ON THE DETERMINANTS OF INDUSTRIAL FIRM FAILURE IN THE UK AND RUSSIA IN THE 1990s

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Abstract
Based on data for corporate insolvency in Russia for 1995-96, a model of failure risk is developed using the familiar logit estimator. The sample size is controlled using the bootstrap to provide alternative estimates of model statistics and by comparison with a similar random sample drawn for the UK over the recession years 1990-91. It has been common approach to apply empirical predictors for the UK and USA to Russian data, which would appear poor practice in the context of an economy in transition. The model for Russia indicates that profitability is the dominant predictor as compared with gearing and liquidity for the UK. In the context of softer budget constraints and the common use of barter in Russian payments, the results suggest that policy makers and practitioners should pay specific attention to the profit position of companies.

JEL Codes: G33

Keywords: Company Failure Risk, Russian Transition, Small Sample, Logit, Bootstrap

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ON THE DETERMINANTS OF INDUSTRIAL FIRM FAILURE IN THE UK AND RUSSIA IN THE 1990s

1. Introduction

In this paper we investigate the determinants of corporate failure risk for UK and Russian industrial companies, using public accounts for the 1990s. We use binomial logit to explain corporate failure following previous UK studies by Peel, Peel and Pope (1986) and Keasey and McGuinness (1990). We examine the ability of ratios from Russian Company accounts to predict company failure, and then explain the differences in accounting predictors for the transitional Russian economy as compared with the UK. At the policy level, there are two obvious reasons for this comparison. Firstly, an increasing number of western businesses have not only decided to export to Russia, but also to set up joint ventures with Russian partners or establish subsidiaries with associated financial linkages. However, foreign companies entering the Russian market face different economic and commercial risks, which are likely to be reduced by knowledge of the key determinants of corporate failure and their difference from the predictors of bankruptcy in the West. Secondly, given the potential severity of the economic and social consequences of a sharp rise in company failures, knowledge of the appropriate failure risk predictors might be of practical use to governmental bodies in Russia, and international agencies providing economic, financial and technical assistance. Early prediction of company distress would provide valuable time for a reassessment of the direction of subsidies or financial restructuring.

For studies of the UK, measures of profitability, financial risk (gearing), turnover (activity) and liquidity are often used. However, the state of transition has placed the Russian economy in a very different position. Developments in the transition economics literature have highlighted soft budget constraints and barter transactions in the Russian corporate sector (Schaffer, 1998; Commander and Mumssen, 1998). Furthermore, the state has been politically sensitive to failure and unemployment, which has forced governments to view debt and insolvency in a more flexible way. Hence, enterprise size is a controlling factor, while financial distress will be less sensitive to measures of indebtedness and liquidity, and much more dependent on profitability and turnover. Irrespective of the true importance of such ratios, policy makers and financial analysts should be aware of their poor predictive power. Even so, the ratios selected are based on primary sources, they are used to assess failure risk and they are representative of the statutory financial accounts of the company.

In Russia, corporate bankruptcy is a relatively new phenomenon, as the legal provision for that exit mechanism only became available from 1992. To permit robust conclusions based on a sample of 48 Russian joint stock companies, a special research strategy is adopted. We indirectly assess the model's usefulness and the informational content of Russian data by imposing similar "experimental" restrictions on a parallel study of the UK. In the UK case, we can compare the obtained empirical determinants of failure with the results of existing studies, whereas similar empirical work does not currently exist for Russia.[1] Hence, bootstrap replications were used to validate the Russian model and similar results obtained for the UK. We construct bootstrap confidence intervals for the estimated logit parameters, using the re-sampling scheme in Adkins (1990). Then we assess classificatory accuracy of the models for the range of cut-off values (Ohlson, 1980) and we provide alternative estimates of the downward bias of the apparent error rate using the formula of Efron (1986).

In section 2 we sketch the background relevant to the specific micro and macroeconomic conditions, in which a Russian industrial firm operates, and specify hypotheses on Russian Company failure. Section 3 outlines sample design and methodology. The empirical results follow in section 4. In section 5 we offer our conclusions.

2. What causes Russian Enterprise to Fail: Hypotheses

The defining characteristic of industrial company performance in post-communist Russia appears to be a dramatic growth of loss-making and illiquid enterprises. According to Goskomstat Yearbook (1997), in a single calendar year between 1995 and 1996, the share of enterprises reporting net losses rapidly increased from 26.4% to 43.5%; a large proportion of large and medium-sized firms in the economy. That was accompanied by a sizeable increase in the accumulation of enterprise arrears.

For the enterprise, financial distress can be broadly defined as an inability to pay debts as they come due, which is caused by (i) lack of cash flow or liquid assets and (ii) absence of the new inflow of external financing. The presence of debt in capital structure is the key determinant of failure triggered by debt default, which is influenced by insufficiency of liquid assets (Davis, 1992). At the firm specific level, business failure is linked to inefficiency and the firm's decisions on entry, output, and exit; the firm's capital structure; and the market structure in which it operates (Lambrecht, 1999). In market economies, illiquid firms are restructured or exit the market; corporate bankruptcy is one such exit.

In Russia the link between distress and exit is tempered by the existence of soft budget constraints (Kornai, 1980). The soft budget constraint is a subsidy paid *ex post* to loss-making firms to guarantee their survival regardless of whether they are economically viable (Schaffer, 1998).

After the reforms of the early 1990s, the pressure of product market shocks, removal of product related subsidies and directed credit, limited lending by banks[2], and heavy taxation appeared to eliminate the soft budget constraint. Recent research has shown that liquidity is created and injected into the enterprise sector by the practice of tax arrears and deferrals to the state[3], and quasi-fiscal institutions like utilities and railways. Soft credits are reallocated across the enterprise sector by a complex system of non-monetary transactions and intermediaries, designed to avoid the banking system altogether; failing firms are indirectly subsidised. Commander and Mumssen (1998) argue that the substitution of indirect credit from the state and workers for bank credit blurs the true position of company profitability and, consequently, short-term liquidity and long-term solvency. The existence of barter, suggesting less reliance on money for transactions, implicit subsidies, and the dearth of short-term finance, gives grounds for the following three hypotheses:

H1: Liquidity does not discriminate between failed and non-failed Russian enterprises.
H2: Gearing does not discriminate between failed and non-failed Russian enterprises.
H3: Russian enterprises will fail because of relatively low turnover and profitability.

In market economies, the firm with the higher debt will represent a poor bankruptcy risk. However, in Russia, long-term debt does not play a significant role in company capital structure, and soft budget constraints imply that short-term debt is not associated with the disciplining of management of poorly performing companies.

The general financial performance of a company may be assessed by its ability to generate income. In Russia, for an enterprise to continue trading, it must be able to trade its goods and services at implicit prices that exceed the costs of production. In an economy where barter is important, profitability is expected to be a significant predictor of failure. In studies of the UK and US, turnover of assets has been observed to have a positive effect on failure, which can be linked to over-trading and rapid expansion.[4] The above argument is consistent with developed financial markets where credit is readily available, whereas for Russia the more direct association between turnover and efficiency implies a negative relationship with failure.

Next we investigate empirically the relationship between the risk of insolvency and the accounting variables. To better interpret the results from the Russian model we contrast them with a similar sized study for the UK.

3. Sample Design and Methodology

According to Altman (1982), existing empirical research shows that public accounts ratios contain sufficient information for *ex-ante* failure prediction, because in almost all cases the fundamental business distress problems lie within the firm. Accounting ratios capture and quantify both the unique financial characteristics of the specific firm (Altman, 1982), and macroeconomic pressures on the corporate sector. Most studies of the UK (Taffler, 1982) have concentrated on the problem of classification based purely on public accounting information. The empirical results due to Peel and Wilson (1989), Keasey and McGuinness (1990), Keasey, McGuinness and Short (1990) and Dunne and Hughes (1994) suggest that profitability, size, leverage and turnover explain failure.[5]

However, any analysis of Russian firms may well depend on different types of information. In the present study, a failed Russian company is an industrial enterprise, organised on a joint stock basis and declared insolvent in 1996 or 1997 by the courts of arbitration. The state of legal bankruptcy is often used as a proxy for business failure (e.g., Goudie and Meeks, 1991; Taffler, 1995). The analysis is based on information observable from statutory financial statements. As publicly available records began in 1995, accounting measures were calculated from end of year financial accounts for 1995 and 1996. The small sample size for Russian companies imposes a constraint on empirical modelling. Initially, in order to provide a desirable solution as to parameter stability tests, we examine predictive accuracy and explanatory power of the empirical model in an out-of-sample forecasting exercise. Available data points were split into an equal-share, training sample of 40 companies with accounts for 1995, and a holdout sample, that contains 1 insolvent and 7 solvent firms with reports for 1996.[6] Not altogether surprisingly a 6-variable model estimated for only 40 observations was overfitted as it misclassifed holdout firms, thus failing to provide an appropriate inference as to

Russian company failure determinants. We do not report the results for this model here.[7] In an attempt to take into account all available information, we utilised in the final analysis the pooled sample containing 21 insolvent companies and 27 solvent firms. A breakdown of companies by economic sector shows that manufacturing firms prevail, with approximately 74% of non-failed companies and 86% of failed firms.

For the UK, company failure occurs when the firm is placed on a formal insolvency regime: administrative receivership, or administration, or winding-up. Failed companies have been taken from various editions of the London Stock Exchange Official Yearbook, and non-failed companies have been selected at random from the *DATASTREAM* database list of quoted industrial companies; accounting information is from *DATASTREAM*. The UK sample is designed to achieve the "closest possible" correspondence to the Russian data set in terms of sample size, proportions of failed and non-failed companies and macroeconomic environment. Accounts of UK companies were drawn from data for 1990-91. Twenty failed companies chosen for the estimation sample published their last accounts in either 1990 or 1991, and similarly, accounts of twenty non-failed companies were obtained for the same years. To determine out-of-sample predictive performance, 25 random holdout samples, each including 1 failed and 7 non-failed firms, where drawn from a larger sample for the years 1992-94. As for the sectoral composition, 50% of non-failed firms and 45% of failed firms in the randomised, training sample came from manufacturing.

For multivariate logit, the accounting ratios and size variable, are contained in a vector $\mathbf{x}$. The linear relationship amongst the independent variables ($\beta'\mathbf{x}$) is bounded to yield predictions in the range [0,1] via the logistic function, which smoothes out extreme values:

$$prob(y_i = 1(Failure)) = \frac{e^{\beta'\mathbf{x}_i}}{1+e^{\beta'\mathbf{x}_i}} = \Lambda(\beta'\mathbf{x}_i). \quad (1)$$

Here y_i are observed by a sequence of 1 or 0 with probabilities $\hat{\pi}_i$ or $1-\hat{\pi}_i$. The maximum likelihood estimate of the parameter vector $\hat{\beta}$

gives estimates of $\hat{\pi}_i$ by substitution in (1) (Greene, 1997) and $\hat{\pi}_i$ is a prediction of the probability, that firm i with covariate vector $\mathbf{x}_i$ is likely to have failed.

Economic and financial theory does not provide a rigorous basis for selecting ratios gathered in **x,** the vector of covariates. Most studies address the selection problem by starting with the widest possible range of ratios and then allow good failure predictors to emerge from the data. Hamer (1983) demonstrates that error rates in distinguishing failed firms from non-failing firms are not affected by the choice variables as long as the ratios represent the major dimensions of financial analysis. For the UK, size measured by the log of net sales is added to 12 accounting ratios. Profitability is given by return on shareholders' equity, return on net fixed assets, and the pre-tax profit margin. Turnover is described by the ratio of net sales divided by the fixed assets, stock turnover, debtors turnover, and creditors turnover. Gearing is measured by capital gearing and income gearing, and common ratios are employed for liquidity: the working capital (current) ratio, the quick assets ratio, and the ratio of stock and work in progress to current liabilities.

For Russia, 12 accounting ratios[8] were selected, along with the log of total assets, to control for enterprise size. Profitability is measured by the return on long-term capital, return on net fixed assets and the pre-tax profit margin. Turnover (or activity) indicators include stock turnover, shareholders' funds turnover, and the ratio of sales to total assets. Gearing[9] is based on three ratios. Capital gearing is the sum of long-term debt and one-year borrowings, divided by the value of the total assets net of intangibles. Following Federal Insolvency Administration Materials (1994) and Astakhov (1996), we include cover for current assets out of the shareholders' funds, assuming all fixed assets have been equity financed. Finally, the ratio of total liabilities, divided by total assets, is considered. There is also a separate ratio of total debtors to total assets used in Russia to analyse assets structure. We also use two liquidity ratios: the ratio of quasi-cash assets defined as a sum of cash, short-term investments and debtors divided by short-term liabilities, and the current ratio.

The use value of the variables is judged by classificatory accuracy and the predictive (out-of-estimation-sample) power of the model as measured by prediction error. A prediction rule is used to decide whether a firm is failed ($\hat{\eta}_i = 1 \text{ if } \hat{\pi}_i > C_0$) or non-failed ($\hat{\eta}_i = 0 \text{ if } \hat{\pi}_i \leq C_0$) for some cut-off C_0. It is common to measure observed accuracy by the average "counting error", and, in the case when the model is applied to the estimation sample, the apparent error rate is:

$$\overline{err} = \#\{y_i \neq \hat{\eta}_i\}/n. \tag{2}$$

Because y was used for both constructing and assessing the prediction rule $\hat{\eta}$, $\overline{err}$ will usually be biased downwards: a new binary outcome might not be predicted, nearly as accurately by the old $\hat{\eta}$. We address the issue of the size of the sample by three different methods: a holdout sample, bootstrap procedures[10] and using the formula in Efron (1986) for approximating the bias in the apparent error rate. Efron's formulation is presented in the Appendix.

State-based (equal-share) sampling, when employed in conjunction with estimators and inference procedures that assume random sampling, yield biased estimates that understate the true error rate for predicting failed firms and overstate the true error rate in predicting healthy companies (Palepu, 1986). To take into account the bias introduced by the unbalanced sample, the cut-off probability C_0 can be adjusted using population priors (Greene, 1997). Cramer (1999) contends that to allow for unequal sample sizes in assessing the within-sample performance of the fitted model, the cutoff value reflecting the improvement of the obtained specification over the base-line model in predicting the outcome for the particular observation *i*, is a cutoff point which is set at the average of the estimated probability of the outcome $y_i = 1$ (or the failure state if the failure outcome is normalised).[11] The procedure advocated by Cramer, receives further support in Bayldon and Zafiris (1999), who examine the bias of disproportionate sampling and the consequences resulting from highly unequal sample proportions in company failure modelling. Bayldon and Zafiris argue that the cutoff probability that is equal to the sample frequency for the failure outcome, is the correct one to use in assessing the fit of the model, irrespective of population size, sample size and sampling rates. Obviously, this cutoff value is neutral with respect to relative misclassification costs, and may not be optimal for prediction in actual decisions. If the costs of misclassifying a failed company are higher than the costs of misclassifying a non-failed company, than the cutoff should be set lower than the average rate of failures in the sample. In the present study, we make no assumptions with regard to the prior probability of industrial firm insolvency or relative misclassification costs, and assess the predictive performance of logit models at various cutoff probability values ranging from 0.125 to 0.875.[12]

4. Empirical Results

The logit results for one year prior to failure for both countries are reported in Tables 1 and 2; comparison with the UK model provides a method of validating the results obtained for Russia. Starting with 13 covariates we eliminate variables by testing down via a sequence of Likelihood Ratio tests. Results for the UK model derived from 40 data points are reported in Table 1. The turnover ratio of net sales over the fixed assets has an ambiguous positive sign,[13] which could point to over-trading as a factor determining corporate failure, although this variable is insignificant. Three covariates are significant at the 5% level, with signs consistent with previous UK work. Lower profitability, higher gearing, and lower liquidity indicate an increased risk of failure.

Turning to classificatory and predictive power, both used as performance measures, then we find that the UK model performs comparatively well at correctly classifying observations in the training sample. Using different cut-off values, overall accuracy varies from 80.0% to 85.0% for the UK model (Panel B of Table 1). The UK model, based on 25 random holdouts of 1 failed and 7 solvent firms, appears to have some predictive power, as on average it correctly forecast from 56.5% to 84.8% of holdout firms. Support for this proposition comes from estimates based on Efron's formula for which the overall error rate bias varies from 2.9% to 16.2%. For direct comparison with the Russian study we also provide bootstrap estimates of prediction errors, based on 300 bootstrap samples. The downward bias in the overall error rate equals 4.6%, 5.5%, 7.0%, 6.3%, and 5.0% for cut-off probability values of 0.125, 0.25, 0.5, 0.75 and 0.875, respectively. The bootstrap estimates of the apparent error rate bias, shown at cut-off points lower than 0.75, are close to the values obtained from the Efron approximation. We can adjust the apparent error rate of the UK model by adding the estimated bias. Choosing the maximum values obtained from the bootstrap and the approximation, the improved estimates of the true overall error rate are 19.6%, 23.0%, 24.8%, 34.1% and 33.7%, corresponding to cut-off values of 0.125, 0.25, 0.5, 0.75 and 0.875, respectively. This assessment of the UK model overall accuracy is consistent with the results obtained from the holdout test when cut-off values of 0.25 and 0.5 are used. The important financial dimensions for distinguishing between failed and non-failed UK companies are profitability, measured by pre-tax profit margin, gearing proxied by capital gearing ratio, and liquidity given by the ratio of stock and work in progress to current liabilities. The results are remarkably similar to existing work for the UK both in terms of forecast performance and the determinants of failure (Alici, 1995; Taffler, 1995).

For the Russian model, liquidity and gearing are absent from the final specification, implying that they do not discriminate between failed and non-failed companies (*H1* and *H2*). The remaining ratios include the log of the total assets (significant at the 5% level), the pre-tax profit margin (significant at the 1% level), and a ratio of shareholders' funds turnover (significant at the 10% level). Negative coefficients are consistent with failure being associated with lower profitability (*H3*) and slower turnover. The coefficient on enterprise size, measured by the logarithm of total assets, implies that smaller firms are more likely to fail. Recall that larger firms provide a social safety net and so are able to bargain to obtain soft finance when there is a risk of failure. Large enterprises might also have easier access to short-term loans or may be able to avoid liquidity problems by arranging debt for equity swaps.

As no additional holdout observations were available to test the Russian model, we set bootstrap confidence intervals for the parameters, based on 5000 replications, constructed using the modified percentile method (Davidson and MacKinnon, 1993). Looking at the bootstrap results for Russia (Panel A in Table 2) we can see that the 90% confidence interval for pre-tax profit margin stresses the statistical significance of profitability in explaining company failure, though the 95% confidence interval indicates greater variation. Confidence intervals for the turnover ratio and the log of total assets say that their coefficients either closely approach or even include zero values, thus indicating a much weaker relation between the covariates and the event of failure. An interesting finding is that confidence intervals for the UK model (Panel A in Table 1) show a similar degree of variability.

We also use the bootstrap to provide a comparative measure of predictive performance. On the estimation sample, the correct classification rate for the Russian model varies from 75.0% to 89.6% (Panel B in Table 2). The bootstrap estimates of the downward bias in the apparent error rate range from 0.3% to 5.2%, whereas Efron's approximation yields higher values from 3.7% to 14.0%. When we correct for the bias in the apparent error rate, the estimated true error rate for the Russian model forms an interval of 20.0% to 32.7%, depending on the cut-off point. The rate of incorrect classification is similar to that for the UK, which is 19.6% to 33.7%. The Russian model validation on the basis of error rates obtained via bootstrapping and analytical approximation supports the conclusion that profitability, turnover, and company size are likely to be the key indicators of failure risk.

5. Conclusions

Failure prediction models appear to depend on profitability, gearing and liquidity for the UK and enterprise size, profitability, and turnover for Russia. Principles accepted in the UK literature on failure modelling were also applied to Russia. Given the small size and narrow time frame available for the Russian study, comparison with the UK was based on a similarly designed study. The empirical investigation of Russian enterprise failure was based on robust statistical techniques using logit analysis supplemented by the bootstrap. Estimation and validation results for Russia were statistically significant and did not reject the hypotheses that liquidity and leverage were unimportant in identifying failure in the period 1995-96, while profitability, size and turnover seemed important predictors. Profitability is the most robust predictor, while size in the context of the Russian case provides a shield against failure. The models demonstrated acceptable classification accuracy and small apparent error rate biases. This supports the use of models of Russian enterprise failure based on data from financial statements, to back-up more judgmental analysis. The UK model also performed well when compared with UK studies based on larger data sets.

The results for Russia provide support for the notion of soft budget constraints. In practice, accurate failure prediction is of use to exporters, to investors and owners of interests in Russia. The Russian government might also employ this methodology to calculate how sensitive the Russian enterprise sector might be to failure. Further, traditional failure risk measures based on UK and US data and variables do not appear appropriate in the Russian context for the 1990s.

Notes

1 To the best of our knowledge, no results from empirical work on corporate failure issues for Russia have been published, with the exception of one paper by Kasatkin (1995), who applied Z-score model (Altman, 1968) to corporate data from the Russian petroleum sector, however, the model's performance is not reported.

2 As Popov (1998) reports, by the end of 1996, total bank credit outstanding fell to about 10% of GDP while total long-term credit shrank to less than 1%. For the UK, the relative size of domestic bank credit was 125.7% of GDP in 1995.

3 Schaffer (1998) reports increased tax arrears in Russia from 1.5% of GDP to 6.5% in 1995, and 12.0% in 1996.

4 Geroski and Gregg (1996) explain that, in the early 1990s, UK company failure was caused by financial over-extension due to acquisition.

5 Work based on neural networks by Alici (1995), Tyree and Long (1995), and Wilson, Chong and Peel (1995) suggest similar predictors: profitability, liquidity, gearing, turnover, size and market value. Neural nets reveal slightly improved out-of-sample predictive accuracy (Fairclough and Hunter, 1998), but are not appropriate given the sample size.

6 The mix of failed and non-failed companies in the holdout resembles the population proportions.

7 See Hunter and Isachenkova (2000) for further details.

8 All Russian accounting ratios are unadjusted for inflation, as such adjustments require more detailed information on items from balance sheets and income statements. In 1996, the annual

inflation rate had fallen to 21.8% (Source: *Russian Economic Trends*, 23 September 1997).

9 We use here a broad meaning of gearing as a measure of a company's total indebtedness.

10 The method used is due to Adkins (1990).

11 Cramer (1999) considers the unavoidable asymmetry in the estimated by maximum likelihood within-sample probabilities $\hat{\pi}_i$ when a standard binary logit is fitted to a sample with the unequal shares of the two outcomes. The asymmetry is a consequence of creating a representative sample. If the company failure outcome is normalised, it follows that in the studies employing representative samples where the size of non-failed group is relatively large, the absolute inequality of sample proportions influences all the estimated probabilities downwards while higher sampling rates for the failure event influence the estimated probabilities for the failure state upwards.

12 Raising the cut-off value increase Type I errors of misclassifying a failed firm, whereas reducing the cut-off value increases Type II errors of misclassifying a non-failed firm.

13 A negative coefficient indicates that an increase in a ratio would reduce the probability of failure, and a positive coefficient suggests that an increase in the ratio increases the failure risk.

14 The pre-tax profit margin and capital gearing are expressed in percentages.

15 The Likelihood Ratio Index is defined as $LRI = 1 - \frac{\ln L(\hat{\beta})}{\ln L_0}$, where $\ln L(\hat{\beta})$ is the log-likelihood evaluated at the maximum and $\ln L_o$ is the corresponding log-likelihood of the base-line model with a constant only (see e.g. Greene (1997)).

16 This χ^2 statistic (Conover, 1971, pp. 141-154) tests whether there is a significant difference between the classification accuracy of a model and the naive model in which all firms classified as failed.

17 The UK holdout results are the averages for 25 samples randomly selected from data specific to year one prior to the event of failure, corresponding to the period of 1992-94. For a further discussion see Hunter and Isachenkova (2000).

TABLES

TABLE 1

Logit Results for UK Data, 1990-91 Estimation Period, State-Based Sample (n=40), One Year Prior to Failure

Panel A: Logit Model UK_L (n=40)

Financial Dimension Accounting Variable[14]	Coefficient	(two-tailed *p*-value of asymptotic *t*-statistic)	Bootstrap Confidence Intervals for a Coefficient, 5000 Replications: 90% Confidence Interval	95% Confidence Interval
Constant	-2.219	(0.247)	(-99.512, 12.608)	(-283.665, 60.942)
Profitability				
Pre-tax Profit Margin	-0.240	(0.022)	(-11.590, -0.065)	(-29.686, -0.061)
Turnover				
Turnover / Fixed Assets	0.350	(0.131)	(-0.286, 14.076)	(-0.041, 38.107)
Gearing				
Capital Gearing	0.083	(0.028)	(0.008, 3.477)	(0.008, 8.284)
Liquidity				
Stock & Work in Progress/ Current Liabilities	-7.473	(0.026)	(-340.736, -1.065)	(-842.846, -0.592)
Log-Likelihood at Convergence			-10.18	
χ^2 statistic of the log-likelihood ratio (*p*-value)			35.10 (0.000)	
Likelihood Ratio Index[15]			0.633	

*Panel B: **Classification and Predictive Ability**, percentage*					
Cut-off Value	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample					
Correct Classification					
Failed	100	95.0	85.0	65.0	65.0
Non-failed	70.0	70.0	85.0	95.0	100
Overall	85.0	82.5	85.0	80.0	82.5
χ^2 test for differences in probabilities[16]	21.54[a]	22.56[a]	32.81[a]	44.65[a]	48.49[a]
Overall Error Rate Bias Estimated by Efron's Formula	2.9	5.2	9.8	14.1	16.2
Bootstrap Estimates of the Expected Error Rate Bias, 300 Replications					
Failed	4.1	5.1	6.9	6.4	5.4
Non-failed	4.6	5.4	6.9	6.2	4.9
Overall	4.6	5.5	7.0	6.3	5.0
Holdout Sample[17]					
Correct Classification					
Failed	100	100	100	95.7	95.7
Non-failed	50.3	71.9	82.6	82.3	82.3
Overall	56.5	75.5	84.8	84.2	84.2
χ^2 test for differences in probabilities	3.82[†]	7.78[b]	7.78[b]	7.78[b]	7.78[b]

[a] Significant at 0.001, 2-tailed, [b] Significant at 0.05, 2-tailed, and [†] Insignificant.

TABLE 2

Logit Results for Russian Data, 1995-96 Estimation Period, 21 Failed and 27 Non-failed Companies (n=48), One Year Prior to Failure

*Panel A: **Logit Model** R_L (n=48)*			
		Bootstrap Confidence Intervals for a Coefficient, 5000 Replications	
Financial Dimension Accounting Variable	Coefficient (two-tailed *p*-value of asymptotic *t*-statistic)	90% Confidence Interval	95% Confidence Interval
Constant	3.116 (0.024)	(0.737, 8.804)	(0.205, 11.443)
Size			
Log Total Assets (Billions of Roubles)	-0.544 (0.049)	(-1.452, 0.086)	(-2.097, 0.044)
Profitability			
Pre-tax Profit Margin	-12.529 (0.007)	(-28.991, -5.765)	(-38.946, -4.877)
Turnover			
Shareholders' Funds Turnover	-0.680 (0.072)	(-2.710, -0.087)	(-4.060, -0.069)
Log-Likelihood at Convergence		-14.39	
χ^2 statistic of the log-likelihood ratio (*p*-value)		37.02 (0.000)	
Likelihood Ratio Index		0.563	

*Panel B: **Classification and Predictive Ability**, percentage*					
Cut-off Value	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample					
Correct Classification					
Failed	95.2	85.7	85.7	76.2	57.1
Non-failed	59.3	74.1	92.6	100	100
Overall	75.0	79.2	89.6	89.6	81.3
χ^2 test for differences in probabilities	23.76 [a]	35.00 [a]	49.72 [a]	59.95 [a]	65.45 [a]
Overall Error Rate Bias Estimated by Efron's Formula	3.7	6.1	9.6	12.6	14.0
Bootstrap Estimates of the Expected Error Rate Bias, 300 Replications					
Failed	6.3	5.1	1.8	0.5	0.7
Non-failed	4.0	3.2	0.7	0.1	0.1
Overall	5.2	4.2	1.3	0.3	0.5

[a] Significant at 0.001, 2-tailed.

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APPENDIX

Appendix: The Bootstrap Procedures and Efron's Formula

Estimates of the true prediction error are calculated by adding a bias correction to the apparent error rate. If the prediction error criterion is $Q[y_i, \hat{\eta}_i]$, then a bootstrap replication of the downward bias is calculated by the formula in Efron and Tibshirani (1993):

$$\omega_b^* = \frac{1}{n}\sum_{i=1}^{n} Q[y_i, \hat{\eta}^*(x_i)] - \frac{1}{n}\sum_{i=1}^{n} Q[y^*_i, \hat{\eta}^*(x_i)]. \tag{3}$$

The expected excess error rate is computed using the average of B bootstrap samples. Otherwise the analytic result from Efron (1986) can be used:

$$\omega(\hat{\pi}) = \frac{2}{n}\sum_{i=1}^{n} \hat{\pi}_i(1-\hat{\pi}_i)\phi\left(\frac{\hat{c}_i}{\sqrt{\hat{d}_i}}\right)\sqrt{\hat{d}_i}\,, \tag{4}$$

$\phi(z) = (2\pi)^{-1/2}\exp(-\frac{1}{2}z^2)$, $\hat{c}_i = \ln\left(\frac{C_0}{1-C_0}\right) - \hat{\beta}'\mathrm{x}_i$, $\hat{d}_i = \mathrm{x}'_i\hat{\Sigma}^{-1}\mathrm{x}_i$ and $\hat{\Sigma} \equiv \sum_{j=1}^{n}\hat{\pi}_j(1-\hat{\pi}_j)\mathrm{x}_j\mathrm{x}'_j$.