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Sources of Short-term Momentum Profits: Evidence from the Russian Stock Market

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Abstract

I show that short-term cross-sectional momentum strategies tend to be profitable after exchange fees on the Russian stock market. I provide a trading strategy similar to Nagel (2012) and Lehmann (1990) of buying relatively outperforming stocks and short selling underperforming stocks in proportion to market-adjusted returns. The portfolio weights are examined using one to five days returns. The strategy generates highest profits after holding a portfolio for one day and then returns partly reverse as the holding period increases. I find that autocorrelation contributes the most to momentum returns, which is consistent with the underreaction theory. The strategy is market neutral but winners and losers portfolios have betas varying conditional on the recent market performance. Neither the expected volatility nor the volatility risk premium drive the strategy returns.

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Contents

1 Introduction

Momentum and reversal effects across various asset classes and markets are extensively studied in the literature. Returns of the cross-sectional momentum strategies refer to the returns of buying relatively outperforming stocks – winners and short selling losers. Reversal strategies do the opposite. Nagel (2012) shows that stock market returns from short-term reversal strategies can be interpreted as a proxy for the returns generated by liquidity providers, therefore momentum profits may refer to their losses. On the U.S. stock market Blitz, Huij, and Marten (2011) show that priced risk factor or market microstructure effects cannot generally explain profits from momentum strategies based on residual stocks returns for portfolio formation. DeMiguel, Nogales, and Uppal (2010) show that the portfolio construction based on daily stock return serial dependence capturing momentum and reversal effects provides a good performance out-of-sample on the U.S. stock market. Thus, the momentum and reversal effects on a given market and a timeframe are likely to persist. Notwithstanding researchers generally focus on the U.S. stock market, Griffin, Kelly, and Nardari (2010) and de Groot, Pang, and Swinkels (2012) apply the methodology from Jegadeesh and Titman (1993) of buying winners and selling losers to stock market of various emerging countries, however, they exclude Russian one. The literature focusing on short-term trading strategies exploiting any effects on the Russian equity market is quite scarce. Galperin and Teplova (2012) provide investment strategies with annual portfolio rebalancing based on dividends and fundamental factors. As for trading strategies, Anatolyev (2005) uses predictors computed from regressions on the weekly data. On the U.S. market there are daily reversals (Nagel (2012)) and there are mainly weekly reversal and long-term momentum effects on emerging markets (Griffin, Kelly, and Nardari (2010)); in this paper I study what effect if any is present on the Russian market. My goal is to fill the gap in the literature on short-term effects on the Russian stock market.

My focus is on daily frequences. Griffin, Kelly, and Nardari (2010) also apply short-term strategies exploiting cross-serial dependence on emerging markets and claim that bid-ask bounce causes most problems dealing with one-two day frequencies. However, bid-ask bounce is one of the profit components of short-term reversals (Nagel (2012)) and the evidence of profits from short-term momentum despite this factor is likely to understate the momentum effect.

The paper contributes to the literature by characterizing the short-term cross-sectional momentum on Russian stock market. I show that cross sectional momentum strategies tend to be profitable after exchange fees. I show the the sources of the effect following the framework of Lewellen (2002), Nagel (2012) and Daniel and Moskowitz (2011).

Specifically, I employ trading strategies based on Lehmann (1990), because of the following two reasons. First, this requires one ruble of capital per trade which allows a comparison between the performance of the strategies. Second, applied trading strategies hold stocks in proportion to its market-adjusted returns. Since the dataset has a relatively small number of stocks availiable in comparison to the U.S. stock market, this portfolio composition technique benefis from this fact and this is better than working with quantiles as in Jegadeesh and Titman (1993), so all the stocks are involved in trading. Next, the paper states that autocorrelations contribute the most to the momentum profits. Then I show that the strategy, first, has no significant relation to the market return and, second, generates a significant positive alpha, market risk adjusted excess return. I further provide the evidence that relationship between parts of the strategy (both long and short) and market returns depend on the recent market performance. I also show that neither the expected market volatility nor the volatility risk premium is a source of the the strategy returns. I conclude that the strategy performance is robust to the inclusion of dead stocks in the formation portfolio, other weighting methods and higher frequency data accounting for broker and short selling costs.

The rest of the paper is organized as follows. Section 2 describes the dataset and the methodology used for my empirical analysis. Section 3 empirically characterizes the performance of the short-term momentum strategies and documements sources of the momentum effect. Section 4 concludes.

2 Data and Methodology

2.1 Data

I use daily and hourly data from Finam website[1] and daily data from the Moscow Exchange website[2] and calculate simple returns from ruble denominated asset prices close-to-close. Since the emphasis is given to the short-term strategies, I use most

[1]http://www.finam.ru/analysis/export/default.asp

[2]http://rts.micex.ru/

liquid and available to short sell stocks. For such stocks I use constituents of MICEX 10 index. If there are missing prices (two indices observations) the closing price of the previous day for these dates is used.

Individual stocks. First, the dataset includes a hourly data for a fixed list of individual stocks currently[3] included in the MICEX10 index, which highlights the changes in most liquid instruments in the equity market. The sample covers the period from 07/16/2008 to 12/28/2012. The period starts at the latest date when currently included stocks began trading. Panel A in Table 1 shows these stocks involved in the analysis. Second, for the further analysis I employ daily data for a list of stocks which changes according to MICEX 10 index updates[4]. I know in what stocks I will have a position tomorrow. I assume if the index rebalances tomorrow and some stocks will get out or other liquid stock will not be traded tomorrow I do not include these stocks in the portfolio formation. The sample for this part of the dataset is from 06/01/1999 to 12/28/2012, includes 26 stocks (even currently not traded).

Industry portfolios. Following Nagel (2012) and Lewellen (2002) I use daily data for industry portfolios, but proxied by MICEX industry indices. Five core MICEX indices being tracked since 05/08/2007 are analyzed (Panel B in Table 1). The sample covers the period from this date to 12/28/2012.

Risk-free rate. I employ Moscow InterBank Offered Rate overnight return [5] daily data over the period from 08/01/2000 to 12/28/2012. If the rate is not available for

[3]Updated on 09/01/2013.

[4]http://rts.micex.ru/a1722

[5]http://www.cbr.ru/mkr_base/

the particular day I use a linear interpolation for these cases.

Volatility. For the analysis of impact of expected volatility on the strategy returns I employ Russian Volatility Index (RTSVX) based the options on RTS index futures contracts and RTS index series for forecasts. The sample for RTSVX series covers the period 01/11/2006-12/28/2012 and for RTSI index 06/01/1999 to 12/28/2012.

Table 1: Dataset

Panel A: Individual stocks from MICEX 10, 07/16/2008 - 12/28/2012

Firm	Ticker	Mean return	Standard dev.
Federal Grid Co Unified Energy System JSC	FEES	0.05	4.47
Gazprom OAO	GAZP	-0.02	3.13
MMC Norilsk Nickel OJSC	GMKN	0.07	3.45
Lukoil OAO	LKOH	0.04	3.02
Rosneft OAO	ROSN	0.06	3.51
Sberbank of Russia	SBER	0.09	3.82
Sberbank of Russia	SBERP	0.12	4
Surgutneftegas OAO	SNGS	0.07	3.5
Uralkali OJSC	URKA	0.07	4.54
VTB Bank OJSC	VTBR	0.03	3.82

Panel B: Industry portfolios, 05/08/2007 - 12/28/2012

Industry	Ticker	Mean return	Standard dev.
Metals and Mining	M&M	0.03	2.57
Mechanical Engineering	MNF	0.01	2.32
Oil & Gas	O&G	0.06	2.67
Power	PWR	-0.03	2.3
Telecommunication	TLC	0.01	2.08

Means and standard deviations are measured in % per day.

2.2 Methodology

Portfolio construction. I consider the trading strategy examined by Lehmann (1990). At the end of the period *t-1* the weight for stock i for holding the position at the period t in the portfolio is given by

$$w_t^i = \frac{r_{t-1}^i - r_{t-1}^m}{\sum_{i=1}^N \mid r_{t-1}^i - r_{t-1}^m \mid}, \tag{1}$$

where $r_t^m = \frac{1}{N}\sum_{i=1}^N r_t^i$ is the equal-weighted market index return, which refers to the market component. Similar to Nagel (2012) assuming 100% margin requirements, the denominator in Equation (1) scales the capital invested per trade to 1 ruble with 50% long and short positions. Hence, total return at the period t for the portfolio is given by

$$R_t = \frac{\sum_{i=1}^N r_t^i (r_{t-1}^i - r_{t-1}^m)}{\sum_{i=1}^N \mid r_{t-1}^i - r_{t-1}^m \mid}.$$

This strategy has an advantage of clear interpretation as equally short and long as well as the strategy requires 1 ruble of capital per trade. This is crucial point when strategy results with exchange fees are compared.

Effect decomposition. My focus is on the strategy with one day for both lookback and holding periods. For the sources of the cross-sectional momentum the framework of Lo and MacKinlay (1988) is applied. Instead of using weights scaled by the random term in Equation (1) of Lehmann (1990) I follow Lewellen (2002) and Moskowitz, Ooi, and Pedersen (2012) who apply Lo and MacKinlay (1988) approach for the portfolio construction and expected portfolio profit decomposition. The portfolio weights for the day t and the stock i are:

$$w_t^i = \frac{1}{N}(r_{t-1}^i - r_{t-1}^m).$$

Total portfolio return is given by

$$R_t = \frac{1}{N}\sum_{i=1}^{N} r_t^i (r_{t-1}^i - r_{t-1}^m).$$

Assuming unconditional means of the assets *1,2,...,N* are equal to $\mu = (\mu_1, ..., \mu_N)'$ and the first order autocovariance matrix is Ω, the expected portfolio return is following:

$$E(R_t) = E\left(\frac{1}{N}\sum_{i=1}^{N} r_t^i r_{t-1}^i - \frac{1}{N}\sum_{i=1}^{N} r_t^i \left[\frac{1}{N}\sum_{j=1}^{N} r_{t-1}^j\right]\right) = \frac{1}{N} tr(\Omega) - \frac{1}{N^2} 1'\Omega 1 + \sigma_\mu^2 =$$

$$= \frac{N-1}{N^2} tr(\Omega) - \frac{1}{N^2}[1'\Omega 1 - tr(\Omega)] + \sigma_\mu^2, \qquad (2)$$

where $\sigma_\mu^2 = \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \frac{1}{N}\sum_{p=1}^{N}\mu_p)^2$ is a cross-sectional variance of the expected mean returns. Terms in Equation (2) are rearranged to separate the sources of the expected portfolio return due to the diagonals and off-diagonals of the autocovariance matrix Ω.

Thus, there are three drivers of the strategy returns: own autocovariances of stocks (diagonals, $tr(\Omega)$), cross autocovariances (off-diagonals, $1'\Omega\ 1 -\ tr(\Omega)$), and cross-sectional variance of the expected mean returns.

The expected portfolio return is positive if, first, there are positive own autocovariances of stocks, second, cross autocovariances are negative or less in magnitude than own autocovariances, third, cross-sectional variance of the expected mean returns is high. The reverse is true to get negative returns.

First, possible positive own autocovariances of stocks (diagonals, $tr(\Omega)$) imply that the stock with high return yesterday is more likely to generate higher returns today. Second, in case of negative cross autocovariances (off-diagonals, $1'\Omega\ 1 -\ tr(\Omega)$)

yesterday's higher gains for the particular stock lead to lower returns for other stocks today. Third, even if $\Omega = 0$, i.e the lack of serial and cross-sectional predictability, and assuming μ is not zero the expected portfolio profit is positive as the investor tends to buy winners with high unconditional means and shorting the opposite.

3 Empirical Implementation and Results

3.1 Strategy performance

For every day I have a set of assets and get simple returns from closing prices to calculate weights, which are used in the holding period. The returns for the portfolio are calculated close-to-close for every period.

Since the short-selling ban was adopted from 09/17/2008[6] to 06/15/2009[7], I exclude short-selling trades during this period. Instead of short selling, the investor just reserves 50% of the capital in cash. The strategy from dollar neutral becomes 50% long.

Lookback period is defined as the number of lags used to compute weights for portfolio construction. Holding period is defined as the number of days the investor holds the portfolio. As emphasis is given to short-term frequencies portfolio returns are calculated for both lookback and holding periods from one to five days (one week). If several portfolios are active at the same time I compute average returns of them similar to Moskowitz, Ooi, and Pedersen (2012).

[6] http://old.ffms.ru/document.asp?ob_no=144259

[7] http://old.ffms.ru/document.asp?ob_no=194504

Table 2 reports results for various periods of returns for calculating weights and days of holding the trading position. There is a clear pattern, where trading strategy returns drop when lookback and holding periods increase. These findings might suggest partial stock reversals over the long-term. Slightly profitable reversals can be discovered for individual stocks at weekly frequencies (five days for both periods).

Surprisingly, my evidence of profitable short-term momentum on the Russian stock market is opposite to Nagel (2012) who finds short-term reversals on the U.S. market for the same frequency. The author also states that long-lived private information is likely to induce negative returns from the reversal strategy in the short-term. The interesting pattern of declining profits when holding periods increases supports findings of Hong and Stein (1999). In their model this effect of high short-term momentum profits is called an underreaction. This is a result of the gradual diffusion of private information and failure of one market participants group ("newswatchers") to exploit this fact. Next, declining momentum profits refer to results of other market participants group ("momentum traders") which overshoots prices causing them to overreact. Thus, one the ideas behind my evidence can be that private information moves slowly among Russian investors.

The further analysis focuses on one day for the lookback and holding periods as the most profitable combination. Table 3 provides more detailed results for this combination. Figure 1 graphically shows the performance of the trading strategies. Figure 1 shows a consistent positive strategy performance and only a huge drop in strategy profits at the beginning of the financial crisis.

First, Panel A in Table 3 shows that mean returns from the individual liquid stocks

Figure 1: Trading Strategy Performance

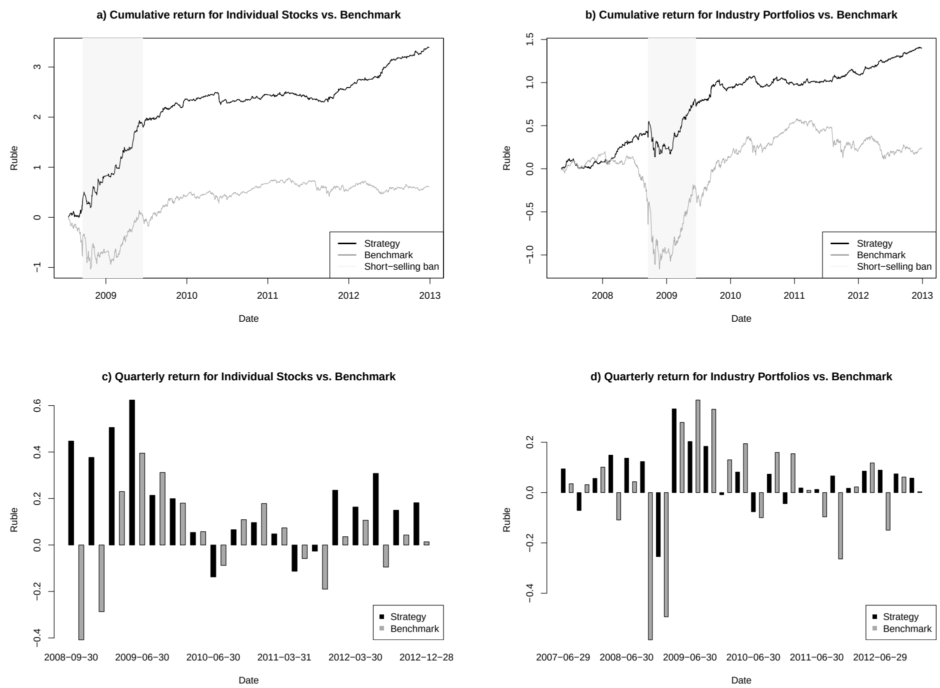

Figure 1 shows cumulative ruble returns close-to-close (a,b) and total returns by quarter (c,d) for individual stocks and industry portfolios before fees vs their benchmarks (equally weighted indices). Benchmark bars on (c,d) for the same quarter are added to the right of Strategy bars. Returns are measured in rubles, i.e. this shows the gain of 1 ruble invested per trade. During the short-selling ban (light grey block (a,b)) the strategy reserves 50% of the capital in cash.

strategies are higher (0.22% vs. 0.05% per day) and have lower volatility (1.54% vs. 3.1% per day) than returns generated by the benchmark (equally weighted index of the assets included in the strategy), so they beat benchmarks over the sample period. Figure 1 (c) and (d) show how volatile benchmarks are and the fact that the strategy generates positive returns for both portfolios for almost every quarter. Furthermore, these returns dramatically beat stock exchange fees of 0.02% per round trip.[8]

As for industry portfolios Panel B in Table 3 shows four times lower average means, but volatility of the strategy returns is also half of the benchmark volatility.

[8] http://www.micex.com/markets/stock/participation/rates/97 and http://rts.micex.ru/s428

Table 2: Strategy mean returns (% per day) for different lookback and holding periods

Panel A: Individual stocks from MICEX 10

	Holding period				
Lookback period	1	2	3	4	5
1	0.219	0.118	0.080	0.058	0.044
2	0.178	0.106	0.070	0.055	0.031
3	0.141	0.082	0.056	0.039	0.011
4	0.114	0.072	0.044	0.023	0.000
5	0.103	0.062	0.029	0.007	-0.005

Panel B: Industry portfolios

	Holding period				
Lookback period	1	2	3	4	5
1	0.080	0.037	0.021	0.015	0.011
2	0.061	0.032	0.017	0.009	0.010
3	0.066	0.041	0.022	0.013	0.014
4	0.055	0.026	0.014	0.015	0.010
5	0.044	0.026	0.021	0.015	0.013

Periods are measured in days.

The industry portfolio strategy generates returns only slightly greater than fees.

In Table 3 the positive skewness of strategy returns and worst day return for individual stocks as well as for industry portfolios show that exposure to asymmetric downside risk is likely to be reduced.

I show that auto- and cross-correlations effects are weak on individual level, but actually they are the main source of positive strategy returns.

First, I start with testing for autocorrelations and cross-correlations among individual stocks and industries. Cross-autocorrelation effects in financial markets are usually tested by vector autoregressive (VAR) models (DeMiguel, Nogales, and Up-

Table 3: Summary Statistics of Momentum Strategy Returns

Panel A: Individual stocks from MICEX 10

	Strategy	Benchmark
Mean return (% per day)	0.22	0.05
Standard deviation (% per day)	1.54	3.1
Skewness	2.3	1.53
Worst day return (%)	-9.41	-21.5

Panel B: Industry portfolios

	Strategy	Benchmark
Mean return (% per day)	0.08	0.02
Standard deviation (% per day)	1.06	2.09
Skewness	1.49	-0.09
Worst day return (%)	-7.23	-17.05

Benchmark refers to returns from the equally weighted index of the assets included in the momentum strategy.

pal (2010) estimate VAR for 25 and 100 individual stocks, Chordia and Swaminathan (2000) use VAR for two portfolios based on trading volume). I employ the following VAR(1) model

$$r_{t+1} = a + Br_t + \xi_{t+1},$$

where $r_{t+1} = (r_t^1, r_t^2 ..., r_t^N)'$ is the the return vector for assets *1,2,...,N* in the portfolio for the day t.

Table A in Appendix A reports the results. Panel A and B show that I fail to reject the null of zero first-order autocorrelation and cross correlation effects for almost all assets on the individual level. The magnitude of coefficients do not exceed 0.3.

Second, I apply the effect decomposition framework according to Equation (2) in Section 2.2. Table 4 shows that positive own autocovariances of stocks contribute the most. I did not find any effect from the unconditional means. The performance of

Table 4: Daily momentum return decomposition

	Auto	Cross	Means	Total
Individual stocks	0.0091**	-0.0033	0.0000	0.0058***
	(0.0051)	(0.0041)	—	(0.0016)
Industry portfolios	0.0047***	-0.0036***	0.0000	0.0011***
	(0.0017)	(0.0015)	—	(0.0004)

Standard errors are in parentheses. Mean returns and standard errors are measured in percent, however the position size changes over time. Auto referes to the own autocovariance component, Cross is the profit component attributed to cross-serial covariance, and Means refers to the unconditional expected returns component. Newey-West long variance is used for calculating standard errors. Significance levels: *** - 1%, ** - 5%, * - 10%.

the momentum strategy also degrades due to the lack of relative winners-losers effect, because cross autocovariances are slightly positive. This performance deterioration is more prominent and statistically significant among industry portfolios. To test for significance I follow Pan, Liano, and Huang (2004) and construct z-statistics which are standard normal under the null hypothesis of no correspondent effect.

Thus, positive autocorrelation is the driver of positive momentum strategy returns, despite the fact of no significant difference of individual stocks autocorrelation from zero. Lewellen (2002) claims that the underreaction is likely to induce positive autocorrelation and cross-serial correlation among portfolios. The provided evidence of profitable short-term mementum on Russian stock market and partial reversal over the larger holding period might be consistent with an underreaction theory and other behavioral theories implying these patterns in returns.

Now I employ the longer version of the individual stocks dataset with varying stocks in my portfolio and extended sample period.

3.2 Beta analysis of the strategy returns

In this section I test to what extent market and its recent performance affect the strategy. The approach is similar to Daniel and Moskowitz (2011).

Table 5: Market beta analysis for the Strategy portfolio

	(1)	(2)	(3)
(Intercept)	0.0018***	0.0016***	0.0016***
	(0.0003)	(0.0004)	(0.0004)
$R_{m,t}$	-0.0179	0.0858**	0.0858**
	(0.0284)	(0.0360)	(0.0360)
I_B		0.0004	-0.0003
		(0.0006)	(0.0008)
$I_B \cdot R_{m,t}$		-0.1654***	-0.2027***
		(0.0471)	(0.0480)
$I_B \cdot I_U \cdot R_{m,t}$			0.0698
			(0.0664)
R^2	0.0008	0.0163	0.0173
Adj. R^2	0.0005	0.0153	0.0160
Num. obs.	3088	3088	3088

Standard errors are in parentheses. Newey-West estimator with 10 lags is used for calculating standard errors. The period is 08/01/2000-12/28/2012. Significance levels: *** - 1%, ** - 5%, * - 10%.

Regression (1) in Table 5 fits a CAPM model to the strategy portfolio

$$R_t = \alpha_0 + \beta_m R_{m,t} + \xi_t,$$

where R_t is the strategy excess return in day t, and $R_{m,t}$ is the excess equally weighted index return in day t (market benchmark from the stocks in the strategy porfolio).

The estimated market beta $\hat{\beta}_m$ is not significantly different from zero, so the strategy turned up to be market neutral. The estimated $\hat{\alpha}_0$ is both economically large (0.18% per day) and statistically significant, therefore the strategy generates a significant premium on top of market returns.

Regression (2) in Table 5 fits a CAPM model conditional on the recent short-term market performance using bear-week indicator I_B

$$R_t = (\alpha_0 + \alpha_B I_B) + (\beta_m + \beta_B I_B) R_{m,t} + \xi_t,$$

where additional variable is I_B, an ex-ante Bear-week dummy variable. The indicator is one if the index five days return up to the close of day $t-1$ is negative, and is zero otherwise.

This specification tries to capture differences in expected alpha and beta of the strategy after the short-term negative market performance. First, the point estimate $\hat{\alpha}_B$ is not statistically different from zero and the strategy alpha $\hat{\alpha}_0$ remains positive. Second, the results show a decrease in market beta after a bear week ($\hat{\beta}_B$ is negative with p-value less than 1%). This is consistent with longer term momentum strategy as in Daniel and Moskowitz (2011) and Grundy and Martin (2001) who find a negative change in market beta in bear markets. After a bear week startegy beta declines and if the market rebounds the strategy does not capture this return, but in the crisis if the market decline continues the strategy slightly benefits from the negative beta.

Regression (3) in Table 5 fits a model to capture the extent to which the up- and down-market betas of the strategy portfolio differ

$$R_t = (\alpha_0 + \alpha_B I_B) + (\beta_m + I_B(\beta_B + \beta_{U,B} I_B)) R_{m,t} + \xi_t,$$

where additional variable is I_U, a current Up-day dummy. This indicator is not ex-ante, i.e. it is one if the index return in day t is positive, and is zero otherwise.

This specification could assess the optionality of the strategy. In other words, I assess nonlinearity of the strategy payoff by testing for changes in beta given the sign of the current market return. Results show no significant optionality of the strategy payoff conditional on the recent market poor performance.

In addition, I test for the optionality of top winner and loser stocks from my basic portfolio separately. The idea behind this is to get an idea of market exposure of long and short parts. I construct weighted portfolios based on winners and losers parts of the strategy according to the positive and negative weights in the original strategy portfolio, adjusting to have 100% of capital employed in the strategy.

Table 6: Market beta analysis for Winners and Losers portfolios

	Winners (only long)	Losers (only short)
(Intercept)	0.0013**	0.0016***
	(0.0006)	(0.0003)
I_B	-0.0001	-0.0005
	(0.0008)	(0.0010)
$R_{m,t}$	1.1581***	-0.9867***
	(0.0635)	(0.0204)
$I_B \cdot R_{m,t}$	-0.2418***	-0.1623***
	(0.0706)	(0.0510)
$I_B \cdot I_U \cdot R_{m,t}$	0.1119*	0.0253
	(0.0625)	(0.0933)
R^2	0.5807	0.7192
Adj. R^2	0.5802	0.7188
Num. obs.	3088	3088

Standard errors are in parentheses. Newey-West estimator with 10 lags is used for calculating standard errors. The period is 08/01/2000-12/28/2012. Significance levels: *** - 1%, ** - 5%, * - 10%.

Regressions in Table 6 show significant alphas and market betas. Thus, both winners and losers parts generate strategy excess return. First, market betas differ in magnitude for winners and losers. The winners portfolio turned out to be a higher beta portfolio conditional on the positive recent market performance. Second, the interesting pattern here that after a bear week betas of both winners and losers decline. The losers portfolio becomes more aggressive and the long portfolio gains a bit of hedge in the case of continuation of the negative recent market performance. Third, there is a borderly significant positive optionality coefficient $\hat{\beta}_{U,B}$ for the winners portfolio. This means that after a bear week the winner portfolio gains sort of long call property. After a bear week if the decline continues the winner portfolio beta is $\hat{\beta}_0 + \hat{\beta}_B = 0.92$ and if there is a reversal $\hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U} = 1.03$. Thus, after a bear week the winners portfolio performance slighltly refers to a long gamma and a positive delta properties like a long call option.

3.3 Volatility and momentum returns

In the Section 3.2 I show a slight optionality embedded in long only (winners) portfolio and variablity of beta conditional on the recent poor market performance. In this section I'd like to test whether a volaility as market turmoil indicator forecasts strategy returns and I try to explore whether the strategy harvests volatility risk premium. If there is an impact of turmoil anticipation on information diffusion, strategy returns will be significantly more likely to change. First, similarly to Daniel and Moskowitz (2011) I test to what extent estimated market volatility forecasts future momentum returns. I also test not only the influence of the expected variance component but the relation of the variance risk premium to the strategy returns similar to Nagel (2012).

For risk premium calculations I employ RTSVX series as a proxy for the expecation of market variance under the risk-neutral measure. This also refers to the market turmoil in general like VIX for the U.S. market. I normalize RTSVX to daily volatility dividing by $\sqrt{252}$ (proxy for trading days in a year, following the literature). I substract my volatility forecast from RTSVX which gives a volatility risk premium: $RTSVX - \sigma$.

I construct market volatility forecast using GARCH(1,1) specification. I make forecasts σ on the 21 days horizon as approximately one month maturity for RTSI options as a proxy for the Russian market. I apply a rolling estimation with a window of 1000 observations.

Table 7: Volatility impact

	Strategy	Winners (only long)	Losers (only short)
(Intercept)	0.0015*	-0.0003	0.0032
	(0.0008)	(0.0024)	(0.0022)
$RTSVX - \sigma$	0.0239	0.1130	-0.0706
	(0.0253)	(0.0946)	(0.0845)
σ	-0.0001	0.0228	-0.0243
	(0.0073)	(0.0226)	(0.0207)
R^2	0.0015	0.0032	0.0012
Adj. R^2	0.0003	0.0021	0.0001
Num. obs.	1740	1740	1740

Standard errors are in parentheses. Newey-West estimator with 10 lags is used for calculating standard errors. The period is 01/11/2006-12/28/2012. Significance levels: *** - 1%, ** - 5%, * - 10%.

Regressions in Table 7 show no significant relationship between the strategy portfolio (both its long ans short parts) and volatility forecast and and ex-ante volatility risk premium. The results differ from Nagel (2012) who find the evidence that both expected volatility component and volatility risk premium forecast short-term reversals on the U.S. stock market. Thus, the strategy does not capture volatility risk premium and the anticipation of market turmoil does not affect the strategy, therefore the strategy does not need to be stopped in the risk-on regime.

3.4 Robustness of results

In this section I provide some robustness checks of the strategy performance. Figure 2 shows that the strategy generates positive returns with different stocks in the portfolio over more than 10 years. Figure 3 shows different specifications of the momentum strategy. Figure 4 provides an evidence of profitability of the strategy after varios costs and accounting for non synchronous trading.

Survivorship bias. According to changes in MICEX 10 index[9] I test the strategy also for currently dead stocks (like RAO UES, YUKOS, etc.). The index is rebalanced on quarterly basis and over the period some stocks which added in the beginning of the sample period are currently completely delisted. I assume if the index rebalances tomorrow and some stocks will be excluded I know in what stocks I will have a position tomorrow. If the stock has ever been included in MICEX 10 index, the strategy has added this stock to the portfolio. Thus, currently dead stocks are included in the analysis. The Figure 2 the similar performance over the period 06/01/1999-12/28/2012.

Alternative weighting. I also conduct a robustness test by employing an alternative

[9] http://rts.micex.ru/a1722

Figure 2: Trading strategy performance for MICEX 10 stocks with varying portfolio

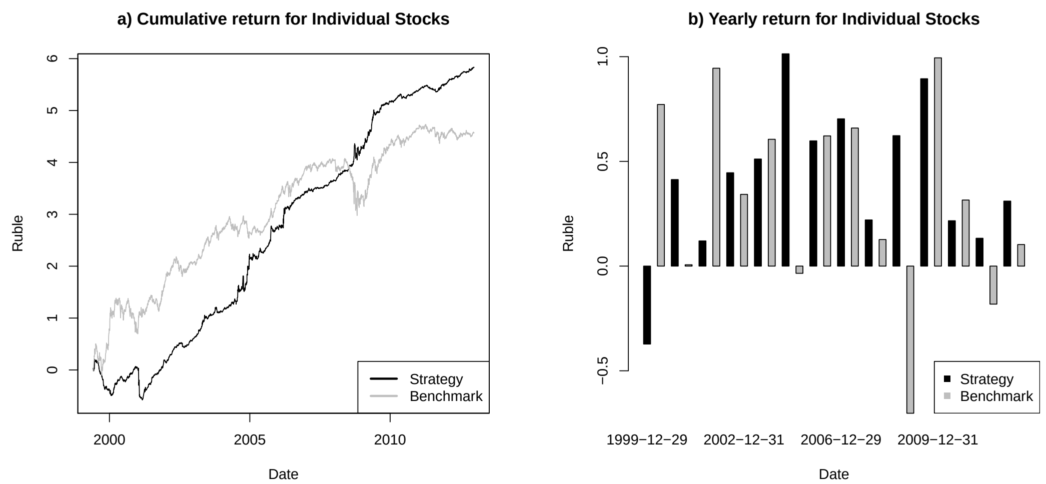

Figure 2 shows cumulative ruble returns close-to-close (a) and total returns by year (b) for individual stocks before fees vs their benchmarks (equally weighted indices). Benchmark bars on (b) for the same year are added to the right of Strategy bars. Returns are measured in rubles, i.e. this shows the gain of 1 ruble invested per trade. During the short-selling ban the strategy reserves 50% of the capital in cash. Dead stocks are considered according to MICEX 10 index.

weighting method, which shows that my findings are robust to various weighting methods. In addition to the original weighting (Equation (1) in Section 2.2) I use min-max approach similar to Balvers and Wu (2006) going one long and one short stocks (MinMax-1), and two stocks long and two short (MinMax-2) with equal weighting. For example, in MinMax-2 specification before the close I sort all the available stocks in the portfolio according to their return from the previous close and then I choose two best and two worst performers. I construct an equally weighted portfolio, i.e. allocating 25%+25% of the capital to the long position in two best performing stocks and the remaining part for selling short equally worst performers. Figure 3 shows yearly returns for these specifications.

Non synchronous trading. I also consider higher frequency data for robustness

Figure 3: Alternative trading strategies performance for MICEX 10 stocks

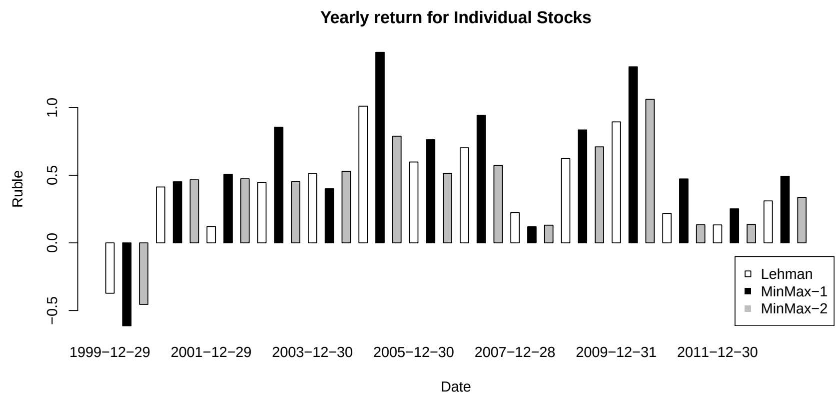

Figure 3 shows total returns by year for individual stocks before fees for three strategies. White bars refer to the original strategy, black bars refer to portfolio formations based on going long top-1 (best) and and short bottom-1 (worst) performers, grey bars refer to the strategy equally weighting in long top-2 and short bottom-2 performers. Returns are measured in rubles, i.e. this shows the gain of 1 ruble invested per trade. During the short-selling ban the strategy reserves 50% of the capital in cash. Dead stocks are considered according to MICEX 10 index rebalancing over the period 06/01/1999-12/28/2012.

check. I apply the fixed list of stocks here. The market closes at 18:45, I start forming trading portfolio at 17:00 for latest available prices and calculate returns based on 18:00 prices. I assume that starting forming portfolio from 17:00 to 18:00 yields expected entry price of 18:00. This delay solves the problem of non synchronous trading and the issue of opening position at the market close. Figure 4 shows that non synchronous trading is not the source of short term momentum profits.

Transaction costs. The profit is varying on the quarter basis. I substract exchange fees of 0.01% per transaction, indicative broker fees of 0.1% per transaction and assuming 20% rate for borrowing for short selling. Figure 4 shows that the strategy seems to be profitable. The above mentioned assumptions of ranking at 17:00 and rebalancing by 18:00 provide the time window for the position entry, therefore execution algorithms could be used to minimize a price impact over the window.

Figure 4: Trading strategy performance based on hourly data after fees

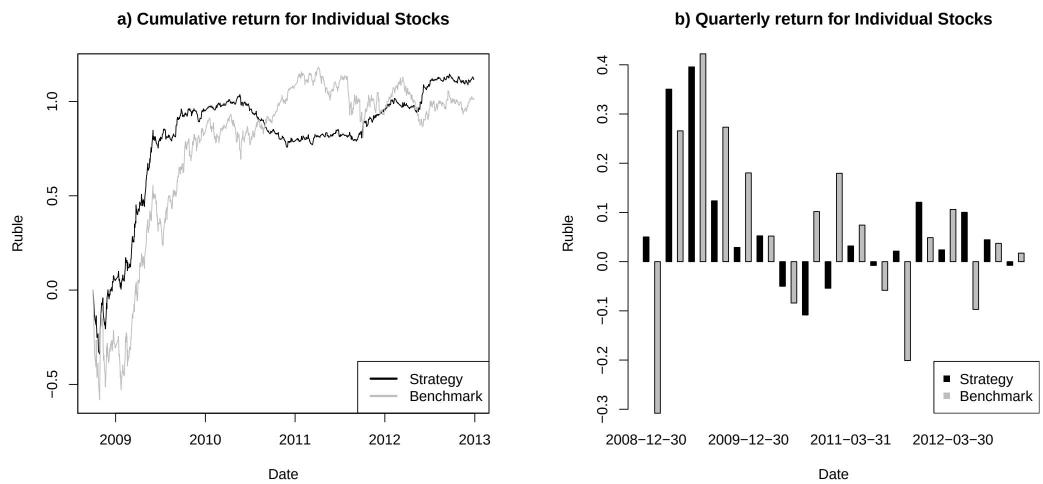

Figure 4 shows cumulative ruble returns close-to-close (a) and total returns by quarter (b) for individual stocks vs their equally weighted indices after fees. The ranking is based on 17:00 prices and the strategy entry and exit prices are computed from 18:00 prices. Benchmark bars on (b) for the same quarter are added to the right of Strategy bars. Returns are measured in rubles, i.e. this shows the gain of 1 ruble invested per trade. During the short-selling ban the strategy reserves 50% of the capital in cash.

4 Conclusion

My focus is on short-term cross-sectional behavior of the Russian stock market. I get the evidence of profitable short-term trading strategies after exchange fees both for liquid individual stocks and industry portfolios. They exploit short-term serial dependence, causing a momentum effect. The strategy generates highest profits after holding a portfolio for one day. Strategy returns partly reverse as the holding period increases. The decomposition of the momentum effect suggests that the main source of momentum profits is positive autocorrelation between stocks, but not a cross-serial correlation. Positive trading strategy returns may arise despite of no significant difference of the autocorrelations from zero. My result is consistent with the underreaction theory, specifically, a result of the slow diffusion of news among Russian investors. Actually, the strategy is a market neutral strategy. But I find the winners portfolio to be a higher beta portfolio conditional a positive weekly market return but after a week of poor market performance betas of both winners and losers decline. There is a slight evidence of long call property embedded in the winners portfolio. I find that expected variance component and the variance risk premium are not sources of short-term momentum profits. Strategy performance is robust to other weighting methods and non synchronous trading.

5 References

Anatolyev, S. (2005): "A ten-year retrospection of the behavior of Russian stock returns.," *Working paper*.

Balvers, R. J., and Y. Wu (2006): "Momentum and mean reversion across national equity markets," *Journal of Empirical Finance*, 13(1), 24–48.

Blitz, D., J. Huij, and M. Marten (2011): "Residual momentum," *Journal of Empirical Finance*, 18(3), 506–521.

Chordia, T., and B. Swaminathan (2000): "Trading Volume and Cross-Autocorrelations in Stock Returns," *Journal of Finance*, 55(2), 913–935.

Daniel, K., and T. Moskowitz (2011): "Momentum crashes," *Columbia Business School Research Paper*, (11-03).

de Groot, W., J. Pang, and L. Swinkels (2012): "The cross-section of stock returns in frontier emerging markets," *Journal of Empirical Finance*, 19(5), 796–818.

DeMiguel, V., F. J. Nogales, and R. Uppal (2010): "Stock Return Serial Dependence and Out-of-Sample Portfolio Performance," *Working Paper*.

Galperin, M. A., and T. V. Teplova (2012): "Dividend Investing Strategies in the Russian Stock Market: Dogs of the Dow and Portfolios Filtered by Fundamental Factors," *HSE Economic Journal*, 16(2), 205–242.

Griffin, J. M., P. J. Kelly, and F. Nardari (2010): "Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets," *Review of Financial Studies*, 23(8), 3225–3277.

Grundy, B. D., and J. S. Martin (2001): "Understanding the Nature of the Risks and the Source of Rewards to Momentum Investing," *Review of Financial Studies*, (14), 29–78.

Hong, H., and J. C. Stein (1999): "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets," *Journal of Finance*, 54(6), 2143–2184.

Jegadeesh, N., and S. Titman (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance*, 48(1), 65–91.

Lehmann, B. N. (1990): "Fads, Martingales, and Market Efficiency," *The Quarterly Journal of Economics*, 105(1), 1–28.

Lewellen, J. (2002): "Momentum and Autocorrelation in Stock Returns," *Review of Financial Studies*, 15(2), 533–564.

Lo, W. A., and A. C. MacKinlay (1988): "Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies*, 1(1), 41–66.

Moskowitz, T., Y. H. Ooi, and L. H. Pedersen (2012): "Time series momentum," *Journal of Financial Economics*, 104(2), 228–250.

Nagel, S. (2012): "Evaporating Liquidity," *Review of Financial Studies*, 25(7), 2005–2039.

Pan, M.-S., K. Liano, and G.-C. Huang (2004): "Industry momentum strategies and autocorrelations in stock returns," *Journal of Empirical Finance*, 11(2), 185–202.

A Appendix

Table 8: VAR(1) estimates of daily return series linear relationship

Panel A: Individual stocks from MICEX 10, 07/16/2008 - 12/28/2012

	$FEES_t$	$GAZP_t$	$GMKN_t$	$LKOH_t$	$ROSN_t$	$SBER_t$	$SBERP_t$	$SNGS_t$	$URKA_t$	$VTBR_t$
$FEES_{t-1}$	0.1553^{***}	-0.0247	-0.0249	-0.0152	-0.0385	0.0013	-0.0149	-0.0379	0.0447	-0.0484
	(0.0544)	(0.0418)	(0.0485)	(0.0348)	(0.0525)	(0.0571)	(0.0537)	(0.0504)	(0.0848)	(0.0493)
$GAZP_{t-1}$	0.1153	0.2459^{**}	0.1056	0.1144	0.2362	0.1248	0.0996	0.1059	0.2455	0.1391
	(0.1595)	(0.1230)	(0.1449)	(0.1179)	(0.1755)	(0.1964)	(0.1932)	(0.1549)	(0.1631)	(0.1691)
$GMKN_{t-1}$	0.0356	0.0693	0.1475	0.0899	0.0300	0.0368	0.0228	0.0010	-0.0536	0.0016
	(0.1027)	(0.0740)	(0.1000)	(0.0642)	(0.0942)	(0.0838)	(0.1003)	(0.0682)	(0.0962)	(0.1130)
$LKOH_{t-1}$	-0.1083	-0.0389	-0.0639	-0.0217	-0.0639	-0.0546	0.0107	0.1524	-0.0392	-0.0634
	(0.1316)	(0.1233)	(0.1318)	(0.1250)	(0.1499)	(0.1570)	(0.1387)	(0.1113)	(0.1377)	(0.1292)
$ROSN_{t-1}$	0.1349	-0.0705	-0.0469	-0.0674	-0.0021	-0.1645	-0.0701	-0.0118	-0.0153	-0.0501
	(0.1281)	(0.0662)	(0.0813)	(0.0714)	(0.0825)	(0.1061)	(0.1081)	(0.0711)	(0.1014)	(0.0935)
$SBER_{t-1}$	-0.1952	-0.235^{*}	-0.0161	-0.1706	-0.2554	-0.0506	-0.0963	-0.2481	-0.44^{**}	-0.3282
	(0.2083)	(0.1248)	(0.1358)	(0.1270)	(0.1922)	(0.1862)	(0.2086)	(0.1634)	(0.2247)	(0.2571)
$SBERP_{t-1}$	0.3087	0.1652	0.0361	0.1092	0.2117	0.1274	0.2748	0.1472	0.2317	0.2677
	(0.1944)	(0.1065)	(0.0895)	(0.1088)	(0.1750)	(0.1711)	(0.1775)	(0.1647)	(0.2236)	(0.2653)
$SNGS_{t-1}$	-0.0345	-0.0175	0.0430	0.0162	-0.0011	0.0033	-0.0105	0.0705	-0.0146	0.0957
	(0.0850)	(0.1051)	(0.1613)	(0.1041)	(0.1166)	(0.1541)	(0.1520)	(0.1002)	(0.1074)	(0.1273)
$URKA_{t-1}$	-0.0347	0.0112	0.0350	-0.0084	0.0283	0.0410	-0.0237	0.0383	0.1337	0.0308
	(0.0743)	(0.0710)	(0.0557)	(0.0730)	(0.0688)	(0.0642)	(0.0625)	(0.0746)	(0.1267)	(0.0625)
$VTBR_{t-1}$	-0.1994	-0.0892	-0.0225	-0.0845	-0.1010	-0.0621	-0.1574	-0.1683	-0.0246	0.0398
	(0.1451)	(0.0741)	(0.0732)	(0.0716)	(0.0943)	(0.0944)	(0.1097)	(0.1088)	(0.1476)	(0.1152)

Panel B: Industry portfolios, 05/08/2007 - 12/28/2012

	$M\&M_t$	MNF_t	$O\&G_t$	PWR_t	TLC_t
$M\&M_{t-1}$	0.1752^{**}	0.1053^{*}	0.0545	0.1008	0.0486
	(0.0879)	(0.0629)	(0.0902)	(0.0754)	(0.0637)
MNF_{t-1}	-0.0993	-0.0373	-0.0798	-0.0440	-0.0790
	(0.0605)	(0.0765)	(0.0846)	(0.0676)	(0.0562)
$O\&G_{t-1}$	0.0251	-0.0708	0.0604	-0.0532	-0.0308
	(0.1052)	(0.0912)	(0.1399)	(0.0875)	(0.0839)
PWR_{t-1}	0.0895	0.1858^{**}	0.0276	0.2556^{***}	0.0901
	(0.0996)	(0.0829)	(0.0932)	(0.0740)	(0.0785)
TLC_{t-1}	-0.0932	-0.0032	-0.1067	-0.1453	0.0792
	(0.0910)	(0.0694)	(0.1028)	(0.0909)	(0.0611)

VAR(1) model is estimated for daily returns. Newey-West estimator with 10 lags is used for calculating standard errors. Significance levels: *** - 1%, ** - 5%, * - 10%.