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SURVIVAL ANALYSIS OF THAI MICRO AND SMALL ENTERPRISES DURING THE COVID-19 PANDEMIC

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Abstract. Micro and small enterprises (MSEs) are important to the local economy and are the most crucial source of employment in Thailand. Using the three-round survey data, we assess the impact of COVID-19 on the survival probability of MSEs in the tourism and manufacturing sectors. Enterprise characteristics such as owner characteristics, employment and business strategies are examined as potential factors to mitigate or stimulate business failures. The Cox proportional hazards model and Kaplan–Meier estimator are employed. Our findings reveal that the survival probability paths from the three rounds of survey show a gradual decrease of survival probability from the first week of interview and approximately 50% of MSEs could not survive longer than 52 weeks during the COVID-19 pandemic. We also find that the survival of MSEs mainly depends on location, number of employees, and business model adjustment, namely operation with social distancing and online marketing. Particularly, retaining employees and not reducing the working hours are one of the key factors increasing the survivability of MSEs. However, the longer length of the crisis reduces the contribution of these key factors. The longer the period of the COVID-19 pandemic, the lower the chance of MSEs survivability.

Keywords: business survival, COVID-19, Cox proportional hazards model, Kaplan–Meier estimator, survey data, Thailand.

JEL Classification: M21, C01, H12.

Introduction

After its outbreak in December 2019, COVID-19 has severely upset businesses around the world and has also led to an increase in the volatility of the economy and social conditions in both developed and developing countries at the same rate (Rashid & Ratten, 2021; Hu

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& Zhang, 2021). Thailand is one of the most severely affected countries in Southeast Asia. Since international flights were suspended in March 2020, the tourism and business sectors have experienced historically sharp shrinkage. Many MSEs have permanently shut down as they failed to adapt to the COVID-19 lockdowns and travel restrictions (Shen et al., 2020; Shafi et al., 2020).

MSEs contribute significantly to the Thai economy. In 2019, MSEs contributed THB 5,963,156 million, equivalent to 35.3% of the Gross Domestic Product (GDP) of the Thai economy. By enterprise size, the micro, small, and medium enterprises contributed 2.9%, 15.3%, and 17.1% to the national GDP, respectively. In terms of growth, the micro-enterprises had the highest growth rate of 8.6%, while the small and medium enterprises grew at 0.7% and 3.9%. Moreover, MSEs have also played an important role in Thailand's labor market, in which MSEs account for 69.48% of total employment. Although the micro enterprises accounted for a lower percentage of GDP, the enterprises hired 31.26% of total employment (Office of SMEs Promotion, 2020).

The growth of MSEs has plummeted due to the COVID-19 pandemic. The crisis has affected the all MSEs in Thailand, especially those in the service sector. The National Economic and Social Development Council (2021) reported that, in the last quarter of 2020, agricultural production increased by 0.9% while the production of the industrial sector decreased by 5.9% and that of the service sector declined by 7.2%. As 41.8% of Thai MSEs belong to the service sector, the COVID-19 pandemic can be viewed as the major risk factor of MSEs. The Asian Development Bank (2020) reports that domestic demand for goods and services produced by SMEs declined by 40% causing 41% of MSEs to cease operations after the national lockdown.

The MSEs everywhere have never experienced a pandemic health crisis like this before (Weaver, 2020); likewise, the failure rate of MSEs has increased in Thailand. Hence, there is an urgent need for knowledge on how MSEs can survive and what are the risk factors for Thai MSEs to fail in this COVID-19 crisis. However, the study on the economic impact of COVID-19 on MSEs is limited. Recent studies on the COVID-19 outbreak have shown the significant effects of the COVID-19 in several aspects such as on society, economy, and environment. (see, for example, Weaver, 2020; Bartik et al., 2020; Shafi et al., 2020; Gregurec et al., 2021). Weaver (2020) revealed that financial performance, resilience strategies and innovation, and geographic location should be considered in examining the impact of COVID-19 on the social enterprise sector. Bartik et al.(2020) confirmed that the pandemic had caused a negative impact on 5,800 small US businesses just a few weeks after the COVID-19 onset. Shafi et al. (2020) assessed the impact of COVID-19 on 184 Pakistan's MSEs and found that most enterprises have been severely affected by this crisis and are facing several obstacles such as financial burden, reduction of the supply chain, and demand and profit loss. Likewise, Gregurec et al. (2021) explained that several countries have suspended business activities and have employed several lockdown policies to control the spread of COVID-19. As a result, many businesses are temporarily halted or permanently closed.

However, COVID-19 impact on the survival probability and the length of MSEs' survivability (business vulnerability) has been overlooked. In addition, no study has been conducted to date to examine the role of the owner-, employment-, business-, and business strategy-specific characteristics on the survival probability and the length of MSEs survivability in Thailand during the ongoing COVID-19 crisis. Therefore, this study seeks to fill the research gap by tracing the survival probability of MSEs in Thailand during this pandemic and investigating the determinants of survivability and time to failure of MSEs. We would like to note that business self-assessment (expectations of business owners) is used as an instrument for evaluating the survivability of MSEs in this study. Specifically, the survey asked businesses, "If Thailand faces COVID-19 for another year, how much longer could your business survive under the current conditions?" and the businesses can choose their answer from 1 week to more than 52 weeks. The answer to this question is used to determine a business's survivability.

The novel aspects of this study are three-fold. First, our analysis considered a multitude of factors that can affect the survival probability of Thai MSEs. These factors are categorized as demographics, characteristics, and strategies of MSEs.These factors refer to the dimensions that the literature and the conventional wisdom believe to be associated with MSEs survival probability. In addition, the government relief programs along with financial information and MSE management structure are taken into account when factors contributing to survivability are evaluated. To the extent of our knowledge, no similar studies have been introduced, and this is the first research to investigate the risk factors of Thai MSEs survival. Second, the Cox proportional hazards model is a standard analytical method to study survival analysis in several fields, namely medicine (e.g., Salinas-Escudero et al., 2020), finance (e.g., Shih & Giles, 2009; Gunsel, 2010), and some aspects of economics (e.g., Babucea & Danacica, 2010; Puttachai et al., 2019). However, it is rare that the method is applied to business survivability, especially that of MSEs. As this study applies the Cox proportional hazards model to MSEs, it supplements existing literature. Besides, as many MSEs' factors are considered, this study ventures into employing the Elastic Net estimation, which has not been widely used in the conventional survival studies. This estimation has been proven to provide more efficient parameter estimation and variable selection, especially when the input factors are highly correlated (Friedman et al., 2009). Third and last, our results can provide specific guidance for MSEs and the government on how to increase the survival probability and strengthen the Thai MSEs during the COVID-19 pandemic. These insights are expected to be of great value for the government and MSEs owners who face difficulty dealing with the negative impact of the COVID-19 pandemic on MSEs' survivability.

The remainder of this study is structured as follows: Section 1 reviews the relevant literature, Section 2 gives details on the methodology and data, Section 3 presents the empirical findings, and the last Section provides the conclusion and policy implications.

1. Literature review

1.1. The impact of COVID-19 on businesses and firms

The impact of COVID-19 is much more challenging to evaluate when compared to ecological disasters and financial disasters as health crises rarely take place (Giunipero et al., 2022). Recently, many existing studies have broadly discussed the impact of COVID-19 on businesses and investigated the risk factors to determine the appropriateness of crisis mitigation strategies for business. The studies of Weaver (2020), Bartik et al. (2020), Shafi et al. (2020), and Gregurec et al. (2021) investigated the role of the COVID-19 pandemic on businesses and confirmed the large negative impact of COVID-19. Shafi et al. (2020) also revealed that businesses had experienced several obstacles such as the financial shortage, disruption of the supply chain, and the reduction in demand. They highlighted that most of the businesses neither are prepared nor have any plan to handle this unprecedented contraction. Therefore, the businesses could survive just one or two months after the COVID-19 onset. These findings are in line with those of Bartik et al. (2020) from their survey of 5,800 small businesses in the USA that highlighted the financial fragility of many businesses and revealed that 43% of the small firms surveyed were temporarily closed due to COVID-19. Also, Gregurec et al. (2021) suggested that small- and medium-sized enterprises should adjust their business plans and seek new opportunities to deal with this unexpected crisis event. These studies have shown empirical evidence supporting an adverse effect of COVID-19 on businesses. However, some studies have argued that businesses in some countries could survive the pandemic. For example, Hu and Zhang (2021) undertook a study to assess the performance of firms worldwide during the COVID-19 pandemic and they reported that the impact of the COVID-19 pandemic on firms is less significant in countries with better institutions, more advanced financial systems, and stronger healthcare systems. According to these heterogeneous impacts, we may conclude that the COVID-19 pandemic has heterogenous effects on the survivability of MSEs with different characteristics under different environments. Shafi et al. (2020) suggested that small enterprises who are more financially fragile and have fewer resources are more likely to be affected by the crisis.

Several studies have also reported that the COVID-19 impacts on businesses vary across their characteristics, demographics, and government supports. Recent studies have shown a growing interest in research on factors affecting businesses. For example, Jin et al. (2022) evaluated the influence of COVID-19 on firm innovation of Chinese companies during January–October 2020. Their results suggested that the crisis has hindered innovations created by Chinese firms as it reduces market demand, as well as affects capital supply and demand. They also found that COVID-19 has a greater negative impact on the innovation of state-owned enterprises compared to non-state-owned enterprises. Similarly, Jiang et al. (2021), from investigating the COVID-19 impacts on business cash flows and investment activities, found that the negative impact of COVID-19 is higher in Chinese state-owned firms with large size and located in the eastern region. Moreover, Fu and Shen (2020) studied the impact of COVID-19 on the energy industry's performance and revealed a negative impact of COVID-19 on energy companies' performance. They also highlighted the significant factors affecting the profit of energy enterprises to include region, size of the enterprise, asset-liability ratio, trade receivable turnover, and income.

Most of the recent studies on the economic effects of COVID-19 on businesses focused on the prediction of business failure. However, the investigation of business survival duration during this recent crisis is still poor. In particular, the prediction of the survival time of businesses is neglected. Moreover, the literature on the survival of MSEs during COVID-19 is scarce, in part, due to data limitations. Little is known how COVID-19 has affected the survivability of Thai MSEs. Therefore, it is worth studying the impact of COVID-19 on the Thai MSEs, and our focus is on the survival probability of MSEs.

1.2. Modelling the survivability

The literature on the prediction of business or MSEs failure has shown that there are many models and techniques that have been developed and applied. One commonly used approach to predicting business failure is the multiple discriminant analysis (MDA), which was introduced by Altman (1968). However, this approach has several drawbacks according to Lane et al. (1986). First, the results obtained from the MDA are limited to the posterior probability that a particular business will fail, and the expected time to failure is not given explicitly. Second, the model cannot be used to predict business failures. Subsequently, the logit and probit models were developed and applied to business studies by Ohlson (1980). Nevertheless, these models still adhere to the normality assumption that not only is often difficult to meet in most empirical applications but also possibly reduces their predictive power.

Later, the survival analysis model or the Cox proportional hazards model was introduced to investigate the survivability of the business. Kim (2019) mentioned that this model provides a more sophisticated analysis compared to the conventional statistical models. Although the machine learning models and business intelligence algorithms were also proposed as competing powerful techniques to predict the failure and have been proven to be superior to the logit and probit models (Tam & Kiang, 1992), these techniques neglect the effect of predictors on the duration of time until the event of business failure occurs. Lane et al. (1986) and Kim et al. (2016) revealed that the omission of time to failure events would reduce the usefulness of the MDA and other statistical models to regulatory agencies. The Cox proportional hazards model of Cox (1972) was introduced to deal with these problems, and it has become more popular in the recent decades.Allison (2010) mentioned that the model itself does not require any information on the underlying distribution, while it also provides the prediction of the probable time to failure. In addition, we can view this model as an early warning system for businesses failure as it can predict the business's failure before it actually happens. The Cox proportional hazards model has been employed for business failure prediction in many studies such as Luoma and Laitinen (1991), Kim et al. (2016), Gémar et al. (2016), Woldehanna et al. (2018) and Pelaez-Verdet and Loscertales-Sanchez (2021). These studies confirmed the higher performance and usefulness of this Cox model compared to the conventional models.

Although studies in recent years have shown a growing interest in research on the COVID-19's impact on businesses, the COVID-19's impact on the survival probability and the length of MSEs survivability has not yet been examined. Specifically, the expected time to failure of MSEs, defined as the time elapsed between the time that the MSEs are interviewed to the end of their business activities, is not given explicitly. The existing literature mainly employed descriptive statistics to explore the consequences of COVID-19 (Shafi et al., 2020; Giunipero et al., 2022), which is not enough to reveal the actual impact of COVID-19. Hence, the main objective of this study is to supplement the existing literature on the prediction of Thai MSEs resolution (i.e., whether they survive or fail and how long they can survive). To the best of our knowledge, the survival analysis on MSEs has not been conducted in this recent crisis context, and we are the first attempting to use the Cox proportional hazards model to examine the risk factors affecting the survival probability of MSEs in Thailand. Specifically, this study answers the question: What considerations should be made to hinder or solve the effect of COVID-19 on the survivability of MSEs and which is the factor leading the longer and higher survival rate of the MSEs?

Furthermore, as our empirical analysis takes into consideration a wide range of factors as well as control variables that are related to the survival probability of MSEs, the multicollinearity problem is likely to occur in our empirical models. To solve this problem, one or more of these correlated variables should be removed. However, if the variables that are significantly relevant to the *survival* probability of MSEs are removed, the traditional Cox proportional hazards model may produce biased and inconsistent estimates, known as the omitted variable bias. Maneejuk and Yamaka (2021) suggested that the omitted variable bias could lead to difficulties in theoretical interpretation of empirical results in social science studies. As the omitted variable bias and multicollinearity problems are our concern in the study, we adopt the elastic net estimation to fit the Cox proportional hazards model (Friedman et al., 2009). This estimation technique is able to select the risk factors associated with survivability and estimate the coefficients in the Cox proportional hazards model simultaneously.

2. Methodology

2.1. The Cox proportional hazards regression model

Survival analysis examines the causal effects of covariate vector $X = (x_1,...,x_k)$ on survival time Y. Cox (1972) assumed that the hazard function $h(Y|X)$ of a subject with covariate vector takes the form of

$$h(Y|X) = h_0(Y)\exp(X'\boldsymbol{\beta}), \tag{1}$$

where $h_0(Y)$ is the hazard baseline which depends only on Y and is left unspecified. $\boldsymbol{\beta} = (\beta_1,...,\beta_k)$ are the partial regression coefficients. By taking logarithm on Eq. (1), we obtain a linear-like model specification for the log hazard as follows:

$$\log h(Y|X) = \alpha + X'\boldsymbol{\beta}, \tag{2}$$

where $\alpha = \log(h_0(Y))$ is the constant term. Note that $\boldsymbol{\beta} > 0$ (hazard ratio = $\exp(\boldsymbol{\beta}) > 1$ indicates that the survival probability of MSEs decreases. On the contrary, if $\boldsymbol{\beta} < 0$ (hazard ratio = $\exp(\boldsymbol{\beta}) < 1$), the survival probability will increase. In practice, it is not necessary that all factors contribute to predicting the survival probability of MSEs; hence we need to explore the key risk factors and quantify their risk effects on the survival probability. As we mentioned in Section 2 that many factors are considered in our study; hence, we employ the Elastic Net penalty (Zou & Hastie, 2005) to estimate the partial likelihood function of the Cox model. This allows us to estimate parameters $\boldsymbol{\beta}$ and select the true risk factors simultaneously. Wu (2012) revealed that the Elastic Net penalty is capable of selecting more predictors than the sample size, and it was proved to provide more efficient results compared to other sparse penalties, such as LASSO (Tibshirani, 1997) and SCAD (Fan & Li, 2002). We can estimate the coefficients of the Cox model by maximizing the Cox log partial likelihood as follows,

$$\log L(\boldsymbol{\beta}) = \sum_{i=1}^{n} \delta_i X'\boldsymbol{\beta} - \sum_{i=1}^{n} \delta_i \log\left(\sum_{j \in R_r} \exp(X'\boldsymbol{\beta}) \right) + \lambda \sum_{j=1}^{k} |\boldsymbol{\beta}| + \frac{\gamma}{2} \sum_{j=1}^{k} \boldsymbol{\beta}^2, \tag{3}$$

where $\delta_i = I(Y_i \leq C_i)$ is the censoring indicator. Y_i and C_i are the failure time and censoring time of business i, $i = 1,...,n$, respectively. From the questionnaire design, $C_i = 52$ weeks in this study. $\lambda \geq 0$, and $\gamma \geq 0$ are regularization parameters of Lasso penalty, $\sum|\boldsymbol{\beta}|$, and ridge penalty, $\sum \boldsymbol{\beta}^2$, respectively. According to Eq.(3), we can say that the Elastic Net penalty is a regularization method that linearly combines the Lasso and ridge penalties. Thus, if $\lambda = 0$, the ridge penalty is used to penalize the partial log-likelihood function of the Cox model, else $\gamma = 0$, the Lasso penalty is used.

To have a better understanding of survival data, we illustrate this concept in Figure 1. In this study, given 52 weeks as a censoring period, we aim to examine whether a business suffers the event of interest (business failure) during the study period (52 weeks after the interview). Note that we consider 52 weeks, equivalent to one year, as a censoring period because it is the standard censoring period usually suggested in the literature, and it is easy to interpret. (Please see the following studies for reference: Puttachai et al., 2019; Salinas-Escudero et al., 2020; Rashid & Ratten, 2021). We can observe that only Business A had not been affected by the event (the survival on COVID-19 crisis without business failure), while Businesses B and C experienced business failure within 52 weeks after they are interviewed.

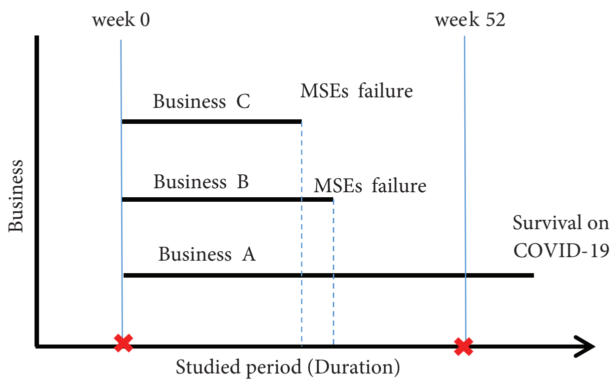

Figure 1. The illustration of survival data

2.2. Kaplan–Meier estimator

The Kaplan–Meier method is a standard way of computing the survival over time conditional on at most one predictor, and it has become one of the most used in survival analysis studies. In other words, the Kaplan–Meier estimate considers only one predictor to generate the survival curve, which is defined as the probability of survivability in a given length of time. This estimator is a nonparametric estimator with extremely few restrictions (Gémar et al., 2016) and the properties that: i) the event of interest is apparent, and the study period is clearly determined; ii)the survival probability of all businesses is the same; and iii) the censored observations have the same survival probability. In practice, the estimator is defined as the fraction of observations who survived under the same circumstances for a certain amount of time.

In our analysis, we are interested in investigating the impact of the significant factors on the survival of MSEs. Thus, only significant factors obtained from the Cox model are used to predict the survival probability during this COVID-19 crisis.

2.3. Data

This study uses a survey conducted as part of The Asia Foundation (TAF)'s revisiting the pandemic project to examine the impact of the COVID-19 pandemic on the survivability of Thai MSEs. The project aims to obtain new and fresh information on the current status of Thai MSEs in the tourism and manufacturing sectors during this recent COVID-19 crisis. The survey also collects the information of owner and firm characteristics and ongoing business strategies since the start of the COVID-19 crisis. As micro and small enterprises are considered in this study, all participants are carefully selected and screened using the International Finance Corporation (IFC) criteria. These criteria include number of employees, asset and/or sale values, and whether the enterprise's loan falls within the relevant loan size.

The survey is a panel-data survey, in which the same sample of businesses were surveyed in three rounds including Round 1 (June 2020), Round 2 (September 2020) and Round 3 (December 2020). The first round of the survey includes a sample of 982 MSEs, 60% of which from the tourism sector and 40% from the manufacturing sector. MSEs from the tourism sector were randomly selected from the TripAdvisor website and the Thai Revenue Department's list of travel agents. MSEs from the manufacturing sector were sampled from the Thai Department of Business Development's list of MSEs (The Asia Foundation, 2021).

For the panel-data survival analysis, it is important to prevent nonrandom withdraws of observations leading to estimation biases (Boel et al., 2021). For this reason, all participants were invited for all three rounds of the surveys, regardless of their business survival. With the effort, there were 16% and 13% sample loss in Round 2 and Round 3, respectively. For this study, the sample only includes 720 MSEs that appear in all three rounds of survey. The sample is from Bangkok and all major regions of Thailand including the North, Northeast, Central, and South. However, the distribution of the sample across provinces within each region varies according to the registered MSEs database. Over the three survey rounds, 60% of MSEs are tourism enterprises, while the remaining 40% are small-scale manufacturing enterprises.

To determine the economic survival probability of Thai MSEs, we requires information of the businesses' survival periods, which is the period from when a business is interviewed in each round to when it expects to face a failure. Note again that in each round, the survey asked, "If Thailand faces COVID-19 for another year, how much longer could your business survive under the current conditions?" and each business could answer 1 week to more than 52 weeks. The answer to this question is used to determine the business's survivability.

To identify the key factors determining the survival probability of MSEs, the explanatory variables considered in this study include owner-specific characteristics, business-specific characteristics, business strategies against COVID-19, and employees of the business.

Table 1 presents the definitions of variables used in this study and their corresponding percentage (%) across the three survey rounds. Note that the average and standard deviations are presented for continuous variables. According to Table 1, we can observe that the percentage of business failure from this crisis decreases from 49.72% to 46.81%. However, the economic survival duration, which is the number of survival weeks, tends to decrease from 46.711 weeks in round 1 to 45.033 weeks in round 3.

Considering the independent variables; about 52.92% of the businesses are owned by female entrepreneurs, indicating that small- and micro-sized businesses in Thailand are achieving gender equality. Most of the owners' ages range between 35–59 years old. Regarding the business size, 59.44% of businesses are small, while about 40% of businesses are micro. Before the COVID-19 crisis, more than 50% of MSEs have total assets and annual sales lower than THB 3 million.

In the case of the financial status of businesses during this crisis, 95.83% of businesses reported having reduced revenue due to COVID-19. To survive the crisis, we find that some MSEs lay off their employees; however, it turns out that more than 50% of MSEs are not reducing working hours to minimize the layoff of employees. If we look at the number of employees laid off due to the COVID-19 pandemic, the average number of laid-off employees is 4.730, 2.800, and 3.254 persons in Rounds 1, Round 2, and Round 3, respectively.

Table 1. Descriptive statistics

Variable	Abbreviation	Description	Round 1	Round 2	Round 3
Dependent variable: Survival data					
MSEs failure	δ	1 = business failure within 52 weeks, 0 = survive more than 52 weeks	49.72%	46.25%	46.81%
Economic survival duration	T	Number of weeks that business can operate (If the business can survive longer than a year, the value is 52).	46.711 (17.864)	47.397 (17.364)	45.033 (19.871)
Independent variable: Owner-specific characteristics					
Gender of owner	gender	1 = female, 0 = male	52.92%	52.92%	52.92%
Age of owner	age_15 to 24	Age 15–24 years old	0.97%		
	age_25 to 34	Age 25–34 years old	20.28%	20.28%	20.28%
	age_35 to 44	Age 35–44 years old	33.33%	33.33%	33.33%
	age_45 to 59	Age 45–59 years old	36.39%	36.39%	36.39%
	age_60 up	Age 60 years old and above	9.03%	9.03%	9.03%
Independent variable: Business-specific characteristics					
Location of business	reg_bkk	Bangkok metropolitan area	19.86%	19.86%	19.86%
	reg_central	Central region	21.67%	21.67%	21.67%

Continued Table 1

Variable	Abbreviation	Description	Round 1	Round 2	Round 3
	reg_northeast	Northeastern region	19.44%	19.44%	19.44%
	reg_north	Northern region	19.86%	19.86%	19.86%
	reg_south	Southern region	19.17%	19.17%	19.17%
Area of business	area	1 = urban, 0 = rural	45.97%	45.97%	45.97%
Size of business	size_business	1 = small enterprise, 0 = micro enterprise	59.44%	59.44%	59.44%
Total assets	total_asset_ business_d1	Total assets less than THB 3 millions	50.27%	50.27%	50.27%
	total_asset_ business_d2	Total assets THB 3–60 millions	46.94%	46.94%	46.94%
	total_asset_ business_d3	Total assets THB 61–100 millions	2.79%	2.79%	2.79%
Annual sales	annual_sale_ business_d1	Annual sales less than THB 3 millions	61.39%	61.39%	61.39%
	annual_sale_ business _d2	Annual sales THB 3–60 millions	37.92%	37.92%	37.92%
	annual_sale_ business_d3	Annual sales THB 61–100 millions	0.69%	0.69%	0.69%
Types of business related to service sector	business_tour_d1	Small & micro (non-tourism)	39.45%	39.45%	39.45%
	business_tour_d2	Gastonomy (i.e. food/ beverage/bakery/snack-tourism related)	18.19%	18.19%	18.19%
	business_tour_d3	Hotel/accommodations	18.19%	18.19%	18.19%
	business_tour_d4	Travel agent/tour guide/ transportation	10.98%	10.98%	10.98%
	business_tour_d5	Other business in tourism sector	13.19%	13.19%	13.19%
Revenue	rev_change_d1	No change in sale/revenue from the COVID-19 pandemic	2.36%	2.36%	2.36%
	rev_change_d2	Sale/revenue has increased from the COVID-19 pandemic	1.81%	1.81%	1.81%
	rev_change_d3	Sale/revenue has decreased from the COVID-19 pandemic	95.83%	95.83%	95.83%
Rent/lease business premises	rent_premises	1 = rent/lease business premises, 0 = own business premises	38.19%	38.19%	38.19%
Business import	business_import	1 = import, 0 = not import	10.28%	10.28%	10.28%
Business export	business_export	1 = export, 0 = not export	8.33%	8.33%	8.33%

Continued Table 1

Variable	Abbreviation	Description	Round 1	Round 2	Round 3
Independent variable: Business strategies against COVID-19					
Business reduces working hours to minimize layoff	reduce_hr_d1	Business reduces the working hours to minimize layoff	25.28%	12.64%	12.08%
	reduce_hr_d2	No change/working as usual (not reduce the working hours to minimize layoff	27.22%	60.42%	51.67%
	reduce_hr_d3	Not reduce the number of hours, but already layoff some/all staff	45.69%	22.78%	26.39%
	reduce_hr_d4	Not reducing number of hours because business is (temporarily) closed	1.81%	4.16%	9.86%
Receiving soft loan	softloan	1 = receiving soft loan, 0 = not receiving soft loan	15.69%	23.06%	25.28%
Business model change from COVID-19 pandemic	business_change_d1	Not yet try anything /No change/No adjustment on the business model	52.64%	43.47%	39.17%
	business_change_d2	Operate while adapting to social distancing	5.69%	5.97%	5.56%
	business_change_d3	Move into new products and services that have high demand during COVID	4.03%	6.67%	9.44%
	business_change_d4	Operate through online markets or social media	22.22%	30.28%	34.03%
	business_change_d5	Discussed with employees to reduce their salary to keep all employees	15.42%	13.61%	11.80%
Independent variable: employees					
Number of employees	employees	Number of employees before COVID-19	9.951 (11.755)	9.951 (11.755)	9.951 (11.755)
Number of female employees	employees_female	Number of female employees before COVID-19	5.284 (6.131)	5.284 (6.131)	5.284 (6.131)
Number of informal employees	employees_informal	Number of informal employees before COVID-19	3.966 (9.726)	3.966 (9.726)	3.966 (9.726)
Number of laid-off employee	employees_lay_off	Number of laid-off employees due to COVID-19	4.730 (10.252)	2.800 (5.759)	3.254 (5.946)
Number of laid-off female employees	employees_female_lay_off	Number of laid-off female employees due to COVID-19	2.618 (4.987)	1.555 (3.458)	1.972 (4.338)

End of Table 1

Variable	Abbreviation	Description	Round 1	Round 2	Round 3
Number of laid-off informal employee	employees_ informal_lay_off	Number of laid-off informal employees due to COVID-19	2.508 (8.825)	1.480 (4.793)	1.929 (4.995)
The number of employees expects to leave within two months.	employees_ expect_to leave	Number of employees that expect to leave within two months due to the COVID-19 pandemic.	0.123 (1.024)	0.108 (0.899)	0.159 (0.847)

Note: The bracket () indicates the standard error of the continuous variable.

3. Empirical results

In this section, we will first present the survival analysis results using the Cox proportional hazards model in Section 3.1. Then, the survival path of MSEs with respect to significant factors will be presented in Section 3.2.

3.1. Estimation results of the Cox proportional hazards model using the Elastic Net estimator

This section presents the Cox proportional hazards model's estimated results. The dependent variable is the MSEs duration measured in weeks, and owner-, employment-, business-, and business strategy-specific characteristics are the predictors. Table 2 presents the coefficient estimates. As shown in the table, some coefficient estimates are dropped out because the Elastic Net penalty has shrunk them to zero. The obtained coefficients, however, cannot be interpreted directly because Cox is a non-linear model and the effect of each independent variable on business failure varies across businesses.

Table 2. Results of the Cox model

Variable	Parameter estimate			Hazard ratio		
	Round 1	Round 2	Round 3	Round 1	Round 2	Round 3
gender	.	.	.	.	.	.
age_25 to 34	.	.	.	.	.	.
age_35 to 44	.	.	0.058	.	.	1.060
age_45 to 59	.	.	.	.	.	.
age_60 up	.	.	.	.	.	.
reg_central	–0.195	–0.132	–0.717	0.823	0.876	0.488
reg_northeast	.	.	–0.074	.	.	0.929
reg_north	.	.	0.080	.	.	1.083
reg_south	.	–0.124	–0.389	.	0.883	0.678
area	.	.	–0.017	.	.	0.983
size_business	.	.	.	.	.	.

End of Table 2

Variable	Parameter estimate			Hazard ratio		
	Round 1	Round 2	Round 3	Round 1	Round 2	Round 3
total_asset_business_d2	.	.	.	.	.	.
total_asset_business_d3	.	–0.028	.	.	0.972	.
annual_sale_business _d2	.	.	.	.	.	.
annual_sale_business_d3	.	.	.	.	.	.
business_tour_d2	.	–0.074	–0.348	.	0.929	0.706
business_tour_d3	0.029	.	0.063	1.029	.	1.065
business_tour_d4	0.116	.	0.164	1.123	.	1.178
business_tour_d5	.	.	.	.	.	.
rev_change_d2	–0.307	.	–0.419	0.736	.	0.658
rev_change_d3	.	0.003	0.123	.	1.003	1.131
rent_premises	0.280	0.260	0.142	1.323	1.297	1.153
business_import	.	.	0.079	.	.	1.082
business_export	.	.	.	.	.	.
reduce_hour_d2	–0.403	–0.391	–0.426	0.668	0.676	0.653
reduce_hour_d3	.	.	–0.421	.	.	0.656
reduce_hour_d4	.	0.094	0.002	.	1.099	1.002
softloan_d2	–0.025	.	–0.043	0.975	.	0.958
business_change_d2	.	.	–0.182	.	.	0.834
business_change_d3	.	.	0.080	.	.	1.083
business_change_d4	–0.020	.	–0.113	0.980	.	0.893
business_change_d5	.	0.095	0.048	.	1.099	1.060
employees	.	.	–0.010	.	.	0.990
employees_female	.	–0.001	.	.	0.999	.
employees_informal	.	.	.	.	.	.
employees_lay_off	0.004	0.013	0.026	1.004	1.013	1.026
employees_female_lay_off	.	.	.	.		
employees_informal_lay_off	.	.	.	.		
employees_ expect_to leave	0.005	0.005	0.022	1.005	1.005	1.022

We present the estimated coefficients corresponding to their hazard ratios in Table 2. Note that variables with the hazard ratio higher than 1 are the inhibiting factor for the survival of MSEs. Otherwise, it is a supporting factor. Our results reveal that, in all three rounds, the variables the Central region (reg_central), rent business premises (rent_premises), not reducing the working hours to minimize layoff (reduce_hour_d2), number of laid-off employees due to COVID-19 (employees_lay_off), and number of employees that expect to leave within two months due to the COVID-19 pandemic (employees_ expect_to leave) are the key factors affecting the survival of Thai MSEs. Note that the full variable description is provided in Table 1.

Overall, we observe that reg_central and reduce_hour_d2 negatively affect the business failure in every round of the survey, indicating an essential role of these variables in enhancing the business survival probability during this pandemic. In contrast, rent_premises, employees_lay_off, and employees_ expect_to leave show a positive sign, implying that these factors hinder business survival. An increase in the number of laid-off employees worsens the business's survival probability. The higher number of laid-off employees leads to an increase in non-survival probability by 0.4%, 1.3%, and 2.6% in Round 1, 2 and 3 (corresponding to the hazard ratio of 1.004, 1.013, 1.026), respectively. Moreover, if a business lays off one additional employee in the next two months, its non-survival probability increases by 0.5%, 0.5%, and 2.2% in Round 1, 2 and 3 (corresponding to the hazard ratio of 1.005, 1.005, 1.022), respectively. Shafi et al. (2020) mentioned that most businesses face a cash-flow shortage during the COVID-19 crisis and, thus, choose to lay off employees or reduce salaries to reduce cost. This should increase survival probability. However, our results show that the employee layoffs are not sufficient for Thai MSEs during the COVID crisis The MSEs who lay off employees still face a significant higher risk of failure than the average. Moreover, we would like to note that our survival probability of the MSEs is derived from the expectations of business owners (self assessment), thus the business that retains employees may have more confidence to survive than the business that lays off employees and reduces the working hours. Furthermore, Marjański and Sułkowski (2021) suggested that laying off employees could hurt businesses in the long term due to insufficient maintenance, loss of human capital, and loss of client engagement.These factors can also stimulate a higher probability that the businesses would fail.

In terms of the rent_premises variable, we find that the hazard ratios are larger than one for all three rounds, indicating that the risk of business failure increases in MSEs that rent premises compared with MSEs that own their property. In particular, the hazard ratios are 1.323, 1.297, and 1.153, which means that the risk of business failure of MSEs that rent are 1.323, 1.297, and 1.153 times higher than those businesses that own their property in the first, second, and third rounds, respectively. On the other hand, it can be seen that some factors do not present significant effects on Thai MSEs' survival probability, i.e. gender (of owner), age (of owner), size_business, annual_sale_business, employees_female_lay_off and employees_informal_lay_off. Thus, we can conclude that these factors do not significantly affect the MSEs' survival probability.

We then explore heterogeneity in business failure with respect to the location of business and types of business.We find that location of the business becomes a more significant factor in the third round of the survey. The MSEs that are located in the Central, Northeastern, and Southern regions have the hazard ratio of 0.488, 0.929, and 0.678 indicating that MSEs in these three regions face a lower risk of non-survival than those in Bangkok and the North. Considering MSEs located in Bangkok as the reference group, the result shows that MSEs located in the Northern region appear to expose to a higher risk of non-survival than Bangkok. Regarding types of business, we find strong evidence that hotel and travel agent businesses (business_tour_d3 and business_tour_d4) are less likely to survive in the first and third surveys as hazard ratios are greater than 1, implying that the failure probability of hotel and travel agent businesses are higher than those other small & micro enterprises. As Pelaez-Verdet and Loscertales-Sanchez (2021) mentioned, the outbreak and the border closure drove the market demand to nearly zero during the period that would have been high season. Hence, many hotels and travel agents had to go out of business before other businesses.

Concerning business strategies for surviving the pandemic, we find that the reduction of working hours (reduce_hour), receiving the soft loan (soft_loan), and adjusting the business model (business_change) contribute a strong mitigation to MSEs in the third round of survey as their coefficients are negative and their corresponding hazard ratio is larger than 1. Our results are consistent with with Breier et al. (2021) that showed that business model strategies and financial support are essential in tackling this current crisis as they will generate new revenue channels and improve liquidity, respectively.

Table 3. Model comparison

Estimation	BIC		
Elastic Net	–123.234	–134.823	–142.278
Lasso	–118.093	–121.562	–136.901
Ridge	–90.783	–94.393	–90.234
Nonpenalized	–90.233	–85.034	–83.093

To provide a robust justification for why the Cox proportional hazards model estimated by Elastic Net is preferred in our analysis, we compare the performance of this estimator with those of Lasso, Ridge, and Nonpenalized estimations using the Bayesian information criterion (BIC). The BIC results in Table 3 indicate that the Cox model estimated by the Elastic Net method outperforms those done by the competing estimators.

3.2. Survival path analysis

This subsection shows an alternative illustration for the survival probability. This tool is called the survival path analysis, which shows the survival probability over time (Puttachai et al., 2019). According to the earlier subsections, we use the Kaplan–Meier estimator in assessing the influence of the individual variables on the survival of the MSEs. Then, we will consider only significant factors suggested by the Cox model in Table 2 for the survival path analysis. The plots of survival probability with respect to significant factors are presented in Figures 2–7.

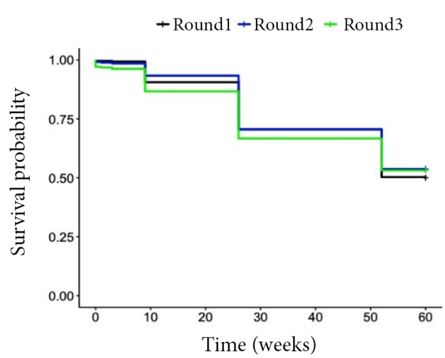

Figure 2. The overall economic survival probability of Thai MSEs in Round 1 (June 2020), Round 2 (September 2020) and Round 3 (December 2020)

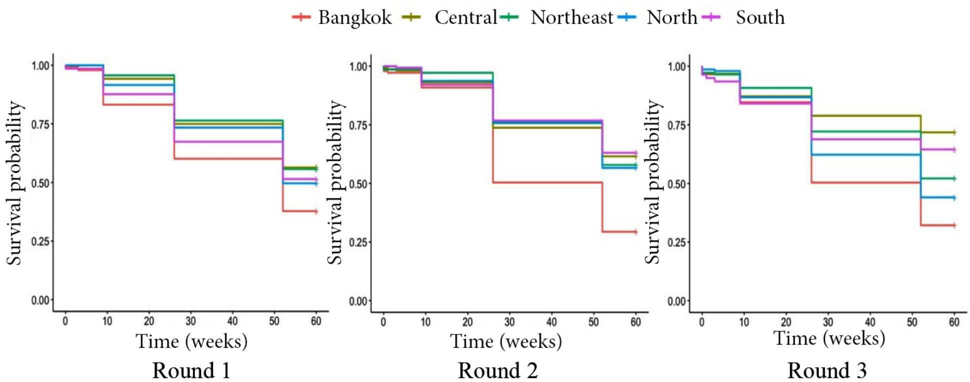

Figure 3. Survival probability of MSEs in different regions in Round 1 (June 2020), Round 2 (September 2020) and Round 3 (December 2020)

Before discussing the results of the survival probability path of MSEs influenced by each significant factor, we analyse all the factors together and illustrate the survival probability path of MSEs of rounds 1, 2 and 3 in Figure 2. The results show that the survival probability paths from the three rounds of survey are not much different, and they are gradually decreasing since the first week of interview and it is found that about 50% of MSEs could not survive for 52 weeks due to the COVID-19 pandemic. This indicates that, at the time of survey, some of the Thai MSEs expect that they will face difficult business environment, and they would not survive if the COVID-19 pandemic continues for another year (more than 52 weeks). We also notice that the survival probability paths of MSEs in the first and the third rounds are slightly different from the second round. We would like to note that the first round survey was conducted during a period of substantial policy uncertainty, the second round survey was conducted during a period of lockdown cancellation, while the third round coincides with the second wave of the COVID-19 spread. This enables us to compare MSE's level of confidence during a period of relative openness with that of a lockdown period and we may conclude that the confidence level of MSEs in round 2 is slightly higher than rounds 1 and 3 due to the lockdown cancellation.

The survival probability for each significant factor is illustrated in Figures 3–7. The survival curves for the MSEs in different regions are shown in Figure 3. It can be seen that the survival functions have a downward stair-shaped slope for all regions in every round. The survival probability is 100% in the first week of the survey and then drops sharply after week 24, especially in Round 2 and Round 3. This implies that the risk of the crisis becomes stronger. However, the survival function becomes a horizontal line in all rounds after 50 weeks. This means that the survival probability no longer drops after 50 weeks. Moreover, the survival probabilities of MSEs vary across regions. It is observed that the MSEs located in Bangkok have the lowest survival probability, while MSEs located in the Northeast seem to endure the longest. This result could be explained by Bangkok MSEs being heavily dependent on international tourists because Thai domestic tourists are less likely to choose Bangkok as their vacation destination.

Figure 4 illustrates the survival probabilities of MSEs that owned their business premises and MSEs that rented. The survival probabilities across the three rounds are not much different. We observe that MSEs that rented are more vulnerable than MSEs that owned their business premises. If we compare the survival probabilities between these two, MSEs that rented have an average of 28.0%, 26.0%, and 14.2% lower survival probability in Round1, Round 2 and Round 3, respectively. Interestingly, the gap of survival probability between these two decreases along the three rounds of survey, indicating that MSEs that owned their business premises and MSEs that rented may have the same survival probability in the future.

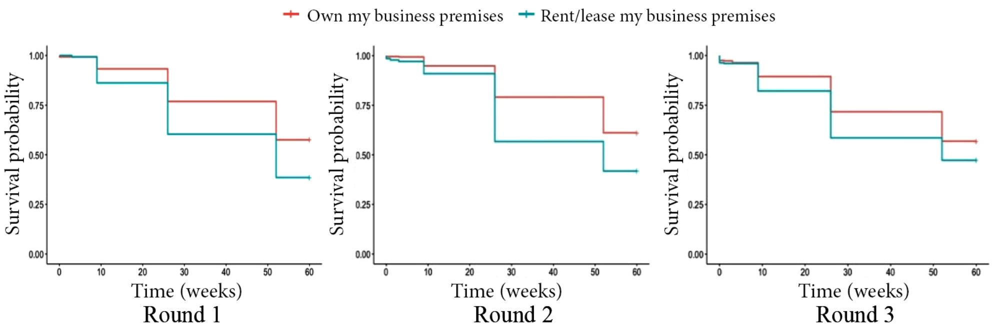

Figure 4. Survival probability concerning different types of business premises in Round 1 (June 2020), Round 2 (September 2020) and Round 3 (December 2020)

Figure 5 shows the survival probability of MSEs that lay off employees. Most MSEs can survive for the first 10 weeks as the survival probabilities from the 1st week to the 10th week are close to 1. We also observe that if MSEs lay off only 1–20 workers, their survival chance is higher than those MSEs that lay off employees more than 20. This result implies that retaining employees during the pandemic may result in a higher chance of getting support from the government, thereby increasing the higher survivability. Like Figure 5, Figure 6 presents the survival probability for the MSEs according to their employees' decision to leave or not to leave during the pandemic. This result is consistent with that illustrated in Figure 5. More leaving workers led to a higher chance of business failure. It can be observed that the survival path of the MSEs whose employees are expected to leave is lower than that of the MSEs whose employees are expected not to leave in all three periods. Nevertheless, the survival probabilities of these two groups are more stable after week 50 with the probability around

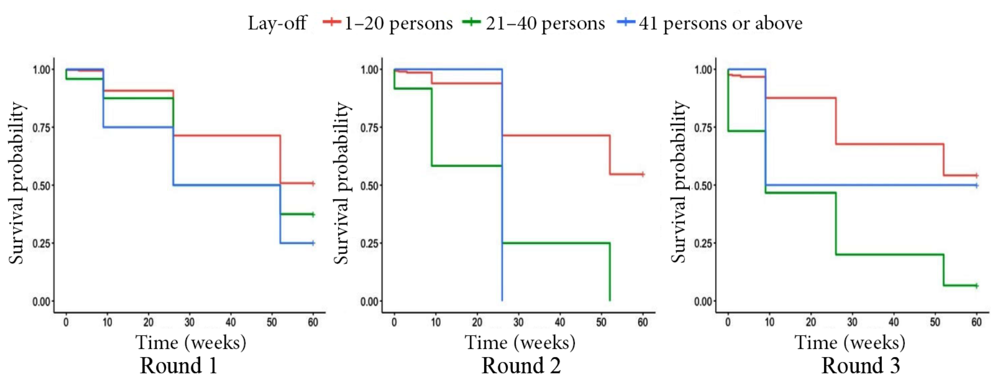

Figure 5. Survival probability of MSEs that lays-off employees in Round 1 (June 2020), Round 2 (September 2020) and Round 3 (December 2020)

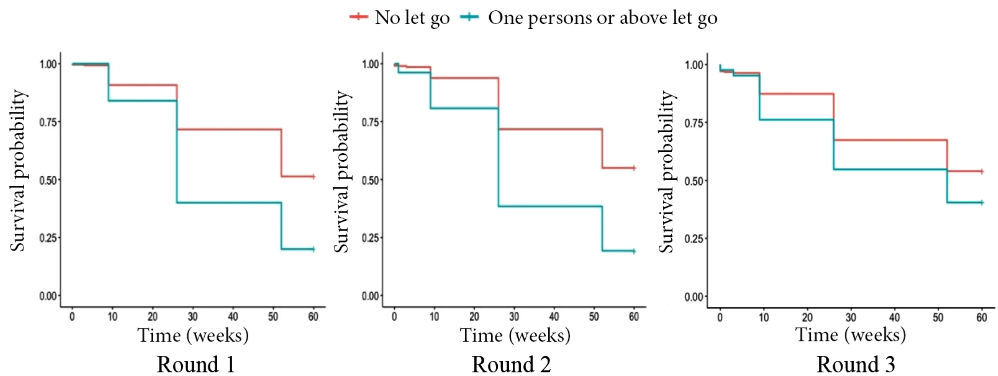

Figure 6. Survival probability of MSEs that employees are expected to leave or not to leave in Round 1 (June 2020), Round 2 (September 2020) and Round 3 (December 2020)

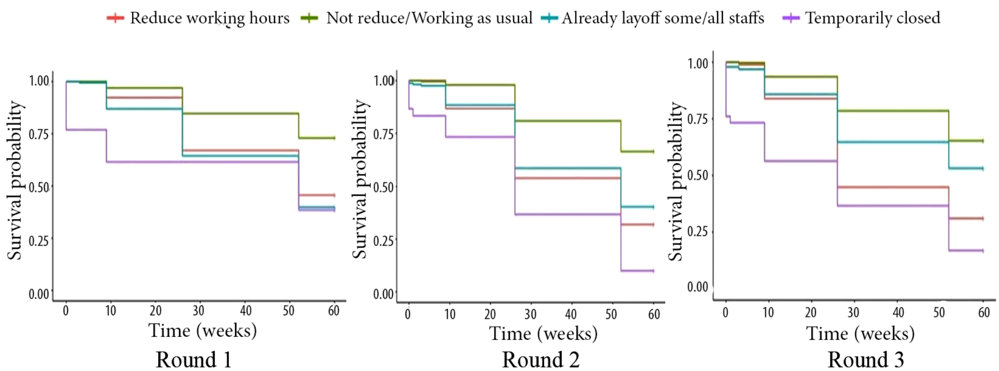

Figure 7. Survival probability of MSEs in different business adjustments in Round 1 (June 2020), Round 2 (September 2020) and Round 3 (December 2020)

25–35% for the MSEs that have employees that are expected to leave, and around 50% for the MSEs that have employees that are expected not to leave.

Finally, regarding the business adjustments during the COVID-19 crisis (Figure 7), MSEs that temporarily closed have a lower chance of survivability than those MSEs that do not lay off employees and that do not reduce the working hours in all three rounds. This result is quite surprising that the MSEs that are temporarily closed tend to have a lower chance of surpassing this crisis. This may be because most Thai MSEs are service businesses, which makes it difficult to reopen again in the near future. Moreover, the lack of demand now emerges as the main obstacle of many businesses. Specifically, many MSEs, particularly service businesses, have had to close permanently, mainly due to the insufficient demand from local and foreign customers. This result is in line with the results of Dai et al. (2021), who investigated the impact of COVID-19 on small- and medium-sized enterprises in China. They revealed that the lack of demand is listed as the top challenge, and service businesses faced more serious demand problems compared to other sectors. Also, Guerra-Marrero et al. (2021) explained that the relationship between supply and demand has dropped, and it would become impossible to keep the service open during the COVID-19 pandemic.

Conclusions

This study considers the COVID-19 crisis that emerged in late 2019 as the main initial fuse for business insolvency in Thailand. In this study, we examine the effects of the owner-, employment-, business-, and business strategy-specific characteristics on the survival rate and the length of MSEs survivability in Thailand. The survey data include 720 MSEs from the tourism and manufacturing sectors collected in Round 1 (June 2020), Round 2 (September 2020) and Round 3 (December 2020).

Our study contributes to the empirical literature on analysing the MSEs survival during the COVID-19 crisis based on data obtained from 720 MSEs in Thailand. We take into consideration various socio-economic and business adjustment variables that can affect the survival probability of MSEs. Our analyses are carried out in two dimensions. First, we are interested in identifying the key risk factors of non-survival MSEs using the Cox proportional hazards model. Second, we adopt the Kaplan–Meier method (Kaplan & Meier, 1958) to estimate the survival probabilities of MSEs across different survival periods.

From the results, the survival probability paths from the three rounds of survey show a gradual decrease of survival probability from the first week of interview and about 50% of MSEs reported that they could not survive for more than 52 weeks during the COVID-19 pandemic. The survival probability paths for MSEs with respect to significant factors (influence in all three rounds of survey) show their gradual decrease from the first week of the interview to the 52nd week. Also, it is found that the survival probability of MSEs influenced by different significant factors are different and so are the survival rates of MSEs across the three rounds. Our results highlight the role of business factors, such as location, total asset, type of business, and business operation, together with the length of the crisis in determining the survival probability of MSEs, for policymakers to consider. The following conclusions and recommendations can be drawn from our research.

First, in Round 1, 2 and 3, 70.97%, 35.42% and 38.47% of MSEs which are severely affected by COVID-19 reduce costs by cutting hours or laying off workers. However, as shown in Figures 5–7, the cost cutting strategies are not nearly enough for business survival. While the layoffs create immediate unemployment, the collapse of MSEs would create a longer-term unemployment. Although the Thai government launched a set of policies to assist MSEs, the evidence calls for a much stronger government interventions targeting both micro and small enterprises, especially travel agents, tour guides and hotels.

Second, in the time of crisis, liquidity is key. MSEs who have more assets, own their business premise, and have access to soft loan have a higher probability to survive. This highlights that it is important to make credit accessible for all businesses in times of crisis. Finally, business model adjustments are likely to have a significant impact on MSEs' likelihood to survive in Round 3. Specifically, businesses that adapt to the COVID situation such as performing social distancing and initiate online marketing faced a lower risk of business insolvency.

This study is relevant because micro and small enterprises play an important role in creating jobs and income in the Thai economy. The majority of MSEs has adopted new business or cost cutting strategies. Moreover, the Thai government provided sizable cash transfers to workers, as well as initiated some programs to stimulate spending on MSEs and the tourism industry. However, most MSEs still reported that they were at risk of failure within a year.

This implies that policies to solve problems after the crises happen are too costly and not sufficient. This crisis highlights the gap in the risk management and social protection system. Thailand needs a social protection system that provides adequate insurance and assistance for all workers and MSEs in crises.

Despite the above significant academic and policy implications regarding the impact of COVID-19 on the survivability of MSEs, some limitations remain for future research. First, the survivability data is self-reported by the MSEs. The COVID-19 situation created unique uncertainty facing businesses both from the economic crisis and policy assistances. As a result, there can be biases due to MSEs' own estimation. Therefore, a retrospect study on the impact of COVID-19 on MSEs using actual business failure data would be useful to validate the results of this study. Second, as MSEs are highly heterogenous, the sample size of MSEs considered in our study may not be enough to examine differentiated impact of COVID-19 on Thai businesses. Therefore, an increase in sample size should be considered in future studies. Moreover, if the data of medium and large enterprises can also be collected, it would be beneficial to compare the impacts across business of different sizes. Finally, besides the immediate economic impacts, the COVID-19 crisis also create new challenges for MSEs in the medium and long run. Therefore, future studies can investigate this issue to address the ongoing impacts of the pandemic and potential adaptations for MSEs.

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Author contributions

WY and SL provide the Conceptualization, NT4 and NT5 collected and arrange the data NT5 and WY prepare the Methodology and estimation. PM and SL write the original draft, NT4 and SL review and edit the paper. All authors have read and agreed to the published version of the manuscript.

Disclosure statement

All authors declare that they have no competing interests.

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