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Short-term Price Overreactions: Identification, Testing, Exploitation

**SHORT-TERM PRICE OVERREACTIONS:
IDENTIFICATION, TESTING, EXPLOITATION**

Guglielmo Maria Caporale*
Brunel University, London, CESifo and DIW Berlin

Luis Gil-Alana
University of Navarra

Alex Plastun
Ukrainian Academy of Banking

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Abstract

This paper examines short-term price reactions after one-day abnormal price changes and whether they create exploitable profit opportunities in various financial markets. A t-test confirm

i.e. after an overreaction day prices tend to move in the same direction for some time. A trading robot approach is then used to test two trading strategies aimed at exploiting the detected anomalies to make abnormal profits. The results suggest 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. By contrast, a strategy exploiting produces profits in the case of the FOREX and the commodity markets, but not in the case of the US stock market.

Keywords: Efficient Market Hypothesis, anomaly, overreaction hypothesis, abnormal returns, contrarian strategy, trading strategy, trading robot, t-test

JEL classification: G12, G17, C63

Corresponding author: Professor Guglielmo Maria Caporale, Department of Economics and Finance, Brunel University, London, UB8 3PH, UK. Tel.: +44 (0)1895 266713. Fax: +44 (0)1895 269770. Email: Guglielmo-Maria.Caporale@brunel.ac.uk

1. Introduction

The Efficient Market Hypothesis (EMH) is one of the cornerstones of financial economics (Fama, 1965). Its implication is that there should not be any exploitable profit opportunities in financial markets. However, the empirical literature has documented the presence of a number of so-profit opportunities.

One of the most famous stock market anomalies is the so-called overreaction hypothesis detected by De Bondt and Thaler (1985), who showed that investors tend to give excessive weight to recent relative to past information when making their portfolio choices. A special case of the overreaction hypothesis is short-term price reactions after one-day abnormal price changes. Empirical studies on various financial markets show that after such price changes there are bigger contrarian price movements than after normal (typical) daily fluctuations (Atkins and Dyl, 1990; Bremer and Sweeney, 1991; Bremer, Hiraki and Sweeney, 1997; Cox and Peterson, 1994; Choi and Jayaraman, 2009; etc).

This paper provides new evidence on the overreaction anomaly by analysing both price counter-movements and movements in the direction of the overreaction and comparing

The remainder of this paper is organised as follows. Section 2 briefly reviews the existing literature on the overreaction hypothesis. Section 3 outlines the methodology followed in this study. Section 4 discusses the empirical results. Section 5 offers some concluding remarks.

2. Literature review

There is a vast empirical literature on the EMH. Kothari and Warner (2006) reviewed over 500 studies providing evidence in support of this paradigm. However, as pointed out by Ball (2009), there is also plenty of evidence suggesting the presence of market anomalies apparently inconsistent with EMH such as over- and under-reactions to information flows, volatility explosions and seasonal yield bursts, yield dependence on different variables such as market capitalisation, dividend rate, and market factors, etc. Over- or under-reactions are significant deviations of asset prices from their average values during certain periods of time (Stefanescu et al., 2012).

The overreaction hypothesis was first considered by De Bondt and Thaler (DT, 1985), following the work of Kahneman and Tversky (1982), who had shown that investors overvalue recent relative to past information. The main conclusions of DT were 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. Overreactions are associated with irrational behaviour of investors who overreact to news arrivals. This leads to significant deviations of asset prices from their fundamental value. Such overreactions normally lead to price corrections. An interesting fact, mentioned by DT, is an asymmetry in the overreaction: its size is bigger for undervalued than for overvalued stocks. DT also reported the existence of a "January effect", i.e. overreactions tend to occur mostly in that month.

Subsequent studies on the overreaction hypothesis include Brown, Harlow and Tinic (1988), who analysed NYSE data for the period 1946-1983 and reached similar conclusions

to DT; Zarowin (1989), who showed the presence of short-term market overreactions; Atkins and Dyl (1990), who found overreactions in the NYSE after significant price changes in one trading day, especially in the case of falling prices; 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, as did Clements et al. (2009).

Overreactions have also been found in other stock markets, including Spain (Alonso and Rubio, 1990), Canada (Kryzanowsky and Zhang, 1992), Australia (Brailsford, 1992; Clare and Thomas, 1995), Japan (Chang et al., 1995), Hong-Kong (Akhigbe et al., 1998), Brazil (DaCosta and Newton, 1994), Richards, 1997), New Zealand (Bowman and Iverson, 1998)), China (Wang et al., 2004)

(only Gold for the trading robot analysis owing to data unavailability). The sample period covers the period from January 2002 till the end of September 2014 (for the trading robot analysis the period is 2012-2014).

3.1 -tests

First we carry out t-tests to confirm (reject) the presence of stock market anomalies after overreactions, then we apply the trading robot approach to establish whether they create exploitable profit opportunities. According to the classical overreaction hypothesis, an overreaction should be followed by a correction, i.e. price counter-movements, and 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.

Therefore the following two

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

We consider three definitions of

- 1) when the current daily return exceeds the average plus one standard deviation

$$R_i > (\bar{R}_n + \sigma_n), \quad (2)$$

where \bar{R}_n is the average size of daily returns for period n

$$\bar{R}_n = \frac{1}{n} \sum_{i=1}^n R_i \quad (3)$$

and σ_n is the standard deviation of daily returns for period n

$$\sigma_n = \sqrt{\frac{1}{n} \sum_{i=1}^n (R_i - \bar{R}_n)^2}. \quad (4)$$

- 2) when the current daily return exceeds the average plus two standard deviations,
i.e.,

$$R_i > (\bar{R}_n + 2\sigma_n). \quad (5)$$

- 3) when the current daily return exceeds the average plus three standard deviations,
i.e.,

$$R_i > (\bar{R}_n + 3\sigma_n). \quad (6)$$

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

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

$$cR_{i-1} = 100\% \frac{(Open_{i-1} - Low_{i-1})}{LOW_{i-1}}, \quad (7)$$

where cR_{i-1} is the counter-reaction size, and $Open_{i-1}$ is the open price.

If the price decreased, then the corresponding definition is:

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

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 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.

3.2 Trading robot analysis

The trading robot approach considers the short-

i.e. whether it is possible to make abnormal profits by exploiting the overreaction anomaly.

The trading robot simulates the actions of a trader according to an algorithm (trading strategy). This is a progr

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 short-term overreaction anomaly, i.e. the presence the abnormal counter-reactions the day after the overreaction day. The algorithm is constructed as follows: at the end of the overreaction day 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 day (for details of how the target profit value is defined see below).
- **Strategy 2 (based on H2)**: This is based on the non-classical short-term overreaction anomaly, i.e. the presence the abnormal price movements in the direction of the overreaction the following day. The algorithm is built as follows: at the end of the overreaction day 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 day.

In order to avoid data-snooping bias and artificial fitting of certain parameters¹ we adopt the following testing procedure.

1. We use a base period (data from 2013) to obtain the optimal parameters for the behaviour of asset prices (an example of such optimisation is reported in Appendix A).

¹ By changing the values of various parameters of the trading strategy one can make it profitable, but this would work only for the specific data set being used, not in general.

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2. We test the trading strategy with the optimal parameters on the base period (2013 data) and two independent (non-

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 day interval;
- Period of averaging (symbol: `period_dz`): the size of data set on which base mean and standard deviation are counted;
- Time in position (symbol: `time_val`): how long (in hours) the opened position has to be held;

As can be seen

Table 4: T-test of Hypothesis 1 - case of commodity markets

Period of averaging (period_dz)	20				30			
Type of asset	Gold		Oil		Gold		Oil	
Indicator	abnormal	normal	abnormal	normal	abnormal	normal	abnormal	normal
Number of matches	536	2637	536	2637	538	2763	496	2667
Mean	0.84%	0.80%	0.84%	0.80%	0.83%	0.79%	1.73%	1.38%
Standard deviation	0.73%	0.77%	0.73%	0.77%	0.75%	0.76%	1.56%	

FOREX. By contrast, there are exploitable profit opportunities in the case of the US stock market and the commodity markets; it should be noted, though, that the

overreaction day. The trading robot analysis shows that Strategy 1, which is based on the assumption that after the overreaction day counter-movements are bigger than after a standard day, is not generally profitable and therefore this anomaly cannot be seen as inconsistent with the EMH. By contrast, to be much more successful and generates profits in the case of the Gold and FOREX (EURUSD and UDSJPY) markets.

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Appendix A

Example of optimisation results: case of EURUSD, period 2013, H1 testing

Fig. A.1 Distribution of results (X profit_koef, Y stop) deeper green means better results

Table A.1 Results of testing: case of EURUSD, period 2013 (changeable parameters profit_koef from 0.5 to 3 with step 0.5; stop from 1 to 5 with step 1), start deposit = 10000\$, size of trading lot =

Table B.2 Statement

#	Time	Type	Order	Size	Price	S / L	T / P	Profit	Balance
1	02.01.2014 23:45	buy	1	0.10	1.3662	1.3584	1.3681		
2	03.01.2014 21:45	close	1	0.10	1.3586	1.3584	1.3681	-76.14	1.3586
3	23.01.2014 23:00	sell	2	0.10	1.3696	1.3770	1.3677		
4	24.01.2014 9:51	t/p	2	0.10	1.3677	1.3770	1.3677	18.83	1.3677
5	28.02.2014 23:00	sell	3	0.10	1.3802	1.3863	1.3787		
6	03.03.2014 0:00	close	3	0.10	1.3788	1.3863	1.3787	13.83	1.3788
7	06.03.2014 23:00	sell	4	0.10	1.3862	4			

Appendix

Testing results for the EURUSD, period 2012-2014

Figure C.1 Testing results for the EURUSD, period 2012-2014 (X sigma_dz, Y time_val)*

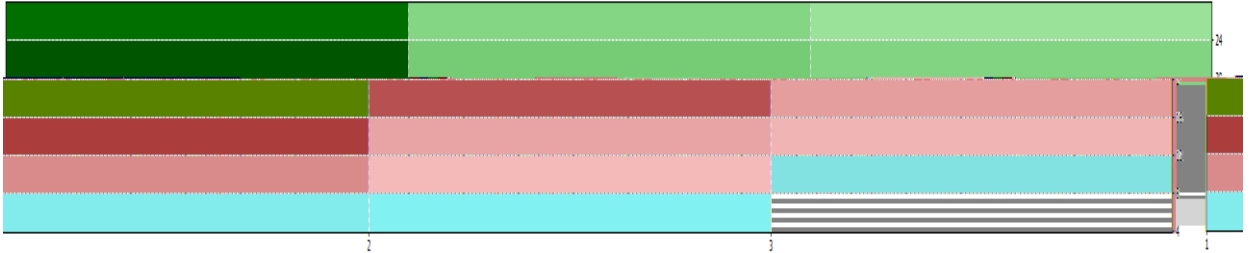


Figure C.2 Testing results for the EURUSD, period 2012-2014 (X sigma_dz, Y profit_koef)*

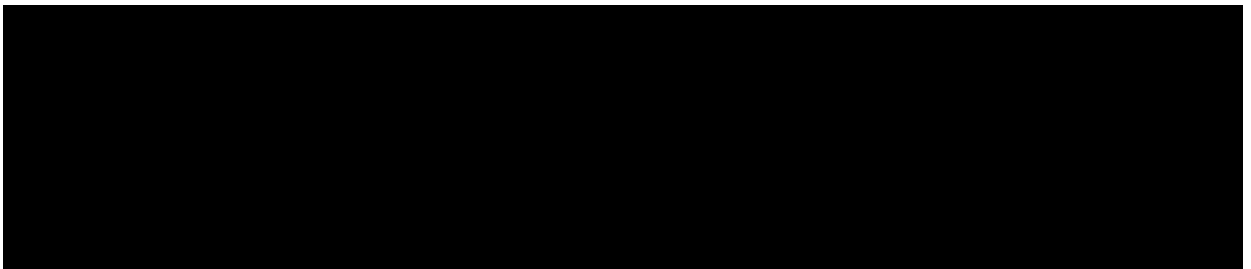
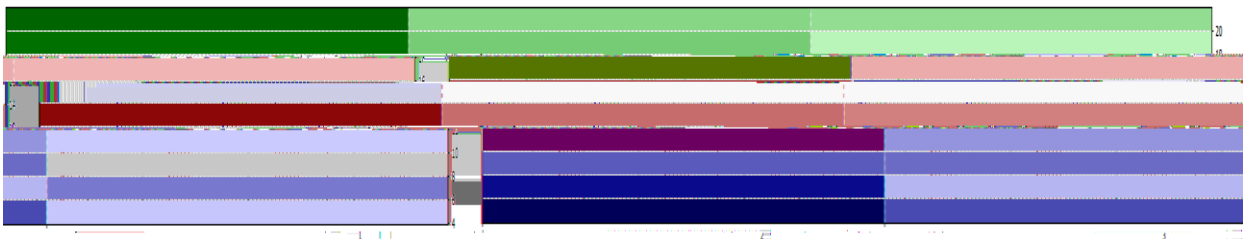


Figure C.3 Testing results for the EURUSD, period 2012-2014 (X sigma_dz, Y period_dz)*



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

Appendix D

Trading results for Strategy 1

Table D.1: Trading results for Strategy 1

	Parameters		2012			2013			2014			2012-2014		
	profit_ koef	stop	% succesfull	profit, USD	annual return	% succesfull	profit, USD	annual return	% succesfull	profit, USD	annual return	% succesfull	profit, USD	average annual return
FOREX														
EURUSD	0,5	2	64,0%	-21	-2%	71,0%	-67	-7%						

