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Indicators of Corporate Default — An EU Based Empirical Study

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Abstract

The present paper contributes to the research on the indicators that provide a warning of company failure by employing micro and macro variables within a framework of survival analysis using a sample of 0.4 million companies from the European Union (EU). The sensitivity of the results is checked using two complementary event definitions — bankruptcy and negative equity. Our results imply that the baseline hazard of a default is a U-shaped function of the time the company has survived. High leverage and a low return on assets appear to be strong predictors of failure. Macroeconomic variables give mixed evidence for old and new member states as well as for the two default definitions.

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Keywords: corporate default, bankruptcy, survival analysis

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Non-technical summary

Bankruptcies of companies result in significant costs to shareholders, creditors and other stakeholders. Moreover, company failures on a larger scale have a considerable adverse macroeconomic impact. Our paper contributes to the increasingly popular research on indicators that provide a warning of company failure. We look for both company-level as well as macroeconomic signals of potential default. Hence, the results of our research may be useful for micro-level credit risk analysis as well as for regulators from the macroeconomic surveillance perspective.

The methodology for our research is survival analysis — one of the more recently favoured approaches in corporate failure prediction literature. We use a sample of more than 0.4 million companies residing in the member countries of the European Union (EU). In order to attest to the reliability of the results, we employ two different failure definitions in a comparative perspective — bankruptcy as a legal definition for default and negative equity as the accounting viewpoint of corporate failure. Altogether over 2,000 incidences of bankruptcy and over 23,000 incidences of negative equity are incorporated into the empirical analysis.

The study reveals that the overall risk of default is a U-shaped function of the time the company has survived. This means that the probability of failure is higher during the early phases of a company's operations and decreases gradually thereafter as the company establishes itself on the market. The probability of failure starts to increase again as the company matures and the internal risk exposures accumulate making it more vulnerable to external shocks. This finding appears to be valid in the cases of both bankruptcy and negative equity. However, as expected, the probability of bankruptcy appears to be significantly lower in comparison to that of experiencing negative equity.

It can be observed that the probabilities of bankruptcy and negative equity are consistently lower in companies of the 15 old member states of the EU, compared to the 12 new countries. Interestingly, it can be noted that newly established companies appear to be at a relatively higher risk of failure in the new member states, potentially explained by investors establishing riskier businesses in these yet developing economies leading to a relatively large portion of businesses to default quickly.

Such financial ratios as liabilities-to-assets and profit-to-assets appear to have good predictive power in distinguishing between failing and non-failing companies with a one-year lead time, both for bankruptcy and negative equity. These financial ratios can thus be seen as robust predictors of company failure.

The results for macroeconomic variables are somewhat weaker and show

more variability across estimations. Companies in the old member states of the EU seem to be more endangered during economic slowdowns, whereas the opposite applies to the 12 new EU countries — high GDP growth ex ante appears to lead to higher bankruptcy rates ex post. The rationale might be that economic growth in the new member states is more likely to bring along overly risky or badly planned projects. However, in the established business environment of the old member states companies appear to experience stress during long-lasting recessions.

Again, the openness of the economy improves the viability of companies in the new EU member states, whilst the opposite effect applies to the 15 old countries. Finally, the results provide some evidence that an increase in real interest rates is among the triggers of bankruptcy, though having a rather weak impact. Our findings also suggest that a credit crunch and real effective exchange rate appreciation undermine company soundness.

Contents

1. Introduction

Corporate failures result in significant costs to both shareholders and stakeholders and may have a considerable adverse macroeconomic impact. Understanding and predicting company default has been an area of extensive research for at least 40 years. The evolving economic environment and advances in research methods have led to the introduction of numerous complex approaches, but there is still neither a common theoretical understanding nor sufficient empirical evidence about what triggers corporate default.

Our paper seeks to provide an EU-wide analysis of the indicators that provide a warning of corporate default using survival analysis methodology. We combine both company- and macro-level variables to capture an imminent default. The results of our research may be useful for micro-level credit risk analysis as well as for regulators from the macroeconomic surveillance perspective. The paper is structured as follows. Section 2 reviews the relevant literature, Section 3 presents the research methodology, the data used for our study is described in Section 4 and Section 5 presents the results. Section 6 concludes the paper.

2. Literature

Several detailed reviews of the literature have been written about corporate failure analysis, including Dimitras et al. (1996), Altman and Narayanan (1997) and Balcaen and Ooghe (2004 and 2006). The following brief review of the literature largely draws on the last of the abovementioned authors.

The literature exploring corporate failure started with the simple univariate discriminant analysis approach, pioneered by Beaver (1967). Models of that kind are appealing in their simplicity, but their main disadvantage lies in their inability to account for the coexisting effects of many different indicators of default. Risk index models, like the ones developed by Tamari (1966) and Moses and Liao (1987), introduce the concept of indexing the individual failure-predicting indicators; however, their approach shares the same weaknesses of univariate analysis and provides largely arbitrary risk-metrics.

The next generation of failure prediction techniques — the multivariate discriminant analysis approach — made a breakthrough with the famous Altman (1968) Z-score model. Although discriminant analysis has remained one of the most widely-used risk analysis tools, probability models, such as the logit and probit models, have overtaken this position. Papers on corporate failure that make use of probability models include Ohlson (1980), Zmijewski (1984), and

Becchetti and Sierra (2002), among many others. Although popular among researchers, the disadvantages of the logit and probit models include a strong sensitivity to multicollinearity, outlying observations and missing values in the data (Balcaen and Ooghe, 2006).

The use of decision trees and neural networks represent non-parametric, artificial intelligence approaches in corporate failure studies. Applying the methodology of decision trees is based on the concept of machine learning and neural networks to use computers to simulate human brain learning processes. Examples of studies based on these methods include Frydman et al. (1985), Coats and Fant (1991) and Back et al. (1996). The main drawback of these approaches is that they identify no measurable links between the causes (variables) and the result (default) (Balcaen and Ooghe, 2006).

Survival analysis is a multi-period modelling technique, the aim of which is to determine a company's hazard rate; that is, the probability of default conditional on survival up to the time under observation. Unlike the static probability models, the survival models are dynamic since they account for the survival time of the company, treating the variables of the same company in different periods as interdependent. It has been applied by Lane et al. (1986), Luoma and Laitinen (1991), Laitinen and Kankaanpää (1999), Shumway (2001), Kauffman and Wang (2001), and Männasoo (2007).

Many other approaches to predicting corporate failure exist. A detailed overview of these alternative models for corporate failure analysis can be found in Balcaen and Ooghe (2004). Even more alternatives are covered in the reviews of the existing literature by Dimitras et al. (1996), Altman and Narayanan (1997), and Altman and Saunders (1998).

3. Methodology

We make use of the survival analysis methodology in our research. The following subsections introduce the definitions of default (i.e. the dependent variables), a range of company financial and structural indicators as well as macro-level variables (i.e. the independent variables) and the econometric model.

3.1. Definitions of default

We use two definitions of default for a comparative perspective — bankruptcy and negative equity.

Bankruptcy represents the legal definition for default. There are significant cross-country differences in bankruptcy legislation (for example, see *The European Restructuring ... (2005)* for an overview of EU bankruptcy legislation), but in general, bankruptcy refers to the situation where a company is legally declared unable to pay its creditors. It has to be noted that there is usually a significant time delay between payment problems arising and a company being legally declared bankrupt. In order to address this time-delay issue and due to the lack of more relevant information, we have invented a number of criteria for the timing of a default; namely, a company that will eventually go bankrupt is deemed to be in the status of bankruptcy starting from the earliest year that the following occurs: (a) negative equity; (b) the absolute value of the company's annual net profit margin is larger than one; i.e., a sign of heavily biased economic activity; (c) the company starts to report its annual financial information in a discontinuous manner; or if none of the above applies, (d) the last year for which financial statements are available.

Negative equity corresponds to the accounting view of default. A company with negative equity does not have sufficient assets to cover its liabilities. However, negative equity as such does not explicitly mean that the company will eventually fail and become legally bankrupt. The book values of assets and liabilities do not necessarily represent their fair values. Moreover, the balance sheet of a company does not reveal whether the company has sufficient liquid assets to cover its liabilities on their due date. Therefore, negative equity is not a *de facto* statement of default but rather a strong sign of distress.

Besides bankruptcy and negative equity, various other definitions for corporate default have been used in research. Examples include loan default (e.g., Ward and Foster, 1997; Campbell et al. 2005), cash insolvency (Laitinen, 1994), several years of negative net operating income, suspension of dividend payments, major restructuring and layoffs (Platt and Platt, 2002). However, information on both bankruptcy and negative equity tends to be more readily available compared to the other indicators of default, providing a better ground for empirical testing as well as for the future practical implementation of our research results.

3.2. Company financial indicators

We use four categories of financial ratios — financial leverage, liquidity, profitability and efficiency — to characterise the financial performance of companies. The selection of ratios is strongly supported by past research based on various methods, time frames, geographical dimensions and sizes of underlying samples (see Appendix 1 for a summary and references).

Financial leverage indicators illustrate the degree to which a company is utilising external finance. Companies that are highly leveraged may be at a higher risk of default if they are unable to make payments on their liabilities or are unable to attract external finance, if needed. We employ three different financial leverage indicators: $F(LIAB)$ (total liabilities divided by total capital at the end of a given financial year; total capital is defined as the aggregate of the book values of liabilities and equity, being equal to the book value of total assets); $F(LOAN)$ (loan liabilities divided by total capital, thus focusing on the use of financial services); and $F(LTERM)$ (long term liabilities divided by total capital).

One of the limitations of the abovementioned leverage indicators is that they are based on book values instead of market values. Liabilities as presented on the balance sheet might include a significant amount of accrued non-cash liabilities, thus distorting leverage analysis. In addition, balance sheet information does not reflect the maturity structure of assets and liabilities and their consequential value implications. However, the market values of debt and equity were not available for the majority of the companies in our sample.

The indicators of liquidity are designed to reflect the extent to which a company is able to meet its short-term obligations. Companies with low liquidity could be at a higher risk of default as a result of their potential inability to pay their liabilities. Three liquidity measures are included in our analysis: $L(CURR)$ or current ratio (current assets divided by current liabilities), $L(CASH)$ or cash ratio (cash divided by total capital); and $L(WCAP)$ (net current assets divided by total capital).

As with financial leverage indicators, the use of book values is problematic. Both current assets and liabilities may include non-cash items, which obstruct adequate liquidity analysis. The book values do not reveal whether a company will have sufficient liquid current assets on the due dates of its liabilities.

Profitability indicators ought to illustrate the ability of a company to earn a profit. A low profitability indicates the company's inability to convert revenue streams into profits, potentially leading to lower than expected distributable profits for investors. Losses may eventually result in the inability to pay back liabilities. We make use of two profitability measurements: $P(NETP)$ or net profit margin (after tax profit divided by net sales for a given financial year); and $P(EBIT)$ or EBIT margin (operating profit divided by net sales).

Profitability ratios calculated on the basis of income statement data may embrace a significant amount of individual assessment (e.g., for non-cash items, such as depreciation). Moreover, due to the features inherent in the financial accounting model, revenues and expenses may not reflect market events (e.g., changes in the competition, customer base, suppliers, employees, etc.) on a timely basis, but only provide an ex post view of limited events in the company's business.

Indicators of efficiency are intended to show how profitable a company is relative to the investment made in its total assets. Low efficiency may be associated with a higher risk of default due to invested capital not generating sufficient profits, potentially leading to the company's failure to pay its liabilities. We use three efficiency ratios: $E(NETP)$ or return on assets (after tax profit of a given year divided by total assets as of the end of that year); $E(EBIT)$ (operating profit divided by total assets); and $E(RET)$ (retained earnings divided by total assets). $E(RET)$ is a combined indicator of past profitability and dividend policy, indicating the percentage of undistributed earnings (and any other equity items besides share capital) in the total amount of capital employed.

In addition to the shortcomings similar to those of the profitability ratios, it has to be noted that the net book value of (fixed) assets might not provide adequate information about their market value, replacement cost or the initial investment in these assets (due to depreciation being subject to individual assessment). Overall, as reliable market information is not commonly at hand, we believe that the use of more readily available accounting values for sustainability analysis is problematic, but justified considering the practical circumstances. We address the problem that the measures of default and selected financial ratios are intertwined by using one-year time-lagged explanatory variables.

3.3. Company structural indicators

We make use of NACE industry classifiers (excluding companies in financial intermediation, public administration and defence sectors, and the activities of households and extra-territorial organisations). The number of employees $(EMPL)$ is incorporated as a company size indicator. In addition, we utilise a binary company type variable $TYPE$. Type A stands for "large" companies; that is, stock corporations or public limited liability companies, depending on the country. Type B stands for "small" companies, specifically limited liability companies or private limited liability companies (please refer to Appendix 2 for the classification by countries). Although the country-wise criteria are different, we seek to distinguish companies that have positioned themselves as large from those who have chosen the (usually procedurally easier) legal form aimed at smaller companies. Companies of all other legal forms than Type A and B (e.g., agricultural unions, non-profit organisations and private entrepreneurs) have been excluded from our analysis. We have also incorporated a binary variable $QUOTE$ into our research, depending on whether the company's shares are quoted (1) or not (0).

3.4. Macroeconomic indicators

The set of macroeconomic indicators used in our research includes core variables reflecting the state of the domestic economy as well as the country's external balance. Real GDP growth $(GDP\ GROWTH)$, the real domestic lending rate $(LEND\ RATE)$ and the private credit share of GDP $(CREDIT\ GDP)$ stand out as key measures of a country's economic cycle and stage of development.

Many of the countries involved in our study are small and therefore highly dependent on foreign markets. Hence, the dynamics on the international level have a strong link with the domestic economy and are likely to have an impact on the sustainability of companies that are involved in international business. The variables selected to represent the countries' external positions are exports plus imports as a percentage of GDP $(EXP\ IMP\ GDP)$ and the real effective exchange rate (REER) index. The first reflects the countries' openness and dependence on foreign trade, whereas the second captures the countries' external balance and competitiveness. REER increase is driven by domestic inflation accompanied by high domestic demand and a worsening of the current account balance.

3.5. Survival analysis model

Survival analysis is one of the more recently favoured approaches in corporate default prediction literature. As with other parametric models, survival analysis enables us to obtain an insight into the effects of individual explanatory variables and thereby learn about the underlying factors of default. The advantage of survival models over standard logit and probit models is that they incorporate a time dimension into the estimation, treating the observations of the same company as interdependent over time.

The core concepts of survival analysis are the survivor function and the hazard function (hazard rate). Given the discrete annual observations, we observe a company's i spell from year $k = 1$ through to year j, at which the company's spell is either complete (i.e. the company goes into default; denoted by event T) or right censored (i.e. the company exits the sample without experiencing a default). The survivor function $S_i\left(j\right)$ reflects the probability Pr of company i surviving beyond year j.

$$S_i\left(j\right) = Pr(T_i > j) \tag{1}$$

In discrete time analysis, the hazard function $h_i\left(j\right)$ or the conditional failure rate is the probability that a failure event occurs within a given year j conditional on surviving until this year.

$$h_i\,(j) = Pr(T_i = j \mid T_i \geq j) \tag{2}$$

Working with annual data from a number of countries we observe several incidences of tied events. Therefore, we use a discrete time survival model designed for grouped or discretely observed events.

To estimate a default we apply a logistic hazard function with time-varying covariates. The logistic hazard model has the following general form:

$$logit\,[h\,(j, X)] = D(j) + \beta' X \tag{3}$$

D (j) denotes the baseline hazard function, being a quadratic polynomial in our case, since the empirical life-table graphs as shown below suggest that the baseline hazard roughly follows the quadratic function. $\beta\, X$ represents the time-varying covariate terms.

Deriving the logistic hazard rate $p(t)$ results in the following:

$$p(t) = [1 + \exp(-D(j) - \beta' X)]^{-1} \tag{4}$$

In a logistic hazard model, the regression coefficients (β) can be interpreted as measures of proportional hazard. Due to the exponent form, all the regression coefficients are positive and represent the proportional percentage change in the hazard rate given a one-percentage change in the covariate. The regression coefficients work in a non-linear manner so that an x% increase in the explanatory variable corresponds to β^x proportional percentage change in the hazard rate. For log-measured covariates, the coefficient can be interpreted as the elasticity of the hazard rate with respect to a particular regressor.

We use the life-table method to investigate empirical time dependent patterns of baseline hazard. Because the annual intervals in observations correspond with the financial (accounting) cycles, we make use of the life-table method without interval-adjusted risk. As the annual accounts are, in general, reported at the end of every year we can track the companies that have dropped out within the annual interval. This is equivalent to the Kaplan-Meier product limit method for continuous time data. An estimate of the hazard rate $\hat{\theta}(j)$ is equal to:

$$\hat{\theta}(j) = \frac{(\hat{S}(j) - \hat{S}(j+1))/(t_{j+1} - t_j)}{(\hat{S}(k) + \hat{S}(k+1))/2} \tag{5}$$

with a survival estimate of:

$$\hat{S}(j) = \prod_{k=1}^{j} \left(1 - \frac{d_k}{N_j}\right) \tag{6}$$

where d_k marks the number of failures observed in the interval and N_j is the number of companies at risk of failure at the start of the interval (Jenkins, 2004).

For the purpose of estimating the possible predictors of corporate default, all explanatory variables enter the econometric model with a lag of one year.

4. Data

Most of the empirical information has been extracted from the Amadeus database by Bureau van Dijk (2006). The version of the database available for our analysis includes data on about 1.5 million European companies. We selected annual financial and other relevant information from the database about companies that were incorporated in one of the 27 EU member states for the period of 1995 to 2005. For every company included in the sample, the deficiencies in the data forced us to constrain the sample to the years for which the following criteria were met: (a) the reports were available for all consecutive years; (b) information regarding balance sheet components as well as sales revenues, operating profit and net profit was available; (c) all components of assets and liabilities were non-negative; and (d) total assets did not differ more than 10% from total liabilities and equity. This was done in order to exclude observations with evidently inappropriate or insufficient data. Finally, the sample was further constrained according to the criteria specified in the previous methodology section (also see Appendices 1 and 2) with the purpose of excluding noisy observations; e.g. specific legal types, industries and activity statuses.

The information about bankruptcies was only available for 10 out of the 27 EU countries. An opportunity arose to append data from the Estonian Commercial Register's annual financial information database into the initial Amadeus dataset, enabling us to include additional bankruptcy information about Estonian companies. By doing this the number of countries with available bankruptcy data rose to 11. Altogether 2,253 incidences of bankruptcy and 22,699 incidences of negative equity are incorporated into the empirical analysis.

The macroeconomic data is extracted from the IMF International Financial Statistics Yearbook 2006 (IMF, 2006).

5. Results

The baseline hazard charts for the sample companies, as shown in Figure 1, indicate non-linear patterns on the time-default scale, showing a U-shape baseline hazard function in the cases of both bankruptcy and negative equity. The default rate is also intuitively higher at the beginning of a company's operations and decreases gradually thereafter as the company establishes itself in the business environment. It would also be natural to expect that the default rate starts to increase again as the company matures and becomes more vulnerable to accumulated internal and external shocks.

The baseline hazard coefficients (see Table 1 for the logistic hazard rate model estimations) show that overall the probability of default is a decreasing function of time for both bankruptcy and negative equity. This strongly supported result is well in line with evidence from the existing literature.

The magnitude of hazard appears to be significantly lower for bankruptcy in comparison to negative equity. This result is expected, since by definition not all the companies suffering at certain periods of time under negative equity will eventually bankrupt.

As expected, the baseline bankruptcy and negative equity hazard rates are higher in the new member states compared to the 15 old EU countries. Interestingly, it can be noted that newly established companies appear to be at a relatively higher risk of default in the new member states in comparison to the old member states. These phenomena may be explained by investors establishing riskier businesses in the yet developing new member states because they have high return expectations. A relatively large percentage of these businesses default quickly as their profit expectations appear overly optimistic.

The univariate analysis, based on the Mann-Withney U-test, showed that all our incorporated micro- and macro-level variables are statistically significant in discriminating between sound and distressed firms. The sole exception was the number of employees, which was deemed to be insignificant in separating bankrupt firms from sound ones. From each of the four groups of financial variables these ratios, where the discriminatory power was highest, passed through to the survival model. These ratios are $F(LIAB)$, $L(CURR)$, $P(EBIT)$ and $E(NETP)$.

Overall, descriptive statistical analysis shows that all the four company-level financial indicators selected perform well in distinguishing default from non-default companies. Cross-industry and cross-country analysis of corporate default carried out by employing all four financial indicators reveals robustness to industry and country specifics for both bankruptcy and negative equity events.

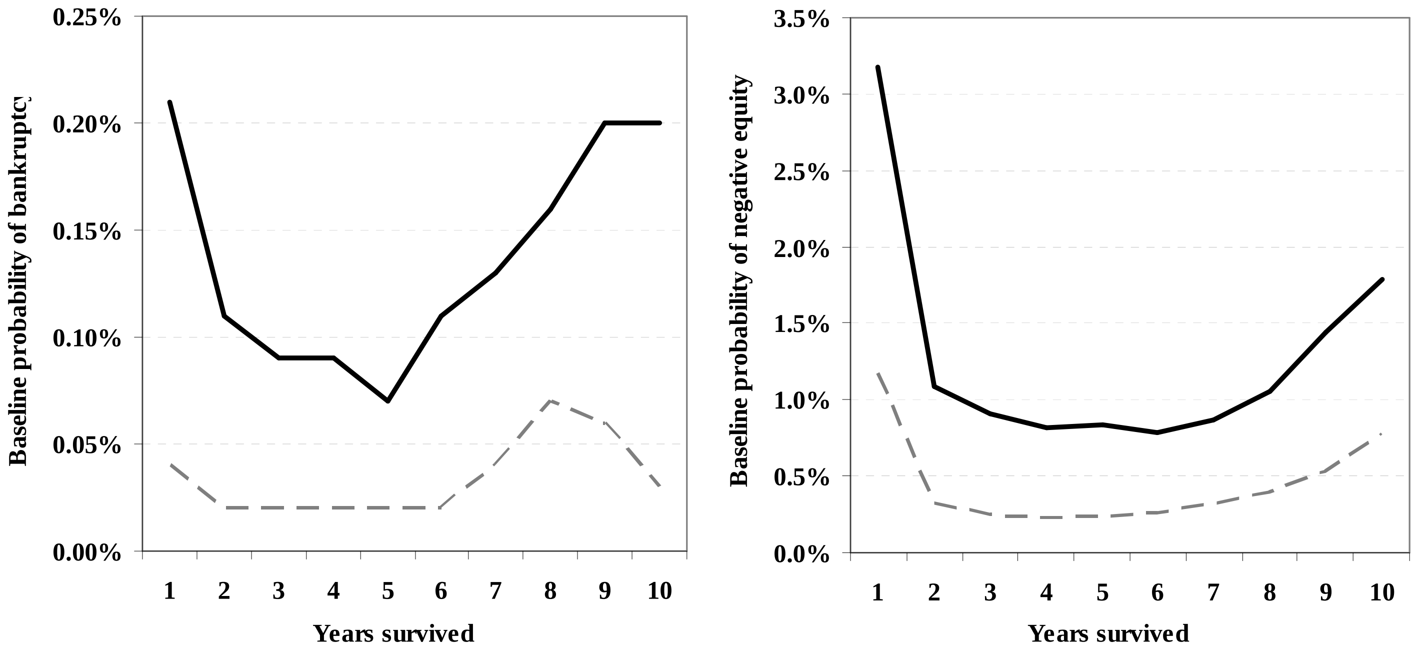

Figure 1: Company baseline hazard charts for bankruptcy and negative equity

Note: The solid line stands for the 12 new and the dashed line for the15 old EU member states.

Table 1: Logistic hazard model estimations, grouped by old EU 15 and new EU 12

	Bankruptcy			Negative equity		
	Total	**EU 15**	**EU 12**	**Total**	**EU 15**	**EU 12**
Baseline hazard	0.993***	0.991***	0.990***	0.990***	0.991***	0.987***
	(-6.49)	(-7.31)	(-3.25)	(-26.56)	(-20.65)	(-15.69)
FINANCIAL INDICATORS						
F(LIAB)	1.015***	1.016***	1.011***	1.093***	1.116***	1.06***
	(13.35)	(13.03)	(6.28)	(86.22)	(71.65)	(51.83)
L(CURR)	0.999**	0.998***	0.999	1.000***	1.000	1.000***
	(-1.95)	(-3.41)	(-1.11)	(6.06)	(0.52)	(7.23)
P(EBIT)	1.000**	1.001	1.000*	0.999***	0.999***	0.999***
	(2.15)	(1.30)	(1.67)	(-4.73)	(-2.68)	(-4.25)
E(NETP)	0.992***	0.988***	0.995***	0.970***	0.966***	0.977***
	(6.49)	(-5.63)	(-5.10)	(-23.78)	(-19.83)	(-13.79)
STRUCTURAL INDICATORS						
TYPE (A = 0)	1.229***	1.455***	0.609***	0.962***	0.985	0.863***
	(3.58)	(6.37)	(-4.33)	(-2.19)	(-0.73)	(-4.17)
ln EMPL	1.013	0.933***	1.256***	1.07***	1.091***	0.994
	(0.79)	(-3.64)	(6.26)	(12.08)	(13.36)	(-0.52)
QUOTE	1.249	0.612	1.130	1.235**	1.430***	0.781
	(0.75)	(-0.83)	(0.34)	(1.97)	(2.87)	(-1.08)
MACROECONOMIC INDICATORS						
GDP GROWTH	0.884***	0.892*	1.038*	0.959***	0.978	1.013
	(-5.24)	(-1.77)	(0.58)	(-9.07)	(-1.36)	(1.49)
d LEND RATE	1.001*	0.964	1.001	1.000	0.999	1.000
	(1.69)	(-0.53)	(0.88)	(1.28)	(-0.10)	(1.55)
d ln REER	1.461	0.352	0.529	2.133***	3.306***	2.367***
	(0.30)	(-0.52)	(-1.22)	(5.55)	(3.77)	(2.62)
EXP IMP GDP	0.972***	1.011***	0.983**	0.998	0.998	1.005
	(-3.96)	(3.78)	(-1.91)	(-0.82)	(-0.757)	(1.45)
d CREDIT GDP	0.943***	0.975	0.964	0.998	0.997*	1.007
	(-4.01)	(-1.45)	(-1.44)	(-1.22)	(-1.69)	(0.92)
DUMMIES						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
MODEL STATISTICS						
Log likelihood	-14,858	-11,891	-2,797	-110,045	-82,370	-26,520
Chi-square	4,002	3,026	565	-	10,349	6,081
Observations (´000)	1,509	1,400	109	1,943	1,699	244
Companies (´000)	289	252	37	414	340	74
Countries	11	6	5	25	15	10

*Note: z-values in brackets, statistical significance levels marked as *** (α <0.01), ** (α <0.05) and * (α <0.1) estimated with robust standard errors. Due to missing data Cyprus and Malta were dropped from the estimations.*

The survival model suggests that of the financial variables $F(LIAB)$ and $E(NETP)$ stand out as the best predictors of both bankruptcy and negative equity one year in advance. They demonstrate that the higher the liability-to-capital ratio is, the higher the probability of failure exists. A lower return on assets increases the probability of default. Although the other financial ratios, $L(CURR)$ and $P(EBIT)$, appear to be statistically significant in the analysis of default, their magnitude remains negligible.

Type B companies seem to be less exposed to experiencing negative capital. However, the picture is less clear in the case of bankruptcies — in the new EU member states Type A companies appear more prone to bankruptcy in contrast to the old member states where Type B companies have a higher probability of bankruptcy. In general, these results suggest that whilst larger companies are more likely to experience negative equity, they remain less prone to ultimate bankruptcy in the old member states of the EU. However, in the new member states the larger firms (i.e., companies of Type A as opposed to Type B) are more likely to suffer from negative capital as well as going bankrupt in the end. This may be explained again by the higher overall risks taken by companies in the new member states, so that even the larger legally required share capital of Type A companies does not enable them to survive if exposed to severe risks of default.

The logarithm of the number of employees is correlated with more frequent incidences of negative equity, though only in the old EU member states. However, similar evidence for bankruptcy remains controversial — a larger number of employees is associated with a higher probability of bankruptcy in the new EU member states, but a lower probability of bankruptcy in the 15 old EU countries. The results with regard to the number of employees do not convey any clear message, whereas we find the coefficients to be conflicting across estimations. This variable may be treated as a control variable of company size rather than a stand-alone trigger of default. The same applies for distinguishing quoted and non-quoted companies in the survival model.

With respect to macro-level indicators, a decrease in real GDP growth appears to precede an increase in the likelihood of a company undergoing a negative equity position as well as going bankrupt in the old member states of the EU. However, the new EU member states demonstrate the opposite result, showing that high real GDP growth is among the signs of higher bankruptcy rates. It is possible to interpret these results in line with the baseline hazard charts as discussed above. Economic growth in the new member states may motivate investors to undertake riskier projects than they would proceed with under the conditions of an economic slowdown or under lower growth rates. However, the failure rate of such risky projects is high. In addition, the creative destruction phenomenon may be used to interpret the results; namely, the newly established companies may crowd out the less viable existing ones. The finding that companies tend to fail following a decrease in the GDP growth rates in the old member states may be explained by the well-established business environment leaving companies at higher risk of default in cases of enduring recession.

Increases in real lending interest rates appear to belong to the triggers of higher bankruptcy probability, though the impact appears to be rather weak.

We also find that companies tend to be more likely to develop negative equity during the times of REER appreciation. However, this effect remains unnoticed in the case of bankruptcy. The openness of the economy, illustrated by the sum of exports and imports as a percentage of GDP, seems to decrease the probability of bankruptcy in the new EU member states, but has the opposite effect in the old member states of the EU. The model estimations also reveal that financial deepening leads to a lower rate of corporate failures both in terms of bankruptcy and negative equity. The explanation from the opposite side might point to a credit crunch phenomenon as a trigger of corporate default.

6. Conclusions

Our paper sets the increasingly popular corporate default issue into a European Union (EU) context, explaining the phenomena with both micro and macro variables within the framework of survival analysis using a sample of 0.4 million companies. The sensitivity of the results of survival analysis is controlled by using two comparative event definitions — bankruptcy as a legal definition for default and negative equity as the accounting viewpoint of corporate failure.

We find the baseline default hazard rate to be a U-shaped function of a company's survival time in the cases of both bankruptcy and negative equity events. As expected, the magnitude of hazard appears to be significantly lower for bankruptcy in comparison to negative equity. It can be observed that bankruptcy and negative equity hazard rates are consistently lower in companies of the 15 old member states of the EU, compared to the 12 new countries. Interestingly, it can be noted that newly established companies appear to be at a relatively higher risk of default in the new member states, potentially explained by investors establishing riskier businesses in these yet developing economies leading to a relatively large portion of businesses to default quickly.

Liabilities-to-assets and profit-to-assets ratios appear to have good discriminative power in distinguishing between default and non-default companies with a one-year lead time both for bankruptcy and negative equity. These ratios can thus be seen as robust predictors of default.

Companies in the old member states of the EU seem to be more endangered during a lasting economic slowdown, whereas the opposite applies to the 12 new EU countries — high GDP growth jumps appear to lead to higher bankruptcy rates there. The openness of the economy, measured using the sum of exports and imports as a percentage of GDP, appears to strengthen the viability of companies in the new EU member states. The opposite effect applies to the 15 old countries. Motivating investors to undertake risky projects, the strong economic growth in the new member states seems to lead to higher corporate failure rates. However, the established business environment of the old member states appears to leave companies at a higher risk of default during long-term stagnation in the economic growth rates as well as in these countries' position in international trade.

The results of our study provide some evidence that an increase in real interest rates is among the triggers of bankruptcy, though having a rather weak impact. Our results also suggest that a credit crunch and real effective exchange rate appreciation undermine a company's outlook for survival.

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Appendix 1. Company financial indicators

Indicator	Definition	H	Reference	Inclusion criteria
Financial leverage				
F(LIAB)	Total liabilities divided by total capital	+	4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15	$0 \leq F(LIAB) < 100$
F(LOAN)	Loan liabilities divided by total capital	+	3, 8, 9, 10, 12	$0 \leq F(LOAN) < 100$
F(LTERM)	Long-term liabilities divided by total capital	+	5, 11	$0 \leq F(LTERM) < 100$
Liquidity				
L(CURR)	Current assets divided by current liabilities; current ratio	-	2, 3, 5, 6, 7, 8, 9, 10, 11, 13, 15	$0 \leq L(CURR) < 100$
L(CASH)	Cash divided by total capital; cash ratio	-	5, 8, 9, 10, 11	$0 \leq L(CASH) \leq 1$
L(WCAP)	Net current assets divided by total capital	-	1, 3, 5, 8, 9, 11	$-1 \leq L(WCAP) \leq 1$
Profitability				
P(NETP)	After tax profit divided by net sales; net profit margin	-	5, 6	$-100 < P(NETP) \leq 1$
P(EBIT)	Operating profit divided by net sales; EBIT margin	-	5, 6, 10	$-100 < P(EBIT) \leq 1$
Efficiency				
E(NETP)	After tax profit divided by total assets; return on assets	-	3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15	$-1000 < E(NETP) < 1000$
E(EBIT)	Operating profit divided by total assets	-	1, 2, 5, 7, 9, 10	$-1000 < E(EBIT) < 1000$
E(RET)	Retained earnings divided by total assets	-	1, 2, 5, 7, 9, 11	$E(RET) \leq 1$

Note: "H" denotes whether the ratio is expected to have a positive (+) or negative (-) relation with the dependent variable.
References: 1) Altman (1968, 2000); 2) Altman, Haldeman and Narayanan (1977); 3) Beaver (1967); 4) Campbell, Hilscher and Szilagyi (2005); 5) Chen and Shimerda (1981); 6) Crouhy, Galai, and Mark (2001); 7) Davydenko (2005); 8) Deakin (1972); 9) Falkenstein, Boral, and Carty (2000); 10) Härdle, Moro and Schäfer (2005); 11) Kahya and Theodossiou (1999); 12) Lízal (2002); 13) Ohlson (1980); 14) Shumway (2001); 15) Zmijewski (1984)

Appendix 2. Company type classification and sample coverage

Country	Type A	Total Type A [5]	incl. bank-rupt [6]	incl. with negative equity [6]	Type B	Total Type B [5]	incl. bank-rupt [6]	incl. with negative equity [6]
AT	AG [1]	79	-	3	GmbH [2]	199	-	13
		28%	*0%*	*4%*		*72%*	*0%*	*7%*
BE	SA [1]	12,867	271	656	SPRL [2]	3,045	104	220
		81%	*2%*	*5%*		*19%*	*3%*	*7%*
BG	AD [1]	1,777	15	101	OOD [2]	3,119	4	314
		36%	*1%*	*6%*		*64%*	*0%*	*10%*
CY	PCLS [1]	34	-	-		-	-	-
		100%	*0%*	*0%*		*0%*	*0%*	*0%*
CZ	AS [1]	1,645	30	102	SRO [2]	11,947	89	1,519
		12%	*2%*	*6%*		*88%*	*1%*	*13%*
DE	AG [1]	863	-	14	GmbH [2]	2,276	-	76
		27%	*0%*	*2%*		*73%*	*0%*	*3%*
DK	AS [1]	5,021	-	184	ApS [2]	1,596	-	97
		76%	*0%*	*4%*		*24%*	*0%*	*6%*
EE	AS [1]	2,456	86	99	OÜ [2]	12,899	201	794
		16%	*4%*	*4%*		*84%*	*2%*	*6%*
ES	SA [1]	27,438	47	780	SL [2]	44,818	66	4,224
		38%	*0%*	*3%*		*62%*	*0%*	*9%*
FI	OYJ [3]	86	-	1	OY [4]	7,115	-	341
		1%	*0%*	*1%*		*99%*	*0%*	*5%*
FR	SA, SAS [1]	42,805	557	2,393	SARL [2]	21,427	521	1,774
		67%	*1%*	*6%*		*33%*	*2%*	*8%*
GB	PLC [3]	2,105	-	73	Ltd [4]	25,624	-	1,296
		8%	*0%*	*3%*		*92%*	*0%*	*5%*
GR	AE/SA [1]	10,863	-	203	EPE [2]	1,398	-	69
		89%	*0%*	*2%*		*11%*	*0%*	*5%*
HU	Rt [1]	28	-	-	Kft [2]	189	-	5
		13%	*0%*	*2%*		*87%*	*0%*	*3%*
IE	PLC [3]	20	-	-	PrC [4]	247	-	8
		7%	*0%*	*0%*		*93%*	*0%*	*3%*
IT	SPA [1]	22,436	64	316	SRL [2]	71,071	106	2,587
		24%	*0%*	*1%*		*76%*	*0%*	*4%*
LT	AB [1]	224	-	2	UAB [2]	3,039	-	117
		7%	*0%*	*1%*		*93%*	*0%*	*4%*
LU	SA [1]	89	-	2	SARL [2]	25	-	1
		78%	*0%*	*2%*		*22%*	*0%*	*4%*
LV	AS [1]	107	1	3	SIA [2]	982	21	125
		10%	*1%*	*3%*		*90%*	*2%*	*13%*
MT	PeC [3]	3	-	-	PeC [4]	21	-	-
		13%	*0%*	*0%*		*87%*	*0%*	*3%*
NL	NV [1]	348	2	9	BV [2]	3,526	35	298
		9%	*1%*	*3%*		*91%*	*1%*	*8%*
PL	SA [1]	1,511	-	52	Sp.z.o.o. [2]	4,100	-	259
		27%	*0%*	*3%*		*73%*	*0%*	*6%*
PT	SA [1]	1,023	4	25	LDA [2]	1,028	2	17
		50%	*0%*	*2%*		*50%*	*0%*	*2%*
RO	SA [1]	5,805	-	137	SRL [2]	19,740	-	2,186
		23%	*0%*	*2%*		*77%*	*0%*	*11%*
SE	AB [3]	495	-	7	AB [4]	30,559	-	1,012
		2%	*0%*	*1%*		*98%*	*0%*	*3%*
SI	DD [1]	438	-	1	DoO [2]	2,108	-	47

Note 1: 1 – stock corporation, 2 – limited liability company, 3 – public limited liability company, 4 – private limited liability company, 5 – per cent of country total, 6 – per cent of type total.
Note 2: Small number of companies has changed legal type over time; percentages show per cent of sample total.