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Price gap anomaly in the US stock market: The whole story☆

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ABSTRACT

This paper analyses the price gap anomaly in the US stock market (comprised of the DJI, S&P 500 and NASDAQ) covering the period 1928 to 2018. This paper aims to investigate whether or not price gaps create market inefficiencies. Price gaps occur when the current day's opening price is different from the previous day's closing price due orders placed before the opening of the market. Several hypotheses are tested using various statistical tests (Student's t-test, ANOVA, Mann-Whitney test), regression analysis, and special methods, that is, the modified cumulative returns and the trading simulation approaches. We find strong evidence in favour of abnormal price movements after price gaps. We observe that during a gap day prices tend to change in the direction of the gap. A trading strategy based on this anomaly was efficient in that its results were not random, indicating that this market was not efficient. The momentum effect was found to be temporary and no evidence of seasonality in price gaps was found. Lastly, our results were also contrary to the myth that price gaps tend to get filled.

1. Introduction

The Efficient Market Hypothesis (EMH) contends that markets are efficient when prices reflect all relevant information. This has been empirically shown not to be the case by academics and practitioners. Anomalies in their various forms exist in international stock markets. The study of anomalies, therefore, remains an active area in the finance literature, including that of price anomalies.

According to Caporale and Plastun (2017), prices gaps occur when the current day's opening price is different from the previous day's closing price due to the orders placed before the opening of the market. The empirical literature on the price gap anomaly is broadly focused on the confirmation of this anomaly (see Caporale, Gil-Alana, Plastun, & Makarenko, 2016, and Yuan, 2015, for example), and the ascertainment of exploitable profits which may arise (see Caporale & Plastun, 2017 & Plastun et al., Plastun, Makarenko, Khomutenko, Shcherbak, & Tryfonova, 2019, for example). However, this literature remains limited in terms of its application to the US stock market.

This paper aims to investigate the existence of the price gap anomaly and its evolution in the US stock market, in order to determine whether the price gap anomaly generates exploitable profits. Specifically, we focus on the Dow Jones Industrial Average index (DJI), the S&P 500 index (S&P 500), and the NASDAQ. Our main focus is the S&P 500 which has the longest sample (1928 and 2018). Several statistical tests (Student's t test, ANOVA test, Mann-Whitney test, and cumulative abnormal returns approach) and

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trading simulation approach will be used. Also, we employ the simulation approach to determine whether the price gap anomaly generates exploitable profits.

A study of this nature, focusing on the such a long period in the US stock market has not been conducted previously, constituting a gap in the literature. To this end, following is a brief review of the relevant literature, a discussion on the data and the methodology, the results, and a conclusion.

2. Literature review

According to Fama (1965, 1970) a market in which investment decisions are made under the assumption that security prices 'fully' reflect all available information, can be considered to be efficient. Furthermore, the extent to which information is reflected in security prices can be categorised and tested in two different forms, that is, the weak form where only historical information affects security prices and the strong form where an investor has private information regarding the price of a security. Therefore, the EMH is simply the assertion that information is 'fully' reflected in security prices, that is, no investor has an opportunity to profit through arbitrage.

However, Akerlof and Shiller (2009), Grossman and Stiglitz (1980), Lo (1991), Mandelbrot (1963), Shiller (2000), and Schwert (2003) amongst other have challenged the EMH on a number of grounds. At a theoretical level (Grossman & Stiglitz, 1980) argue that information, in reality, is costly, therefore, prices cannot fully reflect all the available information. Akerlof and Shiller (2009) and Shiller (2000), highlight the irrational behaviour of investors as such as mass panic as a key argument against the EMH. Schwert (2003) shows how underlying market anomalies disappear after discovery, as market agents implement these anomalous strategies. Others such as Mandelbrot (1963) empirically show that price distributions suffer from fat tails and long memory, amongst others.

Three types of anomalies have been studied in the literature, that is, seasonal, size, and price anomalies (see Jacobsen, Mamun, & and Visaltanachoti, 2005). According to Bildik (2004) anomalies indicate market inefficiency or inadequacies in the underlying asset pricing model and tend to disappear after discovery as traders adapt to their existence. There are numerous reasons for the existence of anomalies, for example, Basu (1977) identified price anomalies by discovering that value stocks had higher risk-adjusted returns compared to growth stocks.

The price gap anomaly falls within this categorisation of anomalies. The price gap anomaly is in essence related to the day of the week effect. Cross (1973) was the first to confirm that the distribution of stock prices changes according to the day of the week, and in particular between Friday and Monday. Other such as Agrawal and Tandon (1994), Cross (1973), Cai, Li, and Qi (2006), French (1980), and Gibbons and Hess (1981) find that the day of the week effect was indeed most pronounced on Fridays and Mondays. This is otherwise known as the weekend effect as studied by Fortune (1998, 1999), Olson, Chou, and and Mossman (2010), amongst others. In summary, Caporale and Plastun (2017) cite the following as the most common reasons for the existence of price gaps:

- Significant time differences between closing and opening prices caused by holidays and weekends
- The advent of after-hours trading;
- Unexpected events that have a bearing on security prices such as earnings and profit warning reports
- Market shocks that can cause significant and sudden shifts in the supply and demand of financial assets
- Other reasons

Seasonal or calendar anomalies have received the most attention in the literature. Studies such as Lakonishok and Smidt (1988) and Plastun, Sibande, Gupta, and Wohar (2019), amongst others, demonstrate the evolution of calendar anomalies from a 'golden' age in the middle of the 20th century, to their disappearance in recent years. Studies on the evolution of the price gap anomaly are less common, with a few exceptions such as Caporale and Plastun (2017), Plastun et al. (2019), and Yuan (2015).

However, studies investigating the overreactive hypothesis (large market opening price changes followed by significant correction) are more common (see Caporale et al., 2016; Fung, Lam, & Lam, 2010; Grant, Wolf, & Yu, 2005 amongst others). For example, Grant et al. (2005) in the US stock index futures markets over 15 years found that significant intraday price reversals, and also that the strength of the overreaction was more pronounced with large positive opening market price changes. However, Grant et al. (2005) could not conclude if the price gap anomaly led to exploitable profits.

Determining whether the price gap anomaly generates exploitable profits remains a gap in the literature. According to Jensen (1978) for an anomaly to be statistically significant, it must generate excess returns. Only recently Plastun et al. (2019) applied the trading simulation approach to the Ukraine stock market and found that a trading strategy based on the price gap anomaly generate profits.

3. Data and methodology

Three US stock market indexes are analysed and tested, that is, the DJI covering the period 1985 to 2018, the S&P 500 covering the period 1928 to 2018, and NASDAQ over the period 1949 to 2018. This data is from the Global Financial Data[2] database. The data were then split into 10-year sub-periods to allow us to explore the evolution of price gap anomaly. 10-year sub-periods also provide enough data points for robust statistical testing. Table 1 below provides summary statistics for three markets.

[2] The data is available for download athttps://www.globalfinancialdata.com.

Table 1
Descriptive statistics for data (close prices).

Parameter	DJI	S&P 500	NASDAQ
Mean	9411.67	421.38	1115.2
Median	9835.53	94.49	256.12
Maximum	26828.39	2930.75	8109.69
Minimum	1242.05	4.41	8.93
Std. Dev.	5990.52	633.78	1636.16
Skewness	0.67	1.76	1.94
Kurtosis	0.02	2.37	3.54
Sum	80846216	10068052	19738969
Observations	8590	23893	17700

The following hypotheses are tested in this study:

- H_1: Price gaps generate momentum effects in the stock market
  H_{1-1}: Prices tend to rise after positive gaps.
  H_{1-2}: Prices tend to fall after negative gaps.
- H_2: Price gap anomaly evolves.
- H_3: Price gaps tend to appear during a specific day of the week.

The main assumption to be tested in this paper is the presence of momentum effects in the price dynamics after gaps in the US stock market. To achieve this, sub-hypothesis H_{1-1} and H_{1-2} are also tested. The aim is to show that prices generate patterns after price gaps. Testing H_1 determines whether or not the price gap anomalies are inconsistent with the EMH.

Testing H_2 provides information about the evolution of the price gap anomaly over time. According to the Adaptive Market Hypothesis, the behaviour of financial markets be different over time. Using the price gap anomaly we will confirm or reject this hypothesis. Testing H_3 ascertains whether any days of the week are more favourable for price gaps, that is, whether price gaps are seasonal.

Testing H_1 determines whether or not the price gap anomalies are inconsistent with market efficiency. To achieve this, sub-hypothesis H_{1-1} and H_{1-2} are also tested. The aim is to show that prices do behave abnormally after price gaps. Testing H_2 provides information about the evolution of price gap anomaly over time. Testing H_3 ascertains whether any days of the week are more favourable for price gaps, that is, whether price gaps are seasonal. The statistical aim is, therefore, to establish whether returns in ‘normal’ periods follow the same distribution as returns in ‘abnormal’ periods when the price gap anomaly is present. To this end, Gap_i in the following manner:

$$Gap_i = \left(\frac{Open_i}{Close_{i-1}} - 1\right)*100\% \tag{1}$$

where Gap_i is the gap size on the gap day in percentage, $Open_i$ is the opening price on the gap day, and $Close_{i-1}$ is the closing price on the day prior to the gap day.

In addition, we define R_i as:

$$R_i = \left(\frac{Open_i}{Close_i} - 1\right)*100\% \tag{2}$$

where R_i is the return on the ith day in percentage, $Open_i$ is the opening price,

$Close_i$ is the close price on the ith day, and $Close_{i-1}$ is the open price on the ith $-$ 1 day. The $Open_i/Close_i$ relation is used in order to avoid incorporating the price gap, as with the standard $Close_i/Close_{i-1}$.

To identify statistically significant differences between “normal” and “abnormal” periods, that is, periods when the price gap anomaly is prevalent in the market and when it is not, we also run the following regressions:

$$R_t = a_0 + a_1 D_t + \epsilon_t \tag{3}$$

where: R_t is the return in period t, a_0 is the mean return in a “normal” period, a_1 is the mean return in an “abnormal” period, D_t is a dummy variable equal to 1 in “abnormal” periods and 0 in “normal” period, and ϵ_t is the random error term. The sign and statistical significance of the dummy coefficients indicate the existence or not of price gaps anomalies. By abnormal period we mean a day when the price gap has occurred. Respectively by normal period we mean a day when no price gaps were detected.

The basic cumulative abnormal returns approach (CAR) is a commonly used method for the events studies. It shows very good efficiency and is rather simple and needs no additional assumptions or limitations on data. To avoid methodological bias, we utilise the modified cumulative abnormal returns approach (MCAR) which was developed by Plastun et al. (2019) based on the work of MacKinlay (1997), and recently utilised by Plastun et al. (2019) in the Ukraine stock market to detect price gap anomalies. Plastun et al. (2019) developed this MCAR approach in the context of calendar anomalies and their evolution over time. In this paper we summarise the MCAR approach, however, further details of the MCAR can be found in Plastun et al. (2019).

The methodology of the MCAR differs significantly from statistical methods and regression analysis with dummy variables. As a result, we have an alternative look at the anomaly and its detection. Abnormal returns are defined as follows:

$$AR_t = R_t - E(R_t) \tag{4}$$

where R_t is the return and AR_t is the abnormal return at time t. $E(R_t)$ is the is corresponding average return computed over the entire sample as follows:

$$E(R_t) = \left(\frac{1}{T}\right) \sum_{i=1}^{T} R_i \tag{5}$$

where T is the sample size.

The cumulative abnormal return denoted as CAR_i is simply the sum of the abnormal returns

$$CAR_i = \sum_{i=1}^{T} AR_i \tag{6}$$

A trend in cumulative abnormal returns data confirms abnormal returns. A simple regression model is built to estimate the trend component. A high multiple $R - squared$ and overall model significance ($F - test$), and the statistical significance ($p - values$) of the coefficients confirm or reject the presence of trend in the abnormal returns.

In instances where a price gap anomaly is detected, we test whether it gives rise to exploitable profits, using the trading simulation approach. The trading simulation approach replicates the actions of a trader given the price anomaly trading strategy. If this trading strategy generates 50 per cent or more profitable trades and produces an overall financial result of more than zero (excluding transaction costs), this indicates that this strategy is efficient. A $z - test$ is then conducted to ensure that the results of the trading strategy are not random, using a 5 per cent level of significance.

The most commonly used approach to analyse the efficiency of the trading strategy is to compare its results with the buy and hold strategy. As such, an additional explanation for the use of a z-test instead is needed.

The EMH is based on the Random Walk Hypothesis. This means that price changes should be unpredictable and there should be no persistence in data. A buy and hold strategy is based on the assumption of data persistence and the presence of a positive trend in financial data. This contradicts the EMH.

In addition, in a bear market, a buy and hold strategy will generate losses in this case. So if our strategy will generate losses but these losses will be less than those from a buy and hold strategy we should conclude that it is efficient. However, this cannot be rational.

Lastly, this paper uses trades in both directions (buy and sell). It will not be correct to compare short trades with long trades (buy and hold strategy deals only with the long ones). That is why in this paper we compared the results of our trading strategy not with the buy and hold strategy but with random trading. This is in compliance with the Random Walk Hypothesis. If results are statistically different from the random, this means the Random Walk Hypothesis is rejected. This contradicts the EMH.

Regarding the trading simulation approach, transaction costs can change the situation dramatically and turn a profitable strategy on paper into a loss generator in real life. Overall trading transaction costs can be divided into fixed and variable. Fixed costs include fees and commissions to the broker, banking fees, costs related to the depository activity, amongst others. Variable costs mostly concerns spread – the difference between the bid and ask prices.

In this paper, we used data for more than 100 years. During such a long period of time transaction costs evolved significantly. As such, it is impossible to incorporate them in this particular case. However, owing to internet trading transaction costs have become less important. Banking and broker fees can influence the efficiency in case of a small number of trades, but not with a large number to the scale effect.

Therefore, the only potentially influencing part of transaction costs is the spread. Nowadays thanks to the development of the Internet and high-frequency trading spreads are really small (at least in the highly liquid markets). It can be as little as 0.01% or 0.02% of the transaction. As such our results can be used as a proxy to analyse efficiency.

In this paper different stock market indexes are used. Overall they are nontradeable assets. But there are different trading substitutes. For example, CFD contracts are widely used to allow trading with Indexes. Another opportunity is the use of futures contracts on Index. Also, Index funds and index-related ETFs can be used. So in general nowadays there will be no problem to realise proposed trading strategies in practice.

4. Results

The results of the S&P 500 are presented and contrasted with those of the DJI and the NASDAQ. We focus on the S&P 500 specifically as it has the longest sample and therefore can offer better insights as compared to the DJI and the NASDAQ. The summary results for the DJI and the NASDAQ can be found in Appendix A. The results of the short term price behaviour tests are in Appendix B. The detailed results of the overall data sets for all indexes can be found in Appendices C to E. The detailed results of the sub-periods within the overall data sets can be found in Supplementary Appendices F to H.

Table 2
Gap size and the number of detected gaps, case of S&P 500 data over the period 2009–2018.

Gap size	0.10%	0.20%	0.30%	0.40%	0.50%	0.60%	0.70%	0.80%	0.90%	1.00%
% gaps in prices	41.05	19.70	10.90	5.71	3.45	2.02	1.35	0.87	0.67	0.52
Number of detected gaps	1038	497	275	144	87	51	34	22	17	13
Number of detected negative gaps	468	230	130	69	44	31	20	10	9	8
Number of detected positive gaps	570	267	145	75	43	20	14	12	8	5

4.1. Price gap size

First, an appropriate gap size must be as a criterion for gap detection. Caporale and Plastun (2017) show that the gap size significantly influences the number of detected anomalies. To confirm this we analyse S&P 500 data for the 2009–2018 sub-period. As can be seen from Table 2 a small gap size choice generates too many gaps to be considered as anomalies. A large gap size provides very few cases for analysis and may lead to statistical insignificance of the results. For this study (which is primarily based on statistical analysis and tests) the number of observations should be around 100 to make results statistically significant. This represents less than 10 per cent of the population and hence can be considered anomalies. As a result gap size is not constant and may differ from index to index, and between sub-periods (see Tables 3 and A.1). This inconsistency in the gap size can be considered additional evidence in favour of price gap anomaly evolution.

4.2. Price gap seasonality

Caporale and Plastun (2017) show that in foreign exchange and commodity markets price gaps tend to appear on Mondays. According to their results, more than 95 per cent of price gaps in foreign exchange markets compared to 65 per cent of price gaps in commodity markets appeared on Mondays. This is rather reasonable because markets are closed on weekends, and as the result of any significant event over the weekend will lead to price gaps on Monday. Surprisingly, this is not the case in this instance (with stock markets) as can be seen in Tables 4 and A.2 Therefore, H_3 is rejected.

4.3. Short term price behaviour

Next, we analyse short-term price behaviour in the US stock market around price gaps to investigate the presence of possible price patterns before and after price gaps. We calculate the number of days with positive (or negative) returns after a positive (or negative) price gaps divided by the total number of price gaps. If this ratio or momentum effect is much higher than 50 per cent this indicates abnormal price behaviour and as the results confirm our hypotheses.

The results are presented in Appendix B. We find no convincing evidence in favour of momentum effect after price gaps (Table B.1) and before them (Table B.2). In general, price gaps are not generated by previous price dynamics (NASDAQ index is an exception as negative gaps appear in 70 per cent of the cases after downward price movements, and after positive gaps in 67 per cent of the cases upward price movements are observed). Our results (see Table B.3 for details) also indicate that the probability that price gaps will be filled within 5 days after appearance is very low at around 20 per cent.

4.4. Price gap evolution

Overall, in probabilistic terms price gaps do not generate any stable patterns. But there can be patterns in terms of size of price movements after gaps. To check this we will test H_1 and H_2. To incorporate price direction in results of analysis H_1, we further test for H_{1-1} and H_{1-2}. The results for the overall data sets are presented in Appendices C to E for the cases of DJI, S&P 500, and NASDAQ, respectively. To ease the interpretation of results we have summarised them in Tables 5 and A.3.

Table 3
Gap size used for different sub-periods, over the period 1929–2018.

Period	S&P 500
1929–1938	1.20%
1949–1958	1.20%
1959–1968	0.70%
1969–1978	0.01%
1979–1988	0.03%
1989–1998	0.01%
1999–2008	0.08%
2009–2018	0.34%
Overall data set	0.70%

Table 4
Day of the week and gaps

Day of the week	S&P 500
Monday	0.23%
Tuesday	0.2%
Wednesday	0.2%
Thursday	0.18%
Friday	0.19%

Table 5
Overall statistical results: S&P 500.

Period/Method	Average analysis	t-test	ANOVA test	Mann-Whitney test	Regression analysis with dummy variables	Modified CAR approach	Overall
Gap day	+	–	–	+	–	+	3
Gap day (Positive gaps)	+	+	+	+	+	+	6
Gap day (Negative gaps)	+	+	+	+	+	+	6
Day after gap (Positive gaps)	+	+	–	+	+	+	5
Day after gap (Negative gaps)	+	+	–	–	+	+	4

Note: "+" indicates that the anomaly is confirmed and "–" indicates that anomaly is not confirmed. The higher the overall rating, the stronger the evidence of the anomaly. The average analysis confirms the price gap anomaly, if the mean return calculated for the gap day data is much higher (lower) compared with the mean return related to non-gap day data. The statistical tests (both parametrical and non-parametrical) rejection of the null hypothesis (data for the gap day and non-gap day data belong to the same general population) also confirms the price gap anomaly if it is statistically significant. The regression analysis with dummy variables gives evidence in favor of anomaly presence if a1 (slope of the dummy variable) is statistically significant ($p < 0.05$). The MCAR approach confirms the price gap anomaly if the trend model based on cumulative abnormal returns data has high multiple R, passes the F test and the regression coefficients are statistically significant (pvalue < 0.05).

Table 5 shows strong evidence confirming H_1 in the S&P 500. Similarly, Table A.3 confirms H_1 for the NASDAQ, but not for the DJI. The difference between the DJI, S&P 500 and NASDAQ results can be explained by the differences in samples (DJI sample is much shorter). This suggests that price gap anomaly may evolve and is, therefore, a preliminary confirmation of H_2.

Tables 6 and 7 confirm H_{1-1} in the S&P 500 on the day of the price gap. That is, on the price gap day prices tend towards the direction of the price gap. However, this is not the case for the day after the price gap, therefore H_{1-2} is not confirmed. It can be concluded that the S&P 500 roughly needs a day to absorb new information. Nevertheless, even a day can be enough to create a profitable trading strategy and generate abnormal profits from trading.

Similar results on the NASDAQ can be found in Tables A.6 and A.7. The longer sample of the NASDAQ allows for the evolution of

Table 6
H_{1-1} summary statistical results: S&P 500 sub-periods.

Period/Method	Average analysis	t-test	ANOVA test	Mann-Whitney test	Regression analysis with dummy variables	Modified CAR approach	Overall
				Day of anomaly			
1929–1938	+	+	+	+	+	+	6
1939–1948	+	–	–	+	–	+	3
1949–1958	+	+	+	+	+	+	6
1959–1968	+	+	+	+	+	+	6
1969–1978	+	+	+	+	+	+	6
1979–1988	+	+	+	+	+	+	6
1989–1998	+	+	+	+	+	+	6
1999–2008	+	+	+	+	+	+	6
2009–2018	+	+	+	+	+	+	6
				Day after anomaly			
1929–1938	+	–	–	–	–	+	2
1939–1948	+	+	+	+	+	+	6
1949–1958	+	–	+	–	+	+	5
1959–1968	+	+	+	+	+	+	6
1969–1978	+	–	+	–	+	+	4
1979–1988	+	–	–	–	–	–	1
1989–1998	–	–	–	–	–	–	0
1999–2008	–	–	–	–	–	–	0
2009–2018	–	–	–	–	–	–	0

Note: "+" indicates that the anomaly is confirmed and "–" indicates that anomaly is not confirmed. The higher the overall rating, the stronger the evidence of the anomaly.

Table 7
H_{1-2} statistical results: S&P 500 sub-periods.

Period/Method	Average analysis	t-test	ANOVA test	Mann-Whitney test	Regression analysis with dummy variables	Modified CAR approach	Overall
				Day of anomaly			
1929–1938	+	+	+	+	+	+	6
1939–1948	+	+	+	+	+	+	6
1949–1958	+	+	+	+	+	+	6
1959–1968	+	+	+	+	+	+	6
1969–1978	+	+	+	+	+	+	6
1979–1988	+	+	+	+	+	+	6
1989–1998	+	+	+	+	+	+	6
1999–2008	+	+	+	+	+	+	6
2009–2018	+	+	+	+	+	+	6
				Day after anomaly			
1929–1938	+	–	–	–	–	+	2
1939–1948	+	+	+	+	+	+	6
1949–1958	–	–	–	–	–	–	0
1959–1968	–	–	–	–	–	+	1
1969–1978	+	+	+	+	+	+	6
1979–1988	–	–	–	–	–	–	0
1989–1998	–	–	–	–	–	–	0
1999–2008	+	–	–	–	–	+	2
2009–2018	+	–	+	–	+	+	4

Note: "+" indicates that the anomaly is confirmed and "–" indicates that anomaly is not confirmed. The higher the overall rating, the stronger the evidence of the anomaly.

the price anomaly. H_{1-1} is therefore confirmed on the day of the price gap anomaly, and the day after the price gap anomaly (in both instances only until the 1990s and has since disappeared). H_{1-2} in both instances is confirmed up until the 1990s. The results of the DJI did not provide strong evidence in favour of H_{1-1} and H_{1-2} on the day after the price gap, but similar to the S&P 500 evidence was strong on the day of the price gap (see Tables A.4 and A.5). These results confirm in the main the price gap anomaly is a reality in the US stock market and that it evolves over time, that is, from prevalence to disappearance.

4.5. Trading simulation

The algorithm of the trading strategy is to buy/sell at the start of the up/down gap day and close this position at the end of this day. To test this strategy data for the DJI and S&P 500 are used (for this case the price anomaly still exists based on the day it occurred). The results for DJI are presented in Table A.8, and for the S&P 500 in Table 8. For the S&P 500 and DJI, the trading strategy built on price gap anomaly is efficient and its results differ from random.

Table 8
Trading simulation results of the price gap anomaly for the S&P 500.

Period	Gap type	Number of trades, units	Number of successful trades, units	Number of successful trades, %	Profit, %	Profit % per year	z-test	Result
1929–1938	Up	131	130	99.2%	181.6%	18.2%	10.65	passed
	Down	110	108	98.2%	189.3%	18.9%	8.76	passed
1939–1948	Up	110	67	60.9%	10.6%	1.1%	0.9	failed
	Down	122	79	64.8%	51.8%	5.2%	4.65	passed
1949–1958	Up	106	105	99.1%	176.5%	17.6%	31.91	passed
	Down	104	103	99%	189.1%	18.9%	23.56	passed
1959–1968	Up	108	106	98.1%	133.1%	11.3%	24.41	passed
	Down	92	91	98.9%	94.8%	9.5%	22.14	passed
1969–1978	Up	85	71	83.5%	112.8%	11.3%	13.61	passed
	Down	96	90	93.8%	126.2%	12.6%	21.18	passed
1979–1988	Up	92	63	68.5%	54%	5.4%	4.95	passed
	Down	123	81	65.9%	51.9%	5.2%	4.96	passed
1989–1998	Up	117	72	61.5%	26.7%	2.7%	2.95	passed
	Down	99	61	61.6%	22.8%	2.3%	3.2	passed
1999–2008	Up	99	65	65.7%	82.8%	8.3%	3.73	passed
	Down	110	72	65.5%	98.7%	9.9%	4.38	passed
2009–2018	Up	106	71	67%	59%	5.9%	4.16	passed
	Down	107	65	60.7%	56%	5.6%	3.62	passed

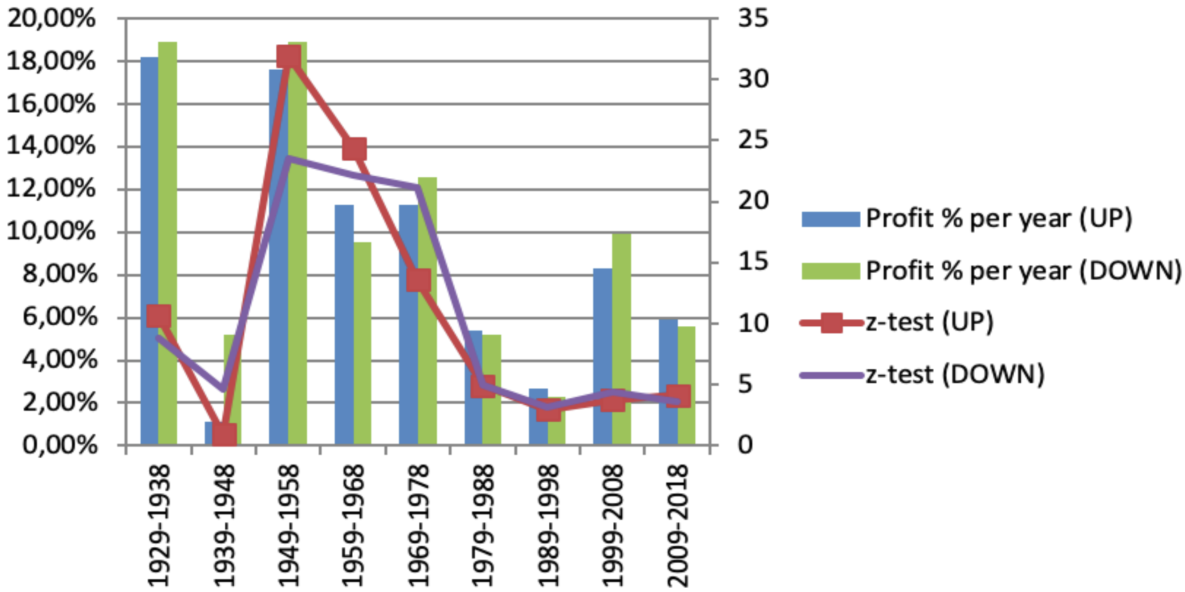

Fig. 1. Trading simulation results of the price gap anomaly for the S&P 500. (Note: The primary axis refers to the percentage profit per year, and the secondary to the $z - test$ statistic.)

One more interesting fact (see Fig. 1) is the decrease of trading strategy efficiency. This is indirect evidence in favour of evolution of the US stock market and its movement from less efficient to more efficient state. Overall it can be concluded that the price gap anomaly is a real market anomaly. The US stock market loses its efficiency after price gaps. This effect is temporary and lasts only for a day. Still, even this time is enough to exploit the "hole" in the market efficiency and generate abnormal profits from trading.

5. Conclusion

We analysed price gap anomaly in the US stock market by using information from three stock market indexes(DJI, S&P 500, and NASDAQ). We tested three hypotheses of interest, that is, H_1: the price gap anomaly exists, H_{1-1}: prices tend to rise after positive gaps, H_{1-2}: prices tend to fall after negative gaps, H_2: the price gap anomaly evolves, and H_3: there is seasonality in price gaps. Various statistical methods including parametric tests (Student's t-tests, ANOVA), non-parametric tests (Mann-Whitney test), regression analysis with dummy variables, MCAR approach, and the trading simulation approach were utilised.

We conclude that the US stock market in the main did not exhibit seasonality in price gaps. Therefore H_3 is rejected. Furthermore, no evidence was found that price gaps in the US stock market were filled within five days of their occurrence. However, strong evidence in favour of abnormal price movements after the gaps were found, confirming H_1 and H_2. Particularly on the day of the occurrence of the gap and not on the day after the price gap. In the DJI and the S&P 500, this pattern persists indicating that these markets take a day to incorporate new information. As the results of the trading simulation indicate, a day is enough to profit from a price gap anomaly trading strategy in the DJI and the S&P 500.

Similar to other studies and other anomalies (see Cajueiro & Tabak, 2004; McLean & Pontiff, 2016; Tiwari, Aye, & Gupta, 2019 for example) the price gap anomaly evolved. It is less prevalent since the 1990s as shown in the S&P 500 and NASDAQ. This pattern of evolution is common amongst most stock market anomalies (see Plastun et al., 2019 on calendar anomalies, amongst others). Our findings, therefore, add on to the existing literature. Finally, in the main, our results are against the EMH and are therefore interesting to both practitioners and academics.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. DJI and NASDAQ summary results

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A.1. Overall results

Tables A.1 and A.2.

Table A.1
Gap size used for different sub-periods, over the period 1929–2018.

Period	DJI	NASDAQ
1929–1938	–	–
1939–1948	–	–
1949–1958	–	0.71%
1959–1968	–	0.95%
1969–1978	–	1.35%
1979–1988	–	1.10%
1989–1998	0.40%	0.68%
1999–2008	0.07%	1.50%
2009–2018	0.20%	1.10%
Overall data set	0.30%	1.10%

Table A.2
Day of the week and gaps.

Day of the week	DJI	NASDAQ
Monday	0.24%	0.2%
Tuesday	0.2%	0.2%
Wednesday	0.17%	0.2%
Thursday	0.19%	0.19%
Friday	0.21%	0.2%

A.2. Statistical tests

Tables A.3–A.7.

Table A.3
Results of the statistical tests for the overall data sets.

Period/Method	Average analysis	t-test	ANOVA test	Mann-Whitney test	Regression analysis with dummy variables	Modified CAR approach	Overall
				Dow Jones Index overall data set			
Gap day	–	–	–	–	–	+	1
Gap day (Positive gaps)	+	–	–	–	–	–	1
Gap day (Negative gaps)	+	–	–	–	–	+	2
Day after gap (Positive gaps)	+	–	–	–	–	–	1
Day after gap (Negative gaps)	+	–	–	+	–	+	3
				NASDAQ overall data set			
Gap day	+	+	+	+	+	+	6
Gap day (Positive gaps)	+	+	+	+	+	+	6
Gap day (Negative gaps)	+	+	+	+	+	+	6
Day after gap (Positive gaps)	+	+	+	+	+	+	6
Day after gap (Negative gaps)	+	+	+	+	+	+	6

Note: "+" indicates that the anomaly is confirmed and "–" indicates that anomaly is not confirmed. The higher the overall rating, the stronger the evidence of the anomaly.

Table A.4
Results of the statistical tests for H_{1-1}: DJI.

Period	Average analysis	t-test	ANOVA test	Mann-Whitney test	Regression analysis with dummy variables	Modified CAR approach	Overall
				Day of anomaly			
1989–1998	+	–	–	–	–	+	2
1999–2008	+	+	+	+	+	+	6
2009–2018	+	+	+	+	+	+	6
				Day after anomaly			
1989–1998	+	–	–	–	–	+	2
1999–2008	+	–	–	–	–	+	2
2009–2018	–	–	–	–	–	–	0

Note: "+" indicates that the anomaly is confirmed and "–" indicates that anomaly is not confirmed. The higher the overall rating, the stronger the evidence of the anomaly.

Table A.5
Results of the statistical tests for H_{1-2}: DJI.

Period	Average analysis	t-test	ANOVA test	Mann-Whitney test	Regression analysis with dummy variables	Modified CAR approach	Overall
				Day of anomaly			
1989–1998	–	–	–	–	–	–	0
1999–2008	+	+	+	+	+	+	6
2009–2018	+	+	+	+	+	+	6
				Day after anomaly			
1989–1998	+	–	–	–	–	+	2
1999–2008	+	–	–	–	–	–	1
2009–2018	+	–	–	–	–	+	2

Note: "+" indicates that the anomaly is confirmed and "–" indicates that anomaly is not confirmed. The higher the overall rating, the stronger the evidence of the anomaly.

Table A.6
Results of the statistical tests for H_{1-1}: NASDAQ.

Period/Method	Average analysis	t-test	ANOVA test	Mann-Whitney test	Regression analysis with dummy variables	Modified CAR approach	Overall
				Day of anomaly			
1949–1958	+	+	+	+	+	+	6
1959–1968	+	+	+	+	+	+	6
1969–1978	+	+	+	+	+	+	6
1979–1988	+	+	+	+	+	+	6
1989–1998	+	–	–	–	–	+	2
1999–2008	+	–	+	+	+	+	5
2009–2018	+	+	+	+	+	+	6
				Day after anomaly			
1949–1958	+	+	+	+	+	+	6
1959–1968	+	+	+	+	+	+	6
1969–1978	+	+	+	+	+	+	6
1979–1988	+	+	+	+	+	+	6
1989–1998	+	–	+	–	+	+	4
1999–2008	–	–	–	–	–	–	0
2009–2018	+	–	–	–	–	+	2

Note: "+" indicates that the anomaly is confirmed and "–" indicates that anomaly is not confirmed. The higher the overall rating, the stronger the evidence of the anomaly.

Table A.7
Results of the statistical tests for H_{1-2}: NASDAQ.

Period/Method	Average analysis	t-test	ANOVA test	Mann-Whitney test	Regression analysis with dummy variables	Modified CAR approach	Overall
				Day of anomaly			
1949–1958	+	+	+	+	+	+	6
1959–1968	+	+	+	+	+	+	6
1969–1978	+	+	+	+	+	+	6
1979–1988	+	+	+	+	+	+	6
1989–1998	–	–	–	–	–	+	1
1999–2008	–	–	+	–	–	–	1
2009–2018	–	–	–	–	–	–	0
				Day after anomaly			
1949–1958	+	+	+	+	+	+	6
1959–1968	+	+	+	+	+	+	6
1969–1978	+	+	+	+	+	+	6
1979–1988	+	+	+	+	+	+	6
1989–1998	+	–	–	–	–	–	1
1999–2008	–	–	–	–	–	+	1
2009–2018	+	–	–	+	+	+	4

Note: "+" indicates that the anomaly is confirmed and "–" indicates that anomaly is not confirmed. The higher the overall rating, the stronger the evidence of the anomaly.

A.3. Trading simulation results

Tables A.8.

Table A.8
Trading simulation results of the price gap anomaly for the DJI: 1989–2018.

Period	Gap type	Number of trades, units	Number of successful trades, units	Number of successful trades, %	Profit, %	Profit % per year	z-test	Result
1989–1998	Up	102	46	45.1%	−1.1%	−0.1%	0.11	failed
	Down	116	49	42.2%	−26.7%	−2.7%	2.42	passed
1999–2008	Up	73	51	69.9%	66.5%	6.6%	3.7	passed
	Down	143	81	56.6%	64.1%	6.4%	3.31	passed
2009–2018	Up	127	88	69.3%	30.8%	3.1%	3.27	passed
	Down	81	47	58%	19.6%	2%	1.84	passed

Appendix B. Short-term price behavior in DJI, S&P 500, and NASDAQ: Price gaps (overall data sets)

Tables B.1–B.3.

Table B.1
Momentum effect in the US stock market after the gap

Instrument	Parameter	Number of days after the gap		
		1	2	3
Dow Jones Index	Positive gaps	53%	57%	61%
	Negative gaps	50%	50%	47%
	All gaps	51%	54%	54%
S&P 500 Index	Positive gaps	4.0%	63%	60%
	Negative gaps	4%	52%	45%
	All gaps	4%	58%	53%
NASDAQ	Positive gaps	32%	65%	67%
	Negative gaps	24%	63%	59%
	All gaps	28%	64%	63%

Table B.2
Momentum effect in the US stock market before the gap.

Instrument	Parameter	Number of days before the gap		
		1	2	3
Dow Jones Index	Positive gaps	56%	49%	52%
	Negative gaps	54%	49%	49%
	All gaps	55%	49%	50%
S&P 500 Index	Positive gaps	57%	57%	52%
	Negative gaps	60%	59%	54%
	All gaps	58%	58%	53%
NASDAQ	Positive gaps	61%	56%	54%
	Negative gaps	68%	69%	70%
	All gaps	64%	63%	63%

Table B.3
Fill gap effect in the US stock market

Instrument	Parameter	Number of days after the gap				
		1	2	3	4	5
Dow Jones Index	Positive gaps	22%	28%	26%	30%	28%
	Negative gaps	25%	33%	36%	42%	46%
	All gaps	24%	30%	31%	35%	37%
S&P 500 Index	Positive gaps	0%	6%	11%	16%	19%
	Negative gaps	1%	10%	19%	26%	27%
	All gaps	1%	8%	15%	20%	23%
NASDAQ	Positive gaps	8%	13%	18%	21%	19%
	Negative gaps	7%	11%	17%	21%	25%
	All gaps	8%	12%	18%	21%	22%

Appendix C. Detailed statistical results: DJI overall data

.

C.1. Average analysis

Tables C.1.

Table C.1
Average analysis

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Mean return (gap day)	0.03%	0.06%	0%	0.05%	−0.03%
Mean return (non-gap day)	0.04%	0.04%	0.04%	0.04%	0.04%
Anomaly	not confirmed	not confirmed	confirmed	not confirmed	confirmed

C.2. Parametric tests: Student's t-test

Tables C.2.

Table C.2
T-test

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
t-criterion	0.16	0.42	0.53	0.15	1.04
t-critical (=0.95)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected

C.3. Parametric tests: ANOVA

Tables C.3.

Table C.3
ANOVA.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
F	0.036	0.18	0.53	0.03	1.4
p-value	0.85	0.67	0.47	0.86	0.24
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected

C.4. Non-parametric tests: Kruskal-Wallis test

Tables C.4.

Table C.4
Kruskal-Wallis test.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Adjusted H	0.82	0.12	1.26	0	4.55
d.f.	1	1	1	1	1
P value:	0.37	0.73	0.26	0.95	0.03
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	not rejected	not rejected	not rejected	rejected

C.5. Regression analysis with dummy variables

Tables C.5.

Table C.5
Regression analysis with dummy variables.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
a_0	0.0004 (0.00)	0.0004 (0.00)	0.0004 (0.00)	0.0004 (0.00)	0.0004 (0.00)
a_1	−0.0001 (−0.19)	0.0002 (0.67)	−0.0004 (0.47)	0.0001 (0.86)	−0.0007 (0.24)
Anomaly	not confirmed	not confirmed	not confirmed	not confirmed	not confirmed

C.6. Modified CAR approach

Tables C.6.

Table C.6
Modified CAR approach.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Multiple R	0.49	0.5	0.25	0	0.92
F-test	233.47 (0.00)	129.13 (0.00)	22.07 (0.00)	0.00 (0.98)	1822 (0.00)
a_0	−0.0041 (0.60)	0.0128 (0.06)	−0.0267 (0.00)	0.0354 (0.00)	0.0319 (0.00)
a_1	−0.0003 (0.00)	−0.0003 (0.00)	−0.0002 (0.00)	0.0000 (0.98)	−0.0008 (0.00)
Anomaly	confirmed	confirmed	confirmed	not confirmed	confirmed

Appendix D. Detailed statistical results: S&P 500 overall data

.

D.1. Average analysis

Tables D.1.

Table D.1
Average analysis

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Mean return (gap day)	0.06%	1.15%	−1.29%	0.17%	−0.11
Mean return (non-gap day)	0.02%	0.02%	0.02%	0.02%	0.02%
Anomaly	confirmed	confirmed	confirmed	confirmed	confirmed

D.2. Parametric tests: Student's t-test

Tables D.2.

Table D.2
T-test.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
t-criterion	0.92	45.46	35.79	4.85	2.71
t-critical (=0.95)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	not rejected	rejected	rejected	rejected	rejected

D.3. Parametric tests: ANOVA

Tables D.3.

Table D.3
ANOVA.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
F	1.55	1162.11	1269.52	18.66	13.6
p-value	0.22	0	0	0	0
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	not rejected	rejected	rejected	not rejected	not rejected

D.4. Non-parametric tests: Kruskal-Wallis test

Tables D.4.

Table D.4
Kruskal-Wallis test.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Adjusted H	13.52	705.16	472.37	39.46	0.04
d.f.	1	1	1	1	1
P value:	0	0	0	0	0.84
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	rejected	rejected	rejected	not rejected

D.5. Regression analysis with dummy variables

Tables D.5.

Table D.5
Regression analysis with dummy variables.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
a_0	0.0002 (0.00)	0.0002 (0.00)	0.0002 (0.00)	0.0002 (0.00)	0.0002 (0.00)
a_1	0.0003 (0.21)	0.0113 (0.00)	−0.0132 (0.00)	0.0014 (0.00)	−0.0014 (0.00)
Anomaly	not confirmed	confirmed	confirmed	confirmed	confirmed

D.6. Modified CAR approach

Tables D.6.

Table D.6
Modified CAR approach.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Multiple R	0.51	0.99	0.99	0.99	0.96
F-test	694.86 (0.00)	325351 (0.00)	145758.2 (0.00)	63459.73 (0.00)	12133.44 (0.00)
a_0	−0.1003(0.00)	0.4081 (0.00)	−0.5444 (0.00)	−0.1088 (0.00)	0.0272 (0.00)
a_1	0.0002 (0.00)	0.0106 (0.00)	−0.0127 (0.00)	0.0016 (0.00)	−0.0016 (0.00)
Anomaly	confirmed	confirmed	confirmed	confirmed	confirmed

Appendix E. Detailed statistical results: NASDAQ overall data

.

E.1. Average analysis

Tables E.1.

Table E.1
Average analysis.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Mean return (gap day)	−0.09%	0.84%	−0.90%	0.22%	−0.37%
Mean return (non-gap day)	0.03%	0.03%	0.03%	0.03%	0.03%
Anomaly	confirmed	confirmed	confirmed	confirmed	confirmed

E.2. Parametric tests: Student's t-test

Tables E.2.

Table E.2
T-test.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
t-criterion	2.30	12.57	13.41	3.06	6.64
t-critical (=0.95)	1.96	1.96	1.96	1.96	1.96
Null hypothesis	rejected	rejected	rejected	rejected	rejected

E.3. Parametric tests: ANOVA

Tables E.3.

Table E.3
ANOVA.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
F	22.89	627.20	884.02	33.30	173.56
p-value	0	0	0	0	0
F critical	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	rejected	rejected	rejected	rejected

E.4. Non-parametric tests: Kruskal-Wallis test

Tables E.4.

Table E.4
Kruskal-Wallis test.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Adjusted H	18.92	360.22	452.48	46.95	104.37
d.f.	1	1	1	1	1
P value:	0	0	0	0	0
Critical value	3.84	3.84	3.84	3.84	3.84
Null hypothesis	rejected	rejected	rejected	rejected	rejected

E.5. Regression analysis with dummy variables

Tables E.5.

Table E.5
Regression analysis with dummy variables.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
a_0	0.0003 (0.00)	0.0003 (0.00)	0.0003 (0.00)	0.0003 (0.00)	0.0003 (0.00)
a_1	−0.0012 (0.00)	0.0081 (0.00)	−0.0093 (0.00)	0.0018 (0.00)	−0.0040 (0.00)
Anomaly	confirmed	confirmed	confirmed	confirmed	confirmed

E.6. Modified CAR approach

Tables E.6.

Table E.6
Modified CAR approach.

Parameter	Gap day	Gap day (Positive gaps)	Gap day (Negative gaps)	Day after gap (Positive gaps)	Day after gap (Negative gaps)
Multiple R	0.69	0.92	0.92	0.72	0.97
F-test	1332.55 (0.00)	3611.02 (0.00)	4423.76 (0.00)	729.03 (0.00)	10828.12 (0.00)
a_0	−1.0646 (0.00)	1.1373 (0.00)	−1.2888 (0.00)	0.3928 (0.00)	−0.2297 (0.00)
a_1	−0.0011 (0.00)	0.0073 (0.00)	−0.0097 (0.00)	0.0017 (0.00)	−0.0039 (0.00)
Anomaly	confirmed	confirmed	confirmed	confirmed	confirmed

Appendix F. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.najef.2020.101177.

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