The Influence of the Financial Status of a Pension Plan Sponsor on the Fund's Solvency

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Abstract

The Enron case brings up the issue that has long worried pension and benefits experts: a retirement plan that is hugely dependent on the health of the company providing it. Enron's own stock accounted for more than 60 percent of the assets in its $2.1-billion 401(k) plan in 2001. It is widely known that some companies have even higher levels, which would create even worse scenarios should these companies fail. Occupational pension funds investing pension reserves in the securities of their own companies are now the most common type in many countries, including Russia. Pension plans used to invest the bulk of equity assets in the company's own stock, representing a worrying concentration of risk for beneficiaries. This investment behavior contradicts standard asset allocation theory. However, employers like to invest in company stock because it allows them to hold on to their valuable cash reserves, and they believe that it helps align the interests of employees with those of the firm.

U.K. law restricts employer-related investments ("self-investment"). Specifically, these investments are restricted to 5 percent of the pension scheme's assets (Dresdner Bank 2000). The laws in the United States and Russia are more liberal. Who is right? We've found that self-investment results in "moral hazard" risks, portfolio risks and credit risks. Our purpose is to establish the right balance between the interests of the company and the requirements of risk management. Hence, we need to create a default probability model that incorporates conditions of rising uncertainty and volatility in the world of financial markets.

1. Introduction

"In the current stock market climate, it is not surprising that questions are being asked about pensions," said Tom Ross, president of the Faculty of Actuaries (Ross 2003). "Schemes invested heavily in equities during the bull markets of the 1980s and 1990s. Why did actuaries not warn pension trustees of the danger?" Concentrating investments in company stock is generally not a good idea. The most obvious harm from overinvesting pension plans in company stock is big losses when things go wrong at the firm. Investing in one stock, rather than a diversified portfolio, creates more risk without providing any increase in expected returns.

Business went rather well until the Enron collapse. The Enron case (U.S. Congress 2001) highlighted the following issues:

- There are no investment limits in the 401(k) plans.
- Self-investments are bad for the pension plans solvency.
- Financial statements can provide a false picture of the company's health.
- High indebtedness in the corporate sector is a big problem.

We analyzed the U.S. stock market and estimated debt ratios and financial losses for selected U.S. companies whose 401(k) pension plans are heavily invested in their own stock.

We considered the Russian experience on financial regulation after stock crises to be useful for asset diversification decisions. We took a tracking error approach to estimate equity risks and also analyzed eurobonds as alternative investments for pension plan asset diversification.

In the current business climate , a pension asset manager has three tasks: (1) asset diversification, (2) financial monitoring and (3) bubble detection. Pension regulators could introduce investment limits for the pension plans and financial criteria of companies' stock participation in pension plans. These measures will help avoid the inclusion of low-quality stocks in pension plans.

It is believed that the problem of a pension fund's solvency depends on proper risk management. Unfortunately, existing approaches to risk management are not perfect. This paper focuses on some current methods of evaluating a stock portfolio's risk. Section 2 discusses some key issues regarding risk management techniques. Section 3 provides an analysis of the market data concerning the role of companies' stock in pension plans and proves the advantage of asset diversification. Section 4 presents the financial monitoring and default probability models as well as some empirical results. Section 5 outlines some crucial steps in modeling self-investment risks, and Section 6 concludes.

2. Overview of Previous Studies of Risk Management in Pension Funds

2.1 Modern Portfolio Theory

According to Brooks et al. (2001), the investment risk of a pension fund is a combination of strategic and active risks. Strategic risk is a risk of the strategic fund allocation relative to the fund's liabilities. Active risk is the risk taken by the investment manager relative to the strategic benchmark. A crucial step of enterprise-wide risk management is the integration of market risk and credit risk. However, according to Kim (2001), several methodological problems need to be overcome. These problems originate from the different characteristics of market risk factors (e.g., yield curves and equity prices) and credit risk factors (e.g., default and downgrade events). Since the market risk factors are asset prices and move continuously, it is difficult to forecast the distribution of market risk factors accurately over long time horizons. Because the credit events occur rarely and discretely, it is difficult to estimate the distribution of credit risk factors accurately over short time horizons.

Under modern portfolio theory, the expected portfolio volatility can be described as a function of the volatility of each individual security in the portfolio, and correlations between those securities. Because security prices are not perfectly correlated, the total risk at the portfolio level is less than sum of the risks of its component securities. One simple method for evaluating risk is the estimation of tracking error. Tracking error is defined as a standard deviation of the excess returns (the difference between portfolio returns and benchmark returns).

We created a simple model for the selected companies using the tracking error approach (standard deviation of excess return); that is,

$$TE = \sqrt{\frac{\sum_{k}^{n} (R_{pk} - R_{bk})^2}{n-1}},$$

where R_{pk} denotes the return of the tracking portfolio in period *k*, R_{bk} the return of the predetermined benchmark portfolio in period *k*, and *n* the sample size.

2.2 Value-at-Risk

Value-at-risk (VaR) is a more complicated technique. VaR summarizes the predicted maximum loss (or worst loss) over the target horizon within the given confidence interval. VaR allows users to measure incremental risk, which measures the contribution of each security to the total portfolio risk.

Using the VaR technique, the risks of an investment portfolio could be estimated as follows. Known parameters include: return, risk/return ratio, tracking error, correlation of asset prices and target return of portfolio (or target risk of portfolio). Calculated parameters include asset weights in the portfolio and the risk of portfolio.

For example, the estimated portfolio consists of four assets:

$$c_1 + c_2 + c_3 + c_4 = 1,\ c_i \text{ - asset weights.}$$

The initial invested capital is u_0 ($u_0 = 100\,000$). The amount of *i* bonds can be estimated as

$$N_i = \frac{u_0 c_i}{x_i},$$

and the investment portfolio consists of:

$$N_1 x_1 + N_2 x_2 + N_3 x_3 + N_4 x_4 = u_0.$$

The day eurobond price changes meet *normal* distribution with the confidence level at 95 percent. We estimated normal distribution parameters using following equation:

$$\mu_i = \frac{1}{K}\sum_{k=1}^{K}\Delta x_{ik} \,,$$

$$\sigma_i^2 = \frac{1}{K-1}\sum_{k=1}^{K}\left(\Delta x_{ik} - \mu_i\right)^2 ,$$

where K is the size of data sample

It is known that α -percentile of normal distribution, when $\alpha = 5\%$, is $\mu_i - 1.65\sigma_i$, where μ_i и σ_i — parameters of normal distribution for the asset *i*. Hence, VaR with a confidence level of 95 percent can be estimated with the following equation:

$$VaR_{95\%} = \mu_i - 1.65\sigma_i = \frac{1}{K}\sum_{k=1}^{K}\Delta x_{ik} - 1.65\frac{1}{K-1}\sum_{k=1}^{K}\left(\Delta x_{ik} - \mu_i\right)^2 .$$

Many VaR models assume that asset returns follow a normal distribution. Normality simplifies VaR calculation because all percentiles are assumed to be multipliers of the standard deviation. A number of studies, however, have found that the empirical distributions of returns are non-normal; that is, they have fat tails and nonzero skewness. In that case, assuming normality in calculating VaR leads to the underprediction of uncommon (but possible) losses.

2.3 Credit Risks Models

Fixed-income risk monitoring mainly consists of watching duration and avoiding low quality. Bond prices change over time in response to three general phenomena: shortening bond maturities, shifting term structures, and changing yield spreads. Bonds are risky because the last two phenomena are uncertain. The core of a bond risk model is, therefore, to estimate the variances and covariances of the term structure and the yield-spread factor excess returns.

Ratings-based techniques attribute a rating to each defaultable investment in a portfolio and then estimate the probability of upward or downward moves in ratings using historical data on ratings transitions for different traded bond issues. The probabilities are collectively termed the ratings transition matrix. The average spreads for bonds from different ratings categories are then combined with the transition probabilities to derive mean and volatility estimates for the return on each credit exposure (JP Morgan's Creditmetrics approach (Nickell, Perraudin, Varotto (2001).

The core of existing methodology for debt risk evaluation is looking at data on historical returns. But emerging high-yield corporate debt markets have lack of transparency. Historical data from these markets is often inaccessible. The new issues of corporate obligations on the emerging markets have no credit ratings. But noninvestment-grade debt—that is, debt below Moody's Baa rating or Standard & Poor's BBB rating—plays a significant role in pension schemes. This problem is especially important for Russia because the recent financial scandals in the United States have undermined confidence in audit firms and rating agencies.

Altman (1996) and Exley and Smith (2002) both discussed issues related to the use of credit risk models. They used a transition matrix of credit ratings and different financial ratios to evaluate debt risks. According to these papers, corporate financial ratios can serve as an acceptable measure of risk if we have the historical data on credit ratings movement.

However, these papers do not answer the question about the optimal investment limit of a company's own securities in the pension fund. Investing in one stock rather than a diversified portfolio creates more risk without providing any increase in expected returns. Yet, plan participants hold an asset whose value is closely correlated with their own earnings. They tend to buy what they know. We think that the risk management department of a corporate pension fund must develop it's own indicators of corporate fragility to serve as an early warning system.

In Vlieghe (2001), the probability of bankruptcy is the probability that losses are so large that they wipe out the entire value of the firm. This approach is close to an equity-based credit risk model. The starting point is the insight that, because of the limited liability, a firm's equity market capitalization may be thought of as the value of a call option written on the firm's underlying assets, with the firm's liabilities acting as a strike price of the option. Furthermore, debt claims may be thought of as default-free debt plus a short position in a put option on the firm's assets.

If assumptions are made about the statistical behavior of assets and liabilities, one can use standard pricing methods to establish a functional relationship linking observed equity market capitalizations with an underlying latent variable for assets and observed liabilities. Using equity and liability data, one may then estimate the parameters of the asset and liability distributions and, indeed, actually infer the levels of assets and liabilities.

3. Analysis of the Market Data and Corporate Accounts

3.1 Equities

One of the tasks of our research is the application of existing techniques of risk management to Russian assets. The Russian stock market provides high returns with high-level volatility to investors. Only a few financial assets have appropriate liquidity for institutional investors, including pension funds. We consider investments in ordinary shares of RJSC UES (utility), RJSC Gazprom (gas exploration and distribution), Rostelecom (communications), Sberbank (savings bank), Tatneft (oil), Lukoil (oil), Surgutneftegaz (oil) and YUKOS (oil) are appropriate for pension funds. These companies have their own occupational pension funds investing in mother-company securities.

We analyzed the equity market of these companies in conjunction with financials. We believed that net income interrelated with market capitalization would be an appropriate indicator for our model of insolvency prediction. This indicator had a high volatility level, especially during 1997-1999 when Russia met its worst economic and financial crisis. Concentrating the majority of pension fund assets in a single equity (the mother company, for example) created a terrible mix for pension-fund health.

We constructed distribution parameters of Russian asset returns and found distribution functions for each asset we analyzed (to apply the VaR technique). We then found standard deviation and risk/return ratios.

It was possible to apply the VaR technique to the Russian most-mentioned "blue-chip" RJSC UES. We used seven- and 14-day investment horizons, and our estimations were based on Pearson and lognormal distribution functions (Table A8).

We provided estimations of tracking errors of the Russian major stocks and constructed a simple model consisting of two stock portfolios: portfolio 1 with a large portion of company stock (100 percent) and portfolio 2 (a "market" portfolio). Then we compared the characteristics of the portfolios and estimated the risks and efficiency of portfolio management.

We considered the Russian stock index RTS ("market" portfolio) as the benchmark for the corporate equities. Then we estimated tracking errors as the standard deviation of excess return for equities and found that even the most profitable Russian blue chips have extremely high tracking errors (Table A3). This situation could establish high risks for the corporate pension funds. But we didn't find any reports regarding huge losses of pension funds, thanks to the high profitability of the Russian stock market. The RTS Index annual average return was 51.07 percent in 1997-2002. RJSC UES and Lukoil posed high risks to investors without sufficient increase in returns. Gazprom provided very low returns with minimal risk.

The less-profitable equities have minimal tracking errors. Investments in Rostelecom and Surgutneftegaz provided risk/return ratio compared with the whole market.

3.2 Corporate Bonds

We also analyzed another asset: corporate bonds. The Russian corporate bond market is less developed, but it's the most dynamic sector of financial market. Only Gazprom corporate bonds have appropriate liquidity and a three-year credit history. We were unable to construct a tracking-error model for this bond because of specific situation in the GKO-OFZ (government bonds) market for the last three years. Government bonds were unattractive to investors during the Russian crisis in 1998. So investors didn't consider GKO-OFZ the benchmark for pricing on the market. Instead, they used commercial banks credit and deposit rates as the benchmark for corporate bonds. Also we were unable to construct the Gazprom yield curve because of lack of historical data (Gazprom issued only two ruble bond emissions).

We could only analyze the financials of Gazprom. We evaluated debt risks of issuers using their IAS and RAS financial statements (Table A1). In our opinion, Gazprom corporate debts have low risk compared with other Russian corporations (Table A2).

3.3 Eurobonds

We also consider Russian eurobonds to be an attractive asset for pension investments. Prices of Russia-30 eurobonds have increased more than 2.5 times since 2000, showing a decrease in credit risks. So investors see Russian eurobonds as very attractive. Some analysts boasted that Russia became the "safe haven" in conditions of financial instability in world financial markets.

Therefore, we considered Russia-30 eurobonds to be a good indicator of the level of foreign investments in the market and simulated an investment portfolio that included the following eurobonds: Russia (S&P: BB/stable), Brazil (S&P: B + /negative), Mexico (S&P: BBB – /stable), Turkey (S&P: B – /negative) and the United States (S&P: AAA/stable) (Akhtyamov, Spivak, 2003).

We researched 2001-2002 data on these markets. First we conducted a descriptive statistical analysis of recent eurobonds markets and found Russian eurobonds to be very attractive in the short-term investment horizon. In our opinion, Russia-30 eurobonds had similar risk/return ratios with U.S. Treasuries and Germany Bundesbunds (Table A4). But with respect to the long-term risk characteristics of Russia-30 eurobonds, tracking error remains more comparable with Brazil eurobonds than Mexico eurobonds, for example, thanks to high volatility in financial markets.

Next we estimated VaR for the different eurobond portfolios. We compared Russia-30 eurobonds with Mexico-31, Brazil-30 and Turkey-30. VaR was 1662.831095 when asset weights were equal. Eurobonds Mexico-31, among others, had minimal VaR. But an investment portfolio with 100 percent Mexico-31 isn't optimal for the private investor.

One of the portfolios (without Brazil-30) had a VaR of 1005.861885 when asset weights were: Brazil-30, 0 percent; Mexico-31, 47 percent; Russia-30, 28.9 percent; and Turkey-30, 24.1 percent. VaR can be a good technique for reducing eurobonds with high risks in the portfolio.

Next we estimated the return for the different eurobond portfolios. The investment portfolios, which included Russian eurobonds, had maximum return with minimal VaR.

We also estimated the monthly return of the eurobonds portfolio with minimal VaR. The average monthly return can be estimated as the geometric mean (compound annual) return:

$$r = \sqrt[k]{(1+r_1)(1+r_2)\cdot\ldots\cdot(1+r_k)} - 1,$$

where k is the number of investment periods ($k = 16$ for the selected portfolio). Hence, the average monthly return would be $r = 0{,}014751$.

With such moderate risk ratios, Russian eurobonds have a very impressive rate of return. With a 24.477 percent Annual Price Index in 2002, Russian eurobonds have no reasonable alternative on the market. So eurobonds could be good investments for diversification of a pension fund portfolio instead of corporate securities (equities and bonds).

4. Model for Estimating Debt and Equities Risks

4.1 Indicators of the Financial Status of the Company

We used some financial indicators to avoid low quality in the debt market in Russia. The following factors have influence on the financial status of the pension plan sponsor:

- The short-term financial stability of the company (this is especially important for short-term bonds), reflecting the ability of the company to pay the current liabilities.
- The long-term financial stability, reflecting a common level of credit status of the company.

The short-term financial indicators are *earnings before interest and taxes (EBIT) margin* and *leverage ratio*; the long-term financial indicators are *debt ratio* and short-term (*S-T) liabilities/sales*.

The credit status is the complex estimation of financial and economic condition and prospects of the company, reflecting effective use of the credit leverage. Asset managers also could use the business reputation and credit history of the company if these data are accessible.

4.2 The Default Probabilities Model

The default probability model given in Vlieghe (2001) can be used as a basis of the model for estimating debt and equity risks. A firm is assumed to go bankrupt when $\Pi + S < 0$, where Π is the level of profit and S is the expected equity value of the firm (ignoring the profit), which satisfies $S = MV - D$; that is, the value of the equity equals the value of the assets minus the value of the debt.

If $\prod$ is a random variable with cumulative distribution function $F(.)$, mean μ_Π and standard deviation σ_Π, the probability of bankruptcy is:

$$\psi = F\left[\frac{-(\mu_\Pi + S)}{\sigma_\Pi}\right].$$

Hence, the probability of bankruptcy is the probability that losses are so large that they wipe out the entire value of the firm. We analyzed the financials of the Russian majors for the last seven years and created the following bankruptcy probability functions:

1. RJSC UES:

$$\Pi_{EES} \sim InvGauss(8430713,0;5449883,0) - 156612,0$$
$$\mu_{EES} = 8274102,0$$
$$\lambda_{EES} = 10485832,0$$
$$\sigma_{EES} = 54020638854360,0$$
$$S_{EES} = 203067441,017$$
$$F_{EES}(x) = \Phi\left[\sqrt{\frac{\lambda}{x}}\left(\frac{x}{\mu} - 1\right)\right] + e^{2\lambda/\mu}\Phi\left[-\sqrt{\frac{\lambda}{x}}\left(\frac{x}{\mu} + 1\right)\right],$$

where

$$\Phi(x) = Erf(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2} dt.$$

2. Lukoil:

$$\Pi_{LKOH} \sim \text{InvGauss}(45818608;\ 3930315)\text{-}635503$$
$$\mu_{LKOH} = 45183106{,}0$$
$$\lambda_{LKOH} = 3930315{,}172$$
$$\sigma_{LKOH} = 234693395558379704{,}0$$
$$S_{LKOH} = 454458437{,}585$$
$$F_{LKOH}(x) = \Phi\left[\sqrt{\frac{\lambda}{x}}\left(\frac{x}{\mu} - 1\right)\right] + e^{2\lambda/\mu}\Phi\left[-\sqrt{\frac{\lambda}{x}}\left(\frac{x}{\mu} + 1\right)\right],$$

where

$$\Phi(x) = Erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt .$$

3. Tatneft:

$$\Pi_{TATN} \sim \text{Lognorm}(29069486;\ 68732733)\text{-}5111688$$

$$\mu_{TATN} = 23957798{,}0$$

$$\sigma_{TATN} = 68732732{,}5516692$$

$$S_{TATN} = 62204085{,}755$$

$$F_{TATN}(x) = \Phi\left[\frac{\ln x - \mu'}{\sigma'}\right],$$

where

$$\mu' = \ln\left[\frac{\mu^2}{\sqrt{\sigma^2 + \mu^2}}\right] \text{ и } \sigma' = \frac{1}{2}\ln\left[1 + \left(\frac{\sigma}{\mu}\right)^2\right].$$

where

$$\Phi(x) = Erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt .$$

4. Gazprom:

$$\Pi_{GAZP} \sim \text{Normal}(30616384;\ 33560649)$$

$$\mu_{GAZP} = 30616384$$

$$\sigma_{GAZP} = 33560649$$

The function for Gazprom is difficult to create.

Although these formulas give rather rough results, the probability of bankruptcy for the selected Russian companies is low (Table A14). This function provides a low probability of bankruptcy when the market capitalization of the companies is rather high. But often we see an increase in asset prices that is not justified by fundamentals. We talk about the "financial bubble." One of the reasons for a financial bubble is the high indebtedness of the corporate sector (Table A16). Some U.S. companies tried to "embellish" their financial statements. The companies borrowed heavily in the 1990s, when the interest rates were rather high. High indebtedness of the corporate sector is not yet a characteristic feature of Russian major companies.

We analyzed the financials of the U.S. companies, introducing debt-to-equity ratio Debt/Mcap: *D*/*MV*, where *D* is the company's debt and *MV* the market capitalization of the company's stock.

We considered companies with high market capitalization and low indebtedness to be eligible for a pension fund's assets. Our analysis can be recommended to the pension regulators and asset managers for estimating the influence of the financial status of the pension plan manager on the solvency of the pension funds.

5. The Evaluation of Self-Investment Risks

We found that investing in a company's own securities results the following risks: moral hazard risks, portfolio risks and credit risks.

5.1 Moral Hazard Risks

Employers like to invest in company stock because it allows them to hold on to their valuable cash reserves, and they believe that it helps align the interests of the employees with those of the firm. Self-investment gives employers a feeling of "security." They want to invest the majority of pension reserves in the own securities if there are not investment limits in the pension plans. The Enron case and other corporate bankruptcies confirmed that this feeling of security was false.

The pension authority should restrict self-investment in pension plans. This is the best way to provide security to the workers and to reduce moral hazard risks.

5.2 Portfolio Risks

Investing in one stock rather than in a diversified portfolio creates more risk without providing any increase in expected returns. Asset managers should use VaR models and tracking error approaches to evaluate portfolio risks

5.3 Credit Risks

Under ERISA (which is useful for other pension laws), an employer pension plan is insolvent if the plan's available resources are not sufficient to pay benefits under the plan when due for the plan year. This may happen when the cost of pension obligations is above the level of pension assets. Insolvency of pension plans may occur because of a fall of stock prices. In the current stock market climate, this problem is very real—for academics, regulators, employers and employees.

ERISA orders the plan sponsor to distribute excess resources to the participants and beneficiaries of the plan. This situation influences the financial status of the pension plan sponsor. Companies can borrow heavily in order to meet pension obligations. It is known that ratings agencies downgraded a number of European companies because of rising pension obligations.

When pension obligations increase, the company's percent payments increase and net income decreases, so market capitalization of the company can fall. The model discussed in Section 4.2 captures these ideas.

6. Conclusion

Investments in companies' own securities results the following risks: moral hazard risks, portfolio risks, credit risks. "Self-investment" had awful consequences in the United States, as seen in the Enron case.

Self-investment must be subject of financial regulation. It is necessary to encourage diversification. Eurobonds, instead of corporate securities (equities and bonds), could be good investments for diversifying pension fund portfolios.

Policymakers should restrict the participation of these corporate securities in pension plans. It is necessary to develop clear criteria, or financial indicators, for these companies.

Appendix

Table A1
Gazprom Financials, Mln. RUR.

	2001	**2002-2**
Assets	2,339,787	2,137,635
Liabilities	519,937	572,651
Debt	348,827	346,349
Sales	588,568	297,577
EBIT	186,417	34,563
Net Income	100,387	16,050
Leverage ratio	0.3	0.27
Debt Ratio	0.15	0.18
S-T Liabilities/Sales	0.73	0.60
EBIT Margin	0.32	0.12

Source: Bank Zenit, December 2002.

Table A2
Russian Oil and Gas Debt Ratios

Company	Debt, USD Mln.	Debt/Assets	Debt/Sales	Debt/EBITDA
Gazprom	15,008	0.21	0.73	1.48
Lukoil	3428	0.17	0.26	0.91
Tyumen Oil (TNK)	2780	0.30	0.45	1.53
Tatneft	1263	0.19	0.28	1.44
Sibneft	923	0.16	0.26	0.51
YUKOS	116	0.01	0.01	0.03
Surgutneftegaz	25	0.00	0.01	0.04

Source: Bank Zenit, December 2002.

Table A3
Tracking Error Estimation

No.	Asset	Annual Average Return %	Tracking Error (Std. Dev. Of Excess Return)	Risk/Return Ratio
1	RJSC UES	79.48	126.87	1.59
2	Tatneft	103.84	98.24	0.94
3	Lukoil	41.42	83.08	2.00
4	Sberbank	128.10	103.48	0.80
5	Surgutneftegaz	36.84	0.03	0.000814
6	Rostelecom	23.11	0.038	0.001
7	YUKOS	200.5	100.42	0.5
8	Gazprom	-3.0	-0.05	0.016

Notes: RTS stock index used as benchmark; annual average return was 51.07%; investment horizon—one-day returns in 1997-2002.

Table A4
Sovereign Eurobonds Risks Estimation

Country	Return in 2002 %	Annual Coupon %	Std. Dev. 2001-2002	Risk/Return Ratio in 2002 %	Tracking Error (U.S. Treasuries as Benchmark)
USA-30	8.9688	5.375	4.34	0.484	-
Germany-30	4.8036	5.50	3.20	0.666	-
Russia-30	24.4770	5	14.32	0.585	2.52
Brazil-30	-24.396	12.25	13.57	-	3.85
Turkey-30	10.75	11.88	7.50	0.697	-

Table A5
Distributions Fits and Parameters

No.	Asset	Starting Date	End Date	Size	Distribution and Parameters	Remarks
1	RJSC UES	05.01.1997	31.12.2002	1504	1) RiskPearson5(5.8337; 1.0196; RiskShift(-0.061063))	
					2) RiskLognorm2(-1.9556; 0.5731; RiskShift(-0.017216))	
2	Tatneft	05.01.1997	31.12.2002	1495	1) RiskInvGauss(24.545; 0.28451; RiskShift(0.023452))	
					2) RiskLognorm2(0.080929; 2.5817; RiskShift(0.042405))	
					3) RiskPareto(0.29470; 0.042500)	
3	Lukoil	05.01.1997	31.12.2002	1504	1) RiskLognorm2(3.6118; 0.13508; RiskShift(-24.601))	
					2) RiskPearson5(98.825; 4881.6; RiskShift(-37.129))	
4	Sberbank	29.01.1997	31.12.2002	1444	1) RiskLognorm2(4.0227; 1.0754; RiskShift(2.8276))	
					2) RiskInvGauss(97.415; 74.11; RiskShift(-2.1271))	
					3) RiskExpon(88.788; RiskShift(6.4385))	
5	Surgutneftegaz	05.01.1997	31.12.2002	1504	1) RiskLogLogistic(-0.012533; 0.2532; 2.7392)	
					2) RiskPearson5(4.5065; 1.392; RiskShift(-0.09222))	
					3) RiskLognorm2(-1.3249; 0.64122; RiskShift(-0.022833))	
					4) RiskInvGauss(0.3444; 0.78126; RiskShift(-0.0382))	
					5) RiskGamma(1.8153; 0.16073; RiskShift(0.014424))	
6	Rostelecom	05.01.1997	31.12.2002	1504	1) RiskInvGauss(1.7624; 2.7847; RiskShift(0.099034))	Multimodal distribution
7	YUKOS	17.06.1997	31.12.2002	1166	1) RiskLogLogistic(-0.35801; 2.7432; 1.8389)	Multimodal distribution
					2) RiskLognorm2(1.1041; 0.81175; RiskShift(-0.63488))	Multimodal distribution

8	Gazprom	05.02.2000	31.12.2002	496	-	Multimodal distribution
9	USA-30	09.02.2001	06.12.2002	96	1) RiskInvGauss(10.22; 52.839; RiskShift(89.598))	
					2) RiskLognorm2(2.2139; 0.43194; RiskShift(89.79))	
					3) RiskWeibull(1.5888; 7.5419; RiskShift(93.0424))	
10	USA-10	10.08.2001	06.12.2002	70	-	Multimodal distribution
11	RUSSIA-30	18.02.2000	06.12.2002	147	-	Multimodal distribution
12	RUSSIA-10	18.02.2000	06.12.2002	145	-	Multimodal distribution
13	BRAZIL-30	25.02.2000	06.12.2002	146	-	Multimodal distribution
14	BRAZIL-12	11.01.2002	06.12.2002	48	-	Multimodal distribution
15	MEXICO-31	10.08.2001	06.12.2002	70	-	Multimodal distribution
16	MEXICO-11	12.01.2001	06.12.2002	100	-	Multimodal distribution
17	BundesBonds-10, 30	27.10.2000	10.01.2003	116	1) RiskChiSq(7; RiskShift(95.6976))	
					2) RiskRayleigh(5.2749; RiskShift(96.0403))	
					3) RiskLognorm2(2.4215; 0.29183; RiskShift(90.936))	

18	MEXGLB31	07.08.2001	10.12.2002	340	1) RiskBetaGeneral(10.107; 2.6254; 72.601; 104.25)	
					2) RiskNormal(97.7217; 3.4318)	
19	POLGLB12	05.09.2002	10.12.2002	68	-	Multimodal distribution
20	TRGLB10	31.10.2000	10.12.2002	532	1) RiskBetaGeneral(2.4605; 1.8322; 72.019; 107.73)	
21	TRGLB30=RR	30.10.2000	10.12.2002	533	1) RiskTriang(69.366; 86; 110.646)	Peak 100,5

Table A6
Distributions Fits and Parameters

No.	Asset	Distributions Fits and Parameters	Std. Dev.
1	RJSC UES	1) RiskPearson5(5.8337; 1.0196; RiskShift(-0.21018))	0.11
		2) RiskLognorm2(-1.9556; 0.5731; RiskShift(-0.16633))	0.10
2	Tatneft	1) RiskInvGauss(24.545; 0.28449; RiskShift(-24.545))	227.99
		2) RiskLognorm2(0.080929; 2.5817; RiskShift(-24.526))	850.01
3	Lukoil	1) RiskPearson5(98.892; 4886.9; RiskShift(-54))	5.07
		1) RiskGamma(23.962; 1.0364; RiskShift(-28.9123))	5.07
4	Surgutneftegaz	1) RiskLognorm2(-1.3249; 0.64122; RiskShift(-0.32904))	0.23
		2) RiskInvGauss(0.3444; 0.78126; RiskShift(-0.3444))	0.23
5	BundesBonds	1) RiskChiSq(7; RiskShift(-6.9847))	3.74
		2) RiskLognorm2(2.4215; 0.29183; RiskShift(-11.746))	3.50
6	MEXGLB31	1) RiskBetaGeneral(10.107; 2.6254; -25.121; 6.5287)	3.46
		2) RiskNormal(0.0000; 3.4318)	3.43

Table A7
Net Income of the Russian Corporations, RUR thousands

	RJSC UES	Tatneft	Lukoil	Sberbank	Surgutneftegaz	Rostelecom	Gazprom
01.04.1997	-403 743.0	-	-	-	873 242.1	340 806.0	-
01.07.1997	2 128 012.2	838 283.1	458 228.0	-	1 690 572.9	661 553.3	10 679 525.0
01.10.1997	3 838 009.0	1 230 848.9	593 707.5	-	2 432 627.9	1 052 218.3	15 019 343.0
01.01.1998	5 731 379.0	1 716 459 635.0	710 784 075.0	2 929 943.0	3 855 500.0	1 930 957.0	38 898 000.0
01.04.1998	1 861 519.0	-1 024 805.0	94 558.0	-	735 336.0	373 660.0	77 639.0
01.07.1998	3 190 709.0	740 086.0	489 777.0	-	1 113 465.0	751 768.0	5 032 149.0
01.10.1998	4 323 108.0	1 440 968.0	1 713 820.0	-	1 766 584.0	1 161 498.0	-40 881 542.0
01.01.1999	4 529 562.0	-4 695 165.0	2 366 558.0	6 570 577.0	4 330 300.0	-3 345 096.0	-30 063 000.0
01.04.1999	1 010 385.0	1 551 681.0	2 764 592.0	770 376.0	3 406 817.0	28 799.0	9 702 721.0
01.07.1999	11 169 206.0	2 695 992.0	6 510 690.0	4 722 292.0	10 043 916.0	887 730.0	25 418 907.0
01.10.1999	11 155 769.0	5 602 925.0	7 798 254.0	9 048 253.0	20 197 159.0	1 714 292.0	35 521 312.0
01.01.2000	5 192 457.0	12 573 975.0	13 447 760.0	8 366 062.0	30 931 896.0	2 846 319.0	66 475 000.0
01.04.2000	727 773.0	5 281 678	13 435 524.0	5 144 103.0	19 574 894.0	33 675.0	30 495 809.0
01.07.2000	1 472 499.0	12 531 280.0	21 392 505.0	5 882 103.0	36 707 825.0	626 064.0	61 957 408.0
01.10.2000	1 018 834.0	14 720 615.0	46 828 000.0	12 105 757.0	54 741 909.0	1 165 640.0	85 882 126.0
01.01.2001	7 957 560.0	23 160 223.0	45 685 529.0	13 264 692.0	31 432 300.0	1 021 844.0	48 540 832.0
01.04.2001	4 866 676.0	4 358 375.0	6 467 154.0	5 878 674.0	13 260 894.0	500 311.0	25 807 775.0
01.07.2001	7 569 772.0	7 681 595.0	18 003 453.0	10 762 588.0	28 521 318.0	1 034 931.0	63 930 195.0
01.10.2001	11 277 168.0	11 619 020.0	18 062 119.0	17 711 843.0	43 862 987.0	1 797 909.0	85 882 126.0
01.01.2002	12 776 798.0	14 791 765.0	20 986 972.0	27 446 904.0	11 772 400.0	2 232 893.0	71 927 743.0
01.04.2002	17 532 988.0	1 759 692.0	5 246 766.0	10 193 908.0	-	1 210 137.0	12 977 647.0
01.07.2002	22 712 951.0	4 349 327.0	17 587 037.0	18 864 729.0	25 651 061.0	1 583 589.0	16 054 192.0
01.10.2002	39 987 103.0	8 547 777.0	33 311 250.0	31 805 681.0	42 837 211.0	4 900 818.0	34 224 544.0

Table A8
VaR Estimation (RJSC UES)

Date	**Price, USD**	**Interval, Days**	**Sum, USD**	**7-Days Um, USD**	**Week Return, USD**	**14-Day Sum, USD**	**2-Week Return, USD**		**Distribution Fits and Parameters**	**VaR**
05.01.1997	0.0936	0	0.0936	0.0936		0.0936		Function	RiskPearson5(5.5373; 4.612; RiskShift(-0.2849))	VaR
06.01.1997	0.0995	1	0.1931	0.6706	0.577	1.3454	1.2518	Shift	-0.284898555	
08.01.1997	0.11	3	0.3031	1.3454	0.6748	2.8953	1.5499	a	5.537332181	
09.01.1997	0.1125	4	0.4156	2.124	0.7786	4.7884	1.8931	b	4.612006711	
10.01.1997	0.126	5	0.5416	2.8953	0.7713	7.1113	2.3229	Confidence level	Time horizon	
13.01.1997	0.129	8	0.6706	3.7638	0.8685	9.0974	1.9861	99%	7 day	0.086
14.01.1997	0.124	9	0.7946	4.7884	1.0246	11.0844	1.987	95%	7 day	0.182
15.01.1997	0.1302	10	0.9248	5.9754	1.187	13.0487	1.9643	90%	7 day	0.246
16.01.1997	0.1326	11	1.0574	7.1113	1.1359	15.215	2.1663	Function	RiskLognorm2(-0.39722; 0.59368; RiskShift(-0.071829))	VaR
17.01.1997	0.138	12	1.1954	8.1864	1.0751	17.1174	1.9024	Shift	-7.18E-02	
20.01.1997	0.15	15	1.3454	9.0974	0.911	20.245	3.1276	Mu	-0.397220697	
21.01.1997	0.1525	16	1.4979	10.1426	1.0452	23.3882	3.1432	Sigma	0.59367673	
22.01.1997	0.1575	17	1.6554	11.0844	0.9418	26.283	2.8948	Confidence level	Time horizon	
23.01.1997	0.1625	18	1.8179	12.0217	0.9373	30.2199	3.9369	99%	7 day	0.097
24.01.1997	0.1575	19	1.9754	13.0487	1.027	34.5075	4.2876	95%	7 day	0.181
27.01.1997	0.1486	22	2.124	14.1287	1.08	39.1865	4.679	90%	7 day	0.242

28.01.1997	0.155	23	2.279	15.215	1.0863	43.6127	4.4262	Function	RiskInvgauss(0.83483; 2.28584; RiskShift(-0.10698))	VaR
29.01.1997	0.152	24	2.431	15.9772	0.7622	48.1585	4.5458	Shift	-1.07E-01	
30.01.1997	0.155	25	2.586	17.1174	1.1402	52.1593	4.0008	Mu	0.834834802	
31.01.1997	0.154	26	2.74	18.651	1.5336	56.1643	4.005	Lambda	2.285836178	
03.02.1997	0.1553	28	2.8953	20.245	1.594	60.5104	4.3461	Confidence level	Time horizon	
04.02.1997	0.1583	29	3.0536	21.814	1.569	64.4554	3.945	99%	7 day	0.099
05.02.1997	0.1625	30	3.2161	23.3882	1.5742	67.5406	3.0852	95%	7 day	0.180
06.02.1997	0.17	31	3.3861	24.6449	1.2567	69.9715	2.4309	90%	7 day	0.240
07.02.1997	0.1817	32	3.5678	26.283	1.6381	72.4057	2.4342			
10.02.1997	0.196	35	3.7638	28.0796	1.7966	74.7731	2.3674		RiskLoglogistic(-0.067124; 1.2722; 2.8242)	VaR
11.02.1997	0.2015	36	3.9653	30.2199	2.1403	77.1337	2.3606	Gamma	-6.71E-02	
12.02.1997	0.2005	37	4.1658	32.4639	2.244	79.6942	2.5605	Beta	1.272224692	
13.02.1997	0.1991	38	4.3649	34.5075	2.0436	82.2057	2.5115	Alpha	2.824194538	
14.02.1997	0.208	39	4.5729	36.6413	2.1338	84.6565	2.4508	Confidence level	Time horizon	
17.02.1997	0.2155	42	4.7884	39.1865	2.5452	86.8852	2.2287	99%	14 day	0.183
18.02.1997	0.23	43	5.0184	41.4187	2.2322	89.7697	2.8845	95%	14 day	0.381
19.02.1997	0.2502	44	5.2686	43.6127	2.194	93.2997	3.53	90%	14 day	0.517
20.02.1997	0.2408	45	5.5094	45.749	2.1363	96.3737	3.074		RiskPearson5(5.7506; 9.72; RiskShift(-0.58402))	VaR
21.02.1997	0.235	46	5.7444	48.1585	2.4095	99.6042	3.2305	Shift	-5.84E-01	
24.02.1997	0.231	49	5.9754	50.1654	2.0069	101.6692	2.065	Alpha	5.750552346	
25.02.1997	0.2275	50	6.2029	52.1593	1.9939	103.7689	2.0997	Beta	9.720031109	
26.02.1997	0.2302	51	6.4331	54.1662	2.0069	105.5574	1.7885	Confidence level	Time horizon	
27.02.1997	0.2316	52	6.6647	56.1643	1.9981	107.1736	1.6162	99%	14 day	0.179

28.02.1997	0.227	53	6.8917	58.3842	2.2199	108.4122	1.2386	95%	14 day	0.371
03.03.1997	0.2196	58	7.1113	60.5104	2.1262	110.0777	1.6655	90%	14 day	0.501
04.03.1997	0.2136	59	7.3249	62.625	2.1146	111.3195	1.2418		RiskLognorm2(0.30849; 0.58129; RiskShift(-0.1528))	
05.03.1997	0.2075	60	7.5324	64.4554	1.8304	112.0521	0.7326	Shift	-1.53E-01	
06.03.1997	0.212	61	7.7444	66.4498	1.9944	112.3811	0.329	Mu	0.308485076	VaR
07.03.1997	0.216	62	7.9604	67.5406	1.0908	112.6512	0.2701	Sigma	0.581286403	
11.03.1997	0.226	66	8.1864	68.7635	1.2229	112.8386	0.1874	Confidence level	Time horizon	
12.03.1997	0.2312	67	8.4176	69.9715	1.208	113.0617	0.2231	99%	14 day	0.199
13.03.1997	0.2286	68	8.6462	71.1333	1.1618	113.402	0.3403	95%	14 day	0.370
14.03.1997	0.2256	69	8.8718	72.4057	1.2724	113.7158	0.3138	90%	14 day	0.494

Table A9

VaR for Different Eurobonds Portfolios

No.	BRAGLB30	MEXGLB31	RUSGLB30	TRGLB30	VaR, USD
1	1	0	0	0	4242.255562
2	0	1	0	0	1224.518443
3	0	0	1	0	1302.109021
4	0	0	0	1	1417.389680
5	0.25	0.25	0.25	0.25	1662.831095
6	0.5	0.5	0	0	2461.180398
7	0.5	0	0.5	0	2556.491164
8	0.5	0	0	0.5	2535.349880
9	0	0.5	0.5	0	1051.221198
10	0	0.5	0	0.5	1063.892290
11	0	0	0.5	0.5	1195.945193
12	0	0.333333333	0.333333333	0.333333333	1023.812056
13	0.333333333	0	0.333333333	0.333333333	1994.507365
14	0.333333333	0.333333333	0	0.333333333	1913.571905
15	0.333333333	0.333333333	0.333333333	0	1931.326782
16	0.000	0.400	0.400	0.200	1013.532042
17	0.000	0.450	0.350	0.200	1008.123397
18	0.000	0.500	0.300	0.200	1007.592203
19	0.000	0.500	0.270	0.230	1006.735021
20	0.000	0.490	0.280	0.230	1006.289802
21	0.000	0.470	0.300	0.230	1005.978506
22	0.000	0.470	0.290	0.240	1005.864115
23	0.000	0.470	0.289	0.241	1005.861885

Table A10

Eurobond Prices Correlation Matrix

	BRAGLB30	**MEXGLB31**	**RUSGLB30**	**TRGLB30**
BRAGLB30	1	0.450902191	0.548950719	0.455605112
MEXGLB31	0.450902191	1	0.348744307	0.26343659
RUSGLB30	0.548950719	0.348744307	1	0.49531803
TRGLB30	0.455605112	0.26343659	0.49531803	1

Table A11

Eurobonds Prices Covariation Matrix

	BRAGLB30	**MEXGLB31**	**RUSGLB30**	**TRGLB30**
BRAGLB30	2.395771606	0.518671114	0.478729818	0.62587329
MEXGLB31	0.518671114	0.552298699	0.146025449	0.173755368
RUSGLB30	0.478729818	0.146025449	0.317445245	0.24768156
TRGLB30	0.62587329	0.173755368	0.24768156	0.787680776

Table A12

The Returns of Simulated Eurobond Portfolios With Different Asset Weights

BRAGLB30	MEXGLB31	RUSGLB30	TRGLB30	VaR	Return
1	0	0	0	4242.255562	-0.255850
0	1	0	0	1224.518443	0.116935
0	0	1	0	1302.109021	0.754098
0	0	0	1	1417.389680	0.348726
0.25	0.25	0.25	0.25	1662.831095	0.126552
0.5	0.5	0	0	2461.180398	-0.106793
0.5	0	0.5	0	2556.491164	0.044982
0.5	0	0	0.5	2535.349880	-0.040885
0	0.5	0.5	0	1051.221198	0.364815
0	0.5	0	0.5	1063.892290	0.221936
0	0	0.5	0.5	1195.945193	0.524932
0	0.333333333	0.333333333	0.333333333	1023.812056	0.359409
0.333333333	0	0.333333333	0.333333333	1994.507365	0.129795
0.333333333	0.333333333	0	0.333333333	1913.571905	0.006521
0.333333333	0.333333333	0.333333333	0	1931.326782	0.067914
0.000	0.400	0.400	0.200	1013.532042	0.361566
0.000	0.450	0.350	0.200	1008.123397	0.332074
0.000	0.500	0.300	0.200	1007.592203	0.303833
0.000	0.500	0.270	0.230	1006.735021	0.295152
0.000	0.490	0.280	0.230	1006.289802	0.300631
0.000	0.470	0.300	0.230	1005.978506	0.311727
0.000	0.470	0.290	0.240	1005.864115	0.308786
0.000	0.470	0.289	0.241	1005.861885	0.308492

Note: Investment horizon 490 days, from 07.08.2001 to 10.12.2002.

Table A13
Returns and Invested Capital for the Eurobonds Portfolio
With Asset Weights 0, 0.470, 0.289 and 0.241

Date	BRAGLB30	MEXGLB31	RUSGLB30	TRGLB30	Sum	Return
12.2002	0	47000	28900	24100	100000	0.008203
11.2002	0	46377.858	28224.76636	24583.7072	99186.33156	0.070036
10.2002	0	44567.99037	27099.37695	21027.0366	92694.40392	0.051624
09.2002	0	43663.05656	25388.78505	19092.20779	88144.0494	-0.015974
08.2002	0	44681.1071	25118.69159	19775.08855	89574.88724	0.054256
07.2002	0	42192.53911	23993.30218	18779.22078	84965.06207	-0.037157
06.2002	0	44058.9651	24893.61371	19291.38135	88243.96016	-0.059027
05.2002	0	45246.69073	25883.95639	22648.87839	93779.52551	-0.011915
04.2002	0	46151.62455	25028.66044	23730.10626	94910.39124	0.033798
03.2002	0	45020.45728	23768.2243	23018.77214	91807.45372	-0.014315
02.2002	0	46434.41637	23858.25545	22848.05195	93140.72377	0.040013
01.2002	0	44850.78219	22057.6324	22648.87839	89557.29298	0.039277
12.2001	0	43663.05656	20572.11838	21937.54427	86172.71921	0.033636
11.2001	0	43323.70638	19131.61994	20913.22314	83368.54946	0.045882
10.2001	0	42984.3562	17150.93458	19575.91499	79711.20577	0.064472
09.2001	0	40043.3213	16430.68536	18409.32704	74883.33369	-0.053463
08.2001	0	43097.47292	17150.93458	18864.58087	79112.98838	

Table A14
The Probability of Bankruptcy of Russian Oil and Gas and Energy Companies

Company	**Net Income Distribution Function**	**Probability of Bankruptcy, ψ**
RJSC UES	Inv. Gauss	≈ 0
Lukoil	Inv. Gauss	≈ 0
Tatneft	Lognormal	≈ 0
Gazprom	Normal	≈ 0

Table A15
401(k) Concentrations in Company Stock and Stock Market Dynamics from 1999-2002

Company	Company Stock as Percent of Total Pension Assets %	Percentage Change in Stock Prices 12.1999 – 09.2002 %
Procter & Gamble	94.7	-18.41
Pfizer	85.5	-10.54
Coca-Cola	81.5	-17.66
General Electric Co.	77.4	-52.21
Texas Instruments	75.7	-69.42
Williams	75.0	-92.60
McDonald's	74.3	-56.18

Source: Munnell and Sunden (2002).

Table A16
U.S. Corporations With High Indebtedness, 2nd Half-Year 2002, USD Mln.

Corporation	Industry	Bonds	Mcap	Bonds/Mcap
General Electric	Machinery	232,882	282,730	82%
Ford Motor Co.	Machinery	167,337	28,134	595%
General Motors	Machinery	166,314	28,503	583%
Verizon Comm.	Telecom	64,326	104,128	62%
Tyco Intl. Ltd.	Machinery	57,117	24,658	232%
AT&T Corp.	Telecom	53,485	36,000	149%
IBM	Computers	27,151	115,724	23%
SBC Comm.	Telecom	26,166	100,072	26%
Sears Roebuck	Retail	25,635	16,461	156%
Qwest Comm.	Telecom	25,003	3,857	648%
WorldCom Inc.	Telecom	24,705	178	13897%
AOL Time Warner	Media	22,840	60,156	38%
AES Corp.	Utility	22,258	2463	904%
Philip Morris Co.	Food	22,102	96,194	23%
Wal-Mart Stores	Retail	21,880	241,973	9%
TXU Corp.	Utility	20,703	14,230	145%
Bell South Corp.	Telecom	20,125	57,358	35%
Chevron Texaco	Oil	17,418	94,578	18%
Sprint Corp.	Telecom	17,313	4797	361%
El Paso Corp.	Transport	17,002	11,468	148%

Source: Tretyakov A. 2002.

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