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Intraday Anomalies and Market Efficiency: A Trading Robot Analysis

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Abstract One of the leading criticisms of the efficient market hypothesis is the presence of so-called "anomalies", i.e. empirical evidence of abnormal behaviour of asset prices which is inconsistent with market efficiency. However, most studies do not take into account transaction costs. Their existence implies that in fact traders might not be able to make abnormal profits. This paper examines whether or not anomalies such as intraday or time of the day effects give rise to exploitable profit opportunities by replicating the actions of traders. Specifically, the analysis is based on a trading robot which simulates their behaviour, and incorporates variable transaction costs (spreads). The results suggest that trading strategies aimed at exploiting daily patterns do not generate extra profits. Further, there are no significant differences between sub-periods (2005–2006—"normal"; 2007–2009—"crisis"; 2010–2011—"post-crisis).

Keywords Efficient market hypothesis · Intraday patterns · Time of the day anomaly · Trading strategy

JEL classification G12 · C63

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1 Introduction

The efficient market hypothesis (EMH) has been highly criticised during the last twenty years, especially on the basis of empirical evidence suggesting the presence of so-called "anomalies", i.e. abnormal behaviour of asset prices which is seen as inconsistent with market efficiency. Since the seminal work of Mandelbrot (1963), several studies have shown that the Gaussian distribution provides a poor fit to the behaviour of asset prices, not being compatible with the random walk model implied by the EMH. As a result of this literature, fat tails, clustered volatility, long memory etc. have become well-known "stylized facts" characterising the behaviour of asset prices. The aim of this paper is to show that apparent statistical "anomalies" do not necessarily mean that the market is inefficient: if it is not possible to generate extra profits by exploiting them, they should be seen simply as statistical phenomena rather than as evidence of market inefficiency.

In particular, we focus on one of the best known anomalies, which is the presence of intraday patterns, i.e. more intensive trading at the beginning and the end of the trading day combined with higher price volatility (Admati and Pfleiderer 1988). For example, Wood et al. (1985) reported that all positive returns are earned during the first thirty minutes and at the market close. Harris (1986) showed that prices and last trades tend to be up during the first 45 min of trading sessions (all days except Monday). Such patterns were also mentioned by Thaler (1987) and Levy (2002). Strawinski and Slepaczuk (2008) found evidence of intraday patterns in the Warsaw Stock Exchange as well.

The main limitation of the above mentioned studies is that they neglect transaction costs: incorporating spreads, commissions and other fees and payments connected with the trading process can change the picture dramatically. Specifically, it can become clear that some of these "anomalies" cannot in fact be exploited, i.e. profitable trading is not possible, and this inability to obtain extra profits is fully consistent with the EMH.

The present study examines intraday patterns using a trading robot which simulates the actions of the trader and incorporates some transaction costs (spreads) into the analysis. The aim is to show that, as mentioned above, the presence of anomalies by itself does not necessarily represent evidence of market inefficiency, since it might not be possible to exploit them in practice. Obviously, speculators searching for profit opportunities are not simply blind followers of the crowd; instead, they quickly react on others' behaviour, and as a result any arbitrage opportunities (based on deviations from fundamentals-based asset prices) will quickly disappear; however, it might be possible to exploit them in the very short run using an appropriate trading strategy. We analyse both a mature and an emerging stock market, namely 27 US companies included in the Dow Jones index, as well as 8 Blue-chip Russian companies. Further, we examine different sub-periods (2005–2006—"normal"; 2007–2009—"crisis"; 2010–2011—"post-crisis") to establish whether there is evidence of changing behaviour depending on the phase of the economic cycle.

The remainder of the paper is structured as follows: Sect. 2 briefly reviews the literature on the efficient market hypothesis and market anomalies. Section 3 explains the method used for the analysis. Section 4 presents the empirical results. Section 5 offers some concluding remarks.

2 Literature Review

The EMH was initially formulated by Fama (1965), who argued that in an efficient market prices should fully reflect the available information and be unpredictable (see also Samuelson 1965). Fama (1970) then defined three forms of market efficiency (weak, semi-strong and strong). This theory has been used for the valuation of financial assets in terms of risk and uncertainty, and for devising portfolio strategies (see, inter alia, Sharpe 1965; Lintner 1965; Mossin 1966, and Treynor 1962). In the 1980's, it was highly criticized as overlooking transaction costs, information asymmetry (Grossman and Stiglitz 1980), irrational behaviour etc. As a result many alternative theories and approaches were developed (behavioural finance, the adaptive market hypothesis, the fractal market hypothesis, etc.).

The main implication of the EMH is that traders should not be able to "beat" the market and make abnormal profits. An extensive literature analyses whether instead there exist market anomalies that can be exploited through appropriate trading strategies. This term was first used by Kuhn (1970). Schwert (2003) is an example of a study providing evidence of abnormalities which are inconsistent with asset pricing theories. Shiller (2000) and Akerlof and Shiller (2009) take the view that there are deep reasons for the presence of anomalies in financial markets, namely irrational behaviour of investors (animal spirits, the herd instinct, mass psychosis, mass panic), which is inconsistent with the EMH paradigm.

Jensen (1978) argued that anomalies can only be considered statistically significant when they generate excess returns. Raghubir and Das (1999) classify them as follows:

- Anomalies related to prices and returns (contrarian trading, value investing, the size effect, momentum effect, the effect of closed-end funds);
- Anomalies associated with trading volume and volatility (panic, bubbles on the markets);
- Anomalies associated with the time series (the M&A effect, the IPO effect);
- Other anomalies.

Jacobsen et al. (2005) distinguished between calendar, pricing and size anomalies. Examples of calendar (time) anomalies (the most frequently observed) are: End-of-Quarter Effect, Annual Worldwide Optimism Cycle Effect, Halloween Effect, 12-Month Cycle for Stock Returns Effect, Mid-year Point Effect, Two-Year Effect, Sector Performance by Calendar Month, Worst and Best Days of the Year Effect, January Effect, Monthly Effect, Turn-of-the-Month Effect, Labor Day Effect, Day of the Dividend Payments Effect, Trading Around Option Expiration Days and others.

Particularly important are intraday anomalies, including Half-of-the-Day Effects (abnormally low returns in the middle of a trading session, accompanied by a sharp fall in trading volumes); Last Hour and First Hour Effects (with the last hour of trading being the best, and the first hour the worst time in terms of returns); and the Time of the day anomaly (with securities tending to be up in the first 45 and last 15 min of the trading day).

Table 1 Intraday anomalies: researches overview

Author	Type of analysis	Object of analysis (time period, market)	Results
Harris (1986)	Statistical analysis	15-min intervals, fourteen months between December 1, 1981, and January 31, 1983, NYSE, USA	The weekend effect spills over into the first 45 min of trading on Monday, with prices falling during this period. On all other days, prices rise sharply during the first 45 min and within the last 5 min of trading
Harris (1989)	F test		
Camino (1996)	Descriptive statistics	Twenty-three months of transaction records of the IBEX-35, at 15-min intervals, Spain	There are significant weekday differences in intraday trading returns in the first four hours of trading. On Monday (and Wednesday) returns are negative, while on the other weekdays they are positive
Brooks et al. (2003)	Test for signal autocoherence	Set of 10-min returns, bid-ask spreads, and volume for a sample of 30 NYSE stocks from 4 January 1999—24 December 2000, USA	Find the signal coherence to be at the maximum at the daily frequency, with spreads mostly following an inverse J -shape through the day and volume being high at the open and at the close and lowest in the middle of the day
Çankaya et al. (2012)	GARCH(p,q) models	15 min intraday values of ISE-100 Index period of August 2007 to February 201, Istanbul Stock Exchange, turkey	Find that strong opening price jumps are present
Chan (2005)	LOGIT model	Hang Seng Index constituent stocks in Hong Kong Stock Exchange from 1998 to 2004	Find that the probability of trade at ask price over the last 1 min of trading time significantly increases. This systematic pattern can explain around one-third of the positive return from the end-of-day effect

Table 1 continued

Author	Type of analysis	Object of analysis (time period, market)	Results
Coroneo and Veredas (2006)	Quantile regression	15 min sampled quotes midpoints during 3 years, from January 2001 to December 2003, of the 35 companies listed in the IBEX-35, Spanish Stock Exchange, Spain	Show that indeed the conditional probability distribution depends on the time of the day. At the opening and closing the density flattens and the tails become thicker, while in the middle of the day returns concentrate around the median and the tails are thinner
Abhyankar et al. (1997)	Generalized method of moments (GMM)	Intra-day bid-ask quotes covering the period 1 January, 1991 to 31 March, 1991 i.e. for the first quarter of 1991, London Stock Exchange	Find that the average bid-ask spread follows a U-shaped pattern during trading hours
Tissaoui (2012)	Temporal analysis and spectrum analysis by using the Fourier Transform fast (FFT)	38 shares, 9 months (October 2008 to the end of June 2009), Tunisian Stock Exchange, Tunisia	Confirms that trading volume, return volatility and liquidity profile follow a U-shaped curve. All these variables are at the highest level at the opening of trading, decline rapidly in the middle of the day and then they increase again during the final minutes of trading
Strawinski and Slepaczuk (2008)	Regression with weights, i.e. robust regression	5-min returns for the period: 2003–2008) and daily data (for 10 years time span: 1998–2008) for WIG20 index futures, Poland	Find strong jumps at the beginning of trading for all days except Wednesday and a positive day effect for Monday, as well as positive, persistent and significant jumps at the end of session

Harris (1986) and Thaler (1987) examined 15-min intervals in asset prices movement to identify patterns in (the volatility of) returns (see also Levy 2002, and Dimson 1988). Harris (1986) found a time of the day anomaly in the first 45 min of a trading session of all days of the week except Monday and at the end of a trading day (approximately the last 5 min of the session). In his study of the Spanish stock market, Camino (1996) found positive returns in the first hour of the trading session in all trading days except Monday and Wednesday, and a strong tendency for prices to rise in the first and last 15-min periods of trading (see also Coroneo and Veredas 2006). Wood et al. (1985) reported jumps at the opening and closing of trading. Brooks et al. (2003) found higher trading volumes in the NYSE at the beginning and the end of the day. The possibility of using the U-shaped pattern by market participants to build trading strategies was emphasized by Abhyankar et al. (1997). The same pattern was found with respect to trading volume, return volatility and liquidity profile by Tissaoui (2012) in the Tunisian Stock Exchange. Table 1 gives details of additional relevant studies.

3 Data and Methodology

Although most studies suggest the presence of anomalies in the first 45 min (or first hour) of the trading session, their results differ in terms of the exact time when the end-of-the-day anomaly emerges: the last transaction, the last 5 min, the last 15 min, the last hour. Chan (2005) reported that the overall average returns per minute in the Hong Kong stock market (over the last 30 min, over the last 10 min, over the last 5 min, and over the last 1 min) are statistically positive. However, the majority of studies consider 15-min intervals. Since the empirical literature does not provide clear evidence on intraday effects on specific weekdays (see, e.g., Strawinski and Slepaczuk 2008; Harris 1989), and since it is difficult to distinguish between time of the day and day of the week effects, we focus specifically on the last 15 min before the end of the trading session (see Levy 2002).

We look at the intraday anomaly from the trader's viewpoint: is it possible to make profits from trading on intraday patterns (which would indicate market inefficiency)? In particular, we test the following hypotheses:

Hypothesis 1: first 45 min up effect exists (H1):

- H1a—case of developed countries
- H1b—case of developing countries

Hypothesis 2 last 15 min up effect exists (H2)

- H2a—case of developed countries
- H2b—case of developing countries

Hypothesis 3 the results for different periods (pre-crisis, crisis, and post-crisis) are statistically different (H3).

We use data at 15-min intervals for 27 US companies included in the Dow Jones index and 8 Blue-chip Russian companies. For the US the sample period is 2005–2011, and the following sub-periods are also considered:

– 2005–2006—normal;
– 2007–2009—crises;
– 2010–2011—post-crises.

For Russia, owing to lack of data, the analysis is carried out only for the period 2011–2013.

Most studies on intraday anomalies do not incorporate transaction costs, even though trading is inevitably connected with spreads, fees and commissions to brokers. These costs can be divided into fixed and variable ones. The latter are present in each transaction. A typical example is the spread, which is incorporated into our analysis. Specifically, we programme a trading robot which automatically opens and closes positions according to the time of the day effect. Positions (in our case only the "long" ones) will be opened on "ask" price and closed on "bid" price, though we will incorporate the variable part of transactional costs in our analysis. The algorithm is constructed such that long positions are opened at the beginning of the trading session and are closed after 45 min (the first 45 min up effect mentioned by Harris (1986) and Levy (2002)), and are also opened at the end of the day. As we consider 15-min intervals, they are opened in the last 15 min of the trading session and are closed at the end of the session (the last 15 min of the day up effect mentioned by Levy 2002). We use a programme in the MetaTrader terminal that has been developed in MetaQuotes Language 4 (MQL4) and used for the automation of analytical and trading processes. Trading robots (called experts in MetaTrader) allow to analyse price data and manage trading activities on the basis of the signals received.

MetaQuotes Language 4 is the language for programming trade strategies built in the client terminal. The syntax of MQL4 is quite similar to that of the C language. It allows to programme trading robots that automate trade processes and is ideally suited for the implementation of trading strategies. The terminal allows not only to programme trading robots, but also to test them by checking their efficiency using historical data. These are saved in the MetaTrader terminal as bars and represent records appearing as TOHLCV (HST format). The trading terminal allows to test experts by various methods. By selecting smaller periods it is possible to see price fluctuations within bars, i.e., price changes will be reproduced more precisely. For example, when an expert is tested on one-hour data, price changes for a bar can be modelled using 1-min data. The price history stored in the client terminal includes only Bid prices. In order to model Ask prices, the strategy tester uses the current spread at the beginning of testing. However, a user can set a custom spread for testing in the "Spread", thereby approximating better actual price movements. Positive profits $> 50\ \%$ imply that H1 and H2 cannot be rejected. As for H3, we carry out t tests: H3 is rejected if $t < tcritical$. The program codes for the trading robots used in this study are presented in Appendix 4 and 5.

4 Empirical Results

The testing procedure comprises two steps, i.e. initially testing the first 45 min up effect, and then the last 15 min up effect.

Table 2 Summary of testing results for the "first 45 min up effect"

Period	Average profit trades (% of total)	Average total net profit	Average net profit per deal
2005–2006	44	−174	−0.374
2007–2009	45	−336	−0.454
2010–2011	43	−142	−0.420

Table 3 t test for profit trades (% of total)

	Mean	Std.Dv.	*N*	Diff.	Std.Dv. Diff.	*T*	*df*	*p*
2005–2006	0.437129	0.047744						
2007–2009	0.446955	0.030631	27	−0.009827	0.043375	−1.17720	26	0.249781
2005–2006	0.437129	0.047744						
2010–2011	0.430666	0.047008	27	0.006463	0.051519	0.65187	26	0.520206
2007–2009	0.446955	0.030631						
2010–2011	0.430666	0.047008	27	0.016290	0.051128	1.65555	26	0.109834

Table 4 t test for net profit per deal

	Mean	Std.Dv.	*N*	Diff.	Std.Dv. Diff.	*T*	*df*	*p*
2005–2006	−0.374775	0.334831						
2007–2009	−0.454636	0.332846	27	0.079861	0.282592	1.46845	26	0.153979
2005–2006	−0.374775	0.334831						
2010–2011	−0.419718	0.199970	27	0.044943	0.267637	0.87257	26	0.390885
2007–2009	−0.454636	0.332846						
2010–2011	−0.419718	0.199970	27	−0.034918	0.319828	−0.56730	26	0.575377

Table 5 Summary of testing results for the "last 15 min up effect"

Period	Average profit trades (% of total)	Average total net profit	Average net profit per deal
2005–2006	26	−235	−0.538
2007–2009	35	−351	−0.512
2010–2011	31	−168	−0.544

The complete results for the former are presented in Appendix 1. A summary for different time periods is shown in Table 2.

As can be seen, all periods were unprofitable, with the probability of a profitable trade being less than 50 %. Hypothesis H1a is rejected, i.e. there is no evidence of a first 45 min up effect in the US stock market. Table 3 reports the t test for H3 for different sub-periods: here is rejected in all cases. Table 4 shows that H3 is not rejected for net profit per deal in any of the sub-periods.

The complete results for the last 15 min up effect are presented in Appendix 2. A summary for the different time periods is displayed in Table 5.

Table 6 t test for profit trades (% of total)

	Mean	Std.Dv.	*N*	Diff.	Std.Dv. Diff.	*T*	*df*	*P*
2005–2006	0.256040	0.078941						
2007–2009	0.352451	0.058585	27	−0.096411	0.059926	−8.35981	26	0.000000
2005–2006	0.256040	0.078941						
2010–2011	0.313853	0.069267	27	−0.057813	0.082721	−3.63156	26	0.001213
2007–2009	0.352451	0.058585						
2010–2011	0.313853	0.069267	27	0.038598	0.043483	4.61237	26	0.000094

Table 7 t test for net profit per deal

	Mean	Std.Dv.	*N*	Diff.	Std.Dv. Diff.	*T*	*df*	*P*
2005–2006	−0.538260	0.477750						
2007–2009	−0.511261	0.489490	27	−0.026999	0.093330	−1.50316	26	0.144847
2005–2006	−0.538260	0.477750						
2010–2011	−0.544096	0.534294	27	0.005836	0.121219	0.25016	26	0.804429
2007–2009	−0.511261	0.489490						
2010–2011	−0.544096	0.534294	27	0.032835	0.104634	1.63058	26	0.115035

Table 8 Summary for the Russian stock market

Hypothesis	Average profit trades (% of total)	Average total net profit per deal
First 45 min up effect	41	−2
Last 15 min up effect	37	−1

All periods were unprofitable, with the probability of a profitable trade being less than 40 %. Hypothesis H2a is rejected: there is no last 15 min up effect in the US stock market.

The t tests for H3 for different sub periods are displayed in Table 6: this hypothesis cannot be rejected, and this applies to all sub-periods.

Table 7 shows that H3 is rejected for net profit per deal. There is no evidence of differences between sub-periods.

The complete results for Russia are presented in Appendix 3. A summary is provided in Table 8: H1b and H2b are rejected again, indicating the absence of the intraday anomaly being considered in a less developed market as well.

5 Conclusions

The empirical relevance of the EMH has been called into question by many studies finding evidence of so-called anomalies seemingly giving agents the opportunity to make abnormal profits. This paper argues that the presence of anomalies does not necessarily represent evidence of market inefficiency (risk-free profit opportunities): using a trading robot simulating the actions of a trader we show in the case of intraday patterns that, if transaction costs are taken into account, there are no profitable trading strategies (i.e. opportunities to make abnormal profits exploiting this type of anomaly), and therefore no evidence against the EMH.

Specifically, we consider a well-known "time of the day anomaly": prices tend to be up during the first 45 min and the last 15 min of the trading session.

We test 3 hypotheses:

– Hypothesis 1: first 45 min up effect exists (H1):
– Hypothesis 2: last 15 min up effect exists (H2)
– Hypothesis 3: results for different periods (pre-crisis, crisis, and post-crisis) are statistically different (H3)

These hypotheses are rejected for both the US and Russia, a mature and less developed stock market respectively. The only exception is H3: the results for the last 15 min up effect vary depending on the sub-period considered.

On the whole, our analysis implies that it is not possible to exploit intraday patterns to make abnormal profits. This suggests that the results from previous studies purporting to provide evidence of exploitable profit opportunities resulting from market anomalies (which would be inconsistent with the EMH) were in fact misleading because they did not take into account transaction costs. The trading robot approach used in the present study can also be used to analyse other anomalies, but this is left for future work.

Acknowledgments We are grateful to a member of the editorial board for useful comments and suggestions.

Appendix 1

First 45 min up effect
2005–2006

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Alcoa	465	195	41.94	−256.1
Altria Group	464	213	45.91	−28.9
American Express Company	465	214	46.02	−46.6
ATT Inc	458	191	41.70	−84.3
Boeing	465	212	45.59	−315.7
Coca-Cola	465	163	35.05	−247.4

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
DuPont	465	217	46.67	−126.3
ExxonMobil Corporation	465	209	44.95	−185.9
General Electric Corporation	465	208	44.73	−85.2
Hewlett-Packard Company	485	278	57.32	138.2
Home Depot Corp	465	208	44.73	−158.8
Honeywell International Inc	465	219	47.10	−90.7
IBM Corporation	465	168	36.13	−646.2
Intel Corporation	465	200	43.01	−101
International Paper Company	465	182	39.14	−256.9
Johnson&Johnson	464	189	40.73	−159.8
JP Morgan Chase	465	225	48.39	−26.1
McDonalds Corporation	465	180	38.71	−270.3
Merck Co Inc	465	229	49.25	−105.4
Microsoft	465	220	47.31	−29
MMM Company	465	197	42.37	−423.8
Pfizer	465	185	39.78	−195
Procter Gamble Company	465	211	45.38	−145.4
United Technologies Corporation	465	173	37.20	−429.1
Verizon Communications Inc	485	185	38.14	−249.1
Wal-Mart Stores Inc	464	213	45.91	−129.1
Walt Disney	465	219	47.10	−54

2007–2009

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Alcoa	740	322	43.51	−447.6
Altria Group	740	322	43.51	−169.3
American Express Company	728	300	41.21	−629
ATT Inc	739	321	43.44	−272.7
Boeing	739	330	44.65	−761.2
Coca-Cola	740	340	45.95	−326.9
DuPont	740	339	45.81	−299.6
ExxonMobil Corporation	740	373	50.41	119.1
General Electric Corporation	740	281	37.97	−559.6
Hewlett-Packard Company	740	381	51.49	58.2

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Home Depot Corp	740	311	42.03	−274.8
Honeywell International Inc	740	328	44.32	−546.7
IBM Corporation	740	331	44.73	−1005.4
Intel Corporation	738	328	44.44	−226.7
International Paper Company	740	338	45.68	−254.4
Johnson&Johnson	740	332	44.86	−286.9
JP Morgan Chase	740	322	43.51	−406.6
McDonalds Corporation	740	317	42.84	−365.4
Merck Co Inc	740	369	49.86	−112.2
Microsoft	740	355	47.97	−102.5
MMM Company	739	335	45.33	−478
Pfizer	740	301	40.68	−200.6
Procter Gamble Company	740	358	48.38	−122.4
United Technologies Corporation	740	301	40.68	−658.7
Verizon Communications Inc	740	319	43.11	−307.7
Wal-Mart Stores Inc	740	330	44.59	−224.7
Walt Disney	740	339	45.81	−208.3

2010–2011

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Alcoa	334	134	40.12	−112.1
Altria Group	339	118	34.81	−129
American Express Company	339	164	48.38	−110
ATT Inc	339	111	32.74	−192.7
Boeing	339	159	46.90	−153.6
Coca-Cola	339	139	41.00	−213.8
DuPont	338	168	49.70	−41.5
ExxonMobil Corporation	339	137	40.41	−215.5
General Electric Corporation	339	142	41.89	−113.3
Hewlett-Packard Company	339	177	52.21	−23.1
Home Depot Corp	339	164	48.38	−44.2
Honeywell International Inc	339	151	44.54	−125.1
IBM Corporation	339	149	43.95	−296.5
Intel Corporation	339	135	39.82	−155.4
International Paper Company	339	166	48.97	−80.1

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Johnson&Johnson	339	141	41.59	−130.8
JP Morgan Chase	339	160	47.20	−162.8
McDonalds Corporation	339	140	41.30	−205
Merck Co Inc	339	134	39.53	−162.2
Microsoft	339	131	38.64	−186.5
MMM Company	338	151	44.67	−144.5
Pfizer	339	131	38.64	−109.9
Procter Gamble Company	339	152	44.84	−141.2
United Technologies Corporation	339	139	41.00	−252.7
Verizon Communications Inc	339	130	38.35	−218.4
Wal-Mart Stores Inc	338	157	46.45	−90.3
Walt Disney	338	158	46.75	−28.9

Appendix 2

Last 15 min up effect
2005–2006

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Alcoa	465	195	41.94	−256.1
Altria Group	464	213	45.91	−28.9
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Boeing	739	330	44.65	−761.2
Coca-Cola	740	340	45.95	−326.9
DuPont	740	339	45.81	−299.6
ExxonMobil Corporation	740	373	50.41	119.1
General Electric Corporation	740	281	37.97	−559.6
Hewlett-Packard Company	740	381	51.49	58.2
Home Depot Corp	740	311	42.03	−274.8
Honeywell International Inc	740	328	44.32	−546.7
IBM Corporation	740	331	44.73	−1005.4
Intel Corporation	738	328	44.44	−226.7
International Paper Company	740	338	45.68	−254.4
Johnson&Johnson	740	332	44.86	−286.9
JP Morgan Chase	740	322	43.51	−406.6
McDonalds Corporation	740	317	42.84	−365.4
Merck Co Inc	740	369	49.86	−112.2
Microsoft	740	355	47.97	−102.5
MMM Company	739	335	45.33	−478
Pfizer	740	301	40.68	−200.6

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Procter Gamble Company	740	358	48.38	−122.4
United Technologies Corporation	740	301	40.68	−658.7
Verizon Communications Inc	740	319	43.11	−307.7
Wal-Mart Stores Inc	740	330	44.59	−224.7
Walt Disney	740	339	45.81	−208.3

2010–2011

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Alcoa	308	58	18.83	−95
Altria Group	308	78	25.32	−101.4
American Express Company	308	127	41.23	−97.5
ATT Inc	308	112	36.36	−89.4
Boeing	308	96	31.17	−210.9
Coca-Cola	308	92	29.87	−198.1
DuPont	308	124	40.26	−93.9
ExxonMobil Corporation	308	106	34.42	−207
General Electric Corporation	308	88	28.57	−94.6
Hewlett-Packard Company	308	107	34.74	−136.9
Home Depot Corp	308	86	27.92	−124.9
Honeywell International Inc	308	122	39.61	−100.2
IBM Corporation	308	34	11.04	−947.6
Intel Corporation	308	91	29.55	−105.5
International Paper Company	308	115	37.34	−79.5
Johnson&Johnson	308	118	38.31	−115.4
JP Morgan Chase	308	119	38.64	−101.1
McDonalds Corporation	308	79	25.65	−250.4
Merck Co Inc	308	94	30.52	−110.5
Microsoft	308	99	32.14	−122.3
MMM Company	308	109	35.39	−190.7
Pfizer	308	76	24.68	−106.3
Procter Gamble Company	308	78	25.32	−236.8
United Technologies Corporation	308	101	32.79	−224.2

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit
Verizon Communications Inc	308	116	37.66	−89.2
Wal-Mart Stores Inc	308	85	27.60	−182.6
Walt Disney	308	100	32.47	−112.8

Appendix 3

Results for Russian stock markets
First 45 min up effect

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
GAZPROM	286	148	51.75	66.5	0.23252
GAZPROM NEFT	264	95	35.98	−173	−0.6553
LUKOIL	287	132	45.99	−557	−1.9408
NORILSKY NICKEL	285	106	37.19	−434	−1.5228
ROSNEFT	287	127	44.25	−123.6	−0.4307
SBERBANK	286	136	47.55	−275	−0.9615
SURGUTNEFTEGAZ	287	134	46.69	−335	−1.1672
VTB BANK	242	50	20.66	−1757	−7.2603

Last 15 min up effect

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
GAZPROM	378	185	48.94	−2.4	−0.0063
GAZPROM NEFT	347	45	12.97	−459	−1.3228
LUKOIL	378	154	40.74	−94	−0.2487
NORILSKY NICKEL	378	168	44.44	−236	−0.6243
ROSNEFT	378	181	47.88	−9.9	−0.0262
SBERBANK	378	171	45.24	−547	−1.4471
SURGUTNEFTEGAZ	378	152	40.21	−179	−0.4735
VTB BANK	320	38	11.88	−26.4	−0.0825

Appendix 4

Program code for the “first 45 min up effect”

```
#define MAGICMA  20050610

extern double Lots              = 0.1;

//+------------------------------------------------------------------+
//| Calculate open positions                                         |
//+------------------------------------------------------------------+
int CalculateCurrentOrders(string symbol)
  {
   int buys=0,sells=0;
//----
   for(int i=0;i<OrdersTotal();i++)
     {
      if(OrderSelect(i,SELECT_BY_POS,MODE_TRADES)==false) break;
      if(OrderSymbol()==Symbol() && OrderMagicNumber()==MAGICMA)
        {
         if(OrderType()==OP_BUY)  buys++;
         if(OrderType()==OP_SELL) sells++;
        }
     }
//---- return orders volume
   if(buys>0) return(buys);
   else       return(-sells);
  }
//+------------------------------------------------------------------+
//| Check for open order conditions                                  |
//+------------------------------------------------------------------+
void CheckForOpen()
  {
   double ma;
   int    res;
   if(Volume[0]>1) return;
   if ((Hour()==00) &&  (Minute()==00))
     {
      res=OrderSend(Symbol(),OP_BUY,LotsOptimized(),Ask,3,0,0,"",MAGICMA,0,Blue);
      return;
     }
//----
  }
//+------------------------------------------------------------------+
//| Check for close order conditions                                 |
//+------------------------------------------------------------------+
void CheckForClose()
  {
   double ma;
//---- go trading only for first tiks of new bar

   if(Volume[0]>1) return;
//----
   for(int i=0;i<OrdersTotal();i++)
     {
      if(OrderSelect(i,SELECT_BY_POS,MODE_TRADES)==false)        break;
      if(OrderMagicNumber()!=MAGICMA || OrderSymbol()!=Symbol()) continue;
```

```
          //---- check order type
          if(OrderType()==OP_BUY)
            {
             if((Hour()>=00))
             if (Minute()>=45)
             OrderClose(OrderTicket(),OrderLots(),Bid,3,White);
             break;
            }
          if(OrderType()==OP_SELL)
            {
             if(Hour()>=22)
             OrderClose(OrderTicket(),OrderLots(),Ask,3,White);
             break;
            }
         }
//----
  }
//+------------------------------------------------------------------+
//| Start function                                                   |
//+------------------------------------------------------------------+
void start()
  {
//---- check for history and trading
   if(Bars<100 || IsTradeAllowed()==false) return;
//---- calculate open orders by current symbol
   if(CalculateCurrentOrders(Symbol())==0) CheckForOpen();
   else                                    CheckForClose();
//----
  }
//+------------------------------------------------------------------+
```

Appendix 5

Program code for the "last 15 min up effect"

```
#define MAGICMA  20050610

extern double Lots              = 1;
//+------------------------------------------------------------------+
//| Calculate open positions                                         |
//+------------------------------------------------------------------+
int CalculateCurrentOrders(string symbol)
  {
   int buys=0,sells=0;
//----
   for(int i=0;i<OrdersTotal();i++)
     {
      if(OrderSelect(i,SELECT_BY_POS,MODE_TRADES)==false) break;
      if(OrderSymbol()==Symbol() && OrderMagicNumber()==MAGICMA)
        {
         if(OrderType()==OP_BUY)  buys++;
         if(OrderType()==OP_SELL) sells++;
        }
     }
//---- return orders volume
   if(buys>0) return(buys);
   else       return(-sells);
  }
//+------------------------------------------------------------------+
//| Check for open order conditions                                  |
//+------------------------------------------------------------------+
void CheckForOpen()
  {
   double ma;
   int    res;
   if ((Hour()==23) &&  (Minute()==45))
     {
      res=OrderSend(Symbol(),OP_BUY,LotsOptimized(),Ask,3,0,0,"",MAGICMA,0,Blue);
      return;
     }
//----
  }
//+------------------------------------------------------------------+
//| Check for close order conditions                                 |
//+------------------------------------------------------------------+
void CheckForClose()
  {
   double ma;
   for(int i=0;i<OrdersTotal();i++)
     {
      if(OrderSelect(i,SELECT_BY_POS,MODE_TRADES)==false)        break;
      if(OrderMagicNumber()!=MAGICMA || OrderSymbol()!=Symbol()) continue;
      //---- check order type
      if(OrderType()==OP_BUY)
        {
         if((Hour()==23))
```

```
            if (Minute()==59)
            OrderClose(OrderTicket(),OrderLots(),Bid,3,White);
            break;
           }
         if(OrderType()==OP_SELL)
           {
            if(Hour()>=22)
            OrderClose(OrderTicket(),OrderLots(),Ask,3,White);
            break;
           }
        }
//----
  }
//+------------------------------------------------------------------+
//| Start function                                                   |
//+------------------------------------------------------------------+
void start()
  {
//---- check for history and trading
   if(Bars<100 || IsTradeAllowed()==false) return;
//---- calculate open orders by current symbol
   if(CalculateCurrentOrders(Symbol())==0) CheckForOpen();
   else                                    CheckForClose();
//----
  }
//+------------------------------------------------------------------+
```

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