The country ICT level and the Fintech firm Performance: Evidence from BRICS Countries

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The country ICT level and the Fintech firm Performance: Evidence from BRICS Countries

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Abstract

Purpose: The scope of this paper is to investigate if the information and communications technology (ICT) can improve the FinTech firm performance in the BRICS countries from monthly macro time series data during 2014M01-2022M12.

Design/methodology/approach: Through the Bayesian VAR-X approach and the time series DYNARDL simulation models, we investigate the impact of the ICT and its components on the firm performance for both the short-run (SR) and the long-run (LR) historical and predictive trend. Besides these regression models, this study applies the Granger Causality (GC) in quantile and the frequency domain (FD) GC tests to show more details about the causality linkage.

Findings: From the BVAR-X approach, historical IRFs conclude that the ICT has positive effect on PI for all countries in the SR and a positive effect in the LR only for China. From the DYNARDL simulation models, predictive IRFs results corroborate with the historical IRFs results except for the China and SA in the SR and for Brazil and India in the LR. We conclude in addition that the predictive positive relationships is driven by MCS for Brazil, IUI for China, FBS for SA, and all of the ICT components for the India case. GC type test results are in accordance with previous results.

Originality: The novelty of this research is based on the idea of studying the effect of the ICT on FinTech firm performance by using several time series data based dynamic technics so that we can estimate and predict the SR adjustments that arise from the impact of ICT to the LR relationship with the firm profitability.

Key Words: FinTech Firm from BRICS area; Bayesian VAR-X model; DYNARDL simulation model; Historical and predictive IRFs for SR and LR effects; Granger Causality test in quantile (QGC); Frequency domain Granger causality (FDC) test.

1. Introduction

The current economic environment is extremely turbulent and this is mainly due to rapid technological change. Policymakers need to better understand how ICTs 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 short-run and long-run. The ICT development can have adverse effect on economic activities. Certain researchers such however question the existence of a positive relationship between ICTs and the firm activity result especially in the short-term.

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

FinTech firms have received increasing attention in recent years owing to their rapid development and expansion across economies. Actually, to address the question about the relationship between ICTs and the firm activity, many studies have based their results on firm level panel data. No one of the previous studies had concern the macro level based on time series data. In this paper, we address the existing gap of the empirical literature by exploiting both micro and macro data that relates ICT variables to country's- or firm's- level indicators of the firm profitability.

There was a lot of literature that discussed the contribution of ICT on firm performance. This study aimed to identify the extent of the influence of ICT in improving firm performance. Does ICT always provide a positive impact on improving company performance? A systematic literature review was conducted to know about the positive and negative impact of ICT and also to find a gap that might still need to be investigated further about the performance of firms that associated with information technology. Despite the large body of literature, gaps in the understanding of the performance effects of ICTs on FinTec firms from BRICS area exist.

This research is realized on the base of BRICS FinTech firms. Using a sample of 316 FinTech firms to address our objective, we provide in first step a micro- and macro- firm profitability index and the ICT country investment measure. Therefore, we contribute to the literature by considering aggregate index for both profitability and the ICT. Then, all firm-level variables (panel data) were converted to yearly time series data via the point estimates of each variable by country. To get viable inference results, all annual data were converted to monthly data by the interpolation method.

We proposed in a second step the use of the Bayesian Vector of Autoregressive (BVAR) approach regarding its relative simplicity and flexibility in dealing with econometric problems. This new method adds to the empirical papers the possibility of analyzing not only the dynamic relationships among the variables but also the shock effects through the impulse response function (IRF). BVAR approach is used to see if the ICT improves firm profitability in the SR and the LR with the presence of some control variables (X) including firm conditions (CET, CR, LA, TDCE, TDTC) and the macroeconomic environment indicators (the GDPG and the inflation rate).

Then, in a third step we use the dynamic DYNARDL simulation approach developed by (Jordan and Philips, 2018) that can efficiently predict, stimulate and immediately plot probabilistic forecasts on the firm profitability due to changes (positive or negative) in the ICT variable (or one of its components) while holding the other control variable constant. The predictive IRF illustrates whether ICT will provide a positive or negative impact on the firm profitability in both the SR and the LR.

Then, a robustness check of our results are done via GC type tests, namely Granger Causality (GC) in quantile (Song & Taamouti, 2020) and the frequency domain (FD) GC tests (Breitung & Candelon, 2006).

The remainder of this paper is organized as follows: Section. 2 presents a literature review and the hypothesis development. Section 3 reports on the data and variable creation and analysis. Section 4 presents methodology and he empirical results. Finally, Section 5 concludes the study with policy implications and directions for future research.

2. Literature review and hypothesis development

The literature that addresses ICT is rich and still growing rapidly. As digital technologies are continuing to progress by leaps and bounds and foster increasingly vibrant digital transformations across nations, conducting extensive surveys of the literature to understand what we have learned and what we will need to further explore in gaining a deeper understanding on the ICT growth links are valuable for academics, policy makers and practitioners (Vu et al., 2020).

Previous studies have revealed mixed evidence regarding the question of whether ICTs enhance or impede productivity and growth. One reason why it is difficult to test this puzzle may be primarily due to the simultaneity between ICTs investment and economic growth, making the direction of this effect ambiguous (Kim 2007; Sepehrdoust and Khodaee 2013; Latif et al., 2018; Rai and Chaturvedi 2022).

There are also studies in business and management that measured the linkage between ICTs and firm performance, which are mainly based on firms' internal expenditure or adoption of ICTs (Gallego et al., 2015; Grimes et al., 2012; Haller & Lyons, 2015).

The relation between IT investment and firm performance has been investigated since 1980. The majority of results studies confirm the IT investment's impact on firm performance. Many theoretical paradigms in evaluating the IT's contribution to firm performance have cited in literature: theoretical model of IT resources, general purpose technology theory, the neoclassical theory, the resource-based theory and the productivity paradox theory. The findings of all studies can be grouping to *three possibilities*: studies confirming *the positive* effects of IT investment on firm performance, studies confirming the *IT paradox* of an immediate *negative impact* but a lagged *positive* impact and studies minority studies have found *no impact of IT* investment on firm performance.

i) Prior studies have reported *mixed findings* on the impact of corporate information technology (IT) investment on firm performance (Kwon 2007; Jung 2009; Kauffman and Liu 2015; Thakur and al., 2023).

Kwon (2007) tested the role of four *moderators* which are role of CIO, mobile technology adoption, IT support and maintenance and IT outsourcing. The results indicate that the impact of IT investment had *positive* effects on five performance variables (firm growth, market competitiveness, customer relations, partnership with providers, operational efficiency) except employment efficiency. In the case of moderating effect, IT support and maintenance (IT outsourcing) showed positive (*negative*) moderating effect partially on relationship between IT investment and firm performance variables. There was no moderating effect of role of CIO and mobile technology adoption.

Jung (2009) investigated IT investment decision and performance of on-line brokerage firms under heterogeneity of IT service *dimension*. Results indicated that IT investment and service quality are different in each dimension. High capability firm invest more in IT system instead of advantage of capability, and they make better financial performance by providing better service quality. The author found that firm's non IT-related capability moderates the service quality effect to performance. He concluded that high capability firm provide better service quality and make better financial performance despite more IT spending. Low capability firm can't make same level of financial performance of high capability firm only by IT investments. Firm's non IT-related capability is a crucial factor in service industry and firms have to build up capability to make better performance.

Kauffman et al. (2015) stated that a firm's senior managers will benefit from deferring technologically investment decisions based on *appropriate expectations*, since information is revealed over time about future trends regarding technology standards and market conditions, as well as the volatility of investment costs and benefits. When the investment decision horizon is more flexible, the firm is more likely to defer its technological investment decisions for longer to maximize the potential of a higher payoff. With higher risk and volatility levels associated with future benefits from technology adoption, the firm will be able to achieve a higher return on investment but the likelihood of a large loss will be greater. When benefit flows revert to equilibrium more quickly, the investment will achieve higher returns.

The study of Thakur and al., (2023) covered the impact of ICT on the profitability of banks. Thirty-three banks are operating in India over a sample period of 10 years (2010 to 2019). The study also provides insight into how ICT helps the banks' profitability during and *post-COVID-*19. They revealed that ICT adversely impacts banks' profitability (NIM) in India in a linear association, while the quadratic association indicates a *positive U-curved* relationship between ICT and profitability. In addition, the Net of Non-Performing Assets significantly but *negatively* impacts the connectivity of ICT and profitability. The findings imply that banks should invest in ICT to maximize the *long-run* profitability. The findings have no significant implication on all stakeholders, including policymakers, shareholders, and managers, to consider implementing ICT tools as an essential factor in enhancing a bank's profitability in the long-run.

ii) Some researchers have found *no impact* of IT investment on firm performance (Ho et al., 2011; Motiwalla et al., 2005).

Ho et al., (2011) investigated the effect of corporate governance, an important management control mechanism, on the relation between IT investment and firm performance in the Taiwanese electronics industry. Results showed a *positive moderating effect* of *board independence* on the IT investment-firm performance relation, especially when competition intensifies. Furthermore, the author found that the greater the foreign ownership in *small firms*, the more *positive* the IT investment-firm performance relation, suggesting that *foreign investors* may bring IT expertise to help small firms reap the benefits of using IT.

Motiwalla et al., (2005) presented an intra- and inter-industry financial performance (FP) analysis of three industries: retail (R), consumer products (CP), and food beverages and tobacco (FBT). Based on the sample data, *no conclusions* can be drawn at the firm level. The proposed model may be suitable for measuring the financial impact of electronic business (EB) activities at the group level.

iii) Studies, supporting *a positive impact* of ICT, are arranged in chronological order (Kim, et al., 2009; Campbell 2012; Kleis et al. 2012; Adekunle and Rafiu 2014; Liao et al. 2015; Saunders 2016; Alam et al. 2022; Enomate and Audu 2022; Amimakmur et al., 2024).

From (Kim, et al., 2009), findings show that IT investment has a positive impact on firm performance in China. Moreover, the impact in China is not different from what occurred in the United States in terms of direction and the size against the assertion of previous studies and expectations.

Campbell (2012) explored the time lag effects of IT investment on firm performance. He found that IT investment has an overall significantly *positive* impact on firm performance over and above the effects of firm size, the relative degree of effective IT use, firm past performance, and industry performance in terms of both profit ratios return on sales (ROS) and operating income to assets (OI/A) and cost ratios cost of goods sold to sales (COGS/S). The results of time-lagged regression analyses demonstrated that it took approximately three years after the year of investment realize the maximal performance gain in (OI/A). It also took as long as two years after the year of investment for the benefits in (OI/A) to start to manifest, while the effects on (ROS) and (COGS/S) appeared as early as the year of the initial IT investment.

Kleis et al. (2012) suggested that IT is vital to intermediate processes such as those that produce intangible output and that its use in *innovation and knowledge creation* processes is the most critical element to a firm's long-term success. Results demonstrated the importance of IT in *creating value* for U.S. manufacturing firms at an intermediate stage of production through improved innovation productivity for 1987 to 1997 period. However, R&D and its related intangible factors (skill, knowledge, etc.) appear to play a more crucial role in the creation of breakthrough innovations.

Adekunle and Rafiu (2014) studied the contribution of ICT to the performance of the South African banking industry over the period 1990-2012. The study analysis used the orthogonal transformation approach and a robustness test affirmed by residual co-integration analysis based on the Pedroni and Kao methods. They found that the ICT *increases* the Return on Capital Employed (ROCE) as well as the Return on Assets (ROA) of the South African banking industry.

Based on the perspective of long-term, non-linear, closed-loop causality, Liao et al. (2015) developed a computerized system dynamics model to analyze the dynamic relationships between organizational IT investment strategy and market performance within information-intensive service industries. The simulation results showed that more IT investment contributes to *increase* firm's service quality, customer satisfaction, market share, and profitability within information-intensive service industries.

Using a panel of 127 firms over the period 2003–2006, Saunders (2016) assessed the value of information technology related intangible assets to understand how business practices and management capabilities value are distributed across firms. The author estimated that there is a 45% to 76% premium in market value for the firms with the highest organizational IT capabilities as compared to those with the lowest organizational IT capabilities. Results suggested that contributions of IT to value depend heavily on other factors.

Alam et al. (2022) found compelling evidence to support the *positive* effects of ICTs on firm-level innovation and performance. ICT strategies and skills are important factors that drive innovation and the overall performance of SMEs. In addition, various conditions, such as an agile *workplace culture and international trade*, can help firms to improve their performance.

Enomate and Audu (2022) showed that investment in the ICT infrastructure has a *positive* effect on the financial performance of listed non-financial firms in Nigeria. This will enhance their efficiency and quality of service delivery that will ensure *customers retention and productivity*, which will translate to the firm profitability.

Amimakmur et al., (2024) provided an empirical evidence on the strategic importance of IT innovation in enhancing financial determinants and offered recommendations for integrating technological advancements in banking strategies to improve overall performance and value. The findings underscore the transformative potential of IT innovation in the financial sector, particularly in emerging markets like Indonesia.

This study aims to further examine the linkage between ICTs and performance with a new perspective and research setting, by investigating the impact of the adoption intensity of BRICS *country's ICT infrastructure on firm performance, as a way to link the macro-level ICT infrastructure to the micro-level firm performance*.

There are several studies that have focused on the country members of BRICS. However, the literature shows that there remains a need for studies that compare the BRICS in terms of the issues of internet connection access, use and related problems.

This paper attempts to investigate the validity of the following three hypotheses.

Hypothesis 1: ICT has significant positive effects on the Finteck firms performance by country from BRICS.

Hypothesis 2: The effects of ICT on the Finteck firms performance will vary across BRICS countries.

Hypothesis 3: ICT has significant positive effects on the BRICS Finteck firm performance in the short- and long-term.

3. Variables and Data analysis

3.1. Variable description

We collect firm financial data from the DataStream database. The ICT *country-related* variables and the *macroeconomic data* are obtained from World bank 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 Performance Index

To proxy the firms' profitability, we use performance index (PI) as *dependent* variable in our regressions, measured as given below (Aduba, et al., 2023; Neifar M. , 2024). We use common firm-level profitability measure ROA_{ijt} (ROE_{ijt}) to account for the performance 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

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

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 performance index (PI) will be estimated using the following equation

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

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 (Mobile cellular subscriptions (MCS%), Individuals using the Internet (IUI%), and Fixed broadband subscriptions (FBS%)) 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

$$\mathrm{ICT}_{jt} = {\textstyle\sum_{k=1}^{3} X_{jtk\_N}}\Big/{3} \tag{3}$$

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).

3.2. Time series data creation and analysis

Our study is an application on 316 FinTech firms from BRICS countries (Brazil, India, China and SA) for the period from 2014 to 2022 ($T = 9$). Having the micro level panel data by firm for each variable by country, we propose to get macro time series data for each variable by country as follow;

$$y_t = \sum_i^{N_i} y_{it} / N_i \, , t = 1, \dots, T = 9.$$

By considering the mean by firm for each panel data variable y_{it}, we'll get global (aggregate or macro) country indicators y_t for each variable from 2014 to 2022. Yearly evolution of each global indicator y_t 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 variable y_t and each country $j = 1, 2, 3, 4$.

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 0.435497, 0.523276, 0.523975, and 0.585799 for Brazil, India, China, and South Africa (SA). 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 SA.

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 matrices are 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.

Before any modeling of the relationship between the dependent and independent variables, we use the ADF and PP unit root tests to check the order of integration of each variable. Results in details are available upon request. In a sum up by country, we can say that almost all variables have unit root and hence proposing their non-stationarity. However, this result can be viable since data are the result of several transformations.

Performance, researchers have reported a mixed result. Therefore, it encourages that the essential character of ICT from the perspective of firm performance needs to be explored further.

4. Methodology and Results

Two TS models will be considered in this section: the BVAR model if we suppose that all considered variables are SL2 in level (or in first difference) and the DYNARDL model if they are mixed.

4.1.The BVAR-X model and the SR Inter-Dependence

We consider the BVAR-X models (based on random parameters) which gives *direction* of the ICT *effect evolution* in the **short-run** (SR) as well as in the LR via the IRF functions, and where X represent some control variables [1]. In particular, we want to examine the SR inter-dependence in the bivariate BVAR-X model and if possible how some control variables X can affect the transmission of ICT shocks to firm profitability for each country [2].

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:

$$Y_t = \sum_{k=1}^{p} \Gamma_k \, Y_{t-1} + X_t B + \mu_0 + u_t, \qquad (4)$$

where

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

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

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

PI_t represents the profitability, X_t is a (1×7) vector of the exogenous (control) variables,

$$X_t = (Macro_t, Fcontrols_t)$$

with $Macro_t$ is a vector of the macroeconomic variables including the GDPG and the inflation rate, and $Fcontrols_t$ is a vector of the 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 the (7×2) matrix B are matrices of random parameters to be estimated. We assume that the innovations have the following characteristics:

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

and priors have a normal probability distribution [3].

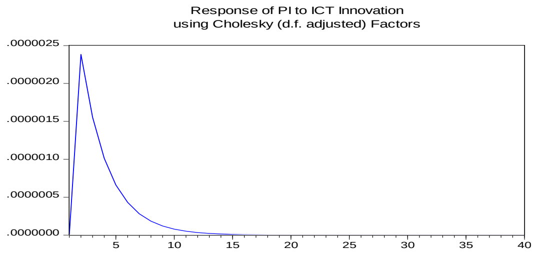
Therefore, in the Bayes approach, a prior distribution of all the parameters is introduced, as part of the model in Eq (4). This prior information will be combined with the model and the data from Y_t, to revise the probability distribution of all the parameters, which is called posterior distribution [4].

Results of Maximum Likelihood estimation are given at Table A3 (in Annex) for each country from the BRICS zone during 2014M01 - 2022M12.

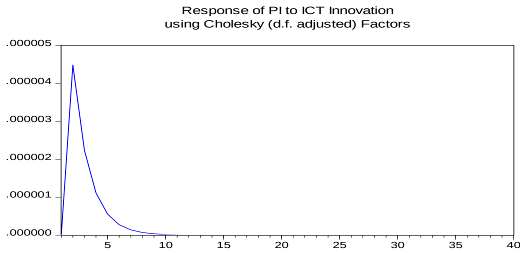
The BVAR model results may be difficult to interpret due to complex interactions and SR feedback between variables considered in the model. The dynamic feature of this Bayesian VAR-X model allows the use of the impulse response functions (IRF) to capture the dynamic relationships among considered variables in the Y_t vector. Then, after fitting the VARs, an IRF is computed to estimate the dynamic multipliers, which describe the impact of a one unit change in a variable on 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 corresponding IRFs 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 1 illustrates the response of PI_t to ICT innovations by country when macro-economic and firms activities are taken into account.

Using *all uncorrelated indicators* as control variable, and looking at Figure 1, there was a sharp positive initial effect from ICT to PI which is followed by null (negative) effect for Brazil and India (SA). It is clear that the temporary positive relationship with the ICT is proved only in the SR for these three countries; positive effect is transitory. Then a permanent null (negative) impact of the ICT was experienced for Brazil and India (SA). ICT was pro-profitable at the beginning say about 13 months for Brazil, 10 months for India and 2 month for SA. Negative effect in SA is permanent. The ICT effect turned out to be worthless in the LR for South African firms.

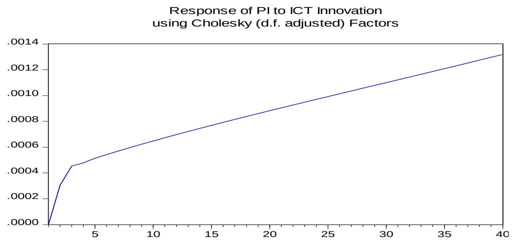
From Figure 1, we conclude that the ICT has a transitory SR positive effect on PI for all countries and a permanent LR positive effect only for China case (permanent LR zero effect in Brazil and India and LR negative effect in SA) during 2014M01 - 2022M12.



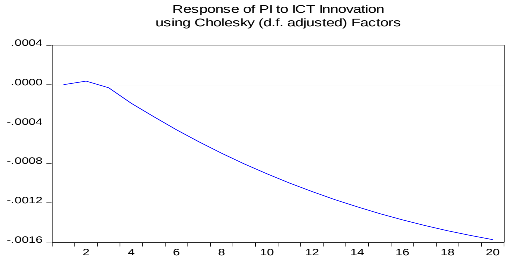
Brazil (BVAR(1))



India (BVAR(1))



China (BVAR(3))



SA (BVAR(3))

Figure 1: IRF of PI to ICT innovation from Eq.(4).

Note: Here the effect of ICT on performance that control for all 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 STATA 17 package, the graphical summary for the ICT parameters do not show any obvious problems. The trace plot reveals a good coverage of the domain of the marginal distribution [5], while the histogram and kernel density plots resemble the shape of the expected distribution. The autocorrelation dies off after about lag 20. Because of space limitation, these figures are not reported here but are available upon request.
These findings related to the impact of ICT on the Fintech firm profitability are limited. The discussion was only specific in terms of whether ICT provides a positive or negative impact on the firm profitability. It needs to be explored further regarding which ICT domain could support the company, whether it was enough to support the Mobile cellular subscriptions (MCS%), the Individuals using the Internet (IUI%), or the Fixed broadband subscriptions (FBS%) in the country so it could provide performance support to the company?

This question is investigated by using the dependent variables ROA and ROE as well as PI (as profitability measures) and the independent variable MCS, IUI, and FBS as well as ICT index in Eq (4). IRF's of all estimation results for each country are given at Figure B4 in the Appendix. Looking at Figure B4, we conclude that MCS (FBS) drives the positive relationship for Brazil, China, and SA (India) in the SR.

In addition, looking at Table A3 (in Annex), it is clear that:

- GDPG has negative effect in Brazil,
- INF has negative (positive) effect in Brazil (India),
- LA has positive (negative) effect in Brazil and India (China),
- LCTE has negative effect in Brazil,
- CR has negative (positive) effect in Brazil and India (SA),
- LTDCE has positive effect in Brazil, India and SA,
- LTDTC has negative effect in Brazil and India.

4.2.The DYNARDL 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 of the ARDL in the ECM form can be used:

$$\Delta PI_t = \mu(t) + \varphi ECT_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta PI_{t-i} + \sum_{i=1}^{q} \beta_i \Delta \mathrm{ICT}_{t-i} + \gamma X_t + \varepsilon_t, \quad (5)$$

$t = 1, \ldots, T$, where, $\mu(t)$ is the deterministic trend,

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

is the error correction term representing the LR relationship and φ the adjustment coefficient captures the sensitivity of the ECT, PI_t represents the profitability measures, X_t is the (1×7) vector of the exogenous (control) variables, $X_t = (Macro_t, Fcontrols_t)$, as given in the previous section, 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,[1] $\triangle = 1 - B$, B is the lag operator, and $\varepsilon_t \sim WN(0, \sigma^2)$.

Results are summed up at Table A4 in the Annex and at Figure B2 in the Appendix. Details are available upon request. From Figure B2, it is clear that the positive effect of ICT on PI is proved only in SR for Brazil and India case. ICT has a negative effect in the LR for the SA case.

Understanding the short-and-long-run effects becomes more difficult as the ARDL model specification have a fairly complex lag structure. To address the shortcomings which characterize the simple ARDL model,[2] the dynamic ARDL (DYNARDL) simulations model will be used. This technic is recently developed by (Jordan and Philips, 2018) that can efficiently predict, stimulate and immediately plot probabilistic forecasts on the dependent variable due to changes (positive or negative) in one explanatory variable while holding the others constant.

The DYNARDL simulations model is presented as follows

$$\Delta PI_t = \mu + \alpha_1 ICT_{t-1} + \beta_1 \Delta ICT_{t-1} + \alpha_2 X_{t-1} + \beta_2 \Delta X_{t-1} + \varepsilon_t. \quad (6)$$

To address the shortcomings and to better interpret the results, the DYNARDL as introduced in Eq.(6) is used. Table A5 in Annex shows the empirical DYNARDL estimation results by country.[3]

While keeping other explanatory variables constant, the DYNARDL automatically plot the forecasts of ICT change and its impact on the dependent variable PI. The effect of ICT is

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

[2] That can only estimate and explore the short- and long-run relationships between the variables.

[3] Looking at Table A5,

- From Panel A, the short-run results are not consistent with those of the long run in the Brazil case. Indeed, the short-run (long-run) evidence affirmed that ICT has a negative (positive) impact on the PI. As such, there is a need for more ICT investment to curb firm performance
- From Panel B, the short-run results are consistent with those of the long run in the Indian case. Indeed, in both short and long-run, ICT has positive effect on PI.
- From Panel C, the short-run results are consistent with those of the long run in the Chinese case. Indeed, in both short and long-run, ICT has negative effect on PI
- From Panel D, SA results are similar to those of China case.

forecasted to 1% increase for each country. The simulation results are presented in Figure 2 (a) for Brazil, Figure 2 (b) for India, Figure 2(c) for China and Figure 2(d) for SA.

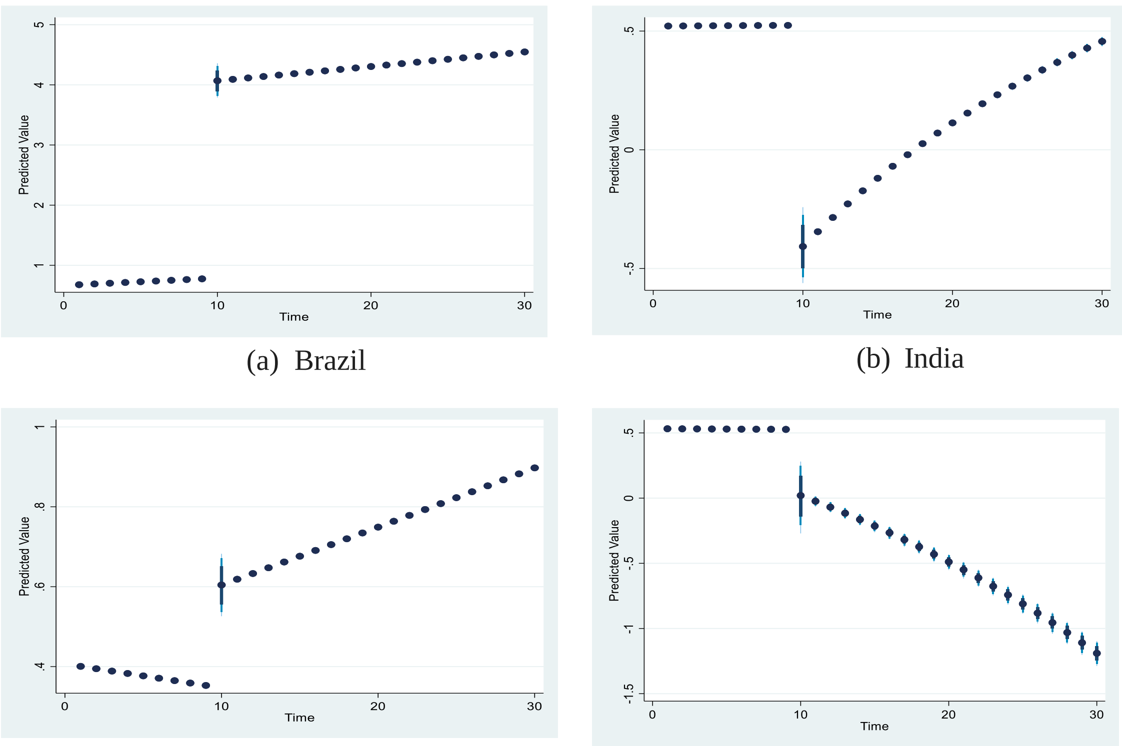
Figure 2 (a) shows the IRF of the relationship between ICT and PI in Brazil. The plot suggests that a rise in ICT *will* contribute to the improvement of the firm performance in both the SR and the LR.

From Figure 2 (b), the IRF plot shows the results for India are similar to those of Brazil case.

For China case, the IRF plot is showed at Figure 2 (c). It is clear that a rise in ICT will deteriorate the performance firm quality in SR, whereas ICT will improve the performance in the LR in China as proved by the BVAR model. The result is also in line with a group of academics whose have found that countries with high levels of ICT benefit the most for their firms (???).

Figure 2 (d) shows the IRF plot of the relationship between ICT and PI in SA. It is clear that a rise in ICT will contribute to deteriorate the firm performance quality in both the SR and the LR in SA.

Again, we note that these findings related to the impact of ICT on the Fintech firm profitability are limited since the discussion was only specific in terms of whether ICT provides a positive or negative impact on the firm profitability. Then, it needs to be explored further regarding which ICT domain could support the firm. As done in the previous section, we re-estimate Eq.(6) to see which component of the ICT drives the firm profitability. Estimation results in details are not reported here. Only IRF's results are illustrated at Figure B5 (in the Appendix). Looking at Figure B5, we conclude that positive relationship is driven by MCS for Brazil in the SR and LR, by IUI for China in the LR, by FBS for SA in the SR, and by MSC and FBS for the India case in the SR and LR.



(a) Brazil

(b) India

(c) China

(d) SA

Figure 2: The impulse response plots for PI predictive reaction.

Legend: Dots specify average prediction value. The dark blue to light blue line denotes 75, 90, and 95% confidence interval, respectively. Source: Figures created by authors.

In addition, looking at Table A5 (in Annex), it is clear that:

- In the LR,
    - GDPG has positive (negative) effect in Brazil and SA (India and China).
    - CR has positive (negative) effect in Brazil (India and China).
    - LCTE has positive (negative) effect in India (Brazil and China).
    - LTDCE has positive (negative) effect in China (Brazil and India).
    - LTDTC has positive (negative) effect in Brazil and India (China).
    - INF and LA have negative effect in SA.
- In the SR,
    - GDPG has positive (negative) effect in India and SA (Brazil and China).
    - CR has positive (negative) effect in India (Brazil and China).
    - LCTE has positive (negative) effect in Brazil and China (India).
    - LTDCE has positive (negative) effect in Brazil and India (China).
    - LTDTC has positive (negative) effect in China (Brazil and India).
    - INF has positive effect and
    - LA has negative effect in SA

4.3 Robustness check

For robustness check of our results, we propose to use the Frequency domain causality (FDC) Granger test (Breitung & Candelon, 2006) to explore the direction of causality between variables in different frequency (short-, medium- and long-run). Results are summed up at Figure B6 in Appendix by country; Panel A for Brazil, Panel B for India, Panel C for China, and Panel D for SA. Only significant results are presented.

Looking at Figure B6, in accordance with BVAR-X estimation results, it is clear that PI (ROA and/or ROE) can be predicted by ICT (or some of its components) in SR for all considered countries. Only China's PI which can predicted in all frequency, short-, medium- and long-term.

This study considers also a causality tests focusing on the Granger causality in quantile (GCQ) as a nonparametric approach (Song & Taamouti, 2020) to detect and quantify *both linear and nonlinear causal effects between variables*.

In a first step, the (Brock, Dechert, Scheinkman, & LeBaron, 1996) (henceforth BDS) test for time based dependence in a series is used for testing against a variety of possible deviations from independence including linear dependence, non-linear dependence, or chaos.

Based on the results presented in Table A6 in Annex (by country), the null hypothesis of i.i.d. series is rejected at all embedding dimensions (m) and for each country, implying that nonlinear behavior can be appropriate for the considered series.

Henceforth, GCQ test is applied and the results are illustrated at Figure B7 (in Appendix) by country; Panel A for Brazil, Panel B for India, Panel C for China, and Panel D for SA. Looking at Figure B7, in accordance with previous results, we conclude that firm performance is predictable in the three quantiles: low, central and height quantiles for Brazil, India and China cases, and in only the low and height quantiles for SA case.

5. Conclusions and political recommendations

The impact of the ICT on firms has been widely discussed in many studies. Regarding the role of ICT on firm performance, researchers have reported mixed results depending on the type of data, the research methodology employed and the geographical configuration considered (emerging vs developed countries).

It was needed to reveal, in what facet of firm performance and with which component ICT could play a significant role. A micro- and macro-side literature review was conducted to get a comprehensive perspective regarding the role of ICT on Firm Performance. This research contributes by providing a country macro side on the role of ICT on FinTech firm performance. This paper explores the LR and SR impact of the ICT on Fintech firm profitability for BRICS countries (except Russia). The analysis employs a panel of 316 FinTech firms. It uses the yearly level time series data: (average by firm for each country) converted by interpolation to monthly time series data from 2014M01 to 2022M12 for each country, and then different adequate econometric technics are applied.

In this study, we adopt two time series based models for each country side. The first is the stationary bivariate VAR-X type model for stationary (SL2) variables. Specifically, the Bayesian version, which assume that all the parameters are random variables is used. Following the estimation of the augmented BVAR (Bayesian VAR-X) model, the analysis computes impulse response functions (IRFs) to track the role of the ICT effect on FinTech firm profitability during 2014M01-2022M12. And, in a second step we apply the DYNARDL simulation technic for mixed processes. For robustness check, we use FDG and QGC tests.

We found compelling evidence to support the positive effects of ICTs on the firm performance. Moreover, we found that ICT drives the overall profitability of the FinTech firms, which implies that if these countries seek to enhance their firm performance, they need to implement specific policies that facilitate investment in ICT.

This type of study is quite rare in the context of BRICS. This paper makes three major contributions to the literature:

- First, it is one of the few studies that have used the macro firm performance index (profitability) regarding the ICT use in a country or a group of countries.
- Second, the paper focuses explicitly on country level that is highly relevant in the short- and long-term investigations.
- Finally, these investigations provide empirical evidence in the BRICS context about the effect of ICTs on firm performance.

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.

BRICS members need to consider not just technical resources when analyzing the role of ICT technologies and the digital economy for their respective FinTech firm performance development, but to take into consideration also the socio-economic and human capital aspects.

Notes:

1. 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).
2. From STATA 17 package, the graphical summary for the ICT parameters do not show any obvious problems. Because of space limitation, the trace plot and the histogram and kernel density plots are not reported here but are available upon request.
3. All lags selections will be based on the lowest value of the Akaike Information Criterion (AIC).
4. 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). 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.
5. That can only estimate and explore the short- and long-run relationships between the variables.

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	
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. Source: Author's calculations.

Table A2: Summary statistics and correlation analysis

Panel A. Summary statistics

BRAZIL	PI	ICT	LCTE	CR	LTDCE	LTDTC	LA	GDPG	INF
Mean	0.435497	0.390366	1.535090	2.208278	1.387596	1.190236	13.38734	0.002914	0.025888
Maximum	0.684173	0.601345	2.239161	4.798351	2.153308	1.752368	14.87321	0.058777	0.040409
Minimum	0.091925	0.294995	0.887996	0.638160	0.002101	-0.046243	11.83346	-0.041370	0.010888
Std. Dev.	0.193178	0.078901	0.308527	1.204023	0.647827	0.544171	0.988182	0.030760	0.011305
Observations	108	108	108	108	108	108	108	108	96
INDIA									
Mean	0.523276	0.351543	2.736457	3.426077	2.324514	2.108840	14.82709	5.667778	0.020803
Maximum	0.652092	0.457729	3.174515	4.118549	2.615442	2.390772	15.29298	10.96575	0.034781
Minimum	0.404511	0.155890	2.455224	2.716008	2.104374	1.896569	14.30114	-6.978773	0.013598
Std. Dev.	0.055789	0.058386	0.199775	0.411489	0.128267	0.120630	0.189552	4.542141	0.005607
Observations	108	108	108	108	108	108	108	108	84
CHINA									
Mean	0.523975	0.481669	3.870260	3.239039	3.021382	2.550854	14.47826	6.072222	0.008558
Maximum	0.755324	0.755723	3.935430	4.002672	3.334582	2.758335	14.96282	8.938368	0.013477
Minimum	0.212144	0.207531	3.819392	2.946983	2.687505	2.317307	13.53481	-2.929757	0.003773
Std. Dev.	0.153467	0.189826	0.032324	0.251350	0.229735	0.159254	0.430952	2.274927	0.002711
Observations	108	108	108	108	108	108	108	108	84
SA									
Mean	0.585799	0.408470	3.279570	2.746521	2.418634	2.125650	14.32342	0.775556	0.021309
Maximum	0.833790	0.590658	3.766988	5.695100	3.255078	2.827486	14.68001	6.115741	0.035315
Minimum	0.435128	-0.008281	2.826494	1.362255	1.576086	1.337563	13.75870	-7.228600	0.013269
Std. Dev.	0.104164	0.145642	0.292883	1.034229	0.418975	0.382154	0.231947	3.057393	0.005533
Observations	108	108	108	108	108	108	108	108	84

Panel B. Correlation matrix of main variables

BRAZIL	PI	ICT	LCTE	CR	LTDCE	LTDTC	LA	GDPG	INF
PI	1.000000								
ICT	-0.137468	1.000000							
	0.1817	-----							
LCTE	-0.718253	-0.411608	1.000000						
	0.0000	0.0000	-----						
CR	-0.669919	-0.263513	0.710126	1.000000					
	0.0000	0.0095	0.0000	-----					
LTDCE	0.873517	0.290699	-0.854239	-0.700642	1.000000				
	0.0000	0.0041	0.0000	0.0000	-----				
LTDTC	0.867904	0.277987	-0.819089	-0.689520	0.997033	1.000000			
	0.0000	0.0061	0.0000	0.0000	0.0000	-----			
LA	-0.758185	0.079680	0.690756	0.287509	-0.623999	-0.590967	1.000000		
	0.0000	**0.4403**	0.0000	0.0045	0.0000	0.0000	-----		
GDPG	-0.336538	-0.363015	0.450425	0.034183	-0.465248	-0.457196	0.333726	1.000000	
	0.0008	0.0003	0.0000	**0.7409**	0.0000	0.0000	0.0009	-----	
INF	-0.538275	0.767676	-0.076527	-0.154427	-0.182858	-0.199290	0.538349	0.004956	1.000000
	0.0000	0.0000	**0.4586**	**0.1330**	**0.0745**	**0.0516**	0.0000	**0.9618**	-----

INDIA	PI	ICT	LCET	CR	LTDCE	LTDTC	LA	GDPG	INF
PI	1.000000								
ICT	-0.522862	1.000000							
	0.0000	-----							
LCET	-0.359494	-0.300199	1.000000						
	0.0008	0.0055	-----						
CR	-0.753078	0.174419	0.248323	1.000000					
	0.0000	**0.1126**	0.0227	-----					
LTDCE	-0.562696	0.286411	-0.110506	0.284211	1.000000				
	0.0000	0.0083	**0.3170**	0.0088	-----				
LTDTC	-0.645837	0.325309	-0.016814	0.339457	0.992656	1.000000			
	0.0000	0.0025	**0.8793**	0.0016	0.0000	-----			
LA	-0.382183	-0.422663	0.622186	0.723556	-0.124233	-0.068153	1.000000		
	0.0003	0.0001	0.0000	0.0000	**0.2602**	0.5379	-----		
GDPG	0.633023	-0.262962	0.243779	-0.748528	-0.736803	-0.728832	-0.254483	1.000000	
	0.0000	0.0157	0.0254	0.0000	0.0000	0.0000	0.0195	-----	
INF	-0.568561	-0.174191	0.601024	0.453337	0.609931	0.658863	0.403311	-0.429345	1.000000
	0.0000	**0.1130**	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	-----

CHINA	PI	ICT	LCET	CR	LTDCE	LTDTC	LA	GDPG	INF
PI	1.000000								
ICT	-0.867836	1.000000							
	0.0000	-----							
LCET	-0.091965	0.290473	1.000000						
	0.4054	0.0074	-----						
CR	0.499385	-0.739413	0.048942	1.000000					
	0.0000	0.0000	**0.6584**	-----					
LTDCE	-0.786442	0.955411	0.390380	-0.753571	1.000000				
	0.0000	0.0000	0.0002	0.0000	-----				
LTDTC	-0.821896	0.971271	0.263932	-0.785722	0.989483	1.000000			
	0.0000	0.0000	0.0153	0.0000	0.0000	-----			
LA	-0.911395	0.969000	0.287863	-0.648011	0.950313	0.962494	1.000000		
	0.0000	0.0000	0.0079	0.0000	0.0000	0.0000	-----		
GDPG	0.353708	-0.396178	-0.402500	-0.165312	-0.211282	-0.212368	-0.370114	1.000000	
	0.0010	0.0002	0.0001	**0.1329**	**0.0537**	**0.0525**	0.0005	-----	
INF	0.225390	0.091834	0.395335	0.063685	-0.020057	-0.041722	-0.089810	-0.614794	1.000000
	0.0393	**0.4061**	0.0002	**0.5649**	**0.8563**	**0.7063**	**0.4165**	0.0000	-----

SA	PI	ICT	LCET	CR	LTDCE	LTDTC	LA	GDPG	INF
PI	1.000000								
ICT	-0.747368	1.000000							
	0.0000	-----							
LCET	-0.823823	0.762087	1.000000						
	0.0000	0.0000	-----						
CR	-0.043665	0.505713	0.411051	1.000000					
	0.6933	0.0000	0.0001	-----					
LTDCE	0.235071	-0.693278	-0.409696	-0.725173	1.000000				
	0.0314	0.0000	0.0001	0.0000	-----				
LTDTC	0.188508	-0.686369	-0.360680	-0.756743	0.993411	1.000000			
	0.0859	0.0000	0.0008	0.0000	0.0000	-----			
LA	0.498535	-0.352484	-0.568423	0.115158	-0.103137	-0.109495	1.000000		
	0.0000	0.0010	0.0000	**0.2969**	**0.3505**	**0.3214**	-----		
GDPG	0.332871	0.126953	-0.130617	0.166696	-0.153869	-0.164346	0.301410	1.000000	
	0.0020	**0.2498**	**0.2363**	**0.1296**	**0.1623**	**0.1352**	0.0053	-----	
INF	0.521250	-0.437605	-0.321022	0.209393	0.366592	0.337985	0.508023	0.386000	1.000000
	0.0000	0.0000	0.0029	0.0559	0.0006	0.0017	0.0000	0.0003	-----

Note: * 5% significance level.

Source: Author's calculations.

Table A3: The BVAR-X model Eq. (4) estimation Results (dep var: PI)

	Brazil		India		China		SA	
PI_{-1}	0.032342	[2.64845]	0.342962	[6.35634]	0.938886	[22.0020]	0.889221	[20.0481]
PI_{-2}					0.090643	[2.15345]	0.084824	[2.03227]
PI_{-3}					-0.010024	[-0.34723]	-0.012382	[-0.43548]
ICT_{-1}	0.243613	[7.69461]	0.830506	[3.98837]	0.083927	[2.28811]	0.001931	[0.11962]
ICT_{-2}					0	[-0.84539]	0	[-0.33570]
ICT_{-3}					0	[-1.79592]	0	[-0.56437]
C	0.547348	[24.5067]	-4.671998	[-3.55911]				
GDPG	-0.750401	[-57.2810]						
INF	-11.75600	[-38.1101]	7.006465	[5.14048]				
LA	0.021099	[8.43304]	0.365398	[4.01038]	-0.001726	[-2.51351]		
LCTE	-0.093726	[-9.94741]	-0.024737	[-0.91999]				
CR	-0.071679	[-99.6981]	-0.127307	[-5.41880]	0.000738	[0.34813]	0.003591	[4.26910]
LTDCE	0.423676	[47.9858]	3.097888	[5.15475]			0.005509	[3.76211]
LTDTC	-0.415405	[-41.5481]	-3.591728	[-5.32752]				
R^2	0.999988		0.985770		0.999614		0.995177	
Adj. R^2	0.999986		0.984253		0.999586		0.994829	
F-statistic	767923.3		649.4600		35901.01		2859.189	

Note: [.] is the t of Student. Source: author' calculation. Source: Author's calculations.

Table A4: Sum up of the ARDL specifications results

Panel A: **LR effect of** ICT

Country and selected models	
Brazil: ARDL(1, 0)	0.394410 (0.0000)
India: ARDL(2, 0)	1.859491 (0.0000)
China: ARDL(4, 0)	-3.426898 (0.0000)
SA: ARDL(2, 1)	-0.662134 (0.0000)

Panel B: **SR effect of** ICT

Country and selected models	Dep var PI
Brazil: ARDL(1, 0)	No effect
India: ARDL(2, 0)	No effect
China: ARDL(4, 0)	No effect
SA: ARDL(2, 1)	-0.662133 (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: φ = 0 vs H_1: φ < 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.

Table A5: DYNARDL simulations estimation results.

Panel A : Brazil case

	Long-run			Short-run	
Variables	**Coef.**	**Std. Err.**	**Variables**	**Coef.**	**Std. Err.**
PI_{-1}	.0030679	.0000287			
ICT_{-1}	**-.0105944***	**.0000438**	ΔICT	**2.188906***	**.0044117**
$GDPG_{-1}$	.0236098*	.0001018	ΔGDPG	-6.474638*	.0045074
CR_{-1}	.0004088*	3.02e-06	ΔCR	-.1003121*	.0001595
$LCTE_{-1}$	-.0059201*	.0000282	ΔLCTE	1.671786*	.0007896
$LTDCE_{-1}$	-.0195069*	.0000842	ΔLTDCE	5.437032*	.0027651
$LTDTC_{-1}$	.0149852*	.0000608	ΔLTDTC	-4.027583*	.0027325
			cons	.0549108*	.0000542
Diagnostic statistics	R^2	1.0000	Adj R^2 1.0000		
	T	107	P-val of F (0.0000)		
	Simulations	1000			

Panel B: India case

	Long-run			Short-run	
Variables	**Coef.**	**Std. Err.**	**Variables**	**Coef.**	**Std. Err.**
PI_{-1}	.0134314*	.0006099			
ICT_{-1}	**.0319029***	**.0026938**	ΔICT	**.0319029***	**.0026938**
$GDPG_{-1}$	-.0003406*	7.94e-06	ΔGDPG	.0168281*	.0001302
CR_{-1}	-.0018244 *	.0000448	ΔCR	.07738*	.0007761
$LCTE_{-1}$	.0037838*	.0000875	ΔLCTE	-.2133465*	.0008762
$LTDCE_{-1}$	-.0705515*	.0022221	ΔTDCE	4.458484*	.0136144
$LTDTC_{-1}$	.0702365*	.0023352	ΔLTDTC	-4.589796*	.0112848
			cons	.0079868*	.0002641
Diagnostic statistics	R^2	1.0000	Adj R^2 1.0000		
	T	107	P-val of F (0.0000)		
	Simulations	1000			

Panel C: China case

Long-run			Short-run		
Variables	**Coef.**	**Std. Err.**	**Variables**	**Coef.**	**Std. Err.**
PI_{-1}	.0029239*	.0002767			
ICT_{-1}	**-.0083929***	**.0008226**	ΔICT	**-.1379854***	**.0057698**
$GDPG_{-1}$	-.0001089*	.0000112	ΔGDPG	-.0035399*	.0000484
CR_{-1}	-.0016865*	.0001797	ΔCR	-.0014053*	.0009937
$LCTE_{-1}$	-.0167918*	.0012735	ΔLCTE	.7169228*	.0111741
$LTDCE_{-1}$	.0118795*	.0014444	ΔTDCE	-.3255516*	.0123325
$LTDTC_{-1}$	-.013169*	.0025346	ΔLTDTC	.8819676*	.019923
			cons	.065033*	.0066247
Diagnostic statistics	R^2 0.9996		Adj R^2 0.9995		
	T 107		P-val of F (0.0000)		
	Simulations	1000			

Panel D: SA case

Long-run			Short-run		
Variables	**Coef.**	**Std. Err.**			
PI_{-1}	.0330775*	.0301706			
ICT_{-1}	**-.0268471***	**.0155188**	ΔICT	**-.5024138***	**.1472687**
$GDPG_{-1}$	.0004937*	.0002674	ΔGDPG	.0064624*	.0019062
INF_{-1}	-.3085411*	3775077	ΔINF	8.019418*	3.186174
LA_{-1}	-.0262261*	.0056349	ΔLA	-.0399416*	.0365784
			cons	.3784013*	.0769645
Diagnostic statistics	R^2 0.6384		Adj R^2 0.5939		
	T 107		P-val of F (0.0000)		
	Simulations	1000			

Note: * , ** and *** denote statistical significance at 1%, 5% and 10% levels, respectively. The dynamic ARDL error correction algorithm uses 1000 simulations.
Source Authors' calculations by STATA 17.

Table A6: BDS test for nonlinearity

Panel A: Brazil case

Variables	Dimension m =	2	3	4	5	6
PI	BDS Statistic	0.196244	0.329567	0.419641	0.480202	0.520989
ROA	BDS Statistic	0.184690	0.307717	0.384997	0.430210	0.453633
ROE	BDS Statistic	0.190286	0.317700	0.399336	0.447410	0.472776
ICT	BDS Statistic	0.207788	0.354801	0.458073	0.529934	0.579378
MCS	BDS Statistic	0.207822	0.353684	0.455799	0.527415	0.577398
IUI	BDS Statistic	0.209053	0.353567	0.453578	0.523049	0.571285
FBS	BDS Statistic	0.197679	0.331478	0.423662	0.487942	0.533601

Panel B: India case

Variables	Dimension m =	2	3	4	5	6
PI	BDS Statistic	0.193297	0.324816	0.411908	0.466963	0.499051
ROA	BDS Statistic	0.195715	0.330870	0.422446	0.483090	0.521794
ROE	BDS Statistic	0.196964	0.332915	0.424855	0.485978	0.523259
ICT	BDS Statistic	0.178441	0.290813	0.362732	0.412029	0.444744
MCS	BDS Statistic	0.189322	0.314593	0.398710	0.455773	0.494931
IUI	BDS Statistic	0.192156	0.322176	0.408170	0.463383	0.497135
FBS	BDS Statistic	0.192332	0.324221	0.413060	0.471198	0.506497

Panel C: China case

Variables	Dimension m =	2	3	4	5	6
PI	BDS Statistic	0.199211	0.334372	0.427691	0.493455	0.540498
ROA	BDS Statistic	0.197652	0.331875	0.424621	0.489660	0.536097
ROE	BDS Statistic	0.200058	0.337112	0.430682	0.495706	0.540555
ICT	BDS Statistic	0.206380	0.349125	0.448352	0.517784	0.566632
MCS	BDS Statistic	0.205604	0.347529	0.445473	0.513260	0.560130
IUI	BDS Statistic	0.203435	0.342949	0.439659	0.507304	0.555190
FBS	BDS Statistic	0.202949	0.343745	0.442212	0.512424	0.563566

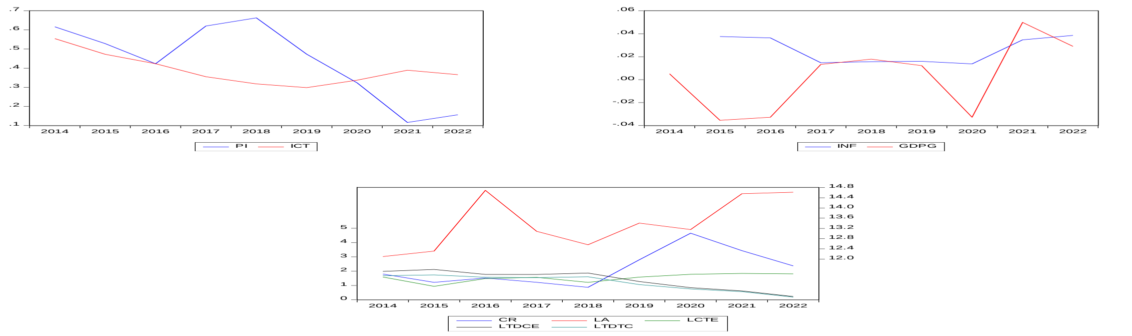
Panel D: SA case

Variables	Dimension m =	2	3	4	5	6
PI	BDS Statistic	0.204582	0.346761	0.443910	0.508735	0.550805
ROA	BDS Statistic	0.183610	0.301106	0.376940	0.428586	0.462477
ROE	BDS Statistic	0.188637	0.314920	0.399525	0.455809	0.492060
ICT	BDS Statistic	0.197459	0.333081	0.424291	0.484035	0.521316
MCS	BDS Statistic	0.194426	0.327094	0.415348	0.471925	0.505977
IUI	BDS Statistic	0.178009	0.290285	0.360574	0.403500	0.428176
FBS	BDS Statistic	0.194080	0.323955	0.411146	0.469882	0.509117

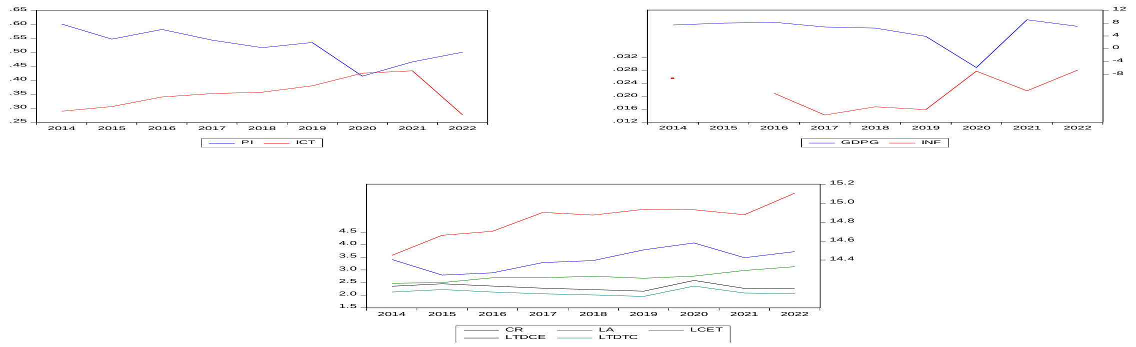
Note p-value = 0.000 for all cases.

Source: Author's calculations

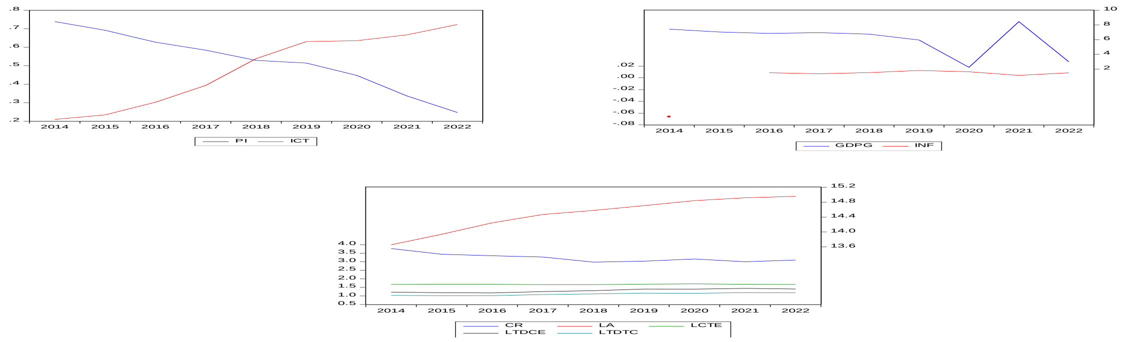
Appendix: Some Figures



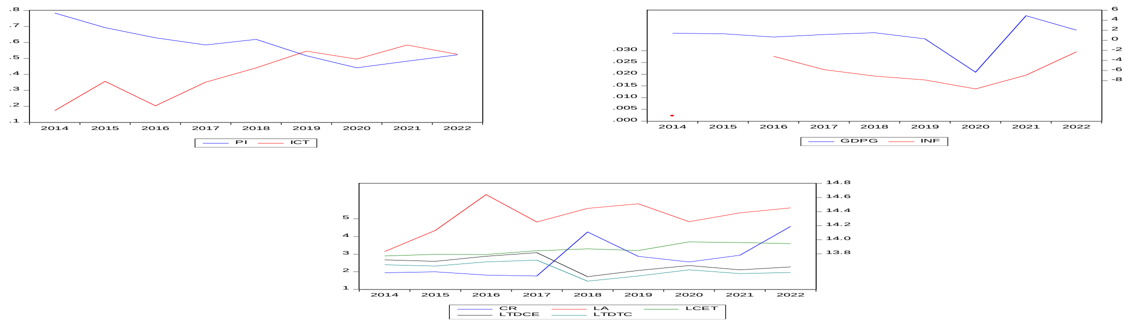
(a) Case of BRAZIL



(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

Source: Author's calculations.

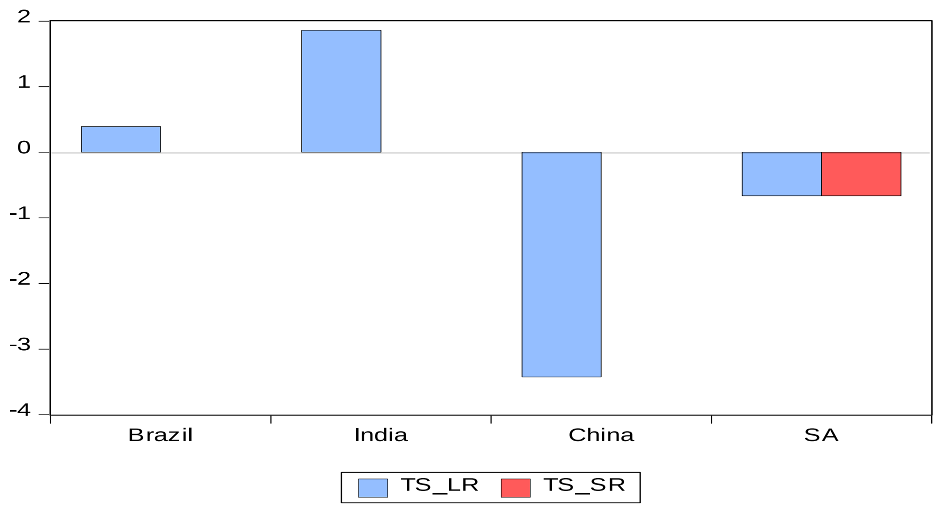


Figure B2: Sum up of reactions to ICT in LR vs SR by country based on Eq. (5)

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

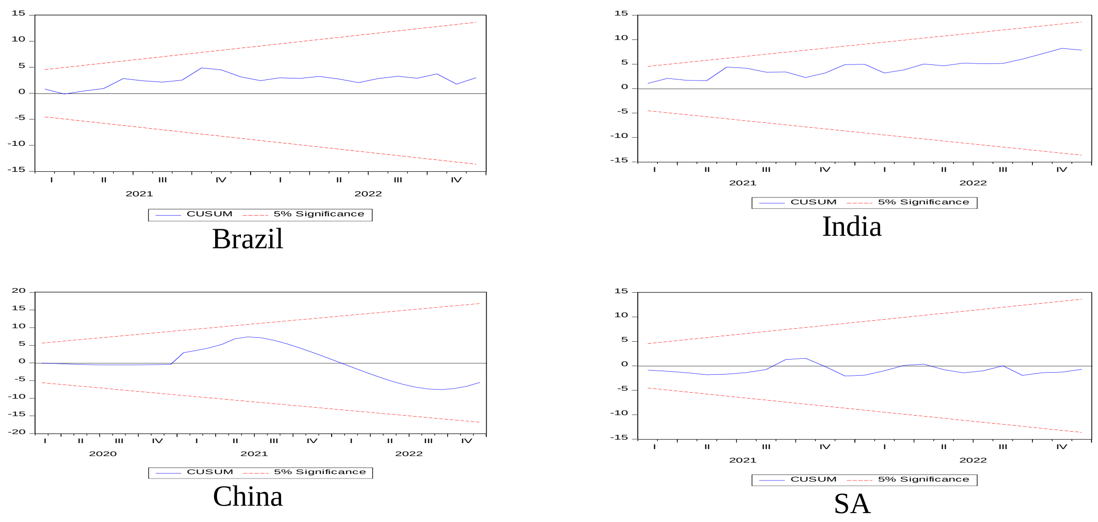
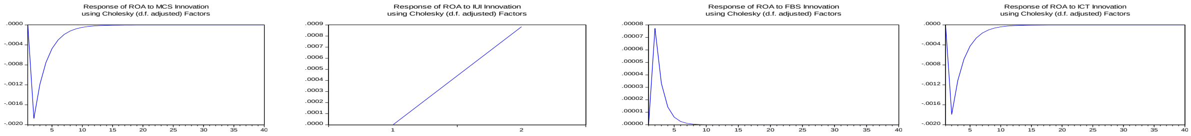


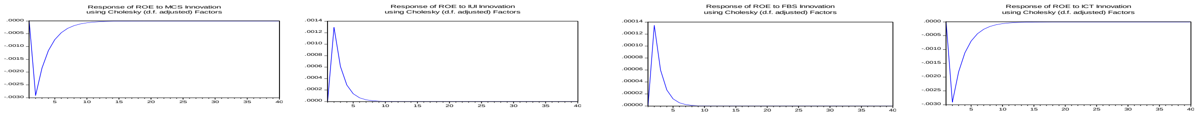
Figure B3: Stability verification for the ARDL specifications

Source: Author's calculations.

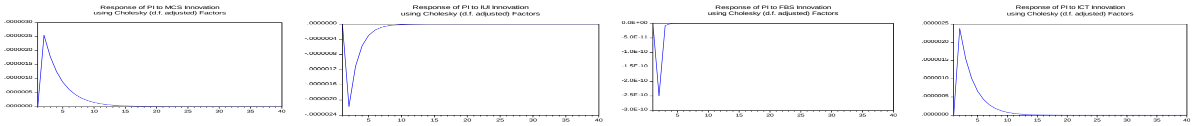
Mobile cellular subscriptions (MCS)	Individuals using the Internet (IUI)	Fixed broadband subscriptions (FBS)	ICT



Dep var ROA



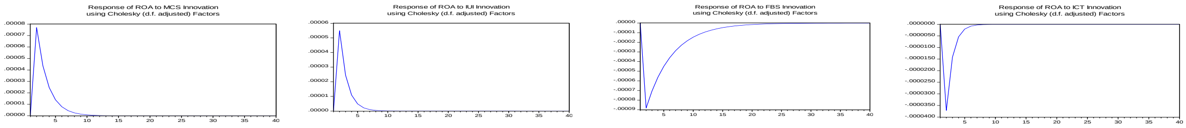
Dep var ROE



Dep var PI

Panel A: the Brazil case

Mobile cellular subscriptions (MCS)	Individuals using the Internet (IUI)	Fixed broadband subscriptions (FBS)	ICT



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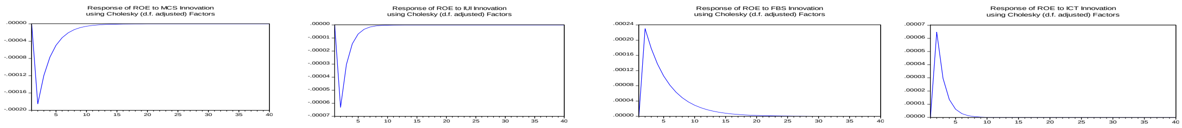

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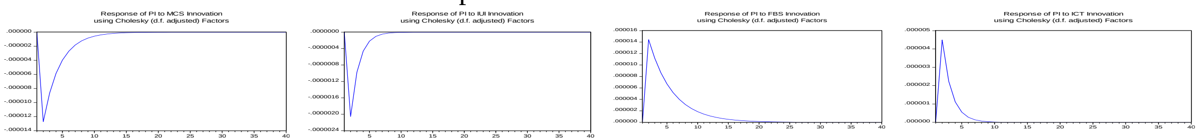
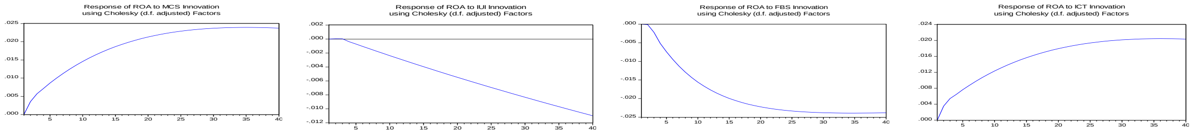


Dep var PI

Panel B: the India case

Mobile cellular subscriptions (MCS)	Individuals using the Internet (IUI)	Fixed broadband subscriptions (FBS)	ICT



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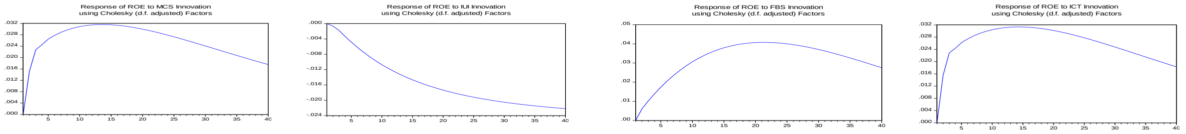

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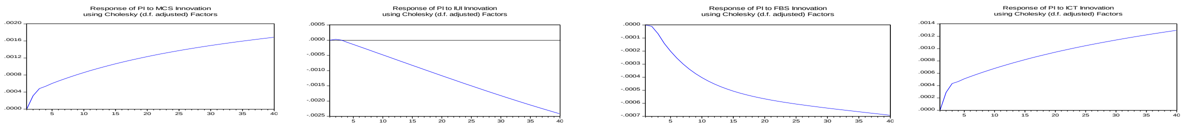
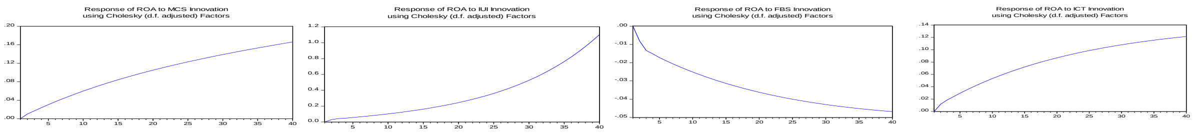


Dep var PI

Panel C: the China case

Mobile cellular subscriptions (MCS)	Individuals using the Internet (IUI)	Fixed broadband subscriptions (FBS)	ICT



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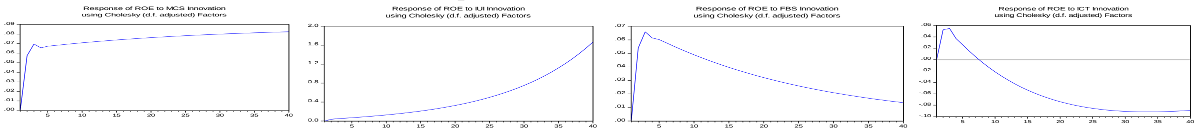

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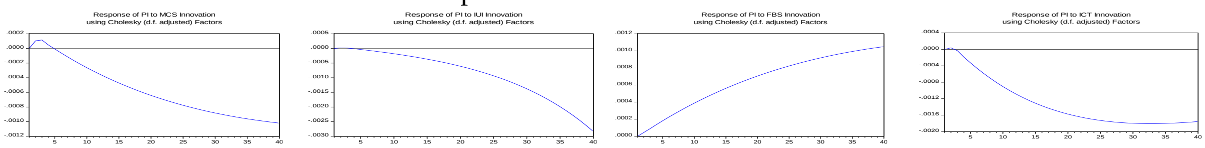


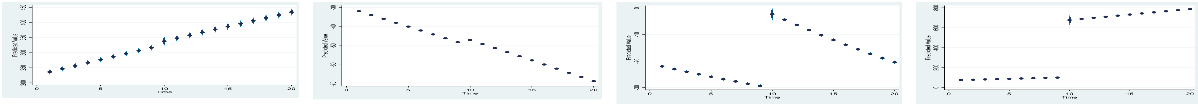
Dep var PI

Panel D: the SA case

Figure B4: IRFs from BVAR models

Source: Author’s calculations.

Mobile cellular subscriptions (MCS)	Individuals using the Internet (IUI)	Fixed broadband subscriptions (FBS)	ICT



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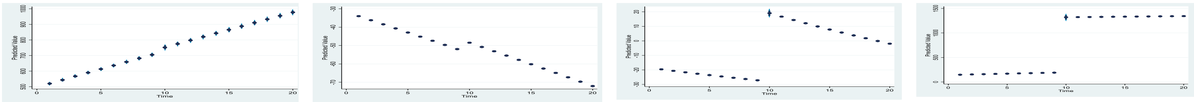

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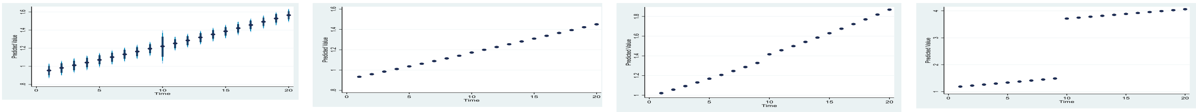
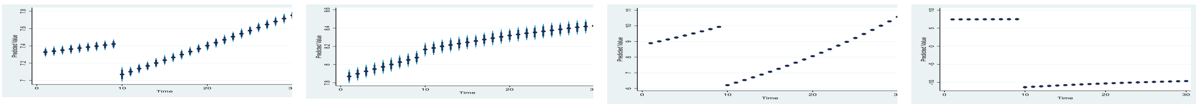


Dep var PI

Panel A: the Brazil case

Mobile cellular subscriptions (MCS)	Individuals using the Internet (IUI)	Fixed broadband subscriptions (FBS)	ICT



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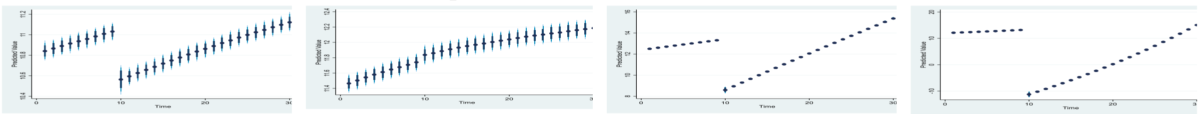

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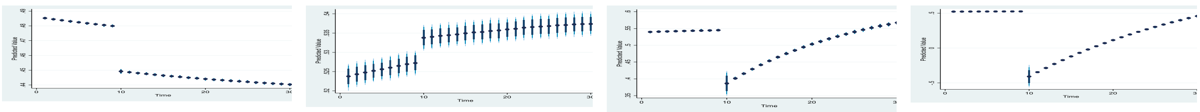
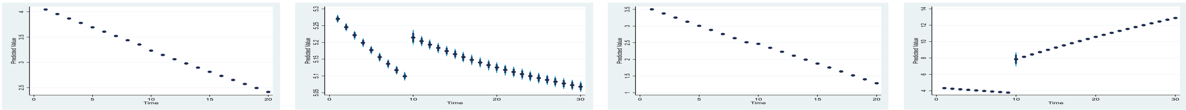


Dep var PI

Panel B: the India case

Mobile cellular subscriptions (MCS) | Individuals using the Internet (IUI) | Fixed broadband subscriptions (FBS) | ICT



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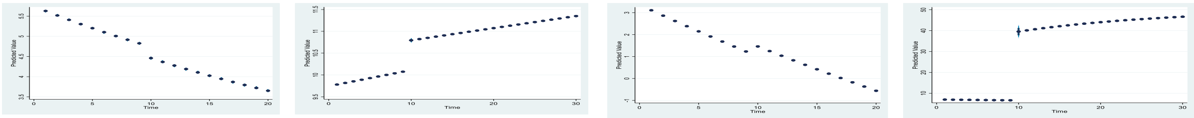

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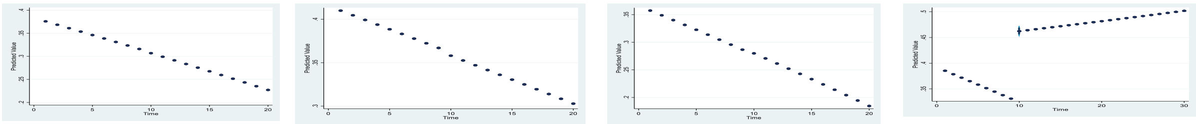
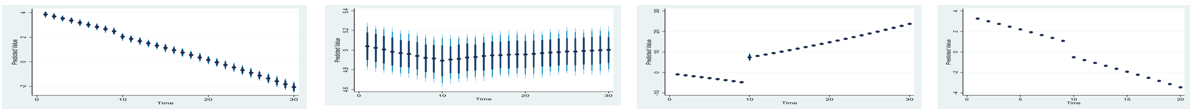


Dep var PI

Panel C: the China case

Mobile cellular subscriptions (MCS) | Individuals using the Internet (IUI) | Fixed broadband subscriptions (FBS) | ICT



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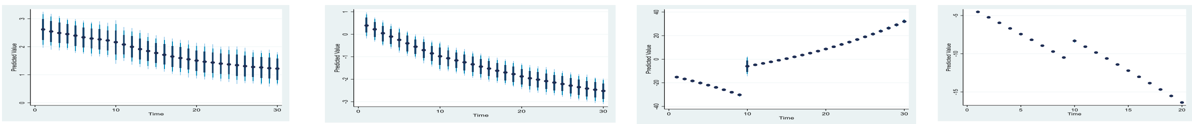

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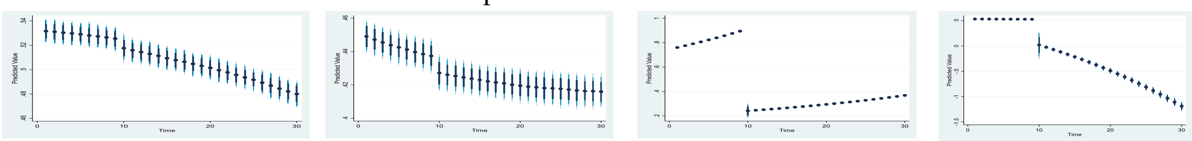
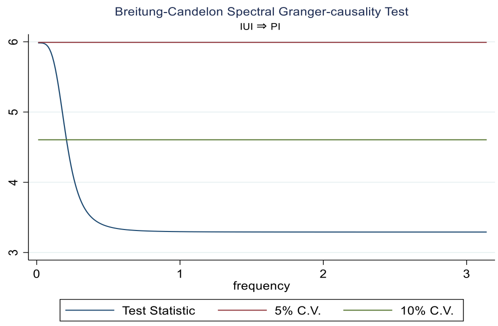


Dep var PI

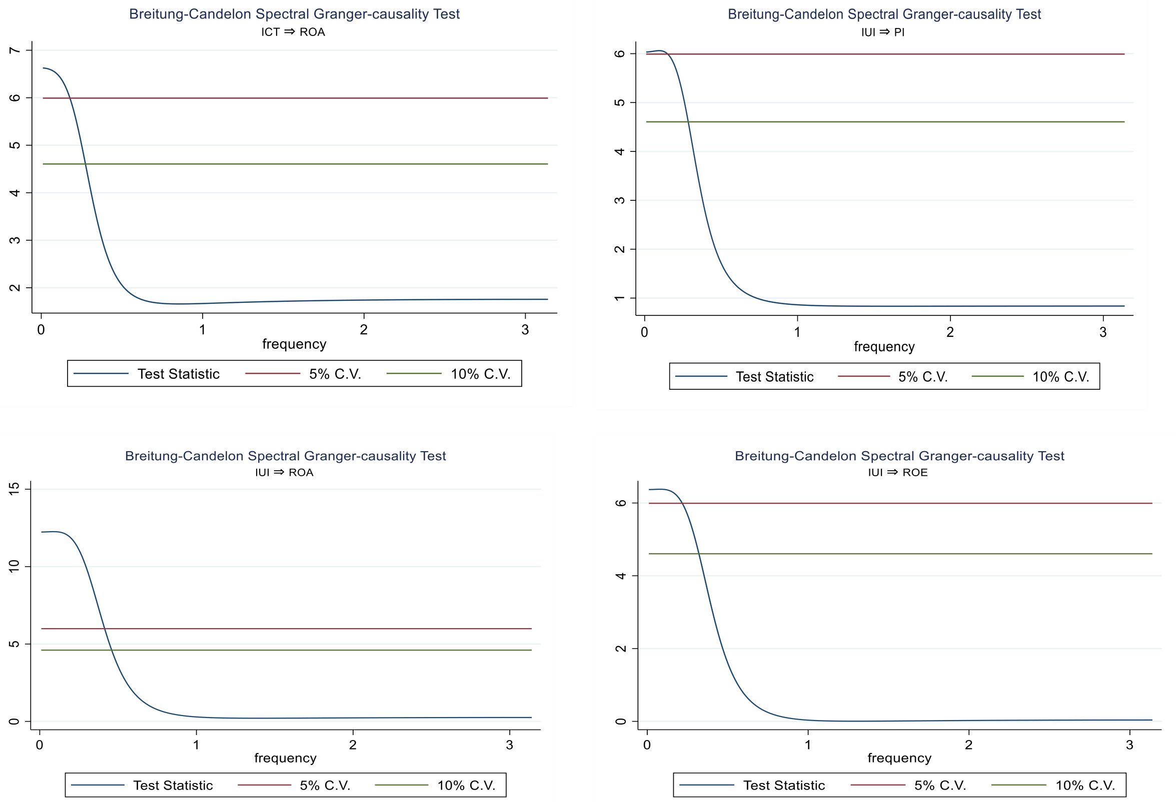
Panel D: the SA case

Figure B5: IRFs from DYNARDL models

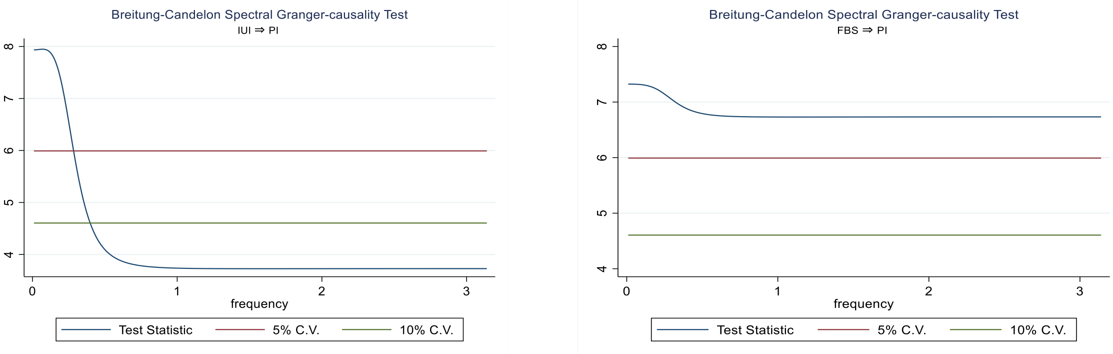
Source: Author’s calculations.

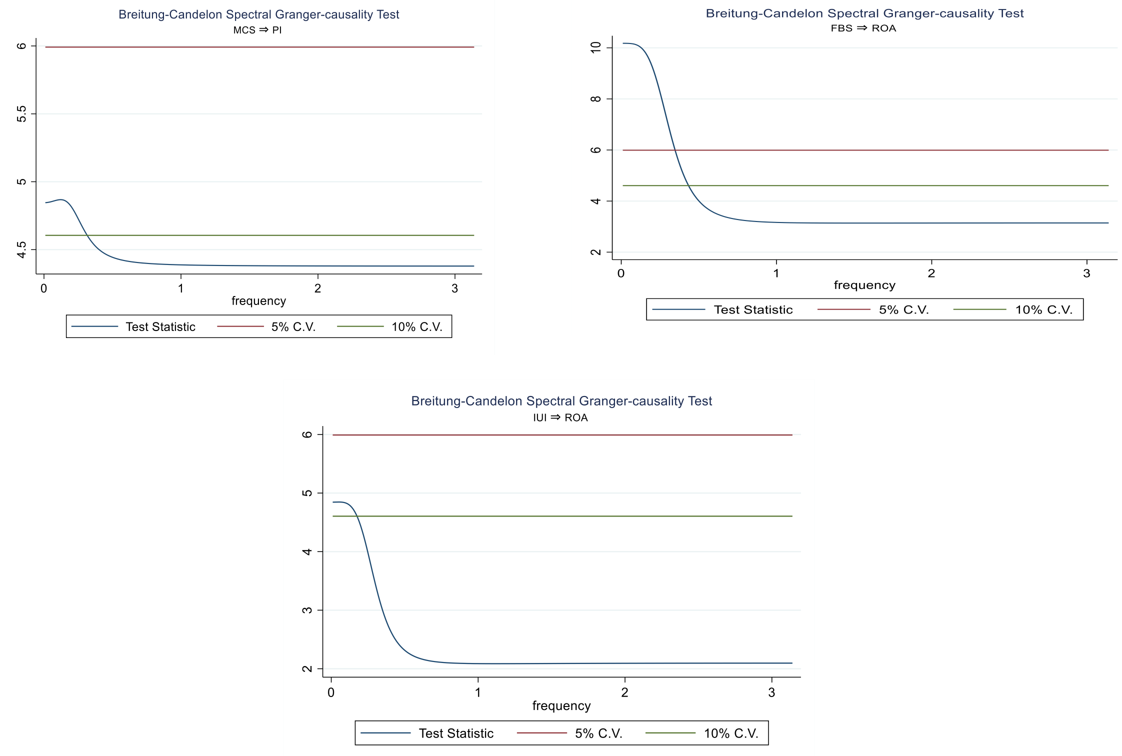


(a) Brazil case

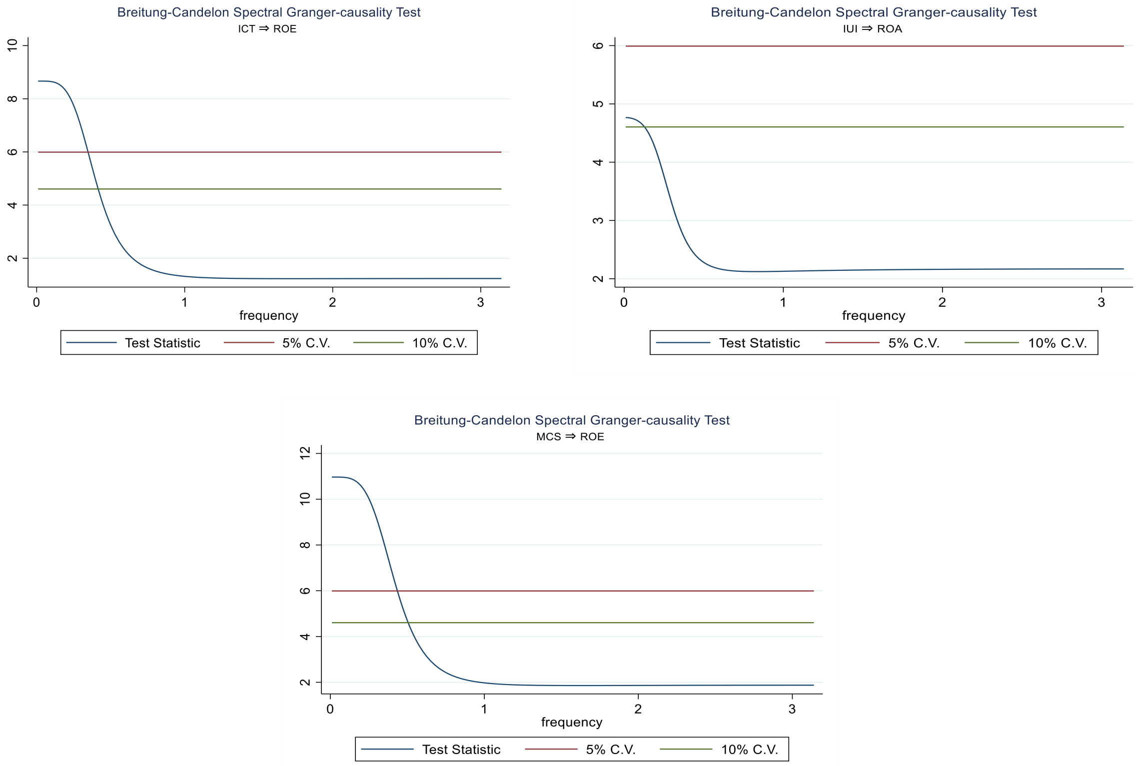


(b) India case





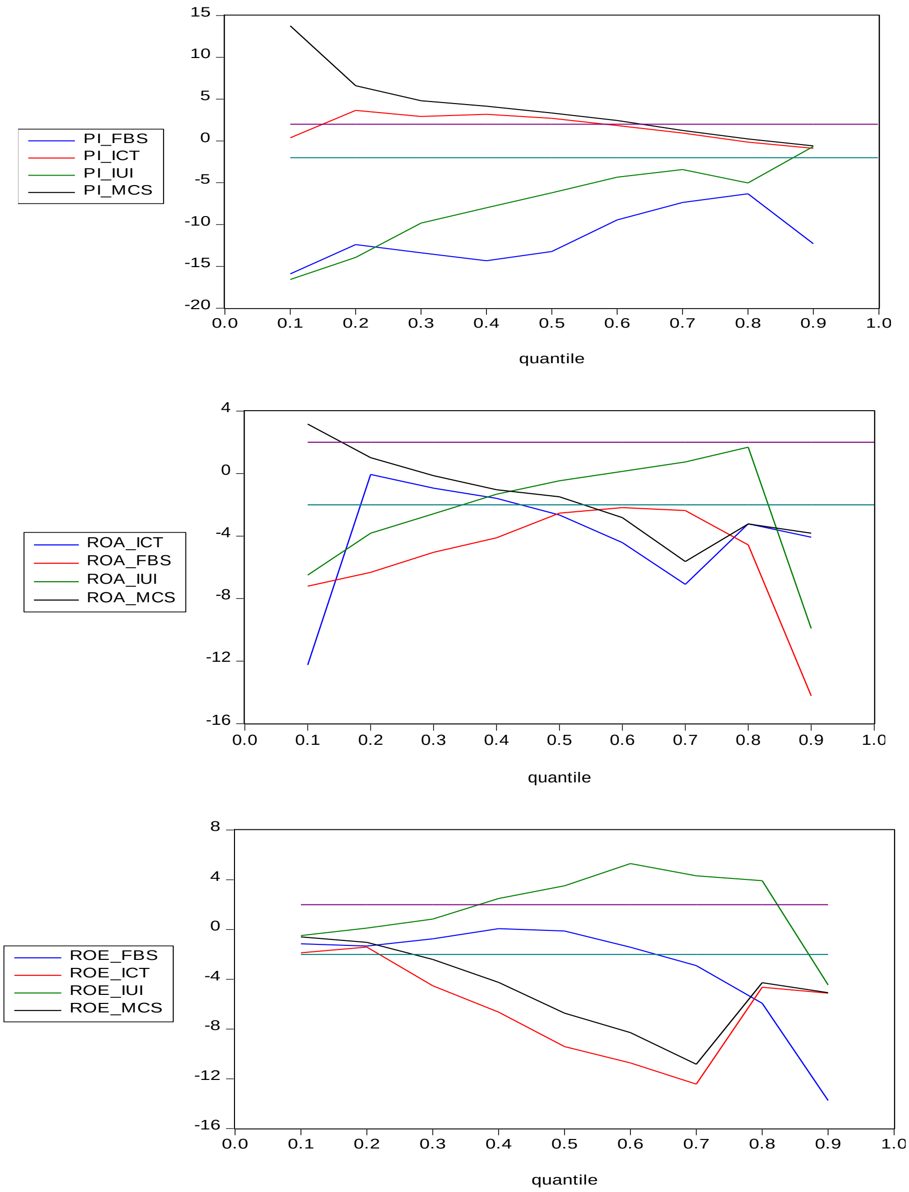
(c) China case



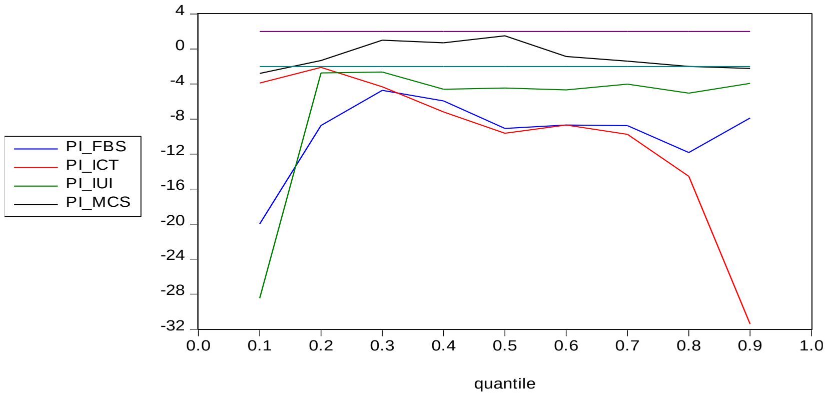
(d) SA case

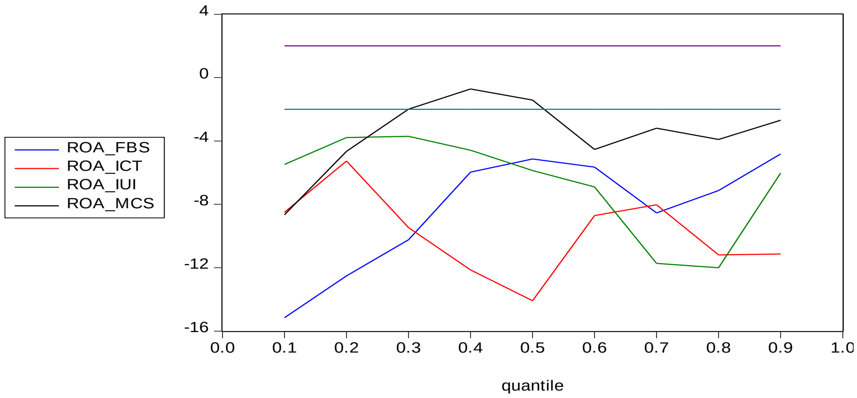
Figure B6: Frequency domain Granger causality test results

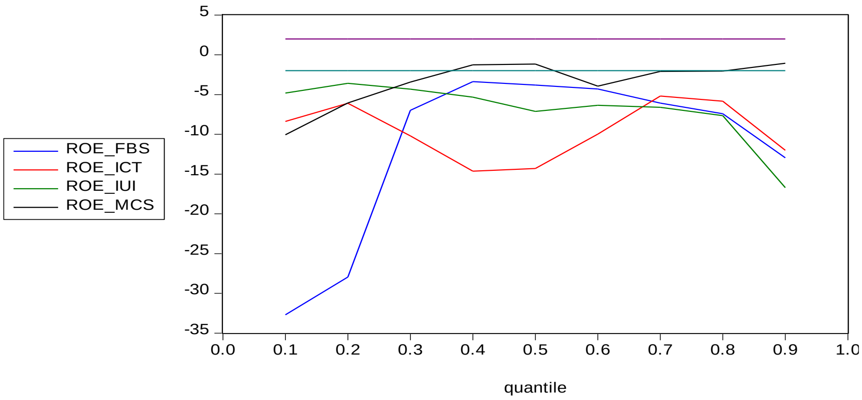
Note: only significant results are presented. Source: Author's calculations. Source: Author's calculations.



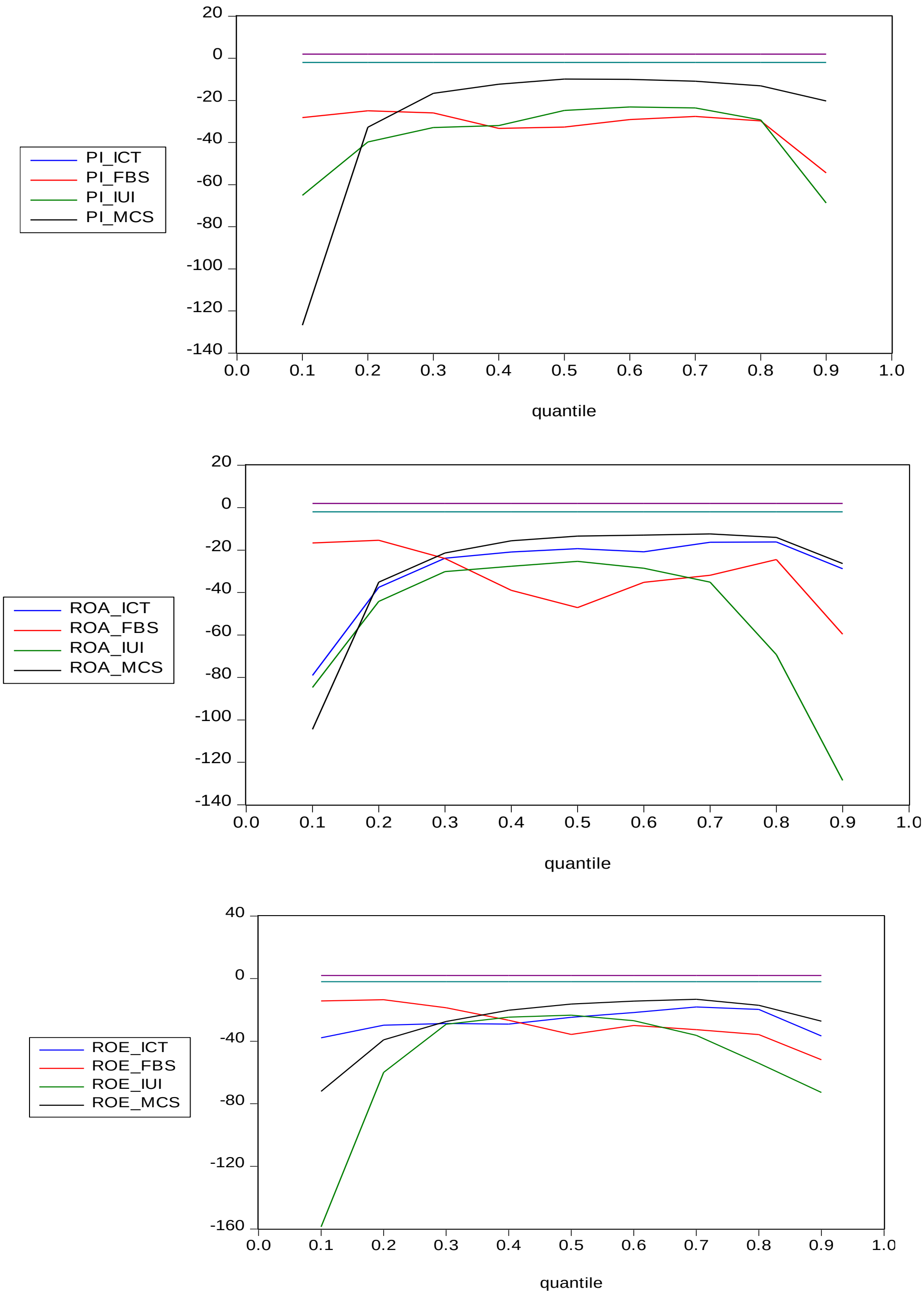
(a) Panel A: Brazil case



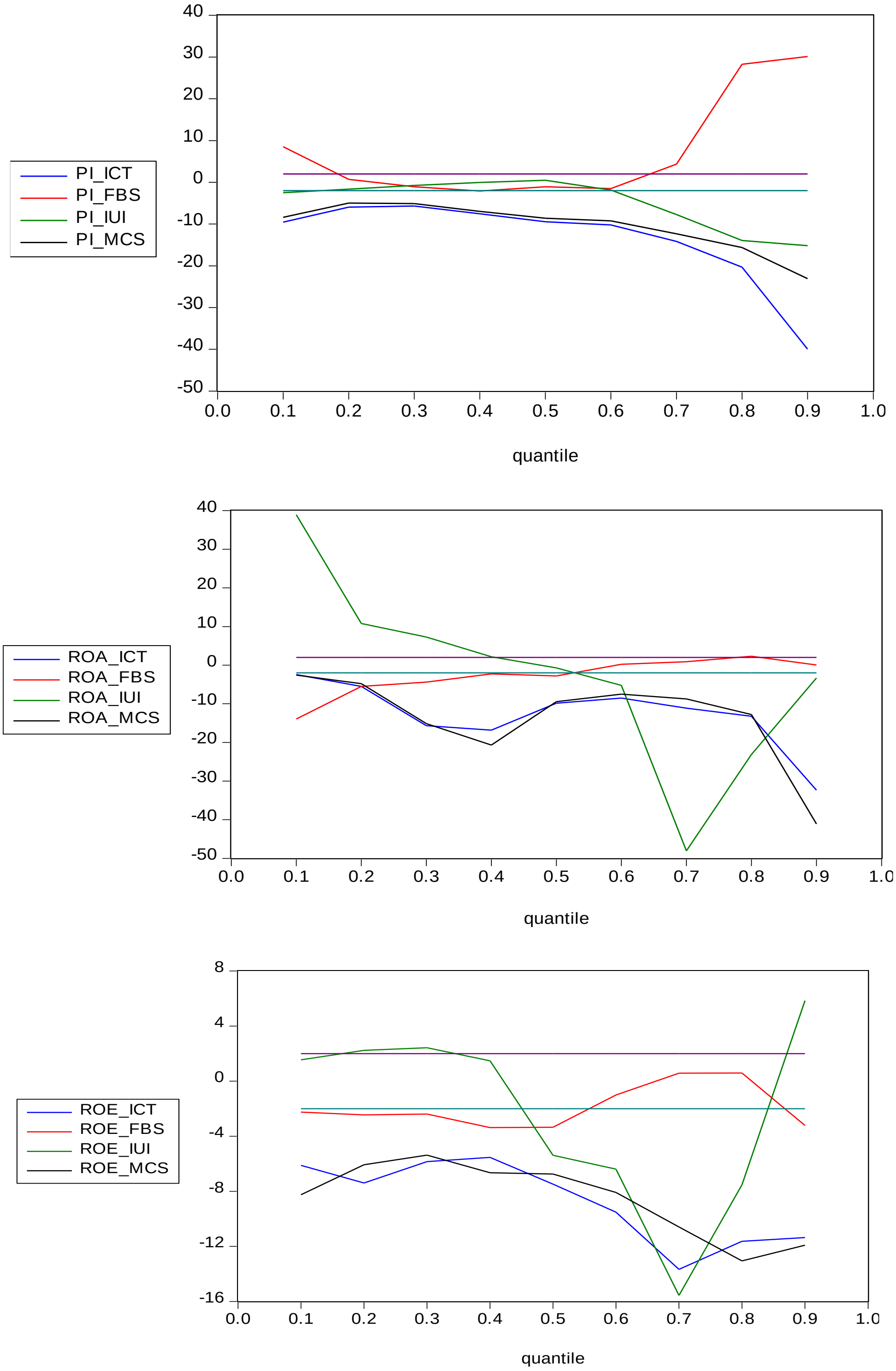




(b) Panel B: India case



(c) Panel C: China case



(d) Panel D: SA case

Figure B7: Granger causality in quantile test results

Source: Author's calculations.

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