Print ISSN: 2288–4637 / Online ISSN 2288–4645
doi:10.13106/jafeb.2022.vol9.no6.0105

Impacts of Financial Distress and ICT on Operating Performance and Efficiency: Empirical Evidence from Commercial Banks in India

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Received: March 10, 2022 Revised: May 21, 2022 Accepted: May 30, 2022

Abstract

With the help of this study, we aim to investigate the influence of Financial Distress (FD) and information and communication technology (ICT) on the operating performance and efficiency of banks in the Indian banking sector. FD can be defined as a position in which a company or individual is not in a condition to fulfill their promise of paying their obligations on time. The term "financial distress" refers to a situation in which a corporation or individual is unable to keep their promise of paying their debts on time. In this work, panel data analysis (PDA) was used to analyze data from 33 Indian banks over ten years (2010 to 2019). According to the findings, FD has a positive and significant impact on bank operational performance and efficiency. The current study will give the banking industry a better understanding of how a bank's performance can be negatively impacted by distressing conditions that render it inefficient and ineffective. Second, it will show investors how the level of distress can have a significant impact on bank performance in the market, finally resulting in the loss of money invested.

Keywords: Financial Distress, Operating Performance, Banks, Panel Data, Bankruptcy

JEL Classification Code: G21, C23, G330

1. Introduction

Investors are always concerned about the money they invest in companies. This fear of monetary loss makes them go through each aspect of the documents shared by the companies in public. Out of all, operating performance is one of the essential elements that investors want to analyze before taking any investment–related decision in a company. An inefficiently working company or a firm in the market is always the last investment choice for investors. As inefficient working creates a terrible image in the concerned industry and market, it can also result in monetary loss to the people who have invested their valuable money. A company's performance and efficiency level critically decide whether it will survive for a longer term in the market or not.

The business environment variables play an essential role in changing these image deciding factors (performance and efficiency). As these environmental variables are not in the control of anyone, it is not possible to ascertain how much they will impact a company's performance. So, in the current paper, we have aimed to observe and prove the impact of one of the significant business environmental factors, financial distress, on the performance and efficiency of the banks working in the Indian banking sector.

Financial Distress (FD) is a term used to refer to an upset financial state where a company is confronted with complications of liquidity and trouble in fulfilling outstanding payable amount of debt, triggering the winding up of the firm (Outecheva, 2007). The actual effect of FD becomes visible when any reputable firm declares itself to

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be in a distressing situation, as it creates a tense environment in the market, leading to a decrease in the market value of all the other companies for some time. Many models have been established till now by scholars in different sectors, such as Farajnejad and Lau (2017) developed an early warning system in the banking sector to predict as well as prevent banking distress or crisis–like situations. Whereas, Hiong et al. (2021) claimed that Altman *Z*–score can be used to predict a company's financial collapse. Similarly, Tunio et al. (2021), focused on corporate distress prediction by employing multi–stage classifiers for Pakistani firms. But still, no system has been developed that can accurately predict the distressing situation and save firms from getting bankrupt.

A firm is distressed when it faces difficulties maintaining liquidity and breaking the trust of creditors, investors, and other company stakeholders (Foster, 1986). FD majorly impacts the way investors build their portfolios. Investors usually avoid companies that either have any record of being distressed in the past or presently facing any distressing situation. A large number of studies have been conducted till now on financial distress. However, the current study involves exploring a new gap in which we have considered observing the impact of FD on operating performance and efficiency level both. This unexplored part of the area of FD has been aimed to be explored in our study.

If we talk about ICT, its development has significantly contributed to the invention of new and user–friendly technologies. If we talk about the banking sector, ICT has brought a far–reaching revolution in societies, which has tremendously transformed most business (banking) scenes (Ovia, 2005). Information and communication technology (ICT) has become the heart of the banking sector, while the banking industry is the heart of every robust economy (Shortis, 2001; Aliyu & Tasmin, 2012; Hamadi & Awdeh, 2012). It has also helped decrease the burden of a large amount of work on the employees in every area. Previously conducted studies have included ICT as one of the major independent factors in their studies. However, none of them has previously included ICT as a moderating variable to mathematically prove its interaction impact on banks' performance and efficiency level, making it a perfect gap to be explored and derive some novel results.

The current study investigates the impact of "Financial Distress" (FD) on the operating performance and efficiency level of the banks working in India. The study includes FD as an independent variable, operating performance and efficiency level as dependent variables, and ICT as a moderating variable. We have decided to include the total time to focus upon as ten years, starting from 2010 till 2019. The following objectives have been included in our study: 1) Finding the amount of impact FD has on the operating performance of banks; 2) Finding the amount of impact FD has on the efficiency of banks, and 3) Finding the impact of FD on the banks under the influence of ICT.

The remaining paper is structured in the following manner. The next section comprises a review of the literature. The subsequent section involves a description of the data, tables, methods, and models used, followed by the result of the study. Finally, the conclusion and limitations section will conclude the paper.

2. Literature Review

This section will cover significant studies conducted in the area of financial distress, firms' performance, efficiency, and information and communication technology. A firm's success is generally measured by how well a firm is performing compared to other companies in the industry. Under–performing firms are never considered to be a company fit for investment. Performing perfectly is itself an art that every organization must learn; otherwise, it will become difficult for them to survive in the market for a more extended period. Many obstacles stand in the path of being a top–performing firm. These issues are sometimes readily manageable, but other times it is important to confront the situation and fight for one's own survival. A financial crisis, difficulty, or insolvency are examples of such situations.

In this study, we consider the influence of only one of those factors, FD. As per Ahmad and Ahmad (2020) and Mahmood et al. (2018), the impact of FD on the performance of firms working in Pakistan is negative but still significant in nature. Karuiki (2011), in his research project conducted in Kenya, finds the same results by stating that a rise in financial distress led to a decrease in financial performance and vice versa. This shows that similar findings come from studies conducted in different parts of the world (Kariuki, 2013).

As far as the impact of FD on a firm's operating performance is concerned, lesser studies have been conducted in this area. As per Fan et al. (2007), the impact of FD on the operating performance of firms working in China is positive and significant. Tan (2012) studied the relationship between FD and firms' performance by considering 277 firms working during the Asian financial crisis from 1997– to 1998. The researcher found out that there is a negative relationship between FD and a firm's performance. Kahl (2001), in his research project, claimed that a firm's short–run and long–run survival probability is positively affected by its operating performance. After including 103 firms, the relationship comes to be positive between FD and operating performance.

Studies stated above regarding the impact on performance have not produced the desired results, which shows that more study is still required in different countries and sectors before generalizing any outcome. As we have decided to focus on the banking sector in our study, we have tried to fill the gap in this area. Thus, we have framed a hypothesis for empirical testing in this study.

H1: *A bank's financial distress significantly impacts the bank's operating performance.*

Efficient companies do not have to advertise their abilities and strength to gain attraction from people. Their efficiency can be seen in their market value and the amount of investors' demand for their shares. Many people think that efficiency can be obtained by working only on some company parts. However, the actual reality is that the whole organization has to work with proper coordination to be called a fully efficient company. Sometimes, even after working with full coordination, some external factors such as FD, inflation, or others can adversely impact a company's performance, and no one can stop being hit by such situations.

To analyze such a profound impact of external factors such as FD on the level of efficiency of the firm, we have studied some essential papers in this area. Starting from the oldest study conducted to explore the relationship, a study conducted by Wruck (1991) claimed that the relationship between FD and organizational efficiency is negative. Similarly, Shahwan and Habib (2019) found that the efficiency score negatively affects the probability of FD in the Egyptian market. Many other studies, such as Wu et al. (2021), Wanke et al. (2015), Shingjergji and Hyseni (2015), and Shagerdi et al. (2020), were conducted in different countries and at different times but still concluded with the same kind of result.

Many studies for finding the impact on efficiency as a significant factor have been conducted till now. However, none combined it with the operating performance factor to determine FD's impact on both factors (FD and efficiency). This gap is enough to justify its involvement in our study. The following hypothesis has been framed for empirically testing the impact of FD on efficiency level.

H2: *A bank's financial distress significantly impacts the bank's efficiency.*

The basic structure of our study involves finding out the impact that FD has on the bank's operating performance and efficiency level. In our research, we include ICT as a moderating variable. Until now, no such research has come to our knowledge that has used ICT as a moderating variable and FD as an independent variable to determine the real impact of FD and ICT on banks' performance and efficiency. This idea itself proves the novelty of our study. Therefore, to fill this significant gap in existing literature, we have framed a hypothesis for empirically testing the combined effect of FD and ICT as independent and moderating variables on the performance of banks working in India's banking sector.

H3: *A firm's financial distress significantly impacts the firm's value under the influence of ICT.*

3. Data and Methodology

3.1. Data

The study uses the data of 33 banks operating in India from 2010–to 2019. Other banks are ignored due to the unavailability of the required data for the analysis. The data source is the CMIE Prowess database and banks' annual reports.

3.2. Methodology

Applying panel data models (PDM), this study performs the data analysis to examine the framed hypotheses. More information, including cross–section and time–series, attributes to bring strong evidence, is the prime reason for applying PDM (Hsiao, 1985; Baltagi & Baltagi, 2008; Charnes et al., 1978). We have mainly used a static model as it is suitable as the dataset does not show multicollinearity (Baltagi & Baltagi, 2008; Wooldridge, 2015). Additionally, we have not performed dynamic models to look for the long–term impact of performance. The static models include three types of models (base model (for a linear association, Square model (for nonlinear), and interaction model (moderating association)) each for four dependent variables for performance (i.e., vrs_te, crs_te, NIM, and ROC) (Tandon et al., 2014). Hence, 12 static models are developed. Similarly, 12 dynamic models are also specified. The following models are developed:

Static Models:

$$\begin{aligned} DV_{it} = {} & \beta_1 ZS\_WS_{it} + \beta_2 ICT_{it} + \beta_3 CAR_{it} \\ & + \beta_4 l\_asset_{it} + \beta_5 l\_mcap_{it} + u_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} DV_{it} = {} & \beta_1 ZS\_WS2_{it} + \beta_2 ICT_{it} + \beta_3 CAR_{it} \\ & + \beta_4 l\_asset_{it} + \beta_5 l\_mcap_{it} + u_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} DV_{it} = {} & \beta_1 ZS\_WS_{it} + \beta_2 ICT_{it} + \beta_3 ZS\_ICT_{it} \\ & + \beta_4 CAR_{it} + \beta_5 l\_asset_{it} + \beta_6 l\_mcap_{it} + u_{it} \end{aligned} \tag{3}$$

Dynamic Models:

$$\begin{aligned} DV_{it} = {} & \beta_1 DV_{it(-1)} + \beta_2 ZS\_WS_{it} + \beta_3 ICT_{it} \\ & + \beta_4 CAR_{it} + \beta_5 l\_asset_{it} + \beta_6 l\_mcap_{it} + u_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} DV_{it} = {} & \beta_1 DV_{it(-1)} + \beta_2 ZS\_WS2_{it} + \beta_3 ICT_{it} \\ & + \beta_4 CAR_{it} + \beta_5 l\_asset_{it} + \beta_6 l\_mcap_{it} + u_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} DV_{it} = \beta_1 DV_{it(-1)} + \beta_2 ZS\_WS_{it} + \beta_3 ICT_{it} \\ + \beta_4 ZS\_ICT_{it} + \beta_5 CAR_{it} + \beta_6 l\_asset_{it} \\ + \beta_7 l\_mcap_{it} + u_{it} \end{aligned} \quad (6)$$

And $u_{it} = \mu_{it} + v_{it}$

(1) and (4) are for linear models, (2) and (5) are for nonlinear models, and (3) and (6) are for interaction models. Where β_j are coefficient. DV indicates the dependent variable. It can take vrs_te, crs_te, NIM, or ROA as the proxies of bank performance (Petersen & Schoeman, 2008). ZS_WS is Altman Zscore for financial distress and is taken as an explanatory variable. ICT is another explanatory variable indicating technology level. ZS_WS2 is the squared term of ZS_WS for quadratic relation. ZS_ICT (ZS_WS*ICT) is an interaction term.

CAR, l_mcap, and l_asset are the control variables for keeping the excellent fitness of models. u_{it} indicating error–term includes μ_{it} (individual–effect) and v_{it} (regular error–term). The subscript 'it' shows bank 'i' at time t(–1) is for lagged value.

4. Results

4.1. Descriptive Statistics and Correlations

The descriptive statistics of the variables and correlation matrix are portrayed in Table 1. The mean values of ZS_O and ZS_WS are 2.61 and 2.08, respectively, and close to Min. values. It shows that banks in India are in the grey zone (prone to face FD). vrs_te and crs_te have average values 0.86 and 0.83 (closure to Max values), respectively. Additionally, these values are closer to each other, showing a good efficiency level of Indian banks. NIM has a mean value of 2.65, which is close to Min. ROA has a mean value of 0.55, which is nearby its Max value showing a moderate performance of banks. l_sales and l_mcap have averages of 11.85 and 9.47 (slightly towards Max), respectively. Both show that banks in India have a moderate bank value. CAR has an average of 13.35, indicating a moderate CAR. For SD (Standard Deviation), only *Z*–scores (ZS_O and ZS_WS) have high SD. It shows varying FD status among banks.

ICT has a positive and significant correlation with ZS_WS and CAR (0.272 and 0.199, respectively). l_asset shows a significant but negative correlation with ZS_WS with a value of –0.144. The highest and most significant correlation between endogenous variables is 0.644 (CAR and l_mcap), somewhat smaller than 0.80. Hence, multi–collinearity is not the issue in models (Baltagi and Baltagi, 2008; Wooldridge, 2015).

4.2. Regression Estimation

There are 24 models specified for the study, including the static and dynamic models. They are mainly based on linear relations (Base Models), nonlinear relations (Square models), and interaction effects (interaction models).

4.2.1. Base Models

Static Models:

Models 1, 2, 3, and 4 look for the linear association between bank performance and FD (see table 2). The *F*-test for fixed effect (FE) and the B–P test for random effects (RE) are applied. Both show a significant *p*-value <0.05. The Hausman test is applied (Baltagi & Baltagi, 2008; Wooldridge, 2015), and it confirms the consistency of Models 1, 2, and 4 with FE, as their *p*-values are less than 0.05. However, Model 3 has compatibility with RE. Furthermore, the Wald test and the Wooldridge tests have *p*-values > 0.05. Hence, the availability of both autocorrelation and heteroscedasticity is ascertained. Thus, we consider the robust estimates for findings (Baltagi & Baltagi, 2008; Wooldridge, 2015).

In Table 2, ZS_WS shows a significant and negative coefficient in Models 1, 2, and 3. Their values are –0.006 and –0.004, respectively with *p*–value <0.05. It indicates that efficiency (crs_te) and NIM reduce financial stability. ZS_WS is not significant in Model 4. ICT is significant in Models 2 and 4. However, it is positive for crs_te and negative for ROA, showing a mixed impact of technology on performance. CAR as a control variable is significant

Table 1: Descriptive Statistics and Correlation

	ZS_WS	ICT	CAR	l_asset	l_mcap	Mean	SD
Zs_WS	1					2.087	11.153
ICT	0.272*	1				4.537	1.650
CAR	0.036	0.199*	1			13.356	2.235
l_asset	–0.144*	–0.006	0.049	1		11.750	1.406
l_mcap	–0.030	0.097	0.644*	–0.014	1	9.470	1.898

Note: *is for significant *p*-value at 0.05.

Table 2: Models for Linear Relationship (Static Panel Data Analysis)

	Model 1 DV:crs_te	Model 2 DV:vrs_te	Model 3 DV: NIM	Model 4 DV: ROA	Model 9 DV: crs_te	Model 10 DV: vrs_te	Model 11 DV: NIM	Model 12 DV: ROA
	Robust	**Robust**	**Robust**	**Robust**	**Robust**	**Robust**	**Robust**	**Robust**
ZS_WS	–0.001*** (0.088)	–0.006* (0.000)	–0.004** (0.031)	0.005** (0.465)	0.00 (0.08*)	–0.000 (0.000)	–0.000** (0.047)	0.000** (0.749)
ICT	–2.8E–06 (0.787)	0.000** (0.044)	–0.000 (0.634)	–0.000** (0.048)	–2.9E–07 (0.982)	0.000** (0.022)	–0.000 (0.713)	–0.000** (0.046)
CAR	–0.013** (0.020)	0.002 (0.830)	0.106* (0.000)	0.186* (0.001)	–0.014* (0.001)	0.001 (0.869)	0.106* (0.000)	0.185* (0.001)
l_asset	–0.090* (0.000)	–0.117* (0.003)	–0.188* (0.005)	–0.09 (0.643)	–0.106* (0.000)	–0.131* (0.001)	–0.181* (0.010)	–0.139 (0.513)
l_mcap	0.001 (0.884)	0.030*** (0.058)	0.094** (0.012)	0.015 (0.848)	0.005 (0.503)	0.038** (0.021)	0.095** (0.013)	0.021 (0.810)
Cons.	2.106* (0.000)	1.895* (0.000)	2.569* (0.000)	–0.897 (0.686)	2.256* (0.000)	1.977* (0.000)	2.471* (0.000)	–0.385 (0.860)
F-test (Model)	9.60* (0.00)	5.79* (0.00)	12.59* (0.00)	12.74* (0.00)	10.59* (0.00)	5.90* (0.00)	80.93* (0.00)	12.59* (0.000)
F-test (Fixed effect)	5.75* (0.00)	2.56* (0.00)	13.07* (0.00)	2.27* (0.00)	6.07* (0.00)	2.59* (0.00)	12.66* (0.00)	2.40* (0.000)
BP–test (Random effect)	96.67* (0.00)	10.32* (0.00)	38.18* (0.00)	8.24* (0.00)	97.59* (0.00)	9.96* (0.00)	382.36* (0.00)	8.42* (0.001)
Hausman Test	21.74* (0.00)	22.16* (0.00)	8.10 (0.15)	17.7* (0.03)	26.54* (0.00)	20.80* (0.00)	6.17 (0.29)	21.61* (0.000)
Wald test for Heteroscedasticity[1]	6.554* (0.00)	390.59* (0.0)	612.17* (0.00)	7346* (0.00)	1080.56* (0.00)	399.96* (0.00)	570.16* (0.00)	7092* (0.00)
Wooldridge Autocorrelation Test[2] AR (1)	8.948* (0.005)	21.69* (0.0)	17.25* (0.00)	10.19* (0.00)	7.17* (0.011)	222.53* (0.00)	17.241* (0.001)	10.167* (0.003)
Sigma_u_i	0.137	0.136	0.383	0.419	0.149	0.140	0.380	0.419
Sigma_v_i	0.091	0.155	0.330	0.644	0.090	0.155	0.332	0.644
rho	0.694	0.434	0.573	0.297	0.732	0.450	0.566	0.297
R–Square	0.142	0.090	0.436	0.179	0.153	0.091	0.464	0.179

Note: [1]Wald test of heteroscedasticity has the null of no heteroscedasticity. [2]Wooldridge test of autocorrelation in the panel has the null of no autocorrelation (with 1 lag). BP test is the Bruesch Pagan test for a random effect. RE and FE stand for random effect and fixed effect model, respectively. Sigma_u_i and Sigma_v_i are the variance of individual effect (firms in this case) and error term, respectively. The rho is the fraction of variance due to ui. Robust estimates are estimated due to significant heteroscedasticity and/or autocorrelation. Parenthesis has a *p*-value. *, **, *** are significance at 0.01, 0.05, and 0.10, respectively. CAR, l_asset, and l_mcap are the control variables. (Authors own compilation).

in Models 1, 3, and 4. However, it is negative in Model 1 and positive in Model 3 and 4. l_asset as the control variable is significant and positive in Model 1, 2, and 3. l_mcap is significant and positive in Model 2, 3.

Dynamic Models:

The dynamic models are tested for autocorrelation and overidentification by the Arellano–Bond and Sargan tests. In most models, the problem of autocorrelation and overidentification is ruled out (Baltagi & Baltagi, 2008; Wooldridge, 2015).

In Table 3, Models 5, 6, 7, and 8 are dynamic models for the linear association. The lag values are found significant and positive in each model. It implies that previous performance improves the current performance. The ZS_WS coefficient is negative and significant in Models 5 and 6 with values of –0. 001 and –0. 006, respectively. Therefore, financial distress positively connects to performance (efficiency). ICT is found to be negative and significant for performance (NIM and ROA) in Models 7 and 8. CAR is positive and significant in Model 5, 7, and 8. l_asset is negative and significant in Model 5, 6, and 7. l_mcap is positive and significant in Model 5, 6, and 7.

4.2.2. Square Models

Static Models:

In Table 2, Models 9, 10, 11, and 12 are concerned with the nonlinear association. As discussed for base models (Static), the Hausman test finds FE is suitable for Models 9, 10, and 12. Model 11 follows RE. Here, robust estimates are also taken to discuss results (existence of autocorrelation and multicollinearity).

In Table 2, ZS_WS2 shows a significant but negative coefficient (–0.000) in Models 9, 10, and 11. This indicates that ZS_WS is negatively and nonlinearly connected (inverted U shape) (vrs_te, crs_te, and NIM, respectively). This indicates that initially, financial stability increases performance to a certain level, then it starts reducing performance. ICT is found significant and positive in Model 10 (for crs_te). However, In Model 12, it is significant but negative (for ROA). The ICT's impact is also significantly less in amount (as the value approaches zero). CAR is significant in Models 9, 11, and 12 (for vrs_te, NIM, and ROA, respectively). It is negative in Model 9 and positive in Model 11 and 12. l_asset is significant and positive in Models 9, 10, and 11(for vrs_te, crs_te, and NIM). l_mcap is also positive and significant in Models 9, 10, and 11.

Table 3: Models for Linear Relationship (Dynamic Panel Data Analysis)

	(Base Models 6,6,7,8)				**Square Models 13,14,15,16)**			
	Model 5 DV:vrs_te	**Model 6 DV:crs_te**	**Model 7 DV: NIM**	**Model 8 DV: ROA**	**Model 13 DV:vrs_te**	**Model 14 DV: crs_te**	**Model 15 DV: NIM**	**Model 16 DV: ROA**
	Coeff. & *P*-value	**Coeff. & *P*- value**	**Coeff. & *P*-value**	**Coeff. & *P*-value**	**Coeff. & *P*-value**	**Coeff. & *P*-value**	**Coeff.& *P*-value**	**Coeff.& *P*-value**
Lag (1)	0.227* (0.000)	0.413* (0.000)	0.300* (0.000)	0.624* (0.000)	0.219* (0.000)	0.405* (0.000)	0.355* (0.000)	0.619* (0.000)
ZS_WS	–0.001* (0.002)	–0.006* (0.000)	–0.001 (0.472)	0.005 (0.749)	–0.000* (0.000)	–0.000* (0.000)	0.000* (0.000)	–0.000 (0.257)
ICT	0.000 (0.878)	–0.000* (0.000)	–0.000* (0.002)	–0.00** (0.076)	0.000 (0.878)	–0.000* (0.000)	–0.000* (0.002)	–0.000 (0.286)
CAR	0.015* (0.000)	0.005 (0.185)	0.027* (0.000)	0.185* (0.001)	–0.015* (0.000)	0.005*** (0.007)	0.023* (0.000)	0.104* (0.000)
l_asset	–0.144* (0.000)	–0.129* (0.000)	0.082** (0.042)	–0.139 (0.513)	–0.166* (0.000)	–0.132* (0.000)	0.136* (0.008)	–0.179* (0.003)
l_mcap	0.014** (0.073)	0.035* (0.073)	0.028* (0.002)	0.021 (0.810)	0.021* (0.003)	0.046* (0.000)	0.031* (0.000)	–0.045*** (0.055)
Cons.	2.419* (0.000)	1.602* (0.000)	0.216 (0.610)	–0.385 (0.860)	2.631* (0.000)	1.514* (0.000)	–0.549 (0.391)	1.333*** (0.088)
Sargan-Test	30.42 (0.70)	30.37 (0.69)	29.61 (0.72)	5.83 (0.87)	29.370 (0.736)	31.017 (0.660)	30.726 (0.674)	–
Arellano-Bond Test	1.51 (0.13)	3.06 (0.002)	124 (0.09)	2.26* (0.02)	1.38 (0.17)	2.921* (0.003)	0.244 (0.806)	–

Note: Saran test is the test of over-identification issues under the GMM framework. The null hypothesis of the Sargan test is that there is no over-identification problem in the dynamic panel data model. Arnello-Bond test used in the analysis is for serial autocorrelation in the first differenced error terms of the order 1. The null hypothesis of the test is that there is no autocorrelation. *, **, *** are significance at 0.01, 0.05, and 0.10, respectively. Coeff. Is the coefficient value of the regression equation. CAR, l_asset, and l_mcap are the control variables. (Authors own compilation).

Dynamic Models:

In Table 3, a positive and significant coefficient value of lag shows that previous performance is positively related to current performance, as shown in base models (dynamic). ZS_WS2 is significant and negative (–0.000) for efficiency (Model 13 and 14). Hence, a negative and nonlinear connection exists between financial stability and performance. However, it is significant and positive for NIM (Model 15). Depending on a different performance measure, the nonlinear establishment shows mixed evidence. ICT is negative and significant in Models 14 and 15 (for crs_te and NIM). This implies that a high ICT level reduces performance, but it is every minute. CAR is positive and significant in all models. l_asset is significant and negative in Models 13, 14, and 16 (for vrs_te, crs_te, and ROA). However, it is positively significant in Model 15. l_ map is positive and significant in Model 13, 14, and 15 (for vrs_te, crs_te, and NIM) and negative in Model 16 (ROA).

4.2.3. Interaction Models

Static Models:

Model 17, 18, 19, and 20 are the static models for investigating the interaction effect (Table 9). The Hausman test supports FE for models 17, 18, and 20. However, Model 19 is found consistent with RE. We consider only the robust estimates due to autocorrelation and heteroscedasticity in all these models.

In Table 4, models 17, 18, and 19 show the significant and negative coefficients (–0.003, –0. 008, and –0. 014, respectively) for vrs_te, crs_te, and NIM. Hence, it indicates that financial distress positively relates to bank performance. ICT is found significant and positive in Model 18 (for vrs_te) but negative in Model 20 (for ROA). It shows that technology has a mixed impact on performance depending on the performance measure. ZS_ICT has significant and positive coefficients in Models 17, 18, and 20 (for vrs_te, crs_te, and ROA). Hence, it implies that financial stability increases performance with improved technology. CAR is significant in Models 17, 19, and 20 (for vrs_te, NIM, and ROA). It is negative for vrs_te and positive for NIM and ROA. l_asset is negative and significant in Models 17, 18, and 19 (for crs_te, vrs_te, and NIM). l_mcap is positive and significant in Models 18 and 19 (for crs_te and NIM).

Dynamic Models:

In Table 5, Models 21, 22, 23, and 24 are dynamic models for interaction effects. Lag has significant positive coefficients in all models, indicating that previous performance positively connects to current performance. ZS_WS has negative and significant coefficients in Model 21, 22, and 24 (for vrs_te, crs_te, and ROA, respectively), showing a negative connection between financial stability to performance. Here too, ZS_ICT has significant and positive coefficients in all four models. Hence, it means financial stability increases performance with improved technology. CAR is significant and negative in Model 21 (for vrs_te) and positive in Model 22, 23, and 24 (crs_te, NIM, and ROA). l_mcap is positive and significant in Models 21, 22, and 23 (for vrs_te, crs_te, and NIM).

4.2.4. Robustness and Endogeneity Check

The Endogeneity check is performed by the Wu–Hausman test and the Durbin–Chisquare test. Both tests revealed that no endogenous variable has a significant *p*-value (Table 11). Hence, both tests cannot reject the null of no endogeneity for exogenous variables as we have tested the impact of FD on bank performance by constructing several models. In most of the cases, almost similar results are found. Therefore, the robustness of the results is warranted.

5. Discussion

The methodology used in this paper has helped prove that the first hypothesis (H1) has been accepted. The second (H2) and third hypotheses (H3) are also accepted. This means that FD is significantly impacting the operating performance and the efficiency of banks in India.

Not much literature is present in finding any association between FD, operating performance, and efficiency. However, some studies that have a similar aim to ours, such as Fan et al. (2007), have claimed that the overall impact of FD on the performance of firms working in the emerging market of China is positively significant. Whereas, Shahwan and Habib (2020), in their paper published in 2019, proved that the probability of FD impacting efficiency scores among the firms working in the Egyptian market is negative. Another study by Vosoughi et al. (2016) investigated the relationship between investment efficiency and FD among the firms listed on the Tehran stock exchange and found a correlation between FD and investment efficiency. Maximum studies have included companies or firms as the main focused area in their respective studies. However, our study is confined to the banks working in India's banking sector. However, no such study has been conducted until now, including finding the interaction impact of FD on operating performance and efficiency level by keeping ICT as a moderating variable.

Even after having many similarities or dissimilarities with previously conducted studies, our study has made significant contributions of novel nature. Some of them are as follows– firstly, the study provides evidence that FD nonlinearly connects to the performance of banks, which means that initially, performance goes down with increasing financial distress. However, beyond a point, as financial distress increases, it starts increasing the performance level as well.

Table 4: Interaction Models Result For Moderating Relation (Static Panel Data Analysis)

	Model 17 DV: vrs_te (FE)		**Model 18 DV: crs_te (FE)**		**Model 19 DV: NIM (RE)**		**Model 20 DV: ROA (FE)**	
	Normal	**Robust**	**Normal**	**Robust**	**Normal**	**Robust**	**Normal**	**Robust**
ZS_WS	–0.003* (0.001)	–0.003* (0.000)	–0.008* (0.000)	–0.008* (0.000)	–0.014* (0.000)	–0.014* (0.001)	0.001 (0.840)	0.001 (0.465)
ICT	0.000 (0.319)	0.000 (0.178)	0.000 (0.012)	0.000** (0.024)	0.000 (0.355)	–0.000 (0.247)	–0.000* (0.006)	–0.000* (0.048)
ZS_ICT	9.79E–06* (0.003)	9.79E–06* (0.000)	0.000** (0.062)	0.000* (0.007)	0.000* (0.000)	0.000* (0.000)	0.000 (0.453)	0.000 (0.298)
CAR	–0.014* (0.001)	–0.014* (0.001)	0.001 (0.821)	0.001 (0.878)	0.103* (0.000)	0.103* (0.000)	0.185* (0.000)	0.185* (0.001)
l_asset	–0.088* (0.000)	–0.088** (0.017)	–0.116* (0.001)	–0.116* (0.004)	–0.198* (0.000)	–0.198* (0.003)	–0.090 (0.521)	–0.090 (0.651)
l_mcap	–0.000 (0.936)	–0.000 (0.951)	0.028** (0.011)	0.028** (0.078)	0.090* (0.000)	0.090** (0.013)	0.012 (0.791)	0.012 (0.879)
Cons.	2.106* (0.000)	2.106* (0.000)	1.896* (0.000)	1.896* (0.000)	2.745* (0.000)	2.745* (0.000)	–0.896 (0.561)	–0.896 (0.685)
F-test(Model)	11.39* (0.000)		5.45* (0.000)		99.93* (0.000)		5.20* (0.000)	
F-test (Fixed Effect)	5.95* (0.000)		2.64* (0.000)		13.67* (0.000)		2.23* (0.000)	
BP-test (Random Effect)	107.37* (0.000)		10.32* (0.000)		412.70* (0.000)		8.16* (0.002)	
Hausman Test	21.74* (0.000)		22.16* (0.000)		6.96 (0.220)		15.00* (0.010)	
Wald test for Heteroscedasticity[1]	436.28* (0.000)		390.59* (0.000)		1146.79* (0.000)		7357.03* (0.000)	
Wooldridge Autocorrelation Test[2] AR (1)	8.543* (0.003)		21.69* (0.000)		17.131* (0.000)		10.128* (0.003)	
Sigma_u_i	0.131		0.136		0.383		0.411	
Sigma_v_i	0.089		0.155		0.323		0.645	
rho	0.681		0.434		0.583		0.289	
R–Square	0.167		0.090		0.447		0.180	

Note: [1]Wald test of heteroscedasticity has the null of no heteroscedasticity. [2]Wooldridge test of autocorrelation in the panel has the null of no autocorrelation (with 1 lag). BP test is the Bruesch Pagan test for a random effect. RE and FE stand for random effect and fixed effect model, respectively. Sigma_u_i and Sigma_v_i are the variance of individual effect (firms in this case) and error term respectively. The rho is the fraction of variance due to ui. Robust estimates are estimated due to significant Heteroscedasticity and/or autocorrelation. Parenthesis has a p-value. *, **, *** are significance at 0.01, 0.05, and 0.10, respectively. CAR, l_asset, and l_mcap are the control variables. ZS_ICT (ZS_WS*ICT) is the interaction term that includes distress and technology.

This kind of relationship is that with an increasing level of FD, banks become more alert about their performance and start working in a comparatively better way, which results in better performance than before. Secondly, as far as proving the natural interaction effect is concerned, a negative impact of ICT as an interaction factor can be seen on the performance of the banks. Hence, the approach used in the current study has provided some new and exciting evidence in FD.

The current study has the following research implications. After going through this paper, the banking industry can understand how badly distressing situations can impact a bank's performance by making them inefficient and

Table 5: Interaction Models For Moderating Relationship (Dynamic Panel Data Analysis)

	Model 21 DV: vrs_te		Model 22 DV: crs_te		Model 23 DV: NIM		Model 24 DV: ROA	
	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value
Lag (1)	0.198*	0.000	0.415*	0.000	0.293*	0.000	0.615*	0.000
ZS_WS (exp_var)	–0.003*	0.000	–0.006*	0.000	–0.003	0.165	–0.00***	0.058
ICT	0.000*	0.000	0.000*	0.000	–0.000**	0.016	–0.000	0.104
ZS_ICT	0.000*	0.000	0.000*	0.000	0.000*	0.000	0.000*	0.001
CAR	–0.014*	0.000	0.006**	0.050	0.027*	0.000	0.101*	0.001
l_asset	–0.150*	0.000	–0.141*	0.000	0.085**	0.047	–0.046	0.546
l_mcap	0.019**	0.021	0.047*	0.000	0.028*	0.004	–0.021	0.181
Cons.	2.468*	0.000	1.602*	0.000	0.195	0.727	–0.281	0.749
Sargan-Test	29.761 (0.718)		29.248 (0.741)		29.177 (0.744)		25.166 (0.889)	
Arellano-Bond Test	1.331 (0.181)		–2.961* (0.003)		0.030 (0.975)		2.360** (0.018)	

Table 6: Endogeneity Test

	ZS_WS	ICT	CAR	l_mcap	l_asset	ZS_WS2	ZS_ICT
Durbin Chi-2	2.0214 (0.1551)	2.0799 (0.1492)	1.7430 (0.1868)	0.0873 (0.7675)	2.2866 (0.1305)	1.9784 (0.1596)	3.8936 (0.0585)
Wu-Hausman Test	1.9775 (0.1610)	2.0357 (0.1551)	1.7030 (0.1932)	0.0873 (0.7712)	2.2395 (0.1359)	1.9263 (0.1665)	3.8232 (0.0518)

Note: Value in () is *p*-value. * shows a significant value at 5% significance level.

ineffective. Secondly, it will help investors realize how significantly the distress level can affect the performance of banks in the market and ultimately lead to the loss of the money investors invested.

6. Conclusion

The current study has been conducted to explore the influence of FD on the operating performance and efficiency level of banks working in the Indian banking sector. The established result has concluded that the impact of FD on a bank's performance and efficiency level is significant and positive. This means that as financial performance goes up, but beyond a point, as the stability of a bank goes up, it erodes the performance. In addition to this, it has also been proved that the impact of FD on the performance level of banks is negatively significant under the influence of ICT as a moderating variable.

Studies in the future can be conducted by including some other types of industries and companies working in different sectors such as the financial sector, corporate sector, or companies incorporated in different indices in stock exchanges worldwide. Future researchers can consider increasing or decreasing the period to focus on their respective studies. Lastly, the researchers can focus on the impact on other significant factors such as ratios, dividend decisions, profitability, and many more.

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