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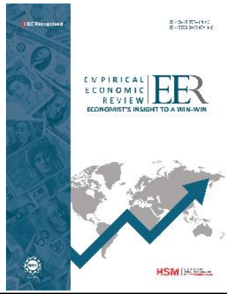

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Profitability of Reversals in Emerging Asian Economies: Role of Industries as Drivers

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Abstract

The current study attempted to examine the predictive ability of industry-specific factors for contrarian strategy payoffs in the Asian emerging markets, that is, India, Pakistan, and Bangladesh. By employing portfolio formation and subsequent rebalancing methodology, the empirical findings provided evidence for short-term industry contrarian effect. Using the data spanning different market states, the study determined that industry contrarian effect was stronger during the Asian and global financial crisis. On the other hand, industry momentum effect was evident after the global financial crisis and during the COVID-19 epidemic. The overall findings imply that industrial aspect cannot be neglected while interpreting the returns of trading strategies in emerging markets. A market timing-based contrarian strategy incorporating industrial factors may create the possibilities of higher strategy returns. The findings imply that the emerging markets in South Asia are not weak-form efficient because various industry-related factors offer higher return opportunities to investors and fund managers.

Keywords: contrarian effect, COVID-19 epidemic, industry-specific factors, South Asian emerging markets

Introduction

Momentum investing is a trading tool used by investors to maximize their profitability in stock markets. Investors take frequent long position in stocks that show an upward pricing trend and shorten the stocks with a downward

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pricing trend. On the other hand, contrarian investors buck against the existing market trend by buying the stocks or other assets that represent the downward pricing trend and selling the stocks with upward pricing pattern. Jegadeesh and Titman (1993) tested momentum strategy in the stock market of United States (US) and reported an annual average return of 12.01%. Since then, several studies have examined the momentum and contrarian effect in US and several other markets. Prior research has demonstrated that momentum impact is mostly dominant in developed equity markets, such as the US and Europe, however, contrarian effect is mainly evident in emerging stock markets. Although, contrarian strategy is a well-known anomaly among investors in emerging markets, the reason of its presence is not yet clear.

One way of examining whether contrarian effect is genuinely an anomaly or an artifact of data mining, is to investigating the alternative datasets that are yet to be studied or have provided inconclusive findings. If contrarian effect persists in different markets, even in varying magnitude, it may be regarded as a systematic risk factor. Moreover, itsexposure could be accounted for through different mean profits. As suggested by the Adaptive Market Hypothesis (AMH) (Lo, 2004), the behavior of equity market anomalies may change over time across markets. Subsequently, the studies document that these variations may be caused by investors' personality characteristics as well as elements related to the specific stock market environment (Akhter & Yong, 2019; Munir et al., 2022; Shi & Zhou, 2017; Urquhart & McGroarty, 2014). Considering the AMH viewpoint, it is important to explore whether the factors related to internal and external environment of stock market influence the performance of stock market anomalies or not. Therefore, the current study attempted to investigate the role of industry-specific factors towards contrarian strategy's profitability.

The study focused on the emerging markets of South Asia due to some distinctive characteristics of these markets in terms of stock market anomaly returns. Most of the existing studies have proved that there is low momentum effect in Asia-Pacific emerging markets and these markets exhibit consistent weak-form market inefficiencies (Chui et al., 2010; Chui et al., 2000; Demirer et al., 2017; Griffin et al., 2003; Hameed & Kusnadi, 2002; Liu et al., 2011; McInish et al., 2008; Munir et al., 2020). Retail investors' characteristics may be blamed for the inconsistency of evidence, indicating low momentum and higher inefficiencies in the emerging markets of South Asia. Recent theoretical and empirical literature provides conclusive evidence of excessive speculation, insider trading, and information asymmetry among investors in these markets (Akhter & Yong, 2019; Huang & Cheng, 2015; Neupane et al., 2017; Zulkifley et al., 2021; Zulkifley et al., 2023). Higher information asymmetry among different classes of investors in these markets may create opportunities for short-term momentum and subsequent reversals for investors. According to Luo et al. (2021), skepticism leads to both momentum and contrarian profits. If investors become skeptical about the signal quality of others and assume that those who were among the first to possess information have learned very little, then, there is underreaction that may cause momentum effect in short-term period. On the other hand, if investors respond promptly to stale information causing an unnecessary increase in stock prices due to overreaction, thus reversals are likely to follow.

Some studies claim that industry-level classification also leads to higher profitability for investment strategies (Demirer et al., 2015; Du & Denning, 2005; Moskowitz & Grinblatt, 1999; O'Neal, 2000). Therefore, the current study performed an in-depth analysis based on industry characteristics to analyze whether industry composition of stocks contributes to higher contrarian profitability in selected stock markets. The study employed the Thomson Reuters Business categorization (TRBC) methodology, a proprietary industry categorization approach administered and controlled by Thomson Reuters. This is a market-oriented classification system where organizations are categorized based on market rather than the specific services or goods offered. Investors and researchers commonly utilize the Industry categorization Benchmark (ICB) or the Global Industry Classification Standard (GICS) for industry categorization. The overall findings reveal that the industry contrarian effect was stronger during the Asian and global financial crises, while the industry momentum effect was evident after the global financial crisis and the COVID-19 pandemic.

Section 2 of the study explains data and methodology. Sections 3 reports the empirical findings and discussions based on industry-specific factors. Section 4 is based on conclusion and some practical implications.

Data and Methodology

Data

The current study gathered data from Thomson and Reuters DataStream and official websites of Bombay Stock Exchange (BSE), Pakistan Stock Exchange (PSX), and Dhaka Stock Exchange (DSE). The dataset comprises the dividend-adjusted close prices of all the listed stocks from various industries in each stock market. The sample period ranged from January 1997 to December 2020. The study eliminated stocks with inconsistent trading pattern to avoid the impact of small and inconsistent stocks. This method also assists in maintaining the sample of stocks in which the least liquid equities are usually excluded. To prevent any false perception of strong return continuation or reversals, the missing values of non-trading days are left blank and not replaced with any previous values. The monthly close prices of all listed equities are converted into monthly returns using the following continuous compounding return equation:

$$R_t = 100 \times ln(\frac{P_t}{P_{t-1}}) \tag{1}$$

where,

R_t represents the stock returns at time t, while P_t is the dividend-adjusted close price of stocks at time t, and P_{t-1} denotes the dividend-adjusted close price of stocks at time t-1.

The study used the Thomson Reuters Business Classification (TRBC) system. This is a market-based categorization system in which companies are classified according to the market instead of the services or products they produce. Many investors and researchers use either ICB or GICS industry classification system, or any local market system developed by FTSE in the UK stock market. However, TRBC classification is more useful and effective since it uses the most robust and objective procedure to identify the sector classification of a company. The TRBC is a five-tier industry categorization system where each tier further divides the stocks into extended specific sectors. Firstly, this classification method uniquely classifies the stocks into 10 economic sectors. Afterwards, each of these sectors are split into 28 business sectors. These business sectors are further sub-divided into 54 industry groups, 136 industries, and finally 837 activities. The current study applied second-tier classification of TRBC and divided the stocks into 22 industries, common in each stock market. The industry classification is conducted in such a way which ensures that sufficient industries are available to form industry portfolios and each industry portfolio contains reasonable number of stocks.

Methodology

The current study formed contrarian style portfolios based on industry-specific factors to investigate the impact of industry characteristics on contrarian effect in selected emerging stock markets. Following Moskowitz and Grinblatt (1999), industry contrarian portfolios were formed. The study first categorized stocks into 22 industry groups based onTRBC. Subsequently, industries were organized into different quintile portfolios on the basis of their past performance. The study formed portfolios on the basis of past 12-month and 6-month formation periods to evaluate the industry contrarian effect deeply. The winner industry portfolios comprise the industries with past 12-month or 6-month cumulative returns in the top 20%. Whereas, loser industry portfolios consist of industries with past 12-month or 6-month cumulative returns in the bottom 20%. Afterwards, contrarian portfolios were formed by augmenting the loser industry portfolios and shortening the winner industry portfolios. Portfolios were formed with one-month lag between formation and holding periods to control the impact of issues pertaining to microstructure. Monthly rebalancing was used to calculate the contrarian (LMW) returns, which are calculated by comparing the returns of equally weighed losers and winners' portfolios over the holding period (t+1) month. As an alternate scheme, the study also evaluated the performance of industry-neutral contrarian portfolios. Moreover, the study also identified the top three common industries that contain the highest number of equities in every stock market. Portfolios are formed within each industry pool to examine whether the contrarian effect holds when industry impact is accounted for. Finally, the study investigated the impact of different market states on industry contrarian effect by dividing the overall study period into crises, non-crises, and COVID-19 sub-periods.

Industry contrarian effect holds if the following equation satisfies:

$$LMW_{Ind,t} = Q_{LInd,t} - Q_{WInd,t} > 0 \tag{2}$$

here,

$LMW_{Ind,t}$ represents the loser minus winner (contrarian) industry portfolios at time-t. Whereas, $Q_{LInd,t}$ and $Q_{WInd,t}$ respectively denote the loser and winner industry portfolios for time-t. The contrarian effect would hold if the loser portfolio outperforms the winner portfolio after the holding period.

Empirical Results and Discussion

Firm-level Characteristics and Contrarian Effect

The current study analyzed the impact of industry factors on contrarian effect in South Asian equity markets over the sample period from January 1997 to December 2020. Tables 1, 2, and 3 present summary statistics and industry breakdowns for the Pakistani, Bangladeshi, and Indian stock markets, respectively. With respect to the number of firms in each sample market, personal goods, financials, and food producing sectors were market leaders. Moreover, another common characteristic of these markets is that the highest mean returns were generated by the healthcare and pharmaceutical sectors. The highest market capitalization for Pakistani stock market belongs to oil and gas industry. On the other hand, fixed line telecommunications industry holds the highest market capitalization for Bangladeshi and Indian stock markets. On the contrary, fixed line telecommunications and electricity are the industries that hold the highest share of trading volume for Pakistani and Bangladeshi markets, respectively. However, media and technology industries lead with the highest share of trading volume in Indian stock market over the whole study period. Overall, the study observed diverse characteristics of different industry groups in each sample of stock market. Moreover, the results further reveal that the cross-sectional mean returns, trading volume, and market capitalization of industry clusters were statistically different from one another in every stock market. Therefore, it is quite important to investigate the impact of industry factors on contrarian effect keeping in mind the dissimilar performance and diverse characteristics of industry groups in the selected contrarian-driven emerging markets.

Table 1

Descriptive Statistics of Industries in Pakistan (January 1997-December 2020)

Name of Industry	No. of firms	Percentage of firms	Avg Market Capitalization (In Millions)	Avg Trading Volume (In Thousands)	Mean Returns	Standard Deviation
Automobiles and Parts	20	4.1%	7048.26	3924.88	0.9576	15.5834
Chemicals	33	6.8%	12606.9	24085.46	0.5303	14.4465
Construction and Materials	30	6.2%	6941.60	19973.30	0.2569	17.0990
Electricity	17	3.5%	14146.52	26390.51	-0.2654	14.0024
Electronic and Electrical Equipment	5	1.0%	728.33	1084.04	0.4703	18.0652
Financials	86	17.7%	12271.58	17956.77	0.2153	17.2724
Fixed Line Telecommunications	4	0.8%	25622.07	115450.61	-0.2235	15.4199
Food Producers	55	11.3%	7616.57	4824.09	0.7588	15.4519
Forestry and Paper	4	0.8%	1790.57	866.56	0.8014	14.2968
General Industrials	16	3.3%	4682.95	15184.98	0.3139	16.3806
Health Care Equipment and Services	3	0.6%	10522.92	685.44	1.4649	14.5039
Household Goods and Home Construction	2	0.4%	4804.49	27862.25	1.2717	16.2181
Industrial Engineering	6	1.2%	1384.28	516.99	0.8477	23.4880
Industrial Metals and Mining	13	2.7%	5552.87	15620.98	0.3209	16.0003
Industrial Transportation	3	0.6%	16054.70	37353.57	0.7558	16.8153
Media	2	0.4%	3303.15	13599.22	-0.5273	22.6327
Oil and Gas	14	2.9%	82599.15	76931.80	0.5995	14.0260
Personal Goods	151	31.0%	1405.58	1826.42	0.3712	19.0492
Pharmaceuticals and Biotechnology	10	2.1%	13449.99	2723.49	1.3946	14.3611

Name of Industry	No. of firms	Percentage of firms	Avg Market Capitalization (In Millions)	Avg Trading Volume (In Thousands)	Mean Returns	Standard Deviation
Real Estate Investment and Services	4	0.8%	7285.73	16387.20	-0.1037	16.4638
Technology	4	0.8%	6290.75	22553.93	1.3116	14.8090
Travel and Leisure	5	1.0%	5146.70	8364.84	0.9032	19.2343
Total	487	100%				

Note. Table 1 provides the summary statistics of industries in Pakistan Stock Exchange (PSX). As per the Thomson Reuters Business Classification (TRBC), stocks are classified into 22 different industry groups based on their market activity. Number of active firms, average market capitalization, average trading volume, mean returns, and standard deviations are reported in this Table. The study period ranges from 1997-2020.

Table 2

Descriptive Statistics of Industries in Bangladesh (January 1997-December 2020)

Name of Industry	No. of firms	Percentage of firms	Avg Market Capitalization (In Millions)	Avg Trading Volume (In Thousands)	Mean Returns	Standard Deviation
Automobiles and Parts	5	1.6%	6033.24	7843.77	0.0014	14.7131
Chemicals	9	2.8%	8594.11	9055.70	0.1675	12.9580
Construction and Materials	17	5.3%	6875.20	7564.80	0.4277	14.8123
Electricity	9	2.8%	24511.82	19623.46	0.4773	11.3839
Electronic and Electrical Equipment	5	1.6%	2454.97	1714.61	0.3075	16.0402
Financials	109	33.9%	5543.54	16029.24	0.8888	13.8737
Fixed Line Telecommunications	4	1.2%	101055.77	12083.31	0.7289	11.7238
Food Producers	18	5.6%	1972.84	6956.57	0.5329	16.8379
Forestry and Paper	4	1.2%	3977.33	6422.83	0.2449	14.9626
General Industrials	9	2.8%	3307.80	14795.29	-0.0430	13.1083
Health Care Equipment and Services	3	0.9%	1126.54	1179.48	0.9614	12.5799

Name of Industry	No. of firms	Percentage of firms	Avg Market Capitalization (In Millions)	Avg Trading Volume (In Thousands)	Mean Returns	Standard Deviation
Household Goods and Home Construction	3	0.9%	2070.82	3569.18	0.9479	15.8500
Industrial Engineering	-	-	-	-	-	-
Industrial Metals and Mining	13	4.0%	6193.14	15117.59	-0.7004	12.9438
Industrial Transportation	3	0.9%	4653.70	17617.37	-0.3920	16.5632
Media	-	-	-	-	-	-
Oil and Gas	6	1.9%	21659.72	10815.76	0.5398	13.7218
Personal Goods	73	22.7%	2900.87	15125.56	-0.1814	14.0108
Pharmaceuticals and Biotechnology	17	5.3%	8797.67	14562.61	0.9947	12.0097
Real Estate Investment and Services	3	0.9%	2554.27	11468.46	0.1583	12.8918
Technology	8	2.5%	1840.96	10343.93	0.8689	12.4558
Travel and Leisure	4	1.2%	6515.26	10832.84	0.4099	11.8448
Total	322	100%				

Note. Table 2 provides the summary statistics of industries in Dhaka Stock Exchange (DSE). As per the Thomson Reuters Business Classification (TRBC), stocks are classified into 22 different industry groups based on their market activity. Number of active firms, average market capitalization, average trading volume, mean returns, and standard deviations are reported in this Table. The study period ranges from 1997-2020.

Table 3

Descriptive Statistics of Industries in India (January 1997-December 2020)

Name of Industry	No. of firms	Percentage of firms	Avg Market Capitalization (In Millions)	Avg Trading Volume (In Thousands)	Mean Returns	Standard Deviation
Automobiles and Parts	45	1.9%	601.13	463.35	0.1233	17.5952
Chemicals	193	8.0%	465.18	422.88	0.2546	19.3642
Construction and Materials	123	5.1%	399.38	384.96	-0.3368	18.8602
Electricity	12	0.5%	134.40	650.69	-0.5697	19.2436

Name of Industry	No. of firms	Percentage of firms	Avg Market Capitalization (In Millions)	Avg Trading Volume (In Thousands)	Mean Returns	Standard Deviation
Electronic and Electrical Equipment	5	0.2%	63.813	185.58	-0.4560	16.6830
Financials	613	25.4%	637.17	429.45	-0.3746	17.1621
Fixed Line Telecommunications	6	0.3%	744.99	648.46	-0.9312	20.3713
Food Producers	203	8.4%	470.96	255.97	-0.0126	17.7009
Forestry and Paper	43	1.8%	564.12	505.85	-0.6360	19.8591
General Industrials	55	2.3%	227.99	197.15	-0.3883	17.7014
Health Care Equipment and Services	22	0.9%	233.91	142.89	0.0713	17.8424
Household Goods and Home Construction	41	1.7%	484.44	159.80	-0.2423	16.4407
Industrial Engineering	121	5.0%	524.40	317.82	0.2519	18.3610
Industrial Metals and Mining	141	5.8%	588.77	649.23	0.2759	19.2625
Industrial Transportation	25	1.0%	391.15	266.54	-0.1277	19.5783
Media	25	1.0%	626.06	1111.14	-0.7338	21.6857
Oil and Gas	13	0.6%	327.54	128.62	0.0148	21.6107
Personal Goods	280	11.6%	265.88	260.94	-0.1286	18.7265
Pharmaceuticals and Biotechnology	118	4.9%	492.08	497.86	0.2840	20.5177
Real Estate Investment and Services	80	3.3%	625.62	633.47	-0.1378	17.8027
Technology	186	7.7%	349.72	779.79	-0.8226	21.3189
Travel and Leisure	63	2.6%	404.88	168.73	-0.3458	18.2375
Total	2413	100				

Note. Table3 provides the summary statistics of industries in Bombay Stock Exchange (BSE). As per the Thomson Reuters Business Classification (TRBC), stocks are classified into 22 different industry groups based on their market activity. Number of active firms, average market capitalization, average trading volume, mean returns, and standard deviations are reported in this Table. The study period ranges from 1997-2020.

Industry Contrarian Effect

In this section, the current study analyzed the performance of industry contrarian strategies based on 22 sectors in each stock market over the whole sample period (January 1997-December 2020). Table 4 provides the excess returns of winners and losers' industries on the basis of past 12- and 6-month cumulative returns of industries. The industry contrarian returns were determined by differentiating the returns of equally weighed loser and winner industry portfolios (LMW).

Table 4 shows that the industry contrarian effect was persistent and strong in all the sample stock markets. Both 12-month and 6-month contrarian strategies produced statistically significant contrarian returns for all the markets, except for 12-month strategy in Indian stock market. The strategy with 12-month formation period generated positive contrarian returns for Pakistani and Bangladeshi stock markets, that is, 0.21% and 0.035% per month, respectively. The same strategy yielded negative (momentum returns) of -0.19% for Indian equity market. However, strategies that require 6-month formation period yielded the strong and persistent contrarian returns for all the stock markets. Although, stock-level contrarian effect was comparatively stronger, trading strategies based on industry clustering also provided persistent and significant returns, especially for strategies with shorter formation period. Moreover, the study determined overreaction effect in most of the cases where loser industry portfolios outperformed their winner industry counterparts by attaining significantly positive returns during the subsequent holding periods.

The evidence of industry contrarian effect, provided in the current study, contradicts with the results of developed markets where significant industry momentum effect was found (Ji & Giannikos, 2010; Moskowitz & Grinblatt, 1999; Swinkels, 2002). Moskowitz and Grinblatt (1999) reported 0.46% monthly momentum returns. While, Swinkels (2002) and Ji and Giannikos (2010) showed 0.65% monthly momentum returns based on industry groups in the European stock markets. Moreover, Li et al. (2014) revealed that significant industry momentum returns may be generated only with longer formation period in Australian equity markets. However, this study presented the evidence that shorter horizon ranking period strategies generate more pronounced and significant contrarian returns in South Asian equity markets. Although, the magnitude of yearly momentum returns is higher in developed markets, the findings provided a hint that in emerging markets, stocks with similar industry show a greater propensity to overreact and hence, produce industry-specific contrarian returns. Further analysis based on industry-neutral portfolios, and sub-sampling holding period analysis of the current study would offer more insights pertaining to the dynamics of industry contrarian effect in selected emerging markets.

Table 4

Profitability of Industry Contrarian Strategies (January 1997-December 2020)

Country		Winner	Loser	Contrarian (LMW)
Pakistan	12-month formation period	0.5059***	0.7201***	0.2142**
		(4.61)	(6.28)	(2.21)
	6-month formation period	0.5842***	0.8405***	0.2563***
		(5.34)	(7.87)	(2.82)
Bangladesh	12-month formation period	0.2893**	0.3243***	0.0350
		(2.19)	(3.06)	(0.28)
	6-month formation period	-0.0104	0.6847***	0.6951***
		(-0.07)	(5.73)	(5.24)
India	12-month formation period	0.1594	-0.0402	-0.1996**
		(1.36)	(-0.43)	(-2.21)
	6-month formation period	-0.1838*	0.1799*	0.3637***
		(-1.65)	(1.87)	(3.98)

Note. Table 4 reports the profitability of industry-specific contrarian strategies based on past 12-month and 6-month formation periods in all the sample countries over the whole sample period (from January 1997-December 2020). At the end of each month (t), the industries are classified into winners and losers portfolios based on past 12- and 6-month cumulative returns of industries. The industries having positive (negative) prior returns during the formation period t-12 to t-1 and t-6 to t-1 are categorized as winner and loser industries. Contrarian profits represent the subsequent returns at (t+1) month holding period, calculated as the difference in return between the equally weighed loser and winner portfolio (LMW). Parentheses show the values of robust t-statistic that are adjusted for heteroskedasticity and autocorrelation based on Newey (1987). *, ** and *** denote the significance level at 10, 5, and 1%, respectively.

To examine the stability of industry contrarian effect in the selected stock markets, the study further explored the profitability of contrarian investment strategies across different time periods. These time periods include the sub-sample of crisis periods (Asian financial crisis, Global crisis, Covid-19) and non-crisis periods. Panels A, B, and C of Table 5 respectively provide the payoffs to winners, losers, and contrarian portfolios during Asian financial crisis, global crisis, and COVID-19's sub-sample periods. The results of sub-period between Asian financial crisis and global crisis are presented in Panel A of Table 5. Whereas, the results of sub-period between global crisis and COVID-19 epidemic are provided in Panel B.

As evident in Panel A of Table 5, contrarian strategy based on 12-month formation period yielded positive contrarian returns for all the markets except for India during the Asian financial crisis. The results are more pronounced and highly significant based on 6-month contrarian strategy in all the markets. Consistent with the stock-level contrarian effect during Asian financial crisis, the findings corroborate that the Asian crisis had a significant effect on the efficiency of South Asian stock markets as compared to global crisis. Afterwards, moving to the global crisis, Panel B depicts that contrarian returns were positive and significant for 12-month contrarian strategy. However, the magnitude was lower than the returns of Asian crisis. This was somewhat expected due to the small effect of global crisis on South Asian stock markets. Finally, contrarian returns were less pronounced and insignificant during the sub-sample of COVID-19 pandemic as evident in Panel C, where the magnitude of returns was either smaller or negative for all the stock markets.

Table 5

Industry Contrarian Effect across Different Time Span (Crises Periods)

Country		Winner	Loser	Contrarian (LMW)
Panel A: Industry Contrarian Returns during Asian Financial Crisis (From Jan 1998 to Dec 1999)				
Pakistan	12-month formation period	-3.3871***	1.4699***	4.8571***
		(-9.48)	(4.09)	(10.79)
	6-month formation period	-2.3409***	0.3310	2.6719***
		(-7.50)	(0.93)	(7.66)
Bangladesh	12-month formation period	-1.5435***	-1.0415**	0.5020
		(-4.58)	(-2.42)	(1.04)
	6-month formation period	-5.1936***	-3.092***	2.1021**
		(-6.85)	(-6.38)	(2.04)

Country		Winner	Loser	Contrarian (LMW)
India	12-month formation period	4.2803***	3.9382***	-0.3421
		(5.56)	(10.29)	(-0.54)
	6-month formation period	1.8426***	4.2787***	2.4361***
		(2.89)	(11.05)	(4.48)
Panel B: Industry Contrarian Returns during Global Financial Crisis (From Oct 2007 to Sep 2009)				
Pakistan	12-month formation period	-4.7616***	-2.772***	1.9900***
		(-9.87)	(-4.97)	(3.95)
	6-month formation period	-0.4679	-2.110***	-1.6419***
		(-0.92)	(-4.36)	(-3.57)
Bangladesh	12-month formation period	4.5179***	5.8852***	1.3672***
		(9.79)	(14.27)	(3.25)
	6-month formation period	2.8207***	5.3737***	2.5529***
		(6.93)	(16.75)	(8.21)
India	12-month formation period	-0.8264	0.1036	0.9301***
		(-1.60)	(0.22)	(4.34)
	6-month formation period	0.1528	0.0692	-0.0836
		(0.39)	(0.16)	(-0.44)
Panel C: Industry Contrarian Returns during Covid19 Pandemic (From Jan 2019 to Dec 2021)				
Pakistan	12-month formation period	1.5946***	1.8770***	0.2824
		(3.78)	(3.99)	(0.87)
	6-month formation period	1.9427***	2.8144***	0.8717***
		(5.20)	(7.35)	(3.10)
Bangladesh	12-month formation period	1.4239***	1.4245***	0.0005
		(4.33)	(4.77)	(0.002)
	6-month formation period	0.6542**	0.8433***	0.1891
		(2.45)	(3.21)	(1.02)
India	12-month formation period	2.4035***	2.3516	-0.0519
		(10.03)	(10.12)	(-0.58)
	6-month formation period	1.7348***	1.6336***	-0.1012
		(6.77)	(8.79)	(-0.80)

Note. Table 5 reports the profitability of industry-specific contrarian strategies based on past 12-month and 6-month formation periods across different time periods. Panels A, B, and C report the returns during Asian Financial crisis, global crisis and COVID-19 sub-periods. At the end of each month (t), industries are classified into winners and losers portfolios based on past 12- and 6-month cumulative returns of industries. The industries having positive (negative) prior returns during the formation period t-12 to t-1 and t-6 to t-1 are categorized as winner and loser industries. Contrarian profits represent the subsequent returns at (t+1) month holding period, calculated as the difference in return between the equally weighed loser and winner portfolio (LMW). Parentheses show the values of robust t-statistic that are adjusted for heteroskedasticity and autocorrelation based on Newey (1987). *, ** and *** denote the significance level at 10, 5, and 1%, respectively.

In a similar vein, industry contrarian effect was again weak during the non-crisis periods as reported in Panels A and B of Table 6 where most of the strategies generated negative (momentum) profits in all the sample markets. The negative returns yielded during the non-crisis periods reveal that the industry contrarian effect was possibly associated with the crisis periods and negative market states. Moreover, the negative or momentum returns observed during COVID-19 and non-crisis sub-periods occurred either due to outperformance of prior winner stocks or due to short-term reversals of prior loser stocks during non-crisis or positive market states. However, some of these results are not statistically significant, and hence lose statistical reliance. The current study again attributed these results to the overreaction phenomenon. Moreover, it also provided behavioral explanation that investors feel fearful during negative market states or crisis periods and search for save havens. Therefore, they flock into high quality winner stocks which lead towards overpricing of these stocks. These overpriced stocks experience short-term reversals when stock market adjusts the prices of underpriced and overpriced stocks. The overall findings of this section comply with prior studies which suggest that the momentum or contrarian impact is highly variable across time and dependent on stock market states (Cooper et al., 2004; Urquhart & McGroarty, 2014).

For robustness of prior findings, the study also examined the behavior of contrarian strategies during the sub-periods that do not include crisis periods and the results are reported in Table 6. The results are not persistent, however, reveal a similar contrarian effect during the time period between Asian financial crisis and global crisis. However, following the global financial crisis, momentum effect was found to be stronger and persistent both statistically and economically. The negative returns of contrarian strategy reported in Panel B of Table 6 show strong momentum effect in the aftermath of the global financial crisis. The winner portfolios generated higher momentum returns, as indicated by the large positive profits during the sub-periods that exclude the two crises. These findings comply with the underreaction hypothesis of Grinblatt and Han (2005) which claims that winners experience more momentum after the decreasing trend of market. Moreover, the findings are also in line with the studies that claim that momentum profits are higher under up states of the market (Cooper et al., 2004; Daniel & Moskowitz, 2016).

Table 6

Industry Contrarian Effect across Different Time Span (Non-Crises Periods)

Country		Winner	Loser	Contrarian (LMW)
Panel A: Industry Contrarian Returns during Jan 2000 to Sep 2007				
Pakistan	12-month formation period	1.5415***	2.0992***	0.5577***
		(7.93)	(9.86)	(3.22)
	6-month formation period	1.3840***	2.7766***	1.3926***
		(7.60)	(15.83)	(9.59)
Bangladesh	12-month formation period	0.5109***	0.5034***	-0.0075
		(3.71)	(4.40)	(-0.06)
	6-month formation period	0.0393	0.7094***	0.6701***
		(0.28)	(5.56)	(4.82)
India	12-month formation period	1.2319***	0.4870**	-0.7449***
		(6.01)	(2.15)	(-4.78)
	6-month formation period	0.4227**	0.4670**	0.0443
		(2.38)	(2.19)	(0.27)
Panel B: Industry Contrarian Returns during Oct 2009 to Dec 2020				
Pakistan	12-month formation period	1.3309***	0.3128**	-1.018***
		(9.63)	(1.96)	(-8.87)
	6-month formation period	0.6591***	0.3671**	-0.2919**
		(4.73)	(2.33)	(-2.45)
Bangladesh	12-month formation period	-0.519***	-0.565***	-0.0467
		(-2.75)	(-3.03)	(-0.38)
	6-month formation period	-0.768***	-0.1357	0.6322***
		(-4.12)	(-0.79)	(6.20)
India	12-month formation period	-0.584***	-0.8388	-0.2545***
		(-6.92)	(-10.22)	(-3.81)

Country		Winner	Loser	Contrarian (LMW)
	6-month formation period	-0.452*** (-5.37)	-0.554*** (-6.64)	-0.1017 (-1.57)

Note. Table 6 reports the profitability of industry-specific contrarian strategies based on past 12-month and 6-month formation periods across different time periods. Panel A reports the results during the period between Asian financial crisis and global crisis, while panel B provides results during the period between global financial crisis and COVID-19 pandemic. At the end of each month (t), the industries are classified into winners and losers portfolios based on past 12- and 6-month cumulative returns of industries. The industries having positive (negative) prior returns during the formation period t-12 to t-1 and t-6 to t-1 are categorized as winner and loser industries. Contrarian profits represent the subsequent returns at (t+1) month holding period, calculated as the difference in return between the equally weighed loser and winner portfolio (LMW). In parentheses are the values of robust t-statistic that are adjusted for heteroskedasticity and autocorrelation based on Newey (1987). *, ** and *** denote the significance level at 10, 5 and 1%, respectively.

Industry-Neutral Contrarian Effect

This section explored the industry-dependent contrarian effect to examine whether industry-dependent portfolios contribute to stock-level contrarian effect in sample emerging markets. To ensure that the portfolios contain sufficient firms, the study selected three largest industries from each stock market. These industries include personal goods, financials, and food producers. Personal goods industry comprises 151, 73, and 280 firms, respectively for Pakistan, Bangladesh, and India. Financial industry consists of 86, 109, and 613 firms for the same set of countries. Finally, the food producer industry comprises 55, 18, and 203 firms, respectively for Pakistani, Bangladeshi, and Indian stock market.

The results reported in Panel A, B, and C of Table 7 show the overall positive returns for contrarian strategies based on 12-month formation periods. However, contrarian returns become higher and more significant with short-distant ranking period of 6 months. For instance, in personal goods industry, contrarian strategy with 6-month formation period yields 6.12%, 2.79%, and 5.27%, respectively for Pakistan and Bangladesh. Similarly, financials and food producers generate more positive returns with

6-month ranking period strategies as compared to 12-month or any other combination of strategies analyzed in previous sections. When contrarian investment strategies are implemented within a similar industry, the magnitude of positive returns observed in previous sections become higher and more significant in all three industries. On average, industry-neutral contrarian portfolios generate monthly mean profit of 3.22%, -0.03%, and 4.30%, respectively for Pakistan, Bangladesh, and India based on the 12-month formation period. Whereas, 4.33% (for Pakistan), 1.95% (for Bangladesh), and 4.56% (for India) mean contrarian returns are yielded based on strategies with 6-month formation period. In other words, industry contrarian effect becomes stronger and highly significant when industry impact is accounted for.

Table 7

Industry-Neutral Contrarian Portfolios

Country		Winner	Loser	Contrarian (LMW)
Panel A: Personal Goods				
Pakistan	12-month formation period	-1.5584*** (4.61)	2.8144*** (6.28)	4.3728*** (2.21)
	6-month formation period	-2.5407*** (5.34)	3.5844*** (7.87)	6.1251*** (2.82)
Bangladesh	12-month formation period	-0.5401*** (2.19)	0.7572*** (3.06)	1.2973*** (0.28)
	6-month formation period	-1.2843*** (-0.07)	1.5084*** (5.73)	2.7928*** (5.24)
India	12-month formation period	-2.6369 (1.36)	2.1827 (-0.43)	4.8196*** (-2.21)
	6-month formation period	-2.9469* (-1.65)	2.3268* (1.87)	5.2737*** (3.98)
Panel B: Financials				
Pakistan	12-month formation period	-1.1649*** (4.61)	2.3939*** (6.28)	3.5589*** (2.21)
	6-month formation period	-1.9476*** (5.34)	2.7919*** (7.87)	4.7396*** (2.82)
Bangladesh	12-month formation period	0.5272** (2.19)	0.6359*** (3.06)	0.1086** (2.17)

Country		Winner	Loser	Contrarian (LMW)
India	6-month formation period	-0.2084	1.9112***	2.1196***
		(-0.07)	(5.73)	(5.24)
	12-month formation period	-1.7810	1.868	3.6491***
		(1.36)	(-0.43)	(-2.21)
	6-month formation period	-1.8421***	1.7830***	3.6252***
		(-1.65)	(1.87)	(3.98)
Panel C: Food Producers				
Pakistan	12-month formation period	0.1043***	1.8227***	1.7184***
		(4.61)	(6.28)	(2.21)
	6-month formation period	0.0352	2.1490***	2.1138***
		(0.55)	(7.87)	(2.82)
Bangladesh	12-month formation period	1.5981**	0.1125***	-1.4856
		(2.19)	(3.06)	(0.28)
	6-month formation period	0.1197	1.0659***	0.9462***
		(0.51)	(4.87)	(3.38)
India	12-month formation period	-2.1242	2.2826	4.4069***
		(1.36)	(-0.43)	(-2.21)
	6-month formation period	-2.5026***	2.2661***	4.7687***
		(-1.65)	(1.87)	(3.98)

Note. Table 7 reports the profitability of industry-neutral contrarian portfolios based on past 12-month and 6-month formation periods. The study identified the top three common industries that contain the highest number of stocks in each stock market (for instance, personal goods, financials, and food producers). Portfolios are formed within each industry pool to examine the industry-neutral contrarian effect. At the end of each month (t), industries are classified into winners and losers portfolios based on past 12- and 6-month cumulative returns of industries. The industries having positive (negative) prior returns during the formation period t-12 to t-1 and t-6 to t-1 are categorized as winner and loser industries. Contrarian profits represent the subsequent returns at (t+1) month holding period, calculated as the difference in return between the equally weighed loser and winner portfolio (LMW). In parentheses are the values of robust t-statistic that are adjusted for heteroskedasticity and autocorrelation based on Newey (1987). *, ** and *** denote the significance level at 10, 5 and 1%, respectively.

The overall findings prove the study hypothesis that the performance of contrarian investment strategy is influenced by the industry characteristics. Therefore, industry aspect cannot be neglected while interpreting the returns of investment strategies in selected emerging markets. The results related to industry contrarian effect are unique in the context of emerging markets. This is because these results contradict with the results of prior studies that observed industry momentum effect in relatively developed markets (Moskowitz & Grinblatt, 1999; Tan & Cheng, 2019). Moreover, the magnitude of industry-neutral contrarian returns was economically larger than the momentum returns observed in the US and European markets. As per Moskowitz and Grinblatt (1999), industry momentum effect may be attributed to herding behavior of investors. However, herding behavior may also cause overpricing of winner stocks when investors follow the herd and invest in hot stocks and flock out of cold stocks within an industry. This behavior may lead to an unnecessary increase in stock prices of hot stocks, which may result in contrarian profits in short-term when these stocks experience subsequent short-term reversals.

The findings regarding the predictability of industry-specific factors provide an important implication for investors and portfolio managers based on the argument of Lee and Swaminathan (2000) that industry factors contain information content. Winner stocks with higher industry returns may face greater information asymmetry. Therefore, overinvestment in these stocks may lead towards significant short-term reversals in subsequent periods. Therefore, the study determined that investors may earn superior returns by carefully forming industry portfolios. Additionally, industry contrarian effect may generate higher returns during crises periods, while momentum would be observed following a down-market trend. The findings of this section imply that the relevance and significance of industry characteristics cannot be ignored in interpreting the anomaly returns. Moreover, industry component should also be considered while pricing various assets. The findings offer an important implication to investors and fund managers that contrarian strategy with value stocks, conditional on industry factors, may yield superior returns in selected emerging stock markets. These findings play an important role in the context of emerging markets since these markets mostly exhibit lower returns for conventional momentum strategies.

Conclusion

The current study examined the predictive ability of various industry-related factors over the profitability of contrarian returns in the context of emerging markets. In the empirical analysis, this study focused on the emerging stock markets of South Asia. This is because these markets are relatively new and some idiosyncratic phenomena characterize these markets which produce unique institution for contrarian strategy returns. These emerging markets offer a unique set of characteristics that relate contrarian and momentum profits to macroeconomic and global risk factors and provide important insights by interacting with local market conditions and volatility factors. Furthermore, these markets have undergone economic transformations over the past 20 years which reduced the trade barriers and increased the foreign investors' participation in these markets. Overall, the study provided unique insights to predict the reversals in the context of emerging markets by examining the predictive ability of various industry-related factors over contrarian strategy payoffs.

The empirical findings show that industry-specific factors significantly contribute towards the profitability of reversal strategy in emerging markets. The past winner industry portfolios grouping the top industry performers experience greater short-term reversals in subsequent periods. These results support the argument of Lee and Swaminathan (2000) who claim that industry-related factors contain information content. The study reveals that winners with higher industry returns face greater information asymmetry, which can lead to short-term reversals. To earn superior returns, investors should carefully form industry portfolios. The study confirms that industries with lower past returns outperform others in subsequent periods. Industry-neutral contrarian portfolios yield the highest contrarian returns, suggesting that investors can increase profits by focusing on specific industries at a time. Asian and global financial crises lead to higher industry contrarian returns, while non-crise periods, particularly after the global financial crisis, primarily witness momentum returns. These results support the underreaction theory of Grinblatt and Han (2005), which suggests that winner portfolios exhibit greater momentum following a down market trend. The study emphasizes the importance of considering industry characteristics when pricing assets.

Recommendations

The findings on the predictability of industry-specific characteristics have significant implications for investors and portfolio managers. Companies with higher industry returns tend to have more information asymmetry. As a result, there is a tendency for overinvestment in these companies, which can lead to big short-term reversals in the following periods. Moreover, the research findings suggest that investors might get higher returns by meticulously constructing industry portfolios. Furthermore, during times of crisis, the industry's contrarian effect can yield superior returns, while a downward market trend typically triggers momentum. These results imply that we cannot overlook the importance of industry factors when analyzing abnormal returns. Additionally, when valuing different assets, one should consider the industry component. The study's overall findings suggest that investors and fund managers should consider employing a contrarian approach with value companies in specific emerging stock markets. If certain company, and industry aspects are considered, this strategy can potentially yield higher returns. These findings have significant importance in the context of developing markets, as these markets often demonstrate weak returns for conventional momentum strategies.

Conflict of Interest

The authors of the manuscript have no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

Data Availability Statement

Data associated with this study will be provided by corresponding author upon reasonable request.

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