LONG-TERM PRICE OVERREACTIONS:

ARE MARKETS INEFFICIENT?

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Abstract

This paper examines long-term price overreactions in various financial markets (commodities, US stock market and FOREX). First, a number of statistical tests are carried out for overreactions as a statistical phenomenon. Second, a trading robot approach is applied to test the profitability of two alternative strategies, one based on the classical overreaction anomaly, the other on a so-called "inertia anomaly". Both weekly and monthly data are used. Evidence of anomalies is found predominantly in the case of weekly data. In the majority of cases strategies based on overreaction anomalies are not profitable, and therefore the latter cannot be seen as inconsistent with the EMH.

Keywords: Efficient Market Hypothesis, anomaly, overreaction hypothesis, abnormal returns, contrarian strategy, trading strategy, trading robot, inertia anomaly

JEL classification: G12, G17, C63

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1. Introduction

The Efficient Market Hypothesis (EMH) is one of the central tenets of financial economics (Fama, 1965). However, the empirical literature has provided extensive evidence of various "anomalies", such as fat tails, volatility clustering, long memory etc. that are inconsistent with the EMH paradigm and suggests that it is possible to make abnormal profits using appropriate trading strategies (Plastun, 2017). A well-known anomaly is the so-called overreaction hypothesis, namely the idea that agents make investment decisions giving disproportionate weight to more recent information (see De Bondt and Thaler, 1985). Clements et al. (2009) report that the overreaction anomaly has not only persisted but in fact increased over the last twenty years. Its existence has been documented in several studies for different markets and frequencies such as monthly, weekly or daily data (see, e.g., Bremer and Sweeny, 1991; Clare and Thomas, 1995; Larson and Madura, 2006; Mynhardt and Plastun, 2013; Caporale et al. 2017).

There exist a significant number of studies on market overreactions but most of them analyse *short-term* price overreactions based on daily data (Atkins and Dyl, 1990; Bremer and Sweeney, 1991; Cox and Peterson, 1994; Choi and Jayaraman, 2009) and focus only on a single market/asset. By contrast, this paper analyses *long-term* overreactions and a variety of markets and frequencies by (i) carrying out various statistical tests to establish whether overreaction anomalies exist using both weekly and monthly data, and (ii) using a trading robot method to examine whether they give rise to exploitable profit opportunities, i.e. whether price overreactions are simply a statistical phenomena or can also be seen as evidence against the EMH. The analysis is carried out for various financial markets: the US stock market (the Dow Jones Index and 10 companies included in this index), FOREX (10 currency pairs) and commodity markets (gold and oil). A similar investigation was carried out by Caporale et al. (2018); however, their analysis focused on short-term (i.e., daily) overreactions, whilst the present study considers a longer horizon, namely a week or a month.

The remainder of the paper is organised 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

The seminal paper on the overreaction hypothesis is due to De Bondt and Thaler (DT, 1985), who followed the work of Kahneman and Tversky (1982), and showed 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. Their explanation was that significant deviations of asset prices from their fundamental value occur because of agents' irrational behaviour, with recent news being given an excessive weight. DT also reported an asymmetry in the overreaction (it is bigger for undervalued than for overvalued stocks), and a "January effect", with a clustering of overreactions in that particular month.

Other studies include Brown, Harlow and Tinic (1988), who analysed NYSE data for the period 1946-1983 and reached similar conclusions to DT; Ferri and Min (1996), who confirmed the presence of overreactions using S&P 500 data for the period 1962-1991; Larson and Madura (2003), who used NYSE data for the period 1988-1998 and also showed the presence of overreactions. Clement et al. (2009) confirmed the original findings of DT using CRSP data for the period 1926-1982, and also showed that the overreaction anomaly had increased during the following twenty years.

In addition to papers analysing stock markets (Alonso and Rubio, 1990, Brailsford, 1992, Bowman and Iverson, 1998, Antoniou et. al., 2005, Mynhardt and Plastun, 2013 among others), some consider other markets such as the gold (Cutler, Poterba, and

Summers (1991)), or the options market (Poteshman, 2001). Finally, Conrad and Kaul (1993) showed that the returns used in many studies (supporting the overreaction hypothesis) are upwardly biased, and "true" returns have no relation to overreaction; therefore this issue is still unresolved.

The other aspect of the overreaction hypothesis is its practical implementation, i.e. the possibility of obtaining extra profits by exploiting this anomaly. Jegadeesh and Titman (1993) and Lehmann (1990) found that a strategy based on overreactions can indeed generate abnormal profits. Baytas and Cakiki (1999) also tested a trading strategy based on the overreaction hypothesis, and showed that contrarian portfolios on the long-term horizons can generate significant profits.

The most recent and thorough investigation is due to Caporale et al. (2018), who analyse different financial markets (FOREX, stock and commodity) using the same approach as in the present study. That study shows that a strategy based on counter-movements after overreactions does not generate profits in the FOREX and the commodity markets, but it is profitable in the case of the US stock market. Also, it detects a brand new anomaly based on the overreaction hypothesis, i.e. an "inertia" anomaly (after an overreaction day prices tend to move in the same direction for some time). Here we extend the analysis by considering long-term overreactions and the possibility of making extra profits over weekly and monthly intervals. The variety of assets and markets (FOREX, stock market, commodities) as well as of time frequencies (weekly, monthly) considered in this study can help to address issues such as robustness, data snooping, data mining etc. Moreover, since according to the Adaptive Markets Hypothesis (Lo, 2004) financial markets evolve and anomalies may disappear during this process, it is important to include the most recent data as we do.

3. Data and Methodology

We analyse the following weekly and monthly series: for the US stock market, the Dow Jones index and stocks of two companies included in this index (Microsoft and Boeing - for the trading robot analysis we also add Alcoa, AIG, Walt Disney, General Electric, Home Depot, IBM, Intel, Exxon Mobil); for the FOREX, EURUSD, USDCHF and AUDUSD (for the trading robot analysis also USDJPY, USDCAD, GBPJPY, GBPUSD, EURJPY, GBPCHF, EURGBP); for commodities, gold and oil (only gold for the trading robot analysis owing to data unavailability). The choice of assets is based on their liquidity, trading volume, data availability, and extent of use. The sample covers the period from January 2002 till the end of December 2016, and for the trading robot analysis the period is 2002-2014 for the FOREX and 2006-2014 for the US stock market and commodity market. These dates are selected on the basis of data availability (especially for the purpose of trading robot analysis) and to include the most recent data since markets can evolve as stressed by the Adaptive Market Hypothesis.

3.1 Student's t-tests

First we carry out Student's t-tests to confirm (reject) the presence of anomalies after overreactions. To provide additional evidence we also conduct ANOVA analysis, and carry out Mann–Whitney U tests not relying on the normality assumption.

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_0– mean volatility for a normal day (the day when there was no volatility explosion);

a_1 – dummy coefficient;

D_{1t} - a dummy variable for a specific data group, equal to 1 when the data belong to a 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 coefficient provide information about possible anomalies.

Then we apply the trading robot approach to establish whether the detected anomalies create exploitable profit opportunities. According to the classical overreaction hypothesis, an overreaction should be followed by a correction, i.e. price counter-movements, and this should be bigger than after normal days. If one day is not enough for the market to incorporate new information, i.e. to overreact, then after one-day abnormal price changes one can expect movements in the direction of the overreaction bigger than after normal days.

The two hypotheses to be tested are therefore:

H1: Counter-reactions after overreactions differ from those after normal periods.

H2: Price movements after overreactions in the direction of the overreaction differ from such movements after normal periods.

The null hypothesis is in both cases that the data after normal and overreaction periods belong to the same population.

As already mentioned, we focus on long-term overreactions, so the period of analysis is one week or one month. The parameters characterising price behaviour over such a time interval are maximum, minimum, open and close prices. In most studies price movements are measured as the difference between the open and close price. In our opinion the weekly (monthly) return, i.e. the difference between the maximum and minimum prices during the week (month), is more appropriate. This is calculated as:

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

where R_i is the % weekly (monthly) return, $High_i$ is the maximum price, and Low_i is the minimum price for week (month) *i*.

We consider three definitions of "overreaction":

1) when the current weekly (monthly) return exceeds the average plus one standard deviation

$$R_i > (\overline{R}_n + \delta_n), \tag{3}$$

where $\overline{R}_n$ is the average size of weekly (monthly) returns for period *n*

$$\overline{R}_n = \sum_{i=1}^{n} R_i / n , \tag{4}$$

and δ_n is the standard deviation of weekly (monthly) returns for period *n*

$$\delta_n = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (R_i - \overline{R})^2} \ . \tag{5}$$

2) when the current weekly (monthly) return exceeds the average plus two standard deviations, i.e.,

$$R_i > (\overline{R}_n + 2 \times \delta_n) . \tag{6}$$

3) when the current weekly (monthly) return exceeds the average plus three standard deviations, i.e.,

$$R_i > (\overline{R}_n + 3 \times \delta_n) . \tag{7}$$

The next step is to determine the size of the price movement during the following week (month). For Hypothesis 1 (the counter-reaction or counter-movement assumption), we measure it as the difference between the next period's open price and the maximum deviation from it in the opposite direction to the price movement in the overreaction period.

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

$$cR_{i+1} = 100\% \times \frac{(Open_{i+1} - Low_{i+1})}{Low_{i+1}}, \tag{8}$$

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

If the price decreased, then the corresponding definition is:

$$cR_{i+1} = 100\% \times \frac{(High_{i+1} - Open_{i+1})}{Open_{i+1}}. \tag{9}$$

In the case of Hypothesis 2 (movement in the direction of the overreaction), either equation (9) or (8) is used depending on whether the price has increased or decreased.

Two data sets (with cR_{i+1} values) are then constructed, including the size of price movements after normal and abnormal price changes respectively. The first data set consists of cR_{i+1} values after period with abnormal price changes. The second contains cR_{i+1} values after a period with normal price changes. The null hypothesis to be tested is that they are both drawn from the same population.

3.2 Trading Robot Analysis

The trading robot approach considers the long-term overreactions from a trader's viewpoint, i.e. whether it is possible to make abnormal profits by exploiting the overreaction anomaly, and simulates the actions of a trader using an algorithm representing a trading strategy. This is 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 to the implementation of trading strategies. The terminal also allows to check the efficiency of trading robots 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 one-minute 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.

We examine two trading strategies:

- **Strategy 1 (based on H1):** This is based on the classical overreaction anomaly, i.e. the presence of abnormal counter-reactions after the overreaction period. The algorithm is constructed as follows: at the end of the overreaction period financial assets are sold or bought depending on whether abnormal price increases or decreased respectively have occurred. An open position is closed if a target profit value is reached or at the end of the following period (for details of how the target profit value is defined see below).
- **Strategy 2 (based on H2):** This is based on the non-classical overreaction anomaly, i.e. the presence the abnormal price movements in the direction of the overreaction in the following period. The algorithm is built as follows: at the end of the overreaction period financial assets are 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 period.

The results of the trading strategy testing and some key data are presented in the "Report" in Appendix A. The most important indicators given in the “Report” are:

- Total net profit: this is the difference between "Gross profit" and "Gross loss" measured in US dollars. We used marginal trading with the leverage 1:100, therefore it is necessary to invest $1000 to make the profit mentioned in the Trading Report. The annual return is defined as Total net profit/100, so, for instance, an annual total net profit of $100 represents a 10% annual return on the investment;
- Profit trades: % of successful trades in total trades;
- Expected payoff: the mathematical expectation of a win. This parameter represents the average profit/loss per trade. It is also the expected profitability/unprofitability of the next trade;
- Total trades: total amount of trade positions;
- Bars in test: the number of past observations modelled in bars during testing.

The results are summarised in the “Graph” section of the “Report”: this represents the account balance and general account status considering open positions. The “Report” also provides full information on all the simulated transactions and their financial results. The following parameters affect the profitability of the trading strategies (the next section explains how they are set):

- Criterion for overreaction (symbol: sigma_dz): the number of standard deviations added to the mean to form the standard period interval;
- Period of averaging (period_dz): the size of the data set used to calculate base mean and standard deviation;
- Time in position (time_val): how long the opened position has to be held.

We carry out t-tests to examine whether the results we obtain are statistically different from the random ones. We chose this approach because the sample size is usually less than 100. A t-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 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.

Example of the t-test results are reported in Table 1. As can be seen the results obtained are not differing from the random ones.

Table 1: t-test for the trading simulation results for Strategy 1 (case of EURUSD, testing period 2001-2014)*

Parameter	Value
Number of the trades	96
Total profit	-1331.03
Average profit per trade	-13.86
Standard deviation	192,27
t-test	-0.70
z critical (0,95)	1.78
Null hypothesis	Accepted

* For data sources see Appendix A

As can be seen, H0 cannot be rejected, which implies that the trading simulation results are not statistically different from the random ones and therefore this trading strategy is not effective and there is no exploitable profit opportunity.

4. Empirical Results

The first step is to set the basic overreaction parameters/criterions by choosing the number of standard deviations (sigma_dz) to be added to the average to form the “standard” period interval for price fluctuations and the averaging period to calculate the mean and the standard deviation (symbol: period_dz).

For this purpose we used the Dow Jones Index data for the time period 1991-2014. The number of abnormal returns detected in the period 1991-2014 is reported in Table 2 (for weekly data) and Table 3 (for monthly data).

Table 2: Number of abnormal returns detections in Dow-Jones index during 1991-2014 (weekly data)

Period_dz	3		5		10		20		30	
Indicator	Number	%	Number	%	Number	%	Number	%	Number	%
Overall	1241	100	1239	100	1233	100	1223	100	1213	100
Number of abnormal returns (criterion =mean+sigma_dz)	251	20	239	19	206	17	198	16	198	16
Number of abnormal returns (criterion= mean+2*sigma_dz)	0	0	0	0	56	5	65	5	69	6
Number of abnormal returns (criterion = mean+3*sigma_dz)	0	0	0	0	0	0	13	1	19	2

Table 3: Number of abnormal returns detections in Dow-Jones index during 1991-2014 (monthly data)

Period_dz	3		5		10		20		30	
Indicator	Number	%	Number	%	Number	%	Number	%	Number	%
Overall	285	100	283	100	278	100	268	100	258	100
Number of abnormal returns (criterion =mean+sigma_dz)	56	20	52	18	45	16	42	15	44	15
Number of abnormal returns (criterion= mean+2*sigma_dz)	0	0	0	0	16	6	20	7	22	8
Number of abnormal returns (criterion = mean+3*sigma_dz)	0	0	0	0	0	0	4	1	6	2

As can be seen from the above tables, both parameters (averaging period and number of standard deviations added to the mean) affect the number of detected anomalies. Changes in the averaging period have relatively small effect on the number of detected anomalies (the difference between the results when the period considered is 5 and 30 respectively is less than 20%). By contrast, each additional standard deviation significantly decreases the number of observed abnormal returns. Therefore 2-4% of the full sample (the number of abnormal returns in the case of 3 sigmas) is not sufficiently representative to draw conclusions. To investigate whether sigma_dz equal to 1 is most appropriate we carry out t-tests of long-term counter-reactions for the Dow Jones index over the period 1991-2014 (see Tables 4 and 5 for weekly and monthly data respectively). As can be seen, the anomaly is most easily detected in the case of sigma_dz= 1 (the t-stat is the biggest), and therefore we set sigma_dz equal to 1.

Table 4: T-test of the counter-reactions after the overreaction for the Dow-Jones index during 1991-2014 (weekly data) for the different values of sigma_dz parameter case of period_dz=30

Number of standard deviations	1		2		3	
	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	198	1015	69	1144	19	1194
Mean	2,36%	1,74%	2,77%	1,78%	3,57%	1,81%
Standard deviation	2,22%	1,52%	2,43%	1,59%	3,15%	1,62%
t-criterion	3,91		3,38		2,44	
t-critical (p=0.95)	1,96		1,96		1,96	
Null hypothesis	rejected		rejected		rejected	

Table 5: T-test of the counter-reactions after the overreaction for the Dow-Jones index during 1991-2014 (monthly data) for the different values of sigma_dz parameter case of period_dz=30

Number of standard deviations	1		2		3	
	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	44	214	22	236	6	252
Mean	4,39%	3,22%	4,25%	3,34%	7,97%	3,31%
Standard deviation	4,09%	2,83%	4,37%	2,96%	6,78%	2,90%
t-criterion	1,90		0,98		1,68	
t-critical (p=0.95)	1,96		1,96		1,96	
Null hypothesis	accepted		accepted		accepted	

Student’s t –tests of long-term counter-reactions for the Dow Jones index over the period 1991-2014 (Tables 6 and 7 for weekly and monthly data respectively) suggest that the optimal averaging period is 30, their corresponding t-statistics being significantly higher than for other averaging periods.

Table 6: T-test of the counter-reactions after the overreaction for the Dow-Jones index during 1991-2014 (weekly data) for the different averaging periods case of sigma_dz=1

Period_dz	3		5		10		20		30	
	abnormal	normal	abnormal	normal	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	251	990	239	1000	206	1027	198	1025	198	1015
Mean	2,05%	1,78%	2,05%	1,78%	2,11%	1,78%	2,24%	1,76%	2,36%	1,74%
Standard deviation	1,78%	1,62%	1,82%	1,61%	1,89%	1,60%	1,94%	1,59%	2,22%	1,52%
t-criterion	2,45		2,26		2,50		3,51		3,91	
t-critical (p=0.95)	1,96		1,96		1,96		1,96		1,96	
Null hypothesis	rejected		rejected		rejected		rejected		rejected	

Table 7: T-test of the counter-reactions after the overreaction for the Dow-Jones index during 1991-2014 (monthly data) for the different averaging periods case of sigma_dz=1

Period_dz	3		5		10		20		30	
	abnormal	normal	abnormal	normal	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	56	229	52	230	45	233	42	226	44	214
Mean	3,59%	3,40%	3,51%	3,42%	3,73%	3,37%	3,80%	3,32%	4,39%	3,22%
Standard deviation	3,37%	2,94%	3,41%	2,95%	3,66%	2,93%	3,80%	2,90%	4,09%	2,83%
t-criterion	0,40		0,20		0,66		0,82		1,90	
t-critical (p=0.95)	1,96		1,96		1,96		1,96		1,96	
Null hypothesis	accepted		accepted		accepted		accepted		accepted	

Therefore the key parameters for the tests of long-term overreaction in different financial markets analysis are set as follows: the period_dz (averaging period) is set equal to 30 and sigma_dz (the number of standard deviations added to mean used as a criterion of overreaction) equal to 1.

The results for H1 are presented in Appendix B (weekly data) and C (monthly data) and are summarised in Tables 8-9.

Table 8: Statistical tests results: case of Hypothesis 1 (weekly data)*

Financial market	FOREX			Commodities		US stock market	
Financial asset	EURUSD	USDCHF	AUDUSD	Gold	Oil	Boeing	Microsoft
T-test	-	-	-	+	+	-	-
ANOVA	-	+	+	+	+	+	-
Mann–Whitney U test	-	-	-	+	+	+	-
Regression analysis with dummy variables	-	+	+	+	+	+	-

* ”+” – anomaly confirmed, “-” - anomaly not confirmed.

As can be seen in the case of weekly data strong statistical evidence in favour of the overreaction anomaly can be found for both Gold and Oil prices, and to some extent for the US stock market (in the case of Boeing) and the FOREX (in the case of USDCHF and AUDUSD).

Table 9: Statistical tests results: case of Hypothesis 1 (monthly data)*

Financial market	FOREX			Commodities		US stock market	
Financial asset	EURUSD	USDCHF	AUDUSD	Gold	Oil	Boeing	Microsoft
T-test	-	-	-	-	-	-	-
ANOVA	-	+	-	+	-	-	-
Mann–Whitney U test	+	-	-	-	-	-	-
Regression analysis with dummy variables	-	+	-	+	-	-	-

* ”+” – anomaly confirmed, “-” - anomaly not confirmed.

The results for the monthly data are significantly different from those for the weekly ones. The evidence of anomalies almost completely disappears, except for EURUSD and USDCHF (in the case of the FOREX) and Gold (in the case of commodities).

Overall, it appears that in the case of H1 weekly data provides the strongest evidence for the classical short-term counter-movement after an overreaction day, which is most noticeable in the case of commodities.

The results for H2 are presented in Appendix D (weekly data) and E (monthly data) and are summarised in Tables 10-11.

Table 10: Statistical tests results: case of Hypothesis 2 (weekly data)*

Financial market	FOREX			Commodities		US stock market	
Financial asset	EURUSD	USDCHF	AUDUSD	Gold	Oil	Boeing	Microsoft
T-test	+	-	+	-	+	-	+
ANOVA	+	+	+	+	+	-	+
Mann–Whitney U test	+	-	+	-	+	-	+
Regression analysis with dummy variables	+	+	+	+	+	-	+

* ”+” – anomaly confirmed, “-” - anomaly not confirmed.

Hypothesis 2 is not rejected in many cases with weekly data. We find very strong evidence in favour of an “inertia anomaly” (prices tend to move in the direction of the overreaction in the following period). This applies to EURUSD and AUDUSD, Oil and Microsoft data, and represents evidence of market inefficiency caused by overreactions.

Table 11: Statistical tests results: case of Hypothesis 2 (monthly data)*

Financial market	FOREX			Commodities		US stock market	
Financial asset	EURUSD	USDCHF	AUDUSD	Gold	Oil	Boeing	Microsoft
T-test	-	-	-	+	+	-	-
ANOVA	-	+	+	+	+	-	+
Mann–Whitney U test	-	-	+	+	+	-	-
Regression analysis with dummy variables	-	+	+	+	+	-	+

* ”+” – anomaly confirmed, “-” - anomaly not confirmed.

The results for the monthly data again are significantly differing from those for the weekly ones. Evidence in favour of the inertia anomaly is present for commodities and only for AUSUSD in the FOREX.

Overall the results from testing Hypothesis 2 suggest that the weekly frequency is the most appropriate to detect the inertia anomaly. The commodity market again look like the most inefficient among those analysed.

The general conclusion from the statistical tests are as follows: anomalies are generally detected using weekly but not monthly data; the commodity markets are the most affected by the overreaction anomalies; the results for the FOREX and US stock markets are mixed.

Next, we analyse whether these anomalies give rise to exploitable profit opportunities. If they do not, we conclude that they do not represent evidence inconsistent with the EMH. We expand the list of assets in order to provide more extensive results. The complete list of assets includes: FOREX (EURUSD, USDCHF, AUDUSD, USDJPY, USDCAD, GBPJPY, GBPUSD, EURJPY, GBPCHF, EURGBP), US stock market (Alcoa, AIG, Boeing Company, Walt Disney, General Electric, Home Depot, IBM, Intel, Microsoft, Exxon Mobil), commodity (Gold).

The parameters of the trading strategies 1 and 2 are set as follows:

- Period_dz = 30 (see above for an explanation);
- Time_val = week (see above);
- Sigma_dz=1 (see above).

The results of the trading robot analysis are presented in Table 12 (Strategy 1) and Table 13 (Strategy 2). The testing periods are as follows FOREX: 2001-2014; US stock market: 2006-2014; Commodities: 2006-2014.

Table 12: Trading results for Strategy 1

Asset	Total trades	Succesfull trades, %	Profit, USD	Return	Annual return	t-test
FOREX						
EURUSD	108	63%	-1584	-158,4%	-11,3%	Accepted
USDCHF	112	63%	-1815	-181,5%	-13,0%	Accepted
AUDUSD	114	66%	-1 690	-169,0%	-12,1%	Accepted
USDJPY	**116**	**69%**	**1 662**	**166,2%**	**11,9%**	**Rejected**
USDCAD	118	66%	-2 121	-212,1%	-15,2%	Accepted
GBPJPY	**111**	**71%**	**3 541**	**354,1%**	**25,3%**	**Rejected**
GBPUSD	116	68%	-135	-13,5%	-1,0%	Accepted
EURJPY	107	64%	-1 829	-182,9%	-13,1%	Accepted

GBPCHF	**106**	**74%**	**3 721**	**372,1%**	**26,6%**	**Rejected**
EURGBP	118	71%	169	16,9%	1,2%	Accepted
US stock market						
Alcoa	64	63%	-2280	-228,0%	-25,3%	Accepted
AIG	64	67%	480	48,0%	5,3%	Accepted
Boeing Company	**87**	**71%**	**3290**	**329,0%**	**36,6%**	**Rejected**
Walt Disney	63	70%	-289	-28,9%	-3,2%	Accepted
General electric	67	64%	-39	-3,9%	-0,4%	Accepted
Home Depot	79	64%	290	29,0%	3,2%	Accepted
IBM	65	63%	-3090	-309,0%	-34,3%	Accepted
Intel	70	54%	-1055	-105,5%	-11,7%	Accepted
Microsoft	74	66%	430	43,0%	4,8%	Accepted
Exxon Mobil	72	67%	773	77,3%	8,6%	Accepted
Commodities						
Gold	78	64,0%	-2091	-209,1%	-23,2%	Accepted

Strategy 1, based on the classical overreaction hypothesis, trades on counter-reactions after periods of abnormal price dynamics. In general, it is unprofitable in the case of the FOREX (7 pairs out of 10 produce negative or statistically insignificant results) and commodity markets (in the case of Gold). For the US stock market the results are mixed (50% of profitable assets), but in general this anomaly does not seem to be exploitable. The assets to be traded on the basis of the classical overreaction hypothesis with weekly data are therefore: GBPCHF (ROI=27% per year), GBPJPY (25%), USDJPY (12%) and Boeing (36.6%). Although as previously shown a non-rejection of the null does not necessarily mean that there exist profit opportunities, it appears that it does mean a higher chance of profitable trading.

Table 13: Trading results for Strategy 2

Asset	Total trades	Succesfull trades, %	Profit, USD	Return	Annual return	t-test
FOREX						
EURUSD	**112**	**58%**	**848**	**84,8%**	**6,1%**	**Rejected**
USDCHF	**119**	**57%**	**690**	**69,0%**	**4,9%**	**Rejected**
AUDUSD	**117**	**56%**	**416**	**41,6%**	**3,0%**	**Accepted**
USDJPY	116	50%	-479	-47,9%	-3,4%	Accepted
USDCAD	**117**	**58%**	**1 829**	**182,9%**	**13,1%**	**Rejected**
GBPJPY	114	47%	-6 766	-676,6%	-48,3%	Accepted
GBPUSD	116	53%	-566	-56,6%	-4,0%	Accepted
EURJPY	**107**	**58%**	**476**	**47,6%**	**3,4%**	**Accepted**

GBPCHF	106	48%	-2 991	-299,1%	-21,4%	Accepted
EURGBP	118	49%	-2 609	-260,9%	-18,6%	Accepted
US stock market						
Alcoa	**68**	**51%**	**877**	**87,7%**	**9,7%**	**Rejected**
AIG	**65**	**60%**	**2390**	**239,0%**	**26,6%**	**Rejected**
Boeing Company	87	44%	-2470	-247,0%	-27,4%	Accepted
Walt Disney	62	47%	-1475	-147,5%	-16,4%	Accepted
General electric	**69**	**51%**	**410**	**41,0%**	**4,6%**	**Accepted**
Home Depot	79	47%	-1557	-155,7%	-17,3%	Accepted
IBM	65	38%	-9236	-923,6%	-102,6%	Accepted
Intel	70	50%	-36,4	-3,6%	-0,4%	Accepted
Microsoft	74	40%	-1814	-181,4%	-20,2%	Accepted
Exxon Mobil	71	50%	-1711	-171,1%	-19,0%	Accepted
Commodities						
Gold	**78**	**58,0%**	**1011**	**101,1%**	**11,2%**	**Rejected**

Strategy 2, based on the so-called "inertia anomaly", trades on price movements in the direction of the overreaction in the following period. In general it is unprofitable for the US stock market (7 assets out of the 10 analysed produce negative results), whilst the results are mixed for the FOREX (there are 50% of profitable assets, but only 3 of the 5 profitable assets pass the t-test on randomness). There is evidence of profit opportunities in the commodity markets. The assets to be traded on the basis of the inertia anomaly with weekly data are therefore: USDCAD (ROI=13% per year), USDCHF (5%), EURUSD (6%), AIG (27%), Alcoa (10%) and Gold (11%).

5. Conclusions

This paper examines long-term price overreactions in various financial markets (commodities, US stock market and FOREX). It addresses the issue of whether they should be seen simply as a statistical phenomenon or instead as anomalies giving rise to exploitable profit opportunities, only the latter being inconsistent with the EMH paradigm. The analysis is conducted in two steps. First, a number of statistical tests are carried out for overreactions as a statistical phenomenon. Second, a trading robot approach is applied to test the profitability of two alternative strategies, one based on the classical overreaction anomaly (H1: counter-reactions after overreactions differ from those after normal periods), the other on an "inertia" anomaly (H2: price movements after overreactions in the same direction of the overreaction differ from those after normal periods). Both weekly and monthly data are used. Evidence of anomalies is found predominantly in the case of weekly data.

More specifically, H1 cannot be rejected for the US stock market and commodity markets when the averaging period is 30, whilst it is rejected for the FOREX. The results for H2 are more mixed and provide evidence of an "inertia" anomaly in the commodity market and for some assets in the US stock market and FOREX. The trading robot analysis shows that in general strategies based on the overreaction anomalies are not profitable, and therefore the latter cannot be seen as inconsistent with the EMH. However, in some cases abnormal profits can be made; in particular this is true of (i) GBPCHF (ROI=27% per year), GBPJPY (25%), Boeing (36%), ExxonMobil (8.6%) in the case of the classical overreaction hypothesis and weekly data, and (ii) USDCAD (13%), USDCHF (5%), EURUSD (6%), AIG (27%), Alcoa (10%) and Gold (11%) in the case of the inertia anomaly and also with weekly data.

A comparison between these results and the daily ones reported in Caporale et al. (2017) suggests that the classic overreaction anomaly (H1) occurs at both short- and long-term intervals in the case of the US stock market and commodity markets. The results for the FOREX are mixed at both intervals, but mostly suggest no contrarian movements after overreactions. The findings concerning the "inertia" anomaly (H2) are more stable and consistent: it is detected for the commodity markets and US stock market at both short- and long-term horizons. As for the FOREX, there is a short- but not a long-term anomaly in most cases. The trading results imply that there is no single profitable strategy: the findings are quite sensitive to the specific asset being considered, and therefore it is necessary to investigate case by case whether it is possible to earn abnormal profits by exploiting the classical overreaction and/or inertia anomaly. Future research will extend the analysis focusing in particular on unusually low returns.

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Appendix A

Example of strategy tester report: case of EURUSD, period 2001-2014, H1 testing

Table A.1 – Overall statistics

Symbol	EURUSD (Euro vs US Dollar)				
Period	1 Hour (H1) 2001.01.01 00:00 - 2014.11.24 23:00 (2001.01.01 - 2015.01.01)				
Model	Every tick (the most precise method based on all available least timeframes)				
Parameters	profit_koef=10; stop=10; sigma_koef=1; period_dz=30; time_val=600000;				
Bars in test	87109	Ticks modelled	92878183	Modelling quality	90.00%
Initial deposit	10000.00			Spread	Current (15)
Total net profit	-1331.03	Gross profit	6349.26	Gross loss	-7680.29
Profit factor	0.83	Expected payoff	-13.86		
Absolute drawdown	1972.07	Maximal drawdown	2457.96 (23.44%)	Relative drawdown	23.44% (2457.96)
Total trades	96	Short positions (won %)	45 (42.22%)	Long positions (won %)	51 (58.82%)
		Profit trades (% of total)	49 (51.04%)	Loss trades (% of total)	47 (48.96%)
Largest		profit trade	200.06	loss trade	-999.97
Average		profit trade	129.58	loss trade	-163.41
Maximum		consecutive wins (profit in money)	5 (492.76)	consecutive losses (loss in money)	5 (-1298.77)
Maximal		consecutive profit (count of wins)	598.95 (3)	consecutive loss (count of losses)	-1298.77 (5)
Average		consecutive wins	2	consecutive losses	2

Figure A.1 – Equity dynamics

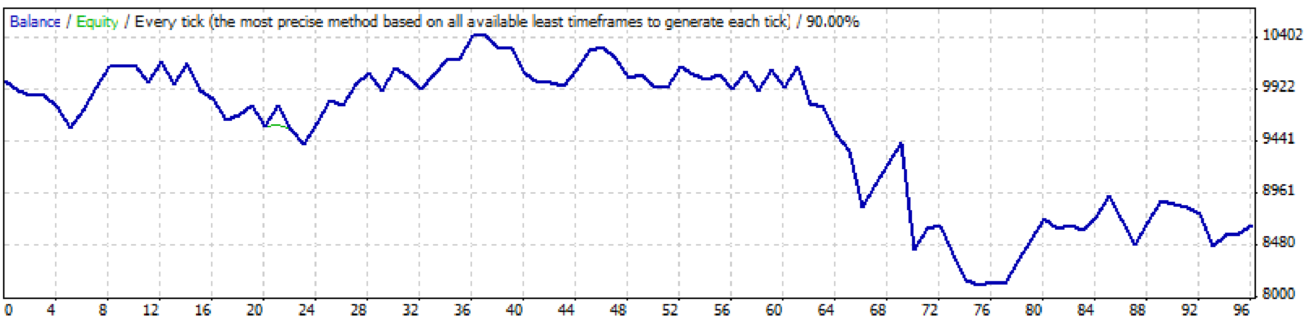

Table A.2 – Statement (fragment)

#	Time	Type	Order	Size	Price	S / L	T / P	Profit	Balance
1	16.03.2001 22:00	buy	1	0.10	0.89765	0.79765	0.91765		
2	23.03.2001 20:40	close	1	0.10	0.88880	0.79765	0.91765	-89.97	9910.03
3	25.01.2002 22:00	buy	2	0.10	0.86585	0.76585	0.88585		
4	01.02.2002 20:40	close	2	0.10	0.86160	0.76585	0.88585	-43.97	9866.06
5	17.05.2002 22:00	sell	3	0.10	0.92100	1.02100	0.90100		
6	24.05.2002 20:40	close	3	0.10	0.92095	1.02100	0.90100	0.57	9866.63
7	31.05.2002 22:00	sell	4	0.10	0.93250	1.03250	0.91250		
8	07.06.2002 20:40	close	4	0.10	0.94335	1.03250	0.91250	-108.43	9758.20
9	21.06.2002 22:00	sell	5	0.10	0.97130	1.07130	0.95130		
10	28.06.2002 20:40	close	5	0.10	0.99075	1.07130	0.95130	-194.43	9563.77
11	28.06.2002 22:00	sell	6	0.10	0.99100	1.09100	0.97100		
12	05.07.2002 20:40	close	6	0.10	0.97335	1.09100	0.97100	176.57	9740.34
13	05.07.2002 22:00	buy	7	0.10	0.97335	0.87335	0.99335		
14	09.07.2002 13:30	t/p	7	0.10	0.99335	0.87335	0.99335	199.58	9939.92
15	19.07.2002 22:00	sell	8	0.10	1.01460	1.11460	0.99460		
16	23.07.2002 8:59	t/p	8	0.10	0.99460	1.11460	0.99460	200.02	10139.94
17	26.07.2002 22:00	buy	9	0.10	0.98745	0.88745	1.00745		
18	02.08.2002 20:40	close	9	0.10	0.98710	0.88745	1.00745	-4.97	10134.97
19	20.09.2002 22:00	sell	10	0.10	0.98180	1.08180	0.96180		
20	27.09.2002 20:40	close	10	0.10	0.97985	1.08180	0.96180	19.57	10154.54
21	01.11.2002 22:00	sell	11	0.10	0.99660	1.09660	0.97660		
22	08.11.2002 20:41	close	11	0.10	1.01335	1.09660	0.97660	-167.43	9987.11
23	07.03.2003 22:00	sell	12	0.10	1.10060	1.20060	1.08060		
24	13.03.2003 19:55	t/p	12	0.10	1.08060	1.20060	1.08060	200.06	10187.17
25	14.03.2003 22:00	buy	13	0.10	1.07445	0.97445	1.09445		
26	21.03.2003 20:40	close	13	0.10	1.05286	0.97445	1.09445	-217.37	9969.80
27	21.03.2003 22:00	buy	14	0.10	1.05275	0.95275	1.07275		
28	27.03.2003 9:51	t/p	14	0.10	1.07275	0.95275	1.07275	198.74	10168.54
29	02.05.2003 22:00	sell	15	0.10	1.12310	1.22310	1.10310		
30	09.05.2003 20:40	close	15	0.10	1.14921	1.22310	1.10310	-261.03	9907.51
31	09.05.2003 22:00	sell	16	0.10	1.14930	1.24930	1.12930		
32	16.05.2003 20:40	close	16	0.10	1.15625	1.24930	1.12930	-69.43	9838.08
33	20.06.2003 22:00	buy	17	0.10	1.16065	1.06065	1.18065		
34	27.06.2003 20:40	close	17	0.10	1.14195	1.06065	1.18065	-188.47	9649.61
35	01.08.2003 22:00	buy	18	0.10	1.12625	1.02625	1.14625		
36	08.08.2003 20:40	close	18	0.10	1.13053	1.02625	1.14625	41.33	9690.94
37	22.08.2003 22:00	buy	19	0.10	1.08905	0.98905	1.10905		
38	29.08.2003 20:40	close	19	0.10	1.09770	0.98905	1.10905	85.03	9775.97
39	05.09.2003 22:00	sell	20	0.10	1.11070	1.21070	1.09070		
40	12.09.2003 20:40	close	20	0.10	1.12985	1.21070	1.09070	-191.43	9584.54

Appendix B

Statistical tests of Hypothesis 1, case of weekly data

Table B.1: T-test of Hypothesis 1, case of foreign exchange market (weekly data)

Type of asset	EURUSD		USDJPY		AUDUSD	
Indicator	abnormal	normal	abnormal	normal	Abnormal	normal
Number of matches	115	634	113	636	116	633
Mean	1,14%	1,13%	1,60%	1,19%	1,63%	1,27%
Standard deviation	1,00%	0,87%	3,60%	0,94%	2,07%	1,13%
t-criterion	0,10		1,20		1,79	
t-critical (p=0.95)	1.96					
Null hypothesis	accepted		accepted		accepted	

Table B.2: T-test of Hypothesis 1, case of US Stock Market and Commodities (weekly data)

Type of a market	Commodities				US Stock Market			
Type of asset	Gold		Oil		Boeing		Microsoft	
Indicator	abnormal	normal	abnormal	normal	Abnormal	normal	Abnormal	normal
Number of matches	114	638	119	630	76	389	102	649
Mean	2.46%	1.74%	4.45%	3.31%	3.44%	2.74%	2.96%	2.48%
Standard deviation	2.88%	1.67%	4.10%	3.21%	2.91%	2.83%	3.04%	2.60%
t-criterion	2.60		2.88		1.93		1.50	
t-critical (p=0.95)	1.96							
Null hypothesis	rejected		rejected		accepted		accepted	

Table B.3: ANOVA test of Hypothesis 1 (weekly data)

Type of a market	FOREX			Commodities		US Stock Market	
Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
F	0,04	7,53	6,20	14,65	6,17	4,28	3,14
P value	0,85	0.006	0,01	0.00	0.01	0.04	0.07
F critical	3,85	3,85	3,85	3,85	3,87	3,86	3,85
Null hypothesis	accepted	rejected	rejected	rejected	rejected	rejected	accepted

Table B.4: Mann–Whitney U test of Hypothesis 1 (weekly data)

Type of a market	FOREX			Commodities		US Stock Market	
Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
Adjusted H	0,07	1,87	0,74	5,32	42.08	7.59	1.58
d.f.	1	1	1	1	1	1	1
P value	0,79	0,17	0,39	0,02	0.00	0.01	0.21
Critical value	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Null hypothesis	accepted	accepted	accepted	rejected	rejected	rejected	accepted

Table B.5: Regression analysis with dummy variables of Hypothesis 1 (weekly data)

Parameter/ Type of asset	FOREX			Commodities		US Stock Market	
Parameter/ Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
Mean volatility (a_0)	0,0112 (0,0000)	0,0127 (0,0000)	0,0119 (0,0000)	0,0174 (0,0000)	0,0332 (0,0000)	0,0275 (0,0000)	0,0248 (0,0000)
Dummy coefficient (a_1)	0,0001 (0,1942)	0,0036 (0,0062)	0,0042 (0,0123)	0,0074 (0,0001)	0,0117 (0,0005)	0,0073 (0,0389)	0,0050 (0,0764)
F-test	0,03 (0.0000)	7,5368 (0.006)	6,28 (0.01)	14,66 (0.0001)	12,16 (0.0005)	4,28 (0.0389)	3,14 (0.0764)
Multiple R	0,007	0,10	0,09	0,14	0,13	0,12	0,06
Anomaly	not confirmed	confirmed	confirmed	confirmed	confirmed	confirmed	not confirmed

* P-values are in parentheses

Appendix C

Statistical tests of Hypothesis 1, case of monthly data

Table C.1: T-test of Hypothesis 1, case of foreign exchange market (monthly data)

Type of asset	EURUSD		USDCHF		AUDUSD	
Indicator	abnormal	normal	abnormal	normal	Abnormal	normal
Number of matches	22	129	16	135	26	125
Mean	2.82%	2.15%	3.77%	2.55%	4.12%	2.77%
Standard deviation	2.13%	2.16%	4.25%	3.19%	3.50%	2.36%
t-criterion	1.37		1.11		1.88	
t-critical (p=0.95)	1.96					
Null hypothesis	accepted		accepted		accepted	

Table C.2: T-test of Hypothesis 1, case of US Stock Market and Commodities (monthly data)

Type of a market	Commodities				US Stock Market			
Type of asset	Gold		Oil		Boeing		Microsoft	
Indicator	abnormal	normal	abnormal	normal	Abnormal	normal	Abnormal	normal
Number of matches	25	126	23	128	9	80	21	130
Mean	6.42%	4.06%	6.88%	6.30%	4.16%	4.96%	5.77%	5.08%
Standard deviation	6.80%	3.16%	6.77%	6.28%	4.67%	4.66%	5.26%	4.73%
t-criterion	1.70		0.38		0.48		0.56	
t-critical (p=0.95)	1.96							
Null hypothesis	accepted		accepted		accepted		accepted	

Table C.3: ANOVA test of Hypothesis 1 (monthly data)

Type of a market	FOREX			Commodities		US Stock Market	
Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
F	2.50	7.07	2.69	8.76	0.33	0.05	0.67
P value	0.11	0.01	0.10	0.00	0.56	0.81	0.41
F critical	3.90	3.84	3.90	3.90	3.90	3.95	3.90
Null hypothesis	accepted	rejected	accepted	rejected	accepted	accepted	accepted

Table C.4: Mann–Whitney U test of Hypothesis 1 (monthly data)

Type of a market	FOREX			Commodities		US Stock Market	
Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
Adjusted H	4.84	2.82	1.87	1.89	0.38	0.05	0.36
d.f.	1	1	1	1	1	1	1
P value	0.03	0.09	0.17	0.17	0.54	0.82	0.55
Critical value	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	accepted	accepted	accepted	accepted	accepted	accepted

Table C.5: Regression analysis with dummy variables of Hypothesis 1 (monthly data)

Parameter/ Type of asset	FOREX			Commodities		US Stock Market	
Parameter/ Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
Mean volatility (a_0)	0,0216 (0,0000)	0,0279 (0,0000)	0,0257 (0,0000)	0,0410 (0,0000)	0,0635 (0,0000)	0,0501 (0,0000)	0,0512 (0,0000)
Dummy coefficient (a_1)	0,0078 (0,1158)	0,0148 (0,0087)	0,0143 (0,1031)	0,0258 (0,0036)	0,0083 (0,5647)	-0.0039 (0,8125)	0,0092 (0,4149)
F-test	2,50 (0.1158)	7.07 (0.0087)	2.69 (0. 1031)	8.76 (0,0036)	0.33 (0,5647)	0.05 (0.8125)	0.67 (0.4149)
Multiple R	0,12	0,21	0,13	0,24	0,05	0,02	0,12
Anomaly	not confirmed	confirmed	not confirmed	confirmed	not confirmed	not confirmed	not confirmed

* P-values are in parentheses

Appendix D

Statistical tests of Hypothesis 2, case of weekly data

Table D.1: T-test of Hypothesis 2, case of foreign exchange market (weekly data)

Type of asset	EURUSD		AUDUSD		USDCHF	
Indicator	abnormal	normal	abnormal	normal	Abnormal	normal
Number of matches	115	634	116	633	113	635
Mean	1,29%	1,01%	1,72%	1,30%	1,33%	1,09%
Standard deviation	1,22%	0,93%	2,38%	1,17%	1,52%	0,88%
t-criterion	2,32		2,86		1.59	
t-critical (p=0.95)	1.96					
Null hypothesis	rejected		rejected		accepted	

Table D.2: T-test of Hypothesis 2, case of US Stock Market and Commodities (weekly data)

Type of a market	Commodities				US Stock Market			
Type of asset	Gold		Oil		Boeing		Microsoft	
Indicator	abnormal	normal	abnormal	normal	Abnormal	normal	Abnormal	normal
Number of matches	114	638	119	630	76	389	102	649
Mean	2,39%	1,98%	4,64%	3,17%	2,89%	2,77%	2,75%	2,20%
Standard deviation	2,48%	1,73%	4,82%	2,92%	3,45%	3,14%	2,48%	2,27%
t-criterion	1.69		3.21		0.27		2.12	
t-critical (p=0.95)	1.96							
Null hypothesis	accepted		rejected		accepted		rejected	

Table D.3: ANOVA test of Hypothesis 2 (weekly data)

Type of a market	FOREX			Commodities		US Stock Market	
Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
F	8.46	9.05	5.64	5.05	20.69	0.13	5.55
P value	0.00	0.00	0.01	0.02	0.00	0.71	0.02
F critical	3.85	3.85	3.85	3.85	3.85	3.86	3.85
Null hypothesis	rejected	rejected	rejected	rejected	rejected	accepted	rejected

Table D.4: Mann–Whitney U test of Hypothesis 2 (weekly data)

Type of a market	FOREX			Commodities		US Stock Market	
Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
Adjusted H	9,09	4,51	1,83	2,56	38,09	0,00	6,04
d.f.	1	1	1	1	1	1	1
P value	0,00	0,03	0,18	0,11	0,00	0,99	0,01
Critical value	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	rejected	accepted	accepted	rejected	accepted	rejected

Table D.5: Regression analysis with dummy variables of Hypothesis 2 (weekly data)

Parameter/ Type of asset	FOREX			Commodities		US Stock Market	
Parameter/ Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
Mean volatility (a_0)	0,0101 (0,0000)	0,0130 (0,0000)	0,0109 (0,0000)	0,0198 (0,0000)	0,0317 (0,0000)	0,0278 (0,0000)	0,0220 (0,0000)
Dummy coefficient (a_1)	0,0028 (0,0037)	0,0043 (0,0027)	0,0024 (0,0173)	0,0042 (0,0247)	0,0150 (0,0000)	0,0014 (0,7125)	0,0057 (0,0186)
F-test	8.46 (0.0037)	9.05 (0.0027)	5.69 (0.0173)	5.06 (0.0247)	20.69 (0.0000)	0.13 (0.7125)	5.55 (0.0186)
Multiple R	0,11	0,11	0,09	0,12	0,16	0,01	0,08
Anomaly	confirmed	confirmed	confirmed	confirmed	confirmed	not confirmed	confirmed

* P-values are in parentheses

Appendix E

Statistical tests of Hypothesis 2, case of monthly data

Table E.1: T-test of Hypothesis 2, case of foreign exchange market (monthly data)

Type of asset	EURUSD		AUDUSD		USDCHF	
Indicator	abnormal	normal	abnormal	normal	Abnormal	normal
Number of matches	22	129	26	125	16	135
Mean	2,53%	2,18%	4,35%	2,38%	3,85%	2,12%
Standard deviation	2,92%	1,80%	6,36%	2,30%	4,02%	1,76%
t-criterion	0.55		1.56		1.70	
t-critical (p=0.95)	1.96					
Null hypothesis	accepted		accepted		accepted	

Table E.2: T-test of Hypothesis 2, case of US Stock Market and Commodities (monthly data)

Type of a market	Commodities				US Stock Market			
Type of asset	Gold		Oil		Boeing		Microsoft	
Indicator	abnormal	normal	abnormal	normal	Abnormal	normal	Abnormal	normal
Number of matches	25	126	23	128	9	80	21	130
Mean	6,23%	3,78%	17,64%	7,22%	6,70%	5,54%	7,59%	4,91%
Standard deviation	4,20%	3,81%	17,01%	6,09%	6,33%	5,23%	8,52%	4,49%
t-criterion	2,70		2,90		0.53		1.41	
t-critical (p=0.95)	1.96							
Null hypothesis	rejected		rejected		accepted		accepted	

Table E.3: ANOVA test of Hypothesis 2 (monthly data)

Type of a market	FOREX			Commodities		US Stock Market	
Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
F	0.95	8.64	12.38	9.87	32.49	0.96	5.98
P value	0.33	0.00	0.00	0.00	0.00	0.33	0.01
F critical	3.90	3.90	3.90	3.90	3.90	3.95	3.90
Null hypothesis	accepted	rejected	rejected	rejected	rejected	accepted	rejected

Table E.4: Mann–Whitney U test of Hypothesis 2 (monthly data)

Type of a market	FOREX			Commodities		US Stock Market	
Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
Adjusted H	0,19	4,18	3,51	10,82	9,59	0,54	1,50
d.f.	1	1	1	1	1	1	1
P value	0,66	0,04	0,06	0,00	0,00	0,46	0,22
Critical value	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Null hypothesis	accepted	rejected	accepted	rejected	rejected	accepted	accepted

Table E.5: Regression analysis with dummy variables of Hypothesis 2 (monthly data)

Parameter/ Type of asset	FOREX			Commodities		US Stock Market	
Parameter/ Type of asset	EURUSD	AUDUSD	USDCHF	Gold	Oil	Boeing	Microsoft
Mean volatility (a_0)	0,0219 (0,0000)	0,0240 (0,0000)	0,0213 (0,0000)	0,0381 (0,0000)	0,0728 (0,0000)	0,0561 (0,0000)	0,0495 (0,0000)
Dummy coefficient (a_1)	0,0045 (0,3293)	0,0212 (0,0038)	0,0195 (0,0006)	0,0267 (0,0020)	0,1112 (0,0000)	0,0183 (0,3306)	0,0300 (0,0156)
F-test	0.95 (0.3293)	8.64 (0.0038)	12.38 (0.0006)	9.87 (0.0020)	32.49 (0.0000)	0.95 (0.3306)	5.98 (0.0156)
Multiple R	0,08	0,07	0,28	0,25	0,42	0,10	0,19
Anomaly	not confirmed	confirmed	confirmed	confirmed	confirmed	not confirmed	confirmed

* P-values are in parentheses