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Integrating Fragmented Networks: Interoperability in Money and Payments

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ABSTRACT: Network effects in payments technologies drive concentration, but interventions to increase choice risk market fragmentation. We study whether interoperability can resolve this dilemma, using data from India's Unified Payments Interface and a major pre-existing digital wallet. When these platforms became interoperable, overall digital payment usage rose. This increase was driven by regions where usage was more fragmented across payment platforms ex ante, consistent with a model in which interoperability expands effective network size without requiring consolidation on a single platform. Model-based estimates imply that interoperability raised total digital payment usage by over 50 percent in the year after integration.

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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, 1986; Farrell and Saloner, 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 payments interoperability, which offers a potential escape from the dilemma yet has not been widely studied academically. By enabling users to transact seamlessly across payments 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 geographic

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

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 geographic granularity. Together, these data allow us to directly examine users' choices across apps offered by different platforms, 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, transactions between users of different UPI apps—which can only occur because UPI makes the apps interoperable—account for a significant share of activity on the platform. 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.

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 introducing interoperability are only marginal, as network

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

benefits are mostly already realized.

Informed by the conceptual framework, we empirically identify the impact of interoperability by combining regional variation in fragmentation with 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, leading to fragmentation between the two platforms' networks. 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 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 districts where digital payments 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 a substantial positive effect of network integration on total usage of digital payments. Over the year after integration, differential growth in the total value of digital payments in more fragmented districts amounted to 93% of more fragmented districts' pre-interoperability mean and to 125% of less fragmented districts' post-interoperability mean. Total digital payments also increased sharply relative to a proxy for cash usage based on ATM withdrawals. This suggests that cross-platform network effects enabled by interoperability induced substitution away from cash.

Three further results point to mechanisms underlying this effect that align closely with our conceptual framework. First, we observe significant differential increases in transaction values after integration for *both* transactions involving the incumbent app *and* transactions involving other UPI apps, consistent with positive spillovers from the ability to reach more users. Indeed, the ability to potentially transact with users on the other platform, even before any cross-platform transactions materialize, would make each individual platform more attractive. Second, we find that after integration newly enabled cross-platform transactions—those between a user of the incumbent's app and a user of another UPI app—were higher in more fragmented districts. This provides additional, direct evidence that greater initial fragmentation made this new functionality more valuable. Third, 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, consistent with our framework's focus on increased adoption. While fragmented districts also saw significant differential increases in the number of transactions per user and the average value per transaction, those margins played 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 incum-

[2]Importantly, these hubs were selected by the incumbent several years 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.

bent platform, we use the distance of each district to the nearest hub as our instrument. We also conduct placebo tests and consider a wide range of alternative specifications.

We combine our theory and cross-district variation in ex-ante fragmentation to derive a model-implied estimate of the aggregate impact of the two networks' integration on total nationwide usage of digital payments. On their own, our empirical estimates—based on cross-sectional variation in ex-ante fragmentation—are not informative about the aggregate impact of integration due to a missing intercept problem (e.g., Wolf, 2023; Buera, Kaboski, and Townsend, 2023; Moll and Hanney, 2025), namely that we do not know the absolute impact of network unification on districts that were less fragmented ex ante. To make progress, we impose additional structure from our model and leverage our theoretical result that interoperability brings no additional gains in regions with no fragmentation prior to integration, since all digital payments users in such regions can already transact with one another.[3] Taking districts with very little ex-ante fragmentation as a proxy for such regions, we can therefore compare each of the remaining districts against this "zero-impact" benchmark. 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.

We then 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.

Finally, we conclude with a discussion of the potential longer-term implications of interoperability for payment network structure. While our analysis focuses on the short-term implications of network integration for user adoption, we note that over a longer horizon interoperability can also affect the investment incentives of network providers. We highlight that developments in the Indian digital payments market raise novel considerations for future work, such as the potential for individual app providers to take actions that re-create proprietary app-level network effects even

[3] Of course, imposing this structure has trade-offs, which we discuss below. In general, we find that imposing our model assumptions leads us to *underestimate* the true impact of integration on usage of digital payments.

while the underlying payment rails remain fully interoperable.

Our results have important implications for policymakers across a wide range of both domestic and cross-border payments settings. Policymakers in many developing economies aim to increase adoption of digital banking and payments as a stepping stone to broader financial inclusion (Agarwal, Alok, Ghosh, Ghosh, Piskorski, and Seru, 2017; Berg, Fuster, and Puri, 2022). Our results highlight that integrating fragmented networks through interoperability can substantially increase uptake of the combined system. Conversely, our results warn that introducing a new, non-interoperable payments platform 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, growing policy emphasis on payments sovereignty is encouraging the development of national and regional payment infrastructures, making the global landscape more multipolar but potentially more fragmented unless these systems are interoperable (Financial Stability Board, 2025; Panetta, 2026).[4] In response, multilateral institutions like the IMF and BIS have advocated for interoperable global platforms that could facilitate cross-border payments and international trading of tokenized financial assets (Adrian, Grinberg, Mancini-Griffoli, Townsend, and Zhang, 2022; BIS, 2023).[5] Our paper speaks to both domestic and cross-border settings, by presenting tightly connected theoretical and empirical results on the impact of integrating large payments networks.

Related literature. We contribute to four main strands of research. First, we contribute to the extensive literature on money and payments. The idea that money functions as a network good dates

[4]More broadly, policymakers are also increasingly raising the possibility of a more multipolar global currency paradigm (Lagarde, 2025; Pan, 2025).

[5]The private sector has also been involved in initiatives to make cross-border payments more interoperable. For example, PayPal World is an initiative connecting PayPal, Venmo, WeChat and UPI for cross-border retail payments. More recently, SWIFT and The Clearing House have each announced infrastructures designed to make tokenized deposits interoperable across banks and between blockchain-based and existing payment rails.

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), Gopinath and Stein (2021), Coppola, Krishnamurthy, and Xu (2023), Crouzet, Ghosh, Gupta, and Mezzanotti (2024), and Goldstein, Yang, and Zeng (2023, 2026). Recent technological innovations—including the rise of public and private fast payments platforms, cryptocurrencies, and central bank digital currencies (CBDCs)—have transformed the payments landscape and posed new challenges for payment systems designers (Brunnermeier, James, and Landau, 2019; Duffie, 2019; Benigno, Schilling, and Uhlig, 2022; Cong and Mayer, 2025; Garratt, Yu, and Zhu, 2025; Parlour and Rajan, 2025; Steinsson, 2025). Concerns have grown in some countries about the dominance of a small number of private firms in payments and the potential negative welfare implications, even as those firms' scale brings welcome network benefits (e.g., Brunnermeier and Payne, 2022).

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 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.

Second, we contribute to a growing literature on the consequences of introducing interoperability in financial and communications technologies.[6] 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

[6]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).

"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' supply decisions: increased competition can reduce their incentives to invest in infrastructure and to expand platform access (Ferrari, Verboven, and Degryse, 2010; Björkegren, 2022; Brunnermeier, Limodio, and Spadavecchia, 2023).[7] 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).[8] We therefore innovate by exploiting within-country variation in interoperability: while the integration of the incumbent platform with UPI occurred nationally, exposure to this increase in interoperability varied across districts depending on their degree of ex-ante fragmentation. When estimating the impact of interoperability on usage of digital payments, we are thus able to draw a tighter comparison than previous work.[9]

Third, a long literature addresses the adoption and diffusion of network technologies, includ-

[7] 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.

[8] 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.

[9] 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.

ing 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 payments 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—once interoperability is introduced—the amplification of strategic complementarities that support adoption.

Finally, our paper relates to a growing literature on the downstream consequences of digital payments technologies, particularly in the context of India's rapid adoption of digital payments over the last decade.[10] Reflecting the speed and scale of the transition, these consequences have been pervasive, affecting investment and employment (Chodorow-Reich, Gopinath, Mishra, and Narayanan, 2020), consumption (Agarwal, Ghosh, Li, and Ruan, 2024), growth (Dubey and Purnanandam, 2023), lending (Ghosh, Vallee, and Zeng, 2022; Alok, Ghosh, Kulkarni, and Puri, 2024; Cramer, Ghosh, Kulkarni, and Vats, 2024; Rishabh, 2024), bank deposits (Di Maggio, Ghosh, Ghosh, and Wu, 2024), risk-sharing (Patnam and Yao, 2020), debt enforcement (Rishabh and Schäublin, 2021), and retail stock market investment (Ayyagari, Ghosh, and Kulkarni, 2026), 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 alternatives. However, this shock alone cannot explain longer-term adoption trends: Crouzet, Gupta, and Mezzanotti

[10]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).

(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, complementary 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 payments app. This perspective helps explain the re-acceleration of aggregate digital payments volumes from late 2017, since UPI integrated with two major pre-existing platform operators during that period—connecting their previously fragmented user bases with each other and with users of other UPI apps, thus unlocking larger network benefits for all users.[11]

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 describes our empirical strategy and tests the model's predictions. Section 5 considers the wider implications of our results, estimating the total national impact on digital payments usage, examining spillovers to credit markets, and discussing longer-term implications for network structure. 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.

[11]For a related discussion of the drivers of digital payments adoption in Latin America, see Argente, Gonzalez Alvarez, Méndez, and Van Patten (2025).

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. UPI was developed by the National Payments Corporation of India (NPCI, regulated by the Reserve Bank of India), which also provides the IMPS payment rails. Users of any UPI app can initiate payments from their accounts at any participating bank to accounts at other participating banks, as well as receive notifications of payments received into their accounts.[12] 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. In the case of TPAP apps, the TPAP provides the front-end application but partners with a payment service provider (PSP) bank that is connected to IMPS and executes the transaction.[13]

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. The extent of this interoperability grew over time through more banks and closed-loop e-money providers joining the system—for instance, through the integration event that we study in Section 4 below. Crucially, end users gained the ability to choose their favorite UPI

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

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

payments app without affecting either the location of their deposits (which remain 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 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 individual app providers under UPI, where interoperability means that network effects operate primarily at the level of the overall UPI ecosystem.

The UPI ecosystem has grown steadily, and now features several hundred participating apps and banks (Figure 1). Transaction volume on the platform has grown exponentially to more than 23 billion transactions 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 four key sources of data. First, we use novel data covering the universe of UPI transactions.[14] We observe monthly totals of value and volume, split by the interaction of the payer's app and the payer's bank branch, from the beginning of UPI's pilot phase in April 2016 through to September 2024.[15] 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 observe 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 disaggregated 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. This provides a proxy for cash usage, which is required since cash usage does not automatically create an electronic transaction record and hence cannot be measured directly.

Finally, we 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

[14] In contrast to previous work on UPI, our dataset covers transactions from *all* apps and banks in the UPI ecosystem, allowing us to provide a comprehensive picture of UPI usage.

[15] 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. Appendix B cross-checks this location proxy against other sources of data on UPI and confirms that it is closely aligned.

panel data on borrowing at the household level.[16]

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

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 are an important element of activity on UPI. Figure 4 plots the share of UPI transactions in which the payer and payee use different UPI apps. On both value and 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.

[16] We also use district-level demographic and descriptive data from the most recent census in 2011. We homogenize all district-level data to consistent district boundaries corresponding with this census.

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 payments 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, cross-app payments also rose rapidly (Appendix Figure A.2).

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 payments 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 C.

3.1 Setup

Environment. We develop a model of payment-method choice and competition, inspired by the modern literature on currency competition as a means of payment (e.g., Farhi and Maggiori, 2018;

Gopinath and Stein, 2021; Coppola, Krishnamurthy, and Xu, 2023; Crouzet, Ghosh, Gupta, and Mezzanotti, 2024). 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 payments platform a, digital payments platform b, and an outside option C, which we label as cash.[17] 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 Cong, Li, and Wang (2021), Alvarez, Argente, Lippi, Méndez, and Patten (2023), and Crouzet, Gupta, and Mezzanotti (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:

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

where $N^*_{d,i}$ is the number of digital payments users that can be *accessed* through platform i in

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

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 banking and payment competition and consumer affinity for different types of service (e.g., Parlour, Rajan, and Zhu, 2022; He, Huang, and Zhou, 2023; Garratt, Yu, and Zhu, 2025), 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—i.e., the share of "a-type" versus "b-type" users. 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 (Chodorow-Reich, Gopinath, Mishra, and Narayanan, 2020), 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.[18]

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.[19]

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 $i \in \{a, b\}$.

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:

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

We construct a benchmark against which to compare the impact of interoperability by first considering the simplified case in which all users value the two digital payments platforms identically.

[18]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 $\lim_{N_{d,i} \to 1} u^i_{d,x,y}(y = 1) = 1 + \kappa < \gamma = u^C_{d,x,y}(y = 1)$.

[19]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.

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 on the smaller platform does not fulfill their expectations, violating our concept of equilibrium.[20] 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 relative to the pooling equilibria that result from homogeneous preferences in Lemma 1.

[20] 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.

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 would result if users had homogeneous preferences and hence all pooled 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 to the level that would 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. 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 increases in adoption vary with the "no-interoperability" degree of 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 corresponds to the degree of fragmentation that results in the absence of interoperability. The next result shows that, interestingly, the greater the no-interoperability fragmentation, the larger the gains from introducing interoperability.

Proposition 3 (Impact on total digital payments by fragmentation level)**.** *The more fragmented users of digital payments are across platforms in the absence of interoperability, the larger the increase in total digital payments usage 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 imply greater unrealized network benefits. In the model, greater fragmentation in the absence of interoperability, corresponding to 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 fragmentation level)**.** *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.*

The key mechanism underlying this result is that the effect summarized in Proposition 3 is itself declining in the degree of no-interoperability fragmentation—i.e., while the red line in Figure 8b is increasing in $\hat{x}_d$ (over the relevant interval $0 < \hat{x}_d < \frac{1}{2}$), its gradient is decreasing in $\hat{x}_d$. Recall that if digital payments users were fully unified on the larger platform even without interoperability—i.e., if $\hat{x}_d = 0$—then introducing interoperability would have no impact on the utility of digital payments, since it would not unlock any new transaction possibilities. When $\hat{x}_d$ rises, this is no longer the case, so interoperability brings an aggregate increase in usage of digital payments, part of which flows to each platform (a and b). However, as $\hat{x}_d$ rises towards $\frac{1}{2}$, the "aggregate gain" in users under interoperability flattens off to a peak—reflecting that the extent of no-interoperability fragmentation is symmetric around $\hat{x}_d = \frac{1}{2}$ and its consequences are continuous in $\hat{x}_d$. In the limit as $\hat{x}_d \to \frac{1}{2}$, a marginal change in $\hat{x}_d$ thus has no impact on the aggregate gain in new digital payments users under interoperability, so for any one platform to see a larger such gain in users the other platform must see a smaller gain in users.[21]

3.3 Empirical predictions

Taking these propositions to the data requires overcoming two additional complexities. First, we must control for the possibility of external shocks that occur alongside the introduction of interoperability. A naïve test of Propositions 1 and 2 would simply compare total adoption of digital payments in a given district before versus after interoperability was introduced. However, such shocks—for instance, falling prices of cellular data—could raise digital payments adoption in the post-interoperability period for reasons unrelated to the introduction of interoperability. In Appendix D, we extend the model to allow for such external shocks, which we denote by ω, and derive an explicit expression for ΔN_d^D, the change in total digital payments between pre-interoperability and post-interoperability equilibria.

Second, $\hat{x}_d$ is not observable, so we cannot directly condition on it in empirical tests. In Appendix D, we therefore also derive an observable measure of the degree of fragmentation in the pre-interoperability equilibrium, which we denote by $F_d := \frac{N_{d,a,-1}}{N^D_{d,-1}}$, where $N_{d,a,-1}$ and $N^D_{d,-1}$ are respectively the observed usage of the smaller platform and of both platforms combined in the

[21]To see the two cases in Proposition 4 in Figure 8b, we first highlight that the black curve need not be symmetrical around $\hat{x}_d = \frac{1}{2}$ (unlike 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 both the black line and the equivalent curve for platform b.

pre-interoperability equilibrium.

Using these two extensions, we can derive empirically feasible tests of our conceptual framework that are robust to the presence of external shocks. Intuitively, if we can observe two districts that (i) have different levels of fragmentation F_d in the pre-interoperability equilibrium, but also (ii) face a common set of shocks ω (i.e., "parallel trends"), then when we compare ΔN_d^D (or the single-platform equivalents $\Delta N_{d,a}$ and $\Delta N_{d,b}$) between the districts the shocks ω cancel out and the variation that remains implies modified versions of Propositions 3 and 4. Specifically, the variation that remains implies the following predictions:

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 the extent of pre-interoperability fragmentation among digital payments users is relatively low, 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* $\frac{\partial \Delta N_{d,b}}{\partial F_d} > 0$.

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 adoption 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.[22] 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.

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 F. 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 payments platforms, which remains unaffected by the introduction of interoperability. This modeling choice significantly simplifies the derivation of the equilibrium,

[22]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.

while still allowing the two platforms to compete for users who would otherwise rely on cash.[23] 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.[24]

4 Empirical Analysis

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

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 had a total transaction value similar to UPI in the month prior to their integration, but UPI was growing substantially faster (Figure 9). Moreover, UPI had a much wider geographic presence: total transaction value on UPI was higher than that on the incumbent's platform in 97% of districts in the month before integration (Figure 10a).

[23] 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.

[24] 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.

The extent to which digital payments were fragmented between the two platforms prior to integration varied substantially across districts. Defining t_{-1} as the month before integration, we construct the following measure of fragmentation in each Indian district d:

$$F_d := \frac{\text{Total value of transactions per capita } \textit{on the smaller platform} \text{ in district } d \text{ in } t_{-1}}{\text{Total value of transactions per capita } \textit{across both platforms} \text{ in district } d \text{ in } t_{-1}}\,, \tag{3}$$

which is the empirical analogue of F_d as defined in Section 3.3. The distribution of this variable is shown in Figure 10b. Values closer to 50% imply that digital payments users were more fragmented across platforms prior to the platforms' integration. Conversely, values closer to zero imply more consolidation on one platform and lower fragmentation. Most districts were relatively unified on one platform prior to integration—the median value of F_d is 7.4%—consistent with the case considered in Prediction 2. For our regressions, described below, we construct a dummy variable F_d^+ that takes value one only in districts with above-median values of F_d.

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

$$y_{dt} = \alpha_d + \alpha_{st} + \beta(F_d^+ \times 1_{\{t \geq t_0\}}) + \beta_Z(Z_d^y \times 1_{\{t \geq t_0\}}) + e_{dt}\,, \tag{4}$$

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^y controls for the level of digital payments usage prior to integration and is discussed further below. Our estimation sample spans from six months before integration to one year after, and we cluster standard errors at the district level (Bertrand, Duflo, and Mullainathan, 2004).

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 pre-integration usage of digital payments. Put differently, we use the low fragmentation districts to observe a counterfactual with fewer unrealized cross-platform network benefits ex ante, and hence lower potential gains from interoperability. To explore the dynamics of this increase, we also run the corresponding event-study specification:

$$y_{dt} = \alpha_d + \alpha_{st} + \sum_{\tau \neq t_{-1}} \beta_\tau (F_d^+ \times 1_{\{t=\tau\}}) + \sum_{\tau \neq t_{-1}} \alpha_\tau (Z_d^y \times 1_{\{t=\tau\}}) + v_{dt} \,, \tag{5}$$

where the succession of month-wise dummies $1_{\{t=\tau\}}$ allows us to estimate differences in y_{dt} between F_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.[25] 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.

We include the term with Z_d^y to account for potential correlation between digital payments fragmentation and overall digital payments usage ex ante. We aim to isolate the impact of integrating more fragmented networks. However, digital payments may have grown differentially in districts where such usage was greater ex ante even in the absence of integration. We control for time trends that vary with the extent of usage prior to integration to account for this possibility. In our baseline specification, we measure Z_d^y using the overall value of transactions per capita across both platforms in period t_{-1} (i.e., the denominator in equation (3)). When examining other outcome variables y, we adjust the definition of Z_d^y accordingly to measure ex-ante usage in a manner consistent with the outcome variable.

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

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 F_d districts relative to low F_d districts, total digital payments y_{dt} may have increased by more in high F_d districts prior to integration. For instance, merchants in high F_d districts may have increased their acceptance of digital payments relative to those in low F_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.[26] Second, such widespread anticipation—if it did occur—would only bias down our estimate of β in equation (4), since higher usage of digital payments in above-median F_d districts ex ante would reduce an estimated increase in usage ex post. Thus this concern would only reduce the likelihood that we 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 (5), we do not see evidence of differential pre-trends between high- and low-F_d districts, suggesting that anticipation is not a significant concern for our results.

[26] To the best of our knowledge, there were no other significant regulatory shifts related to UPI's interoperability coinciding with this announcement or in the subsequent year. Users were able to link accounts at participating banks to participating apps of their choice and make cross-app transactions from the point that UPI was launched. A 2017 NPCI directive that allowed UPI app providers to connect to the underlying IMPS rails via multiple PSP banks had no impact on interoperability from a user-experience perspective. Operating licenses for account aggregators acting as conduits for open banking were only issued starting in 2019.

Identification: parallel trends. In the extended model in Section 3.3, two districts d being compared differ only on the exogenous boundary $\hat{x}_d$, which in turn determines their levels of ex-ante fragmentation F_d. In reality, high- and low-F_d districts could differ in other ways, such that the observed evolution of outcomes y_{dt} in low-F_d districts does not provide an accurate proxy for the potential outcomes of the high-F_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-F_d districts within the same state. Second, we control for differential trends by pre-integration digital payments usage. Thus we control for any factors that affect districts' propensity to use digital payments *in general*, leveraging only differences in the *composition* of that usage across platforms. Third, we find no statistically significant differences in pre-integration trends in y_{dt} between high- and low-F_d districts using equation (5). Fourth, we show that our results remain similar when comparing high-F_d districts to a matched sample of low-F_d districts that are otherwise similar on observables. Fifth, we show that our results also remain similar when instrumenting F_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 (4) are shown in Table 1. Column 1 shows our main test of Prediction 1: the total P2M transaction value per person increased by 8.3 Rupees per person per month more after integration in high-F_d districts than in low-F_d districts. While this figure is small in absolute terms, reflecting the low level of digital payments adoption at the time relative to India's population, the differential increase is economically substantial. Specifically, the increase is 93% of average P2M digital payments in high-F_d districts in the month prior to integration, and 125% of average monthly P2M digital payments in low-F_d districts across the year after integration. Figure 11a shows the dynamics of these differences: low-F_d and high-F_d districts do not differ significantly prior to integration, then substantial and persistent differences emerge after integration. Figure 11b shows that this pattern is similar for total P2M digital payments relative to cash withdrawals, consistent with substitution away from cash, as in the model.

Columns 2 and 3 of Table 1 show our tests of Prediction 2. We find that for both the incumbent's app and other UPI apps, the P2M transaction value per person increased by more in high-F_d districts than in low-F_d districts.[27] This aligns with the model's prediction that more fragmented districts—with more unrealized network benefits ex ante—see larger gains unlocked by interoperability, encouraging greater usage of each platform.[28] 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.

We next consider the role of cross-platform transactions, which were newly enabled by interoperability. These transactions were mechanically zero in all districts prior to integration, so we cannot estimate a comparable difference-in-differences specification for this outcome. Instead, we compare post-integration levels between high-F_d and low-F_d districts while controlling for state-time fixed effects. Column 4 of Table 1 shows that cross-platform transactions were significantly higher after integration in districts that had been more fragmented ex ante. The difference is economically substantial, exceeding 100% of the average post-integration level in low-F_d districts. Figure 12a shows how this difference in levels developed after integration, and Figure 12b shows the cross-sectional relationship one year after integration. Although this is not a difference-in-differences estimate of the cross-platform channel, it provides direct evidence that districts with more unrealized cross-platform links made greater use of the newly enabled functionality.

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

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

[28] Indeed, even before any cross-platform transactions take place, the ability to transact with users on the other platform makes each app more valuable.

of transaction value per capita around the post-interoperability low-F_d sample mean, giving us the shares of the total effect that are explained by changes in each of (i) to (iii).[29] We show the decomposition in Figure 13, and the constituent estimates in Appendix Table A.1. All three margins increased significantly more in high-F_d districts than in low-F_d districts, with (i), (ii) and (iii) increasing by 3.0%, 2.6% , and 18.6% respectively relative to the post-interoperability mean among low-F_d districts. Overall, growth in (iii), the number of users per capita, explained 77% 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 (4) when matching high-F_d districts to low-F_d districts with similar observables, and second, we instrument districts' F_d-status using pre-determined geographic decisions taken by the incumbent. Beyond these two approaches, in Appendix H we also check the robustness of our results to a wide range of alternative specifications, address alternative explanations for our findings, 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-F_d districts provide an accurate measure of the potential outcomes of the high-F_d districts in the counterfactual scenario in which they were less fragmented prior to integration. One potential concern is therefore that the high-F_d districts differed from low-F_d districts in ways not accounted for by our controls and fixed effects. Appendix Figure A.4 shows the association between F_d^+ and a range of district-level

[29] For a full description of our decomposition procedure, see Appendix G.

observables. While high-F_d and low-F_d are similar on most dimensions, high-F_d districts have significantly larger populations.

To mitigate concerns about the impact of this observable difference when comparing the evolution of digital payments usage between F_d^+-groups after the introduction of interoperability, we construct a new sample in which we match each high-F_d district to similar low-F_d districts. We identify the three nearest low-F_d neighbors for each high-F_d district using Mahalanobis distance matching (with replacement) on log population. This process of matching allows us to achieve balance across our high-F_d and low-F_d districts on all observables including population (Appendix Figure A.4), while retaining 500 districts from our baseline sample.[30]

We repeat our baseline from equation (4) 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). As with many platform services, adoption of the incumbent firm's platform began in a small number of cities before spreading nationally. The choice of these cities was a function of a marketing strategy decided well in advance of the subsequent—and unanticipated—integration with UPI.[31] At each 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 alterna-

[30] Low-F_d districts matched to multiple high-F_d districts are weighted by the number of times they are matched. We do not use all low-F_d districts when constructing the matched sample: we discard 54 low-F_d districts that are never one of the nearest neighbors of a high-F_d district. We also discard 19 high-F_d districts with populations outside the range seen for low-F_d districts, since no good match exists for these high-F_d districts.

[31] The incumbent firm's platform was initially launched several years before UPI went live in 2016.

tive, such as UPI (in the pre-integration world, where they were not yet interoperable).[32] We can exploit this variation to isolate variation in F_d that is unlikely to be correlated with any remaining omitted factors that influence both F_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.[33] 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 (and hence the degree of fragmentation) 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 F_d that can be explained by H_d is balanced on observable district characteristics (Appendix Figure A.7b).[34]

To implement our instrumental variable strategy, we first exclude the hub districts from the sample, then repeat equation (4) with the following first stage:

$$(F_d^+ \times 1_{\{t \geq t_0\}}) = \gamma_d + \gamma_{st} + \beta_H (H_d \times 1_{\{t \geq t_0\}}) + \gamma_Z (Z_d^y \times 1_{\{t \geq t_0\}}) + u_{dt} \,. \tag{6}$$

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).

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

[33] 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.

[34] 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. We then discuss the potential longer-term impacts of interoperability.

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.[35] Put differently, our well-identified estimates in the cross section do not directly imply an estimate of aggregate impact. Deriving such an estimate requires overcoming the "missing intercept" problem (e.g., Wolf, 2023; Buera, Kaboski, and Townsend, 2023; Moll and Hanney, 2025), namely that we do not know the absolute impact of network unification on districts that were less fragmented ex ante. To make progress, in this section we impose additional structure from our model, enabling us to derive estimates of the absolute impact of unification on 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 D, 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, net of the observed change in usage in a district whose digital payments users are already*

[35] 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 were *more* fragmented ex ante against one where digital payments were *less* fragmented ex ante.

fully unified prior to interoperability. We have:

$$\Delta^I N^D = \sum_d \left[\Delta N_d^D - \Delta N_{d_0}^D\right] , \tag{7}$$

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 there are no unrealized network benefits ex ante and interoperability does not enable any new connections. 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.[36]

Turning to the data, we proxy the "fully unified ex ante" districts d_0 with the first decile of the F_d distribution.[37] 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 (4). Specifically, we run:

$$y_{dt} = \alpha_d + \alpha_{st} + \sum_{n=2}^{10} \beta_n (F_d^n \times 1_{\{t \geq t_0\}}) + \beta_Z (Z_d^y \times 1_{\{t \geq t_0\}}) + e_{dt} , \tag{8}$$

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 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 Ap-

[36]Of course, by building on our model our aggregation procedure inherits the same assumptions and consequent trade-offs discussed in Section 3.4. In general, as with our district-level results, those considerations lead us to expect that our estimates *under*-state the true impact of integration on usage of digital payments. For instance, in reality even some users in "fully unified ex ante" districts could experience a gain in transaction possibilities under interoperability (e.g., due to new possibilities for cross-district transactions), meaning that our procedure could net out some increases in usage that do in fact result from interoperability.

[37]These districts have a median F_d of 1%, so are indeed very close to "fully unified" prior to integration. We consider the sensitivity of our estimates to using more or fewer districts to proxy for d_0 below.

pendix D, 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 (7). Define $\Delta^I y$ as the population-weighted national average monthly increase in total P2M transaction value per capita that is attributable to interoperability. We calculate:

$$\Delta^I y = \frac{\sum_d \sum_{n=2}^{10} \hat{\beta}_n \times F_d^n \times \text{Population}_d}{\sum_d \text{Population}_d}\,, \tag{9}$$

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 estimate that connecting the two networks raised the population-weighted national average P2M transaction value by $\Delta^I y = 10.2$ Rupees per capita per month during the first year after integration. We compare this estimate with the counterfactual average national monthly P2M transaction value per capita in the integration month and the following year if integration had not occurred. We construct that counterfactual by subtracting $\Delta^I y$ from the observed population-weighted national average in those months. Thus, we estimate that integration raised average national P2M transaction value per capita per month by

$$\frac{\Delta^I y}{\frac{1}{13}\sum_{t\geq t_0}\left(\frac{\sum_d y_{dt}\times \text{Population}_d}{\sum_d \text{Population}_d}\right)-\Delta^I y}\times 100 = 59\% \tag{10}$$

relative to the model-implied value that would have occurred in the absence of the integration event.[38]

Our model-implied estimate therefore suggests that integrating fragmented networks had a substantial aggregate impact on overall usage of the payments system. Indeed, given that UPI ultimately integrated several other pre-existing networks—although none as large as the incumbent platform studied here—our findings suggest that interoperability played a significant role in the system's take-off. Importantly, this conclusion is not based on aggregating the observed cross-platform transaction category alone: instead, our estimation procedure takes into account the total reduced-form effect of network integration, including *both* transactions conducted directly between the two platforms *and* any additional activity induced by the expansion of the accessible network.

5.2 Downstream impact on lending

While our focus in this paper is on how interoperability supports usage of digital payments, a natural follow-on question is: Do the impacts on payments have knock-on consequences downstream? A wide literature has identified several channels through which digital payments can facilitate credit provision (for a survey, see Berg, Fuster, and Puri, 2022). In this section, we therefore examine the spillovers to credit markets from integrating fragmented digital payments networks.

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

[38] Figure A.10 shows that this estimate is robust to using different numbers of districts to proxy for d_0. Specifically, we repeat equation (10) when estimating $\Delta^I y$ using more or fewer quantiles than the ten deciles used in the baseline. Taking the first of a larger number of quantiles proxies d_0 with districts closer to $F_d = 0$, but relies on fewer districts and may therefore increase measurement error. The resulting estimates remain between 40% and 65%.

specification at the household-survey wave level:

$$y_{ht} = \alpha_h + \alpha_{st} + \beta(F_d^+ \times 1_{\{t \geq t_0\}}) + \beta_Z(Z_d^y \times 1_{\{t \geq t_0\}}) + e_{ht}\,. \tag{11}$$

Our dependent variable here is the probability of borrowing from non-banks, as non-bank fintech firms are more likely to be able to draw on the information generated by greater digital payments activity (Ghosh, Vallee, and Zeng, 2022; Cramer, Ghosh, Kulkarni, and Vats, 2024). 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 control for differential trends by overall digital payments usage ex ante and 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 percentage points 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.[39] These patterns reflect gains in financial inclusion: we find similar results within households with no previous borrowing activity (Appendix Table A.2).

In summary, we again find that interoperability provides larger benefits in districts with higher ex-ante fragmentation. As our measure of borrowing focuses exclusively on the extensive margin, our results suggest that greater usage of retail digital payments reduced frictions in credit markets, allowing more households to borrow, consistent with prior work (Ghosh, Vallee, and Zeng, 2022; Ouyang, 2023; Alok, Ghosh, Kulkarni, and Puri, 2024; Cramer, Ghosh, Kulkarni, and Vats, 2024).

[39] 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 (Berg, Fuster, and Puri, 2022).

5.3 Long-term impact on payment network structure

We focus on the demand-side effects of interoperability, examining how integrating previously fragmented payment networks can increase prospective users' adoption of digital payments. We do so by working in a clean setting that allows us to hold the supply side fixed in the short term.

Over longer horizons, the literature shows that design choices like interoperability and standardization can have ambiguous implications for the supply of product features such as quality, functionality, and innovation (Katz and Shapiro, 1985, 1986; Farrell and Saloner, 1985), with recent theoretical work specifically examining interoperability in payments (Brunnermeier and Payne, 2022, 2023). On one hand, interoperability makes firms' decisions strategic complements: a firm invests more when it expects others to invest, because the marginal return to investment is higher when others also invest, a "coordination effect." On the other hand, each firm's investment generates positive externalities for others that it does not fully internalize, which can lead to under-investment, a "free-rider effect."

The recent empirical literature on interoperability has emphasized the latter concern. Increased competition on interoperable rails may weaken providers' incentives to invest in expanding platform access or infrastructure because part of the gains from doing so accrue to other providers (Ferrari, Verboven, and Degryse, 2010; Björkegren, 2022; Brunnermeier, Limodio, and Spadavecchia, 2023). In particular, Brunnermeier, Limodio, and Spadavecchia (2023) show that interoperability in mobile money reduced the incentive for vertically integrated mobile network and mobile money operators to cover the variable costs of operating mobile towers, thereby diminishing network coverage.

However, there is also evidence that coordination can dominate free-rider dynamics in some settings. In the U.S. context, Bian, Huang, Li, and Tang (2024) show that inter-firm data sharing, a form of data interoperability, induces net complementarities in investment: firms increase customer-engagement investment when their data-connected peers do so, and investment falls only when data sharing is curtailed by privacy policy, analogous to a reduction in interoperability.

A natural question, therefore, is whether similar long-run forces operate in the UPI context and how they might qualify the interpretation of our main results, which focus on user adoption. Studying these long-term impacts and full-fledged welfare implications is beyond the scope of this paper. We leave a fuller exploration to future research—as more data on payment providers' investments and innovations become available.

We do, however, highlight developments in the Indian digital payments market that point to the need for a new, more nuanced perspective on longer-term supply-side considerations. The literature largely assumes that interoperability, if implemented, is fully achieved.[40] We document evidence of endogenous responses by UPI app providers to encourage within-app transactions and re-create proprietary, within-provider network effects, even as the underlying payment rails remain fully interoperable. First, many UPI providers initially offered proprietary QR codes to merchants that could only be read by the provider's own app—steering potential customers to also adopt that app. These non-interoperable QR codes were subsequently prohibited by the RBI to reinforce UPI's design as a fully open and interoperable payments system (Reserve Bank of India, 2022). Second, even with interoperable QR codes, some providers branded them in a way that created the impression that the codes were nonetheless only readable by a given app (Phatak, Kumar, Mehta, Ramasastri, Asbe, and Patel, 2020). Third, the major UPI app providers offer referral schemes incentivizing within-app transactions, again re-creating provider-level network effects.[41]

We find suggestive evidence that providers are at least partially successful in these efforts to encourage within-app transactions and re-create proprietary network effects. In roughly half of UPI transactions the payer and payee continue to use the same app, with the ratio of cross-app to within-app transactions remaining broadly stable in recent years (as shown in Figure 4). Indeed, we observe increasing regional concentration over time in the user bases of the two largest apps (Appendix Figure A.11).

Conceptually, considering the possibility that providers may partially respond to interoperabil-

[40] One exception is Bourreau and Kraemer (2023), who model imperfect interoperability as an exogenous parameter constraint, reflecting the government's inability to impose full interoperability on providers of overlapping but distinct services. In contrast, we highlight the case where imperfect interoperability arises endogenously from strategic design choices by providers, who aim to re-create proprietary network effects in response to an interoperability mandate.

[41] See, for instance, referral offers advertised here, here and here.

ity by re-introducing lock-in effects could help better assess the long-term implications for supply. For policymakers, maintaining a truly interoperable system may require continued efforts to respond to such attempts.

6 Conclusion

The presence of network effects in payment technologies leads to an important tradeoff in payment system design. On one hand, such network effects can lead to the dominance of a small number of large platforms and limit the options available to users. On the other hand, disruption from new entrants—including public platforms—could lead to more fragmentation, undermining the inherent network benefits of payments.

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 platforms at a granular geographic level. This allows us to exploit the unique natural experiment created when the two platforms 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 took off more quickly in districts that had been more fragmented ex ante, direct evidence that users valued the additional options provided by interoperability.

These estimates point to important wider effects. 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 payments platforms risks significant costs by increasing fragmentation.

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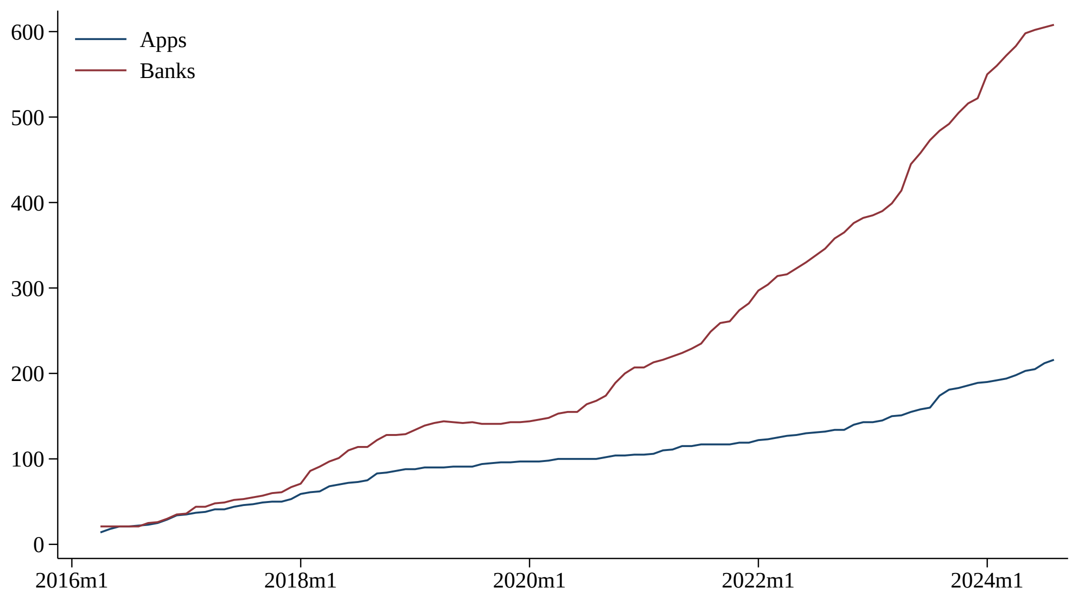
Figures and Tables

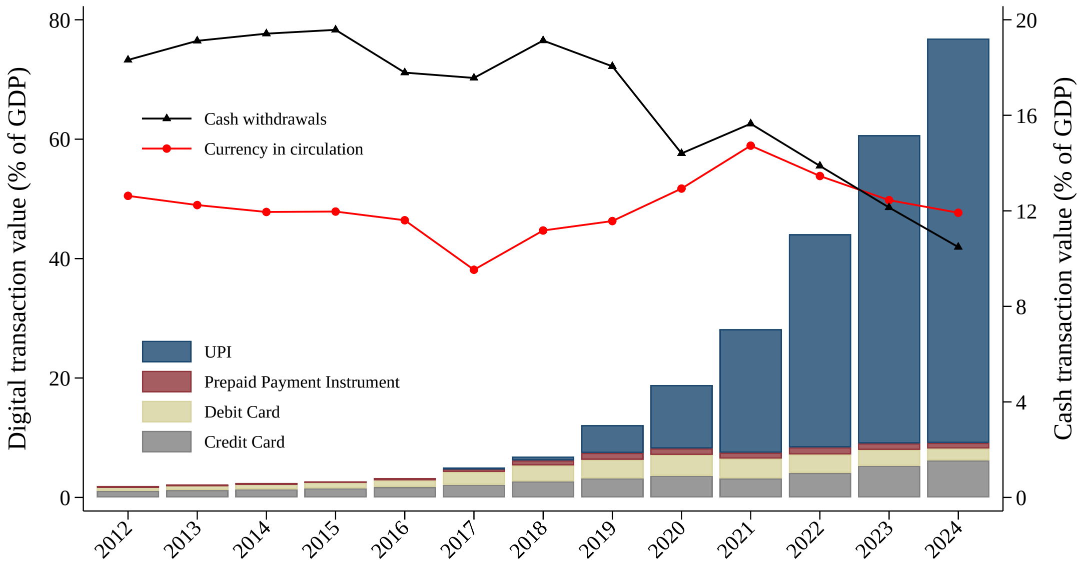
Figure 1: Number of apps and banks participating in UPI



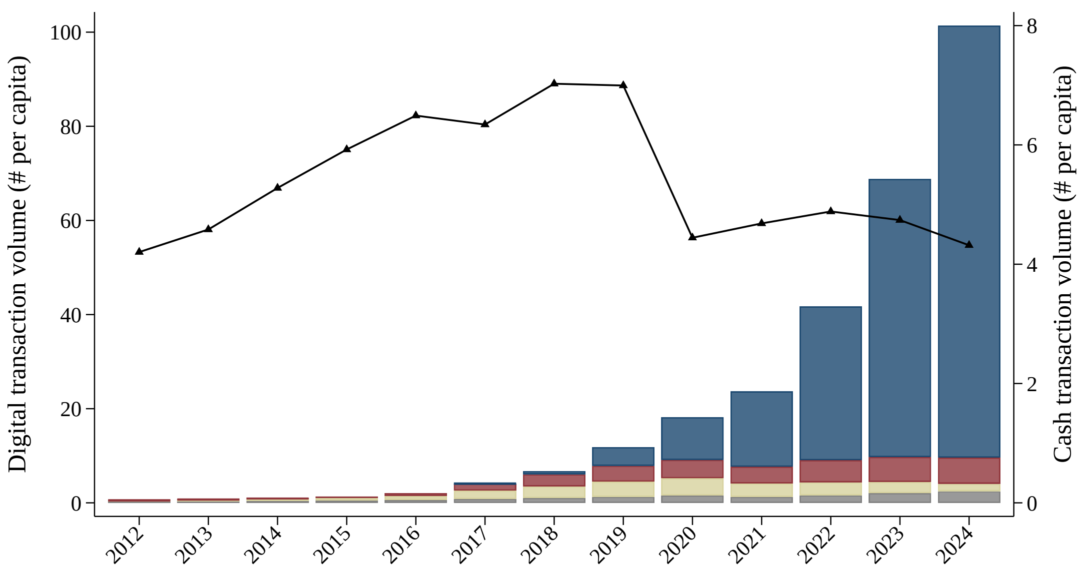
Notes: This graph shows the cumulative number of apps and banks participating in the UPI ecosystem over time. *Source:* NPCI.

Figure 2: Electronic retail payments in India

(a) Value (percent of GDP)

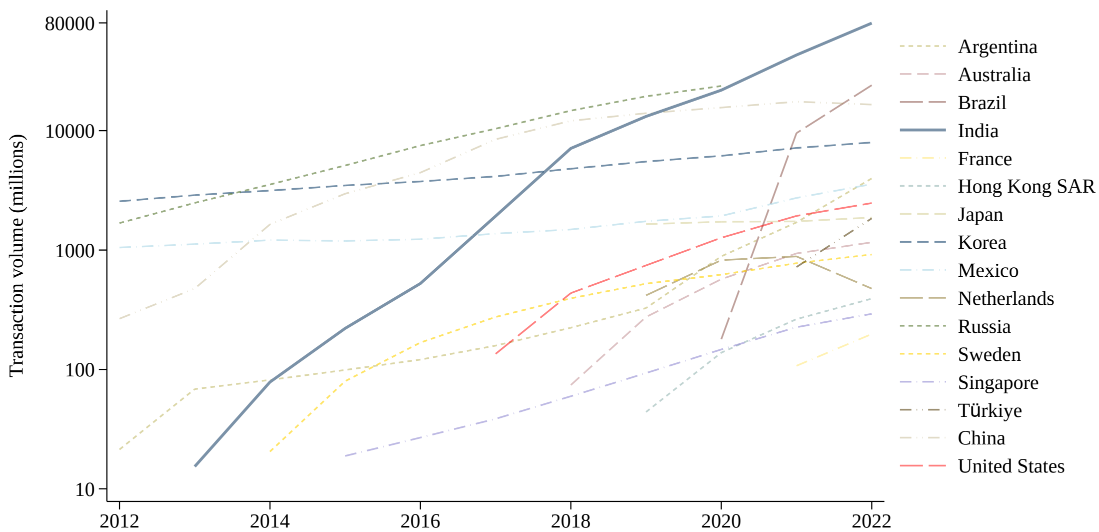


(b) Volume (transactions per capita)



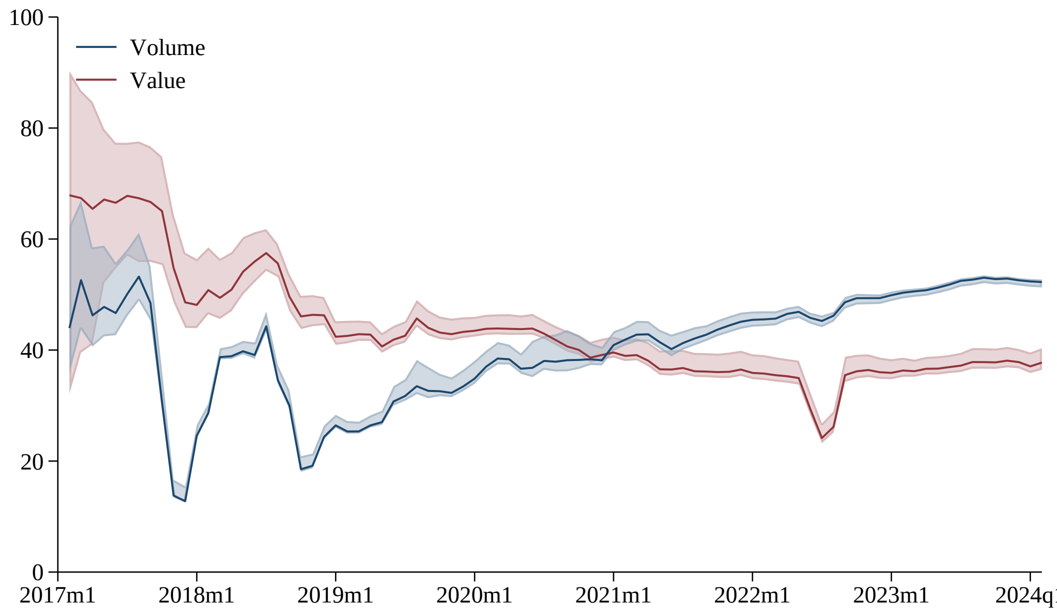
Notes: This graph shows the value and volume of UPI and other electronic retail payment methods in India. Pre-paid payment instruments include smart cards and mobile wallets that are pre-loaded with value using cash, card or other methods. *Source:* RBI, NPCI, Haver Analytics, WDI.

Figure 3: Volume of fast payment transactions (millions)



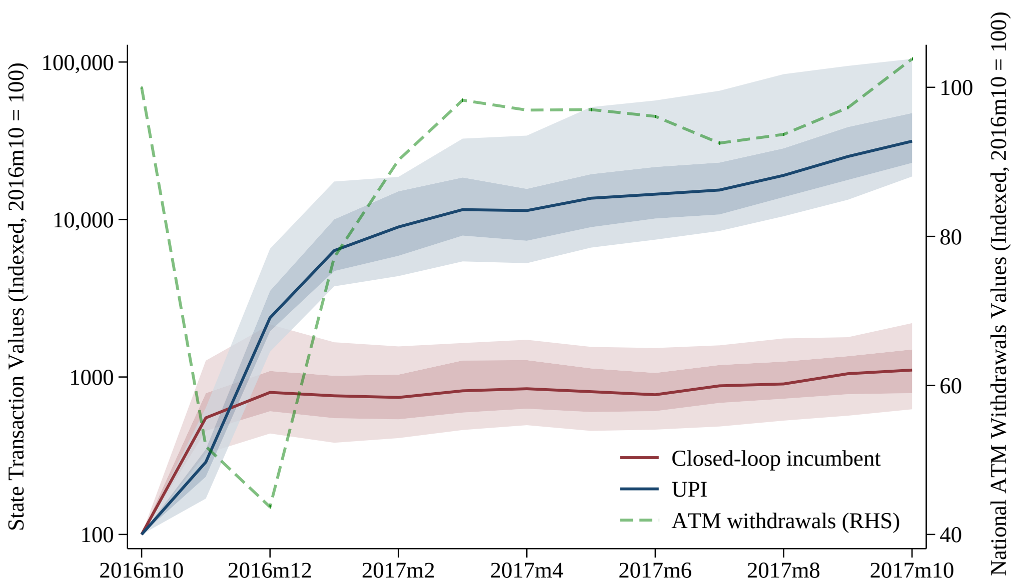
Notes: Fast payments: real-time or near real-time transfers of funds between accounts of end users as close to a 24/7 basis as possible (Frost, Wilkens, Kosse, Shreeti, and Velasquez, 2024). US comprises Zelle from 2017 and RTP from 2020. *Source:* BIS, Statista, The Clearing House.

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



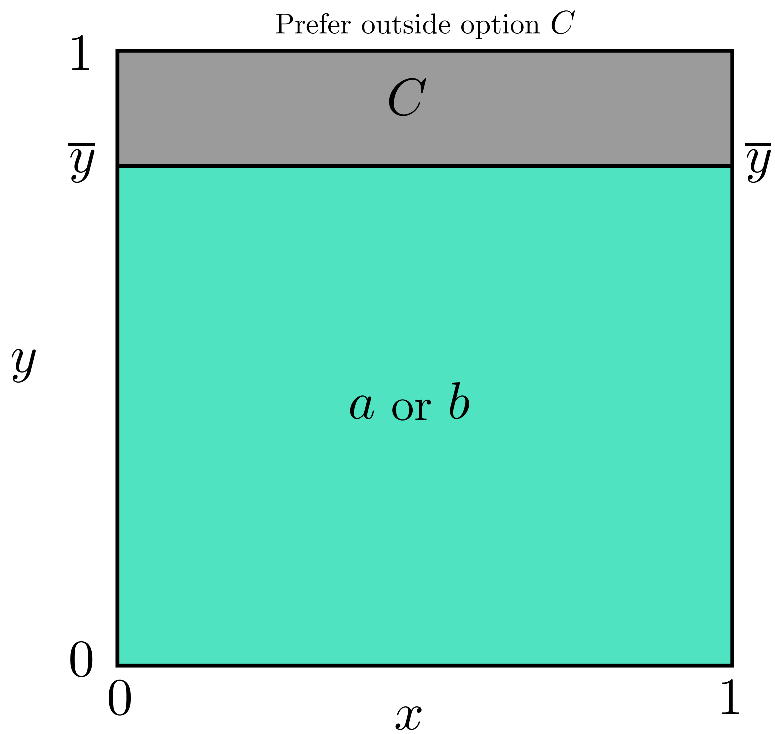
Notes: This graph plots the share of transactions on UPI that occur between two different apps, measured in turn using transaction value and transaction volume. Since we only observe the full payer app-payee app matrix for four major apps plus a consolidated "Other app" category, we estimate the share of cross-app payments in the "Other app" to "Other app" cell using the procedure described in Appendix I. 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)



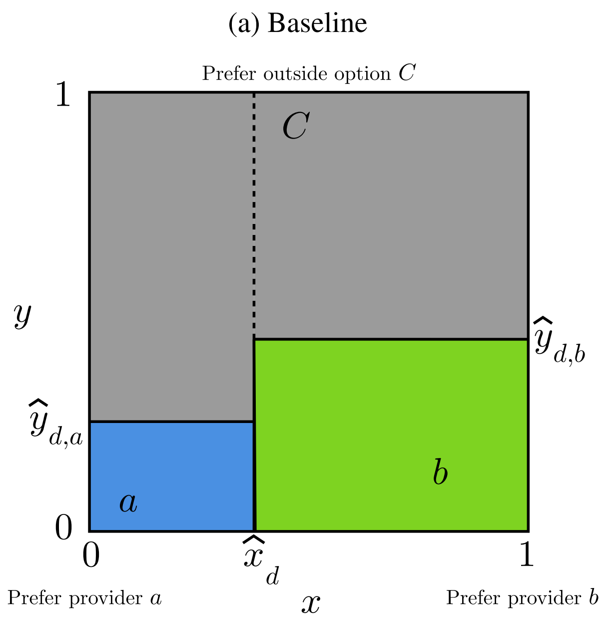
Notes: The green line shows national ATM withdrawals, by value, indexed to 100 in the month before demonetization (October 2016). The red line shows the total value of transactions on a major closed-loop incumbent digital payments platform in the median state, again indexed to 100 in October 2016. The 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—i.e., either all digital payments users select platform a or all digital payments users select platform b. 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.

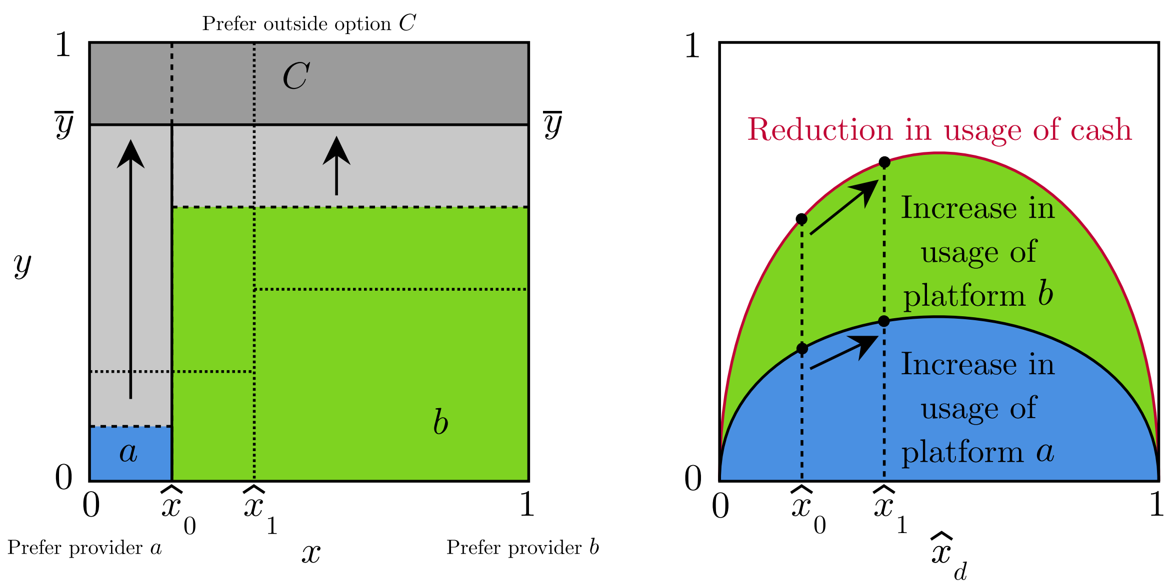
Figure 7: Equilibria for a given boundary $\hat{x}_d$



Notes: Panel (a) depicts the outcome in Lemma 2, in which users are fragmented across platforms and the number of users 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.

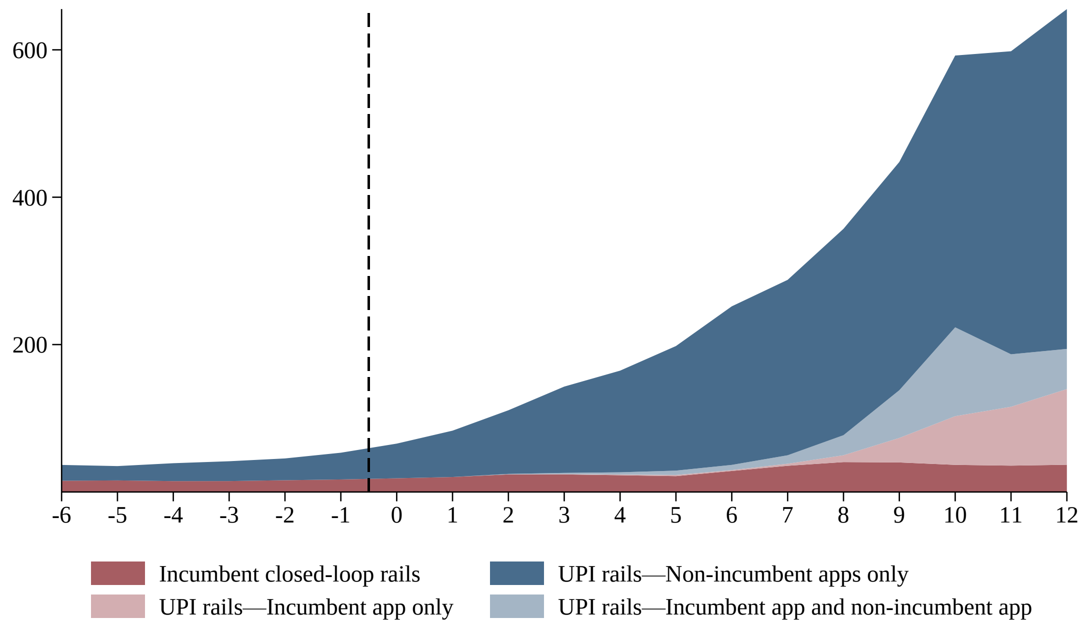
Figure 8: Comparing the impact of interoperability across districts

(a) Pre- and post-interoperability equilibria　　(b) Impact by district's user-type share $\hat{x}_d$



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.

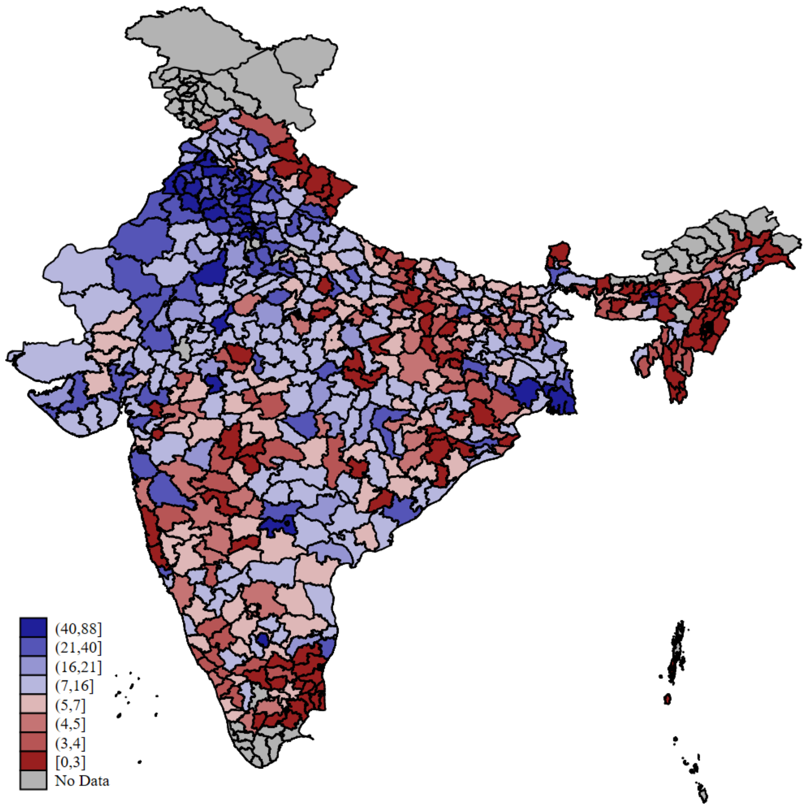
Figure 9: Aggregate value of transactions on UPI and incumbent platform (Rupees, billions)



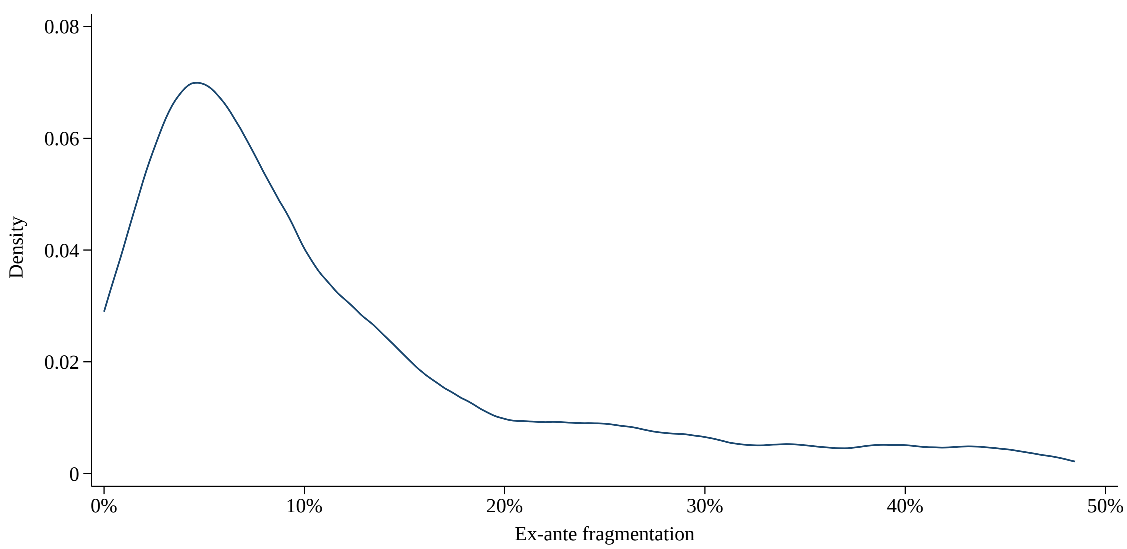
Notes: Each region shows the value of transactions by transaction type. The dark red shaded region shows transactions using the incumbent's closed-loop payments technology, which by definition required both the payer and payee to use the incumbent's app. The pink shaded region shows transactions made through UPI rails, yet where both the payer and payee used the incumbent's app. 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. Finally, 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 horizontal axis shows the number of months before or since the two platforms' integration, which occurred in month zero.

Figure 10: Variation in ex-ante fragmentation

(a) Incumbent market share by district in t_{-1} (percent)



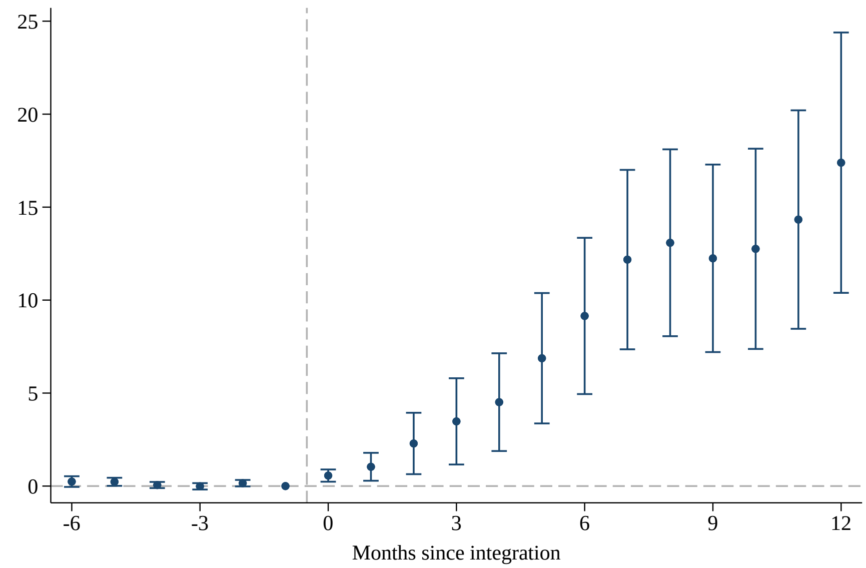
(b) Distribution of F_d



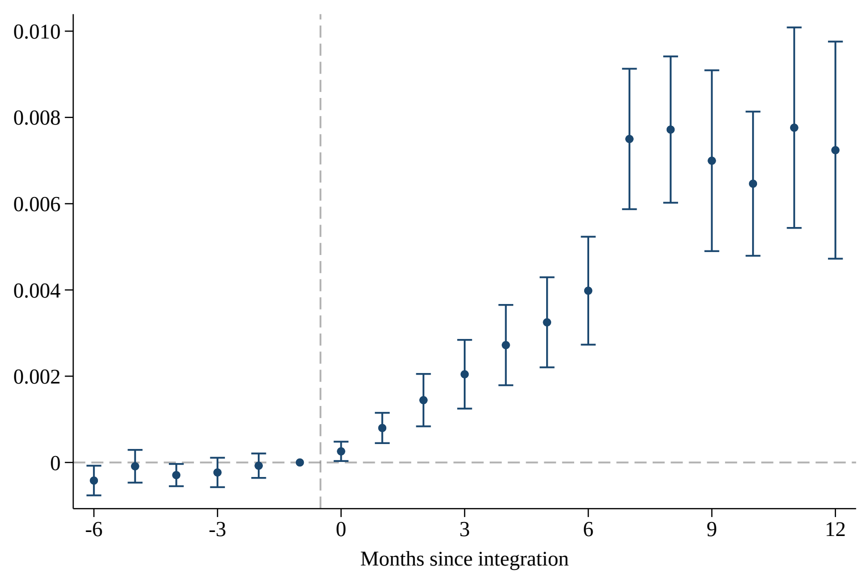
Notes: The first panel shows the market share of the incumbent fintech firm's platform in the month prior to integration. Blue districts indicate an above-median presence of the incumbent and red districts indicate a below-median presence of the incumbent. The second panel plots the estimated probability density of our measure of ex-ante fragmentation, F_d, using an Epanechnikov kernel function.

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

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



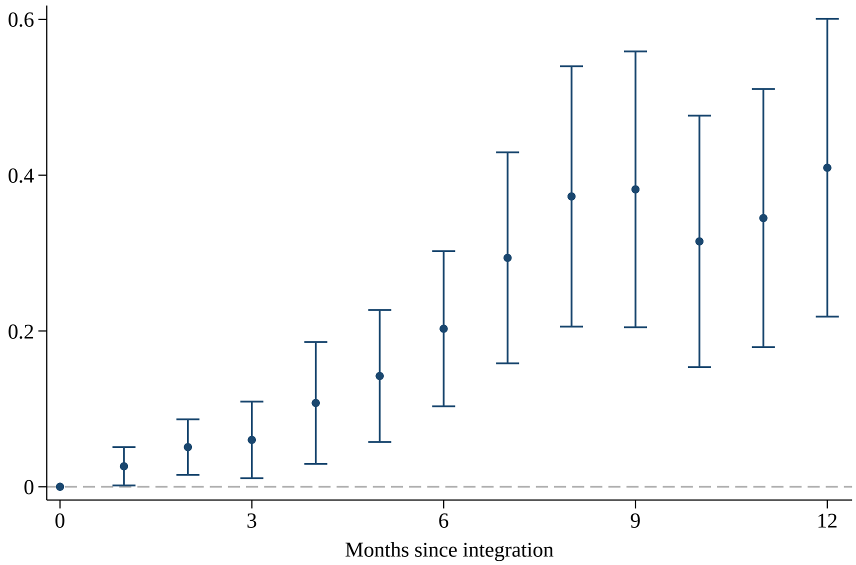
(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



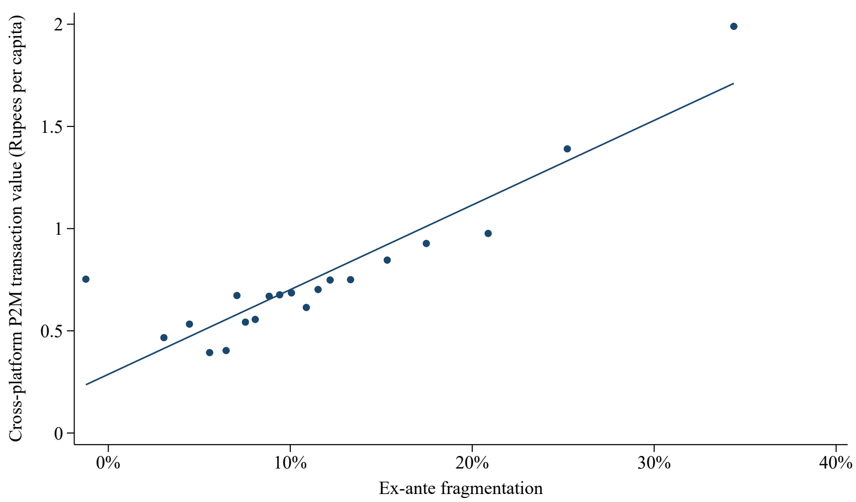
Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-F_d and low-F_d districts, based on equation (5). The first panel normalizes total P2M transaction values relative to population and defines Z_d^y based on total transaction value per capita. The second panel normalizes total P2M transaction values relative to cash withdrawals from ATMs and defines Z_d^y based on total transaction value per Rupee of cash withdrawn. Vertical lines show 95% confidence intervals.

Figure 12: Cross-platform transactions after platform integration

(a) Response dynamics of cross-platform P2M transaction value (Rupees per capita)

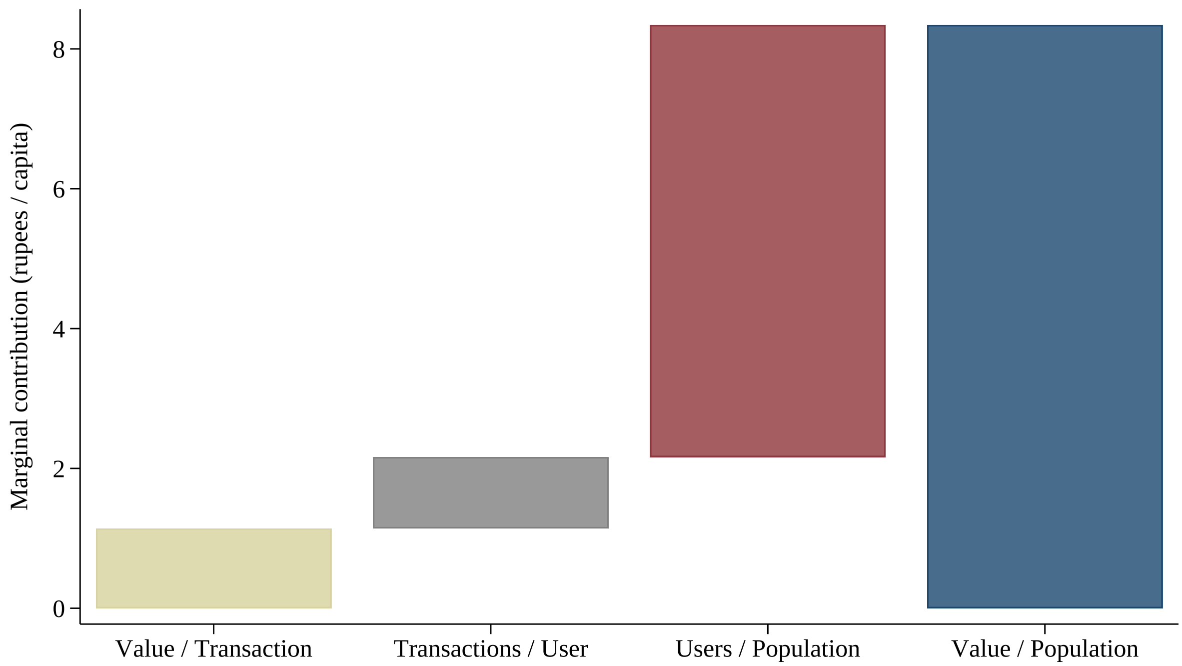


(b) Cross-sectional variation one year after integration



Notes: This figure compares the level of cross-platform P2M transaction values, after integration, between districts with high and low ex-ante fragmentation. (Such transactions were not possible prior to integration, by definition.) The first panel plots the estimates β_τ from $y_{dt} = \alpha_{st} + \sum_{\tau=t_0+1}^{t+12} \beta_\tau (F_d^+ \times 1_{\{t=\tau\}}) + v_{dt}$, estimated on post-integration observations only, where α_{st} are state-time fixed effects. The integration month t_0 is the omitted baseline, so each β_τ reflects the difference between high- and low-F_d districts in post-integration month τ relative to the difference in the integration month. Vertical lines show 95% confidence intervals. The second panel shows a binned scatter plot of cross-platform P2M transaction value per capita against F_d in the twelfth month after integration, residualized on state fixed effects.

Figure 13: 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 G. In short, we take the total derivative of transaction value per capita around the post-interoperability low-F_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)	Incumbent/pop (2)	Other/pop (3)	(Inc↔Oth)/pop (4)
$F_d^+ \times 1_{\{t \geq t_0\}}$	8.342***	4.925***	2.971***	0.208***
	(4.67)	(6.03)	(3.70)	(4.13)
State-Time FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓	
N	10,868	10,868	10,868	7,436
Mean y_{dt} ($F_d^+ = 1, t = t_{-1}$)	9.018	7.089	1.928	
Mean y_{dt} ($F_d^+ = 0, t \geq t_0$)	6.687	1.450	5.294	0.189

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-F_d and low-F_d districts. F_d^+ is a dummy taking value one for districts with above-median fragmentation prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value involving the incumbent's app—i.e., transactions in which at least one counterparty used the incumbent's app—in Rupees per capita; (3) total P2M transaction value involving other UPI apps—i.e., transactions in which at least one counterparty used an alternative UPI app—in Rupees per capita; (4) total cross-platform P2M transaction value—i.e., transactions occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app—in Rupees per capita. Columns (1)–(3) report estimates of specification (4). Column (4) reports the estimate from regressing cross-platform P2M transaction value per capita on F_d^+, controlling for state-time fixed effects, over the post-integration sample. (On this sample, $F_d^+ \times 1_{\{t \geq t_0\}}$ and F_d^+ coincide.) Z_d^y is the total value of digital payments per capita within the channel of the respective y variable in the month before integration. (No such control is included in Column (4), since the corresponding channel value is mechanically zero in that month.) 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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 (1)	Incumbent/pop (2)	Other/pop (3)	(Inc↔Oth)/pop (4)
$F_d^+ \times 1_{\{t \geq t_0\}}$	7.002***	4.524***	2.364***	0.172***
	(4.82)	(6.40)	(3.16)	(3.41)
State-Time FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓	
N	9,500	9,500	9,500	6,500
Mean y_{dt} $(F_d^+ = 1, t = t_{-1})$	8.513	6.631	1.882	
Mean y_{dt} $(F_d^+ = 0, t \geq t_0)$	7.393	1.743	5.713	0.195

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-F_d and low-F_d districts, using a matched sample based on high-F_d districts' three nearest neighbors by log population size (Mahalanobis distance, with replacement, on common support); low-F_d districts are assigned a weight proportional to the number of high-F_d districts to which they are matched. The regressions and the mean rows are weighted by the resulting match weights. F_d^+ is a dummy taking value one for districts with above-median fragmentation prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value involving the incumbent's app—i.e., transactions in which at least one counterparty used the incumbent's app—in Rupees per capita; (3) total P2M transaction value involving other UPI apps—i.e., transactions in which at least one counterparty used an alternative UPI app—in Rupees per capita; (4) total cross-platform P2M transaction value—i.e., transactions occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app—in Rupees per capita. Columns (1)–(3) report estimates of specification (4). Column (4) reports the estimate from regressing cross-platform P2M transaction value per capita on F_d^+, controlling for state-time fixed effects, over the post-integration sample. (On this sample, $F_d^+ \times 1_{\{t \geq t_0\}}$ and F_d^+ coincide.) Z_d^y is the total value of digital payments per capita within the channel of the respective y variable in the month before integration. 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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 3: Response of digital payments adoption to platform integration, instrumented with proximity to incumbent hub districts

	Total/pop (1)	Incumbent/pop (2)	Other/pop (3)	(Inc↔Oth)/pop (4)
$F_d^+ \times 1_{\{t \geq t_0\}}$	17.76***	10.01***	6.311**	0.642**
	(2.74)	(2.97)	(1.98)	(2.37)
State-Time FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓	
K-P F-Stat	20.44	19.88	21.43	23.15
N	10,621	10,621	10,621	7,267
Mean y_{dt} $(F_d^+ = 1, t = t_{-1})$	6.401	4.724	1.662	
Mean y_{dt} $(F_d^+ = 0, t \geq t_0)$	6.622	1.450	5.218	0.186

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-F_d and low-F_d districts, when instrumenting using proximity to hub districts H_d. Hub districts are dropped from the sample prior to estimation. F_d^+ is a dummy taking value one for districts with above-median fragmentation prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value involving the incumbent's app—i.e., transactions in which at least one counterparty used the incumbent's app—in Rupees per capita; (3) total P2M transaction value involving other UPI apps—i.e., transactions in which at least one counterparty used an alternative UPI app—in Rupees per capita; (4) total cross-platform P2M transaction value—i.e., transactions occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app—in Rupees per capita. Columns (1)–(3) report 2SLS estimates of specification (4) using first-stage equation (6). Column (4) reports the estimate from regressing cross-platform P2M transaction value per capita on F_d^+, instrumented with H_d, over the post-integration sample, controlling for state-time fixed effects. (On this sample, $F_d^+ \times 1_{\{t \geq t_0\}}$ and F_d^+ coincide.) Z_d^y is the total value of digital payments per capita within the channel of the respective y variable in the month before integration. The K-P row reports the Kleibergen-Paap first-stage F-statistic. 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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)
$F_d^+ \times 1_{\{t \geq t_0\}}$	0.0113^{**}	0.0192^{**}	0.0136^{***}
	(2.17)	(2.54)	(3.00)
Household FEs	✓	✓	✓
State-Wave FEs	✓	✓	✓
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓
Sample	All	Entrepreneurs	Hawkers
N	898,412	54,161	22,387
Mean $y_{dt}(F_d^+ = 1, t = t_{-1})$	0.0029	0.0039	0.0018
Mean $y_{dt}(F_d^+ = 0, t \geq t_0)$	0.0119	0.0181	0.0135

Notes: This table shows how the response in household-level borrowing from NBFCs (Non-Banking Financial Companies) to integration differed between households in high-F_d and low-F_d districts. This is based on specification (11), using household-level data at a wave frequency of every four months. F_d^+ is a dummy taking value one for districts with above-median fragmentation 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^y is the total value of digital payments per capita 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.

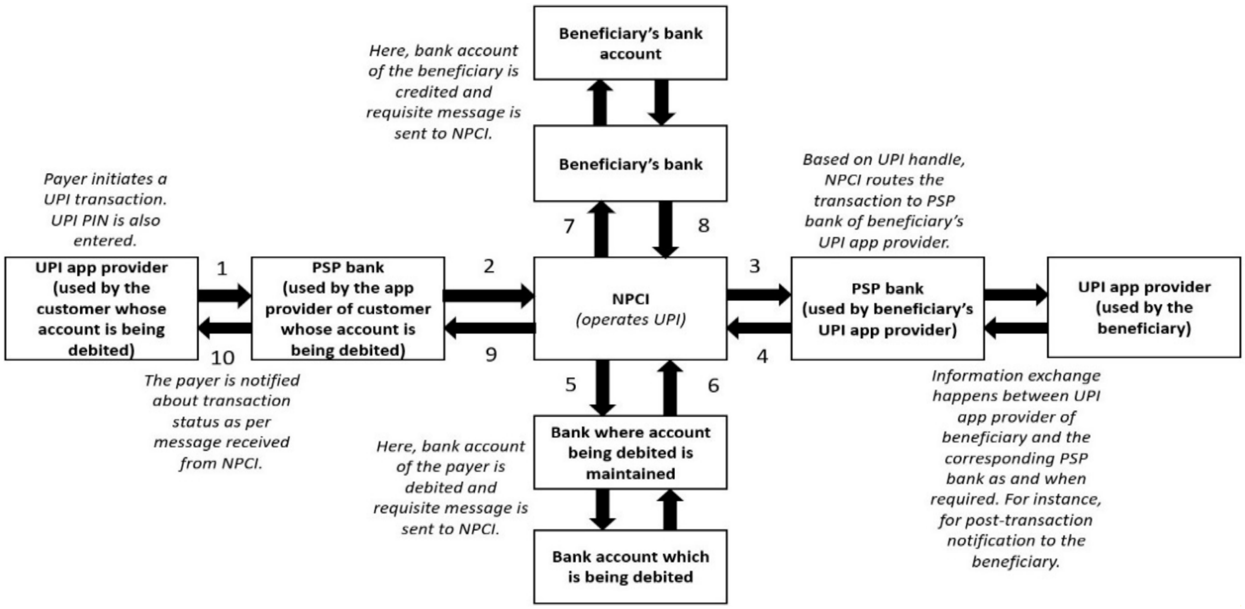
ONLINE APPENDIX TO

Integrating Fragmented Networks: Interoperability in Money and Payments

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

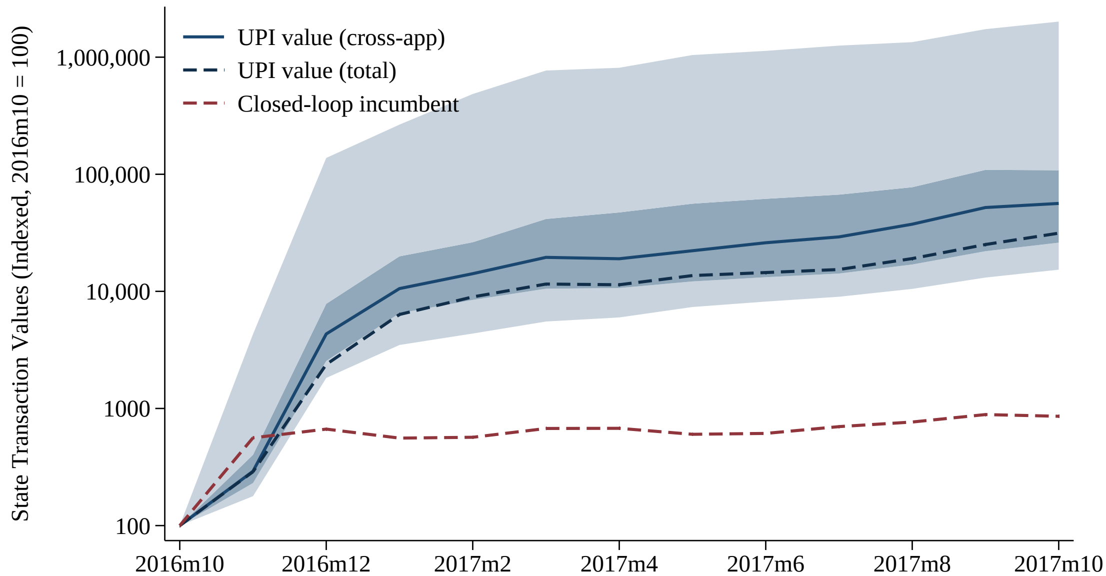
A Additional figures and tables

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).

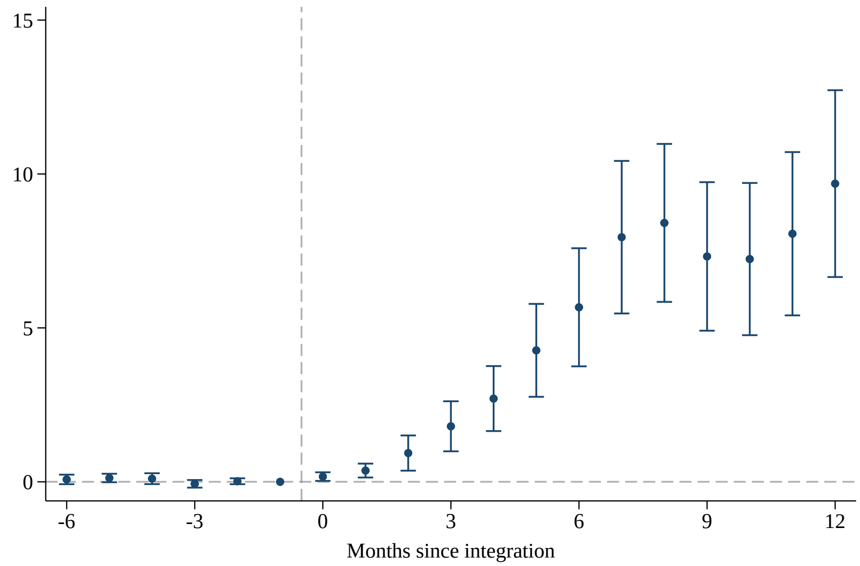
Figure A.2: Cross-app interoperable digital payments after demonetization (indexed)



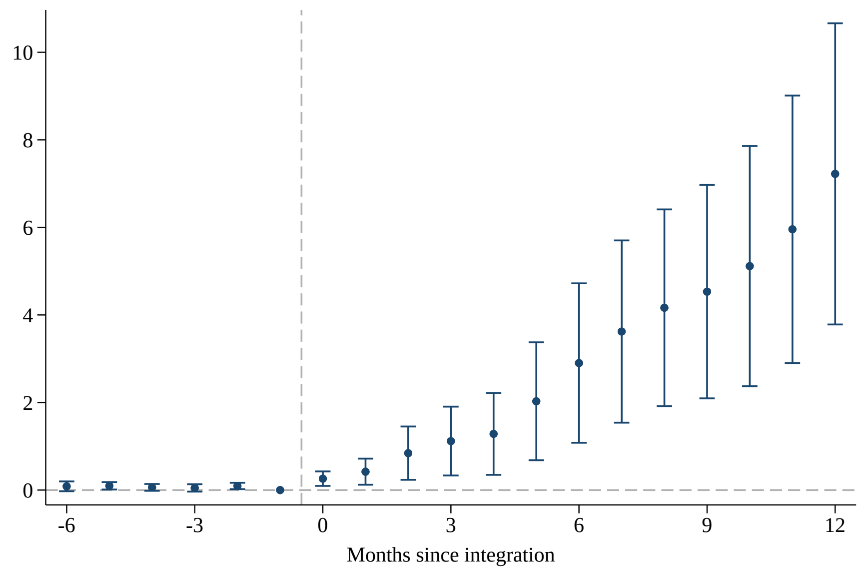
Notes: The blue and red dashed lines repeat those on Figure 5—i.e., they show the total value of transactions on UPI and a major closed-loop incumbent digital payments platform in the median state, indexed to 100 in the month before demonetization (October 2016). The solid blue line plots the same for 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 platform

(a) Transaction value involving the incumbent's app (Rupees per capita)

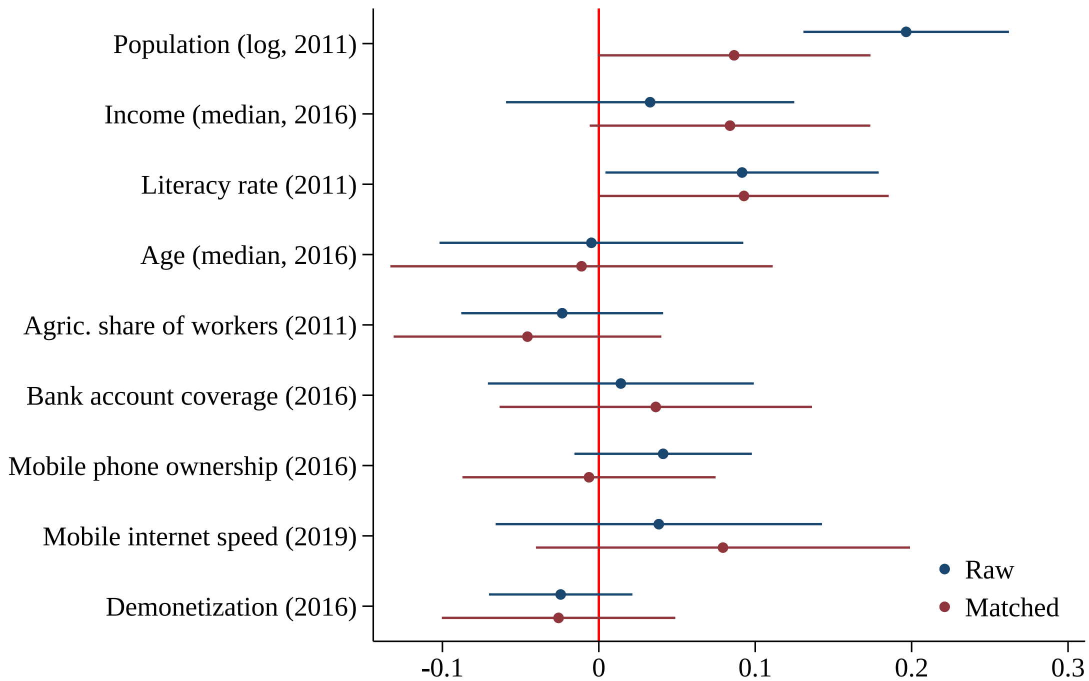


(b) Transaction value involving other UPI apps (Rupees per capita)



Notes: This figure plots the dynamics of the difference in P2M transaction values between high-F_d and low-F_d districts, based on equation (5), for transactions involving the incumbent's app (Panel (a)) and transactions involving other UPI apps (Panel (b)). Vertical lines show 95% confidence intervals.

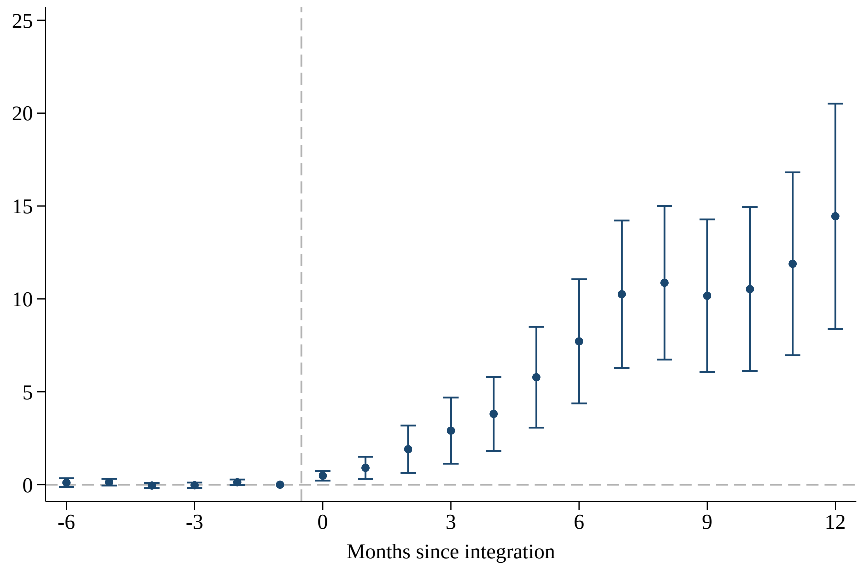
Figure A.4: Association of F_d^+, raw and matched



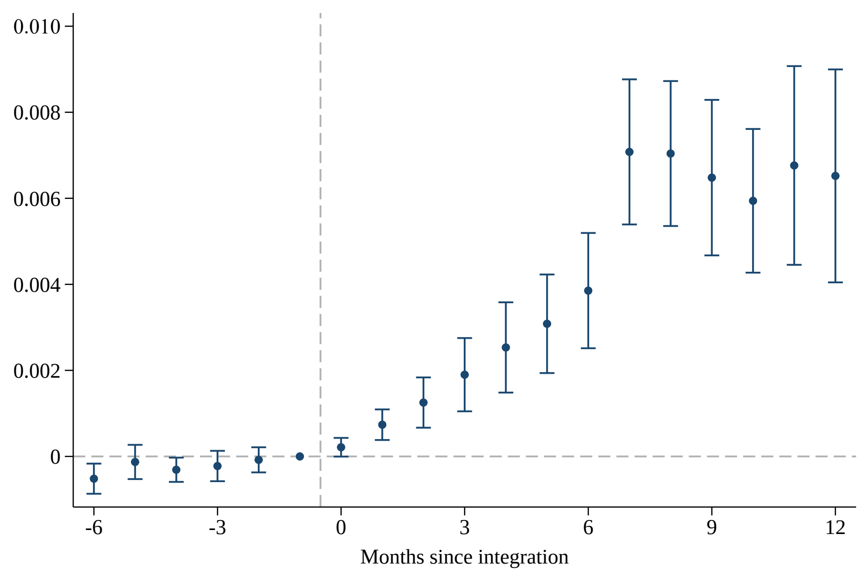
Notes: The figure plots the correlation of various district characteristics with F_d^+ controlling for Z_d^y (the total value of digital payments per capita across both platforms in each district in the month before integration), both in the raw sample and in the sample formed by matching districts on log population size. Specifically, the figure plots the coefficients from regressions of F_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)



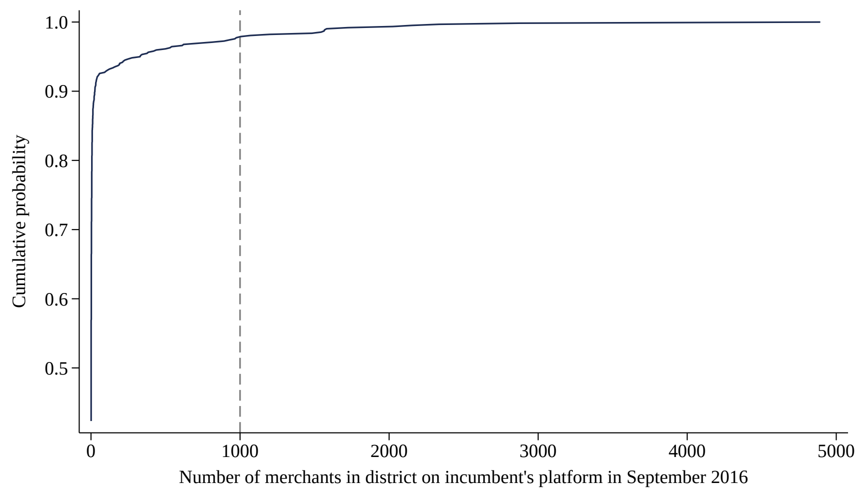
(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



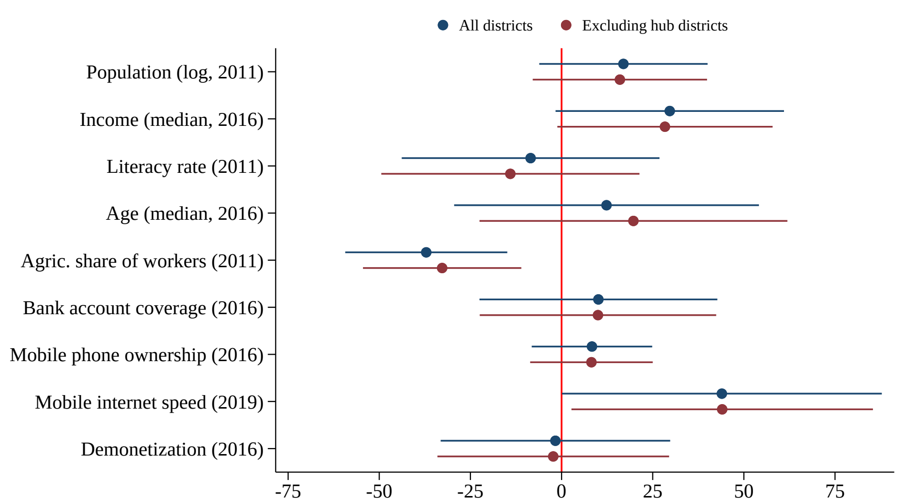
Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-F_d and low-F_d districts when matching districts on log population. The first panel normalizes total P2M transaction values relative to population, and the second panel normalizes total P2M transaction 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



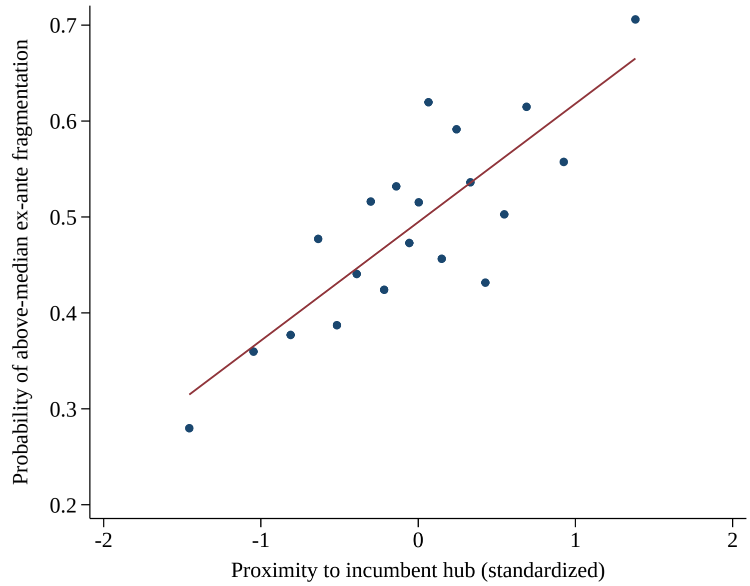
(b) Association with proximity to the incumbent's hubs



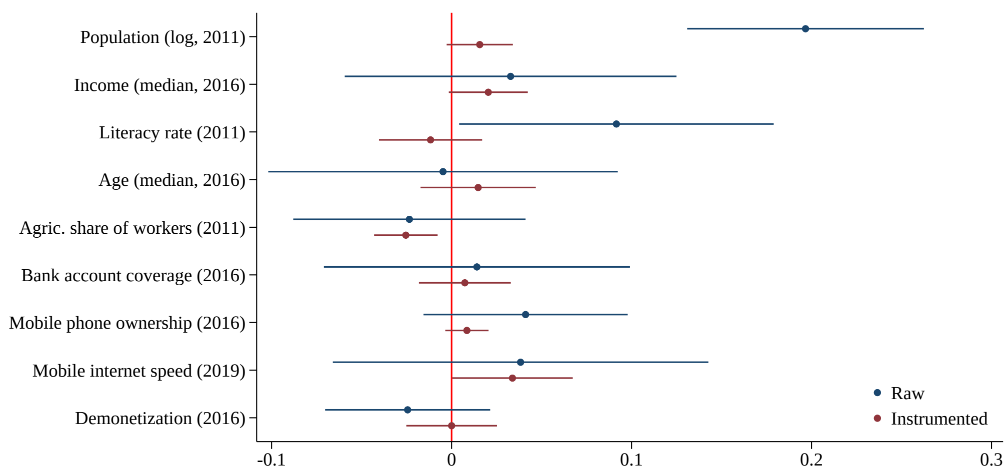
Notes: The first panel plots the cumulative distribution function of the number of merchants in each district that used the incumbent's platform in September 2016. The vertical line indicates the cutoff for defining a hub city. The second panel shows the correlation of various district characteristics 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 F_d^+ with proximity to the incumbent's initial hubs H_d

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



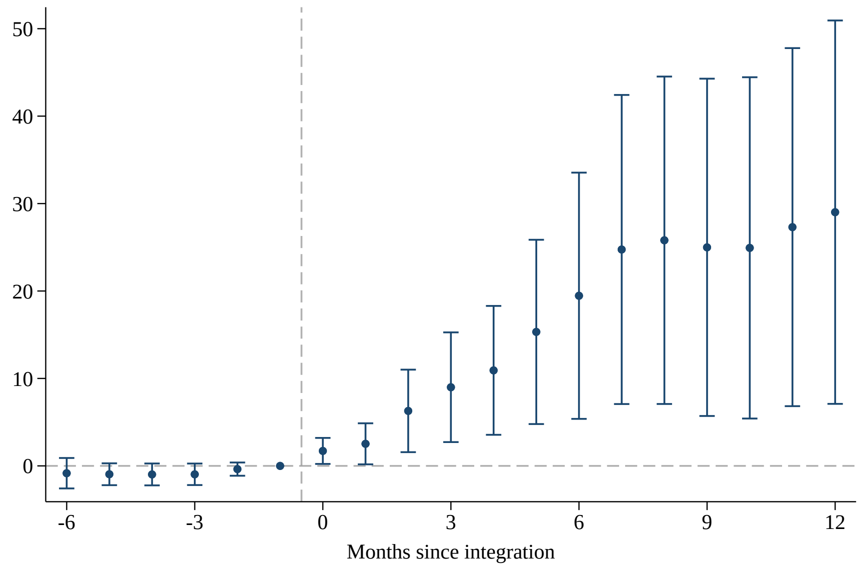
(b) Association with F_d^+



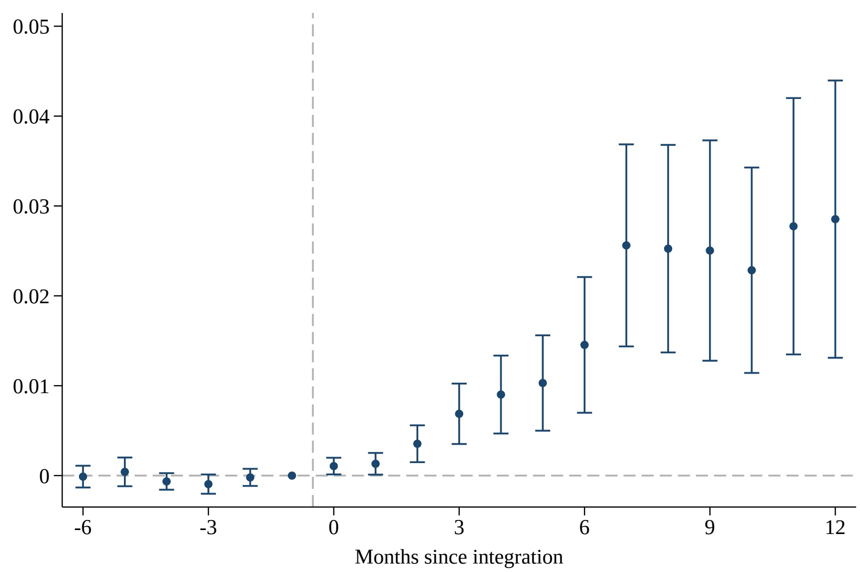
Notes: The first panel shows a binned scatter plot of the cross-sectional first stage relationship between H_d (on the x-axis) and F_d^+ (on the y-axis), after residualizing each on state fixed effects and controlling for Z_d^y (the total value of digital payments per capita across both platforms in each district in the month before integration). The second panel plots the correlation of various district characteristics with F_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 F_d^+—or the predicted value of F_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)

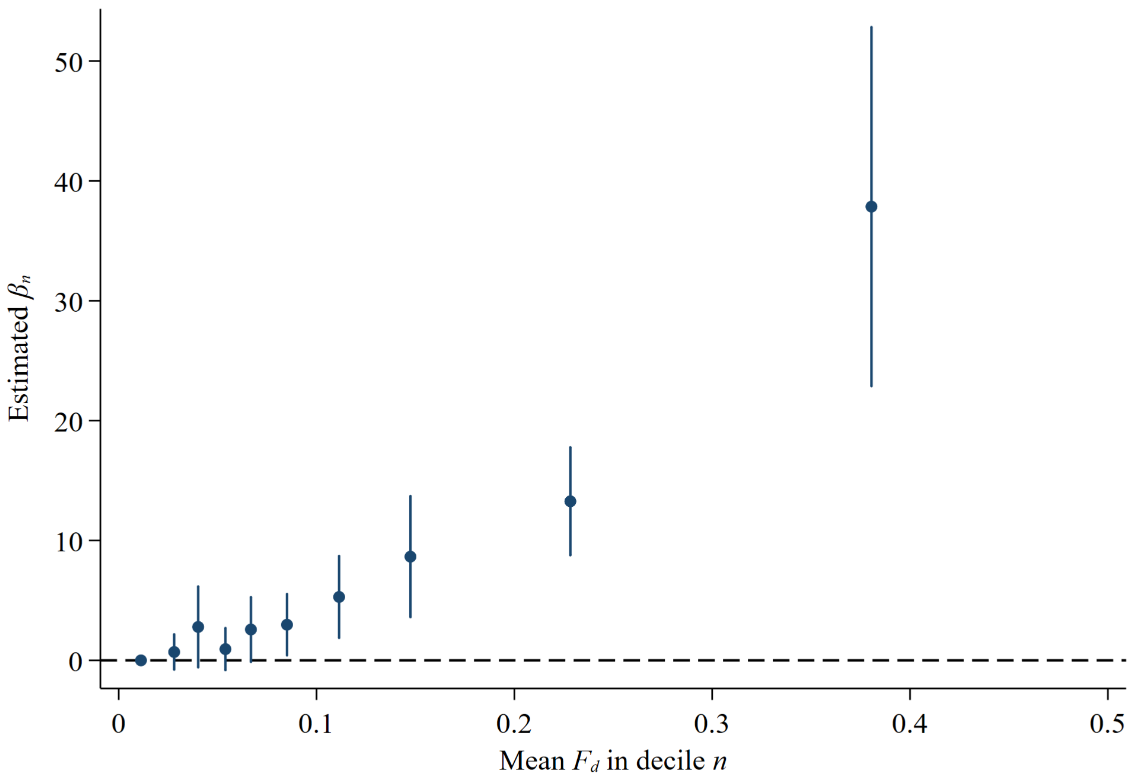


(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



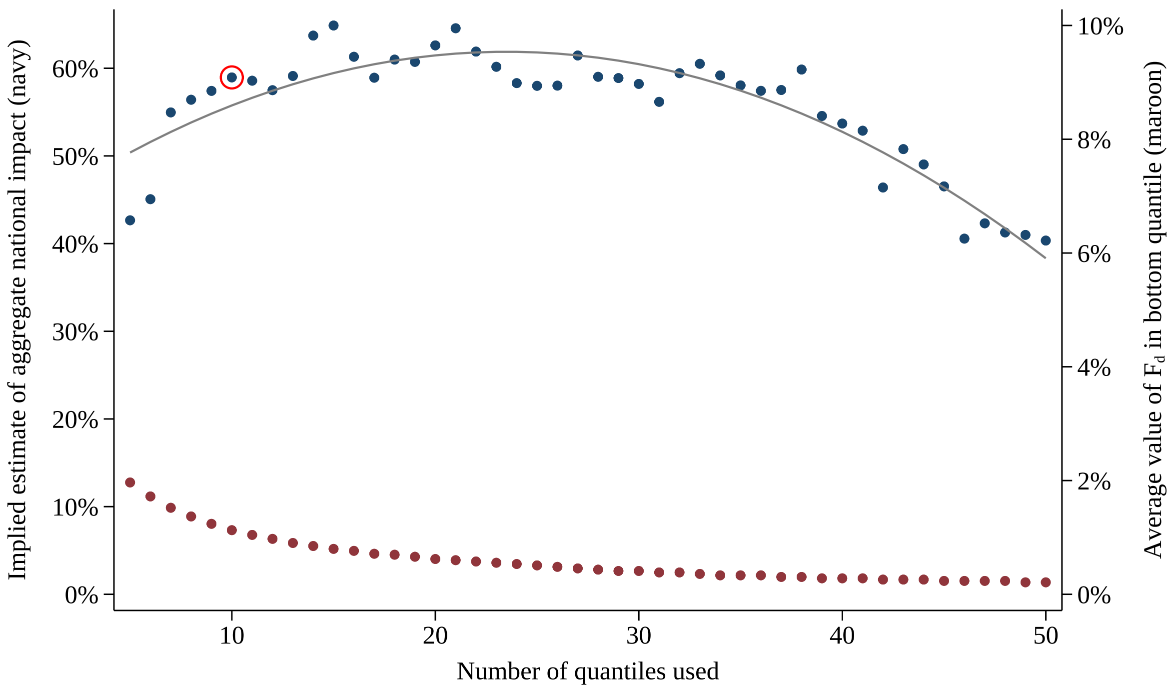
Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-F_d and low-F_d districts when instrumenting using proximity to incumbent hub districts H_d. The first panel normalizes total P2M transaction values relative to population, and the second panel normalizes 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 (8). 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.

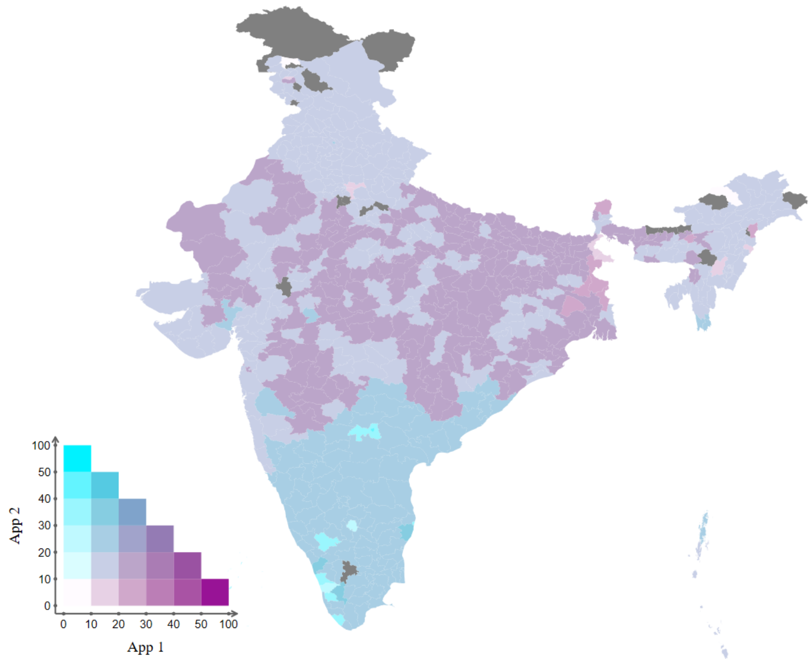
Figure A.10: Implied national impact across alternative numbers of F_d quantiles



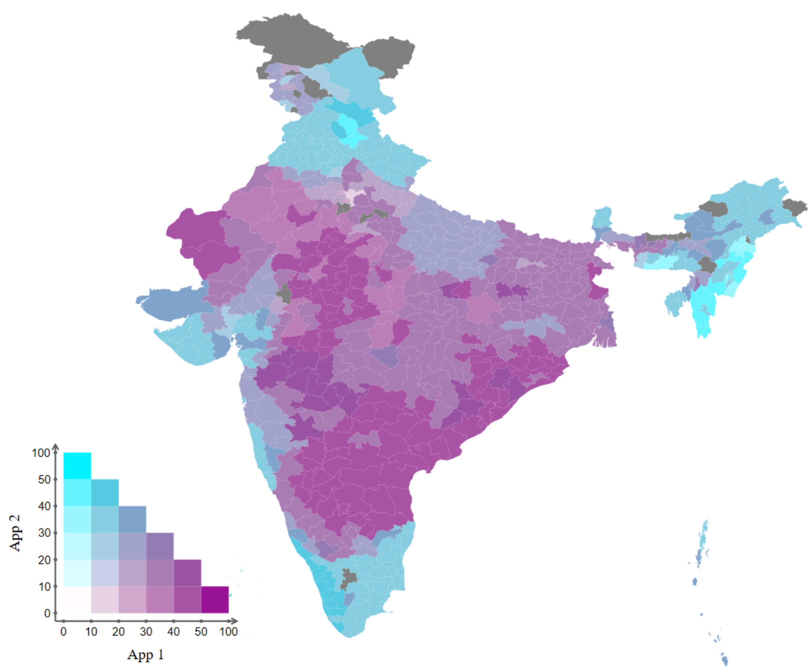
Notes: This figure shows the sensitivity of our implied national-impact estimate (equation (10)) to using different numbers of quantiles of the F_d distribution when proxying for the "fully unified ex ante" districts d_0. The navy points (left axis) plot the implied aggregate national impact when repeating the calculation using between 5 and 50 quantiles; the gray line is a quadratic fit. The red-circled navy point marks the ten-decile baseline used in the text. The maroon points (right axis) plot the average value of F_d among districts in the bottom quantile, which falls as the number of quantiles rises and the bottom quantile approaches $F_d = 0$.

Figure A.11: Shares of the two largest apps, by district (% of aggregate volume)

(a) 2018



(b) 2023



Notes: These maps show the share of aggregate UPI transaction volume facilitated by the two largest apps. The volume counts include both peer-to-merchant and peer-to-peer transactions, and both the payer and the payee sides of each transaction.

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

	Value / Transaction (₹)	Transactions / User (#)	Users / Population (#)
$F_d^+ \times 1_{\{t \geq t_0\}}$	9.181**	0.0958**	0.000923**
	(2.07)	(2.52)	(2.04)
District FEs	✓	✓	✓
State-Time FEs	✓	✓	✓
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓
N	10,860	10,860	10,868
Mean $y_{dt}(F_d^+ = 1, t = t_{-1})$	344.854	3.262	0.002
Mean $y_{dt}(F_d^+ = 0, t \geq t_0)$	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-F_d versus low-F_d districts, based on specification (4). F_d^+ is a dummy taking value one for districts with above-median fragmentation prior to integration. Outcome variables are, in turn: (1) total P2M value per transaction, in Rupees; (2) number of transactions per user; (3) number of users per capita. Z_d^y is the total value of digital payments per capita 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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 household-level NBFC borrowing to platform integration, for households that had never previously borrowed

	NBFC Borrowing (Y/N)		
	(1)	(2)	(3)
$F_d^+ \times 1_{\{t \geq t_0\}}$	0.00803^{**}	0.0135^{**}	0.00616^{**}
	(1.99)	(2.20)	(2.03)
Household FEs	✓	✓	✓
State-Wave FEs	✓	✓	✓
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓
Sample	All	Entrepreneurs	Hawkers
N	591,446	41,094	13,739
Mean $y_{dt}(F_d^+ = 1, t = t_{-1})$	0	0	0
Mean $y_{dt}(F_d^+ = 0, t \geq t_0)$	0.0059	0.0102	0.0059

Notes: This table shows how the response in household-level borrowing from NBFCs to integration differed between households in high-F_d and low-F_d districts. This is based on specification (11), using household-level data at a wave frequency of every four months. F_d^+ is a dummy taking value one for districts with above-median fragmentation 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 that had never previously borrowed. Column (2) restricts this sample to only households for which the primary occupation is 'entrepreneur'. Column (3) instead restricts the sample to only households for which the primary occupation is 'hawker'. Z_d^y is the total value of digital payments per capita 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.

B Cross-checking our location proxy

We received data on the universe of UPI transactions split by the payer's bank branch, which we use to attribute transactions to pincodes and districts. NPCI does not collect data on the exact location of the transaction, but individual app providers such as PhonePe can collect more specific location information for those mobile users who enable location services for their app. To check our location proxy, we therefore compare the subset of our transactions in which the payer used PhonePe to district-level transaction totals reported directly by PhonePe through its PhonePe Pulse platform. The results are shown in Figure B.1a. The two series are closely aligned, with a correlation coefficient of 0.84. Note that even the residual discrepancies do not necessarily imply that our measure is inaccurate, for two reasons: (i) PhonePe's ability to geolocate users who do not enable location services may be limited, and (ii) the values reported on PhonePe Pulse also include transactions using cards and wallets, in addition to UPI.

To further check our location proxy, we exploit an established empirical correlation between UPI transaction values and the presence of banks that were early to join UPI (Dubey and Purnanandam, 2023; Alok, Ghosh, Kulkarni, and Puri, 2024; Ayyagari, Ghosh, and Kulkarni, 2026). Following this literature we construct a pincode-level exposure measure:

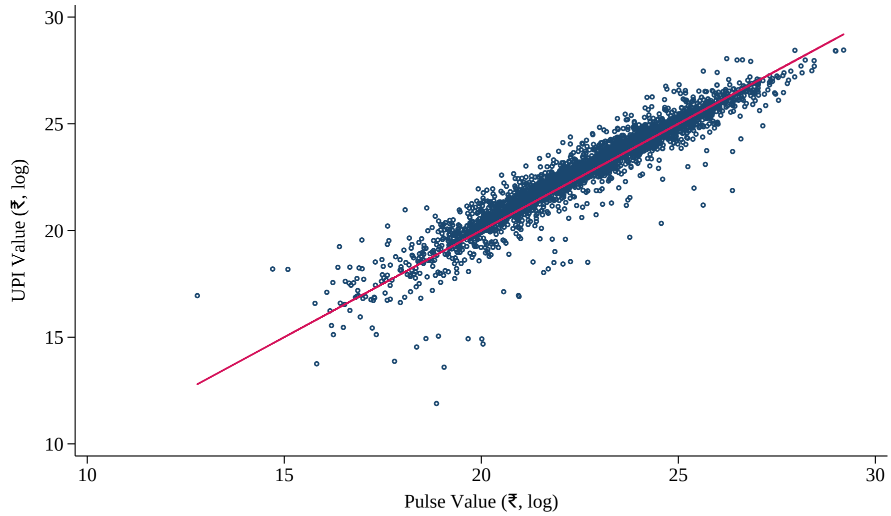
$$\text{Exposure}_p = \frac{\text{Number of branches of early-adopter banks}_{p,2016m10}}{\text{Number of branches of all banks}_{p,2016m10}} \tag{B.1}$$

where early-adopter banks are those that joined UPI prior to demonetization in November 2016. Intuitively, we estimate the extent to which users in each pincode had access to UPI at the moment of demonetization, which has been shown to correlate with initial UPI adoption. Importantly, our data on the number of branches in each pincode comes from Garg and Gupta (2020) and Asher, Lunt, Matsuura, and Novosad (2021), so does not rely on the same location proxy whose validity we are examining. Figure B.1b plots the pincode-level relationship between Exposure_p and total UPI transaction value in the six months after demonetization. Once again, the UPI values based on our location proxy align with the expected pattern. Indeed, note that here we document alignment at the *pincode* level, which is more granular than required for our district-level regressions.

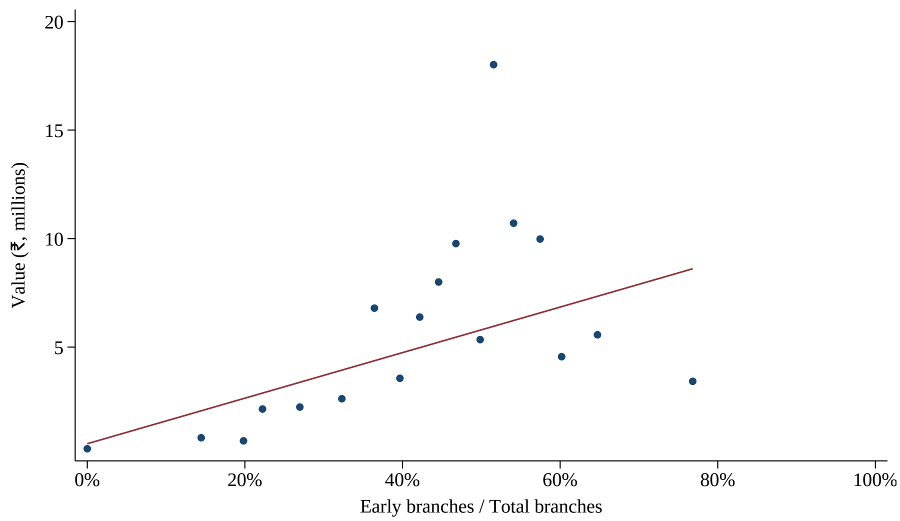
Finally, we consider the potential implications for our main specification (equation (4)) of any residual locational measurement error. First, we note that our binary explanatory variable F_d^+ is relatively robust to measurement error, since to impact our results any such errors in the (continuous) underlying F_d variable would have to be large enough to flip a district from being below the median to above the median. Second, if our outcome variable y_{dt} has independent mean-zero measurement error, we note that by standard reasoning (e.g., Wooldridge, 2015, Section 9-4a) our estimator β remains unbiased and consistent and our inference procedures remain valid, albeit with a larger error variance. The latter simply reduces our power to detect true effects, making our analysis more conservative. Lastly, we note that even if a large locational measurement error in our UPI values affected both y_{dt} and F_d^+, it would induce a *negative* correlation between them, since the UPI transaction value primarily enters F_d in equation (3) through the denominator. Indeed, even such a correlation would not bias our results if it were constant over time, since it would be absorbed by our district fixed effect in equation (4). In summary, we conclude that any locational measurement error in our UPI data is (i) likely to be small, based on our cross-checks, and (ii) unlikely to affect the conclusions of our analysis even if it were large—except to make us *less* likely to find a positive impact of network integration on digital payments adoption.

Figure B.1: Cross-checks of our location proxy

(a) Value of PhonePe transactions reported by NPCI and PhonePe Pulse



(b) Total UPI transaction value by exposure to early-adopter banks



Notes: The first panel plots the total value of PhonePe transactions for each district-quarter pair between 2018Q1 and 2024Q3, both for the data that we received from NPCI—mapped to districts using our location proxy—and for the data reported directly by PhonePe on its PhonePe Pulse platform. The 45° line is shown in red. The second figure shows a binned scatter plot of (i) total UPI transaction value by pincode in the first six months after demonetization against (ii) exposure to early-adopter banks, for pincodes with at least five bank branches.

C Proofs

C.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

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

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

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

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 $N_{d,i} > N_{d,j}$, 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:

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

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

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

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. ■

C.2 Proof of Lemma 2

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

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

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:

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

Thus usage of platform a is:

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

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

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

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:

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

Thus usage of platform b is:

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

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:

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

■

C.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:

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

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:

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

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

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

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

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

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

C.4 Proof of Proposition 1

The result 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

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

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

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

and

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

Combining these gives

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

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

C.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:

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

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 (C.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:

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

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. ■

C.6 Proof of Proposition 3

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

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

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

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

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

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

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

C.7 Proof of Proposition 4

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

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

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

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

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:

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

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

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

Similarly, equation (C.21) in the proof of Proposition 2 gives that the change in usage of platform b under interoperability is:

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

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

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

This is positive when:

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

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

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

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 $\underline{\hat{x}}$. ■

C.8 Proof of Lemma 4

The results follow directly from noting that users' maximization problem in each stage described in Appendix D 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. ■

C.9 Proof of Lemma 5

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

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

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

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

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 (C.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). ■

C.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 (D.9) to give:

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

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

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

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

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

which in turn implies that the term in square brackets in equation (C.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:

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

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. ■

C.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:

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

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

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

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:

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

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

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

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

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

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

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

This is positive when:

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

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

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

Defining $\underline{\hat{x}} \coloneqq \frac{\gamma-\sqrt{\frac{\gamma(\gamma-\kappa)}{1+\omega(\gamma-\kappa)}}}{\kappa}$, 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). ■

C.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

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

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

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

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

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 D gives that the post-interoperability change in total digital payments usage in district d is:

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

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

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

Similarly, from equation (C.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:

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

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

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

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

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

as required. ■

D 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 $0 < \omega < 1 - \frac{1}{\gamma - \kappa}$.[42]

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 (x, y), 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:

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

where

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

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

[42] The upper bound on ω ensures that some users always still choose cash, preserving a cash-digital payments margin of adjustment—i.e., the shock is not so large that it produces full adoption of digital payments.

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:*

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

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

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

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

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

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

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

Intuitively, the maximization decision within each period described in equation (D.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 (D.5) and (D.8), the change in total usage of digital payments between the pre-interoperability and post-interoperability stages is:

$$\Delta N^D_d = N^D_{d,1} - N^D_{d,-1} = \frac{1}{\gamma - \kappa} + \omega - \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} - \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)} \; . \tag{D.9}$$

The empirical identification problem is that while we can observe $N^D_{d,-1}$ and $N^D_{d,1}$, 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 the relative values of ΔN^D_d (Prediction 1), and similarly for $\Delta N_{d,a}$ and $\Delta N_{d,b}$ (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 $F_d \coloneqq \frac{N_{d,a,-1}}{N^D_{d,-1}}$, 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.

E 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. We cannot observe this directly, since we cannot match UPI users to incumbent users prior to integration.[43] We therefore consider the following thought experiment.

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.

Nonetheless, we do not expect this downward bias to be large as the frictions to multihoming in our context are not negligible. For instance, setting up each payment app requires linking one's bank account, undergoing a KYC check, and manually entering any saved contacts. Indeed, after integration—from which point we can observe multihoming that includes the incumbent app—we find that UPI users at the median bank branch use fewer than 1.3 apps each month on average.

[43] We highlight, however, that our setting differs substantially from mature card-payment markets, where merchants typically accept multiple payment networks, albeit often through a single payments facilitator (Rysman, 2009; CGAP, 2019). In our setting, many merchants were adopting digital payments for the first time—through either the incumbent's app or a UPI app—while continuing to accept cash as the commonly available outside option (see, for example: Ligon, Malick, Sheth, and Trachtman, 2019; Crouzet, Gupta, and Mezzanotti, 2023).

F 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' utility from using digital payments platform i thus depends on the total accessible national user base $\sum_{d=1}^{D} N^*_{d,i}$, rather than on 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.

G 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 F_d^+ interacted with the post-interoperability dummy $1_{\{t \geq t_0\}}$. The total derivative of Y with respect to X is:

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

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 $F_d^+ = 0$ and $t \geq t_0$), which we denote by $\bar{U}, \bar{V}$, and $\bar{W}$. Substituting in, we define:

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

Since each outcome variable (Y, U, V, W) is winsorized individually in its respective regression, b may not exactly equal β_X^Y. To account for this, we normalize by b and estimate the relative contributions of each margin using the following shares s:

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

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 13.

H 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 confirm that our results are not driven by differences in the geographic footprint of banks that were early to adopt UPI. We next address other alternative explanations for our findings, specifically private advertising and government campaigns. Finally, we run placebo tests for both the cross-sectional and temporal variation underlying our results.

H.1 Alternative specifications

First, 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 replacing our state-time fixed effects with state-urban-time fixed effects (i.e., the interaction of state, this above-median-density indicator, and month), which absorb any differential trends between urban and rural areas within each state. The results, shown in Appendix Table H.1, confirm the robustness of our baseline estimates.

We also confirm that our results are not sensitive to specific choices in the construction of our main variables. Appendix Table H.2 shows that our results remain similar when restricting our winsorization to only the top 0.5% of district-months, while Appendix Table H.3 shows that they remain similar when using the continuous variable F_d instead of the binary variable F_d^+.

H.2 Exposure to early-adopter banks

We rely on geographic variation in ex-ante fragmentation across *apps*. Other work considers geographic variation in the presence of *banks* that were early participants in UPI (e.g., Dubey and Purnanandam, 2023; Alok, Ghosh, Kulkarni, and Puri, 2024). One could therefore be concerned that our F_d^+ measure is correlated with exposure to early-adopter banks, as defined in Appendix B, and that this differential exposure is the underlying driver of our results. We address this concern in three ways. First, we note that F_d is only weakly correlated with Exposure_d, the district-level counterpart of equation (B.1), with a pairwise correlation coefficient of 0.34. Indeed, after residualizing both variables on state fixed effects and total district-wise digital payments per capita (i.e., after residualizing on the cross-sectional variation underlying our time-varying controls in equation (4)), the residual correlation is only 0.22. Thus F_d^+ in our regressions could at most be only a very weak proxy for Exposure_d.

Second, we note that bank participation in UPI was similar across our high-F_d and low-F_d groups in both the cross-section and the time series. We construct the following variable, similar to equation (B.1) but at the district level and varying over time:

$$\text{Exposure}_{dt} = \frac{\text{Number of branches of UPI-participating banks}_{dt}}{\text{Number of branches of all banks}_{dt}} \, . \tag{H.1}$$

Figure H.1 reveals that the district-wise distribution of this variable was similar between high-F_d and low-F_d groups at each point throughout the period that we study. Moreover, after the initial rapid increase in UPI participation by banks following demonetization, participation quickly reached a plateau, at which it remained throughout the period considered in specification (4). Thus, both our "treatment" and "control" groups had similar distributions of exposure to UPI-participating banks both in the period prior to the integration event that we study, and throughout the post-event period. This underscores that differences in bank participation in UPI are unlikely to explain our findings, namely parallel trends in total digital payments between high-F_d and low-F_d groups in the months before our integration event, but divergent trends in total digital payments thereafter.

Finally, to confirm that our conclusions are not driven by omitting the Exposure_d variable, in Table H.4 we repeat specification (4) with the inclusion of the additional term $\text{Exposure}_d \times 1_{\{t \geq t_0\}}$. Intuitively, we allow for differential exposure to early-adopter banks to have time-varying impacts on total adoption of digital payments. Our results remain robust, reassuring us that differences in exposure to early-adopter banks do not drive our results.

H.3 Other alternative explanations

One possible residual concern is that our results reflect differences in private firms' marketing intensity across districts. Three factors mitigate this concern. First, the primary method through which private providers promoted UPI adoption was cashback offers, which are set nationally (in contrast to, for instance, location-specific physical billboards). A survey of UPI users by the Indian Ministry of Finance finds that cashback schemes are the dominant channel through which private marketing efforts attract UPI users (Government of India, 2026). Under such schemes, users who make transactions over a minimum value receive a digital "scratch card", which for some share of users (those who "win") converts into a monetary reward.[44] These contests are run nationally and are built into national UPI apps (i.e., apps downloaded from the India-specific Google Play Store and Apple App Store).[45] Second, to the extent that providers engage in forms of marketing that vary at the sub-national level, our state-time fixed effects control for any state-wise differential trends in marketing efforts. Finally, our high-F_d and low-F_d districts are similar on demographic observables after conditioning on controls, especially in the matched specification (see Appendix Figure A.4), so any residual marketing efforts targeting such demographics would be correspondingly balanced across our F_d^+ groups.

A second possible concern is that our results reflect differences across districts in government promotional campaigns supporting UPI. However, the government's goal was to increase the *level* of digital payments adoption in India, as part of the national strategy to transition from cash to digital payments (Reserve Bank of India, 2016). As such, promotional efforts did not target the app-wise *composition* of digital payments (i.e., our F_d variable). Thus, government promotional campaigns targeting districts with low usage of digital payments are accounted for in our specification (4) through the control for differential trends by Z_d^y.

A third possible concern is that our results reflect improvements in the quality of the incum-

[44] For examples from the major UPI apps, see here, here and here.

[45] The one exception is Tamil Nadu, which prohibits chance-based prize schemes under the Tamil Nadu Prize Schemes (Prohibition) Act of 1979 (Government of Tamil Nadu, 1979). Users in Tamil Nadu instead receive fixed-rate cashback payments rather than entry into random draws; see, for example, the terms and conditions of PhonePe's cashback scheme here.

bent's app when it integrated with UPI, such as a better user experience for connecting the app to bank accounts. However, while such improvements could contribute to higher *aggregate* adoption, they could not explain the *differential* increase in adoption of the incumbent's app in places where digital payments were more fragmented across platforms ex ante. Furthermore, they could not explain the differential increase in adoption of *other UPI apps* in such places (as discussed in Section 4.2), since the user experience of those apps was not directly affected by the incumbent joining UPI—except for the fact that users of those apps could now pay a larger set of counterparties, as in our model.

A fourth possible concern is that our results could be driven by increases in mobile internet access. The main shock to mobile internet access during the period was the launch of Reliance Jio's 4G service in September 2016. However, this occurred more than a year before our integration shock, while the subsequent waves of expansion did not occur until after the end of our estimation window (Telecom Regulatory Authority of India, 2018). Indeed, Appendix Figure H.2 shows that, during our estimation window, there was no sharp increase in the number of mobile phone users in India. Nonetheless, in Appendix Table H.5 we repeat our baseline specification controlling for the district-level share of households with a mobile phone over time, and find that our results remain similar.[46]

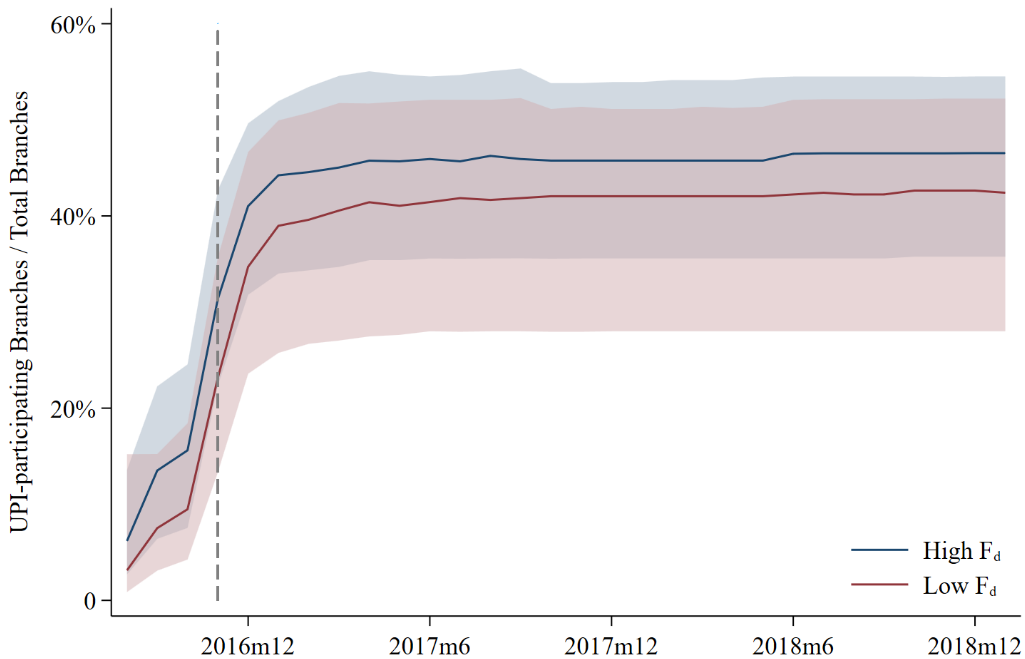
H.4 Placebo tests

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 F_d^+-groups produces median estimated effects centered on zero. Appendix Figure H.3a shows the results. Second, we confirm that our results are not driven by our choice of baseline period. Appendix Figure H.3b repeats Figure 11a for an alternative t_0 set three months prior to that

[46] Our survey dataset does not include a variable for the intensive margin of mobile phone usage. However, we expect our extensive-margin-based control to be highly correlated with the unobserved intensive margin, given that (i) mobile phone ownership was not universal in India during this period (for example, 45% of households reported having a mobile phone in the median district in the month before integration) and (ii) cheaper mobile data would encourage an increase in both margins.

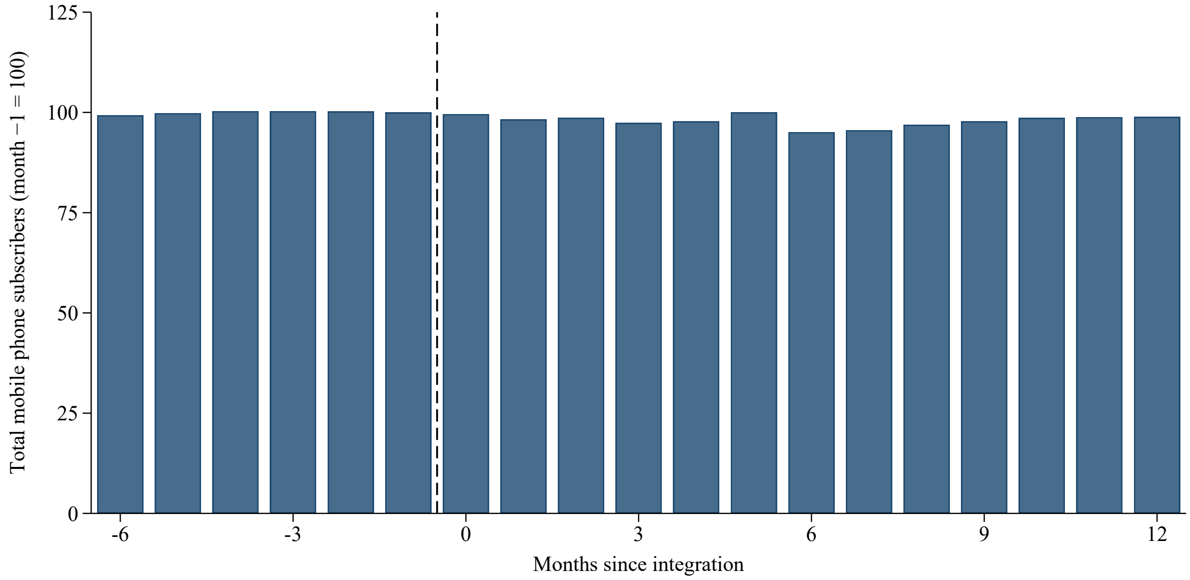
in our baseline specification, and confirms that the differential increase in total digital payments usage per capita does not take off until the true month of integration.

Figure H.1: Banks' UPI participation across districts, by F_d-group



Notes: This figure plots Exposure$_{dt}$—the share of branches in a district that are at banks participating in UPI—over time. The blue line shows the share for the median district in the high-F_d group (i.e., among districts with $F_d^+ = 1$) and the red line shows the same for the median district in the low-F_d group. The blue and red shaded regions show the 25-75th percentiles across districts for the respective groups. The gray dashed line indicates the month of demonetization.

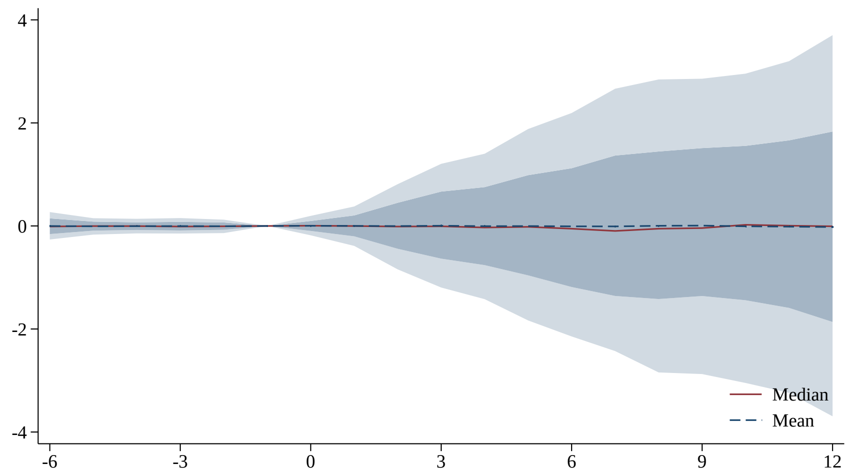
Figure H.2: Number of mobile phone subscribers in India surrounding integration (indexed)



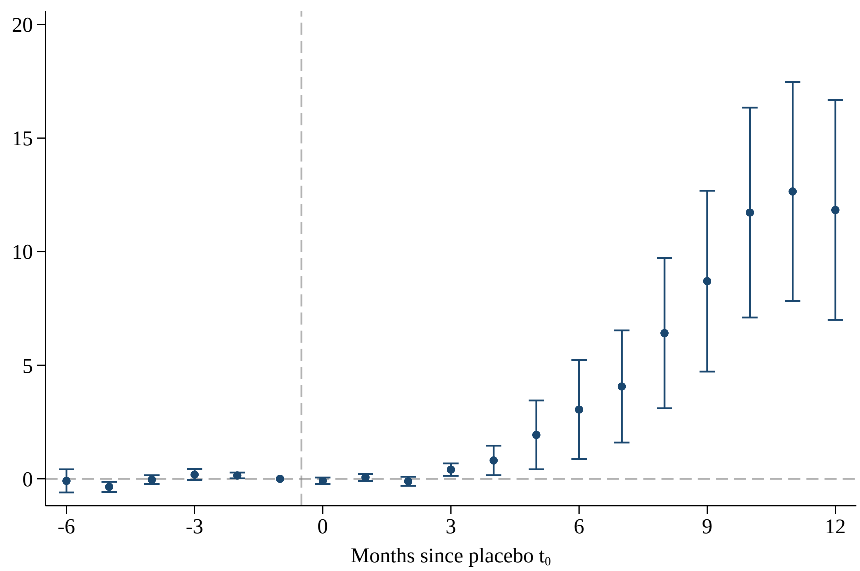
Notes: This figure plots the total number of mobile phone subscribers in India in the months surrounding the integration event (month zero). The series is indexed to 100 in the month before integration. *Source:* Telecom Regulatory Authority of India (2018).

Figure H.3: Placebo tests

(a) Repeating Figure 11a for random draws of F_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-F_d and low-F_d districts, based on equation (5), except changing either the distribution of F_d^+ or the timing of t_0, as described in Appendix H.4. In the first panel, the shaded regions depict the distribution of estimated βs across 1000 random reassignments of F_d^+, with the inner (outer) shaded regions corresponding to the 25-75th (10-90th) percentiles. The red and blue 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 H.1: Response of digital payments adoption to platform integration, controlling for state-urban-time fixed effects

	Total/pop (1)	Incumbent/pop (2)	Other/pop (3)	(Inc$\leftrightarrow$Oth)/pop (4)
$F_d^+ \times 1_{\{t \geq t_0\}}$	5.504***	3.254***	1.820***	0.133***
	(4.30)	(5.53)	(2.67)	(2.78)
State-Urban-Time FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓	
N	10,754	10,754	10,754	7,358
Mean y_{dt} ($F_d^+ = 1, t = t_{-1}$)	9.078	7.153	1.925	
Mean y_{dt} ($F_d^+ = 0, t \geq t_0$)	6.695	1.456	5.294	0.189

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-F_d and low-F_d districts, replacing the state-time fixed effects with state-urban-time fixed effects, where urban is defined by an indicator for above-median population density. F_d^+ is a dummy taking value one for districts with above-median fragmentation prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value involving the incumbent's app—i.e., transactions in which at least one counterparty used the incumbent's app—in Rupees per capita; (3) total P2M transaction value involving other UPI apps—i.e., transactions in which at least one counterparty used an alternative UPI app—in Rupees per capita; (4) total cross-platform P2M transaction value—i.e., transactions occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app—in Rupees per capita. Columns (1)–(3) report estimates of specification (4), with the fixed effects replaced as described above. Column (4) reports the estimate from regressing cross-platform P2M transaction value per capita on F_d^+, controlling for state-urban-time fixed effects, over the post-integration sample. (On this sample, $F_d^+ \times 1_{\{t \geq t_0\}}$ and F_d^+ coincide.) Z_d^y is the total value of digital payments per capita within the channel of the respective y variable in the month before integration. 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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 H.2: Response of digital payments adoption to platform integration, when winsorizing top 0.5% of district-months by value

	Total/pop (1)	Incumbent/pop (2)	Other/pop (3)	(Inc↔Oth)/pop (4)
$F_d^+ \times 1_{\{t \geq t_0\}}$	7.398***	3.694***	2.811***	0.262***
	(3.95)	(5.10)	(3.21)	(3.43)
State-Time FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓	
N	10,868	10,868	10,868	7,436
Mean y_{dt} ($F_d^+ = 1, t = t_{-1}$)	9.018	7.089	1.928	
Mean y_{dt} ($F_d^+ = 0, t \geq t_0$)	6.687	1.450	5.411	0.192

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-F_d and low-F_d districts, when reducing the stringency of winsorization to 0.5% from 1%. F_d^+ is a dummy taking value one for districts with above-median fragmentation prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value involving the incumbent's app—i.e., transactions in which at least one counterparty used the incumbent's app—in Rupees per capita; (3) total P2M transaction value involving other UPI apps—i.e., transactions in which at least one counterparty used an alternative UPI app—in Rupees per capita; (4) total cross-platform P2M transaction value—i.e., transactions occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app—in Rupees per capita. Columns (1)–(3) report estimates of specification (4). Column (4) reports the estimate from regressing cross-platform P2M transaction value per capita on F_d^+, controlling for state-time fixed effects, over the post-integration sample. (On this sample, $F_d^+ \times 1_{\{t \geq t_0\}}$ and F_d^+ coincide.) Z_d^y is the total value of digital payments per capita within the channel of the respective y variable in the month before integration. 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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 H.3: Response of digital payments adoption to platform integration, when using the continuous fragmentation measure F_d

	Total/pop	Incumbent/pop	Other/pop	(Inc↔Oth)/pop
	(1)	(2)	(3)	(4)
$F_d^+ \times 1_{\{t \geq t_0\}}$	1.074***	0.662***	0.336***	0.0210***
	(5.30)	(6.44)	(4.77)	(4.72)
State-Time FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓	
N	10,868	10,868	10,868	7,436
Mean y_{dt} ($F_d^+ = 1, t = t_{-1}$)	9.018	7.089	1.928	
Mean y_{dt} ($F_d^+ = 0, t \geq t_0$)	6.687	1.450	5.294	0.189

Notes: This table shows how the response of digital payments adoption to the platforms' integration varied with districts' level of F_d, replacing the F_d^+ dummy with the continuous fragmentation measure F_d defined in equation (3), measured in percentage points, in all four columns. Each coefficient in Columns (1)–(3) therefore represents the differential monthly increase in the outcome after integration associated with a one-percentage-point higher level of ex-ante fragmentation; the coefficient in Column (4) is the corresponding difference in post-integration levels. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value involving the incumbent's app—i.e., transactions in which at least one counterparty used the incumbent's app—in Rupees per capita; (3) total P2M transaction value involving other UPI apps—i.e., transactions in which at least one counterparty used an alternative UPI app—in Rupees per capita; (4) total cross-platform P2M transaction value—i.e., transactions occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app—in Rupees per capita. Columns (1)–(3) report estimates of specification (4), with F_d in place of F_d^+. Column (4) reports the estimate from regressing cross-platform P2M transaction value per capita on F_d, controlling for state-time fixed effects, over the post-integration sample. Z_d^y is the total value of digital payments per capita within the channel of the respective y variable in the month before integration. 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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 H.4: Response of digital payments adoption to platform integration, controlling for differential exposure to early-adopter banks

	Total/pop	Incumbent/pop	Other/pop	(Inc↔Oth)/pop
	(1)	(2)	(3)	(4)
$F_d^+ \times 1_{\{t \geq t_0\}}$	5.073***	4.395***	1.263***	0.179***
	(4.98)	(5.42)	(3.60)	(3.75)
State-Time FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓	
Control: Exposure$_d \times 1_{\{t \geq t_0\}}$	✓	✓	✓	✓
N	10,830	10,830	10,830	7,410
Mean y_{dt} ($F_d^+ = 1, t = t_{-1}$)	7.863	6.398	1.465	
Mean y_{dt} ($F_d^+ = 0, t \geq t_0$)	6.687	1.450	5.294	0.189

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-F_d and low-F_d districts, when additionally controlling for districts' differential exposure to early-adopter banks. Exposure$_d$ is the share of bank branches in district d belonging to early-adopter banks—those that had joined UPI by the time of the demonetization shock in November 2016. F_d^+ is a dummy taking value one for districts with above-median fragmentation prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value involving the incumbent's app—i.e., transactions in which at least one counterparty used the incumbent's app—in Rupees per capita; (3) total P2M transaction value involving other UPI apps—i.e., transactions in which at least one counterparty used an alternative UPI app—in Rupees per capita; (4) total cross-platform P2M transaction value—i.e., transactions occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app—in Rupees per capita. Columns (1)–(3) report estimates of specification (4), controlling additionally for Exposure$_d \times 1_{\{t \geq t_0\}}$. Column (4) reports the estimate from regressing cross-platform P2M transaction value per capita on F_d^+, controlling for state-time fixed effects and Exposure$_d$, over the post-integration sample. (On this sample, $F_d^+ \times 1_{\{t \geq t_0\}}$ and F_d^+ coincide.) Z_d^y is the total value of digital payments per capita within the channel of the respective y variable in the month before integration. 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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 H.5: Response of digital payments adoption to platform integration, controlling for mobile-phone ownership

	Total/pop (1)	Incumbent/pop (2)	Other/pop (3)	(Inc↔Oth)/pop (4)
$F_d^+ \times 1_{\{t \geq t_0\}}$	6.359***	5.636***	1.396***	0.222***
	(4.19)	(5.06)	(2.78)	(4.12)
State-Time FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	
Control: $Z_d^y \times 1_{\{t \geq t_0\}}$	✓	✓	✓	
Control: Mobile$_{dt}$	✓	✓	✓	✓
N	8,137	8,137	8,137	5,827
Mean y_{dt} ($F_d^+ = 1, t = t_{-1}$)	8.114	6.596	1.518	
Mean y_{dt} ($F_d^+ = 0, t \geq t_0$)	7.189	1.750	5.595	0.192

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-F_d and low-F_d districts, when additionally controlling for mobile-phone ownership over time. Mobile$_{dt}$ is the share of households owning a mobile phone in district d and month t. F_d^+ is a dummy taking value one for districts with above-median fragmentation prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value involving the incumbent's app—i.e., transactions in which at least one counterparty used the incumbent's app—in Rupees per capita; (3) total P2M transaction value involving other UPI apps—i.e., transactions in which at least one counterparty used an alternative UPI app—in Rupees per capita; (4) total cross-platform P2M transaction value—i.e., transactions occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app—in Rupees per capita. Columns (1)–(3) report estimates of specification (4), additionally including Mobile$_{dt}$. Column (4) reports the estimate from regressing cross-platform P2M transaction value per capita on F_d^+, controlling for state-time fixed effects and Mobile$_{dt}$, over the post-integration sample. (On this sample, $F_d^+ \times 1_{\{t \geq t_0\}}$ and F_d^+ coincide.) Z_d^y is the total value of digital payments per capita within the channel of the respective y variable in the month before integration. 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-F_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-F_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.

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

Matrix 2: Condensed

$\sum_{i=3}^{5} a_{i1}$	$\sum_{i=3}^{5} a_{i2}$	$\sum_{i=3}^{5} \sum_{j=3}^{5} a_{ij}$
a_{21}	a_{22}	$\sum_{j=3}^{5} a_{2j}$
a_{11}	a_{12}	$\sum_{j=3}^{5} a_{1j}$

We 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.

We first define two ratios: $\phi_R = \frac{R_{acv}}{R_{awv}}$, where R_{acv} and R_{awv} are respectively the average value of cross-app and within-app transactions within the red region, and $\phi_B = \frac{B_{acv}}{B_{awv}}$ where B_{acv} and B_{awv} are respectively the average value of cross-app and within-app transactions within the blue region. We can measure ϕ_R directly from the data but cannot observe ϕ_B. To proceed, we therefore assume that $\phi_R \approx \phi_B$ and refer to this quantity simply as ϕ.

Using this estimated ϕ, we construct estimators for the unobserved values of B_{acv} and B_{awv} by solving the following system of equations

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

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

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 estimate the average cross-app value in the blue region by

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

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

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

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

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

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

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

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

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