Does ICT Drive Fintech firm Performance? Evidence from BRICS Countries

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Abstrac

Purpose: The scope of this paper is to see if the aggregate information and communications technology index (ICT) drives firm performance (profitability and efficiency) for BRICS countries from a des-aggregate panel data of the firm-yearly level (by country) during 2014-2022, from an aggregate monthly time series data and a panel data of country-monthly level during 2014M01-2014M12, all covering the Covid outbreak event.

Design/methodology/approach: Through static and dynamic long-run (LR) panel models, the Bayesian VAR-X short-run (SR) approach, and the time series and the panel (LR and SR) ARDL models, we investigate the stability of the linkage between firm performance and the aggregate ICT vis à vis the Covid outbreak.

Findings: Using an international sample of 316 FinTech firms from BRICS countries, we find that ICT mechanisms on their own are in general negatively associated with firm performance (profitability and efficiency) with some exceptions. We also find that the ICT and the firm-performance relationship is more significant among countries with respect to the considered pre ou post Covid 19 outbreak period.

Originality: The novelty of this research is based on the idea of studying the effect of the aggregate ICT on firm performance by using several dynamic approaches so that we can estimate the SR adjustments that arise from the impact of ICT to the LR relationship.

Key Words: FinTech Firm performance and ICT; BRICS area; Dynamic Panel Regressions and GMM for firm level panel data; Bayesian VAR-X and ARDL models for TS data; PARDL for macro panel data; Covid 19 outbreak.

JEL classification : C11, C22, C23, O33

I. Introduction

The current economic environment is extremely turbulent and this is mainly due to rapid technological change and the Covid 19 outbreak crisis. The information society and knowledge economy has resulted in the transformation of the economy, contributing to globalization and encouraging intangible economic activity. Particularly, policymakers need to better understand how information and communication technologies (ICTs) country investment lead to informed decisions about the investment and advantages of such technologies. However, at best, the empirical evidence on the economic activities (such as the firm performance) of technology is mixed in relation to Covid 19 outbreak crisis.

During COVID-19, consumers moved dramatically toward online channels, and firms and industries have responded largely in turn. According to a recent global survey (LaBerge, et al., 2020), firms in all sectors and regions have accelerated the digitization of their customer, supply chain interactions, and internal operations by three to four years due to the pandemic. Despite the spike in ICT adoption among firms, the performance gap persists (Alam, et al., 2019; Zhou, et al., 2019).

Despite Ulmanis and Deniņš (2012) stating that while no significant changes had been reported in ICT use, they had observed that the large number of ICT users in general did receive greater increased opportunities from ICTs for facing up to financial crisis challenges. Pantea et al. (2017) concludes, however, that empirical evidence on the effect of ICT at firm level is mixed and inconclusive and therefore, future work should address this topic more directly.

The ICT development can have adverse effect on economic activities. Certain researchers such as Roach (1991) or Carr (2003), however, question the existence of a positive relationship between ICTs and the firm activity result especially in the short term.

FinTech firms have received increasing attention in recent years owing to their rapid development and expansion across economies. In this paper, we address the existing gap in the empirical literature by exploiting micro-and macro data that relates ICT country investment to indicators of country's level or firm's level of firm performance in the BRICS area.

Several econometrics models (static and dynamic) and type of data (panel and time series) are used in this paper. As done in the literature, FE and RE for static and GMM for dynamic panel models are used in first step. Having unexpected results based on firm-yearly dimension panel data by country (**des-aggregate** data), we move to country monthly **aggregate** time series data based models investigations. Specifically, the ARDL and the BVAR-X models are used to check the robustness of our findings.

We use the Bayesian Vector of Autoregressive (VAR) approach regarding its relative simplicity and flexibility in dealing with econometric problems. Bayesian VAR approach is used to see if the ICT country investment drives firm performance pre vs post Covid 19 or in SR vs LR side.

Following the estimation of the Bayesian VAR-X model, the analysis computes impulse response functions (IRFs) to track the role of the ICT effect on FinTech firm performance during 2014-2022 covering the COVID-19 outbreak. This new method adds to the empirical papers the possibility of analyzing not only the dynamic relationships among the variables but also the shocks through the impulse response function (IRF).

Also, having results in line with the previous investigations, we turn to panel data type but this time with country level-monthly spaces panel data. Panel ARDL model investigation results are not in line with previous results. Here ICT country investment is found to have positive relationship with **aggregate** firm performance measures.

The remainder of this paper is organized as follows: Section. II reports on the data and variable creation. Section III presents methodology and he empirical results with some robustness verifications. Finally, Section IV concludes the study with policy implications and directions for future research.

II. Variables and Data analysis

1. Variable description

We collect firm financial data from the DataStream database. The ICT country-related variables and the macroeconomic data are obtained from Worldbank data base. The sample period is from 2014 to 2022 ($T = 9$) covering the Covid 19 outbreak period. The final sample consists of data from $N = 316$ firms ($NT = 2844$ observations per variable) from BRICS zone, including 15 firms from South Africa (SA), 175 firms from China, 120 firms from India, and 6 firms from Brazil (Russia is dropped from the list because of the data missing problem). Table A1 summarizes all the variables, definitions, and data sources. We have chosen BRICS area because BRICS is the leading and one of the fastest growing emerging economies of the world and each BRICS country spend a lot of money on ICT.

The creation of the Firm Profitability Index

To proxy the firms' profitability, we use profitability index (PI) as *dependent* variable in our regressions, measured as given below (Aduba, Asgari, & Izawa, 2023). We use common firm-level profitability measure ROA_{ijt} (ROE_{ijt}) to account for the profitability of firms, which is defined as the ratio of net income before Taxes over total assets (over common equity) (Díaz and Huang, 2017; Mahdi and Abbes, 2018; Shim, 2019).

Each firm-level of these measures will be normalized between 0 and 1, using the following equation

$$X_{ijtk\_N} = {(X_{ijtk} - X_{ijk_{Min}})}\Big/{(X_{ijk_{Max}} - X_{ijk_{Min}})} \quad (1)$$

where $X_{ijk_{Min}}$ ($X_{ijk_{Min}}$) is the Minimum (Maximum) of the k specific measure under consideration, i, j, and t denote respectively the specific firm i, the country j, and the year t.

Then, a firm-level profitability index (PI) will be estimated using the following equation

$$PI_{ijt} = (ROA_{ijt_{-N}} + ROE_{ijt-N})/2 \quad (2)$$

where $ROA_{ijt_{-N}}$ and ROE_{ijt-N} are espectively the normalized ROA and the normalized ROE.

Measuring the country ICT variable

We create a simple country-level ICT index (ICT) as *independent* variable in our regressions as follows: First, we normalized each of the three measures (FBS%, IUI%, and MCS%) of ICT described in Table A1 (in Annex). Using Equation (1), by applying Max–Min normalization we set the range of the common factor scores between 0 and 1. Second, we take the unweighted average (assuming each common ICT measure is equally important) of all normalized measures using equation

$$\mathrm{ICT}_{jt} = \sum_{k=1}^{3} X_{jtk\_N} \Big/ 3 \quad (3)$$

where X_{jtk_N} is the normalized ICT measure (FBS%, IUI%, and MCS%), ICT is the average of all normalized values used for the estimation, j and t denote respectively the specific country and the year t.

Control variables

Based on the existing literature, we select several firm-specific control variables that may influence the relationship between ICT and Fintech firms' performance.

Following (Vazquez and Federico, 2015 and Tang, Hu, et al., 2024), we employ two liquidity indicators **CET** and **CR** computed respectively by the ratio of cash and equivalent over total current assets and total current assets over total current liabilities.

To account for financial leverage, we consider the leverage ratios: the **TDCE** which is defined as the ratio of total debt over common Equity and the **TDTC** which is defined as the ratio of total debt over total capital.

Due to the potential scale economies of large firms, we consider the firm size as a control variable, computed by the logarithm of total assets (**LA**) for the firm (Lepetit et al., 2008; Tran et al., 2016; Díaz and Huang, 2017; Berger et al., 2019; Tang, Hu, et al., 2024).

In addition, to enhance the robustness of our findings we also add the macroeconomic variable GDP to capture the impacts of the macroeconomic environment on firm performance. **GDPG** is measured by the annual growth rate of GDP (Sissy et al., 2017; Davydov et al., 2018; Aduba, et al., 2023). The model also controls for inflation rate, implicitly assuming that consumer price growth (**INF**=Δlog(CPI)) can naturally moderate economic growth that are likely to impact firm performance (profitability and efficiency).

All variables' definitions and data sources are summed up in Table A1 (see Annex).

2. Data analysis

The essential statistical characteristics of the main variables are reported in Table A2 Panel A by country. The mean value of profitability index (PI) are respectively 0.425285, 0.521014, 0.527096, and 0.565584 for BRAZIL, INDIA, CHINA, and SOUTH AFRICA. The minimum value is 0, and the maximum value is 1, which indicates that there are significant differences in the degree of profitability.

The mean value of the ICT index are respectively 0.396438, 0.351342, 0.481669, 0.40847 for BRAZIL, INDIA, CHINA, and SOUTH AFRICA.

The summary statistics for the control variables (CET, CR, LA, TDCE, TDTC) and the macro variables (GDP, INF) are also shown in Table A2 (see Annex).

We conduct Pearson correlation tests for each of the variables used in this study to avoid multi-collinearity issues. The correlation matrix is reported in Table A2 Panel B by country (see Annex). The correlation coefficients between the variables are relatively small, indicating no multi-collinearity problem in almost all of the regression models. VIF criteria will be used to multi-collinearity problem for more verification.

Since the period of study covers the Covid 19 outbreak, dependent variables (profitability index PI and efficiency TA) as well as the independent variable ICT can behave differently for the pre and post Covid periods. Table 1 hereafter presents mean for each dependent variable and the independent variable of interest for the 4 considered countries as well as the p-value and the two sided Student t statistic.

We note that in level the mean of PI and TA is higher pre Covid than post Covid period for all considered countries, while the ICT is lower pre Covid than post Covid period for all considered countries except for the Brazil case.

The Student t-statistic analysis shows that pre Covid 19 the mean of PI, TA and ICT are *significantly* different than their mean values post Covid at 1% level for all the considered countries except for TA in the South Africa.

Table 1: Comparison between pre and post Covid 19 periods

	Brazil				**India**			
	Means				**Means**			
	Pre Covid	Post Covid	Student t	p-value	Pre Covid	Post Covid	Student t	p-value
PI	0.596402	0.294910	2.882735	0.0067	0.552034	0.482238	3.385144	0.0007
TA	1.011429	0.612917	2.436105	0.0191	0.889966	0.748805	3.434459	0.0006
ICT	0.435083	0.349009	4.516807	0.0000	0.329150	0.379261	-17.45664	0.0000
	China				**South Africa**			
	Means				**Means**			
	Pre Covid	Post Covid	Student t	p-value	Pre Covid	Post Covid	Student t	p-value
PI	0.632008	0.395957	15.05575	0.0000	0.651603	0.458061	3.540948	0.0006
TA	0.609346	0.534250	4.203650	0.0000	1.170972	1.030000	1.518550	0.1314
ICT	0.335562	0.664301	-69.89032	0.0000	0.305166	0.537601	-17.06045	0.0000

Note: p_value and t statistic are reported. P-value < 5% indicates rejection of null hypothesis of equality of mean pre and post Covid outbreak. Source: author' calculation.

Before any modeling of the relationship between the dependent and independent panel data variables, we use the ADF Fisher χ^2, PP Fisher χ^2 and Im, Pesaran and Shin (IPS) W-stat unit root tests to check the order of integration of each variable. We use conventional PP and ADF test for time series data (ICT, INF and GDPG). Results in details are available upon request. In a sum up by country, we can say that almost all variables are with no unit root and hence confirming their stationarity. Only ICT variable which is found to be either stationary or nonstationary. However, this result is not viable since $T = 9$ while conventional time series data unit root tests are asymptotic (need a minimum of $T = 30$ to give viable results).

III. Methodology and Results

1 The LR firm level Panel Static and Dynamic Regressions

To investigate the long-run (LR) effect of ICT on FinTech firm performance, we propose the simple baseline long-run static linear empirical model:[1]

$$PERF_{it} = \alpha + \beta_f \mathrm{ICT}_t + \alpha_i + \varepsilon_{it}, \quad (4)$$

where $PERF_{it}$ represents one of the profitability and the efficiency measures (PI_{it}, TA_{it}), ICT_t is the ICT index, constant term α, α_i, and β_f are the parameters to be estimated. Subscripts i and t refer to firm and year respectively. α_i are the *firm fixed or random effects*, ε_{it} refers to the idiosyncratic error.

Several models were estimated to provide a clear understanding of the performance and efficiency metrics by country. The authors examined the influence of ICT on different categories of indicators in turn. Based on the baseline model Eq (4), using Hausman test results, baseline FE model is found to be the more adequate model for all of the considered countries. Looking at Table A3 (see Annex), based on the FE estimation results, ICT is found to have a long-run negative significant impact in all cases except for Brazil with both considered dependent variables (with positive insignificant effects) and for south Africa for the case of TA (with negative insignificant effect).

As a chek of the covid 19 outbreak effect, we'll see if these results remain true once the Covid outbreak is taken into account. Eq (4) will be estimated for two periods: pre and post Covid outbreak. Discussion will be based only on the FE estimation results. Results are given at Table A4 (see Annex) and are summed up in Table 2 hereafter.

Table 2: A sum up of FE model estimation from Eq(4);

	Dep var PI		Dep var TA	
Country	Pre Covid	Post Covid	Pre Covid	Post Covid
Brazil	0.8595	−4.4122 ⋆	0.2939	−0.9744
India	−0.6216	−0.4707 ⋆	−0.6958 ⋆	0.18181
China	−0.5864 ⋆	−2.2414 ⋆	−0.2575 ⋆	−0.42139 ⋆
SA	−0.4182	0.8947	−0.09779	−0.67242

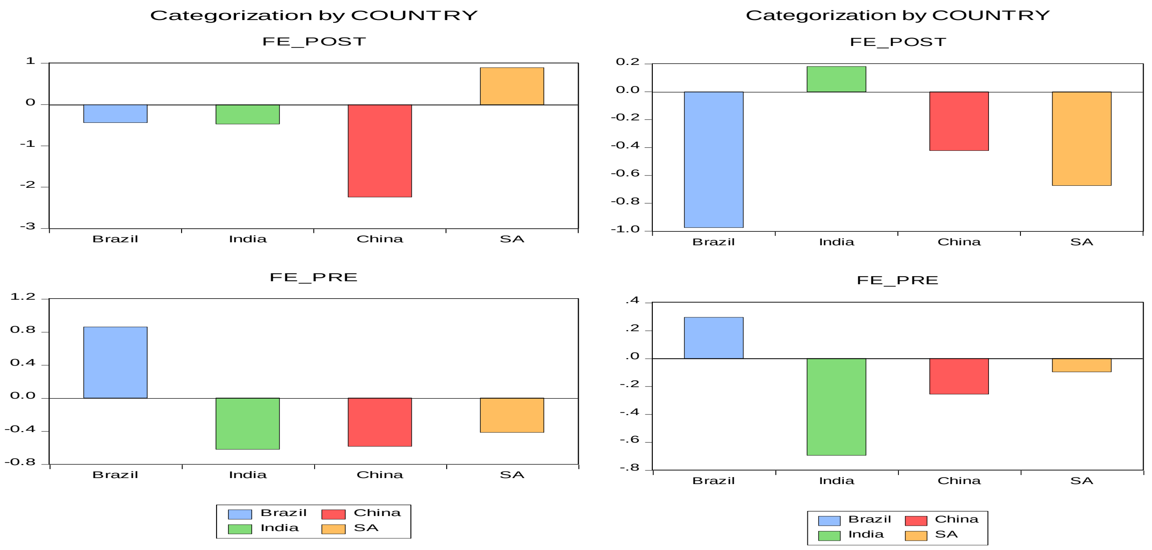
Note: Baseline model $PERF_{ijt} = \alpha + \beta_f FinT_{jt} + \alpha_i + \varepsilon_{ijt}$ is used for estimation. ⋆: significant association with ICT country investment. See more details from Table A4 (in Annex). Source: author' calculation.

These LR results can be illustrated as given by the following Figure 1.

[1] Many studies (Nguyen and Phan, 2017; Phan et al., 2019; D'Mello and Toscano, 2020) drop controlling for year-fixed effects in the model when using macro time series variables (variable is the same for all firms in a given period for a country). Huang et al. (2022) discuss that controlling for year dummy variables can lead to multi-collinearity problems in models which contain macro time series variables with micro-level finance panel data variables.

Looking at Figure 1, it is clear that

- for Brazil firms, the LR impact of ICT on PI and TA is negative (positive) post (pre) Covid, while for the SA firms we get the opposite results.
- The LR impact of ICT on PI and TA is negative for both pre and post Covid for the China firms.
- The LR impact of ICT on PI (TA) is negative for pre and post Covid (positive post and negative pre covid) for India firms.



(a) FE for dep var PI **(b) FE for dep var TA**

Figure 1: Sum up of LR reactions to ICT Pre vs Post Covid based on Eq(4) by firm and year for each country

Note: Blue color, green, red, and orange are used respectively for Brazil, India, China, and South Africa. Source: author' elaboration.

- ➢ In all cases, three out of the four LR impact of ICT on firm performance are negative.

In a cross-firms analysis, controlling for economic activity that can be captured by some macroeconomic indicators is imperative. Economic activity will be captured by GDPG and inflation rate that can harm firm performance.

Therefore, we propose the (empirical multiple long-run static) augmented linear models to control for macro-economic and/or firm activities that are standard for reducing omitted bias procedures:

$$PERF_{it} = \alpha + \beta_f \mathrm{ICT}_t + \gamma_m Macro_t + \alpha_i + \varepsilon_{it}, \tag{4a}$$

and

$$PERF_{it} = \alpha + \beta_f \mathrm{ICT}_t + \lambda_c Fcontrols_{it} + \alpha_i + \varepsilon_{ij} \tag{4b}$$

or the model which can control for both activities

$$PERF_{it} = \alpha + \beta_f \mathrm{ICT}_t + \gamma_m Macro_t + \lambda_c Fcontrols_{it} + \alpha_i + \varepsilon_{it} \tag{5}$$

where $Macro_t$ is the vector of the macroeconomic variables including the GDPG and the inflation rate, $Fcontrols_{it}$ is the series of firm control variables (CET, CR, LA, TDCE, TDTC),

Efficiency measure is the total assets turnover (TA) that is estimated by the ratio of total sales over the average ((Beginning Assets + Ending assets)/2)).
Looking at estimation results from the static augmented models Eq(4a), Eq(4b) and Eq(5), we can say that there is no consensus about positive or negative long-run effect of ICT on FinTec firms performance in each country from the BRICS area. These results are available upon request.

One question arise from these results, did the choice of non-static model will affect the validity of the long-run (LR) firm results? Then, we conducted two robustness checks to evaluate the validity of these results.

In the immediate first steps, since autocorrelation of order 1 and/or 2 is significant for both measures of performance, we will consider rather dynamic multiple model.

Extended models can be written in the dynamic version as follow:

$$PERF_{it} = \alpha + \rho PERF_{it-1} + \beta_f \mathrm{ICT}_t + \gamma_m Macro_t + \alpha_i + \varepsilon_{it} \quad (6a)$$

and

$$PERF_{it} = \alpha + \rho PERF_{it-1} + \beta_f \mathrm{ICT}_t + \lambda_c Fcontrols_{it} + \alpha_i + \varepsilon_{it} \quad (6b)$$

or

$$PERF_{it} = \alpha + \rho PERF_{it-1} + \beta_f \mathrm{ICT}_t + \lambda_c Fcontrols_{it} + \gamma_m Macro_t + \alpha_i + \varepsilon_{it} \quad (7)$$

where constant term α, ρ, α_i, β_f, γ_m and λ_c are parameters to be estimated. Subscripts i and t refer to firm and year respectively. α_i are the *firm fixed or random effects*, ε_{ijt} refers to the idiosyncratic error.

Estimation results based one-step system GMM of Eq (7) are illustrated at Table A5 (see Annex). Here, the Covid outbreak is taken into account by integrating a dummy variable D2019:

$$\mathrm{D2019} = 1 \text{ if year} > 2018 \text{ and } 0 \text{ if not}$$

in Eq(7) for full period. Also, for each country, estimation is done for both sub-periods; pre and post covid outbreak. Results are given in Panel A, B, C and D respectively for Brazil, India, China, and South Africa at Table A5 (see Annex). These results are summed up in Table 3 hereafter.

Table 3: A sum up of One step system GMM estimation for dynamic model Eq(7)

	Dep var PI			Dep var TA		
Country	Full period	Pre Covid	Post Covid	Pre Covid	Post Covid	Full period
Brazil	−2.239	− −	−1.133	−11.29⋆	−5.896	−1.516
India	−1.080 ⋆	−0.598	−1.282 ⋆	0.991	−0.475 ⋆	−0.622 ⋆
China	−0.366 ⋆	−0.190	−0.831 ⋆	0.0340	0.102	0.107 ⋆
SA	−0.409	−0.0871	−0.594	−15.65 ⋆	0.672	+0.245

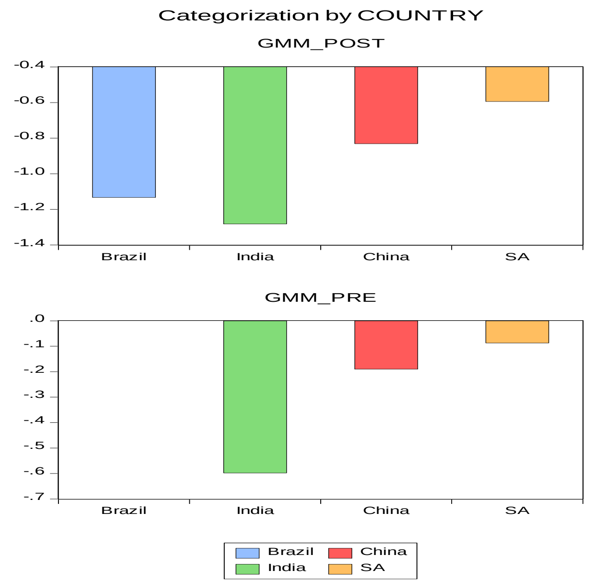
Note: Estimation is based on $PERF_{ijt} = \alpha + \beta_f FinT_{jt} + \gamma_m Macro_{jt} + \lambda_c Fcontrols_{ijt} + \alpha_i + \varepsilon_{ijt}$. ⋆: significant association with ICT. − −: no results because of missing data. See Annex for more details from Table A5. Source: author' calculation.

Pre and post Covid results of ICT LR effect on both firms performance measure (PI and TA) by firm for each country are presented in the following Figure 2.

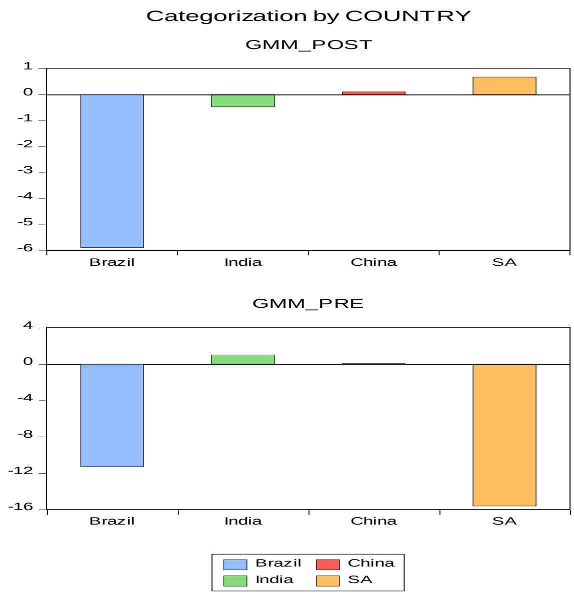
Looking at Figure 2, in the LR

- from the PI side, the impact of ICT on firms is negative for both sub-period pre and post Covid for each country except for Brazil in which ICT has no effect pre Covid period.

- From TA side, ICT is found to impact TA differently pre and post Covid for India and SA firms. ICT has negative (positive) effect pre (post) for SA (India) firms, while for Brazil firms, ICT has negative effect for both sub-periods. For China firms, ICT has positive effect post Covid with no effect pre Covid.



(a) GMM for dep var PI



(b) GMM for dep var TA

Figure 2: Sum up of reactions to ICT by firms Pre vs Post Covid based on Eq(7) for each country

Note: Blue color, green, red, and orange are used respectively for Brazil, India, China, and South Africa. Source: author' elaboration.

- ➢ For PI side, in all cases, the four LR impact of ICT on FinTech firms performance are negative pre and post covid, while for TA this negative effect is proved only for Brazil firms.

In a second steps, the important question is: do these results may change in the ***short-run*** (SR)? To answer this question, we need some investigations with time series data and models. The VAR framework will be in use for stationary series. In the following, the Bayesian version of the VAR model will be considered in the time series version of our data for each country.

2 Monthly macro Time Series data and the LR vs SR investigations

By considering the mean by year for each panel data variable, we'll use global (aggregate or macro) indicators under yearly time series (TS) form for each variable from 2014 to 2022. Yearly evolution of each global indicator by country are illustrated at Figures A1 (see Appendix). Looking at Figures A1, there is no evidence for non-stationarity of these TS. However, with short yearly TS, there is no sufficient degree of liberty for inference since almost all statistic tools for TS are based on asymptotic approximations (any results based on small sample will not be valid). Then annual data (low frequency) are converted to (higher frequency)

monthly data by interpolation method to get a sample of $T = 108$ observations between 2014M01 and 2022M12 for each country.
Two TS models will be considered in this paper: the BVAR and the ARDL.

The BVAR-X model and the SR Inter-Dependence

As a second robustness check, we'll consider the BVAR-X models (based on random parameters) which gives *direction* of the ICT *effect evolution* in **short-run** (SR) as well as in LR via the IRF functions, and where X represent some control variables. [2] In particular, we want to examine the SR inter-dependence in the bivariate BVAR-X model and how some control variables X can affect the transmission of ICT shocks to firm performance for each country?[3]

The objective of using the Bayesian VAR is related to its parsimony, avoiding cumbersome calculations. The considered dynamic Bivariate VAR-X model is specified as in the following framework

$$Y_t = \sum_{k=1}^{p} \Gamma_k \, Y_{t-1} + X_t B + \mu_0 + u_t, \tag{8a}$$

$$Y_t = \sum_{k=1}^{p} \Gamma_k \, Y_{t-1} + Z_t A + \mu_0 + u_t, \tag{8b}$$

where

$$\Gamma_k = \bar{\Gamma}_k + V_k;$$

Y_t is a (2×1) vector of stationary dependent variables:

$$Y_t = (PERF_t, \mathrm{ICT}_t)', \; t = 1, \ldots, T = 108,$$

$PERF_t$ represents either a measure of the profitability or the efficiency (PI_t or AT_t), (X_t, Z_t) is a (1×7) vector of the exogenous (control) variables,

$$X_t = (Macro_t), \; Z_t = (Fcontrols_t)$$

with $Macro_t$ is the vector of the macroeconomic variables including the GDPG and the inflation rate, and $Fcontrols_t$ is the vector of firm control variables (CET, CR, LA, TDCE, TDTC), μ_0 and u_t are (2×1) random vectors of- specific **country**- effects and the idiosyncratic errors, respectively, for each country and month t, $t = 1, \ldots, T = 108$. The (2×2) matrices Γ_k and B and the (5×2) matrix A are matrices of random parameters to be estimated. We assume that the innovations have the following characteristics:

$$u_t \sim (0, \Sigma_u), V_1 \sim (0, \Sigma_v)$$

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[2] The main criticism against the VAR models are related to the over-parametrization problem. It is well known that the advantages of using the VAR methodology relative to other methods are:

(i) VARs are designed to address the endogeneity problem, which is one of the most serious challenges of any empirical research;

(ii) the inclusion of variables lags helps to analyze the disequilibrium (or not) relationships among them. In that sense, impulse response functions based on VARs can effectively account for any delayed effects of the variables under consideration and thus determine whether the effects of those variables are short-lived, long-lived or even both. Such dynamic effects would not have been captured by traditional regressions (Antonakakisa et al., 2017; Da Rocha Lima Filho, 2022).

A good way to smooth the latter critique, is to apply the Bayesian VAR (BVAR), where a priori distribution is used for each of the coefficients instead of restrict them to zero.

[3] One big advantage of using the Bayesian framework relies on the fact that the effect of unobservable variables are fully estimated by using the a priori assumption and when this is updated it culminates in a new a posterior distribution (Da Rocha Lima Filho, 2022).

and priors have a normal probability distribution.[4]

Therefore, in the Bayes approach, a prior distribution of all the parameters is introduced, as part of the model in Eq (8a) or Eq (8b). This prior information will be combined with the model and the data from Y_t, to revise the probability distribution of all the parameters, which is called posterior distribution. [5]

Results of Maximum Likelihood estimation are available upon request. A sum up of the results of ICT effects are given at Table A6 (in Annex) for each country from the BRICS zone and the considered dependent variable from 2014M01 to 2022M12.

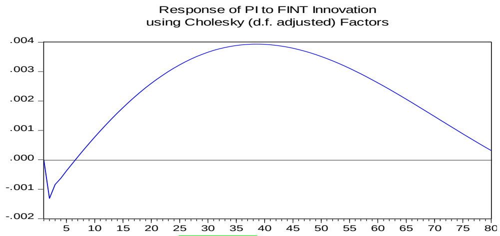
The BVAR model may be difficult to interpret due to complex interactions and SR feedback between variables considered in the model. The dynamic feature of this Bayesian VAR-X model allows the use of the impulse response functions (IRF) to capture the dynamic relationships among considered variables in the vector Y_t. Then, the dynamic properties of the VAR-X will be summarized by the IRF. After fitting the VARs, an IRF will be computed to estimate the dynamic multipliers, which describe the impact of a unit change in one variable on each of the endogenous variable. When the effect of the innovations dies out over time, the shocks effect will be said transitory. In contrast, when the effect does not taper off, shocks effect will be said permanent. Details of the estimation results and the corresponding IRF are not reported here, but are available upon request. Only the response to the innovation effect of the ICT variable which will be considered in the following results discussion. Figure 3 (Panel A and Panel B) and Figure 4 (Panel A and Panel B) illustrate by country the response of PI_t and AT_t to ICT innovation when macro-economic and firms activities are taken into account respectively.

Using the *macro-economic indicators* as control variable, and looking at Figure 3,

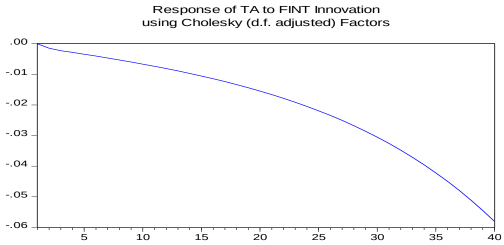
- from the *profitability* side at Panel A, there was a sharp negative (positive) initial effect from ICT to PI which is followed by a positive (negative) effect for Brazil and South Africa (India and China). It is clear that this negative (positive) relationship with the ICT ech penetration is proved only in the short-run. ICT was counter (pro)-profitable at the beginning say 2 months for Brazil and 10 months for South Africa (2months for India and 4 months for for China). Then a final positive (negative) impact of ICT was experienced for Brazil and South Africa (India and China). ICT effect turned out to be worthwhile in the long-run for South African firms.

[4] Bayesian estimation consists of fitting Bayesian models and estimating their parameters based on the resulting posterior distribution.

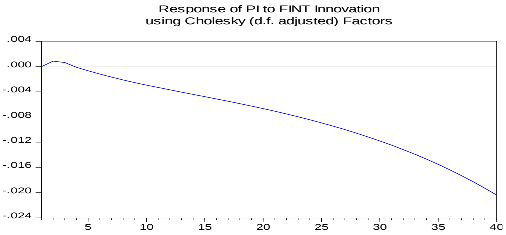
[5] Prior knowledge about parameters is described by prior distributions P[X] and evidence from the observed data is incorporated through a likelihood model. Using the Bayes's theorem; $P[X/Y] \propto P[Y/X]\,P[X]$, the prior distribution and the likelihood model are combined to form the posterior distribution $P[Y/X]$ of model parameters. The posterior distribution $P[X/Y]$ is then used for parameter inference, hypothesis testing, and prediction. Bayesian hypothesis testing computes probabilities of hypotheses conditional on the observed data. The Bayesian hypothesis testing computes the actual probability of a hypothesis H by using the Bayes's theorem $P[H/y] \propto P[y/H]\,P[H]$, where y is the observed data, $[y/H]$ is the marginal likelihood of y given H, and $P[H]$ is the prior probability of H. Two different hypotheses, H_1 and H_2, can be compared by simply comparing $P[H_1/y]$ to $P[H_2/y]$.



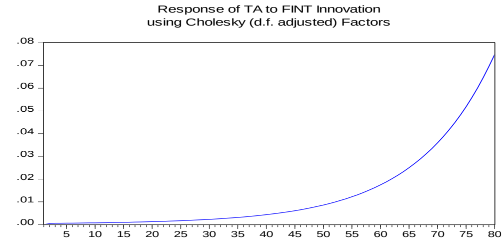
(a) Brazil (BVAR(3))



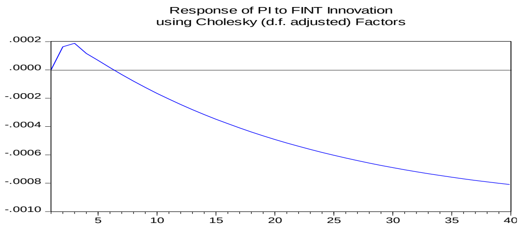
(b) Brazil (BVAR(3))



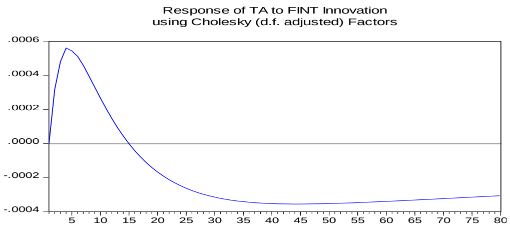
(c) India (BVAR(3))



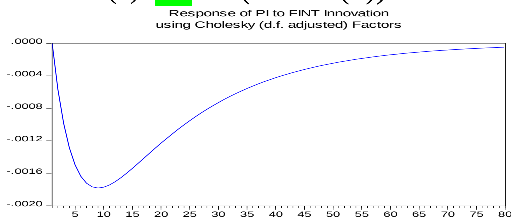
(d) India (BVAR(3))



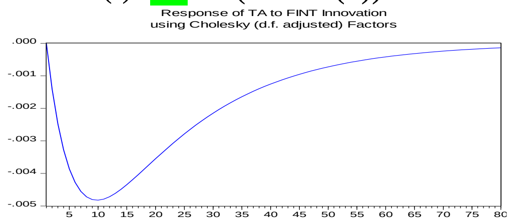
(e) China (BVAR(3))



(f) China (BVAR(4))



(g) SA (BVAR(1))



(h) SA (BVAR(1))

Panel A: IRFs of PI to ICT innovation

Panel B: IRFs of TA to ICT innovation

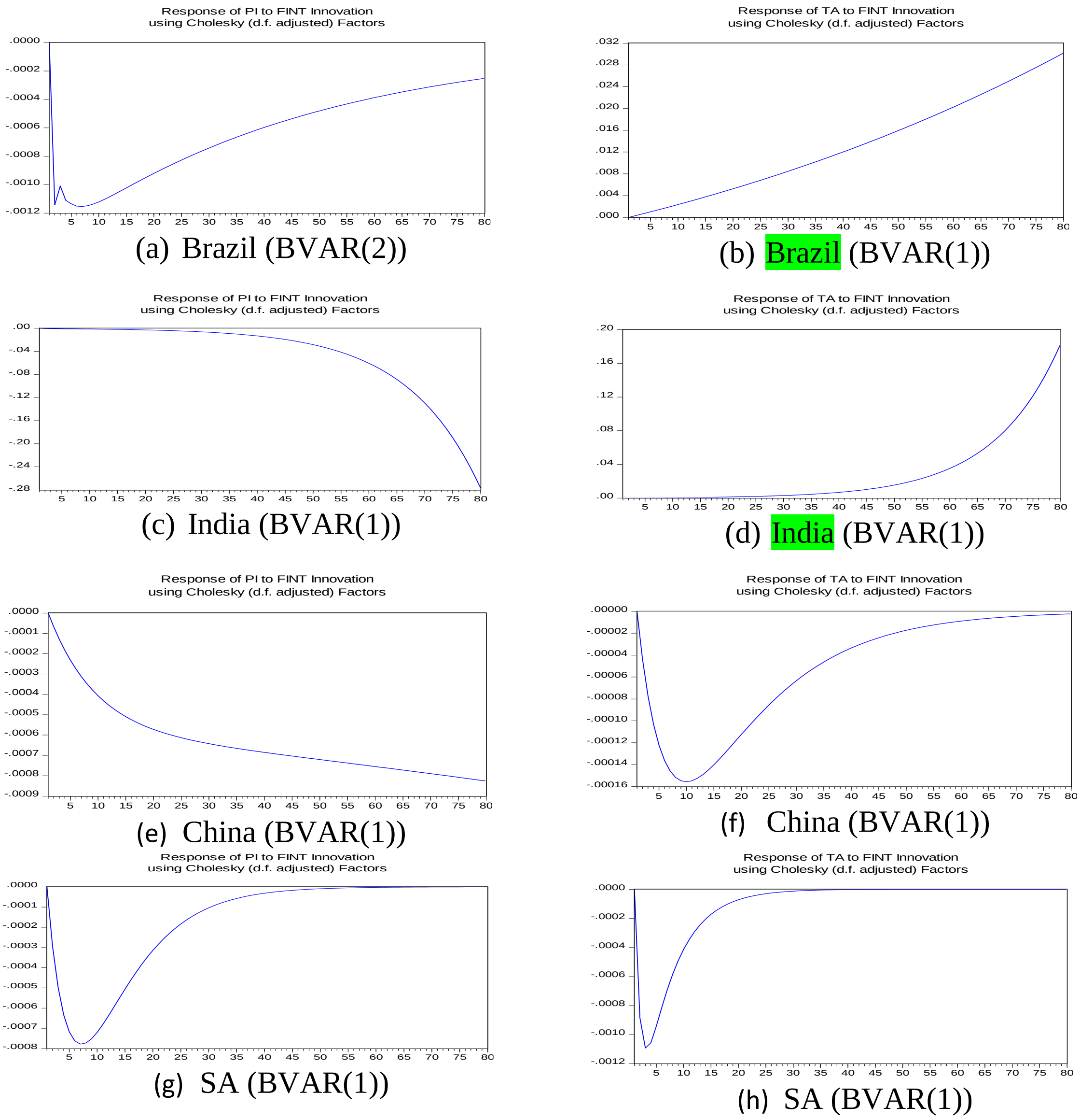
Figure 3: Impulse response functions from Eq(8a).

Note: Here the effect of ICT ech on performance that control for macro-economic indicators. Initial residual covariance: Univariate AR. Prior type: Litterman/Minnesota. Optimal order of the BVAR is based on AIC. Source: author' calculation with Eviews.

- From the *efficiency* side, looking at Panel B, there was a sharp positive (negative) initial effect from ICT which is followed by a decreasing (increasing positive) effect for China (South Africa) case. The final negative (positive) impact of ICT on efficiency suggest that ICT investments might have been counter (pro)-efficiency at the end for China (South Africa). The initial some positive (negative) responses period turned out to be worthless (worthwhile). ICT was counter-efficient "at the beginning" for South Africa. Then a "final" positive impact of ICT was experienced for South Africa. For Brazil (India) case, it is clear that the negative (positive) relationship of the *efficiency* (TA) with the ICT is proved in the short- and long-run.

Using the *firm activity indicators* as control variable, and looking at Figure 4,

- from the *profitability* side at Panel A, there was a negative initial effect from ICT which is followed by a positive effect for Brazil and South Africa. For India and China, it is clear that there is a negative relationship with the ICT that is proved only in the long-run for India.



(a) Brazil (BVAR(2)) (b) Brazil (BVAR(1))

(c) India (BVAR(1)) (d) India (BVAR(1))

(e) China (BVAR(1)) (f) China (BVAR(1))

(g) SA (BVAR(1)) (h) SA (BVAR(1))

Panel A: IRFs of PI to ICT innovation Panel B: IRFs of TA to ICT innovation

Figure 4: Impulse response functions from Eq(8b)

Note: Here the effect of ICT on performance that control for firm variables. Initial residual covariance: Univariate AR. Prior type: Litterman/Minnesota. Optimal order of the BVAR is based on AIC. Source: author' calculation with Eviews 13.

- from the *efficiency* side, looking at Panel B, for Brazil and India cases (China and SA), it is clear that the positive (negative) relationship of the *efficiency* (TA) with the ICT is proved only in long-run (in short-run followed by null effect in the long-run).

A graphical summary for the { ICT } parameter does not show any obvious problems. The trace plot reveals a good coverage of the domain of the marginal distribution,[6] while the histogram and kernel density plots resemble the shape of the expected distribution. The autocorrelation dies off after about lag 20. These figures are not reported here but are available upon request (from STATA 17 package).

The TS ARDL and the LR vs SR relationships

To explore the LR and SR linear relationships between (mixed process: that are either SL2 or I(1)) performance and ICT, the following equation in the ARDL form will be used:

$$\Delta PERF_t = C_1 + \varphi ECT_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta\, PERF_{t-i} + \sum_{i=1}^{q} \beta_i \Delta \mathrm{ICT}_{t-i} + \gamma\, Z_t + \varepsilon_t, t = 1, \ldots, T \quad (9)$$

where,

$$ECT_{t-1} = PERF_{t-1} - \delta \mathrm{ICT}_{t-1}$$

is the error correction term representing the LR relationship and φ the adjustment coefficient captures the sensitivity of the ECT, $PERF_{it}$ represents the profitability and the efficiency measures (PI_t, TA_t), Z_t is a (1×7) vector of the exogenous (control) variables,

$$Z_t = (Macro_t, Fcontrols_t)$$

with $Macro_t$ is the vector of the macroeconomic variables and $Fcontrols_t$ is the series of firm control variables (CET, CR, LA, TDCE, TDTC), C_1 is the intercept, δ represents the long-term relationship (all are real parameters), α_i and β_i represent short-term relationship, p and q are the optimal lags to be used,[7] $\triangle = 1 - B$, B is the lag operator, and $\varepsilon_t \sim WN\,(0, \sigma^2)$.[8]

A negative and significant coefficient of the error correction term, the speed of adjustment φ, indicates that there is a long-run relationship between dependent variable and ICT. F_{PSS} *Fisher* type statistics confirm the existence of long-run equilibrium relationships among the variables for each country in 1% level. These results are available upon request.

All estimation results by country are reported at Table 5. Diagnostic tests (in Table A7 see Annex) suggest adequate specifications for all countries and for both models as the models show free autocorrelation errors and free conditional heteroscedasticity. The structural stability test is conducted by employing the cumulative sum of recursive residuals (CUSUM). The stability tests confirm the stability of the estimated coefficients during considered periods from 2014M01 to 2022M12 (see Figure B2 in Appendix).

All of these results can be illustrated as done in Figure 5.

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[6] Sparseness and trends in the trace plot of a parameter suggest convergence problems.

[7] All lags selections will be based on the lowest value of the Akaike Information Criterion (AIC).

[8] To resolve null hypothesis of no cointegration in the ARDL framework, we use bound test based on F_{PSS} *Fisher* type statistic that can be applied regardless of whether the series are I (0), I (1) or fractionally integrated (but not I(2)) (Pesaran, Shin, & Smith, 2001).

Table 5: Results based on time series ARDL specifications

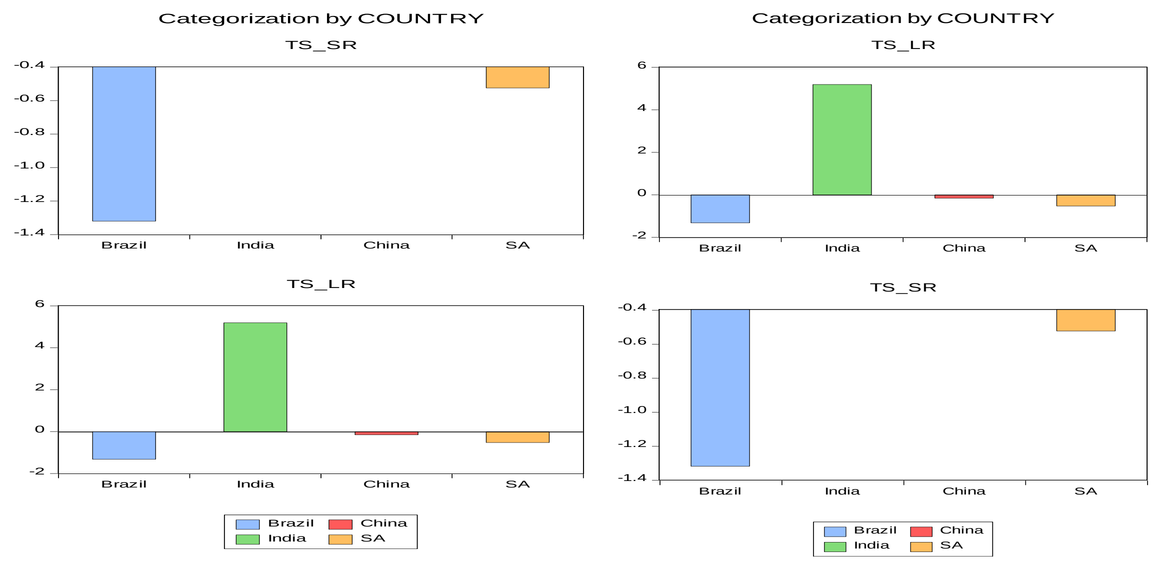
Panel A: **LR effect of** ICT

Country and selected models	Dep var PI	Dep var TA
Brazil: ARDL(1, 0) and ARDL(2, 2)	0.394410 (0.0000)	-1.319975 (0.0000)
India: ARDL(2, 0) and ARDL(1, 0)	1.859491 (0.0000)	5.190863 (0.0000)
China: ARDL(4, 0) and ARDL(1, 0)	-3.426898 (0.0000)	-0.155370 (0.0000)
SA: ARDL(2, 1) and ARDL(2, 1)	-0.662134 (0.0000)	-0.525171 (0.0000)

Panel B: **SR effect of** ICT

Country and selected models	Dep var PI	Dep var TA
Brazil: ARDL(1, 0) and ARDL(2, 2)	No effect	-1.319978 (0.0000)*
India: ARDL(2, 0) and ARDL(1, 0)	No effect	No effect
China: ARDL(4, 0) and ARDL(1, 0)	No effect	No effect
SA: ARDL(2, 1) and ARDL(2, 1)	-0.662133 (0.0000)	-0.525168 (0.0000)

Note: (.) is the p-value for the Student t statistic. LR: long-run. SR: short-run. Null hypothesis of no cointegration can be implemented as a test of H_0: $\varphi = 0$ vs H_1: $\varphi < 0$. From F_{PSS} test statistics results of cointegration between dep var and ICT, all considered long-run relationships are confirmed (details are available upon request). Model selection is based on Akaike info criterion (AIC). *: Wald statistic for the sum of short-run coefficients is used. Source: Authors' calculations.



(a) ARDL for dep var PI **(b) ARDL for dep var TA**

Figure 5: Sum up of reactions to ICT in LR vs SR by country based on Eq(9)

Note: Blue color, green, red, and orange are used respectively for Brazil, India, China, and South Africa. Source: author' elaboration.

From Figure 5, we conclude that ICT has negative effect on PI and TA for all countries in LR and in SR except the positive effect on PI and TA in long-run for India case.

Unlike what is done at the micro level (firms level for each country), we will create panel data with Macro level (for countries level) to distinguish the effect of ICT in the short term versus the long term with regard to the covid crisis.

3 The macro level PARDL models and the LR vs SR ICT effects

We consider a panel ARDL(p, q) framework formulating the SR and LR dynamic relationship as in the following ECM form

$$\Delta PERF_{jt} = C_1 + \varphi_j ECT_{jt-1} + \sum_{i=1}^{p} \alpha_i \Delta\, PERF_{j,t-i} + \sum_{i=1}^{q} \beta_i \Delta \mathrm{ICT}_{j,t-i} + \varepsilon_{j,t}, \quad (10)$$
$$ECT_{jt-1} = PERF_{j,t-1} - \delta_j \mathrm{ICT}_{j,t-1}$$

for $j = 1, 2, 3$, $N = 4$ countries and month t from 2014M01 to 2022M12 ($TN = 108$), where ε_{jt} is the error term which is independently distributed across country j and month t, while the term δ_j are the *heterogeneous slopes*. If $\varphi_j < 0$, then there is error correction, which implies that $PERF_{jt}$ and $\mathrm{ICT}_{j,t}$ are cointegrated, whereas if $\varphi_j = 0$, the error correction will be absent and there is no cointegration.

(Pesaran, Shin, & Smith, 1999) referred to Eq (10) as PMG model if $\delta_j = \delta \; \forall j$.[9] The mean group (MG) estimator will be used for MG model and the pooled mean group (PMG) estimator for PMG model. For the validity of considered models, there are several requirements. First, the coefficient on the error-correction term have to be negative and significant. Second, errors have to be White Noise (WN).

In a first steps we have to decide if the model is with homogeneous or heterogeneous slopes. We will check the slope homogeneity among cross-sections. Results are summed up in Table A9 (see Annex).

Looking at Table A9, the Swamy (Pesaran and Yamagata / Blomquist, Westerlund (BW))' Δ and Adj Δ test statistics give results in favor of PMG for both performace indicators.[10] But, we'll consider heterogeneous and homogeneous panel estimation techniques for the PARDL models since all of these tests are asymptotic.

PMG estimation results and MG estimation results are given in Table 10 and Table 11 successively. Results from MG estimation in Table 11 are given only for reference.

Looking at Table 10, in the LR, ICT is found to be positively (negatively) significant for the BRICS zone pre (post) Covid period for profitability and efficiency (only efficiency). However, by country, cointegration (LR relationship) is found to be true (fault) pre covid except for Brazil (SA) from PI (TA) side, while post Covid results say that cointegration (LR relationship) is found to be fault (true) except for India (SA) from PI (TA) side.

All of the SR results are illustrated at Figure 6.

[9] The main characteristic of PMG model is that it allows short run coefficients, the intercept, the error correction term (φ_j), and error variances (σ_j^2) to be *heterogeneous by country*.

[10] If the statistic is not sufficiently large to reject the null of slope homogeneity at 5% level, we run a model with homogenous slope for LR coefficients of the cointegrating equation and we consider the heterogeneous slope model in the opposite case.

Table 10: LR and SR Effects of ICT from PMG estimation results

Panel A: **Full period**

	Dep var PI		**Dep var TA**	
	LR Effects	SR Effects	LR Effects	SR Effects
Country /BRICS	-4.11708 (0.001) Cointegration?		-.751104 (0.000) Cointegration?	
Brazil	Yes	-3.219439 (0.000)	Yes	-4.8159 (0.000)
India	No	-.2206483 (0.101)	No	.2925004 (0.438)
China	Yes	.0745485 (0.253)	No	.395398 (0.004)
SA	No	-.0389701 (0.289)	Yes	.7921528 (0.004)

Panel B: **Pre Covid**

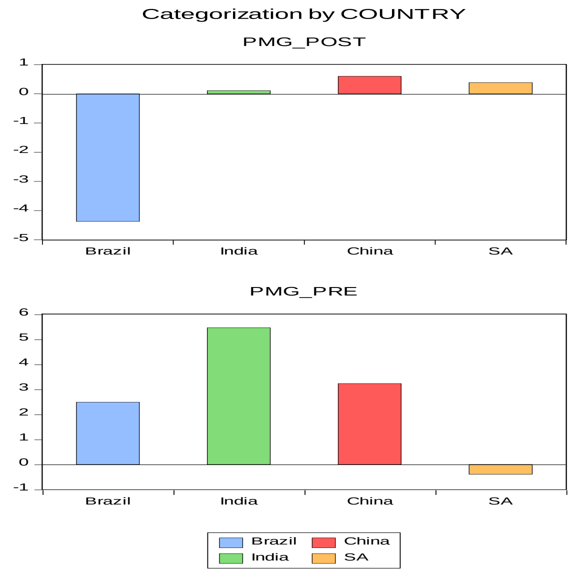
	LR Effects	SR Effects	LR Effects	SR Effects
Country /BRICS	2.270151 (0.000) Cointegration?		.9510967 (0.000) Cointegration?	
Brazil	No	-3.657573 (0.454)	No	2.489831 (0.523)
India	Yes	2.696021 (0.000)	No	5.464443 (0.000)
China	Yes	-1.228302 (0.000)	No	3.231522 (0.000)
SA	Yes	-.277569 (0.000)	Yes	-.39154 (0.487)

Panel C: **Post Covid**

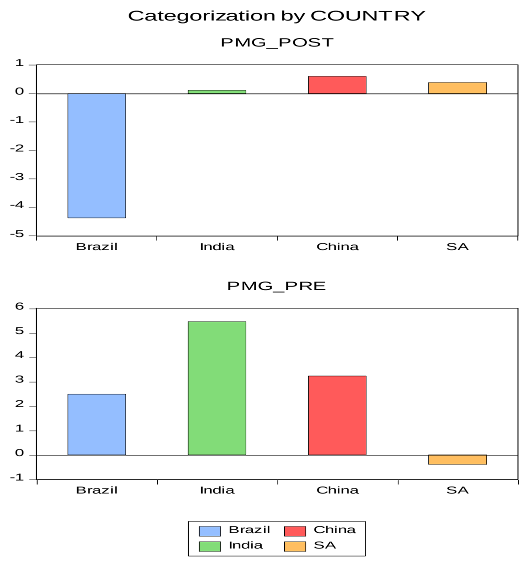
	LR Effects	SR Effects	LR Effects	SR Effects
Country /BRICS	.0371269 (0.497) Cointegration?		-.5105562 (0.000) Cointegration?	
Brazil	No	-3.016473 (0.000)	Yes	-4.373296 (0.000)
India	Yes	-.7660931 (0.002)	Yes	.111137 (0.000)
China	No	-.1048216 (0.402)	Yes	.5995626 (0.000)
SA	No	.4698918 (0.000)	No	.3864872 (0.308)

Note: Numbers in parenthesis (.) are the p-value. **LR**: long-run. **SR**: short-run. PMG estimates the pooled mean-group model where the long-run effects, δ_j, are constrained to be equal across countries while the short-run coefficients are allowed to differ across countries. Null hypothesis of no cointegration for cross-sectional unit *i* can be implemented as a test of H_0: $\varphi_i = \varphi = 0$ vs H_1: $\varphi_i < 0$. Here if φ_j is found significant and negative, we conclude in favor of the cointegration. Two period are considered: pre and post Covid outbreak. Detailed results of the panel ARDL estimation are available upon request from the author. Source: Authors' calculations.

Looking at Figure 6, in the **SR**, the effects of ICT differ from pre to post Covid and between countries for both performance measures. From profitability as well as efficiency side, India and China firms are positively affected pre and post Covid, while China (SA) firms are positively affected only pre (post) Covid.



(a) PMG for dep var PI



(b) PMG for dep var TA

Figure 6: Sum up of reactions to ICT in **the SR** by country Pre vs Post Covid based on Eq(10)
Note: Blue color, green, red, and orange are used respectively for Brazil, India, China, and South Africa.
Source: author' elaboration.

Table 11: LR and SR Effects of ICT from MG estimation results

	Dep var PI			Dep var TA		
periods	LR	Cointegration?	SR	LR	Cointegration?	SR
Full period	-.99251 (0.164)	No	-.7994318 (0.323)	-1.0506 (0.049)	Yes	-.8631416 (0.506)
Pre Covid	-.68882 (0.484)	Yes	-.7852366 (0.628)	-.04656 (0.954)	No	1.923286. (0.017)
Post Covid	-1.6559 (0.111)	No	-.5578333 (0.255)	-1.7947 (0.247)	No	-.98783 (0.465)

Note: Numbers in parenthesis (.) are the p-value. LR: long-run. SR: short-run. MG estimates the mean-group model where the coefficients of the model are calculated from the unweighted average of the unconstrained, fully heterogeneous model.

IV. Conclusions

This paper explores the LR and SR impact of the ICT country investment on Fintech firm performance for BRICS countries. The analysis employs a panel of 316 firms from BRICS countries spanning the period 2014-2022 covering the Covid-19 outbreak event. It uses three type of data:

i) Micro level: panel data of the firm-yearly level (by country) during 2014-2022,
ii) Yearly level time series (average by firm for each country) converted by interpolation to monthly time series data from 2014M01 to 2022M12 for each country,
iii) Macro-level data: panel data of country-monthly level

and then different adequate econometric technics.

Technics and the related results are summed up in the following Table. Table 12 hereafter gives also the exceptions from all of our empirical investigations.

Table 12: Sum up of all results of the effect of ICT

General results		Exceptions			
Technic/model		PI		AT	
Pre vs Post covid		**Pre covid**	**Post Covid**	**Pre covid**	**Post Covid**
FE	< 0	Brazil	SA	Brazil	India
GMM	< 0			India	SA
PARDL	> 0	Brazil and SA	Brazil and SA	Brazil and SA	Brazil and SA
LR vs SR		**LR**	**SR**	**LR**	**SR**
ARDL	< 0	India		India	
BVAR-macro	< 0	Brazil	China	India	China
BVAR-firm	< 0			Brazil and India	Brazil

Note: Exception means positive relationship if the general case is negative and vice-versa.

As can be seen from Table 12, we get negative relationship with all considered technics except for the PMG applied to PARDL model.

The paper contributes to the literature on ICT by being the first to investigate the SR and LR ICT effect on firm performance (Wahyu & KISWARA, 2017) (Serge, Rugemintwari, & Sauviat, 2019) (Sukhinina & Koroleva, 2020).

We found compelling evidence to support the negative effects of ICTs on firm-level performance based on the 316 FinTech firms operating in BRICS regional area. Moreover, we found that ICT drives the overall performance of the FinTech firms. In addition, more ICT country investment post Covid 19 outbreak can't help firms improve their performance.

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The paper makes three mayor contributions to the literature:

- First, it is one of the few studies that have used diversity of firm performance measures (profitability and efficiency) regarding the ICT use.

- Second, the paper focuses explicitly on both the firms and country level that are highly relevant in the short- and long-term investigations and in periods covering the Covid outbreak that was characterized by low economic growth.
- Finally, these investigations provide empirical evidence in the BRICS context about the effect of ICTs on firm performance.

The main contribution of the paper is to explore the profitability and efficiency paradox in BRICS context from 2014- 2022. This type of study is quite rare in the context of BRICS. Therefore, this paper has added a new dimension to the existing literature and will pave the way for future research in this area.

The implications of findings for BRICS area can be useful to other developing countries of the world. The research on ICT impact paradox so far remained confined to developed countries. Very few studies have been conducted on the developing countries of the world.

The study has one limitation. The sample size is small due to the fact that there is no current aggregated official statistics on the ICT variables in Russia. Extension of this study to other developing countries of the world will help to identify if any common pattern exists among the developing countries as far as profitability and efficiency paradox is concerned. It will also pave the way for future policy design. Another area of research can be considered to identify the reasons behind the presence of profitability and efficiency paradox which is outside the scope of this paper.

With the unexpected findings that contradict the commonly accepted view that ICT has a significant bearing on a firm’s performance, we took every effort to ensure that the study was not unduly affected by logical and methodological flaws. Nevertheless, the findings of the study should be interpreted with care since there may be some limitations and issues that need to be addressed by future studies.

Annex: Some Tables

Table A 1: Description and Definition of variables

	Variable	Description	Source	Expected sign
Dependent variables	Performance measures			
	ROA	Return on Assets: Net Income before Taxes/Total Assets	Datastream	
	ROE	Return on Equity: Net Income before Taxes/Common Equity	Datastream	
	Efficiency measure			
	TA	Total assets turnover:[11] Total sales/((Beginning Assets+ Ending assets)/2))	Datastream	
Control variables	Liquidity measures			
	CET	Cash and Equivalent/ Total current assets	Datastream	Positive /Negative[1]
	CR	Total current assets / Total current liabilities	Datastream	Positive /Negative[2]
	Financial leverage measures			
	TDCE	Total debt / Common Equity	Datastream	Positive/Negative[3]
	TDTC	Total debt / Total Capital	Datastream	Positive/Negative[4]
	Size measure			
	LA	Log Assets (size)	Datastream	Positive
Control variables	Macroeconomic measures			
	GDPG	GDP growth	Worldbank data base (https://databank.worldbank.org/source/worlddevelopment-indicators)	
	CPI	Consumer price index (2010 = 100)	Worldbank data base	
Independent variables	Information and communications technology (ICT)			
	FBS%	Fixed broadband subscriptions (per 100 people)	Worldbank data base (https://databank.worldbank.org/source/global-financial-inclusion)	
	IUI%	Individuals using the Internet (% of population)	Worldbank data base	
	MCS%	Mobile cellular subscriptions (per 100 people)	Worldbank data base	

Note: Total capital =Total Debt + Common Equity; Total Debt means total interest-bearing debt. 1 and 2: A positive sign implies sufficient liquidity permits the firm to afford its needs but excessive liquidity indicates a loss of investment opportunities. 3 and 2: positive sign implies sufficient leverage permits the firm to benefit from tax shields but excessive debts engender unsolvability risk.

[11] An indicator of the efficiency with which a company is using its assets to generate revenue.

Table A2: Summary statistics and correlation analysis

Panel A. Summary statistics

BRAZIL	PI	ROA_N	ROE_N	ICT	LCTE	CR	LTDCE	LTDTC	LA	TA	GDPG	INF
Mean	0.425285	0.451672	0.399127	0.396438	1.544225	2.296222	1.204785	1.130401	12.67684	0.798889	0.291356	0.025888
Std. Dev.	0.345687	0.358336	0.359726	0.078623	0.424096	2.878494	1.025503	0.902938	2.002159	0.577346	2.879754	0.011070
Obs	37	41	37	49	45	45	36	40	45	45	54	48
INDIA												
Mean	0.521014	0.524612	0.517415	0.351342	2.728692	3.600000	2.318946	2.130609	14.65924	0.827155	5.667778	-0.002401
Std. Dev.	0.338327	0.347982	0.346585	0.052643	1.679726	4.601926	1.744189	1.588349	2.247953	0.672134	4.293234	0.061922
Obs	1080	1080	1080	1059	1071	1046	818	827	1073	1072	1080	960
CHINA												
Mean	0.527096	0.531318	0.522874	0.481669	3.742545	3.245829	2.167097	1.940270	14.45574	0.576613	6.072222	-0.000775
Std. Dev.	0.330607	0.336634	0.337119	0.187880	0.547278	2.642439	1.849330	1.686093	1.193950	0.349958	1.957653	0.024801
Obs	1575	1575	1575	1575	1544	1544	1279	1281	1544	1544	1575	1400
SA												
Mean	0.565584	0.569026	0.562142	0.408470	3.356896	2.714524	2.420905	2.301057	13.92748	1.109297	0.775556	-0.000988
Std. Dev.	0.328876	0.330471	0.340431	0.139930	0.924655	3.008691	1.953667	1.757893	1.849619	0.523699	2.818463	0.061331
Obs	135	135	135	135	128	126	102	110	128	128	135	120

Panel B. Correlation matrix of main variables

BRAZIL	PI	ROA_N	ROE_N	ICT	LCTE	CR	LTDCE	LTDTC	LA	TA	GDPG	INF
PI	1.000000	**0.970087***	**0.969401***	-0.185530	**-0.52973***	-0.193424	**0.476904***	**0.424343***	**-0.49301***	0.187620	-0.226477	**-0.40833***
ROA_N		1.000000	**0.880811***	-0.109050	**-0.57990***	-0.213615	**0.516598***	**0.463565***	**-0.56662***	0.201665	-0.313131	**-0.39333***
ROE_N			1.000000	-0.251579	-0.446757	-0.161237	**0.407746***	0.358860	-0.388573	0.162001	-0.125071	**-0.39865***
ICT				1.000000	-0.134795	-0.062515	0.020613	0.014007	0.113122	-0.026836	-0.068481	**0.743879***
LCTE					1.000000	**0.366426***	**-0.52600***	**-0.46739***	**0.611510***	-0.160357	0.213881	0.092722
CR						1.000000	**-0.62322***	**-0.62871***	0.030255	-0.206141	-0.091846	-0.055301
LTDCE							1.000000	**0.994897***	-0.218543	0.205671	-0.214447	-0.253820
LTDTC								1.000000	**-0.15954***	0.180389	-0.201180	-0.251273
LA									1.000000	**-0.14407***	0.304572	0.360826
TA										1.000000	-0.053550	-0.076165
GDPG											1.000000	0.404688
INF												1.000000

INDIA	PI	ROA_N	ROE_N	ICT	LCET	CR	LTDCE	LTDTC	LA	TA	GDPG	INF
PI	1.000000	**0.976982***	**0.977359***	**-0.111361***	**-0.163192***	**-0.064042***	0.007867	0.010884	**-0.074737***	-0.008514	0.039262	-0.014798
ROA_N		1.000000	**0.909725***	**-0.101211***	**-0.153140***	-0.048623	-0.009185	-0.005224	**-0.081119***	-0.017072	0.042660	-0.007050
ROE_N			1.000000	**-0.116365***	**-0.165742***	**-0.076425***	0.024423	0.026366	-0.065008	0.000362	0.034107	-0.021810
ICT				1.000000	0.003483	0.054122	0.023478	0.026817	0.000142	-0.043073	**-0.256111***	**0.563900***
LCET					1.000000	0.025030	**-0.246426***	**-0.239116***	**0.334366***	**0.187380***	0.006043	-0.024818
CR						1.000000	**-0.337436***	**-0.333513***	**-0.145498***	**-0.167934***	0.007915	0.014103
LTDCE							1.000000	**0.995205***	**-0.166395***	**0.140759***	-0.000143	0.023843
LTDTC								1.000000	**-0.167780***	**0.119370***	0.000703	0.019800
LA									1.000000	**0.206500***	-0.020059	0.029037
TA										1.000000	0.001778	0.030719
GDPG											1.000000	**-0.200040***
INF												1.000000

Panel B (suite)

CHINA	PI	ROA_N	ROE_N	ICT	LCET	CR	LTDCE	LTDTC	LA	TA	GDPG	INF
PI	1.000000	**0.981853***	**0.981836***	**-0.407814***	-0.057691	-0.054718	-0.002537	0.003499	**-0.147822***	**0.171206***	**0.183909***	**-0.259904***
ROA_N		1.000000	**0.928037***	**-0.418594***	-0.050451	-0.041185	-0.025324	-0.018066	**-0.161280***	**0.167741***	**0.204710***	**-0.259614***
ROE_N			1.000000	**-0.382216***	-0.062838	-0.066270	0.020353	0.024947	**-0.128989***	**0.168455***	**0.156418***	**-0.250755***
ICT				1.000000	0.050223	-0.000636	0.039605	0.034992	**0.298794***	**-0.135553***	**-0.454435***	**0.629606***
LCET					1.000000	**0.339335***	**-0.386962***	**-0.384830***	0.021633	**-0.133562***	-0.033252	0.066368*
CR						1.000000	**-0.476516***	**-0.466949***	**-0.160196***	**-0.207531***	-0.013919	-0.030421
LTDCE							1.000000	**0.995496***	**0.141667***	**0.185606***	-0.006144	0.003350
LTDTC								1.000000	**0.129074***	**0.192194***	-0.003296	0.002359
LA									1.000000	**-0.237142***	**-0.140605***	**0.253927***
TA										1.000000	**0.084784***	**-0.132854***
GDPG											1.000000	**-0.297365***
INF												1.000000
SA	PI	ROA_N	ROE_N	ICT	LCET	CR	LTDCE	LTDTC	LA	TA	GDPG	INF
PI	1.000000	**0.990226***	**0.990643***	**-0.259676***	0.071027	0.020920	-0.060873	-0.057516	-0.111003	0.101489	0.103007	**-0.217747***
ROA_N		1.000000	**0.961924***	**-0.272410***	0.074744	0.042909	-0.084930	-0.078453	-0.096830	0.101326	0.094757	**-0.226491***
ROE_N			1.000000	**-0.242302***	0.066046	-0.000993	-0.036181	-0.035939	-0.122772	0.099728	0.109131	-0.205070
ICT				1.000000	**0.281798***	0.177847	-0.145240	-0.154530	0.056108	-0.152158	-0.026931	0.579175*
LCET					1.000000	**0.509267***	**-0.593575***	**-0.590120***	-0.101792	**-0.486029***	-0.079282	0.166914
CR						1.000000	**-0.500153***	**-0.505568***	-0.070760	**-0.488802***	0.054989	0.090129
LTDCE							1.000000	**0.994643***	**0.352655***	**0.448411***	-0.018058	-0.026325
LTDTC								1.000000	**0.341300***	**0.421057***	-0.023138	-0.038188
LA									1.000000	-0.012375	0.012585	0.181433
TA										1.000000	0.001071	-0.072828
GDPG											1.000000	-0.064558
INF												1.000000

Note: * 5% significance level.

Table A3: Full period results from Baseline model Eq(4)

BRAZIL		Panel 1: dep var PI			Panel 2: dep var TA	
VARIABLES	OLS	FE	RE	OLS	FE	RE
ICT	0.160	-0.197	0.0511	1.150	1.202	1.287
	(0.886)	(0.953)	(0.887)	(1.085)	(1.077)	(1.124)
C	0.333	0.465	0.367	0.263	0.247	0.212
	(0.333)	(0.357)	(0.336)	(0.409)	(0.408)	(0.424)
Hausman(prob)			(0.4767)			(0.7905)
Observations	33	33	33	40	40	40
F-sta(prob)		(.2279)			(0.3936)	
BP chi^2(prob)			(0.4895)			(0.3195)

INDIA		Panel 1: dep var PI			Panel 2: dep var TA	
VARIABLES	OLS	FE	RE	OLS	FE	RE
ICT	-0.701***	-0.698***	-0.699***	-0.621	-0.622***	-0.622***
	(0.197)	(0.189)	(0.189)	(0.387)	(0.181)	(0.181)
C	0.766***	0.765***	0.766***	1.040***	1.040***	1.042***
	(0.0699)	(0.0671)	(0.0676)	(0.138)	(0.0643)	(0.0836)
Hausman(prob)			(0.8893)			(0.9923)
Observations	1,059	1,059	1,059	1,051	1,059	1,059
F-sta(prob)		(0.0000)			(0.0000)	
BP chi^2(prob)			(0.0000)			(0.0000)

CHINA		Panel 1: dep var PI			Panel 2: dep var TA	
VARIABLES	OLS	FE	RE	OLS	FE	RE
ICT	-0.714***	-0.714***	-0.714***	-0.240***	-0.235***	-0.235***
	(0.0405)	(0.0389)	(0.0389)	(0.0474)	(0.0262)	(0.0262)
C	0.871***	0.871***	0.871***	0.692***	0.689***	0.690***
	(0.021)	(0.0201)	(0.0211)	(0.0243)	(0.0135)	(0.0261)
Hausman(prob)			!			(0.6938)
Observations	1,575	1,575	1,575	1,544	1,544	1,544
F-sta(prob)		(0.0000)			(0.0000)	
BP chi^2(prob)			(0.0000)			(0.0000)

SA		Panel 1: dep var PI			Panel 2: dep var TA	
VARIABLES	OLS	FE	RE	OLS	FE	RE
ICT	-0.672***	-0.672***	-0.672***	-0.484	-0.320	-0.351
	(0.195)	(0.186)	(0.186)	(0.334)	(0.252)	(0.257)
C	0.840***	0.840***	0.840***	1.307***	1.240***	1.248***
	(0.0843)	(0.0802)	(0.0843)	(0.144)	(0.109)	(0.136)
Hausman(prob)			(1.0000)			!
Observations	135	135	135	128	128	128
F-sta(prob)		(0.0239)			(0.0000)	
BP chi^2(prob)			(0.0198)			(0.0000)

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Sub-period results from Baseline model Eq(4)

	Panel 1: dep var PI				**Panel 2: dep var TA**			
				Brazil				
	Pre Covid		**Post Covid**		**Pre Covid**		**Post Covid**	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
ICT	0.859568	0.677033	**-4.4122*** **	-3.736701	0.293989	0.675622	-0.974399	-0.347211
C	0.250762	0.482831	1.801873	4.348176	0.804369	4.546991	0.842802	0.856650
F-statistic	0.999448	(0.461148)	4.567928	(0.010455)	14.93206	(0.000104)	0.647964	(0.691436)
				India				
	Pre Covid		**Post Covid**		**Pre Covid**		**Post Covid**	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
ICT	-0.621550	-1.396785	**-0.47066** **	-2.106522	**-0.695776***	-1.741767	0.181810	1.033234
C	0.755449	5.140783	0.658204	7.663494	1.110031	8.411288	0.677058	10.00200
F-statistic	2.429768	(0.000000)	2.204145	(0.000000)	30.78207	(0.000000)	23.38324	(0.000000)
				China				
	Pre Covid		**Post Covid**		**Pre Covid**		**Post Covid**	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
ICT	**-0.5865*** **	-7.754631	**-2.2414*** **	-8.375268	**-0.2575*** **	-4.876536	**-0.4214*** **	-3.012533
C	0.828813	30.75236	1.884921	10.58624	0.695890	36.93504	0.813219	8.769488
F-statistic	2.367536	(0.000000)	2.911199	(0.000000)	14.48977	(0.000000)	23.34720	(0.000000)
				South Africa				
	Pre Covid		**Post Covid**		**Pre Covid**		**Post Covid**	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
ICT	-0.418209	-1.363325	0.894701	0.729087	-0.097790	-0.245869	-0.672420	-0.749099
C	0.779226	7.904359	-0.022931	-0.034697	1.201102	9.324128	1.391376	2.879008
F-statistic	1.785754	(0.058767)	2.169663	(0.023562)	7.482402	(0.000000)	18.76326	(0.000000)

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. (.) is the p_value.

Table A5: One-Step System GMM Estimation results from dynamic model Eq(7)

Panel A: Brazil case

	Dep var PI			Dep var PI	
				one-step system GMM	
VARIABLES	OLS	FE	RE	Full	Post Covid
PI_{-1}				0.479***	0.350*
				(0.107)	(0.160)
ICT	-1.060	-0.947	-0.985	-2.239	-1.133
	(0.819)	(0.869)	(0.810)	(1.509)	(2.894)
GDPG				-1.022	-0.790
				(1.646)	(1.714)
INF				8.155	4.070
				(5.410)	(4.417)
CR				-0.00684	0.000586
				(0.0131)	(0.0133)
CET				0.000311	-0.00106
				(0.00497)	(0.00576)
TDCE				0.00187	0.00290
				(0.00105)	(0.00170)
TDTC				0.000986	-0.000469
				(0.00518)	(0.00700)
D2019	-0.394***	-0.361***	-0.383***		
	(0.107)	(0.120)	(0.108)		
Constant	1.024***	0.963**	0.991***	0.596	0.418
	(0.338)	(0.353)	(0.336)	(0.481)	(1.061)
Sargan/Hansen				1.000	1.000
AB(1)				0.512	0.503
AB(2)				0.405	0.714
Observations	33	33	33	26	19
R-squared	0.310	0.268			
Number of Id		6	6	6	5

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Pre Covid estimation result are not available because of problem of insufficient data. Dummy variable D2019 = 1 if year > 2018 and 0 if not, is used to indicate the post covid outbreak effect.

Panel A: (suite) Brazil case

	Dep var TA			**Dep var TA**		
VARIABLES	OLS	FE	RE	Full	Pre	Post
TA_{-1}				0.507**	0.764	0.325
				(0.183)	(0.385)	(0.223)
ICT	-0.343	-0.349	-0.343	-1.516	-11.29***	-5.896
	(0.996)	(1.001)	(0.996)	(4.654)	(1.413)	(6.467)
GDPG				-0.239	-70.67*	-1.899
				(2.914)	(25.28)	(7.157)
INF				12.83	-104.9	24.40
				(25.90)	(56.15)	(44.06)
CR				-0.0629**	0.176	-0.0407
				(0.0167)	(0.298)	(0.0287)
CET				-0.00219	0.00856	-0.00206
				(0.00294)	(0.00742)	(0.00444)
TDCE				-0.000268	0.00469	0.00142
				(0.00159)	(0.00216)	(0.00342)
TDTC				-0.00114	-0.00684	-0.00564
				(0.00776)	(0.00890)	(0.0109)
D2019	-0.479***	-0.512***	-0.479***			
	(0.122)	(0.124)	(0.122)			
Constant	1.095***	1.103**	1.095***	0.803	6.099**	2.096
	(0.412)	(0.408)	(0.412)	(1.315)	(1.306)	(1.595)
Sargan/Hansen				1.000	1.000	1.000
AB(1)				0.281	0.114	0.153
AB(2)				0.320	0.114	0.496
Observations	40	40	40	31	10	21
Number of Id	6			6	4	6

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A5 (suite)

Panel B: India case

	Dep var PI			**Dep var TA**		
VARIABLES	Full	Pre	Post	Full	Pre	Post
PI_{-1}	0.410***	0.449***	0.367***			
	(0.0454)	(0.0770)	(0.0549)			
TA_{-1}				0.649***	0.915***	0.611***
				(0.141)	(0.189)	(0.139)
TA_{-2}				0.127*	0.0890	0.113*
				(0.0674)	(0.214)	(0.0670)
ICT	-1.080***	-0.598	-1.282***	-0.622***	0.991	-0.475**
	(0.282)	(1.586)	(0.329)	(0.174)	(3.545)	(0.188)
GDPG	0.00299	-0.00559	0.00352	0.00162	0.0284	8.34e-05
	(0.00257)	(0.0173)	(0.00286)	(0.00200)	(0.0245)	(0.00165)
INF	1.172***	5.787	1.349***	0.507***	-5.805	0.396**
	(0.305)	(9.180)	(0.338)	(0.181)	(7.870)	(0.164)
CR	-0.00190	0.00128	0.00148	-0.0193**	-0.0165	-0.0160**
	(0.00515)	(0.00695)	(0.00594)	(0.00739)	(0.0172)	(0.00631)
CET	-0.00182**	-0.00401***	-0.000705	-0.000499	-0.00581	0.00108
	(0.000881)	(0.00151)	(0.00113)	(0.00119)	(0.00462)	(0.00144)
TDCE	-0.00239**	-0.000916	-0.00346**	0.00285*	-0.00225	0.00410**
	(0.00113)	(0.00237)	(0.00173)	(0.00150)	(0.00379)	(0.00162)
TDTC	0.00345	0.00171	0.00431	-0.00899**	-0.00339	-0.00960**
	(0.00310)	(0.00538)	(0.00450)	(0.00362)	(0.00755)	(0.00380)
Constant	0.742***	0.564	0.804***	0.520***	-0.121	0.422***
	(0.116)	(0.707)	(0.136)	(0.124)	(1.243)	(0.101)
Sargan/Hansen	0.999	0.734	0.827	0.581	0.711	0.482
AB(1)	0.000	0.000	0.000	0.022	0.047	0.011
AB(2)	0.936	0.535	0.533	0.206		0.780
Observations	810	364	446	741	300	441
Number of ID	120	116	119	120	111	118

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A5 (suite)

Panel C: China case

	Dep var PI			Dep var TA		
VARIABLES	Full	Pre	Post	Full	Pre	Post
PI_{-1}	0.377***	0.553***	0.254***			
	(0.0777)	(0.191)	(0.0899)			
PI_{-2}	0.0514	-0.165	0.125**			
	(0.0521)	(0.137)	(0.0548)			
TA_{-1}				0.755***	1.125***	0.668***
				(0.0520)	(0.225)	(0.102)
TA_{-2}				0.141*	-0.0578	0.212
				(0.0803)	(0.181)	(0.144)
ICT	-0.366***	-0.190	-0.831***	0.107***	0.0340	0.102
	(0.123)	(0.151)	(0.228)	(0.0322)	(0.0954)	(0.0895)
GDPG	1.223**		0.890	1.013***	-21.99**	0.952***
	(0.554)		(0.577)	(0.295)	(10.87)	(0.290)
INF	20.05***	-4.850	18.00***	4.036**		4.078**
	(3.637)	(14.22)	(4.698)	(1.929)		(1.919)
CR	-0.0189**	0.0362	-0.0286**	0.000148	0.0246	-0.00917*
	(0.00803)	(0.0288)	(0.0116)	(0.00480)	(0.0201)	(0.00520)
CET	0.00142	0.00689**	0.00198	-0.00123**	-0.00560**	-0.000891*
	(0.00111)	(0.00347)	(0.00137)	(0.000514)	(0.00228)	(0.000528)
TDCE	0.000599	-0.00742*	0.00201	-0.000574	-0.00193	-0.000895
	(0.00138)	(0.00446)	(0.00157)	(0.000727)	(0.00258)	(0.000748)
TDTC	-0.00167	0.0225**	-0.00580	0.000654	0.00471	0.00116
	(0.00381)	(0.0112)	(0.00434)	(0.00215)	(0.00729)	(0.00228)
Constant	0.212*	-0.113	0.576***	-0.0491	1.599**	-0.0227
	(0.122)	(0.248)	(0.213)	(0.0554)	(0.784)	(0.0648)
Sargan/Hansen	0.159	0.274	0.199	0.370	0.669	0.251
AB(1)	0.000	0.010	0.000	0.001	0.038	0.084
AB(2)	0.118		.906	0.260		0.251
Observations	1,186	518	668	1,182	514	668
Number of ID	175	175	175	175	175	175

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A5 (suite)

Panel D: South Africa

	Dep var PI			Dep var TA		
VARIABLES	Pull	Pre	Post	Pull	Pre	Post
PI-1	0.245	-0.190	0.176			
	(0.148)	(0.316)	(0.148)			
PI-2	0.188*	-0.0339	0.258**			
	(0.0894)	(0.273)	(0.0979)			
TA-1				0.580***	0.475***	0.705***
				(0.143)	(0.107)	(0.161)
TA-2				0.0430		-0.0598
				(0.122)		(0.110)
ICT	-0.409	-0.0871	-0.594	0.245	-15.65*	0.672
	(0.329)	(0.407)	(1.244)	(0.314)	(7.543)	(0.865)
GDPG	0.00965		0.0109	-0.00773	-447.6*	-0.0133
	(0.0158)		(0.0215)	(0.00703)	(216.9)	(0.00969)
INF	-6.302	-0.00749	-7.043	3.226	-0.0328*	5.169
	(12.57)	(0.0190)	(14.98)	(5.485)	(0.0171)	(5.795)
CR	0.00553	0.00119	0.00626	-0.0269	-0.00353	-0.0250
	(0.0209)	(0.00252)	(0.0239)	(0.0195)	(0.00295)	(0.0205)
CET	5.01e-05		0.000132	-0.00566*	-4.16e-05	-0.00622*
	(0.00184)		(0.00279)	(0.00299)	(2.69e-05)	(0.00296)
TDCE	-9.17e-06		0.00278	0.00352*	0.00115	0.00754***
	(2.15e-05)		(0.00268)	(0.00168)	(0.00322)	(0.00202)
TDTC	0.000122	0.161	-0.00477	-0.0110		-0.0203**
	(0.00215)	(0.134)	(0.00918)	(0.00695)		(0.00715)
Constant	0.572	0.539**	0.667	0.583**	16.21**	0.340
	(0.401)	(0.214)	(0.789)	(0.234)	(7.464)	(0.561)
Sargan/Hansen	1.000	0.999	1.000	1.000	0.964	1.000
AB(1)	0.006	0.016	0.157	0.014	0.292	0.082
AB(2)	0.547	0.370	0.691	0.320		0.956
Observations	89	57	49	88	40	49
Number of ID	15	15	14	15	14	14

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Sum up of the BVAR-X model estimation

Panel A: Results from Eq(8a)

Country / Indep var	Dep var PI				Dep var TA			
	ICT_{-1}	ICT_{-2}	ICT_{-3}	ICT_{-4}	ICT_{-1}	ICT_{-2}	ICT_{-3}	ICT_{-4}
Brazil	−0.87 ⋆	0.476 ⋆	0.517 ⋆		−0.57 ⋆	0.13	0.16	
India	0.2 ⋆	−0.19 ⋆	−0.19 ⋆		0.09 ⋆	−0.05	−0.06	
China	0.036	−0.022	−0.027		0.049	−0.043	0.045	−0.04 ⋆
SA	−0.03 ⋆				−0.11 ⋆			

Panel B: Results from Eq(8b)

Country / Indep var	Dep var PI				Dep var TA			
	ICT_{-1}	ICT_{-2}	ICT_{-3}	ICT_{-4}	ICT_{-1}	ICT_{-2}	ICT_{-3}	ICT_{-4}
Brazil	−0.58 ⋆	0.33			0.12 ⋆			
India	−0.16 ⋆				0.018 ⋆			
China	−0.024				−0.024			
SA	−0.02 ⋆				−0.08 ⋆			

Note: ⋆: significant association with dep var. Source: author' calculation

Table A7: Diagnostic tests for Time series ARDL models

Panel A: BG Serial Correlation LM Test

County/Dep var	PI	TA
Brazil	5.328982 (0.0696)	11.20825 (0.0037)
India	5.138648 (0.0766)	4.266817 (0.1184)
China	63.29356 (0.0000)	61.29473 (0.0000)
SA	6.586223 (0.0371)	3.133947 (0.2087)

Panel B: Heteroskedasticity Test: ARCH

County/Dep var	PI	TA
Brazil	0.058387 (0.8091)	1.180236 (0.2773)
India	2.02E-05 (0.9964)	0.009285 (0.9232)
China	16.39832 (0.0001)	26.55595 (0.0000)
SA	0.083521 (0.7726)	0.027103 (0.8692)

Note: (.) is the p-value.

Table A8: Cross-sectional dependence (CD) tests Results

	Dep var PI			Dep var TA		
Test	**Statistic**	**d.f.**	**p-value**	**Statistic**	**d.f.**	**p-value**
Breusch-Pagan LM	155.9761	6	(0.000)	145.1365	6	(0.000)
Pesaran scaled LM	42.13966		(0.000)	39.01055		(0.000)
Pesaran CD	11.09412		(0.000)	6.270636		(0.000)
Frees (1995)	0.857891		(0.000)	166.0387		(0.000)

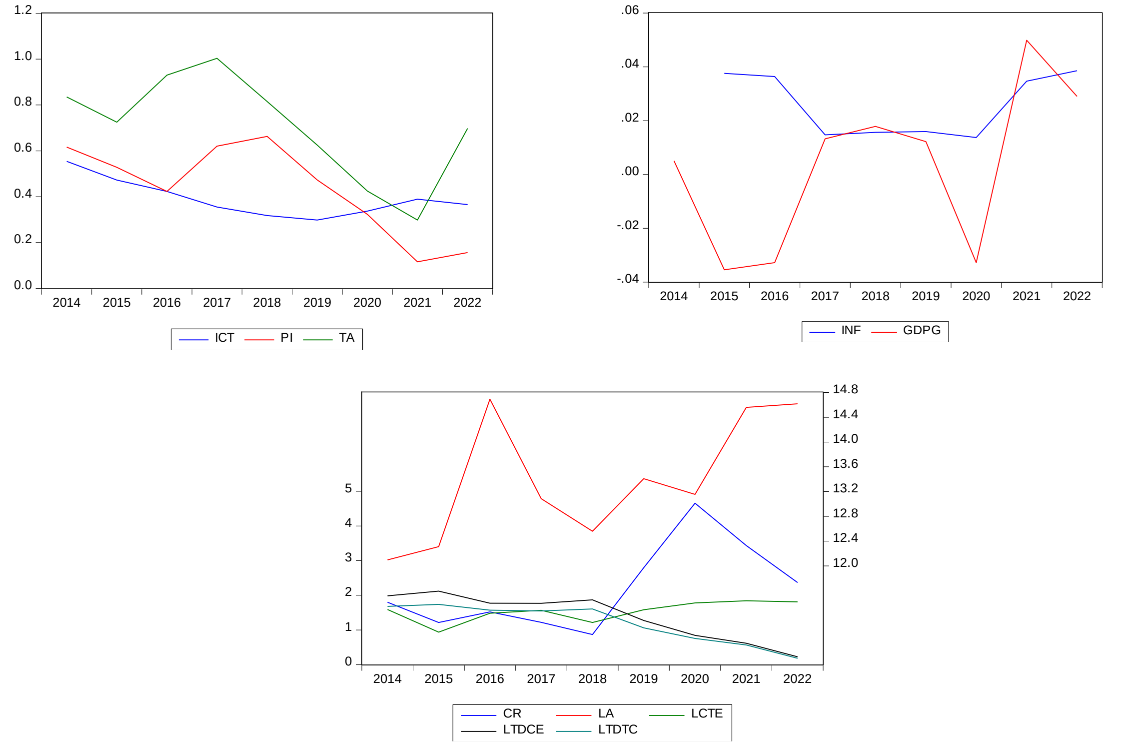
Note: Null hypothesis is H_0: No cross-section dependence in residuals of the FE regression. *: is to indicate the rejection of H_0. CD test is based on the CD in the data or on the regression residuals from LGNI on the 14 independent variables. (Breusch & Pagan, 1980) LM test statistics is $CD_{LM} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 \sim \chi^2_{n(n-1)/2}$, where $\hat{\rho}_{ij}$ is the sample pair-wise residual correlation. LM test is valid for $T\to\infty$ with N fixed and is inappropriate if N is large. If $T\to\infty$ and $N\to\infty$, the scaled version (Breusch & Pagan, 1980) LM test statistics is $CD_{SLM} = \sqrt{\frac{T}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2$. Alternatively, (Pesaran, 2004) proposed the $CD_P = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij} \sim N(0,1)$ under H_0. Critical values from (Frees, 1995)' Q distribution at $\alpha = 0.05$ for the first (second) group is 0.4325 (0.6860). All of these test results are in favor of cross-country dependence. Source: Author's computation by Eviews 13 and STATA 15.

Table A9: Results of slope homogeneity tests

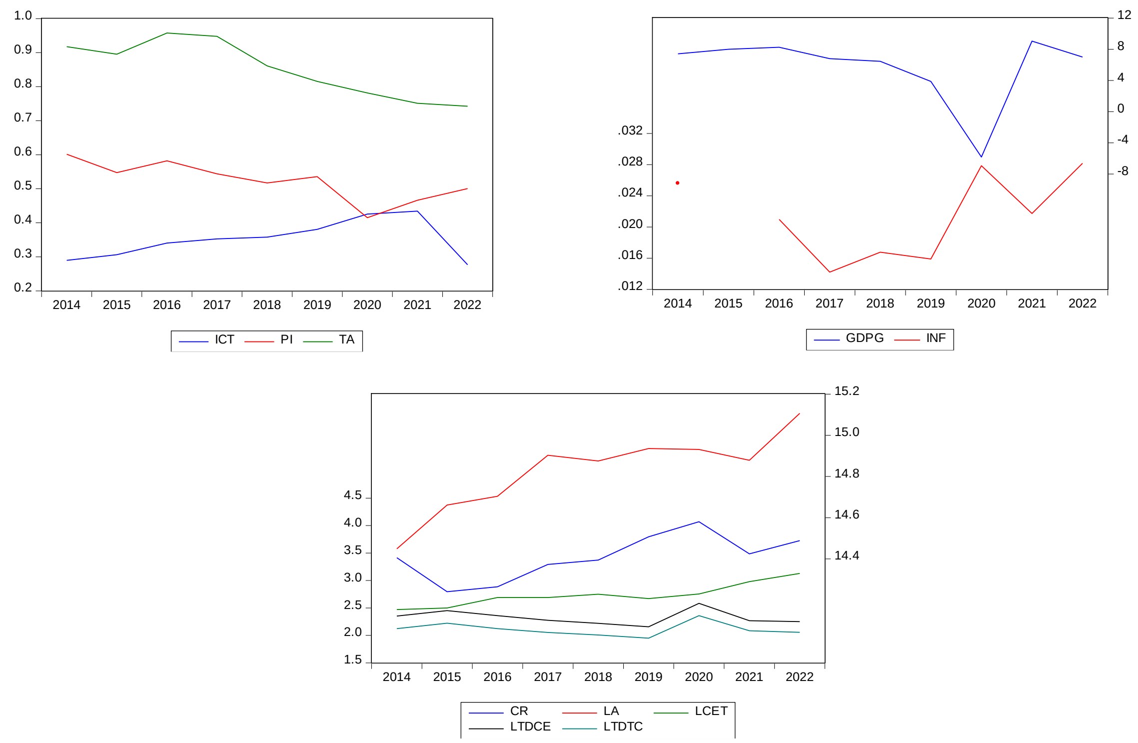
	Dep var PI		Dep var TA	
Tests	**Stat**	**p-value**	**Stat**	**p-value**
(Swamy, 1970)				
Δ	8.870	(0.000)	9.726	(0.000)
Adj Δ	8.996	(0.000)	9.864	(0.000)
(BW. 2013)				
Δ_{HAC}	7.127	(0.000)	12.723	(0.000)
Adj Δ_{HAC}	7.228	(0.000)	12.903	(0.000)

Note:For (Swamy, 1970), H_0: slope (cointegrating) coefficients are homogenous (is improved by (Pesaran & Yamagata 2008) to allow for autocorrelated error case). The latest tests (BW) proposed by (Blomquist & Westerlund. 2013) are the Heteroskedasticity and autocorrelation consistent (HAC) robust version of slope homogeneity test of Pesaran and Yamagata (Δ_{HAC} and Adj Δ_{HAC} test statistics). If H_0 is rejected, then one can use heterogeneous panel estimation techniques (Mean Group (mg) family models). In the opposite case, one can consider rather Pooled Mean Group model (pmg). All of these test results are in favor of slope heterogeneity. Source: Author's computation.

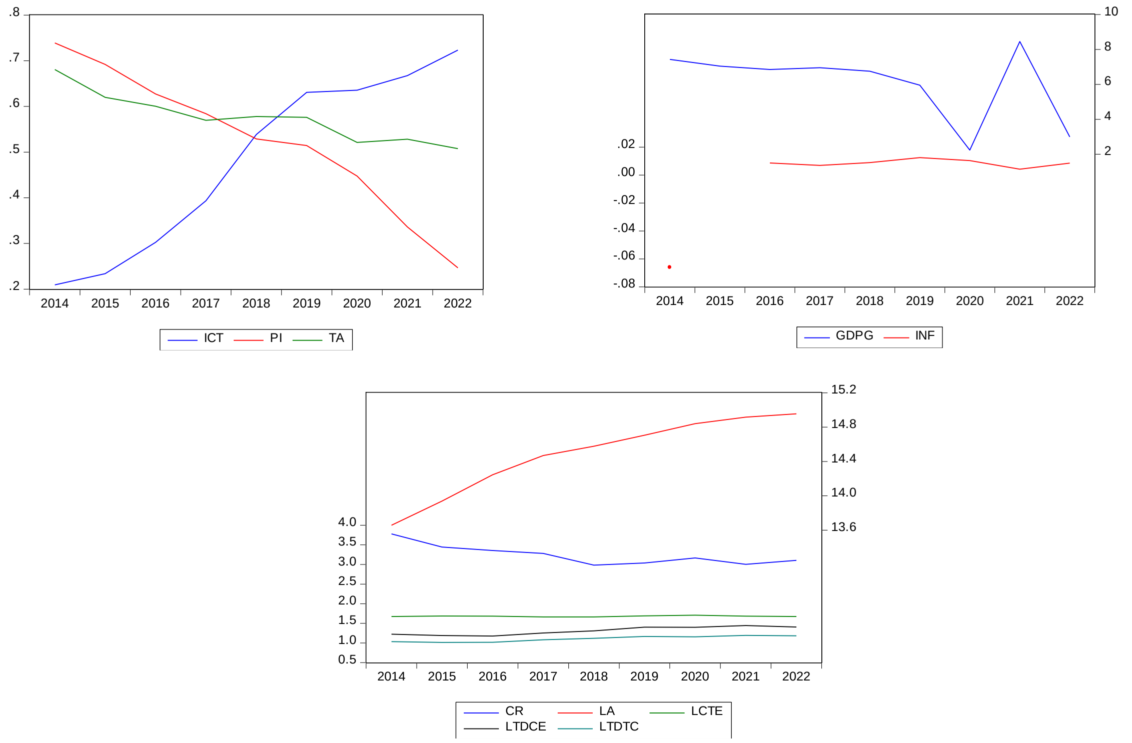
Appendix: Some Figures



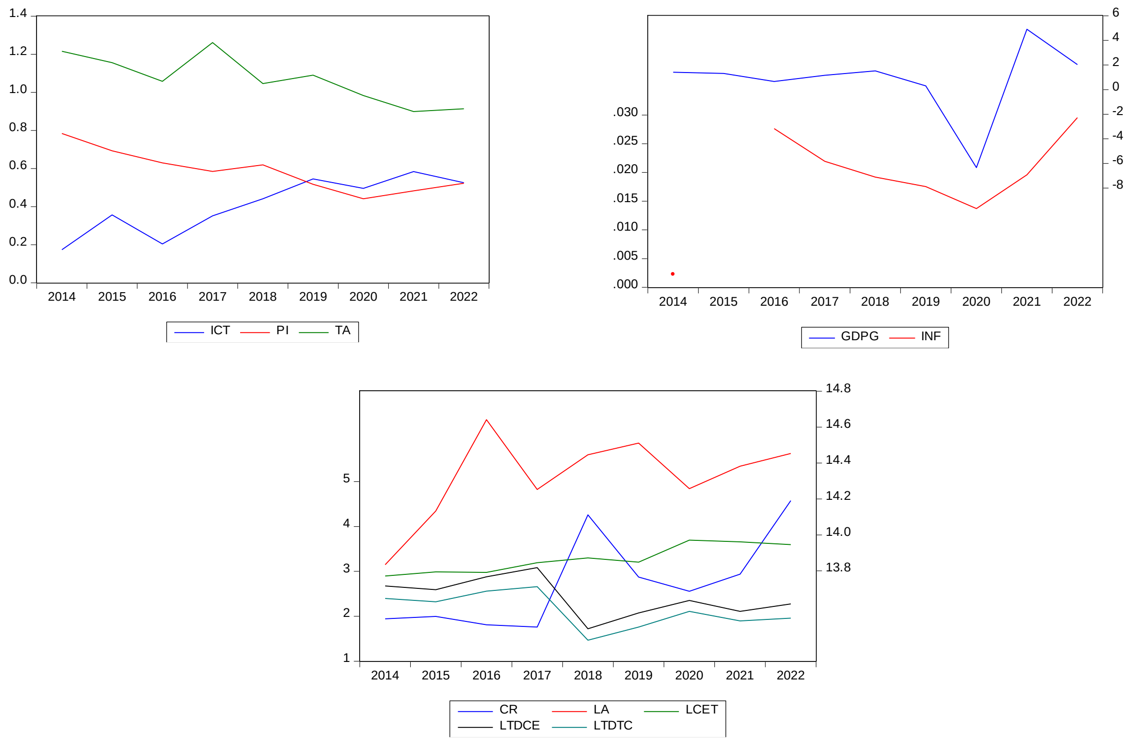
(a) Case of BRAZIL



(b) Case of INDIA

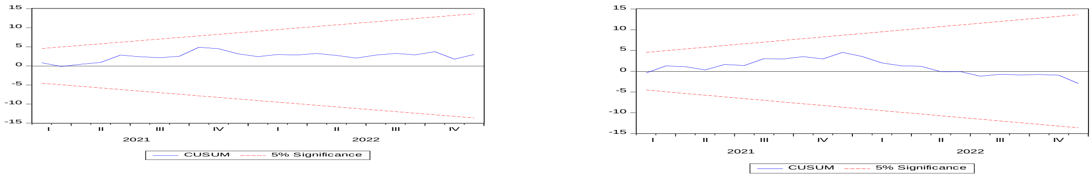


(c) Case of CHINA

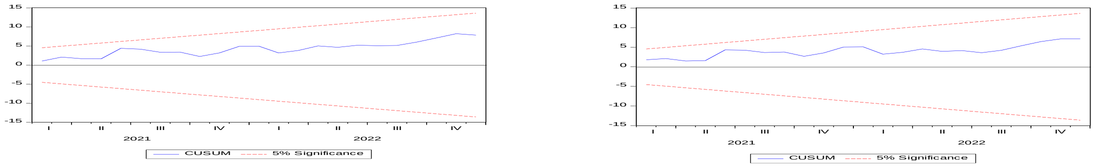


(d) Case of SOUTH AFRICA

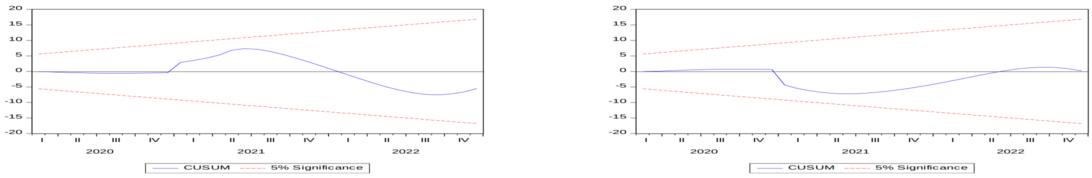
Figure B1: Variable time-evolution in means by Firm for the BRICS countries



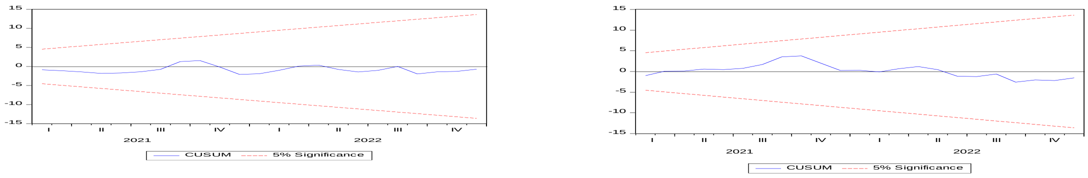
Brazil



India



China



SA

Panel A: Dep var PI

Panel B: Dep var TA

Figure B2: Stability verification for time series ARDL specifications

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