Department of
Economics and Finance

Working Paper No. 15-01

Economics and Finance Working Paper Series

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January 2015

http://www.brunel.ac.uk/economics

LONG-TERM PRICE OVERREACTIONS:

ARE MARKETS INEFFICIENT?

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January 2015

Abstract

This paper examines long-term price overreactions in various financial markets (commodities, US stock market and FOREX). First, t-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, t-test

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. 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. 2014).

This paper analyses long-term overreactions by (i) carrying out t-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. (2014); 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 paper is structured as follows. Section 2 briefly reviews the existing literature on the overreaction hypothesis. Section 3 outlines the methodology. Section 4 discusses the empirical results and Section 5 summarises the main findings.

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. (2014), 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.

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 sample covers the period from January 2002 till the end of September 2014, and for the trading robot analysis the period is 2001-2014 for the FOREX and 2006-2014 for the US stock market and commodity market.

3.1 Student's t-tests

Student's t-tests are carried out for the overreaction hypothesis, according to which an overreaction should be followed by a correction, i.e. price counter-movements, and they should be bigger than after normal periods for as long as it takes the market to process new information.

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. Given the size of our data set, the Central Limit Theorem (Mendenhall, Beaver and Beaver, 2003) can be invoked to justify the assumption of normality required for the t-tests.

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:

$$R_i = \frac{(High_i - Low_i)}{Low_i} \times 100\%, \tag{1}$$

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

$$R_i > (\overline{R}_n + \delta_n), \tag{2}$$

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

$$\overline{R}_n = \sum_{i=1}^{n} R_i / n, \tag{3}$$

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

$$\delta_n = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(R_i - \overline{R})^2}\ . \tag{4}$$

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

$$R_i > (\overline{R}_n + 2 \times \delta_n)\ . \tag{5}$$

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

$$R_i > (\overline{R}_n + 3 \times \delta_n)\ . \tag{6}$$

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:

$$cR_{i+1} = 100\% \times \frac{(Open_{i+1} - Low_{i+1})}{Low_{i+1}}, \tag{7}$$

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

If the price decreased, then the corresponding definition is:

$$cR_{i+1} = 100\% \times \frac{(High_{i+1} - Open_{i+1})}{Open_{i+1}} \quad (8)$$

In the case of Hypothesis 2 (movement in the direction of the overreaction), either equation (8) or (7) 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:

- **<u>Strategy 1 (based on H1)</u>:** 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).
- **<u>Strategy 2 (based on H2)</u>:** 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;
- 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;

- 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.

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 t-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 Tables 8 - 12. In the case of the commodity markets (Table 8), this hypothesis is rejected for both assets with weekly data (this is evidence supporting the existence of an anomaly) but cannot be rejected for oil with monthly data.

Table 8: T-test of Hypothesis 1 - case of commodity markets

Type of data	Weekly data				Monthly data			
Type of asset	Gold		Oil		Gold		Oil	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	146	811	186	1012	35	164	35	220
Mean	2,26%	1,64%	4,04%	3,07%	5,69%	3,75%	9,15%	7,36%
Standard deviation	2,54%	1,60%	4,26%	2,90%	5,21%	3,34%	9,76%	7,42%
t-criterion	2,98		3,10		2,21		1,09	
t-critical (p=0.95)	1.96				1.97			
Null hypothesis	rejected		rejected		rejected		accepted	

The results from testing Hypothesis 1 for the US stock market (see Tables 9 and 10) are unstable across frequencies: the anomaly is found in the case of weekly but not of monthly data.

Table 9: T-test of Hypothesis 1 for weekly data, case of US stock market

Type of asset	Dow-Jones index		Microsoft		Boeing Company	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	198	1015	208	1260	234	1234
Mean	2,36%	1,74%	3,79%	3,21%	3,52%	2,86%
Standard deviation	2,22%	1,52%	3,36%	3,20%	3,05%	2,72%
t-criterion	3,91		2,48		3,32	
t-critical (p=0.95)	1.96					
Null hypothesis	rejected		rejected		rejected	

Table 10: T-test of Hypothesis 1 for monthly data, case of US stock market

Type of asset	Dow-Jones index		Microsoft		Boeing Company	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	44	214	30	286	36	280
Mean	4,39%	3,22%	9,73%	7,55%	4,96%	6,01%
Standard deviation	4,09%	2,83%	10,20%	8,62%	5,33%	5,46%
t-criterion	1,90		1,17		-1,18	
t-critical (p=0.95)	1.97					
Null hypothesis	accepted		accepted		accepted	

By contrast, the results from testing Hypothesis 1 for the FOREX (Tables 11 and 12) are relatively stable, and no anomaly is detected with either dataset.

Table 11: T-test of Hypothesis 1 for weekly data, case of foreign exchange market

Type of asset	EURUSD		USDCHF		AUDUSD	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	112	636	107	597	110	608
Mean	1,11%	1,07%	1,33%	1,20%	1,59%	1,27%
Standard deviation	0,93%	0,86%	1,38%	0,91%	1,85%	1,12%
t-criterion	0,41		0,97		1,86	
t-critical (p=0.95)	1.96					
Null hypothesis	accepted		accepted		accepted	

Table 12: T-test of Hypothesis 1 for monthly data, case of foreign exchange market

Type of asset	EURUSD		USDCHF		AUDUSD	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	17	133	20	121	22	121
Mean	2,80%	2,06%	3,34%	2,42%	4,00%	2,47%
Standard deviation	2,19%	2,09%	3,54%	1,70%	3,80%	2,14%
t-criterion	1,39		1,15		1,89	
t-critical (p=0.95)	1.97					
Null hypothesis	accepted		accepted		accepted	

Overall, it appears that in the case of H1 the best frequency to detect the counter-reactions after long-term overreactions is weekly. H1 cannot be rejected for the US stock market (in all cases with weekly data) and commodity markets. FOREX is not subject to the anomaly described in H1. Therefore the classical long-term counter-movement after overreactions is confirmed in US stock market and commodities markets, but only with weekly data.

The results for H2 are presented in Tables 13 - 17. This hypothesis cannot be rejected for the commodity markets (see Table 13) for both data sets (weekly and monthly).

Table 13: T-test of Hypothesis 2 - case of commodity markets

Type of data	Weekly data				Monthly data			
Type of asset	Gold		Oil		Gold		Oil	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	146	811	186	1012	35	164	35	220
Mean	2,29%	1,76%	4,24%	3,34%	5,98%	3,65%	12,17%	6,96%
Standard deviation	2,58%	1,65%	4,33%	3,16%	4,40%	3,53%	10,50%	5,67%
t-criterion	2,51		2,82		3,14		2,94	
t-critical (p=0.95)	1.96				1.97			
Null hypothesis	rejected		rejected		rejected		rejected	

The results from testing Hypothesis 2 for the US stock markets (Tables 14 and 15) are less stable and are mixed. The anomaly is detected for the Dow Jones and Microsoft data in the weekly but not in the monthly case. For Boeing the opposite conclusion is reached. Overall, there is evidence of an “inertia” anomaly in the US stock market but this is true only for weekly data

Table 14: T-test of Hypothesis 2 for weekly data, case of US stock market

Type of asset	Dow-Jones index		Microsoft		Boeing Company	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	198	1015	208	1260	234	1234
Mean	2,44%	1,65%	4,62%	3,16%	3,20%	2,88%
Standard deviation	3,10%	1,42%	6,08%	3,28%	5,03%	2,95%
t-criterion	3,58		3,44		0,94	
t-critical (p=0.95)	1.96					
Null hypothesis	rejected		rejected		accepted	

Table 15: T-test of Hypothesis 2 for monthly data, case of US stock market

Type of asset	Dow-Jones index		Microsoft		Boeing Company	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	44	214	30	286	36	280
Mean	5,18%	3,83%	8,30%	7,33%	10,55%	7,19%
Standard deviation	5,68%	3,55%	6,64%	9,44%	9,71%	9,36%
t-criterion	1,58		0,80		2,07	
t-critical (p=0.95)	1.97					
Null hypothesis	accepted		accepted		rejected	

The results from testing Hypothesis 2 for the FOREX (Tables 16 and 17) are mixed. No anomaly is detected for the EURUSD (for both data sets), there is evidence of an anomaly with monthly but not weekly data for USD CHF, and this is found in both cases for the AUDUSD.

Table 16: T-test of Hypothesis 2 for weekly data, case of foreign exchange market

Type of asset	EURUSD		USDCHF		AUDUSD	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	112	636	107	597	110	608
Mean	1,23%	1,05%	1,34%	1,11%	1,86%	1,30%
Standard deviation	1,19%	0,97%	1,58%	0,92%	2,46%	1,20%
t-criterion	1,60		1,54		2,37	
t-critical (p=0.95)	1.96					
Null hypothesis	accepted		accepted		rejected	

Table 17: T-test of Hypothesis 2 for monthly data, case of foreign exchange market

Type of asset	EURUSD		USDCHF		AUDUSD	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	17	133	20	121	22	121
Mean	2,85%	2,20%	3,87%	2,15%	5,79%	2,62%
Standard deviation	3,39%	1,71%	3,61%	1,77%	6,69%	2,38%
t-criterion	0,79		2,13		2,22	
t-critical (p=0.95)	1.97					
Null hypothesis	accepted		rejected		rejected	

The general conclusions from the t-test are as follows: an anomaly is generally detected using weekly but not monthly data; FOREX is mostly immune to the "inertia" anomaly; the US stock and commodity markets are most affected by the overreaction anomalies.

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).
- Profit_koef = 1 sigma_dz (1 standard deviation as a measure of the current volatility of the asset).
- Stop = 10 sigma_dz (to prevent a total loss of the investment in case of a market crash).

The results of the trading robot analysis are presented in Table 18 (Strategy 1) and Table 19 (Strategy 2). The testing periods are as follows FOREX: 2001-2014; US stock market: 2006-2014; Commodities: 2006-2014.

Table 18: Trading results for Strategy 1

Asset	Total trades	Succesfull trades, %	Profit, USD	Return	Annual return
FOREX					
EURUSD	108	63%	-1584	-158,4%	-11,3%
USDCHF	112	63%	-1815	-181,5%	-13,0%
AUDUSD	114	66%	-1 690	-169,0%	-12,1%
USDJPY	**116**	**69%**	**1 662**	**166,2%**	**11,9%**
USDCAD	118	66%	-2 121	-212,1%	-15,2%
GBPJPY	**111**	**71%**	**3 541**	**354,1%**	**25,3%**
GBPUSD	116	68%	-135	-13,5%	-1,0%
EURJPY	107	64%	-1 829	-182,9%	-13,1%
GBPCHF	**106**	**74%**	**3 721**	**372,1%**	**26,6%**
EURGBP	**118**	**71%**	**169**	**16,9%**	**1,2%**
US stock market					
Alcoa	64	63%	-2280	-228,0%	-25,3%
AIG	**64**	**67%**	**480**	**48,0%**	**5,3%**
Boeing Company	**87**	**71%**	**3290**	**329,0%**	**36,6%**
Walt Disney	63	70%	-289	-28,9%	-3,2%
General electric	67	64%	-39	-3,9%	-0,4%
Home Depot	**79**	**64%**	**290**	**29,0%**	**3,2%**
IBM	65	63%	-3090	-309,0%	-34,3%
Intel	70	54%	-1055	-105,5%	-11,7%
Microsoft	**74**	**66%**	**430**	**43,0%**	**4,8%**
Exxon Mobil	**72**	**67%**	**773**	**77,3%**	**8,6%**
Commodities					
Gold	78	64,0%	-2091	-209,1%	-23,2%

Strategy 1, based on the classical overreaction hypothesis, trades on counter-reactions after periods of abnormal price dynamics. In general, it is unprofitable for FOREX (7 pairs out of 10 produce negative results) and commodities market (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%), Boeing (36.6%) and ExxonMobil (8.6%).

Table 19: Trading results for Strategy 2

Asset	Total trades	Succesfull trades, %	Profit, USD	Return	Annual return
FOREX					
EURUSD	**112**	**58%**	**848**	**84,8%**	**6,1%**
USDCHF	**119**	**57%**	**690**	**69,0%**	**4,9%**
AUDUSD	**117**	**56%**	**416**	**41,6%**	**3,0%**
USDJPY	116	50%	-479	-47,9%	-3,4%
USDCAD	**117**	**58%**	**1 829**	**182,9%**	**13,1%**
GBPJPY	114	47%	-6 766	-676,6%	-48,3%
GBPUSD	116	53%	-566	-56,6%	-4,0%
EURJPY	**107**	**58%**	**476**	**47,6%**	**3,4%**
GBPCHF	106	48%	-2 991	-299,1%	-21,4%
EURGBP	118	49%	-2 609	-260,9%	-18,6%
US stock market					
Alcoa	**68**	**51%**	**877**	**87,7%**	**9,7%**
AIG	**65**	**60%**	**2390**	**239,0%**	**26,6%**
Boeing Company	87	44%	-2470	-247,0%	-27,4%
Walt Disney	62	47%	-1475	-147,5%	-16,4%
General electric	**69**	**51%**	**410**	**41,0%**	**4,6%**
Home Depot	79	47%	-1557	-155,7%	-17,3%
IBM	65	38%	-9236	-923,6%	-102,6%
Intel	70	50%	-36,4	-3,6%	-0,4%
Microsoft	74	40%	-1814	-181,4%	-20,2%
Exxon Mobil	71	50%	-1711	-171,1%	-19,0%
Commodities					
Gold	**78**	**58,0%**	**1011**	**101,1%**	**11,2%**

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 (6 pairs out of 10 yield negative results). There is evidence of profit opportunities in the commodity market. 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, t-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. (2014) 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.

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Appendix A

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

Table A.1 – Overall statistics

Symbol		GBPJPY (Great Britain Pound vs Japanese Yen)			
Period		1 Hour (H1) 2001.01.01 00:00 - 2014.12.01 14:00 (2001.01.01 - 2015.01.01)			
Parameters		profit_koef=1; stop=10; sigma_koef=1; period_dz=30; time_val=600000;			
Bars in test	87197	Ticks modelled	2167528	Modelling quality	n/a
Mismatched charts errors	1				
Initial deposit	10000			Spread	Current (43)
Total net profit	3541.48	Gross profit	10643.06	Gross loss	-7101.58
Profit factor	1.5	Expected payoff	31.91		
Absolute drawdown	558.1	Maximal drawdown	1853.64 (14.68%)	Relative drawdown	14.68% (1853.64)
Total trades	111	Short positions (won %)	57 (63.16%)	Long positions (won %)	54 (79.63%)
		Profit trades (% of total)	79 (71.17%)	Loss trades (% of total)	32 (28.83%)
	Largest	profit trade	657.75	loss trade	-1543.94
	Average	profit trade	134.72	loss trade	-221.92
	Maximum	consecutive wins (profit in money)	14 (2526.90)	consecutive losses (loss in money)	3 (-454.15)
	Maximal	consecutive profit (count of wins)	2526.90 (14)	consecutive loss (count of losses)	-1543.94 (1)
	Average	consecutive wins	3	consecutive losses	1

Figure A.1 – Equity dynamics

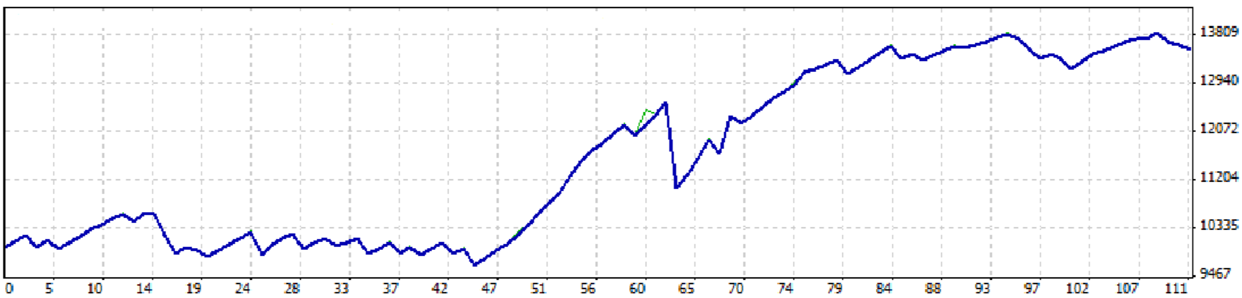

Table A.2 – Statement (fragment)

#	Time	Type	Order	Size	Price	S / L	T / P	Profit	Balance
1	05.01.2001 22:00	sell	1	0.1	175.16	187.126	173.963		
2	08.01.2001 14:50	t/p	1	0.1	173.963	187.126	173.963	100.7	10100.7
3	02.03.2001 22:00	sell	2	0.1	174.94	187.069	173.727		
4	06.03.2001 6:50	t/p	2	0.1	173.727	187.069	173.727	101.71	10202.41
5	25.05.2001 22:00	buy	3	0.1	171.463	157.894	172.82		
6	01.06.2001 20:42	close	3	0.1	168.972	157.894	172.82	-210.13	9992.28
7	15.06.2001 22:00	sell	4	0.1	173.03	189.851	171.348		
8	20.06.2001 9:20	t/p	4	0.1	171.348	189.851	171.348	140.97	10133.25
9	28.09.2001 22:00	sell	5	0.1	176.07	193.342	174.343		
10	05.10.2001 20:42	close	5	0.1	178.149	193.342	174.343	-177.88	9955.37
11	08.03.2002 22:00	buy	6	0.1	182.693	169.362	184.026		
12	15.03.2002 11:46	t/p	6	0.1	184.026	169.362	184.026	112.72	10068.09
13	13.09.2002 22:00	sell	7	0.1	188.99	203.308	187.558		
14	18.09.2002 9:50	t/p	7	0.1	187.558	203.308	187.558	119.86	10187.95
15	20.09.2002 22:00	sell	8	0.1	191.83	206.642	190.349		
16	26.09.2002 16:20	t/p	8	0.1	190.349	206.642	190.349	122.97	10310.92
17	29.11.2002 22:00	buy	9	0.1	190.853	180.282	191.91		
18	02.12.2002 2:30	t/p	9	0.1	191.91	180.282	191.91	89.27	10400.18
19	06.12.2002 22:00	sell	10	0.1	194.71	206.425	193.538		
20	09.12.2002 7:20	t/p	10	0.1	193.538	206.425	193.538	98.59	10498.77
21	31.01.2003 22:00	sell	11	0.1	197.41	209.118	196.239		
22	06.02.2003 15:20	t/p	11	0.1	196.239	209.118	196.239	96.8	10595.57
23	21.02.2003 22:00	buy	12	0.1	187.563	175.68	188.751		
24	28.02.2003 20:42	close	12	0.1	186.041	175.68	188.751	-128.32	10467.25
25	21.03.2003 22:00	sell	13	0.1	189.88	203.283	188.54		
26	25.03.2003 7:20	t/p	13	0.1	188.54	203.283	188.54	112.44	10579.69
27	09.05.2003 22:00	buy	14	0.1	188.063	174.701	189.399		
28	16.05.2003 20:42	close	14	0.1	188.489	174.701	189.399	36.15	10615.84
29	23.05.2003 22:00	sell	15	0.1	191.24	204.879	189.876		
30	30.05.2003 20:42	close	15	0.1	196.071	204.879	189.876	-410.17	10205.67
31	11.07.2003 22:00	buy	16	0.1	191.933	179.934	193.133		
32	18.07.2003 20:42	close	16	0.1	188.115	179.934	193.133	-322.16	9883.51
33	18.07.2003 22:00	buy	17	0.1	188.203	175.63	189.46		
34	21.07.2003 17:50	t/p	17	0.1	189.46	175.63	189.46	106.15	9989.65
35	25.07.2003 22:00	sell	18	0.1	192.59	205.391	191.31		
36	01.08.2003 20:42	close	18	0.1	193.041	205.391	191.31	-40.45	9949.2
37	22.08.2003 22:00	buy	19	0.1	185.243	172.806	186.487		
38	29.08.2003 20:43	close	19	0.1	183.851	172.806	186.487	-117.34	9831.86
39	10.10.2003 22:00	buy	20	0.1	180.723	168.027	181.993		
40	14.10.2003 8:50	t/p	20	0.1	181.993	168.027	181.993	107.27	9939.13
41	09.01.2004 22:00	sell	21	0.1	196.64	208.56	195.448		
42	14.01.2004 9:45	t/p	21	0.1	195.448	208.56	195.448	99.6	10038.73