Asian Journal of Applied Economics Vol. 31 No. 2 (July-December 2024): 1-30

ISSN: 2985-1610 (Online)

Received: 18 June 2024
Received in revised form: 27 August 2024
Accepted: 29 August 2024

An Empirical Analysis of Private SMEs' Insolvency in Thailand Using Machine Learning

Chalerm Jaitang*
Faculty of Economics, Prince of Songkla University, Thailand
and Department of Financial and Business Systems, Lincoln University, New Zealand
Zhaohua Li
Department of Financial and Business Systems, Lincoln University, New Zealand
Christopher Gan
Department of Financial and Business Systems, Lincoln University, New Zealand

Abstract

We investigate the insolvency of private Thai SMEs in the manufacturing, trading, and service sectors from 2017 to 2021. We model insolvency as a function of industry-relative financial ratios, firm characteristics, and local economic conditions using Least Absolute Shrinkage and Selection Operator (LASSO) logistic regression. The analysis shows the significant influence of financial ratios on the probability of insolvency for all sectors, particularly inventory turnover, accounts payable turnover, assets to equity, and debt to assets ratio. The service sector shows a unique positive effect of working capital to total assets on insolvency risk, implying that firms with high current assets or very low current liabilities are more prone to insolvency. Medium-sized firms, those registered as juristic ordinary partnerships, owned by foreigners, and located in less competitive areas are less likely to face insolvency.

Keywords: SMEs; insolvency; financial ratios; LASSO; Thailand
JEL Classification: C23; C53; G33; M21

*Corresponding Author, Address: Faculty of Economics, Prince of Songkla University, Songkhla 90110 Thailand, Email: chalerm.j@psu.ac.th, and Department of Financial and Business Systems, Lincoln University, New Zealand

1. Introduction

Small and Medium-sized Enterprises (SMEs)[1] play a critical role in Thailand's economy. In 2021, there were 464,811 SMEs, with 74.95 percent registered as legal entities. These Thai SMEs represent 14.56 percent of all enterprises and significantly contribute to the country's GDP while generating employment, accounting for approximately 40 percent of total employment (The Office of Small and Medium Enterprises Promotion, 2021).

Based on data from the Department of Business Development of Thailand, 2.39 percent (19,325 firms) of all Thai juristic persons faced insolvency in 2021. The significance of Thai SMEs' insolvency is evident in their substantial impact on Thailand's GDP and employment. Consequently, addressing and understanding the challenges faced by Thai SMEs is crucial for the country's overall economic stability and growth.

Financial distress, often preceding insolvency, refers to a firm's inability to meet its financial obligations or maintain its usual business operations. In the literature, there are several ways to define financial distress based on different financial indicators. Some recent definitions rely on negative growth in net worth for two consecutive periods (Gupta et al., 2018; Tong & Serrasqueiro, 2021), or earnings before interest, taxes, depreciation, and amortization (EBITDA) being less than 80 percent of a firm's expenses in any three consecutive years (Inekwe, 2016). Other studies use negative profits for two consecutive years (Xiao et al., 2012) or negative growth in market value for two consecutive years (Hernandez Tinoco & Wilson, 2013) to detect listed firms' financial distress. The choice of distress definition depends on the researchers' perspective or the specific research context. It is important to note that financial distress differs from insolvency, as the latter is a more severe outcome and can include bankruptcy or liquidation.

Many approaches have been developed to improve the estimation of firms' insolvency by including financial and non-financial variables in the models. These improvements reflect a shift from a simple assessment to a more predictive approach in understanding financial distress and insolvency. Three main methods enhance the accuracy of firms' insolvency estimation: selecting better financial ratios, developing predictive models, and incorporating market and non-financial variables into the model (Muñoz-Izquierdo et al., 2020; Tong & Serrasqueiro, 2021). Many studies use financial or accounting ratios, as well as macroeconomic and market variables, to examine and predict financial distress and firm insolvency. Models that include both accounting and market variables outperform those that rely on only one of these categories (Hernandez Tinoco et al., 2018).

Firm insolvency prediction models have been intensively developed and studied. However, the applicability of these models to SMEs, particularly those not listed on stock markets, remains a challenge. To address this challenge, we use industry-relative (IR) financial ratios. Most studies use unadjusted financial ratios to predict a firm's financial distress and insolvency, which can lead to significant industry sensitivity. However, using IR financial ratios offers two clear advantages (Platt & Platt, 1990): (1) In the same period, all enterprises are measured on the same scale regardless of industry; and (2) across periods, IR financial ratios are more stable, yielding more accurate forecasts of financial status.

[1] Definitions of SMEs provided by the Office of SMEs Promotion of Thailand (see Appendices Table A1)

Recently, machine learning techniques have gained popularity in forecasting, particularly in financial contexts (Malakauskas & Lakstutiene,2021; Tian & Yu, 2017). The Least Absolute Shrinkage and Selection Operator (LASSO) is a machine learning method that automatically selects the explanatory variables for insolvency and explores their forecasting performance using a selected subset of variables. LASSO intuitively addresses the issue of multicollinearity when the explanatory variables exhibit high correlation due to accounting rules in the construction of a firm's financial statements. LASSO provides stable results and is suitable for low-frequency events such as firms' insolvency (Tian & Yu, 2017). For more accurate prediction of rare events such as insolvency, it is imperative to select a robust prediction model that is resilient to minor perturbations in the data.

There are two critical gaps in the literature. First, there is a gap in effectively forecasting insolvency among private SMEs (non-listed) (Camacho-Miñano et al., 2015; Fuertes-Callén et al., 2022). Second, there is a lack of comprehensive studies specifically examining SMEs' insolvency in the context of developing countries like Thailand. These gaps motivated us to investigate SMEs' insolvency in Thailand, given their substantial contribution to the country's GDP and economy.

This study examines how financial ratios affect Thai SMEs' insolvency, which is more evident than financial distress. We use industry-relative financial ratios and add micro and macro-level factors as control variables in three distinct models representing the manufacturing, trading, and service sectors. We implement LASSO logistic regression to systematically select the financial ratios that affect firm insolvency. Subsequently, LASSO inference is applied to evaluate the significance of the selected financial ratios, and the results are complemented by the traditional logistic regression. This study ensures a comprehensive examination of the interplay between financial ratios and insolvency in the context of Thai SMEs in each sector, offering insights for both academic and practical applications. This study's novelty lies in its focus on industry-relative financial ratios in the unique economic and business landscape of Thailand and the use of machine learning models to predict insolvency. By examining financial ratios in Thai SMEs, we seek to provide insights that are not only academically significant but also practically relevant for financial managers and policymakers. Specifically, the study contributes to the literature by identifying critical financial ratios that Thai SMEs should prioritize to decrease the probability of insolvency. Through an empirical design, this study identifies and analyzes significant financial ratios in three distinct sectors (manufacturing, trading, and service).

The paper is organized as follows: Section 2 presents the literature review and hypothesis development. Section 3 describes the data and variables. Section 4 presents the methodology. Section 5 discusses the empirical results, and Section 6 concludes the study with policy implications.

2. Literature Review and Hypotheses Development

The literature consistently demonstrates an inverse relationship between the probability of a firm's insolvency and its profit level (Beaver et al., 2012; Camacho-Miñano et al., 2015; Fuertes-Callén et al., 2022;

Muñoz-Izquierdo et al., 2020; Tian & Yu, 2017; Tong & Serrasqueiro, 2021). Profitability ratios serve as critical metrics, gauging a firm’s ability to generate earnings and profit in relation to its assets or equity. Empirical evidence suggests that firms with higher profits tend to experience a reduced likelihood of insolvency (Fuertes-Callén et al., 2022; Li, 2024; Tong & Serrasqueiro, 2021). This relationship indicates the pivotal role of profitability in contributing to a firm's overall performance and lowering the probability of insolvency.

Similarly, firm liquidity and operational efficiency are anticipated to negatively influence the probability of insolvency. Liquidity, reflecting a firm's capability to meet short-term debt obligations, is notably associated with a diminished likelihood of insolvency (Camacho-Miñano et al., 2015; Fuertes-Callén et al., 2022; Hernandez Tinoco et al., 2018; Hernandez Tinoco & Wilson, 2013; Khoja et al., 2016; Patel et al., 2017). Islam et al. (2013) underscore that liquidity ratios are important in enhancing a firm's financial position, acting as a protective measure against the risk of insolvency.

Operational efficiency, as measured by metrics such as assets turnover and operational expenses to total revenue, provides insights into how effectively firms use their assets to generate income and manage operational costs. Operational efficiency, when high, is correlated with a decreased probability of insolvency (Tian & Yu, 2017). The efficient use of assets and cautious management of operational expenses contribute significantly to a firm's financial robustness, mitigating the risk of insolvency.

In contrast, a firm's debt structure, often measured by its financial position proportion, has a positive correlation with the likelihood of insolvency, as evidenced by several studies (Beaver et al., 2012; Hernandez Tinoco et al., 2018; Hernandez Tinoco & Wilson, 2013; Khoja et al., 2016; Lizares & Bautista, 2021; Tian & Yu, 2017; Tian et al., 2015; Tong & Serrasqueiro, 2021). In particular, Li (2024) underlines that there is no positive association between insolvency and a low level of debt-to-assets ratio. However, a significant positive relationship is observed at high debt-to-assets ratio. Higher debt levels typically result in augmented interest payment obligations, posing a heightened risk to the firm's solvency and overall financial health. Additionally, the study by Rico et al. (2021) underscores the significance of reducing debt, demonstrating its association with a firm's business survival. Tian and Yu (2017) include assets to equity ratio as a candidate predictor to forecast the firm insolvency even though it is insignificant. Additionally, Islam et al. (2013) use assets to equity to create the discriminant score to identify the firm insolvency.

Variables derived from Altman's Z-score are extensively used as explanatory factors in the analysis of firm insolvency and financial distress. The Altman’s Z-score (1968) model comprises five ratios to predict corporate insolvency: working capital to total assets, retained earnings to total assets, earnings before interest and taxes total assets, the market value of equity to total liabilities, and sales to total assets (Altman, 1968). Several studies have consistently identified a negative association between the components of Altman's Z-score and the likelihood of firms encountering insolvency and financial distress (Altman et al., 2017; Muñoz-Izquierdo et al., 2020; Tian & Yu, 2017). In alignment with these findings, it is observed that firms exhibit a higher probability of survival when they maintain elevated levels of working capital (Fuertes-Callén et al., 2022).

Working capital has a crucial role in enhancing a firm's ability to meet its short-term obligations and financial challenges. This understanding contributes to the broader comprehension of several groups of financial ratios that influence firms' insolvency. Based on these findings, we hypothesize the following relationships:

H1: The profitability ratio negatively impacts the insolvency of Thai SMEs.

H2: The liquidity ratio negatively impacts the insolvency of Thai SMEs.

H3: The operational efficiency ratio negatively impacts the insolvency of Thai SMEs.

H4: The financial position proportion ratio positively impacts the insolvency of Thai SMEs.

H5: The financial components of Altman's Z-score negatively impact the insolvency of Thai SMEs.

3. Data Description and Variables

3.1 Data

The primary source of our dataset is the Department of Business Development (DBD) of Thailand. Our sample comprises 5,150 juristic persons from Thai Small and Medium-sized Enterprises (SMEs). This extensive dataset includes 807 firms (3,584 firm-year observations) in the manufacturing sector, 1,692 firms (7,765 firm-year observations) in the trading sector, and 2,651 firms (11,362 firm-year observations) in the service sector, spanning 17 distinct industries. The data is derived from the annual financial reports of these SMEs, covering the period from 2017 to 2021, resulting in a comprehensive set of 22,711 firm-year observations.

The study period from 2017 to 2021 reflects the most up-to-date situation, and the data sourced from the DBD is stable and reliable for identifying firm status. This stability is crucial because legal processes, such as liquidation, dissolution, and bankruptcy, take time to be formally recognized. The data collection was conducted using random sampling to ensure a representative and unbiased sample. To mitigate the impact of extreme values, we applied winsorization at the 1st and 99th percentiles, ensuring the stability and reliability of our findings.

3.2 Variables

The dependent variable in our model is a dummy variable (Insolvent), which equals '1' if insolvent and '0' otherwise. An SME is categorized as insolvent if it undergoes liquidation, dissolution, or bankruptcy, with exceptions for cases involving mergers or takeovers according to the firm's status recorded by the DBD.

The explanatory variables are structured into four primary categories: profitability, liquidity, operational efficiency, and financial position proportion (leverage). We use Altman's Z-score components to evaluate the insolvency probability of Thai SMEs. By examining the individual components of Altman's Z-score rather than the composite score itself, we can achieve a more nuanced understanding of the specific financial ratios that influence insolvency in Thai SMEs. This approach enables a more targeted analysis, allowing policymakers and business owners to identify and address the most critical financial indicators that contribute to insolvency risk. However, we are unable to incorporate retained earnings because of data constraints specific to SMEs. Additionally, two components of Altman's model, earnings before interest and taxes to total assets, and equity to total liabilities, are integrated into the profitability and financial position proportion categories. Table 1 defines all variables used in our study. Our model uses a comprehensive set of 15 essential financial ratios, which are assessed using industry-relative (IR) financial ratios in the respective industries. The use of IR financial ratios ensures uniform measurement across industries, enhancing the stability of our analyses over time. The IR financial ratio of a typical firm is defined as:

$$IR_{it}^{g} = \frac{X_{it}^{g}}{X_{t}^{g}} \tag{1}$$

where: X_{it}^{g} is the unadjusted ratio of firm *i* in industry *g* at time *t*, and $X_{t}^{g} = \sum_{i=1}^{n} X_{it}^{g}/n$ is the average ratio for industry *g* with *n* firms at time *t*.

3.3 Descriptive statistics

Table 2 presents the descriptive statistics of the dependent variables, raw financial ratios, and control variables specific to each sector. Panel A in Table 2 shows data from 3,584 firm-year observations in the manufacturing sector, with 15.62 percent of these observations indicating insolvency. Panel B provides the summary statistics for the trading sector comprising 7,765 firm-year observations, with 16.07 percent indicating insolvency. Panel C presents the 11,362 firm-year observations in the service sector, with 17.60 percent indicating insolvency.

The profitability ratios in Table 2, Panels A, B, and C show that the ROE is consistently higher than the ROA across all sectors. The median ROA values are 2.36, 3.15, and 2.87 percent in the manufacturing, trading, and service sectors, respectively, which are lower than those reported for listed companies by Beaver et al. (2012) at 6.17 percent and Li (2024) at 4.00 percent. The gross profit margins are positive for each sector; a notable finding is the consistent substantial decline in net profit. This pattern shows that, although firms exhibit positive gross profitability, challenges may be present in controlling operational and financial costs.

The median liquidity ratios in the trading sector tend to surpass those in both the manufacturing and service sectors. This suggests that liquidity ratios generally are more important in the trading sector, particularly trade credit, compared with other sectors.

For operational efficiency ratios, firms in the trading sector exhibit a consistently higher value for total assets turnover compared with the manufacturing and service sectors. A noteworthy observation is that the median value of the operational expenses to total revenue ratio is highest for the trading sector.

The financial position proportion ratios in Table 2, Panels A, B, and C show the debt-to-assets ratio in the manufacturing sector exceeds that of both the trading and service sectors. It is noteworthy that the median debt-to-assets ratios of 0.12, 0.08, and 0.03 in the manufacturing, trading, and service sectors, respectively are lower than those reported for listed companies in the studies by Beaver et al. (2012) (0.50), Khoja et al. (2016) (1.1), and Li (2024) (0.48). Possible explanations for such differences include different capital structures, risk management practices, or financing access.

The components of Altman's Z-score, specifically working capital to total assets, and sales to total assets. Notably, the trading sector exhibits the highest median values for both ratios, aligning with the broader context of liquidity and operational efficiency ratios. This suggests that firms in the trading sector maintain a more robust liquidity position. The higher median values for sales to total assets imply superior operational efficiency in the trading sector compared with other sectors.

Table 1: Descriptions of the variables

Category	Variable	Description
Dependent Variable	Insolvent	A binary variable indicating whether a firm undertakes insolvency actions, equals 1 if firm i is insolvent or 0 otherwise, according to the firm's status recorded by the DBD
Profitability Ratios	Return on Assets (%)	Net profit divided by total assets multiplied by 100
	Return on Equity (%)	Net profit divided by equity multiplied by 100
	Gross Profit Margin (%)	Gross profit divided by total revenue multiplied by 100
	Net Profit Margin (%)	Net profit divided by total revenue multiplied by 100
Liquidity Ratios	Current Ratio (times)	Current assets divided by current liabilities
	Accounts Receivable Turnover (times)	Net sales divided by accounts receivable
	Inventory Turnover (times)	Cost of goods sold divided by inventory
	Accounts Payable Turnover (times)	Cost of goods sold divided by accounts payable
Operational Efficiency Ratios	Total Assets Turnover (times)	Total revenue divided by total assets
	Operational Expenses to Total Revenue (%)	Total operating expenses exclude interest and taxes divided by total revenue multiplied by 100
Financial Position Proportion	Asset to Equity Ratio	Total assets divided by equity
	Debt to Assets Ratio	Total liabilities divided by total assets
	Debt to Equity Ratio	Total liabilities divided by equity
Altman's Z-score Components	Working Capital to Total Assets (times)	Difference between current assets and current liabilities divided by total assets
	Sales to Total Assets (times)	Total revenue from selling goods and services divided by total assets
Control Variables	Size (base category: Small size)	Firm size category: Small and Medium SMEs are categorized by the firm's number of employees and annual revenue. (see Appendices Table A1 for definitions)
	Corporate Type (base category: Ordinary Partnership)	Corporate registered type: Ordinary Partnership, Juristic Ordinary Partnership, Limited Company
	Ownership (base category: 100 percent share by Thais)	Ownership structure: 100 percent share by Thais, mixed share by Thais and foreigners, and 100 percent share by foreigners (FDI)
	Region (Location) (base category: Central)	The region where the firm is situated: Central, North, North-east, East, and South
	Gross Regional Products growth	The growth rate of Gross Regional Products in year t

Table 2: The descriptive statistics of the study variables

Panel A. Manufacturing sector (3,584 firm-year observations)

Variable	Mean	Median	S.D.	Min.	Max.
Insolvent	0.156	0	0.363	0	1
ROA (%)	0.492	2.360	21.729	-123.550	57.370
ROE (%)	6.093	4.780	41.185	-171.910	210.650
Gross Profit Margin (%)	25.684	19.090	32.695	-119.680	100.00
Net Profit Margin (%)	-32.380	3.160	207.271	-1,677.890	82.420
CurrentRatio	61.229	7.240	144.744	0.010	929.840
Account Receivable Turnover	68.781	2.950	281.543	0	2,168.460
Inventory Turnover[2]	14.361	0	55.738	0	433.020
Account Payable Turnover	58.283	7.235	157.132	0	1,142.350
Assets Turnover	1.165	0.620	1.746	0	11.00
Operational Expenses to Total Revenue (%)	137.472	93.510	301.348	0	2,622.250
Assets To Equity	1.406	1.040	3.830	-16.570	22.220
Debt To Assets	0.739	0.120	2.512	0	21.690
Debt To Equity	0.406	0.040	3.830	-17.570	21.220
Working Capital to Total Assets	0.290	0.420	0.952	-6.320	1.00
Sales To Total Assets	1.164	0.620	1.713	0	10.910
Gross Regional Products growth	1.094	2.242	4.052	-12.073	5.746

Panel B. Trading sector (7,765 firm-year observations)

Variable	Mean	Median	S.D.	Min.	Max.
Insolvent	0.161	0	0.367	0	1
ROA (%)	1.850	3.150	17.827	-103.180	46.460
ROE (%)	5.514	4.800	27.955	-122.190	145.180
Gross Profit Margin (%)	21.289	12.760	25.998	-37.990	99.980
Net Profit Margin (%)	-23.610	1.970	170.370	-1,426.00	89.610
CurrentRatio	74.282	9.80	169.722	0.020	1,077.130
Account Receivable Turnover	192.903	3.820	811.020	0	6,511.670
Inventory Turnover	21.493	1.350	61.111	0	441.380
Account Payable Turnover	192.493	13.210	516.836	0	3,282.660
Assets Turnover	2.265	0.960	3.508	0	20.250
Operational Expenses to Total Revenue (%)	122.174	96.620	202.814	0	1,784.240
Assets To Equity	1.526	1.050	2.465	-7.970	16.290
Debt To Assets	0.452	0.080	1.405	0	12.400
Debt To Equity	0.526	0.050	2.465	-8.970	15.290
Working Capital to Total Assets	0.472	0.590	0.570	-2.60	1.00
SalesToTotal Assets	2.229	0.960	3.416	0	19.430
Gross Regional Products growth	1.081	2.662	4.022	-12.073	5.746

[2] The 25th and 75th percentile of inventory turnover in the manufacturing sector are 0 and 4.735, respectively.

Panel C. Service sector (11,362 firm-year observations)

Variable	Mean	Median	S.D.	Min.	Max.
Insolvent	0.176	0	0.381	0	1
ROA (%)	1.855	2.865	21.929	-128.680	63.290
ROE (%)	5.351	4.290	32.020	-142.540	163.050
Gross Profit Margin (%)	35.305	26.155	37.645	-93.470	100.00
Net Profit Margin (%)	-24.387	7.215	184.002	-1,397.330	93.330
Current Ratio	85.774	14.265	177.843	0.010	1,076.210
Account Receivable Turnover	42.780	0.750	175.635	0	1,432.960
Inventory Turnover[3]	4.613	0	19.917	0	147.820
Account Payable Turnover	67.160	2.510	201.644	0	1,397.450
Assets Turnover	0.888	0.360	1.605	0	10.820
Operational Expenses to Total Revenue (%)	124.230	88.280	237.110	0	1,956.890
Assets To Equity	1.406	1.020	2.475	-7.210	17.800
Debt To Assets	0.371	0.030	1.212	0	10.080
Debt To Equity	0.407	0.020	2.475	-8.210	16.800
Working Capital to Total Assets	0.396	0.420	0.647	-3.350	1.00
Sales To Total Assets	0.887	0.360	1.593	0	10.800
Gross Regional Products growth	1.005	2.242	4.104	-12.073	5.746

Panel D. Distribution of firm's size, corporate type, ownership structure, and region (in percentage)

	Manufacture (807 firms)	Trade (1,692 firms)	Service (2,651 firms)
Size			
Small	91.95 %	94.68 %	98.19 %
Medium	8.05 %	5.32 %	1.81 %
Corporate Type			
Ordinary Partnership	64.44 %	80.44 %	68.05 %
Juristic Ordinary Partnership	2.60 %	5.14 %	2.04 %
Company Limited	32.96 %	14.42 %	29.91 %
Ownership structure			
100 percent share by Thais	79.55 %	86.88 %	77.18 %
Mixed share by Thais and foreigners	16.36 %	11.47 %	22.41 %
100 percent share by foreigners (FDI)	4.09 %	1.65 %	0.41 %
Region			
Central	24.66 %	29.26 %	22.52 %
North	24.16 %	21.93 %	19.88 %
North-east	24.04 %	24.11 %	27.20 %
East	12.27 %	11.52 %	9.81 %
South	14.87 %	13.18 %	20.60 %

[3] The 25th and 75th percentile of inventory turnover in the service sector are 0.

Panel D in Table 2 presents a breakdown of the distribution of firm characteristics including size, corporate type, ownership structure, and region across three sectors. The dataset includes 5,150 distinct firms, comprising 807 in the manufacturing sector, 1,692 in the trading sector, and 2,651 in the service sector. Most firms are categorized as small-sized, comprising 91.95 percent in manufacturing, 94.68 percent in trading, and 98.19 percent in the service sector. In terms of corporate type, ordinary partnerships represent the largest group, accounting for 64.44 percent in manufacturing, 80.44 percent in trading, and 68.05 percent in the service sector. Ownership structure analysis reveals that most firms are domestically owned by Thais, accounting for 79.55 percent in manufacturing, 86.88 percent in trading, and 77.18 percent in the service sector. The next largest ownership category consists of mixed ownership between Thais and foreigners, and foreign-owned (FDI) firms respectively. Geographically, the central, north, and north-east regions are the largest concentrations of firms, while the east region accounts for the smallest proportion across all three sectors.

4. Methodology

The dependent variable is binary (insolvent or solvent). Thus, we use logistic regression, a widely used method in this context. Given the documented advantages of LASSO in the literature, our analysis primarily focuses on the framework and discussion of the estimated results obtained from LASSO logistic regression in the empirical results and discussion section. We complement these findings with results from traditional logistic regression. We use logistic regression with a shrinkage technique, LASSO, that involves penalizing the coefficients' magnitude. Then, we use the LASSO inferential statistics to complement the traditional logistic regression results. The following sections illustrate the concept of LASSO logistic regression, LASSO inference, and introduce cross-validation.

4.1 Least Absolute Shrinkage and Selection Operator (LASSO) logistic and inference

In the logistic regression, suppose we have n observations in the model. The term Y is an n-dimensional vector of response variables taking value 0 (solvent) or 1 (insolvent). Let the number of explanatory variables (financial ratios and control variables) equal k. The term X stands for $n \times k$ a matrix of explanatory variables. Thus, for the i^{th} individual, we denote $X_i = (x_{i1}, \dots, x_{ik})$.

LASSO logistic regression is a variation of logistic regression that includes a regularization component. In the standard logistic regression; all coefficients in the model are treated equally. The key feature of LASSO is that it can shrink the coefficients of less important variables to zero, effectively performing variable selection. This is particularly useful when dealing with high-dimensional data. According to the shrinkage method, the size of the coefficients is penalized (Tibshirani, 1996) . We incorporate a penalty function in the log-likelihood function.

$$LL_{penalty}(\beta, \lambda, Y) = -LL(\beta, Y) + \lambda P(\beta) \tag{2}$$

The idea of the penalized log-likelihood function, $LL_{penalty}(\beta, \lambda, Y)$, is to add a penalty function, $P(\beta)$, into the log-likelihood function. The penalty function can be viewed as an additional constraint on the model. It is a shrinkage penalty that exhibits a size constraint on the coefficients. However, the penalty function is adjusted by the regularized parameter, whose value is greater than or equal to zero, $\lambda \geq 0$. The idea of the regularized parameter is to control the bias-variance. After obtaining the penalized log-likelihood function, we minimize this function to find the coefficient estimates. The penalty imposes a size constraint on the coefficient to allay the cancellation (Hastie et al., 2009).

The idea of the LASSO penalty is to maximize the log-likelihood function subject to a constraint on the sum of the absolute values of the regression coefficients. According to the constraint, the financial ratios and control variables are unlikely to have a significant impact on the dependent variable, whose coefficient will be set exactly equal to zero. If there is a group of highly correlated predictors, LASSO tends to randomly select one predictor of the group and neglects the remaining predictors. That means LASSO performs variable selection by shrinking some coefficients and setting them to zero. The LASSO penalized log-likelihood function is written as:

$$LL_{penalty}^{Lasso}(\beta, \lambda, Y_i) = \sum_{i=1}^{n}\left\{Y_i \cdot log(p_i) + (1 - Y_i) \cdot log(1 - p_i) - \lambda \sum_{j=1}^{k} \left|\beta_j\right|\right\} \tag{3}$$

Next, we minimize the penalized log-likelihood function, equation (3), with respect to β,

$$\hat{\beta}_{Lasso} = \underset{\beta}{argmin}\left\{LL_{penalty}^{Lasso}(\beta, \lambda, Y_i)\right\} \tag{4}$$

LASSO logistic regression facilitates the selection of covariates and the estimation of coefficients. However, it does not inherently provide the standard errors necessary for statistical inference. In addressing this limitation, we use LASSO-based methods specifically designed for inference to estimate coefficients and their standard errors for a subset of covariates.

LASSO logistic inference aims to tackle the challenges associated with statistical inference and variable selection in logistic regression models incorporating LASSO regularization. Several methods, namely Double Selection, Partialing Out, and Cross-fit Partialing Out (referred to as double machine learning), were introduced to enhance inference in the context of LASSO logistic regression. These methodologies are designed to mitigate issues such as bias in variable selection and the imperative requirement for reliable inference. Their collective objective is to enhance the accuracy and reliability of the estimates, particularly in scenarios involving high-dimensional data and model selection. These solutions use moment conditions and secure robust standard errors. Among the methods, we use the Cross-fit Partialing out solution that stands out as the most effective, permitting a greater number of coefficients in the true model (StataCorp, 2021).

4.2 Cross-validation

Cross-validation serves as a robust validation method to evaluate the performance of predictive models and has been widely adopted for accurate prediction error estimation. The K-fold cross-validation methodology (with the default being 10 subsets or 10-fold) uses part of the available data to fit the model, and a different part to test it (Hastie et al., 2009).

During each iteration, one subset (the K^{th} subset) is designated as the validation set, while the remaining subsets collectively form the training sets for model fitting. The model trained on the training data is subsequently used for prediction with the validation set. This iterative process is repeated for each subset, ensuring a comprehensive evaluation (Hastie et al., 2009).

In this study, cross-validation plays a pivotal role in the selection of the regularization parameter λ that controls the amount of shrinkage applied to the coefficients in each sector. This parameter tuning, facilitated by cross-validation, is instrumental in choosing an optimal λ value tailored to the specific dataset. Thus, cross-validation helps to select the most suitable value of λ for the specific dataset and ensures the selection of a model in the manufacturing, trading, and service sectors that excels in terms of goodness of fit and prediction accuracy (Hastie et al., 2009).

4.3 Model evaluation

Model evaluations are conducted using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Area Under the Receiver Operating Characteristic Curve (AUC) values, and prediction discrepancies derived from both logistic regression and LASSO logistic regression. These metrics are presented in Table 7.

AIC and BIC evaluate the overall goodness of fit. The lower AIC and BIC values are indicative of better model fit, whereas high values correspond to poor fit (Aho et al., 2014). On the other hand, the predictive performance using the AUC value indicates a higher ability for prediction accuracy as the AUC is closer to 1, demonstrating superior discrimination ability (Hanley & McNeil, 1982).

5. Empirical Results and Discussion

5.1 Empirical finding and discussion

This section presents and discusses the estimated results from LASSO logistic regression. We then discuss the effect of industry-relative financial ratios on the probability of insolvency of Thai SMEs by LASSO logistic regression and complement the results with the traditional logistic regression.

LASSO selection and inference

LASSO logistic regression facilitates the precise selection of the variables. The explanatory variables that are not selected indicate that these specific variables are unlikely to have a significant impact on the probability of insolvency of Thai SMEs.Table 3, Column (1) displays the LASSO logistic regression results excluding the current ratio, operational expenses to total revenue, and sales to total assets from the model in the manufacturing sector. The estimates in Table 4, Column (1), for the trading sector indicate that LASSO logistic regression eliminates net profit margin, current ratio, debt to equity ratio, and working capital to total assets. Similarly, Table 5, Column (1), presents the estimates for the service sector, where LASSO logistic regression excludes net profit margin, debt to equity ratio, and sales to total assets from the model.

In the subsequent analysis, we use selected explanatory variables by LASSO[4] to interpret the statistical inference provided by Stata, namely Double Selection, Partialing Out, and Cross-fit Partialing Out (referred to as double machine learning) in LASSO logistic regression. The coefficients and LASSO statistical inferences of the three methods are presented in Table 3-5, Columns (2)-(4), for the manufacturing, trading, and service sectors, respectively. Based on the LASSO inferences presented in Tables 3-5, the Wald Chi-square (χ^2) statistics for all methods across the three sectors are statistically significant at the 1% level. The observed significance shows that at least one of the industry-relative financial ratios significantly influences the probability of insolvency of Thai SMEs across the different panels.

We analyze the effects of financial ratios on the probability of insolvency of Thai SMEs to test our hypotheses. Table 3-5, Column (4), presents the results from LASSO logistic regression with the Cross-fit Partialing Out method to examine the probability of insolvency concerning industry-relative financial ratios. LASSO inference solutions use multiple LASSOs and moment conditions that are robust to model-selection errors made by LASSO, and LASSO inference solutions obtain robust standard errors. These findings are further complemented by the traditional logistic regression results presented in Tables 3-5, Columns (5) and (6).

The effect of profitability ratios on the insolvency probability of Thai SMEs

The results in Tables 3 and 4 show a significant negative relationship between ROA and insolvency probability in the manufacturing and trading sectors. This finding aligns with prior research by Muñoz-Izquierdo et al. (2020) and Tian and Yu (2017), that a higher ROA implies efficient asset utilization and enhanced profitability. Notably, the study concurs with Camacho-Miñano et al. (2015) study that highlights the persistence of low ROA percentiles among insolvent SMEs. It is imperative to underscore the significance of a positive ROA as a critical indicator of financial health, especially in the manufacturing and trading sectors.

Analysis further reveals that ROE significantly negatively affects the insolvency probability but exclusively in the trading sector as shown in Table 4. A higher ROE in the trading sector suggests greater profitability and efficient use of equity to generate profit, thereby reducing the likelihood of insolvency.

In Tables 3 and 5, the negative impact of gross profit margin on insolvency probability in the manufacturing and service sectors is consistent with the findings of Tong and Serrasqueiro (2021) which point out the significance of gross profit to revenue as a crucial indicator negatively correlated with firm failure. Fuertes-Callén et al. (2022) provide additional context, explaining that surviving firms tend to have higher profit than those that do not survive. If Thai SMEs in the manufacturing and service sectors face high raw materials or labour costs, it will decrease the gross profit margin and lead to a negative net profit margin.

The results for profitability ratios support hypothesis H1.

[4] One of the advantages of LASSO is that the model selects the most relevant variables to fit the data.

The effect of liquidity ratios on the insolvency probability of Thai SMEs

The results highlight a significant negative association between accounts receivable turnover and the insolvency probability of Thai SMEs, specifically in the manufacturing sector, as shown in Table 3. This financial ratio gauges a firm's ability to collect its accounts receivable, with a higher ratio suggesting ease in collecting receivables and a greater likelihood of survival. The finding aligns with the findings of Malakauskas and Lakstutiene (2021), who emphasize the importance of accounts receivable turnover in assessing SMEs' financial distress. For Thai SMEs, particularly those in the manufacturing sector, the implications of low accounts receivable turnover pose significant challenges in meeting short-term financial obligations and increase the risk of insolvency.

In Tables 3 to 5, we demonstrate that inventory turnover has a significant detrimental effect on the insolvency probability across the manufacturing, trading, and service sectors. This aligns with the study by Patel et al. (2017), who point out that firms with faster inventory turnover are more likely to survive. A high inventory turnover ratio indicates effective inventory management and quick product sales, reducing the likelihood of insolvency. Thai SMEs with low inventory turnover may face liquidity challenges, impacting holding costs and increasing the risk of insolvency.

Accounts payable turnover exhibits a significant negative impact on the insolvency probability of Thai SMEs in all sectors, as shown in Tables 3 to 5. This ratio measures a firm's ability to pay its accounts payable promptly, reflecting effective management of vendor relationships. Therefore, high accounts payable turnover implies efficient payment practices and, consequently, a reduced likelihood of insolvency across all sectors. The results for liquidity ratios are consistent with our expectations and confirm our hypothesis H2.

The effect of operational efficiency ratios on the insolvency probability of Thai SMEs

In Tables 3 to 5, total assets turnover, evaluating a firm's efficiency in using assets to generate total revenue, reveals a significant negative impact on the probability of insolvency in the trading and service sectors, but not in the manufacturing sector. A high total assets turnover ratio illustrates a lower probability of insolvency. Thai SMEs with inefficient assets utilization or low assets turnover may struggle to cover their operating expenses, leading to financial challenges and an increased risk of insolvency, especially in the trading and service sectors.

Tables 4 and 5 show that the operational expenses to total revenue ratio has a significant positive influence on the probability of insolvency in the trading and service sectors. Operational expenses encompass various costs associated with business operations, including salaries, rent, and utilities. Thai SMEs with inefficient cost controls may encounter challenges in maintaining competitiveness and managing day-to-day operations, thereby increasing the risk of insolvency, especially in the trading and service sectors. Thai SMEs burdened by high operational costs may confront obstacles in achieving economies of scale, potentially resulting in high per-unit operational expenses. The result aligns with the study by Pissarides et al. (2003), who

indicate one important SME constraint is supplier delivery and changes in the price of local goods. This dual challenge not only compromises operational cost efficiency but also heightens the risk of insolvency.
The results confirm our hypothesis H3 that high operational efficiency has a negative impact on the insolvency of Thai SMEs.

The effect of financial position proportion ratios on the insolvency probability of Thai SMEs

The results in Tables 3 to 5 highlight a significant negative association between assets-to-equity and the probability of insolvency of Thai SMEs across the three sectors. This result does not support hypothesis H4. A high assets-to-equity ratio implies a robust financial position, as the firm possesses substantial assets relative to its equity. Firms with high assets-to-equity may indicate that they have better credit terms or trade credit and increased access to financing, supporting their financial stability.

Conversely, Tables 3 to 5 indicate that the debt to assets ratio has a significant positive impact on the probability of insolvency of Thai SMEs in the manufacturing, trading, and service sectors. This finding aligns with previous research by Hernandez Tinoco et al. (2018), Khoja et al., (2016), Lizares and Bautista (2021), Tian and Yu (2017), and Tian et al. (2015) who show that firms with a higher debt to assets ratio are more likely to face insolvency. Fuertes-Callén et al. (2022) explain that more solvent firms tend to have a lower debt to assets ratio. This result is consistent with Rico et al. (2021) who explain that debt reduction increases the probability of SMEs' survival. A high debt to assets ratio indicates that a firm is using a high level of debt to finance its assets and is more financially fragile, which can increase its risk of insolvency if the firm is unable to make its debt payments. This result confirms our hypothesis H4.

The effect of Altman's Z-score components on the insolvency probability of Thai SMEs

Table 5 shows a significant positive relationship between working capital to total assets ratio and the probability of insolvency of Thai SMEs in the service sector, exclusively, which is a unique finding. This finding contradicts our hypothesis H5, indicating that maintaining high current assets and low current liabilities in the service sector may lead to missed business opportunities and challenges in accessing financing. This result contradicts the findings of Muñoz-Izquierdo et al. (2020) and Tian and Yu (2017), who report a negative correlation between the working capital to total assets ratio and firms' insolvency and risk of financial distress. Our findings also challenge the conclusions of Fuertes-Callén et al. (2022), who suggest that firms with a higher working capital to total assets ratio are more likely to survive. Working capital, defined as the difference between current assets and current liabilities, implies that firms with high current assets or very low current liabilities in the service sector are more likely to face insolvency. One contributing factor is that elevated accounts receivable in Thai service-oriented businesses may diminish available cash for operational needs, thereby increasing the likelihood of insolvency. Additionally, SMEs face significant financial accessibility challenges, particularly constrained access to credit, as highlighted by the World Bank Group, (2017) and Yoshino and

Taghizadeh-Hesary (2016). The low current liabilities may signify challenges in accessing financing, further contributing to the increased insolvency risk observed in the service sector.

Control variables

The results in Tables 3 to 5 indicate that firms characterized as medium-sized demonstrate a notably lower probability of insolvency than their smaller counterparts, aligning with findings from the studies by Camacho-Miñano et al. (2015) and Fuertes-Callén et al. (2022). Smaller firms may struggle with constraints such as restricted access to finance, as well as high production or service costs. Furthermore, the legal structure of the juristic ordinary partnership indicates a lower likelihood of insolvency than an ordinary partnership. However, the legal structure of a limited company is more prone to insolvency than an ordinary partnership. Our results also reveal that firms with pure Thai nationality investment face a higher probability of insolvency than those with mixed nationality or foreign direct investment firms. This finding emphasizes the influence of diverse ownership structures in mitigating insolvency risks for Thai SMEs.

Geographical region also plays a significant role since our results in Tables 3 to 5 indicate that firms located in less competitive environments, specifically the north, north-east, east, and south regions, exhibit a reduced likelihood of insolvency than their counterparts situated in the central area where there is the capital city and metropolitan provinces. This geographical distinction sheds light on the varying economic landscape and competitive pressures in different regions.

Table 3: The impact of financial ratios on insolvency in Thai SMEs in the manufacturing sector

Manufacturing Sector	LASSO	LASSO Inference			Logistic	
Dependent variable: equals one if the firm is insolvent and zero otherwise	Selection [λ = 0.0015] (1)	Double Selection (2)	Partialing-out (3)	Cross-fit Partialing-out (4)	Without Controls (5)	With Controls (6)
ROA	-0.007	-0.008 *	-0.008 *	-0.008 **	-0.001	-0.009
		(0.004)	(0.004)	(0.003)	(0.021)	(0.015)
ROE	-0.006	-0.006	-0.005	-0.006	-0.006	-0.002
		(0.004)	(0.004)	(0.004)	(0.033)	(0.024)
Gross Profit Margin	-0.243	-0.266 ***	-0.281 ***	-0.280 ***	-0.960 ***	-0.387 *
		(0.059)	(0.060)	(0.046)	(0.269)	(0.222)
Net Profit Margin	0.008	0.008	0.007	0.007	0.023	0.021
		(0.008)	(0.008)	(0.006)	(0.049)	(0.040)
Current Ratio	Unselected				-0.207	0.178
					(0.171)	(0.117)
Accounts Receivable Turnover	-0.249	-0.530 *	-0.572 *	-0.576 **	-1.250 **	-0.719 **
		(0.283)	(0.301)	(0.279)	(0.498)	(0.362)
Inventory Turnover	-0.046	-0.066	-0.068	-0.068 *	-0.334 ***	-0.119
		(0.045)	(0.049)	(0.036)	(0.112)	(0.161)
Accounts Payable Turnover	-0.473	-0.465 **	-0.508 **	-0.506 ***	-1.517 ***	-0.642 **
		(0.207)	(0.241)	(0.158)	(0.398)	(0.281)
Total Assets Turnover	-0.122	-0.132	-0.130	-0.129	-2.823 **	-0.575
		(0.148)	(0.148)	(0.102)	(1.127)	(0.911)
Operational Expenses to Total Revenue	Unselected				-0.048	-0.017
					(0.136)	(0.151)
Asset to Equity	-0.067	-0.076 ***	-0.082 ***	-0.082 ***	-0.373 ***	-0.115
		(0.026)	(0.026)	(0.018)	(0.139)	(0.101)
Debt to Assets Ratio	0.078	0.073 **	0.072 **	0.072 ***	0.468 ***	0.185
		(0.035)	(0.033)	(0.021)	(0.135)	(0.130)
Debt to Equity Ratio	0.000	0.0001	0.000	0.000	-0.001	0.000
		(0.0002)	(0.0001)	(0.0001)	(0.001)	(0.001)
Working Capital to Total Assets	0.037	0.045	0.036	0.036	-0.170	0.042
		(0.036)	(0.035)	(0.022)	(0.109)	(0.096)
Sales to Total Assets	Unselected				1.114	0.226
					(1.092)	(0.885)
Constant	-0.386				-14.031 ***	-6.465 ***
					(0.646)	(1.671)

Table 3: (Continued)

Manufacturing Sector Dependent variable: equals one if the firm is insolvent and zero otherwise	LASSO Selection [λ = 0.0015] (1)	LASSO Inference			Logistic	
		Double Selection (2)	Partialing-out (3)	Cross-fit Partialing-out (4)	Without Controls (5)	With Controls (6)
Medium Size (b: Small)	-0.679					-3.693 ***
						(1.335)
Corporate Type (b: Ordinary Partnership)						
Juristic Ordinary Partnership	-2.867					0.000
Limited Company	2.176					18.812 ***
						(0.836)
Ownership (b: Thai)						
Mixed (Thai & Foreigner)	-2.218					-17.736 ***
						(1.210)
FDI	-0.864					-11.666***
						(1.390)
Region (b: Central)						
North	-0.972					-3.233 ***
						(0.953)
North-east	-1.465					-6.626 ***
						(0.946)
East						-1.129
						(1.222)
South	-0.941					-2.916 **
						(1.262)
Gross Regional Products growth	0.021					0.036
						(0.067)
Wald Chi-square (χ^2)		63.43 ***	64.17 ***	128.74 ***	147.22 ***	713.18 ***
Number of firms	807	807	807	807	807	786
Number of observations	3,584	3,482	3,482	3,482	3,584	3,482

Note: LASSO inference solutions use multiple LASSOs and moment conditions that are robust to model selection errors made by LASSO. Standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: The impact of financial ratios on insolvency in Thai SMEs in the trading sector

Trading Sector	LASSO	LASSO Inference			Logistic	
Dependent variable: equals one if the firm is insolvent and zero otherwise	Selection [λ = 0.0008] (1)	Double Selection (2)	Partialing-out (3)	Cross-fit Partialing-out (4)	Without Controls (5)	With Controls (6)
ROA	-0.001	-0.001 **	-0.001**	-0.001 **	0.0002	-0.001
		(0.0005)	(0.0004)	(0.0004)	(0.002)	(0.002)
ROE	-0.032	-0.031 ***	-0.035 ***	-0.034 ***	-0.049	-0.024
		(0.008)	(0.008)	(0.007)	(0.036)	(0.034)
Gross Profit Margin	0.008	0.013	0.006	0.001	-0.102	0.020
		(0.058)	(0.056)	(0.038)	(0.168)	(0.177)
Net Profit Margin	Unselected				0.016	0.005
					(0.024)	(0.017)
Current Ratio	Unselected				-0.120	0.089
					(0.092)	(0.085)
Accounts Receivable Turnover	-0.001	-0.001	-0.001	-0.001	-0.041	0.005
		(0.016)	(0.015)	(0.011)	(0.045)	(0.054)
Inventory Turnover	-0.102	-0.110 **	-0.096 **	-0.096 ***	-0.341 ***	-0.142
		(0.047)	(0.048)	(0.035)	(0.116)	(0.166)
Accounts Payable Turnover	-0.121	-0.131 **	-0.136 **	-0.135 ***	-0.207 *	-0.035
		(0.058)	(0.060)	(0.047)	(0.126)	(0.127)
Total Assets Turnover	-0.677	-1.184 **	-1.071 **	-1.281 *	-1.395 *	-0.994
		(0.579)	(0.515)	(0.683)	(0.772)	(1.144)
Operational Expenses to Total Revenue	0.123	0.138 ***	0.130 ***	0.129 ***	0.125	0.081
		(0.025)	(0.025)	(0.022)	(0.153)	(0.160)
Asset to Equity	-0.091	-0.099 ***	-0.102 ***	-0.101 ***	0.551	0.343
		(0.030)	(0.034)	(0.025)	(2.058)	(2.028)
Debt to Assets Ratio	0.065	0.071 ***	0.071 ***	0.070 ***	0.294 ***	0.222 ***
		(0.020)	(0.019)	(0.011)	(0.099)	(0.073)
Debt to Equity Ratio	Unselected				-0.294	-0.158
					(0.716)	(0.699)
Working Capital to Total Assets	Unselected				-0.325	0.300
					(0.291)	(0.231)
Sales to Total Assets	0.405	0.914	0.844	1.046	0.221	0.789
		(0.578)	(0.514)	(0.682)	(0.721)	(1.124)
Constant	-1.736				-14.548 ***	-15.188 ***
					(1.495)	(1.834)
Medium Size (b: Small)	0.383					0.960
						(1.129)

Table 4: (Continued)

Trading Sector Dependent variable: equals one if the firm is insolvent and zero otherwise	LASSO Selection [λ = 0.0008] (1)	LASSO Inference Double Selection (2)	Partialing-out (3)	Cross-fit Partialing-out (4)	Logistic Without Controls (5)	With Controls (6)
Corporate Type (b: Ordinary Partnership)						
Juristic Ordinary Partnership	-2.624					-16.581 ***
						(1.800)
Limited Company	4.108					30.764 ***
						(0.783)
Ownership (b: Thai)						
Mixed (Thai & Foreigner)	-3.655					-28.223 ***
						(1.078)
FDI	-3.106					-25.506 ***
						(2.792)
Region (b: Central)						
North	-0.872					-2.964 ***
						(0.719)
North-east	-0.611					-1.853 **
						(0.838)
East	-0.632					-2.125 **
						(0.934)
South	-0.968					-2.821 ***
						(0.853)
Gross Regional Products growth	0.011					0.016
						(0.046)
Wald Chi-square (χ^2)		121.32 ***	124.30 ***	217.29 ***	130.52 ***	1,870.71 ***
Number of firms	1,692	1,692	1,692	1,692	1,692	1,692
Number of observations	7,765	7,765	7,765	7,765	7,765	7,765

Table 5: The impact of financial ratios on insolvency in Thai SMEs in the service sector

Service Sector	LASSO	LASSO Inference			Logistic	
Dependent variable: equals one if the firm is insolvent and zero otherwise	Selection [λ = 0.0025] (1)	Double Selection (2)	Partialing-out (3)	Cross-fit Partialing-out (4)	Without Controls (5)	With Controls (6)
ROA	-0.001	-0.001	-0.001	-0.001	-0.004	-0.0001
		(0.001)	(0.001)	(0.001)	(0.012)	(0.004)
ROE	-0.0001	-0.001	-0.001	-0.001	0.010	0.007
		(0.003)	(0.003)	(0.003)	(0.020)	(0.011)
Gross Profit Margin	-0.314	-0.330 ***	-0.337 ***	-0.335 ***	-0.486 ***	-0.215 **
		(0.054)	(0.054)	(0.044)	(0.176)	(0.101)
Net Profit Margin	Unselected				0.001	-0.0003
					(0.005)	(0.003)
Current Ratio	0.024	0.024	0.024	0.024	-0.009	0.040
		(0.025)	(0.023)	(0.015)	(0.209)	(0.078)
Accounts Receivable Turnover	-0.006	-0.011	-0.012	-0.012	-0.006	-0.009
		(0.014)	(0.015)	(0.011)	(0.080)	(0.052)
Inventory Turnover	-0.042	-0.047 *	-0.046 *	-0.046 **	-0.340 ***	-0.033
		(0.026)	(0.025)	(0.019)	(0.088)	(0.042)
Accounts Payable Turnover	-0.137	-0.153 *	-0.155 **	-0.157 ***	-0.456 ***	-0.154 *
		(0.079)	(0.075)	(0.051)	(0.082)	(0.080)
Total Assets Turnover	-0.115	-0.123 **	-0.114 **	-0.114 ***	-0.131	-0.079
		(0.048)	(0.047)	(0.035)	(0.333)	(0.326)
Operational Expenses to Total Revenue	0.062	0.063 ***	0.063 ***	0.064 ***	0.477 *	0.068
		(0.019)	(0.019)	(0.014)	(0.286)	(0.076)
Asset to Equity	-0.043	-0.074 ***	-0.074 ***	-0.073 ***	-0.308	-0.063
		(0.025)	(0.026)	(0.019)	(0.296)	(0.131)
Debt to Assets Ratio	0.034	0.037 **	0.034 **	0.034 ***	0.382 ***	0.068
		(0.017)	(0.017)	(0.010)	(0.094)	(0.051)
Debt to Equity Ratio	Unselected				-0.048	-0.011
					(0.040)	(0.029)
Working Capital to Total Assets	0.051	0.055 **	0.052 **	0.052 ***	0.159	0.083
		(0.021)	(0.021)	(0.013)	(0.148)	(0.061)
Sales to Total Assets	Unselected				-0.265	-0.077
					(0.371)	(0.324)
Constant	-0.054				-8.258 ***	1.457
					(0.799)	(1.391)
Medium Size (b: Small)	-1.462					-12.754 ***
						(1.337)

Table 5: (Continued)

Service Sector Dependent variable: equals one if the firm is insolvent and zero otherwise	LASSO Selection [λ = 0.0025] (1)	LASSO Inference: Double Selection (2)	LASSO Inference: Partialing-out (3)	LASSO Inference: Cross-fit Partialing-out (4)	Logistic: Without Controls (5)	Logistic: With Controls (6)
Corporate Type (b: Ordinary Partnership)						
Juristic Ordinary Partnership	-0.955					-3.104
						(1.940)
Limited Company	2.762					21.046 ***
						(0.483)
Ownership (b: Thai)						
Mixed (Thai & Foreigner)	-1.354					-15.348 ***
						(0.584)
FDI	-1.518					-4.861 ***
						(1.651)
Region (b: Central)						
North	-0.813					-3.009 ***
						(0.555)
North-east	-0.684					-2.069 ***
						(0.479)
East	0.003					0.277
						(0.705)
South	-0.434					-1.598 ***
						(0.550)
Gross Regional Products growth	0.035					0.036
						(0.038)
Wald Chi-square (χ^2)		104.32 ***	103.05 ***	188.28 ***	109.84 ***	2,108.33 ***
Number of firms	2,651	2,651	2,651	2,651	2,651	2,651
Number of observations	11,362	11,362	11,362	11,362	11,362	11,362

The marginal effects of financial ratios

The average marginal effects (AME) address a critical gap by providing a measure of the individual instantaneous contribution of a change in the probability of SMEs' insolvency while keeping all other regressors constant (Hernandez Tinoco & Wilson, 2013). For instance, the AME for ROA in the manufacturing sector is -0.0001462. This implies that, on average, a one-unit increase in ROA is associated with a 0.01462 percent decrease in the probability of insolvency while holding all other regressors constant (see Appendices Table A2 for the other AMEs across all sectors).

Figure 1 shows the AME across three sectors, demonstrating the average change in the probability of SMEs' insolvency for individual financial ratios. Notably, the most significant financial ratio in the manufacturing sector, in absolute terms, is accounts receivable turnover. Similarly, in the trading and service sectors, total assets turnover and gross profit margin, respectively, emerge as the most significant financial ratios. The result also provides a comparative view of how different financial ratios impact each sector, offering valuable insights for strategic decision-making and risk management.

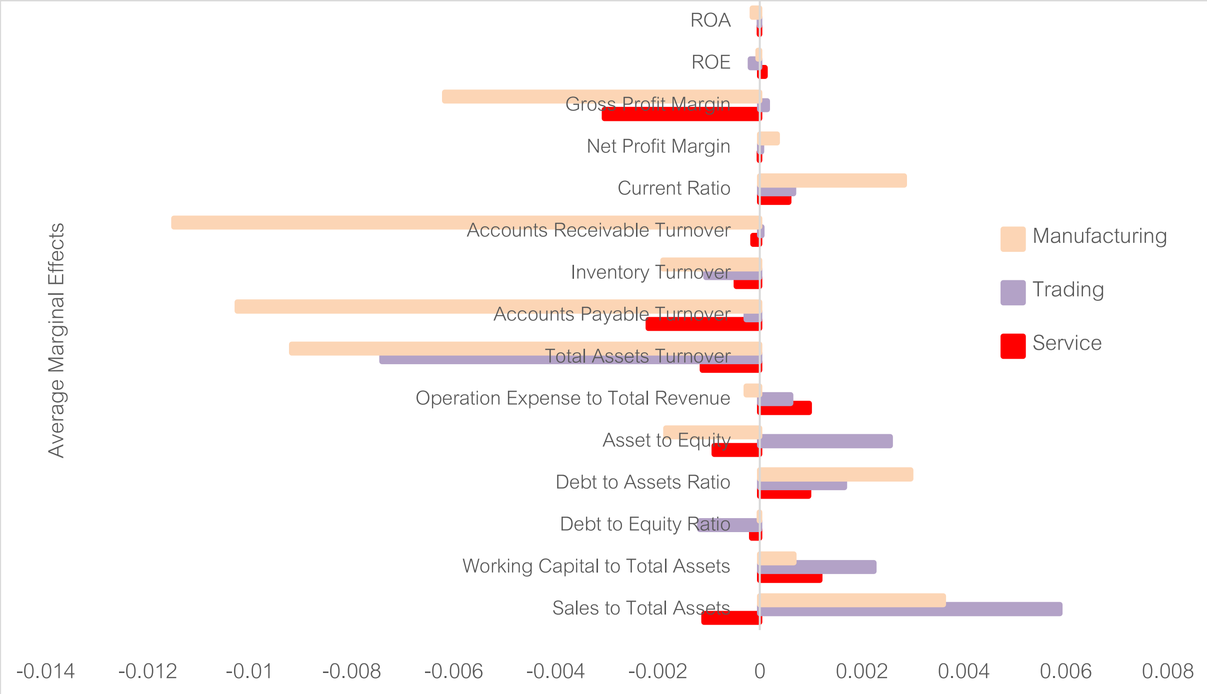

Figure 1: Average marginal effects of different factors across all sectors

The comparison results of three sectors

The empirical findings highlight the critical role that financial ratios play in determining the likelihood of insolvency of Thai SMEs. Within the manufacturing sector, ROA, gross profit margin, accounts receivable turnover, inventory turnover, accounts payable turnover, and assets to equity decrease the probability of insolvency among Thai SMEs. Conversely, the debt-to-assets increases the risk of insolvency of this sector. Notably, among these factors, accounts receivable turnover emerges as the most influential marginal effect on the probability of insolvency within the manufacturing sector.

In the trading sector, distinct financial indicators play pivotal roles. ROA, ROE, inventory turnover, accounts payable turnover, total assets turnover, and assets to equity contribute adversely to the probability of firms' insolvency. Meanwhile, operational expenses to total revenue and the debt-to-assets ratio increase the risk of insolvency. Surprisingly, total assets turnover stands out as the financial metric with the most significant marginal effect on the probability of insolvency in the trading sector.

The findings in the service sector suggest that higher levels of gross profit margin, inventory turnover, accounts payable turnover, total assets turnover, and assets to equity decrease the probability of firms' insolvency, while operational expenses to total revenue, debt-to-assets, and working capital to total assets increase the risk of insolvency. Specifically, gross profit margin emerges as the financial ratio with the most impactful marginal effect on the probability of insolvency within the service sector.

5.2 Analysis of the impact of COVID-19 on financial ratios

This section presents the impact of the COVID-19 pandemic on the financial health of Thai SMEs. The pandemic has had a significant negative effect on SMEs' financial stability and financial health, as highlighted by Mrockova (2022). Table 6 presents descriptive statistics of firms' financial ratios across two study periods: 2017-2019 (non-pandemic years) and 2020-2021 (pandemic years).

Column 7 of Table 6 shows the *t*-statistics of the mean difference test of financial ratios between the two periods (non-pandemic years and pandemic years), offering insight into how the pandemic has influenced key financial metrics. The effects are most evident in profitability ratios, operational efficiency ratios, and leverage ratios. The mean profitability ratios, including ROA, ROE, gross profit margin, and net profit margin, are significantly higher in the non-pandemic period compared to the pandemic period. The average current ratio during non-pandemic years is significantly lower than in the pandemic period. This difference likely reflects firms accumulating higher levels of inventories and experiencing a reduction in inventory turnover during the pandemic. Operational efficiency, as measured by asset turnover and sales to total assets ratios, is also higher in the non-pandemic years, suggesting that firms were more efficient in generating revenue from their assets before the disruptions caused by the COVID-19 pandemic. Conversely, operational expenses to total revenue ratio significantly increased during the pandemic, indicating that firms faced higher costs to maintain operations in their businesses. Furthermore, leverage ratios reveal that firms increased their debt levels during the pandemic, as evidenced by significantly higher debt to assets and debt-to-equity ratios during this period.

In summary, the changes in financial ratios demonstrate the impact of both internal management practices and external factors, particularly the COVID-19 pandemic, on the performance of Thai SMEs (see Table 6). To further validate these findings, we conducted logistic regression and LASSO logistic regression analyses with COVID-19 included as a dummy variable. The coefficient for COVID-19 is not significant, indicating that the main results in this paper remain robust.

Table 6 Descriptive statistics by year group between 2017-2019 and 2020-2021 (pandemic years)

	2017-2019 (13,997 firm-year observations)			2020-2021 (8,714 firm-year observations)			*t*-statistics difference in means
	Mean	Median	S.D.	Mean	Median	S.D.	
ROA (%)	2.717	3.400	20.072	-0.095	2.200	21.282	9.895***
ROE (%)	6.631	5.120	32.107	3.745	3.710	32.709	6.512***
Gross Profit Margin (%)	30.524	20.540	33.700	26.538	16.975	34.131	8.600***
Net Profit Margin (%)	-18.083	4.670	163.856	-37.109	3.150	210.595	7.187***
Current Ratio	75.968	10.970	166.922	81.189	11.435	175.945	-2.217**
Account Receivable Turnover	97.679	1.520	505.429	99.066	1.620	510.816	-0.200
Inventory Turnover	12.187	0.000	45.947	11.499	0.000	43.414	1.135
Account Payable Turnover	108.326	5.800	353.350	109.069	7.110	331.946	-0.160
Assets Turnover	1.450	0.580	2.572	1.326	0.500	2.445	3.636***
Operational Expenses to Total Revenue (%)	118.619	92.230	220.319	136.857	93.700	263.055	-5.400***
Assets To Equity	1.442	1.020	2.768	1.454	1.030	2.670	-0.322
Debt To Assets	0.432	0.050	1.466	0.496	0.050	1.690	-2.895***
Debt To Equity	0.443	0.020	2.768	0.454	0.030	2.670	-0.324
Working Capital to Total Assets	0.408	0.490	0.675	0.401	0.490	0.696	0.679
Sales To Total Assets	1.437	0.580	2.529	1.298	0.500	2.371	4.179***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.3 Model evaluation

Table 7 shows the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values derived from the LASSO logistic model are considerably lower than those of the traditional logistic model across all sectors. This suggests that the LASSO logistic model has a superior fit compared with the traditional logistic model with higher AIC and BIC values.

This study further assesses the predictive performance using the Area Under the Receiver Operating Characteristic Curve (AUC) values, that indicate a higher ability for prediction accuracy as AUC approaches 1. Notably, the LASSO logistic model consistently outperforms the traditional logistic model across all sectors because of the higher AUC values. This underscores the robustness of the LASSO logistic model in terms of predictive accuracy, suggesting its potential as a better model for insolvency prediction.

Prediction discrepancies are presented in Table 7, highlighting the percentage of correct and incorrect predictions. In the manufacturing sector, 1.34 percent is correctly predicted by the traditional logistic regression, whereas the LASSO logistic regression makes an incorrect prediction. Conversely, 4.55 percent is correctly predicted by Lasso logistic, whereas the traditional logistic regression makes incorrect predictions. Similar trends are shown in the trading and service sectors. Therefore, the LASSO logistic model consistently demonstrates fewer prediction discrepancies than the traditional logistic regression in all sectors.

Table 7: Model evaluation with the AIC, BIC, AUC, and prediction discrepancies

Criterion	Manufacturing Sector		Trading Sector		Service Sector	
	Logistic	LASSO Logistic	Logistic	LASSO Logistic	Logistic	LASSO Logistic
(1) AIC	718.236	565.475	1,267.888	1,076.334	2,530.954	2,084.375
(2) BIC	878.275	678.115	1,455.737	1,212.175	2,729.081	2,225.559
(3) AUC	0.818	0.856	0.828	0.849	0.804	0.828
(4) Logit correctly predicts, and LASSO Logit incorrectly predicts (%)	1.34 %		0.49 %		2.41 %	
(5) LASSO Logit correctly predicts, and Logit incorrectly predicts (%)	4.55 %		1.13 %		3.49 %	

Note: Italic numbers represent the better model.

6. Conclusions

This study examines the impact of financial ratios on the probability of insolvency of Thai SMEs with a three-sectoral analysis. To enhance the modelling approach, we introduce industry-relative financial ratios. The strategic advantage is in the normalization of measurements across industries and the stability of IR financial ratios over time. We employ LASSO logistic regression to address multicollinearity issues and enhance predictive accuracy. Additionally, LASSO inference was used to mitigate bias in variable selection, ensuring reliable inference through robust standard errors.

The findings strongly indicate that LASSO logistic regression outperforms traditional methods across sectors in terms of improved goodness-of-fit, predictive performance, and insolvency prediction accuracy. The empirical results highlight the significant role of financial ratios in identifying the probability of insolvency among Thai SMEs. Specific ratios, such as inventory turnover, accounts payable turnover, assets-to-equity, and debt-to-assets, consistently emerge as key determinants of insolvency risk across all three sectors. Further sector-specific insights reveal distinct findings: accounts receivable turnover has the most significant marginal effect on the probability of insolvency in the manufacturing sector, while total assets turnover and gross profit margin stand out as the financial metrics with the most significant marginal effect in the trading and service sectors, respectively.

Given the resource constraints faced by Thai SME owners, it is critical to prioritize these key financial ratios within their respective sectors to effectively mitigate insolvency risk and enhance financial resilience. The study also reveals that medium-sized firms, firms registered as juristic ordinary partnerships, those owned by foreigners, and those located in less competitive areas are less likely to face insolvency.

This study has practical policy implications. The findings suggest that Thai policymakers can leverage significant financial ratios to design strategies that enhance SME operations and performance. For instance, policymakers could organize workshops on trade credit assessment, providing benchmarks for the optimal number of days enterprises should aim to collect payments from customers to reduce insolvency risk.

Additionally, policymakers could develop accessible platforms offering SMEs consultation on critical aspects such as asset and inventory management. Firm managers can derive practical strategies that emphasize boosting liquidity positions to mitigate insolvency risk and ensure sustained business viability. However, we acknowledge the limitations related to sample characteristics and data constraints. The investigation of insolvency using samples of Thai SME juristic persons may reflect unique characteristics due to the specific social and economic context. Furthermore, this study is limited to a dataset from the DBD of Thailand and does not include non-registered firms (natural persons).

References

Aho, K., Derryberry, D., & Peterson, T. (2014). Model selection for ecologists: The worldviews of AIC and BIC. *Ecology*, *95*(3), 631–636.

Altman, E. I. (1968). Financial ratio, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609.

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.

Beaver, W. H., Correia, M., & McNichols, M. F. (2012). Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy? *Review of Accounting Studies*, *17*(4), 969–1010.

Camacho-Miñano, M. del M., Segovia-Vargas, M.J., & Pascual-Ezama, D. (2015). Which characteristics predict the survival of insolvent firms? An SME reorganization prediction model. *Journal of Small Business Management*, *53*(2), 340–354.

Fuertes-Callén, Y., Cuellar-Fernández, B., & Serrano-Cinca, C. (2022). Predicting startup survival using first years financial statements. *Journal of Small Business Management*, *60*(6), 1314–1350.

Gupta, J., Gregoriou, A., & Ebrahimi, T. (2018). Empirical comparison of hazard models in predicting SMEs failure. *Quantitative Finance*, *18*(3), 437–466.

Hanley, J. A., & McNeil, B. J. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology*, *143*(1), 29–36.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). New York: Springer.

Hernandez Tinoco, M., Holmes, P., & Wilson, N. (2018). Polytomous response financial distress models: The role of accounting, market and macroeconomic variables. *International Review of Financial Analysis*, *59*, 276–289.

Hernandez Tinoco, M., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis*, *30*, 394–419.

Inekwe, J. N. (2016). Financial distress, employees' welfare and entrepreneurship among SMEs. *Social Indicators Research*, *129*(3), 1135–1153.

Islam, M. S., Semeen, H., & Farah, N. (2013). The effects of financial ratios on bankruptcy. *Independent Business Review*, *6*(2), 52–67.

Li, K. (2024). Liquidity ratios and corporate failures. *Accounting & Finance*, *64*(1), 1111–1134.

Lizares, R. M., & Bautista, C. C. (2021). Corporate financial distress: The case of publicly listed firms in an emerging market economy. *Journal of International Financial Management & Accounting*, *32*(1), 5–20.

Malakauskas, A., & Lakstutiene, A. (2021). Financial distress prediction for small and medium enterprises using machine learning techniques. Inžinerinė Ekonomika-*Engineering Economics*, *32*(1), 4–14.

Mrockova, N. (2022). Resolving SME insolvencies: An analysis of new Chinese rules. *Journal of Corporate Law Studies*, *22*(1), 469–503.

Muñoz‐Izquierdo, N., Laitinen, E. K., Camacho‐Miñano, M. del M., & Pascual‐Ezama, D. (2020). Does audit report information improve financial distress prediction over Altman's traditional *Z* ‐score model? *Journal of International Financial Management & Accounting*, *31*(1), 65–97.

Patel, P. C., Guedes, M. J., & Pearce, J. A. (2017). The role of service operations management in new retail venture survival. *Journal of Retailing*, *93*(2), 241–251.

Pissarides, F., Singer, M., & Svejnar, J. (2003). Objectives and constraints of entrepreneurs: Evidence from small and medium size enterprises in Russia and Bulgaria. *Journal of Comparative Economics*, *31*(3), 503–531.

Platt, H. D., & Platt, M. B. (1990). Development of a class of stable predictive variables: The case of bankruptcy prediction. *Journal of Business Finance & Accounting*, *17*(1), 31–51.

StataCorp LLC. (2021). *Stata Lasso reference manual release 17*. College Station, TX: Stata Press.

The Office of Small and Medium Enterprises Promotion (OSMEP). (2021). *SME Transformation* (Annual report 2021*)*. Bangkok, Thailand: OSMEP.

Tian, S., & Yu, Y. (2017). Financial ratios and bankruptcy predictions: An international evidence. *International Review of Economics & Finance*, *51*, 510–526.

Tian, S., Yu, Y., & Guo, H. (2015). Variable selection and corporate bankruptcy forecasts. *Journal of Banking & Finance*, *52*, 89–100.

Tibshirani, R. (1996). Regression shrinkage and selection via the Lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288.

Tong, Y., & Serrasqueiro, Z. (2021). Predictions of failure and financial distress: A study on Portuguese high and medium-high technology small and mid-sized enterprises. *Journal of International Studies*, *14*(2), 9–25.

World Bank Group. (2017). *Report on the treatment of MSME insolvency* (Report No. 114823). Washington, D.C: World Bank Group.

Xiao, Z., Yang, X., Pang, Y., & Dang, X. (2012). The prediction for listed companies' financial distress by using multiple prediction methods with rough set and Dempster-Shafer evidence theory. *Knowledge-Based Systems*, *26*, 196–206.

Yoshino, N., & Taghizadeh-Hesary, F. (2016). *Major challenges facing small and medium-sized enterprises in Asia and solutions for mitigating them* (ADBI Working Paper No.564). Tokyo: Asian Development Bank Institute.

Appendices

Table A1: Definitions of Thai SMEs (provided by the Office of SMEs Promotion, Thailand)

Sector	Micro Enterprise		Small Enterprise		Medium Enterprise	
	Annual income (million Baht)	Employment (person)	Annual income (million Baht)	Employment (person)	Annual income (million Baht)	Employment (person)
Manufacture	not more than 1.8	not more than 5	more than 1.8, but not more than 100	more than 5, but not more than 50	more than 100, but not more than 500	more than 50, but not more than 200
Trade and Service	not more than 1.8	not more than 5	more than 1.8, but not more than 50	more than 5, but not more than 30	more than 50, but not more than 300	more than 30, but not more than 100

Note: If the number of employees fits one type of enterprise, but the revenue fits another type, whichever is higher determines the size of the enterprise.

Table A2: The average marginal effects across all sectors (in percentages)

Average Marginal Effects	Manufacture	Trade	Service
ROA	-0.0001462 **	-6.43e-06 **	-1.42e-06
ROE	-0.0000364	-0.0001818 ***	0.0001045
Gross Profit Margin	-0.0061777 ***	0.000146	-0.0030458 ***
Net Profit Margin	0.0003413	0.0000354	-4.08e-06
Current Ratio	0.0028373	0.000663	0.0005693
Accounts Receivable Turnover	-0.0114885 **	0.0000405	-0.0001317
Inventory Turnover	-0.0019005 *	-0.0010561 ***	-0.0004618 **
Accounts Payable Turnover	-0.0102441 ***	-0.0002645 ***	-0.0021859 ***
Total Assets Turnover	-0.0091766	-0.0074112 *	-0.001124 ***

Average Marginal Effects	Manufacture	Trade	Service
Operational Expenses to Total Revenue	-0.0002639	0.0006057 ***	0.0009685 ***
Asset to Equity	-0.0018403 ***	0.0025554 ***	-0.0008914 ***
Debt to Assets Ratio	0.002961 ***	0.001659 ***	0.000956 ***
Debt to Equity Ratio	-7.94e-07	-0.0011764	-0.0001586
Working Capital to Total Assets	0.0006674	0.0022371	0.0011784 ***
Sales to Total Assets	0.0036027	0.0058847	-0.0010953

The significance statistics are based on LASSO logistic regression with the Cross-fit Partilaing-out method.

***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.