EFRI Exclusive Working Papers 2018-001

Separating Winners from Losers: Predicting Firm Failure Using Discrete-time Hazard Approach

Ivana Tomas Žiković*

EFRI WORKING PAPER SERIES

* University of Rijeka, Faculty of Economics, Croatia

This research was supported by the
Faculty of Economics, University of Rijeka
https://www.efri.uniri.hr/en

University of Rijeka, Faculty of Economics
I. Filipovića 4, 51000 Rijeka, Croatia

SEPARATING WINNERS FROM LOSERS: PREDICTING FIRM FAILURE USING DISCRETE-TIME HAZARD APPROACH [1]

Ivana Tomas Žiković
Department of Finance and Banking,
University of Rijeka, Faculty of Economics, Rijeka, Croatia
E-mail: ivana.tomas.zikovic@efri.hr

ABSTRACT

Using an extensive dataset on over 21,000 firms for the period including the upswing and recessionary years, we examine how time-varying firm-specific variables and changes in macroeconomic environment influence firms' default probabilities. Traditional single period approaches used in predicting firm failure are based on unrealistically restrictive assumptions and cannot dynamically account for the changes in financial indicators and macroeconomic conditions. We therefore apply discrete-time hazard models (by using logit and cloglog link) which indicate that default probabilities are strongly influenced by both the firm-specific and the macroeconomic variables. Although firm-specific variables play an essential role, the results show that it is the macroeconomic variables that are important in understanding the fluctuations in default probabilities through time. Moreover, we establish that there are significant variations in default probabilities across industries.

Keywords: firm failure, multi-period logit model, firm-specific variables, macroeconomic shocks

[1] When citing this paper please refer to altered and modified version of this paper: Ivana Tomas Žiković (2018): Challenges in Predicting Financial Distress in Emerging Economies: The Case of Croatia, Eastern European Economics, 56:1, 1-27. DOI: 10.1080/00128775.2017.1387059

1. INTRODUCTION

The last eight years have been marked by an adverse economic environment and the sovereign debt crisis as a result of the global financial crisis. This in turn, resulted in modest or even negative economic growth across the western hemisphere. This is particularly true for EU and especially CEE economies that are traditionally bank oriented when it comes to financing. The weakened European banking sector and harsh refinancing terms as well as the high levels of indebtedness have even further deepened the crisis in CEE countries. Although aggravated business conditions and increased number of distressed firms are present in all CEE countries, our sample includes firms operating in the Republic of Croatia. The case of Croatia is interesting as it is a former socialist country and the last country to enter the EU that has undergone a transition from a manufacturing to a service based economy.

Traditional quantitative analyses of financial distress assume that all relevant information concerning financial and business risks firms face are contained in their financial statements. However, firm-specific variables are not sufficient for predicting financial distress. The cyclical movement of the economy and changes in systematic risk affect firms' business cycles as well as their cash flows and in this way alter their default probabilities. Therefore, in order to yield the best possible approximation of the complex interrelationships when explaining and predicting default probabilities i.e. firm failure, the macroeconomic conditions need also to be taken into account.

In order to bypass the limitations of traditional approaches, we use the hazard analysis as it allows us to include both firm-specific variables and macroeconomic variables common to all firms. Shumway (2001) was the first to show the main advantage of this approach. Namely, it enables the monitoring of changes in explanatory variables over time which is not possible by using static multivariate techniques, such as multi-discriminant analysis (MDA), logit and probit. Hazard analysis offers a valuable tool in understanding the influence of macroeconomic and monetary variables on default probabilities. Consequently, it is possible to determine which, and to what extent, macro variables are significant in predicting distress.

There are only a few papers using a similar approach in predicting financial distress in emerging economies. Hence, the aim of this paper is to fill the gap in the existing literature by examining which firm-specific variables along with macroeconomic and industry variables are relevant in predicting the likelihood of financial distress in European transition economies, in our case, the economy of the Republic of Croatia. Thereby, we tend to apply the latest advances in econometric modelling and provide empirical evidence on firm failure analysing a large database on Croatian firms. The obtained results can be useful in managing firms' credit risk in emerging market conditions.

In emerging economies, a vast number of firms do not initiate bankruptcy procedures when the conditions for it are fulfilled or they declare bankruptcy long after the appearance of problems with outstanding payables. Therefore based on the available data, we propose an additional criterion for determining whether a firm is healthy or in distress as bankruptcy or liquidation is not a sufficient criterion. We formulate and test several models for predicting default probabilities by applying discrete-time hazard analyses (with logit and cloglog link) which allow for time variations in the explanatory variables and the introduction of often neglected macroeconomic variables. The extensive sample of firms and the length of the analysed period enable us to examine, in addition to financial ratios and macroeconomic variables, the significance of the firm size and industry affiliation in predicting default probability.

The empirical results obtained by the discrete-time multi-period logit model are similar to those obtained by the continuous-time cloglog analysis. These results indicate that firm-specific variables, macroeconomic variables and industry variables should all be considered when explaining firm distress. Namely, firm-specific variables including both financial ratios and size have shown to be significant in predicting financial distress as well as macroeconomic variables relating to monetary policies, business cycle stages and financial market stability. Moreover, the results also show that there are differences in the probability of financial distress across industries.

The remainder of the paper is organized as follows: Section 2 presents literature review while Section 3 elaborates on the methodology used in modelling failure probabilities. Section 4 provides the overview of data sources, sample characteristics, definition and classification of distressed firms and selection of variables. The findings are summarized in Section 5. Finally, Section 6 concludes and outlines the recommendations for further research.

1. LITERATURE REVIEW

The research on firms' financial distress can be divided into three main streams. The first stream relates to research using financial ratios in predicting bankruptcy first conducted by Beaver (1966) and Altman (1968). The number and the complexity of research in this field rose dramatically after Altman. Important authors, belonging to this stream, among others, include Edminster (1972), Altman, Haldeman and Narayanan (1977), Taffler (1983), Ohlson (1980), Johnson and Melicher (1994), Zavgren (1985), Altman and Saunders (1998) and Bunn and Rewood (2003). The models developed by the abovementioned authors should be differentiated according to whether they solely use accounting data or accounting and financial market data. In the latter case, the models are developed exclusively for quoted firms and, as such, are not applicable in predicting distress for firms that do not fall into this category.

The second stream refers to papers following developments in time series analysis. The focus is on interactions between aggregate bankruptcies and macroeconomic developments. The most commonly used methods are the Vector Error Correction Model (VECM) and the Autoregressive Distributed Lag (ARDL) bound test. These papers focus on the trends in the number of failed firms and not on individual firms. In examining distress (expressed in terms of the number of bankrupt, insolvent or liquidated firms) authors analysed the impact of various macroeconomic variables, such as: interest rates (Davis 1987, Liu and Wilson in 2002, Liu 2004, Halim et al. 2008), GDP (Davis 1987, Vlieghe 2001, Halim et al. 2008, Salman et al. 2009), money supply (Salman et al.), inflation (Wadhwani, 1986), rate of newly established firms (Cuthbertson and Hudson, 1996, Young 1995, Liu 2004) and changes in bankruptcy legislation (Liu and Wilson 2002; Liu 2004). The main advantage of this stream is that its authors consider the time dimension of variables but, at the same time, completely ignore firm-level data, which is its main drawback.

The third stream relates to research on firm failure that takes into account firm level data and the time dimension of variables. This was made possible by the hazard analysis initiated by Allison (1982), and later advocated and applied by Shumway (2001) which enabled them to monitor the financial health of firms over a longer period of time. The previous generation of logit or probit models provided only a period by period static analysis (Bruneau, et al. 2012).

Moreover, as hazard analysis takes into account changes in explanatory variables over time, both financial ratios and the macroeconomic variables can serve as inputs in predicting and explaining firm failure. This approach was applied by Jacobson (2005, 2013), Carling et al. (2007), Duffie et al. (2007), Nam et al. (2008), Bhattacharjee et al. (2009a, 2009b), Bonfim (2009), Hazak and Männasoo (2010), Bruneau et al. (2012), Charalambakis (2014), Filipe et al. (2016) and others. These authors examine different macroeconomic variables in explaining variations in default probabilities. Jacobson et al. (2005, 2013) used the output gap, inflation rate, nominal interest rate and the real exchange rate, Nam et al. (2008) the volatility of the foreign exchange rate and Bruneau, et al. (2012), similar to Bhattacharjee et al. (2009a, 2009b), the real and nominal interest rates, inflation rate, changes in foreign exchange rates and the rate of newly established firms. In their paper explaining the likelihood of corporate defaults of U.S. listed industrial firms, Duffie et al. (2007) rely on macroeconomic variables observable on the stock market, such as market returns on equity, index S&P 500 and the three-month T-bill rate.

Research using discrete time hazard analysis in explaining financial distress is relatively scarce in emerging market context. Charalambakis and Garrett (2016) investigate how well models based on accounting and market information that are used for predicting financial distress for US firms are applicable for predicting bankruptcy of firms in the UK (another developed economy) and India (an emerging economy). They find that only accounting information is significant when it comes to predicting financial distress in India and that market information does not contain additional predictive power. They examine the aggregate domestic credit to GDP, GDP growth and the inflation as representative macroeconomic variables and their results show that only inflation is found to be significant in predicting the bankruptcy of Indian firms. Moreover, their findings suggest that there is no common model for predicting financial distress in differently developed economies. Furthermore, Filipe et.al (2016) explore distress probabilities in, among other countries, the Czech Republic and Poland as representatives of the eastern European region. They conclude that the same firm-specific factors are essential in predicting financial distress of SME's across Europe. However, when it comes to macroeconomic variables they differ based on the region specific conditions and characteristics. Foreign exchange volatility, the 10-year government bond yield and the GDP growth are identified as the most useful systematic variables for predicting financial distress in these countries. Hazak and Männasoo (2010) investigate corporate default in new EU member countries and the EU-15 and find baseline bankruptcy and negative equity hazard rates to be higher in the new member countries, which, according to them, is a result of riskier investment behaviour in developing countries due to the higher return expectations. Bhattacharjee and Han (2010) analyse listed Chinese companies. They take the index of overall state of the economy, real interest rates, instability in exchange rate and US business cycle (proxy for export demand) as measures of macroeconomic conditions. They find that firm-level characteristics such as age, size, gearing and cash flow to capital to be significant as well as the instability in the interest rate. Finally, Männasoo (2008) demonstrates that firm sustainability in Estonia depends on high and stable asset returns, low leverage, high ratio of sales to operating expenses and a large asset base.

In predicting the likelihood of financial distress, it is also interesting to examine the impact of the industry in which the firms operate. Chawa and Jarrow (2004) conclude that US firms in different industries face different levels of market competition, and thus their probability of failure also varies. A similar approach is followed by Bhattacharjee et al. (2009a, 2009b) and Jacobson et al. (2013) who conclude that the effects of the overall changes are more expressed in industries that are a priori procyclical. Additionally, Charalambakis (2014) and Rommer (2005) recommend taking into account industry effects in predicting financial distress for Greek and Danish private firms respectively.

Moreover, some studies, especially the recent ones, emphasize the impact of a firm's size on its probability of distress. The size of a firm is commonly measured as the logarithm of total assets (Parker, Peters and Turetsky, 2002 Rommer, 2005), the natural logarithm of total assets (Hensher, Jones and Greene, 2007), the logarithm of fixed assets (Bhattacharjee et al. 2009a, 2009b), the logarithm of sales (Laitinen, 1992), the logarithm of the number of employees (Audretsch and Mahmood, 1995, Lennox, 1999, Gupta, Gregoriou and Healy 2014) and the number of employees itself (Hazak and Männasoo, 2010). In this paper, the natural logarithm of the number of employees is used as the measure of a firm's size. It is expected that small firms have a greater probability of distress in relation to large firms as their access to funding is limited and their resistance to external shocks is lower.

2. MODELLING DEFAULT PROBABILITIES

Probability of financial distress may be predicted through a static or dynamic approach. The preferred static techniques include multiple discriminant analysis (MDA) and logistic regression that take into account firms' financial indicators for only a single time period. On the other hand, the dynamic is based on the application of hazard analysis whose application can vary depending on the nature of the available data (discrete or continuous).[2]

The discrete-time survival model is more appropriate in cases when time to the event is recorded in weeks, months or years, while the continuous time model is preferable when the time scale is expressed in seconds, hours or days (Rabe-Hesketh and Skrondal 2012). As the macroeconomic data and the financial ratios used in this research are collected on annual basis, the models are developed for discrete-time data.[3] The two dynamic models meeting this condition are multi-period logit and complementary log-log (cloglog).[4]

The multi-period logit model can be written as:

$$\log\ \mathrm{it}[h(j,X)] = \log\left[\frac{h(j,X)}{1-h(j,X)}\right] = \alpha_j + \beta' X \qquad (1)$$

where $h(j,X)$ is the discrete time hazard rate for time j, $\alpha_j = \log\mathrm{it}[\mathrm{h}_0(j)]$ in which $[\mathrm{h}_0(j)]$ is the corresponding baseline hazard when $X = 0$. X presents the vector of the explanatory variables and β' the estimates of the regression parameters.

Expression (1) is usually rewritten as: $h(j,X) = \dfrac{1}{1+\exp(-\alpha_j - \beta' X)}$ (2)

The cloglog model is expressed as:

$$\log(-\log[1-h_j(X)]) = \beta' X + \gamma_j \longrightarrow h(j,X) = 1 - \exp[-\exp(\beta' X + \gamma_j)] \qquad (3)$$

where γ_j is the log of the difference between the integrated baseline hazard estimated at the end and the beginning of the interval.

According to Beck et al. (1998), the cloglog model, which is actually a grouped duration version of the Cox proportional hazard model and a form of generalized linear model and the

[2] The most commonly applied models in survival analysis rely on continuous-time data. This means that the analyzed event can occur at any point in time i.e. a random process happens in continuous time. However, it often happens that the observations occur at discrete time intervals, for example, at the end of each year (Jenkings, 2005).

[3] Although the time of failure can be viewed as a continuous variable, data concerning a firm's failure are available on discrete-time basis, usually annually.

[4] Cloglog is a discrete time representation of a continuous time proportional hazard model that can be applied when available data are interval censored - grouped or banded into intervals (see Jenkings (2005) for details).

multi-period logit model, should yield almost identical results in real life situations if the average probability of firm's failure is lower than 25% at each point in time.

This convergence has also been confirmed by Jenkings (2005):

$$\operatorname{logit}(h) = \log\left(\frac{\mathrm{h}}{1-\mathrm{h}}\right) = \log(h) - \log(1-h) \text{ and } \log(1-h) \xrightarrow{h \to 0} 0 \ \operatorname{logit}(h) \approx \log(h) \quad (4)$$

providing that h is small.

In the relevant literature, authors usually estimate default probabilities by using one of the aforementioned models. In our research we run both models as their convergence, provided the h is small enough, gives us an opportunity to check if they yield similar classification in identifying distressed firms.

3. DATA, SAMPLE CHARACTERISTICS AND VARIABLE SELECTION

3.1. Data source

To ensure sample consistency in terms of macroeconomic conditions in which they operate, the research deals with firms operating in the Republic of Croatia. The financial ratios are obtained from the Orbis BvD database for the period from 2003 to 2012.[5] In order to examine the influence of macroeconomic variables, annual series of macroeconomic data are obtained from the Croatian Bureau of Statistics (CBS) and the Croatian National Bank (CNB).

3.2. Definition of „distress“

Most authors start from the legal definition of bankruptcy in designing their samples of failed firms as it represents an objective criterion for the categorization of firms into two populations (e.g. Chapter 11 and 7 of the Bankruptcy Code in the United States and Insolvency Act in the United Kingdom). Papers researching firms *in distress* are rare, because there is no unanimous definition of the event, especially in terms of when such an event begins or ends. These

[5] The Orbis database by Bureau van Dijk contains basic data, financial ratios and items from financial statements of firms around the world. The data on Croatian firms have been available since 2003. The access to the database enabled downloading data for all firms (successful and unsuccessful).

authors most often arbitrarily define the criteria for financial distress, depending on their research interest and available data.[6]

Apart from the choice of variables and research methodology, it is of utmost importance to determine what *financial distress* implies. According to Platt and Platt (2006) and Keasey et al. (2014), bankruptcy is only one aspect of distress. Moreover, there are a significant number of firms that do not even initiate bankruptcy when the conditions for it are fulfilled, especially in transition countries. In addition to this, quite often the time between the occurrence of financial problems, among other, due to delayed payments and the declaration of bankruptcy is rather long. This has created the need to introduce additional criteria in sample design within this research. As the research covers both stock companies and limited liability companies, changes in equity prices or non-payment of dividends cannot be taken as criteria for their classification. For most firms, especially small and medium sized ones, there is a lack of data on the amount of unpaid interests and the number of days that a firm's bank account has been frozen. Based on the available data, we formulate our own set of criteria. Apart from firms that are already classified as bankrupt or liquidated according to Orbis BvD database, we classify firms as distressed if they simultaneously meet the following two criteria:

- A firm is in distress if its accumulated losses are equal or greater than equity[7] for at least two consecutive years or if it fulfils this criterion for a year and does not submit financial statements for the consecutive year, and
- A firm is in distress if it has a negative EBIT for at least two consecutive years or if it fulfils this criterion for a year and does not submit financial statements for the consecutive year.

Therefore, in order to be able to classify firms as distressed in 2004 according to our criteria the analysis needs to include data on equity and EBIT for 2003. The same stands for firms in

[6] Based on previous research, Platt and Platt (2009) summarized the different events that classify firms into the distress group: evidence of layoffs, restructurings, missed dividend payments, low interest coverage ratio, cash flow less than current maturties of on behalf of long term debt, change in equity price or a negative EBIT, the negative net income before special items. They formulated their own classification of firms in distress based on whether they meet the following three criteria for two consecutive years (Platt and Platt, 2006): a negative EBITDA interest coverage, negative EBIT and negative net income before special items.

[7] Negative equity corresponds to the accounting view of the firm failure. A firm with negative equity does not have enough funds to cover its liabilities. However, negative equity, as such, does not mean that a firm will eventually fail and/or declare bankruptcy. The book value of assets and liabilities do not necessarily represent their fair value. The balance sheet does not reveal whether the firm has sufficient liquid assets to cover its liabilities but it represents a strong warning (Hazak and Männasoo, 2010).

distress in 2011 as we need to see which firms disappeared from sample in 2012 (did not submit financial statements).

3.3. Sample characteristics

The initial sample consisted of 99,934 firms (limited liability companies and joint stock companies) operating in the Republic of Croatia. The firms left out of the sample included those classified as 'Dissolved' (they either underwent an M&A process or ceased to exist for reasons that do not necessarily imply default), 'Inactive' i.e. those lacking information on the total assets, revenues and number of employees, those having violated accounting principles, those not having more than one employee in at least one of the years during the observed period,[8] those complying with different accounting principles such as those engaged in public administration, financial services, insurance etc. Furthermore, in order to meet the dependent variable criteria, the firms that had not submitted their financial statements for at least two consecutive years are also excluded from the sample. Finally, after conducting the stepwise procedure, the firms lacking data corresponding to the optimal set of variables are also eliminated from the sample. Consequently, the final sample includes 21,129 firms with 106,166 firm-year observations from 2004 to 2011, out of which 4,258 (20.15%) firms are classified as in distress. Based on data covering the period from 2004 to 2010, we estimate the parameters of the discrete-time hazard models. The observed period includes data on 20,935 firms (94,410 firm-year observations), out of which 3,616 firms are classified as distressed. To validate the predictive performance of assessed models, we use estimated parameters to predict financial distress in 2011. The 2011 sample contains financial information on 11,757 firms, out of which 632 firms are classified as in distress. The rationale behind this procedure is to provide evidence on the predictive power of the estimated models.

Table I in the Appendix shows the distribution of observations according to NACE Rev 2 classification, while Table II shows the structure of firms by size. The largest share in the sample is held by firms involved in trade activities (45.6%). These are followed by those involved in manufacturing (18.96%), construction (10.56%) and accommodation and food service activities (6.31%). The sample is found to be representative of the Croatian economy

[8] The justification for this criterion lies in the fact that even though the Orbis database represents one of the best databases for emerging markets, the accounting information for micro-firms is rather scarce.

as the majority of Croatian firms are engaged either in trade, construction, professional, scientific and technical activities, manufacturing or in accommodation and food service activities. Small and medium sized firms account for over 98% of firms in the total sample. This corresponds to the structure of firms in the Croatian economy, where 99% of firms are small and medium size.[9]

3.4. Variable selection

Two sets of explanatory variables are used in the analysis. The first one contains firm-specific variables that capture the firm's financial strength and account for the idiosyncratic risk.[10] The second set includes macroeconomic variables that account for the systematic risk. In order to secure that estimates are not seriously influenced by outliers, observations above the 99th percentile and below the 1st percentile are replaced with their winsorized values. In addition, we estimate hazard models by using lagged macroeconomic variables as explanatory variables.

The optimal set of variables regarding the statistical significance and the correct classification of firms is obtained by using a stepwise "backward" procedure. Thus, a larger number of financial ratios have gradually been removed due to the lack of statistical significance.[11] The threshold for the exclusion of variables is set at 0.1. Correlation analysis is then conducted in order to avoid problems with multicollinearity. In cases when financial ratios have a correlation coefficient above 0.7, the variable kept is that for which the univariate analysis proves a stronger association with default risk. Finally, the following six financial ratios are selected: total debts to total assets (TL/TA), current liabilities to total assets (CL/TA), EBIT margin (EBIT/OR), return on assets using net income (ROA), working capital to total assets (WC/TA) and cash flow to operating revenue (CF/OR).

---

[9] Firm size was determined in accordance with the Accounting Act (Official Gazette 109/2007, Article 3) where: 1) Small firms are those that do not exceed two of the following conditions: a) total assets of 4.33 million EUR, b) income of 8.67 million EUR, c) the average number of employees during the financial year of 50. 2) Medium-sized firms are those that do not exceed two of the following conditions: a) total assets of 17.33 million EUR, b) revenues of 34.67 million EUR, c) the average number of employees during the financial year of 250. 3) Large firms are those which exceed two of the three conditions for medium-sized firms.

[10] A complete list of annual report variables containing ratios from four categories (liquidity, leverage, profitability and cash flow) is available upon request.

[11] In addition to the stepwise procedure, univariate analysis between dependent and each individual independent variable are examined and the variables showing the strongest correlation with default risk are considered.

Table IV in the Appendix reports the summary statistics of selected financial ratios through different estimation periods. The values of the mean and standard deviation are presented for winsorized variables. The financial ratios have indicated a significant difference between healthy firms and those in distress. On average, 92.46% of total assets of firms in distress are financed through debt financing (median: 97.12%), which indicates that these firms are significantly indebted. The problem is even greater as, on average, 77.86% of assets (median 86.41%) are funded through short-term debt. Finally, firms in distress have negative profitability ratios indicating that they are actually generating losses. The mean values of the working capital to total assets, which is a measure of liquidity, are positive for healthy firms and negative for those in distress. This indicates that the latter group of firms has no liquidity reserves. This is particularly important in times of crisis when problems with payment collection occur. The mean value of cash flow to operating revenue is positive for healthy firms and zero for firms in distress. Even though the median for this indicator is positive for both groups, it is three times higher for healthy firms.

During recession, firms are more likely to fail than in times of prosperity, which justifies the introduction of macroeconomic variables as predictors of financial distress. Beside the frequently used variables measuring economic activity (GDP, industrial production index, gross investments in tangible goods, number of building permits issued) and macroeconomic stability (HRK/EUR exchange rate, firm loan growth, interest rates on firm's credits and inflation), the variables used to predict economic trends or cycles are also additionally examined. These leading variables refer to the Crobex stock index and money supply (M1). The impact of unemployment rate is also examined, as it usually increases after an economic slowdown, and therefore represents a lagging variable. Since macroeconomic variables are available with a time delay, we use their past realizations in predicting firm failure. Hence, we lag these variables, as lagged values are more suitable for forecasting. Some of the abovementioned variables did not prove to be significant in predicting financial distress. Aggregate variables considered in the model estimation are presented in Table III in the Appendix.

4. EMPIRICAL RESULTS

The models in Tables 1 and Table VI (Appendix) are derived using a multi-period logit specification, while the hazard models in Table V are derived using a cloglog specification.

The model parameters are estimated by employing financial information from 2004 to 2010. To validate out-of-sample prediction performance of estimated models, we use data from 2011 as a hold-out sample.

First, we evaluate all models using financial ratios as predictor variables. Then, we introduce the firm size variable to examine if size influences the probability of financial distress. We continue by adding industry dummies to investigate which industries are most vulnerable to distress. Finally, we run models including financial ratios, size, industry dummies and macroeconomic variables one per one. This is done in order to identify those macroeconomic variables that significantly influence the probability of firm default and to account for high correlation among them (Table 1 and Table V in appendix). Likewise, Bonfim (2009) provides estimates by adding each macroeconomic variable separately, in order to minimise the loss of information provided by firm heterogeneity. Thus, we begin our analysis of macroeconomic variables by conducting univariate testing in which we estimate the impact and direction of each of the macroeconomic variable on the dependent variable. The variables relating to the industrial production index, firm loan growth and long-term interest rate on firm's credits show the biggest impact on default probabilities. The variables also found to be significant include GDP, HRK/EUR exchange rate, short-term interest rate on corporate loans, money supply, building permits issued and Crobex.[12]

Furthermore, we test the joint effect of combinations of macroeconomic variables that are not significantly correlated (correlation lower than 0.7). Thereby, Models 1 and 2 in Table VI in the Appendix, along with firm-specific variables and industry dummies, include macroeconomic variables from three groups of indicators. Therefore, we introduce at least one business cycle indicator (GDP, industrial production index, gross investments in fixed assets and unemployment rate), one monetary policy indicator (long-term interest rate, firm’s loan growth and monetary base) and one of the financial market stability indicators (exchange rate and Crobex). The remaining specifications in Table VI (Models 3, 4, 5) are derived by adding macroeconomic variables from the two groups of abovementioned indicators.

[12] The variables relating to the inflation rate, unemployment rate and investments did not prove statistically significant in predicting financial distress when standing alone in the model. The results are available upon request.

Table 1: Multiperiod logit estimation results 2004-2010

Variables	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11	Model12
TD/TA	0.0829***	0.0823***	0.0811***	0.0810***	0.0808***	0.0808***	0.0815***	0.0813***	0.0812***	0.0810***	0.0809***	0.0812***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CL/TA	0.0057***	0.0035***	0.0045***	0.0044***	0.0041***	0.0042***	0.0047***	0.0047***	0.0043***	0.0044***	0.0042***	0.0046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBIT/OR	-0.0165***	-0.0144***	-0.0136***	-0.0135***	-0.0131***	-0.0133***	-0.0138***	-0.0139***	-0.0133***	-0.0135***	-0.0132***	-0.0137***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	-0.0190***	-0.0177***	-0.0174***	-0.0174***	-0.0166***	-0.0172***	-0.0162***	-0.0170***	-0.0158***	-0.0173***	-0.0167***	-0.0172***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
WC/TA	-0.0029***	-0.0039***	-0.0021**	-0.0022**	-0.0023**	-0.0023**	-0.0021**	-0.0021**	-0.0022**	-0.0022**	-0.0023**	-0.0021**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CF/OR	-0.0063***	-0.0091***	-0.0092***	-0.0093***	-0.0098***	-0.0096***	-0.0093***	-0.0090***	-0.0098***	-0.0094***	-0.0097***	-0.0092***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln_size		-0.149***	-0.143***	-0.143***	-0.144***	-0.143***	-0.146***	-0.143***	-0.146***	-0.143***	-0.145***	-0.143***
		(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)
dv_a			-0.118	-0.118	-0.119	-0.118	-0.123	-0.120	-0.122	-0.118	-0.122	-0.119
(Agriculture)			(0.147)	(0.147)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.147)	(0.148)	(0.147)
dv_b			0.754**	0.751**	0.750**	0.748**	0.772**	0.765**	0.767**	0.750**	0.751**	0.758**
(Mining&aquarr.)			(0.318)	(0.318)	(0.318)	(0.318)	(0.317)	(0.317)	(0.317)	(0.318)	(0.318)	(0.318)
dv_f			0.186**	0.194**	0.206***	0.203***	0.160**	0.169**	0.181**	0.194**	0.197**	0.179**
(Construct.)			(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
dv_g			0.177***	0.174***	0.167***	0.169***	0.184***	0.183***	0.174***	0.174***	0.170***	0.180***
(Wholesale)			(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
dv_h			0.348***	0.347***	0.341***	0.344***	0.345***	0.348***	0.340***	0.346***	0.343***	0.347***
(Transp.&storage)			(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
dv_i			0.840***	0.841***	0.839***	0.840***	0.838***	0.839***	0.837***	0.841***	0.839***	0.840***
(Accom&food)			(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.076)	(0.077)	(0.076)	(0.077)	(0.076)
dv_j			-0.043	-0.043	-0.045	-0.044	-0.045	-0.045	-0.045	-0.043	-0.044	-0.043
(I&C)			(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)
dv_l			0.304	0.317	0.336	0.332	0.264	0.275	0.299	0.318	0.325	0.294
(Real estate)			(0.216)	(0.216)	(0.216)	(0.216)	(0.217)	(0.217)	(0.217)	(0.216)	(0.217)	(0.217)
dv_m			0.0813	0.0821	0.0815	0.0832	0.0748	0.0788	0.0794	0.0818	0.0777	0.0800
(Prof., sci., tehn. serv.)			(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)

dv_n			0.261**	0.259*	0.256*	0.256*	0.269**	0.267**	0.260**	0.259*	0.260*	0.263**
(Admin.&supp.)			(0.132)	(0.133)	(0.133)	(0.133)	(0.132)	(0.132)	(0.133)	(0.132)	(0.133)	(0.132)
dv_s			0.498***	0.502***	0.514***	0.508***	0.494***	0.492***	0.507***	0.503***	0.511***	0.497***
(Other serv.act.)			(0.131)	(0.131)	(0.131)	(0.131)	(0.131)	(0.132)	(0.131)	(0.131)	(0.131)	(0.131)
GDP				-0.001**								
				(0.0004)								
IP					-0.024***							
					(0.003)							
FX						0.838***						
						(0.166)						
IR - short							0.207***					
							(0.023)					
IR - long								0.118***				
								(0.026)				
LOANS									-0.029***			
									(0.0027)			
M1										-0.005**		
										(0.002)		
CROBEX											-0.0001***	
											(1.55e-05)	
BP												-4.91e-05*
												(2.51e-05)
Constant	-10.55***	-10.05***	-10.23***	-9.947***	-7.643***	-16.37***	-11.76***	-10.99***	-9.889***	-9.983***	-9.884***	-9.604***
	(0.193)	(0.199)	(0.202)	(0.245)	(0.380)	(1.233)	(0.268)	(0.263)	(0.203)	(0.225)	(0.205)	(0.376)
Firm-year obs.	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410
Firms	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935
Pseudo R2	0.2200	0.2228	0.2276	0.2277	0.2297	0.2284	0.2301	0.2283	0.2317	0.2278	0.2299	0.2277
Log-likeli hood	11964.51	-11920.98	-11847.9	-11845.88	-11816.11	-11835.19	-11808.88	-11873.41	-11784.9	-11844.9	-11811.86	-11846
Wald chi2	6794.03***	6836.09***	6982.25***	6986.30***	7045.84***	7007.68***	7060.30***	7003.24***	7108.25***	6988.25***	7054.33***	6986.06***
LR test	-	87.06***	146.16***	4.05**	63.58***	25.43***	78.05***	20.98***	126.0***	6.00**	72.07***	3.81*
ROC(in sample)	0.8618	0.8638	0.8662	0.8656	0.8650	0.8650	0.8683	0.8674	0.8670	0.8657	0.8660	0.8668
ROC(hold-out sample)	0.8528	0.8548	0.8551	0.8555	0.8558	0.8557	0.8552	0.8553	0.8553	0.8555	0.8556	0.8553

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The pseudo-R2 is a measure of goodness of the fit, calculated as function of the model's log-likelihood and of the log-likelihood of the constant-only model. TheWald test evaluates the overall statistical significance of the estimated coefficients.

It can be observed that multi-period logit and cloglog parameter estimations are similar but not identical. In all model specifications, leverage (TD/TA and CL/TA) and profitability ratios (EBIT/OR and ROA) are significant at 1% level and have the expected signs. In addition to these, working capital to total assets and cash flow to operating revenues are found to be significant in all model estimates predicting firm failure but at different level of significance. Thus, the probability of distress is negatively related to profitability ratios, working capital to total assets and cash flow to operating revenues. As expected, it is positively related to leverage ratios.

Indebted firms have to settle high interest costs, regardless of their financial results. Higher costs of financing incur higher expenditures for liabilities, thus reducing firm's profitability and increasing the risk of debt payment default.[13] Such firms lose financial flexibility in finding new funding sources and often have to accept adverse credit conditions due to low(er) creditworthiness. Unlike them, firms with unutilized borrowing capacity have higher flexibility in accessing financing. This gives them greater security in times of crisis and, as such, they have a lower risk of distress. Profitable firms are less likely to experience financial distress since they have access to more internally generated funds and thus have less need for borrowing. Negative and statistically significant coefficients of working capital to total assets and cash flow to operating revenues indicate that the firms with higher liquidity reserves are able to bridge the time between sales and collection of receivables. Precisely due to the lack of working capital, many newly founded firms fail in the first few years. Failure to pay on time or not to pay at all, for the delivered goods and services is widely spread in transition countries, including Croatia. Under these circumstances, an effective management of working capital is of existential importance.

Size is another firm-specific variable that is found highly significant in explaining distress probability in all model specifications. This indicates that smaller firms have higher failure propensity. In comparison to large firms, small firms are often less known and have limited access to financing. As they do not have access to securities market, they rely on bank loans. This generally increases the credit risk in the corporate sector and has a negative impact on the productivity of the entire economy. In times of financial crisis, the funding sources become scarcer for small firms as they face a higher risk of failure.

[13] According to descriptive statistics distressed firms finance over 90% of all asset through debt.

Both multi-period logit and cloglog estimates prove macroeconomic conditions on default probabilities to be significant. Distress rates coincide with the business cycle. They increase in recession times and decrease during prosperity. Economic indicators such as GDP, industrial production index and Crobex are found to be useful in predicting distress. Long and short-term interest rates on firm's credits, firm loan growth, HRK/EUR exchange rate and money supply as monetary policy measures also contribute to explaining default probabilities. The number of building permits issued is found to be significant only in multi-period logit model.

GDP, industrial production index, firm loan growth, money supply, Crobex and the number of building permits issued are negatively related to distress probabilities. In conditions of economic slowdown, firms are more likely to fail due to the decrease in the demand for goods and services. At the same time, due to credit squeeze and thus increased costs of financing, firms refrain from new investments. Moreover, the fall in the stock market indices reflects the fall in investors' confidence.

Long and short-term interest rates as well as the HRK/EUR exchange rate are positively related to default probabilities. The rise in interest rates increases the costs of financing. This in turn, has negative effect on firms, especially those in transition countries, as they largely finance their liquidity problems, development and growth through bank loans. As Croatian firms are mostly import oriented, the growth of the HRK/EUR exchange also contributes to default probabilities.

Moreover, interesting results appear when examining the joint effect of several macroeconomic and firm-specific variables (Table VI).[14] In Model 1, we take into account GDP as a representative business cycle indicator, long-term interest rates and a firm's loan growth as indicators of monetary policy and Crobex as an indicator of financial market stability. These variables are proven to be significant at 1% level and have the expected signs. The slopes of GDP and Crobex, which may reflect future expectations of economic growth, are negatively associated with distress probabilities. The explanation can be found in the fact that negative stock returns are often associated with negative changes in firm production. By

[14] Some of examined variables such as gross invesments in fixed assets and inflation did not prove to be significant or displayed unexpected signs.

examining credit conditions, it is found that firm loan growth is also negatively related with distress, while long-term interest rates show a strong positive marginal effect on distress probabilities. In her research analysing the impact of interest rates, the coincident economic activity indicator and loan growth, Bonfim (2009) comes to similar results. Model 2 uses another set of macroeconomic variables: the unemployment rate, long-term interest rate and Crobex. In line with the previous model specification, Crobex is negatively associated with distress probabilities. Contrary to this, the unemployment rate and long-term interest rates are positively associated with the likelihood of financial distress. The reasons behind this are that a high unemployment rate most commonly results in reduced demand for goods and services while an increase in interest rates aggravates firms' financial situations. The remaining model specifications (Model 3, 4 and 5) all include long-term interest rate and firm loan growth as representative variables of monetary policy. The difference between them lies in the last variable included. Model 3 additionally includes the index of industrial production as a coincident indicator of the business cycle. This indicator exhibits a strong negative marginal effect on default probabilities. The index of industrial production reflects the aggregate demand and sheds light on overall economic activity. Its decrease usually indicates reduced corporate profits and, as such, higher probability of default. Model 4 additionally takes into account money supply. The results indicate that money supply is negatively related to firms' probability of default. This confirms that an increase in money supply encourages consumption and spurs investment, which in turn leads to a higher aggregate demand and consequently lower default probabilities. Finally, Model 5 additionally includes the EUR/HRK exchange rate. The results indicate that depreciation of national currency is positively related to distress. This finding is in line with Felipe et al. (2016) and Nam et al. (2008) who find that the stability of national currencies plays a crucial role in firms' solvency, especially in transitional economies with high import dependency.

In order to test whether there are significant differences regarding the probability of distress across industries, we add dummy variables that control for industry affiliation and omit the dummy variable for manufacturing firms (reference dummy). The results demonstrate that firms belonging to accommodation and food service activities exhibit highest distress probabilities. At the same time, firms belonging to wholesale, transporting and storage, construction, mining and quarrying, administrative and support service activities, and other services activities have higher distress probabilities than those involved in manufacturing.

The usefulness of introducing additional variables is tested by the LR test (likelihood ratio).[15] This is done by performing the LR test for Models 1 and 2 in which Model 2 takes firm size as an additional variable (Table 1 and Table V in the Appendix). The results reveal statistically significant improvement in model fit. Furthermore, we perform the LR test for nested Models 2 and 3 to assess the usefulness of variables that indicate firms' industry affiliation. The null hypothesis that the parameters of these variables are jointly equal to zero is strongly rejected which indicates that the inclusion of industry dummies results in a statistically significant improved model fit. The same applies to all model specifications in which the additional variables refer to firm environment. Hence, macroeconomic variables significantly improve the models. The improvements in model adequacy are seen from the pseudo R^2 statistics indicating higher values for models that beside firm-specific variables include industry and macroeconomic variables. Moreover, it may be noted that the signs of estimated parameters of firm-specific variables remain unaltered in all multi-period logit and cloglog specifications.

In order to evaluate the prediction performance of estimated models, we perform in-sample and out-of-sample testing using the receiver operating curve (ROC). Estimates of area under the ROC (AUROC) are reported in the last two rows of the multi-period logit and cloglog. Moreover, both multi-period logit and cloglog model specifications have similar discriminant power. They exhibit AUROC from 86% to 88% for in-sample testing and 85% to 87% for out-of-sample testing which indicates a very good predictive power.

When size and industry effects are taken into account, the AUROC improves in all model specifications. In addition to this, the hazard models have slightly better out-of-sample-predictive ability when macroeconomic variables are added. These findings provide evidence that firm size, industry and macroeconomic variables should be included in predicting distress probabilities.

In order to perform an additional check of multi-period logit estimates presented in Table VI, we run model specification using the same set of variables but different sampling of firms[16].

[15] The LR test evaluates the difference between nested models i.e. one model is considered nested in another if the first model can be generated by imposing restrictions on the parameters of the second.

[16] Additional tables with models including financial ratios, industry dummies and macroeconomic variables one per one are available upon request.

The overall sample is divided into two sub-samples, one for in-sample and one for out-of-sample testing. In the estimation sample covering the period from 2004 to 2010, we identify 15,129 firms (62,569 firm-year observations), out of which 3,616 are firms in distress. To validate the predictive performance of estimated models, we forecast financial distress in 2011 by using solely financial and non-financial information on firms within the hold-out sample. The hold-out sample contains 5,570 firms of which 322 firms are in distress. The results confirm that expected signs and significance of firm-specific and macroeconomic variables remain unaltered while there are some differences when it comes to industry affiliation. Namely, firms belonging to construction and administrative and support service activities no longer display significantly higher distress probabilities when compared to manufacturing firms.

5. CONCLUSION

The author explore the significance of firm-specific, macroeconomic and industry variables in predicting the likelihood of financial distress of firms operating in the Republic of Croatia, as a transition country. The parameter estimations derived by multi-period logit and cloglog specifications confirm the usefulness of firm-specific variables (financial ratios and firm size), macroeconomic variables and industry variables in predicting firm distress. According to obtained results, firms in distress suffer from working capital deficiency and have negative profitability ratios. They use higher leverage, mostly based on short-term debt. Moreover, cash flow to operating revenue is found to be significant in all model specifications. Small firms have shown to have higher probability of distress. The reason for this may lie in their limited access to funding and weak negotiating power. This should not be neglected by policy makers, as small firms are particularly important for the economy. The results also confirm that there are significant differences in the probability of financial distress across industries. The introduction of time dimension in predicting firm failure provided for the use of commonly neglected macroeconomic variables (especially in studies analysing transition countries). Macroeconomic variables contain relevant information that are independent of information provided by firm-specific variables. Economic activity, measured by GDP, industrial production index, Crobex and number of building permits issued are negatively associated with default probability. The variables reflecting monetary policy measures are also found to be significant. Deterioration of financial conditions through increased interest rates and reduced loan supply index contribute to higher default probabilities. Therefore, in times of crisis when firms tend to overcome their liquidity problems by obtaining bank loans, monetary policy plays a pivotal role. Economic and monetary policy makers should aim towards improving financing conditions and reducing the costs of financing e.g. through some form of incentive, tax treatment or guarantee schemes. To conclude, firm managers should be aware of and understand the impact of both firm-specific and macroeconomic variables to be able to prevent financial distress.

LITERATURE:

1. Allison, P. D. 1982. "Discrete-Time Methods for the Analysis of Event Histories." *Sociological Methodology* 13 (1):61-98.
2. Altman, E. I., and A. Saunders. 1998. "Credit Risk Measurement: Developments over the last 20 years." *Journal of Banking and Finance* 21 (11-12): 1721-1742.
3. Altman, E. I., R. Haldeman, and P. Narayanan. 1977. "ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations." *Journal of Banking and Finance* 1 (1):29-54.
4. Audretsch, D. B., and T. Mahmood. 1995. "New Firm Survival: New Results Using a Hazard Function." *Review of Economics and Statistics* 77 (1):97-103.
5. Beaver, W. H. 1966. "Financial Ratios as Predictors of Failure." *Empirical Research in Accounting , Supplement to Journal of Accounting Research* 4:71-111.
6. Beck, N., J. N. Katz, and R. Tucker. 1998. "Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable." *American Journal of Political Science* 42 (4):1260–1288.
7. Bhattacharjee, A., and J. Han. 2014. "Financial Distress of Chinese Firms: Microeconomic, Macroeconomic and Institutional Influences." *China Economic Review* 30: 244-62.
8. Bhattacharjee, A., S. Holly, and P. Kattuman. 2009a. "Business Failure in UK & US Firms: Impact of Macroeconomic Instability and the Role of Legal Institutions." *Review of Law and Economics* 5 (1):1-32.
9. Bhattacharjee, A., C. Higson, S. Holly, and P. Kattuman. 2009b. "Macroeconomic Instability and Business Exit: Determinants of Failures and Acquisitions of UK Firms." *Economica* 76 (301):108-131.
10. Bonfim, D. 2009. "Credit Risk Drivers: Evaluating the Contribution of Firm Level Information and of Macroeconomic Dynamics." *Journal of Banking and Finance* 33 (2):281-299.
11. Bruneau, C., O. De Bandt, and W. El Amri. 2012. "Macroeconomic Fluctuations and Corporate Financial Fragility." *Journal of Financial Stability* 8 (4):219-235.
12. Bunn, P., and V. Redwood. 2003. "Company Accounts-Based Modelling of Business Failures and the Implications for Financial Stability." Bank of England, Working Paper No. 210.

13. Carling, K., T. Jacobson, J. Lindé, and K. Roszbach. 2007. "Corporate Credit Risk Modeling and the Macroeconomy." *Journal of Banking and Finance* 31 (3):845-868.
14. Charalambakis, E. C. 2014. "On corporate financial distress prediction: what can we learn from private firms in a small open economy?" Bank of Greece, Working Paper No. 188.
15. Charalambakis, E. C., and I. Garrett. 2016. "On the Prediction of Financial Distress in Developed and Emerging Markets: Does the Choice of Accounting and Market Information Matter? A Comparison of UK and Indian Firms." *Review of Quantitative Finance and Accounting* 47 (1):1-28.
16. Chava, S., and R.A. Jarrow. 2004. "Bankruptcy Prediction with Industry Effects." *Review of Finance* 8 (4):537-569.
17. Cuthbertson, K., and J. Hudson. 1996. "The Determinants of Compulsory Liquidations in the UK." *The Manchester School of Economic and Social Studies* 64 (3):298-308.
18. Davis, E. P. 1987. "Rising Sectoral Debt/Income Ratios: a Cause for Concern?" Bank for International Settlements, BIS Economic Papers, No. 20.
19. Duffie, D., L. Saita, and K. Wang. 2007. "Multi-period Corporate Default Prediction with Stochastic Covariates." *Journal of Financial Economics* 83 (3):635–665.
20. Edminster, R. O. 1972. "An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction." *The Journal of Financial and Quantitative Analysis* 7 (2):1477-1493.
21. Filipe, S. F., T. Grammatikos, and D. Michala. 2016. "Forecasting distress in European SME portfolios." *Journal of Banking & Finance* 64 (1):112-135.
22. Gupta, J., A. Gregoriou, and J. Healy. 2014. "Forecasting Bankruptcy for SMEs Using Hazard Function: To What Extent Does Size Matter?" *Review of Quantitative Finance and Accounting* 45 (4):845-869.
23. Halim, A., S. N. Mohd Daud, A. Rizal Mazlan, and A. Marzuki. 2008. "Macroeconomic Determinants of Corporate Failures in Malaysia." *International Journal of Business and Management* 3 (3):3-10.
24. Hazak, A., and K. Männasoo. 2010. "Indicators of Corporate Default – An EU Based Empirical Study." *Transformations in Business & Economics* 9 (1):62-76.
25. Hensher, D. A., S. Jones, and W. H. Greene. 2007. "An Error Component Logit Analysis of Corporate Bankruptcy and Insolvency Risk in Australia." *Economic Record*, 83 (260):86-103.
26. Jacobson, T., J. Lindé, and K. Roszbach. 2005. "Exploring Interactions between Real Activity and the Financial Stance." *Journal of Financial Stability* 1 (3):308-341.
27. Jacobson, T., R. Kindell, J. Lindé, and K. Roszbach. 2013. "Firm Default and Aggregate Fluctuations." *Journal of the European Economic Association* 11 (4):942-972.
28. Jenkins, S. P. 2005. *Survival Analysis*. Lecture notes, Unpublished Manuscript, Institute for Social and Economic Research, University of Essex, Colchester, UK (http://www.iser.essex.ac.uk/survival-analysis)
29. Johnsen, T., and R. W. Melicher. 1994. "Predicting Corporate Bankruptcy and Financial Distress: Information Value. Added by Multinomial Logit Models." *Journal of Economics & Business* 46 (4): 269-286.

30. Keasey, K., J. Pindado, and L. Rodrigues. 2014. “The Determinants of the Costs of Financial Distress in SMEs.“ *International Small Business Journal* 33 (8):862-881.
31. Laitinen, E. K. 1992. “Prediction of Failure of a Newly Founded Firm.“ *Journal of Business Venturing* 7 (4):323-340.
32. Lennox, C. 1999. “Identifying Failing Companies: A Re-Evaluation of the Logit, Probit and MDA Approaches.“ *Journal of Economics and Business* 51 (4)347-364.
33. Liu, J. 2004. “Macroeconomic Determinants of Corporate Failures: Evidence from the UK.“ *Applied Economics* 36 (9):939-945.
34. Liu, J., and N. Wilson. 2002. „Corporate Failure Rates and the Impact of the 1986 Insolvency Act: an Econometric Analysis.“ *Managerial Finance* 28 (6):61-71.
35. Männasoo, K. 2008. "Patterns of Firm Survival in Estonia." *Eastern European Economics* 46, (4):27-42.
36. Nam, C. W, T. S. Kim, N. J. Park, and H. K. Lee. 2008 “Bankruptcy Prediction using a Discrete-Time Duration Model Incorporating Temporal and Macroeconomic Dependencies.“ *Journal of Forecasting* 27 (6):493–506.
37. Ohlson, J. A. 1980. “Financial Ratios and the Probabilistic Prediction of Bankruptcy.“ *Journal of Accounting Research* 18 (1):109–131.
38. Parker, S., G. Peters, and H. F. Turetsky. 2000. “Corporate Governance and Corporate Failure: A survival analysis.“ *Corporate Governance: International Journal of Business in Society* 2 (2):4-12.
39. Platt, H., and M. B. Platt. 2006. “Understanding Differences between Financial Distress and Bankruptcy.“ *Review of Applied Economics* 2 (2):211-227.
40. Platt, H., and M. B. Platt. 2009. **“**Financial Distress Comparison across Three Global Regions.“ *Journal of Risk and Financial Management* 1 (1):129-162.
41. Rabe-Hesketh, S., and A. Skrondal. 2012. Multilevel and Longitudinal Modeling using Stata. Vol II: Categorical Responses, Counts, and Survival. 3rd edition, Stata Corporation, Texas.
42. Rommer, A. D. 2005. “A Comparative Analysis of the Determinants of Financial Distress in French, Italian and Spanish Firms.“ Danmarks Nationalbank, Copenhagen.Working Paper No. 26.
43. Salman, K. A., Y. Friedrichs, and G. Shukur. 2009. “Macroeconomic Factors and Swedish Small and Medium-Sized Manufacturing Firm Failure.“ The Royal Institute of Technology Centre of Excellence for Science and Innovation Studies (CESIS), Working Paper No. 185.
44. Shumway, T. 2001. “Forecasting Bankruptcy More Accurately: A Simple Hazard Model.“ *The Journal of Business* 74 (1):101–124.
45. Taffler, R. J. 1982. “Forecasting company failure in the UK using discriminant analysis and financial ratio dana.“ *Journal of the Royal Statistical Society* 145 (3):342–358.
46. Vlieghe, G. W. 2001. “Indicators of Fragility in the UK Corporate Sector.“ Bank of England Working paper No. 146.
47. Wadhwani, B. S. 1986. “Inflation, Bankruptcy, Default Premia and the Stock Market.“ *The Economic Journal* 96 (381):120-138.

48. Wooldridge, J. M. 2002. Econometric Analysis of Cross-section and Panel Data. 2nd edition, MIT press. Cambridge.
49. Young, G. 1995. “Company Liquidations, Interest Rates and Debt.“ *The Manchaster School Supplement* 63; 57-69.
50. Zavgren, C. V. 1985. “Assessing the vulnerability to failure of American industrial firms: a logistic analysis.“ *Journal of Business Finance and Accounting* 12 (1):19-45.

APPENDIX:

Table I: Classification of firms according to NACE Code

NACE Code	Var.	Total nb. of firms	% total nb. of firms	Firm-years	Nb. of distressed firms	% distressed
A - Agriculture, hunting and forestry	I_a	424	2.01%	2,252	67	1.57%
B - Mining and quarrying	I_b	67	0.32%	368	14	0.33%
C - Manufacturing	I_c	4,006	18.96%	22,048	572	13.43%
F - Construction	I_f	2,231	10.56%	9,880	438	10.29%
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	I_g	9,635	45.60%	50,448	2,083	48.92%
H - Transporting and storage	I_h	535	2.53%	2,448	107	2.51%
I - Accommodation and food service activities	I_i	1,333	6.31%	5,321	480	11.27%
J - Information and communication	I_j	641	3.03%	3,211	90	2.11%
L - Real estate activities	I_l	164	0.78%	565	37	0.87%
M - Professional, scientific and technical activities	I_m	1,247	5.90%	5,814	168	3.95%
N - Administrative and support service activities	I_n	423	2.00%	1,890	92	2.16%
S - Other services activities	I_s	423	2.00%	1,921	110	2.58%
Total		21,129	100.00%	106,166	4,258	100,00%

Source: author's calculations.

Note: Labels for industry variables are assigned according to NACE code. The sample period is from 2004 to 2011.

Table II: Classification of firms according to size

Firm category	Total nb. of firms	% total nb. of firms	Firm-years	Nb. of distressed firms	% distressed
Small firms	19,421	91.92%	94,514	4,044	94.97%
Medium firms	1,318	6.24%	8,956	167	3.92%
Large firms	390	1.85%	2,696	47	1.10%
Total	21,129	100.00%	106,166	4,258	100.00%

Source: author's calculations.

Note: The sample period is from 2004 to 2011.

Table III: Description of variables

Variable	Description
FIRM- SPECIFIC (micro data)	
Total debts to total assets % (TD/TA)	((Non current liabilities + Current liabilities) / Total assets)) * 100
Current liabilities to total assets % (CL/TA)	(Current liabilities / Total assets) * 100
EBIT margin % (EBIT/OR)	(EBIT / Operating revenue) * 100
Return on assets % (ROA)	(P/L after tax / Total assets) * 100
Working capital to total assets % (WC/TA)	((Current assets - Current liabilities) / Total assets)) * 100
Cash flow to operating revenue % (CF/OR)	((Net income + Depreciation) / Operating revenue)) * 100
Size (ln_size)	The natural logarithm of number of employees is used as a proxy for firm size.
Industry sector	Twelve sector dummies according to sectors indicated in table I. Yes = 1 if company belongs to particular sector and 0 otherwise.
AGGREGATE VARIABLES (macro data)	
Gross domestic product (GDP)	Gross domestic product at current market prices (thousands HRK). Used as an indicator of general economic activitiy. It is calculated according to the methodology of the UN System of National Accounts (SNA 1993) and European System of National Accounts (ESA 1995). Source: Croatian Bureau of Statistics.
Industrial production index (IP)	Important short-term indicator of a business cycle that measures results of the industrial sector. It is a central and up-to-date indicator of the development of the industrial sector, which is one of the most volatile component of economy. Industrial production volume indices for various levels of the Nace 2007. are calculated in two stages according to the Laspeyres formula. Source: Croatian Bureau of Statistics.
Registered unemployment rate (UNEMP)	Used as an indicator of general economic activitiy. Source: data on registered unemployment is obtained from the records on unemployed persons kept by the Croatian Employment Service and published by the Croatian Bureau of Statistics.
Exchange rate HRK/EUR (FX)	Period average. Source: Croatian National Bank.
Average annual inflation rate	It is calculated on the basis of the consumers price index data and represents the change in the level of prices of goods and services for the personal consumption between the basic (starting) month and the final month of the selected period. Source: Croatian Bureau of Statistics.

Investment	Gross fixed capital formation in fixed assets in thousands HRK. Source: Croatian Bureau of Statistics.
Interest rate (IR - short)	Banks' interest rates on HRK short-term credits for firms indexed to foreign currency. Source: Croatian National Bank.
Interest rate (IR - long)	Banks' interest rates on HRK long-term credits for firms indexed to foreign currency. Source: Croatian National Bank.
Firm loan growth % (LOANS)	Annual growth rate of firm loans (%). Source: Croatian National Bank.
Money supply (M1)	Variable money supply is approximated by monetary aggregate M1 (cash and deposits on current accounts) in thousands HRK. Source: Croatian National Bank.
Crobex (CROBEX)	Represents official Zagreb Stock Exchange share index and serves as a proxy for investor sentiment. Source: The Zagreb Stock Exchange.
Building permits issued (BP)	Document issued by a competent administrative body on the basis of which it is permitted to start the construction of a new building or a reconstruction of an existing building. Source: Croatian Bureau of Statistics.

Table IV: Summary statistics for financial ratios

Variable	Mean	Stand. dev.	Median
	Healty firms		
TD/TA (%)	66.80	24.64	71.59
CL/TA (%)	53.42	26.14	74.77
EBIT/OR (%)	3.42	10.92	3.25
ROA (%)	4.80	10.14	2.72
WC/TA (%)	15.49	28.62	13.87
CF/OR (%)	7.41	9.81	5.83
	Distressed firms		
TD/TA (%)	92.46	11.36	97.12
CL/TA (%)	77.86	24.03	86.41
EBIT/OR (%)	-4.95	15.34	0.12
ROA (%)	-3.64	13.75	0.12
WC/TA (%)	-6.62	25.27	-5.18
CF/OR (%)	0.06	13.31	1.71

Source: author's calculations.

Note: The sample period is from 2004 to 2011. All ratios are are winsorized at the ninety-ninth and first percentiles.

Table V: Cloglog estimation results 2004-2010

Variables	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11	Model12
TD/TA	0.0818***	0.0811***	0.0800***	0.0798***	0.0796***	0.0797***	0.0803***	0.0802***	0.0799***	0.0798***	0.0798***	0.0800***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CL/TA	0.0053***	0.0033***	0.0041***	0.0039***	0.0036***	0.0037***	0.0043***	0.0043***	0.0039***	0.0039***	0.0038***	0.0041***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBIT/OR	-0.0139***	-0.0120***	-0.0114***	-0.0113***	-0.0109***	-0.0111***	-0.0115***	-0.0116***	-0.0111***	-0.0112***	-0.0110***	-0.0115***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	-0.0167***	-0.0157***	-0.0151***	-0.0153***	-0.0147***	-0.0152***	-0.0140***	-0.0147***	-0.0138***	-0.0151***	-0.0146***	-0.0150***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
WC/TA	-0.0027***	-0.0035***	-0.0020**	-0.0021**	-0.0022**	-0.0021**	-0.0019**	-0.0019**	-0.0020**	-0.0021**	-0.0021**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CF/OR	-0.0051**	-0.0072***	-0.0071***	-0.0073***	-0.0077***	-0.0075***	-0.0072***	-0.0070***	-0.0076***	-0.0073***	-0.0075***	-0.0072***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln_size		-0.132***	-0.126***	-0.126***	-0.128***	-0.126***	-0.128***	-0.126***	-0.128***	-0.126***	-0.128***	-0.126***
		(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
dv_a			-0.099	-0.098	-0.097	-0.097	-0.103	-0.101	-0.099	-0.098	-0.100	-0.099
(Agriculture)			(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)
dv_b			0.677**	0.672**	0.676**	0.672**	0.697**	0.689**	0.696**	0.672**	0.671**	0.680**
(Mining&aquarr.)			(0.293)	(0.293)	(0.294)	(0.294)	(0.293)	(0.293)	(0.294)	(0.293)	(0.293)	(0.293)
dv_f			0.160**	0.170**	0.179**	0.178**	0.137*	0.146**	0.153**	0.169**	0.170**	0.156**
(Construct.)			(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
dv_g			0.186***	0.181***	0.174***	0.176***	0.191***	0.190***	0.182***	0.181***	0.178***	0.187***
(Wholesale)			(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
dv_h			0.327***	0.326***	0.319***	0.322***	0.326***	0.328***	0.319***	0.325***	0.323***	0.327***
(Transp.&storage)			(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)
dv_i			0.727***	0.728***	0.727***	0.728***	0.723***	0.725***	0.724***	0.728***	0.725***	0.727***
(Accom&food)			(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
dv_j			-0.059	-0.06	-0.062	-0.061	-0.059	-0.060	-0.059	-0.059	-0.06	-0.059
(I&C)			(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
dv_l			0.240	0.259	0.274	0.275	0.197	0.211	0.230	0.257	0.259	0.233
(Real estate)			(0.195)	(0.196)	(0.196)	(0.196)	(0.196)	(0.196)	(0.195)	(0.195)	(0.195)	(0.195)
dv_m			0.0606	0.0625	0.0628	0.0641	0.0539	0.0575	0.0591	0.0622	0.0583	0.0598
(Prof., sci., tehn. serv.)			(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)
dv_n			0.237*	0.234*	0.235*	0.233*	0.246**	0.243**	0.242**	0.235*	0.235*	0.238*
(Admin.&supp.)			(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
dv_s			0.455***	0.461***	0.477***	0.469***	0.455***	0.452***	0.472***	0.462***	0.470***	0.454***
(Other serv.act.)			(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)
GDP				-0.001***								

				(0.0004)								
IP					-0.025***							
					(0.003)							
FX						0.937***						
						(0.155)						
IR - short							0.181***					
							(0.0214)					
IR - long								0.096***				
								(0.024)				
LOANS									-0.028***			
									(0.002)			
M1										-0.006***		
										(0.002)		
CROBEX											-0.00013***	
											(1.48e-05)	
BP												-2.96e-05
												(2.33e-05)
Constant	-10.47***	-10.01***	-10.17***	-9.792***	-7.508***	-17.04***	-11.51***	-10.80***	-9.845***	-9.876***	-9.829***	-9.795***
	(0.188)	(0.194)	(0.196)	(0.235)	(0.359)	(1.151)	(0.253)	(0.250)	(0.198)	(0.217)	(0.200)	(0.354)
Firm-year obs.	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410	94,410
Firms	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935	20,935
Log-likelihood	-11966.22	-11927.61	-11859.69	-11855.4	-11820.91	-11841.45	-11824.43	-11851.47	-11793.55	-11854.64	-11819.69	-11858.89
Wald chi2	6745.61***	6822.84***	6958.67***	6967.26***	7036.23***	6995.16***	7029.20***	6975.12***	7090.96***	6968.77***	7038.67***	6960.28***
LR test	-	214.67***	135.83***	8.59***	77.56***	36.49***	70.53***	16.45***	132.29***	10.10***	80.01***	1.62
ROC(in sample)	0.8617	0.8635	0.8656	0.8648	0.8643	0.8641	0.8677	0.8665	0.8665	0.8649	0.8653	0.8660
ROC(hold-out sample)	0.8521	0.8541	0.8542	0.8544	0.8545	0.8546	0.8541	0.8541	0.8542	0.8544	0.8543	0.8542

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The pseudo-R2 is a measure of goodness of the fit, calculated as function of the model’s log-likelihood and of the log-likelihood of the constant-only model. TheWald test evaluates the overall statistical significance of the estimated coefficients.

Table VI: Multi-period logit estimation results 2004-2010 (joint macroeconomic variables)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
TD/TA	0.0811***	0.0811***	0.0812***	0.0812***	0.0811***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CL/TA	0.0041***	0.0043***	0.0043***	0.0043***	0.0042***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBIT/OR	-0.0132***	-0.0133***	-0.0133***	-0.0133***	-0.0133***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	-0.0152***	-0.0156***	-0.0154***	-0.0156***	-0.0156***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
WC/TA	-0.0023**	-0.0022**	-0.0022**	-0.0022**	-0.0022**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CF/OR	-0.0099***	-0.0097***	-0.0098***	-0.0098***	-0.0098***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln_size	-0.147***	-0.146***	-0.146***	-0.146***	-0.146***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
dv_a	-0.126	-0.125	-0.123	-0.122	-0.123
(Agriculture)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)
dv_b	0.772**	0.769**	0.771**	0.771**	0.772**
(Mining&aquarr.)	(0.317)	(0.317)	(0.317)	(0.317)	(0.317)
dv_f	0.183**	0.179**	0.179**	0.177**	0.182**
(Construct.)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
dv_g	0.171***	0.174***	0.174***	0.176***	0.173***
(Wholesale)	(0.057)	(0.056)	(0.056)	(0.056)	(0.056)
dv_h	0.337***	0.340***	0.338***	0.339***	0.338***
(Transp.&storage)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
dv_i	0.835***	0.836***	0.836***	0.837***	0.836***
(Accom&food)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
dv_j	-0.052	-0.051	-0.049	-0.047	-0.050
(I&C)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)
dv_l	0.298	0.291	0.293	0.290	0.294
(Real estate)	(0.218)	(0.218)	(0.218)	(0.217)	(0.217)
dv_m	0.076	0.075	0.078	0.078	0.079
(Prof., sci., tehn. serv.)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)
dv_n	0.265**	0.269**	0.265**	0.264**	0.263**
(Admin.&supp.)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)
dv_s	0.513***	0.509***	0.509***	0.507***	0.508***
(Other serv.act.)	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)
GDP	-0.005***				
	(0.001)				
IR - long	0.364***	0.362***	0.146***	0.112**	0.244***
	(0.064)	(0.047)	(0.038)	(0.049)	(0.055)
LOANS	-0.012***		-0.014***	-0.023***	-0.013***
	(0.003)		(0.004)	(0.004)	(0.004)
CROBEX	-7.64e-05***	-0.0001***			
	(1.79e-05)	(1.72e-05)			
UNEMP		0.084***			
		(0.017)			
IP			-0.021***		
			(0.005)		
M1				-0.007*	
				(0.004)	
FX					1.557***
					(0.362)
Constant	-10.69***	-13.55***	-8.765***	-10.35***	-23.08***

	(0.284)	(0.597)	(0.449)	(0.294)	(3.019)
Firm-year obs.	94,410	94,410	94,410	94,410	94,410
Firms	20,935	20,935	20,935	20,935	20,935
Pseudo R2	0.2336	0.2322	0.2323	0.2319	0.2324
Log-likeli hood	-11755.51	-11777.72	-11776.11	-11782.22	-11744.61
Wald chi2	7167.03***	7122.61***	7125.83***	7113.61***	7128.83***
ROC(in sample)	0.8669	0.8668	0.8670	0.8672	0.8667
ROC(hold-out sample)	0.8553	0.8556	0.8555	0.8553	0.8553

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The pseudo-R2 is a measure of goodness of the fit, calculated as function of the model's log-likelihood and of the log-likelihood of the constant-only model. TheWald test evaluates the overall statistical significance of the estimated coefficients.

Table VII: Multi-period logit estimation results 2004-2010 (alternative sampling)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
TD/TA	0.0772***	0.0772***	0.0773***	0.0773***	0.0772***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CL/TA	0.0031***	0.0032***	0.0031***	0.0032***	0.0031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBIT/OR	-0.0113***	-0.0114***	-0.0114***	-0.0114***	-0.0115***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	-0.0143***	-0.0147***	-0.0145***	-0.0146***	-0.0147***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
WC/TA	-0.0031***	-0.0030***	-0.0030***	-0.0030***	-0.0031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CF/OR	-0.0102***	-0.0099***	-0.0101***	-0.0100***	-0.0100***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ln_size	-0.109***	-0.108***	-0.108***	-0.108***	-0.108***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
dv_a	-0.046	-0.044	-0.042	-0.041	-0.041
(Agriculture)	(0.151)	(0.151)	(0.151)	(0.151)	(0.151)
dv_b	0.595*	0.588*	0.595*	0.594*	0.597*
(Mining&aquarr.)	(0.322)	(0.322)	(0.322)	(0.322)	(0.322)
dv_f	0.119	0.116	0.118	0.115	0.118
(Construct.)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)
dv_g	0.165***	0.167***	0.168***	0.169***	0.168***
(Wholesale)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
dv_h	0.332***	0.333***	0.333***	0.334***	0.333***
(Transp.&storage)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)
dv_i	0.794***	0.795***	0.795***	0.796***	0.795***
(Accom&food)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)
dv_j	0.0116	0.0132	0.0133	0.0151	0.0129
(I&C)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)
dv_l	0.230	0.224	0.227	0.224	0.226
(Real estate)	(0.222)	(0.222)	(0.222)	(0.221)	(0.221)
dv_m	0.076	0.075	0.079	0.08	0.081
(Prof., sci., tehn. serv.)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
dv_n	0.212	0.215	0.211	0.211	0.210
(Admin.&supp.)	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)
dv_s	0.566***	0.562***	0.563***	0.562***	0.561***
(Other serv.act.)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)
GDP	-0.004***				
	(0.001)				
IR - long	0.449***	0.515***	0.301***	0.293***	0.343***

	(0.066)	(0.049)	(0.039)	(0.050)	(0.056)
LOANS	-0.015***		-0.015***	-0.024***	-0.018***
	(0.004)		(0.004)	(0.004)	(0.004)
CROBEX	-9.47e-05***	-0.0001***			
	(1.79e-05)	(1.73e-05)			
UNEMP		0.085***			
		(0.018)			
IP			-0.024***		
			(0.005)		
M1				-0.011***	
				(0.004)	
FX					1.274***
					(0.368)
Constant	-10.75***	-13.76***	-8.652***	-10.56***	-20.82***
	(0.288)	(0.611)	(0.450)	(0.298)	(3.074)
Firm-year obs.	62,569	62,569	62,569	62,569	62,569
Firms	15,129	15,129	15,129	15,129	15,129
Pseudo R2	0.2270	0.2255	0.2256	0.2252	0.2253
Log-likeli hood	-10679.49	-10700.57	-10698.13	-10704.22	-10702.28
Wald chi2	6272.03***	6229.88***	6234.75***	6222.56***	6226.46***
ROC(in sample)	0.8540	0.8536	0.8539	0.8541	0.8535
ROC(hold-out sample)	0.8544	0.8545	0.8545	0.8543	0.8545

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The pseudo-R2 is a measure of goodness of the fit, calculated as function of the model's log-likelihood and of the log-likelihood of the constant-only model. TheWald test evaluates the overall statistical significance of the estimated coefficients.