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AN ASYMMETRIC APPROACH TO THE COST OF EQUITY ESTIMATION: EMPIRICAL EVIDENCE FROM RUSSIA

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AN ASYMMETRIC APPROACH TO THE COST OF EQUITY ESTIMATION: EMPIRICAL EVIDENCE FROM RUSSIA

The choice of an appropriate model for the estimation of the cost of equity in emerging markets is still a very challenging problem. Market inefficiency, limited opportunities for diversification, as well as liquidity issues inspire researches to look for risk characteristics beyond the traditional framework of the classical capital asset pricing model. Various models have been developed over the past several decades proposing new ways of risk assessment. However, the empirical evidence of these models requires careful consideration.

Most asset pricing models were developed in terms of either a symmetric mean-variance or a folded mean-semivariance framework. These models have several drawbacks in capturing investors' attitudes to stock price movements. We provide a brief description of the recently proposed entropic risk characteristics which assign greater weight to the downside movements of asset prices and smaller weight to the upside movements.

The goal of this study is to determine which model has better explanatory power for returns in the Russian capital market. We compare the performance of risk measures in the Russian stock market on a dataset of 63 stocks for the period from 2003 to 2012. Empirical results show certain advantages of entropic risk characteristics over other risk measures in explaining returns on Russian equities.

Keywords: rate of return, cost of equity, CAPM, entropic variance.
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I. Introduction

The Capital Asset Pricing Model (CAPM), introduced by Sharpe (1964) and Litner (1965), was the first attempt to estimate the cost of equity. It has been widely used since. The equation for the model is:

$$E(R_i) = R_f + \beta_i \, (E(R_M) - R_f),$$

where R_i is the return of *i*-th asset, R_f is risk-free rate, R_M is return of the market portfolio, $E(R_i)$ is the expectation of R_i and β_i is a measure of systematic risk which can be obtained as:

$$\beta_i = \frac{\mathrm{cov}(R_i, R_M)}{\sigma^2(R_M)},$$

where $cov(R_i, R_M)$ is covariance between R_i and R_M, $\sigma^2(R_M)$ denotes the variance of market portfolio returns.

The cost of equity estimation based on CAPM faces certain problems. Even the straightforward application of this model to companies from emerging markets is complicated. Based on data from either global or local markets the estimation of the risk free rate and the return of a market portfolio may provide completely different results. Based on global markets characteristics Global CAPM (GCAPM) is applied mostly for companies incorporated in developed countries. While Local CAPM (LCAPM) mainly applies to companies incorporated in developing countries.

The concept of mean-variance behavior is central to CAPM. In other words the utility and therefore the behaviour of an investor are determined by two factors: the mean return and the variance of investor's portfolio (measure of risk). CAPM assumptions imply that the distribution of an asset's return is symmetric and normal. However these implications are not supported by empirical evidence: fat tails and high peaks can be frequently observed in the market, challenging the hypothesis of a normal distribution of returns.

Abbas et al. (2011) in their recent study pointed out that there are three major approaches to CAPM treatment: rejecting CAPM completely; extending classical CAPM by adding factors of size and momentum; modifying CAPM in order to overcome its theoretical flaws. For instance, conditional CAPM was created to overcome the problem of unstable beta. Furthermore higher moments were included in the equation to solve the problem of the non-normal distribution of returns. However, because the proposed modifications of CAPM were also developed in terms of a symmetric framework under the assumption of the equal weights of the upside and downside risk, they do not account for different investor attitudes to the upside and downside stock fluctuations.

Following Markowitz's suggestion, Estrada (2000, 2007) argues that semi-variance is a more suitable measure of risk than variance, arguing that it can be used in cases of both a symmetric and an asymmetric distribution of returns and it also accounts for downside volatility only. It is consistent with the "safety first" rule, which implies that investors try to avoid negative returns only. To support the idea Estrada developed the downside CAPM (DCAPM) model and received favorable results for returns on stocks in emerging markets.

Since then the two models that are most often tested in emerging markets were LCAPM and DCAPM. The popularity of DCAPM can be also explained by the fact that distributions of returns in developing markets are mostly asymmetric.

Downside risk measures take only downside volatility into consideration. However, some researches argue that this assumption is too strong and investors do pay attention to the upside risk to a certain extent especially in the case of a sharp stock rise.

That is why recently introduced entropic deviation (or volatility) as a measure of risk seems to capture the risk attitude of investors better than downside volatility.

In this study we test empirically traditional models with total and downside volatility and compare the results to models with entropic risk characteristics. In other words, the aim of this study is to determine which of the risk measures have more explanatory power and better predict returns in emerging capital markets.

This article is organized as follows: in part II we review the literature on CAPM developments and their empirical studies; part III contains a description of the research method; part IV provides information about the data; part V contains the results of the analysis; and part VI provides some concluding remarks.

II. Literature review

As mentioned above many researchers conclude that CAPM has several drawbacks. Assumptions of a normal distribution of returns and market efficiency do not apply to emerging market stock price fluctuations. These drawbacks led to various modifications of the model. We will start with empirical research of traditional GCAPM and LCAPM.

Bruner et al. (2008) tested GCAPM and LCAPM and obtained the following empirical results: in emerging capital markets the use of the local model is preferable to the global model, while in developed markets both models provide nearly identical results. These results were obtained from a large dataset of stock returns from 48 countries, 10 developed market sectors, 10 emerging market sectors, 10 global sectors and 362 country-specific sectors which covered the period from January 1994 to July 2004. In order to assess the robustness of results, the authors also divided the sample into two sub-periods. Bruner et al. (2008) concluded that beta is quite stable over time, and the results of the comparison of different models are constant and independent of the choice of the period.

Barclay et al. (2010) tested GCAPM and LCAPM, as well as their modifications adding several factors to these models. The sample included data from 20 emerging markets, divided into two sub-periods: 1995-2001 and 2002-2008. Test results showed that different sub-periods require different models for the estimation of the cost of equity. In the first (pre-crisis and crisis) period LCAPM provides better results than the global model in emerging markets while in the post-crisis period GCAPM provides better results.

Nevertheless, LCAPM and GCAPM have certain disadvantages. Indeed the research mentioned double accounting for country risk premium in LCAPM. That is why new models, such as the Godfrey-Espinosa model (1996), were proposed.

Korkmaz et al. (2010) used a different approach. They developed a model with the embedded Markov process, switching between two different modes depending on the volatility of regression residuals. The model with the embedded Markov process takes into account the market reaction to economic shocks. The evaluation of the performance of the model showed that it has greater explanatory power than standard CAPM supporting the hypothesis of beta changing over time. Korkmaz et al. (2010) concluded that CAPM underestimates the systematic risk during periods of high volatility and overestimates it during the periods of low volatility.

Estrada (2000, 2007) introduced the mean-semivariance framework, where investor's utility is determined by the mean and semi-variance of the portfolio return of the investor. The author also developed a new model, downside CAPM (DCAPM), which can be written:

$$E(R_i) = R_f + \beta_i^D (E(R_M) - R_f),$$

where β_i^D is:

$$\beta_i^D = \frac{E\{\min[(R_i - \mu_i),0] \cdot \min[(R_M - \mu_M),0]\}}{E\{\min[(R_M - \mu_M),0]^2\}},$$

where $\mu_i = E(R_i)$ is expected return of the asset *i* and $\mu_M = E(R_M)$ is expected return of the market.

Empirical tests of the DCAPM model in different markets sometimes showed better results than some of the previously mentioned modifications of classical CAPM. In order to demonstrate that DCAPM is consistent with economic realities Estrada (2007) used data from 23 developed and 27 developing countries for the period of 1988-2001. Comparing the results for DCAPM and LCAPM the author came to the conclusion that DCAPM is more statistically and economically significant than LCAPM for developing markets. Estrada (2007) discovered that the downside beta explained over 45% of the volatility in the cross-sectional returns according to empirical results from a joint sample of developed and emerging market data, and almost 55% of the volatility in the cross-sectional returns in emerging markets. The downside model generates a higher required return for emerging markets than for developed markets contradicting the conclusions of CAPM.

Mongrut et al. (2010) considered sample of 32 companies from the Baltic region for the period of 2000-2008. They showed that cost of equity forecasts obtained according to DCAPM are consistent with observations and adequately reflect the differences in the cost of equity for companies from different sectors.

Foong & Goh (2010) tested several risk measures in order to determine the best model for estimating the cost of equity based on the data from Malaysia covering the period of 2000-2007. The authors considered the following risk measures: standard deviation of returns, local beta, global beta, betas from the two-factor model[3], as well as downside modifications of these indicators. Foong & Goh (2010) estimated the regressions and then ranked the risk measures according to their explanatory power. They concluded that their results support the implications of Estrada (2007) regarding the advantage of downside risk measures over symmetric ones. The downside beta outranked local beta, which in turn performed better than global beta. However the best results were obtained with the semi-deviation measure.

Bali, Demirtas & Levy (2009) considered the intertemporal aspect of the mean-semivariance behavior concept. They examined the relationship between expected returns and downside risk, using value at risk (VAR) as a proxy for downside risk. The authors used the data from the US market, i.e. monthly returns of NYSE/AMEX/NASDAQ; NYSE/AMEX; NYSE; NASDAQ indices for the period of 1962-2005. Their results supported the hypothesis of mean-semivariance behavior. A positive and significant relationship between expected returns and downside risk was confirmed. Moreover, VAR outperformed variance and conditional variance risk measures. The authors discovered that as long as VAR accounted for stock returns with high explanatory power, the other measures of downside risk also performed well.

However, the conclusions of other researches were quite the opposite. Thus, Bukhvalov & Okulov (2006) used a sample of 74 Russian companies for the period 1996-2002 and discovered that although DCAPM did show better results than LCAPM, it had weak explanatory power. Teplova & Shutova (2011) also considered data from the Russian stock market: the sample included 50 Russian companies for the period of 2004-2010. Similarly to Bukhvalov & Okulov (2006) the authors came to the conclusion that DCAPM has weak explanatory power. Furthermore, it was shown that downside risk measures do not perform better than classic risk measures. Galagedera (2009) used a dataset from both developed (18) and developing countries (26) for the periods of 1970-2006 and 1993-2006 respectively and did not find any evidence to support DCAPM.

Galagedera & Brooks (2007) considered data from 27 emerging markets for the period of 1987-1994 and examined the validity of DCAPM and models which included several versions of the third-order moment in the downside framework. They tested regression model with three different specifications of downside beta presented by previous researches. Galagedera & Brooks (2007) also developed a new risk measure of co-skewness and named it downside gamma. The

[3] They used local and global risk premiums and local and global betas in the model simultaneously.

authors concluded that downside gamma may be a more appropriate for the explanation of returns than downside beta. Galagedera (2009) tested a sample of data from both developed (18) and developing countries (26) for the periods of 1970-2006 and 1993-2006 and came to the conclusion that DCAPM had weak explanatory power. Again he suggested that downside co-skewness could explain the variation in average excess returns better than beta and downside beta.

On the other hand, Tsonchev & Kostenarov (2010) used data from the Bulgarian Stock Exchange (for the period of 2004-2009) to test five models: DCAPM, LCAPM and three CAPM modifications with different specifications of skewness. The first modification of the model combines both downside and upside betas in the equation for the risk measure. The second modification considers absolute deviation as a measure of risk. Finally the third modification adds skewness as additional premium to the LCAPM. All models demonstrated poor results. Models that accounted for asymmetry did not perform much better than LCAPM.

It is worth mentioning that Bukhvalov & Okulov (2006), Estrada (2007), Foong & Goh (2010), Teplova & Shutova (2011) applied similar approach testing models with different risk measures as independent variables.

Table 1 summarizes the results of studies mentioned above.

Table 1. Summary table of reviewed literature.

Author	Sample	Period	Compared models	Results
Bruner et al. (2008)	48 countries	1994-2004	GCAPM and LCAPM	In the emerging capital markets LCAPM is more preferable.
Barclay et al. (2010)	20 emerging markets	1995-2008	GCAPM and LCAPM	Different models for different sub-periods
Khan et al. (2012)	10 companies from Pakistan market	2006-2010	LCAPM	LCAPM shows poor results
Korkmaz et al. (2010)	23 emerging markets	1995-2009	International CAPM	CAPM underestimates the systematic risk in periods of high volatility and overestimates in the periods of low.
Estrada (2007)	23 developed and 27 developing countries	1988-2001	DCAPM and LCAPM	DCAPM performs better than LCAPM
Bukhvalov & Okulov (2006)	74 Russian companies	1996-2002	DCAPM and LCAPM	DCAPM performs better than LCAPM

Author	Sample	Period	Compared models	Results
Galagedera & Brooks (2007)	27 emerging markets	1987-1994	Downside beta and downside co-skewness	DCAPM has weak explanatory power; downside co-skewness may be a more appropriate risk measure than downside beta
Galagedera (2009)	18 developed and 26 developing countries	1970-2006 (developed countries) 1993-2006 (developing countries)	Downside beta and downside co-skewness	DCAPM has weak explanatory power; downside co-skewness explain the variation in average excess returns better than beta and downside beta
Tsonchev & Kostenarov (2010)	from 29 (in 2004) to 141 (in 2009) Bulgarian companies	2004-2009	LCAPM, DCAPM, three models with skewness	Similar results for downside and symmetric risk measures
Mongrut et al. (2010)	32 companies from the Baltic region	2000-2008	DCAPM, Mariscal and Lee's model, Damodaran's CAPM	DCAPM provided better results
Foong & Goh (2010)	557 Malaysian companies	2000-2007	GCAPM, DCAPM, LCAPM, two-factor model, deviations as risk measures	Downside risk measures perform better
Teplova & Shutova (2011)	50 Russian companies	2004-2010	DCAPM and its modification	DCAPM has weak explanatory power

Source: mentioned articles.

The conflicting results of the empirical tests of downside risk measures could be possibly explained by an underestimation of the investors' reaction to positive fluctuations of returns. In this study we consider a different approach (recently proposed by Dranev (2012)) to estimate the cost of equity. This approach has certain advantages over mean-variance and mean-semivariance frameworks. It allows us to consider downside movements of returns, as well as upside movements with smaller weight attributed to the latter. Dranev (2012) introduced new modifications of risk measures for predicting expected returns: entropic variance and entropic beta. The form of the equations for the proposed entropic risk characteristics were inspired by the concept of entropy, although there is no direct relationship with the entropy which is traditionally defined for distributions, portfolio weights or probability measures in financial mathematics.

Entropic variance can be written in the following form[4]:

$$EV(R_X) = ECOV(R_X, R_X) = (1 + E(R_X))^2 E(D_X Log(1 + D_X)),$$

where R_X is a random market return of the asset X, $E(R_X)$ is expectation of the R_X, $D_X = \frac{R_X - E(R_X)}{1 + E(R_X)}$ is standardized difference between asset return and its expectation. The entropic standard deviation is given by: $ESD_X = \sqrt{EV(R_X)}$.

At this point we need to mention several properties of entropic variance. It is positive. Moreover, it is less than variance for $R_X \geq E(R_X)$ and greater than variance for $R_X \leq E(R_X)$.

The entropic variance is an asymmetric measure of risk. It assigns greater weight to the downside movements of the asset price and smaller weight to the upside movements. There are major difference between entropic and downside risk characteristics: while both types of risk measures are asymmetric, downside risk measures do not account for upside movements, while entropic measures do. Furthermore the mean–entropic variance behavior could be more appropriate for an explanation of stock returns in emerging markets than the mean–variance or mean semi-variance behavior.

The entropic beta was introduced similarly to downside beta. It can be given by the following equation:

$$\beta_i^E = \frac{ECOV(R_i, R_M)}{EV(R_M)} = \frac{\text{cov}(R_i, Log(1 + R_M))}{\text{cov}(R_M, Log(1 + R_M))},$$

where R_M is the market return. The logic that lies behind such a choice of beta is different from the logic that lies behind the concept of beta in classic CAPM since entropic beta is not determined as a solution to the portfolio optimization problem and the capital market line is not linear in the case of a mean-entropic variance framework.

The capital asset pricing model in entropic framework can be written in the following form:

$$E(R_i) = R_f + \beta_i^E (E(R_M) - R_f).$$

In the next sections we test empirically entropic risk characteristics (entropic beta and entropic variance) and compare results with classic and downside beta and variance.

[4] For two different assets X and Y the entropic covariance is given by: $ECOV(R_X, R_Y) = (1 + E(R_X))(1 + E(R_Y))E(D_X Log(1 + D_Y))$. The equation is similar to the equation of Kullback-Leibler divergence, but instead of distributions we use differences between returns and mean returns slightly changing the logarithmic part of the equation. Note that instead of the traditional entropy of the form *-E(ZLogZ)* for some Z we considered slightly modified expression *E(ZLog(1+Z))* with different properties. Since entropic (co)variance, introduced by a number of researches in different forms, has not received wide recognition we call *EV* an entropic variance in this study realizing a certain inconsistency of this definition.

III. Methodology

We consider asset pricing models in a local capital market employing two groups of risk measures, betas and volatility characteristics:

- LCAPM beta, downside beta and entropic beta,
- standard deviation of return, semi-deviation, entropic deviation and entropic variance.

We use a wide range of risk characteristics due mainly to the fact that a number of empirical studies questioned the validity of CAPM (and its LCAPM version) in emerging markets. For example, according to Estrada (2000, 2001) LCAPM betas and stock returns are not significantly correlated. Harvey (1995) also mentioned that betas were very low for emerging markets, questioning the adequacy of the cost of equity estimation. However, Estrada (2000) observed a significant correlation between stock returns and total risk (standard deviation of returns) as well as between stock returns and downside risk (semi-deviation of returns and downside beta). The choice of entropic variance as one of the predictors for stock returns can be explained by the fact that unlike traditional variance it has the same dimension as returns.

We are interested in comparing risk measures to the explanatory power of average stock returns in emerging markets. We adopt the Fama & MacBeth (1973) two stage regression model. A similar model was employed by Estrada (2007), Teplova & Shutova (2010), and Bukhvalov & Okulov (2006). Firstly betas and other risk measures are estimated for each individual stock based on the daily, weekly and monthly observations for the particular period of time. Secondly mean returns of stocks are regressed against corresponding risk measures (cross-sectional regression) estimated at the first stage.

We use the simplest specification of regression with one independent variable:

$$MR_i = \alpha_0 + \alpha_1 \cdot risk\ measure_i + \varepsilon_i \ ,$$

Where MR_i is the mean return of asset i, $risk\ measure_i$ is one of betas and deviations considered.

Beta stability over time is one of the most questionable assumptions of the CAPM framework. Teplova & Selivanova (2007) provided evidence of a significant decrease in beta coefficients compared to those obtained by Estrada (2002) in emerging markets. The development of financial institutions in these countries could probably explain the observed decrease in systematic risk during the last few years. Another major obstacle to beta stability is the constantly changing local index constitution. Questioning stability of betas we believe that volatility characteristics of an asset return could be constant over time.

Our test is based on a sample of weekly and monthly returns. Weekly and monthly observations are preferable than daily returns because of the significant inefficiency of emerging markets mainly due to liquidity problems. Moreover total risk characteristics (betas and volatility) and entropic characteristics become very close to each other for small fluctuations in the stock price. In the absence of major market shocks daily stock returns are very close to zero providing very similar empirical results on daily observations for both groups of models.

IV. Data

We consider 63 Russian stocks listed on MICEX stock exchange. The dataset for this study covers the period from January 2003 until May 2012.

Stock returns are computed as the ratio of current market closing price to the previous market closing price minus one. The proxy for the local market index is the MICEX Index and the proxy for the risk-free rate is the yield of long-term Russian government domestic bonds (OFZ). For every period of time (weeks and months) we used an average of the long term rates published daily by the Central Bank of Russia.

We considered the following sub-periods:

- from January 2003 to December 2007,[5]
- from January 2008 to May 2012,
- from May 2008 to November 2008,
- from January 2003 to December 2011.

In order to account for the crisis period we decided to divide the sample into two sub-periods: pre-crisis (2003-2007) and crisis/post-crisis period (2008-2012). Moreover, we marked out the period from May to November 2008 when the Russian marked collapsed. One can see the negative dynamics of returns in Table 2 for the crisis period of 2008.

Table 2. Summary statistics.

		Weekly			
Year	Mean	Median	Minimum	Maximum	Std. Dev.
2003	3,17	2,98	-3,82	9,83	3,30
2004	2,23	2,22	-3,27	7,04	3,01
2005	4,27	3,68	-21,88	28,01	8,22
2006	5,31	4,36	-10,98	40,22	7,97
2007	1,20	1,17	-9,07	10,49	3,34
2008	-8,81	-9,54	-22,18	2,77	5,02
2009	8,70	9,15	-3,30	20,15	4,87
2010	3,82	2,89	-4,18	37,02	5,32
2011	-3,07	-3,42	-8,75	3,73	3,12
2012	1,02	0,49	-8,50	20,90	4,74
		Monthly			
Year	Mean	Median	Minimum	Maximum	Std. Dev.
2003	0,74	0,73	-0,91	2,23	0,76
2004	0,49	0,49	-1,29	2,06	0,79
2005	-0,69	1,08	-29,63	7,08	8,28
2006	1,27	1,13	-3,33	7,73	1,81
2007	0,32	0,29	-2,30	2,45	0,74
2008	-2,08	-2,16	-5,66	0,52	1,28
2009	1,97	2,09	-0,90	3,85	1,01
2010	0,85	0,65	-1,08	7,34	1,09
2011	-0,69	-0,78	-2,09	0,90	0,74
2012	-0,18	-0,39	-2,17	4,23	1,02

We also examined the dataset on the entire period from 2003-2011.

V. Empirical Results

The cross-sectional analysis of weekly and monthly observations for the period from 2003 to 2007 shows no statistical significance of betas. Although weekly mean returns are significantly correlated at the 5% level with both standard and entropic deviation and at the 10% level with entropic variance. Monthly data shows that deviations and entropic variance are statistically significant at 1% level (Table 3). Moreover, based on monthly observations the regression of mean returns against entropic deviation/variance exhibits a better adjusted R^2 than

[5] Only 31companies were examined for the period.

regression against standard deviation. Compared to monthly returns weekly returns reduce the explanatory power of models because of market inefficiency. Smaller weekly returns also account for the larger number of trend changes.

The entropic variance has the greatest explanatory power over other risk characteristics for the period. Recalling that entropic variance is squared entropic deviation it can be possibly explained by the non-linear relationship between the risk of a security and its returns.

Table 3. Results for the period 2003-2007.

	Monthly							
	Dev		Edev		Ddev		Evar	
α_0	1,4809	**	1,1921		0,5192		2,4831	***
α_1	16,1886	***	19,1678	***	40,2689	***	59,8879	***
R^2	0,2714		0,2764		0,2608		0,3115	
$Adj-R^2$	0,2463		0,2514		0,2353		0,2878	

Here and below: * means 10%, ** - 5% significance level, *** - 1% significance level

For the period of 2008-2012 beta and entropic beta are statistically significant at the 10% level based on weekly data. Weekly downside beta and monthly betas are not statistically significant. All six variables have very low explanatory power. Furthermore, various deviations and entropic variance are not significantly correlated with weekly mean returns. But monthly observations show that standard deviation and entropic variance are statistically significant at the 1% level and entropic deviation is statistically significant at the 5% level (Table 4). Regressions with entropic risk characteristics exhibit a smaller adjusted R^2 compared to the standard deviation. It could possibly be explained by differences in investor's attitudes to risk during periods of market volatility and stable market growth. In other words after the crisis, market fluctuations became large forcing investors to react with caution on both upside and downside movements. On the contrary for the period of stable economic growth investors pay much more attention to downside movements of returns compared to upside movements.

Table 4. Results for the period 2008-2012.

	Monthly							
	Dev		Edev		Ddev		Evar	
α_0	-0,0128	**	-0,0129	*	-0,0051		-0,0061	*
α_1	0,0846	***	0,0860	**	0,0748		0,2493	***
R^2	0,1149		0,0793		0,0101		0,1143	
$Adj-R^2$	0,1003		0,0642		-0,0062		0,0997	

Table 5 shows test results for the period of market collapse from May to November 2008. Beta and entropic beta are statistically significant at the 1% level based on monthly data. Moreover beta outperforms other variables by adjusted R^2.

Tests on weekly data demonstrated very low explanatory power and arguable significance of coefficients. Deviations for both monthly and weekly data are not significant and have low explanatory power. We did not present these results in Table 5.

One can notice that regression coefficients are negative due to the fact that the market declined. It is consistent with the assumption of a negative market premium for the period.

Table 5. Results for the period from May to November 2008.

May-November 2008	Weekly							
	Beta		Ebeta		Dbeta		Evar	
α_0	-0,030	***	-0,029	***	-0,023	***	-0,031	***
α_1	-0,004		-0,005		-0,013		-0,092	
R^2	0,009		0,012		0,042		0,003	

	Beta		Ebeta		Dbeta		Evar	
$Adj-R^2$	-0,008		-0,004		0,026		-0,013	
					Monthly			
	Beta		**Ebeta**		**Dbeta**		**Evar**	
α_0	-0,057	***	-0,059	***	-0,114	***	-0,146	***
α_1	-0,087	***	-0,081	***	-0,035		0,190	
R^2	0,259		0,254		0,018		0,014	
$Adj-R^2$	0,247		0,242		0,002		-0,002	

Table 6 shows test results for the entire period of 2003-2011. There is no significant relation between mean returns and betas for either monthly or weekly data. At the same time based on weekly data, standard deviation and entropic variance are statistically significant at the 5% level and entropic deviation is statistically significant at the 10% level. Monthly data shows that both standard/entropic deviations and entropic variance are statistically significant at the 1% level. However, the determination coefficient R^2 for the regression of mean returns on entropic deviation/variance is smaller than R^2 for the regression of mean returns on standard deviation. Semi-deviation exhibits the smallest of all R^2.

Table 6. Results for the period 2003-2012.

2003-2011					**Weekly**						
	Beta	**Ebeta**	**Dbeta**		**Dev**		**Edev**		**Ddev**	**Evar**	
α_0	0,2059	0,2165	0,4610	**	-0,1067		-0,0805		0,4180	0,0657	
α_1	0,0858	0,0712	-0,1854		4,4821	**	4,3307	*	-2,8322	29,2676	**
R^2	0,0049	0,0032	0,0137		0,0946		0,0471		0,0038	0,0844	
$Adj-R^2$	-	-	-		0,0797		0,0315		-	0,0694	
					Monthly						
	Beta	**Ebeta**	**Dbeta**		**Dev**		**Edev**		**Ddev**	**Evar**	
α_0	1,1112	1,1595	1,6524	*	-0,6815		-0,8603		-0,2502	0,1842	
α_1	0,0809	0,0354	-0,3580		10,7320	***	11,8963	***	13,2944	30,6621	***
R^2	0,0003	0,0001	0,0053		0,1843		0,1295		0,0301	0,1761	
$Adj-R^2$	-	-	-		0,1710		0,1153		0,0142	0,1626	

Similar to the above consideration can be mentioned here. Betas are more strongly affected by changes in market global trends than deviations and variances. Downside risk measures failed to predict mean stock returns for the entire period.

VI. Conclusion

The main purpose of this study was to determine whether entropic risk characteristics can better predict stock returns than CAPM beta, standard deviation and their downside modifications in the Russian equity market. Based on empirical results we can conclude that entropic risk characteristics provide better results in certain cases. Additionally, different types of deviations and entropic variance perform generally better than various betas. Hence we may question the stability of betas over periods of time considered.

In the pre-crisis period the best results were demonstrated by entropic risk characteristics on the monthly dataset. We can conclude that in stable market conditions investors prefer upside stock movements over downside movements to a certain extent. Downside risk measures demonstrated relatively poor results implying that upside risk cannot be excluded from the consideration completely.

The results were different in the period of 2008-2012 in the absence of a stable market trend. The empirical evidence showed that standard deviation was the best predictor of stock returns. Upside and downside stock fluctuations equally bothered investors during the period of high market uncertainty.

Betas showed a significant correlation with stock returns only for the short period of market decline in 2008 which is consistent with our suggestion that beta is unstable over longer periods of time. Based on the monthly data traditional beta had greater explanatory power compared to downside and entropic betas. Thus investors again equally weighted upside and downside price movements in the period of market turmoil.

Similar results were obtained for the entire period from 2003 to 2012 supporting the suggestion of changing investor attitude to market risks and hence the instability of risk measures. The proposed model cannot cope with dramatic changes in market conditions, predicting stock returns poorly on the dataset of returns for the long period of time. The possible solution to this problem could be a modification of the model according to the conditional CAPM.

We plan to extend our dataset of stock returns to the other emerging markets such as Brazil, India, etc. Adding more independent variables in the model could significantly improve empirical results.

To conclude we must note the relatively high explanatory power of entropic risk characteristics over periods of market stability which inspires us to continue working in this area.

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