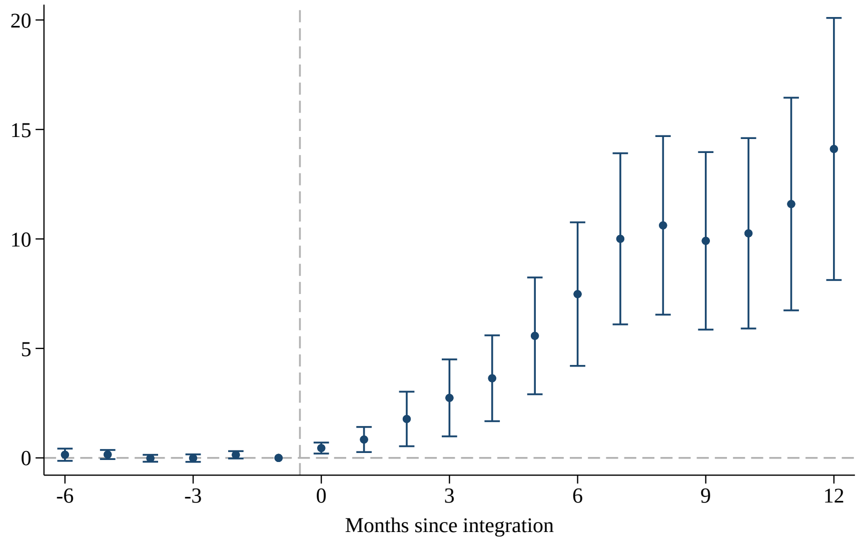


Observations: 521 / 474. R-squared: 0.406 / 0.398. State FEs, and SEs clustered by state.

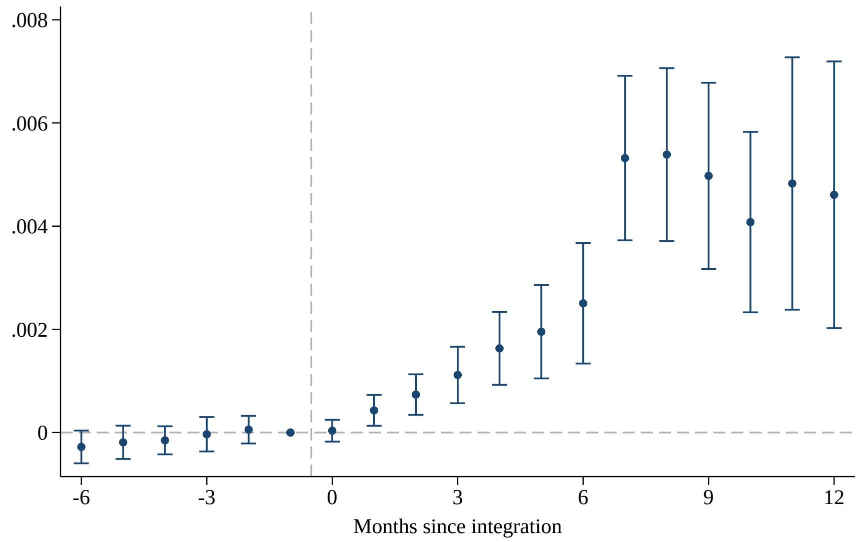
Notes: The figure plots the correlation of various district characteristics with P_d^+ controlling for Z_d (the total value of digital payments across both platforms in each district in the month before integration), both in the raw sample and in the sample formed by matching districts on log population size. Specifically, the figure plots the coefficients from regressions of P_d^+ on a series of district characteristics listed in the figure, each of which is standardized so that the magnitudes of the coefficients are comparable. The regressions include state fixed effects and standard errors are clustered by state. We measure the intensity of the demonetization shock to each district using the deviation of observed cash withdrawals in the district from a polynomial prediction based on pre-demonetization observations. The horizontal lines indicate 95% confidence intervals.

Figure A.5: Response dynamics of total digital payments adoption to platform integration, matching on observables

(a) Total P2M transaction value per person (Rupees per capita)



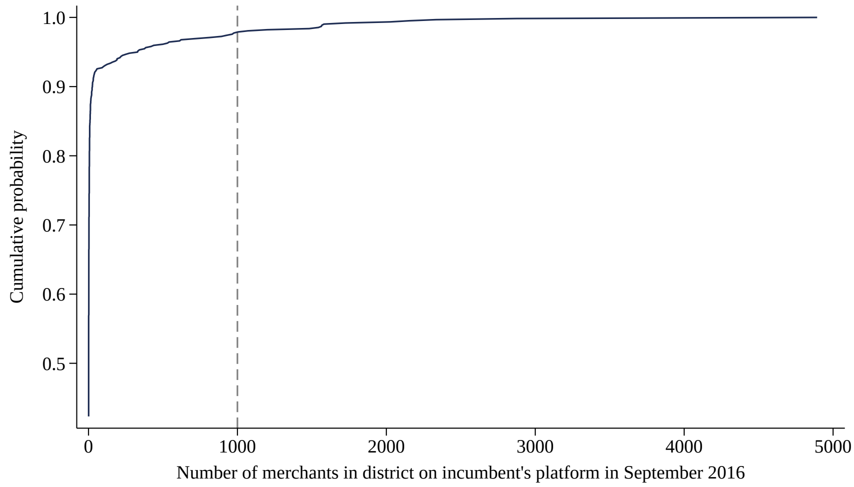
(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



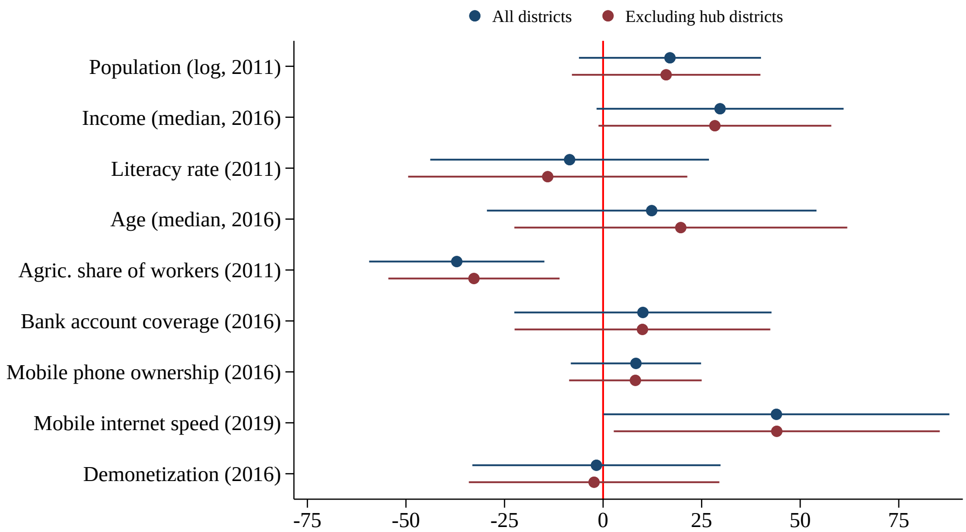
Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-P_d and low-P_d districts when matching districts on log population. The first panel normalizes total P2M transaction values relative to population, and the second panel normalizes total P2M transaction values relative to cash withdrawals from ATMs. Vertical lines show 95% confidence intervals.

Figure A.6: Hub districts

(a) Cumulative distribution of districts by number of merchants using the incumbent's platform in September 2016



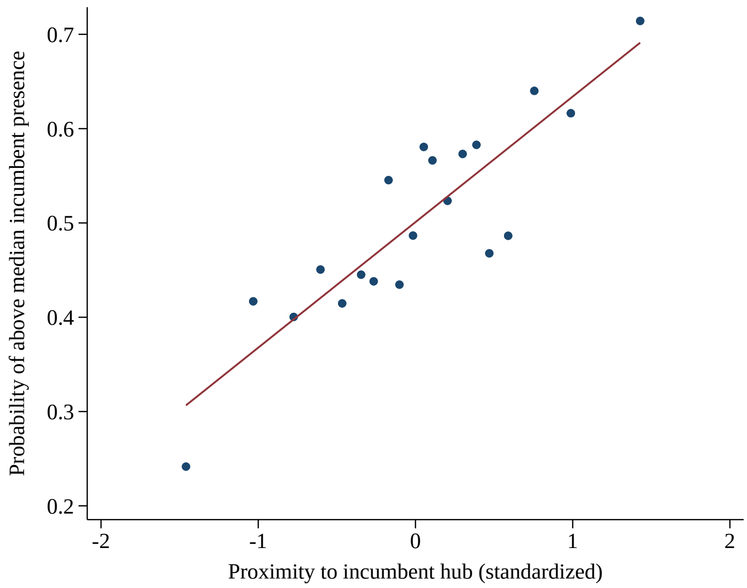
(b) Association with proximity to the incumbent's hubs



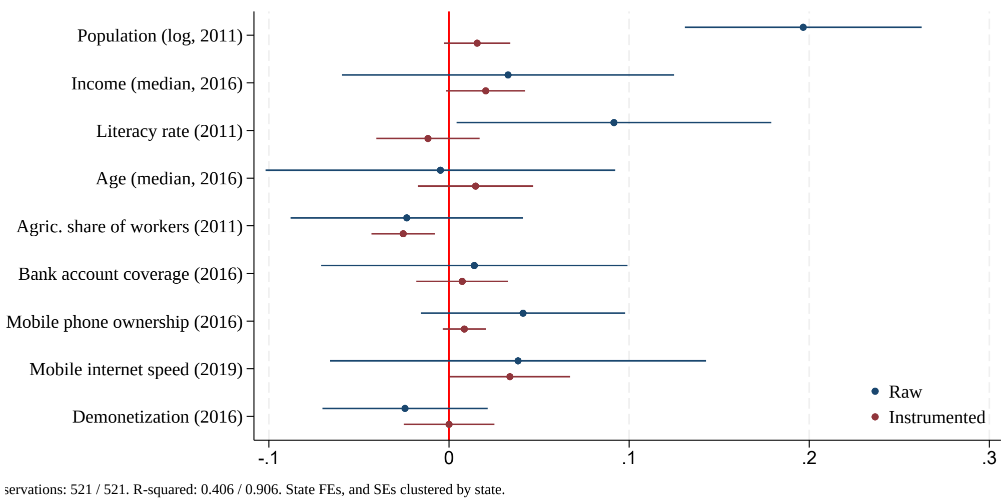
Notes: The first panel plots the cumulative distribution function of the number of merchants in each district that used the incumbent's platform in September 2016. The vertical line indicates the cutoff for defining a hub city. The second panel shows the correlation of various district characteristics with proximity to the districts containing the incumbent's hubs. Specifically, the figure plots the coefficients from regressions of proximity to the incumbent's hubs—defined as the negative of the distance in kilometers from the district's centroid to the centroid of the nearest hub district—on a series of district characteristics listed in the figure, each of which is standardized so that the magnitudes of the coefficients are comparable. The regressions include state fixed effects and standard errors are clustered by state. We measure the intensity of the demonetization shock to each district using the deviation of observed cash withdrawals in the district from a polynomial prediction based on pre-demonetization observations. Estimates in blue show results from a regression that includes all districts, while estimates in red show results from a regression that excludes the hub districts (which by definition have proximity equal to zero). The horizontal lines indicate 95% confidence intervals.

Figure A.7: Instrumenting incumbent presence P_d^+ with proximity to its initial hubs H_d

(a) Cross-sectional first stage relationship between H_d and P_d^+



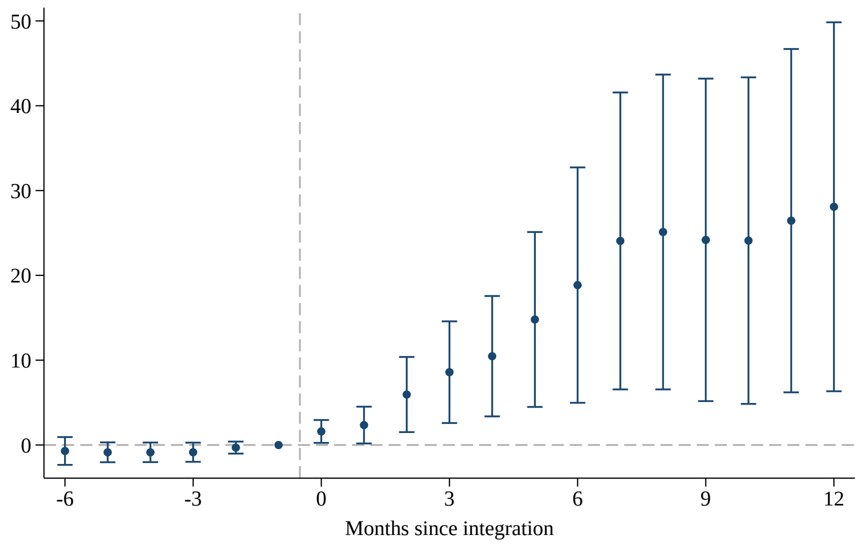
(b) Association with P_d^+



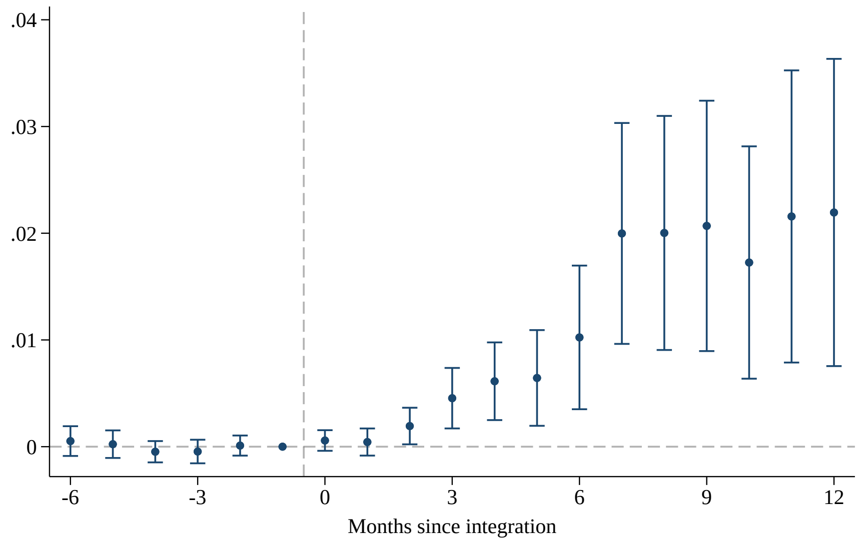
Notes: The first panel shows a binned scatter plot of the cross-sectional first stage relationship between H_d (on the x-axis) and P_d^+ (on the y-axis), after residualizing each on state fixed effects and controlling for Z_d (the total value of digital payments across both platforms in each district in the month before integration). The second panel plots the correlation of various district characteristics with P_d^+, both in its raw form and when instrumented with proximity to the districts containing the incumbent's hubs. Specifically, the figure plots the coefficients from regressions of P_d^+—or the predicted value of P_d^+, when instrumenting with H_d—on a series of district characteristics listed in the figure, each of which is standardized so that the magnitudes of the coefficients are comparable. The regressions include state fixed effects and standard errors are clustered by state. We measure the intensity of the demonetization shock to each district using the deviation of observed cash withdrawals in the district from a polynomial prediction based on pre-demonetization observations. The horizontal lines indicate 95% confidence intervals.

Figure A.8: Response dynamics of total digital payments adoption to platform integration, instrumenting with proximity to incumbent hub districts

(a) Total P2M transaction value per person (Rupees per capita)

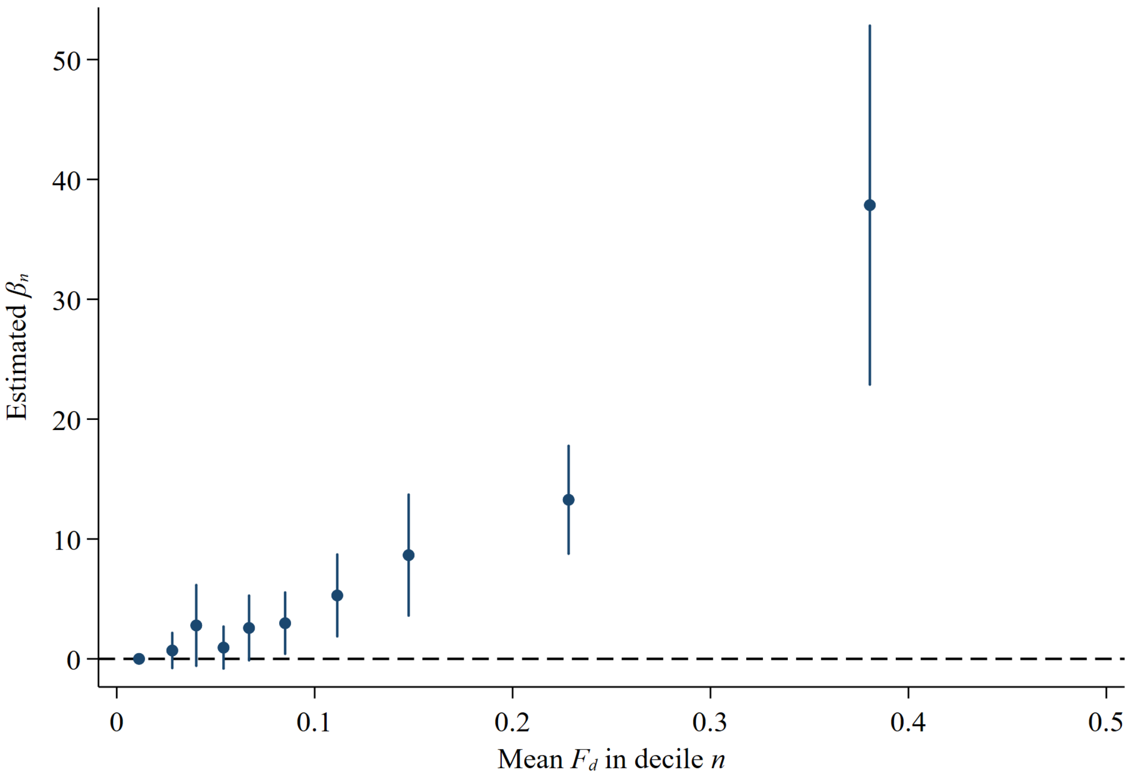


(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-P_d and low-P_d districts when instrumenting using proximity to incumbent hub districts H_d. The first panel normalizes total P2M transaction values relative to population, and the second panel normalizes total P2M transaction values relative to cash withdrawals from ATMs. Vertical lines show 95% confidence intervals.

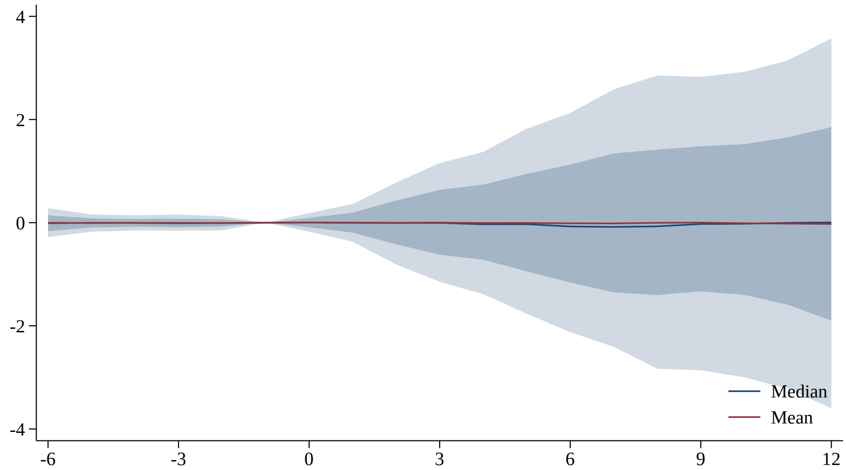
Figure A.9: Estimated impacts of platform integration, by ex-ante fragmentation decile



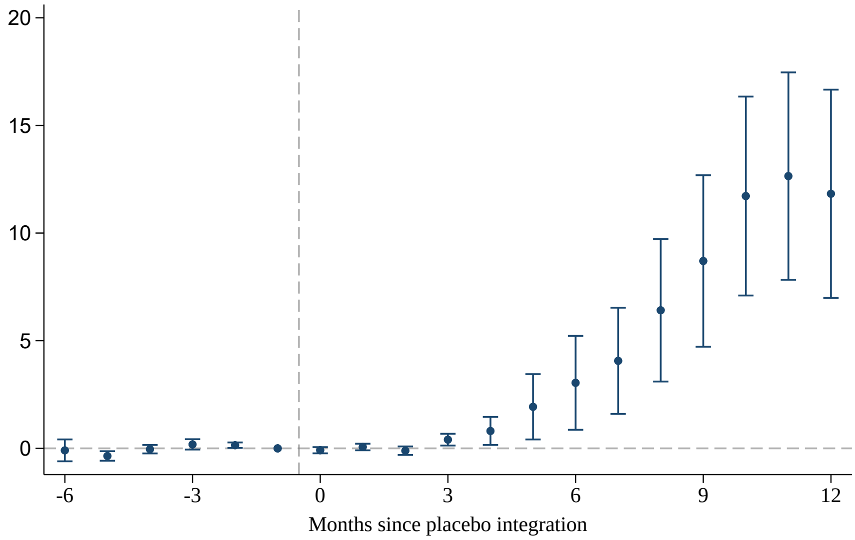
Notes: This figure plots the estimates $\hat{\beta}_n$ from equation (9). Each coefficient's coordinate on the horizontal axis reflects the mean value of F_d among districts d in the decile n for which the coefficient is estimated. Each coefficient's value on the vertical axis shows the monthly average increase in total P2M transaction value per capita after interoperability was introduced, across districts in decile n of the F_d distribution, when controlling for district and state-time fixed effects and differential trends by total pre-integration transaction value. Vertical lines show 95% confidence intervals.

Figure A.10: Placebo tests

(a) Repeating Figure 11a for random draws of P_d^+



(b) Repeating Figure 11a for an alternative t_0 three months earlier



Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-P_d and low-P_d districts, based on equation (6), except changing either the distribution of P_d^+ or the timing of t_0, as described in Section G.2. In the first panel, the shaded regions depict the distribution of estimated βs across 1000 random reassignments of P_d^+, with the inner (outer) shaded regions corresponding to the 25-75th (10-90th) percentiles. The blue and red plotted lines show the median and mean estimates respectively. In the second panel, Figure 11a is repeated except setting an alternative $t_0^{placebo} := t_0 - 3$. Vertical lines show 95% confidence intervals.

Table A.1: Decomposition of impact on value per capita by sub-component

	Value / Transaction (₹)	Transactions / User (#)	Users / Population (#)
$P_d^+ \times 1_{\{t>t_0\}}$	9.354**	0.0939**	0.000832*
	(2.11)	(2.48)	(1.93)
District FEs	✓	✓	✓
State-Time FEs	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓
N	10,868	10,860	10,860
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	344.854	3.262	0.002
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	309.646	3.625	0.005

Notes: This table shows how the value per transaction, transactions per user, and number of unique users grew differentially in high-P_d versus low-P_d districts, based on specification (5). P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M value per transaction, in Rupees per capita; (2) number of transactions per user; (3) number of users per capita. The sample period spans from six months before integration to one year after integration. Standard errors are clustered at the district level. Z_d is the total value of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. *t*-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A.2: Response of digital payments adoption to platform integration, when defining P_d^+ using only P2M transactions

	Total/pop (1)	Total/cash (2)	(Inc→Inc)/pop (3)	(Inc↔Oth)/pop (4)	(Oth→Oth)/pop (5)
$P_d^+ \times 1_{\{t>t_0\}}$	7.183***	0.00217***	11.28***	0.0731**	1.417**
	(4.75)	(3.57)	(6.28)	(2.19)	(2.20)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Control: $Z_d \times 1_{\{t\geq t_0\}}$	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	9.118	0.007	14.365	0	1.936
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	6.795	0.012	2.77	0.191	5.179

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts, based on specification (5) except defining P_d^+ using only P2M transactions. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. Z_d is the total value of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. *t*-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A.3: Response of digital payments adoption to platform integration, when excluding districts in which $P_d > 0.5$

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	5.380***	0.00251***	8.483***	0.0617**	0.993*
	(5.27)	(4.67)	(8.50)	(2.35)	(1.86)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	5.452	0.006	7.638	0	1.643
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	6.763	0.012	2.763	0.189	5.179

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts, based on specification (5) except excluding those districts for which $P_d > 0.5$. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. Z_d is the total value of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. *t*-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A.4: Response of digital payments adoption to platform integration, when controlling for differential trends by baseline level of cash withdrawals

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	5.609***	0.00193***	8.301***	0.0929***	1.796***
	(3.87)	(3.17)	(4.49)	(2.91)	(2.90)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓	✓
Control: $Z_d^{cash} \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓	✓
N	10,867	10,867	10,867	10,867	10,867
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	9.118	0.007	14.365	0	1.936
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	6.795	0.012	2.77	0.191	5.179

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts, based on specification (5), except including an additional control for differential trends by baseline level of cash withdrawals one month prior to integration. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. Z_d is the total value of digital payments in the month before integration. Z_d^{cash} is the total value of cash withdrawals in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value and by total pre-integration cash withdrawals. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. t-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A.5: Response of digital payments adoption to platform integration, using transaction volume rather than value

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	0.0129***	0.00811	0.0217***	0.000133**	0.00101
	(5.48)	(1.61)	(5.90)	(2.45)	(1.15)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Control: $Z_d^{vol} \times 1_{\{t\geq t_0\}}$	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	0.022	0.048	0.034	0	0.004
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	0.035	0.187	0.009	0.001	0.029

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts, based on specification (5), except all quantities are in terms of volume. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction volume per capita; (2) total P2M transaction volume per cash withdrawal from ATMs; (3) total P2M transaction volume for which the payer and the payee both used the incumbent's app, in transactions per capita; (4) total P2M transaction volume occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in transactions per capita; (5) total P2M transaction volume for which the payer and the payee both used an alternative UPI app, in transactions per capita. Z_d^{vol} is the total volume of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction volume. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. *t*-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A.6: Response of digital payments adoption to platform integration, when winzorizing top 0.5% of districts by value

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	7.394***	0.00346***	11.10***	0.0837*	1.520**
	(3.95)	(5.55)	(4.98)	(1.71)	(1.97)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	9.118	0.007	14.365	0	1.936
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	6.795	0.012	2.77	0.194	5.297

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts, based on specification (5) except reducing the stringency of winsorization to 0.5% from 1%. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. Z_d is the total value of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. *t*-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A.7: Response of digital payments adoption to platform integration, controlling for urban-time fixed effects

	Total/pop (1)	Total/cash (2)	(Inc→Inc)/pop (3)	(Inc↔Oth)/pop (4)	(Oth→Oth)/pop (5)
$P_d^+ \times 1_{\{t>t_0\}}$	5.829***	0.00314***	8.844***	0.0767**	1.292**
	(4.40)	(5.36)	(5.71)	(2.32)	(2.06)
District FEs	✓	✓	✓	✓	✓
State-Time FEs	✓	✓	✓	✓	✓
Urban-Time FE	✓	✓	✓	✓	✓
Control: $Z_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	9.118	0.007	14.365	0	1.936
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	6.795	0.012	2.77	0.191	5.179

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts, based on specification (5) except additionally controlling for differential trends in urban districts, defined as districts with above-median population density. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. Z_d is the total value of digital payments in the month before integration. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. t-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

B Proofs

B.1 Proof of Lemma 1

Assume a fulfilled-expectations equilibrium in which utility-maximizing digital payments users divide unequally between the two platforms based on their initial expectations of others' platform choices. Label the platform with more users b. Then we have that

$$u^b_{d,x,y} = 1 + \kappa N_{d,b} > 1 + \kappa N_{d,a} = u^a_{d,x,y} \tag{B.1}$$

since $N_{d,b} > N_{d,a}$, so all users prefer b over a. This contradicts the decision of some users to adopt a, implying that the assumed equilibrium cannot exist.

Two possibilities remain: (i) digital payments users divide equally between platforms, or (ii) digital payments users pool on one platform. In case (i), we have that

$$u^a_{d,x,y} = 1 + \kappa N_{d,a} = 1 + \kappa N_{d,b} = u^b_{d,x,y} \tag{B.2}$$

for all users because $N_{d,a} = N_{d,b}$. However, in this equilibrium, a deviation to platform i from the other platform j by a small but positive mass of users ϵ would raise $N_{d,i} > N_{dj}$, implying $u^i_{d,x,y} > u^j_{d,x,y}$ and so causing the market to tip to i. Thus this equilibrium is not stable.

In case (ii), define by $\bar{y}$ the cash preference of the marginal users between C and the adopted platform i. These marginal users must satisfy:

$$1 + \kappa N_{d,i} = \gamma \bar{y}. \tag{B.3}$$

Since all users with $y \leq \bar{y}$ choose digital payments, we have $N_{d,i} = \bar{y}$. Substituting in, we have:

$$\begin{aligned} 1 + \kappa\bar{y} &= \gamma\bar{y} \\ 1 &= \bar{y}(\gamma - \kappa) \\ \bar{y} &= \frac{1}{\gamma - \kappa}, \end{aligned} \tag{B.4}$$

which is positive since $\gamma > \kappa$ by assumption.

To test the stability of this equilibrium, consider a deviation of the marginal ϵ users from C to i (equivalent to the horizontal line in Figure 6 shifting up by ϵ). The new marginal users derive utility $1 + \kappa(\bar{y} + \epsilon)$ from i and utility $\gamma(\bar{y} + \epsilon)$ from C. The value of i to the marginal user has thus increased by $\kappa\epsilon$, while the value of C to the marginal user has increased by $\gamma\epsilon$. Since $\kappa < \gamma$ by assumption, the new marginal users prefer to stick with C. Thus the market does not tip, and deviating users would re-adopt cash until equilibrium is restored at $\bar{y}$. Analogous reasoning applies to a shift of ϵ users from i to C, so the equilibrium is stable. ■

B.2 Proof of Lemma 2

The marginal users $\hat{y}_{d,a}$ between a and C satisfy:

$$u^a_{d,x,y} = 1 + \kappa N_{d,a} = \gamma\hat{y}_{d,a} = u^C_{d,x,y}. \tag{B.5}$$

All users with $x \leq \hat{x}_d$ reason in the same way as each other, conditional on their cash preference y, so $N_{d,a} = \hat{x}_d\hat{y}_{d,a}$. Substituting in gives:

$$\begin{aligned} 1 + \kappa\hat{x}_d\hat{y}_{d,a} &= \gamma\hat{y}_{d,a} \\ 1 &= \hat{y}_{d,a}(\gamma - \kappa\hat{x}_d) \\ \hat{y}_{d,a} &= \frac{1}{\gamma - \kappa\hat{x}_d}. \end{aligned} \tag{B.6}$$

Thus usage of platform a is:

$$N_{d,a} = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d}. \tag{B.7}$$

Similarly, the marginal users $\hat{y}_{d,b}$ between b and C satisfy:

$$u^b_{d,x,y} = 1 + \kappa N_{d,b} = \gamma \hat{y}_{d,b} = u^C_{d,x,y}. \tag{B.8}$$

All users with $x > \hat{x}_d$ reason in the same way as each other, conditional on their cash preference y, so $N_{d,b} = (1 - \hat{x}_d)\hat{y}_{d,b}$. Substituting in gives:

$$\begin{aligned} 1 + \kappa(1 - \hat{x}_d)\hat{y}_{d,b} &= \gamma \hat{y}_{d,b} \\ 1 &= \hat{y}_{d,b}[\gamma - \kappa(1 - \hat{x}_d)] \\ \hat{y}_{d,b} &= \frac{1}{\gamma - \kappa(1 - \hat{x}_d)}\,. \end{aligned} \tag{B.9}$$

Thus usage of platform b is:

$$N_{d,b} = \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)}. \tag{B.10}$$

Stability in each case follows by analogous reasoning to that in the proof of Lemma 1. Combining these results then gives total usage of digital payments:

$$N_d^{D,Baseline} = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} + \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)}. \tag{B.11}$$

■

B.3 Proof of Lemma 3

Under interoperability, users of both platforms have access to the same user base, N_d^D. Thus the choice between platform i and cash is the same for potential users of both platforms and does not depend on $\hat{x}_d$, allowing us to define the same marginal users of each platform: $\tilde{y}_{d,a} = \tilde{y}_{d,b} = \tilde{y}$. These marginal users must satisfy:

$$u^i_{d,x,y} = 1 + \kappa N_d^D = \gamma\tilde{y} = u^C_{d,x,y}. \tag{B.12}$$

Since the marginal digital payments users' choices do not depend on $\hat{x}_d$, we also have $N_d^D = \tilde{y}$. Substituting in and rearranging gives:

$$\begin{aligned} 1 + \kappa\tilde{y} &= \gamma\tilde{y} \\ 1 &= \tilde{y}(\gamma - \kappa) \\ \tilde{y} &= \frac{1}{\gamma - \kappa} = \bar{y}\,, \end{aligned} \tag{B.13}$$

where the final equality follows from a comparison with equation (B.4) in the proof of Lemma 1. Total digital payments are therefore

$$N_d^{D,Interop} = \frac{1}{\gamma - \kappa} \tag{B.14}$$

and these are distributed between platforms in line with users' heterogeneous preferences:

$$N_{d,a} = \hat{x}_d\tilde{y} = \frac{\hat{x}_d}{\gamma - \kappa}\,, \qquad N_{d,b} = (1 - \hat{x}_d)\tilde{y} = \frac{1 - \hat{x}_d}{\gamma - \kappa}. \tag{B.15}$$

Stability in each case follows by analogous reasoning to that in the proof of Lemma 1. ■

B.4 Proof of Proposition 1

The results follows directly from (i) noting the presence of market fragmentation in Lemma 2, and (ii) comparing the outcomes under interoperability in Lemma 3 with the benchmark derived for the case of homogeneous preferences in Lemma 1. The change in total usage of digital payments under interoperability, relative to the baseline equilibrium, is given by

$$N_d^{D,Interop} - N_d^{D,Baseline} = \frac{1}{\gamma - \kappa} - \left(\frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} + \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} \right) \tag{B.16}$$

from Lemmas 2 and 3. Given $0 < \hat{x}_d < 1$ and $\gamma > \kappa > 0$ by definition, we have that $\gamma - \kappa \hat{x}_d > \gamma - \kappa > 0$ and $\gamma - \kappa(1 - \hat{x}_d) > \gamma - \kappa > 0$. Thus

$$\frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} < \frac{\hat{x}_d}{\gamma - \kappa} \tag{B.17}$$

and

$$\frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} < \frac{1 - \hat{x}_d}{\gamma - \kappa} \, . \tag{B.18}$$

Combining these gives

$$\frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} + \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} < \frac{\hat{x}_d}{\gamma - \kappa} + \frac{1 - \hat{x}_d}{\gamma - \kappa} = \frac{1}{\gamma - \kappa} \, , \tag{B.19}$$

which implies that equation (B.16) is positive. ■

B.5 Proof of Proposition 2

Lemma 2 gives that usage of platform a in the baseline equilibrium without interoperability is $N_{d,a}^{Baseline} = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d}$, while Lemma 3 gives that usage of platform a under interoperability is $N_{d,a}^{Interop} = \frac{\hat{x}_d}{\gamma - \kappa}$. The increase in usage of digital payments platform a under interoperability, relative to the baseline equilibrium, is therefore given by:

$$N_{d,a}^{Interop} - N_{d,a}^{Baseline} = \frac{\hat{x}_d}{\gamma - \kappa} - \frac{\hat{x}_d}{\gamma - \kappa\hat{x}_d}. \tag{B.20}$$

Given $0 < \hat{x}_d < 1$, $\gamma > \kappa$, and $\kappa > 0$ by definition, we have that $\gamma - \kappa\hat{x}_d > \gamma - \kappa$, which implies that the second term in equation (B.20) is smaller than the first. Hence, interoperability increases usage of platform a.

Similarly, Lemma 2 gives that usage of platform b in the baseline equilibrium is $N_{d,b}^{Baseline} = \frac{1-\hat{x}_d}{\gamma-\kappa(1-\hat{x}_d)}$, while Lemma 3 gives that usage of platform b under interoperability is $N_{d,b}^{Interop} = \frac{1-\hat{x}_d}{\gamma-\kappa}$. The increase in usage of digital payments platform b under interoperability, relative to the baseline equilibrium, is therefore given by:

$$N_{d,b}^{Interop} - N_{d,b}^{Baseline} = \frac{1-\hat{x}_d}{\gamma - \kappa} - \frac{1-\hat{x}_d}{\gamma - \kappa(1-\hat{x}_d)}. \tag{B.21}$$

By analogous reasoning to that for platform a, we again have that the second term is smaller than the first, so interoperability also increases usage of platform b. ■

B.6 Proof of Proposition 3

Differentiating equation (B.16) in the proof of Proposition 1 term by term using the quotient rule and rearranging gives:

$$\frac{\partial}{\partial \hat{x}_d}\left(N_d^{D,Interop} - N_d^{D,Baseline}\right) = \gamma\left[\frac{1}{\left(\gamma - \kappa\left(1-\hat{x}_d\right)\right)^2} - \frac{1}{\left(\gamma - \kappa\,\hat{x}_d\right)^2}\right]. \tag{B.22}$$

Since $\gamma > 0$, the sign of this expression depends on the sign of the term in square brackets, which in turn depends on the relative size of the two denominators. Recalling that $0 < \hat{x}_d < \frac{1}{2}$, we know that $1 - \hat{x}_d > \hat{x}_d$, and so

$$\gamma - \kappa\left(1-\hat{x}_d\right) < \gamma - \kappa\,\hat{x}_d \tag{B.23}$$

since $\gamma > \kappa > 0$. Noting that both sides of equation (B.23) must be positive, squaring both sides gives

$$(\gamma - \kappa\,(1 - \hat{x}_d))^2 < (\gamma - \kappa\,\hat{x}_d)^2\,, \tag{B.24}$$

which in turn implies that the term in square brackets in equation (B.22) is positive. Thus $\frac{\partial}{\partial \hat{x}_d}\left(N_d^{D,Interop} - N_d^{D,Baseline}\right)$ is positive. ■

B.7 Proof of Proposition 4

Equation (B.20) in the proof of Proposition 2 gives that the change in usage of platform a under interoperability is:

$$N_{d,a}^{Interop} - N_{d,a}^{Baseline} = \frac{\hat{x}_d}{\gamma - \kappa} - \frac{\hat{x}_d}{\gamma - \kappa\hat{x}_d}. \tag{B.25}$$

Differentiating with respect to $\hat{x}_d$ gives:

$$\frac{\partial}{\partial \hat{x}_d}\left(N_{d,a}^{Interop} - N_{d,a}^{Baseline}\right) = \frac{1}{\gamma - \kappa} - \gamma\frac{1}{(\gamma - \kappa\hat{x}_d)^2}\,. \tag{B.26}$$

Recalling that $0 < \hat{x}_d < \frac{1}{2}$ and $\gamma > \kappa > 0$ (which also imply $\gamma - \kappa\hat{x}_d > 0$), this is positive when:

$$\begin{aligned} \frac{1}{\gamma - \kappa} - \gamma\frac{1}{(\gamma - \kappa\hat{x}_d)^2} &> 0 \\ \frac{1}{\gamma - \kappa} &> \gamma\frac{1}{(\gamma - \kappa\hat{x}_d)^2} \\ (\gamma - \kappa\hat{x}_d)^2 &> \gamma(\gamma - \kappa)\,. \end{aligned} \tag{B.27}$$

Noting that both sides must be positive, taking the (principal) square root of each side gives:

$$\begin{aligned} \gamma - \kappa\hat{x}_d &> \sqrt{\gamma(\gamma-\kappa)} \\ \hat{x}_d &< \frac{\gamma - \sqrt{\gamma(\gamma-\kappa)}}{\kappa} \; . \end{aligned} \tag{B.28}$$

Similarly, equation in the proof of Proposition 2 gives that the change in usage of platform b under interoperability is:

$$N_{d,b}^{Interop} - N_{d,b}^{Baseline} = \frac{1-\hat{x}_d}{\gamma-\kappa} - \frac{1-\hat{x}_d}{\gamma-\kappa(1-\hat{x}_d)}. \tag{B.29}$$

Differentiating with respect to $\hat{x}_d$ gives:

$$\frac{\partial}{\partial \hat{x}_d}\left(N_{d,b}^{Interop} - N_{d,b}^{Baseline}\right) = \gamma\frac{1}{(\gamma-\kappa(1-\hat{x}_d))^2} - \frac{1}{\gamma-\kappa} \; . \tag{B.30}$$

This is positive when:

$$\begin{aligned} \gamma\frac{1}{(\gamma-\kappa(1-\hat{x}_d))^2} - \frac{1}{\gamma-\kappa} &> 0 \\ \gamma\frac{1}{(\gamma-\kappa(1-\hat{x}_d))^2} &> \frac{1}{\gamma-\kappa} \\ \gamma(\gamma-\kappa) &> (\gamma-\kappa(1-\hat{x}_d))^2 \; . \end{aligned} \tag{B.31}$$

Noting again that both sides must be positive, taking the square root of each side gives:

$$\begin{aligned} \sqrt{\gamma(\gamma-\kappa)} &> \gamma - \kappa(1-\hat{x}_d) \\ 1-\hat{x}_d &> \frac{\gamma-\sqrt{\gamma(\gamma-\kappa)}}{\kappa} \\ \hat{x}_d &< 1 - \frac{\gamma-\sqrt{\gamma(\gamma-\kappa)}}{\kappa} \; . \end{aligned} \tag{B.32}$$

Defining $\underline{\hat{x}} := \frac{\gamma-\sqrt{\gamma(\gamma-\kappa)}}{\kappa}$, we thus have that both $\frac{\partial}{\partial \hat{x}_d}\left(N_{d,a}^{Interop} - N_{d,a}^{Baseline}\right) > 0$ and $\frac{\partial}{\partial \hat{x}_d}\left(N_{d,b}^{Interop} - N_{d,b}^{Baseline}\right) > 0$ when $\hat{x}_d < \min(\underline{\hat{x}}, 1-\underline{\hat{x}})$. Therefore, when $\hat{x}_d$—and hence the no-interoperability level of fragmentation—is sufficiently low, a marginally higher level of $\hat{x}_d$ leads to a larger increase in usage of both digital payments platforms under interoperability. Conversely, if $\hat{x}_d$ is above this threshold, a marginally higher level of $\hat{x}_d$ leads to a smaller increase in usage of *at least* one digital payments platform. Combining this observation with Proposition 3, which states $\frac{\partial}{\partial \hat{x}_d}\left(N_d^{D,Interop} - N_d^{D,Baseline}\right)$ is positive, and noting that $N_d^{D,Interop} - N_d^{D,Baseline} = \sum_{i\in\{a,b\}}\left[N_{d,i}^{Interop} - N_{d,i}^{Baseline}\right]$ by definition, we have that a marginally higher level of $\hat{x}_d$ leads to a smaller increase in usage of *exactly one* digital payments platform if $\hat{x}_d > \min(\underline{\hat{x}}, 1-\underline{\hat{x}})$, with the platform ($a$ or b) facing the smaller increase dependent on the value of $\underline{\hat{x}}$. ■

B.8 Proof of Lemma 4

The results follow directly from noting that users' maximization problem in each stage described in Appendix C is analogous to that described for the original model in Section 3.2. Decisions in the pre-interoperability stage are equivalent to those in the original model when no interoperability is imposed. The equilibrium outcomes then follow straightforwardly from Lemma 2. Similarly, since the ω shock is unanticipated, users' decisions in the post-interoperability stage are equivalent to those in the original model when interoperability is imposed, so users' initial equilibrium choices follow straightforwardly from Lemma 3. The shock then shifts the ω marginal users from cash to digital payments. The $\hat{x}_d \cdot \omega$ users who are marginal between platform a and C choose platform a, and the $(1-\hat{x}_d)\cdot\omega$ users who are marginal between platform b and C choose platform b, increasing the total number of digital payments users by ω. Since the shock occurs after all users have made their initial payment choices (but before the payments occur), there is no second-round network effect of the shocked users' payment choices on the choices of other users. Thus the post-shock equilibrium is stable. ■

B.9 Proof of Lemma 5

From the definition of F_d and equations (C.3) and (C.5) we have

$$F_d = \frac{N_{d,a,-1}}{N_{d,-1}^D} = \frac{\frac{\hat{x}_d}{\gamma-\kappa\hat{x}_d}}{\frac{\hat{x}_d}{\gamma-\kappa\hat{x}_d}+\frac{1-\hat{x}_d}{\gamma-\kappa(1-\hat{x}_d)}} \tag{B.33}$$

in equilibrium. Differentiating this with respect to $\hat{x}_d$ gives

$$\frac{\partial F_d}{\partial \hat{x}_d} = \frac{\gamma\left(\gamma+\kappa\left(-2\hat{x}_d^2+2\hat{x}_d-1\right)\right)}{(\gamma+2\kappa(\hat{x}_d-1)\hat{x}_d)^2} \tag{B.34}$$

and it can be verified that this is always greater than zero for $0 < \hat{x}_d < \frac{1}{2}$ and $\gamma > \kappa > 0$. For some intuition on this result, note that from equation (B.33) we can already see that (i) $F_d = 0$ when $\hat{x}_d = 0$, (ii) $F_d = \frac{1}{2}$ when $\hat{x}_d = \frac{1}{2}$, and (iii) $F_d = 1$ when $\hat{x}_d = 1$. Between these points, the curvature of F_d in $\hat{x}_d$ depends on the strength of network effects (κ) relative to cash preferences (γ). ■

B.10 Proof of Prediction 1

We begin by seeking an expression for $\frac{\partial}{\partial \hat{x}_d}\left(\Delta N_d^D\right)$—i.e., for how "the change in total usage of digital payments after interoperability is introduced" itself changes with a district's user-type share. Similar to the proof of Proposition 3, we can differentiate equation (C.9) to give:

$$\frac{\partial}{\partial \hat{x}_d}\left(\Delta N_d^D\right) = \gamma\left[\frac{1}{\left(\gamma-\kappa\left(1-\hat{x}_d\right)\right)^2} - \frac{1}{\left(\gamma-\kappa\,\hat{x}_d\right)^2}\right]. \tag{B.35}$$

Since $\gamma > 0$, the sign of $\frac{\partial}{\partial \hat{x}_d}\left(\Delta N_d^D\right)$ depends on the sign of the term in square brackets, which in turn depends on the relative size of the two denominators. Recalling that $0 < \hat{x}_d < \frac{1}{2}$, we know that $1 - \hat{x}_d > \hat{x}_d$, and so

$$\gamma - \kappa\left(1-\hat{x}_d\right) < \gamma - \kappa\,\hat{x}_d \tag{B.36}$$

since $\gamma > \kappa > 0$. Noting that both sides of equation (B.36) must be positive, squaring both sides gives

$$(\gamma - \kappa (1 - \hat{x}_d))^2 < (\gamma - \kappa \, \hat{x}_d)^2 \, , \tag{B.37}$$

which in turn implies that the term in square brackets in equation (B.35) is positive. Thus $\frac{\partial}{\partial \hat{x}_d} \left(\Delta N_d^D\right)$ is positive: introducing interoperability increases total usage of digital payments by more in districts where a higher share of users perceive benefits from the smaller platform relative to the larger platform.

Finally, since we cannot observe $\hat{x}_d$ directly, we aim to express this result in terms of the variable F_d that we observe. Decomposing the relationship between ΔN_d^D and F_d using the chain rule gives:

$$\frac{\partial}{\partial F_d} \left(\Delta N_d^D\right) = \frac{\partial \left(\Delta N_d^D\right)}{\partial \hat{x}_d} \frac{\partial \hat{x}_d}{\partial F_d} = \frac{\frac{\partial \left(\Delta N_d^D\right)}{\partial \hat{x}_d}}{\frac{\partial F_d}{\partial \hat{x}_d}} \, . \tag{B.38}$$

Using the preceding conclusion that $\frac{\partial}{\partial \hat{x}_d} \left(\Delta N_d^D\right) > 0$, and the result from Lemma 5 that $\frac{\partial F_d}{\partial \hat{x}_d} > 0$, we have that $\frac{\partial}{\partial F_d} \left(\Delta N_d^D\right)$ is the quotient of two positive values, which is itself positive. Thus "the change in total usage of digital payments after interoperability is introduced" increases with the extent of fragmentation of digital payments users across platforms in the pre-interoperability baseline stage. ■

B.11 Proof of Prediction 2

The proof closely follows the proof of Proposition 4. From Lemma 4, the change in usage of platform a when interoperability is introduced is:

$$\Delta N_{d,a} = N_{d,a,1} - N_{d,a,-1} = \frac{\hat{x}_d}{\gamma - \kappa} + \hat{x}_d \cdot \omega - \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} \, . \tag{B.39}$$

Differentiating with respect to $\hat{x}_d$ gives:

$$\frac{\partial}{\partial \hat{x}_d}\left(\Delta N_{d,a}\right) = \frac{1}{\gamma - \kappa} + \omega - \gamma \frac{1}{(\gamma - \kappa \hat{x}_d)^2} \ . \tag{B.40}$$

Recalling that $\omega > 0$, $0 < \hat{x}_d < \frac{1}{2}$ and $\gamma > \kappa > 0$ (which also imply $\gamma - \kappa \hat{x}_d > 0$), this is positive when:

$$\begin{aligned}
\frac{1}{\gamma - \kappa} + \omega - \gamma \frac{1}{(\gamma - \kappa \hat{x}_d)^2} &> 0 \\
\frac{1}{\gamma - \kappa} + \omega &> \gamma \frac{1}{(\gamma - \kappa \hat{x}_d)^2} \\
1 + \omega(\gamma - \kappa) &> \gamma \frac{\gamma - \kappa}{(\gamma - \kappa \hat{x}_d)^2} \\
\left[1 + \omega(\gamma - \kappa)\right](\gamma - \kappa \hat{x}_d)^2 &> \gamma(\gamma - \kappa) \\
(\gamma - \kappa \hat{x}_d)^2 &> \frac{\gamma(\gamma - \kappa)}{1 + \omega(\gamma - \kappa)} \ . \qquad \text{(B.41)}
\end{aligned}$$

Noting that both sides must be positive, taking the (principal) square root of each side gives:

$$\begin{aligned}
\gamma - \kappa \hat{x}_d &> \sqrt{\frac{\gamma(\gamma - \kappa)}{1 + \omega(\gamma - \kappa)}} \\
\hat{x}_d &< \frac{\gamma - \sqrt{\frac{\gamma(\gamma - \kappa)}{1 + \omega(\gamma - \kappa)}}}{\kappa} \ . \qquad \text{(B.42)}
\end{aligned}$$

Similarly, from Lemma 4 the change in usage of platform b when interoperability is introduced is:

$$\Delta N_{d,b} = N_{d,b,1} - N_{d,b,-1} = \frac{1 - \hat{x}_d}{\gamma - \kappa} + (1 - \hat{x}_d) \cdot \omega - \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} \ . \tag{B.43}$$

Differentiating with respect to $\hat{x}_d$ gives:

$$\frac{\partial}{\partial \hat{x}_d}\left(\Delta N_{d,b}\right) = \gamma \frac{1}{(\gamma - \kappa(1 - \hat{x}_d))^2} - \omega - \frac{1}{\gamma - \kappa} \ . \tag{B.44}$$

This is positive when:

$$
\begin{aligned}
\gamma \frac{1}{(\gamma-\kappa(1-\hat{x}_d))^2} - \omega - \frac{1}{\gamma-\kappa} &> 0 \\
\gamma \frac{1}{(\gamma-\kappa(1-\hat{x}_d))^2} &> \frac{1}{\gamma-\kappa} + \omega \\
\gamma \frac{\gamma-\kappa}{(\gamma-\kappa(1-\hat{x}_d))^2} &> 1 + \omega(\gamma-\kappa) \\
\gamma(\gamma-\kappa) &> \left[1+\omega(\gamma-\kappa)\right](\gamma-\kappa(1-\hat{x}_d))^2 \\
\frac{\gamma(\gamma-\kappa)}{1+\omega(\gamma-\kappa)} &> (\gamma-\kappa(1-\hat{x}_d))^2 \,. \qquad \text{(B.45)}
\end{aligned}
$$

Noting again that both sides must be positive, taking the square root of each side gives:

$$
\begin{aligned}
\sqrt{\frac{\gamma(\gamma-\kappa)}{1+\omega(\gamma-\kappa)}} &> \gamma - \kappa(1-\hat{x}_d) \\
1-\hat{x}_d &> \frac{\gamma - \sqrt{\frac{\gamma(\gamma-\kappa)}{1+\omega(\gamma-\kappa)}}}{\kappa} \\
\hat{x}_d &< 1 - \frac{\gamma - \sqrt{\frac{\gamma(\gamma-\kappa)}{1+\omega(\gamma-\kappa)}}}{\kappa} \,. \qquad \text{(B.46)}
\end{aligned}
$$

Defining $\underline{\hat{x}} := \frac{\gamma-\sqrt{\frac{\gamma(\gamma-\kappa)}{1+\omega(\gamma-\kappa)}}}{\kappa}$, we thus have that both $\frac{\partial}{\partial \hat{x}_d}(\Delta N_{d,a}) > 0$ and $\frac{\partial}{\partial \hat{x}_d}(\Delta N_{d,b}) > 0$ when $\hat{x}_d < \min(\underline{\hat{x}}, 1-\underline{\hat{x}})$. Therefore, when $\hat{x}_d$ (and hence F_d, by Lemma 5) is sufficiently low—i.e., when digital payments users are relatively unified ex ante—introducing interoperability increases usage on both platforms by more in districts with higher $\hat{x}_d$ (or equivalently, higher F_d). ■

B.12 Proof of Proposition 5

Define the district-level counterpart of $\Delta^I N^D$, $\Delta^I N^D_d$, as the post-interoperability change in usage of digital payments in district d that results from integrating fragmented networks. From equation

(C.9), we see that this impact—which excludes the effect of shocks ω—is:

$$\Delta^I N_d^D = \frac{1}{\gamma - \kappa} - \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} - \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} \ . \tag{B.47}$$

By definition the aggregate national impact is equal to the sum of the impacts in all districts, so we also have:

$$\Delta^I N^D = \sum_d \Delta^I N_d^D \ . \tag{B.48}$$

To identify $\Delta^I N^D$, we therefore proceed in three steps. First, we derive the missing intercept from a district where users are almost entirely unified on one platform prior to interoperability. Appendix C gives that the post-interoperability change in total digital payments usage in district d is:

$$\Delta N_d^D = \frac{1}{\gamma - \kappa} + \omega - \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} - \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} \ . \tag{B.49}$$

Taking limits as $\hat{x}_d \to 0$, we have

$$\begin{aligned} \lim_{\hat{x}_d \to 0} \Delta N_d^D &= \frac{1}{\gamma - \kappa} + \omega - \frac{1}{\gamma - \kappa} \\ &= \omega \ . \end{aligned} \tag{B.50}$$

Similarly, from equation (B.33) we have $\lim_{\hat{x}_d \to 0} F_d = 0$. Thus in the limit as $\hat{x}_d$, and hence F_d, approaches zero, the observed change ΔN_d^D in district d reveals the size of the external shock—i.e., we have:

$$\Delta N_{d_0}^D = \omega \ . \tag{B.51}$$

Second, we use this intercept to derive the impact of integrating fragmented networks on each district. Combining equations (B.47), (B.49) and (B.51) gives:

$$\Delta N_d^D - \Delta N_{d_0}^D = \Delta^I N_d^D \ . \tag{B.52}$$

Finally, summing over these differences and comparing to equation (B.48) gives

$$\sum_d \left[\Delta N_d^D - \Delta N_{d_0}^D\right] = \sum_d \Delta^I N_d^D = \Delta^I N^D \tag{B.53}$$

as required. ■

C Extended model allowing for external shocks

We extend the model described in Section 3.1 by distinguishing three stages, -1, 0 and 1. In Stage -1, the digital platforms are not interoperable and users make payment choices as in the baseline version of the model described above. In Stage 0, platform interoperability is announced. In Stage 1, users again make payment choices, but this time as described in the version of the model with platform interoperability. However, after these choices have been made, but before the payments occur, an unanticipated shock shifts the marginal ω users from cash to digital payments, where $0 < \omega < \frac{\gamma-\kappa-1}{\gamma-\kappa}$.

We denote the consequences of users' choices in the two payment stages $t \in \{-1, 1\}$ with a t subscript and we use Δ to denote the change in such choices between those stages. For example, $\Delta N_d^D = N_{d,1}^D - N_{d,-1}^D$ is the pre-interoperability to post-interoperability change in total usage of digital payments in district d. We assume that users' types xy, districts' user-type shares $\hat{x}_d$, and parameters κ and γ are constant. Users' problem in Stage $t \in \{-1, 1\}$ is therefore to choose a payment method $p_{d,x,y,t} \in \{a, b, C\}$ that maximizes their utility, given their perceptions of the value of each option and their expectations of others' choices:

$$\max_{p_{d,x,y,t} \in \{a,b,C\}} U_{d,x,y,t} = \begin{cases} u^a_{d,x,y,t} & \text{if } \; p_{d,x,y,t} = a \\ u^b_{d,x,y,t} & \text{if } \; p_{d,x,y,t} = b \\ u^C_{d,x,y,t} & \text{if } \; p_{d,x,y,t} = C \end{cases} \tag{C.1}$$

where

$$u^a_{d,x,y,t} = \begin{cases} 1 + \kappa N^*_{d,a,t} & \text{if } x \leq \hat{x}_d \\ 0 & \text{if } x > \hat{x}_d \end{cases} \qquad u^b_{d,x,y,t} = \begin{cases} 0 & \text{if } x \leq \hat{x}_d \\ 1 + \kappa N^*_{d,b,t} & \text{if } x > \hat{x}_d \end{cases} \tag{C.2}$$

and $u^C_{d,x,y,t} = \gamma y$. We collect equilibrium outcomes in the following lemma:

Lemma 4 (Equilibrium outcomes in extended model)**.** *In the pre-interoperability stage, equilibrium usage of platform a, of platform b, and of both platforms combined is:*

$$N_{d,a,-1} = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} \tag{C.3}$$

$$N_{d,b,-1} = \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} \tag{C.4}$$

$$N^D_{d,-1} = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} + \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} \; . \tag{C.5}$$

In the post-interoperability stage, equilibrium usage of platform a, of platform b, and of both platforms combined is:

$$N_{d,a,1} = \frac{\hat{x}_d}{\gamma - \kappa} + \hat{x}_d \cdot \omega \tag{C.6}$$

$$N_{d,b,1} = \frac{1 - \hat{x}_d}{\gamma - \kappa} + (1 - \hat{x}_d) \cdot \omega \tag{C.7}$$

$$N^D_{d,1} = \frac{1}{\gamma - \kappa} + \omega \; . \tag{C.8}$$

Intuitively, the maximization decision within each period described in equation (C.1) is directly analogous to that in equation (2), so the equilibrium outcomes are directly analogous to those described in Lemmas 2 and 3, except for the impact of the shock in Stage 1.

Combining equations (C.5) and (C.8), the change in total usage of digital payments between the pre-interoperability and post-interoperability stages is:

$$\Delta N_d^D = N_{d,1}^D - N_{d,-1}^D = \frac{1}{\gamma - \kappa} + \omega - \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} - \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} \ . \tag{C.9}$$

The empirical identification problem is that while we can observe $N_{d,-1}^D$ and $N_{d,1}^D$, we do not observe ω, so we cannot attribute ΔN_d^D to interoperability alone—any observed change could instead be driven by the shock. However, when comparing two districts with the same ω, the ω terms cancel out, so any differences between the districts on ΔN_d^D must reflect differences in $\hat{x}_d$. Thus we are able to derive clear predictions for ΔN_d^D (Prediction 1), and similarly for ΔN_d^a and ΔN_d^b (Prediction 2). The requirement that the districts being compared face the same shock ω is the "parallel trends" assumption that we discuss in detail in Section 4.1.

Finally, while the equilibrium quantities in Lemma 4 are expressed as functions of districts' user-type shares $\hat{x}_d$, we cannot observe these directly since we only observe the platform choices of those users who do in fact adopt digital payments. We therefore express our empirical predictions as functions of $F_d := \frac{N_{d,a,-1}}{N_{d,-1}^D}$, which measures the share of all digital payments that occur through the smaller platform (platform a) in the pre-interoperability stage. We note that this can be used as a proxy for $\hat{x}_d$:

Lemma 5 (User-type shares and observed baseline fragmentation)**.** *The degree of fragmentation in a district in the non-interoperable baseline, measured by the share F_d of digital payments occurring through the smaller platform (platform a), is a strictly increasing function of $\hat{x}_d$, the district's share of users that perceive benefits from that platform relative to the other platform (platform b).*

Intuitively, when comparing two districts with different levels of $\hat{x}_d$, the district with higher $\hat{x}_d$ has more users that perceive positive utility from platform a, so will also have higher usage of platform a in the absence of interoperability. This can be seen in Figure 8a, where F_d equates to the ratio of the blue area to the sum of the blue and green areas. District 0 has low $\hat{x}_d$ and the blue area is relatively small; District 1 has higher $\hat{x}_d$, and the corresponding blue area (shown in Figure 7a) is relatively large.

D Implications of potential multihoming

In the model, each user makes only one payment, so they only choose one payment *method* and there is no need to multihome. In reality, users could have maintained accounts on both platforms (UPI and the pre-existing closed-loop incumbent) prior to them becoming interoperable. If multihoming were frictionless, such that switching between platforms carried no cost, then all users would effectively have access to the combined network across both platforms even prior to interoperability, since they could readily switch to their counterparty's platform. Thus, introducing interoperability would have no effect on total usage of digital payments. To the extent that multihoming did in fact occur prior to interoperability, it would therefore make us *less* likely to find a positive impact of network integration. Our empirical results can thus be interpreted as the impact of introducing interoperability even net of any multihoming that did in fact occur ex ante—i.e., as a lower bound on the true effect of introducing interoperability in a world where no multihoming occurs ex ante.

E Implications of cross-district transactions

To illuminate the implications of including cross-district payments in the model, we first consider the polar case where payments from district d flow equally to all districts, rather than only to other users within d. Users' welfare from using digital payments platform i thus depends on the total accessible national user base $\sum_{d=1}^{D} N^*_{d,i}$, rather than only the accessible within-district user base $N^*_{d,i}$. As the total number of districts D tends to infinity, the importance of $N^*_{d,i}$ within $\sum_{d=1}^{D} N^*_{d,i}$ thus tends to zero. Thus in the limit the extent of local fragmentation—which impacts $N^*_{d,i}$—is irrelevant. Instead, only the degree of *national* fragmentation across networks matters for the decision of a user in d. But since the degree of national fragmentation is the same for all districts, by definition, this implies that the impact of introducing interoperability is also the same for all districts. Thus Predictions 1 and 2 no longer hold: instead, we predict that introducing interoperability increases total digital payments by the same amount in all districts, regardless of each district's ex-ante level of fragmentation.

This extreme case highlights the different forces affecting within-district versus across-district payments. Payment choices for within-district payments depend on local fragmentation, whereas payment choices for across-district payments depend on fragmentation in the *destination* districts. We do not observe the destination district in our data, so we focus our analysis on the implications of local fragmentation for within-district payments. To the extent that our outcome variables do in fact include some cross-district payments (for instance, payments to online merchants), this would therefore serve to attenuate our estimates of integration's impact, implying that our estimates are a lower bound on the true impact of network unification.

F Decomposition of the change in value per capita

We have a variable $Y = U \cdot V \cdot W$ and aim to decompose a change in Y in response to another variable X into the parts resulting from changes in each of the constituent variables U, V and W. In our case, Y is the total value of digital payments per capita, U is the average value per transaction, V is the number of transactions per user, W is the number of users per capita, and X is our "treatment" variable P_d^+ interacted with the post-interoperability dummy $1_{\{t \geq t_0\}}$. The total derivative of Y with respect to X is:

$$\frac{\partial Y}{\partial X} = \underbrace{\frac{\partial U}{\partial X} VW}_{\text{via } U} + \underbrace{U \frac{\partial V}{\partial X} W}_{\text{via } V} + \underbrace{UV \frac{\partial W}{\partial X}}_{\text{via } W} \tag{F.1}$$

Table 1 Column 1 gives an estimate of $\frac{\partial Y}{\partial X}$ that we denote by β_X^Y. Similarly, Appendix Table A.1 Column 1 gives an estimate of $\frac{\partial U}{\partial X}$ that we denote by β_X^U, Column 2 gives an estimate of $\frac{\partial V}{\partial X}$ that we denote by β_X^V and Column 3 gives an estimate of $\frac{\partial W}{\partial X}$ that we denote by β_X^W. To estimate the contribution of each margin, we use the "non-treated" districts' sample means for each variable in the post-interoperability period (i.e., the mean for $P_d^+ = 0$ and $t \geq t_0$), which we denote by $\bar{U}, \bar{V}$, and $\bar{W}$. Substituting in, we define:

$$b := \underbrace{\beta_X^U \cdot \bar{V}\bar{W}}_{\text{via } U} + \underbrace{\bar{U} \cdot \beta_X^V \cdot \bar{W}}_{\text{via } V} + \underbrace{\bar{U}\bar{V} \cdot \beta_X^W}_{\text{via } W} . \tag{F.2}$$

We can then estimate the normalized relative contribution of each margin by the following shares s:

$$s_U := \frac{\beta_X^U \cdot \bar{V}\bar{W}}{b}, \qquad s_V := \frac{\bar{U} \cdot \beta_X^V \cdot \bar{W}}{b}, \qquad s_W := \frac{\bar{U}\bar{V} \cdot \beta_X^W}{b} . \tag{F.3}$$

Finally, we use these shares to decompose the overall estimated impact β_X^Y across margins U, V, and W, giving estimated impacts $\beta_X^Y \cdot s_U$, $\beta_X^Y \cdot s_V$ and $\beta_X^Y \cdot s_W$ respectively, as shown in Figure 12.

G Additional robustness checks

This appendix contains additional checks on the robustness of our baseline results. First we examine results from a range of alternative specification choices, then we run placebo tests for both the cross-sectional and temporal variation underlying our results.

G.1 Alternative specifications

Our baseline regressions estimate P_d using all digital payments transactions, not just P2M transactions. This reflects that even a user who, for example, only adopts digital payments to send P2P remittances is nonetheless joining a platform, increasing that platform's share of all users, and hence affecting the size of the user base that that platform brings to the combined network at integration. Nonetheless, Appendix Table A.2 shows that our results are robust to instead defining P_d using only P2M digital payments.

As discussed in Section 4.1, our baseline P_d^+ measure includes some districts where the incumbent platform has a greater than 50% share of pre-integration transaction values. One could thus interpret fragmentation in these districts as being driven by the incumbent's platform being too small, rather than too large (as in the vast majority of districts, where UPI was dominant ex ante). To avoid concerns that these districts are qualitatively different, and such should not be included in our comparisons, Appendix Table A.3 repeats our main results when dropping these districts (and re-computing P_d^+ accordingly). Our results remain similar.

Our baseline results control for differential trends according to the total value of digital payments across UPI and the incumbent platform in the month before integration in a given district. In the stylized framework of our model, where users can only choose between the two digital payments platforms and cash, such a control suffices to also control for differential trends by the level of cash usage ex ante. In reality, while UPI and the incumbent platform accounted for a large share of the total non-cash transaction value prior to integration (see Figure 2), other payment methods were available. The existence of other electronic payment options (e.g., credit and debit cards) could thus lead to variation in the ex-ante proportion of digital payments usage relative to cash that is not accounted for by our baseline control ($Z_d \times 1_{\{t \geq t_0\}}$). To address this potential concern, Appendix Table A.4 shows that our results remain robust when also controlling directly for differential trends by cash usage—i.e., when adding an extra control for differential trends by the total value of cash withdrawals in a district in the month prior to integration.

Our baseline results focus on transaction values rather than volumes, since these capture both the price and quantity margins of digital payments usage. Nonetheless, in Appendix Table A.5 we show that our main findings remain similar even when constructing y_{dt}, P_d and Z_d using volumes alone rather than values. Similarly, our results do not depend on our choice to winsorize values at the 1% level: Appendix Table A.6 shows that our results hold even when restricting winsorizing to the top 0.5% of districts.

Finally, we account for potential differences in trends between rural and urban areas. We construct an indicator for districts that are above the median population density, then repeat our baseline specification with the addition of the interaction between this indicator and period-specific fixed effects. The results, shown in Appendix Table A.7, confirm the robustness of our baseline estimates.

G.2 Placebo tests

We conduct two placebo tests to confirm that our results are not driven by some combination of our specification design and the context we study. First, we confirm that randomly re-assigning districts between P_d^+-groups produces median estimated effects centered on zero. Appendix Figure A.10a shows the results. Second, we confirm that our results are not driven by a combination of exponential growth in digital payments and our choice of baseline period. Appendix Figure A.10b repeats Figure 11a for an alternative t_0 set three months prior to that in our baseline specification, and confirms that the differential increase in total digital payments usage does not take off until the true month of integration.

H Estimating cross-app "Other-Other" transactions

As described in Section 2.2, we only observe a condensed version of the matrix of payer and payee app choices, containing four major apps and a consolidated "Other" category. This entails that for transactions in the "Other to Other" cell we cannot determine whether the transaction occurred between two users of different apps or between two users of the same app. To construct our central estimate of the share of cross-app transactions, we therefore distribute these transactions between the cross-app and within-app categories by combining (i) information revealed in the remainder of the condensed matrix, and (ii) the fact that we can estimate the dimensions of the full matrix (since we also observe information on the full distribution of payer-side app choices, as described in Section 2.2).

To illustrate our procedure, consider the following example where the "full" matrix (Matrix 1) contains five apps but we only observe a "condensed" matrix (Matrix 2) of two apps plus one aggregate “Other” category:

Matrix 1: Full

a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
a_{21}	a_{22}	a_{23}	a_{24}	a_{25}
a_{31}	a_{32}	a_{33}	a_{34}	a_{35}
a_{41}	a_{42}	a_{43}	a_{44}	a_{45}
a_{51}	a_{52}	a_{53}	a_{54}	a_{55}

Matrix 2: Condensed

$\sum_{i=1}^{3} a_{i1}$	$\sum_{i=1}^{3} a_{i2}$	$\sum_{i=1}^{3} \sum_{j=3}^{5} a_{ij}$
a_{41}	a_{42}	$\sum_{j=3}^{5} a_{4j}$
a_{51}	a_{52}	$\sum_{j=3}^{5} a_{5j}$

We thus aim to estimate the share of cross-app transactions in the blue square of Matrix 1, using only the information in Matrix 2 and the dimensions of Matrix 1. To solve this identification problem, we first define a ratio $\phi = \frac{R_{acv}}{R_{awv}}$ where R_{acv} and R_{awv} are respectively the average cross- and within-app transaction values within the red region. We then estimate the equivalent statistics (denoted B_{acv} and B_{awv}) in the blue region by applying this ratio. Specifically, we construct estimators by solving the following system of equations

$$B_w \hat{B}_{awv} + B_c \hat{B}_{acv} = B_v \tag{H.1}$$

$$\hat{B}_{acv} = \phi \hat{B}_{awv} \tag{H.2}$$

where: B_v is the observed total value in the blue “Other-Other” cell, B_w is the observed number of within-app relationships aggregated within the blue cell, and B_c is the observed number of cross-app relationships. We thus estimate the average cross-app value in the blue region by

$$\hat{B}_{acv} = \frac{\phi B_v}{(B_w + \phi B_c)} \tag{H.3}$$

and the average within-app value in the blue region by

$$\hat{B}_{awv} = \frac{B_v}{(B_w + \phi B_c)}. \tag{H.4}$$

This allows us to estimate the total value of within-app transactions in the blue region by calculating

$$\hat{B}_{wa} = \hat{B}_{awv} B_w \tag{H.5}$$

and similarly we estimate the total value of cross-app transactions in the blue cell by calculating

$$\hat{B}_{ca} = \hat{B}_{acv} B_c. \tag{H.6}$$

Turning to our context—with a larger number of apps in both the full and condensed matrices—we apply the same approach. We know that $B_w = n$ and $B_c = n(n-1)$, where n is the number of apps we observe on the UPI network in our complete payer-side data, minus four—i.e., minus the number we observe in our payer-payee matrix. We then construct our central estimate of the share of cross-app transactions (shown in Figure 4) using B_c and $\hat{B}_{acv}$.

PUBLICATIONS

Integrating Fragmented Networks: The Value of Interoperability in Money and Payments
Working Paper No. WP/25/126