Fast payments and banking: Costa Rica's SINPE Móvil

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Abstract

Launched in 2015, the Costa Rican retail fast payment system SINPE Móvil has seen rapid adoption since 2020. As of the second half of 2024, 76% of the Costa Rica´s population older than 15 are active users. The system can be used by natural and legal persons, with each user averaging approximately 180 transactions per year. Higher SINPE Móvil use has been related to lower cash withdrawals, a greater number of users and lower average volumes, suggesting SINPE Móvil has carved a prominent place in retail payments. With a synthetic controls approach comparing Costa Rica to peer countries, we show that wide adoption of SINPE Móvil led to lower non-interest expenses by Costa Rican banks after the pandemic. This suggests that payments innovation can enhance bank efficiency.

Keywords: Digital innovation, fast payments, fast payment systems.

JEL classification: G21, G23, O32.

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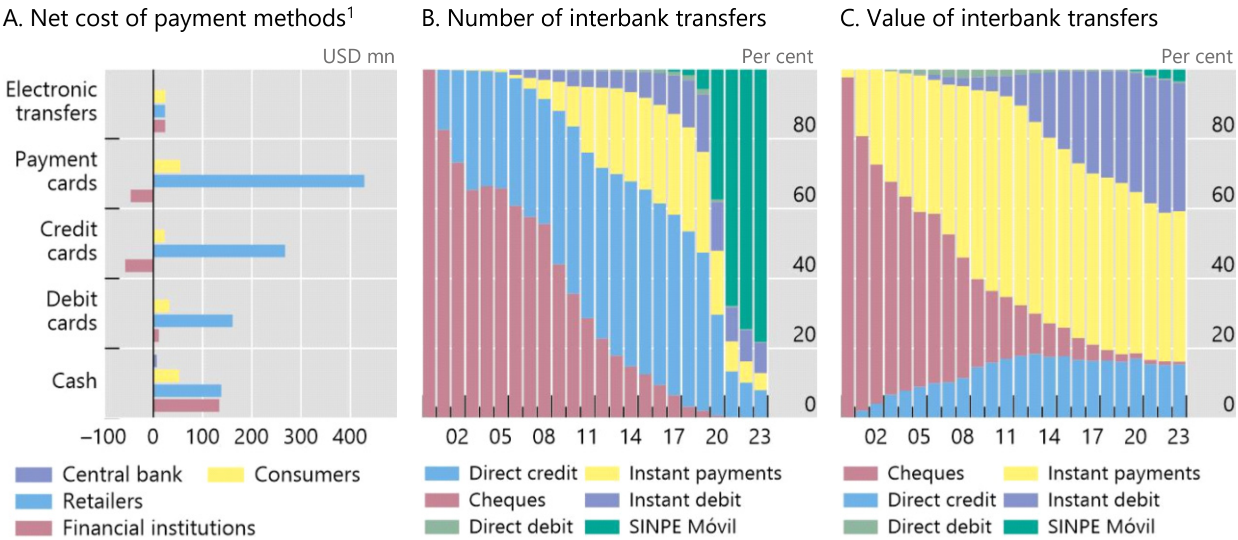
1. Introduction

Digital innovation can have a profound impact on economies and financial systems. In the payments market, new payment methods can alter the availability of funds for payers and payees, the fees paid to intermediaries, the available information about past transactions and much more. For payment intermediaries – notably banks – the adoption of new payment methods can lead to important shifts in payment revenues and expenses. What happens to the banking system when a new method achieves mass adoption across an economy?

In the last several years, Costa Rica has seen a digital revolution in payments with the introduction of a retail fast payment systems (FPS) called SINPE Móvil. SINPE Móvil is operated by the Central Bank of Costa Rica as an open, public infrastructure. All major banks participate, and it is also open to a range of non-banks. Users link their bank (or other) accounts in national currency (Costa Rica Colón) to a mobile phone number. This enables them to make electronic money transfers using a variety of electronic banking channels, such as short message service (SMS), e-banking, mobile web banking, banking apps, online banking or automated teller machines (ATM). It is available every day at all hours and is free of charge up to a certain amount (approximately CRC 100,000 or USD 200 at the time of writing).

Compared with cash and cards, electronic transfers are a low-cost payment method. In Costa Rica, electronic transfers are far cheaper for consumers, retailers, financial institutions and the central bank than other payment methods (Graph 1.A). Cash is the most expensive payment method, particularly for retailers and financial institutions. The total cost of processing cash in Costa Rica amounted to 1% of GDP in 2017 (Cerdas and Rodriguez (2018)). Still, until recently, cash was king, for two reasons. First, it always works at all times, for all individuals, regardless of whether they have a bank account. Second, clearing and settlement are immediate.

SINPE Móvil has carved a prominent place in payments in Costa Rica — Graph 1



[1] Data from 2016. Net costs are calculated as production costs minus fees received in CRC. Exchange rate used was average of 2016.

Sources: Central Bank of Costa Rica; national data.

The debut of SINPE Móvil in 2015 was accompanied by a number of further reforms, such as the introduction of simplified bank accounts. Yet it was not until 2020 that adoption took off, as Costa Rica implemented lockdowns to attenuate the Covid-19 pandemic, and consequently people began to use it more. Transactions with SINPE Móvil then quickly overtook other interbank transfer methods (Graph 1.B). Soon, they accounted for close to 80% of all interbank transfers. By the end of 2022, 52% of the population older than 15 were an active user in SINPE Móvil, and by 2024 this exceeds 76%. Still, SINPE Móvil only represents 4% of the value of all interbank transfers since it is a low-value payment system focused on retail use (Graph 1.C).

This paper explores the experience with and impact of SINPE Móvil. In particular, it assesses the conditions that led to a slow uptake at first, followed by exponential growth. It then looks at how SINPE Móvil evolved to infer whether users are using it in substitution of cash, which would be a powerful sign of its value and a potential source of efficiency for the financial system. To drive this point about efficiency home, we use a synthetic control approach to study the effect of SINPE Móvil on the costs of the Costa Rican banking system. We find that, relative to what Costa Rica would be if SINPE Móvil was not widely adopted, Costa Rican banks had lower non-interest expenses.

This paper contributes to a budding literature on FPS and their impact on macro outcomes. For instance, Natarajan and Balakrishnan (2020), CPMI (2021), Cornelli et al (2024) and Frost et al (2024) look at the design and adoption of FPS. Aguilar et al (2024) look at the impact of digital payments on informality and economic growth, and Araujo et al (forthcoming) document the effects of Brazil's FPS Pix on firm-level outcomes. This paper is most similar in spirit to Alvarez et al (2023), which assesses SINPE Móvil using micro data and finds strong evidence of network effects. In our case, the focus is more on the impact on the banking system. To the best of our knowledge, ours is the first study to explicitly consider how FPS impact on banks' non-interest expenses.

The paper is organised as follows. Section 2 discusses the background, launch and growth of SINPE Móvil. Section 3 discusses the effects on the Costa Rican banking system. Finally, section 4 concludes with some lessons learned on the implementation of SINPE Móvil and its effect on banks.

2. Background, launch and growth of SINPE Móvil

While the success of SINPE Móvil in Costa Rica is recent, the foundations were set far earlier. In 1997, the Central Bank of Costa Rica launched the National Electronic Payments System (SINPE after its name in Spanish).[2] Its first service was clearing and settling cheques, which previously took on average 20 days to redeem (Cerdas and Melegatti (2014)). SINPE had – and still has – the capacity to process operations in real time or deferred, in gross or net form, of low or high values. It can process peer-to-peer (P2P), person-to-business (P2B), business-to-business (B2B), business-to-person (B2P), person-to-government (P2G), government-to-person (G2P) and government-to-government (G2G), and it is open to a wide range of participants. Indeed, types of participants in SINPE include banks, non-bank financial institutions,

2 *Sistema Nacional de Pagos Electrónicos.*

cooperatives, mutual funds, pension funds, public institutions and other payment service providers (PSPs).

From 2000, Costa Rica put in place an FPS called TFT (now PIN), after its name in Spanish[3] – providing instant settlement and clearing, albeit with a focus on retail transfers of higher amounts. Seeking to boost mobile, small-value transfers, in 2015 the Central Bank of Costa Rica introduced SINPE Móvil, a mobile payment system that allows users to make and receive electronic money transfers by linking their accounts to a mobile telephone number (OECD (2020)).[4] In addition to the use of mobile phones as payment medium, the focus on retail transfers is underscored by the no fee commission (up to a certain limit).

Finally, and complementing SINPE Móvil, the central bank introduced three important reforms to the payment system that contributed to wider adoption of electronic payments and lower use of cash. The first step was to modernise the payments infrastructure. In 2015, the central bank enacted regulation that required the migration of its retail payment infrastructure to the Europay, Mastercard and Visa (EMV) chip and contactless technology. At the same time, banks collaborated with transit authorities to establish the Electronic Payments Systems for Public Transportation, which allowed passengers to pay bus and train fares with contactless cards. Second, in 2016 the central bank approved simplified accounts to expedite bank account opening by only requiring an identification document. The central bank also created a unified account database, integrating data about customers from all their accounts (current, savings and simplified). In another landmark reform, in 2019 the central bank introduced the International Bank Account Number (IBAN) to all accounts. The purpose was to standardise accounts and to identify them at the national and international level.

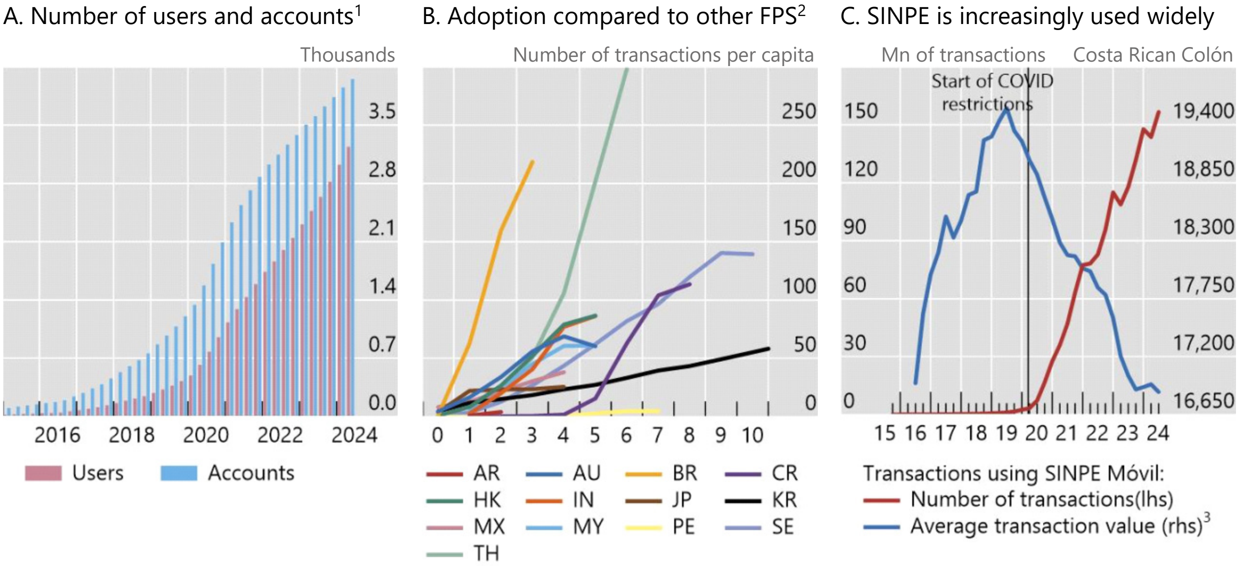
To use SINPE Móvil, clients need to have a transaction account in any of the financial entities that offer the service and an active mobile phone line. While banks in Costa Rica commonly offer US dollar-denominated accounts, only accounts denominated in Costa Rican Colón are eligible for SINPE Móvil, at least for now. Each mobile phone number must be linked to a single account, but the same account can be linked to multiple mobile phone numbers. This allows users to transfer funds knowing only the payee's phone number. Financial institutions and payment service providers have innovated, adding features like quick response (QR) codes and embedding SINPE Móvil in their own apps.

Adoption of SINPE Móvil started slow but then accelerated, particularly during the Covid-19 pandemic (Graph 2.A). By end-2022, there were around 2 million users and more than 3 million accounts. By June 2024, this had risen to nearly 3 million users and 4 million accounts. This makes Costa Rica one of the most active users of fast payments in the world. In terms of transactions per capita, SINPE Móvil holds fourth place in our selection of FPS, behind Thailand's PromptPay, Brazil's Pix (Duarte et al (2022)) and Sweden's Swish. Yet the speed of adoption has been similar to Thailand and Brazil, as evidenced by the slope of the line for these systems' number of transactions (Graph 2.B). As the number of transactions skyrocketed, their average value decreased to around CRC 16,900 (close to $34 USD) by June 2024 (Graph 2.C). This means that consumers increasingly use SINPE Móvil for everyday transactions.

[3] TFT stands for *Transferencias de Fondos a Terceros* while PIN stands for *Pagos Inmediatos.*

[4] Table A1 in the appendix describes SINPE Móvil and compares it with PIN.

SINPE Móvil adoption started slow but then accelerated | Graph 2



[1] The numbers regarding SINPE Móvil users and accounts can change over time, as data reporting is further refined. [2] Systems were selected based on data availability. Data are available until 2019, except for CL and DK where data are available until 2018 and CR available until 2022. [3] Four-quarter moving average; 1 USD~ 600 CR Colón.

Sources: Central Bank of Costa Rica; national data; BIS.

Two aspects were key for adoption. First was the partnership between private banks and the central bank. Private banks agreed that the central bank would aggregate their respective mobile phone registry to create an interbank mobile phone registry, which is the backbone of SINPE Móvil. This avoided siloes that would hamper intercommunication between account holders in different banks. The second characteristic contributing to user acceptance is the integration and interoperability within the national payment system. For users, this means that the money they already have in their respective bank accounts can be transferred through SINPE Móvil, without the need to first transfer it to a wallet. This differentiates the system from most of the private wallets and mobile money solutions from telecom companies in Africa, for example (eg Jack and Suri (2014)).

Even with all this favourable groundwork, it took a combination of factors to drive the rise in adoption only five years after SINPE Móvil was created. The onset of the Covid-19 pandemic and the associated lockdowns were major contributors, as many households used SINPE Móvil for the first time to pay for home-delivered meals, groceries and other goods. Also important is the delayed network effect: as more users experimented with and kept using SINPE Móvil, more people were incentivised to adopt it (Alvarez et al (2023)).

3. Effects on the Costa Rican banking system

SINPE Móvil's fast rate of adoption since early 2020 prompts the question: how did it affect Costa Rican banks? Some potential effects of the wide adoption of free, fast retail payments include:

- Greater financial inclusion, given easier access to digital payments, new simplified accounts and the economic opportunities for informal entrepreneurs arising from easier payments by potential clients.
- Lower costs, as banks adjust the size of their *physical* interface with customers to meet a lower demand for cash: all else equal, customers could be serviced with fewer ATMs, bank branches, etc, and banks and firms may face less costs attached to custody and maintenance of cash.
- Lower revenue, as legacy electronic payment methods, for which customers are typically charged a fee, are replaced with SINPE Móvil.

It is not clear *a priori* which of those effects is dominant. In this section, we explore the data to form a picture of the effects of SINPE Móvil on the Costa Rican banking system. Because these analyses span the pandemic period, which likely had considerable influence both on SINPE Móvil usage and on bank outcomes, the results are necessarily tentative. Still, these analyses can be informative about the direction and scale of responses from the banking sector.

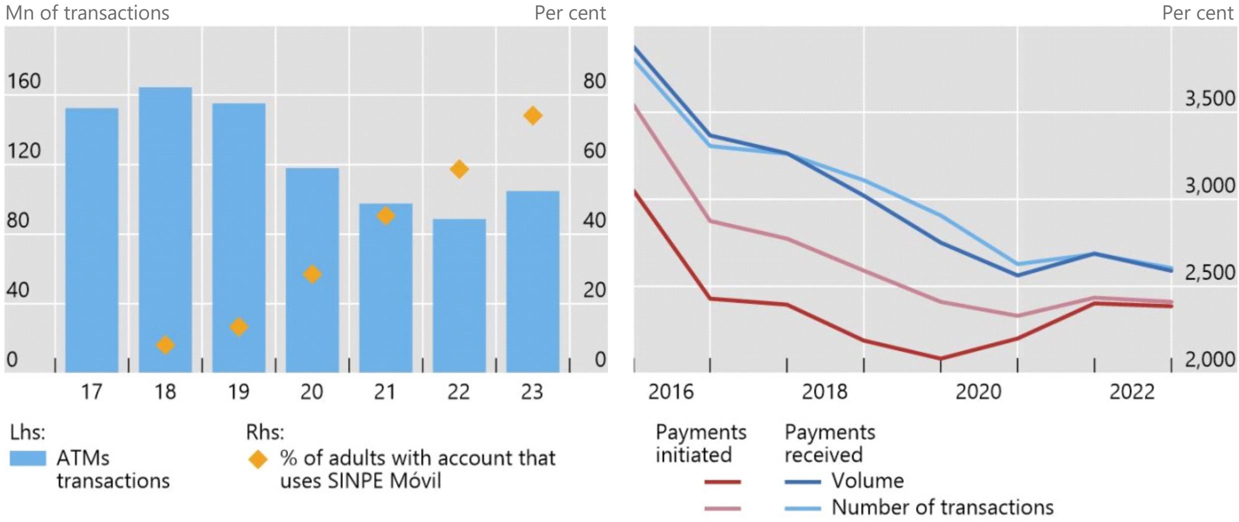
Substitution of cash payments

Use of SINPE Móvil has gone hand-in-hand with an increase in access to and use of transaction accounts – one key element of financial inclusion. First, from 2018 to June 2024, the share of population older than 15 with a bank account rose from around 77% to 90%. Notably, 84% of those with at least one bank account is an active user in SINPE Móvil (Graph 3.A). Second, higher SINPE Móvil use is correlated with lower ATM transactions, hinting at a substitution effect: while Costa Rican households performed 155 million ATM transactions and only 6 million SINPE Móvil payments in 2019, these were matched equally at 104 million ATM transactions and 506 million SINPE Móvil payments in 2023 (Graph 3.A). Extrapolating the costs from the Central Bank of Costa Rica, the estimated benefits from reduced cash use are about 0.5% GDP annually (Cerdas and Rodriguez (2018)). Third, uptake of SINPE Móvil was linked to a decline in market concentration in the payments sector. After its introduction, there is a decline in the Herfindahl-Hirschman Index (HHI) for both payments initiated and payments received (Graph 3.B).

SINPE Móvil promoted competition in the financial system Graph 3

A. As SINPE Móvil goes up, cash use goes down

B. The Herfindahl-Hirschman Index of market concentration has fallen



Sources: IMF; Central Bank of Costa Rica; BIS.

Effects on bank expenses

Next we turn to the effects on the Costa Rican banking system. We are interested in particular in first-order effects on bank expenses, given the impressive level at which users substitute cash with SINPE Móvil and how costly operating cash is usually for banks. The broader societal effects of lower cash use can be complex; for example, less tech-savvy customers or those in areas with less stable internet connection might have a strong preference for cash. Yet for the banking sector specifically, lower aggregate costs would be a positive contribution to its efficiency. A more complete analysis would also look at their revenues to check the extent to which lost fee income from lower use of legacy payment methods was compensated by other fees. Such costs could even be offset by lower delinquency rates on credit as SINPE Móvil offers banks more information with which they can assess prospective borrowers. Yet comparable data from other countries at this level of breakdown are not available.

Our focus then is on answering the following question: have banks' non-interest expenses decreased after SINPE Móvil use took off, compared with an alternative reality where SINPE Móvil use remains low as in its early years? To answer this question, we use synthetic controls (SC) (Abadie (2021)), a prominent methodology for comparative case studies. In short, the SC method entails data-driven counterfactual estimates of the outcome of interest (in this case, non-interest expenses divided by gross income) using peer countries. The observed value is then compared with the estimated counterfactual value: what would have happened in Costa Rica in a scenario where SINPE Móvil adoption had not taken off?

In the canonical methodology (Abadie and Gardeazabal (2003) and Abadie, Diamond and Hainmueller (2010)), estimating SC models entails finding the weights $\widehat{\omega}_j$ that approximate ω_j^*, for

$$Y_{1,t} = \sum_{j=2}^{N+1} \omega_j^* \, Y_{j,t} \text{ for } t < T,\ \sum_{j=2}^{N+1} \omega_j^* = 1 \text{ and all } \omega_j^* > 0, \tag{1}$$

where $Y_{1,t}$ is the outcome variable of interest (in this case noninterest income divided by gross revenues of banks in quarter t), the treated unit is standardised as $j = 1$, T is the intervention date and N is the donor pool size. In the current case, Costa Rica is the "treated" country, ie the one where the intervention occurs, and we consider the first quarter of 2020 as the "intervention date", due to the occurrence of the Covid-19 pandemic, which was a major driver of SINPE Móvil adoption. Once an SC is estimated, the causal effect at time $t > T$ after the intervention is calculated as the difference between the observed outcome variable and the SC, or more formally, $Y_{1,t} - \hat{Y}_{1,t}^{N}$, for $\hat{Y}_{1,t}^{N} = \sum_{j=2}^{N+1} \widehat{\omega}_j \, Y_{j,t}$.

In our setting, data ending in end-2018 are used to find the best way to combine other countries' banking systems' non-interest expenses to form a counterfactual Costa Rica with low SINPE Móvil use. Data from 2019 to 2022 are then used for calculating the causal effect of widespread SINPE Móvil adoption on the cost efficiency of the Costa Rican banking sector. We use data from the IMF's Financial Soundness Indicators (San Jose and Georgiou (2009)).

While the SC method is popular for its ability to combine peer units in a data-driven way, other steps actually end up requiring many subjective judgment calls. How should one select the peer units? How can we best combine peer units to form a counterfactual, especially for data that may have complex, non-linear dynamics? And how can one objectively judge the quality of fit of the SC compared with actual Costa Rica? We follow Araujo (2024) and combine specific machine learning methods to estimate and judge these SC. This makes the selection of the comparison control countries and estimation of the counterfactual Costa Rica fully data-driven. Another advantage is that the estimation of the counterfactual with machine learning more flexibly accommodates potentially complex data generating functions.[5]

The first step is to select the countries that would serve as a pool of potential controls. A natural comparison group would be the immediate neighbouring countries, Nicaragua and Panamá, but that would be too small a sample and leave out possibly relevant cases. Extending to the whole Central America region plus Dominican Republic would seem adequate, but a question arises on whether or not larger neighbours such as Colombia to the South, and Mexico to the North, should also be included. One could consider the United States, which is by far the largest trading partner, and possibly even the Netherlands or Belgium – other relevant export destinations according to World Bank WITS data. That would still leave out other countries with broadly the same population size and social structure, whose outcomes could be correlated with Costa Rica's. One pragmatic way is to select a common-sense group and conduct robustness checks by including and removing a few other countries, especially as the statistical significance of a result may hinge on including or not a specific unit (Klössner et al, 2018).

A data-driven way is to find which countries are more similar to Costa Rica and to each other *as a group* before SINPE Móvil's take-off. Clustering algorithms do exactly that. These are a class of unsupervised machine learning techniques that, in essence, group together units according to their similarity to each other.[6] This sidesteps subjective judgment in the selection of controls, and also may actually uncover other countries that are relevant but were not initially considered. A

5 All analyses were conducted with the open-source gingado package (Araujo (2023)).

6 Alternatively, Abadie and L'Hour (2021) propose the use of penalised linear regressions for the selection of control units.

particular method, *affinity propagation* (Frey and Dueck (2007)) combines many useful properties for SC estimation. First, cluster assignments of each country do not depend on the random initialisation of the search algorithm. Second, all units are eventually assigned to a cluster (even if a solitary one). And third, both the number of clusters and the size of each are purely determined by data, not chosen by the analyst. This flexibility allows clusters assignments to be fully determined by data.

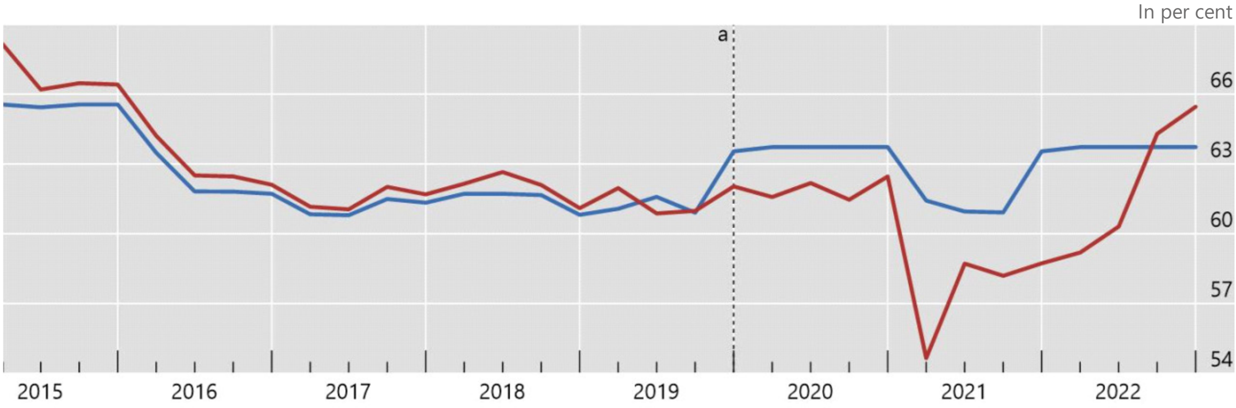
In the case of Costa Rica, using only the outcome variable (noninterest expenses of the banking sector), the cluster contains Bosnia and Herzegovina, Ecuador, Guatemala, Honduras, Lithuania, Madagascar, Nicaragua, Nigeria, North Macedonia, Norway, Paraguay, Romania, Rwanda, Ukraine, United States, Vanuatu and Zambia. Granted, this is hardly a list that any analyst would spontaneously come up with. But, it is the list of countries that are more similar to one another in their noninterest expenses according to an objective and flexible methodology. Thus, this choice of donor pool can be transparently defended as being data-driven. Another advantage of this particular pool of countries is how distant most are to Costa Rica, rendering any direct spillover between their banking systems unlikely. In contrast, if the donor pool consisted only or mostly of Central American countries, then other analyses would be necessary to confirm lack of externalities that would invalidate a causal interpretation of the estimates, since this is a comparative case study.

This exercise shows a strong reduction in noninterest expenses of Costa Rican banks after the rapid adoption of SINPE Móvil. The efficiency effects are economically large and seem to last for a number of quarters. Using this cluster as controls to estimate a counterfactual Costa Rica without the take-off of SINPE Móvil, the analyses suggest that SINPE Móvil adoption is indeed associated with a marked reduction in the cost structure of Costa Rican banks (Graph 4) at first. The ratio of non-interest expenses to gross income for the Costa Rican banking system (red line) fell significantly in 2020 and continued to be lower (compared to past values) for eight quarters afterwards. This observed outcome compares favourably with the estimated non-interest expenses for a counterfactual simulation of Costa Rica in which SINPE Móvil use had not taken off (blue line). While the true Costa Rican banking system and the counterfactual simulation tracked each other quite well in the years before SINPE Móvil was widely adopted, a gap opens afterward. This suggests a contribution of SINPE Móvil to higher cost efficiency in the banking system, especially during the Covid-19 pandemic, when ensuring access to banking and payment services was not straightforward.

Bank expenses were notably lower than in the counterfactual[1]

Graph 4

In per cent



[1] Values for series without SINPE Móvil are estimated with a combination of machine learning algorithms. [a] Dashed line represents the cut-off date for the estimation of synthetic controls: data up until that date is used to estimate the control weights, and from 2019 onwards is used for calculating the effect from SINPE Móvil.

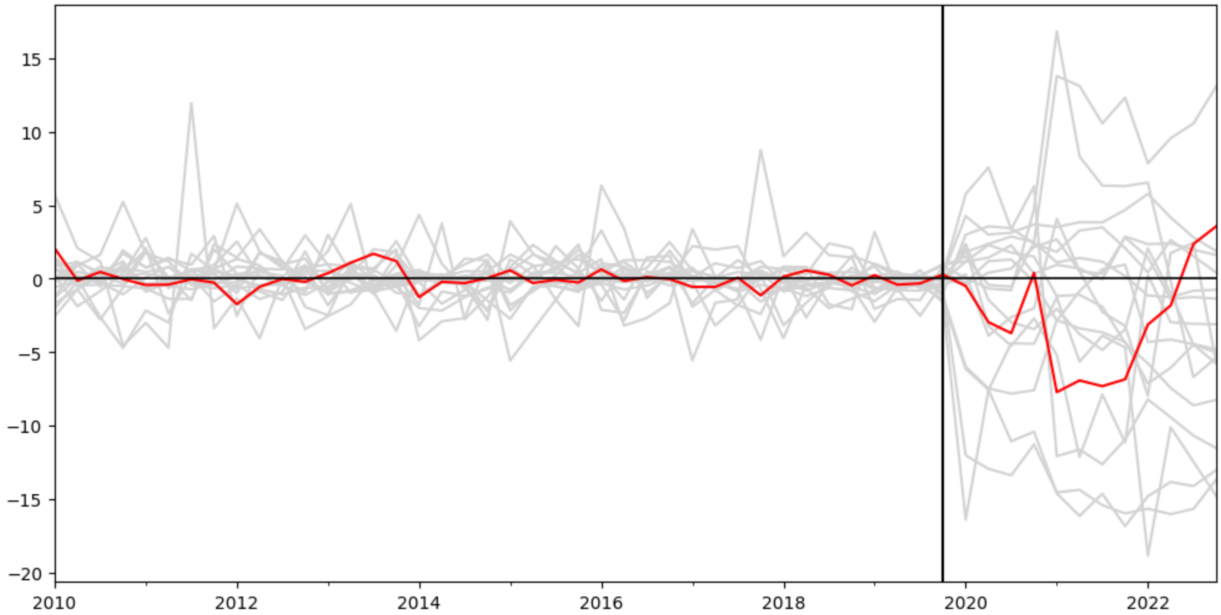
Sources: IMF; Central Bank of Costa Rica; BIS; authors' calculations.

One way to verify the statistical significant of these results is to run so-called *permutation analyses*, ie pretend that each of the control countries without SINPE Móvil adoption were "treated" and see what the post-treatment result would be. If Costa Rica's effect is contained in the range of these placebo calculations, then it suggests that at those periods, the shock is statistically indistinguishable from the effect of other shocks around the same time. Graph 5 presents these permutation analyses. Each line is the difference between the actual country (Costa Rica in red, control countries in grey) and its SC. Note the lower values for Costa Rica during the Covid pandemic time; while these are not strictly out of the range of placebo calculations, they tend to have only a few countries with even lower values. [7]

[7] The analysis period ends in 2022 to more cleanly identify the causal effect of SINPE Móvil's adoption take-off. Noninterest expense increased by more than a counterfactual Costa Rica in 2023. The magnitude of this effect suggests this is another individual "event" happening in the Costa Rican banking system and therefore, could not be separately analysed as part of the effects of SINPE Móvil.

SINPE Móvil adoption lowered bank noninterest expenses by more than most controls Graph 5

In per cent of gross income



Sources: IMF; authors' calculations.

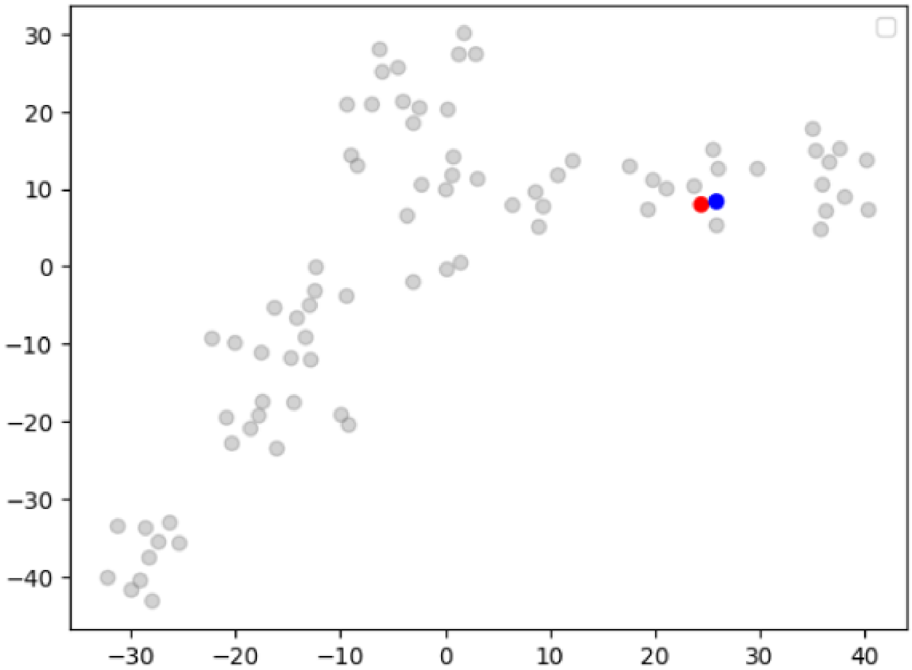
An assessment of the quality of the synthetic Costa Rica helps to support these findings. Also here, machine learning methods can help. Traditionally SCs are assessed in two ways: their fit to the pre-treatment outcome variable for the treated unit, and by comparing a synthetic version of other key variables, constructed using the same weights $\hat{\omega}_j$. While the former remains obviously a key test, the latter is subject to the criticism that conceivably one could simply now show covariates with a good fit. But even when this problem does not occur, a more fundamental question is how to judge these tests: simply comparing weighted averages across a number of variables might be a good approximation, albeit one always depending on the reader's agreement.

A more objective way to test control fit is to represent all relevant data in a lower dimension. This is achievable by algorithms called *manifold learning*, so called because they are calibrated to fit the high-dimensional data distribution using a lower-dimension distribution (formally, an underlying data manifold). Specifically, in the case of time series variables such as this application, the pre-treatment values for Costa Rica, the other countries and the "machine control" are used in a t-distributed stochastic neighbour embedding (t-SNE, van der Maaten and Hinton (2008)). In essence, t-SNE approximates a bivariate distribution with statistical sampling properties resembling the higher dimensional space of the original data. In our application, each point in time is used as a different dimension. Data points more similar as a whole to each other would tend to appear closer in this two-dimensional distribution than more different pairs of points.

Because the result has two dimensions, it can be interpreted as a coordinate system, which offers two convenient advantages. First, the results can be plotted and visually inspected, allowing a quick assessment of how close the control is to the unit of interest – the closer, the better as it means they would be more likely to come from similar areas in the data distribution. Second, and most important, the distance between the unit of interest and all others (including the SC) can be ranked, serving as a form of p-testing and therefore the control power can be tested relative to the population of donors, which was also itself automatically chosen. In this case, the synthetic "machine control" is the closest to pre-2019 Costa Rica compared to the other countries, underscoring the quality of the estimated counterfactual (Graph 6).

The SC estimated with machine learning is the best approximation to actual Costa Rica

Graph 6



Sources: IMF; authors' calculations. Blue: actual Costa Rica; red: synthetic Costa Rica; grey: all other countries. The values in the axes have no intrinsic meaning. The distance between any two dots is proportional to their difference, if they were sampled from a two-dimensional distribution. In other words, closer dots are more likely to be similar than far away dots. Note that synthetic Costa Rica is the closest dot to Costa Rica, confirming numerically it is a good counterfactual. Embeddings in the two-dimensional space calculated with the t-SNE methodology of van der Maaten and Hinton (2008) with data before SINPE Móvil's wide adoption.

4. Conclusion

Costa Rica is an excellent case study for the transformational effect of fast payment systems. While SINPE Móvil took several years to take off, it has now achieved widespread adoption, with the majority of the adult population making transfers of small amounts instead of cash. As we have shown, it has also helped to lower non-interest expenses by Costa Rican banks, and thus to enhance bank efficiency.

These effects are visible in the data we have presented, but also in daily life. If a pedestrian on a main street in Costa Rica passes a street musician, she will no longer be able to use a lack of change as an excuse for not tipping. It is likely that the musician will accept a transfer through SINPE Móvil. Moreover, it is increasingly possible to use SINPE Móvil for daily needs everywhere in Costa Rica: for shopping, for going out to dinner, for paying utilities, rent, etc. Here, it is important to mention that there are other strategies and initiatives in place in Costa Rica regarding the payment system. One of the latest is the electronic payment in public transport, which is expanding and reducing the use of cash in trains and buses in this country.

Finally, the role played by the Central Bank of Costa Rica and other banks committed to electronic fast payments was undeniably critical. The central bank provided leadership started the discussion and brought together key parties. It was the catalytic force that finally overthrew the reign of cash in Costa Rican society.

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Annex A. Characteristics of Costa Rica's FPS

Characteristics of Costa Rica's fast payment systems — Table 1

	TFT/PIN	SINPE Móvil
Type	Retail	Retail
Year of introduction	2000	2015
Rule book and standards	Central bank	Central bank
System operator	Central bank	Central bank
Clearing and settlement	Central bank	Central bank
Standard for the user interface	NA	Central bank
User interface	Private sector	Private sector
Development of other features	Private sector	Private sector
KYC/AML/CFT*	Private sector	Private sector
Settlement model	RTGS (real time settlement)	RTGS (deferred settlement)
Scope or payment types*	P2P, P2B, B2B, B2P, P2G, G2P, G2G	P2P, P2B, B2B, B2P, P2G, G2P, G2G
Average transfer amount (USD)	USD 5,725	USD 30
% of population (15 years and older) using it, as of June 2024	-	76%
Speed	<10 seg	<10 seg
Transactions per capita in 2022	4	71
Transactions per user in 2022	NA	110
Channels	Banking app, online banking or branch office	SMS banking, branch office, ATM banking app, online banking.
Daily transaction value limit (USD)	No limit.	No limit if made through authenticated channels. Mandatory limit up to USD 190 otherwise.[1]
Information for payment	Receiver's IBAN account number	Receiver's cell phone number
Currency	CRC, USD, EUR	CRC
Offline use	No	Yes
Charge to the customer (USD)	Set by banks[2]	No cost if up to USD 190 approx.[3]
Proxy lookup functionality	Yes	Yes
Request-to-pay functionality	-	In development
CAGR* of value of cash withdrawals from ATM* (last 5y)	-13%	
Estimate of cost savings from reduced use of cash (last 5 years) as % GDP	-0.05%	

[1] Private sector can increase the limit to make the service more competitive and depending to their risk appetite and the clients needs. [2] The fees of all participants are published in the web of the CB. [3] Private sector can set the fee above that amount. * KYC: know your client, AML: anti-money laundering, CFT: combating financing of terrorism, CAGR: compound annual growth rate, ATM: automated teller machine, P2P: person-to-person, P2B: person-to.business, P2G: person-to-government, and so forth.