Integrating Fragmented Networks:

The Value of Interoperability in Money and Payments*

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PRELIMINARY

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Abstract

Payments are network goods: their value increases with wider adoption. Recent advances in payments technologies may reinforce these network effects, giving rise to an economic dilemma. On one hand, a few large "BigTech" platforms may dominate. On the other hand, innovation and disruption from new entrants risks market fragmentation. This paper considers whether interoperability can help resolve this tension. We examine this empirically using data from India's Unified Payments Interface—the world's largest fast payment system by volume—as well as from a major pre-existing fintech firm. When the latter integrated its platform with the former, districts where digital payments usage had been more fragmented across platforms ex ante saw a 70% larger increase in the monthly value of digital payments. This increase reflected growth in digital payments both within and between the two platforms and relative to a proxy for cash usage.

Keywords: Payments; Interoperability; UPI; FinTech; Networks.
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1 Introduction

Money and payments are network goods: their value increases as more individuals adopt and accept them (Kiyotaki and Wright, 1989). In the digital age, technological innovations that enable faster transactions, more efficient processing, and enhanced information flows (see Berg et al., 2022, for a review) help increase convenience and reduce search and information frictions (e.g., Jack and Suri, 2014; Muralidharan et al., 2016), which may further amplify such network effects (Crouzet et al., 2023; Alvarez et al., 2023; Higgins, 2024), with profound implications for consumption and investment in the real economy.

However, advances in modern money and payments give rise to an economic dilemma in the design of payment systems. On one hand, improved payment technologies can reinforce network effects, leading to concerns over market concentration and the dominance of a few large platforms, echoing the challenges associated with "BigTech" in financial services (Brunnermeier and Payne, 2022, 2023). On the other hand, payment innovation and disruption from new entrants, while fostering competition, risks market fragmentation (Vayanos, 1999; Duffie, 2023), undermining the inherent network benefits of money and payments. A fundamental question arises: Is there a way to resolve this dilemma and design a payment ecosystem that preserves both the network advantages of money and the benefits of innovation while avoiding fragmentation?

In this paper, we study payment interoperability, which offers a potential escape from this dilemma yet has not been widely studied. By enabling users to transact seamlessly across payment platforms, interoperability resolves market fragmentation without requiring centralization on a single platform provider—preserving competition for users and hence incentives to improve service quality. Users could potentially reap the best of both worlds: the freedom to choose their favorite platform, alongside access to the complete graph of potential counterparties. Despite its importance and anecdotal support, this role of interoperability in encouraging user adoption of digital payments remains largely underexplored, in part due to the absence of a formal analytical framework and comprehensive empirical evidence.

We show conceptually and document empirically that interoperability can increase adoption 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 first empirical contribution is three pieces of descriptive evidence that interoperability accelerated adoption of digital payments in India. First, most early adopters initially used UPI through an app provided by a bank that they already trusted with their deposits, before later switching to apps produced by specialist FinTech firms. Since users were—and remain—fragmented across many banks, this 'bridging' function (onboarding onto the new platform via a trusted existing provider) and subsequent 'upgrading' (e.g., switching to a FinTech app with a better interface) could only occur in an interoperable system. Second, cross-app transactions drove growth in UPI transaction volumes. Most UPI transactions occur between users of two different apps, so directly use interoperability at the payment initiation level. Third, in response to a common shock that increased demand for digital payments, users faced with both an interoperable and a closed-loop payments platform increasingly opted for the former.

We next develop a formal conceptual framework, building on these stylized facts, to show how interoperability can increase adoption of digital payments by integrating fragmented networks. Users choose between two digital payments platforms and an outside option that is already universally accepted (e.g., cash). When users value the platforms identically, the only stable equilibria are those where all users pool on one platform, maximizing network benefits and total digital payments adoption. In contrast, exogenous differences between users in familiarity or preferences regarding the platforms lead them to split between the two, lowering the network benefits associated with each and so reducing total digital payments adoption and welfare. In this context, interoperability—by allowing users to choose one

[1]The fintech firm requested to remain anonymous; we thus refer to it throughout as 'the incumbent platform', or variations thereof, and describe relevant results in event time rather than chronological time.

platform but transact with counterparties on the other—restores the full network benefits and maximizes digital payments adoption and welfare.

To test this framework, we exploit 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, meaning that any two transaction counterparties were required to use the same digital wallet. In the first year of UPI, this platform thus competed with UPI for digital payments users, fragmenting the digital payments market. However, following a directive from the Reserve Bank of India (RBI) mandating interoperability, the incumbent connected its platform to UPI, suddenly expanding the set of accessible counterparties for users on both platforms. Crucially, the pre-integration presence of the incumbent varied across district, so the size of this 'integration shock' varied across districts. We exploit this variation in a heterogeneous adoption design (de Chaisemartin and D'Haultfœuille, 2023), comparing the trends in digital payments adoption of districts whose digital payments markets were more vs. less fragmented ex ante.

We include granular fixed effects and control variables in our baseline specification. We work at the district-month level and include state-month fixed effects. We control for differential trends due to differences in total digital payment usage prior to integration, leveraging only differences in the composition of adoption. Conditional on these control variables, we do not see meaningful differences in trends in digital payments use in districts where digital payments were more fragmented prior to integration.

We find substantial positive effects of network integration on the total adoption of digital payments across both platforms. Over the year after integration, districts whose digital payments markets were more fragmented than the median ex ante (hereafter, 'more fragmented districts') saw a 70% larger increase in the monthly total value of digital payments. Total digital payments also increased relative to a proxy for cash usage based on ATM withdrawals, consistent with the greater usefulness of integrated digital payments platforms encouraging users to transition away from cash.

Dis-aggregating the increase in total digital payments, we find that newly enabled transactions *between* the incumbent platform and other UPI apps take off after integration, providing direct evidence that users valued the cross-network payments capability created by interoperability. Finally, we also observe increases in transaction value *within* both the incumbent platform and other UPI apps after their integration, consistent with the expansion of the accessible user base having spillover benefits to both the previously unconnected platforms.

We present a battery of robustness checks that confirm these empirical findings and support a causal interpretation. In addition to placebo tests and alternative specifications, we use two additional estimation strategies to mitigate concerns that the pre-integration fragmentation of a given district could be endogenous to subsequent trends in its usage of digital payments. First, we instrument the ex-ante digital payments share of the incumbent platform with the distance of each district from one of the 'hub' cities from which the incumbent launched. Between two otherwise-identical districts, users in the district closer to a hub were more likely to encounter the incumbent platform, tilting the pre-integration composition of digital payments usage towards the incumbent's platform. Importantly, these hubs were selected by the incumbent more than a year before integration, and before the demonetization shock radically changed the landscape of digital payments adoption in India (see, for instance, Chodorow-Reich et al., 2020; Lahiri, 2020), mitigating concerns about an interdependency between hub choice and the decision of the incumbent to integrate. Second, we complement this instrumental variables approach with an alternative approach based on matching with districts similar on observables that differ only on ex-ante fragmentation.

We conclude by tracing the knock-on implications for the real economy of this increased uptake of digital payments. We show that lending also accelerated in districts whose digital payments markets were more fragmented prior to integration. Specifically, we show that households in more fragmented markets prior to integration were four times more likely to borrow from non-banks after integration.

Our results have important implications for policymakers both in their role as providers

and regulators of payment technologies. Our results warn that by introducing a new publicly provided payment technology that is not interoperable policymakers could fragment payment markets and reduce welfare. In contrast, developing an interoperable payment technology could deliver the best of both worlds: harnessing the user bases of existing payments networks even while introducing new and improved service quality. Our findings are also relevant to policymakers in their role as regulators of payment technologies. The results underscore that market fragmentation can be avoided without accepting dominance by a single platform, by mandating and ensuring interoperability to maximize the benefits of private FinTech innovation.

Related literature. We contribute to several main areas of research. First, we contribute to the extensive literature on money and payments. The idea that money functions as a network good dates back to Fisher (1911) and has been formalized in modern economic models, such as Kiyotaki and Wright (1989). It is well established that network effects in money and payments can be amplified by advances in search efficiency (Kiyotaki and Wright, 1993), monitoring technologies (Kocherlakota, 1998), and reduction of information asymmetry (Gorton and Pennacchi, 1990). Recent innovations in payment systems, including the rise of fast payment platforms, cryptocurrencies, and central bank digital currencies (CBDCs), have further transformed the landscape (Duffie, 2019). However, alongside these benefits, concerns have also emerged regarding new sources of financial fragility introduced new payment technologies (e.g., Brunnermeier and Payne, 2022; Goldstein et al., 2023). We contribute to this evolving literature by examining the role of interoperability, an increasingly prominent yet understudied feature of payment systems, in shaping the trade-offs between network benefits and competition in the evolution of money and payments.

Second, more broadly, a long literature addresses the adoption and diffusion of network technologies, such as payments. Building on initial theoretical work (e.g., Katz and Shapiro, 1985; Weinberg, 1997; Rochet and Tirole, 2003, 2004), a more recent literature exploits the

availability of new microdata to test and extend our understanding of the mechanisms (e.g., Björkegren, 2019; Agarwal et al., 2020; Higgins, 2024; Crouzet et al., 2024; Wang, 2024). Most closely related to our work are papers by Crouzet et al. (2023) and Alvarez et al. (2023), which each examine the implications of strategic complementarities for the adoption of a mobile payments platform. We build on their insights by considering the implications of network externalities when *multiple* such platforms compete. Such competition can produce network fragmentation, motivating the interoperability policies that are the focus of our paper.

Third, we build on existing work on the consequences of introducing interoperability between networks.[2] 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, abstracting from 'supply-side' considerations that have been the focus of recent work. Specifically, recent papers have highlighted a potential downside of interoperability that can emerge through the the impact on network providers: increased competition can reduce their incentives to invest in expanding platform access (Ferrari et al., 2010; Björkegren, 2022; Brunnermeier et al., 2023).[3] In contrast, in our context the primary costs of providing the network are borne by banks and the state as part of a wider program of investment in digital public infrastructure (Reserve Bank of India, 2022; Alonso et al., 2023), reducing the direct costs to the third-party application providers (TPAPs) through which most users interact with the platform. We therefore focus instead on the demand-side implications of interoperability for user adoption: the benefit to users of being able to use their favorite digital payments app, yet still interact with users across all UPI apps. While present to varying degrees in prior work, these demand-side mechanisms tend to

[2]See Bourreau and Valletti (2015) and Bianchi et al. (2021) 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) and Bourreau and Kraemer (2023).

[3]For instance, in Brunnermeier et al. (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.

be obscured by the supply-side forces, clouding the implications for welfare. In contrast, we spotlight the demand-side mechanisms, which are especially relevant for policymakers seeking to understand how to attract users to new platforms layered on top of existing payments infrastructure (e.g., fast payments systems or intermediated CBDCs that exist primarily as a software layer on top of existing inter-bank payments rails).

Turning to our methodological contribution to the literature on interoperability, our empirical design allows us to relax a previous trade-off between imposing strong assumptions and drawing comparisons between relatively dis-similar units of observation. Specifically, a common challenge for assessing the impact of interoperability empirically is that competition policy is usually set at the national level, requiring the econometrician to either impose significant structural assumptions (as in, for example, Ferrari et al., 2010; Björkegren, 2022), or to use other countries as the counterfactual (as in, for example, Brunnermeier et al., 2023).[4] We therefore innovate by exploiting within-country variation in interoperability: while the integration of the incumbent platform with UPI occurred nationally, the *de facto* increase in interoperability varied across districts.[5] When estimating the impact of interoperability on adoption of digital payments, we are thus able to draw a tighter comparison than previous work.[6]

Finally, our paper relates to a growing literature on the downstream impacts of widespread adoption of digital payments, particularly in the context of India.[7] Reflecting the speed and scale of UPI's take-off, these impacts have been pervasive, affecting risk-sharing (Patnam and Yao, 2020), debt enforcement (Rishabh and Schäublin, 2021), lending (Rishabh, 2023; Ghosh

[4] Brunnermeier et al. (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.

[5] To see this, consider two hypothetical districts of N users where the incumbent has digital payments market shares of zero and 50% prior to integration. In the former district, integration does not enable any new transactions for existing digital payments users: the number of feasible $\{\text{payer}, \text{payee}\}$ transactions remains at $N^2 - N$. In the latter case, the set of feasible transactions expands from $\frac{N^2}{2} - N$ to $N^2 - N$.

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

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

et al., 2022; Alok et al., 2024), bank deposits (Di Maggio et al., 2024), consumption (Agarwal et al., 2024) and growth (Dubey and Purnanandam, 2023), among other outcomes. This extensive literature—including some large estimated benefits of digital payments—raise 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: Figure 1 of Crouzet et al. (2023) shows that usage of a closed-loop electronic wallet contracted once the cash crunch subsided, while Figure 4 in Lahiri (2020) shows that aggregate digital payment transaction volumes in India actually declined in the first half of 2017, before suddenly re-accelerating. Crouzet et al. (2024) offer another explanation for rapid adoption in India: a relatively young population, who prefer mobile payments and so in turn incentivize businesses to adopt the technology.

In this paper, we contribute a third explanation: the creation of an interoperable retail digital payments system, UPI, allowed the integration of fragmented networks without sacrificing app-level competition on quality. This view can explain the rapid acceleration in digital payments volumes in late 2017, since two major platform operators joined UPI in that period, bringing with them their existing user bases—respectively, users of a closed-loop wallet technology and users of a mobile phone operating system. Further, we present direct evidence that the resulting increase in digital payments activity in turn reduced financial frictions in credit markets. Interoperability also contrasts with demonetization and demographics in its implications for policymakers seeking to learn from India's case how to accelerate uptake of a new system. Demographics change slowly and are hard for the policymaker to influence, while demonetization had substantial macroeconomic costs (Chodorow-Reich et al., 2020). In contrast, interoperability can be readily implemented.

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 derives predictions for digital payments adoption

that we can test in the data. Section 4 presents our empirical strategy, tests these predictions and explores robustness. Section 5 extends the analysis to consider the knock-on implications for credit markets. Section 6 concludes.

2 Setting and Descriptive Evidence

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

2.1 Institutional context

UPI is a software layer built on top of India's existing real-time interbank electronic fund transfer service, the Immediate Payment Service (IMPS). Users of UPI apps are able to initiate payments from their accounts at any participating bank to the accounts of other participating banks, as well as to receive notifications that a payment has been received into their account.[8] The underlying transfers between participating banks were interoperable even before UPI, through the existing inter-bank payment rails (IMPS). UPI's innovation was in allowing third-party application providers (TPAPs) to interact with these rails, providing a bridge between ordinary users and bank-based settlement infrastructure. FinTech firms have thus been able to specialize in providing user-friendly payments apps even while the underlying funds remain in accounts at users' banks. Each user is able to choose their favorite UPI payments app, without affecting either the location of their deposits (which stay in their bank) or the set of other UPI users with whom they can transact. This feature is the core interoperability that we focus on in this paper.

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,

[8] Appendix Figure B.1 depicts the transaction flow in detail. Settlement for end users is immediate, while settlement among financial institutions is managed through deferred net settlement with ten daily cycles.

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 app providers under UPI, where interoperability means that network effects operate primarily at the platform level.

The UPI ecosystem has grown steadily, and now features several hundred participating apps and banks (Figure 1). Total transaction values on the platform have grown exponentially, 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 et al., 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 et al., 2023).

2.2 Data

Our primary data source is information on the universe of UPI transactions, provided directly by NPCI. We received 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. For the largest three UPI apps, plus the publicly developed app BHIM (the 'Bharat Interface for Money') and a consolidated 'Other Apps' category, we also received the full matrix of payer and payee app choices—i.e., for the same period, we have monthly totals of value and volume, split by the interaction of the payer's bank branch, the payer's app and the payee's app. In both cases, transaction totals are dis-aggregated into peer-to-peer (P2P) and peer-to-merchant (P2M) transactions. 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.

We supplement this with 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 and volume, again split by P2P and P2M transactions.

We also obtain data from NPCI on 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.

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 allows us to use comprehensive, granular, high-frequency panel data on borrowing at the household level. Surveys that cover borrowing occur in roughly three waves per year. See Dubey and Purnanandam (2023) for a more detailed description of this data.

This novel data enable us to extend previous literature on digital payments in important ways. First, in contrast to previous work on UPI (e.g., Dubey and Purnanandam, 2023; Alok et al., 2024), our dataset covers transactions from *all* apps and banks in the UPI ecosystem, allowing us to provide a comprehensive picture of UPI usage. Second, we have information on both the payer's and the payee's choice of app, allowing us to examine users' app choices *within* UPI, and thus to quantify the extent to which the interoperability of instant payment

systems—in the form of cross-app transactions—is actually used in practice. Third, our data on payments through the incumbent platform allow us to go beyond studies of a single payments platform (e.g., Crouzet et al., 2023; Alvarez et al., 2023) to compare adoption *across* platforms and identify shifts in usage between them.

2.3 Stylized facts

In this section, we present three stylized facts that suggest interoperability supported adoption of digital payments in India.

1. Most early users joined UPI via their pre-existing financial services providers. Before UPI was ubiquitous, it was widely unknown. Similarly, while the major UPI apps are now household names and trusted brands, this familiarity and trust took time to earn. Figure 4 shows that most users in the early years of UPI used the platform through the UPI app produced by their bank. This share was especially high in the New Private Banks (NPBs), consistent with existing evidence that that NPBs are quicker to adopt and upgrade technology than Public Sector Banks (PSBs) and provide apps that users rate more highly.[9] As awareness and adoption of the platform matured, users subsequently migrated to what would become the largest three apps (PhonePe, Google Pay and Paytm), which offer smooth user interfaces and a range of additional features, such as automatic bill payments, rewards, and credit, investment or insurance products. In competing for users, these app providers have also introduced various technological innovations to reduce payment frictions, such as QR codes (which use a smartphone's camera to remove the need to type in a recipient's identification details) and 'soundboxes' (which announce the receipt of funds through a speaker, so that merchants do not need to manually check their phone for confirmation).[10] Interoperability thus allowed users to on-board onto UPI through financial entities that they

[9] See, for instance, Mishra et al. (2022) and Chart II.16 from the RBI's 2023-24 Report on Currency and Finance.

[10] See Chowdhry and Ahmed (2024) for a detailed discussion of how soundboxes reduce barriers to adoption.

already trusted (i.e., their existing banks), then from there to switch from their bank's UPI app to new, higher quality apps provided by specialist FinTech firms. Both these transitions would have been impossible in the absence of an interoperable system.

2. Cross-app transactions drove growth in UPI transaction volumes. Figure 5 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 is consistently above 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.

3. 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 with which we partner 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 impact of demonetization on usage of closed-loop versus interoperable payments. Figure 6 shows the results. In November and December 2016, when the cash shortage was most severe, transaction values increased sharply on both platforms. However, as cash availability returned to normal in early 2017, the trends diverge: growth in total usage of the non-interoperable, closed-loop incumbent payment platform plateaued, even as adoption of UPI continued to grow exponentially. The difference in trends is substantial: while adoption of the non-interoperable alternative was flat between March and October 2017, UPI grew roughly three-fold. Moreover, UPI's interoperability was central to this growth. Cross-app payments rose even more than within-app payments (Appendix Figure B.2), suggesting that the extra feature of UPI relative to the closed-loop incumbent—i.e.,

interoperability—was indeed valued by users.

3 Model

This section introduces a stylized model in which 'users'—representing both households and firms—choose a payment method between two digital platforms and an outside option. After setting up the model, in Section 3.2 we show how interoperability can increase overall adoption of the digital platforms by unifying their previously fragmented networks. In Section 3.3, we use the framework to derive empirical predictions that we then test in Section 4. Section 3.4 discusses modeling assumptions, and proofs are provided in Appendix A.

3.1 Setup

Environment. Many districts $d \in \{1, ..., D\}$ each contain a closed unit square of users, who each seek to make a within-district payment. Three payment methods exist: digital platform a, digital platform b, and an outside option C that we label 'cash'. Users are distributed uniformly on two dimensions, x and y, that determine their choice of payment method. The model is static: all users choose their payment method simultaneously.

Preferences for digital payments. Using digital payments platform $i \in \{a, b\}$ provides user xy in district d with utility:

$$u^a_{dxy} = \begin{cases} 1 + \kappa N^*_{da} & \text{if } x \leq \hat{x}_d \\ 0 & \text{if } x > \hat{x}_d \end{cases} \qquad u^b_{dxy} = \begin{cases} 0 & \text{if } x \leq \hat{x}_d \\ 1 + \kappa N^*_{db} & \text{if } x > \hat{x}_d \end{cases} \tag{1}$$

where N^*_{di} is the number of digital payments users that can be *accessed* through platform i in district d. In the absence of interoperability, this is simply equal to the number of *users* of platform i in district d, which we denote by N_{di}. The parameter $\kappa > 0$ summarizes the network benefit that each accessible user generates for each (other) platform user. The

boundary $\hat{x}_d \in (0, \frac{1}{2})$ denotes the share of users in each district that perceive benefits from platform a relative to platform b. Specifically, we assume that exogenous differences across users in brand familiarity and/or personal preferences split potential users of digital payments into two types on the x-dimension: those who consider adopting platform a, and those who consider adopting platform b. We allow districts to differ in the level of this $\hat{x}_d$. Our lower bound on $\hat{x}_d$ implies that all districts include some users that consider each platform. Our upper bound is 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 measure of pre-interoperability network fragmentation. Aside from differences in $\hat{x}_d$, districts are assumed to be identical.

Preferences for cash. Using cash provides utility $u^C_{dxy} = \gamma y$. All users are assumed to always accept cash, such that its utility to a given user does not depend on other users' choices of payment method. Instead, users differ in a pure cash preference y, which could reflect pure idiosyncratic heterogeneity or differences in adoption costs, demographic preferences (Crouzet et al., 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.[11]

Expectations and equilibrium concept. Users have rational expectations over others' choices, and we follow Bourreau and Kraemer (2023) in focusing on stable, fulfilled-expectations equilibria in pure strategies. Users' expectations of the total mass joining their chosen payment method turn out to be correct. Following a deviation by a small but positive mass of users, users' choices return to the same equilibrium.[12]

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

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

Interoperability. Interoperability is not imposed in the baseline. When it is imposed, it entails that each digital payments platform enables access to the combined user base of both: N^*_{di} becomes $N^D_d := N_{da} + N_{db}$ for both $i \in \{a, b\}$.

3.2 Equilibrium analysis

Users' problem is to choose the payment method that maximizes their utility, given their expectations of others' choices:

$$\max U_{dxy} = \begin{cases} u^a_{dxy} & \text{if choosing digital payments platform } a \\ u^b_{dxy} & \text{if choosing digital payments platform } b \\ u^C_{dxy} & \text{if choosing cash.} \end{cases} \tag{2}$$

We initially focus on a single district and consider equilibria in the baseline and when interoperability is imposed. Since each user's valuation of cash never changes across scenarios, total welfare increases monotonically with the number of digital payments users, allowing us to use total digital payments adoption as a proxy for social welfare.[13]

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

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 adopters pool on one platform. In these equilibria, total digital payments adoption is* $N^D_d = \bar{y} = \frac{1}{\gamma - \kappa}$.

This outcome is depicted in Figure 7. Intuitively, when all users value the two digital

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

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.[14]

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, reducing total network benefits.

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

This outcome is depicted in Figure 8a. Intuitively, the disagreement among users on which digital payments platform is preferable leads them to fragment between the two, reducing the network benefits associated with each and hence lowering adoption and welfare.

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

This outcome is depicted in Figure 8b. Interoperability restores network benefits between users on different platforms, restoring total adoption to the level that results when users all pool on one platform. Combining these results, we have:

Proposition 1 (Interoperability and total adoption)**.** *Interoperability resolves market fragmentation, restoring total adoption and welfare to the level that would result in the absence*

[14] A third equilibrium does exist where adoption of the two platforms is exactly equal, but this outcome is unstable: the deviation of an arbitrarily small but positive mass of users ϵ to platform i would lead all other digital payments users to make the same switch, resulting in a pooling equilibrium once again.

of heterogeneous valuations of platforms between users.

We also note that the cross-platform network effects unlocked by interoperability also make both platforms more valuable to users:

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

3.3 Empirical predictions

We now consider variation across districts, and use the model to derive predictions that we can test using our natural experiment. In short, we use observed variation across districts in platform market shares prior to interoperability to proxy for the unobserved $\hat{x}_d$, then relate this variation to variation in the predicted impact of interoperability on adoption of digital payments.

Comparing two districts with different levels of $\hat{x}_d$, Lemma 2 gives that the district with higher $\hat{x}_d$ will also have higher adoption of platform a in the absence of interoperability. Intuitively, districts in which a higher share of users perceive positive utility from platform a will also have higher adoption of platform a in the baseline. This can be seen by comparing the blue areas in Figures 8a and 9a: district 1 has higher $\hat{x}_d$ than district 0, leading to higher adoption of platform a in the baseline.

Lemma 2 also implies that the district with higher initial fragmentation $\hat{x}_d$ also has lower total adoption of digital payments N_d^D. When interoperability is introduced, both districts converge to the same total level of adoption of digital payments, $\bar{y}$. Therefore, the increase in digital payments (or conversely, the reduction in the usage of cash) when interoperability is introduced is larger in the district with higher $\hat{x}_d$, as shown in Figure 9b.

Combining these observations gives the following testable prediction, analogous to Proposition 1:

Prediction 1 (Interoperability and total adoption)**.** *Introducing interoperability increases total adoption of digital payments by more in districts where digital payments usage is initially more fragmented across platforms.*

Similar reasoning gives the following prediction for adoption of each platform, analogous to Proposition 2:

Prediction 2 (Interoperability and adoption per platform)**.** *Introducing interoperability increases adoption on each platform by more in districts where digital payments usage is initially more fragmented across platforms.*

3.4 Discussion of modeling assumptions

The baseline model is deliberately simple to clarify the key economic channels. Below we discuss several key assumptions.

Static model. Crouzet et al. (2023) and Alvarez et al. (2023) provide detailed investigations of dynamic considerations in the adoption of a single digital payments platform. We follow Farronato et al. (2024), among others, in abstracting from this dimension in order to extend our analysis to the competition between multiple networks while retaining tractability.

Focus on users. 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 on a single interoperable platform thus delivers the same total welfare as the unification on a single private provider that would occur in the absence of heterogeneous platform valuations. In reality, these two outcomes could have quite different implications. As discussed in Section 1, 'winner-takes-all' private unification could lead to rent extraction

from users or reduce incentives to innovate, leading policymakers to prefer the interoperability outcome even if rapid unification on a single private platform is feasible.[15] We abstract from these considerations in the 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 A.2. 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.

Stark boundary $\hat{x}_d$. We assume that the boundary $\hat{x}_d$ partitions users into two groups, who each consider only one digital payments platform.[16] This substantially simplifies the derivation of the non-interoperability equilibrium.[17] 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.[18]

[15] 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.

[16] This is analogous to the assumption of an exogenous cutoff k_1 in Farronato et al. (2024).

[17] Specifically, imposing the stark $\hat{x}_d$ 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.

[18] 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 any 'net switching' (where many move in the same direction). However, we cannot observe such switching in our data. If it occurs, it simply

4 Empirical Analysis

This section uses our data on UPI transactions and transactions on a leading pre-existing fintech platform to formally test our model predictions. Overall, our results confirm our theoretical predictions and corroborate our descriptive evidence in Section 2 that interoperability supported adoption of digital payments in India.

4.1 Estimation Strategy

Variation. To test our model predictions, we exploit the integration with UPI of a major incumbent fintech firm that previously offered only closed-loop payments. Founded before UPI, this firm's platform processed a larger total value of transactions than UPI in the month prior to their integration, but UPI was growing substantially faster (Figure 10). Moreover, UPI had a much wider geographical presence: in the median district, the incumbent platform had only a 7.4% share of total transaction value across the two platforms in the month before integration (Figure 11). Defining t_{-1} as the month before integration, we construct the following measure of the presence of the incumbent across districts d:

$$P_d = \frac{\text{Total value of transactions on the incumbent platform in } t_{-1}}{\text{Total value of transactions across both platforms in } t_{-1}}. \tag{3}$$

Values of P_d closer to 50% imply that users of the two platforms were more fragmented between platforms prior to the platforms' integration. Conversely, values closer to zero or 100% imply greater unification prior to the platforms' integration. In practice, 97% of districts have incumbent shares of less than 50% prior to integration (reflecting the skew in Figure 11a), so higher values of P_d almost always imply higher fragmentation. For our regressions below, we construct a dummy variable P_d^+ that takes value one only in districts with above-median values of P_d. The skew in P_d is such that even the highest value of P_d (87%) implies greater fragmentation than the median value of P_d (7.4%)—there is no district where the

layers an additional benefit of interoperability on top of our mechanisms.

incumbent is so dominant that it reduces fragmentation to a level below the median. Thus, P_d^+ serves as an indicator for both (i) districts having an above-median *presence* of the incumbent platform prior to integration, and (ii) districts with an above-median *degree of fragmentation* between the two platforms prior to integration. Consequently, we use both interpretations interchangeably when describing our empirical results.

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

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

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 is the total value of transactions across both platforms in period t_{-1} (i.e., the denominator in equation 3). We include the Z_d term to account for the fact that districts with higher P_d also tend to have higher total pre-integration transaction values, making it important to distinguish the impact of integrating *more fragmented* networks from any differential impact that integration may have had in districts where digital payments adoption *in general* was greater ex ante. We cluster standard errors at the district level (Bertrand et al., 2003).

Our coefficient of interest, β, thus measures the monthly average increase in y_{dt} after integration in districts that were more fragmented than the median ex ante, relative to districts that were less fragmented, after controlling for district and state-time fixed effects and differential trends by total pre-integration transaction value. To explore the dynamics

of this increase, we also run the corresponding event-study specification:

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

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

Our primary outcome variable is the total peer-to-merchant (P2M) transaction value across both platforms. This is 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.[19] In our baseline specification we winsorize the top 1% of y_{dt} to moderate the influence of a small number of very large districts.

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

Three considerations mitigate this concern. First, the incumbent's decision to integrate

[19] See Section 3.4 and Appendix A.2 for further discussion of the potential implications of including cross-district transactions.

with UPI was immediately preceded by an RBI directive mandating that digital wallet providers make their wallets interoperable through UPI. Accurate anticipation would thus have required detailed knowledge of the regulatory landscape. We do not consider it plausible that such knowledge would have been sufficiently widespread among the general population to affect our results. Second, such widespread anticipation—if it did occur—would only bias down our estimate of β in equation 4, since higher adoption in above-median P_d districts ex ante would reduce an estimated increase in adoption 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 check the dynamics of our estimated effects using specification 5, we do not see evidence of differential pre-trends between high- and low-P_d districts, suggesting that anticipation is not a significant concern for our results.

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

We mitigate this concern in five main ways. First, we include state-time fixed effects, such that we only compare high- and low-P_d districts within the same state. Second, we control for differential trends by total pre-integration transaction value. Thus we control for any factors that affect districts' propensity to adopt digital payments *overall*, leveraging only differences in the *composition* of that adoption. Third, when we compare the pre-integration trends in y_{dt} of high- and low-P_d districts using specification 5, we find that in general they are not significantly different. Fourth, we check the robustness of our results when instrumenting P_d with geographic decisions taken by the incumbent more than a year prior to integration—before the unexpected demonetization shock changed the landscape of digital

payments in India. Fifth, we check the robustness of our results when comparing high-P_d districts to a matched sample of low-P_d districts that are otherwise similar on observables. In both the latter two cases our results are qualitatively similar, and if anything quantitatively larger. Further details and results from the instrumental variable and matching approaches are provided in Sections 4.3.3 and 4.3.4 respectively.

4.2 Estimation Results

Our baseline estimation results for specification 4 are shown in Table 1. Column 1 shows that the total P2M transaction value per person increased by 8 Rupees per person per month more after integration in high-P_d districts than in low-P_d districts. This response is statistically highly significant and economically substantial: the increase is almost twice the size of total pre-integration P2M digital payments in high-P_d districts. While digital payments were growing everywhere, this increase is still 70% larger than the average monthly level of P2M digital payments in low-P_d districts in the year after integration. Digital payments grew not just in absolute terms but also relative to cash: Column 2 shows that total P2M digital payments relative to cash withdrawals similarly increased by substantially more in high-P_d districts than in low-P_d districts.

What drove this increase in usage of digital payments? The final three columns of Table 1 break down the total increase in Column 1 across three different categories of transactions: transactions where both the payer and the payee used the incumbent's app (Column 3), transactions where both the payer and payee used an alternative UPI app (Column 5), and the newly enabled transactions where one of the payer and payee used the incumbent's app, and the other used another UPI app (Column 4). All three transaction categories show increases that are both statistically and economically significant. The coefficient on the increase in transactions between users of the incumbent's app and users of other UPI apps is smaller, since the total value of these transactions begins at zero, but the magnitude is substantial when compared to the average increase in low-P_d districts: the differential

increase in such payments in high-P_d districts is more than 25% of the level reached in low-P_d districts. Turning to transactions between users of the same app, districts that were more fragmented ex-ante again see substantially larger increases in usage post-integration, implying that the greater increase in total network size encouraged users of all apps to use the combined platform more intensively—even for transaction types that were feasible pre-integration. Our results thus suggest that unifying fragmented networks was a 'win-win' in this context: instead of leading to substitution away from one of the previously separate networks, integration increased usage of both.

4.3 Robustness

This section considers the robustness of our findings first to alternative specification choices and second to potential confounds that could prevent a causal interpretation of our findings.

4.3.1 Alternative specifications

Our baseline regressions estimate P_d using all digital payments transactions, not just P2M transactions. This reflects that even a user who, for example, only adopts digital payments to send P2P remittances is nonetheless joining a platform, increasing that platform's share of all users, and hence affecting the size of the user base that that platform brings to the combined network at integration. Nonetheless, Appendix Table B.1 shows that our results are robust to instead defining P_d using only P2M digital payments.

As discussed in Section 4.1, our baseline P_d^+ measure includes some districts where the incumbent platform has a greater than 50% share of pre-integration transaction values. One could thus interpret fragmentation in these districts as being driven by the incumbent's platform being too small, rather than too large (as in the vast majority of districts, where UPI was dominant ex ante). To avoid concerns that these districts are qualitatively different, and such should not be included in our comparisons, Appendix Table B.2 repeats our main results when dropping these districts (and re-computing P_d^+ accordingly). Our results remain

similar.

Our baseline results focus on transaction values rather than volumes, since these capture both the price and quantity margins of digital payments usage. Appendix Table B.3 shows that are results hold similarly when constructing y_{dt}, P_d and Z_{dt} using volumes rather than values. Similarly, our results do not depend on our choice to winsorize values at the 1% level: Appendix Table B.4 shows that our results hold even when restricting winsorizing to the top 0.5% of districts.

4.3.2 Placebo tests

We conduct two placebo tests to confirm that our results are not driven by some combination of our specification design and the context we study. First, we confirm that randomly re-assigning districts between P_d^+-groups produces median estimated effects centered on zero. Appendix Figure B.3a shows the results. Second, we confirm that our results are not driven by a combination of exponential growth in digital payments adoption and our choice of baseline period. Appendix Figure B.3b repeats Figure 12a for an alternative t_0 set three months prior to that in our baseline specification, and confirms that the differential increase in total digital payments usage does not take off until the true month of integration.

4.3.3 Instrumenting ex-ante fragmentation

Technologies diffuse through space (see, for instance, Comin et al., 2012). Like many platform services, the incumbent firm's platform began in a small number of cities before spreading nationally. At any point in time, districts therefore varied in their proximity to the largest clusters of users. Adoption externalities could then imply that, following a shock that increased demand for digital payments, users closest to these clusters would be more likely to choose the incumbent's platform than an alternative, such as UPI (in the pre-integration world, where they were not yet interoperable).[20] We can exploit this variation to isolate

[20] Crouzet et al. (2023) provide an extensive discussion of the possible sources of such adoption externalities in their Online Appendix F.

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

Building on Crouzet et al. (2023), we identify eight 'hub' districts in which at least 500 merchants had adopted the platform by May 2016, which is the first month that we observe. These districts were outliers: 94% of all districts had fewer than 10 merchants signed up, and 63% had zero (Appendix Figure B.4a). However, the districts surrounding these hubs do not look significantly different from other districts (Appendix Figure B.4b): after all, they were not targeted by the incumbent firm, they simply happen to be located near a city that was. To exploit this variation, we define a new proximity variable H_d: the negative of the distance in kilometers from the centroid of district d to the centroid of the nearest hub district. This measure is highly correlated with the presence of the incumbent in the last month before integration (Figure B.5a). 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 et al., 2023). Moreover, the variation in P_d that can be explained by H_d is not significantly correlated with other observable district characteristics, aside from a marginally significant negative correlation with the agricultural share of workers (Figure B.5b).[21]

To implement this strategy, we first exclude the hub districts from the sample, then repeat specification 4 with the following first stage:

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

The results, shown in Table 2, are qualitatively similar, and quantitatively somewhat stronger than the baseline. The dynamics are also similar (Appendix Figures B.6 and B.7).

[21] We discuss this further in the next section.

4.3.4 Matching on district characteristics

Our second alternative approach to support a causal interpretation of our results is to match high-P_d districts to low-P_d districts with similar observables. This approach complements our instrumental variable results. As noted above, our instrumented variation in P_d remains marginally negatively correlated with the agricultural share of workers in a district, reflecting that districts closer to hubs are generally closer to major urban centers.

Our second approach therefore uses matching to ensure that we compare high- and low-P_d districts with similar observables. Specifically, we identify the three nearest low-P_d district neighbors for each high-P_d district using Mahalanobis distance matching.[22] We first note that our raw P_d measure is balanced on a wide range of observables except for a strong correlation with (log) district population and a weaker correlation with median income (Figure B.8). Since these two covariates are themselves correlated, we match on log population. Figure B.8 shows that the matched group of low-P_d districts is similar to high-P_d districts on all observables. We then use the same specification as in Equation 4 to estimate the matching results.

The results, shown in Table 3, are qualitatively and quantitatively similar to the baseline. Again, the dynamics are also similar (Appendix Figures B.9 and B.10) to the baseline.

5 Impact on lending

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

We use a similar heterogeneous adoption design as in our baseline to examine whether

[22] We also exclude high-P_d districts that are too far away from all potential control districts for us to identify any similar control districts.

higher adoption after fragmented networks are integrated leads to more borrowing. We use the following specification at the household-survey wave level:

$$y_{ht} = \alpha_h + \alpha_{st} + \alpha_{ut} + \beta(P_d^+ \times 1_{\{t \geq t_0\}}) + \beta_Z(Z_d \times 1_{\{t \geq t_0\}}) + e_{dt} \tag{7}$$

Our dependent variable here is the probability of borrowing from non-banks, as non-banks are more likely to be able to draw on the information generated by greater payments activity. 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. Importantly, we can now include household fixed effects α_h, as the data is now at the household level. Following Dubey and Purnanandam (2023), we also include time-specific fixed effects for urban districts α_{ut}, allowing for differences in trends between urban and rural areas. We continue to cluster standard errors at the district level.

We find that borrowing does increase more in districts that benefited more from integration of previously fragmented networks after this integration takes place. Table 4 shows the results. After integration, in districts with above median fragmentation, the probability of borrowing increase by 1.1% (about four times as large as the baseline probability of borrowing) relative to districts with below median fragmentation. These increases were larger for households more likely to benefit from digital payments activities (entrepreneurs or hawkers).

Consistent with prior work (Dubey and Purnanandam, 2023; Alok et al., 2024), the greater adoption of retail digital payments driven by interoperability appears to reduce frictions in credit markets, allowing more households to borrow. As our measure of borrowing focuses exclusively on the extensive margin, our results show that more households are able to access credit after integration. These results complement existing work showing that stronger adoption of digital payments support lending as they rely on a very different approach to identification.

6 Conclusion

Significant technological advances have emerged in the digital age that have made payment systems more convenient and reduced search frictions. These advances may amplify network effects in payments, leading to an important tradeoff. On one hand, stronger network effects lead to concerns about the emergence of a few large "BigTech" platforms. On the other hand, disruption from new entrants could lead to more fragmentation, undermining the inherent 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 our data allow us to directly observe the app used on both sides of transactions, and to compare adoption across multiple platforms. This allows us to exploit a unique natural experiment in which a large pre-existing platform integrated with UPI.

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. In more fragmented districts the monthly value of digital payments rose by 70% more after integration. Importantly, newly enabled transactions between the incumbent platform and other UPI apps rose significantly after integration, highlighting that users valued the additional options interoperability provided them. We also see positive spillovers to transactions within each network. Consistent with reduced financial frictions, we show that lending also grew in districts in which interoperability brought larger adoption gains.

Our results are useful for policymakers both as potential providers and as regulators of payment technologies. The introduction of new technologies that are not interoperable could fragment markets and reduce welfare. Such fragmentation can be avoided without accepting the emergence of a single dominant platform by mandating and ensuring interoperability. Interoperability appears to be an important policy lever to reduce tradeoffs between network benefits and competition.

References

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

Agarwal, S., S. Alok, P. Ghosh, S. Ghosh, T. Piskorski, and A. Seru (2017): "Banking the Unbanked: What do 280 Million New Bank Accounts Reveal about Financial Access?" SSRN Scholarly Paper 2906523, Social Science Research Network, Rochester, NY.

Agarwal, S., P. Ghosh, J. Li, and T. Ruan (2024): "Digital Payments and Consumption: Evidence from the 2016 Demonetization in India," The Review of Financial Studies.

Agarwal, S., W. Qian, Y. Ren, H.-T. T. Tsai, and B. Y. Yeung (2020): "The Real Impact of FinTech: Evidence from Mobile Payment Technology," SSRN Scholarly Paper 3556340, Social Science Research Network, Rochester, NY.

Alok, S., P. Ghosh, N. Kulkarni, and M. Puri (2024): "Does Open Banking Expand Credit Access?" NBER Working Papers.

Alonso, C., T. Bhojwani, E. Hanedar, D. Prihardini, G. Una, and K. Zhabska (2023): "Stacking Up the Benefits: Lessons from India's Digital Journey," Tech. rep., International Monetary Fund, Washington, D.C.

Alvarez, F. E., D. Argente, F. Lippi, E. Méndez, and D. V. Patten (2023): "Strategic Complementarities in a Dynamic Model of Technology Adoption: P2P Digital Payments," NBER Working Papers, number: 31280 Publisher: National Bureau of Economic Research, Inc.

Berg, T., A. Fuster, and M. Puri (2022): "FinTech Lending," Annual Review of Financial Economics, 14, 187–207, publisher: Annual Reviews.

Bertrand, M., E. Duflo, and S. Mullainathan (2003): "How Much Should We Trust Differences-In-Differences Estimates?" The Quarterly Journal of Economics, 119, pp. 249–275.

Bianchi, M., M. Bouvard, R. Gomes, A. Rhodes, and V. Shreeti (2021): "Mobile Payments and Interoperability: Insights from the Academic Literature," TSE Working Papers, number: 21-1279 Publisher: Toulouse School of Economics (TSE).

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

——— (2022): "Competition in network industries: Evidence from the Rwandan mobile phone network," The RAND Journal of Economics, 53, 200–225, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12405.

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

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

Brunnermeier, M. and J. Payne (2022): "Platforms, Tokens, and Interoperability," Working Paper, Princeton University. Economics Department.

Brunnermeier, M. K., N. Limodio, and L. Spadavecchia (2023): "Mobile Money, Interoperability, and Financial Inclusion," SSRN Scholarly Paper 4574641, Social Science Research Network, Rochester, NY.

Brunnermeier, M. K. and J. Payne (2023): "Strategic Money and Credit Ledgers,"

NBER Working Papers, number: 31561 Publisher: National Bureau of Economic Research, Inc.

Chodorow-Reich, G., G. Gopinath, P. Mishra, and A. Narayanan (2020): "Cash and the Economy: Evidence from India's Demonetization," The Quarterly Journal of Economics, 135, 57–103.

Chowdhry, B. and A. Ahmed (2024): FinTech for Billions: Simple, Human, Ubiquitous, Penguin Random House India.

Comin, D. A., M. Dmitriev, and E. Rossi-Hansberg (2012): "The Spatial Diffusion of Technology," NBER Working Papers, number: 18534 Publisher: National Bureau of Economic Research, Inc.

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

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

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

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

Ding, D., R. Gonzalez, Y. Ma, and Y. Zeng (2024): "The Effect of Instant Payments on the Banking System: Liquidity Transformation and Risk-Taking," .

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

Duffie, D. (2019): "Digital currencies and fast payment systems: Disruption is coming," in Asian Monetary Forum, May, mimeo.

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

Farronato, C., J. Fong, and A. Fradkin (2024): "Dog Eat Dog: Balancing Network Effects and Differentiation in a Digital Platform Merger," Management Science, 70, 464–483, publisher: INFORMS.

Ferrari, S., F. Verboven, and H. Degryse (2010): "Investment and Usage of New Technologies: Evidence from a Shared ATM Network," The American Economic Review, 100, 1046–1079, publisher: American Economic Association.

Fisher, I. (1911): The purchasing power of money: its' determination and relation to credit interest and crises, Cosimo, Inc.

Frost, J., P. K. Wilkens, A. Kosse, V. Shreeti, and C. Velasquez (2024): "Fast payments: design and adoption," BIS Quarterly Review, library Catalog: www.bis.org.

Ghosh, P., B. Vallee, and Y. Zeng (2022): "FinTech Lending and Cashless Payments," SSRN Scholarly Paper 3766250, Social Science Research Network, Rochester, NY.

Goldstein, I., M. Yang, and Y. Zeng (2023): "Payments, reserves, and financial fragility," Available at SSRN, 4547329.

Gorton, G. and G. Pennacchi (1990): "Financial intermediaries and liquidity creation," The Journal of Finance, 45, 49–71.

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

Jack, W. and T. Suri (2014): "Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution," American Economic Review, 104, 183–223.

Katz, M. L. and C. Shapiro (1985): "Network Externalities, Competition, and Compatibility," The American Economic Review, 75, 424–440, publisher: American Economic Association.

Kiyotaki, N. and R. Wright (1989): "On money as a medium of exchange," Journal of political Economy, 97, 927–954.

——— (1993): "A search-theoretic approach to monetary economics," The American Economic Review, 63–77.

Kocherlakota, N. R. (1998): "Money is memory," Journal of economic theory, 81, 232–251.

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

Liang, P., M. Sampaio, and S. Sarkisyan (2024): "Digital Payments and Monetary Policy Transmission," SSRN Scholarly Paper 4933059, Social Science Research Network, Rochester, NY.

Mishra, P., N. Prabhala, and R. G. Rajan (2022): "The Relationship Dilemma: Why Do Banks Differ in the Pace at Which They Adopt New Technology?" The Review of Financial Studies, 35, 3418–3466, publisher: Society for Financial Studies.

Muralidharan, K., P. Niehaus, and S. Sukhtankar (2016): "Building state capacity: Evidence from biometric smartcards in India," American Economic Review, 106, 2895–2929.

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

Reserve Bank of India (2022): "Discussion Paper on Charges in Payment Systems," .

Rishabh (2023): "Beyond the Bureau: Loan Screening and Monitoring under Open Banking," .

Rishabh, K. and J. Schäublin (2021): "Payment Fintechs and Debt Enforcement," Working papers, number: 2021/02 Publisher: Faculty of Business and Economics - University of Basel.

Rochet, J. and J. Tirole (2004): "Two-Sided Markets: An Overview," .

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

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

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

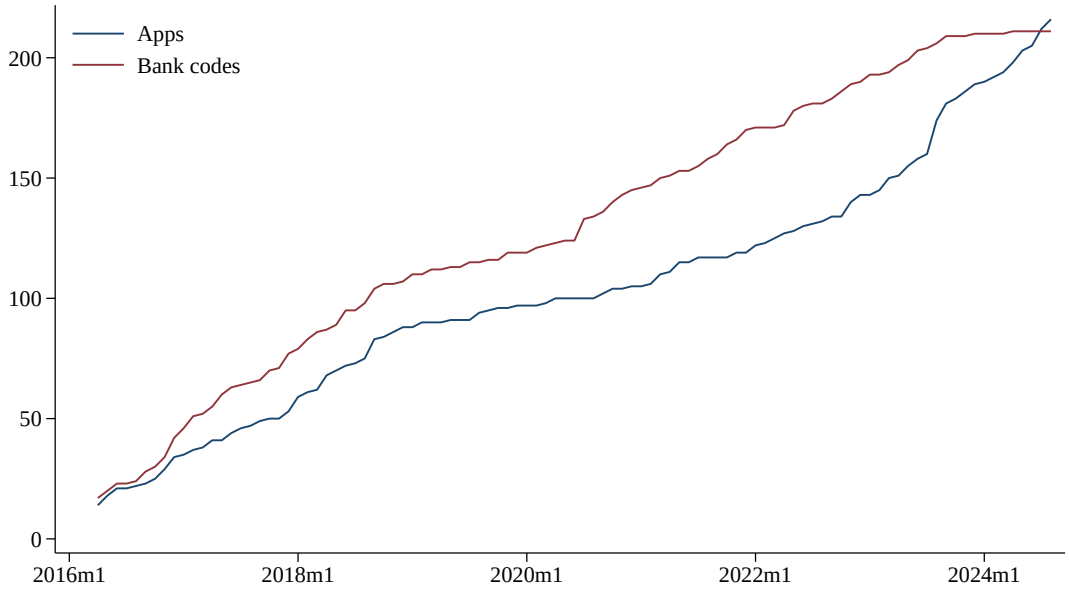
Vayanos, D. (1999): "Strategic trading and welfare in a dynamic market," The Review of Economic Studies, 66, 219–254.

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

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

Figures and Tables

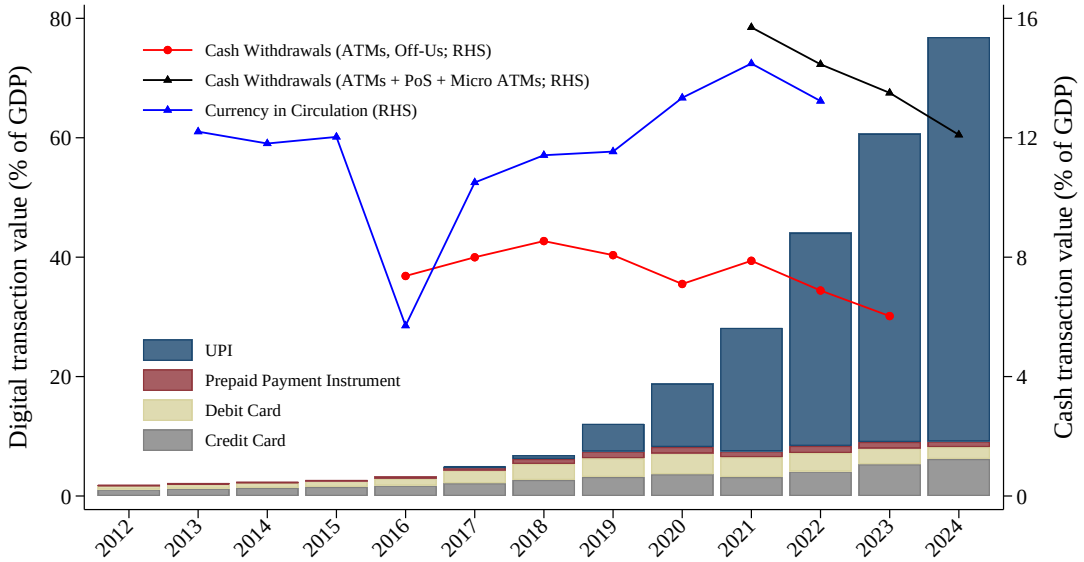
Figure 1: Number of apps and banks participating in UPI



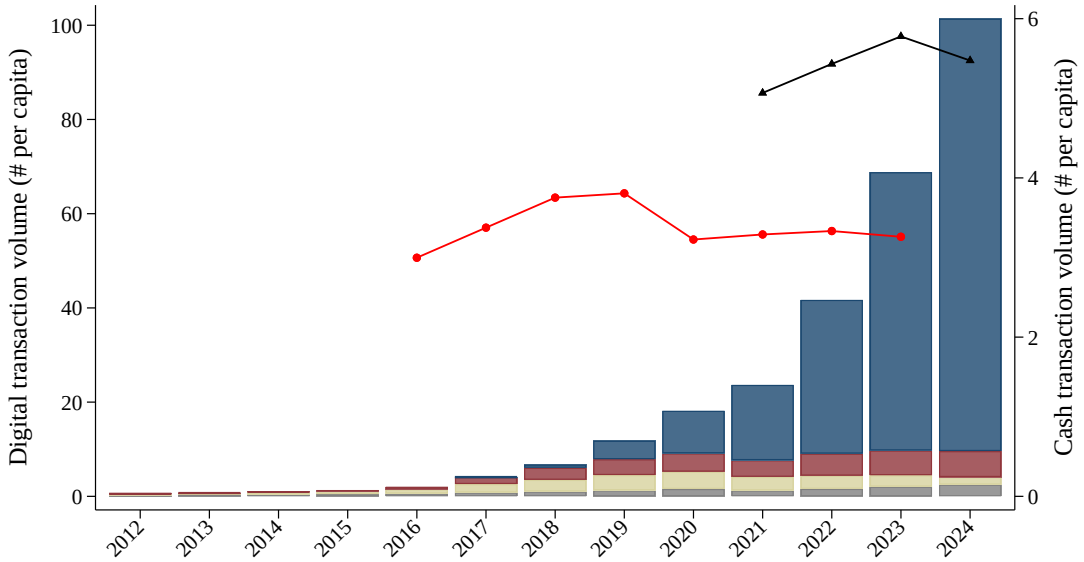
Notes: This graph shows the number of bank codes and apps on UPI that facilitated at least one successful transaction over the sample period.

Figure 2: Electronic retail payments in India

(a) Value (percent of GDP)

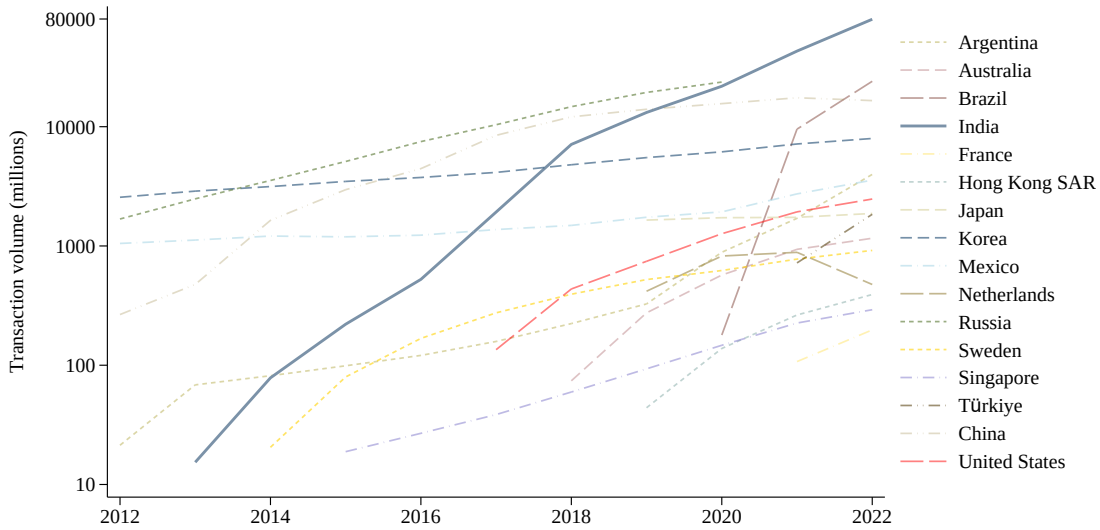


(b) Volume (transactions per capita)



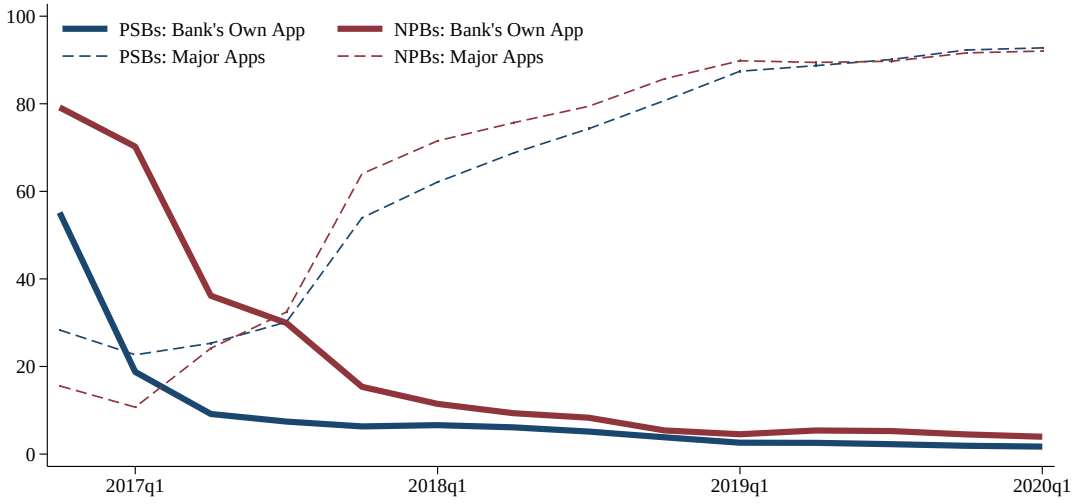
Notes: pre-paid payment instruments include smart cards and mobile wallets that are pre-loaded with value using cash, card or other methods. *Source:* RBI, NPCI, Haver Analytics, WDI.

Figure 3: Volume of fast payment transactions (millions)



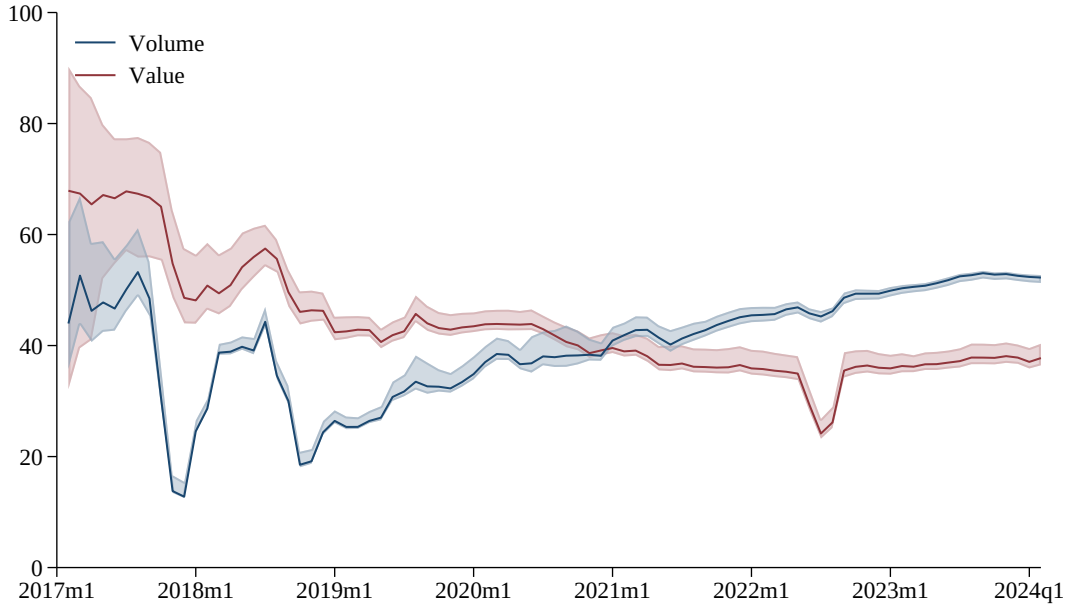
Notes: Fast payments: real-time or near real-time transfers of funds between accounts of end users as close to a 24/7 basis as possible (Frost et al., 2024). US comprises Zelle from 2017 and RTP from 2020. *Source:* BIS, Statista, TCH.

Figure 4: Share of transactions using the payer's bank's app, by value (%)



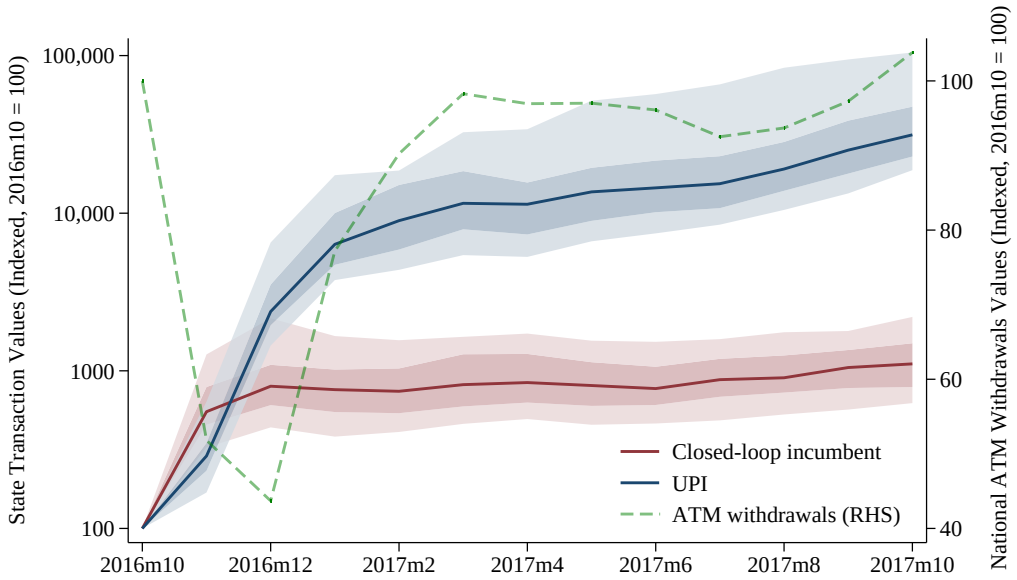
Notes: The solid lines on this graph plot the share of transaction value that was processed by the payer's bank's own app, among each of Public Sector Banks (PSBs) and New Private Banks (NPBs). The dashed lines show, for each group of banks, the share of transaction value that was instead processed by one of the three major apps (PhonePe, Google Pay and Paytm).

Figure 5: Share of cross-app transactions on UPI (%)



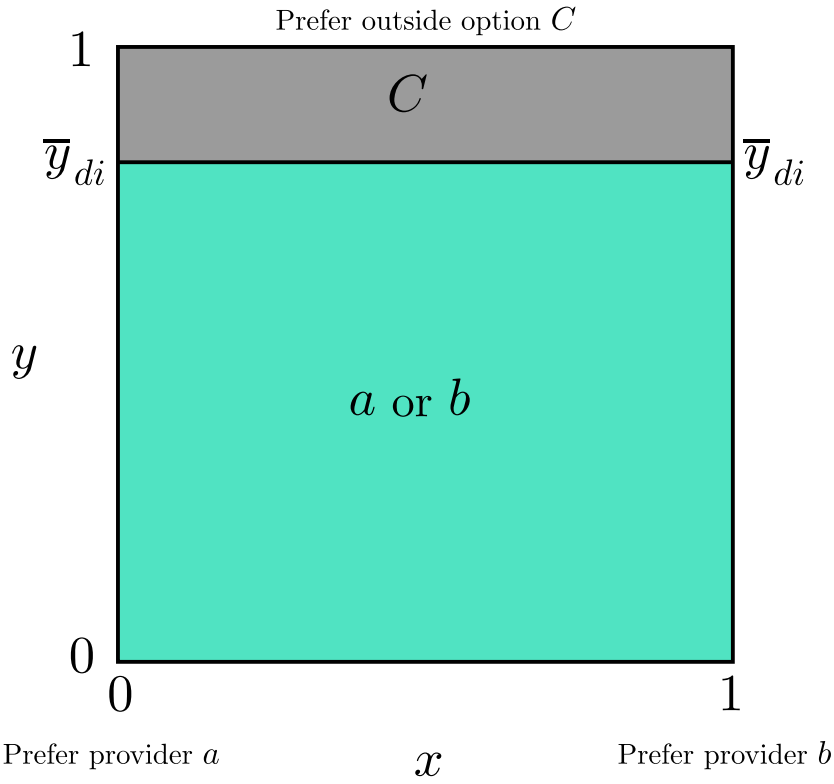
Notes: This graph plots the share of transactions on UPI that occur between two different apps, measured in turn using transaction value and transaction volume. Since we only observe the full payer app-payee app matrix for four major apps plus a consolidated 'Other app' category, we estimate the share of cross-app payments in the 'Other app' to 'Other app' cell using the procedure described in Appendix B.1. 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 6: Closed-loop and interoperable digital payments after demonetization (indexed)



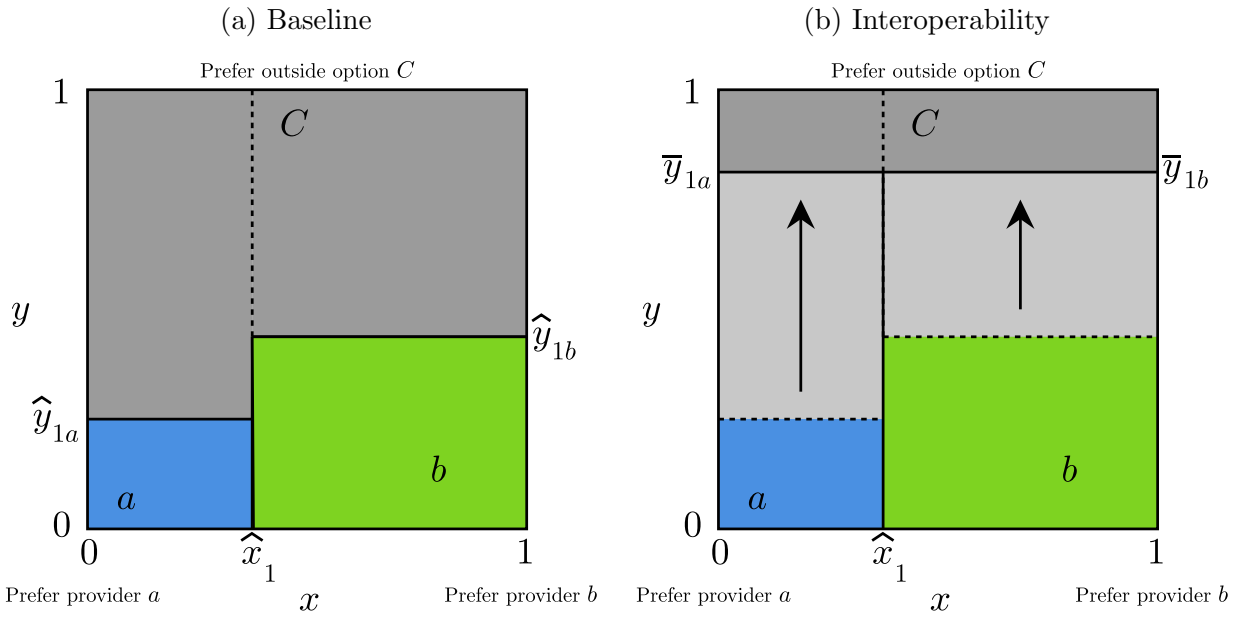
Notes: The green line shows national ATM withdrawals, by value, indexed to 100 in the month before demonetization (October 2016). The red line shows the total value of transactions on a major closed-loop incumbent digital payments platform in the median state, again indexed to 100 in October 2016. The 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 7: Equilibrium when all users value the digital platforms identically



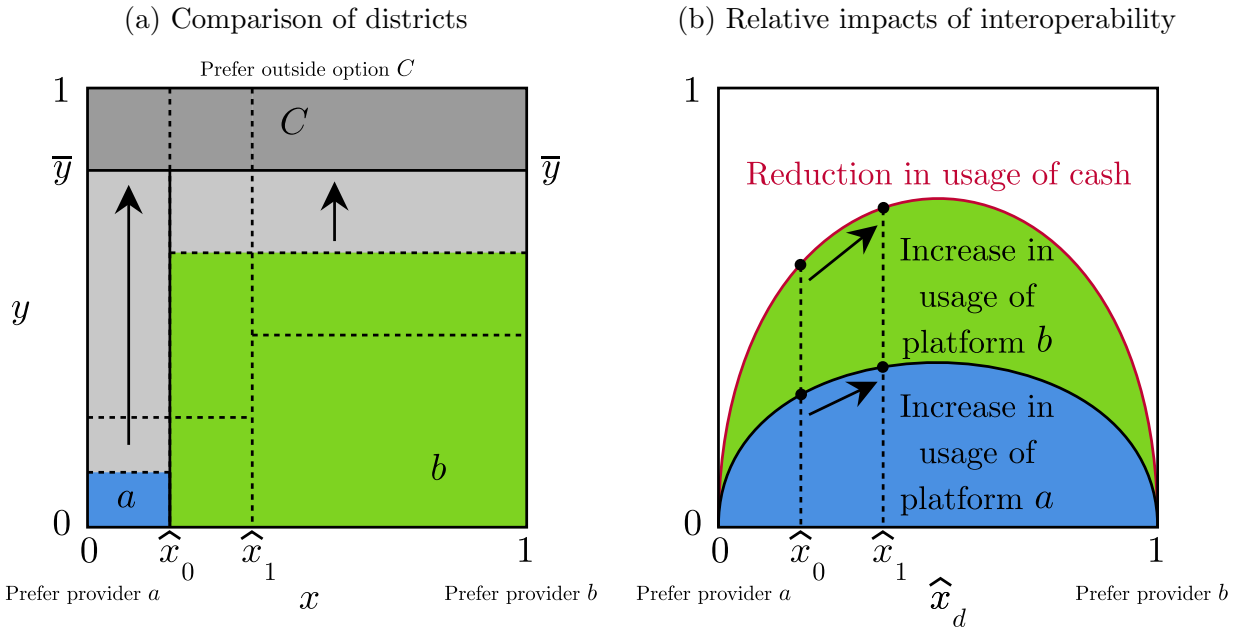
Notes: This figure depicts the outcome in Lemma 1, where users have homogeneous preferences across digital payments platforms, so in equilibrium all pool on one. The resulting level of adoption $\bar{y}_{di}$ provides the benchmark level that results when network benefits are maximized by all digital payments users being unified on one network—against which we compare outcomes when users' preferences are heterogeneous. Shaded regions indicate the equilibrium choices of the users contained within them.

Figure 8: Equilibria for a given familiarity boundary $\hat{x}_d$



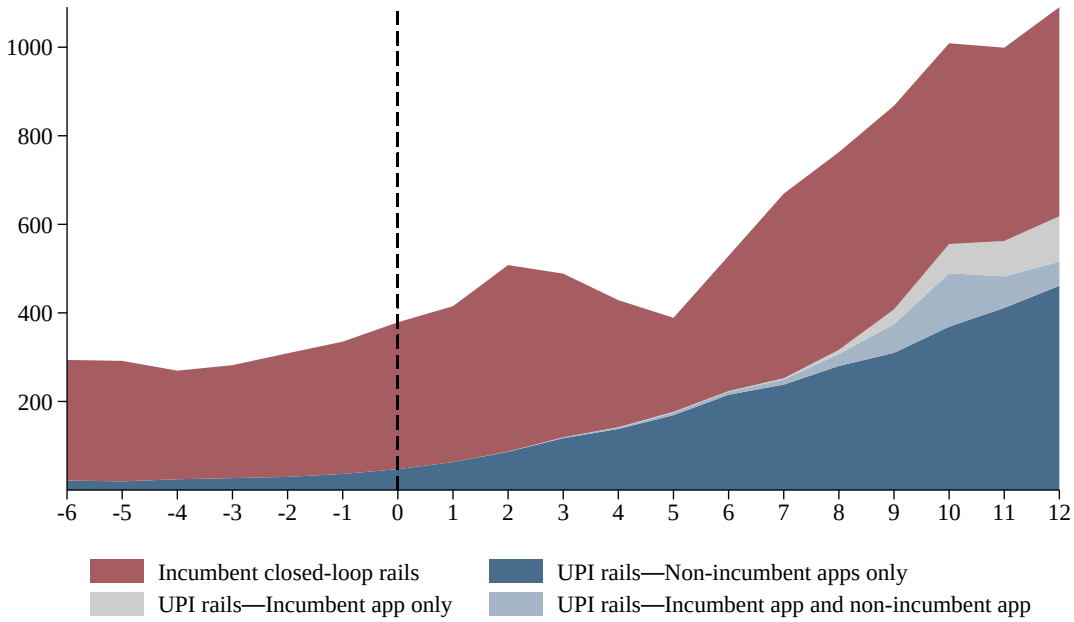
Notes: Panel (a) depicts the outcome in Lemma 2, in which users are fragmented across platforms but adoption of platform b is larger, since $\hat{x}_1 < 0.5$ by assumption. Panel (b) depicts the outcome in Lemma 3, in which interoperability unifies the two fragmented networks, increasing total network spillovers and restoring the benchmark level of adoption $\bar{y}_{di}$ in Figure 7. 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 9: Differential impact of interoperability by familiarity boundary $\hat{x}_d$



Notes: Panel (a) compares the equilibrium outcomes in district 1 in Figure 8b 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 indicate the equilibrium choices of the users contained within them, and regions containing arrows indicate changes in these choices when comparing the baseline equilibrium to the equilibrium with interoperability. In Panel (b), the red line plots the total reduction in usage of cash that results when interoperability is introduced, for a district with boundary $\hat{x}_d$. The blue and green areas show how the users switching away from cash divide between platforms a and b. The arrows indicate the differences in the impacts of interoperability between districts 0 and 1.

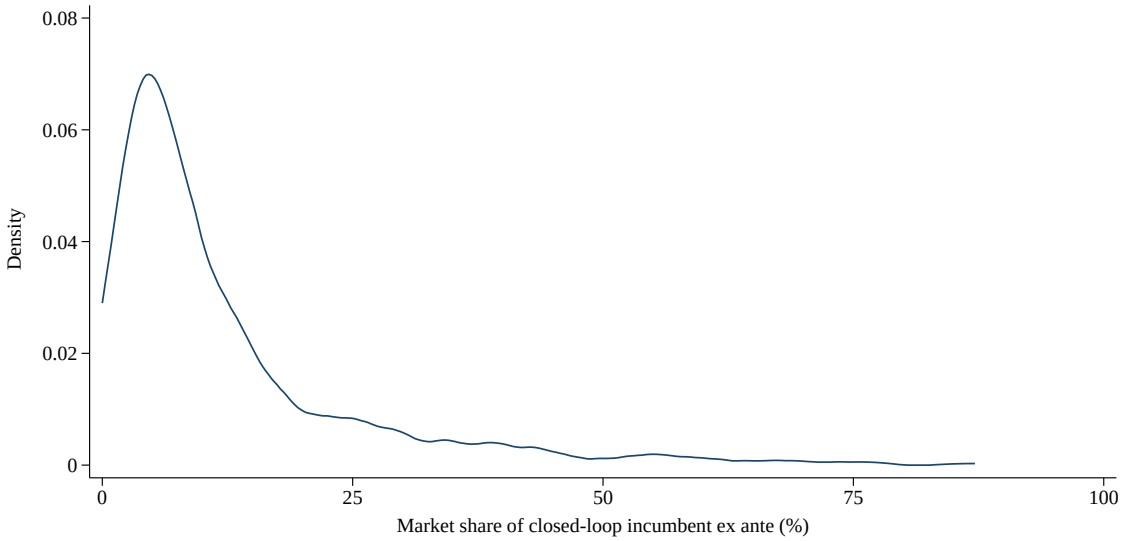
Figure 10: Aggregate value of transactions on UPI and incumbent platform (Rupees, billions)



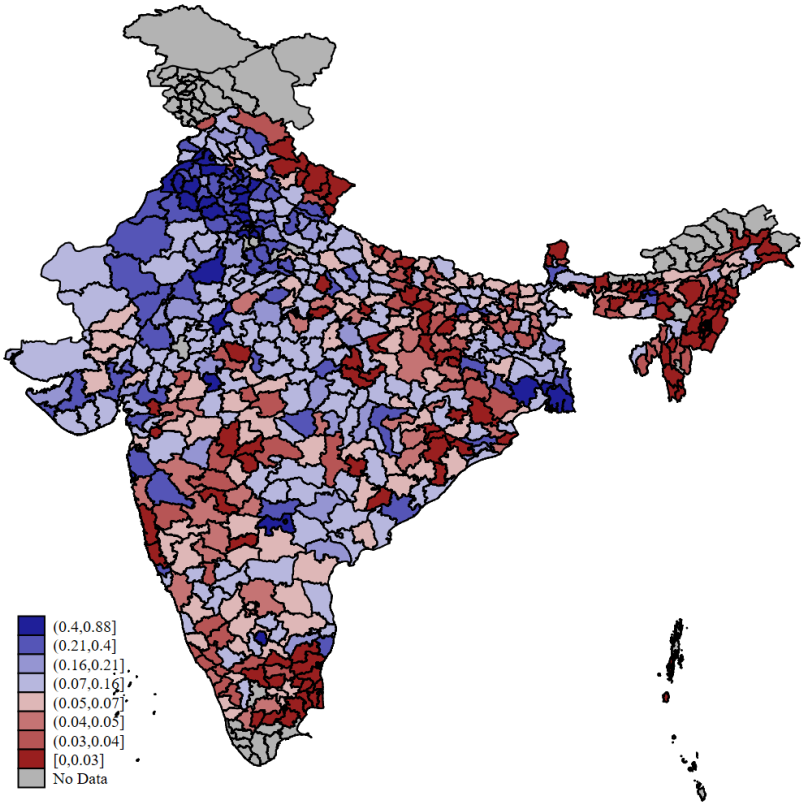
Notes: Each region shows the value of transactions by transaction type. The dark red shaded region shows transactions using the incumbent's closed-loop payments technology, which by definition required both the payer and payee to use their incumbent's app. The dark blue shaded region shows transactions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

Figure 11: Variation in P_d

(a) Density distribution



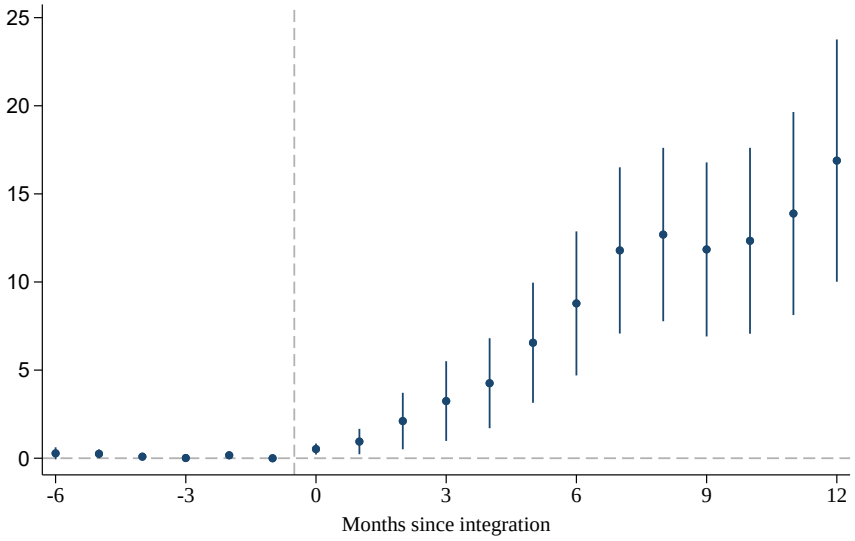
(b) Geographical distribution



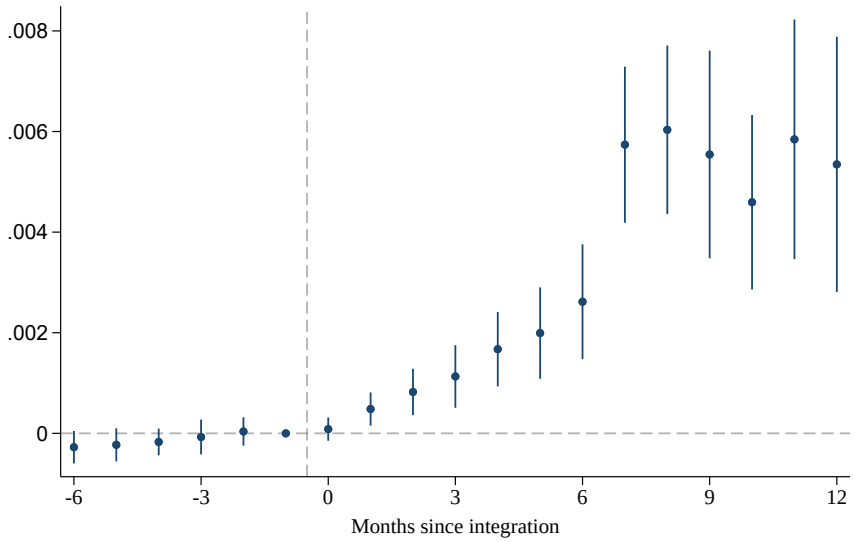
Notes: This figure plots the distribution of P_d, the market share of the incumbent in the month prior to integration. The first panel plots the estimated probability density distribution using an Epanechnikov kernel function. The second panel plots the values of P_d by district, with blue districts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

Figure 12: Response dynamics of total digital payments adoption to platform integration

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



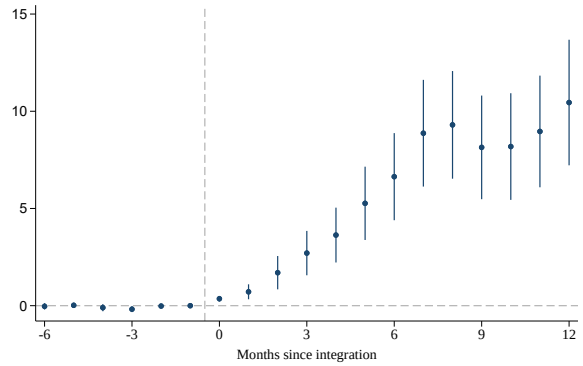
(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



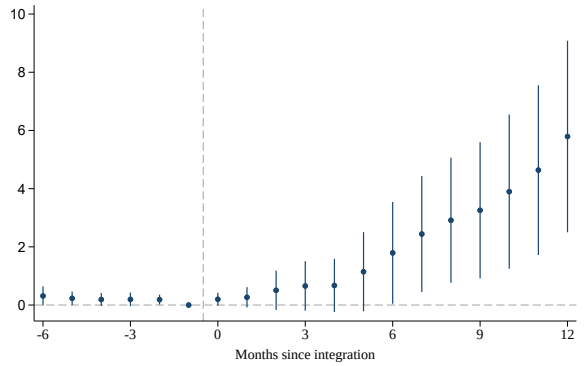
Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-P_d and low-P_d districts, based on specification 5. The first panel normalizes total P2M transaction values relative to population, and the second panel normalizes total P2M transaction values relative to cash withdrawals from ATMs. Vertical lines show 95% confidence intervals.

Figure 13: Response dynamics of digital payments adoption to platform integration, split by transaction participants' app choices

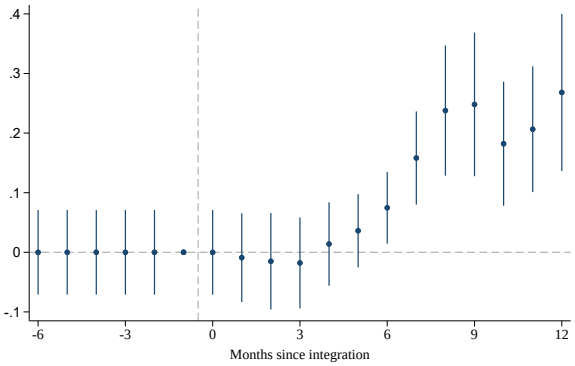
(a) Transactions between two users of the incumbent app (Rupees per capita)



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



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



Notes: This figure plots the dynamics of the difference in P2M transaction values between high-P_d and low-P_d districts, based on specification 5, for different subsets of transactions based on the transaction participants' app choices. The first panel shows results when including only those transactions for which both counterparties used the incumbent firm's app. This includes both transactions that took place on its proprietary closed-loop rails, and transactions that took place through UPI. The second panel shows results when including only those transactions for which both counterparties used other UPI apps. The third panel shows results when including only those transactions for which one counterparty used the incumbent firm's app and the other counterparty used another UPI app. By definition, such transactions were impossible in all districts prior to integration, hence the zero estimates in pre-integration months. Vertical lines show 95% confidence intervals.

Table 1: Response of digital payments adoption to platform integration

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	8.010***	0.00334***	11.75***	0.106***	1.989***
	(4.64)	(5.74)	(5.95)	(2.93)	(2.68)
District FE	✓	✓	✓	✓	✓
State-Time FE	✓	✓	✓	✓	✓
Baseline Total	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	9.118	0.007	1.936	0	14.365
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	11.274	0.019	9.046	0.395	3.178

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

Table 2: Response of digital payments adoption to platform integration, instrumented with proximity to incumbent hub districts

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	17.11***	0.0117***	18.67***	0.299*	5.046*
	(2.71)	(3.30)	(3.03)	(1.78)	(1.90)
District FE	✓	✓	✓	✓	✓
State-Time FE	✓	✓	✓	✓	✓
Baseline Total	✓	✓	✓	✓	✓
K-P F-Stat	25.25	25.25	25.25	25.25	25.25
N	10,621	10,620	10,621	10,621	10,621
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	6.511	0.007	1.656	0	9.613
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	10.973	0.019	8.896	0.387	3.178

Notes: This table shows how the response of digital payments adoption to the platforms' integration differed between high-P_d and low-P_d districts when instrumenting using proximity to incumbent hub districts H_d, using second-stage equation 4 and first-stage equation 6. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) total P2M transaction value per person, in Rupees per capita; (2) total P2M transaction value in Rupees per Rupee of cash withdrawn from ATMs; (3) total P2M transaction values for which the payer and the payee both used the incumbent's app, in Rupees per capita; (4) total P2M transaction values occurring between a payer and payee who between them used both the incumbent's app and an alternative UPI app, in Rupees per capita; (5) total P2M transaction values for which the payer and the payee both used an alternative UPI app, in Rupees per capita. We control for district and state-time fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from six months before integration to one year after integration. The penultimate row shows the mean level of the outcome variable in high-P_d districts in the month before integration. The last row shows the mean monthly level of the outcome variable in low-P_d districts in the year after integration. Standard errors are clustered at the district level. t-statistics are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table 3: Response of digital payments adoption to platform integration, matching districts based on log population size

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

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

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

	NBFC Borrowing (Y/N)		
	(1)	(2)	(3)
$P_d^+ \times 1_{\{t>t_0\}}$	0.0111**	0.0172**	0.0144***
	(2.28)	(2.18)	(3.26)
Household FE	✓	✓	✓
District-Wave FE	✓	✓	✓
Urban-Wave FE	✓	✓	✓
Baseline Total	✓	✓	✓
Sample	All	Entrepreneurs	Hawkers
N	843,841	52,737	22,198

Notes: This table shows how the response in household level borrowing from NBFCs (Non-Banking Financial Company) to integration differed between households in high-P_d and low-P_d districts. This is based on specification 4, using household level data at a wave frequency of every four months. P_d^+ is a dummy taking value one for districts with above-median incumbent market share prior to integration. Outcome variables are, in turn: (1) binary representing whether a household borrowed in a given wave (2) binary representing whether a household borrowed in a given wave if the household's primary occupation is 'entrepreneur'; (3) binary representing whether a household borrowed in a given wave if the household's primary occupation is 'hawker'. We control for district-time, urban-time, and household fixed effects as well as differential trends by total pre-integration transaction value. The sample period spans from sixteen months before integration to thirteen 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

A Theory Appendix

A.1 Proofs

A.1.1 Proof of Lemma 1

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

$$u^b_{dxy} = 1 + \kappa N_{db} > 1 + \kappa N_{da} = u^a_{dxy} \tag{8}$$

so all users prefer b. This contradicts the decision of some users to adopt a, implying that the assumed equilibrium cannot exist.

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

$$u^a_{dxy} = 1 + \kappa N_{da} = 1 + \kappa N_{db} = u^b_{dxy} \tag{9}$$

for digital payments users because $N_{da} = N_{db}$. 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 $N_{di} > N_{dj}$, implying $u^i_{dxy} > u^j_{dxy}$ 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:

$$1 + \kappa N_{di} = \gamma \bar{y}. \tag{10}$$

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

$$\begin{aligned} 1 + \kappa\bar{y} &= \gamma\bar{y} \\ 1 &= \bar{y}(\gamma - \kappa) \\ \bar{y} &= \frac{1}{\gamma - \kappa} \end{aligned} \tag{11}$$

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 7 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 users will 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. ■

A.1.2 Proof of Lemma 2

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

$$u^a_{dxy} = 1 + \kappa N_{da} = \gamma\hat{y}_{da} = u^C_{dxy}. \tag{12}$$

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

$$\begin{aligned} 1 + \kappa\hat{x}_d\hat{y}_{da} &= \gamma\hat{y}_{da} \\ 1 &= \hat{y}_{da}(\gamma - \kappa\hat{x}_d) \\ \hat{y}_{da} &= \frac{1}{\gamma - \kappa\hat{x}_d}. \end{aligned} \tag{13}$$

Thus adoption of platform a is:

$$N_{da} = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d}. \tag{14}$$

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

$$u^b_{dxy} = 1 + \kappa N_{db} = \gamma \hat{y}_{db} = u^C_{dxy}. \tag{15}$$

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

$$\begin{aligned} 1 + \kappa(1 - \hat{x}_d)\hat{y}_{db} &= \gamma \hat{y}_{db} \\ 1 &= \hat{y}_{db}[\gamma - \kappa(1 - \hat{x}_d)] \\ \hat{y}_{db} &= \frac{1}{\gamma - \kappa(1 - \hat{x}_d)} \end{aligned} \tag{16}$$

Thus adoption of platform b is:

$$N_{db} = \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)}. \tag{17}$$

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

$$N^D_d = \frac{\hat{x}_d}{\gamma - \kappa \hat{x}_d} + \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)}. \tag{18}$$

■

A.1.3 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: $\tilde{y}_{da} = \tilde{y}_{db} = \tilde{y}$. These marginal users must satisfy:

$$u^i_{dxy} = 1 + \kappa N^D_d = \gamma \tilde{y} = u^C_{dxy}. \tag{19}$$

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

$$\begin{aligned} 1 + \kappa \tilde{y} &= \gamma \tilde{y} \\ 1 &= \tilde{y}(\gamma - \kappa) \\ \tilde{y} &= \frac{1}{\gamma - \kappa} = \bar{y} \end{aligned} \tag{20}$$

where the final inequality follows from a comparison with equation 11 in the proof of Lemma 1. Total digital payments adoption is therefore

$$N^D_d = \frac{1}{\gamma - \kappa} \tag{21}$$

which is distributed evenly across platforms since $N_{da} = \hat{x}_d \tilde{y}$ and $N_{db} = (1 - \hat{x}_d)\tilde{y}$:

$$N_{da} = \frac{\hat{x}_d}{\gamma - \kappa} \qquad\qquad N_{db} = \frac{1 - \hat{x}_d}{\gamma - \kappa}. \tag{22}$$

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

A.1.4 Proof of Proposition 1

The results follows directly from (i) noting the presence of market fragmentation in Lemma 2, and (ii) comparing the outcomes under interoperability in Lemma 3 with the benchmark derived for the case of homogeneous preferences in Lemma 1. The increase in total usage of

digital payments under interoperability, relative to the baseline equilibrium, is given by:

$$N_d^{D,Interop.} - N_d^{D,Baseline} = \frac{1}{\gamma - \kappa} - \frac{\hat{x}_d}{\gamma - \kappa\hat{x}_d} - \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)}. \tag{23}$$

■

A.1.5 Proof of Proposition 2

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

$$N_{da}^{Interop.} - N_{da}^{Baseline} = \frac{\hat{x}_d}{\gamma - \kappa} - \frac{\hat{x}_d}{\gamma - \kappa\hat{x}_d}. \tag{24}$$

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 is smaller than the first. Hence, interoperability increases adoption of platform a.

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

$$N_{db}^{Interop.} - N_{db}^{Baseline} = \frac{1 - \hat{x}_d}{\gamma - \kappa} - \frac{1 - \hat{x}_d}{\gamma - \kappa(1 - \hat{x}_d)}. \tag{25}$$

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

A.2 Implications of cross-district transactions

To illuminate the implications of including cross-district payments in the model, we first consider the polar case where payments from district d flow equally to all districts, rather than only to other users within d. Users' welfare from adopting a digital payments platform i thus depends on the total accessible national user base $\sum_{d=1}^{D} N_{di}^{*}$, rather than only the accessible within-district user base N_{di}^{*}. As the total number of districts D tends to infinity, the importance of N_{di}^{*} within $\sum_{d=1}^{D} N_{di}^{*}$ thus tends to zero. Thus in the limit the extent of local fragmentation—which impacts N_{di}^{*}—is irrelevant. Instead, only the degree of *national* fragmentation across networks matters for the adoption 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 adoption of 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' impact, implying that our estimates are a lower bound on the true impact of network unification.

B Empirical Appendix

B.1 Estimating the cross-app share of 'Other-Other' transactions

As described in Section 2.2, we only received a condensed version of the matrix of the payer's and payee's 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 receive information on the full distribution of payer-side app choices, as described in Section 2.2). To illustrate our procedure, first consider the 'full matrix' below:

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

The identification problem is that we only observed the following 'condensed matrix':

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

To resolve this, we first define a ratio $\phi = \frac{R_{acv}}{R_{awv}}$ where R_{acv} and R_{awv} are respectively the average cross- and within-app transaction values within the red region. We then estimate the equivalent statistics in the blue region by applying this ratio. We construct estimators

by solving the following system of equations

$$B_w \hat{B_{awv}} + B_c \hat{B_{acv}} = B_v \tag{26}$$

$$\hat{B_{acv}} = \phi \hat{B_{awv}} \tag{27}$$

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

$$\hat{B_{acv}} = \frac{\phi B_v}{(B_w + \phi B_c)} \tag{28}$$

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

$$\hat{B_{awv}} = \frac{B_v}{(B_w + \phi B_c)}. \tag{29}$$

We know $B_w = n$ 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. With these components, we then estimate the total value of within-app transactions in the blue cell by calculating

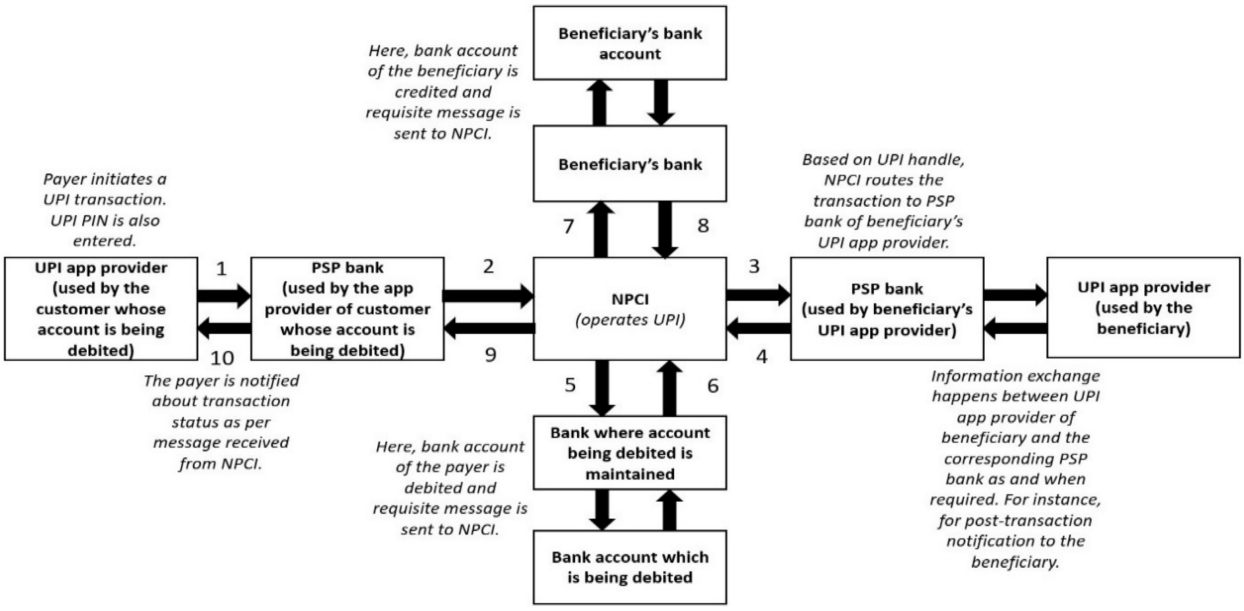
$$\hat{B_{wa}} = \hat{B_{awv}} B_w \tag{30}$$

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

$$\hat{B_{ca}} = \hat{B_{acv}} B_c. \tag{31}$$

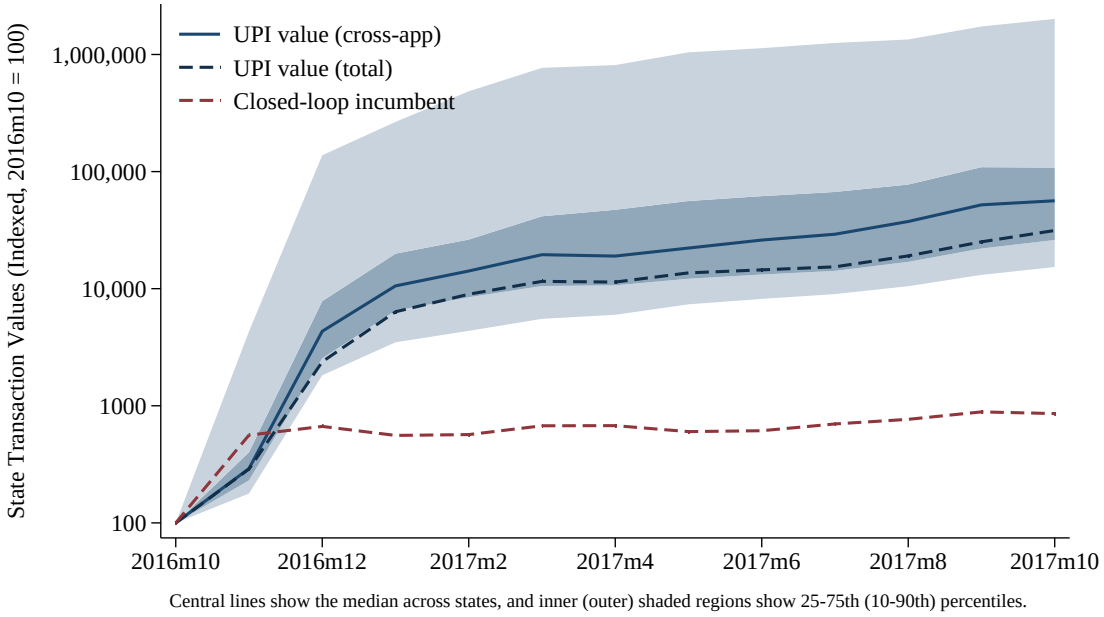
B.2 Additional Figures and Tables

Figure B.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).

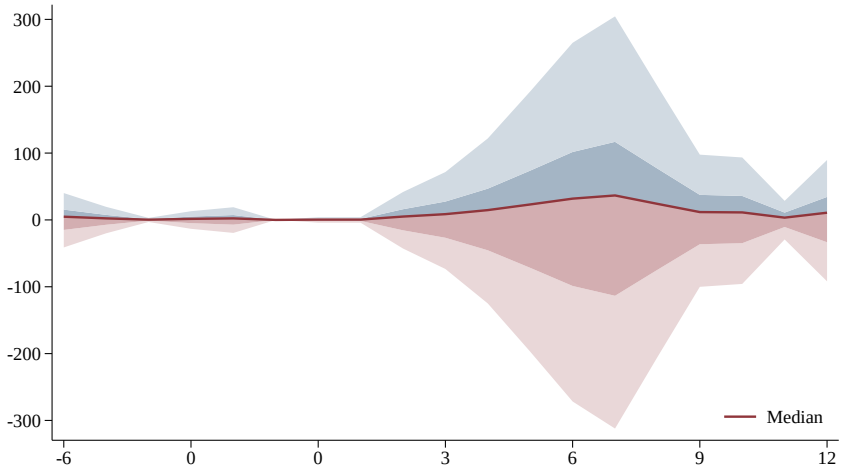
Figure B.2: Cross-app interoperable digital payments after demonetization (indexed)



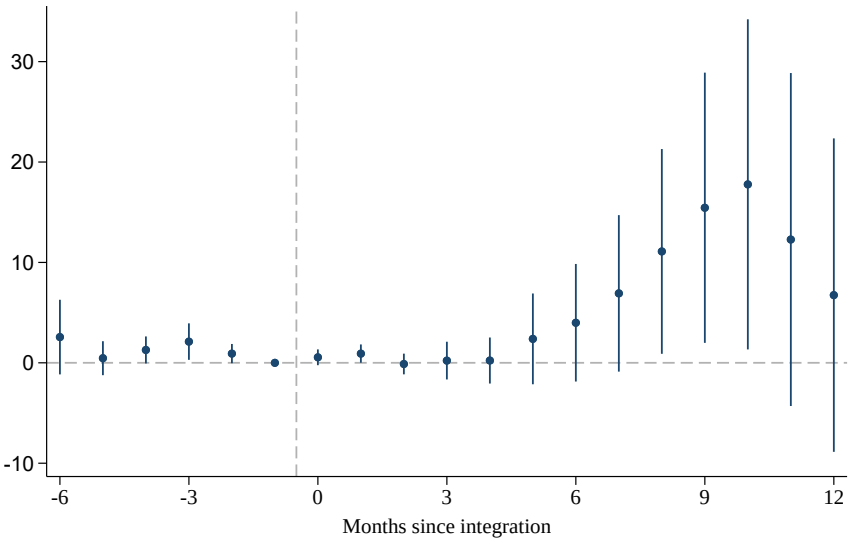
Notes: The blue and red dashed lines repeat those on Figure 6—i.e., they show the total value of transactions on UPI and a major closed-loop incumbent digital payments platform in the median state, indexed to 100 in the month before demonetization (October 2016). The solid blue line plots the same for cross-app UPI payments only. The inner (outer) blue shaded regions show the 25-75th (10-90th) percentiles across states.

Figure B.3: Placebo tests

(a) Repeating Figure 12a for random draws of P_d^+



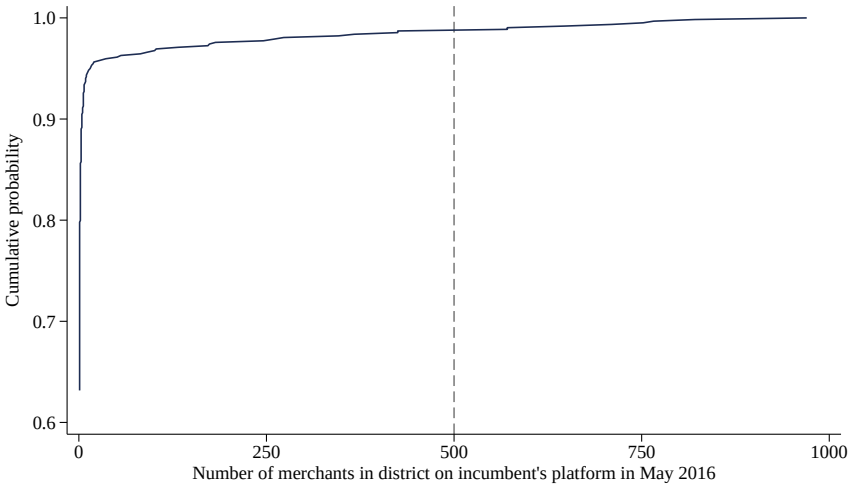
(b) Repeating Figure 12a for an alternative t_0 three months earlier



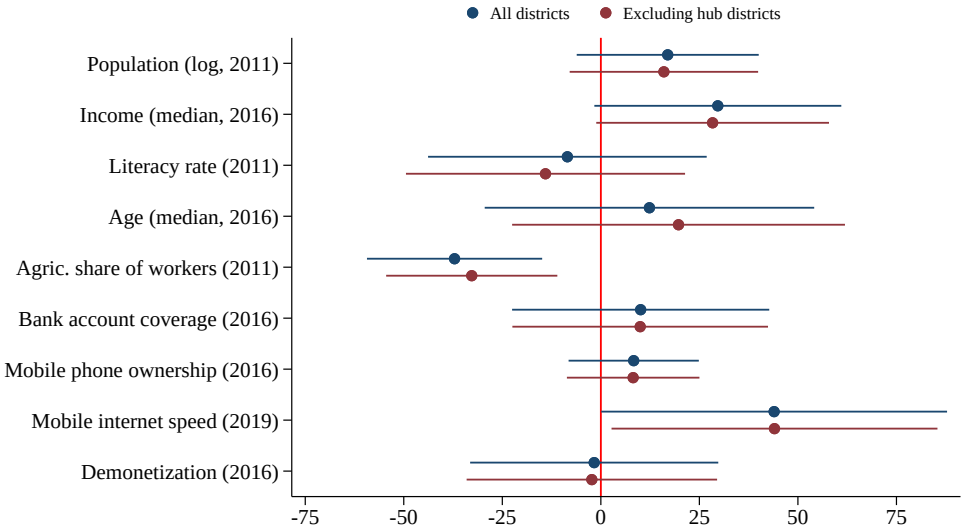
Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-P_d and low-P_d districts, based on specification 5, except changing either the distribution of P_d^+ or the timing of t_0, as described in Section 4.3.2. In the first panel, the shaded region depicts the range of estimated βs across 1000 random draws of P_d^+, while the line shows the median estimate. In the second panel, Figure 12a is repeated except setting an alternative t_0 three months earlier. Vertical lines show 95% confidence intervals.

Figure B.4: Hub districts

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



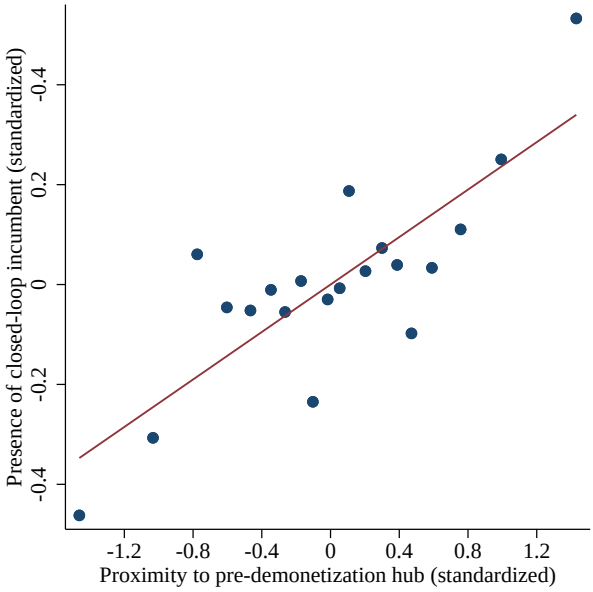
(b) Association with proximity to the incumbent's hubs



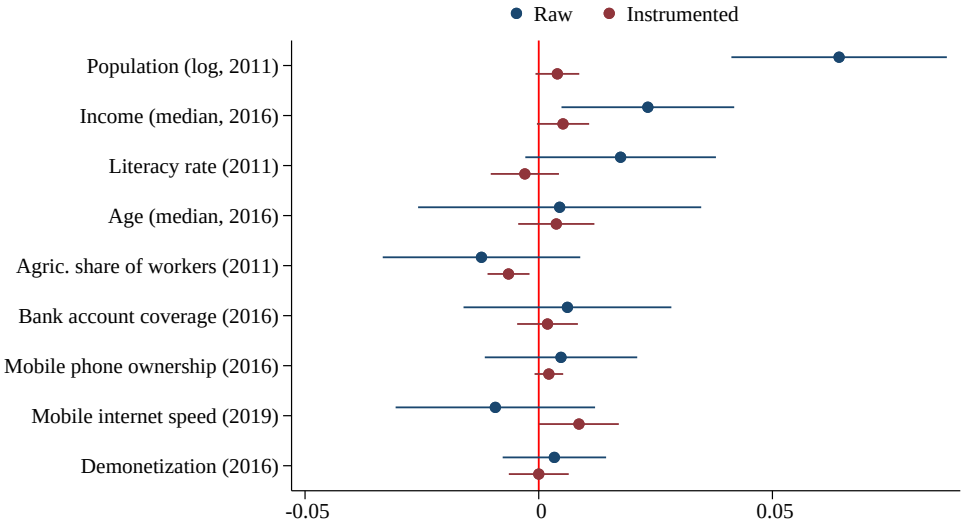
Notes: The first panel plots the cumulative distribution function of the number of merchants in each district that used the incumbent's platform in May 2016. The vertical line indicates the cutoff for defining a hub city. The second panel shows the correlation of various district characteristics with 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 B.5: Instrumenting incumbent presence P_d with proximity to its initial hubs H_d

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



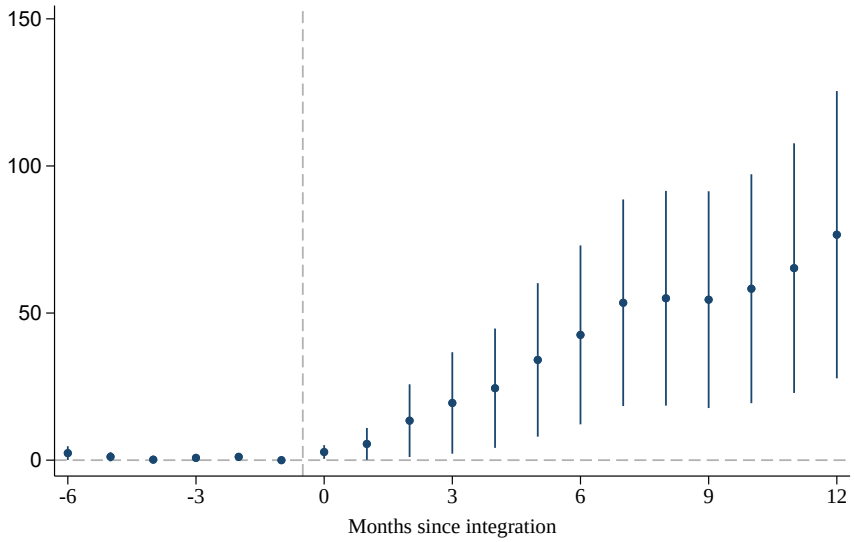
(b) Association with P_d



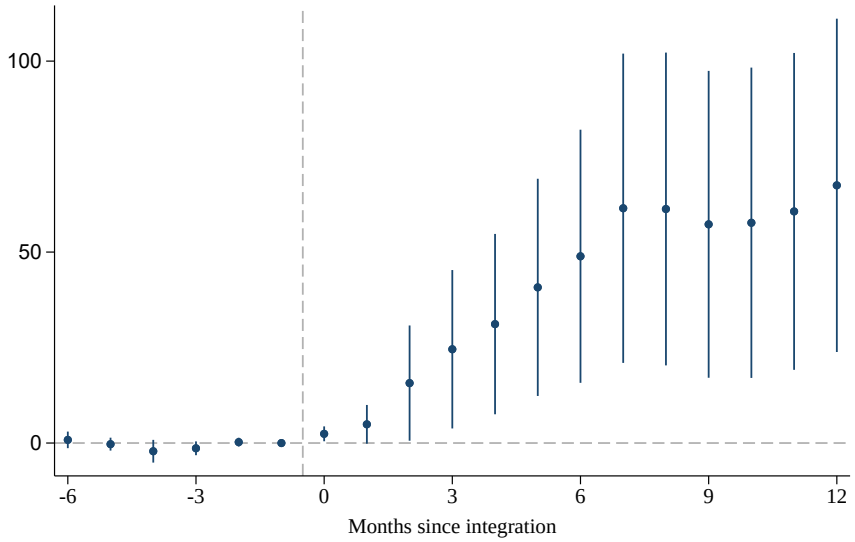
Notes: The first panel shows a binned scatter plot of the cross-sectional first stage relationship between H_d (on the x-axis) and P_d (on the y-axis), after residualizing each on state fixed effects and controlling for Z_d (the total value of digital payments across both platforms in each district in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

Figure B.6: Response dynamics of total digital payments adoption to platform integration, instrumenting with proximity to incumbent hub districts

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



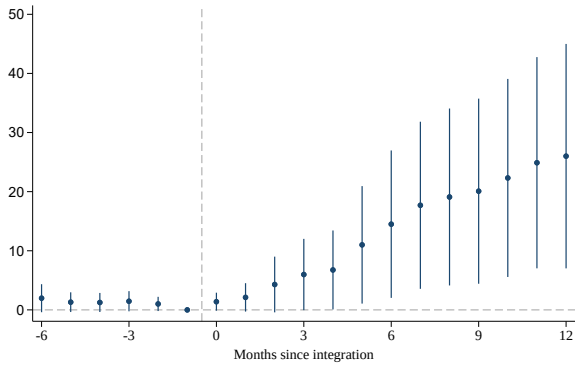
(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



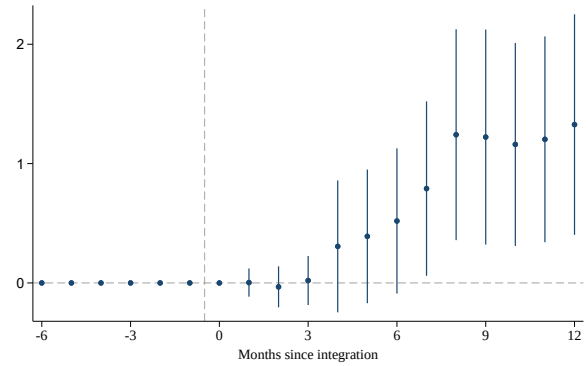
Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-P_d and low-P_d districts when instrumenting using proximity to incumbent hub districts H_d. The first panel normalizes total P2M transaction values relative to population, and the second panel normalizes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

Figure B.7: Response dynamics of digital payments adoption to platform integration, split by transaction participants' app choices, when instrumenting with proximity to incumbent hub districts

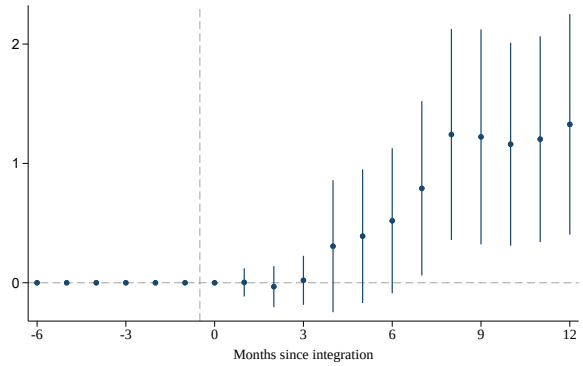
(a) Transactions between two users of the incumbent app (Rupees per capita)



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

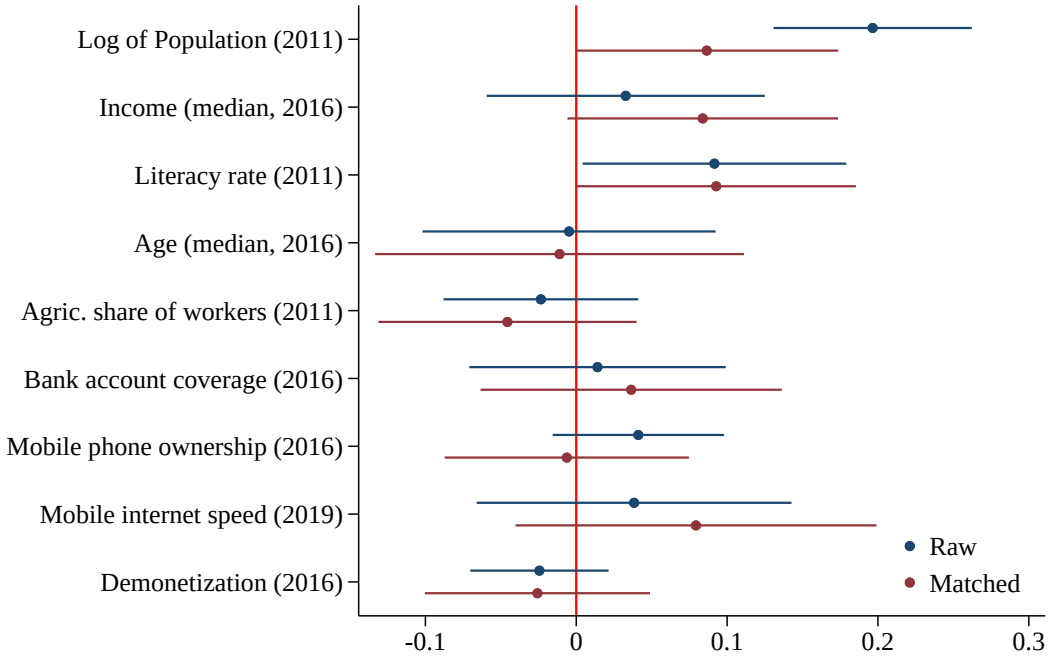


(c) Transactions between a user of the incumbent app and a user of another UPI app (Rupees per capita)



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

Figure B.8: Association of P_d^+, raw and matched

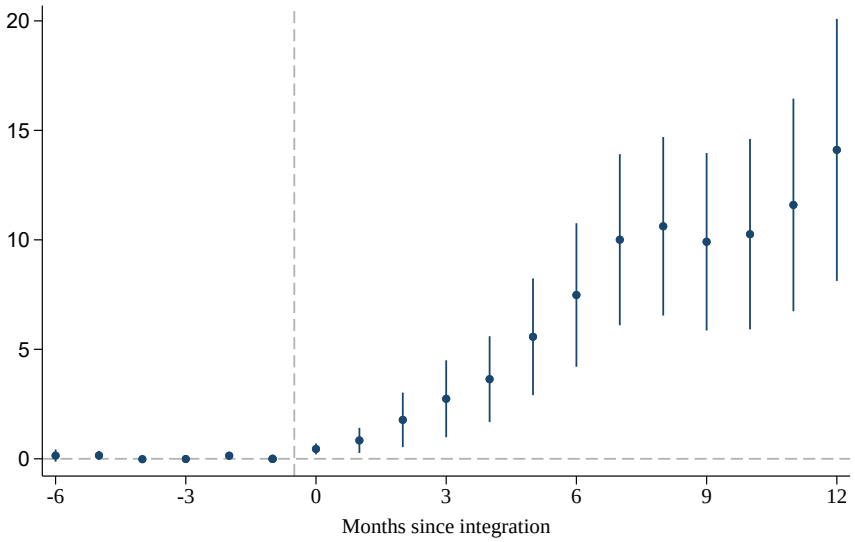


Observations: 521 / 474. R-squared: 0.406 / 0.398. State FEs, and SEs clustered by state.

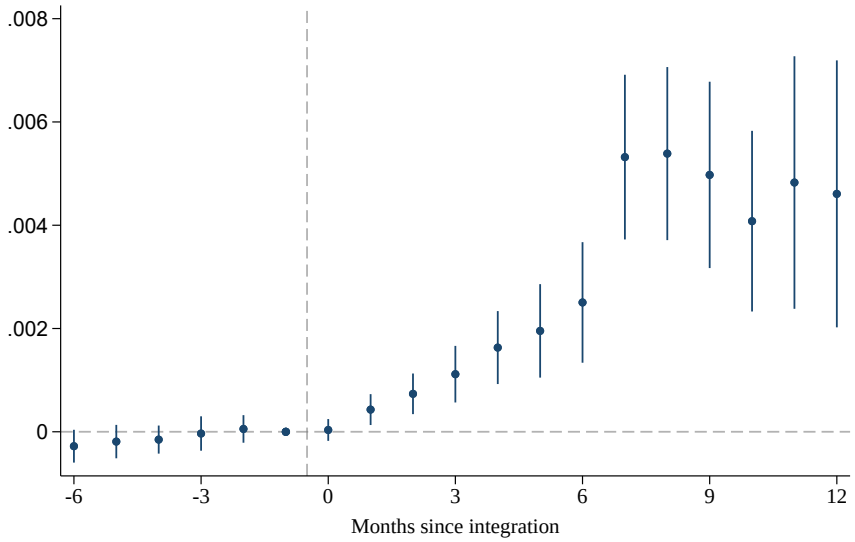
Notes: The figure plots the correlation of various district characteristics with P_d^+, both in its raw form and when districts are matched on log population. Specifically, the figure plots the coefficients from regressions of P_d—or the predicted value of P_d^+, when matching on log population—on a 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 B.9: Response dynamics of total digital payments adoption to platform integration, matching on log population

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



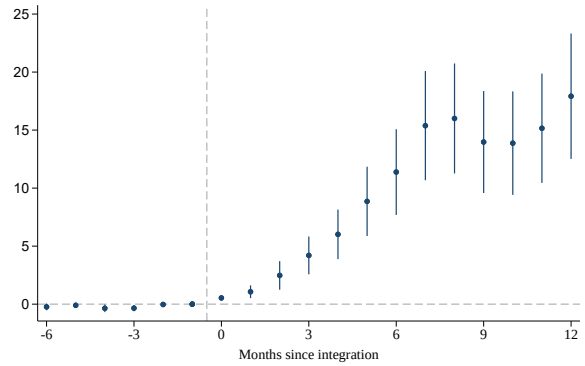
(b) Total P2M transaction value relative to cash withdrawals from ATMs (Rupees of digital payments per Rupee of cash withdrawn)



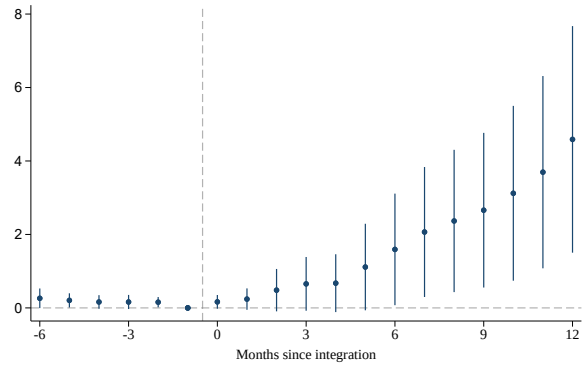
Notes: This figure plots the dynamics of the difference in total P2M transaction values between high-P_d and low-P_d districts when matching districts on log population. The first panel normalizes total P2M transaction values relative to population, and the second panel normalizes total P2M transaction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

Figure B.10: Response dynamics of digital payments adoption to platform integration, split by transaction participants' app choices, when matching on log population

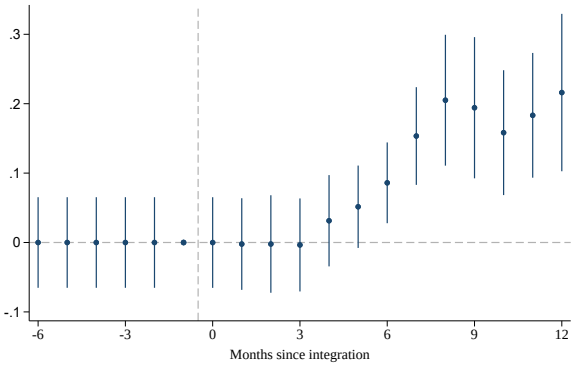
(a) Transactions between two users of the incumbent app (Rupees per capita)



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



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



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

Table B.1: Response of digital payments adoption to platform integration, when defining P_d^+ using only P2M transactions

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	7.183***	0.00217***	11.28***	0.0731**	1.417**
	(4.75)	(3.57)	(6.28)	(2.19)	(2.20)
District FE	✓	✓	✓	✓	✓
State-Time FE	✓	✓	✓	✓	✓
Baseline Total	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	9.118	0.007	1.936	0	14.365
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	11.274	0.019	9.046	0.395	3.178

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

Table B.2: Response of digital payments adoption to platform integration, when excluding districts in which $P_d > 0.5$.

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	5.380***	0.00251***	8.483***	0.0617**	0.993*
	(5.27)	(4.67)	(8.50)	(2.35)	(1.86)
District FE	✓	✓	✓	✓	✓
State-Time FE	✓	✓	✓	✓	✓
Baseline Total	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	5.452	0.006	1.643	0	7.638
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	11.022	0.019	9.023	0.391	3.147

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

Table B.3: Response of digital payments adoption (transaction volumes) to platform integration

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	0.0129***	0.00000317*	0.0217***	0.000133**	0.00101
	(5.48)	(1.84)	(5.90)	(2.45)	(1.15)
District FE	✓	✓	✓	✓	✓
State-Time FE	✓	✓	✓	✓	✓
Baseline Total	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	0.022	00	0.004	0	0.034
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	0.035	00	0.029	0.001	0.009

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

Table B.4: Response of digital payments adoption to platform integration, when winzorizing top 0.5% of districts by value.

	Total/pop	Total/cash	(Inc→Inc)/pop	(Inc↔Oth)/pop	(Oth→Oth)/pop
	(1)	(2)	(3)	(4)	(5)
$P_d^+ \times 1_{\{t>t_0\}}$	7.394***	0.00346***	11.10***	0.0837*	1.520**
	(3.95)	(5.55)	(4.98)	(1.71)	(1.97)
District FE	✓	✓	✓	✓	✓
State-Time FE	✓	✓	✓	✓	✓
Baseline Total	✓	✓	✓	✓	✓
N	10,868	10,867	10,868	10,868	10,868
Mean $y_{dt}(P_d^+ = 1, t = t_{-1})$	9.118	0.007	1.936	0	14.365
Mean $y_{dt}(P_d^+ = 0, t \geq t_0)$	11.434	0.019	9.338	0.417	3.178

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