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# Retail fast payment systems as a catalyst for digital finance

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## Abstract

Retail fast payment systems (FPS) like Brazil's Pix, India's UPI and Switzerland's TWINT have stimulated the diffusion of digital finance apps. With a rich dataset on app downloads and use for 86,163 apps in 95 countries over 2012–22, we find that adoption of finance apps is higher following launch of an FPS, particularly in lower-income economies. FPS are more closely associated with the diffusion of payment apps than with non-payment apps. They are also linked to entry by technological disrupters (fintechs and big techs), more than by apps of incumbent financial institutions. Notably, digital finance app adoption shows a stronger association with FPS that feature active engagement by the central bank, real-time settlement capabilities and open membership to banks and non-banks.

Keywords: fast payment system, digital finance, fintech, big tech, digital adoption.

JEL classification: G21, G23, O32

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# 1. Introduction

The rise of digital technologies in finance has challenged the dominance of incumbent financial institutions. This promises efficiency gains and greater financial inclusion. Research finds that financial technologies (fintech) can contribute to wider access to the financial system, as digital services are generally more accessible for the unbanked and the informal sector (Philippon, 2016; Beck, 2020; Senyo et al, 2023). The spread of these technologies into financial services like payments, credit, investment and insurance has helped to lower costs and increase access to digital payments and other financial services such as mobile loans (Croxson et al, 2023; Dalton et al, 2023). At the same time, it is well documented in the literature that higher access to financial services has a positive effect on economic growth (see eg Levine, 2005; Sahay et al, 2015).

Recently, there is growing interest in policy initiatives to increase the speed and convenience of digital payments. Retail fast payment systems (FPS) are one prominent example. FPS are payment infrastructures that allow the transmission of payment messages and the availability of final funds between individuals, businesses and governments in real time or near real time on a 24/7 basis (CPMI, 2021). FPS facilitate payments between account holders at multiple banks and other payment service providers (PSPs) rather than just between customers of the same PSP. Leveraging on advanced technologies and interoperable platforms, FPS enable individuals and businesses to make electronic payments seamlessly (BIS, 2022; Frost et al, 2024) and access to other financial services such as loans (Aurazo and Franco, 2024).

In a number of economies, FPS have achieved mass adoption, with regular use by a majority of the population. In Brazil, the central bank launched the instant payment scheme Pix in November 2020 (Lobo and Brandt, 2021). Pix allows users to make or receive payments at a cost that is more than 80% lower than traditional alternatives, like domestic transfers, debit or credit cards. Users can make transfers to others with aliases, eg a phone number, email address or quick response (QR) code. Pix is now used by over 90% of Brazilian adults. In India, real-time payments are available since the launch of the Immediate Payment Service (IMPS) in November 2010. Yet the Unified Payments Interface (UPI), launched in April 2016, improved payment services by enabling instant payments with QR codes, mobile numbers and virtual IDs. UPI now processes over 10 billion transactions per month (Sinha et al, 2024). In Switzerland, large-value and retail payments are processed via the Swiss Interbank Clearing (SIC) system. While the system is owned and operated by SIX Payments, the Swiss National Bank plays a vital role in overseeing the system and ensuring its efficiency and reliability. SIC facilitates real-time transfers for individuals and businesses through the TWINT service, launched in 2017.[2]

[2] There are several further examples with widespread adoption. In Thailand, PromptPay was introduced in 2017 with the primary objective of promoting financial inclusion and enhancing digital payments in the country. The system was

Beyond payments, individuals and businesses worldwide are increasingly embracing digital finance also for other financial services. The use of finance apps helps individuals and small businesses to pay and be paid, borrow (Hau et al, 2021), invest in savings products and securities and insure themselves against risks. Apps are offered by fintech firms, big techs and incumbent financial institutions. In some countries, adoption is nearly universal, with nearly all adults having a major payment app and many using digital banking or investment services. In other countries, digital finance app adoption is lower but increasing rapidly.

This paper evaluates how the implementation of FPS has influenced digital finance app adoption – both in the cross-section and in the time series dimension. To do this, we explore a rich new dataset on downloads and use of 86,163 individual digital finance apps at monthly frequency for up to 95 countries around the world over 2012–22. This large dataset gives us much more granular and high-frequency insights into finance app adoption and use than is available in cross-country surveys (eg Demirgüç-Kunt et al, 2018; Chen et al, 2023). It complements existing work looking at the impact of policies and external developments on fintech adoption (eg Hu et al, 2019; Saka et al, 2021). Our empirical analysis sheds light on what explains growth in the use of digital finance apps, and the role FPS has played in this growth. FPS can affect app adoption through several mechanisms, such as stimulating competition and innovation in payments markets, facilitating digital finance adoption via learning effects and broadening access to financial services, particularly in emerging markets and developing economies (EMDEs). This is particularly important as one of the policy objectives of FPS is to promote greater digitalisation of payments, and of other financial services.

Our paper contributes to the budding literature on fintech adoption and the impact of technology on finance and payments. Carlin et al (2022) show that fintech adoption in Iceland reduces financial fee payments and penalties, but only for younger generations (millennials and generation X). Yang and Zhang (2022) show that higher fintech adoption by households in China fosters financial inclusion by promoting consumption. Frost et al (2019) study the drivers and implications of the growth of big tech firms and find that they can use alternative data and machine learning to better predict credit defaults. Beck et al (2018) study the effects of the adoption of mobile money on entrepreneurial growth in Kenya. Fu and Mishra (2022) provide evidence on the acceleration of digital finance and fintech adoption after Covid-19. As part of this growing literature, our research addresses the gap in research on the impact of payment innovations and their relationship with digital financial policies (Goldstein et al, 2019).

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launched under the supervision of the Bank of Thailand, which played a pivotal role in its development and implementation. PromptPay enables users to make instant transfers and payments using mobile phone numbers, QR codes, citizen ID or a specific bank account, significantly reducing reliance on cash and increasing the efficiency of financial transactions. In Costa Rica, SINPE Móvil, a digital payments platform owned by the central bank, was launched in 2015, allows money transfers in real time at no cost, only requiring an ID and a phone number. In Denmark, instant payments were introduced in November 2014 with Nets Real Time 24/7, owned by the Danish Bankers' Association.

To evaluate diffusion patterns in digital finance adoption, we apply the Bass diffusion model of the adoption of new products in a population (Bass, 1969). The Bass model has been used to evaluate the diffusion of earlier technologies such as electric refrigerators, black and white televisions or power lawnmowers. These types of models are frequently applied in various fields, including diffusion processes in marketing research and other disciplines (Comin and Hobijn, 2004; Davis 1989). Our results confirm that network effects are a strong driver of finance app adoption. Furthermore, we expect that the introduction of FPS could exert an additional impact on the speed of the network effect in the adoption of digital finance apps. Our research extends the application of this modelling approach to the realm of financial services, specifically addressing the adoption of finance apps across countries. This innovative perspective allows us to investigate how the implementation of FPS affects the diffusion patterns of digital finance app adoption, offering insights for the industry and central banks into the evolving landscape of financial technology.

Our results corroborate that the diffusion process in digital finance apps accelerates after the launch of a retail FPS in most countries, with a stronger impact in lower-income economies. The magnitude of this association varies depending on specific app characteristics. Countries with FPS see greater adoption of services by technological disrupters, as measured by more downloads of fintech or big tech apps, relative to the apps of incumbent financial institutions. Similarly, downloads after FPS launch are higher for payment apps that are in their early diffusion stages. The association is stronger in countries where the central bank plays a key role in FPS, where the FPS has open membership, where there is real-time settlement and where there are more use cases (eg person-to-government and business-to-business transactions).

Of course, there is the potential concern that greater finance app adoption drives the launch of an FPS (reverse causality) or that both trends are driven by other, unobserved factors (omitted variable bias). To address these concerns, we conduct an instrumental variable (IV) analysis. Drawing on the approach of Acemoglu et al (2019), we instrument a country's adoption of an FPS with the adoption of FPS in bordering jurisdictions. The rationale behind this instrument is that central banks and other public authorities are more likely to launch an FPS if they see positive experiences in neighbouring countries. Anecdotally, this is indeed quite common, with instances of several countries in South America having launched FPS since the successful implementation of Pix in Brazil, and several countries in Asia having followed the lead of UPI in India. The exclusion restriction is plausibly satisfied, as the adoption of FPS in bordering countries affects digital finance app adoption within a country only through the country's own decision to adopt an FPS. As such, the results, which align with our baseline findings, should be interpreted causally.

In addition, Appendix A presents evidence from two complementary tests addressing endogeneity concerns. First, we conduct an event study that exploits the staggered introduction of FPS across countries (ie the heterogeneity in launch dates) and variation in app-level data. Second, we estimate a propensity score matching (PSM) model. The findings from both analyses consistently confirm that the introduction of an FPS serves as a catalyst for increased adoption of digital finance.

Finally, as additional robustness checks, we examine further controls such as the information and communications technology (ICT) capital stock, which measures the overall level of digitalisation in the economy, and additional FPS characteristics for a smaller set of countries. Overall, these results are consistent with our baseline, and show that the speed and extent of adoption of digital finance apps by the population differs in light of both structural factors of economies and policies.

The rest of this paper is organised as follows. Section 2 describes our dataset and empirical approach. Section 3 describes our main empirical findings. Section 4 discusses several robustness checks and extensions. Finally, section 5 concludes.

## 2. Background and stylised facts

### Data description

To explore the relationship between the introduction of FPS and digital finance app adoption, we use app-level data from Sensor Tower, a private app intelligence data provider. Sensor Tower aggregates various app statistics on downloads and use from the Apple App Store, Google Play and a sample of smartphone users in countries around the world. These statistics are available (with a paid subscription) for up to 95 countries, where the country refers to the location of the downloading user. The data at the country-app level are available at daily frequency over January 2012 to July 2022. In addition to aggregate downloads by country, Sensor Tower has estimates of monthly, weekly and daily active users at the country-app level, based on a survey of users. Additionally, a breakdown by gender and age bucket is available at the app level at quarterly frequency.

Sensor Tower provides a league table of the most downloaded app broken down by categories. We focus on the top 25 finance apps in each country as of the date on which data were accessed.[3] We classify these apps in two ways: (i) whether they are for payments or other financial services, and (ii) whether they are offered by a fintech, big tech or incumbent financial institutions. For this classification, we use the methodology of Croxson et al (2023). Fintech firms are defined as companies (often recent entrants) that are specialised in technology-enabled financial innovation.[4] Examples include Venmo, Square,

[3] Of course, the list of top 25 finance apps can change over time. However, by taking the top 25 by downloads as of the latest date, we are focusing on those apps that achieved the highest adoption by the end of the sample period.

[4] More generally, fintech can be defined as technology-enabled innovation in financial services that could result in new business models, applications, processes or products. See FSB (2017) and Cornelli et al (2021).

Adyen or Klarna. Big tech firms are defined as large technology companies whose primary activity is platform-based digital services, rather than just financial services. Examples of big techs are Amazon, Apple, Facebook (Meta) or Google (Alphabet) in the United States and other countries, Alibaba or WeChat in China (see Cornelli et al, 2023) or Mercado Libre in Latin America. Incumbent financial institutions are mainly banks, insurers, credit card networks and other providers (including non-tech corporations or utilities companies) who provide financial services through traditional channels, but who also offer a digital finance app.[5]

With this dataset, we are able to observe finance app downloads and estimated app use for 86,163 apps in up to 95 countries over the period 2012–22. We work with observations at monthly frequency. For each app, we have the app name, launch date and some basic characteristics.

We further collect data on the features of FPS across countries from the BIS Committee on Payments and Market Infrastructures (CPMI). The CPMI conducted a survey on the introduction and use of retail FPS in CPMI jurisdictions over the second half of 2019 and the first quarter of 2020, covering 31 FPS (CPMI, 2021). The survey takes stock of recent developments in retail FPS, including year of introduction, use of FPS measured by the volume of transactions processed per capita, fast payment types processed, transaction value limits, FPS settlement model and the central bank's role in operating and/or overseeing the FPS (see next sub-section).

We combine these data with indicators on country characteristics that we expect may correlate with digital finance app adoption. Adoption can be driven by a number of variables, including demographic factors (eg age distribution, education), digital literacy, government policies, cultural values and exogenous shocks such as natural disasters (see Guha-Sapir et al, 2015). We also use indicators from the Global Findex Database of the World Bank on access to and use of formal and informal financial services.

Our main explanatory variable is the dummy *FPS.* This takes on a value of one if a jurisdiction has introduced a retail FPS, irrespective of the degree of involvement of the public sector, and a value of zero otherwise. The introduction of an FPS refers to the actual launch of the FPS, not to any announcements of potential future launch. We differentiate the impact of FPS on digital finance adoption by type of app. We define a dummy *payment* that takes a value of one if the app mainly provides payment services and a dummy *tech* that takes a value of one if the app is offered by fintech or big tech companies. To capture the differentiated effect of the introduction of FPS on the entrance of new apps or at early diffusion stages, we interact the dummy *FPS* with the variable *app saturation*. This variable corresponds

5 Classifying these apps required some effort by the authors, particularly because many app names are not in English (or even in Latin characters). In cases of doubt, the authors consulted with colleagues at the BIS who are native speakers of Chinese, Russian, Korean, Hindi, Thai and other languages and checked the classification as fintechs, big techs or incumbents.

to one of three possible values: (i) early stage, if the user base of the app is smaller than 0.2% of total population, (ii) an intermediate stage when the user base is between 0.2% and 2% and (iii) a mature stage when the user base is greater than 2% of the population.[6]

Table 1 provides summary statistics for our main variables. The mean finance app is downloaded by 0.14% of the population, and used by 1.27%, in any month (with a large standard deviation). About 22% of all finance apps focus on payments, and about 40% are offered by fintechs or big techs.

Summary statistics

Table 1

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Downloads, % population | 106,574 | 0.14 | 0.24 | 0 | 20.87 |
| Users, % population | 106,574 | 1.27 | 3.14 | 0 | 73.06 |
| FPS (0/1) | 61,338 | 0.64 | 0.48 | 0 | 1 |
| GDP per capita, in USD[1] | 95,945 | 23,861 | 46,328 | 1,466 | 133,252 |
| Population | 106,574 | 90.35 | 235.53 | 0.06 | 1412.36 |
| Internet connections, % population | 76,374 | 71.81 | 21.32 | 4.17 | 100.00 |
| Bank branches, per 100,000 adults | 27,601 | 19.51 | 12.59 | 1.43 | 67.52 |
| Mobile phone subscriptions, per 100 adults | 39,231 | 124.00 | 32.24 | 32.13 | 269.98 |
| Payment app | 106,574 | 0.22 | 0.42 | 0 | 1 |
| Fintech or big tech app | 106,574 | 0.40 | 0.49 | 0 | 1 |
| App saturation | 106,574 | 2.38 | 0.73 | 1 | 3 |
| App age, in months | 94,373 | 61.78 | 34.56 | 1 | 117 |
| FPS, managed by central bank | 15,374 | 0.25 | 0.43 | 0 | 1 |
| FPS, active central bank involvement | 106,574 | 0.09 | 0.29 | 0 | 1 |
| FPS, open membership | 15,374 | 0.43 | 0.49 | 0 | 1 |
| FPS, real-time settlement | 15,374 | 0.64 | 0.48 | 0 | 1 |
| FPS, no transaction limit | 38,987 | 0.15 | 0.35 | 0 | 1 |
| FPS, person-to-government transactions | 38,987 | 0.39 | 0.49 | 0 | 1 |
| FPS, business-to-business transactions | 38,987 | 0.40 | 0.49 | 0 | 1 |

Winsorised at 1%. Data on population percentages in 2022 uses population from 2021, due to a lack of country data in 2022. The following regressions will use the winsorised variables only.

[1] Based on PPP constant 2017 USD.

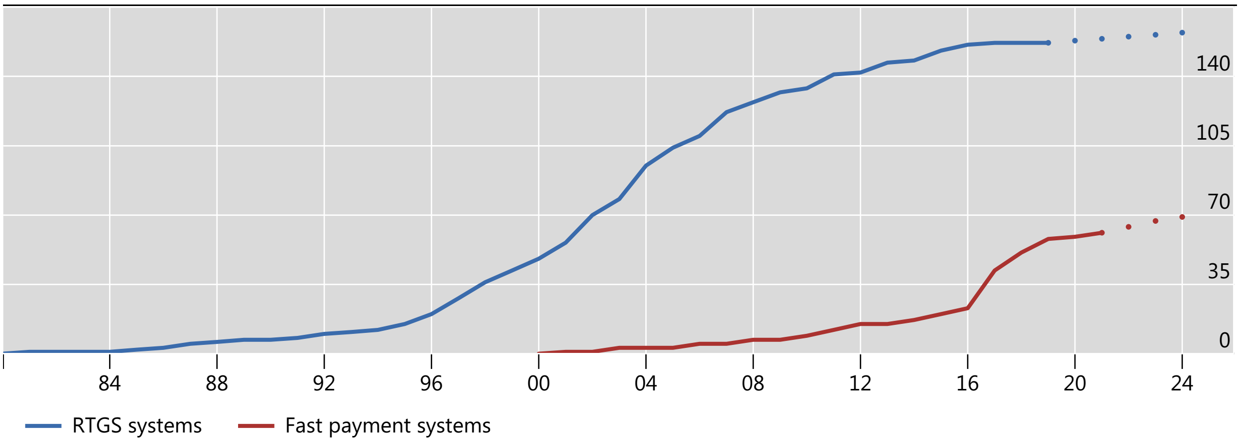
[6] The values of 0.2% and 2% were chosen to ensure that we had a roughly even distribution across the three groups.

## Stylised facts

Over the past twenty years, global adoption of FPS has risen notably. As of 2024, there are over 120 fast payment systems in operation around the world.[7] The proliferation of FPS follows a similar pattern to the spread of real-time gross settlement (RTGS) systems two decades earlier (Graph 1). Many country authorities, especially in EMDEs, have introduced or upgraded payment systems to offer alternative payment options with real-time settlement, lower costs and improved interoperability (Natarajan and Balakrishnan, 2020). The adoption and use of FPS varies among different jurisdictions, with factors such as interoperability, marketing to users and availability and access to technological infrastructure influencing wider adoption (CPMI, 2021).

The adoption of RTGS and FPS systems

Number of countries | Graph 1




The dotted part of the line corresponds to projected implementation of both RTGS systems and FPS. Note that the number of FPS is lower than the World Bank Global Tracker, given the smaller number of jurisdictions covered.

Source: CPMI (2021).

Central banks often play key roles as operators, overseers or catalysts of FPS. There is a continuum of practices. Central banks with a limited operational role act just as settlement institutions for private-sector FPS, and as operators of RTGS systems.[8] These functions guarantee safe implementation of the FPS and instant clearing and settlement of claims between banks (and sometimes also non-bank PSPs). When central banks play an intermediate operational role, they are directly involved in the governance

[7] The World Bank Global Tracker counts all jurisdictions around the world in which users have access to fast payments. See https://fastpayments.worldbank.org/global-tracker. The CPMI counts a smaller number of jurisdictions with FPS (CPMI, 2021).

[8] For instance, central banks can provide FPS operators with RTGS accounts to settle transactions or implement special arrangements enabling payment service providers (PSP) participating in privately operated FPS to back their positions with central bank money. The private sector FPS adopted in countries like Spain (SNCE), Sweden (Swish) and the United Kingdom (Faster Payments Service) have these characteristics (CPMI, 2021).

of an FPS, while the private sector owns and operates the system.[9] Central banks can also play a fully active role as owner and operator of an FPS.[10]

The types and features of FPS also vary by country. The payments processed through FPS can range from person-to-person (P2P) and person-to-business (P2B), to business-to-businesses (B2B), person-to-government (P2G) and government-to-person (G2P) transactions. Other diverging features of FPS include transaction value limits, the channels to access the payments platform, the settlement model for obligations between the PSPs and the level of restrictiveness to allow different PSPs into the system.

The growing interest among authorities in promoting FPS stems from the desire to address various policy goals. FPS allow for lower cost, greater efficiency and more competition in payment services. Unlike other methods, such as domestic bank transfers and card payments, funds are available to the recipient close to real time. The available evidence so far indicates that FPS offer lower costs compared with these alternative payment methods. In many jurisdictions, transaction fees in FPS have been capped. In Brazil, for example, peer-to-peer payments on Pix are free, and merchants pay just 22 basis points on average to accept Pix payments, compared with fees of 2.2% for credit cards (Duarte et al, 2022). In India, there are no charges for UPI-based payments, and the interchange fee is 1% for UPI merchant transactions made through prepaid payment instruments like wallets or cards. In Thailand, fees for the use of PromptPay comprise a joining fee paid by participant financial institutions and a variable fee based on the number of transactions submitted by a participant. However, there are no charges to individuals for payments through digital channels such as internet banking or mobile banking. Central banks or other public authorities may provide full or partial funding to the FPS and the fees charged to participants are based on considerations such as recovering investments, covering operational expenses and preparing for future investment needs (World Bank, 2021).

As FPS make payments from bank and e-money accounts cheaper and more accessible to the whole population, they can support financial inclusion (Aurazo and Franco, 2024).[11] This may be particularly true when FPS are accompanied by other reforms such as simplified transaction account opening or digital identity. In Costa Rica, for instance, the introduction of SINPE Móvil not only facilitated increased digital payments but was also linked to a 10-percentage point rise in the share of adults with a transaction account (Araujo et al, 2024).

Together with progress in implementing FPS, the payments industry has made considerable efforts to develop technologies and features to enhance the speed and efficiency of payments and other financial services. Digital technologies applied to banking and financial services, such as mobile apps, have made

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9 This is the case in countries including Australia (NPP), India (UPI), Hong Kong (FPS) and Switzerland (TWINT).

10 Brazil (Pix), Mexico (CoDi/SPEI) and the United States (FedNow) are examples of this approach.

11 Financial inclusion can be defined as universal access to, and use of, a wide range of reasonably priced financial services. Access to transaction accounts is generally a critical first step. See CPMI and World Bank (2020).

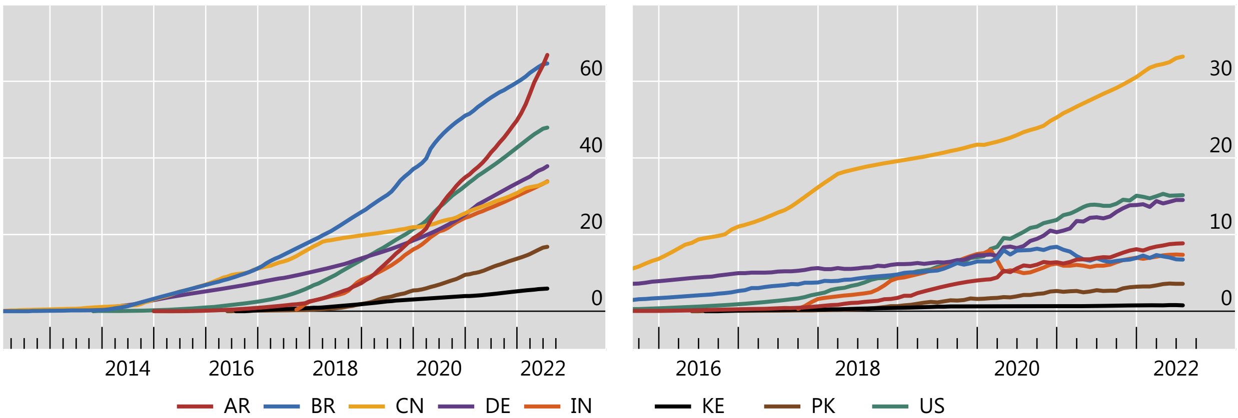
financial services more widely available and affordable to consumers. Over the past decade, digital finance apps have seen a rapid increase in downloads and estimated use. Increasing smartphone penetration, improved internet connectivity and evolving consumer preferences have contributed to the proliferation of these apps. The exogenous shock from the Covid-19 pandemic further accelerated digital finance use, in particular contactless and remote payment solutions (Fu and Mishra, 2020; Auer et al, 2022). The adoption of digital finance is also explained by the existence of network effects, following a similar diffusion dynamic as older technologies (Bass, 1969; Comin and Hobijn, 2004).

Graph 2 presents cumulative downloads and monthly users of the top finance app in selected countries from our sample. We note an upward trend in downloads starting from around early 2018 in most countries. The data also reveal a rise in monthly users of finance apps over time, consistent with those who downloaded apps actively using them. Several factors likely contributed to this rise, including widespread availability of smartphones, improvements in internet infrastructure and connectivity and changes in consumer behaviour due to the convenience, speed and efficiency of digital financial apps.

Aggregate downloads and estimated of the top finance app, by country

As a percentage of population — Graph 2

Cumulative downloads of the top app, by country — Monthly users of the top app, by country



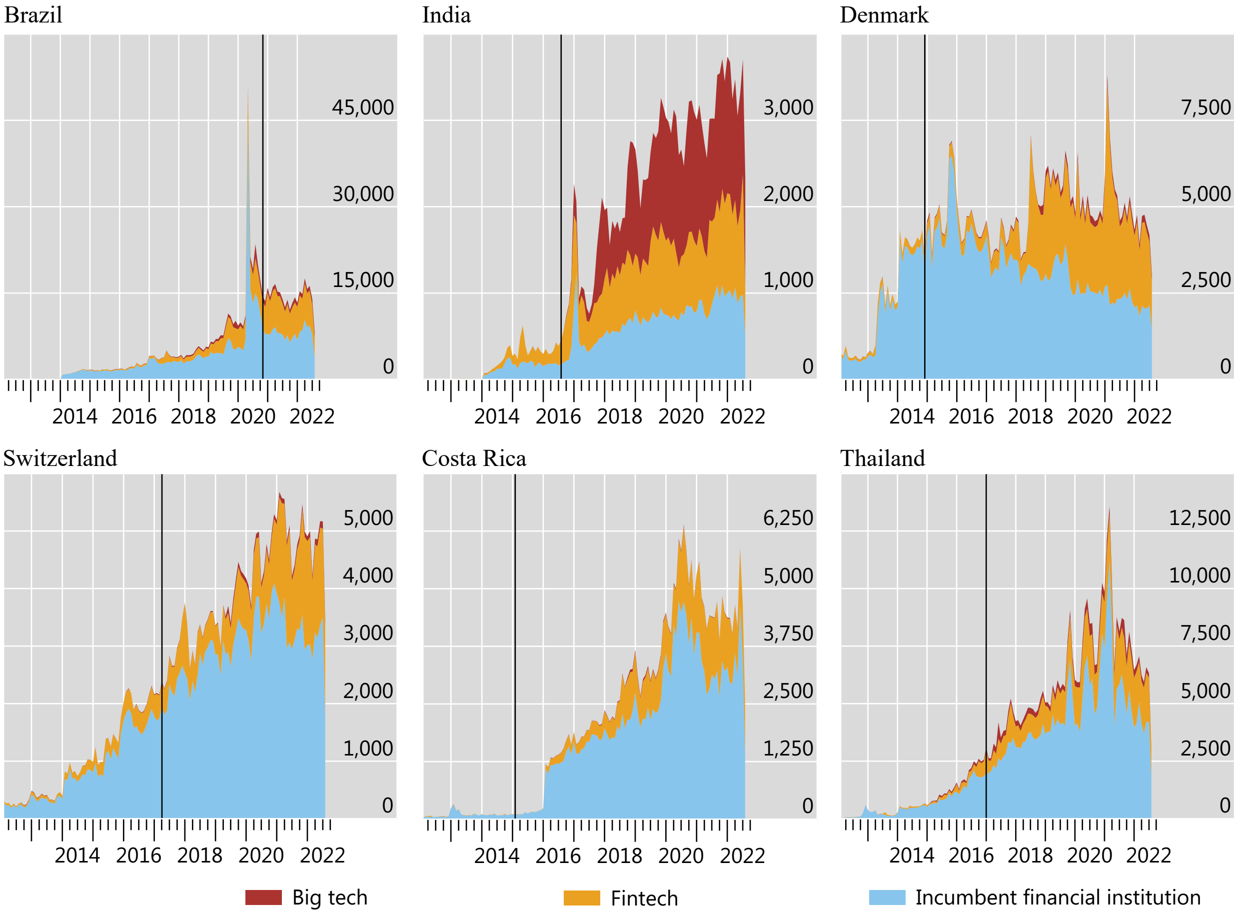

AR = Argentina, BR = Brazil, CN = China, DE = Germany, IN = India, KE = Kenya, PK = Pakistan, US = United States

Sources: Sensor Tower; World Bank; authors' calculations.

Our data further suggest that the adoption of mobile finance apps rises after the introduction of retail FPS in many cases. Graph 3 presents some examples of digital finance app adoption after the launch of an FPS. In India and Denmark, there is a clear increase in finance apps downloads after the FPS was launched. This increase is larger for fintech and big tech apps than for incumbent institution apps. In Brazil, although Pix was launched in November 2020, it was announced to the public for the first time in February 2020. In addition, payments with Pix are available to users through the digital banking app provided by financial institutions. Participation in Pix by banks and other payment institutions is mandatory since it was launched by the Central Bank of Brazil. This may have contributed to an acceleration in the adoption of digital apps offered by incumbent financial institutions (Duarte et al, 2022). In Costa Rica, the use of SINPE Móvil exploded during Covid-19 although it had been in operation since 2015 (Araujo et al, 2024; Alvarez et al, 2023).

The introduction of FPS coincided with an increase in digital finance adoption

Number of downloads of finance apps per 100,000 people | Graph 3




The vertical line indicates the month in which the most recent launch date of a country fast payment system. For Brazil, November 2020; for India, August 2016; for Denmark, December 2014; for Switzerland, April 2017; for Costa Rica, February 2015; for Thailand, January 2017.

Sources: Sensor Tower; authors' calculations.

The widespread adoption of FPS can yield important benefits, but it may face strong resistance from banks and other incumbent financial institutions. In many jurisdictions, banks have initially fought FPS as they worry about a decline in payment revenues, particularly from card transactions (eg interchange fees). While debit card interchange fees are often small, and in some cases capped, banks may still perceive FPS as a threat to these revenue streams in the short term. Over time, as FPS become more relevant, particularly among the unbanked and in transactions previously dominated by cash, banks can monetise the payment data generated through FPS by offering loans and other financial services. Credit card networks may stand to lose revenues to a greater extent, and may thus lobby hard against FPS.

There may be further challenges for authorities and central banks. These include interoperability with other payment systems, trade-offs between fostering innovation and ensuring consumer protection and fraud prevention, and the need to ensure operational resilience and privacy of transaction data. Additionally, addressing technological gaps is crucial to ensure inclusive access to fast payment systems, especially in regions with limited internet connectivity or underdeveloped financial infrastructure (Doerr et al, 2022).

In many cases, digital financial apps have contributed to the disruption of traditional banking models. Fintech companies and startups offering innovative financial services through apps have challenged established financial institutions, driving innovation in the industry. By leveraging technology, fintech firms offer more efficient services that address inefficiencies within the traditional banking sector, usually at lower costs, higher speed and simplified processes.

# 3. Empirical evidence

## Econometric approach

To assess adoption of digital finance apps over time, we estimate the following model:

$$Down_{ijt} = \beta_1 X_{jt} + \beta_2 Z_{it} + \beta_3 User_{ijt} + \beta_4 User_{ijt}^2 + \alpha_j + \theta_t + \epsilon_{ijt} \qquad (1)$$

where $Down_{ijt}$ is the number of new downloads for app *i* in country j during time period t relative to the population, and measures the *speed* of new adoption. (This can be related to the first derivative of the user base in a Bass S-curve model) $User_{ijt}$ is the number of monthly active users for app *i* in country j during time period t relative to the population and measures the *level* of the current user base. To control for the launch of FPS the model includes a vector $X_{jt}$ to denote the existence of an FPS and its characteristics. This is interacted with different app types and the stage of app saturation. $Z_{it}$ are app characteristics, and $\alpha_j, \theta_t$ are the country and time two-way fixed effects. The coefficient $\beta_3$ captures the network effect, while $\beta_4$ test for potential acceleration or saturation on the network effect. Standard errors are clustered at the app-country level.

The key variables of interest are the coefficients $\beta_1$ on vector $X_{jt}$. These allow us to assess how the existence of an FPS, and its characteristics, correlate with the speed of adoption of different finance apps. As we will discuss below, a positive association would not be sufficient evidence of a causal relationship. There is the possibility that greater app adoption could drive authorities to introduce an FPS (reverse causality) or that further factors drive both FPS introduction and app adoption (omitted variable bias). However, further exercises will give greater support that FPS are indeed driving adoption.

We acknowledge that by looking at downloads scaled by the population, we are only studying the effect on the *extensive margin* of adoption. Similarly, our data on use capture the number of active users of an app in a given country and month, but do not contain information on whether these are new or recurrent users. We are not able to observe the number or value of transactions made on apps, nor other indicators of the intensity of use.[12] Therefore, we cannot draw conclusions about effects on the *intensive margin*.

## Baseline results and mechanisms

The findings from our regressions are consistent with our priors regarding the dynamics of digital finance app adoption and the role of FPS. The results in Table 2 show, first, the expected network effects (column I). New downloads of digital finance apps are higher where there is an existing user base, but at a declining rate for higher levels of adoption (as seen in the negative coefficient of the quadratic term). Beyond this, digital finance app adoption is faster after the introduction of an FPS (column II; as seen by the positive coefficient for the FPS dummy). Yet this relationship is larger in countries with a lower GDP per capita (as seen by the negative coefficient for the interaction term). For instance, in the poorest countries in our sample, such as Madagascar, Kenya and Cambodia, an FPS is associated with 20 more monthly downloads per 100,000 of the population. This means an increase in downloads that is about one-fifth of our sample mean.

These results entail that an FPS has a relatively stronger link with digital finance app adoption in EMDEs. This could be attributed to the role of FPS in enhancing financial inclusion. In countries with lower GDP per capita, many individuals are financially excluded and lack access to traditional banking services. The introduction of an FPS could serve as a gateway to more convenient and accessible financial solutions. These services are often offered by fintech companies and other disruptors via digital finance apps.[13]

Our results remain stable when controlling for several country institutional characteristics like the population, the number of internet connections, the number of bank branches and the number of mobile phone subscriptions (column III). Columns IV and V repeat the analysis from columns II and III, respectively, on a smaller sample comprising only those countries that adopted an FPS at some point during the sample period. In other words, we are comparing these countries with themselves (over time), and not with countries that did not introduce an FPS during the sample period. Consistently, we find the

12 Sensor Tower provides data on the average number of sessions in a day at the app-country-month level. These data could be a good candidate to assess the intensity of use of apps. However, they are only available from January 2021, thus being mostly unavailable for our sample period.

13 Ideally, we would like to control for the quality of the existing payment infrastructure, in addition to the general level of economic development. However, we are not aware of any country-level indicator that accurately captures such quality, which likely encompasses multiple dimensions, such as speed, cost, access and security of retail payments.

adoption of finance apps rises after the introduction of an FPS, particularly in lower-income economies.[14][15]

Fast payment systems are associated with higher digital finance adoption — Table 2

| | Downloads, % population | | | | |
|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) |
| Users, % population | 0.1308*** | 0.1321*** | 0.1344*** | 0.1269*** | 0.1277*** |
| | (0.0034) | (0.0036) | (0.0036) | (0.0045) | (0.0045) |
| (Users, % population )^2 | –0.0244*** | –0.0247*** | –0.0254*** | –0.0235*** | –0.0238*** |
| | (0.0010) | (0.0010) | (0.0011) | (0.0013) | (0.0013) |
| FPS (0/1) | | 0.0572*** | 0.0599*** | 0.0670*** | 0.0717*** |
| | | (0.0169) | (0.0168) | (0.0170) | (0.0171) |
| Ln(GDP per capita) | | 0.0000 | 0.0018 | –0.0411*** | –0.0442*** |
| | | (0.0068) | (0.0071) | (0.0149) | (0.0154) |
| FPS * ln(GDP per capita) | | –0.0055*** | –0.0058*** | –0.0065*** | –0.0069*** |
| | | (0.0017) | (0.0017) | (0.0017) | (0.0017) |
| Population | | | –0.0003*** | | –0.0002* |
| | | | (0.0001) | | (0.0001) |
| Internet connections, % Population | | | 0.0003*** | | 0.0001 |
| | | | (0.0001) | | (0.0001) |
| Bank branches, per 100,000 Adults | | | –0.0000 | | 0.0003 |
| | | | (0.0002) | | (0.0003) |
| Mobile phone subscriptions, per 100 adults | | | –0.0000 | | –0.0002** |
| | | | (0.0000) | | (0.0001) |
| Sample | All countries | All countries | All countries | Countries with FPS adoption | Countries with FPS adoption |
| Observations | 106,574 | 95,945 | 91,501 | 56,173 | 53,496 |
| Adj $R^2$ | 0.745 | 0.755 | 0.759 | 0.756 | 0.756 |

Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country and time fixed effects. The table shows the regressions results where the dependent variable corresponds to the number of downloads as a % of the population of the country-specific top 25 finance apps and the independent variables correspond to the ones listed in the first column.

There are at least three potential reasons why digital finance app adoption would increase after the introduction of an FPS. First, FPS can stimulate competition and innovation in payments markets, which could lead greater availability of more convenient services for users. New payment technologies can lead incumbent banks and technological disrupters to compete and provide innovative and complementary services. This could trigger changes in depositor behaviour. In Brazil, for example, Pix has become the preferred payment option by consumers. Its wide use has heightened competition in the

14 Similar results hold when aggregating for all digital finance apps in a given country and month, ie running the analysis at the country-time rather than country-app-time level.

15 Tables A1 and A2 in Appendix A provide additional robustness checks for the results presented in Table 2. In Table A1, the specification is augmented by replacing country fixed effects with country-firm type fixed effects, thereby controlling for unobservable characteristics specific to the country-firm type level. In Table A2, the specification is further enhanced by incorporating app fixed effects to account for app-specific characteristics that might otherwise confound the findings. The results from both robustness tests remain consistent with the hypothesis that the introduction of a retail FPS is associated with increased usage of digital finance apps.

deposit market by increasing the convenience of small bank deposits relative to large banks. This is achieved through a reduction in bank switching costs and the provision of convenient payment options by smaller banks (Sarkisyan, 2024). Notably, not only banks can move to offer more convenient payment options to their clients. When FPS allow for non-bank participation, new entrants have more incentives to develop and deliver new services to customers. This is consistent with the view that the introduction of new technologies and increased convenience can have a positive impact on competition among firms ultimately benefiting end users (He, Huang and Zhou, 2023; Higgins, 2020).[16]

Secondly, FPS can facilitate digital finance adoption through learning effects. The launch of FPS gives users exposure to new payment technologies and digital platforms. As users gain experience in using a technology, the learning costs of using it decrease and they can be more likely to adopt similar technologies (Mukherjee, 2024). Similarly, as individuals become familiar with FPS for daily transactions, they become more comfortably with digital financial services in general. This can encourage the adoption of other related technologies that offer convenience, efficiency and broader financial services. For example, in India, the development of UPI has gone hand in hand with the evolution of the fintech sector. The Indian fintech sector is one of the largest markets globally and the adoption rate of fintech services in the country is above 80% (EY and Payments Council of India, 2022).

A third mechanism is wider access to broader financial services facilitated by FPS. FPS can contribute to financial inclusion by providing convenient and affordable payment solutions, especially in EMDEs where access to traditional banking services is limited. The benefits of fast payments can potentially increase the appeal of having digital financial products. In addition, regulatory measures accompanying FPS implementation contribute to broaden access to financial services. The launch of Costa Rica's SINPE Móvil was accompanied with the introduction of simplified bank accounts to expedite bank account opening. Once users enter the financial sector, they become eligible to access a wider range of financial services offered by traditional and non-traditional financial institutions. This serves as a gateway for users to explore and use digital products and services.

Table 3 shows more granular results for different types of digital finance apps. In particular, payment apps see higher downloads after the launch of an FPS. The result holds true both for all countries (column I) – ie those with and without an FPS at any point – and for  the subsample of countries that introduced an FPS during the sample period (column V). Moreover, FPS are associated with a stronger growth in apps by technological disrupters, ie fintech or big tech companies (columns II and VI).[17] The link is also

16 There is a literature assessing non-linearities in the relationship between competition and innovation in the banking industry. Some find that moderate (neck-and-neck) competition fosters innovation as laggard banks strive to catch up. However, at the extremes, low competition leads to inertia among competitors, while high competition hampers innovation for laggards attempting to keep pace. See eg Aghion et al (2005) and Jaap et al (2013).

17 In these two specifications, the coefficient for the FPS dummy turns significantly negative, implying that the apps offered by incumbents actually see less adoption after an FPS. However, note the much smaller size of the coefficient (less than one-third of the magnitude of the positive coefficient for the interaction term with fintech and big tech apps in both cases).

stronger for apps that are in the early stage of diffusion, as opposed to those that have already reached saturation (columns III and VII). Finally, the launch of an FPS is associated with a stronger growth in younger apps (columns IV and VIII).[18] The results on heterogeneous impacts are consistent with all three mechanisms, as FPS more effectively facilitated the adoption of payment apps, as well as new apps and technological disruptors.

Heterogeneous impact of FPS for different app types — Table 3

| | Downloads, % population | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) | (VI) | (VII) | (VIII) |
| Users, % population | 0.1311*** | 0.1293*** | 0.1047*** | 0.1268*** | 0.1252*** | 0.1238*** | 0.1028*** | 0.1214*** |
| | (0.0034) | (0.0034) | (0.0037) | (0.0035) | (0.0042) | (0.0043) | (0.0048) | (0.0044) |
| (Users, % population)^2 | –0.0245*** | –0.0241*** | –0.0179*** | –0.0230*** | –0.0231*** | –0.0227*** | –0.0175*** | –0.0216*** |
| | (0.0010) | (0.0010) | (0.0011) | (0.0010) | (0.0012) | (0.0012) | (0.0013) | (0.0013) |
| FPS, (0/1) | –0.0023 | –0.0037** | 0.0152*** | 0.0160*** | –0.0017 | –0.0045** | 0.0116** | 0.0139*** |
| | (0.0017) | (0.0019) | (0.0047) | (0.0027) | (0.0018) | (0.0019) | (0.0048) | (0.0025) |
| FPS * payment | 0.0131*** | | | | 0.0136*** | | | |
| | (0.0036) | | | | (0.0043) | | | |
| FPS * tech | | 0.0116*** | | | | 0.0156*** | | |
| | | (0.0029) | | | | (0.0031) | | |
| FPS * app saturation | | | –0.0048*** | | | | –0.0043** | |
| | | | (0.0018) | | | | (0.0019) | |
| FPS * app age | | | | –0.0002*** | | | | –0.0003*** |
| | | | | (0.0000) | | | | (0.0000) |
| Payment | –0.0019 | | | | –0.0021 | | | |
| | (0.0024) | | | | (0.0039) | | | |
| Tech | | –0.0091*** | | | | –0.0135*** | | |
| | | (0.0018) | | | | (0.0027) | | |
| App saturation | | | 0.0298*** | | | | 0.0279*** | |
| | | | (0.0015) | | | | (0.0019) | |
| Sample | All countries | | | | Countries with FPS adoption | | | |
| Observations | 106,574 | 106,574 | 106,574 | 94,373 | 61,338 | 61,338 | 61,338 | 53,871 |
| Adj $R^2$ | 0.746 | 0.747 | 0.763 | 0.753 | 0.749 | 0.749 | 0.761 | 0.763 |

Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country and month fixed effects. The table shows the regressions results where the dependent variable corresponds to the number of downloads as a % of the population of the country-specific top 25 finance apps and the independent variables correspond to the ones listed in the first column. *Payment* corresponds to financial apps that are mainly for payment function. *Tech* corresponds to financial apps that are issued by big technological companies. *App saturation* corresponds to the developmental stage of the app, which can be one of three possible values: an early stage when the userbase of the app is smaller than 0.2% of total population, an intermediate stage when the userbase is between 0.2% and 2%, and a mature stage when the userbase is greater than 2%. Columns IV and VIII have an interaction term of FPS dummy and app age, but do not control for app age.

[18] It could be informative to distinguish those apps that would benefit more from fast payment settlement, and to investigate whether the positive impact of FPS on app adoption is stronger for these apps. Relatedly, it could be relevant to select apps that focus primarily on small businesses. This would allow us to assess whether the introduction of an FPS, and thus more affordable methods of payment, facilitates the adoption of these apps more than other apps. At this point, we do not have sufficiently granular information to classify apps in these ways. We leave this as an avenue for future research.

## Identification and causality

A key concern in establishing a causal relationship between the launch of an FPS and the adoption of digital finance is endogeneity. This may arise from two primary sources: omitted variable bias and reverse causality.

With respect to omitted variable bias, app-country-specific characteristics, such as particular app features enabled in selected or individual countries, could influence both digital finance app adoption and the decision to launch an FPS. For instance, some fintech payment apps could embed a quick response (QR) code functionality, and if this feature by apps is widely adopted, it could encourage a jurisdiction to adopt an FPS. Some apps may also enable advanced authentication through biometric verification (such as facial recognition or fingerprint ID), which may contribute to rapid adoption in countries with supportive legal or technical frameworks. This may signal authorities the need for complementary public infrastructure, like an FPS, to support rising transaction volumes and ensure interoperability across providers. In addition, some disruptive apps may create strategic partnerships with large domestic banks or utility companies in certain countries. These alliances can significantly expand their use base and increase pressure for public infrastructure to support faster payments. In markets where an FPS does not yet exist, some apps may simulate instant functionality and influence policy decisions to implement FPS. To address this concern, we include in the specification more granular fixed effects at the app-country level, replacing the country fixed effects used in the baseline specification.

Second, with respect to reverse causality, one might argue that the relationship we propose could work in the opposite direction. Specifically, it is possible that strong adoption of digital finance apps drives central banks to launch an FPS so as to bring different apps into a unified, competitive ecosystem. To address this concern, in the spirit of Acemoglu at al (2019), we instrument the FPS variable – – using the number of bordering countries that have already adopted an FPS themselves. The rationale is that the decision to launch an FPS in a specific jurisdiction may be influenced by the positive experiences observed in neighbouring jurisdictions. Indeed, there is evidence of countries choosing to adopt an FPS inspired by the successful experiences of their neighbours. In Colombia and Uruguay, for instance, central banks have stated publicly that they have been inspired by the experience of Brazil.[19] The exclusion restriction also appears reasonably satisfied: FPS adoption in bordering countries impacts digital finance app adoption within a country only through the country's own decision to adopt an FPS. Therefore, under this identifying assumption, the results can be interpreted causally.

[19] At the launch of the Colombia Payment Systems Forum, an initiative led by the Central Bank of Colombia to advance interoperable instant payments, the Governor explicitly referred to Brazil's Pix system as an inspiration. He highlighted how Pix had significantly increased the use of digital payments, boosted financial inclusion and served as a catalyst for competition and innovation in Brazil's payment ecosystem. The Governor noted that such experiences offer valuable lessons for Colombia as it moves forward with the implementation of its own FPS. See Villar (2022).

Specifically, we estimate the following first-stage regressions:

$$FPS_{i,c,t} = \beta FPS_{i,c,t}^{bordering\ countries} + \lambda FPS_{i,c,t}^{bordering\ countries} * X + \mu X + \phi app\ age_{i,c,t} + \psi_{i,c} + \theta_t + \varepsilon_{i,c,t} \quad (2)$$

where $i$ denotes apps, $c$ denotes countries, and $t$ corresponds to time (ie month-year). $FPS^{bordering\ countries}$ is the number of bordering countries that adopted an FPS, themselves. $X$ is either an empty vector, or the natural logarithm of GDP per capita, the indicator variable *payment* or the indicator variable *tech*. We estimate the regressions at the app-country-time level to account for the fact that in several jurisdictions the choice of offering FPS connectivity functionalities lies with the individual issuer of the app themselves.[20]

Table 4 reports the results from the estimation of two-stage least squares (2SLS) regressions. Coefficients from column I suggest that the introduction of an FPS leads to higher adoption of finance apps. The coefficients in column I indicate that the introduction of an FPS significantly increases the adoption of digital finance apps. The effect is both statistically significant and economically meaningful – launching an FPS results in a 0.039 percentage point (pp) increase in digital finance app adoption, which represents nearly two-thirds of the average adoption rate.

Consistent with our baseline findings (column II, Table 2), the results in column II confirm that the adoption of digital finance apps accelerates after the introduction of an FPS, as indicated by the positive coefficient of the FPS indicator variable. Moreover, this effect is stronger in countries with lower GDP per capita, as reflected by the negative coefficient of the interaction term.

Notably, columns III and IV indicate that the impact of introducing an FPS is more pronounced for payment apps than non-payment apps, and for apps issued by big techs and fintechs than those offered by incumbent financial institutions. This is evidenced by the positive and statistically significant interaction terms in columns III and IV. Furthermore, the magnitude of these coefficients is economically large. Specifically, following the introduction of an FPS payment apps experience an additional 0.06 percentage point (pp) increase in adoption – approximately the same size as the average adoption rate – relative to non-payment apps. Similarly, apps issued by big tech and fintech firms witness a 0.04 pp increase in adoption compared to those provided by incumbents.

Overall, the instruments seem to satisfy the relevance criteria as suggested by the first stage results (see table A3 in the appendix) and by the respective $F$-statistics which are all reassuringly above 10.

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20 There may be two concerns with the IV approach. One is that the results may be influenced by the choice to estimate the regression at the app-country-time level, while the introduction of the FPS – ie the treatment – is determined at the country-time level. To address this concern, we re-run the analysis at the country-time level by using country-time average values of the relevant variables. Although the results are statistically weaker, the findings presented in Table A4 in the appendix are qualitatively similar to those in Table 4, thereby confirming the robustness of our findings. Another potential concern is that the results may be influenced by the choice treating the instrument as a categorical variable. To address this concern, we re-estimate the regressions treating the instrument as a continuous variable. The results presented in Table A5 in the appendix remain similar and consistent with the ones from Table 4, confirming the robustness of our findings.

Robustness checks in Appendix Tables A4 and A5 show similar results for the IV at country-time level, and as a continuous variable. In summary, the evidence presented supports the conclusion that FPS act as catalysts for the adoption of digital finance.

Digital finance adoption and FPS: instrumental variable (IV) analysis Table 4

| | Downloads, % population | | | |
|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) |
| $\widehat{FPS}$ | 0.039*** | 0.584*** | 0.024** | 0.030*** |
| | (0.012) | (0.154) | (0.011) | (0.011) |
| $\text{FPS} * \ln(\widehat{\text{GDP}}\text{ per capita})$ | | –0.054*** | | |
| | | (0.014) | | |
| $FPS * \widehat{\text{payment}}$ | | | 0.060*** | |
| | | | (0.013) | |
| $\widehat{\text{FPS} * }\text{ tech}$ | | | | 0.040*** |
| | | | | (0.012) |
| ln(GDP per capita) | 0.012 | 0.009 | | |
| | (0.011) | (0.011) | | |
| App age | –0.000** | –0.000*** | –0.000 | –0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 165,210 | 165,210 | 165,210 | 165,210 |
| F-stat | 50.29 | 60.94 | 28.90 | 32.50 |

The table reports the coefficients from panel-IV regressions where $FPS$ is instrumented with the number of bordering countries that adopted an FPS (ie $FPS^{\text{bordering countries}}$). Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include app*country and time fixed effects. The dependent variable corresponds to the number of downloads as a % of the population for the country-specific top 25 finance apps. *Payment* is an app-country-level indicator variable that takes value one for apps in the top 25 finance apps that are mainly for payment function and zero elsewhere. *Tech* is an app-country-level indicator variable that takes value one for apps in the top 25 finance apps that are issued by technological companies (ie big tech and fintech apps) and zero elsewhere.

# 4. Robustness checks and extensions

To assess the robustness of our findings and further address potential concerns about endogeneity, we perform a number of additional checks and extensions.

Another way of addressing the concern of omitted variable bias is to directly control for a variable that captures the level of digitalisation in the economy. One frequently used measure is the stock of information and communication technology (ICT) capital at country level. For this, we have data for 79 countries at annual frequency from 2012–18 from Jorgenson and Vu (2021). Results from Table 5 are similar to those in Table 2. The coefficients of FPS are positive and statistically significant in each of the specifications. Similarly, the coefficients of the interaction term FPS*ln(GDP per capita) are negative and statistically significant. The smaller sample size is relative to the one used in the baseline analysis because the ICT capital stock indicator is only available up to 2018, and we thus lose observations for 2019–22. Overall, the evidence from Table 5 suggests that our results are not confounded by the different levels of ICT stock of capital across countries.

Controlling for ICT capital stock

Table 5

| | Downloads, % population | | | |
|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) |
| Users, % population | 0.1337*** | 0.1351*** | 0.1269*** | 0.1286*** |
| | (0.0047) | (0.0048) | (0.0056) | (0.0058) |
| (Users, % population )^2 | –0.0248*** | –0.0253*** | –0.0232*** | –0.0237*** |
| | (0.0014) | (0.0014) | (0.0016) | (0.0017) |
| FPS (0/1) | 0.0403** | 0.0388** | 0.0479*** | 0.0487** |
| | (0.0179) | (0.0190) | (0.0183) | (0.0195) |
| Ln(GDP per capita) | 0.0550*** | 0.0533*** | 0.0227 | 0.0218 |
| | (0.0165) | (0.0167) | (0.0218) | (0.0222) |
| FPS * ln(GDP per capita) | –0.0036** | –0.0033* | –0.0043** | –0.0043** |
| | (0.0018) | (0.0019) | (0.0018) | (0.0019) |
| ICT capital stock | –0.0336*** | –0.0323*** | –0.0267*** | –0.0269** |
| (2018 PPP, USD trn) | (0.0103) | (0.0109) | (0.0101) | (0.0106) |
| Population | | –0.0001 | | 0.0000 |
| | | (0.0002) | | (0.0002) |
| Internet connections, % | | 0.0006*** | | 0.0004*** |
| population | | (0.0001) | | (0.0002) |
| Bank branches, per 100,000 | | 0.0005* | | 0.0003 |
| adults | | (0.0002) | | (0.0004) |
| Mobile phone subscriptions, | | –0.0000 | | –0.0001 |
| per 100 adults | | (0.0001) | | (0.0001) |
| Sample | All countries | All countries | Countries with FPS adoption | Countries with FPS adoption |
| Observations | 48,718 | 47,265 | 29,831 | 28,598 |
| Adj $R^2$ | 0.764 | 0.763 | 0.769 | 0.768 |

Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country and month fixed effects. The table shows the regression results where the dependent variable corresponds to the number of downloads as a % of the population of the country-specific top 25 finance apps and the independent variables correspond to the ones listed in the first column.

We further evaluate the robustness of our baseline finding – that the introduction of an FPS acts as a catalyst for digital finance adoption – by employing an event study design. For identification, we exploit the staggered introduction of FPS across countries (ie the heterogeneity in launch dates) as well as the variation in the app-level data. The findings, detailed in Appendix A, alongside a comprehensive discussion of the test specifications and results, provide robust evidence supporting the positive impact of FPS on the adoption of digital finance (see Table A6).

Finally, we further address potential endogeneity concerns regarding the observed relationship between FPS implementation and increased app downloads. Specifically, we consider the possibility that this relationship may be driven by pre-existing trends in digitalisation or that app adoption itself could influence the implementation of FPS, rather than FPS directly causing the increase in adoption.

To alleviate these concerns, we employ a propensity score matching (PSM) model. The results, presented in Appendix A, along with a detailed discussion of the test specifications and findings, provide robust evidence supporting the positive effect of FPS on the adoption of digital finance (see Table A7).

### Network effects in jurisdictions with FPS

Table 6 looks more deeply into the strength of network effects in jurisdictions with FPS. Notably, both for all countries (columns I and II) and for those that launched an FPS (columns III and IV), we find that network effects (ie the association between downloads and the existing user base of an app) are weaker after an FPS has been introduced. This is seen in the negative and statistically significant coefficient for the interaction term of FPS with users as a share of the population. This may indicate that newly launched digital finance apps are better able to scale (and the advantage of more established apps is less) in jurisdictions after an FPS has been introduced.

Fast payment systems as a driver of competition — Table 6

| | Downloads, % population | | | |
|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) |
| Users, % population | 0.1312*** | 0.1352*** | 0.1271*** | 0.1301*** |
| | (0.0034) | (0.0036) | (0.0042) | (0.0044) |
| (Users, % population)^2 | –0.0238*** | –0.0248*** | –0.0223*** | –0.0234*** |
| | (0.0010) | (0.0011) | (0.0013) | (0.0013) |
| FPS (0/1) | 0.0064*** | 0.0070*** | 0.0065*** | 0.0062*** |
| | (0.0021) | (0.0022) | (0.0021) | (0.0022) |
| FPS * Users, % population | –0.0050*** | –0.0056*** | –0.0058*** | –0.0057*** |
| | (0.0012) | (0.0012) | (0.0014) | (0.0014) |
| Sample | All countries | All countries | Countries with eventual FPS launch | Countries with eventual FPS launch |
| Other controls[1] | No | Yes | No | Yes |
| Observations | 106,574 | 34,792 | 61,338 | 24,903 |
| Adj $R^2$ | 0.746 | 0.760 | 0.748 | 0.756 |

Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country and month fixed effects. The table shows the regressions results where the dependent variable corresponds to the number of downloads as a % of the population of the country-specific top 25 finance apps and the independent variables correspond to the ones listed in the first column.

[1] Other controls include: the natural logarithm of GDP per capita, population, bank branches per 100,000 adults, mobile phone subscriptions per 100 adults, and the stock of ICT capital.

### Features of FPS

We next use data on features of FPS collected by the CPMI for a selection of central banks. These data are available for the CPMI countries and contain additional characteristics of 31 FPS such as the level of involvement of the central bank in its design and operation, the settlement model (real-time or deferred), transaction value limits and the types of payments processed. While this limits the sample size, it allows for a deeper understanding of how specific design choices are associated with actual adoption.

FPS additional features, CPMI countries — Table 7

| | Downloads, % population | | | | |
|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) |
| Users, % population | 0.0854*** | 0.0854*** | 0.0854*** | 0.0875*** | 0.0765*** |
| | (0.008645) | (0.008645) | (0.008645) | (0.001362) | (0.009390) |
| (Users, % population)^2 | –0.0122*** | –0.0122*** | –0.0122*** | –0.0128*** | –0.0099*** |
| | (0.002354) | (0.002354) | (0.002354) | (0.000371) | (0.002543) |
| FPS, managed by central bank | 0.0148* | 0.0148* | 0.0414** | | |
| | (0.008851) | (0.008851) | (0.017708) | | |
| FPS, active central bank involvement | | | | 0.0159*** | 0.0299*** |
| | | | | (0.001995) | (0.011268) |
| FPS, intermediate central bank involvement | | | | 0.0004 | 0.0137 |
| | | | | (0.001771) | (0.009405) |
| FPS, open membership | | 0.0216* | 0.0393*** | | 0.0416*** |
| | | (0.011684) | (0.010946) | | (0.011026) |
| FPS, real-time settlement | | | 0.0472*** | | 0.0368** |
| | | | (0.013538) | | (0.014596) |
| FPS, no transaction limit | | | –0.0295** | | –0.0174 |
| | | | (0.013990) | | (0.017550) |
| FPS, person-to-government transactions | | | 0.0295** | | 0.0030 |
| | | | (0.013754) | | (0.016197) |
| FPS, business-to-business transactions | | | 0.0265* | | 0.0145 |
| | | | (0.015216) | | (0.011012) |
| Sample | Countries with FPS adoption | Countries with FPS adoption | Countries with FPS adoption | Countries with FPS adoption | Countries with FPS adoption |
| Observations | 15,374 | 15,374 | 15,374 | 19,885 | 13,626 |
| Adj $R^2$ | 0.650 | 0.650 | 0.650 | 0.688 | 0.650 |

Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country and month fixed effects. The table shows the results regressions where the dependent variable corresponds to the % growth of downloads of the country-specific top 20 finance apps and the independent variables correspond to the ones listed in the first column.

The results are shown in table 7. We confirm that adoption is higher when the central bank manages the FPS (column I; significant at the 90% level). Adoption is also higher when there is open membership to banks and non-banks (column II). This is also true when there is real-time (rather than deferred) settlement, person-to-government and business-to-business payments (column III). Somewhat surprisingly, the absence of transaction limits is associated with less adoption (columns III and V).[21] When we distinguish between FPS with different operational roles for the central bank (columns IV and

[21] One possible explanation for this is that the absence of transaction limits is indicative of a less regulated environment. Users might associate a lack of regulation with risks of fraud, which could lead to lower adoption rates. Also, FPS without limits might be present in more mature financial systems where access is already widespread and where there is less policy emphasis on targeting unbanked or underbanked populations. In such cases, digital finance app providers may face more competition from traditional financial institutions, which could dampen app adoption.

V), we find higher adoption when the central bank is actively involved, but not when there is only intermediate involvement by the central bank.

These results could have important implications for policymakers. FPS features such as the level of involvement by the central bank, the type of settlement and the types of payments processed are important considerations in the design of FPS, as part of a wider payment digitalisation process. By expanding the reach and functionality of digital finance apps, well-designed FPS can contribute to the provision of accessible and efficient financial services.

## 5. Conclusion

The rapid rise of digital technologies has reshaped the financial landscape, offering greater efficiency, lower costs and wider access to financial services. In addition, policymakers have aimed to enhance the convenience and speed of digital payments through the introduction of FPS. These payment infrastructures, operating on a real-time or near real-time basis, have contributed to more seamless electronic payments between individuals, businesses and governments. In many jurisdictions, central banks have played a significant role in facilitating FPS operations, ranging from limited operational involvement to full ownership and operation. Their roles often align with specific policy objectives, including wider access, enhanced competition and more efficiency in payments.

This paper provides insights into the relationship between the implementation of FPS and the adoption of digital finance apps. We find that the introduction of an FPS leads to a significantly higher level of digital finance app adoption, particularly for payment apps and apps offered by technological disrupters (fintechs and big techs). Moreover, the link between FPS and digital finance app adoption appears to be particularly strong in emerging market and developing economies, for FPS with open membership, real-time settlement and person-to-government and business-to-business transactions, and in cases where the central bank has an active operational role in the FPS. An instrumental variable approach using the tendency of jurisdictions to follow the lead of neighbours in launching an FPS lends support to interpreting this as a causal relationship. The results from an event study design, which exploits the staggered introduction of FPS across countries and from a PSM model offer further support that the introduction of an FPS is a linchpin of stronger digital finance adoption.

Our results align with the thesis that FPS integration within payment infrastructures does stimulate innovation and digital finance. The speed and convenience facilitated by open instant payment systems incentivise users to embrace digital finance apps.

There are a number of important avenues for future research. One area of research could assess the link between payment apps and apps that support credit, insurance, wealth management and other financial services. Beyond this, there can be value in assessing the impact of digital finance apps on access to financial services for underserved groups, and on the pricing of specific financial services. Further insights into each of these areas could help to better design FPS and other digital infrastructures so as to better achieve public policy goals in the financial system.

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# Appendix A

## OLS analysis: further robustness tests

Another reasonable concern is that our results presented in Table 2 could be driven by characteristics specific to the type of firm providing an app, ie a big tech, a fintech firm or an incumbent financial institution. Furthermore, such characteristics could vary across countries. For example, the business model of a fintech firm operating in Latin America might differ from that of a fintech firm operating in Asia. To address this concern, we estimate Equation 1 replacing country fixed effects with more granular country*firm type fixed effects to control for unobservable characteristics at the country and app publisher type level.

Table A1 shows that the results are similar to the ones reported in Table 2. Consistently, this evidence suggests that the launch of a retail FPS is linked to a higher use of digital finance apps.

Controlling for unobservable characteristics at the country-firm type level — Table A1

| | Downloads, % population | | | | |
|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) |
| Users, % population | 0.1266*** | 0.1274*** | 0.1293*** | 0.1236*** | 0.1241*** |
| | (0.0034) | (0.0035) | (0.0036) | (0.0044) | (0.0045) |
| (Users, % population )^2 | –0.0231*** | –0.0233*** | –0.0239*** | –0.0224*** | –0.0227*** |
| | (0.0010) | (0.0010) | (0.0010) | (0.0013) | (0.0013) |
| FPS (0/1) | | 0.0619*** | 0.0659*** | 0.0711*** | 0.0759*** |
| | | (0.0172) | (0.0172) | (0.0173) | (0.0174) |
| Ln(GDP per capita) | | 0.0050 | 0.0070 | –0.0355** | –0.0384** |
| | | (0.0063) | (0.0066) | (0.0148) | (0.0153) |
| FPS * ln(GDP per capita) | | –0.0059*** | –0.0063*** | –0.0068*** | –0.0073*** |
| | | (0.0017) | (0.0017) | (0.0017) | (0.0017) |
| Population | | | –0.0003*** | | –0.0002** |
| | | | (0.0001) | | (0.0001) |
| Internet connections, % Population | | | 0.0003*** | | 0.0001 |
| | | | (0.0001) | | (0.0001) |
| Bank branches, per 100,000 Adults | | | 0.0000 | | 0.0004 |
| | | | (0.0002) | | (0.0003) |
| Mobile phone subscriptions, per 100 adults | | | –0.0000 | | –0.0002** |
| | | | (0.0000) | | (0.0001) |
| Sample | All countries | All countries | Countries with FPS adoption | Countries with FPS adoption | Countries with FPS adoption |
| Observations | 106,571 | 95,942 | 91,498 | 56,171 | 53,494 |
| Adj $R^2$ | 0.762 | 0.773 | 0.777 | 0.775 | 0.775 |

Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country*firm type and month fixed effects, where firm type indicates the type of firm offering the app, ie fintech, big tech or incumbent financial institution. The table shows the regressions results where the dependent variable corresponds to the number of downloads as a % of the population of the country-specific top 25 finance apps and the independent variables correspond to the ones listed in the first column.

Sources: CPMI (2021); Jorgenson and Vu (2021); Sensor Tower; World Bank; authors' calculations.

In addition, our results may be confounded by unobservable characteristics at the more granular app level. To address this potential concern, we rerun our baseline regression from Table 2 adding app fixed effects to the specification. In other words, the regression that we now estimate includes country-level, app-level and time fixed effects. The results from table A2 are similar and consistent with those reported in Table 2 supporting the robustness of our evidence and confirming that our findings are not confounded by unobservable app-level characteristics.

Baseline regression controlling for app-level unobservable characteristics Table A2

| | Downloads, % population | | | | |
|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) |
| Users, % population | 0.1366*** | 0.1391*** | 0.1423*** | 0.1380*** | 0.1393*** |
| | (0.0034) | (0.0036) | (0.0035) | (0.0043) | (0.0043) |
| (Users, % population )^2 | –0.0242*** | –0.0249*** | –0.0258*** | –0.0246*** | –0.0252*** |
| | (0.0010) | (0.0010) | (0.0010) | (0.0012) | (0.0013) |
| FPS (0/1) | | 0.0338** | 0.0295** | 0.0340** | 0.0352** |
| | | (0.0148) | (0.0148) | (0.0151) | (0.0152) |
| Ln(GDP per capita) | | –0.0037 | –0.0037 | –0.0297** | –0.0368** |
| | | (0.0055) | (0.0057) | (0.0138) | (0.0145) |
| FPS * ln(GDP per capita) | | –0.0032** | –0.0029** | –0.0033** | –0.0035** |
| | | (0.0015) | (0.0015) | (0.0015) | (0.0015) |
| Population | | | –0.0000 | –0.0000 | –0.0000 |
| | | | (0.0001) | (0.0001) | (0.0001) |
| Internet connections, % Population | | | 0.0001 | –0.0001 | –0.0001 |
| | | | (0.0001) | (0.0001) | (0.0001) |
| Bank branches, per 100,000 Adults | | | 0.0001 | 0.0004 | 0.0004 |
| | | | (0.0002) | (0.0003) | (0.0003) |
| Mobile phone subscriptions, per 100 adults | | | –0.0000 | –0.0001 | –0.0001 |
| | | | (0.0000) | (0.0001) | (0.0001) |
| Sample | All countries | All countries | All countries | Countries with FPS adoption | Countries with FPS adoption |
| Observations | 106,573 | 95,943 | 91,499 | 56,171 | 53,494 |
| Adj $R^2$ | 0.859 | 0.870 | 0.874 | 0.878 | 0.878 |

Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country, app and time fixed effects. The table shows the regressions results where the dependent variable corresponds to the number of downloads as a % of the population of the country-specific top 25 finance apps and the independent variables correspond to the ones listed in the first column.

Sources: CPMI (2021); Jorgenson and Vu (2021); Sensor Tower; World Bank; authors' calculations.

Overall, our results are consistent with the idea that the launch of a retail FPS is linked to a higher use of digital finance apps. The enhanced transaction speed and convenience of FPS could encourage the adoption of digital finance apps as users seek faster and more efficient payment options. When FPS provide a seamless and inclusive payments infrastructure they could reach previously underserved populations, including those in remote areas or with limited access to traditional banking services. FPS can also foster synergies in the payment ecosystem, for example, by integrating with other financial infrastructures or platforms, such as e-commerce or mobile banking (BIS, 2020).

## First-stage results and robustness tests for the instrumental variable (IV) analysis

### Digital finance adoption and FPS: IV analysis, first-stage results

Table A3

| | FPS | FPS | FPS * ln(GDP per capita) | FPS | FPS * payment | FPS | FPS * tech |
|---|---|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) | (VI) | (VII) |
| $FPS^{\text{bordering countries}} = 1$ | 0.148*** | –0.306 | –4.675* | 0.146*** | –0.032*** | 0.158*** | –0.042*** |
| | (0.015) | (0.243) | (2.532) | (0.017) | (0.004) | (0.018) | (0.005) |
| $FPS^{\text{bordering countries}} = 2$ | 0.191*** | –0.442 | –7.049* | 0.217*** | –0.051*** | 0.212*** | –0.069*** |
| | (0.024) | (0.353) | (3.777) | (0.027) | (0.007) | (0.027) | (0.008) |
| $FPS^{\text{bordering countries}} = 3$ | 0.293*** | –4.358*** | –48.264*** | 0.308*** | –0.064*** | 0.336*** | –0.086*** |
| | (0.032) | (0.372) | (3.862) | (0.035) | (0.008) | (0.036) | (0.009) |
| $FPS^{\text{bordering countries}} = 4$ | 0.228*** | –4.307*** | –46.644*** | 0.254*** | –0.078*** | 0.291*** | –0.104*** |
| | (0.048) | (0.635) | (6.679) | (0.052) | (0.010) | (0.054) | (0.011) |
| $FPS^{\text{bordering countries}} = 5$ | 0.430*** | 10.705*** | 106.768*** | 0.408*** | –0.086*** | 0.424*** | –0.120*** |
| | (0.077) | (0.573) | (6.005) | (0.083) | (0.012) | (0.089) | (0.014) |
| $FPS^{\text{bordering countries}} = 6$ | 0.268*** | 11.217*** | 111.897*** | 0.264*** | –0.098*** | 0.265*** | –0.135*** |
| | (0.075) | (0.595) | (6.220) | (0.078) | (0.013) | (0.079) | (0.015) |
| $FPS^{\text{bordering countries}} = 7$ | 0.685*** | 9.794*** | 87.846*** | 0.717*** | –0.107*** | 0.732*** | –0.147*** |
| | (0.054) | (2.168) | (21.703) | (0.059) | (0.014) | (0.060) | (0.016) |
| $FPS^{\text{bordering countries}} = 1 * \ln(GDP\ per\ capita)$ | | 0.043* | 0.595** | | | | |
| | | (0.024) | (0.249) | | | | |
| $FPS^{\text{bordering countries}} = 2 * \ln(GDP\ per\ capita)$ | | 0.061* | 0.880** | | | | |
| | | (0.034) | (0.370) | | | | |
| $FPS^{\text{bordering countries}} = 3 * \ln(GDP\ per\ capita)$ | | 0.448*** | 4.960*** | | | | |
| | | (0.036) | (0.380) | | | | |
| $FPS^{\text{bordering countries}} = 4 * \ln(GDP\ per\ capita)$ | | 0.441*** | 4.776*** | | | | |
| | | (0.064) | (0.674) | | | | |
| $FPS^{\text{bordering countries}} = 5 * \ln(GDP\ per\ capita)$ | | –0.965*** | –9.602*** | | | | |
| | | (0.055) | (0.580) | | | | |
| $FPS^{\text{bordering countries}} = 6 * \ln(GDP\ per\ capita)$ | | –1.022*** | –10.164*** | | | | |
| | | (0.057) | (0.602) | | | | |
| $FPS^{\text{bordering countries}} = 7 * \ln(GDP\ per\ capita)$ | | –0.884*** | –7.819*** | | | | |
| | | (0.213) | (2.136) | | | | |
| $FPS^{\text{bordering countries}} = 0 * \text{payment} = 1$ | | | | –0.007 | –1.222*** | | |
| | | | | (0.110) | (0.100) | | |
| $FPS^{\text{bordering countries}} = 1 * \text{payment} = 1$ | | | | 0.026 | –0.900*** | | |
| | | | | (0.106) | (0.096) | | |
| $FPS^{\text{bordering countries}} = 2 * \text{payment} = 1$ | | | | –0.044 | –0.802*** | | |
| | | | | (0.103) | (0.095) | | |
| $FPS^{\text{bordering countries}} = 3 * \text{payment} = 1$ | | | | 0.021 | –0.586*** | | |
| | | | | (0.105) | (0.096) | | |
| $FPS^{\text{bordering countries}} = 4 * \text{payment} = 1$ | | | | –0.018 | –0.612*** | | |
| | | | | (0.094) | (0.085) | | |
| $FPS^{\text{bordering countries}}$ | | | | 0.228 | –0.152 | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $= 5 * \text{payment} = 1$ | | | | (0.143) | (0.139) | | |
| $FPS^{\text{bordering countries}}$ | | | | 0.172 | –0.318* | | |
| $= 6 * \text{payment} = 1$ | | | | (0.172) | (0.164) | | |
| $FPS^{\text{bordering countries}}$ | | | | | | 0.046 | –1.179*** |
| $= 0 * \text{tech} = 1$ | | | | | | (0.106) | (0.095) |
| $FPS^{\text{bordering countries}}$ | | | | | | 0.027 | –0.899*** |
| $= 1 * \text{payment} = 1$ | | | | | | (0.101) | (0.091) |
| $FPS^{\text{bordering countries}}$ | | | | | | 0.022 | –0.755*** |
| $= 2 * \text{tech} = 1$ | | | | | | (0.100) | (0.091) |
| $FPS^{\text{bordering countries}}$ | | | | | | –0.029 | –0.624*** |
| $= 3 * \text{tech} = 1$ | | | | | | (0.100) | (0.090) |
| $FPS^{\text{bordering countries}}$ | | | | | | –0.082 | –0.659*** |
| $= 4 * \text{tech} = 1$ | | | | | | (0.089) | (0.078) |
| $FPS^{\text{bordering countries}}$ | | | | | | 0.141 | –0.243** |
| $= 5 * \text{tech} = 1$ | | | | | | (0.120) | (0.107) |
| $FPS^{\text{bordering countries}}$ | | | | | | 0.212 | –0.289** |
| $= 6 * \text{tech} = 1$ | | | | | | (0.154) | (0.143) |
| App age | –0.001 | –0.001 | –0.007 | –0.001 | –0.001*** | –0.001 | –0.000 |
| | (0.001) | (0.001) | (0.006) | (0.001) | (0.000) | (0.001) | (0.000) |
| Observations | 165,210 | 165,210 | 165,210 | 165,210 | 165,210 | 165,210 | 165,210 |
| Adjusted $R^2$ | 0.76 | 0.77 | 0.77 | 0.76 | 0.80 | 0.76 | 0.81 |

The table reports the coefficients from panel-OLS regressions. Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include app*country and time fixed effects. The dependent variable in columns I, II, IV and VI corresponds to *FPS*, an indicator variable taking value one when the country adopts an FPS and zero elsewhere. The dependent variable in columns III, V and VII correspond to the interaction term of the indicator variable *FPS* with the natural logarithm of GDP per capita, the indicator variable *payment* and the indicator variable *tech*, respectively. $FPS^{\text{bordering countries}}$ is the number of downloads as a % of the population of the country-specific top 25 finance apps. *Payment* is a app-country-level indicator variable that takes value one for apps in the top 25 finance apps that are mainly for payment function. *Tech* is a app-country -level indicator variable that takes value one for apps in the top 25 finance apps that are issued by technological companies (ie big tech and fintech apps).

Digital finance adoption and FPS: IV analysis at the country-time level Table A4

| | Downloads, % population | | | |
|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) |
| $\widehat{FPS}$ | 0.002 | 0.092** | –0.003 | –0.017*** |
| | (0.003) | (0.045) | (0.022) | (0.006) |
| $\widehat{\text{FPS} * \ln(\text{GDP per capita})}$ | | –0.009** | | |
| | | (0.004) | | |
| $\widehat{FPS * \text{payment}}$ | | | 0.026 | |
| | | | (0.113) | |
| $\widehat{\text{FPS} * \text{tech}}$ | | | | 0.083*** |
| | | | | (0.029) |
| ln(GDP per capita) | 0.005 | 0.001 | | |
| | (0.004) | (0.006) | | |
| App age | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 10,000 | 10,000 | 10,000 | 10,000 |
| F-stat | 167.61 | 19.68 | 54.04 | 3.28 |
| Two-step weak IV LC, 95% conf. set ($\widehat{FPS}$) | | | | [–0.04,–0.012] |
| Two-step weak IV LC, 95% conf. set ($\widehat{FPS * tech}$) | | | | [0.039,0.212] |

The table reports the coefficients from panel-IV regressions where $FPS$ is instrumented with the number of bordering countries that adopted an FPS (ie $FPS^{\text{bordering countries}}$). Standard errors clustered by country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country and time fixed effects. The dependent variable corresponds to the average number of downloads as a % of the population for the country-specific top 25 finance apps. *Payment* corresponds to the country-time average of the app-country indicator variable that takes value one for apps in the top 25 finance apps that are mainly for payment function and zero elsewhere. *Tech* corresponds to the country-time average of the app-country-level indicator variable that takes value one for apps in the top 25 finance apps that are issued by technological companies (ie big tech and fintech apps) and zero elsewhere. *App age* corresponds to the country-time average of the app-country-time variable measuring app age. Notably, the F-stat in column IV indicates that the instrument is weak. Therefore, we report the weak instrument two-step identification-robust 95% confidence sets proposed by Andrews (2018) based on linear combination tests. Reassuringly, these confidence intervals do not include zero, thereby suggesting that these results are statistically significant at the 5% level.

| Digital finance adoption and FPS, IV analysis: instrument as a continuous variable | | | | Table A5 |
|---|---|---|---|---|
| | Downloads, % population | | | |
| | (I) | (II) | (III) | (IV) |
| $\widehat{FPS}$ | 0.037** | 1.909** | 0.025 | 0.033** |
| | (0.017) | (0.844) | (0.016) | (0.015) |
| $\widehat{\text{FPS} * \ln(\text{GDP per capita})}$ | | –0.171** | | |
| | | (0.075) | | |
| $\widehat{FPS * \text{payment}}$ | | | 0.057*** | |
| | | | (0.013) | |
| $\widehat{\text{FPS} * \text{tech}}$ | | | | 0.035** |
| | | | | (0.014) |
| ln(GDP per capita) | 0.012 | –0.050 | | |
| | (0.012) | (0.040) | | |
| App age | –0.000** | –0.000** | –0.000 | –0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 165,210 | 165,210 | 165,210 | 165,210 |
| F-stat | 55.18 | 2.28 | 33.42 | 32.67 |

The table reports the coefficients from panel-IV regressions where $FPS$ is instrumented with the number of bordering countries that adopted an FPS (ie $FPS^{\text{bordering countries}}$). Standard errors clustered by app*country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include app*country and time fixed effects.. The dependent variable corresponds to the number of downloads as a % of the population for the country-specific top 25 finance apps. *Payment* is an app-country-level indicator variable that takes value one for apps in the top 25 finance apps that are mainly for payment function and zero elsewhere. *Tech* is an app-country-level indicator variable that takes value one for apps in the top 25 finance apps that are issued by technological companies (ie big tech and fintech apps) and zero elsewhere.

## Event study design: staggered difference-in-difference

In this section, we document the effect of the launch of an FPS on the adoption of digital finance using an event study design. For identification, we leverage the staggered introduction of FPS across countries (ie the heterogeneity in launch dates) as well as the variation in the app-level data.

Ideally, we would compare the adoption of digital finance in two identical countries following the introduction of an FPS, where one country launches the FPS and the other does not. To approximate this scenario, we use countries that never launched an FPS, as well as the pre-launch periods of countries that eventually introduced an FPS, to construct a control group. We estimate a difference-in-difference (DiD) regression with staggered treatment, following the methodology of Borusyak et al (2024). Specifically, we compare the adoption of digital finance apps in countries that introduced an FPS to adoption in countries that either never launched an FPS or had not yet introduced one at the time. The mathematical equation we estimate is as follows:

$$Downloads, \%\, population_{i,c,t} = \sum_{k=-6}^{k=12} \beta_k 1\{t - t_n^* = k\} + \eta \ln\left(GDP\ per\ capita_{c,t}\right) + \delta app\ age_{i,c,t} + \lambda_{i,c} + \theta_t + \varepsilon_{i,c,t} \qquad \text{(A1)}$$

where *Downloads, % population* is the number of downloads of app $i$ in country $c$ in month-year $t$, expressed as a percentage of the population. $t_n^*$ denotes the FPS launch date for country $c$. $\lambda_{i,c}$ are app-country fixed effects. $\theta_t$ are month-year fixed effects. $k$ is the number of months relative to the introduction of the FPS, where $k$<0 denote months prior to the FPS launch and $k$≥0 denote months after the FPS is introduced in country $c$. The indicator variables $1\{t - t_n^* = k\}$ correspond to leads and lags of the specific launch date and, thereby, these $\beta_k$ coefficients capture the dynamic effect of interest.

The estimation results in Table A6 confirm the findings from Table 1, column 1. Notably, coefficients from column 1 indicate a 0.014 pp rise in adoption of digital finance apps in the three-month period following the introduction of the FPS. This effect is economically large and corresponds to roughly 25% higher adoption relative to the mean (ie 0.057%). The effect is also present up to twelve months after the launch date. Importantly, we do not find any significant pre-launch trends in digital finance adoption – the coefficients at $k \in \{-6, -5, -4, -3, -2, -1\}$ are not statistically significant.

Digital finance adoption and FPS: staggered diff-in-diff analysis Table A6

| | Downloads, % population<br>(I) |
|---|---|
| $1\{t - t_n^* = -6\}$ | 0.004 |
| | (0.004) |
| $1\{t - t_n^* = -5\}$ | 0.003 |
| | (0.004) |
| $1\{t - t_n^* = -4\}$ | 0.003 |
| | (0.004) |
| $1\{t - t_n^* = -3\}$ | 0.003 |
| | (0.005) |
| $1\{t - t_n^* = -2\}$ | 0.005 |
| | (0.005) |
| $1\{t - t_n^* = -1\}$ | 0.006 |
| | (0.005) |
| $1\{t - t_n^* = 0\}$ | 0.005*** |
| | (0.001) |
| $1\{t - t_n^* = 1\}$ | 0.005*** |
| | (0.002) |
| $1\{t - t_n^* = 2\}$ | 0.004** |
| | (0.002) |
| $1\{t - t_n^* = 3\}$ | 0.004** |
| | (0.002) |
| $1\{t - t_n^* = 4\}$ | 0.004** |
| | (0.002) |
| $1\{t - t_n^* = 5\}$ | 0.006*** |
| | (0.002) |
| $1\{t - t_n^* = 6\}$ | 0.007*** |

| | |
|---|---|
| | (0.002) |
| $1\{t - t_n^* = 7\}$ | 0.005*** |
| | (0.002) |
| $1\{t - t_n^* = 8\}$ | 0.004* |
| | (0.002) |
| $1\{t - t_n^* = 9\}$ | 0.003 |
| | (0.002) |
| $1\{t - t_n^* = 10\}$ | 0.002 |
| | (0.002) |
| $1\{t - t_n^* = 11\}$ | 0.004* |
| | (0.002) |
| $1\{t - t_n^* = 12\}$ | 0.004** |
| | (0.002) |
| Observations | 156,302 |

The table reports the coefficients estimated from equation A1. Standard errors clustered by country in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include app*country and time fixed effects.. The dependent variable corresponds to the number of downloads as a % of the population for the country-specific top 25 finance apps. $t_n^*$ is the FPS launch date for country *c*.

Overall, the evidence presented in Table A6 is consistent with the findings presented in the previous sections and further confirms the positive effect of FPS on the adoption of digital finance.

## Propensity score matching analysis

Again, a key concern is that the observed relationship between FPS implementation and increased app downloads might be driven by pre-existing trends in digitalisation, or app adoption leading to FPS implementation, rather than FPS causing the increase in adoption. To tackle this issue, we use a propensity score matching (PSM) model, which is a frequently used tool to identifying causal effects (see Rosenbaum and Rubin, 1983).

In a first step, we estimate the probability that a country introduces an FPS, using control variables such as GDP, population and the number of mobile phone subscriptions. This estimation helps to account for factors that could influence both the likelihood of FPS adoption and the increase in app downloads. In a second step, we match countries with a similar probability of an FPS but where one actually did introduce an FPS and the other did not. This matching process allows us to compare otherwise similar countries, thereby isolating the effect of FPS implementation from other confounding factors.

Table A7 investigates the impact of FPS introduction on the adoption of digital financial apps, based on the PSM model. The methodology involves aggregating all observations cross-sectionally and using the aforementioned control variables within a given year to forecast a propensity score for FPS treatment during that period. The matching process is predicted on one year of historical data, resulting in different control and treatment pairs for each year. Panel A shows a positive coefficient for GDP per capita, population, internet connections and mobile subscriptions, and a negative coefficient for bank branches.

Panel B shows the second-stage results. When comparing otherwise similar countries, we obtain a positive and significant estimated relationship, with FPS launch associated with greater downloads of finance apps overall (column I). The results are also positive and significant when differentiating by app type. Indeed, the relationship is present for fintech apps (column II), big tech apps (III) and those of incumbent banks (IV).

Probability of FPS launch, for propensity score matching approach — Table A7

Panel A: first stage results

| | FPS (0/1) |
|---|---|
| | (I) |
| Ln(GDP per capita) | 0.0958 |
| | (0.0169) |
| Population | 0.0001 |
| | (0.00002) |
| Internet connections, % population | 0.0023 |
| | (0.0005) |
| Bank branches, per 100,000 adults | –0.0119 |
| | (0.0004) |
| Mobile phone subscriptions, per 100 adults | 0.0063 |
| | (0.0002) |
| Observations | 1,228,029 |
| Pseudo $R^2$ | 0.099 |

Panel B: second-stage results

| | Total download (%pop) | Fintech download (%pop) | Big tech download (%pop) | Incumbent bank download (%pop) |
|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) |
| FPS (0/1) | 0.0411*** | 0.0417*** | 0.0719*** | 0.0370*** |
| | (0.0005) | (0.0009) | (0.0027) | (0.0007) |
| Observations | 77,073 | 23,730 | 3,532 | 49,811 |

***/**/* indicates statistical significance at the 1/5/10% level. Panel A shows the results of a logit regression where the dependent variable corresponds to an indicator variable that takes on value one from the date of introduction of the most recent FPS for each specific country. Panel B reports the results of a propensity matching model based on time fixed effects and country characteristics, such as GDP per capita, access to internet, density of bank branches and density of mobile phone holders.

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