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# Survival of reorganized firms in France

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## Abstract

This paper investigates the survival prospects of reorganized companies in France. It seeks to identify the determinants that accelerate or reduce the time to failure of reorganized firms in the French context. Our findings reveal that the company's size, profitability, liquidity, the industry profitability, and inflation rate have a positive effect while the leverage and the variation of short-term interest rate have a negative effect on the survival of reorganized firms in France. The study also shows that the failure process of a reorganized firm is similar to the failure process of a new firm.

# **Keywords:**

Bankruptcy; reorganization; survival; time-varying model

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# Abstract

This paper investigates the survival prospects of reorganized companies in France. It seeks to identify the determinants that accelerate or reduce the time to failure of reorganized firms in the French context. Our findings reveal that the company's size, profitability, liquidity, the industry profitability, and inflation rate have a positive effect while the leverage and the variation of short-term interest rate have a negative effect on the survival of reorganized firms in France. The study also shows that the failure process of a reorganized firm is similar to that of a new firm.

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#### 1 Introduction

An efficient bankruptcy system would encourage the reorganization of viable firms and eliminate non-viable ones. However, in practice, many reorganized firms need to be restructured again through a private workout or go into liquidation. This assessment has given rise to many studies relating to various post-bankruptcy aspects. A review of the literature shows that most of the studies on reorganized firms have focused on measuring post-bankruptcy performance of reorganized firms. Measures of performance were based on (i) accounting measures (Hotchkiss, 1995; Denis and Rodgers, 2007; Kalay et al., 2007) (ii) the reorganized firms' cash flows (Hotchkiss, 1995; Alderson and Betker, 1999), and (iii) the stock performance of firms emerging from bankruptcy (Eberhart et al., 1999; Komera and Lukose, 2013; Ahmad et al., 2018).

Other studies examined the reorganization outcome and the factors that influence this outcome (Altman et al., 2009; Altman, 2014a, 2014b; Altman and Branch, 2015; Altman et al., 2019) but most of them used univariate analysis, multivariate discriminant analysis, and conditional probability models that have some common problems. First, most classical methods assume a dichotomous dependent variable (failed and non-failed firms). In reality, corporate failure is not a well-defined dichotomy (Balcaen and Ooghe, 2006). Second, classical statistical models neglect the time dimension of failure. They assume that failure is a steady state and do not consider information on the progress and dynamics of the failure process (Luoma and Laitinen, 1991). By ignoring the fact that firms change through time, static models produce bankruptcy probabilities that are biased and inconsistent (Shumway, 2001).

Moreover, a review of post-bankruptcy literature shows that most of the previous empirical studies were almost based on reorganized firms in the U.S, which are regulated under the U.S. bankruptcy code. There are, in fact, major differences between countries in terms of legal, governance, and institutional settings. Wang (2012) undertook a comparative study to examine the role of institutional factors (bankruptcy codes and judicial efficiency) in the decision to

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resolve bankruptcy through reorganization and liquidation. The author found that the legal origin of the bankruptcy code is important for determining the choice of either reorganization or liquidation. Therefore, it would be interesting to investigate survival prospects of reorganized firms in France where the law is considered among the most debtor-oriented systems in the world (La Porta et al., 1998). Blazy et al. (2011) show that the French Courts work actively for preserving employment, by facilitating continuation against liquidation. More recently, Esquerré (2019) shows that French judges attempt to favor the reorganization of bankrupt firms when the local unemployment rate is high. Thus, by trying too hard to preserve employment, the French law may save non-viable firms.

This paper contributes to post-bankruptcy literature in two ways. First, we use a model with timevarying covariates to investigates the survival of reorganized firms. The advantage of a dynamic model is that it takes into account the progress of the reorganization process and change of firms' characteristics over time. Precisely, we apply Cox regression model to study the failure process of post-bankrupt firms and to identify the determinants that accelerate or reduce the time to failure. The logic behind this methodology is that, a model used to detect corporate distress of healthy firms, might also be effective in assessing the risk of failing of post-bankrupt firms. Recently, Cepec and Grajzl (2020) have used Cox model to investigate the role of debt-to-equity conversion in bankruptcy reorganization as a determinant of post-bankrupt girm survival in Slovenia. But, the model was estimated only with time-invariant covariates.

Second, the paper provides new empirical evidence on survival of reorganized firms in France. Although there are some studies investigating bankruptcy in France (Blazy and Combier, 1997; Blazy and Chopard, 2012; Blazy et al., 2011), little empirical research had been conducted on post-bankruptcy issues. Moreover, most studies that analyze firms after bankruptcy mainly focused on recovery rates in France and its determinants (Davydenko and Franks, 2008; Blazy et al. 2011, 2013). In a more recent study, Esquerré (2019) analyses the impact of local unemployment on the judges decisions and its effect on the firms' survival in France.

The purpose of this paper is to address this lack of data. To conduct our study, we use a sample of 131 firms reorganized in the commercial Court of Paris over the period 2001-2015.

# 2 Data and Methodology

### 2.1. Data

The event of interest in this study is defined as a reorganized company entering into liquidation. Precisely, survival time is defined as the time spent from the confirmation date of the reorganization plan to the liquidation date of the reorganized firm. Our sample consists of 131 firms that had their reorganization plan confirmed by the Court of Paris between 2001 and 2005. For these firms, we collected financial and accounting information (balance sheet and income statement data) from DIANE over the 2001-2015 period.

The explanatory variables include the firm's size, profitability, liquidity, leverage, and industry profitability. We use logarithm of total assets as the proxy for size of the company. We measure return on assets ratio as the proxy for firm's profitability. The liquidity ratio is measured in this study as current assets (excluding inventory) divided by current liabilities. We use two measures for leverage in the present study. First, we examine the leverage ratio measured as total debts divided by total assets. This ratio is often used in predicting failure. Businesses with high total debt ratios are in danger of becoming insolvent and going into liquidation. Second, as a proxy for firm's leverage, we use a dummy variable that takes the value 1 if the firm is "insolvent", and zero otherwise.<sup>1</sup> The choice of this variable is motivated by the study context. In fact, the sample

<sup>&</sup>lt;sup>1</sup> We consider that a firm is "insolvent" if it has more debts than assets, and "solvent" otherwise.

is composed of bankrupt firms that are expected to have a large amount of debt. The highleverage dummy is expected to accelerate the failure process. Moreover, following (Abid et al., 2018), we introduce some macroeconomic variables including an output gap variable, the variation of short-term interest rate and the inflation rate.

An overview of the explanatory variables used in the empirical analysis and their expected signs is contained in Table 1.

Variables	Definition	Expected Sign <sup>(a)</sup>	
Firm size	Natural logarithm of total assets	-	
Profitability ratio	Return on assets ratio <sup>(b)</sup>	-	
Liquidity ratio	(Current assets – inventories) / current liabilities	-	
Leverage ratio	Total liabilities/total assets	+	
High-leverage dummy	Dummy variable, equal to 1 if the firm's leverage ratio exceeds 1	+	
Industry profitability	Industry average of return on assets ratio (based on the NES 114 level) <sup>(b)</sup>	-	
Output gap	Deviation from a linear trend	-	
Inflation rate	Calculated from GDP deflator	-/+	
Interest rate	Variation of short-term interest rate (3 months)	+	

**Table 1: Definition of Variables and Expected Signs** 

(a) A positive (negative) sign implies an increase (decrease) in the risk of failing.

(b) Return on assets is defined as the operating income before depreciation and amortization over assets.

### 2.2. Methodology

To identify the determinants that accelerate or reduce the time to failure of reorganized firms, we apply Cox proportional hazards model proposed by Cox (1972). This model can be expressed as follows:

$$\lambda_j(t) = \lambda_0(t) exp(x_j \beta) \tag{1}$$

Where  $\lambda_j(t)$  is the hazard function for firm *j* at time *t*.  $\lambda_0(t)$  is an arbitrary unspecified baseline hazard rate.  $x_j$  represents the vector of covariates that influence the hazard and  $\beta$  is the vector of their coefficients.

The conditional probability that the  $j^{th}$  case will fail at time  $t_i$  is given by:

$$\Pr\left(t_j = t | R(t_i)\right) = \frac{\lambda_0(t) \exp(x_j \beta)}{\sum_{j \in R(t_i)} \lambda_0(t) \exp(x_j \beta)} = \frac{\exp(x_j \beta)}{\sum_{j \in R(t_i)} \exp(x_j \beta)}$$
(2)

where  $R(t_i)$ , the risk set, is defined as the set of observations that are at risk of experiencing a failure at time  $t_i$ .

Taking the product of the conditional probabilities in (2) over all n firms yields the partial likelihood function:

$$L_p(\beta) = \prod_{i=1}^n \left[ \frac{\exp(x_j \beta)}{\sum_{j \in R(t_i)} \exp(x_j \beta)} \right]^{c_i}$$
(3)

where  $c_i$  is the censoring indicator variable.  $c_i$  is set to 1 if the failure time for the  $i^{th}$  subject is observed and to 0 if it is censored.

The corresponding log-partial-likelihood function is given by:

$$\operatorname{Ln} L_p(\beta) = \sum_{i=1}^n c_i \left[ x_i \beta - \log \sum_{j \in R(t_i)} \exp(x_j \beta) \right]$$
(4)

In a time-varying model, the values of the covariates change with time, and therefore, the model in equation (1) becomes:

$$\lambda_j(t) = \lambda_0(t) \exp\left(x_{j(t)}\beta\right)$$
(5)

Where  $\lambda_j(t)$  is the hazard function for firm *j* at time *t*.  $\lambda_0(t)$  is an arbitrary unspecified baseline hazard rate.  $x_{j(t)}$  denote the value of the covariates vector at time *t* for the firm *j*.

For each firm *j*, we focus on each time interval for which data are available, recording the start time of the interval  $(t_{0j})$ , the end time  $(t_j)$ , whether or not the event of interest occurred during the interval, and the values of all covariates during the interval  $(x_i)$ .

In the time-varying covariates case, equation (4) is modified and estimates of the parameter  $\beta$  may be obtained by maximizing the following log-likelihood function:

$$\operatorname{Ln} L_p(\beta) = \sum_{i=1}^n c_i \left[ x_{i(t)}\beta - \log \sum_{j \in R(t_i)} \exp(x_{j(t)}\beta) \right]$$
(6)

where  $R(t_i)$  is the set of observations k that are at risk at time  $t_i$  (i.e., all k such that  $t_{0k} < t_i \le t_k$ ), and  $c_i$  is the censoring indicator variable.  $c_i$  is set to 1 if the failure time for the  $i^{th}$  subject is observed and to 0 if it is censored.

# **3** Empirical results

Table 2: Cox proportional hazards me	odels	estimation
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Panel A : Time-invariant covariates								
	Model (1)			Model (2)				
	Coef.	SE (a)	p-value	HR <sup>(b)</sup>	Coef.	SE <sup>(a)</sup>	p-value	HR <sup>(b)</sup>
Size	- 0.2034	0.1462	0.164	0.8159	- 0.1840	0.1522	0.227	0.8319
Firm Profitability	- 0.0147***	0.0065	0.005	0.9854	- 0.0152***	0.0056	0.008	0.9849
Liquidity ratio	- 0.0030	0.0031	0.196	0.9970	- 0.0027	0.0030	0.224	0.9733
Leverage ratio	- 0.0513	0.1037	0.621	0.9499	-	-	-	-
High- leverage dummy	-	-	-	-	0.0126	0.4360	0.780	1.0126
Industry profitability	- 0.00617	0.0249	0.805	0.9938	- 0.00548	0.0229	0.848	0.9945
Partial LR test	14.84**			14.62**				
Probability > Chi2	0.0111			0.0121				
BIC	467.060			468.274				

(a) SE : Standard error ; (b) HR : Hazard ratio ; \*significant at 10% , \*\* significant at 5%, \*\*\* significant at 1%

	Model (1')		Model (2')		Model (3')	
	Coef.	HR <sup>(b)</sup>	Coef.	HR <sup>(b)</sup>	Coef.	HR <sup>(b)</sup>
Size	- 0.2724 <sup>***</sup> (0.096)	0.7615	- 0.2240 <sup>***</sup> (0.1011)	0.7993	- 0.2159** (0.0994)	0.8058
Firm Profitability	-0.0151*** (0.0066)	0.9850	- 0.0128 <sup>***</sup> (0.0039)	0.9872	- 0.0130 <sup>***</sup> (0.0035)	0.9870
Liquidity ratio	- 0.0608 <sup>***</sup> (0.0021)	0.9410	- 0.0467** (0.0023)	0.9543	- 0.0493** (0.0022)	0.9518
Leverage ratio	- 0.0723 (0.124)	0.9302	-	-	-	-
High-leverage dummy	-	-	0.6090 <sup>*</sup> (0.3013)	1.8385	0.5579 <sup>*</sup> (0.3038)	1.7469
Industry profitability	- 0.0089 <sup>*</sup> (0.0798)	0.9911	- 0.0088 <sup>*</sup> (0.0797)	0.9912	- 0.0070 <sup>*</sup> (0.0706)	0.9930
Output gap	-	-	-	-	- 0.0043 (0.022)	0.9957
Inflation rate	-	-	-	-	- 1.1761 <sup>**</sup> (0.5029)	0.3084
Interest rate	-	-	-	-	0.8253 <sup>**</sup> (0.096)	2.2825
Partial LR test	56.71***		57.13***		62.69***	
Probability > Chi2	0.0000		0.0000		0.0000	
BIC	413.019		412.052		409.325	

#### Panel B : Time-varying covariates

(a) SE : Standard error ; (b) HR : Hazard ratio ; \*significant at 10% , \*\* significant at 5%, \*\*\* significant at 1%

We display in Table 2 the estimation results of five Cox hazards models. Models (1) and (2), in Panel A, are estimated with time-invariant covariates (measured at the confirmation year) while models (1'), (2'), and (3'), in Panel B, are estimated with time-varying covariates. In models (1) and (1') we used the debts-to-assets ratio whereas in models (2) and (2'), we used high-leverage dummy variable. In model (3') we introduced macroeconomic variables.

As shown in Table 2, models (1) and (1'), respectively models (2) and (2'), show that all parameters have the expected signs except for leverage ratio which is not significant in both models (1) and (1'). By considering the p-value, both time-invariant models (Panel A) show that there is only one covariate that has a significant effect on the risk of failing. This covariate is the firm's profitability and is highly significant at the 1% level. The negative sign of the coefficient

indicates that the more profitable a firm at the confirmation year is, the lower the probability that it will fail at a given point of time. On the other hand, time-varying models (Panel B) show more significant variables in explaining failure risk. Four covariates in Model (1') and five covariates in Model (2') are significant and the sign of their coefficients are consistent with theoretical predictions.

Table 2 also reports the Bayesian Information Criterion (BIC) statistics. Time-varying models are considered better than time-invariant model since they show smaller values BIC. Overall, time-varying models provide more statistically significant coefficients with the expected signs and a better fit. This result is consistent with the findings of (LeClere, 2005). Consequently, in what follows more attention will be paid to Cox regression model with time-varying covariates. The estimation results in Panel B show that the covariates related to the firm's size, profitability, liquidity, and industry's profitability are statistically significant in the three models and have the expected signs. Moreover, the leverage variable is significant only for Models (2') and (3'). Precisely, the firm's leverage does not have an impact on the risk of failing when we use the debts-to-assets ratio, but it has an impact when we use the high-leverage dummy variable as a proxy. This finding suggests that leverage has a threshold effect on the survival of bankrupt firms. Our interpretation for this finding lies in the specificity of the sample used in the study. In fact, the sample is exclusively composed of bankrupt firms. An important stylized fact is that leverage ratios of bankrupt firms remain very high several years following reorganization. Therefore, a decrease in the leverage ratio following confirmation from 1.1 to 0.9, for example, indicates that the firm will move from an "insolvent" entity to a "solvent" one. This change would be perceived as a positive signal about the firm's future prospects and may result in a regain of trust. Table 2 also shows that Model (2') has higher values for partial likelihood ratio test and lower values for BIC criterion than Model (1') confirming that Model (2') is preferred to Model (1').

The estimation results in model (3') show that both microeconomic and macroeconomic variables affect the probability of failing. In particular, interest rate has a positive impact on the risk of failing while inflation rate has a negative impact. Compared with Model (2'), Model (3') has higher values for partial likelihood ratio test (62.69 versus 57.13) and lower values for BIC criterion (409.325 versus 412.052). Thus, in what follows we will focus on the estimation results of Model (3').

Although the signs of coefficients indicate the directional impact of an increase in coefficients on risk, the magnitudes of the coefficients are not so easily interpreted. For this reason, we choose to interpret the hazard ratios obtained by exponentiating the coefficients, which is more straightforward. The coefficient of firm's profitability is highly significant and has a negative sign which means that an increase in profitability decreases the risk of failing. For example, a 10% increase in profitability decreases the risk of failing by 12.19%.<sup>2</sup> The coefficient on leverage dummy variable is significantly positive. It means that a 1-unit increase in this covariate moves the firm from having fewer debts than assets (leverage dummy=0) to having more debts than assets (leverage dummy=1). The reported hazard ratio for the leverage dummy is equal to 1.7469, meaning that an "insolvent" firm faces a risk 1.7469 times greater than a "solvent" firm. In the same way a "solvent" firm faces a risk 0.1743 times lower than an "insolvent" one.<sup>3</sup>

Once the model has been estimated, a time-varying risk score defined as  $(x_{i(t)}\hat{\beta})$  can be calculated for each firm by time horizon t, where t varies from one year to ten years after the plan's confirmation.  $\hat{\beta}$  is the vector of estimated coefficients shown in Table 2 and  $x_{i(t)}$  is the vector of covariates for a given firm at time t. According to equation (5), the larger the value of

<sup>&</sup>lt;sup>2</sup>The hazard ratio corresponding to an increase of 10 units in the covariate  $x_{profitability}$  is obtained by  $exp(10 * \hat{\beta}_{profitability}) = 0.8781$ .

<sup>&</sup>lt;sup>3</sup>The hazard ratio corresponding to a 1-unit decrease in the dummy variable  $x_{leverage}$  is obtained by  $exp(-\hat{\beta}_{leverage}) = 0.1743$ .

the risk score is, the higher the risk of failing is. Survival probabilities can be easily generated using the estimated risk scores.



Figure 1 presents the survival function of an average business. Specifically, the survival probabilities used to create this graph were calculated by averaging the estimated survival probabilities at every time horizon. This graph reveals a linear decline in the survival rate of a firm over the first four years following plan's confirmation. During this period, the survival probability of a firm decreases by approximately 2.5% each year. Then, the survival probability reduces by more than 10% from the fourth year to the fifth year. However, after five years, the survival probability does not drop significantly and it is still reasonably high. One can notice that the failure process of a reorganized firm in France is similar to that of a new firm which takes at least five years to be considered as an established firm, and therefore much less likely to fail than a new firm.



Finally, in Figure 2 we present the survival functions for a typical active firm and a typical failing firm. Specifically, the survival functions shown in the graph are produced by averaging the estimated survival probability by firm status, "active" or "failing". The top curve depicts the survival profile for a typical active firm whereas the bottom curve shows the survival profile for a typical failing firm. As expected, the survival probabilities of failing firms are lower than active ones at every time horizon. Moreover, the vertical distance between the two curves represents the estimated reduction in survival probability for the failing firms relative to the active ones at every time horizon.

# 4 Conclusion

Several conclusions and observations can be drawn from our study. First, we investigate the impact of financial factors on the risk of failing of reorganized firms. The estimation results show the superiority of time-varying models. This result is predictable because a dynamic model that considers the progress of the reorganization process and the change of firm's characteristics over time is more appropriate than a static model. Second, the estimation of time-varying models

shows that firm's characteristics variables, industry variable, and macroeconomic variables affect the survival prospects of reorganized firms in France. Five covariates have a positive effect on survival including the company's size, profitability, liquidity, the industry profitability and the inflation rate while the variation of interest rates and the leverage have a negative effect. Moreover, evidence suggests that leverage has a threshold effect. Precisely, the firm's leverage does not have an impact when it is measured as a debts-to-assets ratio, but it has an impact when the firm's status moves from "solvent" to "insolvent" entity and vice-versa. One possible explanation lies in the specificity of the sample used in the study which is exclusively composed of bankrupt firms. Thus, when the bankrupt firm becomes solvent, this will be perceived as a positive signal about the firm's future prospects. Third, the survival function suggests that the failure process of a reorganized firm is similar to that of a new firm. Once the firm has survived for five years or more, the likelihood it will fail in the near future becomes low.

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