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Failure Risk:
a Comparative Study of UK and Russian Firms

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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 by the bootstrap estimates of model statistics and by comparison with a similar random sample drawn for the UK over recessionary years, 1990-91. It has been common to apply models for the UK and USA to Russian data but this 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.

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

JEL classification: G33

I. Introduction

In this paper we investigate the determinants of corporate failure risk for UK and Russian industrial companies, using recent public accounts data for the 1990s. In particular, by applying logit, we aim to examine the ability of ratios from Russian company accounts, to predict the event of company failure, and then explain the differences in accounting predictors of failure risk in 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 may find it desirable not only to export to Russia, but to set up joint ventures with Russian partners or establish subsidiaries with associated financial linkages. However, foreign companies entering the Russian market face economic and commercial risks and in this respect the nature of the key determinants of corporate failure in Russia and the way they differ from the predictors of bankruptcy risk in the West, might be useful for a better understanding of the evolving transitional economy. Secondly, given the potential severity of the economic and social consequences of a sharp rise in company failures, a comparative description of failure risk predictors might be of practical use to governmental bodies in Russia itself and, also, to 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.

A vast amount of research exists for western economies, which attempts to explain a discrete outcome of company failure using accounting data. According to Altman (1982), the empirical studies proved 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 and macroeconomic pressures on the corporate sector. For the UK, Taffler and Tisshaw (1977), Marais (1979), Taffler (1982) have concentrated on the problem of classification based purely on public accounts information. A typical paper by Taffler (1995) describes an operational model using Z-score, which provides true *ex ante* predictive ability based on a one year forecasting horizon. The four preselected terms in the scoring function, reflect profitability, working capital, financial risk (gearing), and liquidity, measured by: pre-tax profit over current liabilities, current assets over total liabilities, current liabilities over total assets, and no-credit interval. Goudie (1987) and Goudie and Meeks (1991) use a discriminant model derived from the period 1960-74, as a final tier in the three-component macro-micro model of company failure, developed to link the probable effects of variations in the exchange rate and other exogenous variables upon the viability of individual companies. The discriminant model, classifying companies into survivors and failures on the basis of forecasted accounts, depends on five predictor-variables measuring profitability, liquidity, cash flow, income gearing, and capital gearing. Peel and Wilson (1989) employ binomial logit analysis, which provides a direct model for the predictive probabilities, and find that failed companies are characterised by smaller size expressed as a log of deflated total assets, higher leverage measured by the net worth over total assets, and lower turnover measured by sales over total liabilities. Keasey and McGuinness (1990) also utilise binomial logit and report that for their 1976-84 sample of UK companies, the three key dimensions important for explaining failure, include profitability measured by the pre-tax profit margin, turnover (activity) measured by the ratio of inventory over sales, and liquidity proxied by the ratio of current assets over current liabilities. Multinomial logit results from the same data set are given in Keasey, McGuinness and Short (1990), but the key predictors are similar to binomial logit with the addition of the cash to assets ratio. Fundamental dimensions of profitability, liquidity, gearing (financial risk), turnover (activity) along with measures of size and share price performance are reflected again in the ratios presented in more recent UK work by Alici (1995), Tyree and Long (1995), and Wilson, Chong and Peel (1995), who employ neural networks to classify the data. Such models reveal slightly improved within-sample and out-of-sample predictive accuracy when compared with conventional discriminant and logit models[1].

The economic and financial theory of company failure does not provide a rigorous basis for selecting particular ratios, which themselves relate to unobservables and yield imperfect proxies of the interrelated features generating the firm's financial profile. As a result, empirical studies of failure prediction for industrial firms have examined sets of ratios viewed as being important in explaining financial health. Hamer (1993) demonstrates that there is no significant difference in the reported error rates which can be attributed to differences in the variable sets as long as the sets of ratios are comprehensive and represent the major dimensions of financial structure of the firm. No dominant or unique ratio set with respect to corporate performance exists in the literature on failure modelling. Furthermore, most studies, to address the selection problem have started with the widest possible range of ratios and then allowed good failure predictors to emerge from the analysis. The usefulness of the resulting model covariates as failure risk determinants is judged by classificatory accuracy and predictive (out-of-estimation-sample) power of the model as measured by prediction error. A similar, but more subtle risk exists when the non-parametric estimates implicit in neural networks are used (Fairclough and Hunter (1998)).

[1] For instance, Alici (1995) reports that for the neural networks, the overall error rate obtained from the holdout sample was in the range from 26 to 30.1 per cent as compared to the higher error rates of the discriminant model and the logit, where 35 and

Here, in our comparative study of UK and Russian firms, we use explanatory variables suggested in the UK literature, that measure profitability, liquidity, financial risk (gearing), turnover (activity), and, in addition, include a control for company size. We utilise the much favoured binomial logit method to explain the event of corporate failure thus following the previous UK studies by Peel and Wilson (1989) and Keasey and McGuinness (1990). We find that the dimensions of liquidity and gearing are not effective in explaining failure for Russian companies, whereas the measures of profitability, size and turnover appear potentially to be robust predictors. Companies of smaller size, lower profitability and slower turnover are more likely to become bankrupt. The Russian results are remarkably consistent with recent developments in the transition economics literature, concerning soft budget constraints and the all pervasive barter transactions in the Russian corporate sector (see, e.g., Schaffer (1998), Commander and Mummsen (1998)). Our logit results for UK firms indicate the importance of profitability, gearing, and liquidity in explaining the event of failure, as one would expect from relevant UK research.

In Russia, corporate bankruptcy is a relatively new phenomenon as the legal provision for that "classical" (Hoshi (1998)) exit mechanism only became available since 1992[2]. It follows that the empirical modelling of failure risk is constrained by the availability of much needed representative data. To permit robust conclusions based on a sample of 48 Russian joint stock companies, a special research strategy is adopted. We indirectly assess the models usefulness and informational content of Russian data by imposing similar "experimental" restrictions on a parallel analysis of UK company failure. A small random sample of UK companies that entered legal insolvency regimes in the recessionary years of the early 1990s, is employed to construct a model of failure and test its *ex ante* performance. In the UK case, we can compare the obtained empirical determinants of failure with the results of existing studies. In comparison, virtually no published empirical work on Russian company failure exist[3]. Therefore, in this study, numerical analysis, based on bootstrap simulations, is used to validate the Russian model. Firstly, in model assessment we construct bootstrap confidence intervals for model parameters, using the resampling scheme due to Adkins (1990). Secondly, aside from assessing by the bootstrap procedure the model classificatory accuracy for the

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34 per cent of firms were misclassified. Sample size precludes this form of analysis in this case.

[2] The first Insolvency Law was enacted in November 1992 and has been replaced by the 1997 Federal Law on Insolvency (Bankruptcy). The total of distressed enterprises recognised insolvent by arbitrage courts on the national level, grew from 50 in 1993 to 1,035 in 1996 (*Bulletin of the High Court of Arbitration* of the RF (1997)).

[3] 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 performance is not reported.

range of cutoff values[4], we also provide alternative estimates of the downward bias of the apparent error rate approximated by Efron's formula (Efron (1986)).

We proceed as follows. In Section II 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 III outlines sample design and methodology. A presentation and discussion of the empirical results follows in Section IV. In section V we offer our conclusions.

II. 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, just within one year from 1995 to 1996 the share of enterprises reporting net losses, rapidly increased from 26.4 to 43.5 per cent, constituting the majority of large and medium-sized firms in the economy. That was accompanied by large-order accumulation of enterprise arrears. In 1996, for companies in manufacturing and fuel and energy sectors, the total of accounts receivable reached 54 per cent of the total accounts payable which is two times more when compared with 1995. The phenomena of negative net profits, inability to meet debt obligations, arrears to trade creditors, non-payments of taxes and wages common to Russian enterprises in transition, are widely described in the literature on post-communist economies under the generic term of "enterprise bankruptcy" or "financial distress".

However, failure of Russian private industrial enterprise differs from company financial distress in market economies due to: (i) the different role of the state in economic activities and resource allocation and (ii) the existence in the market economies, of the functional financial systems and institutional, regulatory, and legal arrangements necessary for sustaining financial discipline in the corporate sector and for providing a mechanism for managing financial distress.

Enterprise financial distress can be broadly defined as 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, for instance, in the form of credit or equity. 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)). Failure is an interaction of various macro and micro factors, but at a firm specific level, business failure is linked to

[4] In providing errors for different cutoff values we follow Ohlson (1980).

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)). Major dimensions of company financial analysis capture that interaction. A lack of liquid funds can result from insufficient operating profits; overexpansion or overtrading; and from high gearing which together with the interest rate impinges upon the firm's ability to service debt. The firm may become illiquid or financially distressed even when it is seen as economically valuable, i.e. the firm covers its basic operating costs and has positive net trading profit which is independent of the firm's capital structure and could be measured by earnings before interest, profit tax and depreciation. In market economies, the number of illiquid firms is constrained by the existence of institutions facilitating their timely exit or financial restructuring, and corporate bankruptcy (insolvency) is one of a number of possible exit solutions. The financial literature often use a state of legal bankruptcy to proxy the highest level of financial distress or business failure (e.g., Goudie and Meeks (1991); Taffler (1995)) despite the fact that bankruptcy has a formal legal status, which may not correspond exactly with the economic state.

It is possible to analyse Russian enterprise distress using the concept of soft budget constraints due to Kornai (1980). The soft budget constraint is defined in the literature as a subsidy paid *ex post* typically by the paternalistic state to loss-making firms to guarantee their survival regardless of whether or not they are economically viable (Schaffer (1998)). The consequences of soft budget constraints are that (i) debt is not associated with the disciplining of the management of poorly performing firms, and (ii) performance *per se* is not a condition for the injection of finance. In contrast, in a market economy, the private firm faces hard budget constraints, which means that if it made losses it would not normally be rescued by the state.

In Russia, after the reforms of the early 1990s, the pressure of product market shocks, removal of product related subsidies and directed credit[5], very limited lending by banks[6], and heavy taxation[7] can be linked to the elimination of soft budget constraints for a private industrial enterprise. However, recent research provide an analytical framework and empirical evidence that liquidity is created and injected to the enterprise sector by the

[5] By the middle of 1998 directed credits have been phased out, and explicit subsidies to the enterprise sector diminished to no more than 2 per cent of GDP (Commander and Mumssen (1998)).

[6] As Popov (1998) reports, by the end of 1996, total bank credit outstanding fell to about 10 per cent of GDP while total long term credit shrank to less than 1 per cent. In contrast, in the UK the relative size of domestic bank credit was 125.7 per cent of GDP in 1995.

[7] In 1995 there were some 200 identified taxes in Russia, with the corporate profit tax in the range of 25-42 per cent and pension tax of 42 per cent *(OECD* Economic Surveys: 1997-98 (1998); *EBRD* Transition Report (1994); Shama and Merrell (1997)).

practice of tax arrears and deferrals to the state[8] and quasi-fiscal institutions like utilities and railways (Commander and Mumssen (1998), Gaddy and Ickes (1998), Grigoriev and Kuznetsov (1998), Schaffer (1998)). These soft credits are then reallocated across the enterprise sector by using a complex system of non-monetary transactions and intermediaries, designed to avoid the banking system altogether, which encompasses barter trade[9], promissory notes, in kind or late payments of wages, taxes, and utility bills. A financial transfer from the state to a continuing firm is not associated with its profitability and takes place where a flow of tax and utility arrears is not getting paid at all, or is being written off, or is being paid in kind at overvalued prices, which means that failing firms are being *ex post* indirectly subsidised, hence the soft budget constraint.[10] Commander and Mumssen (1998) argue that the substitution of indirect credit from the state and workers for bank credit and a thick non-cash market blur the true position of company profitability and, consequently, short-term liquidity and long-term solvency. Thus, economically unviable and technically insolvent (i.e. unable to pay their debt) enterprises obtain protection from market competition which is associated with considerable efficiency costs.

Soft financing and non-monetary instruments impact the conventional pattern the dimensions of financial analysis are related to company failure risk. Firstly, it is likely, that relevance of short-term liquidity characteristics which is centrally crucial for company survival in market economies, will be unhelpful in distinguishing between failed and non-failed Russian companies. Illiquidity and soft finance are not incompatible with enterprise survival. The firm may be able to repeat the operating cycle and generate revenues on the continuous basis with the lower level of cash reserves. Reduced flows of cash and non-monetary transacting limit usefulness of the analysis of the enterprise cash position. Although in financial statements debtors represent sales, they do not represent cash amounts due from customers. Similarly, creditors may not represent levels of future cash outflows. Therefore, both failed and non-failed enterprises are unlikely to have consistent differences concerning the levels of traditional liquidity ratios. Our first hypothesis is suggested in relation to corporate liquidity:
H1: the liquidity position will be irrelevant for the purpose of discriminating between the failed and non-failed Russian enterprises.

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[8] Schaffer (1998) reports growing stocks of tax arrears in Russia from 1.5 percent of GDP to 6.5 per cent in 1995, and 12.0 per cent of GDP in 1996.
[9] Hendley et al. (1999) refer to the *Russian Economic Barometer* and *World Bank-Russian Academy of Science* survey estimates that, between the first quarter of 1995 and 1997, barter increased as a share of industrial sales from under 20 per cent to 43 per cent, that indicates the thickness of barter market.
[10] The growth in tax arrears over the period 1995-98 implies an implicit fiscal annual subsidy to the enterprise sector of 5 per cent of GDP (IMF Staff Country Report No. 99/10 (1999)).

As far as capital structure is concerned, in market economies, debt imposes conditions that can trigger default, because the higher debt is expected to result in higher fixed financing costs and, therefore, in increased gearing and financial risk for the same level of variance with respect to the firm sales. The firm with the higher debt will represent a poor bankruptcy risk. On the other hand, the theory of debt and managerial ownership points to the role of high leverage in providing financial discipline on company managers and enhancing performance (e.g., Aghion and Bolton (1992), Jensen (1989 and 1991)). In today's Russia, the long-term debt does not play a significant role in company capital structure, and the short-term debt seem does not discipline management of poorly performing companies because of the existence of soft budget constraints. Therefore, there is unlikely to be a significant difference in levels of gearing, measured by debt ratios, between the failed and non-failed Russian firms. Our second hypothesis is proposed for examining the differences of the failed and non-failed Russian enterprises in terms of gearing measures:

H2: the gearing position will be irrelevant for the purpose of discriminating between failed and non-failed Russian enterprises.

Third, general financial performance of a company may be assessed by its ability to generate income. Eroded earning power of an enterprise entails inability to serve its debts. In order to continue trading an enterprise must be able to sell its goods and services at prices that exceed the costs of production, therefore profitability is expected to be a significant predictor of failure. Higher turnover (activity) of assets improves profitability and therefore should have a negative effect on the probability of failure. For a Russian firm a negative relation between turnover and failure is expected to overweigh an opposite impact of a highly unlikely condition of overtrading due to rapid expansion, as was the case for many UK firms that failed during the period of the early 1990s.

H3: A Russian enterprise will fail because of its relatively poor financial performance in terms of turnover and profitability.

In what follows we attempt to obtain a clearer, yet practical understanding of Russian company failure by investigating empirically the relationship between the risk of insolvency and the accounting variables. To allow for better interpreting of the Russian model we contrast the results with a similarly-sized study of UK company failure.

III. Sample Design and Methodology

The Russian Company Sample

A sampled, failed Russian company is an industrial enterprise, organised as a joint stock company, which was declared insolvent in 1996 or 1997 by courts of arbitration, that deal with insolvency cases. The definition of failure as legal insolvency allows us to obtain consistency in separating out the failing, loss-making companies, which despite being in payment arrears, continued trading in 1996-97, as compared with those enterprises, which had eventually failed in those two years. The overall sample contains 21 insolvent companies and 27 solvent firms. Insolvent companies were identified from the list of court insolvency cases published in 1996-97 in the periodical *The Bulletin of the High Court of Arbitration.* Selection criteria for including an insolvent firm in the sample were: firstly, the firm should be organised as a joint-stock company as those firms were likely to be of medium or large size, and play a dominant role in the Russian economy in terms of output and employment[11]; second, sectoral requirements were defined using the failed company list and their industrial classification codes available from the State Committee on Statistics. For consistency in accounts and similar experience of the transition process only manufacturing, retail, and construction companies were included. The non-failed company names were selected randomly from the relevant sectoral lists of joint-stock companies at the State Committee on Statistics. Russian companies breakdown by economic sector (Table A1 in the Appendix) shows that manufacturing firms prevail with approximately 75 per cent of non-failed companies and 85 per cent of failed firms. The selected Russian firms seem also to be representative of the population in terms of size measured by the number of employees: the mean and median values are 1034 and 850 employees for the failed group and 2216 and 1579, respectively, for the non-failed group.

The State Committee on Statistics was the source of statutory financial statements. Since publicly available records began in 1995, the analysis one year prior to legal insolvency is based on accounting measures calculated from 1995 and 1996 financial accounts of failed companies. Similarly, non-failed companies were assigned from the same time segment a "year" to collect financial statement information.

Available data points were initially split into an estimation and a holdout samples. There are 20 failed and 20 non-failed companies in the first estimation sample with data pertaining to 1995, and 1 insolvent and 7 solvent firms in the holdout with accounting data on 1996 results[12]. Additionally, in an attempt to take into account all available information, we utilised in the analysis the pooled sample of 48 observations.

The UK Company Sample

For the UK model we equate company failure with the event of the firm placed on a formal insolvency regime: administrative receivership, or administration, or winding-up. Names of failed companies have been taken from various editions of the London Stock Exchange Official YearBook. Names of non-failed companies were selected at random from the *Datastream* list of quoted industrials. Accounts items are also obtained from *Datastream*. In designing the UK estimation and holdout sample, we aim at achieving the "closest possible" similarity with the Russian data set in terms of sample size and proportions of failed and non-failed companies. We also take account of the timing frame as macroeconomic conditions of transitional depression have been influencing enterprise failure in Russia. For comparative purposes, we sample UK observations from the time period of a full blown recession. However, as there exists no universally accepted definition of a recession, in deciding on the years to sample UK observations from we look at unemployment rates. Firstly, employment and unemployment typically respond with a lag to changes in economic activities, and, secondly, according to *Datastream* figures, the years 1991-93 saw a steady increase in unemployment: unemployment rate was 8.0 per cent in 1991, 9.7 per cent in 1992, and 10.3 per cent in 1993. Thus, taking account for the one year lag, we determined the period 1990-91 from which accounts of UK companies are drawn. 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 are obtained for the same years.

Validation tests of the UK model are performed on 25 random holdout samples each including 1 failed and 7 non-failed firms to resemble the structure of the Russian holdout. Those holdouts pertain to years 1992-94. As for the sectoral composition, UK and Russian samples are somewhat similar: 50 per cent of non-failed firms and 45 per cent of failed firms in the randomised training sample, came from manufacturing (see Table A2 in the Appendix).

[11] At the time of gathering the data, none of the sampled open joint-stock companies was quoted on stock exchanges, thus, market based approaches for modelling Russian company failure (e.g., the use of stock prices to generate the measure of insolvency risk) could not be utilised.

[12] Financial year ends for Russian data were December 1995 and December 1996.

Independent Variables

We have selected for the analysis of Russian company failure a set of 12 accounting ratios[13] along with the log of total assets, to control for enterprise size. This combination represents a relatively wide variety of covariates to capture dimensions of enterprise financial structure. The profitability dimension is given by return on long-term capital, return on net fixed assets and pre-tax profit margin. Turnover (or activity) indicators include stock turnover, shareholders' funds turnover, and the ratio of sales to total assets. Gearing is proxied by three ratios: first, capital gearing obtained as a sum of long-term debt and one year borrowings, divided by the value of the total assets net of intangibles; second, we include a measure specific to the Russian practice of financial analysis[14], of the cover for current assets out of the shareholders' funds, (providing that all fixed assets have been equity financed); third, the ratio of the total liabilities divided by the total assets is considered. There also is a separate ratio of the total debtors divided by the total assets, which is used in Russia for the analysis of assets structure. Lastly, we utilise two liquidity ratios: the ratio of quasi-cash assets defined as a sum of cash, short-term investments and debtors divided by the short-term liabilities, and the current ratio.

For the UK sample of 40 companies we utilised the set of accounting ratios available from *Datastream* for quoted industrials. The set includes a size measure, which in the UK case is given by the log of net sales, and 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.

Statistical Model and Procedures for Assessing Predictive Ability

The phenomenon of company failure we seek to examine is discrete, and in this case the dependent variable describing outcomes is a binary response, which means that we equate the event of "failure" with 1 and the event of "non-failure" with 0. To model the dependence of the response and the covariate vector, logit is utilised in this paper - the non-linear estimator common in studies of company failure (e.g. Ohlson (1980), Zavgren (1985), Peel, Peel and Pope (1986), Keasey and McGuinness (1990)).

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[13] All Russian accounting ratios are unadjusted for inflation as such adjustments require more detailed information on items from balance sheets and profit and loss accounts. In 1996, the annual inflation rate had fallen to 21.8 per cent (Source: *Russian Economic Trends*, 23 September 1997).

[14] For instance, this measure is utilised in Federal Insolvency Administration Materials (1994), and in Astakhov (1996).

In the logit situation, we believe that a set of predictor-variables (accounting ratios), gathered in a vector $\mathbf{x}$, explains company failure, and we transform a linear combination of the independent variables $\beta'\mathbf{x}$ into a probability of failure using the logistic cumulative distribution function:

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

Here the y_i independently equal 1 or 0 with probabilities π_i or $1-\pi_i$. The maximum likelihood estimate of the parameter vector $\hat{\beta}$ gives estimates $\hat{\pi}_i$ by substitution in (1). The $\hat{\pi}_i$ is considered as predicting whether an observation with the covariate vector x_i will be failure or non-failure, by using the realised prediction rule $\hat{\eta}$:

$$\begin{aligned} \hat{\eta}_i &= 1 \text{ if } \hat{\pi}_i > C_0 \\ \hat{\eta}_i &= 0 \text{ if } \hat{\pi}_i \le C_0, \end{aligned} \tag{2}$$

for some cutoff point C_0[15].

The explanatory power of the model fitted to the estimation sample and hence the relevance of obtained determinants of the risk of insolvency are judged by the model classification accuracy and ability to predict the response value for the observations, which lie outside the estimation period. It is common to measure observed inaccuracy by the criterion of the average "counting error", and in the case when the model is applied to the estimation sample, the apparent error rate is:

$$\bar{e}\mathrm{er} = \#\{y_i \ne \hat{\eta}_i\}/n. \tag{3}$$

Because $\mathbf{y}$ was used for both constructing and assessing the prediction rule $\hat{\eta}$, $\bar{e}\mathrm{er}$ will usually be biased downwards: a new binary outcome might not be predicted as nearly as accurately by the old $\hat{\eta}$. Aside from that, the small size of the estimation sample results in a small number of observations from the response group per independent variable, that leads to the model being overfitted, and thus to the less reliable parameter estimates, which implies limited ability of predicting correctly the response value for the future observations. Nonetheless, financial studies examining models of company failure often involve small overall sample sizes and independent variables that are skewed, collinear, and non-stationery, i.e. suffer from distributional problems of ratios obtained from accounting statements[16]. It is

[15] We use definitions and notations which are given in Efron (1986).
[16] For instance, Goudie and Meeks (1991) estimated the five-variable discriminant model using a sample where a number of response group observations was limited to 24 failed firms. Altman and Narayanan (1997), in their international survey, refer to

necessary, therefore, to give special attention to the problem of model accuracy arising due to the small sample size.

In this paper we have assessed the usefulness of failure models estimated on small samples, by employing three different solutions: a holdout sample, bootstrap procedures, and Efron's formula for approximating the bias in the apparent error rate in logit (Efron (1986)). For the pooled sample of all available 48 data points used in the training set, the bootstrap procedures were employed, firstly, to obtain confidence intervals for model parameters[17] and, secondly, to measure the expected bias in the apparent error rate and to obtain an improved estimate of prediction error of a model. We use the resampling plan of constructing the bootstrap binary response, suggested for probit in Adkins[18] (1990).

For example, if the logit model is defined as:

$$y_i = \beta'\mathbf{x}_i + \varepsilon_i$$

where ε_i is IID and has a logistic distribution, y_i takes 0 and 1,

then the steps to obtain the bootstrap confidence intervals for parameters are:

(1) estimate $\hat{\beta}$ by the logit maximum likelihood estimator,

(2) generate a vector of uniform random numbers $\varepsilon^* \sim [0,1]$

(3) generate bootstrap values for the response variable $y^*{}_i$ by

$$\begin{cases} y_i^* = 1 \text{ if } 0 \le \varepsilon_i^* \le \Lambda(\hat{\beta}'\mathbf{x}_\mathrm{i}); \\ y_i^* = 0 \text{ if } \Lambda(\hat{\beta}'\mathbf{x}_\mathrm{i}) < \varepsilon_i^* \le 1. \end{cases}$$

(4) compute a new $\hat{\beta}^*$ using $\mathbf{y}^*$, and

(5) repeat (2) - (4) B times to compute the bootstrap confidence intervals for parameters.

The same resampling scheme is used to obtain the bootstrap estimates of the expected downward bias in the apparent error rate as an estimator of the true error rate. A bias correction is added to the apparent error rate so as to obtain an improved estimate of prediction error. If we denote a prediction error criterion by $Q[y_i, \hat{\eta}_i]$, then a bootstrap sample produced by our resampling plan, gives a replication of the bias which can be calculated as (see Efron and Tibshirani (1993)):

$$\omega^* = \frac{1}{n}\sum_{i=1}^{n} Q(y_i, \hat{\eta}^*(x_i)) - \frac{1}{n}\sum_{i=1}^{n} Q(y^*{}_i, \hat{\eta}^*(x_i)). \tag{4}$$

a number of carried out for developed and developing countries studies of corporate failure, which employed small paired samples.

[17] In small samples the asymptotic estimate of the standard errors using the information matrix consistently underestimates their true values (Jeong and Maddala (1993)).

[18] The paper by Adkins is cited as given in Jeong and Maddala (1993).

The bootstrap estimate of the expected excess error rate is the average obtained for a set of B bootstrap samples.

An alternative solution is to approximate the downward bias analytically (Efron, 1986):

$$\omega(\hat{\pi}) = \frac{2}{n}\sum_{i=1}^{n}\hat{\pi}_i(1-\hat{\pi}_i)\phi\left(\frac{\hat{c}_i}{\sqrt{\hat{d}_i}}\right)\sqrt{\hat{d}_i}\ , \tag{5}$$

where $\phi(z) = (2\pi)^{-1/2}\exp(-\frac{1}{2}z^2)$,

$$\hat{c}_i = \ln\left(\frac{C_0}{1-C_0}\right) - x_i'\hat{\beta}\ , \tag{6}$$

$$\text{and } \hat{d}_i = \mathbf{x'}_i\,\hat{\boldsymbol{\Sigma}}^{-1}\mathbf{x_i}\ ;\ \ \hat{\boldsymbol{\Sigma}} \equiv \sum_{j=1}^{n}\hat{\pi}_i(1-\hat{\pi}_i)\mathbf{x_j}\mathbf{x'_j}\ . \tag{7}$$

Then matrix $\hat{\boldsymbol{\Sigma}}^{-1}$ is the usual estimate for the covariance matrix of $\hat{\beta}$. The resulting estimate is a nearly unbiased estimator and has a small standard deviation.

There also is a methodological flaw related to the equal-share (state-based) groups utilised in both estimation samples of Russian companies. Equal-share sampling yields a biased estimate, understating the models true error rate in predicting failed firms and overstating the true error rate in predicting healthy companies (see Palepu (1986)). To take into account the bias introduced by the unbalanced sample, the cutoff probability C_0 in (2) can be adjusted using the population priors (see Greene (1997)). The obvious proxy for the prior probability of failure is the annual frequency rate of corporate insolvencies, however such data are not available for the Russian sample, therefore the predictive performance of logit models described below, was analysed by applying different cutoff values.

IV. Empirical Results

The logit results for one year prior to failure, for both countries, are reported in tables 1, 2, and 3.

[Tables 1, 2, and 3 go here]

Failed companies form the response category and are assigned a 1, whereas non-failed companies were assigned a 0, that implies that 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. In modelling we start from 13 covariates and test down the specific models. Variables were eliminated by using the sequential likelihood ratio tests.

The Russian model R-1_L estimated on 40 data points (Panel A in Table 1) produces a somewhat disappointing result, as it indicates that two ratios measuring return on long-term capital and return on net fixed assets are insignificant and other four covariates, which include pre-tax profit margin, stock and shareholders' funds turnover ratios, and the ratio of debtors over total assets - are significant only at the 10% level, which might not be adequate for the small sample, thus not allowing us to make inference on hypotheses in respect of Russian company failure. The coefficients for significant variables have signs suggesting that failed firms are less profitable, have lower turnover and higher ratio of accounts receivable to the total assets. Poor significance of the covariates might be attributed to the poor information content of the small Russian sample or to some collinearity amongst variables, though the overall performance is acceptable.

Results for the UK model derived from 40 data points are reported in table 2. The turnover ratio of net sales over the fixed assets has an ambiguous positive sign, which could point to overtrading as a factor determining corporate failure for our data, although this variable is insignificant. The three covariates, which are significant at the 5% level, show expected signs consistent with the previous UK work, indicating that lower profitability, higher gearing, and lower liquidity, are likely to be indicators of the probability of insolvency. Turning to the analysis of classificatory and predictive power, which is used as a performance measure[19], then we find that both Russian and UK models perform comparatively well at correctly classifying observations in the training sample. Using different cutoff values, overall accuracy varies from 77.5 per cent to 95 per cent for the Russian model, and ranges between 82.5 percent and 85 per cent for the UK model (Panel B in Table 1 and Panel B in Table 2).

However, on the holdout observations, taken from outside the training sample time frame, the model R-1_L demonstrates no predictive ability. Obtained analytically by Efron's formula estimates of the bias in the apparent error rate for the model R-1_L are consistent with the holdout test, as the bias values range from 70.6 per cent to 77.8 per cent indicating the effect of overfitting. The UK model forecasting performance, when assessed on 25 random holdouts mimicking the Russian holdout mix of failed and non-failed cases, contrasts sharply with the Russian results as the UK model appear to have some predictive power when, on average, it correctly classifies from 56.5 per cent to 84.8 per cent of holdout observations. The analytical estimates of the overall error rate bias, vary from 2.9 per cent to 9.8 per cent also pointing up the predictive ability of the UK model derived from the small random sample. In summary, on the basis of the results from the model validation by using holdout tests and the analytical approximation of the apparent error rate bias, one can conclude, that the important financial dimensions for distinguishing between failed and non-failed UK companies, are likely to be profitability as measured by the pre-tax profit margin, gearing proxied by the capital gearing ratio, and liquidity shown by the ratio of stock and work in progress over current liabilities. These results are remarkably similar to other work on the UK both in terms of forecasting performance and the determinants of failure (see, e.g., Alici (1995), Taffler (1995)).

As indicated above, we attempt to improve the training sample for the Russian logit model by using all available data points for estimation. The resulting logit model R-2_L can be seen in table 3. The covariates defining the second Russian model R-2_L, reveal the financial characteristics crucial for identifying failed enterprises. As expected, liquidity and gearing ratios did not pass likelihood ratio tests and are absent from the final specification thus supporting hypotheses *H1* and *H2* that in terms of liquidity and gearing positions there exist no significant difference between failed and non-failed industrial companies in today's Russia. The final set of three ratios includes the log of the total assets (significant at the 10% level), the pre-tax profit margin (significant at the 5% level), and a ratio of shareholders' funds turnover (significant at the 10% level)[20]. The negative signs of the coefficients are consistent with the directions suggested by hypothesis *H3* that failure is associated with lower profitability and slower turnover. The model also yields enterprise size, measured by the logarithmic total assets, as an additional failure predictor, implying that smaller firms have higher incidence of failure. Enterprise size might be important for a number of reasons. One is that larger firms provide employment and the social safety net and, therefore, they are likely to have more bargaining power in obtaining soft finance, because the cost to the society of large enterprise failures might be viewed greater than the costs of bankruptcies of small enterprises. Another reason is that larger enterprises might have easier access to short-term loans when approaching credit institutions, or stand a better chance in overcoming illiquidity problems by arranging debt for equity swaps. In addition to that, large firms might have more diversified operations and therefore have greater potential to succeed in the barter trade.

[19] Classification errors are assumed to be equally costly in this study, and accuracy is given for a range of cutoff probability values. Raising the cutoff value increase Type I errors of misclassifying of a failed firm, whereas reducing the cutoff value increases Type II errors of misclassifying a non-failed firm.
[20] Notice, that is based on the assumption that sign is important, then the 10% significance test is valid the 5% level when a one-tailed test is considered.

As no new holdout observations are available to test the second Russian model, we set bootstrap confidence intervals for the parameters, based on 5000 replications[21] and constructed using the modified percentile method (Davidson and MacKinnon (1993)). For the purpose of comparison, we also estimated bootstrap confidence intervals for parameters of the UK model. Looking at the bootstrap results for Russia (Panel A in Table 3) we can see that the 90% confidence interval for the pre-tax profit margin coefficient, stresses statistical significance of profitability in explaining company failure, although, the 95% confidence interval indicates greater variation of the coefficient. 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 2) also show large variability of coefficients of all ratios and do not rule out zero values, thus suggesting that financial measures, proxied by covariates, might have no association with the event of failure. That revelation contradicts the UK model good performance on the holdout sample making general results less conclusive. We also use the bootstrap for the second Russian model predictive performance assessment in order to supplement classification accuracy measured by the apparent error rate obtained on the training sample. Correct classification rate for the final Russian model R-2_L , obtained on the estimation sample, varies from 75.0 per cent to 89.6 per cent (Panel B in Table 3), and might be unrealistically high as the same observations are used both for building and assessing the model.

The bootstrap estimates of the downward bias in the apparent error rate, based on 300 replications[22], range from 1.3 to 5.2 per cent, whereas Efron's approximation yields higher values from 3.7 to 9.6 per cent. When we correct for the bias in the apparent error rate, approximated by Efron's formula, the estimated true error rate for the Russian model R-2_L form an interval of 20.0 per cent to 28.7 per cent depending on given cutoff points. The assessed accuracy is analogous to the UK model, which yields the estimates of the true error rate from 17.9 per cent to 24.8 per cent. In summary, the 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, even given the small cross section of Russian firms used.

[21] We use here 5000 bootstrap replications which appears an adequate number for obtaining bootstrap confidence intervals (see, e.g., Efron and Tibshirani (1993)).
[22] Efron (1986) and Efron and Tibshirani (1993) state that 300 replications is an appropriate number of bootstrap replications to approximate prediction error for classification problems.

V. Some Conclusions

We have constructed and compared the performance of failure prediction models for two countries: UK and Russia. The resulting models used the following determinants of failure: for the UK measures of profitability, gearing and liquidity; and for Russia measures of enterprise size, profitability, and turnover. The classification and forecasting results are related to the year prior to failure. The strategy adopted in this study, allows for comparison of performance of Russian and UK models, in terms of explanatory power and predictive ability. Firstly, we applied principles, accepted in the UK literature on failure modelling, to empirical research into Russian company financial distress. Account is taken of the specific micro and macroeconomic conditions relevant to the current position of Russian industrial enterprises. Secondly, given the small size and narrow time frame of the available Russian data set, we performed the UK study under similar conditions. A similarly sized random sample of UK industrial companies is employed to permit correct comparison of the test statistics and diagnostics. Third, we based our empirical investigation of Russian enterprise failure on robust statistical techniques by using logit analysis supplemented by the bootstrap to test the Russian and UK models. Estimation and validation results from the Russian model were statistically significant and did not reject our hypotheses, that liquidity and leverage were unimportant in identifying failure for the specific environment associated with 1995-96, while profitability and turnover seem to be important predictors. The model demonstrated acceptable classification accuracy and small apparent error rate biases. This is an interesting research outcome as it supports the use of models of Russian enterprise failure based on data from financial statements, to back-up more judgmental analysis. The Russian model results also support the theory that a Russian industrial enterprise has soft budget constraints, and emphasises the clear differences with determinants of UK company failure where liquidity and leverage along with profitability are important in identifying corporate financial distress. The UK results performed well when compared with UK studies based on a larger dataset.

Subject to the obvious limitation of the sample used, the results presented here suggest that low profitability is the key indicator of failure. Liquidity measures, which even in the UK can be manipulated, are not relevant, which is not surprising given soft budget constraints. Size in the context of the Russian case provides a shield against failure, large firms would seem less likely to be allowed to fail. Turnover, which has no designation for sign, is the least important variable to differentiate the UK from the Russian case. Clearly, traditional Z-score measures based on UK and US data and variables, are not valid for the analysis or the prediction of failure risk in Russia. Accurate failure prediction is of use to exporters, to investors and owners of interests in Russia. Furthermore, the Russian government might employ this type of methodology to calculate how sensitive the Russian enterprise sector might be to failure.

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Table 1. Logit Results for Russian Data, 1995 Estimation Period, Matched Sample (N=40)

Panel A: Logit Model R-1$_L$ (N=40)

Dimension: *Variable*	Coefficient	Asymptotic *t*-ratio
Profitability:		
Pre-tax Profit Margin	-31.796*	-1.915
Return on Long-term Capital	52.810†	1.683
Return on Net Fixed Assets	-23.568†	-1.175
Turnover:		
Stock Turnover	-1.105*	-1.888
Shareholders' Funds Turnover	-3.327*	-1.957
Assets Structure:		
Debtors/Total Assets	131.969*	1.884
Constant	5.041**	2.044
Log-Likelihood at Convergence	-8.128	
χ^2 statistic of the log-likelihood ratio (*p*-value)	39.20	(0.000)
LRI[23]	0.707	

Panel B: Classification and Predictive Ability, Percentage

	Cutoff Value		
	0.125	0.25	0.5
Estimation Sample			
Correct Classification			
Failed	95.0	95.0	95.0
Non-failed	60.0	80.0	95.0
Overall	77.5	87.5	95.0
χ^2 for the test for differences in probabilities[24]	18.14[a]	27.69[a]	37.18[a]
Overall Error Rate Bias Estimated by Efron Formula	70.6	73.6	77.8
Holdout Sample[25]			
Correct Classification			
Failed	100	100	100
Non-failed	0.0	0.0	0.0
Overall	12.5	12.5	12.5
χ^2 test for differences in probabilities	0.0	0.0	0.0

** Significant at 0.05.
* Significant at 0.10.
[a] Significant at 0.001, 2-tailed.
[b] Significant at 0.01, 2-tailed.
[c] Significant at 0.05, 2-tailed.
† Insignificant

[23] The likelihood ratio index is (Greene (1997)): $LRI = 1 - \frac{\ln L}{\ln L_0}$, where $\ln L$ is the log-likelihood at convergence, and $\ln L_0$ is the base-line log-likelihood.
[24] This χ^2 statistic (Conover (1971, 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.
[25] The holdout sample includes accounting data on 1 failed and 7 non-failed Russian companies, for 1996.

Table 2. Logit Results for UK Data, 1990-91 Estimation Period, Matched Sample (N=40)

Panel A: Logit Model UK_L (N=40)

Dimension: *Variable*	Coeffi-cient	Asymptotic *t*-ratio	Bootstrap Estimates of Coefficient Confidence Intervals 5000 Replications, 90% Confidence Interval	95% Confidence Interval
Profitability:				
Pre-tax Profit Margin	-0.240**	-2.290	(-11.590, -0.065)	(-29.686, -0.061)
Turnover:				
Turnover / Fixed Assets	0.350†	1.509	(-0.286, 14.076)	(-0.041, 38.107)
Gearing:				
Capital Gearing	0.083**	2.196	(0.008, 3.477)	(0.008, 8.284)
Liquidity:				
Stock & Work in Progress/Current Liabilities	-7.473**	-2.223	(-340.736, -1.065)	(-842.846, -0.592)
Constant	-2.219†	-1.158	(-99.512, 12.608)	(-283.665, 60.942)

Log-Likelihood at Convergence	-10.175	
χ^2 statistic of the log-likelihood ratio (*p*-value)	35.10	(0.000)
LRI	0.633	

*Panel B: Classification and Predictive Ability**,** Percentage*

	Cutoff Value 0.125	025	0.5
Estimation Sample			
Correct Classification			
Failed	100	95.0	85.0
Non-failed	70.0	70.0	85.0
Overall	85.0	82.5	85.0
χ^2 for the test for differences in probabilities	21.54 [a]	22.56 [a]	32.81 [a]
Overall Error Rate Bias Estimated by Efron Formula	2.9	5.2	9.8
Holdout Sample[26]			
Correct Classification			
Failed	100	100	100
Non-failed	50.3	71.9	82.6
Overall	56.5	75.5	84.8
χ^2 test for differences in probabilities	3.82†	7.78 [c]	7.78 [c]

** Significant at 0.05.
* Significant at 0.10.
[a] Significant at 0.001, 2-tailed.
[b] Significant at 0.01, 2-tailed.
[c] Significant at 0.05, 2-tailed.
† Insignificant

[26] The UK holdout results are the averages for 25 samples randomly selected from a one year prior to failure data set which covers the period of 1992-94. The mix of each random sample is designed to mimic the proportions of the Russian holdout sample, i.e. each UK random holdout includes 1 failed and 7 non-failed firms.

Table 3. Logit Results for Russian Data, 1995-96 Estimation Period, 21 Failed and 27 Non-failed Companies (N=48)

Panel A: Logit Model R-2_L (N=48)

Dimension: *Variable*	Coeffi-cient	Asymptotic *t*-ratio	Bootstrap Estimates of Coefficient Confidence Intervals, 5000 Replications, 90% Confidence Interval	95% Confidence Interval
Size:				
Log Total Assets	-0.544*	-1.971	(-1.452, 0.086)	(-2.097, 0.044)
Profitability:				
Pre-tax Profit Margin	-12.529**	-2.678	(-28.991, -5.765)	(-38.946, -4.877)
Turnover:				
Shareholders' Funds Turnover	-0.680*	-1.801	(-2.710, -0.087)	(-4.060, -0.069)
Constant	3.116**	2.265	(0.737, 8.804)	(0.205, 11.443)

Log-Likelihood at Convergence	-14.386	
χ^2 statistic of the log-likelihood ratio (*p*-value)	37.02	(0.000)
LRI	0.563	

Panel B: Classification and Predictive Ability, Percentage

	Cutoff Value 0.125	025	0.5
Estimation Sample			
Correct Classification			
Failed	95.2	85.7	85.7
Non-failed	59.3	74.1	92.6
Overall	75.0	79.2	89.6
χ^2 for the test for differences in probabilities	23.76 [a]	35.00 [a]	49.72 [a]
Overall Error Rate Bias Estimated by Efron Formula	3.7	6.1	9.6
Bootstrap Estimates of Expected Excess Error Rate, 300 Replications			
Failed	6.3	5.1	1.8
Non-failed	4.0	3.2	0.7
Overall	5.2	4.2	1.3

** Significant at 0.05.
* Significant at 0.10.
[a] Significant at 0.001, 2-tailed.
[b] Significant at 0.01, 2-tailed.
[c] Significant at 0.05, 2-tailed.

Appendix: Sectoral Composition of Sampled Firms

Table A1. Sectoral Composition of Russian Company Sample, 1995-96.
(Percentages in parentheses)

Sample	Economic Groups									
	General Industrials		Consumer Goods		Services		Telecom-munications		Total	
Panel A. Sample Split into Estimation (n=40, 1995) and Holdout (n=8, 1996)										
Estimation Sample										
Non-Failed	15	(75.0)	1	(5.0)	-	-	4	(20.0)	20	(100)
Failed	17	(85.0)	2	(10.0)	1	(5.0)	-	-	20	(100)
Holdout Sample										
Non-Failed	5	(71.4)	1	(14.3)	1	(14.3)	-	-	7	(100)
Failed	1	(100)	-	-	-	-	-	-	1	(100)
Panel B. Pooled Sample (n=48, 1995-96)										
Estimation Sample										
Non-failed	20	(74.1)	2	(7.4)	1	(3.7)	4	(14.8)	27	(100)
Failed	18	(85.7)	2	(9.5)	1	(4.8)	-	-	21	(100)

Table A2. Sectoral Composition of the Estimation Sample of UK Companies, 1990-91.
(Percentages in parentheses)

Estimation Sample	Economic Groups									
	General Industrials		Consumer Goods		Services		Utilities		Total	
Non-Failed	10	(50.0)	4	(20.0)	6	(30.0)	-	-	20	(100)
Failed	9	(45.0)	2	(10.0)	9	(45.0)	-	-	20	(100)

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