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Price gaps: Another market anomaly?

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ABSTRACT
This paper analyses price gaps in financial markets, also known as trading, opening, common, stock or morning gaps – all these terms being used to indicate that the current day's opening price is not the same as the previous day's closing price. To test for the presence of such an anomaly in price dynamics stock, FOREX and commodity market daily data were used. The sample period went from 2000 to 2015. Applying a variety of statistical tests, we tested six different hypotheses and are able to show that in most cases the observed price behaviour is not inconsistent with market efficiency, the exception being FOREX. In this case, a trading strategy based on exploiting the observed anomaly can generate abnormal profits.

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Introduction

This paper analyses price gaps (also known as trading, opening, common, stock or morning gaps – all these terms being used to indicate that the current day's opening price is not the same as the previous day's closing price), which have been detected at times in stock, FOREX and commodity markets. A positive (negative) gap corresponds to a higher (lower) opening price vis-à-vis the previous closing price. Applying a variety of methods, we are able to show that in most cases the observed price behaviour is not inconsistent with market efficiency, the exception being the FOREX. In this case, a trading strategy based on exploiting this anomaly generates abnormal profits.

Specifically, using data from different financial markets (FOREX, commodities, US and Russian stock markets) we analyse various hypotheses of interest by means of descriptive statistics, statistical tests such as *t*-tests, ANOVA and Kruskal-Wallis tests, and regression analysis with dummy variables. Then a trading robot approach is implemented to establish whether or not price gaps represent an exploitable profit opportunity.

The layout of the paper is as follows. The next section briefly reviews the relevant literature. The section thereafter describes the data and outlines the empirical methodology. This is followed by a section that presents the empirical results. The final section offers some concluding remarks.

Literature review

According to the efficient market hypothesis (EMH; see Fama, 1970), prices should fully incorporate available information and follow a random walk; therefore, it should not be possible to make systematic profits on the basis of their past behaviour. However, several studies have provided evidence of abnormalities that could represent exploitable profit opportunities inconsistent with market efficiency (see, e.g., Schwert, 2003). Since the seminal work of Mandelbrot (1963), numerous

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papers have shown that the Gaussian distribution provides a poor fit for price dynamics: fat tails, clustered volatility, long memory, etc. have become well-known ‘stylised facts’ characterising the behaviour of asset prices. Shiller (2000) and Akerlof and Shiller (2009), among others, attributed the presence of anomalies in financial markets to animal spirits, the herd instinct, mass psychosis, mass panic and other forms of irrational behaviour of investors. For example, De Bondt and Thaler (1985) showed that investors tend to give excessive weight to recent information relative to past information when making their portfolio choices. As a result, overreactions may occur in financial markets. Ball (2009) systematically analysed these issues and highlighted the following deviations from the EMH: over- and under-reactions to information flows, volatility explosions and seasonal yield bursts, yield dependence on different variables such as market capitalisation, dividend rate, market factors, etc.

Jacobsen, Mamun and Vyshaltanachoty (2005) distinguished between calendar, pricing and size anomalies. Jensen (1978) argued that anomalies can only be considered statistically significant when they generate excess returns. Jegadeesh and Titman (1993) developed a trading strategy based on the overreaction anomaly and found that it generates a 12% profit per year. Other strategies to make abnormal profits by exploiting market anomalies were analysed by Lehmann (1990), Abhyankar, Ghosh, Levin, and Limmack (1997), Baytas and Cakiki (1999), Caporale, Gil-Alana, Plastun, and Makarenko (2016a).

Anomalies have been observed in different financial markets: stock markets (Mynhardt & Plastun, 2013; Yuan, 2015), FOREX (Caporale et al., 2016a), commodity markets (Cutler, Poterba, & Summers, 1991), futures markets (Grant, Wolf, & Yu, 2005), option markets (Poteshman, 2001), etc. They could, however, be fading over the time. For example, Fortune (1998, 1999), Schwert (2003) and Olson, Chou, and Mossman (2010) showed that the weekend effect has become less important over the years. In fact, financial markets are always changing and evolving, and new anomalies might appear over time (Lo, 1991). Price gaps are one of them. They occur when the current day’s opening price differs from the previous day’s closing price. They might reflect buy or sell orders placed before the market opens that push the opening price above or below the previous day’s close. This is a rather unusual situation (especially if the gap is sizeable) and may signal changes in investor’s behaviour.

Gaps in financial markets tend to appear on Mondays. They may be the result of the two-day pause in trading over the weekend and some unexpected event taking place during that period. They may therefore be connected to some extent to the well-known weekend effect. This effect was detected by Cross (1973) and has been widely discussed in the subsequent literature (French, 1980; Keim & Stambaugh, 1984; Agrawal & Tandon, 1994; Racicot, 2011; Caporale, Gil-Alana, & Plastun, 2016b and many others). The following are the most common explanations for the existence of price gaps:

1. Unexpected events, such as earning or other important news announcements;
2. Dramatic changes in market conditions, such as sudden shifts in supply-demand for financial assets;
3. Development of after-hours trading;
4. Significant time lags between previous closing and current opening prices (caused by weekends or holidays);
5. Technical reasons (for example, a significant widening of the bid-ask spread);
6. Other reasons.

Price gaps as an anomaly have not been widely discussed in the academic literature. An exception is the study by Yuan (2015) who finds highly significant intraday price reversals in the US stock index futures market following large price changes at the market opening. However, no systematic study of their behaviour has been carried out to date. Analysing it in depth is our objective. Moreover, we aim to establish whether such an anomaly can be exploited to make abnormal profits, which would represent evidence against the EMH (see Caporale et al., 2016a, for details).

Data and methodology

We examine the following series: FOREX (EUR/USD, GBP/USD and USD/RUB exchange rates), commodity prices (Oil, Gold), US stock market (Dow Jones index + one of the blue chips, IBM), and Russian stock market (MICEX + one of the blue chips, Sberbank). The US and Russian stock markets are selected as an example of an efficient and inefficient market respectively (see Mynhardt, Plastun, & Makarenko, 2014, for details). The chosen frequency is daily because gaps are most noticeable in daily charts (statistically significant price gaps are mostly found at this frequency). The sample period is 2000−2015. The following hypotheses are tested:

H1: Prices tend to rise after positive gaps;

H2: Prices tend to fall after negative gaps;

H3: Prices tend to rise before positive gaps;

H4: Prices tend to fall before negative gaps;

H5: Price gaps are short-lived;

H6: Returns around price gaps differ from normal ones.

Testing H1 and H2 provides information about price behaviour after gaps appear. Testing H3 and H4 sheds light on whether or not the emergence of gaps is predictable. Testing H5 is informative about the validity of the old saying 'the market abhors a vacuum and all gaps will be filled' (see Peacock, 1997, p. 9). Finally, testing H6 allows to establish whether or not price gaps are an anomaly that is inconsistent with market efficiency.

To test H1-H2 we calculate the number of days with positive (negative) returns after positive (negative) gaps divided by the number of gaps. To test H3-H4 we use the same procedure but for the number of days before gaps occur. This yields the probability of price movements in a given direction for a positive (negative) gap. If it is significantly higher than 50%, it may be seen as evidence in favour of the null hypothesis. The time horizon varies from one to three days. The testing approach for H5 is very similar: we calculate the number of gaps filled after one to five days divided by the total number of gaps. If this number is significantly higher than 50%, it suggests a specific pattern in price behaviour. Finally, to test H6, we use the following techniques:

- parametric tests (Student's t-tests, ANOVA);
- non-parametric tests (Kruskal-Wallis test);
- regression analysis with dummy variables.

Returns are calculated in the standard way as follows:

$$\mathrm{R_i} = \left(\frac{\mathrm{Open_i}}{\mathrm{Close_i}} - 1\right) \times 100\%, \tag{1}$$

where R_i – returns on the *i-th* day in %;
$Open_i$ – open price on the *i-th* day;
$Close_i$ – close price on the *i-th* day.

Essentially, the statistical tests carried out aim to establish whether or not returns follow the same distribution during 'normal' and 'abnormal' periods, the latter being characterised by the presence of price gaps. Both parametric and non-parametric tests are carried out given the evidence of fat tails and kurtosis in returns. The null hypothesis (H0) in each case is that the data belong to the same population, a rejection of the null suggesting the presence of an anomaly.

We also run regressions, including a dummy variable, to identify statistically significant differences between 'normal' and 'abnormal' periods:

$$Y_t = a_0 + a_1 D_t + \varepsilon_t \tag{2}$$

where: Y_t – return in period t;

a_0– mean return in a 'normal' period;

a_1– mean return in an 'abnormal' period;

D_t– a dummy variable equal to 1 in 'abnormal' periods and 0 in 'normal' periods;

ε_t – Random error term for period t.

The size, sign and statistical significance of the dummy coefficients provide information about possible anomalies. When anomalies are detected using the previous methods, we examine whether they give rise to exploitable profit opportunities using a trading robot approach. This considers the detected anomalies from the point of view of a trader who is interested in making abnormal profits by exploiting them. The trading robot simulates the actions of a trader according to an algorithm (trading strategy). This is a program 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. One of the biggest advantages of this approach is that a wide range of parameters can be tested. Further, it incorporates the analysis transaction costs. A strategy resulting in a number of profitable trades > 50% and positive total profits is seen as evidence of an exploitable market anomaly.

To make sure that the results we obtain are statistically different from the random trading ones, we carry out z-tests. A z-test compares the means from two samples to see whether they come from the same population. In our case, the first is the average profit/loss factor of one trade applying the trading strategy, and the second is equal to zero because random trading (without transaction costs) should generate zero profit. The null hypothesis (H0) is that the mean is the same in both samples, and the alternative (H1) that it is not. The computed values of the z-test are compared with the critical one at the 5% significance level. Failure to reject H0 implies that there are no advantages from exploiting the trading strategy being considered, whilst a rejection suggests that the adopted strategy can generate abnormal profits.

Empirical results

First an appropriate gap size should be chosen as a criterion for gap detection. For that purpose, we analyse the commodity markets (Oil and Gold prices – see Table 1).

It is apparent that choosing a relatively small gap size of 0.1% would generate too many gaps (almost 20% in the case of Gold) to consider them abnormalities in price dynamics. On the other hand, a big gap size would yield very few cases. In order to have a sufficient number of observations to carry out statistical tests we therefore choose a gap size of 0.2% for Gold and Oil; this gives more than 100 observations, which is sufficient for statistical inference; further, they represent only 5–6% of the population, and hence can be considered anomalies. The selected gap size, generating the same percentage of gaps (5–6%) in the data set, is instead, 8% for the Russian stock market.

Table 1. Number of gaps by gap size: The case of Oil and Gold (daily data, period 2000–2015).

Gap size	0.10%	0.20%	0.30%	0.40%	0.50%	0.60%	0.70%	0.80%	0.90%	1.00%
OIL % gaps in prices	10.13	6.24	4.25	3.13	2.51	2.07	1.81	1.55	1.27	1.14
Number of detected gaps in OIL prices	391	241	164	121	97	80	70	60	49	44
GOLD % gaps in prices	17.71	5.67	2.85	2.24	1.70	1.12	0.81	0.64	0.54	0.44
Number of detected gaps in GOLD prices	522	167	84	66	50	33	24	19	16	13

Table 2. Day of the week and gaps.

Day of the week	Commodities		FOREX			Stock market	
	OIL	GOLD	EUR/USD	USD/RUB	GBP/USD	US (Dow Jones Index)	Russian (MICEX)
Monday	66%	65%	96%	95%	95%	19%	22%
Tuesday	12%	12%	1%	0%	2%	20%	17%
Wednesday	5%	7%	1%	2%	1%	22%	22%
Thursday	7%	6%	0%	0%	0%	15%	20%
Friday	9%	11%	2%	2%	2%	23%	18%

Table 2 sheds light on the extent to which the time interval between the closing and reopening of markets might account for the emergence of gaps by calculating the number of gaps for different days of the week. Gaps in the commodity and FOREX markets appear to emerge mainly after weekends, whilst there is no clear pattern in the case of stock markets.

Next, we test hypotheses H1-H5. The results for commodity, FOREX and stock markets are presented in Appendices A and B. There is not much evidence that prices tend to increase after positive gaps (H1) in any of the markets examined over time horizons from one to three days (see Table A.1), although there are a few exceptions such as the Dow Jones Index (prices increase in 80% of the cases after positive gaps). As for H2, prices fall in 50% of the cases after negative gaps (see Table A.1 for details). Overall, it appears that gaps do not affect price dynamics and cannot be considered an anomaly. The results for H3 and H4 (see Table A.1) suggest that gaps are not generated by previous price dynamics (the Russian rouble is an exception: positive gaps appear in 70% of the cases after upward price movements), at least over a time horizon from one to three days before the gap. As for H5 (see Table B.1), the evidence suggests that up to 80% of gaps are not filled within five days.

Overall, the results for H1-H5 lead to the conclusion that price gaps are not an anomaly in probabilistic terms. Testing H6 instead provides information on whether they can be seen as an anomaly in terms of size (see Appendices C, D and E). Tables 3–6 provide a summary of the results based on the various techniques used for each of the markets in turn.

As can be seen, there is no indication that gaps play any role in the case of commodity prices.

In the FOREX (EUR/USD and GBP/USD exchange rates), instead, it is clear that price dynamics in gap days differ from normal ones; specifically, they are affected by positive gaps

Table 3. Results of the statistical tests for H6: The case of commodities.

Statistical test	Gold			Oil		
	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap
T-test	+	+	+	+	+	+
ANOVA test	+	+	+	+	+	+
Kruskal-Wallis test	+	+	+	+	+	+
Regression analysis with dummy variables	+	+	+	+	+	+

Notes: * '+': null hypothesis not rejected; '–': null hypothesis rejected.

Table 4. Results of the statistic tests for the H6: Case of FOREX.

Statistical test	EURUSD			GBPUSD			USDRUB		
	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap
T-test	+	+	+	+	+	+	+	+	+
ANOVA test	–	+	+	–	+	+	+	+	–
Kruskal-Wallis test	+	+	+	+	+	+	+	+	–
Regression analysis with dummy variables	–	+	+	–	+	+	+	+	–

Notes: * '+': null hypothesis not rejected; '–': null hypothesis rejected.

Table 5. Results of the statistic tests for the H6: The case of the US stock market.

Statistical test	Dow Jones Index			IBM		
	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap
T-test	+	+	+	+	+	+
ANOVA test	–	+	+	–	+	+
Kruskal-Wallis test	+	+	+	+	+	+
Regression analysis with dummy variables	–	+	+	–	+	+

Notes: * '+': null hypothesis not rejected; '–': null hypothesis rejected.

Table 6. Results of the statistical tests for the H6: The case of the Russian stock market.

Statistical test	MICEX			Sberbank		
	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap
T-test	+	+	–	+	+	+
ANOVA test	+	+	–	+	–	+
Kruskal-Wallis test	+	+	–	+	–	+
Regression analysis with dummy variables	+	+	–	+	–	+

Notes: * '+': null hypothesis not rejected; '–': null hypothesis rejected.

(see Tables D.1, D.2, D.4, D.5, D.7 and D.8 for details). Since the sign of the dummy coefficient in the regression is negative after a positive gap, the following trading strategy should be tested to see if it is profitable: sell EURUSD and GBPUSD and close the position at the end of the day. As for the USD/RUB exchange rate, there is some evidence that price dynamics before gaps are abnormal and might be generating them.

The results for the US stock market are mixed, but there is some evidence that price dynamics in the gap day differs from normal ones. In case of the Dow Jones Index, when positive gaps emerge, prices tend to increase, whilst the price of IBM shares moves down after any gaps, whether positive or negative. Therefore, profitable trading strategies might be the following: in the case of the Dow Jones index, long positions should be opened after positive gaps; as for IBM shares, short positions should be opened after any gaps. In both cases, the opened positions should be closed at the end of the day.

The results for the Russian stock market differ from those for the US one, possibly reflecting lower efficiency, but are consistent with those for the USD/RUB exchange rate: abnormal price dynamics signal forthcoming gaps in less efficient markets. In the specific case of Sberbank, price dynamics differ from normal ones only after a negative gap. Therefore, a profitable trading strategy would be to sell in the day after a negative gap, and to close the opened positions at the end of the day.

Because the clearest evidence of abnormal price behaviour associated with the emergence of gaps is found in the case of the FOREX, we implement for this market a trading robot approach to test whether the trading strategy already mentioned (sell the currency pair EUR/USD[1] or GBP/USD after positive gaps and close the position at the end of the day) is indeed profitable. The only parameter to be set is the gap size, which is chosen using an optimisation procedure with 0.05–1% as the range of possible values and with 0.05% steps. The five most profitable strategies are shown in Table 7.

Clearly, there is a profit/risk trade-off. For the EUR/USD, the most profitable strategy corresponds to a gap size of 0.05%, but the drawdown (risk) is almost double compared to the case with gap size 0.1%; therefore, the latter is preferable. For the GBP/USD, a gap size of 0.05% should be chosen on the basis of the same trade-off. The results based on these gaps are displayed in Table 8.

As can be seen, they are rather stable over time. The average probability of profitable trading is higher than 60%. Losses are incurred in only three out of 16 years in the case of the EUR/USD, and two out of 16 in the case of the GBP/USD. The z-tests in Table 9 show that the results obtained using the trading strategy are statistically different from the random ones.

Table 7. Choice of the gap size for the trading strategy (period 2000–2015, 0.05–1% parameter range, 0.05% steps).

	EUR/USD			GBP/USD		
Gap size	Total profit	Number of the trades	Drawdown, %	Total profit	Number of trades	Drawdown, %
0.05%	1927	92	5.1	**4820**	**221**	**5.6**
0.10%	**1835**	**58**	**2.8**	2191	113	6.8
0.15%	1741	40	2.8	2065	69	5.9
0.20%	1397	29	2.8	1692	41	5.6
0.25%	1504	23	2.8	1704	27	4.9

Table 8. Results of trading strategy testing (GBP/USD and EUR/USD).

	EUR/USD (gap size 0.1%)			GBP/USD (gap size 0.05%)		
Period	Financial result (points)	% of successful trades	Number of trades	Financial result (points)	% of successful trades	Number of trades
2000	172	60	10	467	63	19
2001	−5	60	5	398	62	13
2002	−284	40	5	−294	33	9
2003	112	50	10	299	53	17
2004	73	50	12	25	64	11
2005	−40	50	4	150	56	9
2006	215	100	4	423	69	13
2007	393	67	9	218	64	14
2008	−56	63	19	1137	65	20
2009	218	50	16	867	54	13
2010	770	71	14	357	63	16
2011	302	80	10	185	64	11
2012	362	80	10	159	69	16
2013	175	63	8	−323	20	10
2014	98	100	4	191	63	16
2015	137	63	8	383	75	12
Overall	**2659**	**63.5**	**148**	**4775**	**60**	**221**

Table 9. Results of the z-tests (GBP/USD and EUR/USD).

Parameter	EUR/USD	GBP/USD
Number of the trades	148	221
Total profit	2659	4775
Average profit per trade	18	22
Standard deviation	90	102
z-test	2.43	3.15
z critical (0.95)	1.96	1.96
Null hypothesis	rejected	rejected

Conclusions

In this paper, we have analysed price dynamics around gaps in various (stock, commodity and FOREX) financial markets by testing six different hypotheses by means of appropriate statistical methods. We find that in most cases there is no significant evidence of anomalous price behaviour associated with the emergence of gaps that could be inconsistent with market efficiency. Further, in the FOREX and commodity markets gaps usually appear after weekends; in less efficient markets (in Russia) previous price dynamics signal the emergence of gaps.

The exception is FOREX, for which there is some evidence of abnormal returns around gaps, which could indicate that this market is not efficient. A trading robot approach confirms that there exist profitable strategies based on exploiting these anomalies. The probability of profitable trading is higher than 60%, and these results are significantly different from the random ones. Further investigation of these issues, for a wider set of markets, should be carried out in the future.

Note

1. EUR/USD or GBP/USD are currency pairs traded in the FOREX as financial instruments. To sell EUR/USD (GBP/USD) means that the trader sells EUR (GBP) for USD, or equivalently buys USD for EUR (GBP). This dual operation can be executed at once using the trading instruments EUR/USD and/or GBP/USD.

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Appendices

Appendix A

Testing results for H1-H4: The case of commodities, FOREX and stock markets

Table A.1. Testing results for H1–H4: The case of commodities, FOREX and stock markets.

			Number of days after the gap			Number of days before the gap		
Financial market	Instrument	Parameter	1	2	3	1	2	3
Commodities	Oil	Positive gaps	45%	47%	51%	44%	44%	50%
		Negative gaps	55%	53%	48%	57%	52%	48%
		All gaps	50%	50%	49%	51%	48%	49%
	Gold	Positive gaps	54%	50%	50%	53%	53%	53%
		Negative gaps	43%	48%	48%	52%	52%	48%
		All gaps	50%	49%	50%	53%	53%	51%
FOREX	EUR/USD	Positive gaps	26%	35%	33%	62%	65%	61%
		Negative gaps	45%	48%	43%	61%	56%	53%
		All gaps	36%	42%	38%	62%	60%	57%
	GBP/USD	Positive gaps	42%	51%	51%	58%	49%	49%
		Negative gaps	50%	44%	42%	64%	61%	67%
		All gaps	47%	47%	46%	61%	56%	60%
	USD/RUB	Positive gaps	52%	48%	50%	70%	66%	64%
		Negative gaps	49%	53%	47%	45%	47%	57%
		All gaps	50%	50%	49%	57%	56%	60%
Stock market	Dow Jones Index	Positive gaps	80%	57%	64%	52%	50%	43%
		Negative gaps	53%	55%	51%	45%	56%	51%
		All gaps	61%	56%	55%	47%	54%	48%
	IBM	Positive gaps	54%	52%	52%	49%	50%	50%
		Negative gaps	60%	53%	51%	52%	47%	48%
		All gaps	57%	53%	51%	50%	49%	49%
	MICEX	Positive gaps	64%	63%	58%	53%	47%	42%
		Negative gaps	59%	57%	47%	72%	62%	63%
		All gaps	61%	60%	52%	63%	55%	53%
	Sberbank	Positive gaps	38%	38%	40%	53%	50%	48%
		Negative gaps	38%	35%	40%	55%	63%	62%
		All gaps	38%	37%	40%	54%	56%	55%

Appendix B

Testing results for H5: The case of commodities, FOREX and stock markets

Table B.1. Testing results for H5: The case of commodities.

Financial market	Instrument	Parameter	Number of days to fill the gap 1	2	3	4	5
Commodities	Oil	Positive gaps	45%	46%	41%	40%	41%
		Negative gaps	32%	38%	46%	45%	46%
		All gaps	38%	42%	44%	42%	44%
	Gold	Positive gaps	30%	40%	44%	36%	33%
		Negative gaps	45%	43%	47%	50%	55%
		All gaps	35%	41%	45%	41%	41%
FOREX	EUR/USD	Positive gaps	41%	50%	47%	53%	50%
		Negative gaps	31%	32%	43%	44%	45%
		All gaps	35%	40%	45%	48%	48%
	GBP/USD	Positive gaps	42%	40%	35%	42%	37%
		Negative gaps	35%	39%	45%	45%	45%
		All gaps	38%	39%	41%	44%	42%
	USD/RUB	Positive gaps	18%	14%	22%	26%	28%
		Negative gaps	17%	17%	26%	23%	28%
		All gaps	17%	16%	24%	24%	28%
Stock market	Dow Jones Index	Positive gaps	18%	30%	32%	25%	30%
		Negative gaps	31%	34%	40%	42%	44%
		All gaps	27%	33%	37%	36%	39%
	IBM	Positive gaps	11%	24%	25%	27%	28%
		Negative gaps	12%	15%	19%	19%	24%
		All gaps	12%	20%	22%	23%	26%
	MICEX	Positive gaps	19%	27%	34%	40%	42%
		Negative gaps	16%	26%	38%	41%	39%
		All gaps	18%	26%	36%	40%	40%
	Sberbank	Positive gaps	26%	34%	34%	36%	37%
		Negative gaps	32%	31%	38%	41%	40%
		All gaps	29%	33%	36%	39%	39%

Appendix C

Results of the statistical tests for H6: The case of commodities

Parametric tests: Student's *t*-test

Table C.1. T-test of H6: The case of commodities.

Instrument	Gold			Oil		
Parameter	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap
t-criterion	0.07	0.93	0.16	0.93	0.28	1.15
t-critical (p = 0.95)	1.96	1.96	1.96	1.96	1.96	1.96
Null hypothesis	Not rejected	Not rejected	Not rejected	Not rejected	Not rejected	Not rejected

Parametric tests: ANOVA

Table C.2. ANOVA test of H6: The case of Gold.

Instrument	Gold			Oil		
Parameter	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap
F	0.01	1.12	0.05	1.08	0.08	1.53
p-value	0.93	0.29	0.81	0.30	0.77	0.21
F critical	3.84	3.84	3.84	3.84	3.84	3.84
Null hypothesis	Not rejected	Not rejected	Not rejected	Not rejected	Not rejected	Not rejected

Non-parametric tests: Kruskal-Wallis test

Table C.3. Kruskal-Wallis test of H6: The case of Gold.

Instrument	Gold			Oil		
Parameter	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap
Adjusted H	0.00	2.81	0.02	1.72	0.10	3.27
d.f.	1	1	1	1	1	1
p-value	0.97	0.09	0.89	0.19	0.76	0.07
Critical value	3.84	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected	not rejected

Regression analysis with dummy variables

Table C.4. Regression analysis with dummy variables for H6: The case of Gold.

Instrument	Gold			Oil		
Parameter	Gap day	Day after gap	Day before gap	Gap day	Day after gap	Day before gap
a_0	0.0003 (0.10)	0.0004 (0.06)	0.0004 (0.09)	0.0004 (0.28)	0.0003 (0.37)	0.0004 (0.26)
a_1	−0.086 (0.93)	−0.001 (0.29)	0.0002 (0.81)	−0.0015 (0.30)	−0.0004 (0.77)	−0.0017 (0.21)
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected	not rejected

Note: * P-values are in parentheses

Appendix D

Results of the statistical tests for H6: the case of FOREX

Parametric tests: Student's t-test

Table D.1. T-test of the Hypothesis 6: The case of EURUSD.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
t-criterion	1.84	3.90	0.62	0.53	0.78
t-critical ($p = 0.95$)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	rejected	not rejected	not rejected	not rejected

Table D.2. T-test of H6: The case of GBP/USD.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
t-criterion	1.31	1.93	0.14	0.08	0.90
t-critical ($p = 0.95$)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected

Table D.3. T-test of H6: The case of USD/RUB.

Parameter	Gap day	Day after gap	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
t-criterion	0.68	0.17	1.59	1.61	0.56
t-critical ($p = 0.95$)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected

Parametric tests: ANOVA

Table D.4. ANOVA test of H6: The case of EUR/USD.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
F	4.36	19.15	0.43	0.48	0.92
p-value	0.04	0.00	0.51	0.49	0.34
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	rejected	not rejected	not rejected	not rejected

Table D.5. ANOVA test of H6: The case of GBP/USD.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
F	3.97	9.80	0.04	0.01	1.14
p-value	0.05	0.00	0.84	0.91	0.28
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	rejected	not rejected	not rejected	not rejected

Table D.6. ANOVA test of H6: The case of USD/RUB.

Parameter	Gap day	Day after gap	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
F	1.42	0.07	8.29	10.10	1.45
p-value	0.23	0.78	0.00	0.00	0.23
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	not rejected	rejected	rejected	not rejected

Non-parametric tests: Kruskal-Wallis test

Table D.7. Kruskal-Wallis test of H6: The case of EUR/USD.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
Adjusted H	3.26	15.85	0.76	0.04	0.22
d.f.	1	1	1	1	1
p-value	0.07	0.00	0.38	0.84	0.64
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	rejected	not rejected	not rejected	not rejected

Table D.8. Kruskal-Wallis test of H6: The case of GBP/USD.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
Adjusted H	2.08	4.53	0.08	0.89	1.12
d.f.	1	1	1	1	1
p-value	0.15	0.03	0.77	0.35	0.29
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	rejected	not rejected	not rejected	not rejected

Table D.9. Kruskal-Wallis test of H6: The case of USD/RUB.

Parameter	Gap day	Day after gap	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
Adjusted H	0.28	0.24	7.34	12.46	0.24
d.f.	1	1	1	1	1
p-value	0.60	0.62	0.01	0.00	0.62
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	not rejected	rejected	rejected	not rejected

Regression analysis with dummy variables

Table D.10. Regression analysis with dummy variables for H6: The case of EUR/USD.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
a_0	0.0000 (0.43)	0.0000 (0.43)	0.0001 (023)	0.0001 (023)	0.0001 (023)
a_1	−0.0011 (0.04)	−0.0033 (0.00)	0.0005 (0.51)	−0.0004 (0.49)	−0.0005 (0.34)
Null hypothesis	rejected	rejected	not rejected	not rejected	not rejected

Note: * P-values are in parentheses.

Table D.11. Regression analysis with dummy variables for H6: The case of GBP/USD.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
a_0	0.0000 (0.40)	0.0000 (0.63)	0.0000 (0.63)	0.0000 (0.63)	0.0000 (0.63)
a_1	−0.0011 (0.05)	−0.0027 (0.00)	0.0000 (0.97)	0.0000 (0.91)	−0.0006 (0.30)
Null hypothesis	rejected	rejected	not rejected	not rejected	not rejected

Note: * P-values are in parentheses.

Table D. 12. Regression analysis with dummy variables for H6: The case of USD/RUB.

Parameter	Gap day	Day after gap	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
a_0	0.0004 (0.02)	0.0004 (0.02)	0.0004 (0.00)	0.0005 (0.00)	0.0005 (0.00)
a_1	−0.0010 (0.23)	0.0002 (0.78)	0.0025 (0.00)	0.0035 (0.00)	0.0013 (0.23)
Null hypothesis	not rejected	not rejected	rejected	rejected	not rejected

Note: * P-values are in parentheses

Appendix E

Results of the statistical tests for H6: the case of the Stock Market

Parametric tests: Student's *t*-test

Table E.1. T-test of H6: The case of the Dow Jones Index.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
t-criterion	1.37	2.41	0.03	0.38	0.32
t-critical (p = 0.95)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	rejected	not rejected	not rejected	not rejected

Table E.2. T-test of H6: The case of IBM.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
t-criterion	0.98	0.57	1.19	0.01	0.69
t-critical (p = 0.95)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected

Table E.3. T-test of H6: The case of MICEX.

Parameter	Gap day	Day after gap	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
t-criterion	0.71	0.30	3.19	0.52	5.45
t-critical (p = 0.95)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	not rejected	rejected	not rejected	not rejected

Table E.4. T-test of H6: The case of Sberbank.

Parameter	Gap day	Day after gap	Day after gap (Positive gaps)	Day after gap (Negative gaps)	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
t-criterion	0.57	1.58	0.69	1.60	0.96	0.36	2.18
t-critical (p = 0.95)	1.96	1.96	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected	not rejected	rejected

Parametric tests: ANOVA

Table E.5. ANOVA test of H6: The case of the Dow Jones Index.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
F	7.81	28.08	0.00	0.42	0.43
p-value	0.00	0.00	0.96	0.51	0.51
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	rejected	not rejected	not rejected	not rejected

Table E.6. ANOVA test of H6: The case of IBM.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
F	4.38	2.49	2.52	0.00	0.91
p-value	0.04	0.11	0.11	0.98	0.34
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	not rejected	not rejected	not rejected	not rejected

Table E.7. ANOVA test of H6: The case of MICEX.

Parameter	Gap day	Day after gap	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
F	2.07	0.29	31.85	1.33	51.94
p-value	0.15	0.59	0.00	0.25	0.00
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	not rejected	rejected	not rejected	rejected

Table E.8. ANOVA test of H6: The case of Sberbank.

Parameter	Gap day	Day after gap	Day after gap (Positive gaps)	Day after gap (Negative gaps)	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
F	1.50	9.25	2.09	10.27	3.71	0.70	16.15
p-value	0.22	0.00	0.15	0.00	0.05	0.40	0.00
F critical	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	rejected	not rejected	rejected	not rejected	not rejected	rejected

Non-parametric tests: Kruskal-Wallis test

Table E.9. Kruskal-Wallis test of H6: The case of the Dow Jones Index.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
Adjusted H	1.95	19.62	1.28	2.27	0.14
d.f.	1	1	1	1	1
p-value	0.16	0.00	0.26	0.13	0.71
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	rejected	not rejected	not rejected	not rejected

Table E.10. Kruskal-Wallis test of H6: The case of IBM.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
Adjusted H	0.00	1.35	1.52	0.28	0.45
d.f.	1	1	1	1	1
p-value	0.99	0.25	0.22	0.60	0.50
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected

Table E.11. Kruskal-Wallis test of H6: The case of MICEX.

Parameter	Gap day	Day after gap	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
Adjusted H	1.93	1.64	24.92	0.61	41.11
d.f.	1	1	1	1	1
p-value	0.16	0.20	0.00	0.44	0.00
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	not rejected	rejected	not rejected	rejected

Table E.12. Kruskal-Wallis test of H6: The case of Sberbank.

Parameter	Gap day	Day after gap	Day after gap (Positive gaps)	Day after gap (Negative gaps)	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
Adjusted H	0.17	6.98	5.67	1.14	2.34	0.01	7.68
d.f.	1	1	1	1	1	1	1
p-value	0.68	0.01	0.02	0.29	0.13	0.92	0.01
Critical value	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	rejected	rejected	not rejected	not rejected	not rejected	rejected

Regression analysis with dummy variables

Table E.13. Regression analysis with dummy variables for H6: The case of the Dow Jones Index.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
a_0	0.0003 (0.16)	0.0003 (0.14)	0.0003 (0.14)	0.0003 (0.14)	0.0003 (0.14)
a_1	0.0027 (0.00)	0.0084 (0.00)	0.0000 (0.96)	−0.0006 (0.51)	−0.0006 (0.51)
Null hypothesis	rejected	rejected	not rejected	not rejected	not rejected

Note: * P-values are in parentheses.

Table E.14. Regression analysis with dummy variables for H6: The case of IBM.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap	Day before gap
a_0	0.0006 (0.01)	0.0006 (0.01)	0.0006 (0.01)	0.0006 (0.01)	0.0006 (0.01)
a_1	−0.0021 (0.04)	−0.0022 (0.11)	−0.0021 (0.11)	−0.0000 (0.98)	0.0009 (0.34)
Null hypothesis	rejected	not rejected	not rejected	not rejected	not rejected

Note: * P-values are in parentheses.

Table E.15. Regression analysis with dummy variables for H6: The case of MICEX.

Parameter	Gap day	Day after gap	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
a_0	0.0007 (0.03)	0.0007 (0.03)	0.0007 (0.03)	0.0007 (0.02)	0.0007 (0.02)
a_1	−0.0021 (0.15)	−0.0001 (0.59)	−0.0080 (0.00)	−0.0023 (0.25)	−0.0132 (0.00)
Null hypothesis	not rejected	not rejected	rejected	not rejected	rejected

Note: * P-values are in parentheses.

Table E.16. Regression analysis with dummy variables for H6: The case of Sberbank.

Parameter	Gap day	Day after gap	Day after gap (Positive gaps)	Day after gap (Negative gaps)	Day before gap	Day before gap (Positive gaps)	Day before gap (Negative gaps)
a_0	0.0009 (0.05)	0.0009 (0.05)	0.0009 (0.03)	0.0009 (0.04)	0.0009 (0.04)	0.0009 (0.04)	0.0009 (0.03)
a_1	0.023 (0.22)	−0.0054 (0.00)	−0.0033 (0.14)	−0.0077 (0.00)	−0.0035 (0.05)	0.0020 (0.40)	−0.0096 (0.00)
Null hypothesis	not rejected	rejected	not rejected	rejected	rejected	not rejected	rejected

Note: * P-values are in parentheses