Price effects after one-day abnormal returns in developed and emerging markets: ESG versus traditional indices

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Highlights

•Study price effects after one-day abnormal return in developed and emerging markets.
•Use daily data from 2000 to 2020 and compare ESG versus conventional stock indices.
•Find quite similar price effects for both indices, yet their power is dissimilar.
•A contrarian effect is seen in the US stock market after one-day abnormal returns.
•The main results offer additional evidence against the Efficient Market Hypothesis.

Abstract

This paper examines the price effects related to one day abnormal returns on the stock market indices of both developed and emerging countries while accounting for differences between environmental, social, and governance (ESG) indices as well as conventional ones. Using daily data from MSCI family indices from 2007 to 2020 and employing various methods to avoid methodological bias, the following hypotheses are tested. After one day abnormal returns, specific price effects (momentum/contrarian) appear (H1) in cases of positive (H1.1) and negative (H1.2) returns. Price effects after one-day abnormal returns are stronger in the case of traditional indices as compared to ESG ones (H2). Price effects after one-day abnormal returns are stronger during a crisis period (H3), and a dynamic trigger approach is more appropriate for defining abnormal returns than a static approach (H4). Price effects after one-day abnormal returns are stronger in emerging markets as compared to developed ones (H5). The results are mixed in the case of H1, and there is no evidence in favor of H2–H5. There are no significant differences between ESG and conventional indices. The types of detected price effects are the same for the cases of ESG and conventional indices; their power is different in some cases. Overall, a strong contrarian effect is observed in the US stock market after one-day abnormal returns; accordingly, a trading strategy constructed based on this observation could generate profits from trading. The main results offer additional evidence against the efficient market hypothesis, which can assist practitioners in beating the market.

Keywords: Abnormal returns; momentum effect; contrarian effect; ESG; developed and emerging stock markets

JEL classification: G12, C63

1. Introduction

The academic literature on stock market prices has grown substantially, largely refuting Fama's random walk hypothesis (1965). Previous studies have indicated that the dynamics of stock indices can be predicted based on a set of fundamental variables (economic, financial, geopolitical, etc.) (see, among others, Rapach et al., 2005; Chen, 2009; Alqahtani et al., 2020; Bouri et al., 2020). Various evidence has also been provided in favor of particular patterns in stock price dynamics, such as calendar anomalies (e.g., Plastun et al., 2019)[1] or force majeure; evidence of these patterns indicate market inefficiency. Another group of anomalies that disturbs market efficiency is the significance of the overreaction hypothesis, through which investors respond too strongly to both unfavorable and favorable information (De Bondt and Thaler, 1985; Richards, 1997; Malin and Bornholt 2013; Alves and Carvalho, 2020).[2] However, prices tend to move in the opposite direction after these overreactions (Jegadeesh and Titman, 1993), leading to a price reversal, which is also called a contrarian effect and can be explained by irrational investor behaviour. One specific example of the overreaction hypothesis is price behaviour after one-day abnormal returns. Bremer and Sweeney (1991) have found evidence of price reversals after one day of decline in the stock market.[3] Recent studies have shown mixed results depending on the stock markets and datasets used. For example, Caporale and Plastun (2020) have uncovered evidence in favor of momentum effects in the cryptocurrency market after one-day abnormal returns. In fact, differences in results can be explained by the differences in the

[1] These can include seasonal or other time-based factors, like day of the week or month of the year.

[2] Such anomalies are related to the existence of fat tails in the financial data, which are against the normal data distribution and can therefore be classified as the non-random specific of price behavior.

[3] Some studies have confirmed the existence of the contrarian effect after one-day abnormal returns in the foreign exchange market (Parikakis and Syriopoulos, 2008). Other studies have found evidence in favor of momentum effects after one-day abnormal returns in the cryptocurrency market (Caporale & Plastun, 2019).

applied methods. There are two major approaches for defining abnormal returns—static and dynamic—that can provide different results even if the same datasets are used. Furthermore, previous studies have mostly drawn conclusions based on the economies of the US and other developed countries; they also have mostly considered conventional stock indices, ignoring environmental, social, and governance (ESG) stock indices, which can be different. ESG investment has become a large and influential industry, constituting a significant portion of global equity portfolios and funds (Daugaard, 2020), and numerous studies have pointed to its ability to generate abnormal returns (e.g., Henke, 2016). Notably, institutional investors, as the largest players in the ESG investment universe, tend to focus on the ESG characteristics of stocks more than the fundamentals (Cao, Titman, Zhan, & Zhang, 2019). Accordingly, socially responsible funds tend to continue to hold stocks with high ESG ratings, even after the announcement of adverse news or fundamentals (Starks, Venkat, & Zhu, 2017). In fact, preferences for ESG can affect the overreactions of investors to news and announcements related to ESG investment, which can ultimately affect market inefficiency.

The issue of ESG investment has become even more relevant after the crisis caused by pandemic. According to Global Institutional Investor survey, up to 80% of investors increased their ESG investments significantly or moderately in 2020. In case of institutional investors with over $200 billion of assets, this figure increased to 90%.

The main idea of this paper is to see whether ESG indices are more or less efficient compared with conventional indices. Such a comparison can be done in a number of ways, for example, by exploring the level of persistence. In this study, the following idea is used instead: the presence of market anomalies is usually a key argument against market efficiency, which is why ESG indices vs conventional indices can be analyzed through the prism of price effects after abnormal returns as one of the market anomalies.

To be included in ESG indices, companies should be socially responsible. Accordingly, ESG indices are based on social responsibility criteria to screen and select their components.

Companies included in ESG indices provide more complicated and transparent reporting. In theory, this should lead to a lower information asymmetry and higher market efficiency. As a result, ESG indices might be less prone to market anomalies.

Despite significant empirical evidence related to stock price effects after abnormal returns, many unanswered questions remain. For example, which type of market is more vulnerable to price effects after one-day abnormal returns, developed or emerging? Are there any differences in price effects over the crisis and non-crisis periods? Which methodology is better for defining abnormal returns, dynamic or static? Are the price effects after one-day abnormal returns in ESG indices different from those in conventional stock indices?

This paper extends the literature on price effects after one-day abnormal returns by providing answers to these research questions. Different hypotheses are tested. After one-day abnormal returns, specific price effects (momentum/contrarian) appear (H1) in cases of positive (H1.1) and negative (H1.2) returns. Price effects after one-day abnormal returns are stronger in the case of traditional indices as compared to ESG indices (H2), and price effects after one-day abnormal returns are stronger during the crisis period (H3). The dynamic trigger approach is more appropriate for defining abnormal returns in stock markets than the static one (H4), and price effects after one-day abnormal returns are stronger in emerging markets as compared to developed ones (H5). For these purposes, different statistical tests and methodological approaches are used, including average analysis, the modified cumulative abnormal returns approach, regression analysis with dummy variables, R/S analysis, the parametric Student's t-test and ANOVA, non-parametric Mann-Whitney tests, and the trading simulation approach.

The presence of typical patterns would be indirect evidence against market efficiency. Another contribution of this research is related to purely practical aspects: if patterns are present, they could be exploited by traders and investors to generate abnormal profits.

The layout of the paper is organized as follows. Section 2 reviews the literature, section 3 describes the data and methodology, section 4 presents the empirical results, and section 5 offers some concluding remarks.

2. Literature review

The idea of price effects as a reaction to price changes came from De Bondt and Thaler (1985), who showed that stock prices that experience long-term gains will tend to underperform in the future and vice versa. Following that study, many papers have been published to either confirm or reject the overreaction hypothesis and examine the price effects of abnormal returns. In this regard, developed stock markets were the primary subject for earlier studies (see Cox and Peterson, 1994; Clements et al., 2009; Dyl et al., 2019, among others), while later studies have considered emerging markets (e.g., Boubaker et al., 2015; Pokavattana et al., 2019; Zaremba, 2019).[4] Existing evidence is mixed; contrarian effects were detected by Bremer and Sweeney (1991), Jegadeesh and Titman (1993), Richards (1997), and Kudryavtsev (2013). Conversely, Jegadeesh (1990) and Caporale and Plastun (2019) have found evidence in favor of momentum effects. These differences can be explained by the differences in their approaches to defining abnormal returns. Bremer and Sweeney (1991) have proposed a 10% price change as the measure of an abnormal return, which is defined as the static approach. Caporale et al. (2018), in contrast, have identified abnormal returns based on the number of standard deviations added to the average return, which is called the dynamic trigger approach.

Studies considering the price effects of abnormal returns are relatively understudied in terms of ESG data. ESG investing has experienced tremendous growth over the past decade, especially following the 2008 global financial crisis, during which ESG investments outperformed their conventional counterparts (Andersson et al., 2020). Numerous studies on the performance of ESG investments have been conducted in developed countries; fewer studies

[4] Other studies consider the commodity markets (e.g., Borgards et al., 2021).

have focused on emerging countries (see Daugaard, 2020).[5] Most of the existing studies on ESG have examined the relationship between socially responsible investing and price over/underperformance (Flammer, 2015). Chang and Witte (2010) and Derwall and Koedijk (2009) have found evidence indicating the overperformance of ESG companies. Conversely, Jegourel and Maveyraud (2010) have reported a negative relationship between social responsibility and returns, while Cui and Docherty (2020) have explored the effects of negative ESG news on price reactions and found a contrarian effect in stock prices. Krueger (2015) and Capelle-Blancard and Petit (2019) have reported that the stock market reacts to ESG news asymmetrically by showing that there is a significant negative reaction to bad ESG news but little reaction to good news, which contradicts Starks et al. (2017). Several papers have explored the influence of different factors (e.g. financial, economic, and seasonal) on the performance of ESG-related indices and companies. Hanif et al. (2021) have analyzed connectedness between the European emission allowance prices and renewable energy indices and showed positive and dynamic dependence between the carbon prices and both clean and solar indices. Yao et al. (2021) have explored the effect of green credit policy on firm performance of listed firms in China and observed the decrease of investment level. Uddin et al. (2019) have examined the influence of financial, economic, and seasonal factors on the performance of international equity, fixed income, cash, and balanced Islamic mutual funds.

Although papers have been devoted to price effects after abnormal returns in conventional stock indices, little is known about price effects after abnormal returns in ESG indices. Importantly, the relevant literature has ignored comparing ESG and conventional stock market indices regarding their price effects after one-day abnormal returns. The question of whether effects after abnormal returns in ESG stock indices differ as compared with those in conventional stock indices has not been answered. Interestingly, ESG data are important because environmental, social, and corporate governance criteria have gained more and more traction

[5] The existing literature highlights the importance of the institutional setting and investors' preferences for ESG stock price performance.

among investors. But does incorporation of these criteria influence the efficiency of the market indices? Are ESG indices less vulnerable to price effects after abnormal returns? Furthermore, questions regarding the differences of price effects after abnormal returns on developed and emerging markets remain relevant. This paper extends the literature by answering these research questions.

3. Data and Methodology

This study uses daily data from a family of MSCI indices (https://www.msci.com/) for both traditional and ESG in the US, UK, and Japan (developed markets) as well as India and China (emerging markets). The sample period was from October 1, 2007 to February 10, 2020, according to price data availability.

The following five hypotheses are tested:

- Hypothesis 1: after one-day abnormal returns, specific price effects (momentum/contrarian) appear.
- Hypothesis 1.1: – after one-day abnormal positive returns, specific price effects appear.
- Hypothesis 1.2 – after one-day abnormal negative returns, specific price effects appear.
- Hypothesis 2: price effects after one-day abnormal returns are stronger in cases of traditional indices as compared to ESG indices.
- Hypothesis 3: price effects after one-day abnormal returns are stronger during the crisis period.
- Hypothesis 4: the dynamic trigger approach is more appropriate for defining abnormal returns in the stock markets than the static one.
- Hypothesis 5: price effects after one-day abnormal returns are stronger in cases of emerging markets as compared to developed ones.

We define the momentum effect as the tendency of the stock index to maintain its trend—that is, a rising stock index will rise further, and a falling stock index will fall further. The contrarian or reversal effect is the tendency of the stock index to reverse its current trend.

Various techniques were used to test H1–H5, including average analysis, parametrical tests (Student's t-tests and ANOVA analysis), non-parametrical tests (Mann-Whitney tests), a modified cumulative abnormal returns approach, regression analysis with dummy variables, and the trading simulation approach. The average analysis was used to assess potential differences between returns. Parametric and non-parametric tests were used to determine the presence of fat tails and excess kurtosis in the return series. The null hypothesis is that the data comes from the same population; a rejection of the null indicates an anomaly. The student's t-tests were used to assess whether a return series for a given day comes from the same population; a rejection of the null at a significance level below 95% indicates an anomaly on a particular day. The index return at time t is calculated as

$$\mathrm{R_i} = \left(\frac{\text{Index close}_\mathrm{i}}{\text{Index close}_\mathrm{i\text{-}1}}\text{-}1\right) \times 100\% \tag{1}$$

As indicated in the introduction section, it is important to define abnormal returns given the fact that previous studies provide various threshold levels in this regard. While Bremer and Sweeney (1991) have used a 10% price change, other studies have indicated potential bias in the results deriving from a constant value (e.g., Cox & Peterson, 1994) because various time periods can be described by various measures of volatility. Therefore, Caporale et al. (2018) have defined abnormal returns using a dynamic trigger approach. Accordingly, positive abnormal returns are computed as

$$R_i > (\overline{R}_n + k \times \delta_n) \tag{2}$$

while negative abnormal returns are computed as:

$$R_i < (\bar{R}_n - k \times \delta_n) \tag{3}$$

where $\overline{R}_n$ is the average of daily returns in period *n*, *k* is the number of standard deviations used to compute abnormal returns, and δ_n is the standard deviation of daily returns in a period *n*.

We used calculations based on both the dynamic trigger approach and the static approach to test Hypothesis 4 and avoid biased results that could potentially be driven by the specifics of the approach used to define abnormal returns.

The dynamic trigger approach is sensitive to the number of standard deviations added to the mean return to measure one-day abnormal returns. Another crucial parameter is the period value used to calculate the average and standard deviation. In this paper, two standard deviations and a period of 50 were used to calculate abnormal returns. The rationale for this is provided by Plastun et al. (2021).

Two datasets are constructed using equations (2) and (3). The first contains returns after days with positive/negative abnormal returns, and the second contains returns on standard days (days with normal returns).

To uncover the patterns in price behavior after days with abnormal returns, we employ regressions with a binary variable as

$$\mathrm{Y_t} = \mathrm{a_0} + \mathrm{a_1 D_{1t}} + \varepsilon_\mathrm{t} \tag{4}$$

where Y_t denotes index returns on day *t*, and $\mathrm{a_n}$ denotes the mean return on a day that does not exhibit abnormalities. $\mathrm{D_{nt}}$ denotes a binary variable for a specific data group, which takes the value of 1 when the data the data shown an abnormal return day and 0 otherwise, and ε_t is a random error term at time *t*. Notably, the magnitude, sign, and significance of the binary coefficients are used to make inferences regarding market anomalies.

We define abnormal returns as

$$AR_t = R_t - E(R_t) \tag{5}$$

where R_t is the index return at time *t*, and $E(R_t)_m$ is the average return calculated for the sample period *m* as follows

$$E(R_t)_m = (\tfrac{1}{T}) \sum_{i=1}^{T} R_i \tag{6}$$

where T is the sample size of period m.

Following MacKinlay (1997), the cumulative abnormal return (CAR_i) is given by

$$CAR_i = \sum_{i=1}^{T} AR_i \tag{7}$$

If there is a trend in the CAR dataset, then there is abnormal behavior in the data over the period m. Time regression is used to detect trends, and the hypotheses are accepted or rejected based on the regression of multiple R^2 and the p-value of F statistics as well as the significance of the slope coefficient.

An algorithm based on the detected effects is used to evaluate the possibility of exploiting potential anomalies to make abnormal profits, which is done by replicating the behavior of a trader who opens and holds positions for a certain time. The trading process is simulated as follows. First, we calculate result of the trade

$$\%\, result = \frac{100\% \times P_{open}}{P_{close}} \tag{8}$$

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

If the sum of results (total profit parameter) from each deal is positive, then there is an exploitable market anomaly. Conversely, a negative sum indicates no possibility for exploiting a market anomaly in profitable trades.

T-tests on the means of the two samples, based on a 5% critical value, were conducted to ensure that the obtained results are statistically different from the random trading ones. Null hypothesis (H0) in this test is that the mean comes from the same population in both samples. The rejection of H0 would indicate that the adopted strategy can produce abnormal profits. An example of the t-test is presented in Table 1.

Table 1: Example of the t-test for evaluating trading strategy effectiveness: MSCI ESG US testing for the case of a contrarian effect after positive abnormal returns

Parameter	Value
Number of the trades	74
Total profit	32,67%
Average profit per trade	0,44%
Standard deviation	2,04%
t-test	1,86
t critical (0,95)	1,78
Null hypothesis	rejected

Note: This table presents the trading simulation results for the case of a contrarian effect after negative abnormal returns from 1900–1909. The first column specifies parameters, and the second shows the values of those parameters. Total profit is calculated as a sum of results of trades.

As can be seen, there is a statistically significant difference in terms of total net profits relative to the random trading case, which confirms market inefficiency.

4. Empirical results

We start with the traditional indices. Empirical results for the case of positive abnormal returns are presented in Appendix A, and results for the case of negative abnormal returns are shown in Appendix B. For the case of positive abnormal returns, the results of the simple average analysis are displayed in Table A.1 and Figure A.1. As can be seen, the results are mixed. Emerging countries demonstrated the momentum effect; on the day after an abnormal increase, prices tended to increase further. Developed countries (except the UK), however, tended to show contrarian effects. These observations are true for both the dynamic and static approaches.

ANOVA analysis results are presented in Table A.2, showing that previously observed effects are statistically significant only for developed countries. In Japan and the UK, the difference in approach affected the results. The dynamic approach happened to be more effective for Japan but less effective for the UK; the opposite was true for the static approach.

Results of the t-tests (Table A.4) also showed that in the case of the US, returns on the day after positive abnormal returns differ from those from normal days; this difference is statistically significant. An anomaly was not confirmed for most of the other cases.

A non-parametrical Mann-Whitney test (Table A.3) confirmed results for the US but also revealed anomalies in emerging countries in terms of the dynamic approach.

Results of the Modified CAR approach (Table A.5) confirmed the presence of abnormal price behavior on the day after positive abnormal returns for all of the analyzed data, with the exception of China, in terms of the static approach.

Regression analysis with dummy variables (Table A.6) provided results similar to the ANOVA analysis; contrarian effects were found in the developed countries, and statistically insignificant momentum effects were found in the emerging markets. A statistically significant momentum effect was observed for the case of the UK using the data static approach to define abnormal returns.

We used the trading simulation approach to see whether the detected effects were real market anomalies (i.e., if they can "beat the market"). The algorithm of the trading strategy is simple: buy right at the start of the day after the positive abnormal returns in case of the momentum effect and sell in case of the contrarian effect. Positions should be closed at the end of the day. Transaction costs (e.g., spread, commissions to the broker, and commissions to the bank) are ignored because it is almost impossible to incorporate them correctly for different indices and time periods.

Results of the trading simulations are presented in Table A.7 and Figure A.2. They show that the contrarian effect detected in the US data is not just a statistical anomaly; it can also be used to generate extra profits from trading. All other countries failed to pass the t-test, meaning that their results do not significantly differ from random trading.

Table 2: Overall results for one-day abnormal positive returns for both the dynamic and static approaches

Period	Average analysis	Student's t-test	ANOVA	Mann-Whitney test	Modified CAR	Regression with dummy variables	Trading simulation	Overall
				Dynamic				
USA	1	1	1	1	1	1	1	7
UK	1	0	0	0	1	0	0	2
Japan	1	0	1	0	1	1	0	4
China	1	0	0	1	1	1	1	5
India	1	0	0	1	1	0	0	3
				Static				
USA	1	1	1	1	1	1	1	7
UK	1	0	1	1	1	1	0	5
Japan	1	0	0	0	1	0	0	2
China	0	0	0	0	0	0	0	0
India	1	0	0	0	1	0	0	2

Note: This table presents the overall results for the case of positive abnormal returns. "1" indicates that the anomaly is confirmed, and "0" indicates that it is not. The average analysis confirms the anomaly if the mean return calculated for the abnormal return day data is much higher (lower) compared with the mean return for data from non-abnormal returns days. The statistical tests' (both parametrical and non-parametrical) rejection of the null hypothesis, such that data for the abnormal returns day and normal returns day data belong to the same general population, also confirms the anomaly if it is statistically significant. The regression analysis with dummy variables gives evidence in favor of the presence of an anomaly if a1 (the slope of the dummy variable) is statistically significant ($p < 0.05$). The MCAR approach confirms the anomaly if the trend model, based on cumulative abnormal return data that has a high multiple R, passes the F test and the regression coefficients are statistically significant (p value < 0.05). The higher the overall rating, the stronger the evidence of the anomaly.

A summary of the results for the case of positive abnormal returns is presented in Table 2. The dynamic approach detected the contrarian effect in the US and Japanese stock markets and the momentum effect in the Chinese stock market. The static approach was less efficient, indicating strong evidence in favor of anomalies for only the US and UK.

Similar analysis is provided for negative abnormal returns. Simple average analysis provided evidence in favor of contrarian effects on the days after negative abnormal returns as compared to standard days in the developed countries for both the dynamic and static approach (Table A.1 and Figure A.1.). However, these differences were statistically significant for only the US and Japan (see Tables B.2 and B.4 for parametrical ANOVA and t-tests and B.3 for the non-parametrical Mann-Whitney test). This observation was confirmed by the modified CAR approach (Table B.5) and the regression analysis with dummy variables (Table B.6).

Trading simulations (Table B.7 and Figure B.2) show that the results that are statistically different from random results are only obtained for the contrarian effect in the US and Japan. All other cases could not provide results that were statistically different from random trading.

Table 3: Overall results for one-day abnormal negative returns for both the dynamic and static approaches

Period	Average analysis	Student's t-test	ANOVA	Mann-Whitney test	Modified CAR	Regression with dummy variables	Trading simulation	Overall
				Dynamic				
USA	1	0	1	1	1	1	1	6
UK	1	0	0	0	1	0	0	2
Japan	1	1	1	1	1	1	1	7
China	1	0	1	0	0	0	0	2
India	1	0	0	0	0	0	0	1
				Static				
USA	1	1	1	1	1	1	1	7
UK	1	0	0	0	1	1	0	3
Japan	1	1	1	1	1	1	1	7
China	0	0	0	0	1	0	0	1
India	1	0	0	0	1	0	0	2

Note: This table presents the overall results for the case of positive abnormal returns. "1" indicates that the anomaly is confirmed and "0" indicates that it is not. The average analysis confirms the anomaly if the mean return calculated for the data from the abnormal returns day is much higher (lower) than the mean return for the data from the non-abnormal returns day. The statistical tests' (both parametrical and non-parametrical) rejection of the null hypothesis, such that the data for the abnormal returns day and normal returns day belong to the same general population, also confirms the anomaly if it is statistically significant. The regression analysis with dummy variables gives evidence in favor of the presence of an anomaly if a1 (the slope of the dummy variable) is statistically significant ($p < 0.05$). The MCAR approach confirms the anomaly if the trend model, based on cumulative abnormal returns data, has a high multiple R, passes the F test, and the regression coefficients are statistically significant (p value < 0.05). The higher the overall rating, the stronger the evidence of the anomaly.

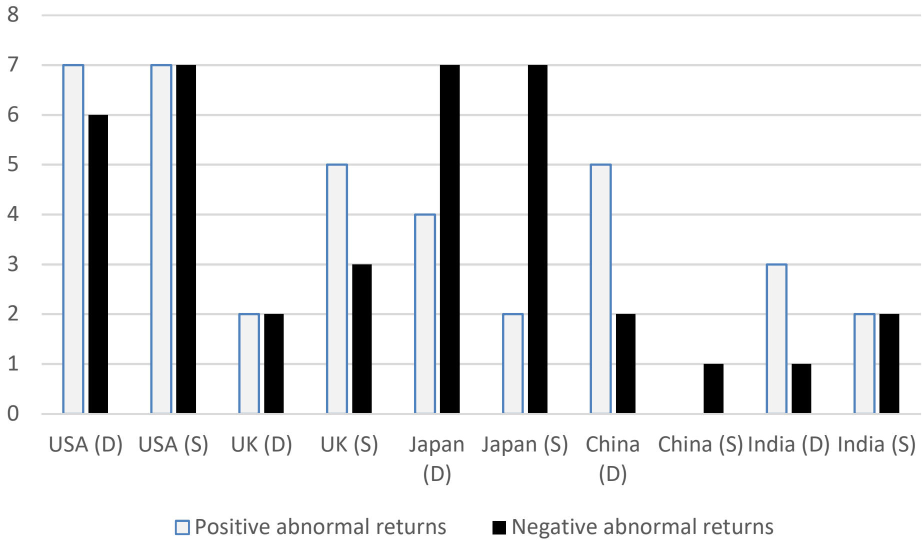

Figure 1: Visualization of the price effects after one-day abnormal returns in traditional indices for both the dynamic and static approaches

Note: This figure displays the power of the price effects after one-day abnormal returns. The y-axis refers to the overall rating for the anomaly presence (the higher the overall rating, the stronger the evidence of the anomaly, and the x-axis shows data sets.

A summary of results for the case of negative abnormal returns is presented in Table 5 and the visualization of the price effects after one-day abnormal returns is shown in Figure 1. Significantly strong anomalies are present only in the US and Japan. Negative abnormal returns generate more powerful effects, and emerging markets are mostly immune to the price effects of one-day abnormal returns. No convincing evidence was found in favor of the increased efficiency of either the dynamic or static approach. A typology of these effects (momentum or contrarian) is presented in Table 4.

Table 4: Typology of the price effects after one-day abnormal returns in the case of traditional indices for both the dynamic and static approaches

Period	Positive abnormal returns		Negative abnormal returns	
	Type of effect	Power	Type of effect	Power
		Dynamic		
USA	contrarian	7	contrarian	6
UK	momentum	2	contrarian	2
Japan	contrarian	4	contrarian	7
China	momentum	5	contrarian	2
India	momentum	3	momentum	1
		Static		
USA	contrarian	7	contrarian	7
UK	momentum	5	contrarian	3
Japan	contrarian	2	contrarian	7
China	no effect	0	no effect	1
India	momentum	2	momentum	2

Note: This table presents the typology of the price effects in the stock markets after one-day abnormal returns for different time periods. The first column reports values for the period being considered, the second and fourth report the types of effects (contrarian or momentum) for the cases of positive and negative abnormal returns, respectively, the third and the fifth report the power of the detected effects (the higher the parameter, the stronger the evidence of the anomaly) for the cases of positive and negative overreactions, respectively.

Next, similar analysis is provided for the ESG data (see Appendices C and D for the cases of positive and negative abnormal returns, respectively). A summary of the results for the case of positive abnormal returns is presented in Table 5.

Table 5: Overall results for one-day abnormal positive returns for both the dynamic and static approaches

Period	Average analysis	Student's t-test	ANOVA	Mann-Whitney test	Modified CAR	Regression with dummy variables	Trading simulation	Overall
				Dynamic				
USA	1	1	1	0	1	1	1	6
UK	0	0	0	0	1	0	0	1
Japan	1	1	1	1	1	1	1	7
China	1	0	0	0	1	0	0	2
India	0	0	0	1	1	0	0	2
				Static				
USA	1	1	1	1	1	1	1	7
UK	1	1	1	1	1	1	1	7
Japan	0	0	0	0	1	0	0	1
China	0	0	0	0	1	0	0	1
India	1	0	0	0	1	0	0	2

Note: This table presents the overall results for the case of positive abnormal returns. "1" indicates that the anomaly is confirmed and "0" indicates that it is not. The average analysis confirms the anomaly if the mean return calculated for the data from a day of abnormal returns is much higher (lower) as compared to the mean return for data from a day of non - abnormal returns. The statistical tests' (both parametrical and non-parametrical) rejection of the null hypothesis, such that data for the abnormal returns day and normal returns day belong to the same general population, also confirms the anomaly, if it is statistically significant. The regression analysis with dummy variables gives evidence in favor of the presence of an anomaly if a1 (slope of the dummy variable) is statistically significant ($p < 0.05$). The MCAR approach confirms the anomaly if the trend model, based on cumulative abnormal return data, has a high multiple R, passes the F test, and has statistically significant regression coefficients (p value < 0.05). The higher the overall rating, the stronger the evidence of the anomaly.

Again, developed countries are quite sensitive to the price effects of one-day positive abnormal returns; the contrarian effect was observed on the day after an abnormal return day. These effects can be exploitable for generating abnormal trading profits (Table C.7). Emerging markets are immune to the price effects after positive one-day abnormal returns. A summary of the results for the case of negative abnormal returns is presented in Table 6.

Table 6: Overall results for one-day abnormal negative returns for both the dynamic and static approaches

Period	Average analysis	Student's t-test	ANOVA	Mann-Whitney test	Modified CAR	Regression with dummy variables	Trading simulation	Overall
				Dynamic				
USA	1	0	1	1	1	1	1	6
UK	1	0	1	0	0	1	0	3
Japan	1	1	1	1	1	1	1	7
China	1	0	1	0	1	1	0	4
India	1	0	0	0	0	0	0	1
				Static				
USA	1	1	1	1	1	1	1	7
UK	1	0	0	0	0	0	0	1
Japan	1	1	1	1	1	1	1	7
China	1	0	0	0	1	0	0	2
India	1	0	0	0	1	0	0	2

Note: This table presents the overall results for the case of positive abnormal returns. "1" indicates that the anomaly is confirmed, and "0" indicates that it is not. The average analysis confirms the anomaly if the mean return calculated for data from a day with abnormal returns is much higher (lower) than the mean return for data from a day with non- abnormal returns. The statistical tests' (both parametrical and non-parametrical) rejection of the null hypothesis, such that the data for the abnormal returns day and normal returns day belong to the same general population, also confirms the anomaly if it is statistically significant. The regression analysis with dummy variables gives evidence in favor of the presence of an anomaly if a1 (slope of the dummy variable) is statistically significant ($p < 0.05$). The MCAR approach confirms the anomaly if the trend model, based on cumulative abnormal returns data, has a high multiple R, passes the F test, and has statistically significant regression coefficients that are statistically significant (p value < 0.05). The higher the overall rating, the stronger the evidence of the anomaly.

Results for the negative abnormal returns are in line with those for the positive ones. Strong contrarian effects are detected in the developed markets, and no effects are observed in the emerging markets. A visualization of the price effects of one-day abnormal returns for the ESG indices is presented in Figure 2. As can be seen, the results are in line with those for the positive abnormal returns.

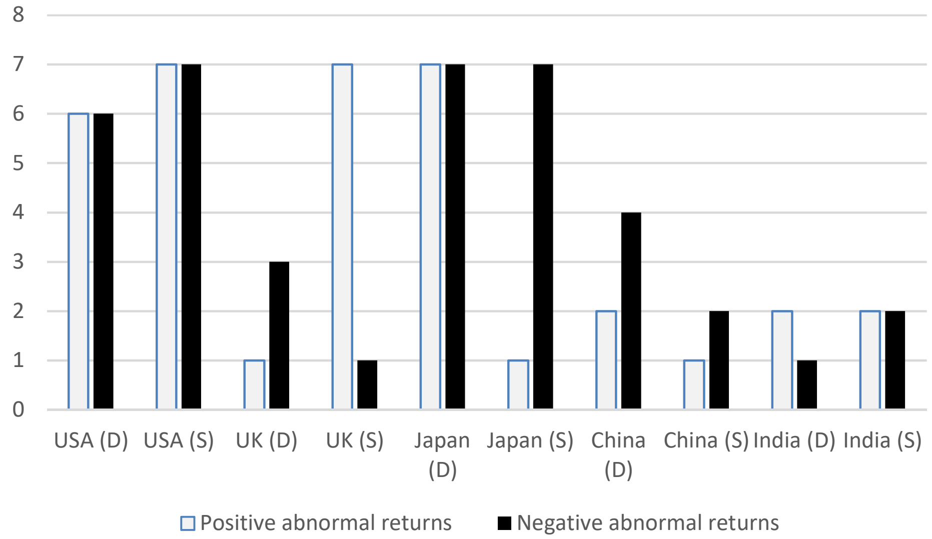

Figure 2: Visualization of the price effects after one-day abnormal returns in the ESG indices for both the dynamic and static approaches

Note: This figure displays the power of the price effects after one-day abnormal returns. The y-axis refers to the overall rating for the anomaly presence (the higher the overall rating, the stronger the evidence of the anomaly) and the x-axis shows data sets.

A typology of the detected effects (momentum or contrarian) is presented in Table 7. The power of detected effects for the ESG data and traditional indices were compared to test Hypothesis 2. Results for the positive and negative abnormal returns are presented in Table 8 and 9, respectively.

Table 7: Typology of the price effects after one-day abnormal returns for both the dynamic and static approaches

Period	Positive abnormal returns		Negative abnormal returns	
	Type of effect	Power	Type of effect	Power
		Dynamic		
USA	contrarian	6	contrarian	6
UK	momentum	1	contrarian	3
Japan	contrarian	7	contrarian	7
China	momentum	2	contrarian	4
India	momentum	2	momentum	1
		Static		
USA	contrarian	7	contrarian	7
UK	momentum	7	contrarian	1
Japan	contrarian	1	contrarian	7
China	contrarian	1	contrarian	2
India	momentum	2	momentum	2

Note: This table presents the typology of the price effects in the stock markets after one-day abnormal returns for different time periods. The first column reports values for the period being considered, and the second and fourth report the types of effects (contrarian or momentum) for the cases of positive and negative abnormal returns, respectively; the third and the fifth report the power of the detected effects (the higher the parameter, the stronger the evidence of the anomaly) for the cases of positive and negative overreactions, respectively.

Table 8: Comparison of the price effects after one-day positive abnormal returns: ESG vs traditional indices

Period	ESG		Traditional	
	Type of effect	Power	Type of effect	Power
		Dynamic		
USA	contrarian	6	contrarian	7
UK	momentum	1	momentum	2
Japan	contrarian	7	contrarian	4
China	momentum	2	momentum	5
India	momentum	2	momentum	3
		Static		
USA	contrarian	7	contrarian	7
UK	momentum	7	momentum	5
Japan	contrarian	1	contrarian	2
China	contrarian	1	no effect	0
India	momentum	2	momentum	2

The results from Table 8 show no evidence in favor of Hypothesis 2; effect types are the same for both the ESG and traditional indices. The power of detected effects is different across countries and approaches, but there is no detectable pattern in these differences. No ESG or traditional indices are more vulnerable to the price effects after one-day positive returns.

Table 9: Comparison of the price effects after one-day negative abnormal returns: ESG vs traditional indices

Period	ESG		Traditional	
	Type of effect	Power	Type of effect	Power
		Dynamic		
USA	contrarian	6	contrarian	6
UK	contrarian	3	contrarian	2
Japan	contrarian	7	contrarian	7
China	contrarian	4	contrarian	2
India	momentum	1	momentum	1
		Static		
USA	contrarian	7	contrarian	7
UK	contrarian	1	contrarian	3
Japan	contrarian	7	contrarian	7
China	contrarian	2	no effect	1
India	momentum	2	momentum	2

According to results in Table 9, the types of effects are the same for ESG and traditional indices, and their power in the analyzed data sets is almost identical. Hypothesis 2 is therefore rejected; the price effects after one-day abnormal returns are not stronger for traditional indices than for ESG ones.

Next, we analyzed the price effects after one-day abnormal returns for the data set from 2007–2009, a period that is commonly recognized as a global financial crisis (see Appendices E and F). ESG indices acted as objects of analysis. Results from the crisis period were compared with those for the overall data set for both ESG and traditional indices to test Hypothesis 3; results for cases of positive and negative abnormal returns are presented in Table 10 and 11, respectively.

Table 10: Comparison of results of price effects after one-day abnormal positive returns based on dynamic and static approaches for cases of crisis and the overall data sets

Country	Effect (crisis)	ESG	Traditional	Crisis (ESG)
		Dynamic		
USA	contrarian	-0,44% (2.07)	**-0,43% (2.28)**	-0,70% (1.23)
UK	contrarian	0,10% (0.39)	**0,10% (0.44)**	-0,05% (0.06)
Japan	contrarian	**-0,33% (2.44)**	-0,21% (1.27)	-1,02% (1.56)
China	no effect	0,09% (0.35)	**0,35% (1.91)**	0,00% (0.03)
India	contrarian	0,11% (0.26)	0,11% (0.26)	**-0,31% (0.61)**
		Static		
USA	contrarian	-0,65% (2.61)	**-0,65% (2.61)**	-0,47% (0.98)
UK	contrarian	**0,35% (1.69)**	0,30% (1.23)	-0,05% (0.09)
Japan	contrarian	-0,05% (0.32)	-0,15% (0.64)	**-0,53% (0.86)**
China	contrarian	-0,03% (0.25)	0,00% (0.13)	**-0,87% (1.37)**
India	contrarian	0,25% (0.56)	0,25% (0.56)	**-0,68% (0.73)**

Note: * t criterion in parentheses.

Table 11: Comparison of results of price effects after one-day abnormal negative returns based on dynamic and static approaches for cases of crisis and the overall data sets

Country	Effect (crisis)	ESG	Traditional	Crisis (ESG)
		Dynamic		
USA	contrarian	0,36% (1.65)	0,34% (1.48)	**0,77% (1.67)**
UK	contrarian	**0,36% (1.47)**	0,13% (0.60)	1,03% (1.24)
Japan	contrarian	**0,48% (1.93)**	0,44% (1.78)	1,06% (1.81)
China	contrarian	**0,28% (1.18)**	0,11% (0.34)	1,34% (1.00)
India	momentum	-0,10% (0.64)	-0,10% (0.64)	**-0,36% (0.85)**
		Static		
USA	contrarian	**0,71% (2.27)**	0,63% (1.96)	0,82% (1.06)
UK	contrarian	0,18% (0.54)	0,20% (0.69)	**0,63% (0.93)**
Japan	contrarian	0,47% (1.69)	**0,50% (1.87)**	0,64% (1.06)
China	contrarian	0,20% (0.59)	-0,01% (0.11)	**1,01% (0.81)**
India	momentum	-0,10% (0.51)	-0,10% (0.51)	**-0,63% (0.82)**

Note: * t criterion in parentheses.

As can be seen, neither the dynamic nor the static approach offered in the case of crisis data provided evidence in favor of Hypothesis 3. The price effects during the crisis were generally weaker, especially for the dynamic approach. For the static approach, the price effects for the case of negative abnormal returns looked stronger as compared to the overall data but not strong enough to be anomalies, as the t-tests were not passed.

Overall, no serious evidence was found in favor of the idea that price effects tend to be stronger during crisis periods. At the same time, stock markets tend to demonstrate contrarian effects after negative abnormal returns; the only exception was the Indian stock market. These effects are stronger for developed countries (US and Japan). The results are concluded as follows.

- Hypothesis 1 is not rejected for developed countries. In most cases, for both ESG and traditional indices, after one-day abnormal returns, contrarian effects do appear and can be used to generate abnormal profits from trading. This is true for both one-day abnormal positive returns (Hypothesis 1.1) and one-day abnormal negative returns (Hypothesis 1.2).

- Hypothesis 1 is not rejected for emerging countries. In most cases, for both ESG and traditional indices, there are no statistically significant price effects after one-day abnormal returns.

- Hypothesis 2 is rejected, which suggests that price effects are not stronger for traditional indices as compared to ESG indices.

- Hypothesis 3 is rejected, which implies that price effects after one-day abnormal returns are not stronger during a crisis period.

- Hypothesis 4 is rejected, which indicates that the dynamic trigger approach shows no better overall efficiency for defining abnormal returns in stock markets than the static approach.

- Hypothesis 5 is rejected, which suggests that price effects after one-day abnormal returns are not stronger for emerging markets as compared to developed ones. In fact, they are stronger for developed markets.

Results of this study show no evidence to indicate that low stock market efficiency leads to market anomalies; emerging stock markets, which should be less efficient, are immune to price effects after one-day abnormal returns, but developed markets are vulnerable. Price effects are not stronger for traditional indices as compared to ESG indices.

The question of the best methodology for defining abnormal returns is still open; in some cases, the dynamic approach is more sensitive and provides better results, and in other cases, the static approach is best. Accordingly, each data set requires additional calculations to justify the choice.

Another important conclusion of this study is that US stock market is still extremely vulnerable to the price effects of abnormal returns; prices tend to move in the opposite direction the day after abnormal returns. These effects can be exploited to generate abnormal profits.

The nature of the price effects after one-day abnormal returns is still unclear, but the statistical significance of the results shows that detected anomalies can be utilized by practitioners (traders, investors, etc.) to generate profit and that trading based on contrarian strategies can be profitable. Possible explanations for the presence of contrarian effects in the US stock market include behavioral biases (e.g., overreaction/underreaction to new information and pure emotions, such as fear and greed); the existence of "noisy" traders with their chaotic trading activity; and technical reasons, such as profit fixations. Overall, these results expand upon a variety of empirical evidence from academics related to price patterns after one-day abnormal returns.

5. Conclusions

This paper examined the price effects (momentum and contrarian) after one-day abnormal returns in the stock markets of both developed and emerging countries while comparing ESG stock indices to conventional stock indices. A number of hypotheses were tested. For these purposes, different statistical tests and methodological approaches were used, including average analysis, the modified cumulative abnormal returns approach, regression analysis with dummy variables, R/S analysis, the parametric student's t-test and ANOVA, non-parametric Mann-Whitney tests, and the trading simulation approach.

The results were mixed for H1 and provided no evidence in favor of H2–H5. The US stock market is extremely vulnerable to the price effects of one-day abnormal returns; contrarian price movements often occur. Some strong effects were observed in the data from the Japanese stock market. Emerging markets are immune to the price effects; no stable, specific patterns with statistically significant results were found. Results involving ESG indices were generally in line with those for the conventional indices, and types of detected effects were the same for both. The power of the effects was different in some cases but not significantly so; no patterns in their appearance were detected. The price effects were not more or less significant during a period of crisis.

The results of this paper provide new empirical evidence related to the price effects of one-day abnormal returns in the understudied universe of ESG stock indices. In terms of economic theory, the results provide additional evidence against the efficient market hypothesis and indicate that markets are partially efficient. For example, the US stock market continues to be extremely vulnerable to price effects after abnormal returns, which can be exploited to generate abnormal profits from trading. Attempts to "beat the market" therefore make sense. Practitioners can use the results of this paper to generate extra profits from trading based on detected price patterns. Future studies could consider the stability and time variation in the price effects in both conventional and ESG stock indices or the determinants of the price effect and whether they differ between conventional and ESG indices.

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