Examining and Forecasting Financial Vulnerability for Australian Unlisted Firms[1]

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Based on firm-level data in the Business Longitudinal Analysis Data Environment (BLADE) from 2006 to 2019, this project aims to examine financial vulnerability and forecast insolvency of Australian unlisted firms. To do so, we design and develop a sectoral financial vulnerability metric of unlisted firms. A model combination approach of five methods, including Merton's Distance to Default, Altman Z-score, and machine learning methods, is utilised to conduct the project. We build a Dashboard tool to demonstrate the cross-sector Financial Vulnerability Index heatmap of a specific year and the time-series graph of each sector through years.

1. Introduction

Given the profound impact of the ongoing pandemic on the Australian economy, there has been a substantial discussion concerning the financial health of Australian firms, especially unlisted firms. Therefore, there is an urgent need for new research measuring and monitoring the financial vulnerability of Australian unlisted firms. The project aims to construct a sectoral financial vulnerability indicator of Australian unlisted firms and provides policymakers with targeted policy recommendations for identified financially vulnerable sectors, maintaining the financial health of Australian unlisted firms, and facilitating Australian economic recovery.

The remainder of this report is organized as follows: The methodology is presented in Section 2. In addition, models and the calculation for sectoral financial vulnerability, and insolvency forecast are also described in this section. Data is described in Section 3. The empirical result analysis is discussed in Section 4. Concluding remarks are provided in the final section.

2. Methodology and Implementation

This section presents the methodology and implementation steps. First, we calculate each firm's Financial Vulnerability Index. To do so, we employ five methods, including Merton's Distance to Default Model, Altman's Z Score, which are fundamental models in credit risk modelling, and three machine learning models (LASSO, Elastic-Net, Ridge Regression). After that, we apply the model combination technique to integrate results from those five models to

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produce the combined Financial Vulnerability Index (FVI) for each firm. Based on the combined FVI, we calculated the Sectoral Financial Vulnerability Index using weighted average with total assets as the weight. Then, we can forecast future values of Sectoral Financial Vulnerability Index and Insolvency Numbers. The process of this calculation is shown in Figure 1.

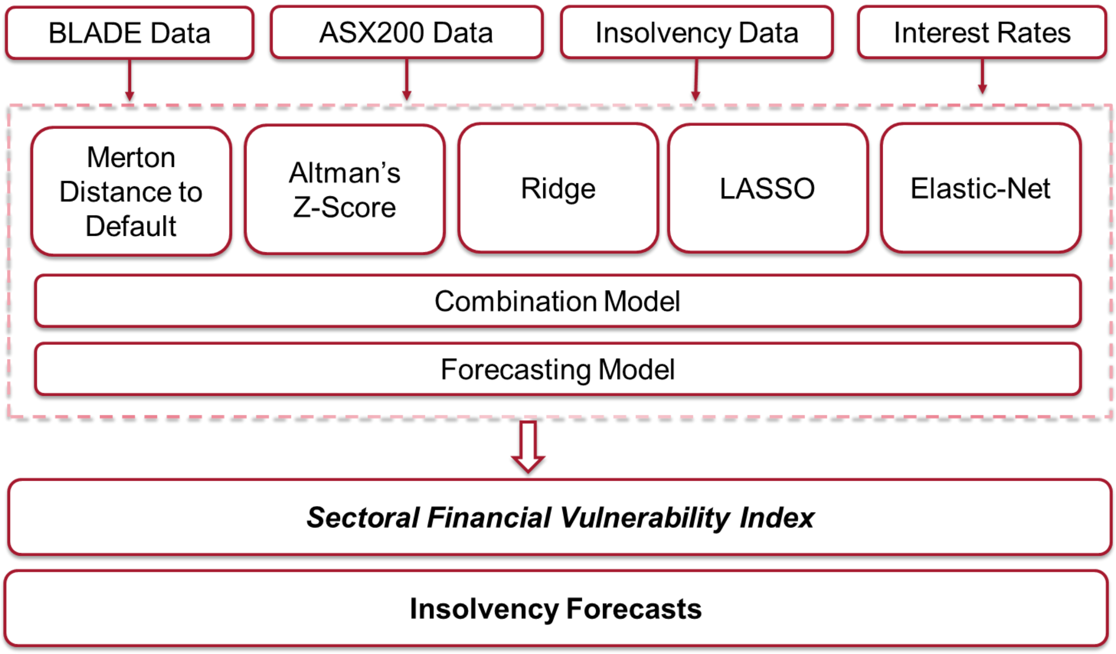


Figure 1: The process of calculating sectoral financial vulnerability index and forecast insolvency of unlisted firms

2.1. Merton's Distance to Default

Merton (1974) laid the foundation on the structural approach to credit risk modelling. The Merton model is used to assess the credit risk of a company's debt. Analysts and investors utilise the Merton's model to understand how capable a company is at meeting financial obligations, servicing its debt, and weighing the general possibility that it will go into credit default. With listed firms, we can estimate a financial default of a company using equity price, debt level, implied volatility, time to debt maturity and current market interest rate level. But with unlisted firms, we do not have volatility data, so we have updated the method by using volatilities of sales revenue instead. Thus, in this project, we compute the revised Merton's Distance to Default model using volatilities of Sales Revenue, Assets, Debt Level, and Interest Rate data.

2.2. Altman's Z Score

The Altman Z-score is the output of a credit-strength test that gauges a company's likelihood of bankruptcy. A score below 1.8 means it is likely that the company is headed for bankruptcy, while companies with scores above 3 are not likely to go bankrupt. In this project, building on Gepp et al. (2010), we apply the revised Altman's Z Score formula:

$$Z = 0.528 * Current\ Ratio + 0.514 * Return\ on\ Assets\ Ratio + 0.491 * Asset\ Turnover\ Ratio + 0.328 * Sector\ Average\ Market\ Cap/(Sector\ Average\ Total\ Equity + Sector\ Average\ Long - term\ Debt)$$

2.3. Machine learning methods

We employed three machine learning methods, including LASSO Regression, Elastic-Net Regression and Ridge Regression. These three techniques take in a large field of variables that are related to financial vulnerability, testing them on a training outcome (i.e., default probability), and repeatedly running improved regressions until the best results are obtained. Twelve firm-level financial ratios are used in each algorithm to reduce predictor counts towards an optimal state, including Working Cap/Total Assets (TA), Sales/TA, Owners' Equity/TA, Current Ratio, Return on Asset, Profits/Sales, Sales/Liabilities, EBIT/TA, Current Assets/TA, Net Interest Coverage, Total Liabilities/Total Assets, Current Liability/Total Assets.

2.4. Model Combination

After obtaining each firm's Financial Vulnerability Indicator by each in five models, we perform a horse-race for five models in a computational "global minimum variance portfolio". This means optimally selected weights are assigned to each model, for each firm. Specifically, the model combination is consistent with the Minimizing Mean Squared Forecast Errors (MSFE) method used in Bu et al. (2018). The formula of this method is:

$$\hat{S}_{t|t-1} = \alpha_0 + \sum_i^5 \omega_{i,t} \hat{S}_{i,t|t-1},$$

where, $\hat{S}_{t|t-1}$ is the weighted combination of the individual models, α_0 is the estimated bias correction term, and $\hat{S}_{i,t|t-1}$ and $\omega_{i,t}$ are the predicted values from each single model and associated weights of the model in the model combination. According to MSFE, the loss function can be decomposed into forecasting bias and forecasting variance.

It remains to describe the rationality of the bias-corrected optimal weighting scheme. Figure 2 shows bias-variance trade-off framework. In this figure, the forecast bias on the *y*-axis is plotted against the forecast variance (standard deviation) on the *x*-axis. The scatted internal dots are the status of diverse individual forecasts which exhibit various levels of bias and variance. A hypothetical estimation frontier can be generated on basis of the bias-variance trade-off framework. As seen from this figure, *GMV* is a combination of single forecast where *minimum variance* is produced. Point *M* indicates an *unbiased* combination of single forecast. Point *O* describes the ideal situation of an unbiased forecast with a minimum variance, which cannot be achieved by any sing individual forecast. In order to achieve this ideal situation, we use a global minimum variance weighting scheme to generate an optimal combination of individual bias-corrected single models.

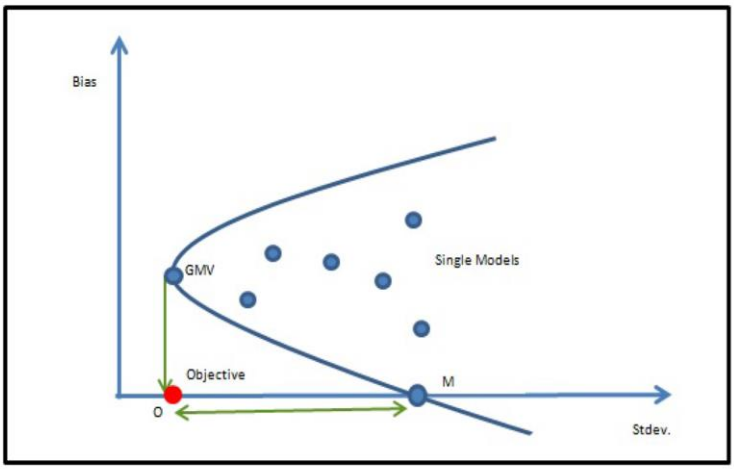


Figure 2: Estimation frontier

2.5. Sectoral Financial Vulnerability Index (SFVI)

The Sectoral Financial Vulnerability Index (SFVI) of each sector can be calculated using FVI of firms in their sector regarding their weight using the total asset ratio as the following formula:

$$SFVI_{jt} = \left(1/Sector\ Total\ Assets_{jt}\right) * \sum_{i=1}^{nj} Firm\ FVI_{it} * Firm\ Total\ Assets_{it},$$

where $SFVI_{jt}$ is the SFVI of the *j* sector at time *t*, *nj* is the number of firms in the *j* sector. Then, we can use the Autoregressive Integrated Moving Average (ARIMA) method to construct a forecast model for each sector to predict the future SFVI.

2.6. Insolvency Forecast

After having SFVI, we can forecast the Insolvency numbers for each sector by implementing the following process (Figure 3). We use ASIC Insolvency data from 2014 to 2021 to regress on Sector Financial Vulnerability Index (SFVI) to construct within-sample models for each sector, then apply forecasted SFVI data to the constructed models to forecast Insolvency numbers for each sector from 2022 to 2024.

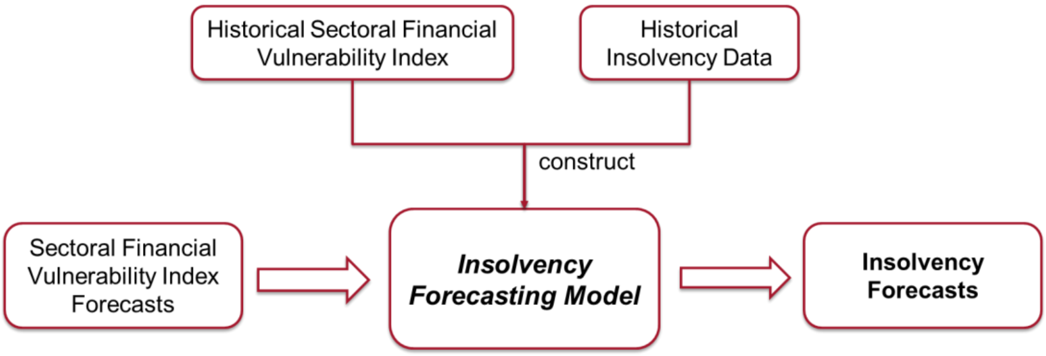


Figure 3: Insolvency forecast process for sectors (2022-2024)

3. Data

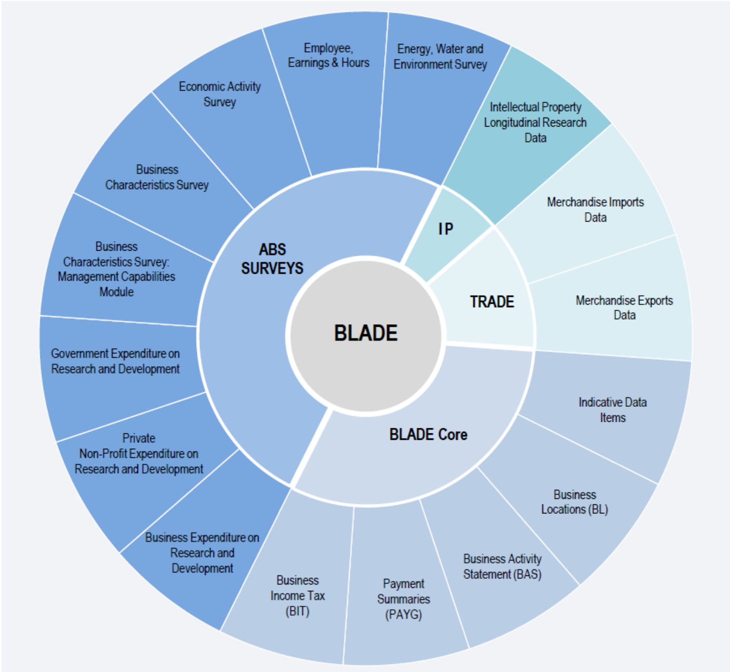
Our project collects data from various sources: BLADE data, ASX200, Insolvency, and Australia's risk-free rate.

3.1. BLADE Data

The project collects unlisted firms' data from the Business Longitudinal Analysis Data Environment (BLADE**)** provided by the Australian Bureau of Statistics (ABS) spanning from 2006 to 2019. BLADE is a statistical resource that contains information on Australian businesses, combining tax, trade, and intellectual property data. An overview of BLADE data is displayed in Figure 4. After collecting the data from BLADE data, we filter data from BLADE. We obtain around 5.7 million firms and 49 million rows of detailed data.

In this project, we mainly use data from the BLADE Core module that contains:

- *Indicative Data Items*: The ABS Business Register (ABSBR) is the integrating spine of the BLADE and uses the ABS economic units model to determine the structure of Australian businesses and other organisations. The majority of business indicators on BLADE come from the ABSBR.
- *Business Activity Statements (BAS)*: are submitted to the ATO by businesses to report their Goods and Services Tax (GST) obligations. The data items available include total sales, other GST free sales, non-capital purchases, capital purchases, export sales and wages and salaries.
- *Business Income Taxation (BIT):* BIT Business Income Taxation (BIT) forms are submitted to the ATO by businesses to report taxable income or loss.



Source: ABS

Figure 4: BLADE Data overview

In order to access BLADE data and work in DataLab provided by ABS, it is necessary to be approved by ABS.

3.2. Other Data

We extract Market Capital, Equity and Debt data of ASX200 companies from the Bloomberg database to calculate Sector Average Market Cap, Sector Average Total Equity and Sector Average Debt for revised Altman's Z Score method. Additionally, Australia's Interest Rates are collected from DataStream, and Insolvency Data are provided by ASIC.

4. Results and Implications

The Financial Vulnerability Index (FVI) provides a view of the estimated vulnerability/ insolvency risk of Australian unlisted firms. The way to interpret the FVI is by assessing it relative to history and periods of known stress. Thus, in the project, we built a Dashboard tool that demonstrates the cross-sector FVI heatmap of a specific year and the time-series graph of each sector through years.

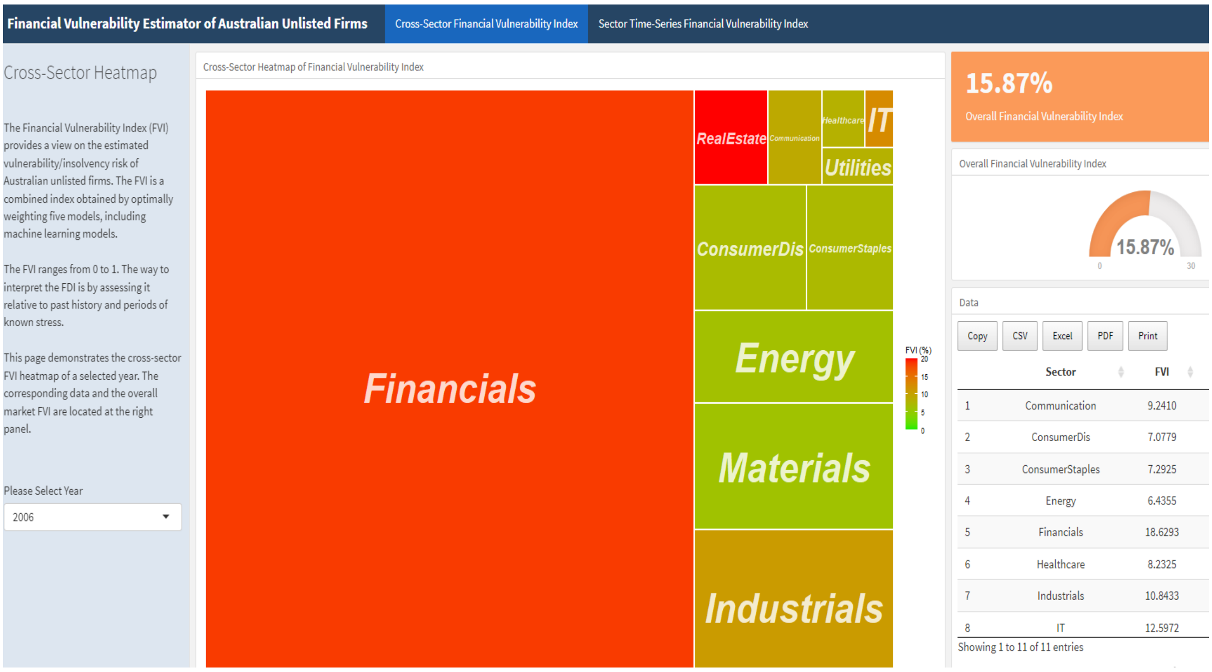


Figure 5: The cross-sector FVI heatmap of year 2006.

The heatmap provides an overview of all sectors' FVI. The area is based on sector total assets. As seen in Figure 5, the FVI of the financial sector and real estate sector are high in 2006 before the financial crisis 2007-2008. The time-series diagram in Figure 6 provides another view that details the variation of each sector's FVI over a period of time.

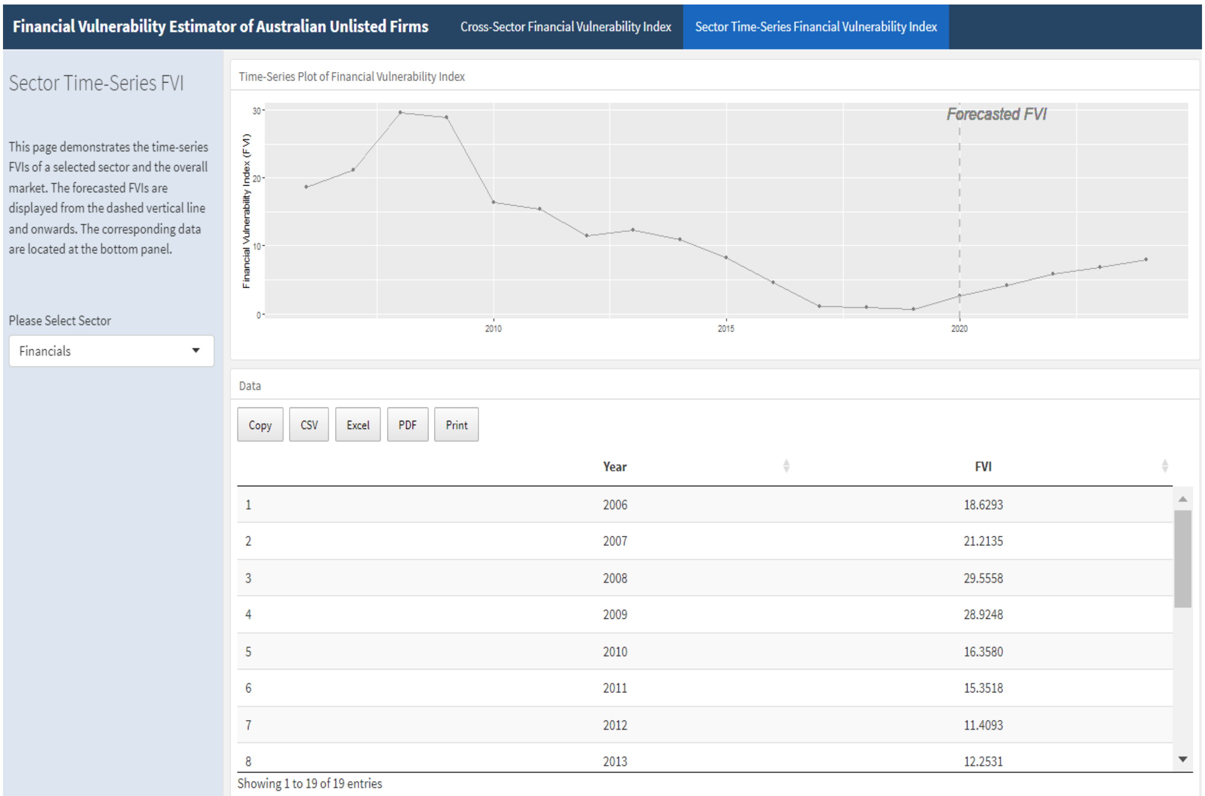


Figure 6: The time-series diagram of the Financials sector

After obtaining the sectors' FVI, we can forecast the insolvency numbers from 2022 to 2024 of each sector from the ASIC historical insolvency data and the sectors' FVI. For convenience to have a clear look at the sectors, we separate the Sectors according to their insolvency forecast values. Figure 7 shows three sectors with larger values while Figure 8 illustrates the remaining sectors with smaller values.

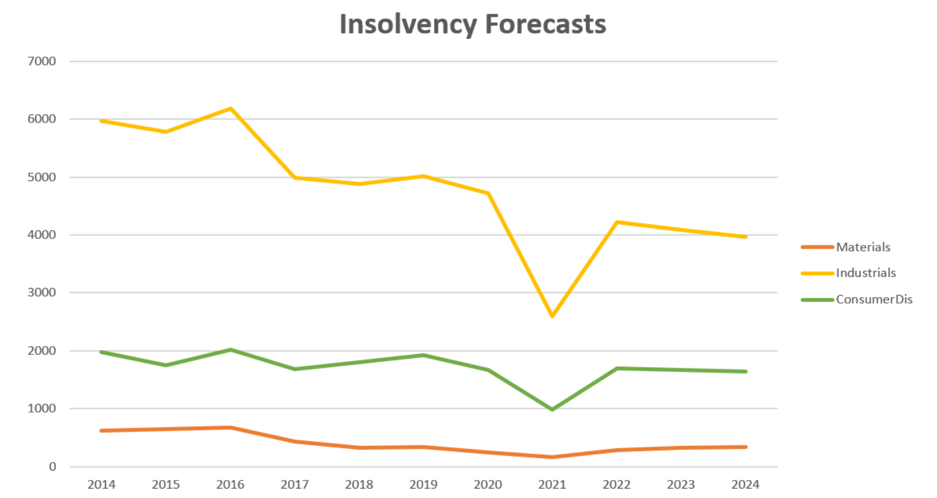


Figure 7: Insolvency forecast in the period 2022–2024 of Materials, Industrials, and Consumer Discretionary Sectors.

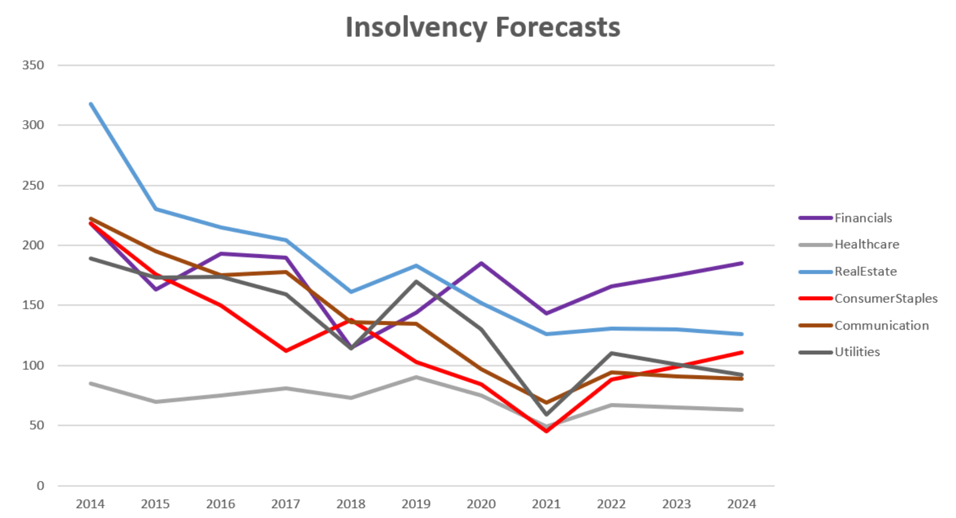


Figure 8: Insolvency forecast in the period 2022–2024 of other sectors.

The findings of this project provide implications for policymakers to identify financially vulnerable sectors or areas of unlisted firms and develop targeted policy instruments, benefiting the financial health of Australian unlisted firms.

5. Conclusion

To examine financial vulnerability and forecast insolvency of Australian unlisted firms, this project utilises a model combination approach that integrates five methods with optimal weighting scheme to produce a combined Sectoral Financial Vulnerability Index. A Dashboard is provided to demonstrate the cross-sector FVI heatmap of a specific year and the time-series diagram of each sector through years.

References

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