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On stock price overreactions: frequency, seasonality and information content

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ABSTRACT

This paper explores the frequency of price overreactions in the US stock market by focusing on the Dow Jones Industrial Index over the period 1990–2017. It uses two different methods (static and dynamic) to detect overreactions and then carries out various statistical tests (both parametric and non-parametric) including correlation analysis, augmented Dickey–Fuller tests (ADF), Phillips-Perron (PP) tests, Granger causality tests, and regression analysis with dummy variables. The following hypotheses are tested: whether or not the frequency of overreactions varies over time (H1), is informative about crises (H2) and/or price movements (H3), and exhibits seasonality (H4). The null cannot be rejected except for H4, i.e., no seasonality is found. On the whole, it appears that the frequency of overreactions can provide useful information about market developments. A sharp increase in the number of overreactions occurs in crisis periods. The frequency of overreactions is linked to the VIX index and therefore could be used as an alternative measure of market sentiment and market fear, and it also affects stock returns. Further, our findings provide evidence supporting market inefficiency since price predictability can allow investors to design profitable trading strategies; in addition, the fact that the frequency of overreactions varies over time is consistent with the Adaptive Expectations Hypothesis.

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Stock markets; anomalies; overreactions; abnormal returns; VIX; frequency of overreactions

1. Introduction

The most recent decades have been characterised by considerable turbulence in the international financial markets, with a number of crises occurring, such as the East Asian and the Russian crises in the 1990s, the Dotcom bubble of 1997–2001, and the global financial crisis of 2007–8; this has generated a great deal of interest in developing early warning indicators based on macroeconomic series. However, alternative measures exploiting the information contained in asset prices might also be useful since these react almost simultaneously to changes in the economic environment; price dynamics and trends, trade volumes, price volatility, correlation between assets, price persistence can all provide information about market developments.

In particular, abnormal price changes have been extensively analysed by both academics and practitioners. Some of the questions addressed by the literature concern their

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drivers (new information, cognitive biases, high-frequency trading or presence of noise traders in the market – Sandoval & Franca, 2012), the subsequent price movements (contrarian movements – Atkins & Dyl, 1990; Bremer & Sweeney, 1991; Cox & Peterson, 1994; Bremer, Hiraki, & Sweeney, 1997 or momentum effects – Schnusenberg & Madura, 2001; Lasfer, Melnik, & Thomas, 2003), their effects on markets and market participants (changes in trading volumes, forecast revisions – Feldman, Livnat, & Zhang, 2012; Sandoval & Franca, 2012; Savor, 2012), and their exploitation (trading strategies, price predictions, price patterns, etc. – Caporale, Gil-Alana, & Plastun, 2018).

However, the frequency of abnormal price changes, normally described as overreactions, is still relatively unexplored. Only a few studies have analysed it (Angelovska, 2016; Govindaraj, Livnat, Savor, & Zhaoe, 2014; Sandoval & Franca, 2012), mainly concentrating on the response of prices to the arrival of new information. But the frequency of overreactions can provide further information about financial markets concerning crisis prediction, price prediction (enabling investors to design profitable trading strategies) and market sentiment.

The aim of the present paper is to fill this gap in the literature. Specifically, we analyse the case of the US stock market by focusing on the Dow Jones Industrial Index over the period 1990–2017. As a first step, we assess the robustness of the overreaction results by using two different detection methods: static (based on the frequency distribution) and dynamic (dynamic trigger values). Then, we test various hypotheses of interest, namely whether or not the frequency of overreactions varies over time, is informative about crises and/or price movements, and exhibits seasonality. For this purpose, a variety of statistical methods (parametric and non-parametric) are used including ADF tests, Phillips-Perron tests, Granger causality tests, and regression analysis with dummy variables.

The remainder of the paper is organised as follows: Section 2 contains a brief review of the literature on price overreactions in financial markets. Section 3 describes the methodology. Section 4 discusses the empirical results. Section 5 provides some concluding remarks.

2. Literature review

Various types of anomalies in financial markets have been examined in the literature; these include calendar effects (weekend effect, month-of-the-year and end-of-the-year anomalies, intraday anomalies, January effect, etc.), size effects, volatility explosions and price bubbles, momentum effects and contrarian trading, yield dependence on different variables (market capitalisation, dividend rate, and market factors, etc.), price over- and under-reactions. Price overreactions, in particular, can be an important source of information about financial markets: whilst many other anomalies have disappeared or faded over time (see Plastun, Sibande, Gupta, & Wohar, 2019), they appear to be ever-present and to play a crucial role. However, their frequency and its possible use for prediction and other purposes have not been thoroughly investigated in the existing literature, a gap the present study aims to fill.

Price overreactions are significant deviations of asset prices from their average values during certain periods of time. The relevant theory was developed by De Bondt and Thaler (1985) showed that the best (worst) performing portfolios in the NYSE over a 3-year period tended to under(over)-perform in the following 3 years. The behavioural finance literature suggests some of the possible reasons for overreactions, such as over-confidence (investors often overestimate their ability to analyse the market situation), the so-called representativeness effect (investors frequently ignore the laws of probability and behave as if the recent events are typical), fear and panic, greed and crowd effects, and other forms of irrational behaviour.

The current consensus is that overreactions lead to significant deviations of asset prices from their fundamental values and normally lead to price corrections. This is known as the overreaction hypothesis: if investors overreact in a given period, they are expected to move in the opposite direction in the following period (see Bremer & Sweeney, 1991; Caporale et al., 2018; Ferri & Min, 1996; Mynhardt & Plastun, 2013; Zarowin, 1989). The overreaction hypothesis has been investigated in various markets (stock markets, FOREX, commodity markets), assets (stock prices/indices, currency pairs, oil, gold, etc.) and countries (both developed and emerging) at different time frequencies (monthly, weekly, daily, etc.). Some of most influential studies focus on the New York Stock Exchange (NYSE) include those by: Brown, Harlow, and Tinic (1988), who analysed price data for the period from 1946 to 1983 and found that portfolios with the worst/best dynamics during a given period tend to produce the best/worst results in the following period; Atkins and Dyl (1990), who investigated the behaviour of prices after significant price changes in one trading day and found evidence of overreactions, especially in the case of falling prices; Larson and Madura (2003), who showed the presence of overreaction effects in the 1988–1998 period; Clements, Drew, Reedman, and Veeraraghavan (2009), who analysed the period 1983–2007 and concluded that overreactions have become more pronounced in the most recent years. Some of the latest papers examine overreactions in the cryptocurrency market. For example, Caporale and Plastun (2019) show that there are price patterns after overreactions: the next-day price changes in both directions are bigger than after "normal" days.

Overreactions are investigated to test market efficiency and also to detect possible profit opportunities that can be exploited by means of appropriate trading strategies. Lehmann (1990), Jegadeesh and Titman (1993), Pritamani and Singal (2001), and Caporale et al. (2018) all show that it is possible to generate abnormal returns from a strategy based on overreactions at different frequencies (monthly, weekly and daily). However, other studies reach the opposite conclusion (see, e.g., Lasfer et al., 2003). The different results most likely reflect the different methods and data used, as well as the fact that some studies incorporate transaction costs whilst others do not.

As can be seen, the focus of market overreaction studies is rather narrow, namely, they tend to examine the overreaction hypothesis and its implications in terms of testing market efficiency and designing trading strategies. However, their frequency can also be a very useful source of information about the behaviour of markets. Only a handful of papers have considered it. Sandoval and Franca (2012) use the frequency of abnormal negative price changes in the stock market as a crisis identifier. De Bondt and Thaler (1985) show that overreactions tend to occur mostly in a specific month. Govindaraj et al. (2014) and Angelovska (2016) carry out frequency analysis to show that positive and negative price shocks are based on new information. Investigating the frequency of overreaction can provide useful information for predicting price movements, developing profitable trading strategies, and testing market efficiency. The present study is the first to conduct a systematic analysis of the frequency of overreactions examining issues such as their seasonal patterns and the information content (see below). Our analysis is of interest to both academics (to develop methods for crisis and price prediction and to analyse market sentiment), and practitioners (to design profitable trading strategies based on price prediction).

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3. Methodology

Our sample includes daily data from the US stock market (the Dow Jones Industrial Index) for the period 01.01.1990–31.12.2017; the data source is Yahoo! Finance (https://finance.yahoo.com). We also use monthly data on the VIX for the period 01.01.1990--31.12.2017; in this case, the data source is the Chicago Board Options Exchange (www.cboe.com/VIX). The monthly frequency is chosen since the analysis below uses the monthly frequency of overreactions.

There is no consensus in the literature on how to define and detect overreactions. For example, Bremer and Sweeney (1991) use a 10% price change as an overreaction criterion. Howe (1986) defines abnormal (weekly) price changes as those above 50%. Pritamani and Singal (2001) suggest to scale returns using their volatilities. Wong (1997) argues that using a constant value may lead to biased results and proposes a dynamic trigger values approach. Caporale et al. (2018) also use a dynamic approach and define overreactions on the basis of the number of standard deviations to be added to the average return.

In this paper, we apply both static and dynamics methods to detect overreactions. The static approach is based on the methodology proposed by Sandoval and Franca (2012). Returns are defined as:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

where R_t stands for returns, and P_t and P_{t-1} are the close prices of the current and previous day. The next step is analysing the frequency distribution by creating histograms. We plot values 10% above or below those of the population. Thresholds are then obtained for both positive and negative overreactions, and periods can be identified when returns were above or equal to the threshold.

In the dynamic approach (see Lasfer et al., 2003; Caporale et al., 2018), having calculated returns as in (1), an overreaction is defined by the following inequality:

$$R_i > (\overline{R_n} + k \times \delta_n), \tag{2}$$

where k is the number of standard deviations used to identify the overreaction,

$\overline{R}_n$ is the average size of daily returns for period n

$$\overline{R_n} = \sum_{i=1}^{n} R_i/n \tag{3}$$

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

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

Such a procedure generates a data set with the frequency of overreactions (at a monthly frequency), which is then divided into three subsets including, respectively, the frequency of negative and positive overreactions, and of them all. In this study, we also use an additional measure (named the "Overreactions multiplier"), namely the negative/positive overreactions ratio:

$$Overreactions\ multiplier_i = \frac{frequency\ of\ negative\ overreactions_i}{frequency\ of\ positive\ overreactions_i} \tag{5}$$

Then, the following hypotheses are tested:

Hypothesis 1 (H1): The frequency of overreactions varies over time.

Visual inspection is already useful to reveal patterns in the frequency of overreactions during crisis periods and financial bubbles. Parametric (ANOVA analysis) and non-parametric (Kruskal–Wallis test) test statistics can provide more formal evidence.

Hypothesis 2 (H2): The frequency of overreactions is informative about crises.

To test this hypothesis we analyse the relationship between the frequency of overreactions and the VIX, the most commonly used market sentiment indicator and fear index (see Figure C1 for its evolution over time; note that the VIX has also been found to have predictive power for future returns – see Chow, Jiang, & Li, 2014; Giot, 2005; Guo & Whitelaw, 2006). To do this, we carry out augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) to establish the order of integration of the series, and Granger causality tests for causality linkages. We also estimate the following regression model to analyse the relationship between the VIX and the frequency of overreactions:

$$\mathrm{Y_t = a_0 + a_1^+ D_{1t}^+ + a_1^- D_{1t}^- + \varepsilon_t} \tag{6}$$

where Y_t – VIX log differences on day t;

$\mathrm{a_0}$–VIX mean log differences;

a_1^+ (a_1^-) – slopes for the positive and negative overreactions, respectively;

$\mathrm{D_{1n}^+}$ (D_{1n}^-) a dummy variable equal to 1 for the frequency of positive (negative) overreactions, and equal to 0 otherwise;

ε_t – Random error term at time t.

The size, sign and statistical significance of the slope coefficients provide information about the possible influence of the frequency of overreactions on the VIX.

Hypothesis 3 (H3): The frequency of overreactions is informative about price movements.

There is a body of evidence suggesting that typical price patterns appear in financial markets after abnormal price changes. The relationship between the frequency of overreactions and the Dow Jones Industrial Index (DJI) is investigated using the same methods as for H2, in this case running regression (6) with the DJI as the dependent variable.

Hypothesis 4 (H4): The frequency of overreactions exhibits seasonality

We perform a variety of statistical tests, both parametric (ANOVA analysis) and non-parametric (Kruskal–Wallis tests), for seasonality in the monthly frequency of overreactions, which provides information on whether or not overreactions are more likely in some specific months of the year.

4. Empirical results

As a first step, the frequency distribution of the Dow Jones is analysed by using the raw data to obtain log returns (see Table 1) and construct histograms (see Figure 1).

The next step is the choice of thresholds for detecting overreactions. To obtain a sufficient number of observations we consider values ±10% the average from the population (these thresholds are selected to obtain sufficient data and to analyse abnormal price returns), namely −0.005 for negative overreactions and 0.01 for positive ones. Detailed results for the static and dynamic (float) approach, respectively, are presented in Appendices A and B.

Tables A1 and B1 provide data on the frequency of overreactions over the period 1990–2017 on an annual basis for the static and dynamic (float) approach, respectively; the corresponding graphs are included in Figures A1 and A2. The annual frequency of overreactions over the period 1990–2017 (Table A1 and Figure A1) is clearly unstable, since it rose from 15 in 1993 to 127 (more than eight times higher) in 2002; this implies that H1 cannot be rejected. Further, it appears to be correlated to crisis episodes in the international or US stock markets: it increased significantly during the Dotcom bubble of 1997–2001 and the global financial crisis of 2007–2009, rising from 25 in 2005 to 133 in 2008.

Table 1. Frequency distribution of the Dow Jones industrial index, 1990–2017.

Plot	Frequency
−0.025	129
−0.02	122
−0.015	216
−0.01	442
−0.005	883
0	2547
0.005	2034
0.01	1105
0.015	548
0.02	218
0.025	107
more	122

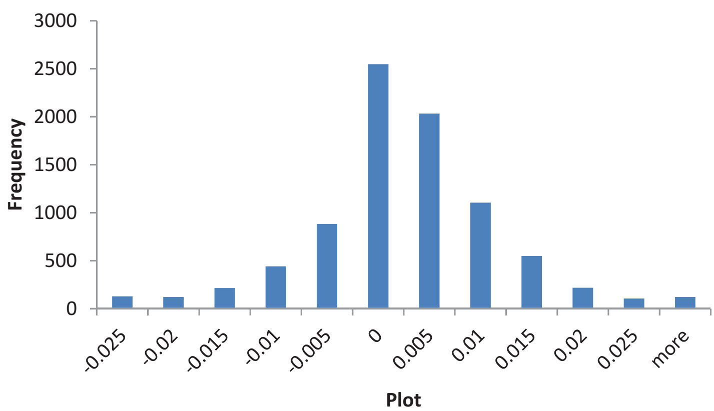

Figure 1. Frequency distribution of the Dow Jones industrial index, 1990–2017.

Table 2 shows that the two sets of data (based on static and dynamic) are not correlated, which implies that the results are sensitive to the detection method used.

Further evidence is provided by parametric ANOVA and non-parametric Kruskal–Wallis tests (see Tables 3 and 4 respectively). We have used both static and dynamic (float) approaches. The ANOVA results (Table 3) show the presence of statistically significant differences between the two data sets in all cases: Frequency of negative overreactions, Frequency of positive overreactions, and Frequency of overreactions (overall). The F statistic is much above its critical value and the p-values are far below 0.05. Similar results are obtained using the non-parametric Kruskal–Wallis test (Table 4) for the Frequency of positive overreactions and the Frequency of overreactions (overall), which suggests that our findings are robust to the method chosen.

To provide additional evidence on H1, we carry out again the ANOVA analysis and Kruskal–Wallis tests to see whether or not there are statistically significant differences between years (Table 5). In both cases, the p-values are below 0.05 and the F statistic is much higher than its critical value, which implies significant differences, i.e., that the frequency of overreactions varies over time consistently with H1.

Table 2. Results of correlation analysis: float vs static approach.

Parameter	Frequency of negative overreactions	Frequency of positive overreactions	Frequency of overreactions (overall)
Monthly data	0.00	0.02	0.30
Yearly data	−0.25	0.12	0.05

Table 3. Results of parametric ANOVA test – float vs static approach.

	F	p-Value	F critical	Null hypothesis
Frequency of negative overreactions	9.08	0.0027	3.86	Rejected
Frequency of positive overreactions	29.82	0.0000	3.86	Rejected
Frequency of overreactions (overall)	24.46	0.0000	3.86	Rejected

Table 4. Results of non-parametric Kruskal–Wallis test – float vs static approach.

Parameter	Frequency of negative overreactions	Frequency of positive overreactions	Frequency of overreactions (overall)
Adjusted H	0.02	22.33	7.75
d.f.	1	1	1
P value:	0.88	0.00	0.01
Critical value	3.84	3.84	3.84
Null hypothesis	Not rejected	Rejected	Rejected

Table 5. Results of ANOVA and non-parametric Kruskal–Wallis tests for statistical differences in the frequency of overreactions between different years, 1990–2017.

ANOVA test			
F	p-value	F critical	Null hypothesis
12.05	0.0000	1.52	Rejected
Kruskal-Wallis test			
Adjusted H	p-value	Critical value	Null hypothesis
241.17	0.0000	36.41	Rejected

`

To choose between static and float data sets we do some visual inspection of Figures A1-A3 (static approach) and Figures B1-B3 (floating approach); a comparison with Figure C1 suggests that the static results are more informative, and therefore henceforth we shall focus on these.

One more interesting finding is that the ratio of negative to positive overreactions changes over time: the overreactions multiplier (see equ. 5) is less than 1 during tranquil periods, i.e., positive overreactions are more frequent than negative ones, whilst it exceeds 1 during crisis periods, i.e., negative overreactions are more frequent in this case (see Figures A2 and A3). Therefore, the overreactions multiplier appears to contain some information about market developments and crises (H2).

Further, there is evidence that the VIX is highly correlated to the frequency of overreactions (see Table 6). The highest degree of correlation (0.81) is found between the VIX and the frequency of overreactions (overall), but there is a significant correlation also with the Frequency of negative overreactions and of positive overreactions (0.77 and 0.66, respectively).

To examine whether the VIX and the frequency of overreactions data belong to different populations we carry out a number of statistical tests. Both the Kruskal–Wallis test (Table 8) and the ANOVA results (Table 7) provide convincing evidence in favour of this hypothesis.

Next, we analyse further the relationship between the VIX and the frequency of overreactions. First, we carry out ADF and Phillips-Perron tests on the series of interest (see Table 9). All test results imply that the series is stationary at the 1% confidence level.

Table 6. Results of correlation analysis: VIX vs overreactions frequency.

Parameter	Value
VIX vs frequency of negative overreactions	0.77
VIX vs frequency of positive overreactions	0.66
VIX vs frequency of overreactions (overall)	0.81

Table 7. Test for difference between VIX vs overreactions frequency data sets: case of parametric ANOVA.

Parameter	F	p-Value	F critical	Null hypothesis
VIX vs frequency of negative overreactions	1548.32	0.0000	3.86	Rejected
VIX vs frequency of positive overreactions	1564.01	0.0000	3.86	Rejected
VIX vs frequency of overreactions (overall)	964.17	0.0000	3.86	Rejected

Table 8. Test for difference between VIX vs overreactions frequency data sets: non-parametric Kruskal–Wallis test.

Parameter	Frequency of negative overreactions	Frequency of positive overreactions	Frequency of overreactions (overall)
Adjusted H	503.88	504.95	464.61
d.f.	1	1	1
P value:	0.00	0.00	0.00
Critical value	3.84	3.84	3.84
Null hypothesis	Rejected	Rejected	Rejected

Table 9. Augmented Dickey–Fuller and Phillips-Perron tests: VIX and overreactions frequency data*.

Parameter	VIX data	Over_all	Over_negative	Over_positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller (Phillips-Perron) test statistic	−5.21 (−4.93)	−4.68 (−9.46)	−5.69 (−10.69)	−5.33 (−14.09)
Augmented Dickey-Fuller (Phillips-Perron) probability	0.0000 (0.0000)	0.0001 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Augmented Dickey-Fuller (Phillips-Perron) test critical values (1% level):	−3.45 (−3.45)	−3.45 (−3.45)	−3.45 (−3.45)	−3.45 (−3.45)
Augmented Dickey-Fuller (Phillips-Perron) Null hypothesis status	rejected (rejected)	rejected (rejected)	rejected (rejected)	rejected (rejected)
Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller (Phillips-Perron) test statistic	−5.20 (−4.93)	−4.67 (−9.45)	−5.67 (−10.68)	−5.32 (−14.08)
Augmented Dickey-Fuller (Phillips-Perron) probability	0.0000 (0.0003)	0.0009 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Augmented Dickey-Fuller (Phillips-Perron) test critical values (1% level):	−3.45 (−3.98)	−3.45 (−3.98)	−3.45 (−3.98)	−3.45 (−3.98)
Augmented Dickey-Fuller (Phillips-Perron) Null hypothesis status	rejected (rejected)	rejected (rejected)	rejected (rejected)	rejected (rejected)
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller (Phillips-Perron) test statistic	−15.82 (−24.27)	−13.49 (−46.98)	−14.32 (−43.57)	−14.19 (−79.04)
Augmented Dickey-Fuller (Phillips-Perron) probability	0.0000 (0.0000)	0.0001 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
Augmented Dickey-Fuller (Phillips-Perron) test critical values (1% level):	−3.45 (−3.45)	−3.45 (−3.45)	−3.45 (−3.45)	−3.45 (−3.45)
Augmented Dickey-Fuller (Phillips-Perron) Null hypothesis status	rejected (rejected)	rejected (rejected)	rejected (rejected)	rejected (rejected)

* Lag Length: 0 (Automatic – based on Schwarz information criterion, maxlag = 16)

Consequently, standard Granger Causality tests can be performed. Both the F statistic and the p-values suggest the existence of bidirectional causality between the VIX and the frequency of overreactions, although the evidence of causality running from the former to the latter is stronger (see Table 10).

Finally, a simple linear regression *VIXi = f(OFi)* is estimated; the results are reported in Table 11.

They imply that the VIX can be described by the following equation:

$$VIX_i = 11.50 + 1.57 \times OF_i, \tag{7}$$

i.e., there is a strong positive relationship between the VIX and the frequency of overreactions. We also estimate a regression with dummy variables for *logdiffVIX = f(OF-;OF+)*; the results are shown in Table 12.

Table 10. Granger causality test: VIX vs overreactions frequency.

	F	p-Value
VIX vs Over_all		
Granger Causality Test: Y(VIX) = f (Over_all)	6.45	0.0115
Granger Causality Test: Y(Over_all) = f(VIX)	88.47	0.0000
VIX vs Over_negative		
Granger Causality Test: Y(VIX) = f(Over_negative)	3.62	0.0579
Granger Causality Test: Y(Over_negative) = f(VIX)	25.60	0.0000
VIX vs Over_positive		
Granger Causality Test: Y(VIX) = f(Over_positive)	3.47	0.0631
Granger Causality Test: Y(Over_positive) = f(VIX)	227.80	0.0000

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Table 11. Regression analysis results: case of VIXi = f(OFi).

Parameter	Value
Mean VIX (a_0)	11.50 (0.00)
Slope for the overreactions (a_1)	1.57 (0.00)
F-test	652.53 (0.00)
Multiple R	0.81

* P-values are in parentheses.

Table 12. Regression analysis results: case of logdiffVIX = f(OF-;OF+).

Parameter	Value
Mean log return VIX (a_0)	−0.0248 (0.02)
Slope for the negative overreactions (a_1^+)	0.0164 (0.00)
Slope for the positive overreactions (a_1^-)	0.0018(0.64)
F-test	11.31 (0.00)
Multiple R	0.18

* P-values are in parentheses.

The estimated coefficients suggest that negative overreactions are associated with a higher VIX, whilst positive overreactions do not have a statistically significant effect. A comparison between the current value of the VIX and that implied by the estimated regression could be useful to investors to infer its likely future movements. On the whole, the above evidence supports H2.

To investigate the possible linkages between the frequency of overreactions and stock returns (H3) the following regression is estimated: *logreturnDJI = f(OF-;OF+)*; the results are displayed in Table 13.

Although the explanatory power of the model is rather low (the Multiple R is less than 0.1), negative overreactions again are found to have a significantly negative effect on the Dow Jones; therefore we find empirical support for H3. We also estimate a linear regression with this as the only independent variable, namely *logreturnDJIi = f(OFi-)*; the results are reported in Table 14.

Table 13. Regression analysis results: case of logreturnDJI = f(OF-;OF+).

Parameter	Value
Mean log return (a_0)	0.0110 (0.00)
Slope for the negative overreactions (a_1^+)	−0.0018 (0.03)
Slope for the positive overreactions (a_1^-)	−0.0015(0.08)
F-test	2.82 (0.06)
Multiple R	0.09

* P-values are in parentheses.

Table 14. Regression analysis results: case of logreturnDJIi = f(OFi-).

Parameter	Value
Mean DJI (a_0)	0.011 (0.00)
Slope for the negative overreactions (a_1)	−0.002 (0.04)
F-test	4.05 (0.04)
Multiple R	0.11

* P-values are in parentheses.

This model has a higher explanatory power, and both the intercept and slope are statistically significant. This implies that the DJI dynamics are influenced by the frequency of overreactions and can be described by the following equation:

$$logreturnDJI_i = 0.011 - 0.002 \times OF_i^- \tag{8}$$

Finally, we address the issue of seasonality (H4). Figure 2 provides no graphical evidence of any seasonal patterns.

To test this hypothesis formally parametric (ANOVA) and non-parametric (Kruskal–Wallis) tests are performed; the results are presented in Tables 15 and 16.

As can be seen, in all cases (Frequency of negative overreactions; Frequency of positive overreactions; and Overall frequency of overreactions) the null hypothesis cannot be rejected on the basis of both the parametric ANOVA test and the non-parametric Kruskal–Wallis test. In other words, there are no statistically significant differences between the frequency of overreactions in different months of the year (i.e., no evidence of seasonality), and therefore H4 can be rejected.

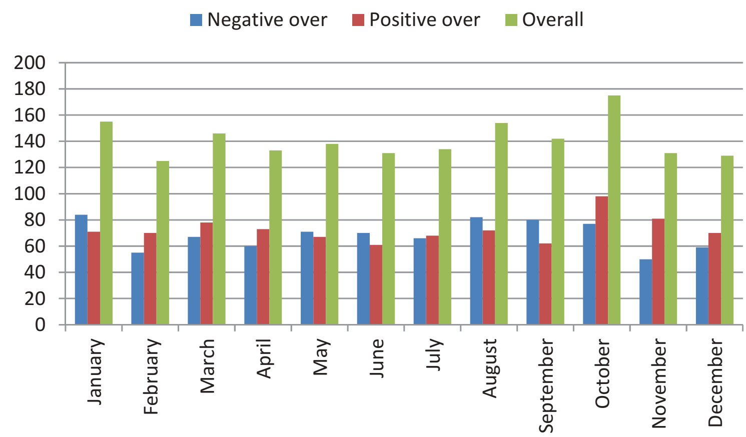

Figure 2. Monthly seasonality in overreaction frequency.

Table 15. Parametric ANOVA.

	F	p-Value	F critical	Null hypothesis
Frequency of negative overreactions	0.74	0.6980	1.82	Not rejected
Frequency of positive overreactions	0.84	0.5992	1.82	Not rejected
Frequency of overreactions (overall)	0.47	0.9183	1.82	Not rejected

Table 16. Non-parametric Kruskal–Wallis.

Parameter	Frequency of negative overreactions	Frequency of positive overreactions	Frequency of overreactions (overall)
Adjusted H	7.86	4.74	2.63
d.f.	11	11	11
P value:	0.73	0.94	0.99
Critical value	19.675	19.675	19.675
Null hypothesis	Not rejected	Not rejected	Not rejected

To sum up, we find the following about the frequency of overreactions:

- It is informative about crises – a sharp increase in the number of overreactions is associated with a crisis period;
- It is linked to the VIX index and therefore could be used as an alternative measure of market sentiment and market fear;
- It affects stock returns and can be used as a predictor of future prices in the US stock market;
- It does not have a seasonal pattern;
- It varies over time.

These findings provide evidence against market efficiency (since prices appear to be predictable) and in favour of the Adaptive Expectations Hypothesis. They are also of interest to investors and traders for the purpose of predicting prices and designing profitable trading strategies in the US stock market. For example, the frequency of negative overreactions can be used to predict future returns of the DJI. The model allows estimating a "fair" value for the DJI, which can be useful to agents to make investment decisions; for example, if it exceeds the current price, traders will buy.

5. Conclusions

This paper examines the frequency of price overreactions in the US stock market by focusing on the Dow Jones Industrial Index over the period 1990–2017. It uses two different methods (static and dynamic) to detect overreactions and then tests a number of hypotheses of interest by carrying out various statistical tests (both parametric and non-parametric) including correlation analysis, augmented Dickey–Fuller tests (ADF), Granger causality tests, and regression analysis with dummy variables. As a first step, the robustness of the detection results in the chosen method is investigated. Then, the following hypotheses are tested: whether or not the frequency of overreactions varies over time (H1), is informative about crises (H2) and/or price movements (H3), and exhibits seasonality (H4).

The main results can be summarised as follows: The frequency of overreactions is unstable and varies over time. It is also informative about crises: a sharp increase in the number of overreactions is associated with a crisis period. Further, it can be seen as an alternative measure to the VIX for market sentiment and market fear, and can also be used as a predictor of future prices in the US stock market and as the basis for profitable trading strategies. Finally, there is no evidence of seasonality in the frequency of overreactions.

As already pointed out, our findings have a number of important implications. Specifically, the detected price predictability is inconsistent with market efficiency and can be the basis for profitable trading strategies. Further, the fact that the frequency of overreactions varies over time provides support for the Adaptive Expectations Hypothesis.

Disclosure statement

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Appendix A. Frequency of overreactions: static approach

Table A1. Frequency of overreaction over the period 1990–2017, annual.

Year	Negative over	Positive over	All over	Mult
1990	41	32	73	1.3
1991	21	34	55	0.6
1992	13	18	31	0.7
1993	6	9	15	0.7
1994	19	13	32	1.5
1995	6	11	17	0.5
1996	17	26	43	0.7
1997	33	45	78	0.7
1998	35	49	84	0.7
1999	34	49	83	0.7
2000	51	51	102	1.0
2001	49	48	97	1.0
2002	**73**	**54**	**127**	**1.4**
2003	33	41	74	0.8
2004	22	22	44	1.0
2005	15	12	27	1.3
2006	11	14	25	0.8
2007	30	24	54	1.3
2008	**75**	**58**	**133**	**1.3**
2009	52	56	108	0.9
2010	34	35	69	1.0
2011	45	46	91	1.0
2012	17	23	40	0.7
2013	10	14	24	0.7
2014	18	18	36	1.0
2015	34	37	71	0.9
2016	24	26	50	0.9
2017	4	6	10	0.7
Mean	29	31	60	0.9
Std. Dev.	18.4	16.0	33.5	0.25

Table A2. Descriptive statistics for monthly data.

	Over_all	Over_negative	Over_positive	VIX
Mean	5.038690	2.446429	2.592262	19.39634
Median	4.000000	2.000000	2.000000	17.43500
Maximum	20.00000	13.00000	9.000000	59.89000
Minimum	0.000000	0.000000	0.000000	9.510000
Std. Dev.	3.905028	2.399649	2.018674	7.522532
Skewness	0.882069	1.218182	0.755046	1.698597
Kurtosis	3.349655	4.381906	3.170769	7.457552
Jarque-Bera	45.28216	109.8374	32.33352	439.7498
Probability	0.000000	0.000000	0.000000	0.000000
Sum	1693.000	822.0000	871.0000	6517.170
Sum Sq. Dev.	5108.497	1929.036	1365.140	18,957.15
Observations	336	336	336	336

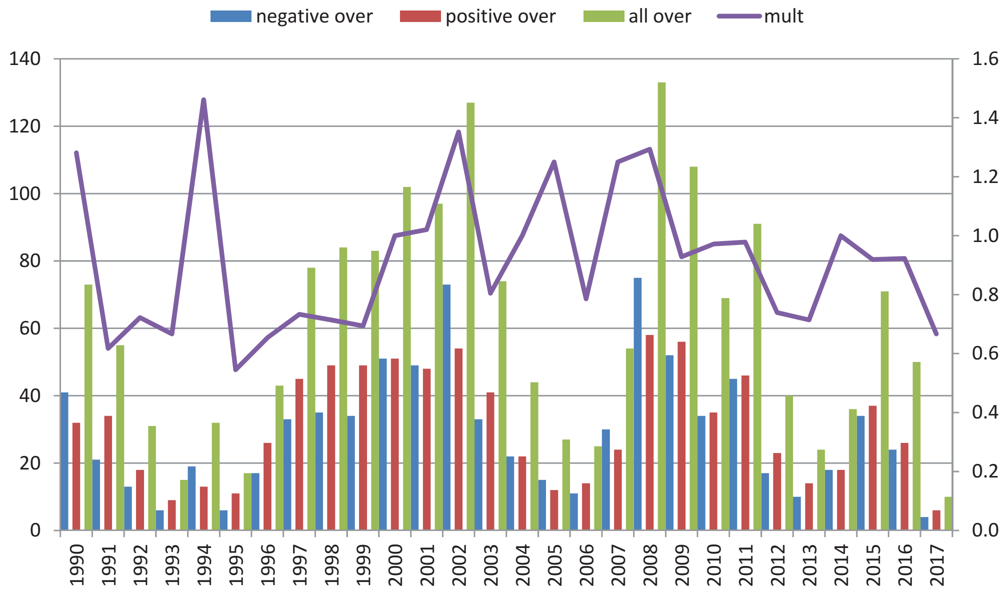

Figure A1. Frequency of overreactions: dynamic analysis over the period 1990–2017, annual data.

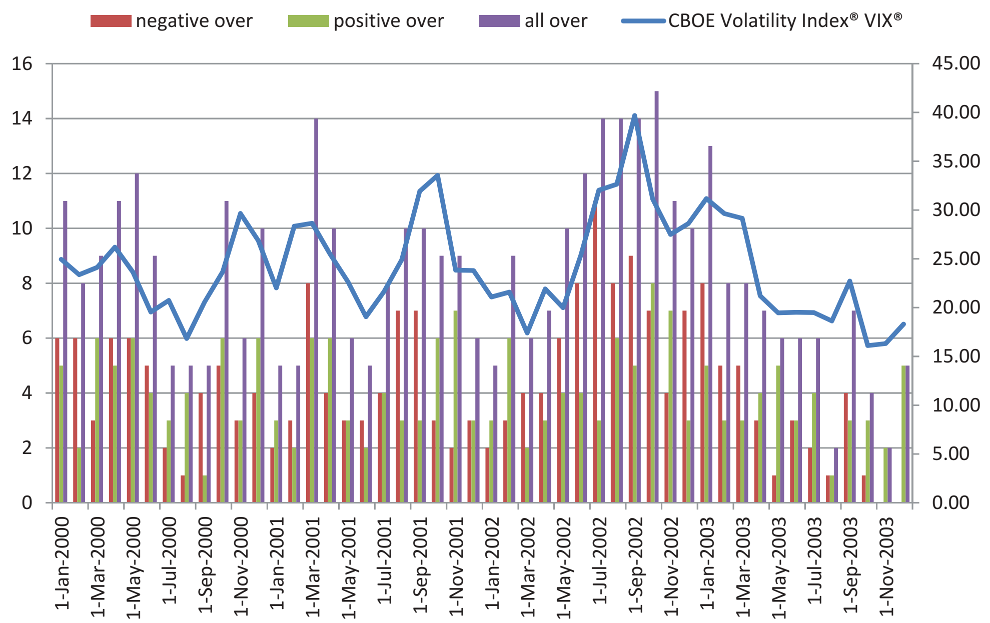

Figure A2. Frequency of overreactions and VIX index: dynamic analysis over the period 2000–2004, monthly data.

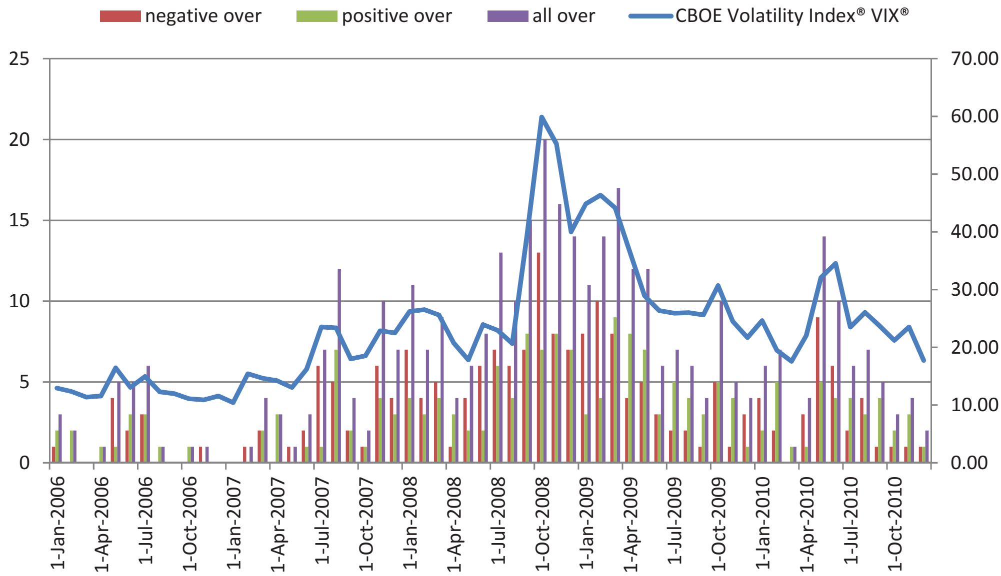

Figure A3. Frequency of overreactions and VIX index: dynamic analysis over the period 2006–2010, monthly data.

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Appendix B

Table B1. Frequency of overreactions over the period 1990–2017, annual data (dynamic trigger approach).

Year	Negative over	Positive over	All over	Mult
1990	19	23	42	0.8
1991	24	13	37	1.8
1992	19	18	37	1.1
1993	19	19	38	1.0
1994	19	20	39	1.0
1995	30	14	44	2.1
1996	24	19	43	1.3
1997	22	21	43	1.0
1998	22	15	37	1.5
1999	27	16	43	1.7
2000	17	23	40	0.7
2001	16	23	39	0.7
2002	24	21	45	1.1
2003	30	15	45	2.0
2004	29	29	58	1.0
2005	17	28	45	0.6
2006	26	19	45	1.4
2007	21	29	50	0.7
2008	24	36	60	0.7
2009	24	24	48	1.0
2010	27	20	47	1.4
2011	24	30	54	0.8
2012	32	26	58	1.2
2013	35	27	62	1.3
2014	30	35	65	0.9
2015	25	24	49	1.0
2016	21	17	38	1.2
2017	26	14	40	1.9
Mean	24	22	46	1.2
Std. Dev.	4.8	6.1	8.0	0.41

Table B2. Descriptive statistics for monthly data.

	Over_all	Over_negative	Over_positive	VIX
Mean	3.842262	2.002976	1.839286	19.39634
Median	4.000000	2.000000	2.000000	17.43500
Maximum	12.00000	6.000000	7.000000	59.89000
Minimum	0.000000	0.000000	0.000000	9.510000
Std. Dev.	2.100917	1.232637	1.521313	7.522532
Skewness	0.439100	0.444480	0.777084	1.698597
Kurtosis	2.943479	2.974661	3.161425	7.457552
Jarque-Bera	10.84202	11.07250	34.18094	439.7498
Probability	0.004423	0.003941	0.000000	0.000000
Sum	1291.000	673.0000	618.0000	6517.170
Sum Sq. Dev.	1478.640	508.9970	775.3214	18,957.15
Observations	336	336	336	336

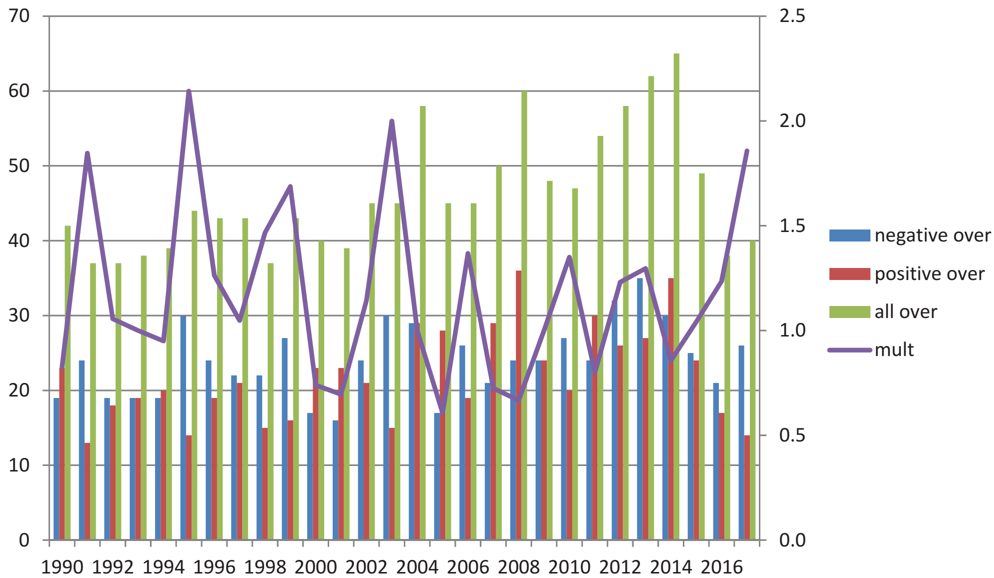

Figure B1. Frequency of overreactions: dynamic analysis over the period 1990–2017, annual data.

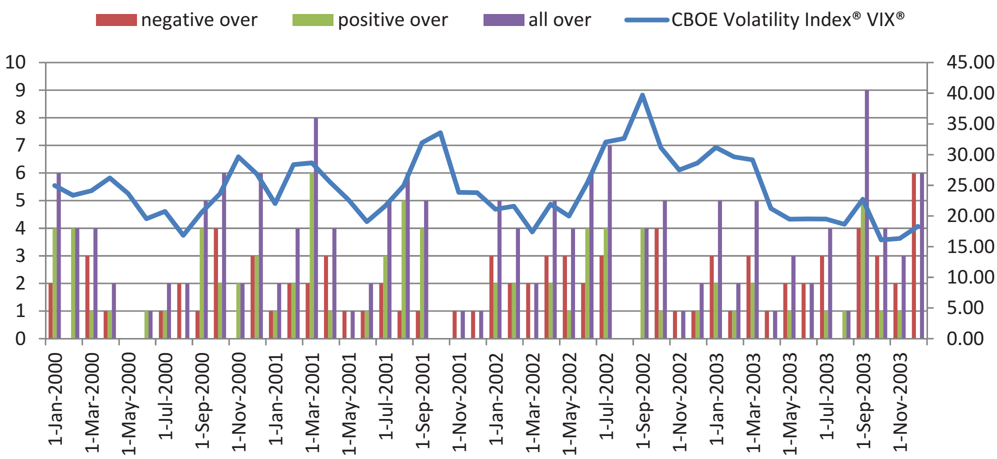

Figure B2. Frequency of overreactions and VIX index: dynamic analysis over the period 2000–2004, monthly data.

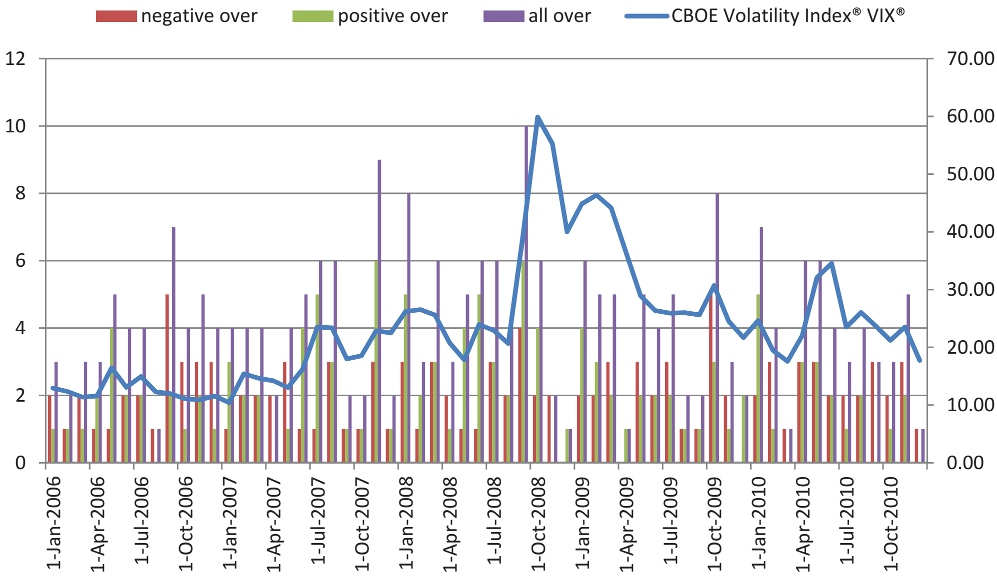

Figure B3. Frequency of overreactions and VIX index: dynamic analysis over the period 2006–2010, annual data.

Appendix C

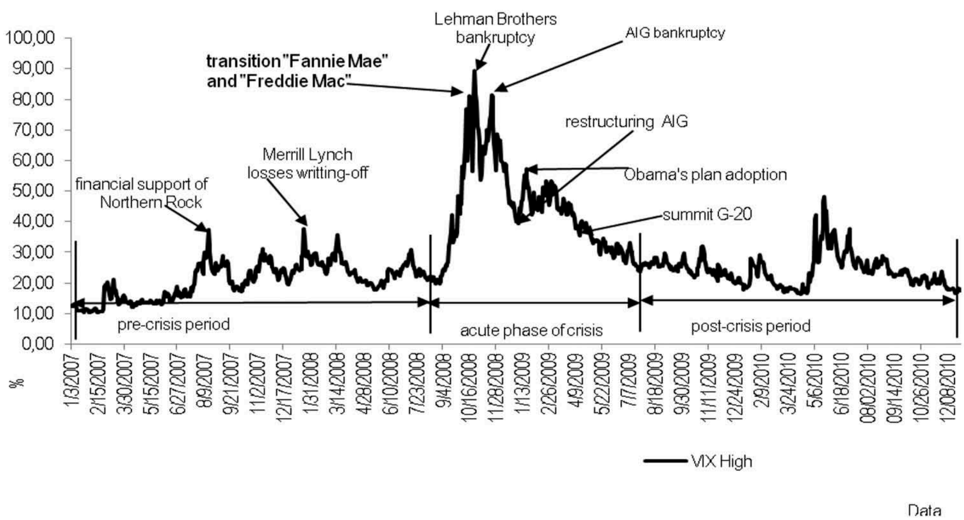

Figure C1. Dynamics of the VIX Index in 2007–2010 (taken from Caporale, Gil-Alana, Plastun, & Makarenko, 2016).