Interoperability, Payment Substitution, and Household Financial Fragility *

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Abstract

This paper estimates the causal effect of the Central Reserve Bank of Peru's (BCRP) Retail Payments Interoperability Strategy on payment instrument choice and household financial fragility in Peru. Interoperability connected previously segmented digital-wallet networks and payment rails, reducing compatibility and coordination frictions that limit the effective use of digital payments. I combine quarterly microdata from Peru's National Household Survey (ENAHO) with administrative information to build a predetermined district-level exposure measure based on the relative pre-rollout presence of institutions that became interoperable across implementation phases. I exploit the staggered rollout and this territorial heterogeneity in a staggered-adoption difference-in-differences design following Callaway and Sant'Anna (2021), complemented with robustness checks and placebo tests. The results suggest a reallocation away from traditional instruments toward more digitized payment channels enabled by interoperability. In particular, I find a decline in cash use for everyday and recurring expenditures and a reduction in card use, alongside an increase in digital channel use (internet banking: +3.3 pp). In parallel, financial fragility falls by 3.5–3.8 pp, consistent with lower liquidity frictions and a greater ability to smooth shocks through timely transfers. The evidence is consistent with a technology channel, as more exposed districts experience a 7.5–7.9 pp increase in the probability of having prepaid mobile internet, in line with households acquiring the minimum connectivity needed to operate mobile payments. Effects concentrate in districts with higher pre-treatment connectivity, human capital, and formality, indicating that interoperability can accelerate the transition away from cash, although its reach remains constrained by persistent structural barriers.

JEL codes: E42, E41, D14, G21, O33, L86, D83.

Keywords: Payment systems; interoperability; digital wallets; demand for cash; retail payments; household finance; mobile internet; network externalities.

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1 Introduction

How retail payments are organized shapes the cost of day-to-day transactions, the fluidity of commerce, and households' effective access to basic financial services. Yet even in economies where payment technologies diffuse rapidly, the transition toward digital instruments is not automatic. International evidence documents that cash often persists and that substitution away from it tends to be gradual (Bech et al., 2018; Von Kalckreuth et al., 2014; Rogoff, 2015). A natural reading is that the challenge is not purely technological but also one of market organization, because the adoption and use of digital payments face frictions in compatibility, coordination, and acceptance.

These frictions are especially relevant in payment markets with network externalities and a two-sided structure. Consumers' incentives to adopt a payment instrument depend on its acceptance by merchants and other users, while merchants' incentives to invest in acceptance depend on the expected mass of adopters. Recent empirical evidence shows that shocks that expand adoption on one side of the market can spill over to the other and shift the usage equilibrium (Higgins, 2024). In this context, interoperability—understood as the integration of previously segmented networks—emerges as a natural policy tool to reduce compatibility and coordination costs (Bianchi et al., 2023).

This paper studies the Retail Payments Interoperability Strategy promoted by the Central Reserve Bank of Peru (BCRP), which aimed to integrate previously segmented payment networks and digital wallets and to reduce frictions in digital transfers and payments (García et al., 2024). The policy was rolled out in phases and implemented in a context where cash use coexisted with a growing—yet geographically uneven—adoption of digital solutions. At the same time, connectivity and financial access exhibited persistent gaps. This setting provides meaningful variation to assess whether interoperability accelerates the transition toward digital payments and displaces traditional instruments such as cash and cards.

The paper addresses four questions. First, does interoperability reduce cash use, both within expenditure categories and in broader margins of cash reliance? Second, does it affect the use of other instruments, particularly cards and digital channels? Third, does it improve outcomes related to household financial well-being, in particular household financial fragility, which I define as a limited ability to self-insure against short-run shocks because liquid buffers and readily accessible funds are scarce, so that even moderate shocks force costly adjustments such as dissaving or borrowing (Lusardi et al., 2011; Kaplan et al., 2014)? Fourth, does connectivity operate as a mechanism that facilitates adoption and use of digital rails?[1]

To identify causal effects, I exploit two sources of variation. The first comes from the staggered timing of the phase-based rollout. The second comes from predetermined cross-district heterogeneity in potential exposure to interoperability, measured using pre-treatment information on the relative local presence of the institutions that later become interoperable. In the baseline specification, I define a district-level absorbing treatment dummy equal to one from the first quarter in which a district is exposed to a phase of the strategy, and zero beforehand. A district is considered exposed when the pre-treatment coexistence of institutions belonging to the blocks that become interoperable in a given phase implies positive interoperability potential. I proxy this coexistence using district-level deposits measured before the rollout, and in robustness exercises I augment this measure with local financial-access infrastructure. Leveraging this variation, I estimate a staggered-adoption difference-in-differences design following Callaway and Sant'Anna (2021) and report robustness using alternative estimators (Sun and Abraham, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Borusyak et al., 2024; de Chaisemartin and D'Haultfœuille, 2024), as well as placebo tests.

The results indicate economically meaningful shifts in payment choices. In more exposed districts, cash use declines in everyday and recurring categories, especially utilities and cooking fuels, while broader reliance on cash also falls, as reflected in a 2.9 pp decline in cash-use intensity and a 2.3 pp decline in the probability of using only cash across the nine main spending categories. Card use also declines, including in utilities and cooking fuels. This pattern suggests that adjustment is not a simple "cash $\rightarrow$ card" substitution, but a shift toward interoperable account-to-account transfers and wallet-based payments with lower coordination and acceptance frictions. In parallel, use of the comparable internet-banking channel rises by 3.3 pp relative to a pre-treatment mean of 6.0%, and a broader proxy combining internet banking and digital wallets under the expanded 2024 ENAHO questionnaire rises by 5.0 pp, although this latter estimate should be interpreted as complementary rather than directly comparable to the baseline IB outcome. By contrast, I find no robust effects on the extensive margin of financial inclusion.

I also find a decline in household financial fragility of 3.5–3.8 pp. While the channel cannot be separately identified, the pattern is consistent with lower short-run liquidity frictions and improved access to funds when shocks hit.

[1] A key measurement limitation is that interoperable transactions are not directly observed at the individual level. I therefore infer substitution from changes in cash and card use, together with movements in proxies for the use of digital channels.

The evidence is also consistent with a technological mechanism. In more exposed districts, prepaid mobile internet access increases by 7.5–7.9 pp, a pattern consistent with households acquiring the minimum connectivity needed to operate mobile payments.

2 Literature review

This paper sits at the intersection of three literatures: (i) cash demand and payment choice; (ii) payment systems as two-sided markets with compatibility frictions; and (iii) welfare effects of digital payments.

2.1 Cash demand and the choice of payment instruments

A first reason cash persists is that payment choice depends not only on available technology, but also on the cost of accessing liquidity and on the attributes users attach to cash. Lower withdrawal costs and easier access to liquidity reduce transaction demand for cash, yet cash continues to be valued for its convenience and broad acceptance, so displacement is neither frictionless nor uniform across users and transactions (Alvarez and Lippi, 2009; Rogoff, 2015). Consistent with this view, cross-country evidence shows that electronic payments often expand alongside cash rather than fully replacing it, implying gradual and incomplete substitution (Bech et al., 2018).

Micro evidence highlights that payment choice reflects systematic two-stage decisions. Individuals first adopt instruments (e.g., cards) and then choose the means of payment transaction by transaction based on relative costs, perceived attributes, and contextual features (Von Kalckreuth et al., 2014). This distinction is central for interpreting policies that promote digitalization.

2.2 Digital payment adoption, network externalities, and two-sided markets

The economics of digital payments is naturally framed through two-sided markets in which platforms intermediate interactions between consumers and merchants. In this setting, cross-side network externalities imply that adoption and usage depend not only on the level of prices, but also on their structure across sides of the market (Rochet and Tirole, 2003, 2006). This framework highlights a central tension in retail payments. Network effects create forces toward concentration, while incompatibility across platforms can fragment the market by narrowing the set of feasible transactions. In this setting, compatibility and interoperability are economically relevant because they lower coordination costs, broaden effective acceptance, and reshape the equilibrium path of adoption and use (Rysman, 2009; Chiu and Wong, 2022).

Interventions that expand consumer-side adoption can induce merchant acceptance and further user adoption through indirect network effects, while shocks that reduce reliance on cash can generate persistent increases in digital-payment use together with higher spending (Higgins, 2024; Agarwal et al., 2024). More directly, the gains from interoperability depend on how networks are connected and on the frictions surrounding the payment ecosystem. When integration occurs in settings with greater ex ante fragmentation, total digital-payment use tends to rise more strongly (Bianchi et al., 2023; Copestake et al., 2025). This logic suggests that the marginal effects of interoperability are shaped by initial ecosystem structure and motivates the use of a predetermined exposure measure based on the relative presence of participants that later become interoperable.

For Peru, the available evidence points to persistent barriers to the diffusion of digital financial services and to a strong concentration of digital-payment use in better-connected and more advantaged segments and locations. In particular, digital-payment use remains more prevalent among urban, connected, more educated, and formally employed individuals, and in districts with greater financial-system presence (Sotomayor et al., 2018; Robles et al., 2024; Aurazo and Vega, 2021). Related work also emphasizes the relevance of effective access, user experience, pricing, and merchant acceptance for digital-payment adoption in Peru (Chong and Ventura, 2024; Andia et al., 2025; Ancalle and Garcia, 2024; Azevedo et al., 2025).

These findings also clarify why architecture matters for interpretation and external validity. As Aurazo and Gasmi (2024) emphasize, there is no single successful model of digital payments across emerging economies. Unlike Peru, where interoperability was introduced ex post by connecting incumbent private and bank-led schemes, Brazil's Pix was launched as a centrally coordinated public infrastructure, while India's UPI was developed as an open public digital infrastructure (Duarte et al., 2022; Sampaio and Ornelas, 2024; Alok et al., 2024; Mahadevan and Srinivasan, 2025; World Bank, 2021). What remains largely missing is causal evidence on whether connecting fragmented incumbent-led payment networks shifts payment use away from cash and cards, and whether such substitution translates into improvements in short-run household financial resilience.

2.3 Digital payments and financial well-being

Digital payments can improve financial well-being primarily by easing short-run liquidity constraints, strengthening informal risk-sharing, and making consumption less sensitive to idiosyncratic shocks (Jack and Suri, 2014; Riley, 2018). Consistent with this mechanism, greater digital-payment use can raise spending even after cash availability recovers (Agarwal et al., 2024). Any effect through the generation of verifiable transaction histories and improved access to formal credit is likely a complementary, longer-run margin (Alok et al., 2024; Carriere-Swallow et al., 2021).

This literature also provides a natural link to household financial fragility. If many households are unable to absorb even moderate short-run shocks, the relevant question is not only whether digital payments expand financial-service adoption, but whether they ease the liquidity constraints that force households to dissave or borrow in response to temporary shortfalls (Lusardi et al., 2011). For Peru, the available evidence suggests that effective use depends on the interaction between access and trust, since lowering access costs alone does not ensure active financial behavior (Gertler et al., 2016).

3 The Peruvian context: the Retail Payments Interoperability Strategy

By 2022, roughly 89% of Peruvians reported using cash to make payments, and 56% reported using only cash (Ipsos Perú, 2022). García et al. (2024) emphasize that this heavy reliance on cash reflects not only preferences for anonymity and operational simplicity, but also limited physical access to financial infrastructure (branches, ATMs, banking agents, and POS terminals) outside major cities, as well as perceived and actual costs of using digital instruments in low-income and highly informal settings (BCRP, 2023).

On the supply side of payment infrastructure, the country had been moving, although incompletely, towards a more digital ecosystem. The National Payment System comprised the real-time gross settlement system (LBTR) for large-value payments and the electronic clearinghouse (CCE) for retail interbank transfers, complemented by card payment agreements (APT) and electronic money payment agreements (APDE), such as BIM (BCRP, 2023). Within strictly retail payments, the most relevant digital instruments were: (i) debit and credit card payments at merchants; (ii) intra- and interbank transfers via internet banking, mobile banking, ATMs, and banking agents; and (iii) digital wallets linked to bank accounts (Yape, Plin) and to e-money (BIM) (García et al., 2024).

The BCRP's Digital Payments Indicator (IPD)[2] reports sustained growth in the number of digital transactions per capita between 2015 and 2022, rising from 29 to 174 digital payments per capita, with a pronounced acceleration starting with the COVID-19 shock in 2020. International comparisons, however, indicate that this level still lagged behind regional economies such as Brazil or Costa Rica, suggesting that digitalization was advancing but from a still-limited base and one heavily concentrated among urban, higher-income segments with better access to financial and telecommunications infrastructure (BCRP, 2023).

Looking at the composition of digital payments prior to interoperability, the ecosystem appears fragmented and strongly intrabank. In December 2022, intrabank transfers accounted for about 61% of the number and 79% of the value of non-cash retail payments, indicating that a large share of transactions were processed within each institution rather than over shared infrastructures such as the CCE (Vásquez, 2024). Digital wallets represented roughly 47% of retail payments by number, but only about 4% of total value, reflecting their predominant use for small-ticket transactions (García et al., 2024).

The main retail payment rails operated as "closed loops." Yape and Plin, which by 2022 concentrated most digital wallet users, enabled payments only within each ecosystem: a Yape user could not send funds directly to a Plin user, and vice versa.[3] Both wallets processed transactions over card infrastructure (Visa Direct) and did not interoperate with the CCE's instant transfers (García et al., 2024). Similarly, the card-payment rail operated separately from the account-to-account transfer rail, so that a user of instant transfers could not send funds from mobile banking to a digital-wallet user using the recipient's phone number or QR code (García et al., 2024). In the same vein, the APDE BIM functioned as a closed-loop e-money scheme without effective interconnection to bank accounts or bank-based wallets, fragmenting the user experience and limiting network externalities in digital payments, in addition to its limited reach and interconnection (Vega and Vásquez, 2022).

Fragmentation also manifested in the use of QR codes and in barriers to entry for new payment service providers. Before interoperability, QR codes issued by one provider (e.g., Yape) were not necessarily readable by other wallets, forcing some merchants to display multiple QR codes

[2] It includes client operations of LBTR participants and retail digital payments: credit and instant transfers via the CCE, intra- and interbank transfers via wallets and other digital channels, payment cards, direct debit, and e-money operations (BIM) (BCRP, 2025).

[3] By end-2022, Yape had 11.8 million users, while Plin had 8.6 million users (Castillo et al., 2023).

and raising adoption costs (García et al., 2024). In addition, payments fintechs faced obstacles to accessing bank accounts, the CCE, and transactional data, which constrained the supply of innovative solutions and reinforced concentration among a few incumbent actors (Vega and Vásquez, 2022; García et al., 2024).

3.1 The BCRP Interoperability Strategy

In response to the frictions described above, the BCRP introduced in 2022 a strategy designed to accelerate the widespread adoption of retail digital payments in Peru. The central objective was to enable any person to pay digitally regardless of the wallet, bank, or institution holding their funds. In economic terms, interoperability can be viewed as a tool to internalize network externalities: by connecting rails and payment agreements that were previously isolated, it expands each provider's potential user base and reduces the value of continuing to rely on cash as the dominant payment instrument (Castillo et al., 2023; García et al., 2024).

Additional objectives included: (i) increasing convenience for end users by simplifying the payment experience and reducing time and monetary costs; (ii) improving payment-system efficiency by promoting the use of shared infrastructures such as the CCE for low-value payments; (iii) strengthening competition in the retail payments market by leveling the playing field between large and small institutions and including microfinance institutions and new providers; (iv) fostering financial inclusion by leveraging digital payments as an entry point into other formal financial services; and (v) laying the groundwork for further innovation in payment services and, eventually, for the international interconnection of payment systems (García et al., 2024).

In 2022, through Circular No. 024-2022-BCRP, the BCRP launched the Retail Payments Interoperability Strategy, implemented in four phases (see Figure A.1).[4]

3.1.1 Phase 1. Interoperability between Yape and Plin (March 2023)

Phase 1 centered on interoperability between the digital-wallet payment agreements managed by incumbent banks: the Yape payment agreement—led by Banco de Crédito del Perú (BCP)—and the Plin payment agreement—led by BBVA, Scotiabank, and Interbank (García et al., 2024). This phase required that Yape users be able to send and receive payments to and from Plin users, and

[4] Circular No. 0024-2022-BCRP, "Regulation on Interoperability of Payment Services provided by Payment Service Providers, Payment Agreements and Payment Systems," Central Reserve Bank of Peru (BCRP). Available at: https://www.bcrp.gob.pe/docs/Transparencia/Normas-Legales/Circulares/2022/circular-0024-2022-bcrp.pdf.

vice versa, using either a phone number or a QR code, while keeping the underlying card infrastructure and payment agreements. In practice, this entailed interconnecting alias directories (phone numbers) and defining operational and settlement rules for P2P transactions across wallets, under BCRP supervision and with support from acquirers and technology processors.[5] The regulatory framework set March 31, 2023 as the deadline for interconnecting the main digital wallets (BCRP, 2022). Production began with a controlled group in the last week of March—including testing with the BCRP team—and the mass rollout to users was completed gradually between April 1 and May 8 (see Figure A.2 for further implementation details for Phase 1).

Early outcomes indicate that this phase quickly translated into a high volume of interoperable wallet-to-wallet transactions. By March 2024, interoperable transactions associated with Phase 1 exceeded 2.5 million operations per day, roughly 70 million transactions per month, with a clear predominance of payments initiated from Plin to Yape (García et al., 2024). By March 2025, interoperable transactions reached 125 million (García et al., 2025), indicating that wallet interoperability had become a central rail for everyday P2P payments in Peru.

3.1.2 Phase 2. Instant transfers and interoperable QR codes (September 2023)

Phase 2 extended interoperability beyond wallets to include account-to-account instant transfers (TIN) and QR-code payments. This phase began in September 2023, enabling interoperability between digital wallets and instant-transfer services offered by banks, cajas, and finance companies through their mobile-banking apps using the user's phone number, and introducing interoperability among QR codes issued by different providers (Fernández and García, 2024).[6]

Phase 2 generalized the use of aliases for the Interbank Account Code (CCI), which are simplified identifiers—typically linked to the user's phone number—used in lieu of the full CCI in the transaction. This mechanism allows users to receive instant transfers from any institution without revealing full bank-account details (García et al., 2025). In addition, the policy leveraged the

[5] A concise summary of the phases and the main actors is provided in García et al. (2025). Table B.1 reports the list of participating institutions by phase and period.

[6] The Interoperability Strategy initially set June 30, 2023 as the deadline for entities offering instant payment functionalities, instant transfers, and QR-code payments to move interoperable services into production (BCRP, 2022). However, to ensure operational security and stability during implementation and to formally incorporate technology providers into the scheme, the BCRP Board modified these deadlines through Circular No. 0013-2023-BCRP, extending the maximum go-live date to September 13, 2023, and to December 31, 2023 for entities that did not yet offer instant transfers (Circular No. 0013-2023-BCRP, "Amends Circular No. 0024-2022-BCRP approving the Interoperability Strategy of Payment Services provided by Payment Service Providers, Payment Agreements and Payment Systems," BCRP. Available at: https://www.bcrp.gob.pe/docs/Transparencia/Normas-Legales/Circulares/2023/circular-0013-2023-bcrp.pdf. See also the annex: https://www.bcrp.gob.pe/docs/Transparencia/Normas-Legales/Circulares/2023/circular-0013-2023-bcrp-anexo.pdf.).

QR Code Registry and set technical parameters so that codes generated by acquirers and wallets could be read by any participating application, thereby reducing the need for multiple QR codes per merchant and lowering coordination costs for small businesses.[7]

Following Phase 2, instant transfers through the CCE expanded rapidly. Between December 2023 and December 2024, monthly operations rose from 1.5 to 18.2 million, and transacted value increased from S/ 0.2 to S/ 2.3 billion (García et al., 2025). In parallel, QR payments through acquirers (Niubiz, Izipay) grew alongside a decline in average ticket size, consistent with rising adoption for low-value purchases at physical merchants and small businesses (García et al., 2025).

3.1.3 Phases 3 and 4. Integrating e-money (December 2023) and open payments

Phase 3 sought to incorporate e-money issuers into the interoperable scheme, in particular the BIM payment agreement, by enabling direct or sponsored access to the CCE and the LBTR (Vásquez, 2025). Compartamos Banco played a central role as BIM's sponsoring institution in connecting it to the interoperable infrastructure, while other e-money issuers have gradually adopted the new scheme. For this study, I do not construct a phase-specific district-level exposure measure for Phase 3, as I lack consistent information to assign additional territorial variation relative to earlier phases. Moreover, available evidence suggests that its relative scale has been limited. As of June 2025, BCRP reports attribute 70.7% of interoperable transactions to Phase 1, 27.6% to Phase 2, and 1.7% to Phase 3 (García et al., 2025). This composition is consistent with Phase 3 not yet being a quantitatively important driver of interoperability, and the analysis therefore focuses on the effects of Phases 1 and 2.

Finally, Phase 4 envisages an *open payments* framework based on payment initiators and standardized APIs, with the goal of extending interoperability to new providers—such as fintechs, bigtechs, or telecommunications operators—under user consent. This stage remains under regulatory and technical design and is outside the analysis period (García et al., 2025).

[7] The Registry of QR Code and Digital Wallet Providers (Registro QR) was established by the Regulation on QR-code payment services, approved through Circular No. 0003-2020-BCRP. Available at: https://www.bcrp.gob.pe/docs/Transparencia/Normas-Legales/Circulares/2020/circular-0003-2020-bcrp.pdf.

4 Data and descriptive statistics

4.1 National Household Survey (ENAHO)

The main data source is the National Household Survey on Living Conditions and Poverty (ENAHO) conducted by Peru's National Institute of Statistics and Informatics (INEI). ENAHO is nationally representative, has been fielded since 2003, and covers both urban and rural areas in all departments and in Callao. For our analysis, I use quarterly microdata for the 2022–2024 period[8], which allow the construction of comparable individual- and household-level indicators of payment-method use and socioeconomic conditions.[9]

Following Aurazo and Vega (2021), I exploit ENAHO's employment module, which since 2015 has asked adults (18 years or older) about financial inclusion and the instrument used to pay for purchases in specific categories of goods and services. In particular, the questionnaire records the payment method used (e.g., cash, debit card, credit card, and mobile/internet banking, among others) for nine consumption categories, capturing primarily P2B (person-to-business) decisions rather than P2P (person-to-person) transactions. Consistent with this structure, I construct binary indicators of cash use and card use by expenditure category (e.g., food, utilities, fuels, clothing, etc.), as well as aggregate measures of internet-banking/digital-payment use. I also construct two aggregate measures of cash use. The first is a cash-use-intensity measure, defined as the ratio between the number of main spending categories in which the individual reports using cash and the total number of main categories. The second is a dummy for cash-only use, equal to one if the individual reports using only cash in all nine main spending categories.[10]

A key measurement issue concerns the digital-channel outcomes. In 2024, INEI changed the wording of the item associated with internet banking by explicitly incorporating additional channels, including mobile banking and ATM-based operations. This change breaks strict intertemporal comparability with the pre-2024 item. To preserve comparability, all estimates for the Internet Banking (IB) outcome are restricted to the 2022–2023 sample. I also report a broader proxy for digital-channel use, denoted IB + Digital Wallets, which combines reported use of internet bank-

[8] The baseline analysis excludes pre-2022 data to avoid introducing the COVID-19 pandemic as a confounding factor. For the placebo analysis, I use data from 2021Q3 through 2023Q1 to test for the absence of spurious effects around the onset of treatment while keeping pandemic exposure limited (see Section 8 for details).

[9] According to INEI technical documentation, ENAHO relies on a probabilistic, stratified, multi-stage sample design. It supports annual inference domains and, at least for national, urban, and rural aggregates, quarterly inference.

[10] Respondents can report more than one instrument for a given category. The survey does not provide intensity (number of payments) nor transaction amounts, so these variables capture extensive-margin adoption/use.

ing with digital-wallet use under the expanded 2024 questionnaire.[11] This variable is informative about broader digital-payment adoption, but it should not be interpreted as a harmonized extension of the IB series over the full sample period. In particular, because digital-wallet use is not separately observed in a comparable way before 2024, the data do not allow identification of a stand-alone causal effect on wallet use. Accordingly, I treat IB as the main comparable digital-channel outcome and IB + Digital Wallets as supplementary evidence on broader digital-payment adoption under the revised 2024 instrument.

To proxy short-run financial fragility, I use ENAHO's module on governance, democracy, and transparency, drawing on data for the 2022–2025 period.[12] This module asks about the household's current economic situation (whether it is able to save, whether it barely balances income and expenditures, or whether it is forced to draw down savings or to borrow). Based on this question, I construct a financial-fragility dummy equal to one if the individual reports that the household currently *(i)* must spend down savings or *(ii)* must borrow, and zero otherwise.[13] I also define an individual-level measure of financial inclusion equal to one if the individual reports having an account and/or a card (debit or credit), and zero otherwise.

In addition, because digital infrastructure is a key determinant of electronic-payment adoption, the baseline analysis incorporates measures of internet access: fixed internet and mobile internet (prepaid and postpaid). As a complement, I construct a set of connectivity variables used exclusively to explore effect heterogeneity across districts' initial (pre-interoperability) conditions, including internet service use, mobile phone ownership, and having one's own phone, among others (see Chapter 9 for details).[14]

Finally, I include a broad set of socioeconomic covariates constructed from standard ENAHO modules[15]: (i) education; (ii) monetary poverty; and (iii) labor informality and receipt of social program transfers (Juntos and Pensión 65).[16]

[11] In practice, this proxy is a dummy equal to one if the individual reports using internet banking and/or digital wallets, and zero otherwise.

[12] Unlike the employment and income module, INEI releases the governance module on a quarterly basis, so publicly available data extend through 2025Q4.

[13] This construction captures an operational margin closely related to liquidity constraints: the need to dis-save/borrow to sustain current expenditures.

[14] This approach allows testing whether the impact of interoperability differs systematically between districts with higher versus lower pre-existing digital penetration, consistent with the idea that new-technology adoption may depend on access constraints and on reaching a critical mass of users.

[15] I primarily rely on the education, summary, and employment and income modules.

[16] As with the connectivity variables, these socioeconomic characteristics are used primarily to examine heterogeneity across districts' initial conditions. For instance, I study whether interoperability generated larger impacts in districts with higher human capital, lower poverty, or lower informality prior to implementation, or whether effects were relatively larger in more constrained territories.

Table 1: Descriptive statistics

Variable	Mean	SD	Min	Max	N
Panel A: Cash use					
Groceries	0.92	0.28	0	1	233,196
Ready-to-eat food	0.91	0.28	0	1	233,196
Laundry	0.90	0.30	0	1	233,196
Utilities	0.86	0.35	0	1	233,196
Cooking fuels	0.79	0.41	0	1	233,196
Personal hygiene	0.91	0.28	0	1	233,196
Clothing and footwear	0.85	0.36	0	1	233,196
Furniture and appliances	0.29	0.46	0	1	233,196
Household appliances	0.11	0.31	0	1	233,196
Other	0.87	0.34	0	1	233,196
Cash use intensity	0.73	0.22	0	1	233,196
Uses only cash	0.07	0.26	0	1	233,196
Panel B: Card use					
Groceries	0.04	0.20	0	1	233,196
Ready-to-eat food	0.04	0.19	0	1	233,196
Laundry	0.04	0.19	0	1	233,196
Utilities	0.02	0.15	0	1	233,196
Cooking fuels	0.01	0.11	0	1	233,196
Personal hygiene	0.04	0.18	0	1	233,196
Clothing and footwear	0.04	0.20	0	1	233,196
Furniture and appliances	0.01	0.10	0	1	233,196
Household appliances	0.01	0.10	0	1	233,196
Other	0.02	0.14	0	1	233,196
Card use intensity	0.03	0.12	0	1	233,196
Uses only cards	0.00	0.03	0	1	233,196
Panel C: Financial inclusion, fragility, internet banking, and digital payments					
Financial inclusion	0.52	0.50	0	1	233,196
Financial fragility	0.19	0.39	0	1	124,222
Internet banking use	0.06	0.25	0	1	155,995
Internet banking and digital payments	0.13	0.33	0	1	233,196
Panel D: Internet connectivity and mobile phone					
Fixed internet connection	0.30	0.46	0	1	142,380
Postpaid mobile internet connection	0.52	0.50	0	1	141,268
Prepaid mobile internet connection	0.68	0.47	0	1	141,268
Internet use	0.68	0.47	0	1	233,126
Mobile phone access	0.96	0.21	0	1	233,215
Own mobile phone	0.83	0.38	0	1	233,127
Panel E: Socioeconomic variables					
Age 18–24	0.15	0.35	0	1	233,196
Age 25–40	0.29	0.45	0	1	233,196
Age 41–64	0.39	0.49	0	1	233,196
Age 65+	0.17	0.38	0	1	233,196
Elementary education	0.31	0.46	0	1	233,127
High school education	0.38	0.48	0	1	233,127
Technical education (non-university)	0.14	0.35	0	1	233,127
University education	0.17	0.38	0	1	233,127
Poverty	0.22	0.41	0	1	233,215
Informal employment	0.78	0.42	0	1	174,417
Urban	0.68	0.47	0	1	233,196
Female	0.52	0.50	0	1	233,196
Juntos transfer income	0.05	0.22	0	1	233,196
Pension 65 transfer income	0.05	0.22	0	1	233,196

Note: The descriptive statistics correspond to the 2022–2024 period for all variables, except financial fragility, which is constructed using data available through 2025. All variables in the table are dummies equal to one if the condition holds and zero otherwise, except for cash-use intensity and card-use intensity, which are defined as the share of the nine main spending categories in which the individual reports using cash or a card, respectively. Cash-only use and card-only use are dummies equal to one if the individual reports using only cash or only cards, respectively, in all nine main spending categories.

4.2 Superintendency of Banking, Insurance and Private Pension Funds (SBS)

4.2.1 Deposits by branch and institution

I complement ENAHO with administrative data from Peru's financial supervisor (SBS). Specifically, I use the reports on Direct Credit and Deposits by Branch, available in the Financial System Statistics section of the SBS website.[17] These reports provide balances at the branch and institution level, allowing me to observe simultaneously (i) the local mass of formal savings mobilized in each territory and (ii) its composition by institution, an input that is crucial to proxy each district's exposure to the interoperability strategy.

For the empirical design, I use only two cross-sections (December 2022 and March 2023) of total deposits.[18] The December 2022 cross-section is the main *pre-treatment* measurement because it precedes the interoperability rollout and supports constructing a predetermined exposure measure based on the relative local presence of participating institutions in each phase. The March 2023 cross-section is used as a robustness exercise to assess the sensitivity of results to an alternative exposure measurement taken close to the start of the rollout.

4.2.2 ATMs and banking agents

To proxy local financial infrastructure beyond the presence of branches, I use SBS information on the number of automated teller machines (ATMs) and banking agents/correspondents by institution–district.[19]

As part of the empirical analysis, I build this dataset for December 2022 to construct an alternative exposure measure based on financial-access infrastructure (ATMs and banking agents).[20] This

[17] These series are constructed from information submitted by supervised institutions through annexes and reports from the Accounting Manual. See https://www.sbs.gob.pe/normativa-y-estandares/normativa/normativa-sbs/plan-de-cuentas/planes-de-cuenta-del-sistema-financiero/informacion-complementaria-de-manual-de-contabilidad. The statistical information is available at https://www.sbs.gob.pe/estadisticas-y-publicaciones/estadisticas-/sistema-financiero.

[18] Under SBS definitions, *total deposits* correspond to the sum of demand, savings, time, and CTS deposits. Monetary variables are reported in thousands of soles, converting foreign currency at the month-end accounting exchange rate.

[19] In SBS regulation, these service points are classified as *complementary channels of customer service* distinct from branches, including (i) banking agents, (ii) basic-operations establishments, and (iii) ATMs. For expositional convenience, I use "banking agents" as a synonym for "correspondent agents." For the analysis, I include only the number of ATMs and banking agents. SBS produces this information from regulatory reports submitted by supervised institutions. Report No. 30 of the SBS Accounting Manual records, among other fields, the UBIGEO (department–province–district), address and geographic coordinates of the service point, as well as the total number of ATMs by address/network and the number of banking agents by establishment. The report indicates that the information corresponds to channels available at the end of each quarter (March, June, September, and December), and instructs institutions to report ATMs even when they operate through third-party networks under agreement, as well as banking agents affiliated directly or through aggregators.

[20] SBS updated the applicable format of Report No. 30 starting with the information corresponding to December 2022,

measure is used as a robustness exercise, comparing results against the deposit-based exposure measure by branch–district. Incorporating these complementary channels helps, on the one hand, capture the presence of financial services in districts without formal branches but with in-person access points that facilitate basic operations (withdrawals, deposits, and low-value transactions). On the other hand, it leverages institution-by-district granularity to more precisely measure the relative presence of participating institutions, reducing potential measurement error in exposure.

5 Identification strategy

Given the implementation design of Peru's retail payments interoperability strategy—rolled out in a staggered fashion across phases and progressively incorporating different sets of participants—the analysis exploits variation in treatment timing and in potential exposure intensity at the district level. In a market where adoption and effective use of digital payment instruments depend, in part, on the pre-existing local presence of financial institutions and their associated infrastructure, it is natural to proxy treatment through a predetermined exposure measure that captures, in each district, the scope for interaction between the institutions that become connected in each phase.

Identification relies on a staggered difference-in-differences design that compares the evolution of outcomes between exposed and non-exposed districts around each implementation milestone, under the assumption of parallel trends in the absence of interoperability. The baseline estimation follows Callaway and Sant'Anna (2021), which identifies cohort- and relative-time effects and aggregates them transparently, avoiding the biases of TWFE in staggered settings with heterogeneous effects (De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021).

5.1 Exposure measure

Given the Peruvian institutional setting, interoperability reduced transaction frictions between payment networks that had previously been segmented and that required users either to coordinate across multiple apps/rails and/or to hold balances in more than one wallet. Accordingly, economically relevant district-level exposure does not depend solely on the size of a single block—i.e., the set of participants or financial institutions that belonged to distinct networks prior to the strategy—but rather on the potential for cross-network matches between two blocks of institutions that become interoperable in a given phase.

which is consistent with the baseline period used in the analysis.

For example, in Phase 1, interoperability connected two pre-existing ecosystems—*Yape* on one side and *Plin* on the other—so that the marginal benefit of the policy in a district does not depend only on how widespread a single wallet was (e.g., *Yape* alone), but on the degree to which both networks coexisted locally.

I consider a district to be exposed when, prior to interoperability, comparable masses of deposits were present in institutions belonging to both blocks. In the baseline (preferred) exposure measure, this coexistence is proxied using the district distribution of total pre-treatment deposits—measured at τ = December 2022—for the financial institutions that comprise each block in each phase of implementation.[21]

I use administrative information on deposits at the district–institution–month level. Using pre-treatment deposits offers three advantages: (i) it anchors a predetermined measure and mitigates simultaneity concerns (deposits are not affected by interoperability at τ); (ii) deposits reflect the local stock of formal financial relationships and therefore the potential mass of users who could benefit from interoperable transactions; and (iii) it allows construction of exposure with full coverage and homogeneous measurement across districts.

Given the staggered nature of treatment, for each phase $k \in \{\text{F1}, \text{F2}, \text{BN}\}$ there are two sets of institutions G_{1k} and G_{2k} (blocks) that become interoperable.[22] Let $\text{Dep}_{db\tau}$ denote the amount of deposits in district d at institution b, measured at τ. I define the deposit mass in district d associated with block G in phase k as[23]:

$$D^{G}_{dk}(\tau) = \sum_{b \in G} w_{b,G}\, \text{Dep}_{db\tau}. \tag{1}$$

[21] As a robustness exercise, I construct an alternative exposure measure that is not limited to pre-treatment deposit mass but also incorporates the operational presence of participating institutions in each block. Specifically, in addition to deposits, I use two proxies of district-level financial-access infrastructure: (i) the number of ATMs and (ii) the number of banking agents associated with the same institutions. This measure aims to capture not only the pre-existing financial mass but also the operational capillarity through which users can fund, withdraw, and transact using financial services linked to participants in each block. Results using this alternative measure, along with other robustness checks, are reported in Section 8.

[22] For a detailed list of participating institutions by phase, see Table B.1.

[23] To allow for institutions that belong to both blocks (overlap), I assign weights $w_{b,G} \in [0, 1]$. In particular, if an institution belongs simultaneously to G_{1k} and G_{2k}, I weight it 50/50 in both blocks so that its total mass is not double-counted:

$$w_{b,G_{1k}} = w_{b,G_{2k}} = \tfrac{1}{2} \quad \text{if } b \in G_{1k} \cap G_{2k}, \qquad w_{b,G} = 1 \text{ if } b \in G \text{ and } b \notin (G_{1k} \cap G_{2k}).$$

The relative share of block G_{1k} in district d is defined as:

$$s_{dk}(\tau) = \frac{D_{dk}^{G_{1k}}(\tau)}{D_{dk}^{G_{1k}}(\tau) + D_{dk}^{G_{2k}}(\tau)}. \tag{2}$$

Based on $s_{dk}(\tau)$, I construct the phase-specific exposure index as:

$$E_{dk}(\tau) = \frac{2\, s_{dk}(\tau)\, \left[1 - s_{dk}(\tau)\right]}{0.5} = 4\, s_{dk}(\tau)\, \left[1 - s_{dk}(\tau)\right] \in [0, 1]. \tag{3}$$

Intuitively, $2s(1-s)$ is proportional to the probability that a district is exposed to interoperability—the normalization by 0.5 ensures a maximum of 1. $E_{dk}(\tau)$ is maximized when both blocks are balanced ($s_{dk} \approx 0.5$), and approaches zero when one block dominates ($s_{dk} \approx 0$ or 1). In districts where $D_{dk}^{G_{1k}}(\tau) + D_{dk}^{G_{2k}}(\tau) = 0$, I set $E_{dk}(\tau) = 0$, interpreting this as no economically meaningful exposure.[24] Appendix C provides additional details on the construction of the exposure measure. Figure C.1 displays the distribution of exposure, and Panel (a) of Figure C.2 shows its spatial distribution by phase.

5.2 Main empirical strategy

Exposure-induced treatment cohorts. Let t denote calendar quarter and d denote district. I define districts as "exposed" in phase k if $E_{dk}(\tau) > 0$. The first treatment date T_d is assigned as the earliest implementation milestone for which the district is exposed:

$$T_d = \begin{cases} t_{\text{F1}}, & \text{if } E_{d,\text{F1}}(\tau) > 0, \\ t_{\text{F2}}, & \text{if } E_{d,\text{F1}}(\tau) = 0 \;\&\; E_{d,\text{F2}}(\tau) > 0, \\ t_{\text{BN}}, & \text{if } E_{d,\text{F1}}(\tau) = E_{d,\text{F2}}(\tau) = 0 \;\&\; \text{BN}_d = 1, \\ \infty, & \text{if never treated,} \end{cases} \tag{4}$$

where $(t_{\text{F1}}, t_{\text{F2}}, t_{\text{BN}})$ are the start quarters for each phase (with Phase 1 becoming operational in 2023Q2, Phase 2 in 2023Q4, and the incorporation of Banco de la Nación (BN) into Phase 2 in January 2024). The absorbing treatment indicator is then:

$$D_{dt} = \mathbb{1}\{t \geq T_d\}. \tag{5}$$

[24]In the final dataset, zero-denominator cases are coded as 0 to preserve the full district universe.

Let Y_{idt} denote the outcome of individual i in district d and quarter t, with potential outcomes $Y_{idt}(1)$ and $Y_{idt}(0)$. The central object in Callaway and Sant'Anna (2021) is the cohort-by-time average treatment effect:

$$\mathrm{ATT}(g,t) = \mathbb{E}[\, Y_{idt}(1) - Y_{idt}(0) \mid T_d = g \,], \qquad t \geq g. \tag{6}$$

From $\mathrm{ATT}(g,t)$, I construct (i) a dynamic event-study profile by relative time $\ell = t - g$ and (ii) post-treatment averages (e.g., the average for $\ell \geq 0$), following the aggregation schemes proposed in Callaway and Sant'Anna (2021).

Under no anticipation and parallel trends for untreated outcomes, $\mathrm{ATT}(g,t)$ is identified by comparing changes in outcomes for cohort g with units that are *not yet treated* at time t:

$$C_{g,t} = \{d : T_d > t\}. \tag{7}$$

Operationally, I estimate $\mathrm{ATT}(g,t)$ using the Callaway and Sant'Anna (2021) estimator, which implements clean comparisons (treated units versus not-yet-treated units) and allows transparent aggregation in the presence of cohort and relative-time heterogeneity. Standard errors are clustered at the district level.

6 Results

This section presents the main results on (i) cash and card use, (ii) digital payments and financial inclusion, and (iii) a proxy for household financial fragility.[25]

6.1 Effects on cash and card use

Tables 2 and 3 show that interoperability reduces the use of both cash and cards. For cash, interoperability lowers cash-use intensity by 2.9 pp and reduces the probability of using only cash across the nine main expenditure categories by 2.3 pp, a decline of roughly one third relative to its pre-treatment mean. These effects are concentrated in recurring and everyday payments, with the largest reductions in utilities (-4.4 pp) and cooking fuels (-5.2 pp), alongside significant declines in ready-to-eat food, clothing and footwear, and household appliances. Overall, the decline in cash

[25] Coefficients are interpreted as percentage-point (pp) changes in binary outcomes, with standard errors clustered at the district level. I report multiple-testing adjusted p-values using the Benjamini–Hochberg procedure (p *BH*), which I use as the benchmark for statistical significance.

use reflects a broad-based reduction across expenditure categories rather than a single adjustment margin. For dynamic effects on cash use, see Figures D.1 and D.2 in Appendix D.

Table 2: Interoperability and its effect on cash use by expenditure category

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean
Groceries	-0.017*	0.009	0.057	0.068	0.911
Ready-to-eat food	-0.019**	0.008	0.023	0.040	0.909
Laundry	-0.017*	0.009	0.044	0.059	0.896
Utilities	-0.044***	0.011	0.000	0.001	0.859
Cooking fuels	-0.052***	0.013	0.000	0.001	0.794
Personal hygiene	-0.015*	0.007	0.044	0.059	0.910
Clothing and footwear	-0.031***	0.010	0.002	0.006	0.838
Furniture and appliances	-0.036*	0.021	0.082	0.090	0.253
Household appliances	-0.031**	0.013	0.017	0.040	0.106
Other	-0.006	0.014	0.663	0.663	0.836
Cash use intensity	-0.029***	0.008	0.000	0.001	0.719
Uses only cash	-0.023**	0.010	0.023	0.040	0.065
N			233,196		
N Clusters			1,347		

Note: This table reports the effect of district-level exposure to interoperability on cash use by expenditure category. The exposure measure is constructed using district-level deposits prior to interoperability (Dec-2022) for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using cash for the corresponding expenditure category. Cash-use intensity is the share of the nine main spending categories in which the individual reports using cash, and cash-only use is a dummy equal to one if the individual reports using only cash in all nine categories. Estimation uses the staggered difference-in-differences approach of Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance denoted by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Card use also declines. Card-use intensity falls by 1.1 pp relative to a pre-treatment mean of 3.6%. The reduction is again concentrated in everyday expenditures, with significant effects in groceries, laundry, utilities, cooking fuels, personal hygiene, and clothing and footwear. By contrast, I do not detect meaningful effects in lower-frequency categories such as furniture and appliances, household appliances, or the residual *other* category. I also find no significant effect on the probability of using only cards, although this margin is economically less informative given its very low baseline prevalence. For dynamic effects on card use, see Figures D.3 and D.4 in

Appendix D.

Table 3: Interoperability and its effect on card use by expenditure category

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean
Groceries	-0.014**	0.006	0.019	0.039	0.055
Ready-to-eat food	-0.010	0.006	0.094	0.141	0.050
Laundry	-0.014**	0.006	0.018	0.039	0.047
Utilities	-0.017***	0.004	0.000	0.001	0.031
Cooking fuels	-0.010**	0.003	0.002	0.012	0.019
Personal hygiene	-0.017**	0.006	0.003	0.012	0.048
Clothing and footwear	-0.013**	0.006	0.027	0.046	0.054
Furniture and appliances	-0.003	0.003	0.416	0.555	0.012
Household appliances	0.001	0.003	0.685	0.747	0.012
Other	0.001	0.004	0.831	0.831	0.023
Card use intensity	-0.011**	0.004	0.007	0.020	0.036
Uses only cards	-0.000	0.001	0.601	0.721	0.001
N			233,196		
N Clusters			1,347		

Note: This table reports the effect of district-level exposure to interoperability on the use of cards (debit and credit) by expenditure category. The exposure measure is constructed using district-level deposits prior to interoperability (Dec-2022) for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using a card for the corresponding expenditure category. Card-use intensity is the share of the nine main spending categories in which the individual reports using a card, and card-only use is a dummy equal to one if the individual reports using only cards in all nine categories. Estimation uses the staggered difference-in-differences approach of Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance denoted by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing ($^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Taken together, these results suggest that interoperability did not simply shift transactions from cash into cards. Rather, by reducing compatibility and acceptance frictions, it made interoperable transfers and wallet-based payments more attractive relative to both traditional instruments, especially in repeated, low-value transactions (Bech et al., 2018; Bianchi et al., 2023). This mechanism is particularly plausible in Peru, where Phase 2 expanded instant phone-based transfers through mobile banking applications and enabled QR interoperability, thereby intensifying competition across payment instruments and use cases (Fernández and García, 2024; García et al., 2025).

6.2 Financial inclusion, internet banking, and digital payments

Table 4 highlights a contrast between (i) the extensive margin of inclusion and (ii) the usage margin of digital channels. First, I find no statistically significant effects on financial inclusion. This is plausible because opening and maintaining a formal account depend on barriers that interoperability does not directly remove, including documentation requirements, perceived costs, trust, financial and digital literacy, and the availability of suitable products (Allen et al., 2016; Ahamed and Mallick, 2019). On the other hand, within the phased rollout, expansion toward less banked segments may become more salient as additional participant types are incorporated (e.g., e-money) and onboarding processes improve. Indeed, institutional evidence suggests that the incorporation of actors such as Banco de la Nación or the maturation of Phase 3 (e-money/BIM) could be particularly relevant for expanding coverage, but its effects on broader outcomes may materialize with lags (Fernández and García, 2024; García et al., 2025).[26]

By contrast, I find an increase in internet banking usage of +3.3 pp.[27] Moreover, when I broaden the measure to capture combined use of internet banking and wallets (IB + Digital Wallets), the estimated effect rises to +5.0 pp. In relative terms, these magnitudes imply increases on the order of 55–80% compared to pre-treatment levels, indicating that interoperability operates strongly on the intensive margin of payment digitalization. For dynamic effects, see Figure D.5 in Appendix D.

This result is consistent with two complementary pieces of evidence. First, the international literature shows that shocks that reduce frictions—whether in adoption, acceptance, or coordination—can generate persistent increases in digital payment usage (Agarwal et al., 2024; Higgins, 2024). Second, descriptive evidence documents rapid and sustained growth in interoperable transactions following the rollout of Phases 1 and 2 as more entities and use cases were incorporated (Vásquez, 2024; García et al., 2025; Fernández and García, 2024).

6.3 Household financial fragility

Table 5 shows that interoperability reduces household financial fragility. Across the two exposure measures, the estimated effects imply a decline of 3.5–3.8 pp in the probability that the household is forced to draw down savings or borrow under its current economic situation. Relative to a pre-

[26] As discussed in Section 3, by June 2025 Phases 1 and 2 accounted for 98.3% of all interoperable transactions, whereas Phase 3 accounted for the remaining 1.7% (García et al., 2025).

[27] As noted in Table 4, this estimate is restricted to 2023 due to changes in the INEI questionnaire in 2024.

Table 4: Interoperability and its effect on financial inclusion, internet banking usage, and digital payments

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean	N	N Clusters
Financial Inclusion	-0.026	0.016	0.113	0.113	0.524	233,196	1,347
Internet Banking (IB)	0.033***	0.012	0.007	0.010	0.060	155,995	1,306
IB + Digital Wallets	0.050***	0.011	0.000	0.000	0.060	233,196	1,347

Note: This table reports the effect of district-level exposure to interoperability on financial inclusion, internet banking usage, and digital payments. For financial inclusion, the outcome is an indicator equal to 1 if the individual reports having an account and/or a card (debit or credit), and zero otherwise. Internet banking usage is an indicator equal to 1 if the individual reports using this channel for at least one of the nine expenditure categories. The measure IB + Digital Wallets additionally incorporates, for 2024, reported use of digital wallets. The exposure measure is constructed using district-level deposits prior to interoperability (Dec-2022) for institutions participating in each phase of the strategy. Estimation uses the staggered difference-in-differences approach of Callaway and Sant'Anna (2021). Starting in 2024, INEI expanded the response option associated with internet banking to explicitly include additional channels (mobile banking and ATMs). Therefore, the Internet Banking (IB) outcome is estimated using only the 2022–2023 sample to preserve comparability. The variable IB + Digital Wallets is a broader, non-harmonized proxy for digital-channel use that leverages the expanded 2024 questionnaire and is reported as complementary evidence rather than as a baseline comparable outcome. Standard errors are clustered at the district level. Statistical significance denoted by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

treatment mean of 21.2%, this corresponds to a reduction of roughly 16–18%. For dynamic effects, see Figure D.6 in Appendix D.

Taken together with the evidence on payment substitution, this pattern is consistent with interoperability easing short-run liquidity management. While the data do not yet allow me to isolate the exact mechanism, lowering transfer frictions and enabling faster remittances and person-to-person transfers can plausibly strengthen risk sharing and help households smooth shocks with less reliance on dissaving or emergency borrowing. Evidence from Kenya shows that mobile money reduced transaction costs, increased remittances, and improved risk sharing, while evidence from Uganda shows that mobile money users were better able to prevent consumption declines after village-level rainfall shocks. In this setting, the fragility result is therefore consistent with a mechanism in which interoperability improves immediate access to funds when households face short-run liquidity needs (Jack and Suri, 2014; Riley, 2018).

7 Mechanisms

On the one hand, effective use of digital wallets and digital payments typically requires connectivity (a smartphone plus mobile data), so interoperability can raise the private return to maintaining mobile internet access. Table 6 shows that, in more exposed districts, the probability of reporting prepaid mobile internet increases by 7.5 to 7.9 pp (depending on the exposure measure), while

Table 5: Interoperability and its effect on household financial fragility

	Financial Fragility
Interoperability Exposure 1 x Post	-0.035**
	(0.015)
Interoperability Exposure 2 x Post	-0.038**
	(0.015)
Pre-treatment mean	0.212
N	124,222
N Clusters	1,349

Note: This table reports the effect of district-level exposure to interoperability on a measure of household financial fragility. I estimate the effect using two exposure measures. The first measure (*Interoperability Exposure 1* $\times$ *Post*) is constructed using district-level deposits prior to interoperability (Dec-2022) for institutions participating in each phase of the strategy, while the second measure (*Interoperability Exposure 2* $\times$ *Post*) additionally incorporates the number of ATMs and banking agents at the same level. Financial fragility is an indicator equal to 1 if the individual reports that, under the household's current economic situation, the household is forced to draw down savings or to borrow. Estimation uses the staggered difference-in-differences approach of Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance denoted by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

fixed internet access declines by about 3.8 pp; I find no statistically precise effects on postpaid mobile internet. Because prepaid plans usually involve lower commitment and greater flexibility for households facing tighter budget constraints, this pattern is consistent with an adjustment toward a "minimum digital capacity" needed to operate payments via mobile phones, particularly for P2P uses and low-value transactions. For dynamic effects, see Figure D.7 in Appendix D.

Table 6: Effect of interoperability on household internet access by connection type

	Fixed Internet	Postpaid Mobile	Prepaid Mobile
Interoperability Exposure 1 x Post	-0.038*	0.024	0.079***
	(0.021)	(0.022)	(0.021)
Interoperability Exposure 2 x Post	-0.038*	0.008	0.075***
	(0.021)	(0.022)	(0.021)
Pre-treatment mean	0.376	0.551	0.548
N	142,366	141,255	141,255
N Clusters	1,303	1,303	1,303

Note: This table reports the effect of district-level exposure to interoperability on three measures of household internet access. I estimate effects using two exposure measures. The first measure (*Interoperability Exposure 1* $\times$ *Post*) is constructed using district-level deposits prior to interoperability (Dec-2022) for institutions participating in each phase of the strategy, while the second measure (*Interoperability Exposure 2* $\times$ *Post*) additionally incorporates the number of ATMs and banking agents at the same level. Outcomes are indicators equal to 1 if the household reports having fixed internet, postpaid mobile internet, or prepaid mobile internet access. Estimation uses the staggered difference-in-differences approach of Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance denoted by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

This evidence should be interpreted cautiously—it does not establish a unique channel—but it is consistent with prior work documenting that shifts in the value of connectivity can translate into adoption of digital services and changes in economic behavior (Hjort and Poulsen, 2019; Aker, 2010). In our setting, interoperability increases the marginal utility of mobile data in districts with greater scope for cross-network matches, reinforcing the displacement from cash toward digital payments documented in Tables 2 and 4.

As discussed earlier, retail payment markets often exhibit network externalities and coordination problems, meaning that the value of using a given instrument depends on how likely it is that the counterparty (a person or a merchant) can accept it and on how costly compatibility across networks is (Rochet and Tirole, 2002; Rysman, 2009). Interoperability targets this friction directly by increasing connectivity across ecosystems (initially P2P and, progressively, P2B), thereby raising the probability of "cross-network matches" within each district. In addition, implementation features that strengthen the coordination channel—with emphasis on end-user experience, monitoring of failed transactions, and operational follow-up—and efforts to expand the set of connected participants over time plausibly amplify the effects as the network grows (Vásquez, 2024; García et al., 2025; Aguirre, 2023).

A classic barrier to displacing cash is not only consumer preferences but also merchants' acceptance costs, including infrastructure requirements, fees, compatibility constraints, and learning costs (Allen et al., 2016, 2022). As interoperability extends to merchant payments and common standards consolidate, acceptance costs for small businesses fall because standardization replaces the need to display multiple provider-specific codes or solutions and enables a single acceptance point that works for users across different wallets and applications (García et al., 2024).

This mechanism is consistent with the fact that the largest cash effects concentrate in everyday and recurring payments (Table 2), where acceptance frictions and convenience tend to be first-order determinants of payment choice. It also helps interpret why, in some categories, declines in cash do not map into increased card usage (Table 3). If interoperable rails become relatively more convenient or cheaper to accept than traditional card infrastructure, they may displace both cash and cards in certain use cases (Bianchi et al., 2023; Alok et al., 2024).

The results on financial fragility (Table 5) are consistent with a liquidity-management and informal insurance channel. Greater payment connectivity may enable (i) more timely transfers within family and friend networks (P2P) and (ii) lower frictions in mobilizing liquid resources, for instance by receiving support during transitory shortfalls, which can reduce the need to draw down savings or borrow at the margin through improved risk-sharing and shock smoothing (Jack and Suri, 2014; Riley, 2018).

8 Robustness

This section assesses the sensitivity of the main findings along four dimensions: (i) the choice of estimator in staggered-adoption settings, (ii) an expanded exposure measure that combines deposits with physical financial infrastructure (ATMs and banking agents), (iii) the choice of the pre-treatment date used to construct exposure, and (iv) plausible sources of time-coincident confounding. I also report the results of a placebo test.

(i) Estimator choice. Given the well-known limitations of TWFE under staggered adoption with heterogeneous effects, I replicate the baseline estimates using the approaches proposed by Sun and Abraham (2021), Borusyak et al. (2024), and de Chaisemartin and D'Haultfœuille (2024). The goal is to verify that the results are not driven by a particular implicit weighting scheme or by restrictive homogeneity assumptions. The main conclusions—a decline in cash use, an increase in the use of digital channels/payments, and a reduction in financial fragility—are robust across estimators (see Figures D.1 through D.6). In particular, the event-study profiles show (i) no systematic pre-trends in the leads, consistent with parallel trends, and (ii) a gradual build-up of effects in the post-treatment period.

(ii) Expanded exposure measure based on deposits and physical financial infrastructure. Because effective adoption of digital payments may be shaped by cash-in/cash-out frictions and access to financial services, especially in districts with sparse infrastructure, I replace the baseline exposure measure (pre-treatment deposits) with an alternative measure that incorporates, in addition to deposits, the number of ATMs and banking agents associated with the institutions in each block.[28] This expanded measure is designed to capture not only the stock of deposits that could plausibly be mobilized through interoperable payments, but also the operational capillarity that facilitates funding, withdrawals, and day-to-day use of financial services.

Starting from the deposits-based exposure measure $E_{dk}(\tau)$ in equation (3), I construct an analogue based on physical infrastructure. For each phase $k \in \{\mathrm{F1}, \mathrm{F2}, \mathrm{BN}\}$ and each block $G \in \{G_{1k}, G_{2k}\}$, I define the "mass" of access points associated with block G in district d as

$$C_{dk}^{G}(\tau) = \sum_{b \in G} w_{b,G}\, \mathrm{AP}_{db\tau}, \tag{8}$$

[28] Panel (b) of Figure C.2 displays the spatial distribution of this alternative exposure measure. Panel (b) of Figure C.3 shows the evolution of the evaluation panel, tracking treated individuals by phase.

where $\mathrm{AP}_{db\tau}$ denotes the number of ATMs and banking agents of institution b in district d, measured at $\tau =$ December 2022, and $w_{b,G}$ are the same weights used in (1) to handle institutions that belong to both blocks. The relative share of block G_{1k} in terms of physical infrastructure is defined as

$$\tilde{s}_{dk}(\tau) = \frac{C_{dk}^{G_{1k}}(\tau)}{C_{dk}^{G_{1k}}(\tau) + C_{dk}^{G_{2k}}(\tau)}. \tag{9}$$

Analogously to (3), I define an infrastructure-based exposure index as

$$\tilde{E}_{dk}(\tau) = 4\,\tilde{s}_{dk}(\tau)\left[1 - \tilde{s}_{dk}(\tau)\right] \in [0,1], \tag{10}$$

which is maximized when both blocks have a balanced presence of access points in the district and converges to zero when one block dominates or when infrastructure associated with both blocks is essentially absent (in that case, I set $\tilde{E}_{dk}(\tau) = 0$).

To combine deposits and physical infrastructure in a parsimonious way, I standardize both phase-specific exposure indices and construct, at the district level, a composite measure that averages the two dimensions. Let $\bar{E}_k$ and $\sigma(E_k)$ denote the mean and standard deviation of $E_{dk}(\tau)$ across districts in phase k, and let $\bar{\tilde{E}}_k$ and $\sigma(\tilde{E}_k)$ denote the analogous objects for $\tilde{E}_{dk}(\tau)$. I then define the expanded exposure measure as

$$E_{dk}^{\text{expanded}}(\tau) = \frac{1}{2}\left(\frac{E_{dk}(\tau) - \bar{E}_k}{\sigma(E_k)} + \frac{\tilde{E}_{dk}(\tau) - \bar{\tilde{E}}_k}{\sigma(\tilde{E}_k)}\right). \tag{11}$$

By construction, $E_{dk}^{\text{expanded}}(\tau)$ takes high values in districts where (i) deposits are relatively balanced across the two blocks that begin to interoperate and (ii) the ATM/correspondent infrastructure associated with those blocks is relatively dense. Conversely, the index approaches zero or becomes negative in districts where exposure through deposits and/or infrastructure is low or highly skewed toward one block. I use $E_{dk}^{\text{expanded}}(\tau)$ as an alternative pre-treatment exposure measure to define district treatment cohorts in the staggered difference-in-differences design.[29]

In terms of interpretation, this expanded exposure measure differs from the baseline in how the set of treated districts is defined. Under the main specification, a district is considered exposed in phase k whenever the deposits-based exposure $E_{dk}(\tau)$ is strictly greater than zero, i.e., whenever there is any economically meaningful mass associated with the blocks that begin to interoper-

[29] The composite measure preserves the differential exposure structure of the baseline design while explicitly incorporating local access to physical financial infrastructure, which is plausibly first-order for the adoption and effective use of digital payments.

ate. Under the expanded measure, I use $E_{dk}^{\text{expanded}}(\tau)$ and classify a district as treated when this composite index is greater than zero, which effectively selects districts with combined exposure (deposits and infrastructure) above the national mean for the corresponding phase. Thus, while the baseline measure separates districts along an extensive margin of exposure, the expanded measure emphasizes districts with high relative exposure, allowing me to assess robustness by focusing on locations where the presence of participating institutions is strongest in both financial and operational terms.

At an aggregate level, the pattern of results is unchanged: (i) cash use declines (see Table E.1); (ii) card use falls (see Table E.2); (iii) the use of digital channels rises—internet banking and wallets (see Table E.3); (iv) financial fragility declines (see Table 5); and (v) prepaid mobile internet access increases (see Table 6). The consistency in signs and orders of magnitude across exposure measures indicates that the findings do not hinge on a single proxy for exposure and alleviates concerns that the estimates are merely capturing pre-existing differences in physical capillarity.

(iii) Choice of the pre-treatment date used to construct exposure. As an additional robustness check, I reconstruct the exposure measure using deposits as of March 2023, the last month prior to the start of interoperability in Phase 1. The purpose of this exercise is to show that the exposure variable is stable over a reasonable pre-treatment window. In practice, results based on March 2023 deposits closely mirror the baseline results using December 2022 deposits (see Tables E.4, E.5, and E.6).

(iv) *Not-yet-treated* controls versus never-treated controls. As a further robustness exercise, I restrict the sample to districts with at least one ATM or banking agent to improve comparability between treated and comparison units. The qualitative patterns remain unchanged, suggesting that the changing composition of the control group is not driving the findings. For details, see Tables E.7, E.8, and E.9.

(v) Multiple-testing correction. Because I estimate multiple outcomes by spending category, all tables report p-values adjusted using Benjamini and Hochberg (1995), and I primarily assess statistical significance based on that column. This criterion is especially relevant in Tables 2–4, where closely related margins (spending categories) are tested and the goal is to mitigate false positives arising from multiplicity.

(vi) Placebo test. As an additional validation of the identification strategy, I conduct a placebo exercise in which I restrict the sample to the pre-treatmen period, from 2021Q3 through 2023Q1, and assign placebo treatment dates to the three district cohorts. Specifically, I impute placebo adoption dates of 2022Q1, 2022Q2, and 2022Q3 for the cohorts that in the actual implementation begin operating in 2023Q2, 2023Q4, and 2024Q1, respectively. I keep the same predetermined exposure measure and estimate the regressions using the staggered difference-in-differences estimator of Callaway and Sant'Anna (2021). For cash use (see Table E.10), placebo coefficients are small and statistically indistinguishable from zero in almost all categories. Only the "Other" category exhibits a positive and significant coefficient, which is modest in magnitude and opposite in sign relative to the negative effects in the baseline specifications, suggesting an isolated finding likely attributable to sampling noise. For card use (see Table E.11), none of the placebo coefficients are significant, and point estimates are very close to zero across all spending categories. Similarly, Table E.12 shows that placebo estimates for financial inclusion, financial fragility, internet banking, and digital payments are very small and not statistically significant. Taken together, the absence of systematic placebo effects indicates that district-level exposure to interoperability is not proxying for pre-existing trends or anticipated shocks over 2021Q3–2023Q1, thereby reinforcing the causal interpretation of the estimated effects in the main tables.

9 Heterogeneity

The effects of interoperability need not be spatially homogeneous. In Peru, persistent gaps in financial access and digital payment use suggest that ex ante differences in connectivity, human capital, formality, and exposure to social programs may shape both substitution away from cash and adoption of digital payments (García and Andía, 2022; Vega and Vásquez, 2022). To study this margin, I construct district-level covariates measured in 2022 and split districts at the median of each variable. This approach relies exclusively on pre-treatment information and yields transparent and comparable partitions across dimensions.

To estimate heterogeneous effects, I use the difference-in-differences estimator of Borusyak et al. (2024), which imputes counterfactual outcomes for treated units based on the trajectory of not-yet-treated districts and computes the post-treatment effect as the average gap between observed outcomes and the imputed counterfactual within each group (high vs. low) defined by pre-treatment characteristics. Coefficients are interpreted as percentage-point changes in the probability of the outcome.

Motivated by the main findings, I focus on four outcomes: (i) cash use for utilities, (ii) cash use for household fuels, (iii) internet-banking use, and (iv) digital-payments use.

Cash substitution in household expenditures. Cash substitution exhibits a clear gradient across districts' initial conditions. Interoperability reduces cash reliance more in districts with stronger pre-treatment digital readiness and less in districts with high informality and greater exposure to social programs. This pattern is visible both in aggregate measures and in category-specific outcomes. Cash-use intensity falls more in districts with better connectivity, greater mobile-phone access, lower informality, and higher urbanization, while the decline in cash-only use follows the same ordering, albeit less sharply. The category-specific results for utilities and household fuels reinforce this pattern: reductions are around -5.4 to -5.8 pp in high-connectivity or low-informality districts and are close to zero in their less connected or more informal counterparts. Urbanization matters more for utilities than for fuels, while lower exposure to Juntos or Pensión 65 is again associated with larger declines. Taken together, the evidence suggests that interoperability has larger effects when constraints on access to and use of digital payment instruments are less binding, and when the private value of cash as a less traceable instrument is lower (Andia et al., 2025; Rogoff, 2016; Immordino and Russo, 2018; Kleven et al., 2011; Pomeranz, 2015; Naritomi, 2019). See Figures F.1, F.2, F.3, and F.4.

Adoption of internet banking and digital payments. Digital-channel use displays analogous gradients. Internet banking rises mainly in districts with stronger pre-treatment digital infrastructure and capabilities. In districts with high internet access or usage, and with higher ownership of a personal cellphone, internet-banking use increases by about +7.4 to +7.7 pp, whereas in low-connectivity districts effects are small and statistically indistinguishable from zero. The increase in digital payments is more widespread but preserves the same ranking, with effects around +9.4 to +9.6 pp in highly connected districts and much smaller, often insignificant, effects in low-connectivity districts.

These gradients also track human capital, formality, and urbanization. Effects are larger where the share with only elementary schooling is lower and where informality is lower, suggesting that learning and adoption costs remain relevant. Urbanization further amplifies adoption, consistent with the view that outside urban areas, constraints in local acceptance, connectivity, and learning may prevent interoperability from translating into effective use, or may redirect transactions toward instruments not fully captured by the outcomes analyzed. See Figures F.5 and F.6.

Household financial fragility. Heterogeneity in the fragility results is much more limited. The estimated effects are negative for nearly all splits by human capital, digital infrastructure and usage, socioeconomic characteristics, and exposure to social programs, suggesting that the reduction in household financial fragility is broadly shared across districts rather than concentrated only in those with stronger ex ante digital readiness. If anything, the decline appears somewhat larger in districts with higher informality and greater exposure to Juntos, while differences by connectivity and education are comparatively small. This pattern is consistent with a liquidity-management mechanism. By making transfers faster and easier, interoperability may improve short-run risk sharing and help households cope with liquidity needs even in districts where substitution away from cash in day-to-day expenditures remains limited. Accordingly, the heterogeneity in financial fragility appears less tied to local merchant acceptance or advanced digital usage than the heterogeneity in cash-substitution margins, and more closely related to the ability to receive funds promptly when households face short-run shocks (Jack and Suri, 2014; Riley, 2018). See Figure F.7.

10 Conclusions

This paper studies the effects of the BCRP's Retail Payments Interoperability Strategy on payment-instrument choice and household financial fragility in Peru. Interoperability reduced reliance on traditional payment instruments and increased the use of digital channels. Cash use declines in everyday and recurring expenditures, broader cash reliance falls, card use declines, and internet banking and digital-payment use rise. I find no robust effects on the extensive margin of financial inclusion, but I do find a decline in household financial fragility, with exposed households less likely to report that they must draw down savings or borrow.

The evidence on mechanisms and heterogeneity helps interpret these results. In more exposed districts, prepaid mobile internet access rises, consistent with households acquiring the minimum connectivity needed to operate mobile payments. Effects on payment substitution and digital-channel use are stronger in districts with better pre-treatment connectivity, higher human capital, lower informality, and lower exposure to social programs, indicating that interoperability interacts with existing local conditions rather than operating in isolation. By contrast, heterogeneity in financial fragility is more limited, which is consistent with a liquidity-management channel that depends less on merchant acceptance or advanced digital usage than on the ability to send and receive funds quickly.

Two limitations bound the scope of the findings. First, ENAHO records digital-wallet use only from 2024 onward, so there is no pre-treatment baseline that would allow me to assess parallel trends and estimate the causal effect on that outcome directly. Second, the lack of granular territorial information on electronic-money issuers limits the analysis of Phase 3, although this constraint is less consequential given the relatively limited scale of Phase 3 through 2025, as documented in earlier sections.

Overall, the results suggest that interoperability can accelerate the transition away from cash and improve short-run household financial resilience, but its effects are not uniform across space. Reducing interoperability frictions was an important step in modernizing the payments system, yet the magnitude of the gains depends on complementary conditions such as digital infrastructure, user capabilities, and the degree of formality in local economic activity. From a policy perspective, interoperability appears to be a necessary but not sufficient condition for broad-based digitalization, and its effects are likely to be amplified by complementary investments in connectivity, digital and financial literacy, and policies that reduce the incentives to remain informal.

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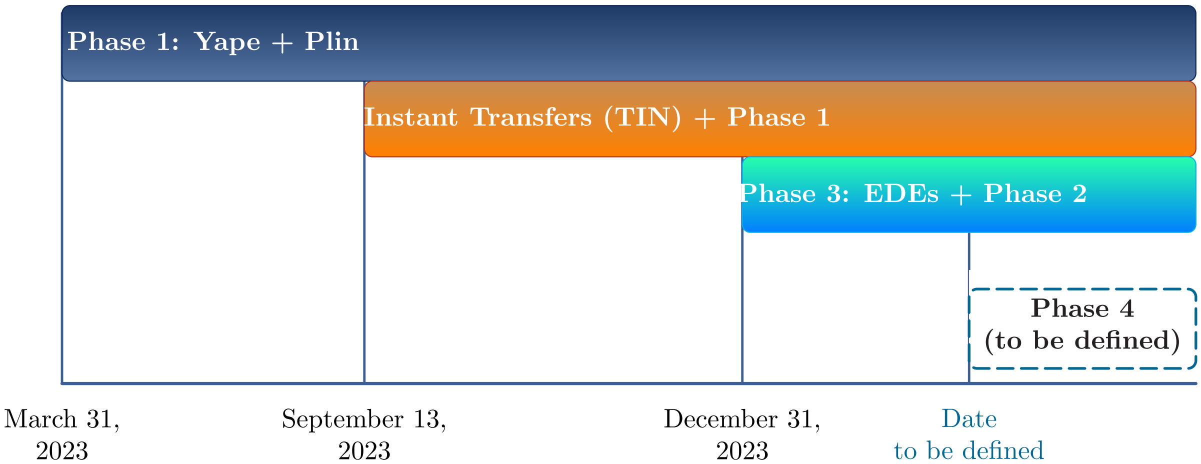
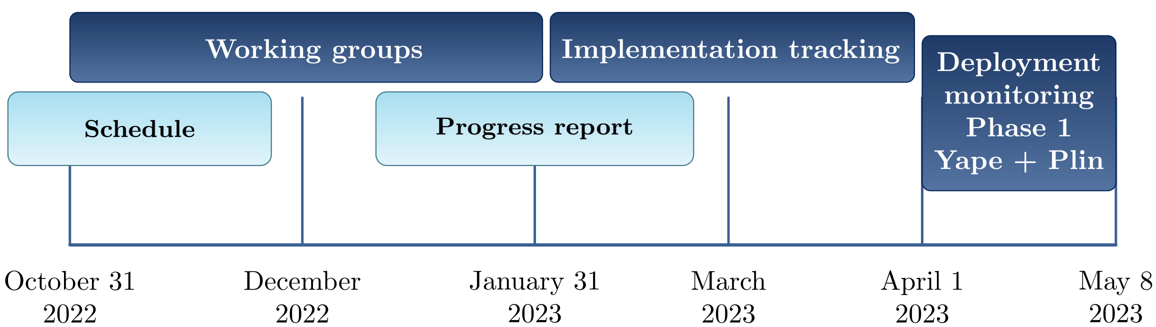
A Appendix: Interoperability Strategy Timeline

Figure A.1: Timeline of the implementation of the Retail Payments Interoperability Strategy



Source: Author's elaboration based on BCRP reports.

Figure A.2: Phase 1 implementation



Source: Author's elaboration based on BCRP reports.

B Appendix: Participating Entities

Table B.1: Entities participating in the Retail Payments Interoperability Strategy

Phase 1: Yape-Plin Interoperability				
Type of institution	Entity	Yape user	Plin user	Start Phase 1
Bank	Banco de Crédito del Perú (BCP)	X		31 mar. 2023
Bank	Mibanco	X		31 mar. 2023
Bank	BBVA		X	31 mar. 2023
Bank	Interbank		X	31 mar. 2023
Bank	Scotiabank Perú		X	31 mar. 2023
Bank	Alfin Banco		X	31 mar. 2023
Bank	BanBif		X	31 mar. 2023
CMAC	CMAC Arequipa		X	31 mar. 2023
CMAC	CMAC Huancayo	X	X	31 mar. 2023
CMAC	CMAC Ica	X	X	31 mar. 2023
CMAC	CMAC Piura	X		31 mar. 2023
CMAC	CMAC Tacna	X		31 mar. 2023
CMAC	CMAC Trujillo	X		31 mar. 2023
CMAC	CMCP Lima (Caja Metropolitana)	X		31 mar. 2023
Financiera	Financiera Confianza		X	31 mar. 2023
Phase 2: Instant transfers and interoperable QR codes				
Type of institution	Entity	Phase 2 Participant		Start of Phase 2
Bank	Banco de Comercio	X		13 sep. 2023
Bank	Banco Pichincha	X		13 sep. 2023
Bank	Banco GNB	X		13 sep. 2023
Bank	Banco Falabella	X		13 sep. 2023
Bank	BanBif	X		13 sep. 2023
Bank	Alfin Banco	X		13 sep. 2023
Bank	BBVA	X		13 sep. 2023
Bank	Banco de Crédito del Perú (BCP)	X		13 sep. 2023
Bank	Interbank	X		13 sep. 2023
Bank	Mibanco	X		13 sep. 2023
Bank	Scotiabank Perú	X		13 sep. 2023
Bank	Citibank del Perú	X		13 sep. 2023
Bank	Banco de la Nación	X		Ene 2024
CMAC	CMAC Arequipa	X		13 sep. 2023
CMAC	CMAC Cusco	X		13 sep. 2023
CMAC	CMAC Ica	X		13 sep. 2023
CMAC	CMAC Piura	X		13 sep. 2023
CMAC	CMAC Sullana	X		13 sep. 2023
CMAC	CMAC Trujillo	X		13 sep. 2023
Financiera	Crediscotia	X		13 sep. 2023
Financiera	Financiera Oh!	X		13 sep. 2023
Financiera	Compartamos Banco	X		13 sep. 2023

Note: Own elaboration based on the Retail Payments Interoperability Strategy (Circular N.º 024-2022-BCRP) and progress reports from the García et al. (2024); García et al. (2025).

C Appendix: Exposure Measure

Exposure measure: To illustrate the construction, consider the district of Chachapoyas (province of Chachapoyas, Amazonas region), which had 12 financial institutions (banks, municipal savings banks, and finance companies). Of these, 4 institutions were *Yape* participants, 2 were *Plin* participants, one institution participated in both networks, and 5 institutions participated in neither. The first step in the exposure measure is the weighted sum of district-level deposits for each group: in this district, I construct two deposit masses, one for the *Yape* block and one for the *Plin* block.[30]

Using these masses, I compute each group's relative share and then the exposure index defined in Equations 2 and 3, which takes values in $[0, 1]$. High values indicate a more balanced distribution of deposits across groups and therefore greater interoperability potential; low values reflect concentration in a single group and lower (though not necessarily zero) potential. Exposure equals zero when one group concentrates 100% of deposits and also when there is no deposit information. To mitigate the latter limitation, as a robustness check I construct an alternative measure that incorporates, in addition to deposits, the number of ATMs and banking agents, capturing exposure in districts without deposits reported but with relevant financial infrastructure.

In Phase 2, district-level exposure is also constructed from two groups. The first group concentrates the deposit mass of Phase 1 participant institutions in the predetermined period, while the second group aggregates the deposit mass of institutions that enter as Phase 2 participants. This definition captures that districts not exposed in Phase 1 can become exposed in Phase 2 as new institutions join the interoperability strategy.

For the Banco de la Nación entry phase, I follow an analogous procedure. Group 1 concentrates the deposit mass of institutions participating in Phases 1 and 2, and Group 2 includes exclusively the deposit mass of Banco de la Nación, capturing exposure associated with its incorporation in January 2024. The resulting distribution (Panel (c) of Figure C.1) shows that a large fraction of districts have zero exposure, mainly because they do not register Banco de la Nación deposits or, in some cases, only register deposits from that institution, implying no possibility of cross-block interoperability. This pattern is consistent with Banco de la Nación's broader territorial coverage in districts where other institutions do not operate; in contrast, in Phases 1 and 2 the presence of more participant institutions in both groups tends to increase district-level interoperability potential.

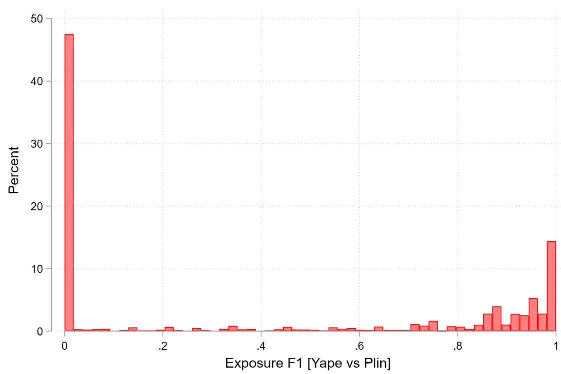
Exposure measures are constructed independently by phase and then translated into a stag-

[30] For institutions that participate in both *Yape* and *Plin*, I use a weight of 0.5 in each group so that the exposure index captures the possibility of interoperability for users of these institutions without double-counting their deposits.

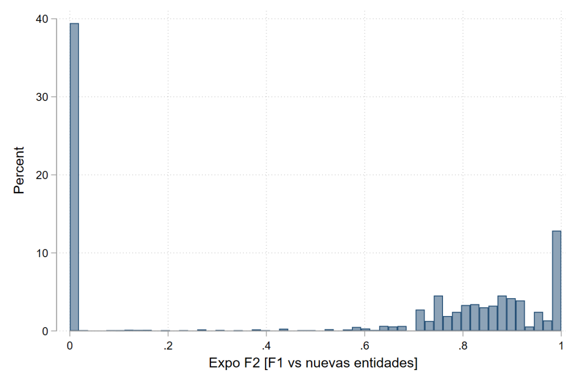
gered treatment variable following Equations 4 and 5. Specifically, a district is classified as treated in Phase 1 when its exposure measure is positive. For Phase 2, a district is considered treated if it has positive exposure and was not treated in Phase 1. Similarly, in the Banco de la Nación phase, a district is treated when its exposure is positive and it was not treated in earlier phases. The resulting staggered assignment is illustrated in Figure C.3.

Figure C.1: Distribution of Exposure Measure

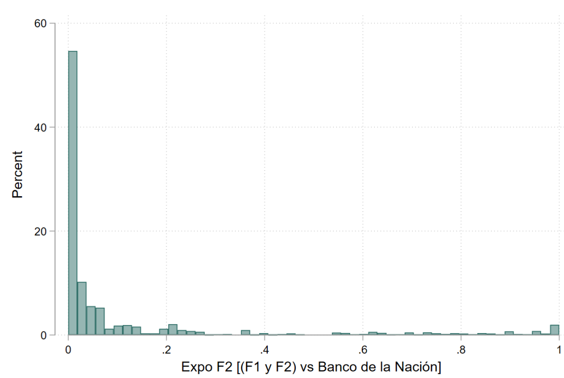
(a) Phase 1



(b) Phase 1 + Phase 2



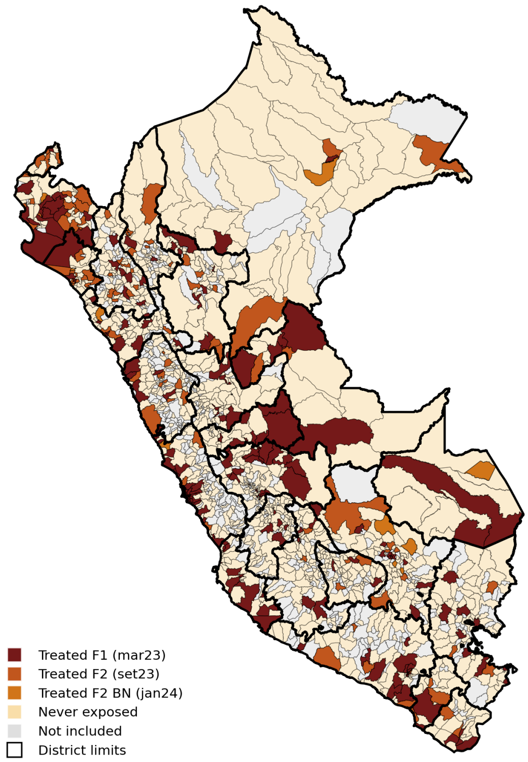
(c) Phase 1 + Phase 2 + Banco de la Nación



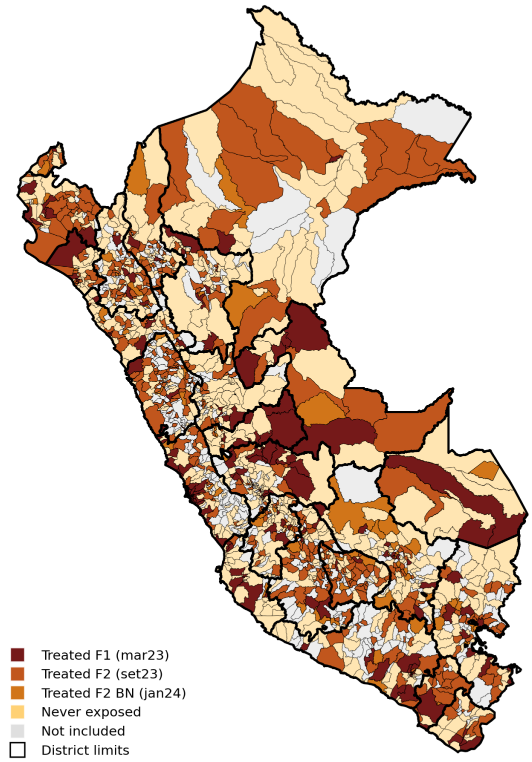
Note: This figure shows the distribution of district-level exposure, computed using district deposits for the groups of institutions participating in each interoperability phase. Panel (a) displays the distribution of the Phase 1 exposure measure, using deposits of institutions participating in this phase (Yape and Plin users). Panel (b) displays the distribution of the Phase 2 exposure measure, using the deposit mass of financial institutions participating in Phase 1 and the institutions that enter in Phase 2, in order to capture interoperability at this stage. Finally, Panel (c) displays the distribution of the exposure measure incorporating Banco de la Nación, using the deposit mass of institutions participating in the previous phases and Banco de la Nación.

Figure C.2: Map: district-level exposure

(a) Exposure measurement 1



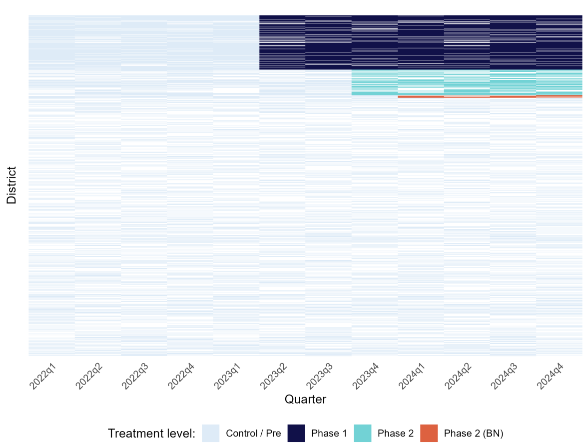
(b) Exposure measurement 2



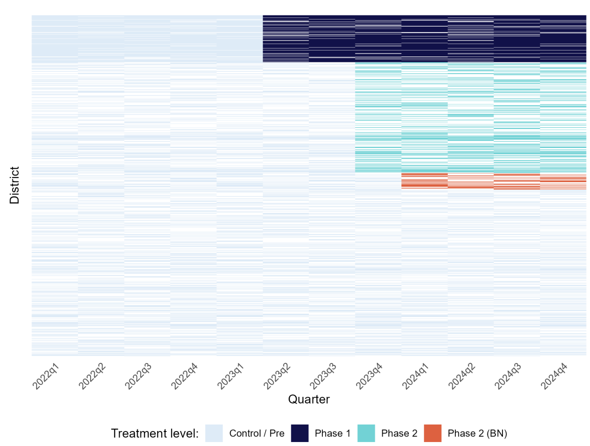
Note: The figure shows the distribution of exposure at the district level, in its two versions. Exposure measure 1 (Panel a) is calculated using district-level deposits of the groups of institutions participating in each phase of interoperability, while the second exposure measure (Panel b) includes, in addition to deposits, the number of ATMs and banking agents.

Figure C.3: Quarterly district panel assessment (2022q1-2024q4)

(a) Exposure measurement 1



(b) Exposure measurement 2

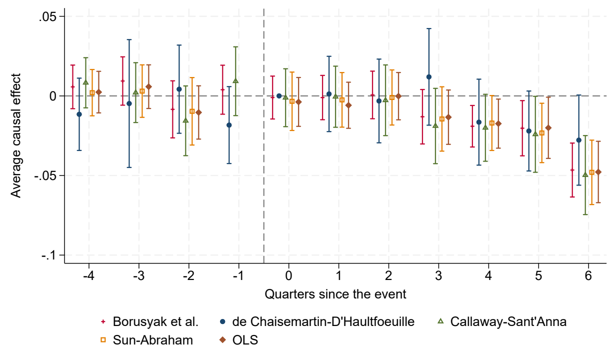


Note: Own work based on the PanelView package in R, developed by Mou et al. (2023).

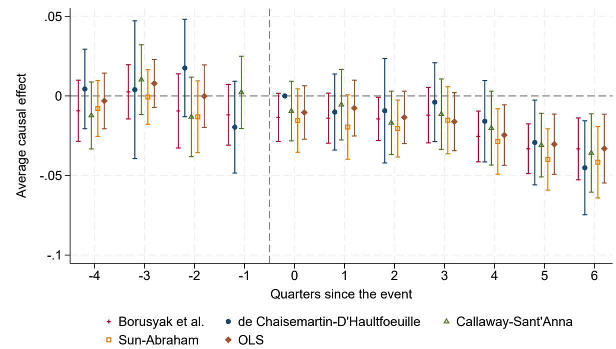
D Appendix: Dynamic Effects

Figure D.1: Dynamic effects on cash use by expenditure category

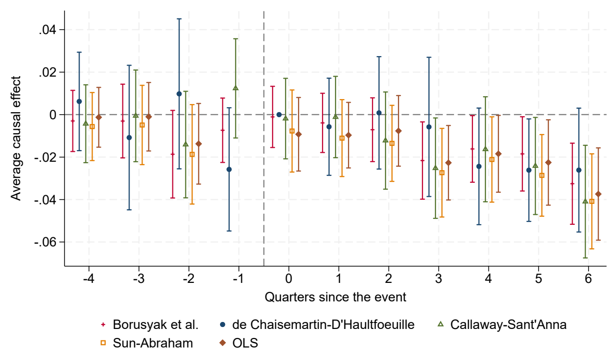
(a) Groceries



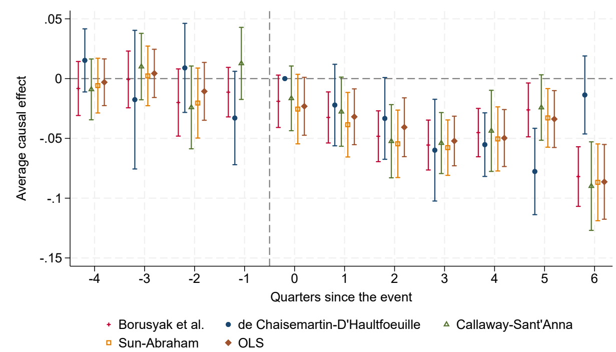
(b) Ready-to-eat food



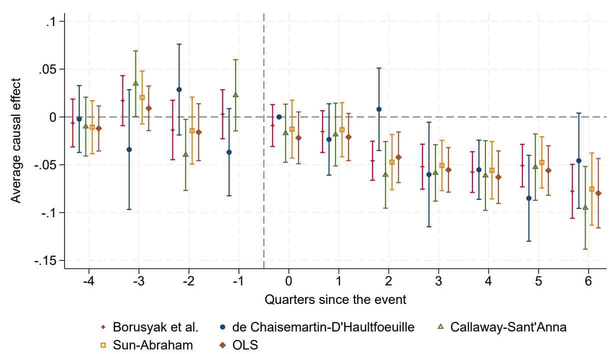
(c) Laundry



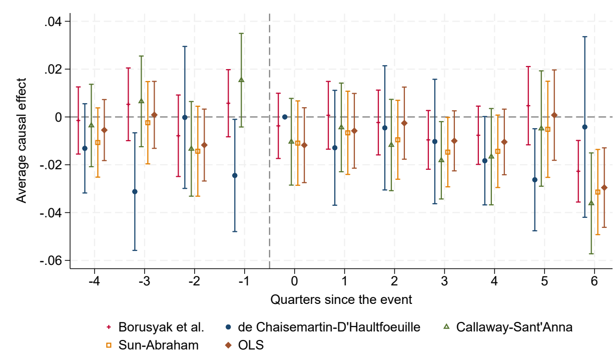
(d) Utilities



(e) Cooking fuels



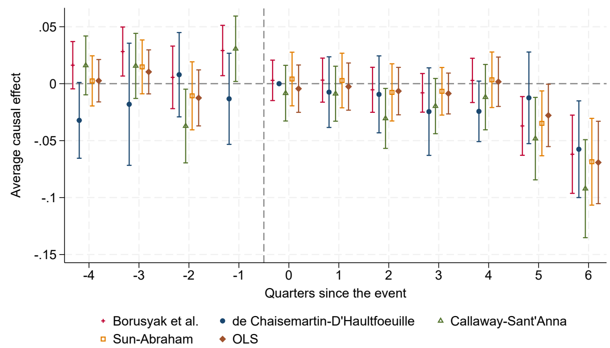
(f) Personal hygiene



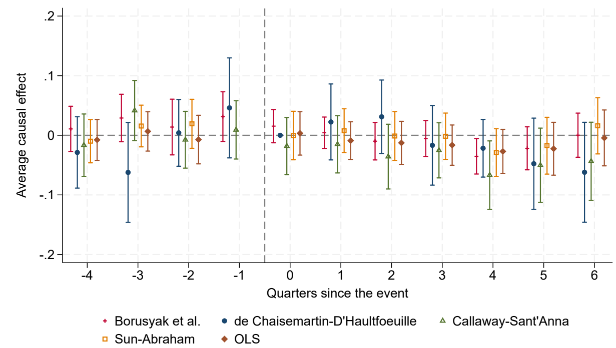
Note: This figure reports dynamic effects of district-level exposure to interoperability on cash use by expenditure category. The exposure measure is constructed from district-level deposits in the pre-interoperability period (December 2022) for institutions participating in each phase of the strategy. Outcomes are indicators equal to one if the individual reports using cash for the corresponding expenditure category. Estimation uses staggered-adoption difference-in-differences methods following Callaway and Sant'Anna (2021); de Chaisemartin and D'Haultfœuille (2024); Borusyak et al. (2024); Sun and Abraham (2021). Standard errors are clustered at the district level.

Figure D.2: Dynamic effects on cash use by expenditure category

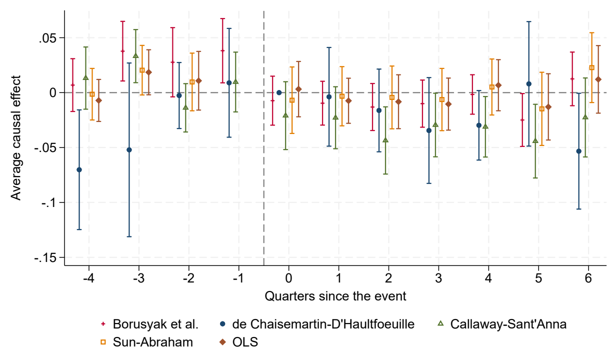
(a) Clothing and footwear



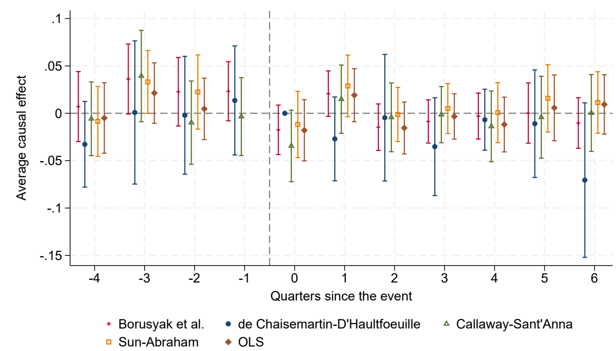
(b) Furniture and appliances



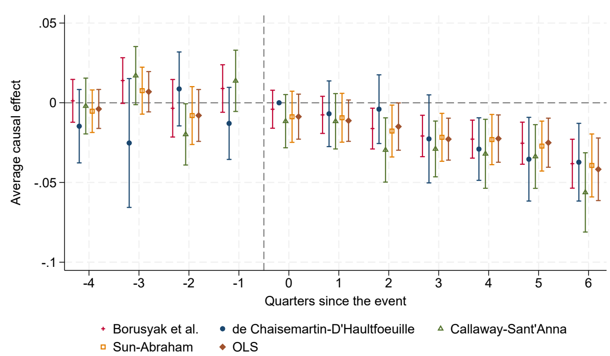
(c) Household appliances



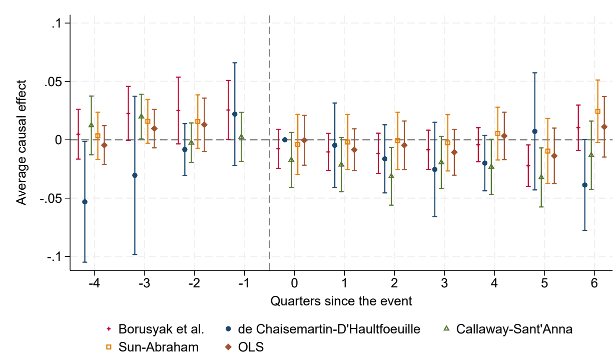
(d) Other



(e) Cash use intensity



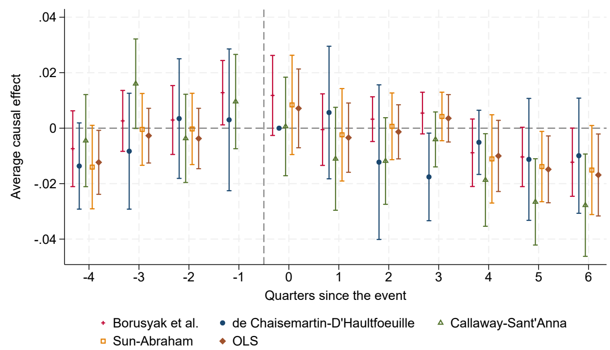
(f) Uses only cash



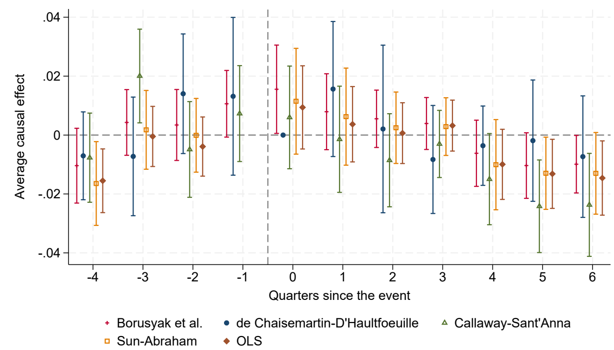
Note: This figure reports dynamic effects of district-level exposure to interoperability on cash use by expenditure category. The exposure measure is constructed from district-level deposits in the pre-interoperability period (December 2022) for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using cash for the corresponding expenditure category. Cash-use intensity is the share of the nine main spending categories in which the individual reports using cash, and cash-only use is a dummy equal to one if the individual reports using only cash in all nine categories. Estimation uses staggered-adoption difference-in-differences methods following Callaway and Sant'Anna (2021); de Chaisemartin and D'Haultfœuille (2024); Borusyak et al. (2024); Sun and Abraham (2021). Standard errors are clustered at the district level.

Figure D.3: Dynamic effects on card use by expenditure category

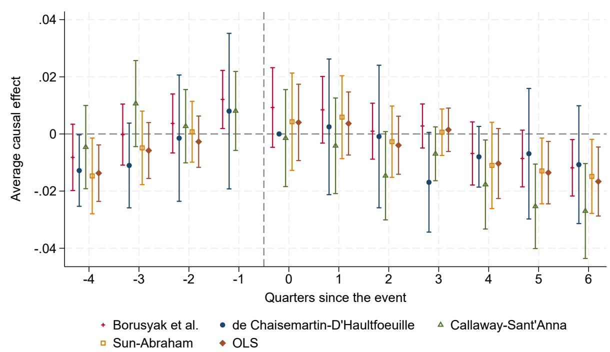
(a) Groceries



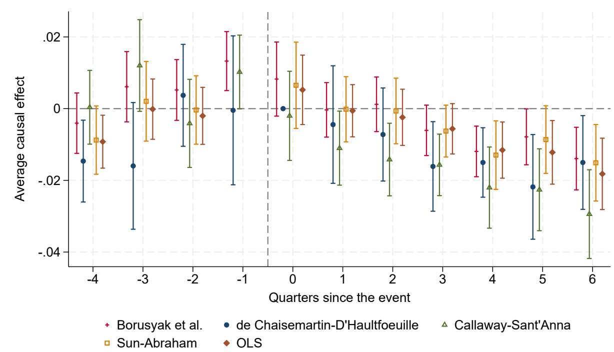
(b) Ready-to-eat food



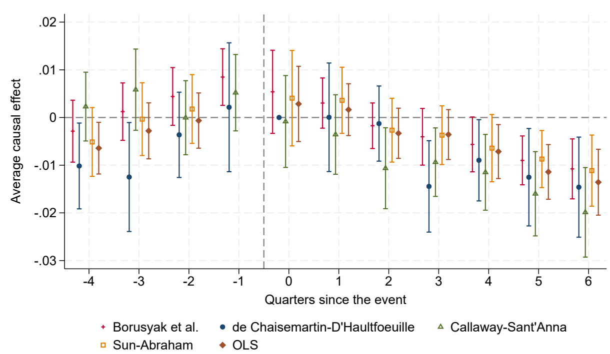
(c) Laundry



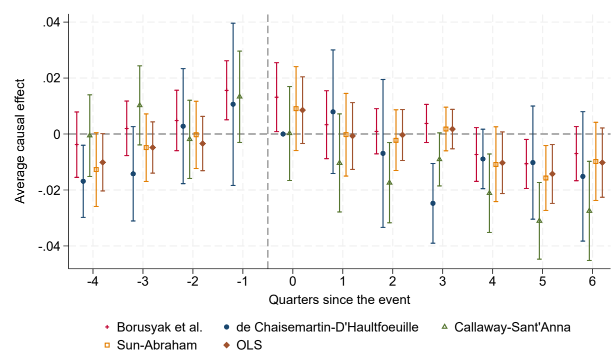
(d) Utilities



(e) Cooking fuels

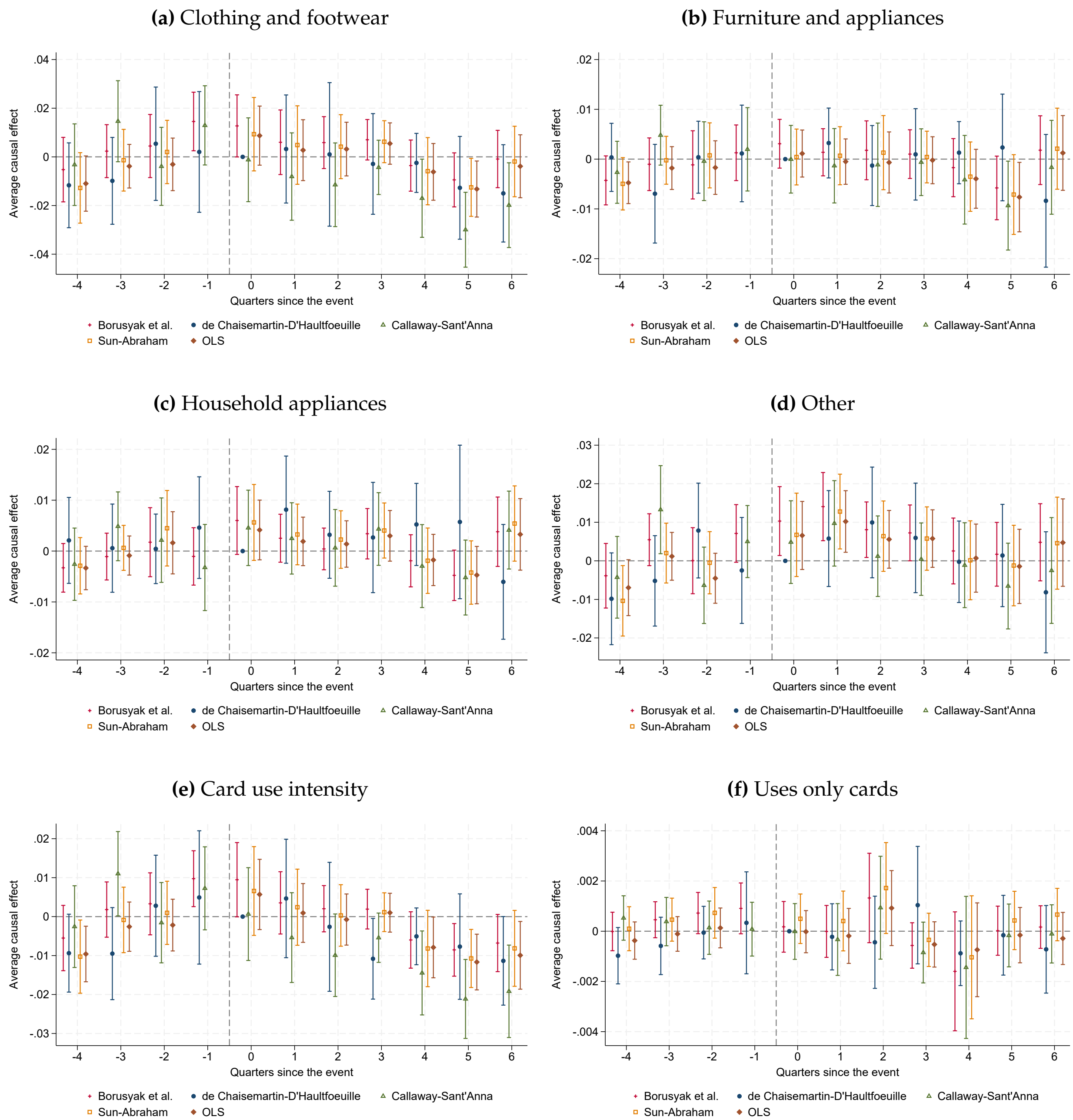


(f) Personal hygiene



Note: This figure reports dynamic effects of district-level exposure to interoperability on card use (debit and credit) by expenditure category. The exposure measure is constructed from district-level deposits in the pre-interoperability period (December 2022) for institutions participating in each phase of the strategy. Outcomes are indicators equal to one if the individual reports using at least one type of card for the corresponding expenditure category. Estimation uses staggered-adoption difference-in-differences methods following Callaway and Sant'Anna (2021); de Chaisemartin and D'Haultfœuille (2024); Borusyak et al. (2024); Sun and Abraham (2021). Standard errors are clustered at the district level.

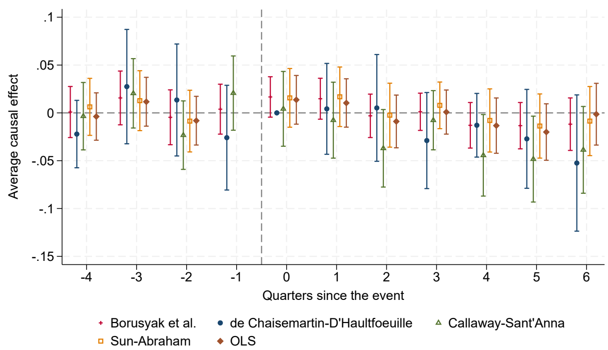
Figure D.4: Dynamic effects on card use by expenditure category



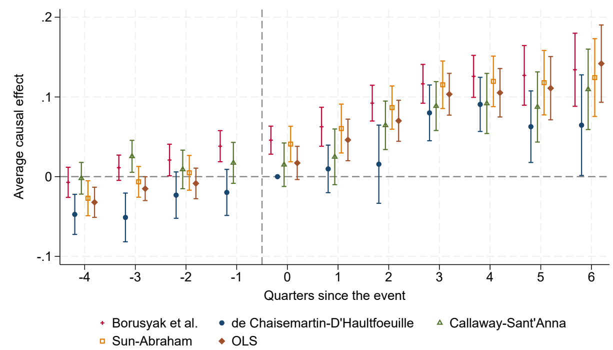
Note: This figure reports dynamic effects of district-level exposure to interoperability on card use (debit and credit) by expenditure category. The exposure measure is constructed from district-level deposits in the pre-interoperability period (December 2022) for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using a card for the corresponding expenditure category. Card-use intensity is the share of the nine main spending categories in which the individual reports using a card, and card-only use is a dummy equal to one if the individual reports using only cards in all nine categories. Estimation uses staggered-adoption difference-in-differences methods following Callaway and Sant'Anna (2021); de Chaisemartin and D'Haultfœuille (2024); Borusyak et al. (2024); Sun and Abraham (2021). Standard errors are clustered at the district level.

Figure D.5: Dynamic effects on financial inclusion and digital payment use

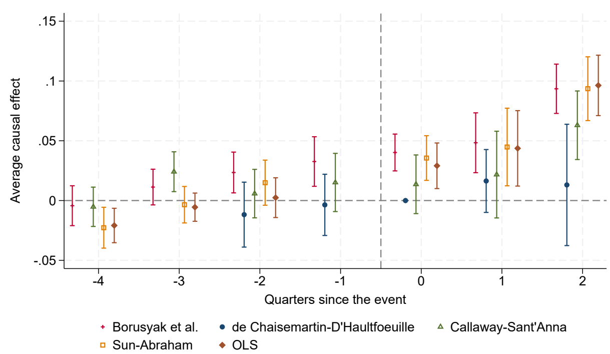
(a) Financial inclusion



(b) Digital payments + internet banking

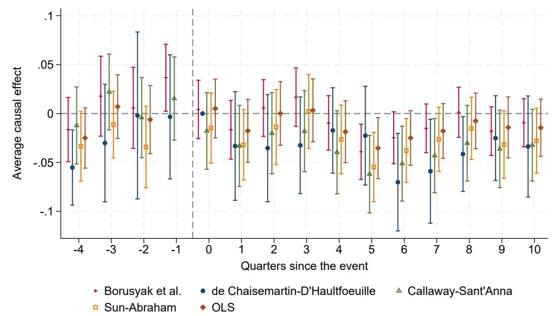


(c) Internet banking



Note: This figure reports dynamic effects of district-level exposure to interoperability on financial inclusion, digital payment use, and internet banking. The exposure measure is constructed from district-level deposits in the pre-interoperability period (December 2022) for institutions participating in each phase of the strategy. For financial inclusion, the outcome is an indicator equal to one if the individual reports having an account and/or a card (debit or credit), and zero otherwise. For internet banking, the outcome is an indicator equal to one if the individual reports using internet banking for at least one of the nine expenditure categories. The variable IB + Digital Wallets additionally incorporates digital wallet use in 2024. Estimation uses staggered-adoption difference-in-differences methods following Callaway and Sant'Anna (2021); de Chaisemartin and D'Haultfœuille (2024); Borusyak et al. (2024); Sun and Abraham (2021). Standard errors are clustered at the district level.

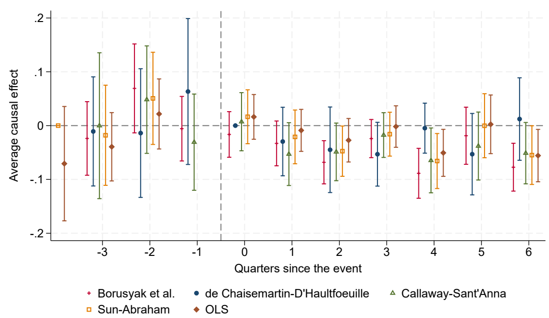
Figure D.6: Dynamic effects on household financial fragility



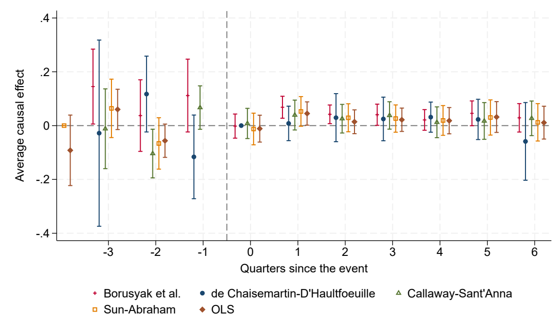
Note: This figure reports dynamic effects of district-level exposure to interoperability on a measure of household financial fragility. The exposure measure is constructed from district-level deposits in the pre-interoperability period (December 2022) for institutions participating in each phase of the strategy. Financial fragility is an indicator equal to one if the individual reports that, given the household's current economic situation, the household is forced to draw down savings or borrow. Estimation uses staggered-adoption difference-in-differences methods following Callaway and Sant'Anna (2021); de Chaisemartin and D'Haultfœuille (2024); Borusyak et al. (2024); Sun and Abraham (2021). Standard errors are clustered at the district level.

Figure D.7: Mechanisms: dynamic effects on internet access

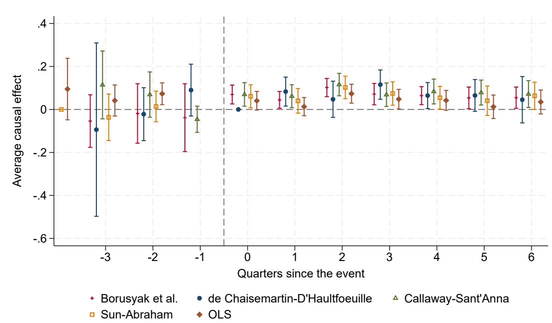
(a) Fixed



(b) Postpaid mobile



(c) Prepaid mobile



Note: This figure reports dynamic effects of district-level exposure to interoperability on three measures of household internet access. The exposure measure is constructed from district-level deposits in the pre-interoperability period (December 2022) for institutions participating in each phase of the strategy. Outcomes are indicators equal to one if the household reports having access to fixed internet, postpaid mobile internet, and prepaid mobile internet, respectively. Estimation uses staggered-adoption difference-in-differences methods following Callaway and Sant'Anna (2021); de Chaisemartin and D'Haultfœuille (2024); Borusyak et al. (2024); Sun and Abraham (2021). Standard errors are clustered at the district level.

E Appendix: Robustness Exercises

Table E.1: Robustness to the expanded exposure measure (deposits + ATMs/agents): effect on cash use

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean
Groceries	-0.015	0.009	0.082	0.126	0.911
Ready-to-eat food	-0.013	0.008	0.084	0.126	0.909
Laundry	-0.014	0.009	0.102	0.136	0.896
Utilities	-0.030**	0.011	0.004	0.017	0.859
Cooking fuels	-0.046***	0.013	0.000	0.005	0.794
Personal hygiene	-0.010	0.007	0.146	0.159	0.910
Clothing and footwear	-0.025**	0.010	0.011	0.032	0.838
Furniture and appliances	-0.033	0.021	0.116	0.140	0.253
Household appliances	-0.028*	0.013	0.031	0.074	0.106
Other	-0.003	0.014	0.851	0.851	0.836
Cash use intensity	-0.024**	0.008	0.002	0.010	0.719
Uses only cash	-0.020*	0.010	0.047	0.093	0.065
N			233,196		
N Clusters			1,347		

Note: This table reports the effect of district-level exposure to interoperability on cash use by expenditure category. The exposure measure is constructed using district-level deposits and the number of ATMs and banking agents, measured prior to interoperability (December 2022), for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using cash for the corresponding expenditure category. Cash-use intensity is the share of the nine main spending categories in which the individual reports using cash, and cash-only use is a dummy equal to one if the individual reports using only cash in all nine categories. Estimation uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.2: Robustness to the expanded exposure measure (deposits + ATMs/agents): effect on card use

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean
Groceries	-0.013*	0.006	0.032	0.055	0.055
Ready-to-eat food	-0.009	0.006	0.126	0.189	0.050
Laundry	-0.013**	0.006	0.022	0.044	0.047
Utilities	-0.014***	0.004	0.000	0.005	0.031
Cooking fuels	-0.011***	0.003	0.001	0.008	0.019
Personal hygiene	-0.013**	0.005	0.014	0.043	0.048
Clothing and footwear	-0.013**	0.006	0.022	0.044	0.054
Furniture and appliances	-0.004	0.003	0.167	0.222	0.012
Household appliances	-0.001	0.003	0.711	0.711	0.012
Other	-0.002	0.004	0.591	0.644	0.023
Card use intensity	-0.010**	0.004	0.008	0.032	0.036
Uses only cards	-0.001	0.001	0.330	0.397	0.001
N			233,196		
N Clusters			1,347		

Note: This table reports the effect of district-level exposure to interoperability on card use (debit and credit) by expenditure category. The exposure measure is constructed using district-level deposits and the number of ATMs and banking agents, measured prior to interoperability (December 2022), for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using a card for the corresponding expenditure category. Card-use intensity is the share of the nine main spending categories in which the individual reports using a card, and card-only use is a dummy equal to one if the individual reports using only cards in all nine categories. Estimation uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.3: Robustness to the expanded exposure measure (deposits + ATMs/agents): effect on digital payments and financial inclusion

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean	N	Clusters
Financial Inclusion	-0.019	0.016	0.237	0.237	0.524	233,196	1,347
Internet Banking (IB)	0.034***	0.012	0.005	0.008	0.060	155,995	1,306
IB + Digital Wallets	0.033***	0.011	0.003	0.010	0.060	233,196	1,347

Note: This table reports the effect of district-level exposure to interoperability on financial inclusion, internet banking use, and digital payments. For financial inclusion, the outcome is an indicator equal to one if the individual reports having an account and/or a card (debit or credit), and zero otherwise. For internet banking, the outcome is an indicator equal to one if the individual reports using internet banking for at least one of the nine expenditure categories. The variable IB + Digital Wallets additionally incorporates digital wallet use in 2024. The exposure measure is constructed using district-level deposits and the number of ATMs and banking agents, measured prior to interoperability (December 2022), for institutions participating in each phase of the strategy. Estimation uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Starting in 2024, INEI includes mobile banking and ATMs as options in the internet-banking question, so I restrict the sample through 2023 for the internet-banking outcome. I also report estimates for IB + Digital Wallets, which leverages the expanded set of questions in 2024 on mobile banking, ATMs, and digital wallets. Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.4: Robustness using March 2023 deposits for exposure: effect on cash use

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean
Groceries	-0.017*	0.009	0.055	0.066	0.911
Ready-to-eat food	-0.019**	0.008	0.023	0.040	0.909
Laundry	-0.017*	0.009	0.048	0.064	0.896
Utilities	-0.044***	0.011	0.000	0.001	0.859
Cooking fuels	-0.051***	0.013	0.000	0.001	0.794
Personal hygiene	-0.015*	0.007	0.038	0.058	0.910
Clothing and footwear	-0.031***	0.010	0.002	0.007	0.838
Furniture and appliances	-0.038*	0.021	0.073	0.080	0.253
Household appliances	-0.031**	0.013	0.016	0.039	0.106
Other	-0.005	0.014	0.700	0.700	0.836
Cash use intensity	-0.029***	0.008	0.000	0.001	0.719
Uses only cash	-0.023**	0.010	0.023	0.040	0.065
N			233,196		
N Clusters			1,347		

Note: This table reports the effect of district-level exposure to interoperability on cash use by expenditure category. The exposure measure is constructed using district-level deposits measured prior to interoperability (March 2023) for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using cash for the corresponding expenditure category. Cash-use intensity is the share of the nine main spending categories in which the individual reports using cash, and cash-only use is a dummy equal to one if the individual reports using only cash in all nine categories. Estimation uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.5: Robustness using March 2023 deposits for exposure: effect on card use

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean
Groceries	-0.014**	0.006	0.021	0.041	0.055
Ready-to-eat food	-0.010	0.006	0.091	0.137	0.050
Laundry	-0.014**	0.006	0.019	0.041	0.047
Utilities	-0.017***	0.004	0.000	0.001	0.031
Cooking fuels	-0.010**	0.003	0.002	0.013	0.019
Personal hygiene	-0.017**	0.006	0.003	0.013	0.048
Clothing and footwear	-0.013**	0.006	0.028	0.047	0.054
Furniture and appliances	-0.003	0.003	0.410	0.547	0.012
Household appliances	0.001	0.003	0.680	0.742	0.012
Other	0.001	0.004	0.839	0.839	0.023
Card use intensity	-0.011**	0.004	0.007	0.021	0.036
Uses only cards	-0.000	0.001	0.601	0.721	0.001
N			233,196		
N Clusters			1,347		

Note: This table reports the effect of district-level exposure to interoperability on card use (debit and credit) by expenditure category. The exposure measure is constructed using district-level deposits measured prior to interoperability (March 2023) for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using a card for the corresponding expenditure category. Card-use intensity is the share of the nine main spending categories in which the individual reports using a card, and card-only use is a dummy equal to one if the individual reports using only cards in all nine categories. Estimation uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.6: Robustness using March 2023 deposits for exposure: effect on digital payments and financial inclusion

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean	N	N Clusters
Financial Inclusion	-0.025	0.016	0.125	0.125	0.524	233,196	1,347
Internet Banking (IB)	0.033***	0.012	0.006	0.009	0.060	155,995	1,306
IB + Digital Wallets	0.051***	0.011	0.000	0.000	0.060	233,196	1,347

Note: This table reports the effect of district-level exposure to interoperability on financial inclusion, internet banking use, and digital payments. For financial inclusion, the outcome is an indicator equal to one if the individual reports having an account and/or a card (debit or credit), and zero otherwise. For internet banking, the outcome is an indicator equal to one if the individual reports using internet banking for at least one of the nine expenditure categories. The variable IB + Digital Wallets additionally incorporates digital wallet use in 2024. The exposure measure is constructed using district-level deposits measured prior to interoperability (March 2023) for institutions participating in each phase of the strategy. Estimation uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Starting in 2024, INEI includes mobile banking and ATMs as options in the internet-banking question, so I restrict the sample through 2023 for the internet-banking outcome. I also report estimates for IB + Digital Wallets, which leverages the expanded set of questions in 2024 on mobile banking, ATMs, and digital wallets. Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing ($^* p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.7: Robustness restricting to districts with at least one ATM or banking agent: effect on cash use

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean
Groceries	-0.016*	0.009	0.072	0.087	0.910
Ready-to-eat food	-0.020**	0.008	0.019	0.039	0.909
Laundry	-0.017*	0.009	0.047	0.070	0.896
Utilities	-0.044***	0.011	0.000	0.002	0.858
Cooking fuels	-0.052***	0.013	0.000	0.001	0.794
Personal hygiene	-0.014*	0.007	0.056	0.075	0.910
Clothing and footwear	-0.031***	0.010	0.003	0.009	0.837
Furniture and appliances	-0.037*	0.021	0.086	0.094	0.251
Household appliances	-0.030**	0.013	0.019	0.039	0.106
Other	-0.005	0.014	0.734	0.734	0.835
Cash use intensity	-0.029***	0.008	0.000	0.001	0.719
Uses only cash	-0.022**	0.010	0.029	0.050	0.065
N			226,304		
N Clusters			1,252		

Note: This table reports the effect of district-level exposure to interoperability on cash use by expenditure category. The exposure measure is constructed using district-level deposits measured prior to interoperability (December 2022) for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using cash for the corresponding expenditure category. Cash-use intensity is the share of the nine main spending categories in which the individual reports using cash, and cash-only use is a dummy equal to one if the individual reports using only cash in all nine categories. Estimation restricts the sample to districts with at least one ATM or banking agent and uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.8: Robustness restricting to districts with at least one ATM or banking agent: effect on card use

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean
Groceries	-0.015**	0.006	0.017	0.031	0.055
Ready-to-eat food	-0.010	0.006	0.088	0.132	0.051
Laundry	-0.014**	0.006	0.014	0.031	0.048
Utilities	-0.017***	0.004	0.000	0.000	0.031
Cooking fuels	-0.011***	0.003	0.001	0.009	0.019
Personal hygiene	-0.017**	0.006	0.003	0.010	0.048
Clothing and footwear	-0.014**	0.006	0.018	0.031	0.055
Furniture and appliances	-0.003	0.003	0.388	0.518	0.012
Household appliances	0.001	0.003	0.754	0.823	0.012
Other	0.001	0.004	0.889	0.889	0.023
Card use intensity	-0.011**	0.004	0.005	0.015	0.037
Uses only cards	-0.000	0.001	0.438	0.525	0.001
N			226,304		
N Clusters			1,252		

Note: This table reports the effect of district-level exposure to interoperability on card use (debit and credit) by expenditure category. The exposure measure is constructed using district-level deposits measured prior to interoperability (December 2022) for institutions participating in each phase of the strategy. Category-specific outcomes are indicators equal to one if the individual reports using a card for the corresponding expenditure category. Card-use intensity is the share of the nine main spending categories in which the individual reports using a card, and card-only use is a dummy equal to one if the individual reports using only cards in all nine categories. Estimation restricts the sample to districts with at least one ATM or banking agent and uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.9: Robustness restricting to districts with at least one ATM or banking agent: effect on digital payments and financial inclusion

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Pre-treatment mean	N	Clusters
Financial Inclusion	-0.024	0.017	0.140	0.140	0.525	226,304	1,252
Internet Banking (IB)	0.033**	0.012	0.007	0.011	0.061	151,356	1,218
IB + Digital Wallets	0.049***	0.011	0.000	0.000	0.061	226,304	1,252

Note: This table reports the effect of district-level exposure to interoperability on financial inclusion, internet banking use, and digital payments. For financial inclusion, the outcome is an indicator equal to one if the individual reports having an account and/or a card (debit or credit), and zero otherwise. For internet banking, the outcome is an indicator equal to one if the individual reports using internet banking for at least one of the nine expenditure categories. The variable IB + Digital Wallets additionally incorporates digital wallet use in 2024. The exposure measure is constructed using district-level deposits measured prior to interoperability (December 2022) for institutions participating in each phase of the strategy. Estimation restricts the sample to districts with at least one ATM or banking agent and uses the staggered-adoption difference-in-differences method following Callaway and Sant'Anna (2021). Starting in 2024, INEI includes mobile banking and ATMs as options in the internet-banking question, so I restrict the sample through 2023 for the internet-banking outcome. I also report estimates for IB + Digital Wallets, which leverages the expanded set of questions in 2024 on mobile banking, ATMs, and digital wallets. Standard errors are clustered at the district level. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the mean of each outcome in the pre-treatment period (before 2023Q2).

Table E.10: Placebo: effect on cash use

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Mean
Groceries	0.003	0.008	0.724	0.994	0.911
Ready-to-eat food	-0.002	0.010	0.807	0.994	0.905
Laundry	-0.002	0.009	0.777	0.994	0.897
Utilities	-0.001	0.011	0.924	0.994	0.858
Cooking fuels	0.011	0.014	0.440	0.994	0.795
Personal hygiene	0.001	0.009	0.889	0.994	0.910
Clothing and footwear	0.020	0.014	0.161	0.484	0.828
Furniture and appliances	-0.000	0.022	0.994	0.994	0.250
Household appliances	0.020	0.014	0.144	0.484	0.104
Other	0.058**	0.020	0.003	0.038	0.826
Cash use intensity	0.005	0.008	0.498	0.994	0.718
Uses only cash	0.016	0.011	0.139	0.484	0.062
N			136,080		
N Clusters			1,276		

Note: This table reports a placebo exercise to assess the validity of the identification strategy. I restrict the sample to the pre-treatmen period 2021Q3–2023Q1 and assign placebo treatment dates to the three cohorts, imputing adoption dates 2022Q1, 2022Q2, and 2022Q3 for the cohorts that in the actual rollout begin in 2023Q2, 2023Q4, and 2024Q1, respectively. I keep the same predetermined exposure measure constructed from district deposits (December 2022) of participating institutions in each phase and estimate a staggered-adoption difference-in-differences model following Callaway and Sant'Anna (2021), clustering standard errors at the district level. Category-specific outcomes are indicators equal to one if the individual reports using cash for the corresponding expenditure category. Cash-use intensity is the share of the nine main spending categories in which the individual reports using cash, and cash-only use is a dummy equal to one if the individual reports using only cash in all nine categories. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the outcome mean in the pre-treatment period (before 2023Q2).

Table E.11: Placebo: effect on card use

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Mean
Groceries	-0.007	0.007	0.265	0.624	0.053
Ready-to-eat food	-0.008	0.007	0.233	0.624	0.049
Laundry	-0.007	0.007	0.312	0.624	0.046
Utilities	-0.000	0.004	0.934	0.934	0.029
Cooking fuels	0.006	0.003	0.021	0.246	0.017
Personal hygiene	-0.003	0.006	0.626	0.752	0.046
Clothing and footwear	-0.002	0.006	0.715	0.781	0.052
Furniture and appliances	0.004	0.003	0.113	0.624	0.011
Household appliances	-0.003	0.003	0.289	0.624	0.012
Other	0.002	0.004	0.549	0.752	0.022
Card use intensity	-0.002	0.004	0.586	0.752	0.035
Uses only cards	-0.001	0.001	0.517	0.752	0.001
N			136,080		
N Clusters			1,276		

Note: This table reports a placebo exercise to assess the validity of the identification strategy. I restrict the sample to the pre-treatmen period 2021Q3–2023Q1 and assign placebo treatment dates to the three cohorts, imputing adoption dates 2022Q1, 2022Q2, and 2022Q3 for the cohorts that in the actual rollout begin in 2023Q2, 2023Q4, and 2024Q1, respectively. I keep the same predetermined exposure measure constructed from district deposits (December 2022) of participating institutions in each phase and estimate a staggered-adoption difference-in-differences model following Callaway and Sant'Anna (2021), clustering standard errors at the district level. Category-specific outcomes are indicators equal to one if the individual reports using a card for the corresponding expenditure category. Card-use intensity is the share of the nine main spending categories in which the individual reports using a card, and card-only use is a dummy equal to one if the individual reports using only cards in all nine categories. Statistical significance indicated by *, **, and *** is based on the adjusted p-value reported in column p BH, computed using the Benjamini–Hochberg procedure to correct for multiple testing (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). The last column reports the outcome mean in the pre-treatment period (before 2023Q2).

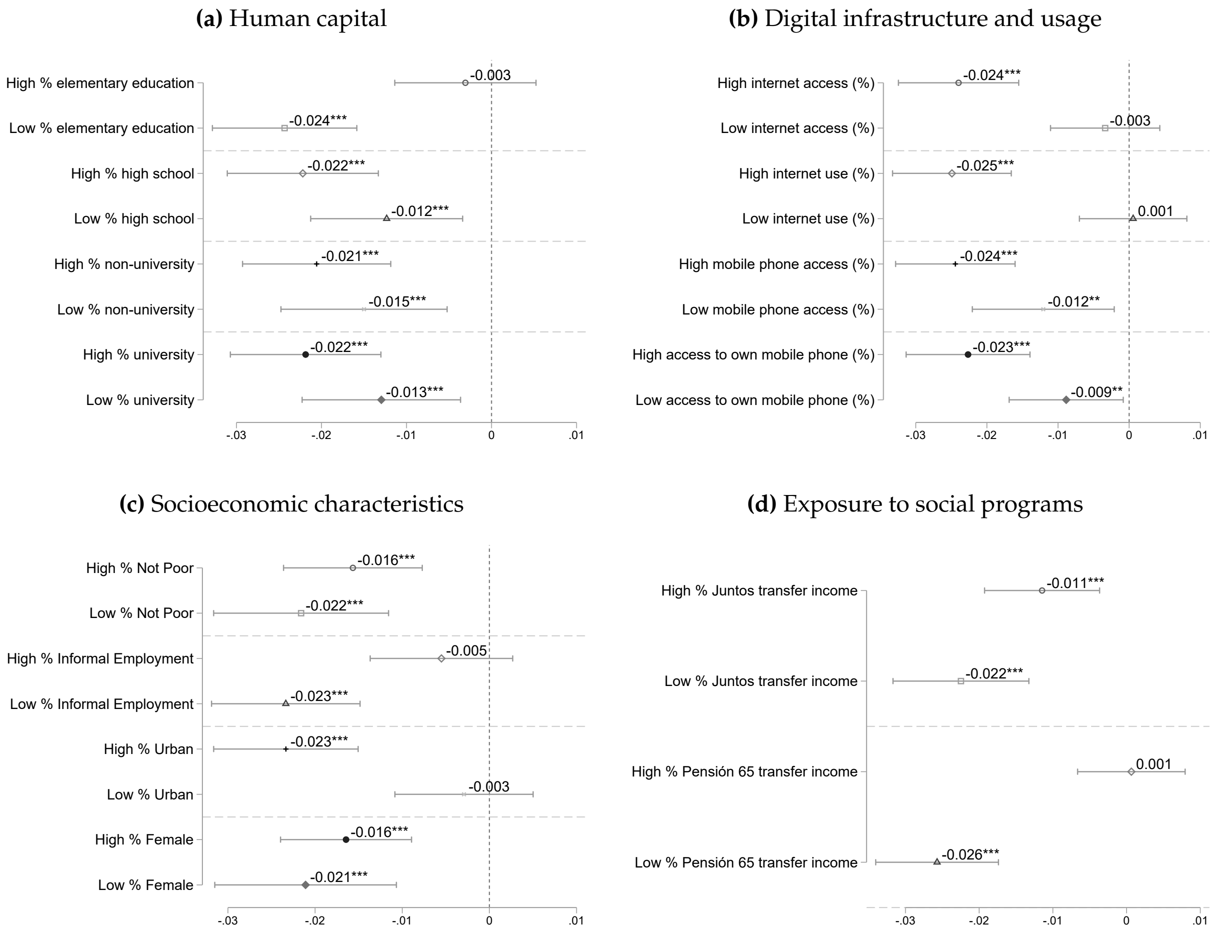
Table E.12: Placebo: effect on digital payments, financial inclusion and financial fragility

	Interoperability Exposure x Post	Std. Error	p-value	p BH	Mean	N	Clusters
Internet Banking (IB)	0.009	0.007	0.148	0.198	0.056	136,080	1,276
IB + Digital Wallets	0.009	0.007	0.148	0.198	0.056	136,080	1,276
Financial Inclusion	0.001	0.014	0.962	0.962	0.520	136,080	1,276
Financial Fragility	0.031	0.016	0.054	0.217	0.211	136,080	1,276

Note: This table reports a placebo exercise restricting the sample to the pre-treatmen period 2021Q3–2023Q1 and imputing placebo adoption dates (2022Q1, 2022Q2, and 2022Q3) to the three cohorts. I keep the same predetermined exposure measure (district deposits in December 2022 of participating institutions) and estimate a staggered-adoption difference-in-differences model following Callaway and Sant'Anna (2021), with standard errors clustered at the district level. Outcomes include individual indicators for financial inclusion (having an account and/or a card), internet banking (IB), and a harmonized measure IB + Digital Wallets; because the INEI question changes starting in 2024, estimation for IB is restricted through 2023. Statistical significance is based on Benjamini–Hochberg adjusted p-values (column p BH), and the last column reports the pre-treatment mean (before 2023Q2). (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

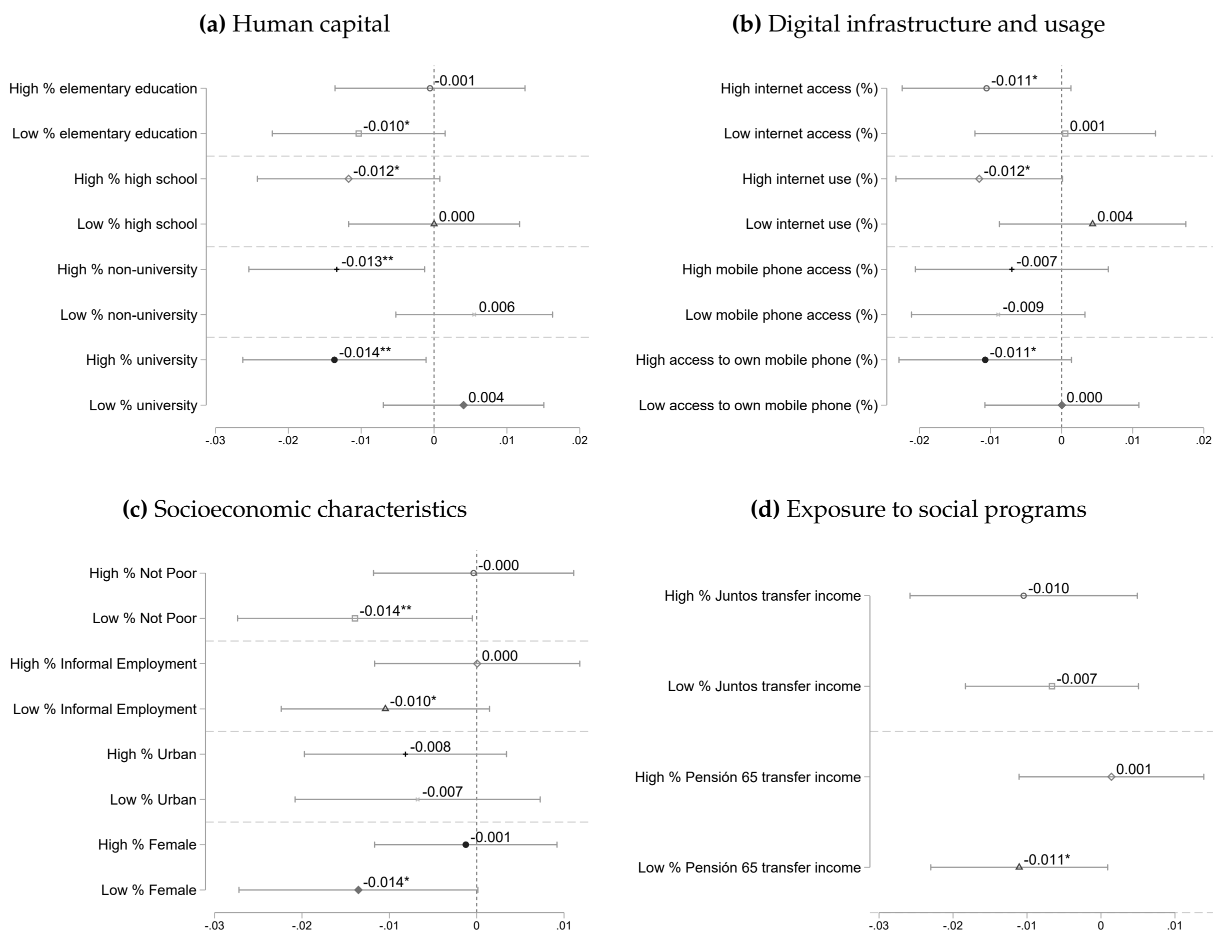
F Appendix: Heterogeneous Effects

Figure F.1: Heterogeneous effects on the intensity of cash use



Note: This figure reports the estimated heterogeneous effects of interoperability on the intensity of cash use, using the imputation-based difference-in-differences estimator of Borusyak et al. (2024) with standard errors clustered at the district level. The outcome represents the share of payments made in cash across the nine main spending categories. Heterogeneity is defined using indicators for district pre-treatment characteristics measured in 2022, splitting districts into "high" and "low" groups depending on whether each covariate is above its median. The panels summarize four dimensions: human capital, digital infrastructure and usage, socioeconomic characteristics, and exposure to social programs. Coefficients are interpreted as percentage-point changes.

Figure F.2: Heterogeneous effects on the use of cash only



(a) Human capital

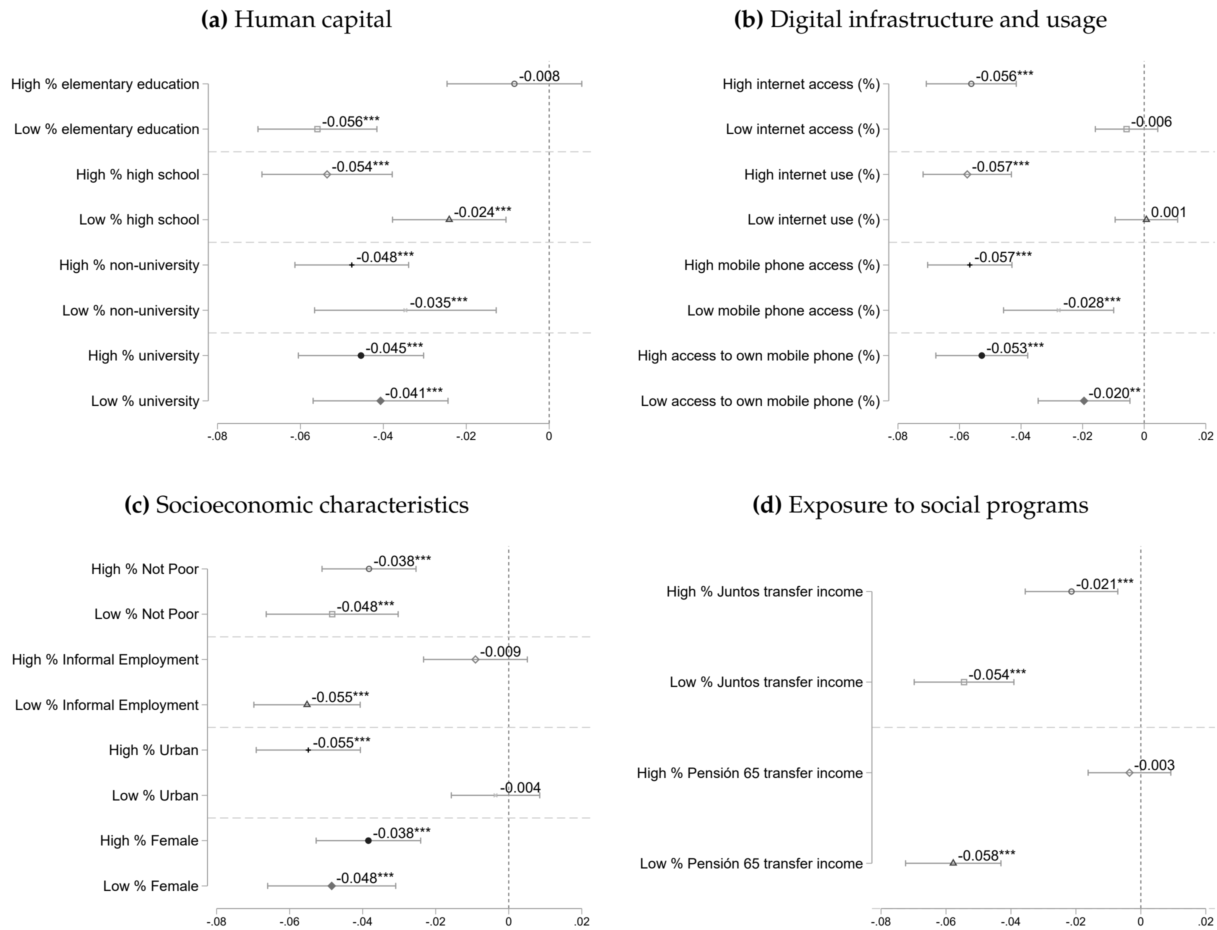
(b) Digital infrastructure and usage

(c) Socioeconomic characteristics

(d) Exposure to social programs

Note: This figure reports heterogeneous-effects estimates of interoperability on the use of cash only, using the imputation-based difference-in-differences estimator of Borusyak et al. (2024) with standard errors clustered at the district level. The outcome is a dummy equal to one if the individual reports using only cash in all nine main spending categories. Heterogeneity is defined using indicators for district pre-treatment characteristics measured in 2022, splitting districts into “high” and “low” groups depending on whether each covariate is above its median. The panels summarize four dimensions: human capital, digital infrastructure and usage, socioeconomic characteristics, and exposure to social programs. Coefficients are interpreted as percentage-point changes.

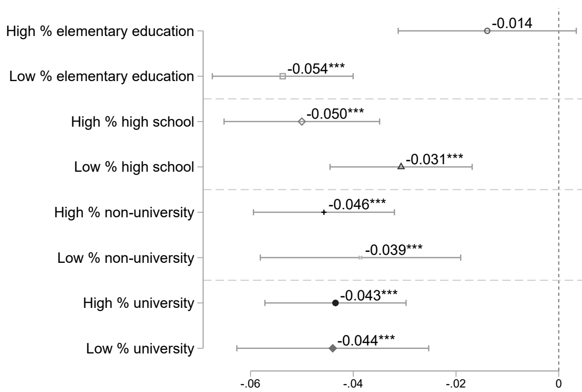
Figure F.3: Heterogeneous effects on cash use for utilities



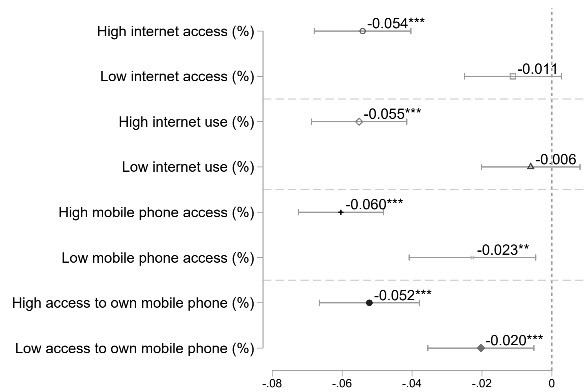
Note: This figure reports heterogeneous-effects estimates of interoperability on cash use for utilities, using the imputation-based difference-in-differences estimator of Borusyak et al. (2024) with standard errors clustered at the district level. The outcome is an indicator equal to one if the individual reports using cash for housing payments. Heterogeneity is defined using indicators for district pre-treatment characteristics measured in 2022, splitting districts into "high" and "low" groups depending on whether each covariate is above its median. The panels summarize four dimensions: human capital, digital infrastructure and usage, socioeconomic characteristics, and exposure to social programs. Coefficients are interpreted as percentage-point changes.

Figure F.4: Heterogeneous effects on cash use for cooking fuels

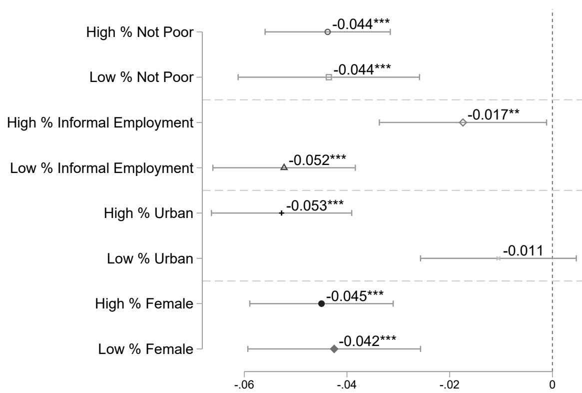
(a) Human capital



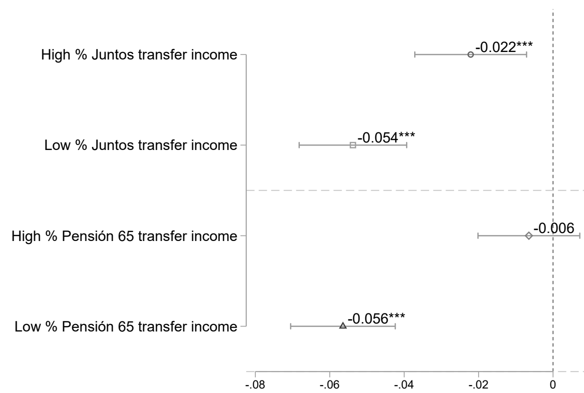
(b) Digital infrastructure and usage



(c) Socioeconomic characteristics

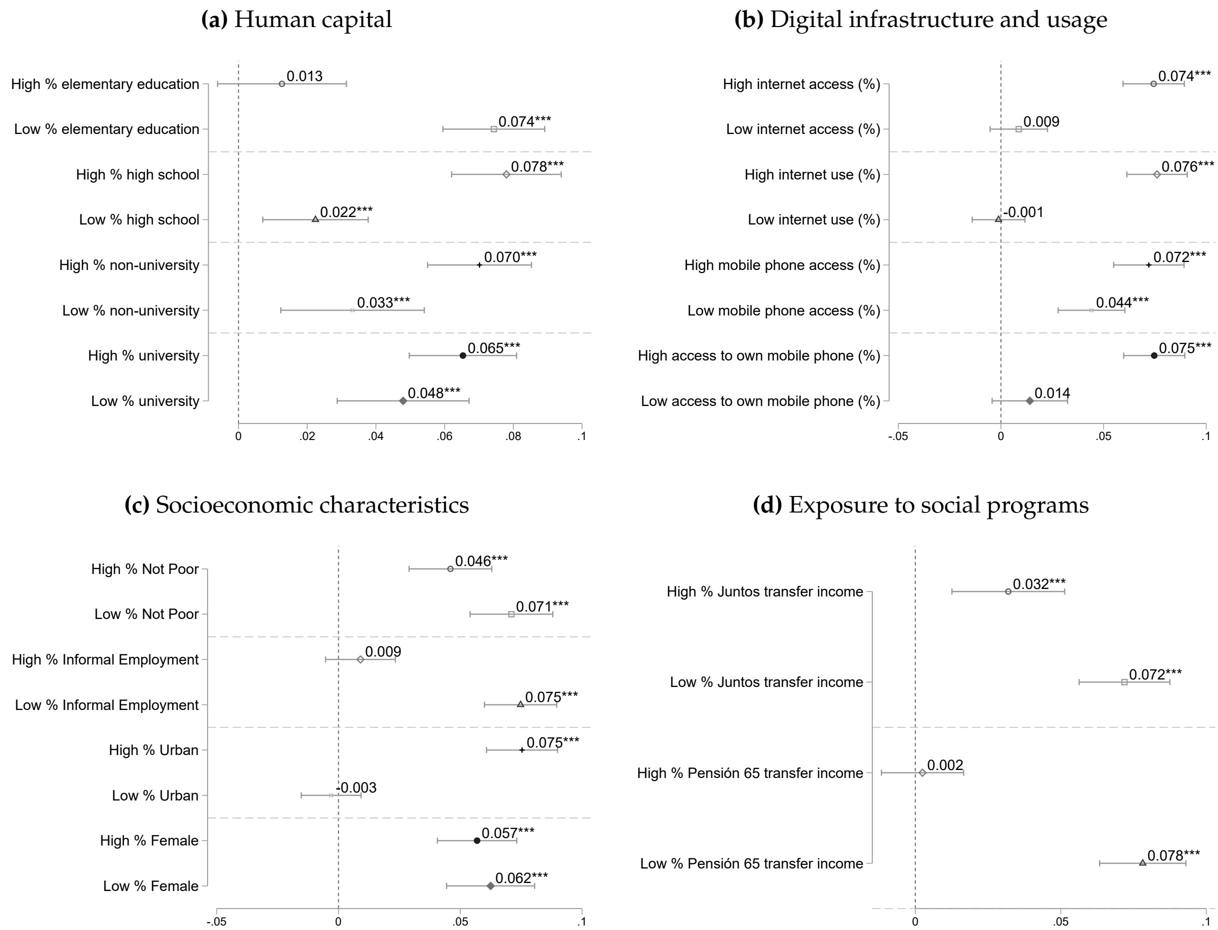


(d) Exposure to social programs



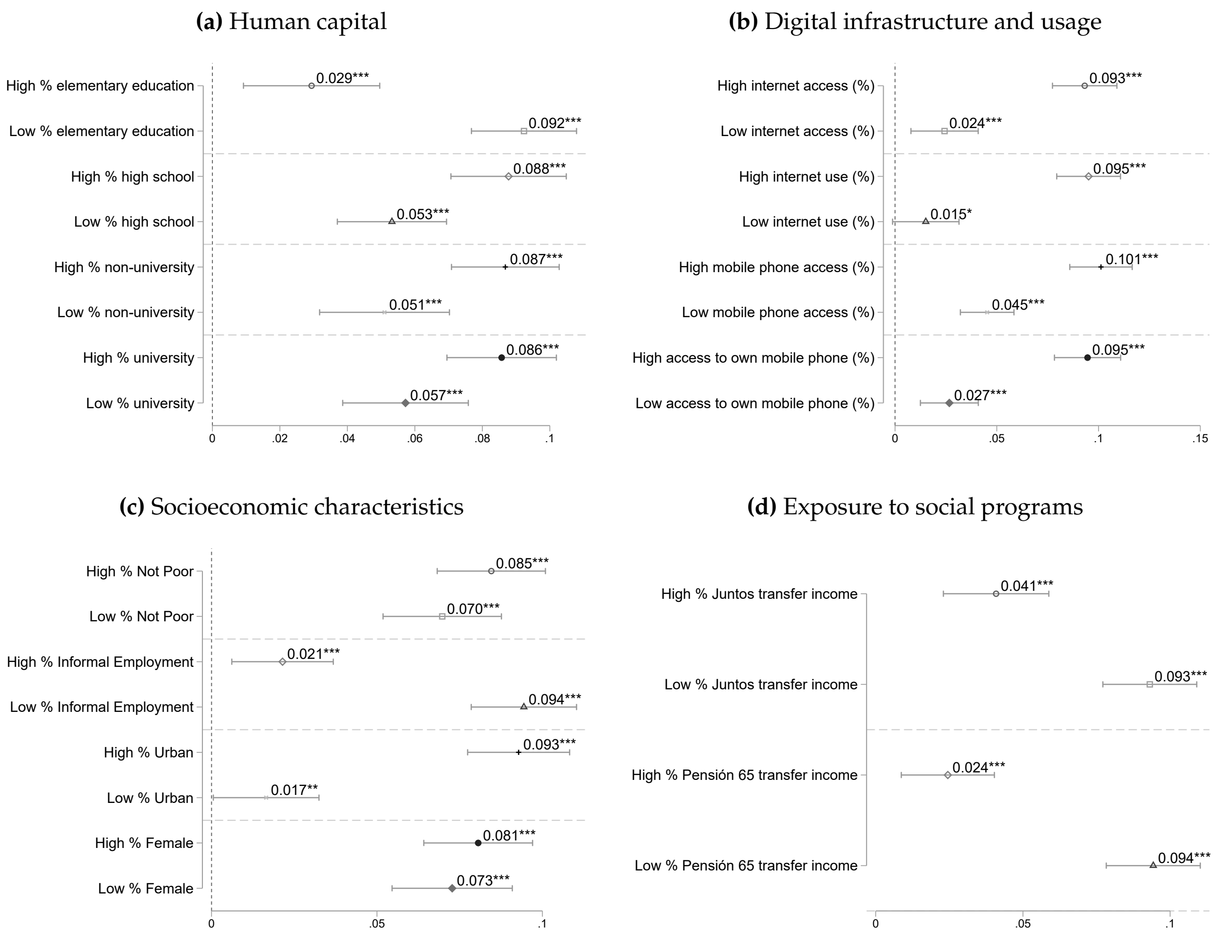
Note: This figure reports heterogeneous-effects estimates of interoperability on cash use for cooking fuels, using the imputation-based difference-in-differences estimator of Borusyak et al. (2024) with standard errors clustered at the district level. The outcome is an indicator equal to one if the individual reports using cash for cooking-fuel expenditures. Heterogeneity is defined using indicators for district pre-treatment characteristics measured in 2022, splitting districts into "high" and "low" groups depending on whether each covariate is above its median. The panels summarize four dimensions: human capital, digital infrastructure and usage, socioeconomic characteristics, and exposure to social programs. Coefficients are interpreted as percentage-point changes.

Figure F.5: Heterogeneous effects on internet banking use



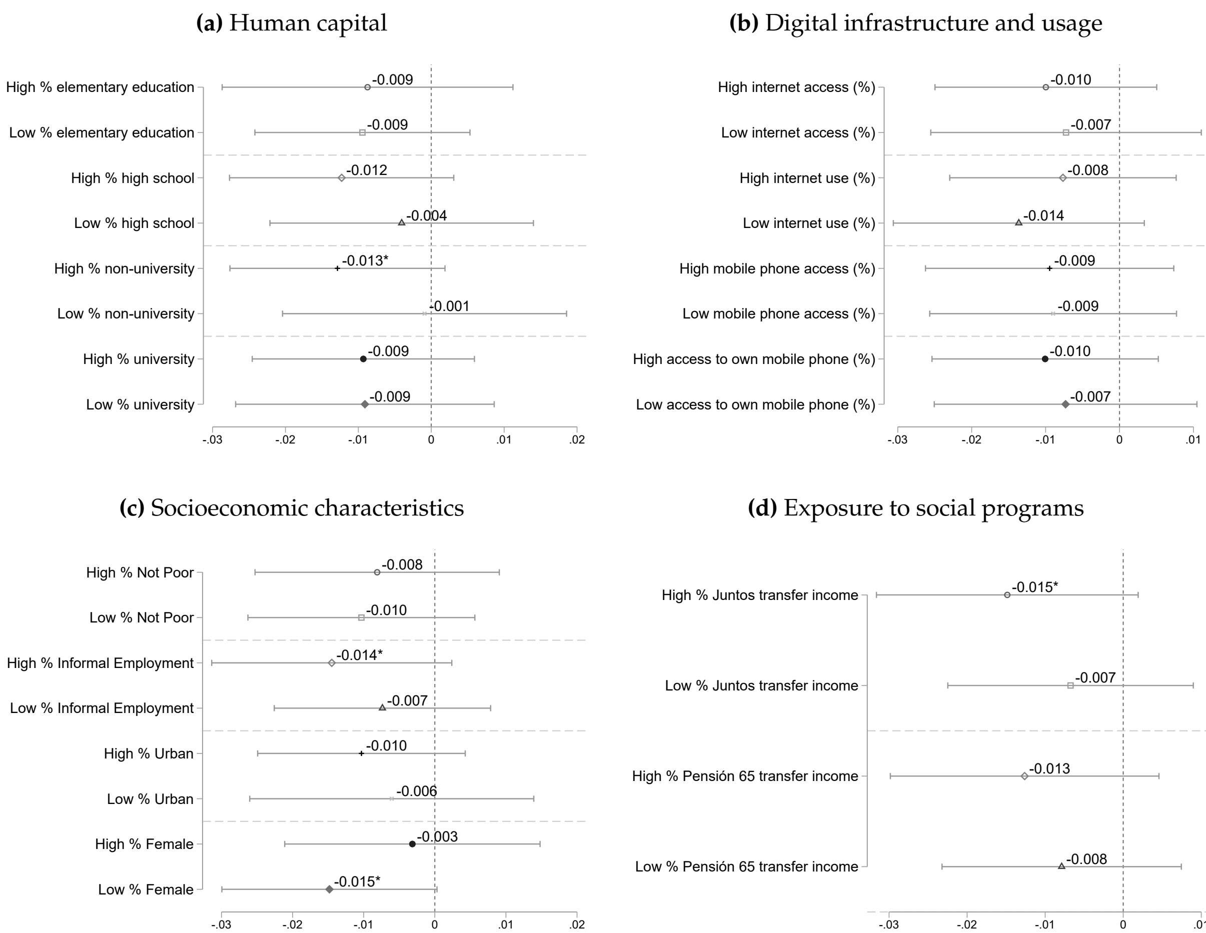
Note: This figure reports heterogeneous-effects estimates of interoperability on internet banking use, using the imputation-based difference-in-differences estimator of Borusyak et al. (2024) with standard errors clustered at the district level. The outcome here is an indicator equal to one if the individual reports using internet banking. Heterogeneity is defined using indicators for district pre-treatment characteristics measured in 2022, splitting districts into "high" and "low" groups depending on whether each covariate is above its median. The panels summarize four dimensions: human capital, digital infrastructure and usage, socioeconomic characteristics, and exposure to social programs. Coefficients are interpreted as percentage-point changes.

Figure F.6: Heterogeneous effects on digital payment use



Note: This figure reports heterogeneous-effects estimates of interoperability on digital payment use, using the imputation-based difference-in-differences estimator of Borusyak et al. (2024) with standard errors clustered at the district level. The outcome here is an indicator equal to one if the individual reports using digital payments (internet banking and/or digital wallets, depending on availability). Heterogeneity is defined using indicators for district pre-treatment characteristics measured in 2022, splitting districts into "high" and "low" groups depending on whether each covariate is above its median. The panels summarize four dimensions: human capital, digital infrastructure and usage, socioeconomic characteristics, and exposure to social programs. Coefficients are interpreted as percentage-point changes.

Figure F.7: Heterogeneous effects on financial fragility



Note: This figure reports heterogeneous-effects estimates of interoperability on financial fragility, using the imputation-based difference-in-differences estimator of Borusyak et al. (2024) with standard errors clustered at the district level. The outcome here is an indicator equal to 1 if the individual reports that, under the household's current economic situation, the household is forced to draw down savings or to borrow. Heterogeneity is defined using indicators for district pre-treatment characteristics measured in 2022, splitting districts into "high" and "low" groups depending on whether each covariate is above its median. The panels summarize four dimensions: human capital, digital infrastructure and usage, socioeconomic characteristics, and exposure to social programs. Coefficients are interpreted as percentage-point changes.