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Annotation

The paper aims at evaluating the performance and examining dynamic strategies of Russian equity mutual funds. It serves as the first attempt to apply the modern econometric techniques and performance measurement concepts to data on Russian mutual funds, covering all equity funds existing by March 2003.

The paper consists of three main parts. The first part employs the market model with constant beta and measures performance using conventional indexes, such as Jensen alpha, Treynor and Sharpe ratios. The study reports no significant evidence of positive or negative stock-picking ability, as most funds have insignificant alphas. However, seven out of eight open-end funds and four out of six interval funds have positive alphas, one of which is significant, which may indicate the presence of some stock-picking ability among them. Then the behavior of fund investors is studied, yielding the conclusion that fund cash flows are related mostly to the market growth. This fact reduces the incentive of the managers to earn abnormal return and may partly explain the insignificance of the results on stock-picking ability.

Since the results on stock-picking ability may be driven by the assumption of constant market beta, in the rest of the paper dynamic strategies of the fund managers are analyzed. The second part turns to investigating both stock-picking and market-timing ability of the funds. Examining the post-crisis data yields mostly negative estimates of the market-timing coefficients, two of which are significant. However, three out of four funds operating in 1998, the year of the crisis, have significantly positive estimates. It is demonstrated that the post-crisis results can be partly attributed to the passive effects. Moreover, fund managers may not exhibit significant market timing after the crisis because of transaction costs, which may exceed potential profits. The second part also addresses volatility timing and employs an innovative approach to study its nature, trying to distinguish between reaction of the managers to anticipated and unanticipated volatility shocks. Given mostly insignificant estimates of the volatility timing coefficients, it is not surprising that no general pattern of reaction to these kinds of shocks emerges.

The third part of the paper explores other dynamic beta strategies. The paper presents firm evidence against beta stability over time and limited evidence of managers timing of macroeconomic variables. Considering various dynamic beta strategies helps to draw more reliable conclusions about the mutual fund performance, lending additional support to the view that the managers of Russian open-end funds may have stock-picking ability.

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Introduction

It is widely believed that the development of Russian mutual fund industry is the key to the successful development of Russian financial markets. At present, the financial markets in Russia are underdeveloped compared to the financial markets of CEE countries. For example, the capitalization of Russian stock market in July 2002 was about 120 billion dollars, or about one third of GDP, whereas in Hungary, Czech Republic and Poland the capitalization of the stock market exceeded the GDP volume. The same picture holds for mutual funds: Grigoriev et al., 2003, report that in July 2002 the total capitalization of Russian mutual funds was only 350 million dollars, whereas in January 2002 the capitalization of Hungarian, Polish and Czech mutual funds was 2600, 1700 and 2400 million euro, respectively.

These figures are even more striking taking into account the fact that Russian population and GDP exceed greatly the population and GDP of the aforementioned countries, and the stock market in Russia grew in the past three years more rapidly than any stock market in CEE. For example, the RTS index grew by 82% in 2001, by 36% in 2002 and by 28% in the first five months of 2003. These figures show that despite all risks, Russian stock market has been very attractive for investment.

The easiest and the cheapest way for private investors to invest in stock market, without being exposed to great non-systematic risks, is to buy shares of a mutual fund. A mutual fund allows everybody to hold a part of a well-diversified and professionally managed portfolio. However, due to a number of institutional factors, most private investors are reluctant to place their savings in mutual funds. Grigoriev et al, 2003, report that in 2001, when the market was most rapidly growing, only 3% of the growth of mutual fund industry could be attributed to the inflow of new money.

The paper focuses on studying the performance of Russian equity funds, which take 53% of the total capitalization of Russian mutual funds industry. It is important to know whether Russian equity funds can earn abnormal return and match other needs of private investors to see if the underdevelopment of the industry is really driven by various institutional factors or by bad management that makes it unattractive for investors.

The paper consists of three main parts. The first part employs the market model with constant beta and measures performance using conventional indexes, such as Jensen alpha, Treynor and Sharpe ratios. Then the behavior of fund investors is studied to see if the investors really favor the funds earning positive abnormal return.

Since the results on stock-picking ability may be driven by the assumption of constant market beta, in the rest of the paper dynamic strategies of the fund managers are analyzed. The second part turns to investigating both stock-picking and market-timing ability of the funds. The second part also addresses volatility timing and employs an innovative approach to study its nature, trying to distinguish between reaction of the managers to anticipated and unanticipated volatility shocks.

The third part of the paper explores other dynamic beta strategies, among which is the strategy relating the beta to basic macroeconomics indices, as considering the strategies helps to draw more reliable conclusions about the mutual fund performance.

Chapter 1
The Market Model and Performance Measurement

1.1 A Short Overview of the Literature on Performance Measurement

The studies of mutual funds performance date back to the early 1960s, when Sharpe proposed the simplest model relating the returns on financial assets to a benchmark named market portfolio (see Sharpe, 1963). This model was then simply an econometric phenomenon, which found its theoretical base in the CAPM few years later (see Sharpe, 1964, Lintner, 1965, Mossin, 1966). However, it is not necessary to view the market model and the security market line (SML) as a corollary of the CAPM. Rather, it can be considered the simplest factor model based on no-arbitrage considerations. This is the approach followed in this study, based on the difficulty to verify the validity of the CAPM for Russian data. The main empirical problem with the verification of the CAPM at the modern stage of development of financial econometrics is the low power of the tests (see Campbell et al, 1997). For Russian data these theoretical results mean that the straightforward statistical verification of the CAPM is impossible (see Barinov, 2002).

The market model combined with the basic results of the mean-variance analysis has led to the derivations of a number of indexes measuring the performance of a mutual fund (a portfolio) with respect to a benchmark. Traditionally, in the studies of the US market a capital-weighted representative index, such as S&P 500 or CRSP index, is chosen as a benchmark, if it is not known that the fund pursues a specific strategy (investing in small-cap stocks, growth stocks etc.). In our study, we use the RTS index, which is the capital-weighted index of the biggest Russian trading platform. During the four years studied the index included from 37 to 63 stocks of the leading Russian companies listed on the RTS market.

The three indexes used in our study are the Jensen alpha, Treynor ratio and Sharpe ratio. The Jensen alpha is defined as the intercept from a regression of the excess returns (returns less the risk-free rate) of the portfolio of a fund (its proxy) on the excess returns of the market portfolio (see Jensen, 1968), and measures the vertical distance between the portfolio of a fund and the SML in the "return-beta" space. The positive alpha reflects stock-picking skills of the managers.

The Treynor ratio is defined as $(R_P - RF)/\beta_{P,M}$, where $\beta_{P,M}$ is the slope of the aforementioned regression (see Treynor, 1965). It measures the slope of the line connecting the risk-free rate and the return on the portfolio in the "return-beta" space. If the slope exceeds the slope of the SML, the fund is said to overperform the benchmark.

The Sharpe ratio is defined as $(R_P - RF)/\sigma_P$ (see Sharpe, 1966) and measures the slope of the line connecting the risk-free rate and the return on the portfolio in the "return-standard deviation" space. If the line is steeper than the capital market line (CML), when the fund is said to overperform the benchmark.

The main difference between the Jensen alpha and the Treynor ratio, on the one hand, and the Sharpe ratio, on the other, is that, firstly, the former measure the "depth" of the management, and the latter measures its "breadth" (for a more thorough discussion see, e.g., Haugen, 2001). Under "depth" one understands the ability to find mispriced stocks and make profit on them (the "deeper" is the management, the more profit can it make on a mispriced stock). Under "breadth" one understands the ability to form a well-diversified portfolio overperforming the market.

Consequently, the Jensen alpha and the Treynor ratio are valid in the situation when an investor can form a well-diversified portfolio by herself and wants to see if the addition of a certain fund to the portfolio can improve the portfolio's performance. The Sharpe ratio is relevant if the investor can invest only in the risk-free asset and one of the funds. In this case the investor should choose the fund with the highest Sharpe ratio.

1.2 Data Characteristics

The study examines the data on total net assets and share value for fourteen Russian equity funds. In Russia, there exist nearly 50 mutual funds, split almost equally in six groups. Firstly, the funds can be open-end (that is, offering the shareholder a right to sell the share to the fund any time she likes) and interval (that is, offering this right at fixed dates separated by a fixed intervals of time). Closed-end funds, which do not offer such a right, leave the shareholder the only opportunity to sell the share in the market, did not exist in Russia until recently, due to some problems with the law status of a mutual fund share. After the law about mutual funds passed the Duma in November 2001, several closed-end mutual funds entered the market, but their limited experience and extremely thin market for their shares do not allow a thorough analysis of their performance.

Secondly, Russian mutual funds can be subdivided into equity funds (investing only in stocks), bond funds and mixed funds (investing in both stocks and bonds). In this study it was chosen to analyze the performance of the equity funds, as the Russian bond market is very thin and there is no proxy (index) for it.

In Russia there are fourteen equity funds, eight of which are open-end funds. Most of them entered the market after the crisis, so the study uses only post-crisis data. For open-end funds it means that at most 1050 daily observations are available, which means that the asymptotic theory for the regression estimates should be applied with caution, given the autocorrelation and heteroskedasticity in errors.

The study, however, relies on the asymptotic theory as the most solid benchmark for inference, but it is chosen to employ as many observations as possible, which leads to unequal sample sizes for different funds. It means that the estimates of the performance measures cannot be used directly to compare funds, though there is some statistical evidence, obtained, for example, using Kalman filter, which suggests that alphas are more or less stable over the post-crisis period. Still the unequal sample size is worth being mentioned, but it should not be treated as an obstacle for the study, as it mostly aims to analyze the performance of each fund with respect to the market benchmark.

The most obvious problem of the Russian data is the absence of the risk-free asset. After the collapse of the market for short-term government bonds in 1998, it is difficult to say whether the existing government debt instruments are viewed as risk-free assets by investors. For the daily returns, studied below, there are, however, several quite plausible hypotheses about the risk-free rate, necessary to generate the series of excess returns.

First of all, the availability of risk-free rate for an investor should be considered. Since mutual funds are oriented on a private investor, it is natural to assume that the risk-free rate is the deposit rate at large commercial banks. Taking into account the high frequency of our data, it can be also assumed that the risk-free asset for this planning horizon is the money itself, so the nominal risk-free rate is zero. This approach was first proposed in Tobin, 1958.

The second approach has it that mutual funds can be an object of investment for other market agents. So an approach parallel to taking the return on the Treasury bill for the US market is proposed. The risk-free rate can thus be the overnight rate for the loans offered by the Central bank. This rate changes slowly, as the refinancing rate changes. The second variant under this approach is to equal the risk-free rate to the monthly average of MIACR (Moscow Interbank Actual Credit Rate).

Consider first the regression of the logarithmic gross return of a fund on the return of the RTS index, which can be treated as the proxy to the market portfolio. If the risk-free rate is zero, the intercept of the regression is the Jensen alpha for the fund. If the risk-free rate differs from zero, one should take the excess returns as regressors.

However, the regression described above can yield biased estimates for the beta due to the infrequent trading. The possibility of beta mismeasurement in "thin markets" was first noted in Scholes and Williams, 1977, and Dimson, 1979, and then used extensively in the econometric analysis of "thin markets" (see, e. g., Busse, 1999). The main message of these papers is that the real beta under infrequent trading is the sum of the estimates of the coefficients for leads and lags included. It should be mentioned that this technique is innovative for Russian stock market, as other studies of it have not taken this effect into account, yielding upward biased alpha estimates.

In the paper, the reported estimates for beta are the sum of the estimates of the coefficients for the excess return on RTS itself and its two lags. The standard errors for the sums are computed under the assumption that the estimates of the coefficients before the return to RTS and its lags are independent. Given the small values of the covariances between the estimates, it seems to be a reasonable approximation. In further analysis the risk-free rate is assumed to be equal to the deposit rate, as this assumption seems to have more theoretical ground than the other three do. However, this assumption is not at all crucial, and the regressions using the data on other funds, confirm it.

1.3 The Stock-Picking Ability of the Fund Managers

Table 1 below presents the results of the primary analysis of the stock-picking ability of the funds managers. The intercepts in the regressions, which are the Jensen alpha, are all but one insignificant, that is, to put it in the formal way, one cannot reject the hypothesis of zero intercept given the data. The only fund, which has significantly positive Jensen alpha, is "Dobrynya", run by "Troika", which is known to be the most well informed fund. The point estimates suggest that seven of the eight funds in the table bring positive abnormal returns. One can apply the sign test, which is based on the fact that under the null of no stock-picking ability the number of positive alpha estimates is distributed binomially with the parameter p=1/2. Simple calculations show that under the null the probability to get seven and more positive alpha estimates is 0,035, so the null that the open-end fund managers have no stock-picking ability can be rejected at 5% level of significance. One can also notice that, after the point estimates, all the funds with positive alphas yield considerable positive abnormal return. So, the statistical insignificance should be taken with caution. It can be partly explained by mentioning that the sample size is small to estimate precisely such small figures as daily returns.

To draw conclusions about the significance of the differences between Sharpe and Treynor ratios of a fund and of the market one has to rely on asymptotic theory. The asymptotic distribution of the Sharpe ratio is easy to derive, as it is proportionate to the conventional t-statistic: $\sqrt{n}(\widehat{S}-(\mu-RF)/\sigma_x)\xrightarrow{d}N(0;1)$, where μ & σ_x are the true mean of market return and its true standard deviation. To put it simpler, $\sigma(\widehat{S})\approx 1/\sqrt{n}$. The derivation of the asymptotic distribution for Treynor ratio is more complicated and calls for the delta-method. It can be shown that under some regularity conditions the estimates of the beta and the mean of market return are asymptotically jointly normal and uncorrelated. Applying the delta-method yields $\sqrt{n}(\widehat{T}-(\mu-RF)/\beta)\xrightarrow{d}N(0;(\sigma_x^2/\beta^2+\mu^2\cdot\sigma_\varepsilon^2/\beta^4\cdot Ex^2))$, where σ_ε^2 is the variance of the residuals in the market model. To simplify the calculations, the second term can be omitted, as for a well-diversified portfolio the variance of the residuals in the market model is very small, at least relative to the variance of the market portfolio, and the square of the market return is also much smaller than the fourth power of the beta. So, it can be stated that $\sigma(\widehat{T})\approx 1/\sqrt{n}\times\sigma_x/\beta$.

The results reported in Table 1 show that the difference between Sharpe and Treynor ratios of the market and of a fund is never greater than one standard error. Taking into account that the standard error for Treynor ratio is underestimated as the result of the omission of the second asymptotic variance term, one can state with confident that for all the funds Sharpe and Treynor ratios do not differ significantly from these of the market.

Table 1. Open-End Funds Performance

Open-End	N obs.	Mean	Std. Dev.	Sharpe	Treynor	Alpha, % a year	Beta
AURI	1050	0,0020	0,034	0,058 (0,031)	0,0020 (0,0010)	12,7 (15,4)	0,996 (0,056)
RTS		0,0015	0,028	0,064	0,0018	0	1
BASIC	372	0,0016	0,020	0,082 (0,052)	0,0016 (0,0010)	12,5 (11,5)	1,00 (0,053)
RTS		0,0011	0,020	0,056	0,0011	0	1
DOBRYNYA	1050	0,0023	0,029	0,079 (0,031)	0,00225 (0,0009)	26,4 (11,3)	1,007 (0,039)
RTS		0,0015	0,028	0,064	0,0018	0	1
ENERGO-CAPITAL	435	0,0012	0,013	0,0915 (0,048)	0,0023 (0,0012)	13,3 (10,2)	0,51 (0,038)
RTS		0,0014	0,021	0,068	0,0014	0	1
PALLADA	373	0,00245	0,020	0,124 (0,052)	0,0041 (0,0017)	29,8 (18,4)	0,599 (0,082)
RTS		0,00245	0,022	0,111	0,00245	0	1
PERSPECTIVA	824	0,0006	0,017	0,035 (0,035)	0,0011 (0,0012)	-4,2 (10,4)	0,530 (0,035)
RTS		0,0014	0,026	0,053	0,0014	0	1
PIOGLOBAL	961	0,0018	0,031	0,056 (0,032)	0,0018 (0,0010)	5,3 (11,5)	1,006 (0,041)
RTS		0,0015	0,029	0,051	0,0015	0	1
STOLYPIN	1045	0,0018	0,027	0,0675 (0,031)	0,0022 (0,0010)	16,3 (13,4)	0,801 (0,032)
RTS		0,0015	0,028	0,0535	0,0015	0	1

(standard errors in parentheses)

Table 2. Interval Funds Performance

Interval	N obs.	Mean	Std. Dev.	Sharpe	Treynor	Alpha, % a year	Beta
ALPHA-CAPITAL	25	0,014	0,088	0,156 (0,200)	0,019 (0,024)	2,7 (10,1)	0,72 (0,01)
RTS		0,016	0,108	0,146	0,016	0	1
ENERGY	45	0,020	0,102	0,195 (0,150)	0,024 (0,019)	-5,3 (11,4)	0,815 (0,105)
RTS		0,030	0,141	0,214	0,030	0	1
INDEX	80	0,0001	0,0083	0,0125 (0,111)	0,0001 (0,0009)	-0,61 (0,28)	1,023 (0,041)
RTS		0,0006	0,0077	0,078	0,0006	0	1
LUKOIL 1	21	0,023	0,082	0,279 (0,218)	0,029 (0,023)	2,4 (9,4)	0,78 (0,13)
RTS		0,027	0,088	0,303	0,027	0	1
LUKOIL 2	21	0,023	0,079	0,292 (0,218)	0,030 (0,022)	3,2 (9,2)	0,768 (0,123)
RTS		0,027	0,088	0,303	0,027	0	1
LUKOIL 3	18	0,025	0,086	0,287 (0,236)	0,030 (0,025)	1,2 (10,1)	0,818 (0,117)
RTS		0,030	0,093	0,324	0,030	0	1

(standard errors in parentheses)

Turning to the point estimates, one can notice that for all the open-end funds, except "Perspectiva", Sharpe and Treynor ratios are greater than these of the market index are. Applying the sign test, it can be concluded, as for the alphas, that the null that the open-end funds have no stock-picking ability, is rejected.
As Table 2 above shows, there are no significant alpha estimates among the interval funds, and, as the point estimates of the alphas show, they appear to bring less abnormal return. Also it should be noted that among the six estimates only four are positive, and the sign test does not allow rejecting the null that the interval fund managers have no stock-picking ability. Moreover, the interval funds can have some additional risks compared to the open-end funds, for example, the liquidity risk, as no secondary market for their shares exist. So, higher return to compensate for the risks may be required, and using the single-factor model for measuring performance of the interval funds may result in upward-biased estimates of the alpha.
The differences between Sharpe and Treynor ratios of all the interval funds and of the market index are insignificant. It can be said that the asymptotic results based on the delta method are not reliable for this sample size, but these standard errors are obviously better than nothing. Turning to the point estimates, one can notice that four of the six funds have Treynor ratio greater than that of the market index, but only one of them – "Alpha Capital" – has Sharpe ratio greater than that of the market index. Taking all that into account, it can be concluded that the interval fund managers do not have any stock-picking ability, and, on average, perform worse than the open-end fund managers.
It is believed among the practitioners (see, e.g., Capitan et. al, 2002) that daily returns should not be used in the analysis of performance, as their usage is economically groundless. In Capitan et al., 2002, it is claimed that one should employ the returns at the frequency at which the fund managers are likely to rebalance their portfolio, and thus analyzing monthly returns is suggested.

Table 3. Alpha and Beta Estimates for Different Sampling Frequencies

Daily	Mean	Std. Dev.	Alpha, % a year	Beta	Sharpe	Treynor
PIOGLOBAL	0,0018	0,031	5,3 (11,5)	1,006 (0,041)	0,056 (0,032)	0,0018 (0,0010)
RTS	0,0015	0,029	0	1	0,051	0,0015
Weekly	Mean	Std. Dev.	Alpha, % a year	Beta	Sharpe	Treynor
WPIO	0,0093	0,069	7,9 (10,0)	0,985 (0,0517)	0,135 (0,072)	0,0093 (0,0050)
WRTS	0,0084	0,067	0	1	0,125	0,0084
Fortnightly	Mean	Std. Dev.	Alpha, % a year	Beta	Sharpe	Treynor
FPIO	0,019	0,109	7,6 (8,1)	0,997 (0,0714)	0,174 (0,102)	0,019 (0,011)
FRTS	0,016	0,100	0	1	0,160	0,016

(standard errors in parenthesis)

However, this argument seems to be misleading, as monthly returns are just the sum of the daily returns. If a manager improves monthly returns, she has no other way to do it, but improve the daily performance. To support the latter proposition, the same regressions as above using weekly and fortnightly returns are run for "Pioglobal". The results for other funds are not reported to save space, but they lead to essentially the same conclusion. Table 3 above shows the results.
The estimates of the alpha, expressed as abnormal return per annum, for the three data frequencies do not significantly differ from each other, confirming that the portfolio rebalancing argument does not apply here, as the estimates based on high-frequency data

measure the average stock-picking ability. Thus, it can be concluded that using high-frequency data for performance measurement is preferable, as it lends more power to the tests of the results' significance.

It can also be observed that the estimates of the beta are almost the same for all the data frequencies, which means that the infrequent trading was taken into account properly.

1.4 Cash Flows Predictability and the Factors of Fund Growth

One of the reasons why the managers of Russian equity funds do not exhibit statistically significant stock-picking ability is that they can have distorted incentives. For example, given that data collecting in this field is rather difficult, private investors do not usually employ econometric techniques necessary to measure abnormal returns even if they have the appropriate data and there is no rating agency to help them, it is probable that the managers do not care about getting abnormal returns as much as they should. To find out, to what extent the investors motivate the managers to think about abnormal return, it is useful to find out, which factors determine the cash flows to the funds, as managerial compensation often depends on the rate of TNA (total net assets) growth.

Table 4 below shows the results of predicting cash flows of the funds, for which data on TNA are available. The cash flows are computed following Gruber, 1996, and Sirri and Tufano, 1998: $CF_t = (TNA_t - (1+R_t) * TNA_{t-1})/TNA_{t-1}$. The table consists of four panels. The first panel reports the slope from the regression of the cash flows of the first lag of the excess return of the fund, run for the open-end funds. The excess return to a fund is a very crude measure of performance, but given poor cross-section sample, it is chosen not to follow the approach presented in Gruber, 1996, and Sirri and Tufano, 1998, who run for this purpose a cross-sectional regression of monthly cash-flows on their lags and monthly alphas, measured a year ago.

The second panel reports the slopes from the regression of the cash flows on the first lag of the market return, premultiplied by the beta estimate and the first lag of the alpha for the open-end funds. Here the assumption of constant beta is relaxed at the first time, and the estimates of alpha and beta are obtained by using Kalman filter. The reason to run two separate regression is multicollinearity in the joint regression and the absence of at least strong instruments for either the market return or the excess return of a fund, due to the fact that the returns are almost unpredictable, which follows from the efficient market hypothesis. The third and the fourth panels report the slopes of the same regressions run for the interval funds.

The first and the third panels suggest that the growth is driven by the excess return of the fund, as they report four significantly positive estimates and six of the other eight point estimates are also positive, but insignificant. This result, however, is not conclusive, as excess returns of the market and to a fund are strongly correlated, and it may be the case that the excess return of a fund has predictive ability only because of this correlation. Indeed, when joint regressions of the cash flows on both the excess return of the market and of a fund are run, the excess return to a fund often looses significance and changes its sign, whereas the estimates of the market excess return influence are much more robust. However, the joint regression suffers from multicollinearity and yields sometimes negative and significant estimates of the excess return influence, so the results are not reported here.

The results reported in the second and the fourth panels use the decomposition of the excess return of a fund into the compensation for the systematic risk and the alpha and show that the cash flows are driven mostly by the market return, as five of the twelve regressions yielded positive and significant estimates of its influence on the cash flows. Among the other coefficients before it, four are insignificant and positive and three are insignificant and negative. So, the fact that the market growth causes the cash inflows to the equity funds, is beyond doubt. It is also interesting that despite the noise in the daily data, the open-end funds have four significant estimates of the coefficient and the interval funds have only one, suggesting that the noise is less harmful for the estimates in this case than the small sample size. Since four point estimates of the coefficient for the interval funds are positive and the negative point estimates are very small, it may be suggested that the insignificance results mostly from the small sample size.

As for the alpha, it does not seem to influence the cash inflows. Among the twelve estimates of the alpha influence, there are six estimates of each sign and none of them is significant. Thus, it can be concluded that alpha does not influence the fund growth through cash inflows, though they certainly influence it through the growth of the money, which has already been invested.

Table 4. Predicting Cash Flows

Open-End Funds	Panel 1	Panel 2		Interval Funds	Panel 3	Panel 4	
	ERET(-1)	MKT(-1)	ALPHA(-1)		ERET(-1)	MKT(-1)	ALPHA(-1)
AURI (1365 observations)				ALPHA CAPITAL (25 observations)			
Coefficient	***0,083***	***0,416***	-9,609	Coefficient	0,082	-0,003	2,661
Std. Error	***0,046***	***0,067***	15,285	Std. Error	0,136	0,191	2,488
DOBRYNYA (1435 observations)				ENERGY (45 observations)			
Coefficient	***0,184***	***0,404***	-0,964	Coefficient	***0,395***	***0,553***	0,014
Std. Error	***0,038***	***0,053***	18,076	Std. Error	***0,137***	***0,115***	0,436
ENERGOCAPITAL (165 observations)				INDEX (80 observations)			
Coefficient	0,076	0,192	-0,068	Coefficient	-0,055	0,254	0,184
Std. Error	0,081	0,121	0,095	Std. Error	0,148	0,239	0,158
PALLADA (373 observations)				LUKOIL 1 (21 observations)			
Coefficient	-0,044	-0,350	-58,048	Coefficient	0,033	0,070	0,329
Std. Error	0,173	0,620	55,703	Std. Error	0,088	0,110	0,236
PERSPECTIVA (830 observations)				LUKOIL 2 (21 observations)			
Coefficient	0,152	***0,453***	23,241	Coefficient	0,01	0,003	0,031
Std. Error	0,155	***0,236***	18,939	Std. Error	0,011	0,008	0,071
STOLYPIN (1450 observations)				LUKOIL 3 (18 observations)			
Coefficient	***0,141***	***0,412***	-0,042	Coefficient	0,002	-0,018	-0,324
Std. Error	***0,039***	***0,053***	0,928	Std. Error	0,128	0,179	0,297

(significant estimates appear in bold italics)

To conclude, the evidence presented in this section suggests that the growth of the equity funds industry mentioned in the introduction is driven by the market growth. What is more important, even the 3% of the growth attributed to cash inflows are also driven by it. The investors do not seem to take into account the performance of the fund managers, thus reducing their incentive to look for stocks bringing positive abnormal return. This fact can partly explain the results of the previous sections, which offer only moderate support to existence of stock-picking ability, limited to the open-end funds.

Chapter 2
The Timing Ability

2.1 A Dynamic Beta Strategy: First Evidence

The first extension of the market model to be considered here is the separate regressions for the bullish and bearish markets. They can both serve as the first evidence of the market timing ability of the fund managers and offer a more precise estimate of the alpha, especially if the strategies of the managers turn out to be different in the two markets.

At first, the conventional regression for determining the alpha is run on the subsamples where the returns on RTS are positive and negative. Daily, weekly and fortnightly returns are employed. The results are presented in Table 5 below.

Table 5. Performance of "Pioglobal" in Bullish and Bearish Markets

	Daily returns			Weekly returns			Fortnightly returns		
Sample	all	rts_ret>0	rts_ret<0	all	wrts>0	wrts<0	all	frts>0	frts<0
Alpha (st. e.)	0,0002 (0,0004)	0,002 (0,00145)	-0,001 (0,0013)	0,00155 (0,0019)	0,00375 (0,00425)	0,01135 (0,0047)	0,003 (0,0035)	0,0225 (0,01)	0,0156 (0,097)
Beta (st. e.)	1,0122 (0,0419)	0,918 (0,08)	1,04 (0,076)	0,985 (0,052)	0,9156 (0,078)	1,158 (0,093)	0,997 (0,07)	0,772 (0,118)	1,22 (0,09)
Alpha (% a year)	5,3	65	-28,5	8,2	21,8	81	8,0	78	50
Chow test	p-value=0,000042			p-value=0,000065			p-value=0,000086		

The results for the daily returns (beta is the sum of coefficients from the regression of excess returns on the fund on the excess returns on RTS and their two first lags) do not differ much for both subsamples and the whole sample. However, the Chow test shows that there is considerable evidence for different models in the bullish and bearish market at all frequencies. The p-values in the table show that the null of the same model for the bullish and bearish markets is rejected at every level of confidence.

The results for the fortnightly data are strong, as the alpha in the separate models for bullish and bearish market is almost seven times as much as the alpha for the pooled sample and turns out to be significant at 5% confidence level. Actually, it means that, if the performance is measured properly (i.e., taking into account the different strategies in the bullish and bearish markets), "Pioglobal" shares bring, averaging between the bullish and bearish periods, 64% of abnormal return a year.

The evidence about the beta is also very interesting. Though the market-timing effort of "Pioglobal" managers enhances its performance, the managers time the market negatively, that is, they increase the exposure to it when it goes down. There are some possible explanations for this phenomenon, and the rest of the chapter will discuss them in detail. Meanwhile, the next section will proceed to show that negative market timing is observed for most of the funds and is robust to employing different data frequencies.

2.2 Market Timing

The evidence on the beta cited above demonstrates an apparent contradiction with the view the managers have market-timing ability, as it is expected that a good manager will increase the exposure of the fund to the market factor when the market grows.

The studies of market-timing ability of fund managers date back to Treynor and Mazuy, 1966, whose method of testing the hypothesis of absence of the market-timing ability has become classical and is employed in a number of works (see, e.g., Edelen, 1999, Bollen and Busse, 2001, Ferson and Schadt, 1996). The idea is that to test the absence of the market-timing ability one should include in the conventional regression used to determine fund alpha, the

squared term of the market return, assuming that beta is a linear function of market return, $\widetilde{\beta}_t = \beta_0 + \beta_1 * RTS_t$. The market-timing ability will mean then that the coefficient before this term is positive.
The second approach to testing the timing ability, first offered by Henriksson and Merton, 1981, is to introduce a slope dummy for bullish market and to test its significance, assuming that the managers set their beta equal to two values: one for bullish market and one for bearish market, $\widetilde{\beta}_t = \beta_0 + \beta_1 * I(RTS_t > 0)$. This is what is realized in the previous section with a minor difference expressed by introducing an intercept dummy in the regressions.
Table 6, presented below, employs both Treynor and Mazuy and Henriksson and Merton approaches to testing for market-timing ability of open-end fund managers at the fortnightly frequency. The fortnightly results appear to be decisive there, as daily results seem to be very noisy given the fact that managers rebalance their portfolio quite infrequently and care mostly about the final result and not about how many days will bring positive return during the period between rebalancement.

Table 6. Market Timing: Open-End Funds

	Fortnightly, T&M			Fortnightly, H&M		
	Alpha	Beta	FRTS^2	Alpha	Beta	FBull
	AURI			AURI		
Coef	0,0044	0,950	0,005	0,008	0,986	-0,071
SE	0,0046	0,079	0,268	0,006	0,112	0,153
	BASIC			BASIC		
Coef	0,0008	0,95	1,06	0,005	1,078	-0,046
SE	0,005	0,01	0,83	0,007	0,186	0,244
	DOBRYNYA			DOBRYNYA		
Coef	0,0094	1,079	-0,141	0,015	1,062	-0,155
SE	0,0046	0,058	0,206	0,005	0,063	0,098
	ENERGOCAPITAL			ENERGOCAPITAL		
Coef	0,007	0,49	-0,58	0,011	0,496	-0,180
SE	0,006	0,1	0,81	0,008	0,109	0,207
	PALLADA			PALLADA		
Coef	0,009	0,65	-0,4	0,014	0,757	-0,192
SE	0,009	0,1	0,73	0,013	0,175	0,269
	PERSPECTIVA			PERSPECTIVA		
Coef	0,0007	0,633	-0,583	0,001	0,581	-0,094
SE	0,0043	0,097	0,506	0,007	0,166	0,210
	PIOGLOBAL			PIOGLOBAL		
Coef	0,012	1,04	-0,99	0,016	1,158	-0,342
SE	0,004	0,03	0,14	0,007	0,097	0,161
	STOLYPIN			STOLYPIN		
Coef	0,0098	0,720	-0,145	0,011	0,759	-0,077
SE	0,0068	0,065	0,394	0,010	0,138	0,198

At first glance, Table 6 offers no conclusive evidence on market-timing ability of the fund managers, as only two of the sixteen estimates of the market-timing coefficient are significant. The insignificance of the other results leads to the conclusion that one cannot reject the hypothesis of the absence of market-timing ability.
However, if one turns to the first panel of the table, one will see that, after the point estimates, six of the eight funds time the market negatively, and for one of them – "Pioglobal" – the coefficient is significant. Implementing the sign test described in the first chapter, we come to the conclusion that under the null of no timing effort the probability to get six or more

negative estimates is 0,145. It does not allow concluding with certainty that the negative timing is present. However, the insignificance may be attributed to the small sample size.
The second panel of the table offers more conclusive results, as all the estimates of the slope dummy are negative, and one of them, again that of "Pioglobal", is significant. The sign test now allows rejecting the null of no market-timing ability even at 1-% level of significance. So, it may be the case that the managers really set beta equal to two values, one for each direction of market movement, rather than update it continuously basing on the value of the market return. Then the estimates of the first panel are biased, and the presence of negative market timing can be stated basing on the sign test applied to the results of the second panel.
Table 7 applies the same approaches to the interval funds. The evidence presented there is not conclusive and favors the absence of any timing effort of interval funds managers. Four of the six funds are positive market timers, and five coefficients are insignificant. However, the only significant estimate is negative, and it is "Alpha Capital" that is the negative market timer, which is known to have the greatest number of shareholders among all Russian mutual funds.

Table 7. Market Timing: Interval Funds

T&M	Alpha	Beta	RTS^2	H&M	Alpha	Beta	Bull
ALPHA CAPITAL				ALPHA CAPITAL			
Coefficient	0,020	0,660	-1,430	Coefficient	0,030	1,023	-0,648
Std. Error	0,009	0,050	0,319	Std. Error	0,011	0,080	0,176
ENERGY				ENERGY			
Coefficient	-0,004	0,817	-0,029	Coefficient	-0,003	0,832	-0,032
Std. Error	0,011	0,126	0,265	Std. Error	0,012	0,193	0,191
INDEX				INDEX			
Coefficient	-0,0006	1,023	1,654	Coefficient	-0,001	0,984	0,081
Std. Error	0,0003	0,041	2,654	Std. Error	0,000	0,068	0,105
LUKOIL 1				LUKOIL 1			
Coefficient	-0,005	0,753	0,928	Coefficient	-0,011	0,570	0,369
Std. Error	0,012	0,139	1,118	Std. Error	0,014	0,253	0,314
LUKOIL 2				LUKOIL 2			
Coefficient	-0,004	0,745	0,846	Coefficient	-0,009	0,586	0,320
Std. Error	0,012	0,134	1,016	Std. Error	0,014	0,243	0,302
LUKOIL 3				LUKOIL 3			
Coefficient	-0,006	0,797	0,765	Coefficient	-0,009	0,681	0,242
Std. Error	0,014	0,127	1,077	Std. Error	0,016	0,247	0,323

To sum up, it can be concluded that negative market timing is observed for two Russian equity funds, and it is the largest funds that time the market negatively. If one chooses to consider the point estimates, taking into account that the insignificance may be a result of small sample size, more than a half of the funds can be viewed as probable negative market-timers. It can also be concluded basing on the sign test that on average the open-end funds time the market negatively. So, the results of the section document at least certain bias towards negative market timing, which should be taken seriously and will be considered in the rest of the chapter.

2.3 Volatility Timing

There is, however, one more reason, beyond insignificance, why the results of the preceding section may be inconclusive. The managers of the funds could time volatility, that is, reduce the exposure to the market during booms to reduce the volatility of the returns on the fund. At troughs, however, they have to increase the exposure to the market, as they have to care for the returns at first and then about the volatility. Beyond this, they may just wish to keep the volatility constant, and given the positive dependence of the returns on volatility, it implies negative volatility and market timing.

The volatility timing was first considered in the 1990-s (see, e.g., Brown et al., 1996, and Busse, 1999). It is usually asumed that beta depends linearly on the market standard deviation, $\tilde{\beta}_t = \beta_0 + \beta_1 * \sigma_t^{RTS}$. Studying volatility timing can be fruitful, as volatility influences the risk-adjusted returns and the main indexes used to measure performance of mutual fund and it is much more predictable then returns on either a market proxy or a fund. In an efficient market, the returns tend to be completely unpredictable, whereas the conditional variance can be successfully modeled (see, e. g., Engle, 1982). It was shown in Busse, 1999, that a fund should reduce its market exposure in high-volatility periods, if $\partial ER_m / \partial \sigma_m < 0$. Backus and Gregory, 1993, offer a version of a dynamic asset-pricing model supporting this relationship.

However, Russian data cannot offer any conclusive evidence for or against this relationship. The most straightforward way to check it is to run ARCH-M on either daily or monthly returns on RTS. These regressions yield insignificantly positive and insignificantly negative coefficients for the GARCH term in the conditional mean equation, respectively. Another way to check the sign of the derivative is to run an AR (p) on the monthly standard deviation of RTS and check if the correlation between the random shocks to it and the returns is negative. The data, however, yield the insignificantly positive correlation.

Still Busse, 1999, shows that the zero or slightly positive derivative will also do the job. So it might be assumed that a Russian fund timing the volatility should reduce the exposure to the market when its volatility is high.

To test for volatility timing the approach of Busse, 1999, was used. For each month in the sample, the beta was estimated and than regressed on the monthly returns on RTS (MRTS) and its monthly standard deviation (STDRTS). The results show that the evidence for negative market timing deteriorates if volatility timing is taken into account. However, the deterioration has quantitative rather than qualitative character, as the signs and significance remain the same as they were in the first panel of Table 6.

Table 8. Volatility Timing

	Panel 1				Panel 2				Panel 3				Panel 4	
	STDRTS		MRTS		STDRTSE^2		STDRTSF		STDRTSE(-1)^2		STDRTSF		STDRTSE(1)	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Auri	4,28	5,92	0,34	0,33	***638,9***	***274,0***	-1,77	6,65	145,2	377	-0,86	9,87	-3,76	4,15
Basic	7,60	6,35	-0,41	0,48	-182,4	1317	-1,32	21,18	2058	1995	-9,19	25,1	-14,41	11,00
Dobrynya	***4,10***	***1,30***	0,00	0,10	***97,82***	***24,05***	***8,18***	***1,69***	91,9	77,16	***7,51***	***1,56***	-0,93	3,25
Energo Capital	-3,80	7,42	0,48	0,37	3042	1955	10,87	47,06	1068	1350	***347,1***	***124***	2,43	8,78
Pallada	17,17	17,81	0,27	0,85	-387,2	4619	82,59	152,54	***4281***	***1574***	***-629***	***113***	31,79	19,92
Perspectiva	***-17,6***	***3,98***	-0,02	0,31	81,58	438,8	***-31,4***	***6,47***	54,59	490,5	***-35,6***	***7,72***	-10,86	6,95
Pioglobal	-1,05	3,21	*-0,55*	*0,17*	-49,0	151,8	6,64	5,27	***-1114***	***601***	1,85	7,60	-5,84	4,49
Stolypin	0,09	0,35	-0,62	4,45	8,68	9,39	-1,87	2,53	-94,27	113,7	-0,41	8,21	0,79	4,70

(significant coefficients appear in bold italics)

As for the volatility timing itself, the first panel reports one positive and one negative significant estimate. The leader of the industry, "Dobrynya", which is known to have the best-informed managers, has a significant positive coefficient for volatility. The other significant estimate is that of "Perspectiva" and it turns to be negative, but the performance of "Perspectiva" can serve as an example that this strategy does not pay off. Other estimates are not significant showing slight tendency towards positive volatility timing, contrary to the prediction of Busse, but similar to the prediction of Scruggs, who showed in Scruggs, 1998,

that under ICAPM a good volatility timer should increase its exposure to market in high-volatility periods as reducing beta also exposes the investors to other risks, such as interest rate risk.
The insignificance of the estimates is no wonder given that the analysis bases at most on fifty monthly observations. The point estimates suggest that five of the eight funds may be viewed as probable positive volatility timers and they also have the volatility timing coefficients of greater magnitude. By and large, the result is somewhat surprising, as the main reason to time volatility positively is that when it is high the return is also high, but it was already shown in the previous section that the managers do not time the market return itself, at least in the usual fashion. Given that they do not do it directly, it is strange that they choose to do it indirectly, through volatility.
The second panel of Table 8 tries to find out if the managers respond to predictable or unpredictable movements in volatility. In order to find it out, the monthly beta estimates are regressed on the squared shocks to the volatility (STDRTSE^2) and its forecasted value (STDRTSF) obtained from AR (1) model for the monthly standard deviation of RTS. The monthly returns to the RTS index are also included, but the estimates are not reported, as they do not differ much from those reported in the first panel and their values are not relevant for the current discussion. At the first glance, the results suggest that the funds really respond to these volatility movements differently. However, the signs in both columns of the second panel differ greatly from the signs reported in the first panel and it forces to conclude that these regressions should be interpreted only as a robustness check, which all the funds, except "Dobrynya", failed to pass. The tumult of the signs suggests that there is no firm relationship between beta and market volatility for the majority of the funds.
The third panel replaced in the regression the squared shock to volatility by its lagged value (STDRTSE (-1)^2), to find out if it is the long-term sum of the shocks and the average volatility, determined by institutional factors, or last period shocks, which are most useful for predicting the current value of the volatility that managers take into account. If the second panel tries to answer the question if the managers respond to predictable or unpredictable movements in the volatility, the third panel aims to find out if it is short-run predictable movements of the volatility or some long-run considerations that are the most important for the managers in the predictable movements. These ideas to see what the managers really take into account when they time volatility are innovative for the literature on volatility timing. Unfortunately, the Russian data do not let to draw any firm conclusions on the subject, as even the signs of the insignificant estimates are spread quite chaotically.
However, if one examines the behavior of "Dobrynya", "Montes Auri", "Basic" and "Pallada", for which the results are quite robust, one may draw a tentative conclusion that positive volatility timers time both unexpected and predictable movements positively, but time long-run volatility movements negatively. The latter fact may be interpreted as the wish of the managers to have less volatile market. The former results show that, nevertheless, the managers are eager to take the market as it is and increase the exposure to the sharp price movements if they are properly compensated for that.
The fourth panel presents the results of regression of the monthly beta estimates on future shocks to volatility (STDRTSE (1)), obtained from the AR (1) model. This regression aims to test the ability of the managers to forecast volatility movements better than others do (Busse, 1999, refers to this as "ex-ante response to volatility shocks"). If they have this ability, the signs will be the same as in the first panel. Clearly, that is not the case, and even the four funds, which behaved more or less well in the first three panels, have the signs different from the expected. Thus, it can be concluded that the managers of Russian equity funds have no superior ability to forecast future volatility shocks and use this information in their volatility timing effort.
To go back to the punch line of the chapter, it should be pointed out that very limited evidence for volatility timing was found in the data, and even though it reduces the extent of the

negative market timing, that is not the end of the story and alternative explanations of this phenomenon have to be found. The next section proceeds to look for them and discuss the results of the search.

2.4 Other Possible Explanations of the Negative Market Timing Bias

The first one is the explanation usually held by practitioners. They have it that fund managers tend to buy shares near the trough, when they are underpriced, and sell them near the peak, when they are overpriced. However, this strategy can be successful only if the market is very inefficient and investors strongly overreact.

The data do not support this hypothesis, as it implies that the returns to the funds should be negatively autocorrelated. Estimating AR-models for different data frequency suggests that the autocorrelation is mostly positive, so there is no point in going against the market. This result can be partly explained by the impact of infrequent trading in some securities forming the fund, which brings about spurious positive autocorrelation. However, it is very unlikely that infrequent trading drives the result to the extent that it oppresses the existing overreaction and brings the opposite estimates. Moreover, the positive autocorrelation persists, losing significance sometimes, for other frequencies, for which the impact of infrequent trading is negligible.

The second possible explanation is the presence of passive effects for the stocks, which form the portfolio held by the fund. It can happen that the general decline in the market increases the riskiness of some firms, for example, by causing financial distress. Thus, the beta for individual stocks can increase just in the time periods the managers does not want it to, and all their positive market-timing effort can be insufficient to eliminate the passive effects.

The usual way to address this problem may be found, e. g., in Bollen and Busse, 2001. It is usually suggested to construct passive portfolios mimicking the portfolio of the fund, and to see if these portfolio will demonstrate "market timing" significantly different from that of the fund. To construct the mimicking portfolio, one has to know the portfolio structure of the fund in each period of time (usually a month), classify the stocks it holds into a number of broad classes (if one has four capitalization classes, four book-to-market classes and five beta classes, one obviously has 80 classes in total) and pick up from the stock universe grouped in the same classes arbitrary stocks. The stocks should be taken arbitrarily from each class, but so that the weight of each class in the mimicking portfolio was the same as the weight of this class in the fund's portfolio. This operation can be repeated, following the bootstrap framework, and the probability to have the same market-timing coefficient as the fund has (or greater) is estimated. If the probability is small, the fund is considered a successful positive market timer.

For a pity, this algorithm cannot be implemented with the data available. The portfolio structure is usually reported by the funds for a recent period of time, and they are reluctant to reveal the historical data on it. However, even if they did, it would be of little help, as the stock universe in Russia is very thin and the sample, from which the mimicking portfolio will have to be constructed, will not allow employing any statistical sampling procedures.

The simplest thing that can be done for Russian data is running regressions on excess returns of the most actively traded stocks on the excess return to the RTS index and its lags and the square of the excess return. Table 9 presents the estimates obtained from these regressions.

The results suggest that there is hardly any systematic bias in favor of positive or negative market timing effect. However, it is possible that a fund that does not time the market picks up a portfolio composed of stocks with negative point estimates of the gamma. Such a fund would have an insignificant negative market-timing coefficient. So, the results reported in Table 9 may partly explain the tendency towards negative market timing that is reported in Table 6. To find out if they do, a more through analysis is required, calling for the mimicking portfolio procedure, described above.

Instead, the results in Table 9 suggest that one should care more about positive alpha bias, as the shortcomings of the market model bring about the tendency for individual stocks to have small positive alphas. Comparing the passive alpha estimates from Table 9 with mutual funds alpha estimates in Tables 1 and 2, one may conclude that the passive positive alpha effects may turn to be enough to explain the positive alphas of the funds. However, the passive positive alpha effects cannot explain, why the Sharpe ratios of the funds tend to exceed the Sharpe ratio of the market.
Thus, it is not obvious that the passive positive alpha effect, even if it exists (the estimates of alphas for individual stocks are still mostly insignificant), can undermine the conclusion about the stock-picking ability of mutual funds managers, made in the previous chapter. However, further analysis of the biases of this kind is required, and it seems that at this stage of development of Russian stock market it is virtually impossible, as simple ways out like the regressions summarized in the table above do not suffice to answer the challenge and constructing mimicking portfolios is required.

Table 9. Market Model Violations for Individual Stocks

AERO	Coef	SE	GAZP	Coef	SE	LUK	Coef	SE	MENG	Coef	SE	NNIK	Coef	SE
alpha	0,001	0,001	alpha	0,000	0,001	alpha	-0,001	0,000	alpha	-0,001	0,001	alpha	0,001	0,002
beta	0,430	0,068	beta	0,787	0,098	beta	1,007	0,048	beta	1,085	0,069	beta	0,724	0,099
gamma	-1,089	0,877	gamma	-1,380	2,352	gamma	0,684	0,319	gamma	0,151	0,956	gamma	-2,487	2,319
RAO	Coef	SE	ROST	Coef	SE	SBER	Coef	SE	SIBN	Coef	SE	SIBT	Coef	SE
alpha	-0,001	0,001	alpha	-0,001	0,001	alpha	0,003	0,001	alpha	0,001	0,001	alpha	0,000	0,002
beta	1,288	0,063	beta	1,061	0,066	beta	0,665	0,071	beta	0,977	0,122	beta	0,414	0,157
gamma	0,881	0,425	gamma	-1,247	0,958	gamma	-2,870	1,551	gamma	1,725	1,490	gamma	2,590	1,810
SURG	Coef	SE	SURGP	Coef	SE	TATN	Coef	SE	YUKO	Coef	SE			
alpha	0,000	0,001	alpha	0,001	0,001	alpha	0,000	0,001	alpha	0,003	0,001			
beta	1,092	0,066	beta	1,017	0,065	beta	1,122	0,065	beta	0,980	0,069			
gamma	-0,752	0,798	gamma	-1,629	1,002	gamma	0,435	1,327	gamma	0,768	0,964			

The Estimated Model:

$$R_{it} - RF_t = \alpha + \sum_{j=-p}^{p} \beta_j (R^m_{t-j} - RF_{t-j}) + \gamma \left(R^m_t - RF_t \right)^2$$

***Results**: Alphas – 3 significant, 11 insignificant; 10 positive, 4 negative.*
Gammas – 2 significant, 2 marginally significant, 10 insignificant; 7 positive, 7 negative

The third and the last possible explanation of the negative market timing bias to be discussed here is that the managers do not find profitable to time the market given the transaction costs it requires, though they may have the ability to do it. It is known that Russian stock market is going up steadily and rapidly throughout all the post-crisis history, with two minor slowdowns in the beginning of 2000 and 2003. Thus, if a manager is interested in low frequency (e. g., monthly) returns, she can feel pretty sure that whatever happens in the coming month, the resulting return will be at least positive, so the incentives to time the market are quite small.
To see if that is the case, it is reasonable to look at a different time period, where the incentives to time the market were greater. Luckily, among the fourteen funds there are four open-end funds, which survived after the crisis. The following table (Table 10) explores the performance of the four funds in 1998.
Table 10 consists of four panels. The second two panels compare the performance of the four funds after and during the crisis using daily data. First of all, it can be observed that, after the

point estimates, all the funds except "Stolypin" may be viewed as negative market timers at present, though the estimates of the market-timing coefficient are not statistically significant. However, the situation changes drastically if one considers the financial crisis of 1998, which brought Russian stock market into recession long before the devaluation. Using the crisis data yields positive market timing estimates for all funds, for "Stolypin" and "Dobrynya" the coefficients are highly significant, for "Pioglobal" the coefficient is marginally significant. The result is quite strong, as the sample consist of only 250 observations.

Table 10. Performance of the Funds During the Crisis

Daily	After the Crisis			During the Crisis			Weekly	After the Crisis			During the Crisis		
	Alpha	Beta	RTS^2	Alpha	Beta	RTS^2		Alpha	Beta	RTS^2	Alpha	Beta	RTS^2
	AURI			AURI				AURI			AURI		
Coef	0,0011	0,987	-0,805	-0,0003	0,821	0,586	Coef	0,0062	0,854	-0,737	-0,0001	0,835	0,452
SE	0,0006	0,069	0,452	0,0030	0,093	0,518	SE	0,0032	0,064	0,466	0,0166	0,082	0,533
	DOBRYNYA			DOBRYNYA				DOBRYNYA			DOBRYNYA		
Coef	0,0010	1,007	-0,124	-0,0030	0,846	1,439	Coef	0,0075	1,027	-0,577	-0,0026	0,821	0,134
SE	0,0005	0,039	0,438	0,0029	0,078	0,687	SE	0,0022	0,067	0,392	0,0051	0,073	0,342
	PIOGLOBAL			PIOGLOBAL				PIOGLOBAL			PIOGLOBAL		
Coef	0,0002	1,057	-0,119	-0,0013	0,888	1,559	Coef	0,0024	0,920	-0,179	0,0047	0,907	0,422
SE	0,0005	0,032	0,446	0,0035	0,093	0,939	SE	0,0022	0,033	0,244	0,0176	0,115	0,708
	STOLYPIN			STOLYPIN				STOLYPIN			STOLYPIN		
Coef	0,0005	0,801	0,166	-0,0026	0,627	1,734	Coef	0,0062	0,706	-0,553	0,0064	0,759	0,535
SE	0,0006	0,032	0,321	0,0027	0,061	0,610	SE	0,0032	0,034	0,315	0,0039	0,060	0,268

The last two panels show that the same result holds for weekly data, providing a robustness check for the frequency of the data used and showing that the results for daily data are not due to their noisiness. For the weekly data, only one market-timing coefficient during the crisis turned out to be significant, but it can be easily explained by the fivefold reduction of the sample size.

Thus, the results above show that the managers of at least the four funds considered in Table 10 have market-timing ability, and they can use it right in the period when it is most needed. It is highly unlikely that the managers forgot how to time the market during the post-crisis period, so it has to be concluded that at present they do not think that market timing will pay off compared to the transaction costs it requires.

One objection can be raised, however. As it was mentioned in the beginning of the section, the evidence for market timing can be spurious due to passive effects. But in this particular case the passive effects are not likely to drive the results. The intuition for passive effects, presented in the beginning of the section, says that they are likely to be negative, as the market fall can cause financial distress. Though the positive passive effects can exist, as it is shown in Busse, 1999 and Bollen and Busse, 2001, it is highly unlikely that they came into play during the crisis, when financial distress and the leverage effect influenced greatly the market movement and the behavior of a number of stocks.

One more interesting piece of evidence can be obtained from Table 10. The first two panels suggest that the performance of the funds, measured by the Jensen alpha, was worse during the crisis. Even if one chooses to measure the abnormal return as the sum of the intercept and the market-timing term, it is obvious that the intercept has to be higher in the bullish market than in the bearish market in order to make the two abnormal returns equal. The reported evidence contradicts the view usually held among private investors that mutual funds can offer a kind of insurance against a crisis. To put it in the language of financial economics, the funds know

better than others do how to cope with a crisis and thus can earn more abnormal return during a crisis when during any other period.
However, the evidence on the alphas, presented in Table 10, is not conclusive, as it may be a result of an omitted factor bias. The factors priced by the market during the crisis (e.g., financial distress) are most likely to influence the price negatively, causing negatively biased alpha estimates when they are omitted. So, a more comprehensive study, using the data from the post-crisis period and more funds, is required to see if the alphas of Russian equity funds really depend positively on the market return. Table 11 presents the results of such study.

Table 11. The Jensen Alpha in Bullish and Bearish Market

Open-End Funds	Coef	SE	Interval Funds	Coef	SE
Auri	0,0058	0,0037	Alpha Capital	-0,0091	0,0265
Basic	-0,0013	0,0021	Energy	0,0276	0,0246
Dobrynya	0,0010	0,0020	Index	0,0001	0,0009
EnergoCapital	0,0016	0,0016	Lukoil 1	***0,0583***	***0,0321***
Pallada	-0,0042	0,0027	Lukoil 2	***0,0585***	***0,0333***
Perspectiva	***0,0034***	***0,0017***	Lukoil 3	***0,0906***	***0,0173***
Pioglobal	***0,0048***	***0,0026***			
Stolypin	***0,0056***	***0,0021***			

(significant estimates appear in bold italics)

The table presents the estimates of the bullish market dummy included in the regression of the excess return to the fund on the excess return to the RTS index, its relevant lags and its square, which is added to avoid the biases in the alpha estimates, which can emerge when the timing effort is not taken into account. As it was argued above, the null of equal performance in bullish and bearish market, measured as the sum of abnormal returns from stock-picking and timing ability, implies that the alphas are greater in the bearish market. Among the fourteen estimates, however, eleven are positive and six of them are significant. It allows concluding that the market growth enhances the performance of at least some funds and there is no evidence for the opposite impact.

2.5 An Intermediate Conclusion on Market Timing

The second chapter documents positive market timing ability for the funds, which existed during the crisis, but does not report conclusive evidence on market timing in the post-crisis period. Moreover, it reports many insignificant negative estimates of the timing coefficients, two of which are significant. The sign test shows that one can draw a conclusion for the presence of negative market timers among the open-end funds despite the insignificant estimates. The negative market timing bias in the estimates and the disappearance of the positive market timing effort among the funds, which demonstrated the ability to time the market during the crisis, is surprising and needs to be explored.
It was found out that the bias is not likely to be driven by strategies of the type "buy at a trough, sell at a peak". The passive effects present in individual stocks may explain it only partly. The third explanation, which has it that given the present situation the managers do not find market timing profitable, gained some support from the crisis data, but it is clearly not the end of the story, as the evidence from the crisis period concerns only four of the fourteen funds under study.
The volatility timing argument yielded the opposite results it was expected to. If the managers had timed volatility negatively, it would have been clear that the negative market timing bias could be driven by the volatility timing effort. However, it is not the case, and the results of the third section suggest that the managers time the volatility positively. So, an apparent

contradiction emerges, as positive volatility timing has mostly the same motivation as positive market timing.

It can be said that the volatility is more convenient to time as it is much more predictable than the returns, and if there is some evidence that the volatility and market returns are positively interrelated, the returns can be more conveniently timed via the volatility. However, this argument is misleading, as the unpredictability of the returns comes from the efficient markets hypothesis, which states that abnormal returns are unpredictable (or there is no opportunity to earn abnormal returns using some amount of information). So, timing the market via the volatility is useless, as it increases only gross return, but not abnormal return (alpha) to a fund. Managers can adopt this strategy only if the investors are not qualified enough to distinguish between gross and abnormal return and there is no rating agency to help them. The first chapter shows that it is what really happens in Russia, probably, because Russian mutual funds reveal information only about their gross return. This information is enough for a sophisticated investor to see if a fund has positive alphas; but in Russia many private investors do not use econometrics to measure the performance of the fund, in which they want to invest.

But even if the managers time the market via the volatility, it answers only a part of the question. It shows why the timing estimates for the market return are noisier then the estimates of volatility timing, but it does not answer what causes the negative bias.

So, there are two major directions for future research in this area, which should aim to explain the negative market timing bias. The first one comes from the belief that the managers do not find market timing profitable now. But a theoretical model is needed to predict what should happen that managers start to time the market. Having such a model, one can easily find the time periods when managers should time it and see if they time the market when. If they do, it should be interpreted as the evidence for the timing ability, and vice versa.

The second direction is more within the mainstream, as negative market timing is also documented for US market. However, the literature on US market employs the approaches, which cannot be applied to Russian data, as the data are scarce and the market is thin and underdeveloped. The most popular idea explored in the literature is the impact of cash flows and liquidity trading of the shareholders (see, e. g., Edelen, 1999). To implement the methods studied there, one should have detailed information on cash inflows and outflows to the funds under study. So, this area of research depends in Russia on the wish of the funds to reveal information about themselves.

Chapter 3
More on Beta Dynamics

3.1 An Introduction to the Topic

By now, the study explored simple beta strategies, connected only with market movements. However, managers do not have to limit themselves by increasing beta when the market goes up or when the volatility increases. They may react to different changes in the economic environment, even if these macroeconomic (and other) factors are not explicitly priced in the market.

To put it mathematically, the first three dynamic specifications for beta already considered in the second chapter are:

- $\widetilde{\beta}_t = \beta_0 + \beta_1 * RTS_t$ - Treynor & Mazuy specification
- $\widetilde{\beta}_t = \beta_0 + \beta_1 * I(RTS_t > 0)$ - Henriksson & Merton specification
- $\widetilde{\beta}_t = \beta_0 + \beta_1 * \sigma_t^{RTS}$ - volatility timing specification

However, one can turn to a more general model $\widetilde{\beta}_t = X_t\beta$, where X is a matrix of different factors managers find important for the fund's performance. In this chapter the approach of Ferson and Schadt, 1996, is followed, allowing to view the estimated model presented below as a conditional CAPM version or as a multifactor model.

The motivation to consider the strategies of this kind is not only the strategies *per se*, but also avoiding biases in the estimation of the alpha. Obviously, it is possible to estimate both the coefficients of the dynamic beta function and the alpha:

$$R_{it} - RF_t = \alpha + \widetilde{\beta} \cdot (R_{mt} - RF_t) + \varepsilon_t \Leftrightarrow R_{it} - RF_t = \alpha + \beta_0 * (R_{mt} - RF_t) + \sum_{j=1}^{N} \beta_j \cdot x_j \cdot (R_{mt} - RF_t) + \varepsilon_t$$

It is also possible to consider non-structural, or purely statistical specification for beta. For example, using Kalman filter estimation, where beta is assumed to be a random walk variable, usually provides good fit to data. The random walk specification is not completely senseless, as it should not be viewed as a specification, which assumes that the beta changes chaotically and managers cannot influence it at all. Rather, it should be treated as a specification, assuming that shocks to the beta, which are the decisions of the managers to change it, are highly persistent.

This chapter will first consider the results of estimating different dynamic beta specifications and try to find out if the managers time some macroeconomic variables. It will then proceed to examine the implications these dynamic strategies have for performance management, namely, their influence on the estimates of the alphas.

3.2 Estimating Dynamic Beta Strategies

Table 12 and 13 presented below consist of two panels. The first panel employs the described approach to go back to volatility timing. As a measure of volatility the forecasted value from a GARCH model for RTS is used. The excess return to a fund is regressed on the excess return to the market and its lags and on the product of the excess return to the market and the forecasted volatility. The coefficient before the product is the timing coefficient (the slope of the linear dynamic beta function).

The results show that using daily data the conclusion on the volatility timing changes greatly. Almost all the coefficients are negative and five of them are significant. However, there are also two significantly positive coefficients. The change in the results can be driven by two factors. Firstly, the impact of the omitted factor, which was used in the previous chapter regression, following the approach of Busse, 1999, namely, the market return. However, the results do not change drastically when RTS squared is included in the regression. Also, it was shown in the section on volatility timing that the results of estimating the dynamic beta function using the Busse procedure are robust to omitting monthly RTS return, if a fund really times the volatility (see Table 8, the second and the third panels). Secondly, it is probable that the unknown factor that drives the negative market timing result has a short-term effect or at least it has more chance to influence the volatility timing also when the volatility and the market returns are closely interrelated, as it is the case for daily data (evidence from ARCH-M models is relevant here). It can be also recalled here that using the Busse procedure resulted in shifting the market-timing coefficient upwards, though the omitted factor bias in Treynor-Mazuy regression (the volatility was omitted there) should have caused positive, and not negative, bias, given positive volatility timing.

Table 12. Estimating Dynamic Beta Strategies I: Open-End Funds

Open-End Funds	Volatility		IndProd		Oil		USD		MIACR		Inflation	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Auri	-18,02	20,23	-10,07	14,14	-0,45	1,27	9,53	9,06	53,50	142,40	14,31	64,23
Basic	-366,3	270,60	-7,26	23,98	***-1,58***	***0,63***	11,34	19,75	256,78	256,69	-45,48	123,62
Dobrynya	-2,27	37,82	-2,25	9,62	-0,09	0,85	***22,51***	***7,98***	88,23	136,61	-8,06	64,86
Energo-Capital	***-649,37***	***116,47***	***-24,59***	***13,90***	-0,09	0,74	-21,9	17,18	99,76	179,62	-130,0	89,00
Pallada	***218,97***	***60,52***	***-40,16***	***21,27***	-0,44	1,20	8,53	45,16	-539,6	405,33	28,14	175,15
Perspectiva	***-186,44***	***30,90***	***-11,39***	***6,66***	0,47	0,79	-2,10	4,51	-282,6	99,64	***-239,04***	***74,68***
Pioglobal	-17,40	15,78	19,27	8,40	-7E-05	6E-05	-0,57	0,81	0,70	8,33	-157,1	108,69
Stolypin	-9,82	18,61	-1,62	7,45	0,77	0,73	4,45	6,55	-59,34	64,61	79,38	48,04

(significant coefficients appear in bold italics)

The Estimated Model: $R_{it} - RF_t = \alpha + \sum_{j=-p}^{p} \beta_j (R_{t-j}^m - RF_{t-j}) + \gamma * (R_t^m - RF_t) * Variable(s)$

Table 13. Estimating Dynamic Beta Strategies I: Interval Funds

Interval Funds	Volatility		IndProd		Oil		USD		MIACR		Inflation	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Alpha Capital	***20,43***	***6,52***	-2,76	1,08	0,43	0,80	-35,51	21,76	-0,04	0,07	-3,05	18,52
Energy	-6,79	6,59	31,66	20,9	1,06	0,65	***16,17***	***4,63***	***-0,05***	***0,02***	***-511,7***	***223,99***
Lukoil 1	***-86,57***	***39,40***	2,65	2,22	***1,52***	***0,90***	-42,85	41,63	0,19	0,13	47,26	29,09
Lukoil 2	***-79,64***	***36,54***	2,23	2,03	1,27	0,71	-36,11	37,45	***0,18***	***0,11***	36,18	25,33
Lukoil 3	***-81,41***	***35,09***	2,35	2,13	1,07	0,72	-24,11	42,00	0,13	0,13	30,45	25,51

(significant coefficients appear in bold italics)

The Estimated Model: $R_{it} - RF_t = \alpha + \sum_{j=-p}^{p} \beta_j (R_{t-j}^m - RF_{t-j}) + \gamma * (R_t^m - RF_t) * Variable\ (s)$

The second panels of Tables 12 and 13 present the results of regressing the excess returns to a fund on the excess return to the market and its lags and on the product of the excess return to the market and various macroeconomic variables. The figures reported in the table are the coefficients of these interaction variables or the slopes in the linear multivariate dynamic beta function, where the macroeconomic variables are used as strategy determining factors.

The results show that there is no common line of behavior for all the funds under study. However, some general patterns within each class of the funds are observed. For example, the open-end funds time industrial production growth and oil price changes negatively and movements of MIACR (Moscow Interbank Actual Credit Rate) positively, whereas there is no general pattern in their timing of the inflation and the exchange rate of ruble to US dollar. Interval funds, on the contrary, time industrial production and oil prices positively, exchange rate movements negatively, and show no general pattern in timing inflation and MIACR.

Some intuition explaining the results can be presented. The results for the interval funds are more or less intuitive. It is natural to believe that a good state of national economy *ceteris paribus* results in better stock market dynamics than a bad one. So, it is also natural that the interval funds invest more heavily in the stock market when the industrial production and oil prices, which are vital for Russian economy, go up, and reduce the exposure to it when the ruble depreciates, reflecting declining competitiveness of Russian goods in foreign markets.

The results for the open-end funds are opposite. It can be argued that the results are driven by the difference in the samples. For the interval funds, the data for the last two or three years are available, whereas for the open-end funds the data for earlier years are also used. In 1999, however, the industrial production growth was the highest, but the fund managers can have lower exposure to the market than afterwards, as they grew suspicious after the crisis. But the results reported in Table 12 are quite robust to changing the sample size within the post-crisis period and the funds with shorter history do not behave differently from the others. Given this, it is hard to say what motivates the managers to time oil prices and industrial production growth negatively. The only plausible explanation is that these results are another side of the negative market timing bias, which was documented for the open-end but not for interval funds, except for "Alpha Capital".

So, a robustness check is necessary. Tables 12 and 13 report many insignificant estimates, and it is interesting to speculate if this results are due to the small sample size or they show that managers really do not time certain factors. The results in Tables 12 and 13 can also suffer from multicollinearity, as the correlation between the excess return to RTS and its product with a macroeconomic factor can be great, since macroeconomic factors, such as the industrial production growth and the inflation rate, are quite stable over time and reported monthly, so the 'daily' data on them used to get the figures in Table 12 are obtained by assuming them constant over a month.

So, it is useful to estimate the dynamic beta function directly. Luckily, one can get daily data on beta by running Kalman filter estimation with time-varying random walk beta. These estimates can be regressed directly on the macroeconomic variables and the forecasted volatility from a GARCH model. Tables 14 and 15 below report the slope estimates from these regressions.

Consider first the regression of the beta estimates on the volatility forecast. The tables show that the results reported above in this section for the interval funds are robust to this change in the estimation procedure. The results for the open-end funds are less robust and half of the coefficients change their sign. It suggests that either the beta estimates using Kalman filter are too noisy for daily data or half of the funds do not really time the volatility.

Turning to the regression with the macroeconomic variables, the results of which are presented in the second panel of Tables 14 and 15, it should be noted that the main conclusion discussed above about timing the industrial production growth and oil prices remains also in this estimation procedure, showing that the different behavior of the open-end and interval funds really exists. As for the exchange rate, the interval funds time it negatively, whereas the open-end funds begin to time it positively, after the new estimation procedure.

The discussion of the results for individual funds is beyond the scope of the paper, but given the absence of some general pattern in the results it grows very important. If one wants to know if particular fund times certain factor positively or negatively, one should use both estimation techniques. If both estimates are significant, one can be sure that the sign reflects the character of the timing correctly. If the signs are the same, but there is no significance, more tentative statement about the timing should be drawn. If the signs are different, and there is no significance, it should be interpreted as the absence of the timing effort. There are other possible situations, but they do not occur in reality, and the results in Tables 12-15 show that this algorithm works well.

Table 14. Estimating Dynamic Beta Strategies II: Open-End Funds

Open-End Funds	Volatility		IndProd		Oil		USD		MIACR		Inflation	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Auri	***130,90***	***48,59***	-11,4	19,22	-0,39	0,66	7,54	5,07	***218,71***	***131,32***	***103,10***	***65,32***
Basic	-147,9	280,35	-7,83	16,81	-0,57	0,63	7,29	9,47	165,25	108,03	-8,61	96,22
Dobrynya	54,24	31,11	-1,46	9,66	-0,12	0,36	***11,03***	***5,59***	***240,04***	***73,67***	72,91	52,40
Energo-Capital	***-1020,0***	***197,29***	***-31,77***	***13,47***	0,13	0,46	-4,36	9,35	42,04	140,18	-59,44	79,78
Pallada	309,37	213,79	***-54,88***	***18,72***	0,38	0,55	***34,87***	***16,39***	***468,18***	***157,99***	73,78	98,99
Perspectiva	***-266,73***	***46,93***	-1,72	11,74	-0,19	0,46	1,88	5,97	-52,14	138,81	***-189,74***	***95,08***
Pioglobal	-16,62	16,94	0,84	2,27	***-7E-05***	***4E-05***	-0,23	0,25	1,10	5,60	15,22	53,67
Stolypin	27,55	22,52	6,66	6,69	***0,65***	***0,35***	3,18	2,30	-159,44	67,04	***225,40***	***34,36***

(significant coefficients appear in bold italics)

Estimated Model: $\hat{\beta}_i = c + \gamma * Variable\,(s)$ $\hat{\beta}_i$ ***is computed using Kalman filter.***

Table 15. Estimating Dynamic Beta Strategies II: Interval Funds

Interval Funds	Volatility*		IndProd		Oil		USD		MIACR		Inflation	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Alpha Capital	*7,98*	*1,17*	-0,15	0,18	*-0,07*	*0,04*	-2,37	1,60	*-0,01*	*0,00*	1,89	1,30
Energy	*-19,39*	*9,60*	-11,6	18,3	0,50	0,47	1,37	5,64	-0,02	0,03	-258,2	315,3
Lukoil 1	*-42,54*	*16,29*	1,19	1,49	*1,23*	*0,55*	-8,94	16,30	0,02	0,03	1,68	7,35
Lukoil 2	*-44,30*	*16,06*	1,15	1,53	*1,23*	*0,54*	-9,36	17,40	0,02	0,03	1,01	7,69
Lukoil 3	*-36,88*	*10,91*	0,98	0,95	*0,92*	*0,54*	-6,81	19,36	0,01	0,02	-1,31	8,97

(significant coefficients appear in bold italics)

Estimated Model: $\hat{\beta}_i = c + \gamma * Variable(s)$ $\hat{\beta}_i$ ***is computed using Kalman filter.***

The discussion of the results for individual funds is beyond the scope of the paper, but given the absence of some general pattern in the results it grows very important. If one wants to know if particular fund times certain factor positively or negatively, one should use both estimation techniques. If both estimates are significant, one can be sure that the sign reflects the character of the timing correctly. If the signs are the same, but there is no significance, more tentative statement about the timing should be drawn. If the signs are different, and there is no significance, it should be interpreted as the absence of the timing effort. There are other possible situations, but they do not occur in reality, and the results in Tables 12-15 show that this algorithm works well.

3.3 Dynamic Beta Strategies and Performance Measurement

It was already mentioned that considering dynamic beta strategies might solve the omitted variable problem in the regressions measuring performance. However, including irrelevant variables in the dynamic beta function can also cause significance problems because of efficiency loss. Given the small sample size and other estimation problems described above it is probable, however, that the insignificant variables in the dynamic beta function can still be

present in the true data generating process for the beta. So, one has to watch carefully the behavior of the estimates and their standard errors while including or excluding variables from the dynamic beta function.
Table 16 presents estimates of the alphas measured as yearly abnormal returns using different specifications of the dynamic beta function. It should be mentioned that in this section we follow the approach of Ferson and Schadt, 1996, who argue that the managers should not be rewarded for using publicly available information in their timing effort. If the return, which is generated by the dynamic beta strategies, is not considered abnormal, the intercept (alpha) from the regressions can be viewed as the only measure of the abnormal return. However, it may be argued that this approach assumes that the investors can time the market as efficiently as the managers do. The plausibility of this assumption is debatable, but it is also possible that investors will react to the news in the fashion, which will result in the necessary timing. So, the plausibility of the assumption enters the domain of the endless debate in various fields of economics, which aims to find out if agents can be assumed taking unconsciously or on average very sophisticated decisions. Taken literally, most of the assumptions, on which textbooks are based, are false, taken more abstractly, they may serve as a good approximation of reality.
As the estimates reported in Table 16 are mostly insignificant, the results should be viewed mostly as a check of robustness of the alpha estimates to different return generating processes, allowing drawing more firm conclusion even lacking the statistical significance. The conclusions to be drawn about possible biases that are revealed by these estimates are mostly speculative.

Table 16. Dynamic Beta Strategies and Performance

Alpha, % a year	Market Model		Treynor and Mazuy		Volatility Timing		Macro Factors		Kalman Filter	
Open-End Funds	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Auri	12,7	15,4	***31,7***	***16,9***	21,7	18,7	***38,6***	***16,5***	***47,4***	***12,4***
Basic	12,5	11,5	16,2	16,5	11,9	11,5	10,1	16,8	4,8	12,3
Dobrynya	***26,4***	***11,3***	***29,5***	***14,1***	***26,5***	***11,3***	***27,2***	***13,4***	18,1	16,0
EnergoCapital	13,3	10,2	1,1	12,1	12,7	9,6	5,2	10,6	11,2	13,0
Pallada	29,8	18,4	-8,2	25,1	27,2	17,6	-2,8	24,3	10,9	16,9
Perspectiva	-4,2	10,4	11,5	12,1	-1,9	9,7	10,0	12,0	-10,6	9,9
Pioglobal	5,3	10,1	5,6	13,2	21,1	16,6	10,3	13,3	-22,7	22,8
Stolypin	16,3	13,4	12,6	15,5	16,7	13,4	14,3	20,8	***43,8***	***17,5***
Interval Funds	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Alpha Capital	2,7	9,9	***26,7***	***10,9***	13,7	12,7	16,3	13,3	5,3	7,7
Energy	-5,3	11,4	-4,7	13,7	-6,4	10,9	-0,5	12,1	-1,2	5,4
Index	-2,5	1,2	***-3,0***	***1,3***	***-2,6***	***1,2***	-	-	***-3,7***	***0,4***
Lukoil 1	2,4	9,4	-5,6	15,7	-3,7	9,9	-10,0	12,7	-4,6	8,6
Lukoil 2	3,1	9,1	-4,3	15,0	-2,5	9,2	-6,7	11,8	-1,7	8,6
Lukoil 3	0,1	10,0	-7,2	17,8	-6,8	10,2	-9,7	14,0	-5,7	9,1

(significant coefficients appear in bold italics)

Table 16 consists of five panels. The first panel presents the estimates from the conventional market model with lags of RTS and repeats the results already reported in Tables 1 and 2. This panel serves as a benchmark for evaluating the results of the following four panels.
The second panel reports the alphas from the Treynor and Mazuy regression. There is no evidence that taking into account the market timing resulted in upward or downward movement in the estimates. Also, the standard errors of the alphas increase for all the funds

under study. It suggests that the true dynamic beta function may not contain the market return, as its inclusion does not lead to any bias correction, but increased the standard errors, which is a typical result of including a redundant variable in a regression.

The third panel documents the intercept from the regression, the slopes of which are reported in the first panels of Tables 12-15. This regression assumes that the betas depend linearly on the market volatility, which is estimated using a GARCH model for the RTS index. The standard errors do not show any trend, suggesting that the volatility is less likely to be a redundant variable in the dynamic beta function that the market return. However, the trend in the estimates themselves is rather strange from the statistical point of view, as the alphas increase for the funds, which are successful volatility timers, as Tables 9 and 12-16 suggest. Still, this result can be explained economically, as the ability of the managers to time volatility should bring more abnormal return than simple stock picking, as long as they find it profitable to implement. So, the market model may ignore this return, and the more sophisticated model may reveal it.

The fourth panel reports the results of assuming the dependence of beta on different macroeconomic factors. To avoid inefficiency, the insignificant macroeconomic variables were omitted. Still, the results are similar to those of the second panel, suggesting that there is little evidence on that the managers really time the macroeconomic factors.

The last panel uses Kalman filter estimation and the assumption that the betas are random walk (the shocks on them are very persistent). Again no trend in the estimates is observed and there are some strange point estimates (for example, "Pioglobal" is reported to have the abnormal return of –22,7% per year and "Montes Auri" – 47% per year, which is too great to be true). The standard errors also deteriorated, though a more efficient estimation technique – maximum likelihood – was used. It suggests that either the process for the betas does not fit the data well or there are some computational problems.

Looking now at the rows, one can conclude that using different beta specification as a robustness check mostly does it job. The signs and even the magnitudes of the estimates usually persist, especially when the volatility timing is taken into account, which is the most reasonable dynamic beta specification, as the discussion above suggests. The signs of the alphas for LUKOIL funds in the dynamic beta specifications are all negative, lending support to the doubts in the quality of its management, which appeared after analyzing the cash flows. Some of the coefficients turn out to be significant in some specifications, mostly confirming the conclusion drawn on the evidence from the market model. There are also some cases, where the signs and the magnitudes of the alphas fluctuate across the specifications, so the absence of stock-picking ability is documented. It is an important feature, as a robustness check should be able reject as well as accept.

To sum up the evidence cited in this chapter, it should be noted that there is only limited evidence that the managers are engaged in macroeconomic variables timing. In any case, there is no common pattern of macroeconomic variables timing, which is not surprising given the evidence that macroeconomic factors are not priced in Russian stock market. However, considering the dynamic beta strategies can offer some additional evidence on the stock-picking ability and provide a good robustness check of the results from the first chapter.

Conclusion

The paper tried to present a comprehensive overview of Russian equity funds performance and their dynamic beta strategies. Being the first paper in this field, which applies modern econometric techniques and results of financial economics to Russian data, it succeeded to reach several important conclusions, revealed the interesting phenomenon of the negative market timing bias and left vast room for further research.

Summing up the evidence presented in the chapters above, it should be said first that no firm conclusion for superior stock-picking ability of the fund managers can be drawn, as only one of the fourteen alpha estimates is positive and significant. However, the sign test suggests that the open-end fund managers have some stock-picking ability, as seven out of the eight point estimates are positive. As for the managers of the interval funds, our study favors the view that they have no stock-picking ability, as none of the alpha estimates is significant and only four out of the six point estimates are positive.

The results can be safely generalized to the level of the whole industry, as the study employs post-crisis data and thus avoids the survivorship bias. The results documented in this paper are free from the biases, from which the early studies of Russian mutual funds industry suffered. The impact of infrequent trading and dynamic beta strategies on the estimates of the alphas was properly controlled and various robustness checks were used, demonstrating that the results are robust to employing different data frequencies and estimating different specifications of the pricing model. It was also found out that the alphas are significantly lower in bearish market, contrary to the opinion of some investors who hold it that investing in mutual funds offers some insurance against downward market movements.

Analyzing the cash flows lets to conclude that the investors pay much more attention to the overall market growth that to the excess or abnormal return of a particular fund. Moreover, the relationship between the excess return and the cash flows is more pronounced and unambigious than that between the abnormal returns and the cash flows. It suggests that Russian equity fund managers have fewer incentives to seek for investment bringing abnormal return than they should. This result can partly explain the reported insignificance of the alpha estimates.

Considering dynamic beta strategies reveals the phenomenon of the negative market timing bias, which is also reported in the literature on US mutual funds. Among the fourteen estimates of the market-timing coefficient, two are significantly negative and no estimate is significantly positive. The sign test leads to the conclusion that the open-end funds tend to time the market negatively, as using the Henriksson and Merton specification resulted in negative point estimates of the market-timing coefficient for all the open-end funds.

The methods, which can be applied to the data, brought only partial explanation of this phenomenon. When the data from the crisis year of 1998 are used, the funds, which seem to be negative market timers in the post-crisis sample, turn into significantly positive market timers. This evidence suggests that the managers have the timing ability, but either choose not to use it at present, or the timing estimates suffer from some biases, which did not play an important role during the crisis. One of the possible biases documented in the chapter are the passive effects for individual stocks, as it may be enough to pick some stocks with insignificantly negative relationship between the beta and the market return to get the insignificantly negative timing estimates.

Analyzing other dynamic beta strategies does not help to explain the negative market timing bias, but provides useful robustness checks for the estimates of the alphas, letting to control for various possible biases. It was found out that the macroeconomic factors, such as industrial production growth, inflation, exchange rate, oil prices and interbank interest rates, are timed by a small number of the funds. No general conclusion about the preferred macroeconomic factor and the usual way to time it can be made from the estimates, which is not surprising given the evidence that macroeconomic factors do not seem to be priced in Russian stock market.

As for the volatility timing, the results are not conclusive, as the study reports one significantly positive and one significantly negative volatility-timing coefficient. Various robustness checks lead to a tentative conclusion that it is probable that half of the managers time the volatility positively and the other half does not time it at all. That fact causes some doubts in the statement that the managers do not time the market positively because they think that it is not profitable, as positive volatility timing is driven mostly by the positive relationship between return and volatility. It also suggests that the biases in the timing estimates appear to be a more promising area for future research than trying to explain when it is profitable to time the market. However, the latter question is still quite interesting to answer, and the answer does not have to be at odds with the future biases studies.

Going back to the volatility timing, it should be noted that the paper tried to explore the issue, which has not been addressed in the literature yet. The different reaction of the fund managers on the unpredictable, predictable short-run volatility movements and long-run considerations was studied. However, the small sample size did not allow reaching a definite conclusion on this issue, but the results of the estimates provided a good robustness check, which allowed distinguishing real volatility timers from spurious ones. Still, a tentative conclusion can be made at this stage of research, stating that the volatility timers respond in the same way to predictable and unpredictable shocks, but may react on the long-run volatility level negatively even if they time the volatility positively. This fact, presumably, reflects the wish to have a less volatile market. It is also important to note that despite the managers time both predictable and unpredictable shocks in the same way, they have no superior ability to predict volatility movements and to time future shocks to the volatility.

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