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The influence of the business cycle on bankruptcy probability

Abstract:
I combine two fields of research on default prediction by empirically testing a bankruptcy prediction function where unlisted firms are evaluated on the basis of both their financial statement analysis and the macroeconomic environment. This combination is found to improve the default prediction compared to financial statements alone. The GDP-gap, a production index and the money supply M1 in combination with some financial health indicators for individual firms are found to be significant predictors on default for Norwegian firms during both a recovery and expansion in the 1990's.

Keywords: bankruptcy prediction; macroeconomic environment; financial ratios; logit model.

JEL classification: G32, G33

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1 Introduction

Default prediction studies up till now have been concentrated mainly on distinguishing healthy from bankrupt companies according to financial differences (see Dimitras et al., 1996 for an overview, Westgaard and van der Wijst, 2001; Bystroem et al., 2005). Alternatively and at a lesser scale, bankruptcy is predicted at an industry level according to movements in macroeconomic factors (see e.g. Levy and Bar-Niv, 1987; Archibald and Baker, 1998; Hol, 2001). Banks use bankruptcy prediction models as a tool for monitoring credit risk in their portfolio. After the revised Basel rules[1], there is an increased interest in these models, as banks have to make credible efforts to manage their portfolio risks. Improved bankruptcy prediction models will reduce the capital a bank is required to hold.

I combine these two fields of research on default prediction by empirically testing a bankruptcy prediction function where unlisted firms are evaluated on the basis of both their financial statement analysis and movements in the business cycle, in the spirit of the credit risk model Credit Portfolio View. McKinsey's CPV model deals with cyclical factors by directly including the relationship between rating transition probability and macro-factors (Wilson, 1997). Thus it predicts the credit risk based on the influence of the macroeconomic environment. The purpose of this paper is to add to the ongoing research on the effect of the economic environment on the probability to default for non-financial firms by analyzing Norwegian data for unlisted firms over a recovery and expansion. Using financial statement data for the individual firms widens the application area of the default model in this paper, since no market equity prices are required as in Merton-type mod-

[1] See the publication of International Convergence of Capital Measurement and Capital Standards: a Revised Framework, the new capital adequacy framework commonly known as Basel II: http://www.bis.org/publ/bcbs107.htm

els. I also compare the model with a model of default prediction that only uses firm-specific data to highlight how the inclusion of the macroeconomic variables contributes to the default risk prediction model. The probability of default predicted correctly increases strongly, while some of the financial variables that are highly significant in the financial variables only model loose their explanatory power. In the next section I will give an overview of the default prediction literature based on financial and macro-economic variables. Section 3 provides the data I use in the paper. The econometric results are discussed in section 4, while section 5 concludes.

2 Literature review

In the 1960's and 1970's several empirical models to predict business failure were developed, often by combining publicly available company data with statistical classification techniques. Since then numerous empirical studies have been published that distinguish between bankrupt and non-bankrupt firms.

In this section I will present a short review on default prediction models based on financial variables, and a more detailed review of models based on variables representing the macroeconomic conditions.

2.1 Default prediction models based on financial variables

Empirical studies of bankruptcy prediction often use ratios to indicate the financial characteristics of firms. Beaver (1966) used univariate financial accounting ratio models and Altman (1968) advanced to multivariate financial ratios models. In Beaver (1966) explanatory variables are used to indicate either the cash flow of a firm, its income, debt, current assets or working capital. To improve the predictive ability, Altman (1968)–and many studies after his–utilized discriminant analysis to predict bankruptcy. Discriminant analysis classifies firms as bankrupt or not bankrupt, based on several financial ratios that give a comprehensive profile of a firm. These variables include earnings, working capital, value of equity and sales. Beaver (1968) considered the impact of firm bankruptcy on stock returns. He used equity returns to predict bankruptcy, which anticipated failure earlier than financial ratios. Ohlson (1980) employed assets, liabilities, working capital, income and funds provided by operations in a logistic regression and a non-matched sample of firms to predict bankruptcy. Logistic regression requires less restrictive statistical assumptions than multiple discriminant analysis used in earlier works.

The empirical financial ratio models of bankruptcy in previous studies have distinguished between bankrupt and non-bankrupt firms with relative accuracy. There is a wide dispersion in the financial variables used to predict default, see e.g. the overview of empirical models in Dimitras et al. (1996). Given this large variety in default prediction models, I utilize a default prediction model developed on Norwegian data (Westgaard and van der Wijst, 2001). I will describe the financial variables in this model, which are common default prediction models, in the proxy variables section.

2.2 Macroeconomic studies and bankruptcy prediction models

In contrast to the financial ratios models of default, there exist considerably fewer studies that relate default probability to the business cycle. It is likely that not only internal factors but also external factors influence the bankruptcy rate, e.g. the characteristics from the industry a company belongs to or the state of the economic cycle. Of the four large credit portfolio models used in financial risk management CreditMetrics, KMV, CreditRisk+ and CreditPortolioView, Wilson's (1997) CPV is the only that allows macroeconomic variables[2] to influence the probability of default. Any firm specific information is lost in CPV, however, as the defaults are grouped and modeled at a national level. If credit risk models overstate default risk in bad times, then internal bank capital requirements will be too high, which forces banks to restrict lending in recessions and vice versa. BIS (2001) gives more details on the possible procyclical effects of regulatory policy across different countries.

Business cycles themselves are a much-researched area. The definition of a business cycle is the more or less regular pattern of expansion and contraction in economic activity around the path of trend growth. There need not be regularities in business cycles; the length of a cycle can vary from a short period to more than five years. Business cycle movements need not be regular in size neither have a constant trend growth rate. Furthermore, also in acquiring data on business cycles, with e.g. a Hodrick-Prescott (1997) methodology, the trend is not a given fact. Several parameters in the model need to be adjusted, thus leaving the actual values up to some discretion. In the literature on business cycles variables as profits, investment, money, credit, interest rates and assets (Zarnowitz, 1997) have been used to represent the macroeconomic environment. These variables are also often used in the literature to explain the probability of default in empirical papers.

The determinants of firm failure are approached from a different point of view; using different kind of data and methodology. Zarnowitz and Lerner

[2]The macroeconomic variables used in CPV are unemployment, interest rate, growth in gross domestic product and government consumption (Crouhy and Galai, 2000).

(1961) relate the business cycle to failure rates by analyzing the number of failures, the average liability and the aggregate liabilities of failed firms over the cycle. Altman (1968) uses a multiple regression model to explain corporate bankruptcies with the change of gross national product lagged one quarter, S&P 500 stock index and money supply M1. Rose et al. (1982) select a large variety of lagged macroeconomic variables, amongst others S&P 500 stock index, the prime interest rate, 3 month T-bill rate, gross private domestic investment/GNP and retail sales/GNP to predict the level of business failure rates based on stepwise regression. The resulting relations are mixed, though; the estimated coefficient of the three-month T-bill rate is positive while the prime rate is negative. All variables are significant and the model has a high explanatory power (R^2 of 0.912). In Altman (1983) a distributed lag regression model is developed to explain business failure rates. The estimated coefficients of change in S&P 500, new business incorporations and money supply M2 with several lags, are significantly different from zero, while the change in gross national product is insignificant. Fama (1986) finds an indication that the business cycle influence default probability by plotting the forward term premiums, which vary with the business cycle. Levy and Bar-Niv (1987) hypothesize that fluctuation in income and price level adversely affects the well being of the business sector. They find with an ordinary least squares regression that the annual number of bankruptcies per 10,000 firms is positively correlated with the variance of GNP over 24 quarters and the GNP deflator, and negatively with the covariance of GNP and the deflator. The underlying idea is that the greater and more frequent the fluctuations of GNP, the more drastic and frequent the changes in the demand for a firm's product. When there is little demand for a firm's product, it could go bankrupt. Melicher and Hearth (1988) use credit conditions to explain aggregate business failure. They found that aggregate failure activity lags behind the volatility of interest rates, the cost of short-term credit (3 month T-bill) and the availability of short-term credit (free bank reserves). Lane and Schary (1989) explain the percentage of failed firms with 21 macroeconomic variables, the age of the firm and it's founding year. Most variables are not significantly different from zero, with the exception of the prime rate, the interest rate of a bond rated with credit risk level Baa lagged one period, and the change in private investments by nonresidentials multiplied by a dummy for young firms lagged one period. More recently, Hol (2001) models the losses of loans for banks in Norway related to the macroeconomic environment. Hol finds the relevant lags for GDP, the industrial production index, interest rates on loans and money supply M1 to explain the Norwegian losses on loans. I will use this model to relate the influence of the macroeconomic environment on the bankruptcy prediction model of Westgaard and van der Wijst (2001). The macroeconomic explanatory variables used in this model will be further discussed in the data section.

There exist only a few papers that combine both the financial and the macroeconomic information available to predict bankruptcy of firms. Cressy (1992) has focused on macroeconomic effects on the prediction of bankruptcy of small firms. It differs from this paper as it includes year dummies to proxy the macroeconomic environment whereas I include macroeconomic variables directly. Including year dummies could catch the effect of not only the macroeconomic environment, but also possible yearly trends in other financial variables. Burn and Redwood (2003) use both information on company accounts and the overall economic condition to explain the probability of default. These measures include profitability, interest cover, capital gearing, liquidity, company size, industry and subsidiary dummies and the growth of GDP. In Duffie and Singleton (2003, chapter 3) the default rates of speculative grade debt is found to be negatively correlated with GDP in 1983-1997, especially in the 1990-1991 recession, though only a small positive correlation is found in the decade before. In Benito et al. (2004) real GDP growth and interest costs of debt are significant additional predictors of a firm's probability to default for Spanish firms.

Many different variables are found to be significant in predicting bankruptcy under different circumstances. The most common are production (GDP), the monetary side (M, an interest rate or CPI) and variables like unemployment and stock indices. Finally, one can see from Table 1 that these empirical studies are mostly performed on US data using different time periods.

Table 1: Overview empirical studies where the response variable bankruptcy is explained with macroeconomic variables

Paper	Country	Time period
Altman (1971)	US	1947 - 1970
Rose et al. (1982)	US	1970 - 1980
Altman (1983)	US	1951 - 1978
Levy and Bar-Niv (1987)	US	1947 - 1982
Melicher and Hearth (1988)	US	1950 - 1983
Lane and Schary (1989)	US	1950 - 1987
Hol (2001)	Norway	1991 - 1999
Burn and Redwood (2003)	UK	1991 - 2001
Carling et al. (2004)	Sweden	1994 - 2000
Benito et al. (2004)	Spain	1984 - 2001

3 Data

The data used in this study are taken from two databases. The accounting data come from the Dun and Bradstreet register that is comprised of all Norwegian limited liability companies (AS Companies). This database is very large (over 100,000 companies per year) and several selections were made to obtain a manageable data set. First, the period was restricted with 1995-2000, as there is detailed accounting data available from 1995. Second, non-operative companies, i.e. companies with total assets or total sales less than 100,000 Norwegian kroner (approximately $15,000), are excluded from our analysis, effectively excluding non-operative companies established for e.g. tax advantages only. Third, all companies in the financial sector are excluded. In this register also the dates are given for all companies that defaulted. The sample contains 483 firms that went bankrupt in 2001 and handed in their financial statements for 2000. These statements are taken from the preceding year, since firms that fail are not likely to have contemporary data. A ten times larger random sample of non-bankrupt companies was selected, resulting in 3,459 firms after selection. Similar numbers for the other years are 148 and 3,596 (1995), 345 and 3,488 (1996), 344 and 2,344 (1997), 456 and 3,052 (1998) and 475 and 3,013 (1999).

The macroeconomic data stem from Ecowin. The measure of GDP used is GDP at constant market prices. The GDP gap is calculated by Statistics Norway with a Hodrick-Prescott (1997) filter with a parameter of 40,000. The Basel committee has asked for minimum 5 years of data to base models on, though even this could be too short depending on the size of the business cycle. In the time period which is available for testing in this paper, the GDP gap increases from below trend (recovery) to above trend (expansion). As such a part of a whole cycle is captured (see Figure 1), though I lack data from the firms in a cyclical downturn. The industrial production index is an index from the manufacturing industry, which excludes oil and gas industry. The money supply M1 is deflated with CPI. Figures 1 to 5 show the behavior and some descriptive statistics of the main explanatory variables used in this paper. For each figure, I show the mean value of the financial ratios for the bankrupt and non-bankrupt firms. The financial ratios are rather stable over the time sample. For all variables the hypothesis of stationary cannot be rejected, either at level (default, GDP gap, interest rate, all financial ratios) or at the first difference (GDP, industrial production index, M1).

4 Model specification

Over the last 30-40 years, a plethora of empirical bankruptcy prediction models have been developed. At the end of the 60's researchers started to use discriminant analysis pioneered by the work of Altman (1968). Later in the 70's linear probability models and logit/probit models were applied (see Martin, 1977; Ohlson, 1980). In the mid 80's, along with increased computer power, the use of mathematical programming techniques arose (see e.g. Frydman et al., 1985). In the 90's more advanced multinomial logit models appeared (Johnsen and Melicher, 1994). At the end of the 90's there was also the development of advanced econometric techniques using the time series models and logit models integrated (Wilson, 1997). I use a logit approach with time series data to model the default probability of a firm. A further discussion on logit models can be found in e.g. Greene (1993). The response variable in this study is a dummy for bankruptcy. The variables used to identify the failing firms are based on two previous studies, which have studied Norwegian data with microeconomic financial ratios (Westgaard and van der Wijst, 2001) or with macroeconomic variables (Hol, 2001).

The information can be divided into three main groups: financial ratios, firm characteristics and macroeconomic variables.

$$(1) \qquad P[Y_t = 1] = F(a + \sum_i b_i XF_{ti} + \sum_j c_i FC_{tj} \sum_k d_k XM_{tk}$$

where $F(x_t) = \frac{1}{1+\exp(-x_t)}$. This implicates that the probability for a firm Y to go bankrupt at a certain time t is given by the logistic distribution function which argument is a linear function of a constant, some financial explanatory variables (XF), some firm characteristics (FC) and some macroeconomic explanatory variables (XM).

The financial variables in empirical bankruptcy models should according to Westgaard and van der Wijst (2001) relate to the properties of the cash flow in combination with firm value after the current period and debt obligations. Four financial ratios are used to predict bankruptcy. These include the theory-based variables cash flow to debt, financial coverage to financial costs, liquidity to current debt and solidity to total capital. Cash flow (operating income plus depreciation) over total debt gives a direct measurement of the cash inflows in relation to the size of the outstanding debt obligations. Elbowroom in debt servicing is reflected in the financial coverage ratio. The last two financial ratios represent the value of the firm on short and long-term basis. I expect these variables to be negatively related to the probability of default as they reflect income or value over debt obligations.

Firm characteristics included in the model are the size of the firm and industry type. Firm size (here measured in total assets) is generally expected to be positively related to less volatile cash flows, and thus lower default probabilities. Dummies for 'real estate and services' (sector 7 in Dun and Bradstreet) and 'hotels and restaurants' (sector 5) are included to capture the specific effect associated with these industries. The real estate sector indicates in Norway an industry with a (relative to the other sectors) low default frequency, while the hotel sector is at the opposite end of the scale of default frequencies.

Hol (2001) analyses the losses of loans in Norwegian banks based on macro-economic variables, which indicate the business cycle based on the monetary, supply, save/investment theories and coincident/leading variables from previous research. Four macroeconomic variables are used to explain losses in loans; these I will use to explain default probability. There is a lag in the effect of the business cycle and macroeconomic environment on the default probability. The appropriate lags were found with the Akaike information criterion. The variables are the change in the money supply (M1) lagged 7 quarters, change in the production index lagged 6 quarters, the logarithm of the gross domestic product (GDP) lagged 8 quarters and the interest rate lagged 2 quarters. In addition the gap to GDP trend is included, which can be used as an indicator for demand conditions (Carling et al., 2004) and thus affect the default risk. The relative growth of GDP, the GDP gap and the industrial production index indicate the well being of the economy, thus a negative relation is expected. The sign for the money supply M1 and interest rates on loans are uncertain, however. Using a mechanism like the IS-LM model, more money supply will affect the interest rate negatively, increasing the spending rate and the well being of the economy positively. On the other hand, low interest rates induce firms to invest in new projects rather than repaying the outstanding debts. This possibly increases the probability of default.

The three groups of proxy variables combined will be used to estimate the probability of default in the next section.

5 Empirical results

To highlight how the macroeconomic variables contribute to default risk, I present 1) the results of the model with accounting ratios and firm characteristics, 2) the same model extended with year dummies as an initial indication of the business cycle, and 3) the model with macroeconomic variables and financial variables, in Tables 2 to 6.

Table 2: Financial variables model

Variable	Estimate	t-value
constant	0.10	0.63
cashdebt	-0.07***	-6.13
financov	-0.001***	-5.59
liquid	-0.22***	-7.58)
solidit	-0.75***	-18.30
size	-0.21***	-11.30
dummy hotel	0.13**	2.44
dummy real estate	-0.63***	-8.78
pseudo-R^2	0.13	

Note: ***/** means significant at the 1/5 percent level

Table 3: Actual and predicted bankruptcies for the financial model

financial	non-bankrupt	bankrupt	sum actual
non-bankrupt	16870	163	17033
bankrupt	2028	156	2184
sum predicted	18898	319	

With exception of the intercept, all the coefficients of the microeconomic model in Table 2 are significantly different from zero at the 5 percent level.

Similar to Westgaard and van der Wijst (2001) the estimates for the financial ratios cash flow to debt, financial coverage to financial costs, liquidity to current debt and solidity to total capital are negative. If these four financial variables are high, this reduces the probability to default. Also the firm characteristic size is significantly negative; small firms are more likely to fail than large ones. The estimated coefficients for the two sector dummies imply that firms in the hotel and restaurant sector are more likely to default than those in other industries, while the opposite is found for firms in the real estate sector. The default probability decreases when firms belong to the latter sector. Thus, when I look at firm data, firms that are more likely to default are characterized by a lower cash flow to debt, financial coverage, a worse liquidity and solidity and a smaller size. As a measure for goodness of fit the likelihood ratio (pseudo) R^2. This statistic indicates the proportional reduction in the absolute value of the loglikelihood, where the absolute value of the loglikelihood - the quantity being minimized to select the model parameters - is taken as a measure of variation (Menard, 2001). It is not analogous to the R^2 in a linear regression model, and it is more usual to look at the table of predicted values (see Table 3) where the actual and predicted values for the financial models are given. Minimizing the Type 1 and Type 2 errors in this table is the most important test of the model, i.e. classifying bankrupt firms as non-bankrupt and classifying non-bankrupt firms as bankrupt. Here 163 of the 17,033 firms are predicted to go bankrupt when they actual were non-bankrupt, while 2,028 of the 2,184 firms that actually went bankrupt were predicted to be healthy with the financial model. Obviously, these values can be improved, and the variables used in Table 2 give only a partial explanation of the probability of default.

As a first extension of the microeconomic model some studies, i.a. Cressy

(1992) and Benito et al. (2004), allow for the effect of the macroeconomic environment by including year dummies. These year dummies are included to proxy the impact of all possible relevant variables. The effect of the year dummies on the microeconomic model can be seen in Table 4. All financial variables are still significant and negative. The year dummies themselves are significantly different from zero at the 1 percent level and increase the pseudo-R^2 to 15 percent. The number of firms classified incorrectly as bankrupt increases slightly to 171, while the number of firms classified incorrectly as healthy decreases slightly to 1,989, see Table 5. The year dummies increase the explanatory power of the financial model somewhat. However, including dummies is not very useful for forecasting. Furthermore, year dummy vari- ables could indicate not only the macroeconomic fluctuations, but also some structural yearly features of microeconomic variables. Therefore, I replace the year dummies with several potentially relevant macroeconomic variables proposed by Hol (2001).

Table 4: Financial variables model and year dummies

Variable	Estimate	t-value
constant	-0.95***	-5.20
cashdebt	-0.07***	-5.89
financov	-0.001***	-5.45
liquid	-0.22***	-7.63
solidit	-0.75***	-18.10
size	-0.24***	-12.00
dummy hotel	0.14**	2.59
dummy real estate	-0.62***	-8.51
1996	0.96***	8.73
1997	1.41***	12.70
1998	1.41***	13.20
1999	1.50***	14.20
2000	1.39***	13.10
pseudo-R^2	0.15	

Note: ***/** means significant at the 1/5 percent level

Table 5: Actual and predicted bankruptcies for the financial and time dummies model

financial and year dummies	non-bankrupt	bankrupt	sum actual
non-bankrupt	16862	171	17033
bankrupt	1989	195	2184
sum predicted	18851	366	

The results of the full model with both macro and microeconomic variables are presented in Table 6. Three of the five macroeconomic variables are clearly significantly different from zero. The GDP gap and the industrial production index have a significantly negative influence on the probability of default. In addition the monetary supply M1 has a significant positive effect. Clearly, the change in GDP is not informative when the GDP gap is included. Including the macroeconomic variables has a large effect on the significance of the financial variables compared to including year dummies. Two of the four financial ratios, cash flow to debt and financial coverage, become insignificant in explaining the default probability. The other financial variables stay significant with the expected sign. The sector dummies remain stable as well, but also become insignificantly different from zero. The addition of the macroeconomic variables increases the pseudo-R^2 to over 90 percent indicating that the added explanatory variables increase the predictive ability of the model.

The most common way of interpreting the coefficients in a logit model is converting them to odds, i.e. the ratio of the probability that the firm will default to the probability that it is healthy, by taking the exponent of the estimates. I will discuss only the effect of the significant variables. If the liquidity and solidity of a firm increase by one unit, then the odds will decrease by around 0.86, while an increase in size by one unit has a smaller effect on the odds (around 0.61). This is an intuitive result; larger firms that have more liquidity and solidity are more likely not to go bankrupt. Furthermore, an increase in the money supply M1 increases the odds by around 5, while a better economic environment indicated by a larger GDP-gap or an increase in the industrial production index decreases the odds with around 0.53. Also the interest rate decreases the odds, but less with around 0.16. Thus an increase in the money supply has a larger effect on the odds than the other variables. The combined intuition of the macroeconomic variables is that a tighter monetary situation decreases the odds, while a better macroeconomic environment decreases the odds. More firms are likely to be profitable in such an environment.

Even though the data series available in this paper is too short to cover an entire business cycle, these aggregate variables contribute to explain- ing default probability; decreasing both Type-I and Type-2 errors in classification. The number of firms classified wrongly as bankrupt is totally avoided, while the number of incorrectly classified as non-bankrupt decreases to 29. The predictive ability of a default probability model is thus improved by including information on the business cycle, see also Table 7.

6 Conclusions

In this paper I have constructed a model to explain the bankruptcy of non–financial firms based on both financial ratios and the influence of the business cycle. Around 19,000 observations for bankrupt and non-bankrupt firms over a recovery and expansion in Norway during the late 1990's are used. In the combined model the liquidity, solidity and size of the firm remain significant predictors of bankruptcy, while the cash flow and financial coverage loose

Table 6: Financial and macro variables model

Variable	Estimate	t-value
constant	36.66***	4.46
cashdebt	0.02	1.50
financov	-0.0003	-0.59
liquid	-0.15***	-2.41
solidit	-0.14***	-2.87
size	-0.49***	-3.17
Δgdp	0.82	0.91
gdp gap	-0.63***	-3.37
ipx	-0.63***	-5.65
M1	1.59***	3.59
interest	-1.81**	-2.75
dummy hotel	0.20	0.48
dummy real estate	-0.62	-0.48
pseudo-R^2	0.97	

Note: ***/** means significant at the 1/5 percent level

Table 7: Actual and predicted bankruptcies for the financial and macrovariables model

macro and financial	non-bankrupt	bankrupt	sum actual
non-bankrupt	17033	0	17033
bankrupt	29	2155	2184
sum predicted	17062	2155	

power compared to the model with financial variables only. The GDP gap, an industrial production index and the money supply M1 are significant additional predictors of the bankruptcy probability. Controlling for firm-level characteristics, a firm is more likely to fail during when the gross domestic product is below trend, than when it is above. Interestingly, the growth of the economic activity is not significant in explaining the default probability. The use of this model can enhance the possibility to identify failing firms, which is one of the main concerns in financial risk management. It would be interesting to apply this model to predict default probability with data over a whole or several business cycles in future work.

7 References

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8 Appendix

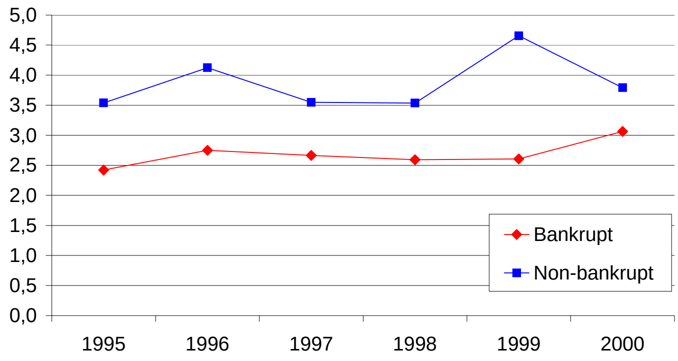

Figure 1: Mean cash/debt for bankrupt and non-bankrupt firms.

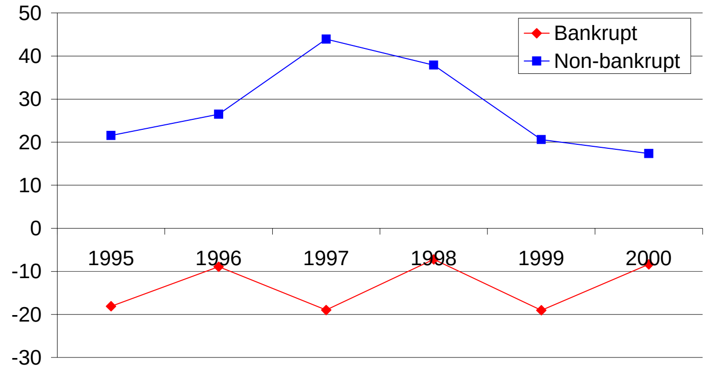

Figure 2: Mean financial coverage for bankrupt and non-bankrupt firms.

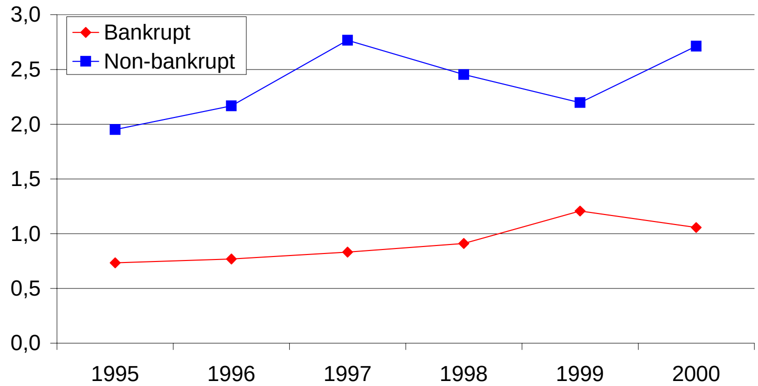

Figure 3: Mean liquidity for bankrupt and non-bankrupt firms.

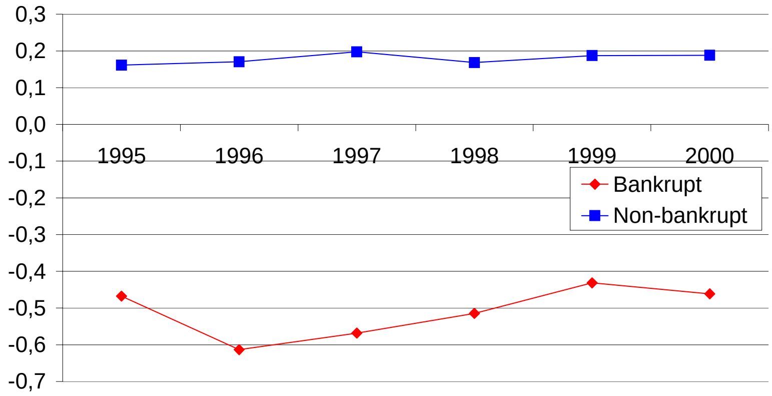

Figure 4: Mean solidity for bankrupt and non-bankrupt firms.

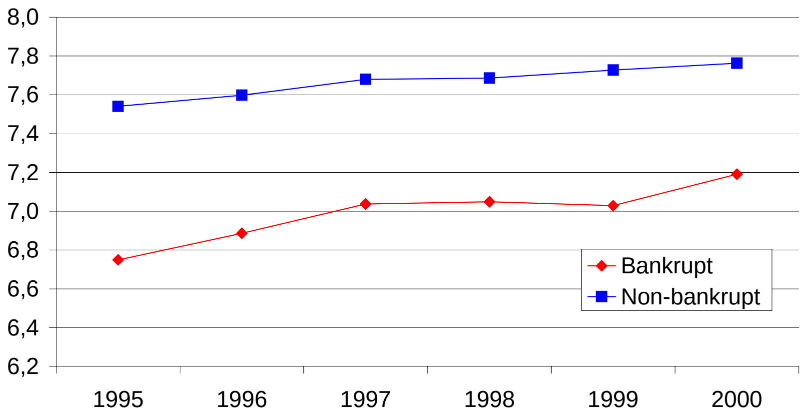

Figure 5: Mean size for bankrupt and non-bankrupt firms.

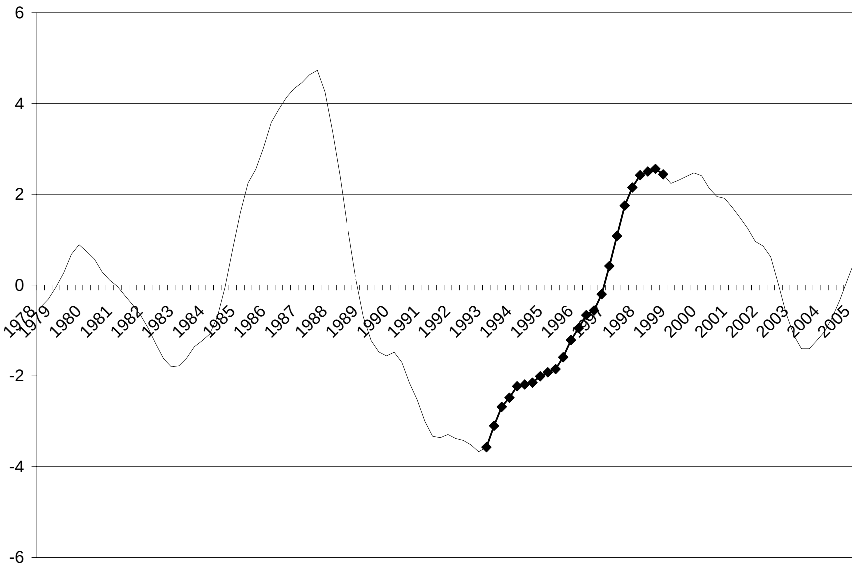

Figure 6: Gross domestic product gap.

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