American International Journal of Business Management (AIJBM)
ISSN- 2379-106X, www.aijbm.com Volume 3, Issue 5 (May 2020), PP 122-127

The Causal Analysis of Financial Distress Risk and Performance

Zahra Faraji(PhD)
Department of Financial Service Analytics Alfred Lerner College of Business & Economics
University of Delaware
**Corresponding Author: Zahra Faraji, zfaraji@udel.edu*

ABSTRACT:- The goal of this study is investigating the effect of financial distress on firm performance. We examine the causal effect of financial distress on the firm performance for US public firms using the Inverse Probability Weighting (IPW). We extend the standard IPW model with Bayesian approach. We confirm the presence of a causal relationship between these variables by providing the posterior predictive distribution of the causal effect. After removing the spurious correlation caused by the confounders, we find weaker effect of financial distress likelihood on firm performance compared with the literature.

Keywords:- Financial Distress, Firm Performance, Causal Inference, Inverse Probability Weighting, Bayesian Inference

I. INTRODUCTION:

The firm performance is associated with many financial variables [1]. One of the most important variables which can influence the firm performance is the financial distress. Financial distress shows the situation in which firms cannot meet the financial obligations [2]. There are different reasons that degrade the firm financial health such as economic environment, low demand, role of competitors, poor managerial performance, increasing debt, and higher costs [3]. The financial distress is a highly controversial topic as it determines the future decisions and performance of the firms ([4]; [5]; [6]; [3]). The consequences of the financial distress are so critical for long term performance of the firms. The high risk of financial distress leads to uncertainties for all the related stakeholders. When there is a considerable failure risk for firms, it is crucial to evaluate how the future firm performance would be affected.

Many empirical and theoretical research has been investigated the different effects of financial distress [2]. However, most of the related studies in literature consider only the association between the financial distress and other financial and non-financial variables. The correlation-based results may be biased because of the chance or confounder variables. Especially, when we have observational data, more assumptions are required to evaluate the correlation-based model such as regression models. In order to examine how the firm performance are impacted by the probability of distress risk, we should remove all the spurious correlations caused by undesirable variables to make more reliable and concrete results. The reason is that the standard regression models provide associations, which can overestimate or underestimate the actual effect size. Standard regression models may work well for randomized studies, but its limitations degrade its application for the observational data.

We should pay attention to the differences between the observational and the data that comes from randomized experiments. But randomized trials are not always possible because of the related cost, risk, and ethical issues [7]. So, the question is that how we can rely on the correlation-based results for observational data when we are aware that the variable of interest is not randomly assigned to the observations. This point seems to be missed in the related literature, as most of the studies have applied models for the observational data which are designed for randomized experiments. Causal inference can help when we have limited observational data to investigate the causal effect instead of biased association. Causal models leverage assumptions and causal language to examine more accurate effect size. The causal analysis has been applied in many fields to answer the questions that are not motivated by correlation. In financial literature, we barely can find any studies that apply causal model to investigate the effect of financial distress on firm performance.

The purpose of this study is to seeks the causal effect of financial distress on the firm performance. In addition, because of the expected financial distress for many US public firms based on the corona-virus pandemic, the results of this study may help many firms to assess their future performance and make proper decisions in advance. In particular, the causal analysis provides more valid insight for decision makers rather than correlation results. This study is motivated by the lack of concrete results relating to the financial distress effects. The goal is to see is there any causal relationship between these variables or it is only based on the spurious association.

The rest of this paper is as follows. The next section provides summary of the related literature. Statistical model presents more details about the causal model of this study and the data description. The empirical result section describes the causal results of for the sample dataset of this study. In the last section, the conclusions and the limitation of this study is presented.

II. LITERATURE REVIEW:

Uncertainty in the economic and business environment threatens the firm survival. When a firm is not able to make the financial obligations or on the other hand its liabilities are more than the asset, the firm is subject to a financially distressed situation ([8]; [2]). Many internal and external reasons can lead to higher level of financial distress and weaken the firm performance [3]. Some of these reasons are internal and related to the management decisions, which reveal the role of poor management performance in increasing the risk of failure [9]. Which provide the opportunity to lessen the potential failure risk and improve the performance. Financial distress has been widely studied in the past to see how it changed the firm performance. Also, we expect that the financial distress and its effects will be more attractive within the next years because of the consequences of the coronavirus pandemic.

Financial distress shows the possibility of failure for a firm in the future. This information can help different groups of stakeholders to analysis the performance of the firm and adjust their decisions [9]. Assessing the firm financial health has attracted significant attention and different researchers provided prediction models to estimate the failure possibility. Altman (1968) developed Altman z-Score as a multivariate financial distress prediction model, which provides a proxy for financial distress based on the financial factors such as profitability and solvency. More detailed information about Altman Z-score model is provided in the next section.

Similar to the financial distress, the form performance has been extensively investigated in the finance literature ([1]; [10]; [11]; [5]). When a firm suffering from unstable financial health, it leads to higher cost, lower earing, and weak performance [8]. Different studies argued the presence of a strong association between financial distress and firm performance (e.g., [8]; [9]; [5]; [6]; [3]). Koon (2012) investigated the relationship between financial stress and firm performance for Asian firms. Their results showed that the financial crises resulted in more negative relationships between these two variables, and firms with higher leverage had worse performance during the crises. According to Choy et al. (2011), Malaysian firms with risk of financial distress had unsustainable profits. They compare the performance before and after the financial crises and concluded that the firms performed better after the crises as the previous firm performance leaded to the distress. Opler and Titman (1994) examined the relationship between financial distress and corporate performance; their findings affirmed the higher financial distress for the firms with specialized products. Notta and Vlachvei (2014) studied the effect of financial crises on the firm performance for Greek food manufacturing firms. They found higher profitability before the crisis compared with the time during the crisis for most of the firms. Some of the related studies provide strong associations, but still there is inconsistency on the effect size.

To tease out the true effect size of the financial distress on firm performance, more investigation is required. Also, to analyzing important relationships like the effect of financial distress risk and firm performance, we need more reliable results using the lens of causality. The question of this study is to investigate the causal effects between these variables and examine the effect size after removing the effect of confounders and spurious associations. We incorporate Bayesian analysis with standard inverse probability weighting model as combining different techniques can provide more flexibility to handle the real-world problem and provide better results ([3]; [12]; [13]). Bayesian approach helps to make better inferences when frequentist estimators may not be ideal. With Bayesian causal models like Bayesian IPW we provide posterior predictive distribution of the causal effect. In addition, Bayesian approach does well when we have sparse data to calculate the conditional probabilities, which is so helpful for limited observational data and missing problem of causality.

III. STATISTICAL MODEL AND DATA:

Inverse Probability Weighting (IPW)

Inverse probability weighting is one the most popular causal problems that has been used extensively in the literature. There are three causal assumptions that are essential to validate the results of the causal models for observational data. These assumptions are the positivity, exchangeability, and consistency assumptions. IPW is one of the g-methods that is applicable to estimates the unbiased treatment effect for observational data [7]. When all the observations in the study have the positive probability of receiving the treatment values, the Positivity assumption is satisfied. The exchangeability assumption states that observations which received the treatment have the same distribution of outcomes as the untreated observations when they receive the similar level of treatment [7]. When there is a set of measured confounders then conditional exchangeability should be considered. Consistency assumption requires the well-defined treatment for all the observations [7].

Follow the notation of Hernan (2010), we provide a summary of IPW method. Here, we consider a as the binary intervention, Y as the potential outcome, Z as a vector of confounders. So $y^{a=1}$ and $y^{a=0}$ are the

treated and untreated potential outcomes. For observational data, we only observe one of these potential outcomes, the other is missed. This is the reason that makes the casual analysis harder for observation data.
Pseudo-population is used with IPW models in which any observations has a propensity score value. The propensity score represents the probability of treatment assignment with considering a group of confounders. In Pseudo-population each observation has a weight as the inversed propensity score. The weights can vary across the observations because of the different confounders' values. Therefore, the association between treatment and outcome in the pseudo-population can be equal to the treatment effect.

The propensity scores or the conditional probability of treatment are presented as $Pr[A = 1|Z]$ for treated observations and $1 - Pr[A = 1|Z]$ for the untreated observations. In order to estimate the average treatment effect, the inverse probabilities of treatment should be assigned to the observations, which are shown by $1 / Pr[A = 1|Z]$ and $1 / 1 - Pr[A = 1|Z]$. With a binary treatment, a logistic regression model is used to estimate the conditional probabilities and generate the pseudo-population. In the next step, the difference between $\hat{E}[Y|A = 1] - \hat{E}[Y|A = 0]$ represents the average treatment effect for the pseudo-population. The last step is based on the linear regression, and the coefficient of treatment represents the average causal effect in the population.

The novelty of our approach relies on extending the traditional IPW model with Bayesian analysis. Instead of using logistic regression for binary treatment, we use Bayesian statistical model to model the relationships between the treatment and confounders and estimate the propensity scores. Also, we use Bayesian model for the final step to prepare posterior predictive distribution for the average treatment effect (ATE) instead of a single number. The new model is a general-purpose model and is applicable for any dataset that has binary treatment with continuous or binary confounders and outcomes. Indeed, we mitigate the shortcomings of the standard IPW model and make it applicable for more real-world datasets.

Data:

The data for this study is provided by Compustat and CRSP. All the required information for active firms is based on the end of the fiscal year for the study. We consider the data which covers 2018, the reason is that the more recent data would be more helpful for future decisions. But the research question can be replicated for any desired years. As the goal of this study is to investigate the effect of financial distress on firm performance, we choose well-stablished measures for them based on the literature. In this study, the firm performance is measured by Return on Asset (ROA) which is an accounting-based measure ([1]; [10]). This measure is a reliable accounting-based performance measure calculated as the ratio of net income to total assets. Many prior studies apply ROA as the firm performance measure (e.g., [14]; [15]; [1]; [16]; [17]; [10]).
Also, Altman Z-Score is used as the probability of financial distress, which is based on different variables such as total asset, total liabilities, working capital, sale, and retained earnings [6]. Altman Z-Score has been widely applied to evaluate the probability of financial distress [3]. This measure has high accuracy to evaluate the financial distress as it is based on different financial ratios such as profitability, solvency, and liquidity [6]. The calculation of Altman Z-Score is shown in equation (1) which incorporates different financial ratios with pre-specified coefficients. The range of the output of this model provides information about the financial distress probability [4].

The Altman Z-Score is as follows:

$$X1 = Working\ Capital\ /\ Total\ Assets$$
$$X2 = \text{Retained Earnings / Total Assets}$$
$$X3 = \text{Earnings before Interest and Taxes / Total assets}$$
$$X4 = Market\ Value\ of\ Equity\ /\ Total\ Liability$$
$$X5 = \text{Sales / Total Assets}$$

In this study, Z-score bankruptcy for public firms' model is used which is as follows:

$$Z = 0.12\text{X1} + 0.14\text{X2} + 0.33\text{X3} + 0.006\text{X4} + 0.999\text{X5} \qquad (1)$$

The range of output for this model determines the likelihood of financial distress. If Z-Score is below the 1.81 shows the high financial distress risk, the Z-Score value above 3 shows in the safe zone, gray zone is assigned for any score between 1.81 and 3 [4].
There are some variables that should be controlled to remove the spurious association between financial distress likelihood and firm performance. These variables are considering as the confounders. Based on the literature, the confounder variables are the firm size, firm age, the ratio of EBIT over sale, the growth opportunity, and the debt ratio ([18]; [1]; [19]; [10]; [3]). Firm Size is calculated as the natural log of total assets for each firm and age is measured by the natural log of the years that a firm has been active. Here, the growth opportunity is measured based on the total asset [3]:

$$\text{Growth Opportunity} = \frac{\text{Total Asset (t)} - \text{Total Asset (t}-1)}{\text{Total Asset (t}-1)} \qquad (2)$$

The following table shows the descriptive sample statistics for the sample dataset.

Variable	Mean	Sd	Median	Min	Max
Age	20.55	15.61	18.00	1.00	57.00
Total Assets	10067.3	37087.35	1198.6	0.3	707794.0
EBIT	762.11	2775.05	62.75	-4711.00	70662.00
Total Liabilities	6200.3	21985.53	589.1	0.0	355294.0
Retained Earnings	2460.5	16369.47	41.1	-97193.0	402089.0
Net Sales	6639.3	26046.92	872.0	0.0	496785.0
Working Capital	471.36	3317.98	105.76	-32500.00	101056.00
Net Income	459.36	2201.57	22.35	-22355.00	59531.00
ROA	-0.10051	0.84	0.02609	-28.65000	2.55101
Size	6.955	2.31	7.089	-1.204	13.470
Growth Opportunity	0.08705	0.46	0.00000	-0.96309	12.66629

Table (1): Descriptive statistics of sample data

Here, the probability of financial distress is assumed as the treatment (A), firm size, firm age, the ratio of EBIT over sale, the growth opportunity, and the debt ratio are the confounder variables (Z), and the outcome (Y) is the firm performance. The causal diagram shows that the confounder variables has effects on both treatment and outcomes. Indeed, part of the association between treatment and outcome may be caused by the confounders. By using IPW, we remove the effect of confounders in the pseudo-population.

Because of the distribution of this Z-Score measure for our dataset, we categorize the firms to high level and low level of financial distress risk. Most of the Z-Score values are below 1.81 or above the 3, so consider the firms with Z-score lower than 1.81 as firms with high distress risk and firms above 1.81 as firm with low distress risk. As the treatment is financial distress, then the firm with higher risk are assumed as treated firms (A=1) and firms with lower risk assumed as untreated firm (A=0).

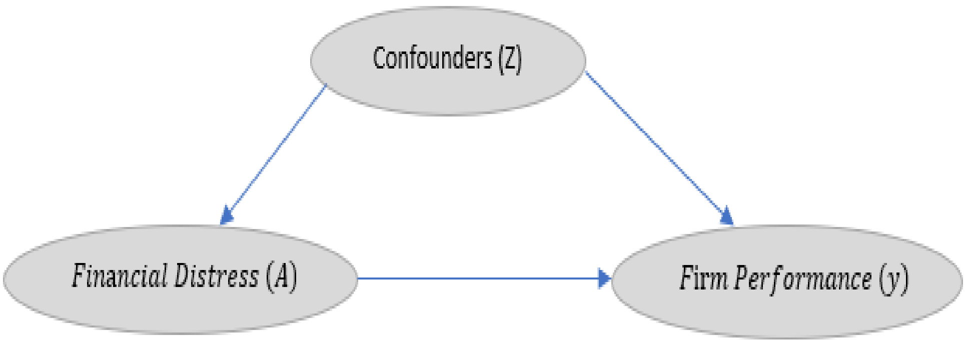

Figure (1): Causal diagram

The Bayesian statistical model for our research question is as follows:

We first model the treatment and confounders to estimate the propensity scores in the sample dataset.

$$\text{Financial Distress (A)} \sim \beta_0 + \beta_1 * \text{Size} + \beta_2 * \text{Age} + \beta_3 * (\text{EBIT/Sale}) + \beta_4 * \text{Growth Opportunity} + \beta_5 * \text{Debt Ratio} \qquad (3)$$

Then, we find the propensity score as $Pr[A = 1|Z]$ and $1 - Pr[A = 1|Z]$ for treated and untreated observations, respectively. Based on the propensity scores, we find the inverse probability weights:

Inverse probability weights for firms with high financial distress level: $\frac{1}{Pr[A=1|Z]}$

Inverse probability weights for firms with low financial distress level: $\frac{1}{1-Pr[A=1|Z]}$

We make the pseudo-population by weighting the observations using estimated propensity scores. Now we can find the association between firm performance and financial distress for the weighted population which represents the size of causal effect. We use Bayesian model with weakly informative prior distribution. We prefer the weakly informative prior as we do not have strong beliefs about the prior distributions. Also, weakly informative prior distributions have better performance than the non-informative priors [3].

$$\text{For Pesudo} - \text{Population: } y \sim normal\ (\mu, \sigma) \qquad (4)$$
$$\mu \ = \ \beta_0 + \beta_1 A$$
$$\beta_0 \sim cauchy\ (0, 10)$$
$$\beta \sim cauchy\ (0, 2.5)$$
$$\sigma \sim cauchy\ (0, 1)$$

The posterior draws of the β_1 shows the effect size for the sample dataset. By taking all the mentioned steps for the sample dataset of this study, we estimate the average treatment effect. The results are shown in the next section.

IV. EMPIRICAL RESULTS:

We apply IPW model with Bayesian approach for the sample dataset by considering financial distress as binary treatment and firm performance as continuous outcome. The following figure illustrate the average causal effect of the financial distress on the firm performance.

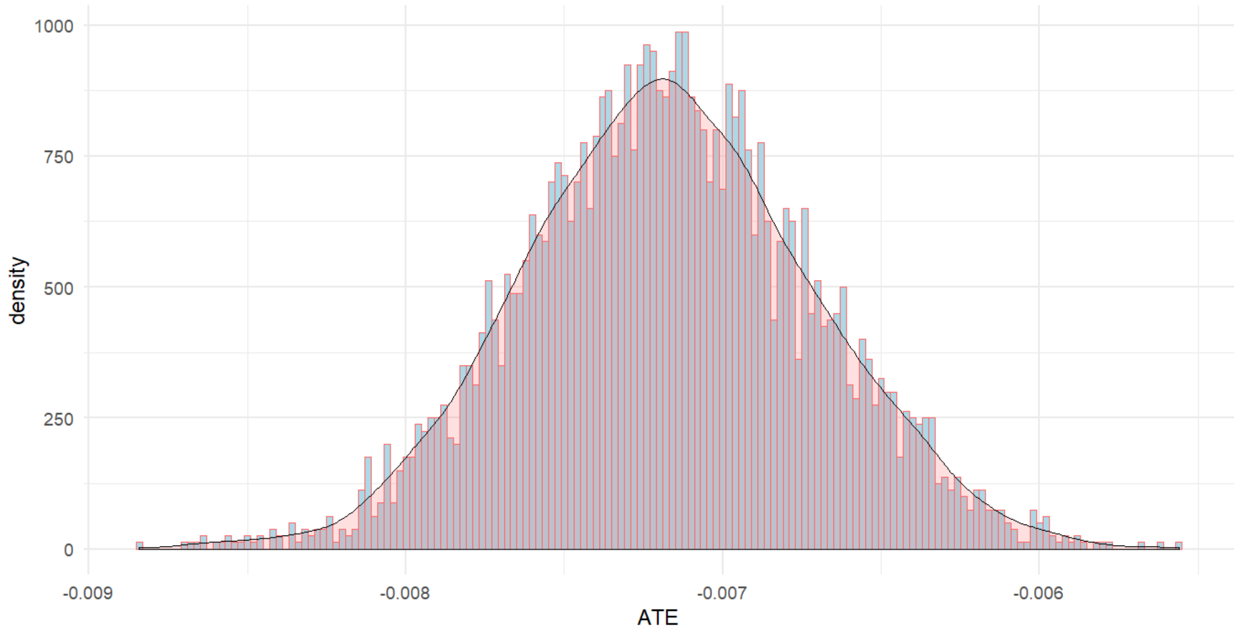

Figure (2): Posterior predictive distribution of ATE

As we can see in the figure, all the values are negative, which indicates the negative effect of financial distress on the performance; means that the firms with higher risk of distress experience lower performance compared with the less risky firms with higher financial health. The average effect is almost around -0.01 which is not too strong also not too weak. Considering the average values of firm performance (-0.10051), this can be interpreted as a semi-strong effect. More detailed information about the summary of Bayesian model for the causal effect is provided in the following table.

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Financial Distress likelihood	-0.01	0.00	-0.01	-0.01	0.01	3204	2468

Table (1): Summary of ATE distribution

V. CONCLUSION:

Using the causal lens, we examined the possibility of the causal relationship between financial distress and firm performance. We applied Bayesian IPW as a causal model for US public firm's data. First, we consider the three main assumptions of positivity, consistency, and conditional exchangeability for the sample datasets. Based on our results, there is a causal relationship between these variables. Considering the distribution of the outcome variables, we conclude that the financial distress on average has negative effects on the firm performance. Which means that firms with higher probability of financial distress have weaker performance compared with the firms with lower financial distress probability. However, the results are based on the available data for US public firms which covers one year, the results may be different for another period or area. Also, the data belongs to a good economic time; we expect the causal effect would be stronger for the recession time. For future research, we encourage the researchers to repeat our model for firms with higher distress risk because of coronavirus pandemic.

REFERENCES:

[1]. Campa, Jose Manuel, and Simi Kedia. "Explaining the diversification discount." The journal of finance 57, no. 4 (2002): 1731-1762.

[2]. Platt, Harlan D., and Marjorie B. Platt. "Understanding differences between financial distress and bankruptcy." Review of Applied Economics 2, no. 1076-2016-87135 (2006): 141-157.

[3]. Faraji, Z. & Fleischhacker, A. (2020). Overstatement of Firm Diversification effect on Bankruptcy Risk Reduction. International Journal of Applied Decision Sciences, Vol. 13, No. 3, (Forthcoming) DOI: 10.1504/IJADS.2020.10027736.

[4]. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The journal of finance, 23(4), 589-609.

[5]. Tan, Tih Koon. "Financial distress and firm performance: Evidence from the Asian financial crisis." Journal of Finance and Accountancy 11 (2012): 1.

[6]. Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. Journal of International Financial Management & Accounting, 28(2), 131-171.

[7]. Hernan, M. A., & Robins, J. M. (2010). Causal inference. Boca Raton, FL: CRC.

[8]. Pindado, Julio, and Luis Rodrigues. "Determinants of financial distress costs." Financial Markets and Portfolio Management 19, no. 4 (2005): 343-359.

[9]. Choy, Steven Liew Woon, Jayaraman Munusamy, Shankar Chelliah, and Ally Mandari. "Effects of financial distress condition on the company performance: A Malaysian perspective." Review of Economics & Finance 1, no. 4 (2011): 85-99.

[10]. Hauser, Roie. "Busy directors and firm performance: Evidence from mergers." Journal of Financial Economics 128, no. 1 (2018): 16-37.

[11]. Notta, Ourania, and Aspasia Vlachvei. "The impact of Financial Crisis on firm performance in case of Greek food manufacturing firms." Procedia Economics and Finance 14 (2014): 454-460.

[12]. Safari, Hossein, Zahra Faraji. "Identifying and evaluating enterprise architecture risks using FMEA and fuzzy VIKOR." Journal of Intelligent Manufacturing 27, no. 2 (2016): 475-486.

[13]. SM Ezzatollah Asgharizadeh, Hossein Safari, Zahra Faraji, Supply chain Performance Measurement by combining criterions of SCOR, Gunasekaran and BSC models with REGIME Technique, Journal of Basic and Applied Scientific Research 4, 3. (2014) 309-320.

[14]. Lang, Larry HP, and Rene M. Stulz. "Tobin's q, corporate diversification, and firm performance." Journal of political economy 102, no. 6 (1994): 1248-1280.

[15]. Servaes, Henri. "The value of diversification during the conglomerate merger wave." The Journal of Finance 51, no. 4 (1996): 1201-1225.

[16]. Santalo, Juan, and Manuel Becerra. "Competition from specialized firms and the diversification–performance linkage." The Journal of Finance 63, no. 2 (2008): 851-883.

[17]. Bennett, Benjamin, J. Carr Bettis, Radhakrishnan Gopalan, and Todd Milbourn. "Compensation goals and firm performance." Journal of Financial Economics 124, no. 2 (2017): 307-330.

[18]. Barberis, Nicholas, Ming Huang, and Tano Santos. "Prospect theory and asset prices." The quarterly journal of economics 116, no. 1 (2001): 1-53.

[19]. Mansi, Sattar A., and David M. Reeb. "Corporate diversification: what gets discounted?." The Journal of Finance 57, no. 5 (2002): 2167-2183.

[20]. Opler, Tim C., and Sheridan Titman. "Financial distress and corporate performance." The Journal of finance 49, no. 3 (1994): 1015-1040.

***Corresponding Author: Zahra Faraji, PhD Candidate,**
Department of Financial Service Analytics Alfred Lerner College of Business & Economics
University of Delaware*