VOLATILITY EXPLOSIONS AND PRICE PREDICTION: CASE OF OIL MARKET

Alex Plastun *, Serhii Bashlai **

* Sumy State University, Ukraine
** Sumy National Agricultural University, Ukraine

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Abstract

This paper explores behavior of oil market after volatility explosions (days with abnormally high price volatility). It examines possible price patterns and whether they create exploitable profit opportunities from trading. A number of statistical tests both parametrical (t-test, ANOVA, regression analysis with dummy variables) and non-parametrical (Mann–Whitney U test) confirm presence of price patterns after volatility explosions: the next day price changes in both directions are bigger than after "normal" days. Oil prices (case of Brent) for the period from January 2000 till the end of 2016 (for the trading robot analysis the period is 2014-2016) are analyzed in this paper. To incorporate transactional costs in results a trading robot approach is used. Testing of two trading strategies based on detected anomalies shows that a strategy based on counter-movements after volatility explosions produces profits and the one based on so called "inertia anomaly" does not generate profits in oil market. An important result of this paper is that presence of statistical anomaly does not necessarily means anomaly in price behavior and inconsistency with the Efficient Market Hypothesis.

Keywords: Efficient Market Hypothesis, Volatility Explosion, Anomaly, Overreaction Hypothesis, Abnormal Returns, Contrarian Strategy, Trading Strategy, Trading Robot

1. INTRODUCTION

Sudden jumps in volatility are rather typical but abnormal element of price dynamics in financial markets. The question is, do they give any useful information? Will it lead to appearance of certain patterns in price dynamics? And if it so, can they be exploited?

According to the Efficient Market Hypothesis (Fama, 1965) the answer is "no". Prices follow random walk and it is impossible to "beat the market" and there should not be any exploitable profit opportunities in financial markets.

Still there are many evidences in favor of so-called "market anomalies", patterns in price behaviour that may be exploited to create profits from trading.

Volatility explosions are among them. First they were detected by De Bondt and Thaler (1985) in form of market overreactions and lead to appearance of so-called overreaction hypothesis. Overreactions in general are significant deviations in price changes on assets from their average (typical) values during certain period of time.

Empirical studies on various financial markets show that after overreactions there are bigger contrarian price movements than after normal (typical) fluctuations (Atkins and Dyl, 1990; Bremer and Sweeney, 1991; Cox and Peterson, 1994; Choi and Jayaraman, 2009; Mynhardt and Plastun 2013; Caporale et al., 2017 etc).

Overreactions as an anomaly are widely explored in the different stock markets, but much less attention is paid in case of commodity markets and especially in Oil market. Still oil market is the most volatile among others (FOREX, Stock Market, Gold Market). One more important aspect is that overreactions as a rule are analyzed for the case of price returns and not for the case of price volatility.

In this paper we want to expand empirical literature and to fill existing gaps for the case of Oil market. This paper provides new evidence on the overreaction anomaly for the case of volatility by analysing both price counter-movements and movements in the direction of the overreaction and comparing them to those after normal days. To do to this, we carry out a number of statistic tests (both parametric and non-parametric) to establish whether prices are the same after days of volatility explosion and typical days and to detect patterns in price dynamics. To prove that these patterns are not just statistical anomalies and that they could result in extra profit opportunities we use a trading robot approach. It allows examining trading strategies based on the detected anomalies whether they are profitable or not. The analysis is carried out for the Oil market (case of Brent).

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on the overreaction hypothesis. Section 3 describes the methodology used in this study. Section 4 discusses the empirical results. Section 5 provides some concluding remarks.

2. LITERATURE REVIEW

According to behaviorists investors are not rational. The direct result of this is existence of so called market anomalies: price bubbles; seasonal patterns in price dynamics; volatility explosions; yield dependence on different variables and other deviations from rationality. Kahneman and Tversky (1982) show, that investors overvalue recent relative to past information. They inspire De Bondt and Thaler (1985) who had shown that the best (worst) performing portfolios in the NYSE over a three-year period tended to under (over)-perform over the following three-year period. This laid the basis for the overreaction hypothesis - one of the most famous market anomalies. According to this hypothesis, investors overreact in a given period, but the next period they act in opposite direction, i.e. if the price has increased one day, then the next day it will fall and vice versa.

Further evidences in favor of market overreactions were provided by Brown, Harlow and Tinic (1988), Zarowin (1989), Atkins and Dyl (1990), Ferri and Min (1996), Larson and Madura (2003), Clements et al. (2009), Mynhardt and Plastun (2013) and others.

Overreactions are deviations from normality. They are the result of psychological, technical, fundamentals and other factors or their combinations (see table A.1, Appendix A for details).

One of the most explored price patterns caused by overreactions is that prices are generally found to be reversed following the day of overreaction. Bremer and Sweeney (1991) proved the fact that after a very strong negative price movement positive price movement occurs. Their size exceeds ordinary movements. Analysis of negative daily changes which in size exceeded 10% showed that the next day price increased on average by 1.77%.

Despite a number of evidences in favor of market overreactions and their reasonable explanations there are also researches where overreaction hypothesis is rejected. For example, Atkins and Dyl (1990) show that incorporation of transactional costs in calculations may dramatically change the results: abnormal returns become too small and statistically insignificant in some cases, in other cases generation of profits after spread incorporation become impossible. Similar results are obtained by Lehman (1990), Cox and Peterson (1994), Hamelink (1999), Fehle and Zdorovtsov (2002) and others. The most common approach to prove that pure statistical anomaly is also a real market anomaly is development of a trading strategy based on overreaction price pattern. In case of profitability of such a strategy anomaly is recognized as a market one (see. Jegadeesh and Titman, 1993; and Lehmann, 1990 for details).

That is why it is quite important to incorporate transactional costs in calculations to avoid miss interpretation of the results.

It should be mentioned that investigations of overreactions as a rule are performed on the stock market data. Usually as an object of analysis acts the US stock market. But other markets are much less explored and number of paper devoted to other markets is limited. As examples can be named papers by Cutler, Poterba, and Summers (1991) devoted to gold market and Poteshman (2001) who analyzed the option market. Oil market as a part of commodity market was analyzed by Caporale et al (2017).

Oil market volatility as an object of research is widely discussed in the empiric literature (Yang et al, 2002; Regnier, 2007). But most of these studies are concentrated on the reasons of volatility: supply and demand shocks (Hubbard, 1986; Baumeister and Peersman, 2008), monetary policy changes (Cogley and Sargent, 2005), inventory behavior and speculations, market emotions like fear and greed etc. (Alquist and Kilian, 2010).

Matar et al (2013) and Salisu (2014) discuss modelling and forecasting crude oil price volatility. Persistence of volatility in petroleum future prices is analyzed by Kang et al (2009) and Alom et al (2012).

One more aspect influencing this research is evolution of financial markets (see Lo, 2004 for details). It means that some anomalies may fade in time. So it is important to analyze the most recent data.

In this paper we will try to fill gaps in existing literature on overreactions and explore Oil market with the most recent data, incorporating transactional costs in our research.

3. DATA AND METHODOLOGY

We analyze Oil prices (case of Brent) for the period from January 2000 till the end of 2016 (for the trading robot analysis the period is 2014-2016).

Standard approach which is used to analyze overreactions was proposed by MacKinlay and Richardson (1991). It is called Generalized Method of Moments (GMM) and is used to estimate the expected returns. Then the cumulative abnormal returns are calculated.

In our case this methodology is not appropriate because instead of price returns we analyze price volatility.

That is why to confirm (reject) the presence of anomalies in Oil prices after volatility explosions first we use simple average analysis. Then we carry out Student's t-tests. To provide additional evidences in favor of the tested hypotheses we use ANOVA analysis. Also we provide Mann–Whitney U tests. We use these test to overcome normal distribution limitations.

To identify anomalies we run multiple regressions including a dummy variable:

$$Y_t = a_0 + a_1 D_{1t} + \varepsilon_t \qquad (1)$$

where Y_t – volatility on the period t;

a_n– mean volatility for a normal day (the day when there was no volatility explosion);

D_{nt} – a dummy variable for a specific data group, equal to 1 when the data belong to the day of volatility explosion, and equal to 0 when they do not;

ε_t – Random error term for period *t*.

The size, sign and statistical significance of the dummy coefficients provide information about possible anomalies.

In case of confirmation of tested hypotheses we use the trading robot approach to establish whether detected anomalies create exploitable profit opportunities. According to the Efficient Market Hypothesis it is impossible to beat the market and generate abnormal profits from trading. So the real market anomaly is the one which generates profits from trading based on it.

According to the standard overreaction hypothesis, an overreaction should be followed by a correction, i.e. price reversal, and it should be bigger than after normal days. But what if one day is not enough for the market to incorporate new information, i.e. to overreact or overreaction causes directional movement appearance? In this case after one-day abnormal price changes we can expect movements in the direction of the overreaction and it should be bigger than after normal days.

These situations are opposite; therefore two different hypotheses need to be tested:

H1: Counter-reactions after volatility explosions differ from those after normal days.

H2: Price movements after volatility explosions in the direction of the overreaction differ from such movements after normal days.

The null hypothesis is in both cases that the data after normal and volatility explosion days belong to the same population.

We analyse volatility explosions during one trading session, so the period of analysis is 1 day. To calculate volatility we use the following formula:

$$R_i = \frac{(High_i - Low_i)}{Low_i} \times 100\% , \quad (2)$$

where R_i is volatility in %, $High_i$ is the maximum price, and Low_i is the minimum price for day *i*.

We consider the following definition of “volatility explosion”:

$$R_i > (\bar{R}_n + k \times \delta_n) , \quad (3)$$

where k - the number of standard deviations used to identify volatility explosion,

$\bar{R}_n$ is the average size of daily volatility for period n

This approach is consistent with methodology used to identify positive and negative shocks proposed by Lasfer et al. (2003).

To calculate the size of the counter-reaction we calculate the difference between the next day’s open price and the maximum deviation from it in the opposite direction to the price movement in the volatility explosion day.

If the price increased, then the size of the counter-reaction is calculated as:

$$cR_{i+1} = 100\% \times \frac{(Open_{i+1} - Low_{i+1})}{Low_{i+1}} , \quad (4)$$

where cR_{i+1} is the counter-reaction size, and $Open_{i+1}$ is the next day’s open price.

If the price decreased, then the corresponding definition is:

$$cR_{i+1} = 100\% \times \frac{(High_{i+1} - Open_{i+1})}{Open_{i+1}} . \quad (5)$$

As the results there are two data sets with cR_{i+1} values. The first one consists of cR_{i+1} values after one-day abnormal price changes. The second contains cR_{i+1} values after a day with normal price changes. The null hypothesis to be tested is that they are both drawn from the same population.

One more important aspect of our methodology is incorporation of transaction costs in results. Transaction costs connected with speculative trading operations in the Oil market can be divided into fixed (fees and commissions to brokers, bank payments etc) and variable ones (spread). Spread as a typical representative of transactional costs is present in each transaction and can significantly influence the overall financial results from trading. That is why it will be incorporated into our analysis.

To do this we programme a trading robot which automatically opens and closes positions according to the detected price pattern. Variable part of transactional costs in our analysis will be incorporated the following way: long positions will be opened on “ask” price and closed on “bid” price and vice versa for the case of short positions. Operations of the trading robot fully replicate the actions of the real trader on a real market. That is why its results may be interpreted as a final criterion in hypothesis testing (practice).

Trading robot is a program in the MetaTrader terminal developed in MetaQuotes Language 4 (MQL4). It allows analyzing price data and managing trading activities on the basis of the signals received according to a certain algorithm. If it is possible to make abnormal profits from trading based on detected anomaly, we may conclude that this anomaly is not just a statistical phenomenon, but the real “hole” in market efficiency.

One of the main problems in the use of trading robots is danger of data-snooping bias. To avoid or at least partially reduce it we will use some special procedures.

1. Optimal parameters of the trading strategy will be obtained in a base period (2015).
2. Optimal parameters will be tested on two independent (non-optimised) periods (2014 and 2016) to see whether it is profitable.
3. To obtain average results for the trading strategy we will perform overall testing for the whole period (2014-2016).

4. To make sure that the results we obtain are statistically different from the random ones we carry out t-tests.

In t-test we analyze two data samples to see whether they come from the same population. One of them consists of financial results from trading applying the trading strategy, and another one is formed from random trading results which should generate zero profit in the end. 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 t-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.

4. EMPIRICAL RESULTS

Exploring volatility explosions it is crucial to set the trigger value which will be defined as event (volatility explosion). This trigger value is not self-evident. For example Bremer and Sweeney (1991) use as a trigger value 10%. So in case of daily returns exceed 10% they are defined as an event. But Cox and Peterson (1994) note that the use of this set up may induce a bias. It means that for a certain data period this value will be the best fit and anomaly will be detected. But for other data period results may be even opposite. That is why it is important to use certain methodology of calculation instead of constant values.

In this paper we use dynamic trigger values approach proposed by Wong (1997). To set the basic parameters/criterions for volatility explosion event we use the number of standard deviations to be added to the average volatility. One more important aspect in this case is the averaging period using to calculate the mean and the number of standard deviations used to identify anomaly.

To do this we analyze the number of days, when volatility differs from its mean using different averaging periods (10, 20 and 30). Results are presented in Table 1.

Table 1. Number of volatility explosions detected in Oil prices during 2000-2016

Period of averaging	*10*		*20*		*30*		*40*	
Indicator	*Number*	*%*	*Number*	*%*	*Number*	*%*	*Number*	*%*
Overall	5612	100	5601	100	5591	100	5580	100
Number of volatility explosion (criterion =mean+ standard deviation)	907	16	925	17	896	16	861	15
Number of volatility explosion (criterion= mean+2 standard deviation)*	157	3	293	5	280	5	263	5
*Number of volatility explosion (criterion = mean+3*standard deviation)*	0	0	112	2	110	2	103	2

As can be seen, each additional standard deviation significantly decreases the number of observed volatility explosions. Methodology of this research is based mostly on statistical methods therefore sample size is critical parameter. 100-200 observations during 16 years are not sufficient to report statistically significant and convincing results. That is why further in this research the number of standard deviations to be added to the average to will be equal 1.

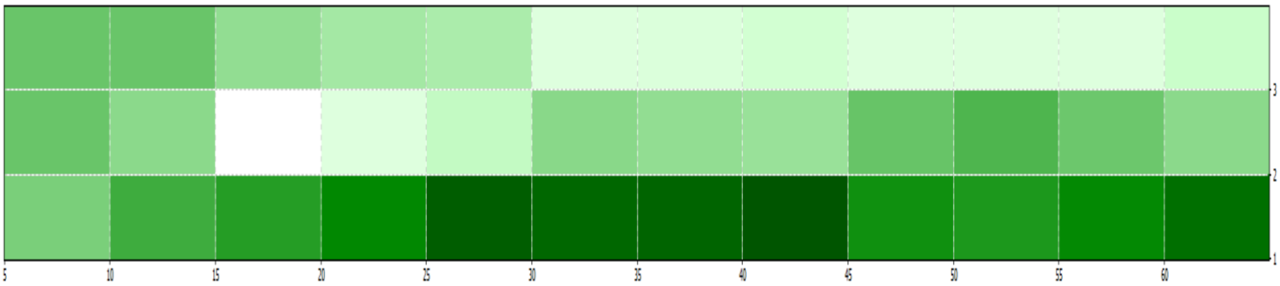
Concerning the averaging period the situation is much less clear. That is why we provide additional calculations. Student's t–tests of the counter-reactions after the day of the volatility explosion carried out for Oil prices over the period 2000-2016 (see Table 2) suggest that the optimal averaging periods starts from 30 (t-tests are passed the most convincing in these cases).

Table 2. T-test of the counter-reactions after the day of the volatility explosion for the Oil prices during 2000-2016

Period	*10*		*20*		*30*		*40*	
Parameter	*Normal*	*Abnormal*	*Normal*	*Abnormal*	*Normal*	*Abnormal*	*Normal*	*Abnormal*
Mean	1,20%	1,32%	1,20%	1,33%	1,18%	1,42%	1,18%	1,46%
Standard deviation	1,42%	1,55%	1,41%	1,58%	1,40%	1,63%	1,40%	1,65%
Number of matches	4703	907	4674	925	4693	896	4718	861
t-criterion	2,10		2,39		4,16		4.68	
t-critical (p=0.95)	1,96							
Null hypothesis	rejected		rejected		rejected		rejected	

To choose among 30 and 40 periods of averaging we test the trading strategy based on counter-reactions after the day of the volatility explosion with a different set of parameters (see Figure 1). The results provide evidence in favour of 40 as an appropriate value for the period parameter. Also we get additional evidences that the most appropriate number of standard deviations is 1.

Figure 1. Testing results for the Oil, period 2014-2016 (X – sigma_dz, Y – period_dz)*



* The darker the bars, the more profitable the trading strategy is.

The results for H1and H2 are presented in Appendix B and are summarized in Table 3.

Table 3. Statistical tests results: summarizing*

Hypothesis	***Hypothesis 1***	***Hypothesis 2***
Average analysis	+	+
T-test	+	+
ANOVA	+	+
Mann-Whitney U test	+	+
Regression analysis with dummy variable	+	+

* ”+” –hypothesis confirmed, “-” - hypothesis rejected.

As can be seen, both Hypotheses are confirmed. It means that after volatility explosions Oil prices demonstrate higher volatility after the day of volatility explosions then after normal day. This confirms the presence of a statistical anomaly in the price dynamics in the Oil market after volatility explosions.

To make sure that detected anomalies are not just statistical phenomenon, but the real inefficiency in the Oil market we analyse whether these anomalies can generate profits from trading. If they do not, we conclude that they do not represent evidence inconsistent with the EMH.

According to our results both Hypothesis were confirmed: after volatility explosions price movements the next day are abnormal. Both for the case of contrarian movement the next day and price changes in the direction of overreaction.

That is why we developed two trading strategies.

Strategy 1 is based on the typical overreaction anomaly. It means that there are abnormal counter-reactions the day after the volatility explosion day. According to the Strategy 1 Oil is sold (bought) on the open price of the day after the volatility explosion day in case of abnormal price decrease (increase) has occurred. Opened position is closed if a target profit value is reached or at the end of the following day.

Strategy 2 is based on so called “inertia anomaly” (see Caporale et al., 2017 for details). According to this anomaly the presence the abnormal price movements in the direction of the volatility explosion the following day. The algorithm is built as follows: at the end of the volatility explosion day Oil is bought or sold depending on whether abnormal price increases or decreases respectively have occurred. Again, an open position is closed if a target profit value is reached or at the end of the following day.

There are to variable parameters in both strategies:

- Expected profit per trade or Take Profit (profit_koef): the size of profit expected to result from a trade, measured as:

$$Take\ Profit = profit\_koef * sigma\_dz \tag{6}$$

- Maximum amount of losses per trade or Stop Loss (stop): the size of losses the trader is willing to incur in a trade, defined as follows:

$$Stop\ Loss = stop * sigma\_dz \tag{7}$$

As for the other parameters: averaging period and number of standard deviations; we use values substantiated earlier in this paper. We use averaging period = 40 and the number of standard deviations = 1.

During testing only variable parameters are optimized.

Example of optimization report is presented in Appendix C. According to our methodology optimization is provided for the period 2015. The other periods (2014, 2016) are used as independent samples.

The results of the parameter optimization and of the trading robot analysis are presented in Table 4.

Table 4. Optimal parameters for the trading strategies

Parameters	***Strategy 1***	***Strategy 2***
profit_koef	3	1,5
stop	2	2

The next step is testing of these parameters on two independent periods and overall testing (whole period 2014-2016). Example of strategy tester report is presented in Appendix D.

The results of the trading robot analysis are presented in Appendix E.

As can be seen, results of Strategy 1 are rather stable and evidence in favor of exploitable profit opportunities from trading based on counter-movements after volatility explosions. All of the analyzed periods are profitable. Still results of t-tests are mixed (see Appendix F for details). Test is passed only for the case of overall testing. It means that for the separate periods results are close to the random ones. Indirect evidence of this is the number of profitable trades which is close to 50%.

Strategy 2 does not generate profits and therefore this anomaly cannot be seen as inconsistent with the EMH.

An important conclusion is that the presence of statistical anomaly in price behavior does not necessarily means anomaly in price behavior and inconsistency with the Efficient Market Hypothesis. For example statistical anomaly for Hypothesis 2 is very strong, but its incorporation in real life (by using trading robot approach) shows that it is unable to generate extra profits from trading and so it can't be considered as the inconsistency with the Efficient Market Hypothesis.

Concerning the future directions of research of this topic it should be mentioned that such aspects as reasons for volatility explosions in the Oil market, prediction of volatility explosions, and character of volatility explosions in different market conditions need further exploration.

5. CONCLUSIONS

This paper examines behavior of oil market after the days with abnormally high price volatility (volatility explosions). It aims to find daily patterns in oil market caused by the volatility explosions and to prove that detected anomalies are not simply statistical phenomena, but are real inconsistencies with the EMH (it is possible to make extra profits exploiting them). To do this a variety of statistical tests (average analysis, t-test, ANOVA, regression analysis with dummy variables, Mann–Whitney U test) were performed. Both Hypotheses (H1: counter-reactions after volatility explosions differ from those after normal days; and H2: price movements after volatility explosions in the same direction of the overreaction differ from those after normal days) were confirmed. It means that volatility explosions cause statistically abnormal price behavior in the oil market.

To incorporate transactional costs in the results and to prove that statistical anomaly is able to generate profits from trading a trading robot approach was used. Trading robot simulates the behaviour of traders in real life and tests the ability of two alternative strategies, based on detected anomalies, to generate profits from trading.

Strategy 1, which is based on the assumption that after the volatility explosion day counter-movements are bigger than after a standard day, generates stable profits therefore this anomaly can be seen as inconsistent with the EMH. Strategy 2, based on the "inertia anomaly", appears to be unprofitable and can't be seen as inconsistent with the EMH.

Overall we might conclude that exploring market anomalies it is crucial to incorporate transactional costs in calculations. As for the volatility explosions in the oil market, results show that they cause abnormal price behavior and formation of price patterns. One of them can generate abnormal profits from trading. This provides evidences against the EMH.

An important conclusion is that the presence of statistical anomaly in price behavior does not necessarily means anomaly in price behavior and inconsistency with the Efficient Market Hypothesis. For example statistical anomaly for Hypothesis 2 is very strong, but its incorporation in real life (by using trading robot approach) shows that it is unable to generate extra profits from trading and so it can't be considered as the inconsistency with the Efficient Market Hypothesis.

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APPPENDIX

Appendix A

Table A.1 Reasons for overreactions

Group of factors	***Factors***	***Authors***	***Description***
Psychological reasons	overreaction to new information	Griffin and Tversky (1992)	Instead of comparing new information with existing information and taking rational decisions, investors act under emotions and herd effect.
	existence of "noise" traders	Aiyagari and Gertler (1999)	Irrational investors take investment decisions on fragmentary information and current price fluctuations. Their activity increases the price fluctuations in the markets.
	representativeness effect	Barberis et al. (1998)	Investors often ignore the laws of chance and behave as if the events, that took place recently, are typical.
	psychological flaws	Daniel et al. (1998)	Typical human psychological flaws can explain why "rational" investors buy assets higher than their fundamental value and sell below their fair value.
	overconfidence and biased attitude	Daniel et al. (1998)	Investors often overestimate their ability to analyze the market situation. In this regard, they underestimated the likelihood of errors in the prediction of a certain event.
Technical reasons	signals from technical analysis	Mynhard and Plastun (2013)	It is widely believed that the current movement in the price of assets can generate specific trading signals from various technical indicators that will lead to massive operations/trading in the current movement direction and will strengthen it causing overreaction.
	execution of "stop-losses" ("stops")	Duran and Caginalp (2007)	Execution of stops means opening positions in the direction of current movement (forced closure of the short positions means opening of the long positions and vice versa). Stops execution acts as a movement catalyst or accelerator, and leads to increase in the scale of basic movement and loss of control over its size.
	margin-call theory	Aiyagari and Gertler (1999)	In case of large and unexpected movement in the markets margin-call mechanism often comes into action, closing the most unprofitable position of the client to release the margin. Closure of unprofitable positions means, that opposite positions are opened, i.e. positions in the direction of current movement, thus increasing its scale.
Fundamental reasons	price-ratio hypothesis	Dreman (1982)	Companies with low P/E ratio are undervalued. However, usually there are few investors who wish to buy stocks of these companies. It happens because past negative still strong in the memory of investors. Nevertheless, when negative news on such companies end and positive news become dominant, the demand for shares increases dramatically. That leads to abnormal movements. Opposite situation is observed for overvalued shares.
	low liquidity	Jegadeesh and Titman (1993)	The lack of liquidity in the market. Even small numbers and amounts of transactions can lead to significant price fluctuations.

Appendix B. Statistical tests of Hypotheses 1 and 2

Average analysis

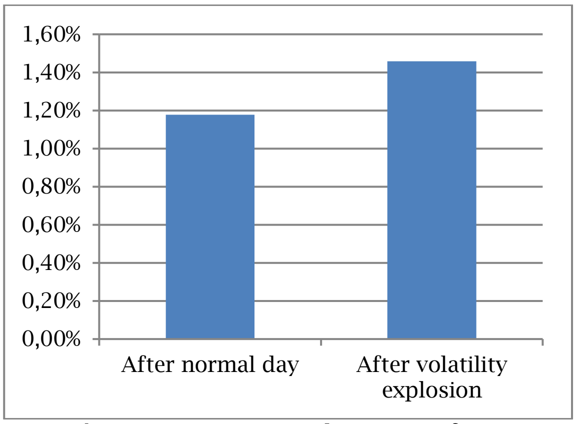

Figure B.1 Average analysis case of H1

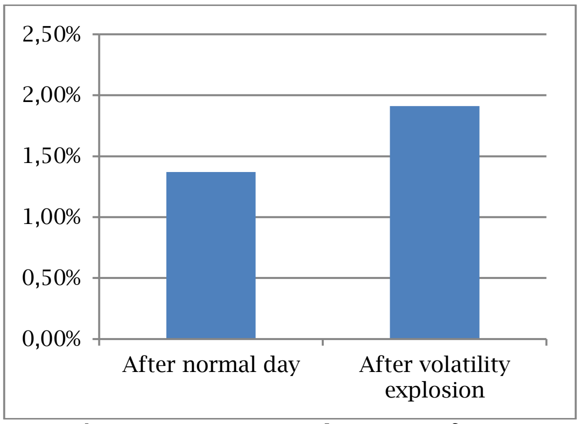

Figure B.1 Average analysis case of H2

Parametric tests: Student's t-test

Table B.1 T-test of Hypotheses 1 and 2 (averaging period = 40, number of standard deviations used to detect volatility explosion = 1)

Hypothesis	***Hypothesis 1***		***Hypothesis 2***	
Indicator	***After normal day***	***After volatility explosion***	***After normal day***	***After volatility explosion***
Mean	1,18%	1,46%	1,37%	1,91%
Standard deviation	1,40%	1,65%	1,46%	2,07%
Number of matches	4718	861	4718	861
t-criterion	4.68		7.33	
t-critical (p=0.95)	1.96			
Null hypothesis	rejected		rejected	

Parametric tests: ANOVA

Table B.2 ANOVA test of Hypotheses 1 and 2 (averaging period = 40, number of standard deviations used to detect volatility explosion = 1)

Hypothesis	***Hypothesis 1***	***Hypothesis 2***
F	27.68	86.61
P value	0.00	0.00
F critical	3.84	3.84
Null hypothesis	rejected	rejected

Non-parametric tests: Mann-Whitney U test

Table B.3 Mann-Whitney U test of Hypotheses 1 and 2 (averaging period = 40, number of standard deviations used to detect volatility explosion = 1)

Parameter	***Hypothesis 1***	***Hypothesis 2***
Adjusted H	18,21	32,98
d.f.	1	1
P value:	0,00	0,00
Critical value	3,84	3,84
Null hypothesis	Rejected	Rejected

Regression analysis with dummy variables

Table B.4 Regression analysis with dummy variables of Hypotheses 1 and 2 (averaging period = 40, number of standard deviations used to detect volatility explosion = 1)*

Parameter	*Hypothesis 1*	*Hypothesis 2*
Mean volatility (a_0)	0,0118 (0,0000)	0,0137 (0,0000)
Dummy coefficient (a_1)	0,0028 (0,0000)	0,0054 (0,0000)
F-test	27.68 (0.0000)	86.61 (0.0000)
Multiple R	0,07	0,12
Anomaly	confirmed	confirmed

* P-values are in parentheses

Appendix C. Example of optimisation results: case of Oil, period 2015, H1 testing

Figure C.1. Distribution of results (X – profit_koef, Y – stop) – deeper green means better results

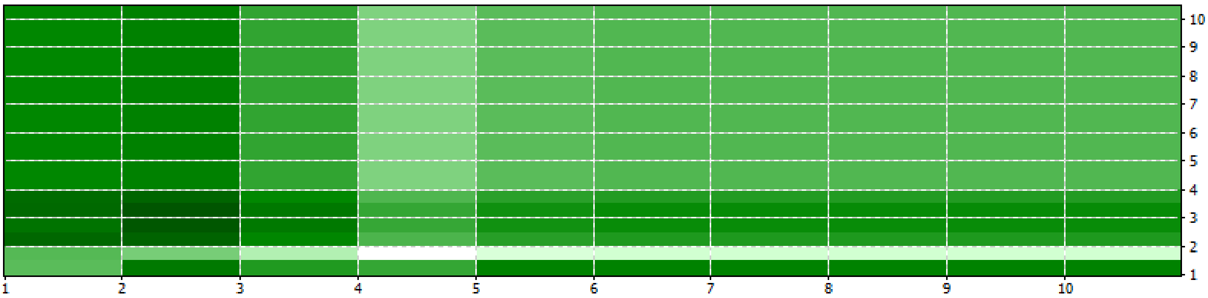

Table C.1 Results of testing: case of Oil, period 2015 (changeable parameters profit_koef from 0.5 to 10 with step 0.5; stop from 1 to 10 with step 1), start deposit = 10000$, size of trading lot = 10000$, margin (credit) leverage = 100, period_dz=40, sigma_koef=1 (fragment, best 20 results)

Number of simulation	*Profit, $*	*Total trades*	*Profit factor*	*Expected payoff*	*Drawdown, $*	*Drawdown, %*	*Profit_koef*	*Stop*
24	699.00	33	1.41	21.18	679.00	6.33%	3	2
23	694.00	33	1.41	21.03	649.00	6.04%	2.5	2
22	635.00	33	1.38	19.24	584.00	5.46%	2	2
25	625.00	33	1.37	18.94	797.00	7.38%	3.5	2
3	616.00	27	1.52	22.81	434.00	4.06%	2	1
5	611.00	27	1.51	22.63	511.00	4.77%	3	1
6	598.00	27	1.50	22.15	592.00	5.48%	3.5	1
4	564.00	27	1.47	20.89	450.00	4.21%	2.5	1
43	538.00	33	1.29	16.30	691.00	6.77%	3	3
20	535.00	34	1.45	15.74	511.00	5.04%	1	2
42	533.00	33	1.28	16.15	691.00	6.77%	2.5	3
38	496.00	33	1.29	15.03	797.00	7.47%	10	2
37	496.00	33	1.29	15.03	797.00	7.47%	9.5	2
36	496.00	33	1.29	15.03	797.00	7.47%	9	2
35	496.00	33	1.29	15.03	797.00	7.47%	8.5	2
34	496.00	33	1.29	15.03	797.00	7.47%	8	2
33	496.00	33	1.29	15.03	797.00	7.47%	7.5	2
32	496.00	33	1.29	15.03	797.00	7.47%	7	2
31	496.00	33	1.29	15.03	797.00	7.47%	6.5	2
30	496.00	33	1.29	15.03	797.00	7.47%	6	2
29	496.00	33	1.29	15.03	797.00	7.47%	5.5	2
28	496.00	33	1.29	15.03	797.00	7.47%	5	2

Appendix D. Example of strategy tester report: case of Oil, period 2015, H1 testing

Table D.1 Overall statistics

Symbol		_BRN (BRENT CRUDE OIL)			
Period		1 Hour (H1) 2015.01.02 09:00 - 2015.12.31 00:00 (2015.01.01 - 2015.12.31)			
Model		Every tick (the most precise method based on all available least timeframes)			
Parameters		profit_koef=3; stop=2; sigma_koef=1; period_dz=40			
Bars in test	6518	Ticks modelled	127322	Modelling quality	90.00%
Mismatched charts errors	0				
Initial deposit	1000.00			Spread	Current (2)
Total net profit	719.00	Gross profit	2403.00	Gross loss	-1684.00
Profit factor	1.43	Expected payoff	21.79		
Absolute drawdown	304.00	Maximal drawdown	670.00 (6.25%)	Relative drawdown	6.25% (670.00)
Total trades	33	Short positions (won %)	5 (60.00%)	Long positions (won %)	7 (71.43%)
		Profit trades (% of total)	18 (54.55%)	Loss trades (% of total)	15 (45.45%)
Largest		profit trade	309.00	loss trade	-211.00
Average		profit trade	133.50	loss trade	-112.27
Maximum		consecutive wins (profit in money)	4 (526.00)	consecutive losses (loss in money)	3 (-233.00)
Maximal		consecutive profit (count of wins)	526.00 (4)	consecutive loss (count of losses)	-372.00 (2)
Average		consecutive wins	2	consecutive losses	2

Figure D.1. Equity dynamics

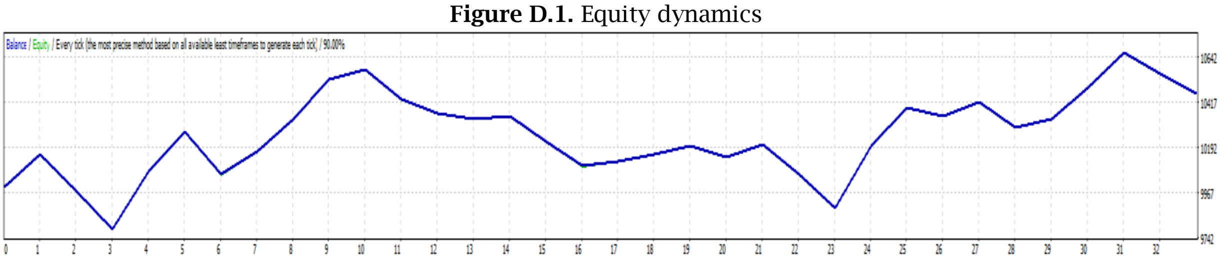

Table D.2. Statement (fragment)

#	Time	Type	Order	Size	Price	S / L	T / P	Profit	Balance
1	16.01.2015 3:00	buy	1	0.10	48.34	46.19	51.57		
2	19.01.2015 3:00	close	1	0.10	49.95	46.19	51.57	161.00	10161.00
3	02.02.2015 3:00	sell	2	0.10	51.89	53.72	49.15		
4	02.02.2015 12:46	s/l	2	0.10	53.72	53.72	49.15	-183.00	9978.00
5	03.02.2015 3:00	sell	3	0.10	54.90	56.79	52.07		
6	03.02.2015 11:20	s/l	3	0.10	56.79	56.79	52.07	-189.00	9789.00
7	04.02.2015 3:00	sell	4	0.10	57.19	59.12	54.30		
8	04.02.2015 21:15	t/p	4	0.10	54.30	59.12	54.30	289.00	10078.00
9	05.02.2015 3:00	buy	5	0.10	54.86	52.83	57.90		
10	05.02.2015 23:00	close	5	0.10	56.84	52.83	57.90	198.00	10276.00
11	06.02.2015 3:00	sell	6	0.10	56.70	58.81	53.53		
12	06.02.2015 12:50	s/l	6	0.10	58.81	58.81	53.53	-211.00	10065.00
13	26.02.2015 3:00	sell	7	0.10	61.83	63.81	58.85		
14	26.02.2015 23:00	close	7	0.10	60.66	63.81	58.85	117.00	10182.00
15	19.03.2015 2:00	sell	8	0.10	56.02	57.93	53.16		
16	19.03.2015 23:00	close	8	0.10	54.40	57.93	53.16	162.00	10344.00

#	Time	Type	Order	Size	Price	S / L	T / P	Profit	Balance
17	06.04.2015 3:00	buy	9	0.10	55.61	54.30	57.57		
18	06.04.2015 18:10	t/p	9	0.10	57.57	54.30	57.57	196.00	10540.00
19	09.04.2015 0:00	buy	10	0.10	56.08	54.75	58.07		
20	09.04.2015 22:02	close	10	0.10	56.59	54.75	58.07	51.00	10591.00
21	16.04.2015 0:00	sell	11	0.10	62.78	64.26	60.56		
22	16.04.2015 20:40	s/l	11	0.10	64.26	64.26	60.56	-148.00	10443.00
23	24.04.2015 0:00	sell	12	0.10	64.68	66.10	62.54		
24	24.04.2015 22:02	close	12	0.10	65.28	66.10	62.54	-60.00	10383.00
25	08.05.2015 0:00	buy	13	0.10	65.67	64.07	68.06		
26	08.05.2015 22:02	close	13	0.10	65.42	64.07	68.06	-25.00	10358.00
27	01.06.2015 3:00	sell	14	0.10	65.25	66.72	63.05		
28	01.06.2015 23:00	close	14	0.10	65.06	66.72	63.05	19.00	10377.00
29	18.06.2015 0:00	sell	15	0.10	63.73	65.02	61.80		
30	18.06.2015 22:02	close	15	0.10	64.32	65.02	61.80	-59.00	10318.00
31	07.07.2015 0:00	buy	16	0.10	56.80	55.60	58.59		
32	07.07.2015 17:15	s/l	16	0.10	55.60	55.60	58.59	-120.00	10198.00
33	08.07.2015 0:00	sell	17	0.10	57.33	58.53	55.53		
34	08.07.2015 22:05	close	17	0.10	57.08	58.53	55.53	25.00	10223.00
35	04.08.2015 0:00	buy	18	0.10	49.71	48.58	51.40		
36	04.08.2015 22:03	close	18	0.10	50.05	48.58	51.40	34.00	10257.00
37	12.08.2015 0:00	buy	19	0.10	49.20	48.05	50.93		
38	12.08.2015 22:03	close	19	0.10	49.61	48.05	50.93	41.00	10298.00
39	20.08.2015 0:00	buy	20	0.10	46.92	45.74	48.69		
40	20.08.2015 22:02	close	20	0.10	46.38	45.74	48.69	-54.00	10244.00
41	25.08.2015 0:00	buy	21	0.10	42.58	41.35	44.43		
42	25.08.2015 12:50	t/p	21	0.10	44.43	41.35	44.43	185.00	10429.00
43	28.08.2015 0:00	sell	22	0.10	47.53	48.99	45.34		
44	28.08.2015 17:40	s/l	22	0.10	48.99	48.99	45.34	-146.00	10283.00
45	31.08.2015 3:00	sell	23	0.10	49.49	51.16	46.99		
46	31.08.2015 18:40	s/l	23	0.10	51.16	51.16	46.99	-167.00	10116.00
47	01.09.2015 0:00	sell	24	0.10	52.89	54.95	49.80		
48	01.09.2015 18:50	t/p	24	0.10	49.80	54.95	49.80	309.00	10425.00
49	02.09.2015 0:00	buy	25	0.10	48.57	46.31	51.96		
50	02.09.2015 22:05	close	25	0.10	50.44	46.31	51.96	187.00	10612.00

Appendix E. Trading results for Strategy 1

Table E.1. Trading results for Strategy 1

Period	Parameters	Strategy 1	Strategy 2
	profit_koef	3	1,5
	stop	2	2
2014	% successful	53,19%	42,86%
	profit, USD	508	-1239
	number of trades	47	49
	t-test	failed	failed
2015	% successful	54,55%	48,48%
	profit, USD	719	-540
	number of trades	33	33
	t-test	failed	failed
2016	% successful	51,11%	47,83%
	profit, USD	185	-594
	number of trades	45	46
	t-test	failed	failed
2014-2016	% successful	52,80%	46,09%
	profit, USD	1432	-2373
	number of trades	125	128
	t-test	passed	failed

Appendix F. z-tests for trading results

Table F.1 z-test for trading results: case of Strategy 1

Parameter	*2014*	*2015*	*2016*	*2014-2016*
Number of the trades	47	33	45	125
Total profit	508	719	185	1432
Average profit per trade	10,81	21,79	4,11	11,46
Standard deviation	119,62	143,51	105,55	122,01
t-test	1,19	1,27	0,90	1,97
t critical (0,95)	1,78	1,78	1,78	1,78
Null hypothesis	confirmed	confirmed	confirmed	rejected

Table F.2 z-test for trading results: case of Strategy 2

Parameter	*2014*	*2015*	*2016*	*2014-2016*
Number of the trades	49	33	46	128
Total profit	-1239	-540	-594	-2373
Average profit per trade	-25,29	-16,36	-12,91	-18,54
Standard deviation	104,00	131,34	87,88	106,74
t-test	-1,03	-0,28	-0,22	-0,91
t critical (0,95)	1,78	1,78	1,78	1,78
Null hypothesis	confirmed	confirmed	confirmed	confirmed