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On the Frequency of Price Overreactions

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), 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 and for designing trading strategies.

JEL-Codes: G120, G170, C630.

Keywords: stock markets, anomalies, overreactions, abnormal returns, VIX, frequency of overreactions.

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

However, the frequency of abnormal price changes is still relatively unexplored. 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 overreactions results to 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 the 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, 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 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) who had shown that the best (worst) performing portfolios in the NYSE over a three-year period tended to under(over)-perform in the following three years. 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 Zarowin, 1989; Bremer and Sweeney, 1991; Ferri and C. Min, 1996; Mynhardt and Plastun, 2013; Caporale et al., 2018).

Numerous empirical papers have investigated overreactions for 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.), and have also considered alternative possible reasons for overreactions (behavioural biases, information inflows, technical and fundamental factors, the existence of noise traders etc.). Some of most influential studies include Brown et al. (1988), Atkins and Dyl (1990), Larson and Madura (2003), Clements et al. (2009).

The mostly commonly investigated effects of overreactions are those for trading strategies. Lehmann (1990), Jegadeesh and Titman (1993), Pritamani and Singhal (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 at al., 2003).

Only a handful of papers have considered the issue of the frequency of overreactions. 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. The present study is the first to conduct a systematic analysis of the frequency of overreactions examining issues such as their seasonal patterns and information content (see below).

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).

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 methodology proposed by Sandoval and Franca (2012). Returns are defined as:

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

where S_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 and 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 3 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 (Kruskall-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 C.1 for its evolution over time; note that the VIX has also been found to have predictive power for future returns - see Giot, 2005; Guo and Whitelaw, 2006; Chow et al., 2014); specifically, we carry out augmented Dickey–Fuller tests (ADF) and Granger causality tests, and run the following regression:

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

where Y_t – VIX log differences on day *t;*

$\mathrm{a_n}$–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 on positive (negative) overreaction days, 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 (Kruskall-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.

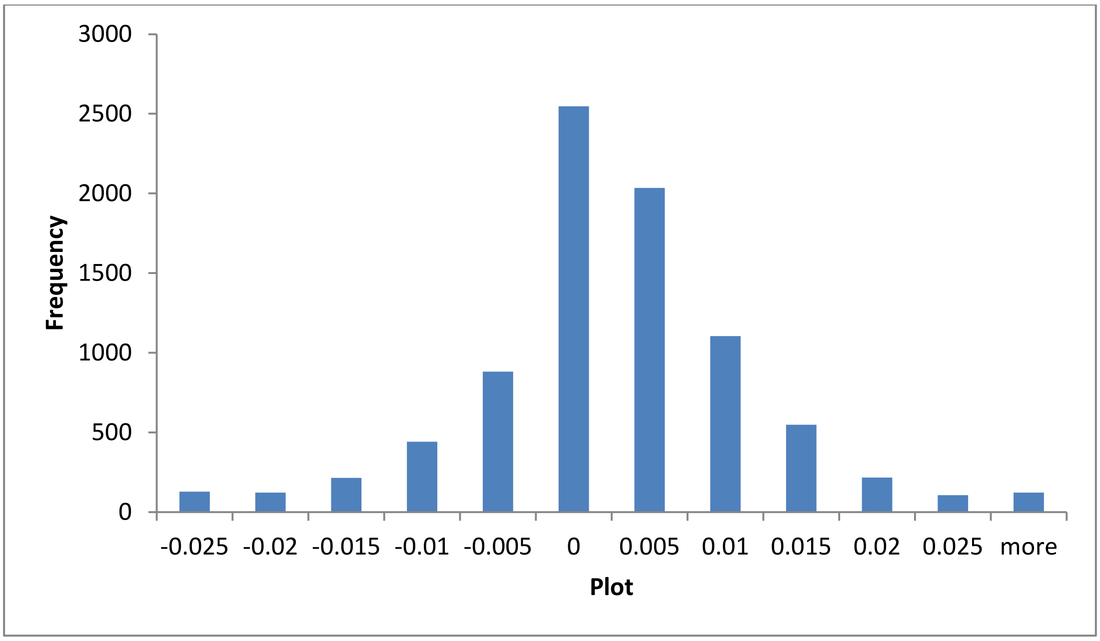
4. Empirical Results

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).

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



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, 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 Appendix A and B. Table 2 shows that the two sets of data are not correlated, which implies that the results are sensitive to the detection method used.

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

Further evidence is provided by parametric ANOVA and non-parametric Kruskal-Wallis tests (see Tables 3 and 4 respectively), again confirming the sensitivity of the results to the approach taken to detect overreactions.

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

Visual inspection of Figures A.1-A3 (static approach) and Figures B.1-B3 (floating approach) suggests that the static results might be more informative, and therefore henceforth we shall focus on these. The annual frequency of overreactions over the period 1990-2017 (Table A.1 and Figure A.1) 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.

To provide additional evidence on H1 we carry out again ANOVA analysis and Kruskall-Wallis tests; both confirm that the differences between years are statistically significant, i.e. that the frequency of overreactions varies over time consistently with H1.

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

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 A.2 and A.3). 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 statistical tests reported in Table 7 and 8 confirm that the results are not the same for negative and positive overreactions respectively and for overreactions as a whole.

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

Next, we analyse further the relationship between the VIX and the frequency of overreactions. First, we carry out ADF tests on the series of interest (see Table 9).

Table 9: Augmented Dickey-Fuller test: VIX and overreactions frequency data*

Parameter	VIX data	Over_all	Over_negative	Over_positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-5.209931	-4.683439	-5.689236	-5.328103
Probability	0.0000	0.0001	0.0000	0.0000
Test critical values (1% level):	-3.449679	-3.449679	-3.449679	-3.449679
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller test statistic	-5.204140	-4.671935	-5.675151	-5.324200
Probability	0.0000	0.0009	0.0000	0.0000
Test critical values (1% level):	-3.449679	-3.449679	-3.449679	-3.449679
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller test statistic	-15.82351	-13.48730	-14.32303	-14.19260
Probability	0.0000	0.0001	0.0000	0.0000
Test critical values (1% level):	-3.449679	-3.449679	-3.449679	-3.449679
Null hypothesis	rejected	rejected	rejected	rejected

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

Since all series appear to be stationary Granger Causality tests can be performed. These confirm the existence of linkages between the VIX and the frequency of overreactions (see Table 10).

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

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

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

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

$$VIX_i = 11.50 + 1.57 \times OF_i \qquad (7)$$

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 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

As can be seen, there is an inverse relationship between the frequency of (negative) overreactions and the VIX. 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.

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

We find empirical support for H3, since negative overreactions appear to be a statistically significant driver of the Dow Jones. We also estimate a linear regression with these as the only independent variable, namely *logreturnDJIi=f(OFi-)*; the results are reported in Table 14.

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

They imply that the DJI dynamics are influenced by the frequency of overreactions and can be described by the following equation:

$$logreturnDJI_i = 0.011 - 0.002 \times OF_i^- \quad (8)$$

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

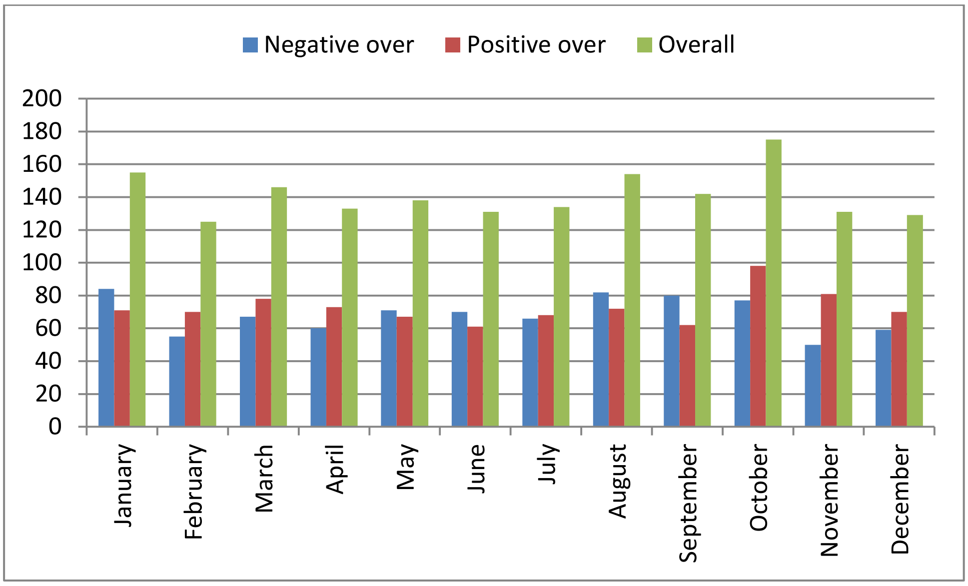


Figure 2: Monthly seasonality in overreaction frequency

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

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 negative overreactions	0.84	0.5992	1.82	Not rejected
Frequency of negative overreactions	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

As can be seen, 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.

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 to 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 null cannot be rejected except for H4, i.e. no seasonality is found.

Our findings have a number of important implications. First, it appears that the frequency of overreactions is related to crises and their phases: a sharp increase in the number of overreactions and the overreactions multiplier is associated with a crisis period. Further, it 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. On the whole, it can provide useful information about market developments and for designing trading strategies.

References

Angelovska J., (2016), Large share price movements, reasons and market reaction, Management, Vol. 21, 2016, 1, pp. 1-17.

Atkins, A.B. and E.A. Dyl, (1990), Price Reversals, Bid-Ask Spreads, and Market Efficiency. Journal of Financial and Quantitative Analysis, 25, 535 – 547.

Bremer, M. and R. J. Sweeney, (1991), The reversal of large stock price decreases. Journal of Finance 46, 747-754.

Bremer, M., T. Hiraki and R.J. Sweeney, (1997), Predictable patterns after large stock price changes on the Tokyo Stock Exchange. Journal of Financial and Quantitative Analysis 33, 345-365.

Brown, K. C., W.V. Harlow and S. M. Tinic, (1988), Risk Aversion, Uncertain Information, and Market Efficiency. Journal of Financial Economics 22, 355 - 385.

Caporale, G.M. and Gil-Alana, L., Plastun, A. and I. Makarenko (2016), Long memory in the Ukrainian stock market and financial crises. Journal of Economics and Finance. April 2016, Volume 40, Issue 2, pp 235-257

Caporale, G.M., Gil-Alana, L. and A. Plastun (2018), Short-term Price Overreactions: Identification, Testing, Exploitation, Computational Economics Volume 51, Issue 4, pp 913–940.

Chow, V., Jiang, W. and Li, J., 2014, Does VIX Truly Measure Return Volatility? Working Paper, West Virginia University.

Clements A., M. Drew, E. Reedman and M. Veeraraghavan, (2009), The Death of the Overreaction Anomaly? A Multifactor Explanation of Contrarian Returns. Investment Management and Financial Innovations 6, 76-85.

Cox, D. R. and D. R. Peterson, (1994), Stock Returns Following Large One-Day Declines: Evidence on Short-Term Reversals and Longer-Term Performance. Journal of Finance 49, 255-267.

De Bondt W. and R. Thaler, (1985), Does the Stock Market Overreact? Journal of Finance 40, 793-808.

Feldman, R., Livnat, J., and Zhang, Y. (2012), Analysts' Earnings Forecast, Recommendation and Target Price Revisions. Journal of Portfolio Management 38, 3, 120–132.

Ferri, M., G. and C. Min, (1996), Evidence that the Stock Market Overreacts and Adjusts. The Journal of Portfolio Management 22, 71-76.

Giot, P., 2005, Relationships Between Implied Volatility Indexes and Stock Index Returns, Journal of Portfolio Management 26, 12-17.

Govindaraj, S., Livnat, J., Savor P. and Zhaoe Ch. (2014), Large price changes and subsequent returns. Journal Of Investment Management, Vol. 12, No. 3, 31–58.

Guo, H., and R. Whitelaw, 2006, Uncovering the Risk-Return Relationship in the Stock Market, Journal of Finance 61, 1433-1463.

Howe, J. S. (1986): Evidence on Stock Market Overreaction, Financial Analysts Journal, 42, 74-77.

Jegadeesh, N. and S. Titman, (1993), Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance 48, 65-91.

Larson, S. and J. Madura, (2003), What Drives Stock Price Behavior Following Extreme One-Day Returns. Journal of Financial Research Southern Finance Association 26, 113-127.

Lasfer, M. A., Melnik, A., Thomas, D. (2003): Stock Price Reaction in Stressful Circumstances: An International Comparison, Journal of Banking and Finance, 27, 1959-1977.

Lehmann, B., (1990), Fads, Martingales, and Market Efficiency. Quarterly Journal of Economics 105, 1-28.

Mynhardt, R. H. and A. Plastun, (2013), The Overreaction Hypothesis: The case of Ukrainian stock market. Corporate Ownership and Control 11, 406-423.

Pritamani, M., Singal, V. (2001): Return Predictability Following Large Price Changes and Information Releases, Journal of Banking & Finance, 25, 631-656.

Sandoval, Leonidas, Franca, Italo De Paula, (2012), Correlation of financial markets in times of crisis, Physica A: Statistical Mechanics and its Applications, Volume 391, Issues 1–2, Pages 187-208.

Savor, P. (2012). Stock Returns after Major Price Shocks: The Impact of Information, Journal of Financial Economics 106, 3, 635–659.

Schnusenberg, Oliver & Madura, Jeff. (2001). Do U.S. Stock Market Indexes Over- Or Under-React?. Journal of Financial Research. 24, 2, 179-204

Wong, M., (1997), Abnormal Stock Returns Following Large One-day Advances and Declines: Evidence from Asian-Pacific Markets, Financial Engineering and Japanese Markets, 4, 71-177.

Zarowin P., (1989), Does the Stock Market Overreact to Corporate Earnings Information?. The Journal of Finance 44, 1385-1399.

Appendix A

Frequency of overreactions: static approach

Table A.1: 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 A.2: 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	18957.15
Observations	336	336	336	336

Figure A.1: Frequency of overreactions: dynamic analysis over the period 1990-2017, annual data

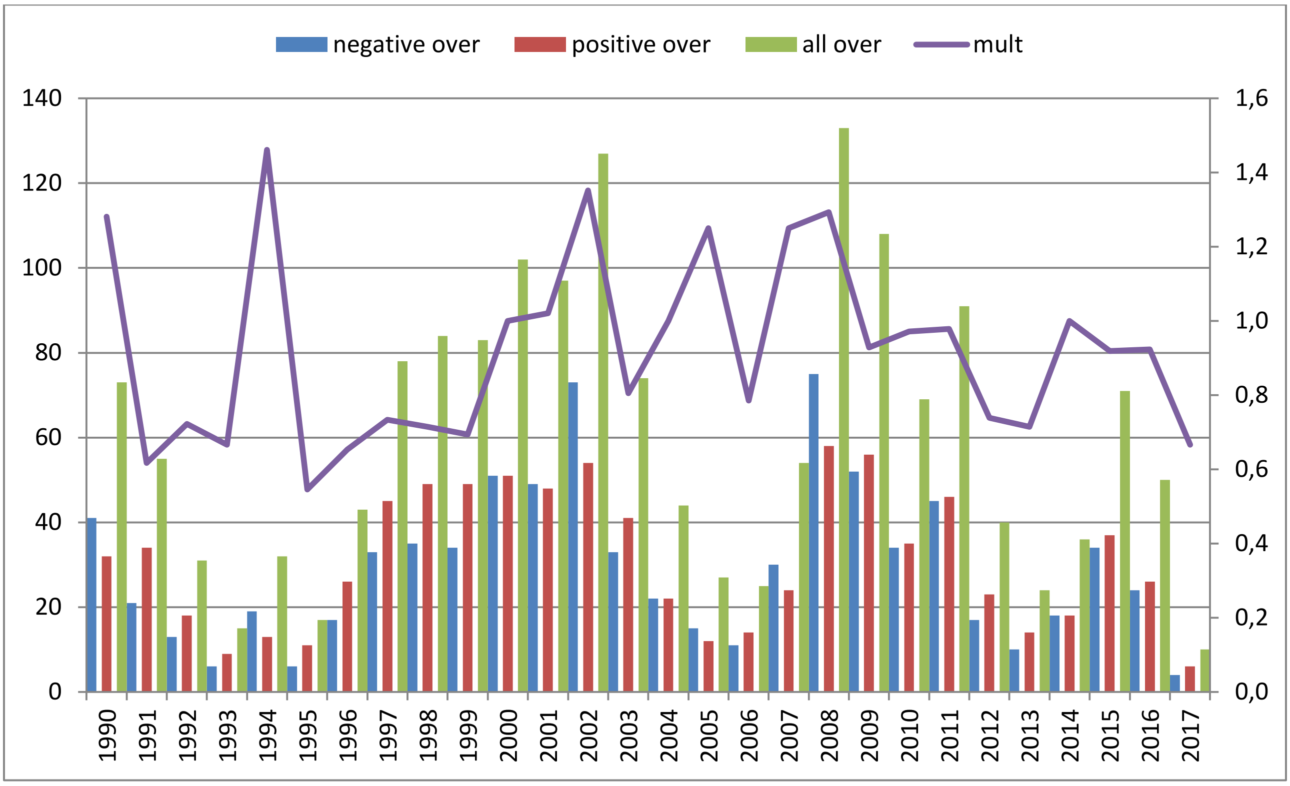


Figure A.2: Frequency of overreactions and VIX index: dynamic analysis over the period 2000-2004, monthly data

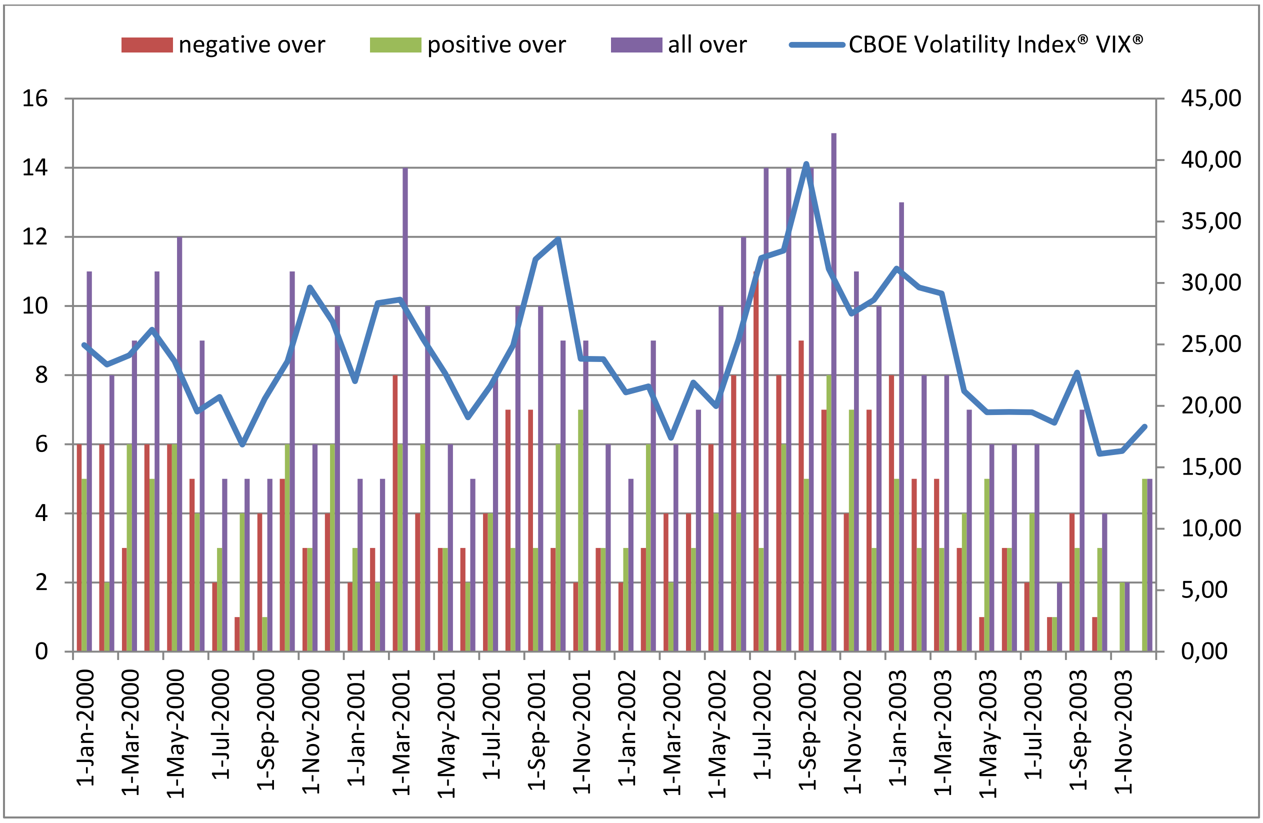
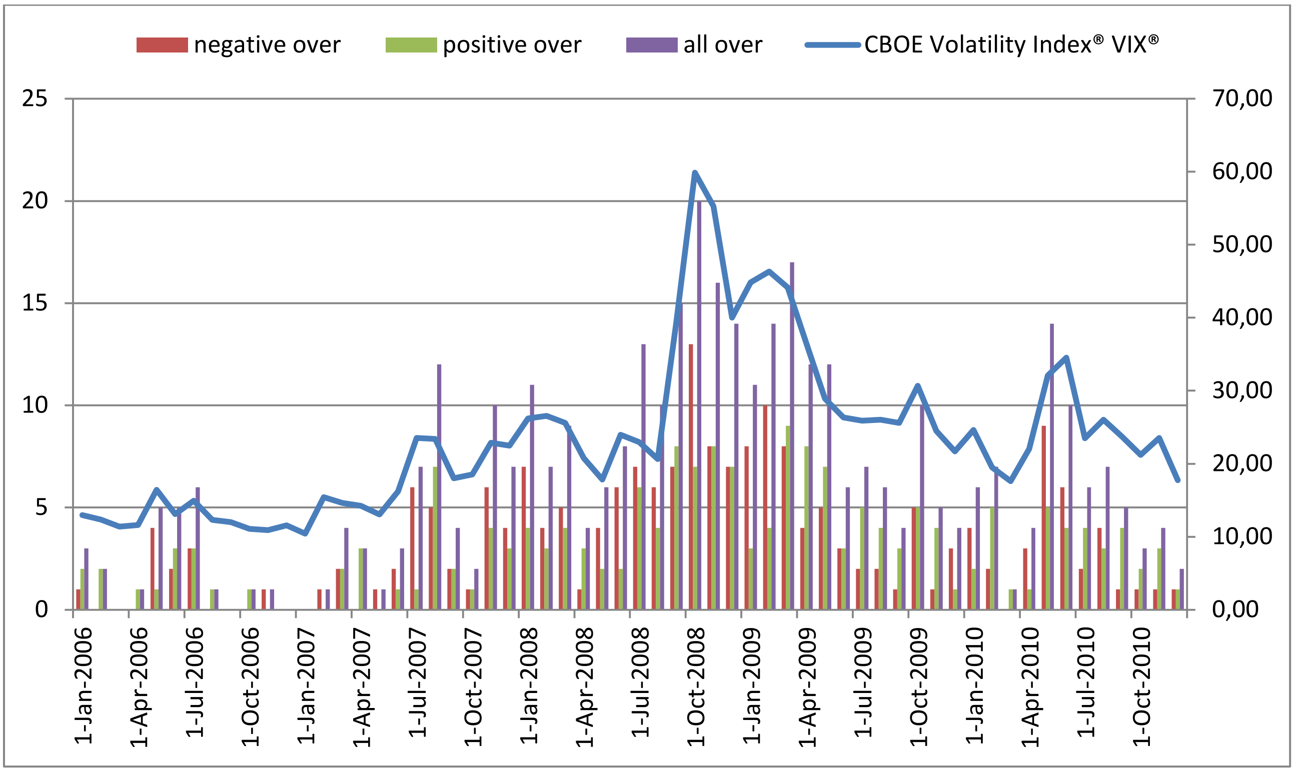


Figure A.3: Frequency of overreactions and VIX index: dynamic analysis over the period 2006-2010, monthly data



Appendix B

Table B.1: 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 B.2: 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	18957.15
Observations	336	336	336	336

Figure B.1: Frequency of overreactions: dynamic analysis over the period 1990-2017, annual data

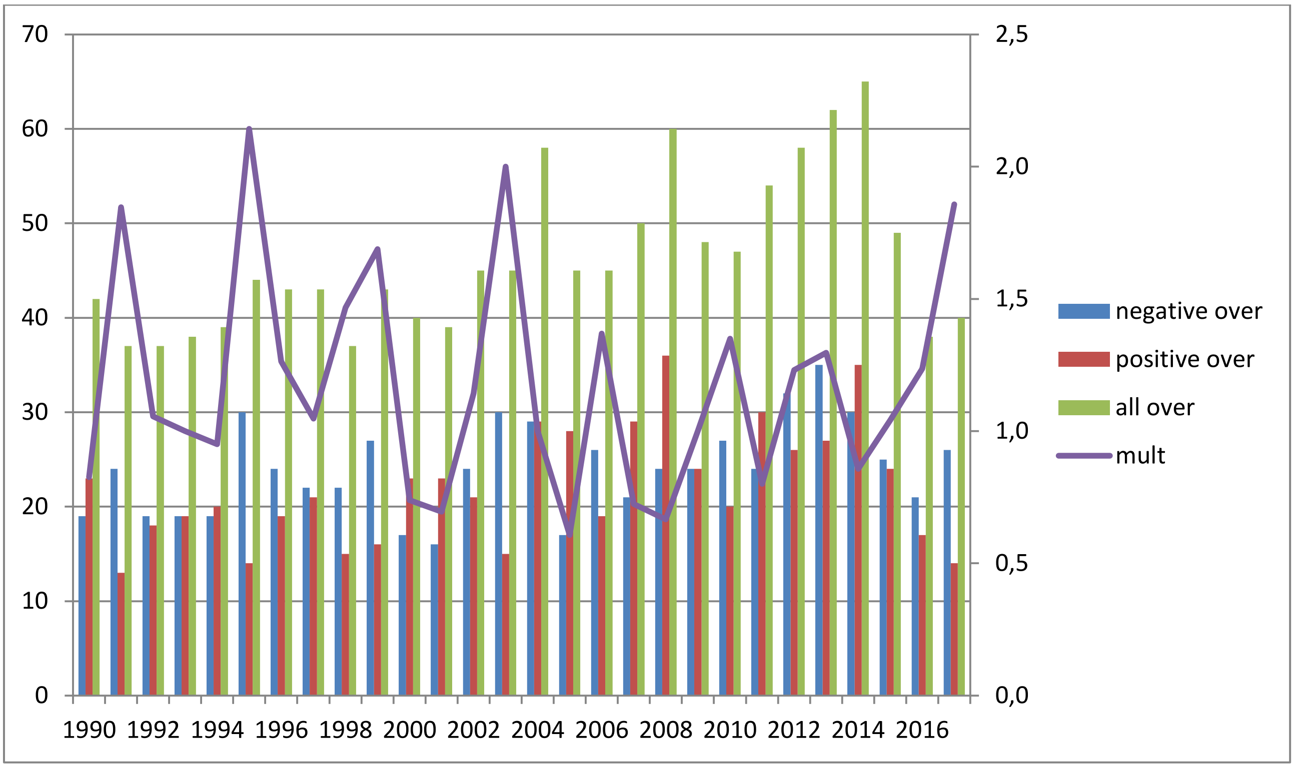


Figure B.2: Frequency of overreactions and VIX index: dynamic analysis over the period 2000-2004, monthly data

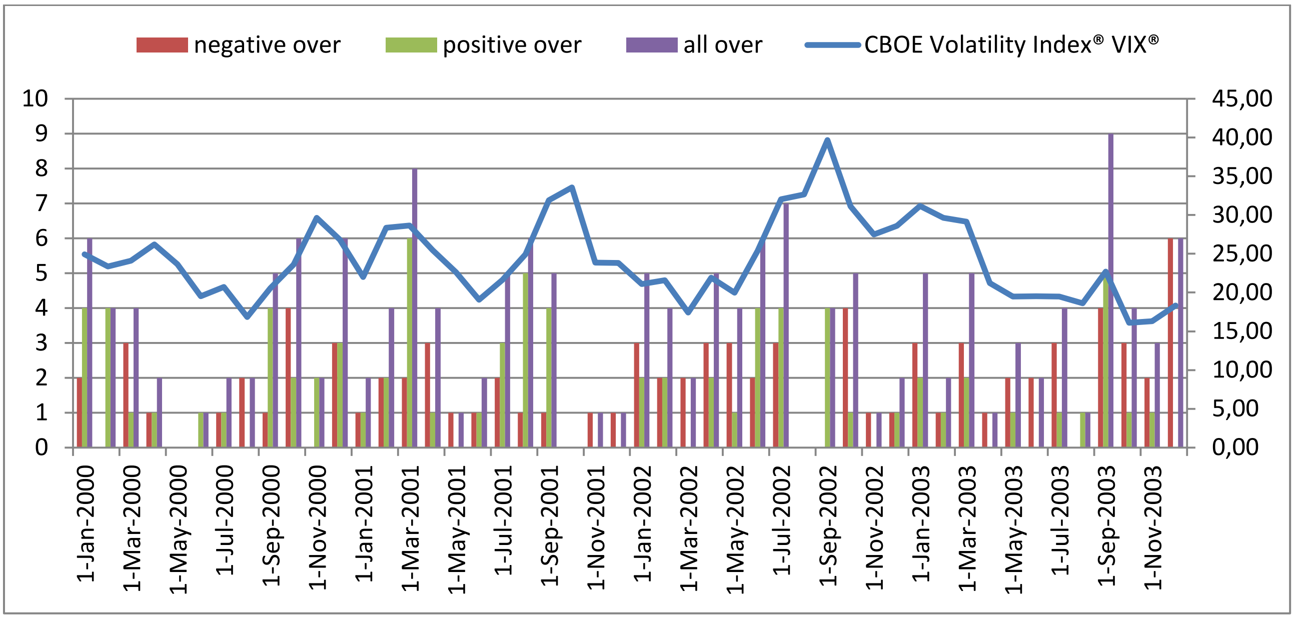
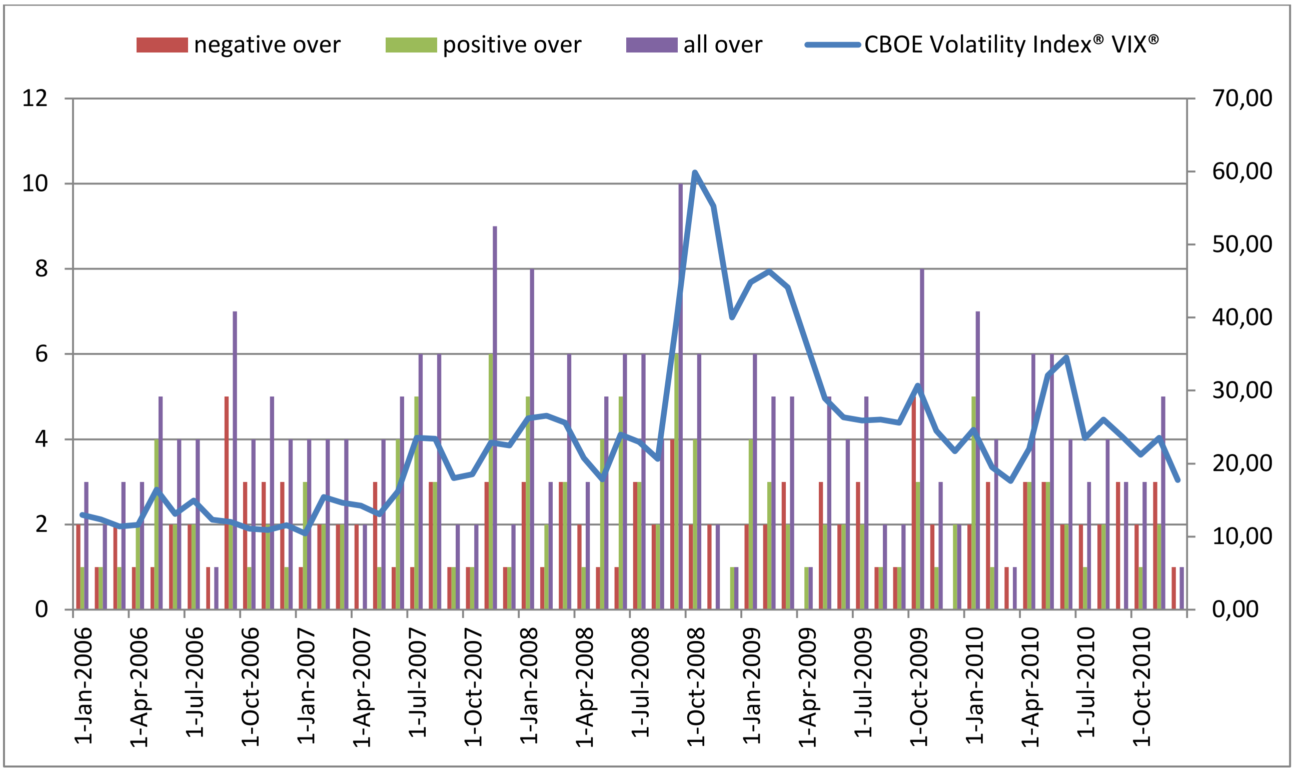


Figure B.3: Frequency of overreactions and VIX index: dynamic analysis over the period 2006-2010, annual data



Appendix C

Figure C.1: Dynamics of the VIX Index in 2007-2010 (taken from Caporale et al., 2016)