INSTANT PAYMENTS AND BRAZILIAN PIX: LESSONS FROM THE INDIAN EXPERIENCE IN THE 2010'S

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Abstract

This paper aims to extract lessons from the Indian experience with the Unified Payments Interface (UPI), for the Brazilian PIX. Using Non-Linear Autoregressive Distributed Lag Models (NARDL), we intend to empirically test the relationship of UPI with selected economic variables: credit and debit card flows, mobile banking transactions, real-time gross settlement flux, ratios on the depth of financialization of the economy and popularity of banking apps. Therefore, the estimations used data from 2016 to 2020. The empirical results show that substitutes for instant payments (credit and debit cards) are complementary in nature, while the measure of relative popularity of mobile banking (MB/WLESS) and degree of sophistication of the financial system (M1/GDP) has an immediate effect on these flows. Short-term negative asymmetric shocks have had greater impacts on instant payment systems.

Keywords: PIX; Unified Payments Interface; Central Bank; NARDL models.

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1. Introduction

Payment systems are the pulse of capitalism, an essential component of the financial infrastructure, and necessary for any market economy that depends on the daily settlement of thousands of transactions resulting from the purchase/sale of goods, services, and assets. The internet changed the way agents interact with their investments and resources, especially with the widespread use of mobile phones and apps. Provoking a shift in how payment systems interact with the economy.

Considering new technologies, decentralized finance, digital assets, the Brazilian Central Bank (BCB) has decided to take on the implementation of the Instant Payment System (SPI). Numerous instant payments use cases around the world could be a parameter to the Brazilian Pix, like CODI in Mexico[1]. However, being a BRIC member, the Indian Unified Payment Interface (UPI) was chosen as a study case.

This paper directly contributes to the growing literature in payment system innovations[2]. It's motivation is focused on instant payment mechanisms and to test hypothesis towards their underlying explanatory variables: financial sophistication (M1/GDP), economic growth (RTGS), payment substitutes (NT1/ NT2) and a measure of relative popularity of banking apps (MB/WLESS). With an Indian dataset (April 2016 to November 2020), and time-series methodology, specifically Autoregressive Distributed Lag Models (ARDL)[3] and Nonlinear Autoregressive Distributed Lag Models (NARDL) inferences are made.

Results indicate that financial deepening and economic growth significantly affect instant payment mechanisms and vice versa. Payment options such as credit and debit cards will complement these mechanisms, while the increase in mobile transactions will enhance transaction speed. The popularity of banking apps, reflected in mobile subscription bases and transaction volumes, highlights the need for developing a national internet telecommunications infrastructure.

This article is divided into six main parts, including this introduction. In the next

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[1] ALFONSO, Viviana C. *et al.* Retail payments in Latin America and the Caribbean: present and future. BIS Quarterly Review, 2020.

[2] The articles that motivated our work were the Reserve Bank of India report (RBI, 2020a), Raj *et al.* (2020), Chaudhari *et al.* (2019), Reddy; Kumarasamy (2017), Yilmazkuday (2011).

[3] ARDL estimations are not presented in the paper owing to space limitations. We debate the main results were NARDL estimations are presented.

section, the Brazilian PIX and the Indian Unified Payment Interface (UPI) will be defined and briefly debated, following an empirical review on payment systems and dataset. In the fourth section NARDL methodology and model specifications are presented. Subsequently asymmetric relationships are calculated. Finishing the article with our main conclusions.

2. Instant payments: pix and unified payments interface (UPI)

In an environment where agents are progressively used to instant communication, payments have evolved to offer the same experience in commercial transactions. Fast payments[4] can be defined by two key features: speed and continuous service availability. According to the BIS report: "fast payment" is defined as a payment in which message transmission and availability of "final" funds to the payee occur in real-time or near-real-time as near as a 24-hour and seven-day (24/7) basis as possible" (BIS; 2016, p.6). Final funds are received such that the payee has unconditional and irrevocable access to them, providing strong certainty of payment to the payee (BIS, 2016)[5] .

The Brazilian Central Bank (BCB) has actively taken a catalyst, oversight, and operational role, with a high degree of involvement in Pix's development. Broad coverage, interoperable systems, network effects, and potential long-term positive externalities that are difficult to measure presently, are very strong arguments to understand why the Brazilian Central Bank (BCB) engaged in such enterprise. Conveying user-centric modernization of Brazilian retail payments and considered a strategic public policy objective, arguments favouring Pix's implementation will be discussed alongside its technical attributes.

With more than 60 million keys registered, in the first week of November 2020, and 700 institutions authorized by the Central Bank to offer Pix, it entered the payment market to spearhead the digital revolution in the National Financial System (SFN), propelling inter-bank payments instantly. Designed primarily to improve the experience of payers and payees, the goal was to build a solution that would be easy and quick as making a cash payment while also using the backend architecture (RTGS) already built with the reestablishment of the Brazilian Payment System in the 2000s.

[4] The terms used for fast payments may vary, although the underlying meaning could still be the same. Other common terms are "instant", "immediate", "real-time" or "faster payments" (BIS, 2016).
[5] An interesting point made by Giraldo-Mora *et al.* (2020) is that a real-time payment only needs to provide the perception of an instant payment, in the foreground, with no regard to the actual process in the background. Considering these technical and organizational conceptualizations of real-time, the authors define instant payments a little differently: as a traceable and predictable payment instrument in which funds are made available to end consumers just in time for the payment context (Giraldo-Mora *et al.*, 2020, p.3).

Pix went into restricted operation (test mode) on November 3rd 2020, and in full operation on November 16th 2020. It enables only "push" transactions, with payment orders and fund availability in real-time. Requiring previous registration, the payer will use his keys to link his accounts through the bank's API. Payers can initiate payments in different ways (Article 12, BCB Resolution No. 1): a) using keys or nicknames to identify the transactional account, such as a cell phone number, individual registration number (CPF), legal entity registration number (CNPJ), an e-mail address or a random key created through the banking app; b) through QR Code (static or dynamic). Each recipient will freely choose the type of instant payment initiation he or she will accept. If none of the options available are acceptable, informing complete data account users can proceed with settlement manually (BCB, 2020).

When correctly identifying the receiver, the payer sends an instruction that will eventually reach the payment service provider and the direct participant in the Instant Payment System (SPI). The message will pass through the addressing dataset and the unique Real-Time Gross Settlement infrastructure. The SPI direct participant is warned that his or her client will receive a credit in his account, after information verification, settling the transaction.

Formally inaugurated by the Reserve Bank of India (RBI) Governor and launched for public use in August 2016, the Unified Payments Interface (UPI) is an Indian network for real-time payments. An around-the-clock platform that offers a set of Application Programming Interface (API) specifications to facilitate online payments.

Built over the Immediate Payment Service (IMPS) infrastructure, UPI is used as a switching mechanism to enable digital instant payments between financial institutions. A single mobile application that powers multiple accounts, working as a common layer that orchestrates transactions and settlement across participating banks. Using the existing systems to ensure payment reliability across various channels, it takes advantage of infrastructure investments made so far.

With full interoperability, this unified layer offers peer-to-peer immediate payment, an interface designed for account holders to transfer funds, without entering any compelling information, through smartphones with a single identifier (payment identity) which can be either an Aadhaar[6] number, mobile number, a virtual payment address (VPA) or a UPI ID (NPCI, 2015; Gochhwal, 2017; NPCI, 2021; RBI,2021).

Due to UPI's *sui generis* characteristics[7] taking full advantage of mapping payment flow, it has witnessed rapid growth in the last years. Treating digital payments as a "public good"[8] and an important "infrastructure", design of the Indian Payment System challenges the business case for stand-alone private systems, establishing that central banks can be proactive and partners with the private sector counterparts when it comes to fostering technological innovation in the financial sphere.

The same argument can be directed to Brazil's Pix. While it is still in its infancy, potential market failure could be a valid reason for why the National Payments Corporation of India (NPCI), and the Brazilian Central Bank (BCB), played an important oversight and operational role in the implementation of these payment rails, sustaining the importance of governmental participation wherever private firms find insufficient market opportunity (Abraham, 2020). For a better understanding of these payment instruments, a comparative table was provided in the appendix.

Where payment provision is limited and mobile phone penetration is high, fast payments have developed more rapidly, overcoming barriers to financial inclusion and/by boosting access to the banking system. Real-time services magnify scalability meaning that they can be applied to hundreds of millions of customers, increasing payment volumes, bringing efficiencies to retail and small-scale transactions, providing cheap payment services to ordinary citizens (D'Silva *et al.*, 2019).

Looking at the bigger picture around faster payments, for countries that are in development like Brazil and India, problems like digital literacy, internet infrastructure, access

[6] India is the only country which was able to register more than one billion (88.6% of its population) on its identification dataset, Aadhaar. The aadhaar system is purely focused on identity, as it collects minimal data or just enough to provide unique identity (name, date of birth, gender, and residential address). Aadhaar was predominantly used for transferring government benefits through the Pradhan Mantri Jan Dhan Yojana (PMJDY) initiative (NPCI, 2015; Thomas; Chatterjee, 2017, D'Silva, 2019).

[7] The key aspects of the Unified Payments Interface are: a) permits payments via mobile app, web; b) payments can be both sender and receiver initiated; c) payments are carried out in a secure manner, aligned with RBI guidelines; d) payments can be done using Aadhaar Number, Virtual Address, Account Number & Indian Financial System Code (IFSC), Mobile Number and MMID (Mobile Money Identifier); e) the payment uses 1-click, 2-factor authentication, biometric authentication and the use of the payer's smartphone for secure credential capture (NPCI, 2016).

[8] India's approach is built upon four pillars: (i) providing digital financial infrastructure as a public good; (ii) encouraging private innovation by providing open access to this infrastructure; (iii) creating a level playing field through the regulatory framework; and (iv) empowering individuals through a data-sharing framework that requires their consent. India offers important lessons that are equally relevant for both advanced economies and emerging market and developing economies (D'Silva *et al.*, 2019, p.1).

to bank accounts, a mobile number and a smartphone are still questionable. Especially considering economic inequality coupled with rural poor telecommunication coverage.

However, the progressive dematerialization of currency and the financial dimension of digital sovereignty have become a priority for many countries. To better understand this phenomenon, through an economic perspective UPI was chosen as a study case due to specific characteristics: as a member of BRICS, demographic, territory dimensions, instant mobile transfer, 24/7 money transfer, four-year data availability and statistic correlation[9]. Aware of local cultural specificities and the differences between systems, UPI can bring some light to what we can expect aggregately for the Brazilian instant payment system. An empirical review will be done in the following section, paving our way to the chosen methodology, dataset and model specifications.

3. Empirical review on payment systems and dataset

Empirical literature examining the role of electronic payment systems and their dynamics towards economic development is quite sparse (Bech & Hobijin, 2006; Rooj & Sengupta, 2020). Only picking up speed in the last few years with the increasing importance of these innovations (Reddy & Kumarasamy, 2017).

Raj *et al.* (2020) develop a menu of models through ARIMA, ARCH, ARDL estimations, to find that currency circulation in India has been moderated over the last decade, reflecting innovations in digital payment technology (debit and credit cards). Chaudhari *et al.* (2019); Reddy; Kumarasamy (2017)[10] reached the same conclusion, in which digital volume transactions through payment innovations have a statistically significant inverse relationship with India's currency demand in the long run.

Incorporating both the role of inside money and the role of outside money Lubis *et al.* (2019) explores the relationship between efficiency of payment system services and financial intermediation. Generalized method of moments (GMM) and vector correction model (VECM) were applied to a data set collected from Indonesia, only to conclude that financial intermediation is inversely affected by currency in circulation. Card-based payment systems have a statistically significant impact (through long run effects with debit cards and short run effects with credit cards) on the reduction of money demand.

[9] Statistical correlation between M1/GDP India and M1/GDP for Brazil is above 50% (0.56) between 2010 (Q2) and 2021 (Q3).

[10] While credit cards decrease currency demand due to fewer cash transactions, debit cards increase money requirements increasing its marginal utility (Reddy & Kumurasamy, 2017).

Yilmazkuday (2011) investigated the credit channel of the monetary transmission mechanism through credit card usage, in a small economy (Turkey). Through a reduced-form Vector Autoregression (VAR) framework[11] both the credit view (through credit cards) and the monetary view (through short-term interest rates) seem to be important during high inflationary episodes for the real side of the economy. Specifically, credit cards have been positively and significantly affected mostly through shocks of output and lagged credit card usage, suggesting its role as a consumption-smoothing tool.

In addition to monetary policy, economic growth is crucial while analysing electronic payments. The Reserve Bank of India report (RBI, 2020a) published a study supporting a statistically significant Granger unidirectional causal relationship from the growth of nominal GDP and private final consumption expenditure to the growth of digital retail transaction value. Using an autoregressive distributed lag model (ARDL) as an additional framework, a long run relationship between digital retail transactions and private final consumption was revealed.

Rooj; Sengupta (2020), through a multivariate bayesian autoregressive vector model (BVAR) uncovered that high-value online transactions and economic growth are closely interlinked, indicating a presence of bidirectional causality between Real-Time Gross Settlement Systems (RTGS) and economic expansion in India. Lee; Yip (2008) argue that the RTGS system is a good performance indicator for the economy: high turnover of the RTGS system is usually associated with a growing economy. Gross Domestic Product (GDP) and employment can boost the transacted volume (with a positive sign), increasing proportionally is the quantity of money publicly held (M1) (M1/GDP)[12].

The Indian Central Bank (RBI) uses currency over GDP (CIC/GDP) as a measure of currency in circulation. However, Gala; Araújo, and Bresser-Pereira (2010) as a measure of the degree of financialization of an economy uses M1/GDP[13], based on Edwards (1995).

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[11] Sample period (2002-2009).

[12] To calculate a proxy for monthly GDP, the strategy was to find the ratio of annual imports (the sum of monthly imports) to India's annual GDP. With the annual percentage, the share of imports to GDP is calculated:

$$Monthly\ GDP = \frac{Monthly\ Imports}{Percentage\ of\ Imports\ by\ GDP(reference\ year)}$$

[13] An underlying assumption is that there may be endogeneity in relation to M1/GDP (explanatory variable) to the volume of transactions carried out by UPI (dependent variable). To better understand the nature of these variables, a Granger causality test was performed using Eviews 10. Considering six lags and p-value inferior to 0.05. It clearly appoints to a bidirectional movement: UPI Granger causes M1/GDP, and M1/GDP Granger causes UPI. This estimate provides some substance to the notion that UPI does in fact impact the degree of financialization of the Indian economy.

It is relevant to notice that, statistical correlation between M1/GDP India and M1/GDP for Brazil is above 50% (0.56) between 2010 (Q2) and 2021 (Q3), making it a good proxy for the Brazilian economy[14].

Credit (NT1) and debit cards (NT2) are included as the closest substitute for fast payments, whereas a negative and opposite sign can be expected between them. To enhance econometric procedures, total volume of transactions via mobile banking was divided by telephone wireless subscription base in millions (counting urban and rural telephone subscribers)[15,16] creating a ratio that describes popularity of banking apps (MB/WLESS). Access to new communication rails, like an increase in mobile phone usage and wireless subscription is expected to directly influence instant payment flows.

Monthly data was collected (from April 2016 to November 2020) with 56 observations. To not only capture effects on payment volumes and telecommunications infrastructure, but also technological innovations and currency demand, these factors can be better explained when indicators[17] are taken in volume rather than in value terms (Chaudhari *et al.*, 2020).

Volume of transactions via UPI was retrieved from the National Payments Corporation of India (NPCI). RTGS data, volume of transactions via mobile banking (MB), total number of credit card transactions at POS terminals (NT1) and debit card transactions at POS terminals (NT2), from the Reserve Bank of India (RBI). India's M1 was taken from the Federal Reserve Bank of Saint Louis (FRED) and telephone wireless subscription base in millions (WLESS) from the Telecom Regulatory Authority of India (TRAI).

Table 1 presents the descriptive statistics of the analysed variables. Data from payment systems are in Lakh[18] volume in millions of transactions. Out of all three payment system data, mobile banking has the biggest amount of customer transactions, followed by UPI and finally RTGS (although important in value, RTGS has small volumes of customer transactions). The M1/GDP ratio shows stability around 2.55 throughout the sample period,

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[14] Quarterly data on M1 and Real Gross Domestic Product (GDP) for Brazil and India was taken from the Federal Reserve Bank of Saint Louis (FRED). Correlations were estimated with Eviews 10.

[15] Since mobile banking is considered to be an I(2) variable, mobile banking in first differences was divided by wireless subscription base in millions: $\left(\frac{DMB}{WLESS}\right)$, in order to be estimated in the ARDL framework.

[16] Traditional unit root tests were used to diagnose stationarity such as the Dickey-Fuller (DF), the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. It is not necessary that the variables be stationary, but that at least one of them must be non-stationary.

[17] UPI transactions, credit card, debit card, mobile banking and real time gross settlement transactions are in volume. The other two indicators M1/GDP and MB/WLESS were c in ratios.

[18] Lakh is an Indian unit of measure that is equal to 100.000 Rupees. For example, in India, 150.000 Indian Rupees becomes 1.50 lakh. So, if I have 236.93 Lakh in transactions (October 2019) there are 236.93 * 100,000 = 23.693 million in transactions.

peaking in the first months of 2020. The underlying hypothesis is that COVID-19 increased significantly physical currency demand M1 (the most liquid portions of money supply), and provoked a decrease in economic activity (GDP), increasing the overall ratio.

The total number of debit card transactions at the point of sale (POS) terminals (NT2) is much bigger in the Indian economy than the total number of credit card transactions at the point of sale (POS) terminals (NT1). This might be the case because debit cards, in addition to functioning as an alternative medium of payment (compared to cash and instant payments), are also used as a medium for immediate liquidity, employed to withdraw money from bank accounts. Mobile banking volumes to telephone wireless subscription (MB/WLESS) ratio shows relative stability. Nonetheless, a sharp decrease in this ratio at the beginning of 2020 (second quarter) was then followed by a spike, that accounts for an increase in mobile applications usage through social distancing impositions.

Table 1 - Descriptive statistics of the analysed variables (Indian Dataset) - April 2016 to November 2020 (Not seasonally adjusted)

Unit	Variable	Mean	Median	St. Dev	Minimum	Maximum
Lakh (Mn in vol)	UPI	563,82	279,19	610,26	0,00	2.210
Mn (Transactions)	NT1	134.121.119	132.319.906	35.652.698	72.827.537	204.968.027
Mn (Transactions)	NT2	318.054.207	337.317.940	95.431.068	118.203.204	458.447.093
Lakh (Mn in vol)	MB	6.683,45	3.744	6.495	486,67	22.713
Lakh (Mn in vol)	RTGS	106,36	107,89	18,50	53,34	136,53
Ratio	M1/GDP	2,54	2,33	0,72	1,44	5,57
Ratio	MB/WLESS	0,32	0,15	0,68	-1,49	3,58

Note: Data computed through software EViews 10. Not seasonally adjusted. *Mn: million; *Mn in vol: million in volume. Data source: National Payments Corporation of India (NPCI), Telecom Authority of India (TRAI), Reserve Bank of India (RBI), and Federal Reserve Bank of Saint Louis (FRED), (2021).

Data was seasonally adjusted with EViews 10, Census-13 tool, using x-11 and TRAMO/SEATS[19]. Two different methods were employed to seasonally adjust, due to better fit in data idiosyncrasies[20]. Given the recent empirical literature on the subject, most of the studies presented are based on an aggregate behaviour macro framework[21]. Which

[19] X-11 bases seasonal adjustment with automatic ARIMA selection. SEATS bases seasonal adjustment with automatic outlier detection and TRAMO automatic ARIMA.
[20] By seasonally adjusting UPI and Mobile Banking, some variables become negative. This happens when time series are very close to zero, and by seasonally adjusting them, you take away the seasonal effect of that period. So, if the variable is already at a very low level, it becomes negative.
[21] Using macroeconomic data.

theoretically substantiates the chosen dataset, methodology and empirical analysis.

By capturing the relevance of digitalization in India through long, short run and nonlinearities, important inferences about Unified Payment Interface (UPI) can be made. Considering: financial sophistication, payment substitutes and relative popularity of banking apps, these estimations with India's experience support lessons for other developing BRICS countries like Brazil, their public policy towards telecommunications and payment infrastructure. Proceeding to empirical analysis, nonlinear autoregressive distributed lag (NARDL) methodology will be briefly explained detailing the necessary unit root tests, diagnostic tests for the estimation done in the next section.

4. NARDL methodology, model specifications, and results

A linear econometric analysis, like an autoregressive distributed lag model (ARDL) doesn't clarify much of UPI's underlying functioning. Knowing that instant payment mechanisms may be subject to asymmetries (positive and negative shocks due to economic activity) analysis is developed by applying a nonlinear autoregressive distributed lag (NARDL) approach to estimated ARDL equations[22].

Shin *et al.* (2014) advanced NARDL modelling as an extension of the ARDL framework (Pesaran & Shin, 1998; Pesaran *et al.*, 2001) in which short and long-run nonlinearities are introduced via positive and negative partial sum decompositions of the explanatory variables. Asymmetry occurs when positive and negative variations of the explanatory variable (X) do not have the same impact (in magnitude) on the dependent variable (Y). By decomposing these shocks, it is possible to verify if relationships are nonlinear.

[22] Due shortage of space we did not present the short and long run ARDL estimations.

The NARDL equation is as follows:

$$\Delta_{y_t} = \alpha_0 + \alpha_{1t}\tau + \rho y_{t-1} + \delta_1^+ x_{1t-i}^+ + \delta_1^- x_{1t-1}^- + \delta_2^+ x_{2t-1}^+ + \delta_2^- x_{2t-1}^- + \ldots + \sum_{i=0}^{p-1} \lambda_i \Delta y_{t-i} + \sum_{i=0}^{q} \varphi_{1i}^- \Delta x_{1t-1}^- + \sum_{i=0}^{r} \varphi_{1i}^+ \Delta x_{1t-1}^+ + \sum_{i=0}^{s} \varphi_{2i}^- \Delta x_{2t-1}^- + \sum_{i=0}^{p} \varphi_{2i}^+ \Delta x_{2t-i}^+ + \varepsilon_t$$

The first variable Δ is the first difference operator; α_0 the constant; $\alpha_{1t}\tau$ the trend; δ_i, i = 1,2 are the long run parameters; φ_i, i = 1,2 are the short run parameters; and ε_t is the error term that must be a white noise (i.i.d). The equation has two distinctive parts comprising the short run and the long run, where x_t^+ and x_t^- are partial sums of positive (+) and negative (-) changes in x_{1t} and x_{2t}" (Shin *et al.*, 2014; p.8). Measuring separate responses to positive and negative shocks of the regressors on the dependent variable, the nonlinear autoregressive distributed lag model (NARDL) shows the same advantages as the ARDL framework: it exhibits small sample properties, and it is appropriate regardless of variable stationarity. It yields estimates of both short and long run coefficients, it is free of residual correlation (it is not prone to omitted lag bias) and solves multicollinearity through the choice of the appropriate lag length of variables (Jareño *et al.*, 2020).

Long run ARDL levels equation showed that credit card transactions at POS terminals (NT1), debit card transactions at POS terminals (NT2), mobile banking (MB), and M1 ratio to Gross Domestic Product (M1/GDP), have long run impacts on Unified Payments Interface (UPI). UPI empirical models (April 2016/ November 2020) confirm very high adoption rates in the first months of implementation, in which credit and debit card usage are expected to propel instant payments.

Possible substitution characteristics between UPI, credit and debit cards were emphasized through academic literature. However, from a macro standpoint and due to the short time frame studied, they are not so much substitutes as they are means that increase instant payment usability and acceptability (complementary). This also occurs with mobile banking. A bigger usage of banking apps in India, induces more UPI transactions, intensifying money transactions, currency circulation domestically, with a deeper profusion of digitalization.

Interlinked with economic growth, and considered a proxy for all payments made in the Indian economy (Rooj & Sengupta, 2020; Lee & Yip, 2008) Real Time Gross Settlement System (RTGS) is statistically relevant in the short run with positive effects on instant payments (volume wise). Credit card transactions (NT1) have a lag effect, while MB/WLESS and M1/GDP ratios can produce an immediate impact on instant payment transactions.

Therefore, are there non-linearities that have not surfaced through ARDL estimations? Do they provide important insights into instant payments? Four NARDL equations were selected, with positive and negative shocks of the explanatory variables. Only mobile banking (MB) and debit card transactions in POS terminals (NT2) were not accounted for because they did not show significant statistical results[23].

With the main diagnostic tests done, including the bounds testing approach (Narayan, 2004; Pesaran *et al.,* 2001) it is time to advance to the long and short run NARDL estimations. Since econometric analysis is restricted to variables with significant p-values ($p < 0.01$, $p < 0.05$, $p < 0.10$), none of the long run level coefficients of the NARDL estimated models had relevant p-values. Consequently, it is not possible to affirm long run non-linearities between the explanatory and dependent variables[24]. However, evidence was found of additive short run asymmetries enabling coefficient analysis and testing (Table 2).

Table 2 - Estimated NARDL models. Dataset from Indian payment systems

Model ARDL	Method	Dependent Variable	Positive and Negative Shocks	Dependent Variables	Model Selected
1	NARDL	UPI	RTGS +, RTGS -	D(MB)/WLESS, RTGS +, RTGS -, M1/GDP	(6,1,6,6,6)
2	NARDL	UPI	NT1 +, NT1 -	D(MB)/WLESS, NT1+, NT1 -, M1/GDP	(6,0,2,6,2)
3	NARDL	UPI	M1/GDP +, M1/GDP -	D(MB)/WLESS, M1/GDP+, M1/GDP-, NT2	(1,5,0,4,4)
4	NARDL	UPI	NT1 +, NT1 -	D(MB), NT1 +, NT1-, M1/GDP	(6,2,6,0,2)

Note: ARDL models with a maximum of six (6) lags. Model choice based on Akaike Information Criteria. Author's elaboration. Data output from EViews 10.

Table 2 displays short run estimations of the four NARDL models, coefficients and p-values.[25] In model 01 UPI's past volumes will have a negative impact on its present values

[23] Similarly to ARDL estimations, a dummy variable was applied to the year 2020. Akaike information criteria was used to identify optimal lag length and HAC (Newey-West) coefficient covariance matrix was applied for robust estimates. Parameter stability and diagnostic tests were also performed to attest autocorrelation, heteroskedasticity, and overall econometric consistency.

[24] Even though two NARDL models presented relevant long run asymmetries through the Wald Test (models 02 and 05).

[25] Only statistically relevant calculations (<0.01, < 0.05, < 0.10) are presented.

(one and five periods previously). Two to three months beforehand, there is a positive and significant impact on instant payment volumes increasing in 0.37 and 0.47 lakh transactions. Ratio of mobile banking transactions to mobile phone subscriptions (MB)/WLESS and level of sophistication of the financial system M1/GDP increased UPI transactions in 1.01% and 1.11%. Positive and negative decompositions of Real-Time Gross Settlement Systems (RTGS), five months prior, were significant (p-value < 0.05). Inferring that instant payments are a positive function of both positive and negative changes in RTGS in the short-run (a positive RTGS shock increases UPI transactions, and a negative one decreases them).

In conformity to its trend, in model 02, UPIs past transactions will also impact its present volumes positively and negatively. Decomposing credit card transaction volume (NT1) shows that UPI volume is a positive function of both positive and negative changes in credit card transactions. With an increase in credit card transactions, there will be a concurrent increase (in 0.000002) in instant payment volumes. A decrease will reduce UPI volumes (in 0.000005 lakh transactions). On the other hand, M1/GDP past value has a 0.95% positive impact on instant payment transactions (p-value < 0.05).

Usage of mobile banking transactions to mobile phone users (MB/WLESS), gains relevance in model 03, whereas up until four lags it is possible to affirm statistical significance. Its immediate impact is positive and significant, increasing volume of instant payments in 0.53%, converting then to negative shocks. Not all mobile phone users will be mobile banking or UPI clients, producing an inverse relationship as time passes. The decomposition of the level of sophistication of the Indian financial system (M1/GDP) affects UPI payments immediately in -0.42%. After two lags, the previous increase of currency in circulation would convert into a bigger quantity of deposits, incentivizing the use of instant payments, with a rise in 0.64% in volume of instant payment transactions (p-value < 0.10).

Table 3 - NARDL Short Run Dynamics: Error Correction and Significant Variables, for the four specified models (Indian Dataset)

ARDL Model	1		2		3		5
NARDL	(6,1,6,6,6)	NARDL	(6,0,2,6,2)	NARDL	(1,5,0,4,4)	NARDL	(6,2,6,0,2)
Variables	Coef [Prob]	Variables	Coef [Prob]	Variables	Coef [Prob]	Variables	Coef [Prob]
D(UPI (-1))	(-0.52) [0.002]*	D(UPI (-1))	(-0.25) [0.03]*	D(MB)/WLESS	53.61 [0.00]	D(UPI (-1))	(-0.25) [0.03]*
D(UPI (-2))	0.37 [0.00]*	D(UPI (-2))	0.35 [0.00]*	D(MB)/WLESS (-1)	(-65.29) [0.00]	D(UPI (-2))	0.34 [0.00]*
D(UPI (-3))	0.460 [0.00]*	D(UPI (-4))	(-0.25) [0.08]*	D(MB)/WLESS (-2)	(-71.29) [0.00]*	D(UPI (-4))	(-0.25) [0.07]*
D(UPI (-5))	(-0.30) [0.03]*	D(UPI (-5))	(-0.15) [0.08]*	D(MB)/WLESS (-3)	(-17.95) [0.09]*	D(UPI (-5))	(-0.16) [0.07]*
D(MB)/WLESS	101.35 [0.00]*	D(NT1 POS)	0.000004 [0.00]*	D(MB)/WLESS (-4)	(-39.25) [0.00]*	D(NT1 POS)	0.000003 [0.00]*
D(RTGS POS (-5))	5.03 [0.000]*	D(NT1 POS) (-1))	0.000002 [0.01]*	D(M1/GDP POS)	(-42.26) [0.04]	D(NT1POS) (-1)	0.000002 [0.01]*
D(RTGS NEG (-1))	5.127 [0.00]*	D(NT1 NEG (-1))	0.000005 [0.00]*	D(M1/GDP POS (-2))	64.40 [0.09]*	D(NT1 NEG) (-1)	0.000005 [0.00]*
D(RTGS NEG (-2))	3.57 [0.04]*	D(NT1 NEG (-3))	0.000002 [0.00]*	D(M1/GDP POS (-3))	(-74.42) [0.02]*	D(NT1 NEG) (-3)	(0.000002) [0.00]*
D(RTGS NEG (-4))	7.21 [0.00]*	D(NT1 NEG (-4))	0.000002 [0.00]*	D(M1/GDP NEG (-1))	112.23 [0.01]*	D(NT1 NEG) (-4)	(0.000002) [0.00]*
D(RTGS NEG (-5))	3.96 [0.012]*	D(NT1 NEG (-5))	0.000001 [0.03]*	D(M1/GDP NEG (-2))	(-156.85) [0.00]*	D(NT1 NEG) (-5)	(0.000001) [0.03]*
D(M1/GDP (-1))	111.365 [0.00]*	D(M1/GDP (-1))	95.56 [0.00]*	D(M1/GDP NEG (-3))	171.34 [0.00]*	D(M1/GDP (-1))	95.370 [0.002]*
D(M1/GDP (-2))	62.39 [0.017]*						
D(M1/GDP (-3))	48.43 [0.050]*						
D(M1/GDP (-4))	78.06 [0.00]*						
DUMMY	114.400 [0.00]*	DUMMY	41.48 [0.02]*	DUMMY	32.10 [0.05]*	DUMMY	41.06 [0.02]*
CointEq (-1)	(-0.03) [0.00]*	CointEq (-1)	(-0.08) [0.00]*	CointEq (-1)	(-0.03) [0.00]*	CointEq (-1)	(-0.08) [0.00]*
R-Squared (R^2)	0.94	R-Squared (R^2)	0.91	R-Squared (R^2)	0.89	R-Squared (R^2)	0.91
Durbin-Watson Statistic	2.40	Durbin-Watson Statistic	2.28	Durbin-Watson Statistic	2.40	Durbin-Watson Statistic	2.28

Note: Software used for estimation EViews 10. ARDL models considered are case II: Restricted Constant and No Trend. * Relevant estimations.
Source:Authors' elaboration

Negative shocks of M1/GDP will also produce diminishing volumes of transactions in 1.12%. With a decreasing M1, after the second period, more people would use their money in the bank to consume, increasing instant payments by 1.56%. Overall, UPI payments suffer a bigger impact through negative shocks than positive shocks. In periods of economic downturns, agents prefer to retain liquidity (paper money or demand deposits) postponing spending due to economic uncertainty (Keynes, 1996), limiting their expenses to autonomous consumption. Currency allows agents to keep options open in face of unpredictable outcomes (precautionary demand).

As seen in models 01 and 02, in **model 04** UPI's past volumes have negative and positive impacts on UPI present value. Similar to model 02, credit card transactions in point-of-sale terminals (NT1) are decomposed in positive and negative variations. Positive shocks to credit card transactions increase the volume of UPI instant payments immediately in 0.000003 and in 0.000002[26] after a lag (at a p-value < 0.05).

Negative shocks will also affect UPI transactions, considering the estimated lags in Table 03. Level of development of the financial system (M1/GDP) will increase instant payments in 0.95%. Dummy coefficients are significant in all four models and error correction terms (CointEq), were negative and relevant at the 1% level. In models 01 and 03, 3% of deviations from the long-term trajectory will be corrected in the next month (two years for total conversion). In models 02 and 04, 8% of deviations will be corrected in the next period, with full adjustment occurring in a year.

Estimations confirm that mobile banking volumes are relatively constant over time; however, an immediate positive short run shock, incentivizes instant payment transactions. Directly impacted by the central bank's monetary policy towards currency emission, M1/GDP can negatively impact UPI transactions, converting into a positive impact owing to a rise in deposits. Monetary economics are highly prone to downturns in economic activity, in which valleys becomes deeper and steeper than peaks: *"The substitution of a downward for an upward tendency often takes place suddenly and violently, whereas there is, as a rule, no such sharp turning point when an upward is substituted for a downward tendency"* (Shin *et al.*, 2014 *apud* Keynes, 1996, p.314).

These dynamics most clearly show the prevalence of nonlinearities in economics. Three out of four models presented statistically relevant short run asymmetries. Since payment system volumes are closely linked to major economic upturns and downturns, and particularly prone to habits developed by economic agents, correctly capturing short run asymmetries are important to illuminate response differences. Asymmetric Wald tests will confirm short-run relationships.

[26] Even though some coefficients are quite small, the impact is accounted for and the probability is relevant.

5. Asymmetric relationships

The final procedure is to test if the difference in asymmetric coefficients is statistically significant. Short run non-linearities according to Shin *et al.* (2014, p.17) are considered an: "*impact asymmetry, associated with the inequality of the coefficients on the contemporaneous first differences* Δx_t^+ *and* Δx_t^-*.*" In other words, the short run Wald Test evaluates the equality of the sum of the positive and negative lags of each regressor. The null hypothesis H_0 states that the two impacts are the same (symmetrical) and there is no short run asymmetry. Rejecting H_0 of summative symmetric adjustment and accepting the alternative is evidence of short run asymmetry:

$$H_0: \sum_{i=l}^{q} \sigma_i^+ = \sum_{i=l}^{q} \sigma_i^-$$

$$H_A: \sum_{i=l}^{q} \sigma_i^+ \neq \sum_{i=l}^{q} \sigma_i^-$$

The Wald statistic follows an asymptotic χ^2 distribution. Using the stepwise regression with a unidirectional selection method (forward) and a stopping criterion at the 0.05 p-value on short run coefficients, asymmetries were tested (Table 04). Even though there was indication of short run asymmetries between UPI and RTGS, NARDL model 01 (6,1,6,6,6), with 6 lags was unable to provide consistent estimates. Examining model 02 (6,0,2,6,2), with positive and negative shocks of credit card transactions in volume (NT1), the short run Wald test found Chi-square (χ^2) statistic that confirmed asymmetry between NT1 and instant payments (UPI) at a 5% p-value. The NARDL model 04, also arrived at the same results, with a Chi-square (χ^2) estimate that corroborated short run asymmetry between NT1 and UPI (p-value < 0,05). These correlations show that short run negative shocks from credit card transactions (NT1) will produce bigger spill overs to instant payments[27].

[27] Performing the long run asymmetric Wald test on models 02 and 04, there are significant nonlinearities in which magnitude of change in instant payments are bigger when credit card volume decreases (becomes negative). Long run positive shocks produce instant payments increase, but a negative shock increases even more the volume of instant payments, indicating possible substitution effects on the long run. Long run or reaction asymmetry is identified through the following Wald test, (which is basically a division of the negative and positive shocks by the dependent variable coefficient).

$$H_0: \frac{-\gamma^+}{\rho} = \frac{-\gamma^-}{\rho}$$

$$H_A: \frac{-\gamma^+}{\rho} \neq \frac{-\gamma^-}{\rho}$$

The null hypothesis H_0 states that the two impacts are the same (symmetrical) and there is no long run asymmetry. The alternative hypothesis H_A, confirms the existence of long run asymmetry between the

Table 4 - Short run Asymmetric Wald Test. All four NARDL models (6 lags). Dependent variable Unified Payments Interface (UPI) (Indian Dataset).

	Positive and Negative Shocks	Model	Lags	Wald Test [Prob]
Model 01	RTGS +, RTGS -	NARDL (6,1,6,6,6)	6 lags	-
Model 02	NT1 +, NT1 -	NARDL (6,0,2,6,2)	6 lags	χ^2 (1) 23,130 [0,000]
Model 03	M1/GDP +, M1/GDP -	NARDL (1,5,0,4,4)	6 lags	χ^2 (1) 8,335 [0,003]
Model 04	NT1 +, NT1 -	NARDL (6,2,6,0,2)	6 lags	χ^2 (1) 22,923 [0,000]

Note. NARDL model with a maximum of six (6) lags. Model choice based on Akaike Information Criteria. *case 1: no constant and no trend, **case 2: restricted constant and no trend, ***case 3: unrestricted constant and no trend, ****case 4: unrestricted constant and no trend; *****case 5: unrestricted constant and unrestricted trend. Source: author's elaboration (EViews 10).

Giving further emphasis to level of financial sophistication (Gala; Araújo & Bresser-Pereira, 2010; Edwards, 1995), positive short run impacts of the M1/GDP ratio (model 03) demonstrate how monetary policy and economic growth are important to volume of instant payments. Technological enhancements in payment systems can reach sectors of society that are not completely integrated with the financial system, the partially unbanked. Macroeconomic policies will have a significant short run impact. Negative M1/GDP shocks will produce an immediate response with retraction throughout the economy, counter cycle measures will only produce positive outcomes with a lag. Depending on which direction public policies are taken and economic conditions, there will be excessive volume changes on instant payments.

In comparison with the reviewed literature Reddy; Kumarasamy (2017), Chaudhari *et al.* (2019), Raj *et al.* (2020), Lubis *et al.* (2019), Yilmazkuday (2011) Rooj; Sengupta (2020), this paper identifies underlying instant payments characteristics, through financial sophistication (M1/GDP), economic growth (RTGS), payment substitutes (NT1/ NT2) and a measure of relative popularity of banking apps (MB/WLESS).

UPI empirical models (April 2016/ November 2020) confirm very high adoption rates in the first months of implementation, in which credit and debit card usage is expected

coefficients. Rejecting H_0 and accepting the alternative, means that there is long run asymmetry, and the magnitude of the change in Y when X increases (decreases) is not the same as when X decreases (increases).

to propel instant payments. Taking into account the timeframe studied (April 2016 to November 2020) with 56 observations, they are much more a complementary means that increase faster payments usability and acceptability. Bigger usage of banking apps in India, induces more instant payment transactions and financial deepening (M1/GDP).

Interlinked with economic growth, and considered a proxy for all payments made in the Indian economy (Rooj & Sengupta, 2020; Lee & Yip, 2008) Real Time Gross Settlement System (RTGS) is statistically relevant in the short run with positive effects on instant payments (volume wise). Credit card transactions (NT1) have a lag effect, while MB/WLESS and M1/GDP ratios can produce an immediate impact on instant payment transactions. However, negative shocks on instant payments, can also be explained through bigger positive changes in these variables.

Short-run non-linear (NARDL) estimations revealed that both the ratio of mobile banking transactions to mobile phone subscriptions (MB/WLESS) and the level of financial system development (M1/GDP) contribute to increased instant payment volumes. Specifically, a rise in mobile banking transactions relative to mobile phone usage results in an immediate increase of 0.95% in payment volumes (models 02 and 04). Additionally, the proxy for depth and sophistication of the financial system, as indicated by the M1/GDP ratio (Gala, Araújo & Bresser-Pereira, 2010; Edwards, 1995), have a significant impact on real-time payments, highlighting a bidirectional causality between these factors.

Decomposing credit card transaction volume (NT1) (models 02 and 04) and M1/GDP, UPI volume responds positively to credit card transactions and inversely to M1/GDP in which impacts will only be felt with a lag. Concluding that instant payments are more affected by short run negative shocks than by positive ones. Highly sensitive to economic conditions, agents shade themselves retaining liquidity and limiting consumption. Credit, debit card and mobile transaction volumes are viewed as means to increase UPI/Pix usability and acceptability through payer/payee flow mechanisms in the short run.

6. Final remarks

This paper aims to test empirically, via nonlinear autoregressive distributed lag model (NARDL), the instant payment phenomenon in the Indian economy with data ranging from 2016 to 2020. The main contribution of this paper, in comparison with the reviewed literature, was to analyse the effects of instant payments on the economy, as well as their relationship with some selected economic variables.

The Indian Unified Payments Interface (UPI) was chosen as a study case to understand the instant payment phenomenon, in comparison to the Brazilian Pix.

Empirical models (April 2016/ November 2020) confirm very high adoption rates in the first months of implementation, in which credit and debit card usage is expected to propel instant payments. Taking into account the timeframe studied with 56 observations, they are much more a complementary means that increase faster payments usability and acceptability. Bigger usage of banking apps in India induces more instant payment transactions and financial deepening (M1/GDP).

Interlinked with economic growth, and considered a proxy for all payments made in the Indian economy (Rooj & Sengupta, 2020; Lee & Yip, 2008) Real Time Gross Settlement System (RTGS) is statistically relevant in the short run with positive effects on instant payments (volume wise). Credit card transactions (NT1) have a lag effect, while MB/WLESS and M1/GDP ratios can produce an immediate impact on instant payment transactions.

Short run non-linear (NARDL) estimations showed that ratio of mobile banking transactions to mobile phone subscriptions (MB/WLESS) and level of development of the financial system (M1/GDP), increased instant payment volumes. If there is increasing mobile banking transactions to mobile phone usage, this causes an immediate impact of 0.95% (models 02 and 04). The proxy for depth and sophistication of the financial system (M1/GDP) (Gala; Araujo & Bresser-Pereira, 2010; Edwards, 1995), has a clear effect on real-time payments.

Decomposing credit card transaction volume (NT1) (models 02 and 04) and M1/GDP, UPI volume responds positively to credit card transactions and inversely to M1/GDP in which impacts will only be felt with a lag. Concluding that instant payments are more affected by short run negative shocks than by positive ones. Highly sensitive to economic conditions, agents shade themselves retaining liquidity and limiting consumption. Credit, debit card and mobile transaction volumes are viewed as means to increase UPI/Pix usability and acceptability through payer/payee flow mechanisms in the short run.

The importance of instant payments is that they will capture a portion of clientele in the payments market, just like credit cards and debit cards, becoming a complementary instrument, in the growing list of possibilities. Both credit and debit card transaction volumes show a positive correlation, to instant payments at least at a 10% significance level[28]. These instruments will enhance instant payments usage, which will gradually occupy a bigger portion of the retail payments market. Nonetheless it will not eliminate other payment options altogether.

Reducing transaction fees through instant payments enhances economic activity, assisting the informal sector redirecting transfers to the real side of the economy. If per capita income and standard living are rising, economic logic leads us to the understanding that purchasing power grows incentivizing transactions, deepening development and sophistication of the national payment system.

Academic evidence of the importance of using digital technologies and internet services for economic and social development are abundant (Alves *et al.*, 2018). Domestic context plays into the main challenges for financial inclusion such as adequate digital infrastructure (broadband coverage), affordable electronic devices, digital, financial literacy, assuring population accessibility (Araujo, 2022). Half of all Indians do not own a smartphone capable of downloading an app to transact over a 3G/4G network. Adequate internet connectivity coverage may also be lacking in important and relatively remote areas (Eichengreen *et al.*, 2022).

Internet access services are also unevenly distributed across the Brazilian territory, with infrastructure gaps in lower-income regions. There is an overall concern that a shift away from cash will disintermediate the elderly, the poor and the technologically disadvantaged. Public policies towards universalizing quality signal, is not only necessary to develop financial sophistication but to promote economic growth: *internet inequality not only reflects the country's socioeconomic disparity but also helps reinforce it* (PwC, Instituto Locomotiva; 2022, p.27).

Nevertheless, to confirm if PIX/UPI are effectively reaching the informal economy and the unbanked, a thorough analysis must be taken on, investigating which sectors of society reached higher acceptance rates. Due to the continental dimension of both India and

[28] ARDL estimations.

Brazil, telecommunications, infrastructure and internet diffusion polices to remote places must be put in place to reap bigger benefits of such initiatives, promoting a greater impulse for instant payment applications. This is a highly important avenue for future studies; internet connectivity in low-income districts might have a relevant impact on information access, reducing inequality, digital and financial inclusion[29].

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Appendix

Table A1 - Comparative Table UPI and PIX

	UPI	PIX
Operator	National Payments Corporation of India (NPCI)	Brazilian Central Bank (BCB)
Definition	A system that powers multiple bank accounts into a single mobile application (of any participating bank).	Pix is the instant payment solution, created and managed by the Central Bank of Brazil (BC), which provides transfers and payments.
Infraestruture	Immediate Payment Interface (IMPS)	Real Time Gross Settlement System (RTGS)
Storage of User Data Information	Decentralized model data is stored in their provider's database.	Kept in a centralized directory at the BCB (DICT).
Fund Transfer Limit	1 Lakh per day (one hundred thousand Rupees)	The values for Pix transfers are restricted to the daily and monthly transfer limit the customer has available in his account.
Device	Mobile Phone, Feature Phone	Computer, Laptop, Tablet, Smartphone (conditioned to internet availability)
Authentication	VPA of recipient & MPIN	Pix Key (e-mail, mobile number or QR Code).
Fund Transfer Time	Instant	Instant
24 x 7 Money Transfer	Yes	Yes
Money Collector	Push and Pull Payments	Push Payments
Cost of Fund Transfer	Free customer fees	Free customer fees
Money Transfer Abroad	No	No
Bank Account	Yes (There is access to more than one bank account, separating customer experience with account ownership)	Yes (presently, PIX favours directly participating financial institutions that offer bank accounts).
Banks Offering payment method	224 banks (May 2021)	757 institutions (May 2021 counting direct, indirect and optional participants).
E-Commerce transactions	Yes	Yes

Source: Brazilian Central Bank (BCB), Reserve Bank of India (RBI), National Payments Corporation of India (NPCI).