# Corporate Financial Distress and Financial Fragility: Empirical Analysis Based on SVAR Model

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**Abstract—**Financial fragility is the own property of the financial system. As an important participant in the financial market, companies are closely related to the financial system. Based on this, from the perspective of corporate financial distress, SVAR model is adopted to study its impact on financial fragility. The results show that financial distress has a large positive impact on financial fragility in the short term and has a time delay effect. Further discussion shows that corporate financial distress can affect financial fragility through the macroeconomic environment and the banking sector, and the banking sector plays a more significant role.

**Keywords-** financial distress; financial fragility; SVAR model

## 1 INTRODUCTION

Financial distress is also called “financial crisis” [1]. In recent years, China’s corporate financial crisis events occur frequently, from Jiangsu Zhongda to Letv, to the current “Ocean- wide” and Evergrande Group, a spate of defaults could seriously undermine investor confidence, at a time of huge asset bubbles and high leverage, maybe it could trigger natural vulnerabilities in the financial system.

Many studies have focused on the relationship between corporate financial distress and macro economy. One kind of literature holds that corporate financial distress is the result of the influence of macroeconomic variables. For example, Sharma & Mahajan (1980) divided the causes of financial distress into two parts: internal causes and external causes. Internal causes focus on management strategy and implementation, while external causes include changes in the economic situation, policy environment and market demand. Another type of literature holds that companies are the basic unit of social economy, and their financial status is bound to have an impact on the macro economy. Related research can be divided into theoretical and empirical levels. In terms of theoretical research, Lown & Morgan (2006) believed that corporate financial distress will weaken their production capacity, then affect bank credit policies, and ultimately cause a huge impact on the macro environment. Wang Tieming (2003) pointed that corporate financial distress will cause direct losses of commercial bank loans and increase the loan risks of the banking system. Wang Keming (2004) further analyzed and pointed out that corporate financial distress will seriously affect the confidence of investors in the financial market and set off a chain reaction. It will also cause investors to rejudge the value of the company's assets, resulting in violent fluctuations in asset prices. At the level of empirical research, Sommar &

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Shahnazarian (2009) proved the long-term relationship between expected bankruptcy rate and macroeconomic development by using vector error correction model. To sum up, foreign researches focus on the analysis of the impact of macro economy on corporate financial distress, while relevant domestic literatures mainly analyze the impact of corporate financial distress on financial fragility from a theoretical perspective, and rarely use quantitative empirical analysis methods.

Based on this, this paper selects the quarterly data from the fourth quarter of 2010 to the first quarter of 2021, constructs comprehensive indexes that can measure the corporate financial distress and financial fragility through principal component analysis, and uses SVAR model to empirvely study the dynamic impact of financial distress on financial fragility. In order to provide a new perspective and basis for maintaining the stability of China's financial market under the background of increasing corporate leverage ratio and increasing corporate financial risks.

## 2 MATERUALS & METHODS

### 2.1 Sample selection and data processing

Taking into account data availability, the time interval of the sample is from the fourth quarter of 2010 to the first quarter of 2021. Data from the National Bureau of Statistics, the People's Bank of China, WIND and RESSET, etc. The financial distress index is compiled for the non-financial listed companies in Shanghai and Shenzhen A-share markets, and the companies with missing data are excluded.

Since some indicators are monthly data, this paper converts them into quarterly data by quadratic interpolation method. At the same time, in order to eliminate the dimensional influence and facilitate comprehensive evaluation, the data are standardized and forward processing. All data were processed by SPSS 23 and EVIEWS 8.

### 2.2 Index and model construction

#### 2.2.1 Corporate Financial Distress Index (FD)

The corporate financial distress reflects the overall problems in the operation process of companies. A more feasible method is to use comprehensive financial indicators to measure it. Reference to the existing early-warning models of financial distress variables selection and data availability [2]. In this paper, a total of 20 financial indicators in four categories are selected to comprehensively reflect the company's solvency, profitability, growth ability and operating ability [3]. The specific indicators are as follows: Asset-liability ratio, Quick ratio, Ratio of current assets to total assets, Ratio of cash to current liabilities, ROE, EBIT, ROA, Ratio of profits to cost, Main business vivid rate, TATO, Stock turnover, AR turnover, Ratio of operating assets to total assets, Ratio of working capital to sales revenue, FATO, MBRG, Capital accumulation rate, TAGR, Operating profit growth rate, LOG (total assets).

Considering that this study adopts a macro perspective [4], so we construct the corporate financial distress index by PCA based on the concept of corporate financial distress in industries and regions proposed by Gu Qianping et al. (2007) and the financial index system of listed companies proposed by Zhao Dewu et al. (2012). The larger the financial distress index is, the more likely the company is to get into financial distress [5]. The specific steps of index construction are as follows: First, due to the different dimensions and magnitudes of basic indicators, all indicators need to be forward and standardized before calculation. Secondly, principal component analysis was performed on the treated indexes. The number of principal components was determined according to the principle that the cumulative variance contribution rate should not be less than 85%, then the score of each principal component was calculated. Finally, according to the proportion of the variance contribution rate of each principal component to the accumulated variance contribution rate of the extracted principal components, the score of the principal components was weighted and summed.

### 2.2.2 Financial Fragility Index (FT)

Financial fragility is an inherent characteristic of the financial system and manifests widely. The fragility in the traditional credit market mainly stems from the credit of financial institutions, such as the separation of time between the use and repayment of bank credit funds. The fragility in financial markets comes from the volatility of asset prices and the synergistic effects of volatility [6]. At present, many domestic and foreign researches also include macroeconomic fluctuations in the framework of financial fragility measurement. Referring to the index construction by Wu Zhiwen (2002), He Chang and Xing Tiancai (2018), this paper constructs a financial fragility index system covering macro and micro factors in four dimensions [7]. The specific indicators are shown in Table 1.

**TABLE 1.** FINANCIAL FRAGILITY INDEX SYSTEM

| Dimension | Indicator | Influence Direction |
|---|---|---|
| Macro-economic Environment | GDP Growth Rate | - |
| | Growth Rate of Fixed Assets | - |
| | CPI Growth Rate | - |
| Financial Regulation | M2 Growth Rate | - |
| | M2/M1 | + |
| | One-year Real Deposit Rate | - |
| | Growth Rate of Financial Institution Loan | + |
| | Ratio of M2 to foreign exchange reserves | - |
| | Current Account Balance | - |
| | Growth Rate of Total Imports | - |
| Financial Market | Price-to-earnings | + |
| | Ratio of Total Stock Market Value to GDP | + |
| | Volatility of the Shanghai Composite Index | + |
| | Ratio of Fiscal Deficit to GDP | + |
| Banking Sector | NPL Ratio of State-owned Banks | + |
| | State-owned Bank Capital Adequacy Ratio | - |
| | State-owned Bank Capital Profit Ratio | - |
| | State-owned Bank Liquidity Ratio | - |

Referring to the construction method and steps of corporate financial distress index, the China's financial fragility can be concluded as shown in Figure 1. At the same time, using the methods of Wu Zhiwen (2009) and Wan Xiaoli (2008) for reference, the average value of the financial fragility index plus 0.5 times the standard deviation of the financial fragility index is set as a warning line to judge whether China's financial system is in a fragile state [8].

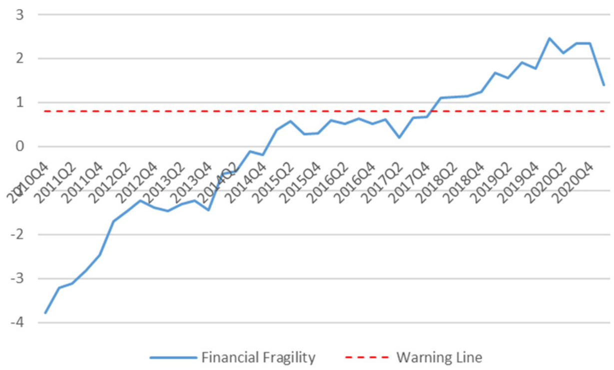


**Figure 1.** China's Financial Fragility from 2010 to 2021

### 2.2.3 SVAR model construction

Conventional VAR models usually do not consider the constraints in the economic sense, and hide the structural correlation between the internal variables of the model system into the "variance-covariance" matrix of the random disturbance term, so that the unique impulse response function cannot be obtained. As the extension and extension of VAR model, structural vector auto-regression (SVAR) model adds structural impact constraint to identify the current relationship between variables, which makes up for the deficiency of VAR model in identifying the relationship between variables to a certain extent. SVAR model is set as follows:

$$AX_t = B_0 + B_1 X_{t-1} + B_2 X_{2-1} + c + \varepsilon_t \tag{1}$$

$X_t$ is the column vector containing two endogenous variables. B matrix is the response coefficient of each endogenous variable to the current impact. $\varepsilon_t$ is the disturbance term, which is generally white noise. Meanwhile, in order for the model to be estimated, equation (1) needs to be transformed:

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} + d + \mu_t \tag{2}$$

$\mu_t$ is structural impact, and $\mu_t = A^{-1} B \varepsilon_t$ . In addition, A and B matrices need to be constrained. The constraint conditions are as follows:

$$A = \begin{bmatrix} 1 & 0 \\ a_{21} & 0 \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \tag{3}$$

# 3 RESULTS & DISCUSSION

## 3.1 Stationarity test and lag order test

In order to avoid the occurrence of "spurious regression", this paper adopts the ADF, PP, KPSS unit root test. The results are shown in Table 2.

**TABLE 2.** UNIT ROOT TEST OF VARIABLE SEQUENCE

| | ADF Test | PP Test | KPSS Test | Conclusion |
|---|---|---|---|---|
| FD | -2.690 | $-7.958^{***}$ | $0.139^{***}$ | Non-stationary |
| $\triangle_{(FD)}$ | $18.256^{***}$ | $-25.857^{***}$ | $0.118^{***}$ | Stationary |
| FT | -2.452 | -2.318 | $0.176^{***}$ | Non-stationary |
| $\triangle_{(FT)}$ | $7.760^{***}$ | $-7.760^{***}$ | $0.066^{***}$ | Stationary |

△ Means first-order difference, ** and ***mean significant at 5% and 1%

As can be seen from the results in Table 2, after the first-order difference, each variable is a stationary series at the significant level of 1%. In order to properly estimate the model, this paper uses LR, FPE, AIC, SC and HQ criterion to select the lag period. The results are shown in Table 3, and the optimal lag order is determined to be 3.

**TABLE 3.** OPTIMAL LAG ORDER

| Lag | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|
| 0 | NA | 0.133 | 3.661 | 3.747 | 3.692 |
| 1 | 12.042 | 0.116 | 3.527 | 3.786 | 3.619 |
| 2 | 5.4051 | 0.122 | 3.574 | 4.005 | 7.354 |
| 3 | $57.602^{*}$ | 0.023 | $1.927^{*}$ | $2.530^{*}$ | $2.141^{*}$ |

* indicates the lag order selected in each column of criteria

## 3.2 Johansen cointegration test

FD and FT are both subject to first-order integration, and the co-integration test can be further performed on them. The results are shown in Table 4. The test results show that at the significance level of 5%, both eigenvalue and trace statistics reject the null hypothesis, so there is a long-term stable relationship between the two variables.

**TABLE 4.** JOHANSEN SYSTEM CO-INTEGRATION TEST

| Null Hypothes | Eigenvalue | Trace Statistic | 0.05 Critical Value | Prob |
|---|---|---|---|---|
| None | 0.694 | 50.775 | 18.397 | 0.00 |
| At most 1 | 0.108 | 4.500 | 3.8414 | 0.03 |

### 3.3 Granger causality test

On the basis of co-integration between variables, this paper further analyzes the relationship between financial distress and financial fragility through Granger causality test. The test results are shown in Table 5. The test results show that corporate financial distress and financial fragility are each other's Granger cause, which is consistent with the conclusion of current research. Companies falling into financial distress may aggravate financial fragility through the feedback effect of banks. Meanwhile, financial fragility, as an aspect reflecting macroeconomic fluctuations, is also one of the important systemic risks faced by companies [9].

**TABLE 5.** PAIRWISE GRANGER CAUSALITY TESTS RESULTS

| Null Hypothesis | F-Statistic | Prob | Result |
|---|---|---|---|
| $\triangle_{(FD)}$ does not cause $\triangle_{(FT)}$ | 0.689 | 0.508 | Reject |
| $\triangle_{(FT)}$ does not cause $\triangle_{(FD)}$ | 0.748 | 0.480 | Reject |

### 3.4 Robustness test of VAR model and estimation of SVAR model

In order to ensure the validity of empirical results, AR unit root is adopted in this paper to test the stability of VAR (3) model. The results are shown in FIG. 2.

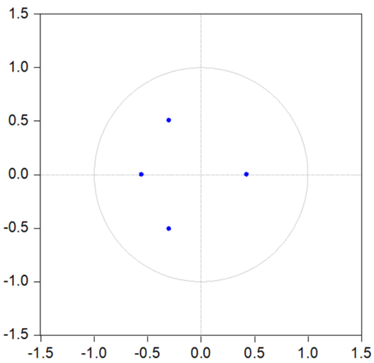


**Figure 2.** Stability Test of VAR Model

We can see that the characteristic roots all fall within the unit circle, indicating that the VAR (3) model is stable. Based on the VAR model and combining with the economic significance, the AB-SVAR model is estimated, and the matrix estimation results are obtained as follows. The results show that $a_{21}$ is positive and can pass the significance test of 1%, indicating that corporate financial distress has a significant positive impact on financial fragility.

$$A = \begin{bmatrix} 1 & 0 \\ 0.15181 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 1.00691 & 0 \\ 0 & 0.29864 \end{bmatrix}$$

### 3.5 Analysis of impulse response function

The impulse response function can analyze the dynamic influence between variables. Figure 2 shows how FT is affected when FD is given a standard unit of forward impact. It can be seen that the current period has a positive impact on the corporate financial distress, and the financial fragility will have a temporary negative effect, and then show a long-term positive effect, and the positive effect reaches the maximum 0.09 percentage points in the second period. This may be because macroeconomic indicators always lag behind the real economy in the short term. From the third to the fifth period, the impact of financial distress on financial fragility shows a decreasing negative effect to an increasing positive effect, but the overall fluctuation is small. Since then, the positive and negative effects continue to converge to 0. This pulse trajectory shows that the financial distress will aggravate financial fragile in the short term, but in the medium and long term, the impact is not significant.

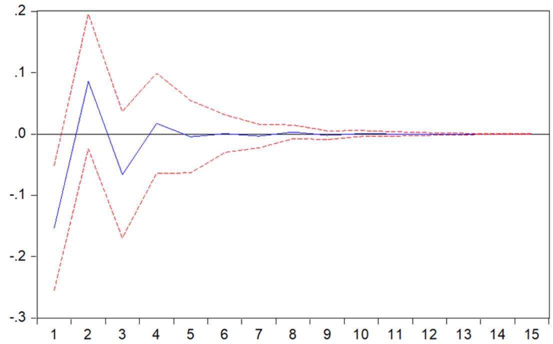


**Figure 3.** Impulse Response of FT to FD

### 3.6 Variance decomposition analysis

Variance decomposition is used to analyze the contribution of each variable to financial fragility, and the results are shown in FIG. 3. As can be seen from Figure 3, the financial fragile has the biggest impact on itself, and it has been kept above 70%. The contribution of financial distress to financial fragility increased gradually over time, and stabilized at 26.8% after the fifth phase.

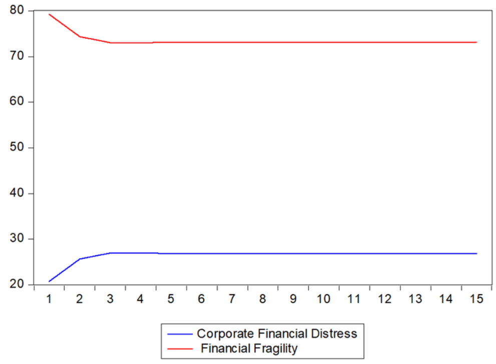


**Figure 4.** Variance Decomposition of Financial Fragility

### 3.7 Further discussion

In order to further analyze the transmission mechanism, influence degree and lag time of financial fragility caused by corporate financial distress, two variables of macroeconomic environment and banking sector were added into the above econometric model, and corresponding indexes were measured [10]. Among them, index selection and index construction follow the methods mentioned above.

According to the results of Granger causality test, corporate financial distress is the Granger cause of banking sector fragility, and it is also the Granger cause of financial fragility. Corporate financial distress and macroeconomic environ- ment are each other's Granger causes. Macro-economic environment fragility is the Granger cause of financial fragility. This shows that macroeconomic environment fragility, banking sector fragility and corporate financial distress can all explain financial fragility.

From the results of variance decomposition of macroeconomic environment fragility and banking sector fragility which are shown in FIG. 4, it can be seen that the impact of corporate financial distress on banking sector fragility is greater than that of macroeconomic environment fragility, and in the short term, the banking sector is more sensitive to the impact of corporate financial distress. The reason is that corporate financial distress results in direct loan losses of commercial banks and loan risks of the banking system. Commercial banks further pass on capital shopping malls or financial markets through capitalization of securities or borrowing from the central bank, and finally cause the fluctuations of the overall macroeconomic environment.

## 4 CONCLUSIONS

The above research results show that: In the short term, corporate financial distress increases financial fragility, but in the medium and long term, the impact on the financial fragility is not significant. Corporate financial distress mainly affects the financial fragility through the macro-economic environment and the banking sector, and the banking sector has a significant transmission effect. The impact of financial distress on financial fragility has a time lag effect.

According to the above conclusions, in order to effectively reduce China's financial fragility, the following policy suggestions are put forward: The government can develop regional equity trading market, Internet equity-based crowd- funding and other ways to broaden the financing channels of companies, break the financing mode of companies based on creditor's rights, and reduce the possibility of companies falling into financial difficulties. The government can also improve the construction of social credit system by guiding banks to establish a unified data credit system and urging associations of various industries to publish social credit data to reduce the risk transmission caused by information asymmetry. Banks can use diversified fintech tools to strengthen company risk assessment and credit decision support, so as to avoid falling into the collective behavior of borrowers in the financial system.

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