

Evolution of Price Effects After One-Day of Abnormal Returns in the US Stock Market

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Abstract

This paper provides a comprehensive analysis of price effects after one-day abnormal returns and their evolution in the US stock market for the case of Dow Jones Index over the period 1890-2018. Using different statistical tests (both parametrical and non-parametrical) as well as additional technics like modified cumulative abnormal returns approach, regression analysis with dummy variables, R/S analysis and a trading simulation approach; four hypotheses were tested, which are (H_1): the after one-day of abnormal returns specific price effects (momentum/contrarian) do appear; (H_2): the price effects after one-day of abnormal returns vary in time and evolve; (H_3): the price effects after one-day of abnormal returns can be exploited to generate profits from trading; and (H_4): the level of persistence in anomalies related data set differs from the normal data set persistence. The results suggest that price effects after one-day abnormal returns during the analyzed period tend to be rather unstable both from the position of their strength and direction (momentum or contrarian effect). Between the 1940s and the 1980s a strong momentum effect after a day of positive abnormal returns was present and it was exploitable for profit. However, after the 1980s this has since disappeared. Nowadays the after one-day of abnormal returns price effects in the US stock market are rather weak and do not generate profit opportunities. The results, therefore, are consistent with the Adaptive Market Hypothesis.

Keywords: Overreaction, Momentum Effect, Contrarian Effect, Abnormal Returns, Stock Market; Dow Jones Index.

JEL Codes: G12, C63

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1 Introduction

According to the Efficient Market Hypothesis as described by [Fama \(1965, 1970\)](#) price overreactions in the short or long term should not exist since market participants must utilise all available information to make rational choices. However, [De Bondt and Thaler \(1985, 1987\)](#), and [Jegadeesh and Titman \(1993\)](#) have shown that price overreactions exist, and therefore that markets can be inefficient.

However, the reasons for price overreactions remain varied and to some extent uncertain. Some point to market size and liquidity shortages as key explanations ([Fama and French \(1993\)](#) and [Lasfer et al. \(2003\)](#)), instead of market behaviour (for example [Kudryavtsev \(2013\)](#)). While some did not confirm the existence of price overreactions ([Fama and French \(1995\)](#) and [Clements et al. \(2009\)](#)). Others such as [Cox and Peterson \(1994\)](#) and [Zarowin \(1990\)](#) highlight the importance of the overreaction window to the stability of the momentum or the contrarian price effects. In particular [Lehmann \(1990\)](#) highlights the importance of studying short term price overreactions in developed markets as these overreactions tend to disappear in the longer term in efficient markets. Recently, [Dyl et al. \(2019\)](#) questions the underlying reasons for the overreaction hypothesis after finding contradictory investor behaviour regarding the rational use of price related information. In general, new evidence ([Zaremba \(2019\)](#), [Caporale et al. \(2019\)](#), [Caporale and Plastun \(2019a\)](#), and [Zaremba et al. \(2020\)](#)) is emerging about the existence price overreactions.

The lack of certainty on the historical existence and therefore reasons for price overreactions, particularly in the short term and the effect of sample sizes on the detection of price overreactions necessitates a long period study to ascertain a wider historical understanding of price overreactions. Based on Dow Jones Index daily data over the period 1890 to 2018 we analyse the price effects after one-day abnormal returns in the US stock market and their evolution in time. To do this we employ various standard statistical techniques (average analysis, Student's t-test, ANOVA, the Mann-Whitney test), as well as modified cumulative abnormal returns approach, regression analysis with dummy variables and a trading simulation approach. In addition we use R/S analysis which allows exploring persistence of data (both normal and abnormal) over different periods of time to find more evidence for or against abnormal price behaviour after overreactions.

The results show that both the momentum and contrarian effects existed at some point in the US stock market. Evidence of these anomalies was supported by the R/S analysis and the trading robot approach which showed significant differences between the "normal" sample versus the "abnormal" sample. However, these have since disappeared which is inline with the Adaptive Market Hypothesis

The layout of the paper is as follows. Section 2 briefly reviews the overreaction hypothesis and price effects after one-day abnormal returns. Section 3 describes the data and outlines the empirical methodology. Section 4 presents the empirical results.

Section 5 offers some concluding remarks.

2 Literature Review

De Bondt and Thaler (1987) define a market overreaction as the systematic price reversals of stock prices that experience long term gain or losses, where losers outperform winners significantly. That is, the overreaction is biased to a negative market events. In asking the question "what are the equilibrium conditions for markets in which some agents are not rational in the sense that they fail to revise their expectations according to Bayes' rule?" De Bondt and Thaler (1985) postulated the overreaction hypotheses.

However, the overreaction hypothesis has various dimensions. What is defined by De Bondt and Thaler (1985, 1987), and Jegadeesh and Titman (1993), amongst others, is known as the contrarian effect. This is also known as the "winner-loser reversals" (Richards (1997)). On the opposite end, Jegadeesh (1990) describe the momentum effect over a longer period. That is winners and losers do not experience price (or return) reversals instead continue to benefit (lose) based on past performance. Campbell and Limmack (1997) highlight an essential element of the overreaction hypothesis that it is not necessarily symmetrical. That is, some studies (for example Pettengill and Jordan (1990)) found a tendency for losers to become winners (a price reversal) but that winners did not have the tendency to become losers, and that this was highly depended on the overreaction window period.

Implicit in the overreaction hypothesis is that the overreaction of market participants, in particular to bad market events as compared to good market events, must be driven by the behaviour of market participants and not other market factors, and that there is an appropriate level of reaction to compare with. Therefore, according De Bondt and Thaler (1985) to the overreaction of market participants is an empirical question to test if the overreaction hypothesis is in essence predictive.

The debate in the literature has centred on those supporting the overreaction hypothesis and those that do not. For example (Brown et al. (1988) suggest that dramatic market events cause both risk and expected returns to increase systemically causing market prices to react more strongly to negative market events than to positive market events. De Bondt and Thaler (1987) found no evidence to support role for size and risks in explaining market overreactions. Clements et al. (2009) extended the sample period of De Bondt and Thaler (1987) to 2003 and also confirmed the overreaction hypothesis, however, Clements et al. (2009) did not confirm overreaction using the Fama and French (1993) method. Bremer and Sweeney (1991) also found evidence of market overreaction using a sample of firms after a 10% fall in the stock price. In summary, a number of studies have confirmed the overreaction hypothesis (Fama and French (1988), Poterba and Summers (1988), Chopra et al. (1992), and Campbell and Limmack (1997)).

However, others have attributed the "overreaction" to other market factors such as market liquidity, firm size, risk and the seasonality of returns. [Fama and French \(1993\)](#) and [Fama and French \(1995\)](#) highlighted the relevance of size and overall market factors in explaining stock market returns. [Lasfer et al. \(2003\)](#) attributed market overreaction to market liquidity by showing that emerging markets with low liquidity reaction to a market shock in a more pronounced manner as compared to developed market. However, this reaction depended on the size and the speed with which the shock is absorbed. [Zarowin \(1990\)](#) showed that to an extent of the overreaction can be thought of as the January effect as the overreaction mainly occurred in January in some markets. Recently, [Dyl et al. \(2019\)](#) found that after one day of abnormal returns investors overreacted to non-information price movements and under-reacted to firm specific public information raising further questions about the underlying reasons for the overreaction hypothesis.

Others such as [Conrad and Kaul \(1993\)](#), [Cox and Peterson \(1994\)](#), and [Brown et al. \(1988\)](#) showed the importance of methodological biases in confirming the overreaction hypothesis. [Conrad and Kaul \(1993\)](#) showed that measurement bias in the computation of long term returns showing that the "true" returns have no relation to overreaction. Whilst [Cox and Peterson \(1994\)](#), [Brown et al. \(1988\)](#) showed that the choice of the overreaction window is important. [Cox and Peterson \(1994\)](#), in particular, found that overreaction with a short window (10 days) but not with a longer window.

Particularly relevant to this study, [Lehmann \(1990\)](#) states that in efficient markets such as the US changes fundamental valuations of stocks should only occur over long periods. Furthermore, [Lehmann \(1990\)](#) highlights the fact that it is only in the short term that one can distinguish between returns that vary through time through some mean reverting but efficient mechanism, or that returns reflect some overreaction in stock prices in the form of "fads" as outlined by [Shiller \(2000\)](#). Succinctly, short run price changes do not necessary provide much information about long term stock price valuations, but may signal inefficiencies in a stock market.

Several studies with short overreaction windows were conducted ([Zarowin \(1990\)](#), [Cox and Peterson \(1994\)](#), [Atkins and Dyl \(1990\)](#), [Kudryavtsev \(2013\)](#), and [Grant et al. \(2005\)](#) amongst others). In earlier works [Atkins and Dyl \(1990\)](#) and [Bremer and Sweeney \(1991\)](#) found evidence of price reversals after one day of price declines. However, [Cox and Peterson \(1994\)](#) did not find evidence consistent with the overreaction hypothesis after one day of large price declines in the US stock market. More recently [Kudryavtsev \(2013\)](#) found evidence of price reversals in the Dow Jones Industrial Index after a day of large high (low) to close prices. Furthermore, [Caporale and Plastun \(2019a\)](#) extended the literature on the US stock market by investigating the frequency of overreactions and found that these were linked to volatility (VIX index). This suggested that overreactions could be used as predictors of market sentiment. No profitable trading opportunities from overreactions were found by [Caporale and Plastun \(2019a\)](#) suggesting market efficiency. Evidence of overreactions were also found by [Caporale et al. \(2019\)](#) in the US stock market using weekly data.

In summary, the literature on short term overreactions remains vibrant with studies on emerging markets (for example [Boubaker et al. \(2015\)](#), [Pokavattana et al. \(2019\)](#), [Zaremba \(2019\)](#), and [Mynhardt and Plastun \(2013\)](#)), cross sectional international studies (for example [Blackburn and Cakici \(2017\)](#)), and studies on other markets such as the cryptocurrency market (for example [Caporale and Plastun \(2019b\)](#), and [Caporale and Plastun \(2019c\)](#)). The historical question on the existence and the reasons of market overreactions remains relevant today in developed markets and can even collaborate what is observed in new markets.

3 Data and Methodology

Daily data from the Dow Jones Index (DJI) for the years 1890 to 2018 was utilised for this study. This data were sourced from the Global Financial Database¹. This data were then split into 10-year sub-periods to allow for study of the evolution of price effects after one day of abnormal returns. These sub periods are sufficient to test the following hypotheses:

- H_1 : the after one-day of abnormal returns specific price effects (momentum/contrarian) do appear. This hypothesis is split into two, that is, H_{11} : after one-day of abnormal positive returns specific price effects do appear, and H_{12} : after one-day of abnormal negative returns specific price effects do appear;
- H_2 : the price effects after one-day of abnormal returns vary in time and evolve;
- H_3 : the price effects after one-day of abnormal returns can be exploited to generate profits from trading;
- H_4 : the level of persistence in the anomaly related data set differs from the normal data set persistence.

To test the validity of these hypotheses we employ several techniques which include the average analysis, parametrical tests (Students t-tests, ANOVA analysis), non-parametrical tests (Mann-Whitney tests), the modified cumulative abnormal returns approach, regression analysis with dummy variables, and a trading simulation approach. In this case, the average analysis provide initial evidence of daily abnormal returns, whilst both the parametric, non parametric tests, test for fat tails and kurtosis in the daily returns to determine if all the data belong to the same population (or that price effects exist). To this end, the daily returns are calculated as follows:

$$R_i = \left(\frac{Close_i}{Close_{i-1}} - 1 \right) \times 100 \quad (1)$$

¹Please see <https://www.globalfinancialdata.com>

where R_i is the return on the i^{th} day in percentage, $Close_i$ is the close price on the i^{th} day, and $Close_{i-1}$ is the open price on the $i - 1^{th}$ day.

A key issue is how the threshold levels are defined in the determination of the overreactions. For example, [Bremer and Sweeney \(1991\)](#) used a 10% price change to determine an overreaction. However, as shown by [Cox and Peterson \(1994\)](#) the use of a constant threshold level can lead to biased results as price volatility varies overtime. To that effect, the dynamic trigger approach as outlined by [Lasfer et al. \(2003\)](#), amongst others, is used in this paper. This approach states that abnormal returns are defined in terms of the number of standard deviations that are to be added to the mean.

Using this approach, the data are split into positive abnormal returns, negative abnormal returns, and normal returns. This is done using equations 2 and 3 which calculate overreactions as follows:

$$R_i > (\bar{R}_n + k \times \delta_n) \quad (2)$$

$$R_i > (\bar{R}_n - k \times \delta_n) \quad (3)$$

where \bar{R}_n is the average daily return in period n , δn is the standard deviation on daily returns in period n , and k is the overreaction identification parameter.

In addition, a multiple regression analysis was conducted on the abnormal returns to provide additional evidence of positive and negative overreactions. This was implemented in the following manner:

$$R_i = a_0 + a_1 D_i + \epsilon_i \quad (4)$$

where R_i is the return in period t , a_0 is the mean return in a normal day, a_1 is the mean return on an overreaction day, D_i is a dummy variable equal to 1 on an overreaction day and 0 in a normal day, and ϵ_i is the random error term of the i^{th} day. The sign and statistical significance of the dummy coefficients indicate the existence or not overreactions.

[MacKinlay \(1997\)](#) sets out the standard for event studies. In particular, according to [MacKinlay \(1997\)](#) the cumulative approach returns approached defines abnormal returns as follows:

$$AR_i = R_i - E(R_i) \quad (5)$$

where R_i is the daily return and AR_t is the abnormal daily return at time i . $E(R_i)$ is the average return computed over the entire sample as follows:

$$E(R_i) = \left(\frac{1}{T}\right) \sum_{i=1}^T R_i \quad (6)$$

where T is the sample size.

CAR_i denotes the cumulative abnormal returns and is the sum of the abnormal returns as follows:

$$CAR_i = \sum_{i=1}^T AR_i \quad (7)$$

A simple regression model is implemented on the CAR_i to determine the presence of a trend. The presence of a trend in the CAR_i indicates abnormal returns. Therefore, a significant p -value on the trend term, along with a model significant (F -test) confirm abnormal returns.

In order to determine whether a detected anomaly provides for exploitable profit opportunities we first define $\%Result$ from each trade as follows:

$$\%Result = \frac{100 \times P_{open}}{P_{close}} \quad (8)$$

where P_{open} is the opening price, and P_{close} is the closing price.

Next, the result of each trade are summed to determine the total financial result from trading. A positive financial result indicates exploitable profits based on that specific market anomaly. A negative total financial result indicates the opposite. A t-test is carried out on the results to determine if they are statistically different from random trading. A t-test instead of a z-test was utilised since the sample size of each sub period is less than a 100. A t-test compares the means from two samples to test whether these means originate from the same population. In our case, the first is the average profit/loss factor of one trade applying the trading strategy, and the second is equal to zero because random trading (without transaction costs) should generate zero profit. A failure to reject H_0 (means are the same in both samples) in this instance indicates that the specific anomaly does not generate exploitable profit opportunities.

Lastly, to test H_4 we utilise R/S analysis as in [Caporale et al. \(2018\)](#) and [Plastun et al. \(2019\)](#). In general the test is as follows.

First, a time series of length M is transformed into length $N = M - 1$ using logs and converting stock prices into returns in this manner:

$$N_t = \log \left(\frac{Y_t}{Y_{t-1}} \right), t = 1, 2, 3, \dots, (M - 1) \quad (9)$$

Second, this length is divided into contiguous A sub-periods with length n , such that $A_n = N$, then each sub-period is identified as I_a , given the that $a = 1, 2, 3, \dots, A$. Each element I_a is represented as N_k with $k = 1, 2, 3, \dots, N$. For each I_a with length n the average is defined as e_a :

$$e_a = \frac{1}{n} \sum_{k=1}^n N_{k,a}, k = 1, 2, 3, \dots, N, a = 1, 2, 3, \dots, A \quad (10)$$

Thirdly, the accumulated deviations $X_{k,a}$ from the average e_a for each sub-period I_a are defined as follows:

$$X_{k,a} = \sum_{i=1}^k (N_{i,a} - e_a) \quad (11)$$

The range is defined as the maximum index $X_{k,a}$ minus the minimum $X_{k,a}$, within each sub-period I_a :

$$R_{I_a} = \max X_{k,a} - \min X_{k,a}, 1 \leq k \leq n \quad (12)$$

Fourthly, the standard deviation S_{I_a} is calculated for each sub-period I_a as:

$$S_{I_a} = \left(\left(\frac{1}{n} \right) \sum_{k=1}^n (N_{k,a} - e_a)^2 \right)^{0.5} \quad (13)$$

Fifthly, each range R_{I_a} is normalised by dividing by the corresponding S_{I_a} . Therefore, the re-normalised scale during each sub-period I_a is R_{I_a}/S_{I_a} . In step 2 above, adjacent sub-periods of length n are obtained. Thus, the average R/S for length n is defined as:

$$(R/S)_n = \frac{1}{A} \sum_{i=1}^A (R_{I_a}/S_{I_a}) \quad (14)$$

Sixthly, the length n is increased to the next higher level, $(M-1)/n$, and must be an integer number. In this case, n -indexes that include the start and end points of the time series are used, and steps 1 to 5 are repeated until $n = (M-1)/2$.

Then $\log(R/S) = \log(c) + H * \log(n)$ is estimated using the least square method. The slope term is an estimate of the Hurst exponent (H) (Hurst (1951)). The H values fall in to three categories which can be identified as follows:

- $0 \leq H < 0.5$: the series are anti-persistent and returns are negatively correlated;
- $H = 0.5$: the series are random and returns are uncorrelated;
- $0.5 < H \leq 1$: the series are persistent and returns are highly correlated.

4 Empirical Results

We start with the defining crucial parameters for this research. That is, the number of standard deviations added to the mean return to measure one-day abnormal returns and period used to calculate both average and standard deviation. In Table 1, we calculate the number of abnormal returns detected based on different parameters of interest.

Table 1 shows that the number of abnormal return detections is very dependent on the number of standard deviations added to the mean return. Three standard deviations generate rather an insignificant number of abnormal returns to test statistically.

However, with one standard deviation, we found almost 25% of abnormal returns from the overall data set which is inconsistent with the definition of the overreaction anomaly. The use of two standard deviations on average provides 5% of abnormal returns from the overall data set. This percentage is rather stable in the various periods and therefore is a good proxy for the purposes of this study. To find the best period based on specific of this paper t-tests for differences between the overreaction and normal data sets in different periods were conducted and presented in Table 2.

The t-tests reveal statistically significant differences between the overreaction days and the normal days. Overall the longer the period is, the more significant the difference. Therefore the purposes of this paper we chose 50 days. The empirical results for the positive and negative overreactions are presented in Appendices A and B respectively. We start with the positive overreactions.

The results of the simple average analysis are displayed in Table A.1 and Figure A.1. In most periods (with only a few exceptions) the returns on the day after positive overreactions differ from those during the normal days. An important observation is that in most periods the momentum effect is observed, that is, the next day after abnormal growth prices tend to grow further.

This overreaction only changed in the 21st century where contrarian movements dominated. Based on the ANOVA-multiplier (F/F_{crit} ratio which allows seeing how statistically significant the difference is when this multiplier is above 1 it might be concluded that there is a statistically significant difference between returns in different days) it can be concluded that these differences were statistically significant between the 1940s and 1980s.

To provide a more detailed analysis of statistical differences several parametrical (ANOVA analysis, t-tests) and non-parametrical methods (Mann-Whitney test), as well as additional technical tests (modified CAR approach and regressions analysis with dummy variables) are used.

The ANOVA analysis results are presented in Table A.2. Results of t-tests (Table

Table 1: Number of one-day abnormal returns detections depending on the period and overreaction criterion

Period	Indicator	Overall	Number of abnormal returns (criterion =mean+ standard deviation)	Number of abnormal returns (criterion = mean+2* standard deviation)	Number of abnormal returns (criterion = mean+3* standard deviation)
5	Number	32076	7290	2406	951
	Percent	100%	23%	8%	3%
10	Number	32076	7290	1837	519
	Percent	100%	23%	6%	2%
20	Number	32076	7462	1688	394
	Percent	100%	23%	5%	1%
30	Number	32076	7603	1608	387
	Percent	100%	24%	5%	1%
40	Number	32076	7661	1588	376
	Percent	100%	24%	5%	1%
50	Number	32076	7687	1595	363
	Percent	100%	24%	5%	1%

Table 2: t-test for differences in overreaction and normal data sets: case of different time periods

Period	Data set	Mean	Standard deviation	Number of values	t-criterion	t-critical (=0.95)	Null hypothesis
5	Normal	0.50%	0.52%	24780	4.30	1.96	rejected
	Overreaction	0.73%	0.85%	2406			
10	Normal	0.48%	0.48%	24775	4.76	1.96	rejected
	Overreaction	0.79%	1.10%	1837			
20	Normal	0.46%	0.44%	24593	5.69	1.96	rejected
	Overreaction	0.84%	1.15%	1688			
30	Normal	0.45%	0.42%	24442	6.35	1.96	rejected
	Overreaction	0.89%	1.24%	1608			
40	Normal	0.45%	0.42%	24374	6.58	1.96	rejected
	Overreaction	0.90%	1.26%	1588			
50	Normal	0.44%	0.41%	24338	7.01	1.96	rejected
	Overreaction	0.92%	1.27%	1595			

A.4) also show that between the 1940s and 1980s returns on the day after positive overreactions differ from those during the normal days and this difference was statistically significant. These results are confirmed by the non-parametrical Mann-Whitney test in Table A.3.

The results of the Modified CAR approach (Table A.5) confirm the presence of abnormal price behavior on the day after positive overreactions during all of the analysed periods except 1900 to 1909. The regression analysis with dummy variables (Table A.6) revealed the presence of the momentum effect between the 1940s and the 1980s.

To detect if these anomalies allowed market participants to beat the market we use the trading simulation approach. The algorithm of the trading strategy is very simple. Buy right at the start of the day after the positive overreaction in case of the momentum effect and sell in case of a contrarian effect. Positions should be close at the end of the day. Transaction costs (spread, commissions to the broker, commissions to the bank, etc.) are ignored because it is almost impossible to incorporate them correctly during such a long period.

The results of the trading simulations are presented in Table A.7 and Figure A.2. The momentum effect from the 1940s until the end of the 1970s was exploitable, that is, it generated profits which were not the result of random trading. These results are fully consistent with the results from the statistical tests. A summary of the results for the case of positive abnormal returns is presented in Table 5.

We provide a similar analysis for the negative overreactions. The simple average analysis was in favour of much higher returns on the days after a negative overreaction compared with the normal days (Table A.1 and Figure A.1.). However, these differences were statistically significant only for the half of the analysed periods (see Tables B.2 and B.4 for parametrical ANOVA and t-test and B.3 for non-parametrical Mann-Whitney test).

The overall results are very mixed and unstable. This is confirmed by the Modified CAR approach (Table B.5) and regression analysis with dummy variables (Table B.6). The period between the 1900s and the 1930s is characterised by a strong contrarian effect, that is, prices tend to grow after the days with negative abnormal returns. But between 1940 and 1949 and between 1970 and 1979 a very strong momentum effect was observed. In the other periods, no prices patterns were detected or the results were unconvincing.

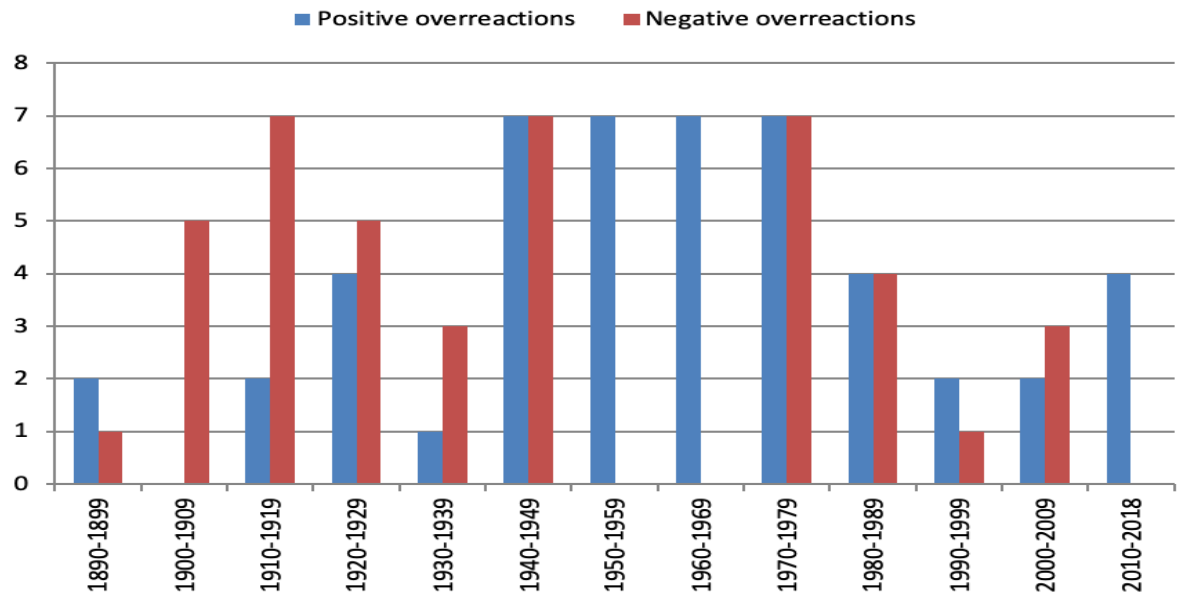
The trading simulations (Table B.7 and Figure B.2) show that statistically different from random results were obtained only during two periods (momentum effect in the periods 1940 to 1949 and 1970 to 1979). Contrarian strategies with only one exception (1910-1919) can not provide results statistically different from random trading results. A summary of results for the case of negative overreactions is presented in Table 4.

Table 3: Overall results for the one-day abnormal positive returns: case of Dow Jones index, 1900-2018

Period	Average analysis	Students t-test	ANOVA	Mann- Whitney test	Modified CAR	Regression with dummy variables	Trading simula- tion	Overall
1890-1899	+	-	-	-	+	-	-	2
1900-1909	-	-	-	-	-	-	-	0
1910-1919	-	-	-	+	+	-	-	2
1920-1929	+	-	+	-	+	+	-	4
1930-1939	-	-	-	-	+	-	-	1
1940-1949	+	+	+	+	+	+	+	7
1950-1959	+	+	+	+	+	+	+	7
1960-1969	+	+	+	+	+	+	+	7
1970-1979	+	+	+	+	+	+	+	7
1980-1989	+	-	+	-	+	+	-	4
1990-1999	+	-	-	-	+	-	-	2
2000-2009	+	-	-	-	+	-	-	2
2010-2018	+	-	+	-	+	+	-	4

Note: + means the that anomaly is present, and - means that it is not present. The overall column simply counts the number of + with a higher number indicating stronger evidence of the anomaly

Figure 1: Evolution of the price effects after one-day abnormal returns in the US stock market: the case of the Dow Jones Index during 1900-2018



Note: The scale is from 0 to 4, where 0 is total absence of anomaly and 4 is the most convincing presence of anomaly

A summary of the price effects after one-day abnormal returns evolution is presented in Figure 1. Since the 1980s the efficiency of the US stock market has increased which lead to the disappearance of price effects after one-day abnormal returns. Nevertheless, there are periods in the history of the US stock market when the one-day abnormal returns generated one-day abnormal returns price effects. The typology of these effects (momentum or contrarian) is presented in Table 5.

Table 4: Overall results for the one-day abnormal negative returns: case of Dow Jones index, 1890-2018

Period	Average analysis	Students t-test	ANOVA	Mann- Whitney test	Modified CAR	Regression with dummy variables	Trading simula- tion	Overall
1890-1899	+	-	-	-	-	-	-	1
1900-1909	+	-	+	+	+	+	-	5
1910-1919	+	+	+	+	+	+	+	7
1920-1929	+	-	+	+	+	+	-	5
1930-1939	+	-	-	+	+	-	-	3
1940-1949	+	+	+	+	+	+	+	7
1950-1959	-	-	-	-	-	-	-	0
1960-1969	-	-	-	-	-	-	-	0
1970-1979	+	+	+	+	+	+	+	7
1980-1989	+	-	+	-	+	+	-	4
1990-1999	-	-	-	-	+	-	-	1
2000-2009	+	-	+	-	-	+	-	3
2010-2018	-	-	-	-	+	-	-	0

Note: + means the that anomaly is present, and - means that it is not present. The overall column simply counts the number of + with a higher number indicating stronger evidence of the anomaly

Table 5: Typology of the price effects after one-day abnormal returns: case of Dow Jones index, 1890-2018

Period	Positive overreactions		Negative overreactions	
	Type of effect	Power	Type of effect	Power
1890-1899	contrarian	2	contrarian	1
1900-1909	no effect	0	contrarian	5
1910-1919	momentum	2	contrarian	7
1920-1929	momentum	4	contrarian	5
1930-1939	contrarian	1	contrarian	3
1940-1949	momentum	7	momentum	7
1950-1959	momentum	7	no effect	0
1960-1969	momentum	7	no effect	0
1970-1979	momentum	7	momentum	7
1980-1989	momentum	4	momentum	4
1990-1999	momentum	2	contrarian	1
2000-2009	contrarian	2	contrarian	3
2010-2018	contrarian	4	no effect	0

Table 6: Persistence of the prices: case of Dow Jones index, 1890-2018

Period	Data after negative overreactions	Data after positive overreactions	Usual days
1890-1899	0.71	0.98	0.54
1900-1909	0.31	0.52	0.60
1910-1919	0.49	0.93	0.56
1920-1929	0.84	0.55	0.53
1930-1939	0.21	0.80	0.62
1940-1949	0.31	0.41	0.56
1950-1959	0.51	0.66	0.60
1960-1969	0.55	0.62	0.55
1970-1979	0.60	0.52	0.53
1980-1989	0.36	0.71	0.61
1990-1999	0.42	0.24	0.51
2000-2009	0.58	0.81	0.53
2010-2018	0.44	0.61	0.54
Average	0.47	0.62	0.56
Stand deviation	0.17	0.19	0.04
Typical interval	0.30-0.64	0.43-0.8	0.52-0.60

To find additional evidence in favour of abnormal price behaviour after one-day abnormal returns we run an R/S analysis (Table A.7). The R/S analysis shows that the Hurst exponent on days after one-day abnormal returns differs from the Hurst exponent values on normal days. This means that the level of persistence is different for the analysed data sets. In theory, this persistence should be the same. This is additional evidence in favour of abnormal price behaviour after the days of overreactions.

Overall, we find convincing evidence in favour of the evolution of these price effects in the US stock market after one-day abnormal returns. These effects are different for the positive and negative overreactions. For example, the momentum effect is much more typical for the case of positive overreactions and the contrarian effect tends to happen more often after the days with negative overreactions.

The period 1940 to 1979 is the likely "golden" era for the price anomalies and price effects in the US stock market after one-day abnormal returns. But since the 1990s these anomalies have mostly disappeared.

Another important observation is the changeable character of price effects: momentum effects are followed by contrarian and vice versa for different sub-periods. There were also periods when detected anomalies provide opportunities for extra profits gen-

eration. However, in most periods it was impossible to show trading results based on detected effects which would be different from the random.

Between the 1940s and the 1980s, positive overreactions generate very strong and stable price patterns (prices tend to change in the direction of an overreaction- momentum effect). This also was true for negative overreactions for the periods 1940 to 1949 and 1970 to 1979. Since then these price effects have mostly disappeared in the US stock market. A possible explanation for this is that the performance of anomalies disappears after academic publications ([McLean and Pontiff \(2016\)](#)).

The results of this study clearly show that the market inefficiency of the stock market is strongly related to market anomalies. This can even be currently be seen in emerging stock markets which are less efficient than developments, where price effects after one-day abnormal returns can still be detected.

Furthermore, the instability of the price effects confirm the work of [Pettengill and Jordan \(1990\)](#) who found that the overreaction hypothesis is not necessary symmetrical. Suggesting that one is unlikely to see a clear persistence of the contrarian effect, for example. This is particularly evident in the short term, for example [Kudryavtsev \(2013\)](#), who found both positive and negative overreactions after a high (low) close price. Using a sample of 71 countries from 1830 to 2019, [Zaremba et al. \(2020\)](#) also found that long term price reversals were highly unstable overtime.

Despite the absence of a clear understanding of reasons and factors influencing the appearance of the price effects after one-day abnormal returns, these can be utilised by practitioners (traders, investors, etc.) for profit. Trading based on momentum/contrarian strategies can be profitable.

Overall these results explain a variety of empirical evidence from academics related to price overreactions and observed price patterns after one-day abnormal returns. Our results support the Adaptive Markets Hypothesis, that is, financial markets evolve and can be inefficient from time to time, but overall the evolution is towards market efficiency.

5 Conclusion

In this paper, we have examined price effects (momentum and contrarian) after one-day abnormal returns in the US stock market (Dow Jones Index) over the period 1890 to 2018. This was done using a variety of methods (average analysis, modified cumulative abnormal returns approach, regression analysis with dummy variables, R/S analysis, parametric Students t-test, and ANOVA, non-parametric Mann-Whitney tests and trading simulation approach) to avoid methodological bias.

The following hypotheses were tested: after one-day abnormal returns, specific price

effects (momentum/contrarian) do appear (H_1); price effects after one-day abnormal returns vary in time and evolve (H_2); price effects after one-day abnormal returns can be exploited to generate profits from trading (H_3); the level of persistence in anomalies related data set differs from the normal data set persistence (H_4).

The results suggest that between the 1940s and the 1980s a strong momentum effect after positive abnormal returns was present and it was exploitable (it was possible to generate abnormal profits from trading). But since the 1980s the power of price effects after one-day abnormal returns disappeared and no longer provide profit opportunities in the US stock market. This can be the result of market evolution and its movement from a less efficient state to a more efficient one. These conclusions are confirmed by the persistence analysis. Therefore, our results support the Adaptive Market Hypothesis.

The results suggests to regulators and practitioners that price overreactions are indeed exploitable for benefit. However, these overreactions historically are unstable and are highly depended on the overreaction window, but are in particularly emphasised in the short term. Therefore, with appropriate technologies, in the right market conditions, traders can benefit from these market anomalies. The results also suggest that the study of these price overreactions may have contributed to their disappearance from the US stock market.

Therefore, this paper adds to the literature that confirms these anomalies. That these anomalies evolve overtime reconciles the debate in the literature around sample bias, that is, these anomalies are not always prevalent. However, this paper did not directly address causal factors such as firm size, liquidity, and broad market factors. This can be area of enquiry for future studies to determine if market size or liquidity shortage can historically explain the existence of price effects utilising the full sample size of the US stock market.

References

- Atkins, A. B. and Dyl, E. A. (1990). Price reversals, bid-ask spreads, and market efficiency. *Journal of Financial and Quantitative Analysis*, 25(4):535–547.
- Blackburn, D. W. and Cakici, N. (2017). Overreaction and the cross-section of returns: International evidence. *Journal of Empirical Finance*, 42(C):1–14.
- Boubaker, S., Farag, H., and Nguyen, D. K. (2015). Short-term overreaction to specific events: Evidence from an emerging market. *Research in international business and finance*, 35:153–165.
- Bremer, M. and Sweeney, R. J. (1991). The reversal of large stock-price decreases. *The Journal of Finance*, 46(2):747–754.
- Brown, K. C., Harlow, W. V., and Tinic, S. M. (1988). Risk aversion, uncertain information, and market efficiency. *Journal of Financial Economics*, 22(2):355–385.
- Campbell, K. and Limmack, R. J. (1997). Long-term over-reaction in the uk stock market and size adjustments. *Applied Financial Economics*, 7(5):537–548.
- Caporale, G., Gil-Alana, L., and Plastun, A. (2018). Is market fear persistent? A long-memory analysis. *Finance Research Letters*, (27):140–147.
- Caporale, G. M., Gil-Alana, L., and Plastun, A. (2019). Long-term price overreactions: are markets inefficient? *Journal of Economics and Finance*, 43(4):657–680.
- Caporale, G. M. and Plastun, A. (2019a). On stock price overreactions: frequency, seasonality and information content. *Journal of Applied Economics*, 22(1):602–621.
- Caporale, G. M. and Plastun, A. (2019b). Price overreactions in the cryptocurrency market. *Journal of Economic Studies*.
- Caporale, G. M. and Plastun, O. (2019c). Momentum effects in the cryptocurrency market after one-day abnormal returns.
- Chopra, N., Lakonishok, J., and Ritter, J. R. (1992). Measuring abnormal performance: Do stocks overreact? *Journal of Financial Economics*, 31(2):235–268.
- Clements, A., Drew, M. E., Reedman, E. M., and Veeraraghavan, M. (2009). The death of the overreaction anomaly? A multifactor explanation of contrarian returns. *Investment Management and Financial Innovations*, 6(1):76–85.
- Conrad, J. and Kaul, G. (1993). Long-term market overreaction or biases in computed returns? *The Journal of Finance*, 48(1):39–63.
- Cox, D. R. and Peterson, D. R. (1994). Stock returns following large one-day declines: Evidence on short-term reversals and longer-term performance. *The Journal of Finance*, 49(1):255–267.

- De Bondt, W. F. and Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3):793–805.
- De Bondt, W. F. and Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, 42(3):557–581.
- Dyl, E. A., Yuksel, H. Z., and Zaynutdinova, G. R. (2019). Price reversals and price continuations following large price movements. *Journal of Business Research*, 95:1–12.
- Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, 38(1):34–105.
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2):383–417.
- Fama, E. F. and French, K. R. (1988). Permanent and temporary components of stock prices. *Journal of Political Economy*, 96(2):246–273.
- Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.
- Fama, E. F. and French, K. R. (1995). Size and book-to-market factors in earnings and returns. *The Journal of Finance*, 50(1):131–155.
- Grant, J. L., Wolf, A., and Yu, S. (2005). Intraday price reversals in the us stock index futures market: A 15-year study. *Journal of Banking & Finance*, 29(5):1311–1327.
- Hurst, H. (1951). Long-term storage of reservoirs. *Transactions of the American Society of Civil Engineers*, 1(116):770–799.
- Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of finance*, 45(3):881–898.
- Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1):65–91.
- Kudryavtsev, A. (2013). Stock price reversals following end-of-the-day price moves. *Economics Letters*, 118(1):203–205.
- Lasfer, M. A., Melnik, A., and Thomas, D. C. (2003). Short-term reaction of stock markets in stressful circumstances. *Journal of Banking & Finance*, 27(10):1959–1977.
- Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, 105(1):1–28.
- MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, 35(1):13–39.

- McLean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? *The Journal of Finance*, 71(1):5–32.
- Mynhardt, R. and Plastun, A. (2013). The overreaction hypothesis: The case of ukrainian stock market. *Corporate Ownership and Control*, 11(1 E):406–422.
- Pettengill, G. N. and Jordan, B. D. (1990). The overreaction hypothesis, firm size, and stock market seasonality. *Journal of Portfolio Management*, 16(3):60.
- Plastun, A., Sibande, X., Gupta, R., and Wohar, M. E. (2019). Rise and fall of calendar anomalies over a century. *The North American Journal of Economics and Finance*, 49:181–205.
- Pokavattana, N., Sethjinda, T., and Tangjitprom, N. (2019). The over-reaction effect in the stock exchange of thailand: An empirical study. *Journal of Community Development Research (Humanities and Social Sciences)*, 12(3):92–106.
- Poterba, J. M. and Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. *Journal of Financial Economics*, 22(1):27–59.
- Richards, A. J. (1997). Winner-loser reversals in national stock market indices: Can they be explained? *The Journal of Finance*, 52(5):2129–2144.
- Shiller, R. J. (2000). *Irrational exuberance*. Princeton University.
- Zaremba, A. (2019). Performance persistence in anomaly returns: Evidence from frontier markets. *Emerging Markets Finance and Trade*, pages 1–22.
- Zaremba, A., Kizys, R., and Raza, M. W. (2020). The long-run reversal in the long run: Insights from two centuries of international equity returns. *Journal of Empirical Finance*, 55:177–199.
- Zarowin, P. (1990). Size, seasonality, and stock market overreaction. *Journal of Financial and Quantitative Analysis*, 25(1):113–125.

Appendices

A The case of positive overreactions

Table A.1: Average returns for the usual days and days after positive overreaction: the case of the Dow Jones Index during 1890-2018

Period	Usual day	Day after positive overreaction
1890-1899	0.00%	-0.01%
1900-1909	0.04%	0.04%
1910-1919	0.04%	0.04%
1920-1929	0.07%	0.25%
1930-1939	0.00%	-0.05%
1940-1949	0.03%	0.30%
1950-1959	0.05%	0.26%
1960-1969	0.02%	0.26%
1970-1979	0.00%	0.33%
1980-1989	0.02%	0.17%
1990-1999	0.03%	0.08%
2000-2009	0.02%	-0.13%
2010-2018	0.04%	-0.13%

Figure A.1: Average returns for the usual days and days after positive overreaction: the case of the Dow Jones Index during 1890-2018

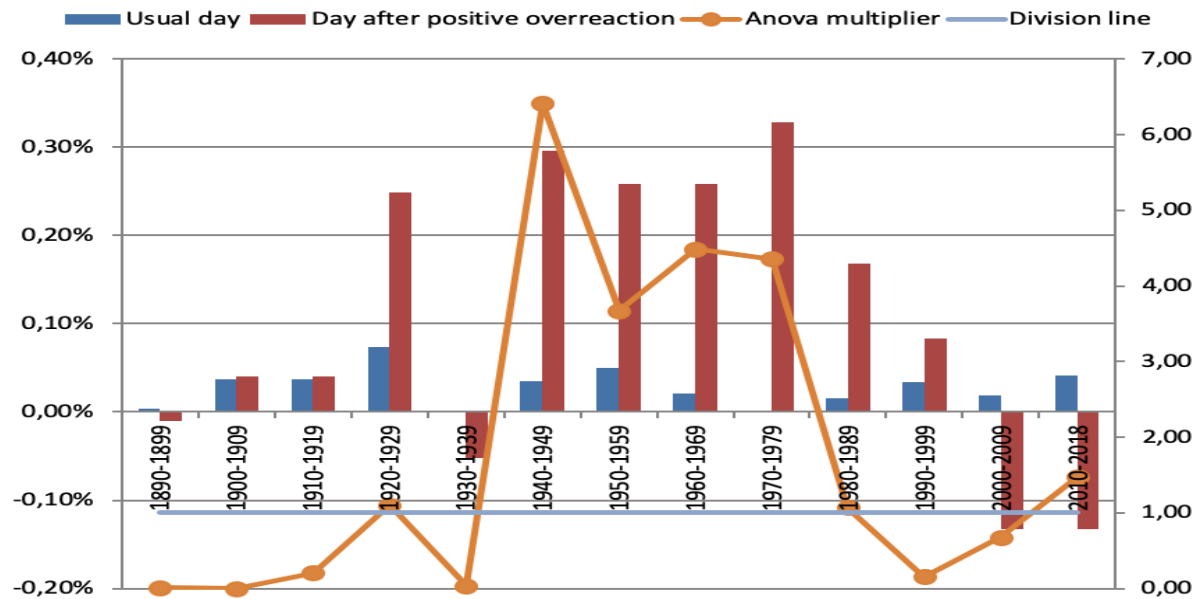


Table A.2: ANOVA test of the price effects after positive overreactions for the Dow Jones Index during 1890-2018

Period	F	p-value	F critical	Null hypothesis	Anomaly	Anova multiplier
1890-1899	0.04	0.85	3.85	not rejected	not confirmed	0.01
1900-1909	0.00	0.96	3.85	not rejected	not confirmed	0.00
1910-1919	0.79	0.37	3.85	not rejected	not confirmed	0.21
1920-1929	4.24	0.04	3.85	rejected	confirmed	1.10
1930-1939	0.14	0.71	3.85	not rejected	not confirmed	0.04
1940-1949	24.64	0.00	3.85	rejected	confirmed	6.41
1950-1959	14.13	0.00	3.85	rejected	confirmed	3.67
1960-1969	17.25	0.00	3.85	rejected	confirmed	4.49
1970-1979	16.76	0.00	3.85	rejected	confirmed	4.36
1980-1989	4.11	0.04	3.85	rejected	confirmed	1.07
1990-1999	0.59	0.44	3.85	not rejected	not confirmed	0.15
2000-2009	2.59	0.11	3.85	not rejected	not confirmed	0.67
2010-2018	5.66	0.02	3.85	rejected	confirmed	1.47

Table A.3: Mann-Whitney test of the price effects after positive overreactions for the Dow Jones Index during 1890-2018

Period	Adjusted H	d.f.	P value	Critical value	Null hypothesis	Anomaly	Kruskall multiplier
1890-1899	0.00	1.00	0.99	3.84	not rejected	not confirmed	0.00
1900-1909	0.29	1.00	0.59	3.84	not rejected	not confirmed	0.08
1910-1919	24.82	1.00	0.00	3.84	rejected	confirmed	6.46
1920-1929	0.01	1.00	0.94	3.84	not rejected	not confirmed	0.00
1930-1939	0.91	1.00	0.34	3.84	not rejected	not confirmed	0.24
1940-1949	18.29	1.00	0.00	3.84	rejected	confirmed	4.76
1950-1959	8.63	1.00	0.00	3.84	rejected	confirmed	2.25
1960-1969	9.46	1.00	0.00	3.84	rejected	confirmed	2.46
1970-1979	5.36	1.00	0.02	3.84	rejected	confirmed	1.40
1980-1989	1.97	1.00	0.16	3.84	not rejected	not confirmed	0.51
1990-1999	0.86	1.00	0.35	3.84	not rejected	not confirmed	0.22
2000-2009	0.58	1.00	0.45	3.84	not rejected	not confirmed	0.15
2010-2018	1.24	1.00	0.27	3.84	not rejected	not confirmed	0.32

Table A.4: T-test of the price effects after positive overreactions for the Dow Jones Index during 1890-2018

Period	Parameter	Usual day	Day after positive overreaction	Period	Usual day	Day after positive overreaction
1890-1899	Mean,%	0.00%	-0.01%	1960-1969	0.02%	0.26%
	Stand. Dev., %	0.59%	1.07%		0.38%	0.59%
	Number of values	2251	82		1822	44
	t-criterion	0.11			2.68	
	Null hypothesis	not rejected			rejected	
	Anomaly	not confirmed			confirmed	
1900-1909	Mean,%	0.04%	0.04%	1970-1979	0.02%	0.26%
	Stand. Dev., %	0.58%	1.08%		0.38%	0.59%
	Number of values	2251	64		1822	44
	t-criterion	0.02			2.11	
	Null hypothesis	not rejected			rejected	
	Anomaly	not confirmed			confirmed	
1910-1919	Mean,%	0.03%	0.09%	1980-1989	0.00%	0.33%
	Stand. Dev., %	0.55%	1.19%		0.55%	1.10%
	Number of values	2170	69		1806	51
	t-criterion	0.43			1.20	
	Null hypothesis	not rejected			not rejected	
	Anomaly	not confirmed			not confirmed	
1920-1929	Mean,%	0.07%	0.25%	1990-1999	0.02%	0.17%
	Stand. Dev., %	0.61%	1.26%		0.62%	1.08%
	Number of values	2233	53		1894	73
	t-criterion	1.01			0.64	
	Null hypothesis	not rejected			not rejected	
	Anomaly	not confirmed			not confirmed	
1930-1939	Mean,%	0.00%	-0.05%	2000-2009	0.03%	0.08%
	Stand. Dev., %	1.04%	2.45%		0.51%	0.60%
	Number of values	2258	60		1877	60
	t-criterion	0.17			1.09	
	Null hypothesis	not rejected			not rejected	
	Anomaly	not confirmed			not confirmed	
1940-1949	Mean,%	0.03%	0.30%	2010-2018	0.02%	-0.13%
	Stand. Dev., %	0.39%	0.64%		0.74%	1.11%
	Number of values	2253	57		1816	65
	t-criterion	3.06			1.07	
	Null hypothesis	rejected			not rejected	
	Anomaly	confirmed			not confirmed	
1950-1959	Mean,%	0.05%	0.26%			
	Stand. Dev., %	0.38%	0.61%			
	Number of values	1973	48			
	t-criterion	2.37				
	Null hypothesis	rejected				
	Anomaly	confirmed				

Table A.5: Modified CAR approach: results of the price effects after positive overreactions for the Dow Jones Index during 1890-2018

Period	Multiple R	F-test	a0	a1	Anomaly
1890-1899	0.27	6.25 (0.01)	-0.0221 (0.00)	-0.0003 (0.01)	confirmed
1900-1909	0.20	2.58 (0.11)	0.0143 (0.00)	0.0002 (0.11)	not confirmed
1910-1919	0.56	30.69 (0.00)	0.0417 (0.00)	0.0006 (0.00)	confirmed
1920-1929	0.46	16.65 (0.00)	-0.0294 (0.00)	0.0006 (0.00)	confirmed
1930-1939	0.60	33.61 (0.00)	-0.1378 (0.00)	0.0016 (0.00)	confirmed
1940-1949	0.96	666.86 (0.00)	-0.0325 (0.00)	0.0033 (0.00)	confirmed
1950-1959	0.97	736.19 (0.00)	-0.0073 (0.01)	0.0027 (0.00)	confirmed
1960-1969	0.93	279.05 (0.00)	0.0095 (0.00)	0.0019 (0.00)	confirmed
1970-1979	0.90	205.83 (0.00)	0.0455 (0.00)	0.0034 (0.00)	confirmed
1980-1989	0.67	57.38 (0.00)	0.0412 (0.00)	0.0014 (0.00)	confirmed
1990-1999	0.70	54.65 (0.00)	0.0174 (0.00)	0.0005 (0.00)	confirmed
2000-2009	0.65	45.30 (0.00)	-0.0392 (0.00)	-0.0009 (0.00)	confirmed
2010-2018	0.83	102.71 (0.00)	-0.0213 (0.00)	-0.0015 (0.00)	confirmed

Note: P-values are in parentheses

Table A.6: Regression analysis with dummy variables: results of the price effects after positive overreactions for the Dow Jones Index during 1890-2018

Period	Multiple R	F-test	α_0	α_1	Anomaly
1890-1899	0.00	0.04 (0.84)	0.0000 (0.78)	-0.0001 (0.84)	not confirmed
1900-1909	0.00	0.00 (0.96)	0.0004 (0.00)	0.0000 (0.96)	not confirmed
1910-1919	0.02	0.79 (0.37)	0.0002 (0.03)	0.0006 (0.37)	not confirmed
1920-1929	0.04	4.24 (0.04)	0.0007 (0.00)	0.0018 (0.04)	confirmed
1930-1939	0.01	0.14 (0.71)	0.0000 (0.98)	-0.0005 (0.71)	not confirmed
1940-1949	0.10	24.64 (0.00)	0.0003 (0.00)	0.0027 (0.00)	confirmed
1950-1959	0.08	14.13 (0.00)	0.0005 (0.00)	0.0021 (0.00)	confirmed
1960-1969	0.09	17.25 (0.00)	0.0002 (0.02) ⁺	0.0024 (0.00)	confirmed
1970-1979	0.09	16.75 (0.00)	0.0000 (0.92)	0.0033 (0.00)	confirmed
1980-1989	0.04	4.11 (0.04)	0.0001 (0.31)	0.0015 (0.04)	confirmed
1990-1999	0.02	0.59 (0.44)	0.0003 (0.00)	0.0005 (0.44)	not confirmed
2000-2009	0.04	2.59 (0.11)	0.0002 (0.29)	-0.0015 (0.11)	not confirmed
2010-2018	0.06	5.66 (0.02)	0.0004 (0.00)	-0.0018 (0.02)	confirmed

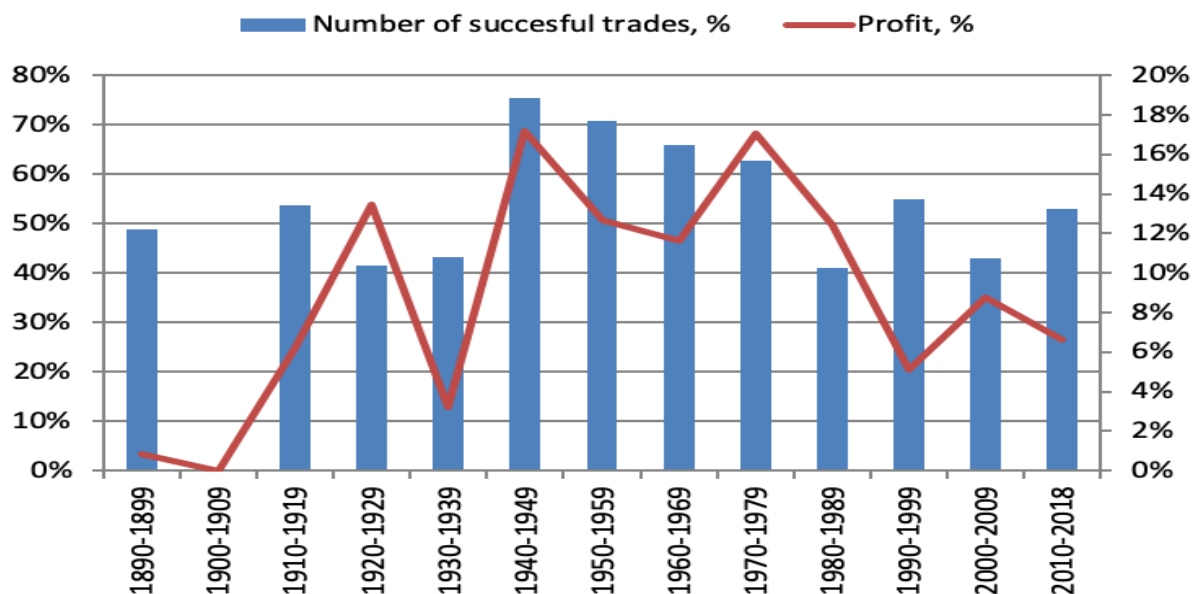
Note: P-values are in parentheses

Table A.7: Trading simulation results of the price effects after positive overreactions for the Dow Jones Index during 1890-2018

Period	Number of trades, units	Number of successful trades, unit	Number of succesful trades, %	Profit, %	Profit % per year	Profit % per trade	t-test calculated value	t-test status
1890-1899**	82	40	49%	1%	0	0	0.08	not rejected
1900-1909***	-	-	-	-	-	-	-	-
1910-1919*	69	37	54%	6%	0.62%	0.09%	0.63	not rejected
1920-1929*	53	22	42%	13%	1.34%	0.25%	1.46	not rejected
1930-1939**	60	26	43%	3%	0.32%	0.05%	0.17	not rejected
1940-1949*	57	43	75%	17%	1.72%	0.30%	3.54	rejected
1950-1959*	48	34	71%	13%	1.27%	0.26%	3.01	rejected
1960-1969*	44	29	66%	12%	1.16%	0.26%	2.99	rejected
1970-1979*	51	32	63%	17%	1.71%	0.33%	2.17	rejected
1980-1989*	73	30	41%	12%	1.24%	0.17%	1.34	not rejected
1990-1999*	60	33	55%	5%	0.51%	0.09%	1.10	not rejected
2000-2009**	65	28	43%	9%	0.88%	0.13%	0.98	not rejected
2010-2018**	49	26	53%	7%	0.66%	0.14%	0.84	not rejected

Note: * refers to momentum effect, ** refers to contrarian effect, and *** refers to no specific effect detected

Figure A.2: Trading simulation results of the price effects after positive overreactions for the Dow Jones Index during 1890-2018



B The case of negative overreactions

Table B.1: Average returns for the usual days and days after negative overreaction: the case of the Dow Jones Index during 1890-2018

Period	Usual day	Day after negative overreaction
1900-1909	0.00%	0.02%
1900-1909	0.04%	0.23%
1910-1919	0.03%	0.40%
1920-1929	0.07%	0.28%
1930-1939	0.00%	0.21%
1940-1949	0.03%	-0.26%
1950-1959	0.05%	0.04%
1960-1969	0.02%	-0.02%
1970-1979	0.00%	-0.34%
1980-1989	0.02%	-0.40%
1990-1999	0.03%	0.13%
2000-2009	0.02%	0.24%
2010-2018	0.04%	0.07%

Figure B.1: Average returns for the usual days and days after negative overreaction: the case of the Dow Jones Index during 1900-2018

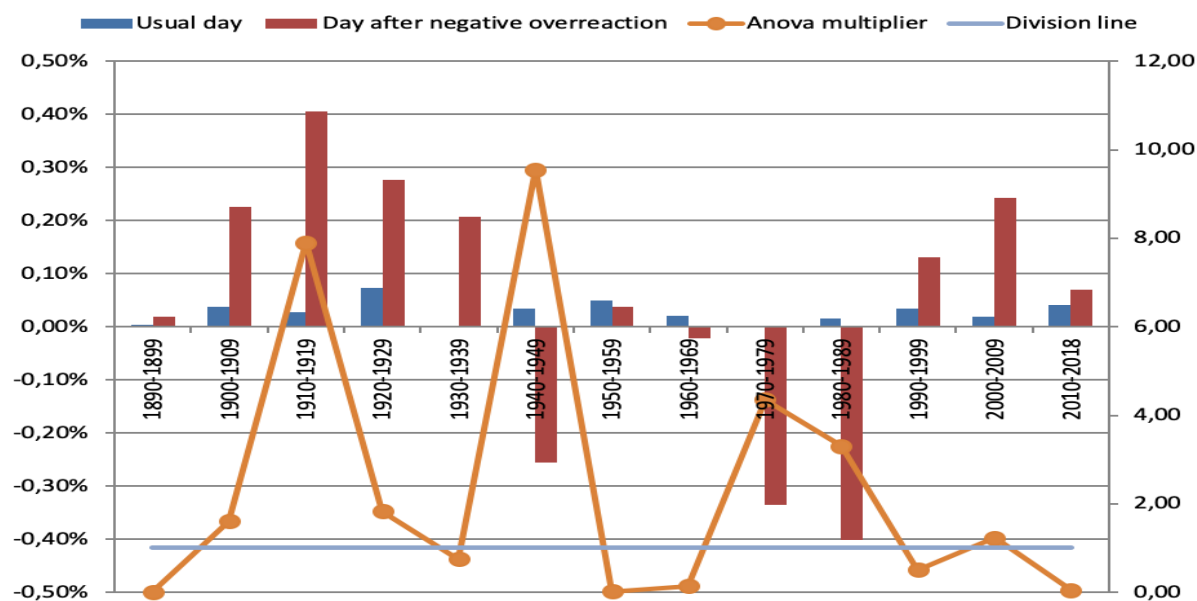


Table B.2: ANOVA test of the price effects after negative overreactions for the Dow Jones Index during 1890-2018

Period	F	p-value	F critical	Null hypothesis	Anomaly	Anova multiplier
1890-1899	0.04	0.85	3.85	not rejected	not confirmed	0.01
1900-1909	6.18	0.01	3.85	rejected	confirmed	1.61
1910-1919	30.39	0.00	3.85	rejected	confirmed	7.90
1920-1929	7.04	0.01	3.85	rejected	confirmed	1.83
1930-1939	2.90	0.09	3.85	not rejected	not confirmed	0.75
1940-1949	36.72	0.00	3.85	rejected	confirmed	9.55
1950-1959	0.06	0.81	3.85	not rejected	not confirmed	0.01
1960-1969	0.55	0.46	3.85	not rejected	not confirmed	0.14
1970-1979	16.75	0.00	3.85	rejected	confirmed	4.36
1980-1989	12.72	0.00	3.85	rejected	confirmed	3.31
1990-1999	1.96	0.16	3.85	not rejected	not confirmed	0.51
2000-2009	4.71	0.03	3.85	rejected	confirmed	1.22
2010-2018	0.19	0.66	3.85	not rejected	not confirmed	0.05

Table B.3: Mann-Whitney test of the price effects after negative overreactions for the Dow Jones Index during 1890-2018

Period	Adjusted H	d.f.	P value	Critical value	Null hypothesis	Anomaly	Kruskall multiplier
1890-1899	1.17	1.00	0.28	3.84	rejected	confirmed	0.30
1900-1909	4.41	1.00	0.04	3.84	rejected	confirmed	1.15
1910-1919	8.08	1.00	0.00	3.84	rejected	confirmed	2.11
1920-1929	10.02	1.00	0.00	3.84	rejected	confirmed	2.61
1930-1939	10.02	1.00	0.00	3.84	rejected	confirmed	2.61
1940-1949	9.16	1.00	0.00	3.84	rejected	confirmed	2.38
1950-1959	0.05	1.00	0.82	3.84	not rejected	not confirmed	0.01
1960-1969	1.25	1.00	0.26	3.84	not rejected	not confirmed	0.33
1970-1979	13.51	1.00	0.00	3.84	rejected	confirmed	3.52
1980-1989	1.00	1.00	0.32	3.84	not rejected	not confirmed	0.26
1990-1999	0.59	1.00	0.44	3.84	not rejected	not confirmed	0.15
2000-2009	1.27	1.00	0.26	3.84	not rejected	not confirmed	0.33
2010-2018	0.60	1.00	0.44	3.84	not rejected	not confirmed	0.16

Table B.4: T-test of the price effects after negative overreactions for the Dow Jones Index during 1890-2018

Period	Parameter	Usual day	Day after negative overreaction	Period	Usual day	Day after negative overreaction
1890-1899	Mean, %	0.00%	0.02%	1960-1969	0.02%	-0.02%
	Stand. Dev., %	0.59%	2.28%		0.38%	1.42%
	Number of values	2251	87		1822	67
	t-criterion	0.06			0.24	
	Null hypothesis	not rejected			not rejected	
	Anomaly	not confirmed			not confirmed	
1900-1909	Mean, %	0.04%	0.23%	1970-1979	0.00%	-0.02%
	Stand. Dev., %	0.58%	2.05%		0.55%	1.42%
	Number of values	2251	82		1806	67
	t-criterion	0.83			2.16	
	Null hypothesis	not rejected			rejected	
	Anomaly	not confirmed			confirmed	
1910-1919	Mean, %	0.03%	0.40%	1980-1989	0.02%	-0.34%
	Stand. Dev., %	0.55%	1.60%		0.62%	1.07%
	Number of values	2170	82		1894	47
	t-criterion	2.14			0.83	
	Null hypothesis	rejected			not rejected	
	Anomaly	confirmed			not confirmed	
1920-1929	Mean, %	0.07%	0.28%	1990-1999	0.03%	-0.40%
	Stand. Dev., %	0.61%	2.15%		0.51%	3.49%
	Number of values	2233	93		1877	49
	t-criterion	0.91			0.58	
	Null hypothesis	not rejected			not rejected	
	Anomaly	not confirmed			not confirmed	
1930-1939	Mean, %	0.00%	0.21%	2000-2009	0.02%	0.13%
	Stand. Dev., %	1.04%	2.50%		0.74%	1.31%
	Number of values	2258	88		1816	63
	t-criterion	0.77			1.13	
	Null hypothesis	not rejected			not rejected	
	Anomaly	not confirmed			not confirmed	
1940-1949	Mean, %	0.03%	-0.26%	2010-2018	0.04%	0.24%
	Stand. Dev., %	0.39%	1.19%		0.48%	1.47%
	Number of values	2253	90		1582	55
	t-criterion	2.30			0.17	
	Null hypothesis	rejected			not rejected	
	Anomaly	confirmed			not confirmed	
1950-1959	Mean, %	0.05%	0.04%			
	Stand. Dev., %	0.38%	0.78%			
	Number of values	1973	76			
	t-criterion	0.13				
	Null hypothesis	not rejected				
	Anomaly	not confirmed				

Table B.5: Modified CAR approach: results of the price effects after negative overreactions for the Dow Jones Index during 1890-2018

Period	Multiple R	F-test	α_0	α_1	Anomaly
1890-1899	0.07	0.37 (0.54)	0.0074 (0.40)	-0.0001 (0.54)	not confirmed
1900-1909	0.80	145.15 (0.00)	0.0353 (0.00)	0.00206 (0.00)	confirmed
1910-1919	0.78	125.39 (0.00)	-0.0534 (0.00)	0.0028 (0.00)	confirmed
1920-1929	0.70	90.59 (0.00)	0.0592 (0.00)	0.0010 (0.00)	confirmed
1930-1939	0.78	131.49 (0.00)	0.0639 (0.00)	0.0026 (0.00)	confirmed
1940-1949	0.97	1587.63 (0.00)	-0.0375 (0.00)	-0.0030 (0.00)	confirmed
1950-1959	0.15	1.72 (0.19)	-0.0191 (0.00)	-0.0001 (0.19)	not confirmed
1960-1969	0.08	0.40 (0.53)	-0.0124 (0.01)	0.0000 (-0.53)	not confirmed
1970-1979	0.90	186.73 (0.00)	-0.0416 (0.00)	-0.0026 (0.00)	confirmed
1980-1989	0.87	144.02 (0.00)	0.0758 (0.00)	-0.0059 (0.00)	confirmed
1990-1999	0.52	22.87 (0.00)	-0.0693 (0.00)	0.0012 (0.00)	confirmed
2000-2009	0.10	0.55 (0.46)	0.0240 (0.03)	0.0002 (0.46)	not confirmed
2010-2018	0.24	3.99 (0.05)	0.0405 (0.00)	0.0005 (0.05)	confirmed

Note: P-values are in parentheses

Table B.6: Regression analysis with dummy variables: results of the price effects after negative overreactions for the Dow Jones Index during 1890-2018

Period	Multiple R	F-test	a_0	a_1	Anomaly
1890-1899	0.00	0.04 (0.85)	0.0000 (0.82)	0.0001 (0.85)	not confirmed
1900-1909	0.05	6.18 (0.01)	0.0004 (0.01)	0.0019 (0.01)	confirmed
1910-1919	0.11	30.39 (0.00)	0.0002 (0.04)	0.0038 (0.00)	confirmed
1920-1929	0.05	7.04 (0.01)	0.0007 (0.00)	0.0020 (0.01)	confirmed
1930-1939	0.03	2.90 (0.09)	0.0000 (0.98)	0.0021 (0.09)	not confirmed
1940-1949	0.12	36.72 (0.00)	0.0003 (0.00)	-0.0029 (0.00)	confirmed
1950-1959	0.01	0.06 (0.81)	0.0005 (0.00)	-0.0001 (0.81)	not confirmed
1960-1969	0.02	0.55 (0.46)	0.0002 (0.05)	-0.0004 (0.46)	not confirmed
1970-1979	0.09	16.75 (0.00)	0.0000 (0.92)	-0.0034 (0.00)	confirmed
1980-1989	0.08	12.71 (0.00)	0.0001 (0.42)	-0.0042 (0.00)	confirmed
1990-1999	0.03	1.96 (0.16)	0.0003 (0.01)	0.0010 (0.16)	not confirmed
2000-2009	0.05	4.71 (0.03)	0.0002 (0.30)	0.0023 (0.03)	confirmed
2010-2018	0.01	0.19 (0.66)	0.0004 (0.00)	0.0003 (0.66)	not confirmed

Note: P-values are in parentheses

Table B.7: Trading simulation results of the price effects after negative overreactions for the Dow Jones Index during 1890-2018

Period	Number of trades, units	Number of successful trades, unit	Number of successful trades, %	Profit, %	Profit % per year	Profit % per trade	t-test calculated value	t-test status
1890-1899**	87	36	41%	2%	0	0	0.08	not rejected
1900-1909**	82	37	45%	19%	1.88%	0.23%	1.01	not rejected
1910-1919**	82	33	40%	34%	3.36%	0.41%	2.32	rejected
1920-1929**	93	41	44%	26%	2.60%	0.28%	1.25	not rejected
1930-1939**	88	47	53%	19%	1.85%	0.21%	0.79	not rejected
1940-1949*	90	42	47%	23%	2.32%	0.26%	2.05	rejected
1950-1959***	-	-	-	-	-	-	-	-
1960-1969***	-	-	-	-	-	-	-	-
1970-1979*	47	30	64%	16%	1.61%	0.34%	2.20	rejected
1980-1989*	49	27	55%	20%	2.00%	0.41%	0.82	not rejected
1990-1999**	63	27	43%	8%	0.83%	0.13%	0.80	not rejected
2000-2009**	55	26	47%	14%	1.36%	0.25%	1.25	not rejected
2010-2018***	-	-	-	-	-	-	-	-

Note: * refers to momentum effect, ** refers to contrarian effect, and *** refers to no specific effect detected

Figure B.2: Trading simulation results of the price effects after negative overreactions for the Dow Jones Index during 1890-2018

