International Research Journal of Finance and Economics
ISSN 1450-2887 Issue 164 November, 2017
http://www.internationalresearchjournaloffinanceandeconomics.com

Time-series and Cross-sectional Momentum in the Saudi Arabia Stock Market Returns

Shah Saeed Hassan Chowdhury
Assistant Professor, Department of Accounting and Finance
Prince Mohammad University, Saudi Arabia
E-mail: schowdhury@pmu.edu.sa; hchowdh@yahoo.com
Tel: +966 531 409382

Abstract

This paper investigates the presence of time-series and cross-sectional momentum profits and the relationship between these two types of profits in the Saudi Arabia stock market. Results confirm that both time-series momentum and cross-sectional contrarian profits are present in this market. The presence of cross-sectional contrarian profits is stronger than that of time-series momentum profits. Cross-sectional profits are so strong that it remains even after time-series momentum and other market risk factors are considered. An observation period of three months gives the best opportunity to provide cross-sectional contrarian profits. Finally, there is a relationship between these two types of momentum profits in the short holding period, but as the holding period increases the relationship fades away.

Keywords: Time-series momentum; Cross-sectional momentum; Behavioral finance; Saudi stock market; Emerging markets; Frontier markets.
JEL Classification: G11, G12, G15

1. Introduction

Predictability of stock returns is of prime interest for finance academicians and investors. In the 1970s research broadly concluded that stock returns were unpredictable – in other words, stock market was efficient. Research in the 1980s showed the predictability of stock returns and the notion of market efficiency was seriously questioned [French (1980); Keim (1983); DeBondt and Thaler (1985, 1987); Lo and MacKinlay (1988)]. In the 1990s, some studies – such as, Jegadeesh and Titman (1993, 1995) – also confirmed the presence of various forms of return regularities. Hence, extant research provides a strong argument in favor of market predictability, which indicates that investors may be able to make abnormal returns.

Presence of contrarian and momentum profits is considered to be one of the most common forms of return regularities in the stock markets. There is a huge literature on the presence of contrarian and momentum profits in the developed markets. In general, contrarian and momentum profits are considered to be relatively long- and medium-term phenomenon. Contrarian profits arise when the previous period's best (worst) performing stocks systematically become worst (best) performing stocks in the next period. On the other hand, momentum profits occur when the previous period's best-performing stocks consistently continue to do well in the next period. Thus, contrarian and momentum profits may possibly be related to the overreaction and underreaction of stock prices to new information, respectively.

DeBondt and Thaler (1985, 1987) are the first two studies to show that contrarian profits are present in the U.S. stock market in the long-run investment horizon. Thus, investors may benefit from buying past losers and selling past winners. Jegadeesh (1990), Lehman (1990) and Chopra *et al.* (1992) also provide evidence in favor of short- and long-term contrarian profits. Jegadeesh and Titman (1993, 2001) show the presence of momentum profits in the U.S. market in the short- and medium-term investment horizon. Some of the relatively recent studies also document the presence of momentum profits in developed markets [Avramov *et al*. (2007); Fama and French (2012); Novy-Marx (2012); Asness *et al*. (2013)]. Momentum profits are so prevalent that some of the later research has focused on the possible presence of such profits in other asset classes. Moskowitz *et al*. (2012) report momentum profits in other kinds of assets such as equity indexes, currency, commodities and bond futures. Similarly, Asness *et al.* (2013) report the presence of momentum profits not only for stocks but also for other financial assets.

Behavioral explanations for the link between stock market over- and under-reaction and momentum and contrarian profits are nicely presented by Daniel, Hirshleifer, and Subrahmanyam (hereafter DHS, 1998) and Hong and Stein (hereafter HS, 1999). HS believe that there are two types of investors – well-informed investors and technical analysts. Informed investors obviously react to new information first. Then technical analysts react to the same information, resulting in driving the stock prices more in the same direction. Thus, if positive news about a firm is released, the stock price may go up in two stages – initial under-reaction to information and subsequent occurrence of momentum profits. On the other hand, DHS assume that investors have their own information and value their stock selection skills very highly. This overconfidence leads these investors to overreact to new information, which drives the stock prices to go away from their fundamental values. In the long run, the market realizes that stocks are overvalued and makes necessary corrections. This phenomenon causes momentum profits initially and contrarian profits in the longer investment horizons.

Literature indicates two types of momentum profits – cross-sectional and time series. Most of the research on momentum is in fact cross-sectional in nature since momentum profits are calculated from the cross-section of winner and loser stocks of the past. On the other hand, time-series momentum profits are calculated from an asset's own past returns. Since both types of momentum profits are somehow related to the past, they may be correlated. Thus, it would be interesting to know how these two are related. Especially, it is important to examine if the so-called presence of cross-sectional momentum is just a manifestation of time-series momentum.

Any pattern in stock price movements indicates predictability. Such a predictable behavior in stock prices is an ominous sign for a frontier/emerging market such as Saudi Arabia because only a handful of big individual and institutional investors can possibly exploit the resultant profit opportunities, which could significantly damage the confidence of small investors. Since most of the emerging and frontier markets are dominated by individual investors, it may take a very long period of time to restore confidence. Moreover, in order to ensure proper functioning of the channel between the surplus and deficit units in the economy, small investors' interests must be protected. If not so, the market will simply fail to develop over time, resulting in an ultimate serious setback in the investment and production of the economy.

Most of the previous papers have attempted to detect the presence of momentum and contrarian profits in the developed markets. Academicians have conducted research more seriously on the frontier and emerging markets since the early 1990s, mainly because these markets historically have low correlation with developed markets, creating opportunities for global portfolio managers to achieve additional diversification benefits. Obviously, research in this context has not really focused on the frontier and emerging stock markets. Since there are only few studies on the momentum and contrarian profits in the Saudi stock market and these profits are present almost everywhere in the world, it would be interesting to investigate more on these two profit opportunities. Definitely, institutional investors in general and foreign investors in particular need to know more about these return regularities. Finally, momentum and contrarian profits need to be examined to confirm whether or not these still exist after other market risk factors are accounted for.

This paper primarily focuses on the presence of time-series and cross-sectional momentum profits and the relationship between these two in the Saudi stock market over the period January 2000 through December 2015. I follow the methodology of Moskowitz *et al*. (2012) to estimate the time-series momentum profits of the market. For cross-sectional momentum, I follow the methodology of Lo and MacKinlay (1990) to form portfolios with a weighted relative strength scheme (WRSS).

The rest of the paper is structured as follows. I provide a brief survey of the relevant literature in section 2. Section 3 discusses data and methodology used in the study. Section 4 analyzes the results. Section 5 concludes the paper.

2. Literature Review

DeBondt and Thaler (1985) are the first to report contrarian profits in the U.S. stock returns in the three- to five-year investment horizon. Many subsequent research papers, including DeBondt and Thaler (1987) and Jones (1993), find similar results. Jegadeesh (1990), Lehman (1990), and Chopra *et al*. (1992) give evidence of contrarian profits even in weekly returns. Jegadeesh and Titman (1995) argue that contrarian profits occur due to overreaction to firm-specific information. Boudoukh *et al.* (1994) and Conrad *et al*. (1997) argue that market microstructure is the main cause of observed contrarian returns. Wongchoti and Pyun (2005) show that long-term contrarian profits are still present even after adjusting for relevant risk.

After the discovery of contrarian returns in the long-term investment horizon many financial economists focus on short-run investment horizon. Jegadeesh and Titman (1993) first detect the presence of momentum profits in the U.S. market for the investment horizon of three to 12 months. Later, many other papers provide the evidence of momentum returns in the short- and medium-term investment horizon. Some of these papers shed light on the reasons for such return regularities. Subsequent research shows that momentum profits are related to the state of the market, size of firms, industry, investor behavior, analyst attention, credit ratings, volume of trade and the volatility of growth.

Conrad and Kaul (1998) argue that momentum profits occur due to the cross-sectional differences in risk. Moskowitz and Grinblatt (1999) suggest that industry risk factors explain observed momentum profits. Liu and Zhang (2008) find that industrial production explains more than half of momentum profits and this macroeconomic factor is important to explain extant evidence of momentum profits. Since size is an important risk factor, some studies attempt to address momentum profits with respect to firm size. Hong *et al.* (2000) find that small firms attract low analyst attention and hence are more susceptible to momentum phenomena. Avramov *et al*. (2007) show that credit rating influences momentum profits and momentum profitability is particularly strong for low-rated firms. Fama and French (2012) report that except for Japan, there are momentum profits in the North America, Europe, Japan, and Asia Pacific markets and spreads in average momentum profits decrease from smaller to bigger stocks.

Novy-Marx (2012) finds that strategies based on intermediate horizon past performance (seven to 12 months prior to portfolio formation) produces momentum profits for the largest, most liquid stocks. Sagi and Seasholes (2007) attempt to link observable firm attributes to momentum profits and find that firms with high revenue growth volatility produce higher momentum profits compared to firms with low revenue growth volatility. More recently some papers attempt to examine the behavioral and cultural explanations of momentum profits. For example, Chui *et al.* (2010) suggest that momentum is related to individualism, culture and investor psychology. Some studies focus on the relationship between momentum profits and state of the market and find that such profits occur only in the "up" market [Daniel *et al.*(1998); Cooper *et al.* (2004); Huang (2006)]. However, Griffin *et al.*

(2003) suggest that momentum profits are large and exist in both good and bad states and that profits tend to reverse over an investment horizon of one to five years.

Some papers concentrate on the relationship between momentum profits and relatively less-known causes. Lee and Swaminathan (2000) show that momentum profits are more prevalent in high-turnover stock returns. George and Hwang (2004) report that 52-week high price can be used with the current stock price information to profit from momentum investing. Asness *et al*. (2013) consider value effect and momentum jointly and report consistent value and momentum return premia across eight diverse markets and asset classes.

Momentum studies primarily rely on the relative performance of the stocks in the cross-section, whereas time series momentum is a timing strategy using each asset's own past returns. Most of the contrarian and momentum studies available in the finance literature are cross-sectional in nature. The benefit of time series momentum strategy is its easy applicability for different asset types. Moskowitz *et al.* (2012) document significant time series momentum in equity indexes, currency, commodity, and bond futures for each of the 58 liquid instruments they use in their study. They also report that momentum profits persist for one to 12 months and partially reverse over longer horizons.

Many papers have focused on the presence and sources of momentum and contrarian profits in international markets. The international presence of momentum profits is confirmed in several studies [Rouwenhorst (1999); Naranjo and Porter (2007)]. On the other hand, McInish *et al*. (2008) show that short-term trading strategies based on past returns are not profitable in the Pacific Basin markets except Japan and Hong Kong. These two markets, in fact, provide contrarian profits.

Since Saudi Arabia is a frontier market, research on the presence of momentum and contrarian profits in emerging and frontier stock markets is of high relevance. It is noteworthy that this market is considered as a frontier market just because of the restriction on foreign investors. Otherwise, it fulfills all other requirements for an emerging market. As the market partially opened to foreign investors in June 2015, it is now expected that it will be upgraded to the status of an emerging market within next few years.

Two of the most dominant emerging stock markets in the world today are China and India and thus academicians and practitioners attempt to investigate contrarian and momentum profits in these two markets. The evidence generally supports the presence of contrarian profits in the Chinese markets. Kang *et al*. (2002) report the presence of short-term contrarian and medium-term momentum profits in the Chinese stock market. Findings of Li *et al.* (2010) also support the presence of contrarian profits in Chinese stock market in the short investment horizon. Xu and Qiu (2012) also report short- and medium-term contrarian profits in the Chinese stock market and claim lead-lag effect as the principal cause for this phenomenon.

Several studies have focused on the momentum and contrarian effects in the Indian stock returns. Shegal and Balakrishnan (2002) and Balakrishnan (2012) report strong presence of short-term momentum and long-term return reversal in Indian market. Bernard and Deo (2015) and Shegal and Jain (2011) find strong presence of momentum profits in the Indian stock market in the investment horizon of three and six months, respectively. However, Locke and Gupta (2009) and Chowdhury (2010) report the presence of contrarian profits in short-term investment horizon and the influence of size to explain such profits.

Some studies consider other prominent emerging and frontier markets. Hameed and Ting (2000) investigate the influence of trading volume on contrarian profits in Malaysian market and find that contrarian profits are stronger for actively traded firms than for less traded firms. Galariotis (2004) finds that firm-specific component is the main source of short-term contrarian profits in the Athens Stock Exchange. In a similar study for Asia-Pacific markets, Ding *et al*. (2008) show that likelihood of high-volume firms to have price reversals is more than that of low-volume ones. However, Ding *et al.* (2009) suggest that the reason for the lack of momentum profits in Taiwan market is related to the state dependence rather than the cultural differences between Asian and developed markets. De Groot *et al.* (2010) report momentum return of about 1% per month for 24 frontier stock markets. Cakici *et al.*

(2013) – in a study of 18 emerging stock markets – report the presence of momentum profits in all but four Eastern European countries.

Emerging markets are different from developed markets in terms of liquidity, corporate governance, quality of analysts, participation of institutional investors, role of media, etc. Difference in other factors such as religious and cultural biases could be important too. Morck *et al.* (2000) add political influence and private property rights as two big issues that make stocks in respective emerging markets to move more in the same directions than stocks in developed markets. Therefore, findings on momentum in the developed markets may differ from that in the emerging markets. In this backdrop, there is almost no published paper on momentum profits in the Saudi stock market.

However, there are a few momentum-related papers on other GCC (Gulf Cooperation Council) markets. Since Saudi market is one of the members of the GCC region and the behavior of these markets may be similar, it is relevant to discuss the findings on these markets. Al-Muhairi (2011) reports the presence of momentum profits for zero-cost portfolios in the U.A.E. market. Gharaibeh (2015) documents strong evidence of profits from the short-term contrarian strategy in the Kuwait stock exchange and such profits cannot be explained by January effect. Alsubaie and Najand (2009) report that price momentum profitability in the Saudi stock market is very similar in magnitude and significance to those found in developed markets.

3. Data and Methodology

3. 1. Data

Monthly stock price index, market capitalization and price to book value data for the Saudi stocks are collected from Thomson Datastream. Daily stock return index is used to find monthly market volatility. I also collect it from the same source mentioned above. This study covers the period from January 2000 through December 2015. Returns are calculated as the log difference of stock price indices times 100. In the case of time-series momentum, conditional volatility (standard deviation) needs to be estimated before testing for the momentum in stock returns. This is discussed in the following sub-section.

3. 2. Methodology

3.2.1. Estimation of Volatility Measures

This study uses two types of conditional volatility. First one is the standard deviation estimated from a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) type model. More precisely, an AR(1)-GARCH(1,1) model is used to estimate daily conditional volatility.

$$r_t = \mu + \beta r_{t-1} + u_t \tag{1a}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{1b}$$

where σ_t^2 and r_t are conditional variance and return, respectively, at time t.

Conditional volatility measured by eq. (1b) is estimated based on the behavior of the whole return series. But, next period's expected volatility may be independent of returns series of the whole period. Volatility measure of eq. (2) is free from such a look-ahead bias mainly because it is created from the daily returns data of a given month. It can be modified to consider a certain number of daily returns data on a rolling basis. This model for volatility is given by

$$\sigma_t = \sqrt{\frac{252}{n} \sum_{t=1}^{n} r_t^2}, \tag{2}$$

where n is 22 since a month has approximately 22 trading days.

Monthly returns are scaled by the standard deviation of the previous month. Such a scaling of returns makes it easier to compare between the returns of different investment horizons. Relationship between return at month *t* and that at *k* months before can be expressed by the following model

$$r_t/\sigma_{t-1} = \alpha + \beta_k\, r_{t-k}/\sigma_{t-k-1} + \varepsilon_t. \tag{3}$$

Another way of detecting time-series predictability of stock returns is to look at the sign of past returns. In the following model only the sign of r_{t-k} is used.

$$r_t/\sigma_{t-1} = \alpha + \beta_k sign(r_{t-k}) + \varepsilon_t\,. \tag{4}$$

3.2.2. Estimation of Time-series Momentum Profits

Similar to the estimation for cross-sectional momentum, time-series momentum also needs evaluation period (*j*) and holding period (*k*). For each month *t*, I look back for *j* months to find whether the returns are positive or negative. If return in the past *j* months is positive (negative), I buy (sell) that instrument (in this case, portfolio of stocks). Then this instrument is held for next *k* months. Every (*j*, *k*) trading strategy provides a single continuous time-series of monthly returns regardless of the size of holding period. This time-series momentum return series is denoted by $r_t^{TSM(j,k)}$. To evaluate the abnormal returns from these strategies, I compute alphas from the following regression model:

$$r_t^{TSM(j,k)} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t\,, \tag{5}$$

where *MKT*, *SMB*, *HML* and *UMD* are market return, return difference between small-size and large-size firms, return difference between high BV/MV and low BV/MV firms, and cross-sectional momentum premium, respectively. It is possible that time-series momentum is related to cross-sectional momentum since many papers mentioned above have reported the presence of cross-sectional momentum in both developed and emerging stock markets. After the inclusion of cross-sectional momentum profits (CSM_t), eq. (5) becomes as follows:

$$r_t^{TSM(j,k)} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 CSM_t + \varepsilon_t. \tag{6}$$

3.2.3. Construction of Portfolios to Estimate Cross-sectional Momentum Returns

I use the weighted relative strength scheme (WRSS) of Lo and MacKinlay (1990) to construct riskless (zero weight) portfolios. The formation and holding periods are of 1- through 3- and 1- through 12-month duration, respectively. That is, I create portfolios considering the performance of the past *j* months where *j* =1, 2 and 3 months. This is called the formation or ranking period. Then, the performance of the portfolio is evaluated during the next 1, 2, 3, 4, 6, 9 and 12 months. This duration is called the evaluation or holding or tracking period. Thus, the trading strategies are *j*=1, *k*=1, 2, 3, 4, 6, 9, 12; *j*=2, *k*=1, 2, 3, 4, 6, 9, 12; and *j*=3, *k*=1, 2, 3, 4, 6, 9, 12 – a total of 21 strategies. Under this portfolio formation strategy, the stocks with positive (negative) return (i.e., higher (lower) return than the market return) over the formation period are bought (sold). The stocks that have higher (lower) return than the market are considered to be the winners (losers). The stocks that have larger magnitude of positive (negative) return in the formation period have larger positive (negative) weights in the portfolios. Thus, the weight of an individual stock depends on the magnitude of its performance in the formation period. Every stock maintains the same given weight during the holding period. During each holding period, each stock in the portfolio is assigned with the weight of

$$w_{i,t} = \frac{1}{N}\left(r_{i,t-1} - \bar{r}_{t-1}\right), \tag{7}$$

where $r_{i,t-1}$is the return of stock *i* at time *t*-1, *N* is the number of stocks at period *t*-1, and $\bar{r}_{t-1}$ is the equal weighted market return at time *t*-1. Thus, the weight of a portfolio becomes zero if individual stock weights are summed up. The momentum or contrarian profit, π_t, is given by

$$\pi_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t}\left(r_{i,t-1} - \bar{r}_{t-1}\right). \tag{8}$$

As mentioned above, there are 21 trading strategies that involve short to medium-term trading horizons. After a portfolio is made, its cumulative return in the holding period is calculated. Respective portfolio's momentum/contrarian profit in the holding period k = 1, 2, 3, 4, 6, 9 and 12 months is given by

$$\pi_{J,t}(k) = \sum_{i=1}^{N_j} w_{i,t}\, r_{i,t+k}, \tag{9}$$

where $J = L$ (loser portfolio), W (winner portfolio), C (contrarian portfolio), $w_{i,t}$ is the weight of respective stocks in the portfolio, and N_j is the number of stocks in the portfolio during the formation (ranking) period. As mentioned above, the weight of individual stocks does not change during the holding (evaluation) period.

4. Empirical Results and Analyses

4. 1. Descriptive Statistics

Table 1 exhibits the descriptive statistics of monthly equal weighted Saudi market returns. Average of monthly returns for the whole period is about 0.87%. The Saudi market provides higher returns than many emerging markets during the same period. The reason is the strong oil-generated revenues even during the global economic slowdown since 2008. The kurtosis of 4.18 indicates that monthly returns are distributed with fatter tails and more peaked at the mean than a normally distributed random variable with the same mean and variance. Negative skewness of Saudi stock returns implies that the returns series is negatively skewed – that is, the left tail is longer. Very high first-order positive autocorrelation of 0.19 suggests that the market is predictable to some extent.

Table 1. Descriptive Statistics of Monthly Returns

Mean	**0.8664**
Median	1.64
Standard Deviation	9.50
Minimum	-44.53
Maximum	22.38
Kurtosis	4.18
Skewness	-1.24
Autocorrelation (1)	0.1923
Autocorrelation (2)	-0.0526
Autocorrelation (3)	-0.0341
Autocorrelation (6)	0.0760
Autocorrelation (9)	0.0451
Autocorrelation (12)	-0.0464
Observations	190

4. 2. Presence of Time-Series Momentum Return

Figure 1 plots *t*-statistics from regressions when current returns are regressed on returns of one through 12 own lagged months (as shown by eq. (3)). Significantly positive *t*-statistics for one-month lagged return implies continuation of returns for a short period of time. Although insignificant, negative *t*-statistics at longer horizons indicates a tendency of ultimate return reversals. Figure 2 plots *t*-statistics of the coefficients of lagged returns where only the signs of past returns are used. Thus, this is similar to figure 1 – only difference is that this is free from magnitude of returns. Both the figures exhibit similar behavior of returns. Thus, as evidenced by both figures, return continuation in the Saudi stock market is a short-run phenomenon.

Figure 1. ***t*-statistic of Coefficients at Different Lag Lengths (eq. 3)**

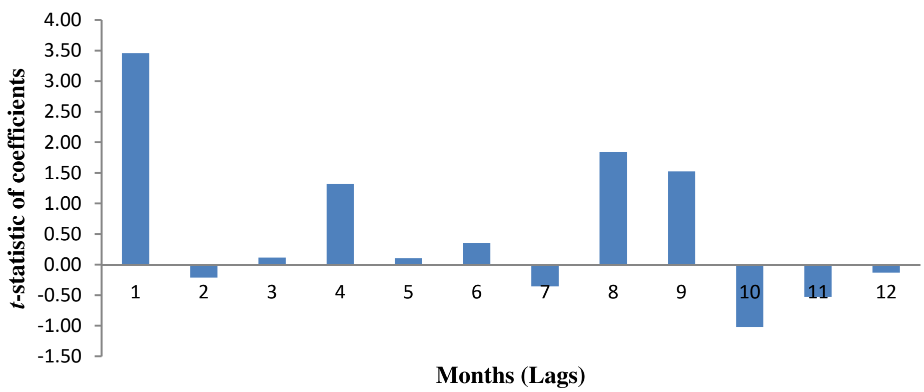

Figure 2. ***t*-statistic of Coefficients at Different Lag Lengths (eq. 4)**

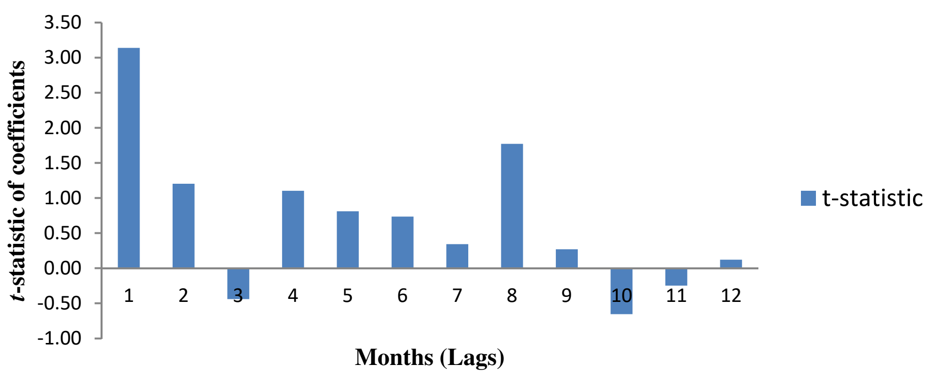

Table 2 provides time-series momentum returns for j=1, 2 and 3 and k=1, 2, 3, …, 12 month trading strategies. j and k denote formation and holding period, respectively. Thus, as mentioned before, there are (3x12=) 36 trading strategies. Intercept terms are of main interest because a significant intercept term indicates that time-series momentum profit is not completely explained by other market risk factors. Only j=1, k=1 strategy gives significant momentum profits at 10% level. All other intercept terms are not even close to being significant at 10% level. It implies that one-month formation period is not an effective strategy to choose an appropriate momentum portfolio and hold it for future profits. Hence, formation periods of more than a month may be required so that well-observed portfolios can be chosen and tracked later on during different holding periods.

Table 2. Time-Series Momentum at Different Monthly Lag Lengths (j=1, k=1, 2, …, 12)

Strategies	*Intercept*	*HML*	*SMB*	*UMD*	*MKT*
j=1, k=1	1.2120	0.1124	-0.0368	0.4321	-0.0559
	(1.68)*	(0.77)	(-0.48)	(0.80)	(-0.57)
j=1, k=2	0.0805	-0.6082	0.4148	-0.2259	0.0023
	(0.08)	(-2.84)**	(3.68)**	(-0.28)	(0.02)
j=1, k=3	0.4610	-0.2149	0.5874	1.2468	0.3733
	(0.35)	(-0.82)	(4.24)**	(1.27)	(2.12)**
j=1, k=4	0.7458	-0.4216	-0.0300	0.5057	0.5795
	(0.47)	(-1.32)	(-0.18)	(0.43)	(2.71)**
j=1, k=5	0.7509	0.1728	0.1674	2.5726	0.3577
	(0.41)	(0.47)	(0.86)	(1.88)*	(1.45)
j=1, k=6	0.7454	0.2491	0.1266	2.7409	0.0246

Strategies	*Intercept*	*HML*	*SMB*	*UMD*	*MKT*
	(0.37)	(0.61)	(0.21)	(-1.81)*	(0.09)
j=1, *k*=7	0.1983	0.0963	-0.4586	-0.2254	0.6310
	(0.09)	(0.22)	(-1.98)**	(-0.14)	(2.14)**
j=1, *k*=8	2.6782	0.8410	-0.4481	3.0013	0.6759
	(1.14)	(1.77)*	(-1.80)*	(1.72)*	(2.13)**
j=1, *k*=9	2.0804	-0.2342	0.8539	-1.2522	0.2057
	(0.81)	(-0.46)	(3.16)**	(-0.66)	(0.60)
j=1, *k*=10	2.0486	0.0938	0.7090	-1.1307	0.4772
	(0.73)	(0.17)	(2.41)**	(-0.55)	(1.28)
j=1, *k*=11	1.8733	0.3592	0.3355	1.6568	1.0212
	(0.63)	(0.60)	(1.07)	(0.75)	(2.56)**
j=1, *k*=12	0.7705	-0.8551	-0.1892	-0.2434	0.5691
	(0.24)	(-1.34)	(-0.56)	(-0.10)	(1.34)

t-statistics are reported in parentheses. ** and * indicate significance at 5% and 10%, respectively. This table provides the results of the regression model $r_t^{TSM(j,k)} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t$. The portfolio formation period and tracking/holding period are denoted by *j* and *k*, respectively. This table provides results for *j*=1 and *k*=1, 2, 3, …,12 trading strategies.

Next, formation period of two months is used with one through 12 months of holding periods. Interestingly, as shown by intercept terms, strong momentum profits occur from holding periods of five months and above. Only holding period of eight months provides momentum profits at 5% significance level. Significant momentum profits are always positive in sign regardless of trading strategies. Since usual market risk factors have already been taken into account, the presence of positive momentum profits must be considered as non-negligible. One can guess that longer formation period has probably added more insight about the future performance of the portfolio. Consequently, the formation period can be extended to three months.

Table 3. Time-Series Momentum at Different Monthly Lag Lengths (j=2, k=1, 2, …, 12)

Strategies	*Intercept*	*HML*	*SMB*	*UMD*	*MKT*
j=2, *k*=1	0.5946	0.0004	-0.0092	0.5727	-0.1061
	(0.82)	(0.003)	(-0.12)	(1.06)	(-1.09)
j=2, *k*=2	-0.0317	-0.8336	0.3681	0.5881	0.0558
	(-0.03)	(-3.96)**	(3.32)**	(0.75)	(0.40)
j=2, *k*=3	1.5005	-0.2592	-0.0349	0.3353	0.4025
	(1.09)	(-0.93)	(-0.24)	(0.32)	(2.16)**
j=2, *k*=4	2.5375	-0.2034	-0.0736	1.3115	0.3604
	(1.58)	(-0.63)	(-0.43)	(1.09)	(1.66)*
j=2, *k*=5	3.3940	0.2994	0.3997	2.9335	0.1408
	(1.88)*	(0.82)	(2.09)**	(2.18)**	(0.58)
j=2, *k*=6	2.7468	0.0632	0.2041	0.2448	0.8365
	(1.39)	(0.16)	(0.98)	(0.17)	(3.14)**
j=2, *k*=7	3.6641	-0.0027	-0.3208	2.4468	0.7908
	(1.69)*	(-0.01)	(-1.40)	(1.52)	(2.71)**
j=2, *k*=8	5.8487	0.0271	-0.3192	-1.3632	0.1566
	(2.45)**	(0.06)	(-1.27)	(-0.77)	(0.49)
j=2, *k*=9	4.6450	-0.5417	0.7827	-1.2233	0.5847
	(1.84)*	(-1.07)	(2.95)**	(-0.66)	(1.74)*
j=2, *k*=10	4.8927	-0.3558	0.8562	0.5978	0.6339
	(1.78)*	(-0.65)	(2.97)**	(0.29)	(1.73)*
j=2, *k*=11	5.0423	0.2523	0.4402	0.2468	1.2556
	(1.72)*	(0.43)	(1.43)	(0.11)	(3.22)**
j=2, *k*=12	5.3121	0.4854	0.0448	1.6733	0.7954
	(1.66)*	(0.77)	(0.13)	(0.72)	(1.88)*

t-statistics are reported in parentheses. ** and * indicate significance at 5% and 10%, respectively. This table provides the result of the regression model $r_t^{TSM(j,k)} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t$. The portfolio formation period and tracking/holding period are denoted by j and k, respectively. This table provides results for j=2 and k=1, 2, 3, …, 12 trading strategies.

When formation period is extended to three months, there seems to be an even stronger presence of time-series momentum profits. There are significant momentum profits for the holding periods of six through 12 months. If table 2, 3 and 4 are juxtaposed, the presence of momentum profits for three-month formation period is very obvious since intercepts and *t*-values of coefficients in table 4 are larger in magnitude. This result suggests that with three months of observation traders can select momentum portfolios more effectively, which ultimately gives stronger profits during holding periods of longer lengths. Thus, a portfolio investor can devise appropriate trading strategies based on the past performance of stocks and earn significant momentum profits later on. For example, for a j=3, k=6 strategy an investor can buy previous winners stocks and sell (short) previous loser stocks and keep the portfolio for at least six months to make significant momentum profits.

Table 4. Time-Series Momentum at Different Monthly Lag Lengths (j=3, k=1, 2, …, 12)

Strategies	***Intercept***	***HML***	***SMB***	***UMD***	***MKT***
j=3, k=1	1.6858	-0.1049	0.0468	1.0241	-0.0760
	(2.39)**	(-0.74)	(0.62)	(1.93)*	(-0.80)
j=3, k=2	1.2051	-0.5645	0.1148	-1.3088	0.2419
	(1.11)	(-2.59)**	(1.00)	(-1.62)	(1.66)*
j=3, k=3	1.1979	-0.6461	0.3329	0.9083	0.4885
	(0.90)	(-2.42)**	(2.37)**	(0.92)	(2.74)**
j=3, k=4	2.5282	-0.0559	0.2178	2.4974	0.4140
	(1.59)	(-0.17)	(1.29)	(2.11)**	(1.93)*
j=3, k=5	2.9098	0.0827	-0.1855	3.0294	0.7067
	(1.61)	(0.23)	(-0.97)	(2.25)**	(2.91)**
j=3, k=6	4.2783	-0.3102	0.1038	2.5499	0.1907
	(2.13)**	(-0.77)	(0.49)	(1.71)*	(0.71)
j=3, k=7	5.8080	-0.1775	-0.1202	-1.0838	-0.1062
	(2.63)**	(-0.40)	(-0.52)	(-0.66)	(-0.36)
j=3, k=8	7.1637	0.5236	-0.0406	-1.5898	0.6050
	(3.04)**	(1.11)	(-0.16)	(-0.91)	(1.92)*
j=3, k=9	6.4070	-0.4526	0.7790	0.8275	0.7202
	(2.56)**	(-0.91)	(2.97)**	(0.45)	(2.16)**
j=3, k=10	5.9245	-0.2649	0.8047	-0.0034	1.1621
	(2.21)**	(-0.50)	(2.86)**	(-0.00)	(3.26)**
j=3, k=11	6.3509	0.9270	0.4270	3.2450	1.7520
	(2.24)**	(1.65)	(1.44)	(1.57)	(4.66)**
j=3, k=12	5.4600	-0.4326	0.0924	0.0968	0.8606
	(1.71)*	(-0.69)	(0.28)	(0.04)	(2.04)**

t-statistics are reported in parentheses. ** and * indicate significance at 5% and 10%, respectively. This table provides the result of the regression model $□_{□}^{□□□(□,□)} = □ + □_1□□□_□ + □_2□□□_□ + □_3□□□_□ + □_4□□□_□ + □_□$. The portfolio formation period and tracking/holding period are denoted by j and k, respectively. This table provides results for j=3 and k=1, 2, 3, …, 12 trading strategies.

4. 3. Presence of Cross-sectional Momentum Profits

Time-series momentum returns may be related to cross-sectional momentum returns. As a sharp contrast to the former, the latter momentum return is created from the cross-section of stock returns. Obviously, for the latter, portfolios are created from the performance of individual stocks during formation period. Table 5 exhibits the momentum/contrarian profits from the WRSS portfolios derived from 21 trading strategies. As discussed before, WRSS portfolios have zero weight and thus these portfolios should not make any significant profits. Any presence of profits for these portfolios is an indication of market inefficiency. For shorter holding periods, there are no momentum profits. But for holding periods beyond six months, there is evidence of highly significant negative momentum profits regardless of length of formation period. More precisely, significant negative momentum profits suggest the presence of cross-sectional contrarian profits in the Saudi stock market.

As far as trading is concerned, an active trader only needs to sell the winner stocks from the past one to three months and buy the loser stocks and hold the portfolio for six to 12 months. This strategy provides significant riskless contrarian profits – a major blow to the concept of market efficiency. Another important observation is the outcome of stronger profits from subsequent tracking or holding periods when longer formation period is used to construct portfolios. Hence, longer formation period provides better judgment to pick the stocks for the buy and sell portfolios. The importance of longer observation period has also been evident in the case of strategies for time-series momentum reported in table 4. Thus, it seems that longer-horizon observation of individual firms by investors is the key to make such abnormal returns.

Table 5. Cross-sectional Momentum at Different Monthly Lag Lengths

Strategies	***k* = 1**	***k*=2**	***k*=3**	***k*=4**	***k*=6**	***k*=9**	***k*=12**
j=1	-5.6983	-6.7785	-9.4590	-8.9206	-14.9342	-14.6295	-16.6889
	(-1.49)	(-1.61)	(-1.69)*	(-1.51)	(-2.11)**	(-2.55)**	(-2.81)**
j=2	-6.4331	-10.5603	-14.0624	-17.0137	-24.0141	-25.8995	-29.3362
	(-1.20)	(-1.32)	(-1.68)*	(-1.74)*	(-2.20)**	(-2.86)**	(-3.20)**
j=3	-8.4050	-14.6585	-19.5356	-22.9434	-30.1328	-36.1667	-40.5899
	(-1.32)	(-1.67)*	(-2.06)**	(-2.18)**	(-2.72)**	(-3.38)**	(-3.73)**
t-statistics are reported in parentheses. ** and * indicate significance at 5% and 10%, respectively.							

4. 4. Relationship between Time-Series and Cross-Sectional Momentum

Now, it is important to know if cross-sectional momentum profits can explain time-series momentum profits and vice versa. Table 6 presents the results of the models where time-series momentum and cross-sectional contrarian returns are used as dependent and independent variables, respectively. For short horizon formation and holding periods there is a significant presence of influence of cross-sectional momentum on time-series momentum returns. Since intercept terms are usually insignificant and coefficients for cross-sectional momentum are significant for j = 1 and 2 and k = 1, 2 and 3, the effect of cross-sectional momentum on time-series momentum is strong.

However, in the case of j = 2 and 3 and k = 6, 9 and 12, intercept terms are always highly significant while coefficients of cross-sectional momentum are insignificant, suggesting that as the length of holding period increases, the effect of cross-sectional momentum on time-series momentum gradually fades away. Thus, the relationship between time-series and cross-sectional momentum exists only for short and medium terms and probably there is no such relationship in the long term.

Table 6. Impact of Cross-sectional Momentum on Time-series Momentum

Strategies	***k* = 1**	***k*=2**	***k*=3**	***k*=4**	***k*=6**	***k*=9**	***k*=12**
Panel A: One-month Formation Period (j=1)							
Intercept (α)	1.4610	1.5039	1.8247	1.9959	0.7691	3.3860	2.5634
	(2.27)**	(1.46)	(1.40)	(1.29)	(0.38)	(1.30)	(0.80)
Coef. (β_1)	0.0698	0.0820	0.0721	0.0527	0.0175	0.0332	0.0419
	(5.72)**	(4.62)**	(4.25)**	(2.76)**	(0.85)	(1.00)	(1.06)
Panel B: Two-month Formation Period (j=2)							
Intercept (α)	0.7781	1.6158	2.4006	3.0773	3.4629	6.5286	5.8033
	(1.16)	(1.62)	(1.79)*	(1.95)*	(1.73)*	(2.51)**	(1.81)*
Coef. (β_1)	0.0381	0.0550	0.0286	0.0107	0.0109	0.0228	0.0198
	(4.17)**	(6.04)**	(2.44)**	(0.90)	(0.81)	(1.09)	(0.77)
Panel C: Three-month Formation Period (j=3)							
Intercept (α)	1.9211	2.2414	2.4745	3.1288	4.9286	7.2455	6.5099
	(2.81)**	(2.06)**	(1.80)*	(1.96)**	(2.45)**	(2.77)**	(2.04)**
Coef. (β_1)	0.0201	0.0135	0.0081	0.0111	0.0081	-0.0110	0.0040
	(2.56)**	(1.49)	(0.77)	(1.00)	(0.61)	(-0.62)	(0.19)
t-statistics are reported in parentheses. ** and * indicate significance at 5% and 10%, respectively. This table provides the result of the regression model $□_{□}^{□□□(□,□)} = □ + □_{1}□_{□}^{□□(□,□)} + □_{□}$. The formation period and tracking period are denoted by *j* and *k*, respectively. *j*=1, 2, or 3 and *k*=1, 2, 3, 4, 6, 9 or 12 provide (3x7=) 21 possible trading strategies.							

Table 7 provides the results of the regression models that capture if time-series momentum profits can explain cross-sectional contrarian profits. This table shows that time-series momentum can explain cross-sectional contrarian profits for relatively short holding period. However, as the holding period increases, the influence of time-series momentum decreases. For example, in the case of *k*=6 or more, the intercept terms are always significantly negative and the coefficients for time-series momentum are always insignificant, which indicates that cross-sectional contrarian profits are only explained by itself and not by time-series momentum.

Table 7. Impact of Time-series Momentum on Cross-sectional Momentum

Strategies	***k*= 1**	***k*=2**	***k*=3**	***k*=4**	***k*=6**	***k*=9**	***k*=12**
Panel A: One-month Formation Period (j=1)							
Intercept	-7.9700	-7.9674	-10.8694	-10.0699	-15.0484	-15.1153	-16.9730
(α)	(-2.24)**	(-1.98)**	(-2.03)**	(-1.72)*	(-2.12)**	(-2.62)**	(-5.75)**
Coef. (β_1)	2.1364	1.2543	1.2348	0.7534	0.2248	0.1675	0.1524
	(5.72)**	(4.62)**	(4.28)**	(2.76)**	(0.85)	(1.00)	(1.06)
Panel B: Two-month Formation Period (j=2)							
Intercept	-7.6284	-13.6605	-16.2522	-18.2198	-25.0844	-27.5812	-30.2334
(α)	(-1.48)	(-1.86)*	(-1.96)**	(-1.84)*	(-2.28)**	(-3.00)**	(-3.26)**
Coef. (β_1)	2.2419	2.9962	1.0954	0.4165	0.3343	0.2887	0.1718
	(4.17)**	(6.04)**	(2.44)**	(0.90)	(-0.81)	(1.09)	(0.77)
Panel C: Three-month Formation Period (j=3)							
Intercept	-11.3855	-16.4632	-20.4512	-24.3596	-31.3399	-34.6495	-40.9066
(α)	(-1.79)*	(-1.87)*	(-2.14)**	(-2.30)**	(-2.78)**	(-3.15)**	(-3.71)**
Coef. (β_1)	1.7011	0.88	0.3953	0.4925	0.2577	-0.1984	0.0491
	(2.56)**	(1.49)	(0.77)	(1.00)	(0.61)	(-0.62)	(0.19)

t-statistics are reported in parentheses. ** and * indicate significance at 5% and 10%, respectively. This table provides the result of the regression model $\square_{\square}^{\square\square(\square,\square)} = \square + \square_1 \square_{\square}^{\square\square\square(\square,\square)} + \square_{\square}$. The formation period and tracking period are denoted by *j* and *k*, respectively. *j*=1, 2, or 3 and *k*=1, 2, 3, 4, 6, 9 or 12 provide (3x7=) 21 possible trading strategies.

The strong presence of cross-sectional momentum profits needs further examination. Specially, can such profit opportunities exist if Fama-French risk factors are introduced in the model? In order to save space, I report only the intercept terms, *t*-statistic and R^2 for every regression. The presence of cross-sectional momentum profits has already been reported and discussed above. For one-month formation period and every holding period (except four-month holding period), results in table 8 show that profits are still present even after Fama-French factors are considered. However, from table 5 it is already known that cross-sectional contrarian profits for short investment horizons are insignificant and hence statistically significant intercept terms in table 8 only indicate that such profits are only explained by itself but not by other risk factors and time-series momentum.

Panel C of table 8, in this regard, gives an indication of the presence of strong cross-sectional contrarian profits. In shorter holding periods R^2 is very high, but as the investment horizon gets longer, it decreases simply because market risk factors and time-series momentum lose power to explain cross-sectional contrarian profits. As usual, for a trader the best option will be to observe the performance of stocks for three months to construct a portfolio and then keep it for anywhere between six to 12 months, depending on his preference for investment horizon.

Table 8. Cross-sectional Momentum after Time-series Momentum and Fama-French Factors are Considered

Strategies	***k*=1**	***k*=2**	***k*=3**	***k*=4**	***k*=6**	***k*=9**	***k*=12**
Panel A: One-month Formation Period (j=1)							
Intercept	-7.3599	-8.2635	-9.5129	-8.6802	-14.8823	-15.5183	-17.0291
	(-2.11)**	(-2.27)**	(-1.87)*	(-1.46)	(-2.04)*	(-2.63)**	(-2.78)**
R^2	0.25	0.31	0.23	0.07	0.02	0.02	0.02
Panel B: Two-month Formation Period (j=2)							
Intercept	-6.4586	-11.2167	-14.8878	-14.4594	-25.1939	-26.1883	-29.2804
	(-1.54)	(-1.73)*	(-1.82)*	(-1.46)	(-2.22)**	(-2.78)**	(-3.09)**
R^2	0.44	0.39	0.12	0.07	0.01	0.02	0.03
Panel C: Three-month Formation Period (j=3)							
Intercept	-8.0498	-18.1258	-18.3821	-20.4467	-31.1085	-34.8248	-38.1845
	(-1.82)*	(-2.21)**	(-1.95)*	(-1.95)*	(-2.68)**	(-3.09)**	(-3.39)**
R^2	0.57	0.20	0.09	0.09	0.01	0.01	0.03

t-statistics are reported in parentheses. ** and * indicate significance at 5% and 10%, respectively. This table provides the result of the regression model $□_{□}^{□□(□,□)} = □ + □_1□□□_{□} + □_2□□□_{□} + □_3□□□_{□} + □_4□□□_{□} + □_5□□□_{□} + □_{□}$. The formation period and holding period are denoted by *j* and *k*, respectively. *j*=1, 2, or 3 and *k*=1, 2, 3, 4, 6, 9 or 12 provide (3x7=) 21 possible trading strategies.

5. Conclusion

This paper investigates the presence of cross-sectional and time-series momentum profits in the Saudi stock market and the relationship between these two types of momentum strategies. Results show a very strong presence of cross-sectional contrarian profits in this market. There is also some evidence of time-series momentum profits in the relatively longer investment horizon. The presence of cross-sectional contrarian profits is stronger than that of time-series momentum profits. The relationship between these two types of momentum exists for short period of time. Finally, it seems that a formation period of three months gives the best opportunity to a trader to construct a zero-cost portfolio so that significant contrarian profits can be made by holding it for the desired investment horizon.

It is not a surprising finding since the Saudi market is dominated by uninformed individual investors and in a recent paper Rahman *et al.* (2015) report that these retail investors are the main players for creating herding phenomenon for the overall market. Both contrarian profits and herding are related to systematic behavior of investors and thus the possibility of contrarian profits in the Saudi stock market cannot be ignored. This market opened to large foreign investors in June 2015. Since this market is relatively unknown to the potential foreign investors, the findings of this paper may help them to know more about this market.

References

[1] Al-Muhairi, M. (2011), Assessing momentum investment strategies in the U.A.E. stock markets, PhD Thesis, University of Portsmouth.

[2] Alsubaie, A. and Najand, M. (2009), “Trading volume, price momentum, and the 52-week high price momentum strategy in the Saudi stock market”, *International Journal of Finance*, Vol. 21 No. 1, pp. 5070-5096.

[3] Asness, C., Moskowitz, T. J. and Pederson, L. H. (2013), “Value and momentum everywhere”, *Journal of Finance*, Vol. 68 No. 3, pp. 929-985.

[4] Avramov, D., Chordia, T., Jostova, G. and Philipov, A. (2007), “Momentum and credit rating”, *Journal of Finance*, Vol. 62 No. 5, pp. 2503-2520.

[5] Balakrishnan, A. (2012), “Contrarian and momentum strategies: Further evidence for Indian stock market”, *International Journal of Economics and Management Science*, Vol. 2 No. 1, pp. 116-121.

[6] Bernard, M. S. and Deo, M. (2015), "Price momentum strategies: Evidences from Indian equity market", *IUP Journal of Applied Finance*, Vol. 21 No. 1, pp. 5-21.

[7] Boudoukh, J., Richardson, M. P. and Whitelaw R. F. (1994), "A tale of three schools: Insights of autocorrelations of short-horizon stock returns", *Review of Financial Studies*, Vol. 7 No. 3, pp. 539-573.

[8] Cakici, N., Fabozzi, F. J. and Tan, S. (2013), "Size, value, and momentum in emerging stock returns", *Emerging Markets Review*, Vol. 16, pp. 46-65.

[9] Chopra, N., Lakonishok, J. and Ritter J. (1992), "Measuring abnormal performance: Do stocks overreact?" *Journal of Financial Economics*, Vol. 31 No. 2, pp. 235-268.

[10] Chowdhury, S. S. H. (2010), "Sources of momentum and contrarian profits in the Indian stock market", PhD Dissertation, Middle Tennessee State University, USA.

[11] Chui, A. C. W., Titman, S. and Wei, K. C. J. (2010), "Individualism and momentum around the world", *Journal of Finance*, Vol. 65 No. 1, pp. 361-392.

[12] Conrad, J. and Kaul, G. (1998), "An anatomy of trading strategies", *Review of Financial Studies*, Vol. 11 No. 3, pp. 489-519.

[13] Conrad, J., Gultekin, M. and Kaul, G. (1997), "Profitability of short-term contrarian strategies: Implications for market efficiency", *Journal of Business and Economic Statistics*, Vol. 15, pp. 386-397.

[14] Cooper, M., Gutierrez, R. and Hameed, A. (2004), "Market states and momentum", *Journal of Finance*, Vol. 59 No. 3, pp. 1345-1365.

[15] Daniel, K., Hirshleifer, D. and Subrahmanyam, A. (1998), "Investor psychology and security market under- and over-reactions", *Journal of Finance*, Vol. 58 No. 6, pp. 2515-2547.

[16] DeBondt, W. and Thaler, R. (1985), "Does the stock market overreact?" *Journal of Finance*, Vol. 40 No. 3, pp. 793-805.

[17] DeBondt, W. and Thaler, R. (1987), "Further evidence on investor overreaction and stock market seasonality", *Journal of Finance*, Vol. 42 No. 3, pp. 557-581.

[18] De Groot, W., Pang J. and Swinkels, L. (2010), "Value and momentum in frontier emerging markets", Working Paper, Rebeco Asset Management.

[19] Ding, D. K., McInish, T. H. and Wongchoti, U. (2008), "Behavioral explanations of trading volume and short-horizon price patterns: An investigation of seven Asia-Pacific markets", *Pacific-Basin Finance Journal*, Vol. 16 No. 3, pp. 183-203.

[20] Ding, D., Huang, Z. and Liao, B. (2009), "Why there is no momentum in the Taiwan stock market", *Journal of Economics and Business*, Vol. 61 No. 2, pp. 140-152.

[21] Fama, E. F. and French, K. R. (2012), "Size, value, and momentum in international stock returns", *Journal of Financial Economics*, Vol. 105 No. 3, pp. 457-472.

[22] French, K. R. (1980), "Stock returns and the weekend effect", *Journal of Financial Economics*, Vol. 8 No. 1, pp. 55-69.

[23] Galariotis, E. C. (2004), "Sources of contrarian profits and return predictability in emerging markets", *Applied Financial Economics*, Vol. 14 No. 14, pp. 1027-1034.

[24] George, T. J. and Hwang, C. (2004), "The 52-week high and momentum investing", *Journal of Finance*, Vol. 59 No. 5, pp. 2145-2176.

[25] Gharaibeh, O. (2015), "Short-term contrarian profits in the Kuwait stock market", *International Journal of Business and Management*, Vol. 10 No. 1, pp. 92-103.

[26] Griffin, J. M., Ji, X. and Martin, S. (2003), "Momentum investing and business cycle risk: Evidence from pole to pole", *Journal of Finance*, Vol. 58 No. 6, pp. 2515-2547.

[27] Hameed, A. and Ting, S. (2000), "Trading volume and short-horizon contrarian profits: Evidence from Malaysian stock market", *Pacific-Basin Finance Journal*, Vol. 8 No. 1, pp. 67-84.

[28] Hong, H. and Stein, J. (1999), "A unified theory of underreaction, momentum trading, and overreaction in asset markets", *Journal of Finance*, Vol. 54 No. 6, pp. 2143-2184.

[29] Hong, H., Lim, T. and Stein, J. (2000), "Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies", *Journal of Finance*, Vol. 55 No. 1, pp. 265-295.

[30] Huang, D. (2006), "Market states and international momentum strategies", *Quarterly Review of Economics and Finance*, Vol. 46 No. 3, pp. 437-446.

[31] Jegadeesh, N. (1990), "Evidence of predictable behavior of security returns", *Journal of Finance*, Vol. 45 No. 3, pp. 881-898.

[32] Jegadeesh, N. and Titman, S. (1993), "Returns to buying winners and selling losers: Implications for stock market efficiency", *Journal of Finance*, Vol. 48 No. 1, pp. 65-91.

[33] Jegadeesh, N. and Titman, S. (1995), "Overreaction, delayed reaction, and contrarian profits", *Review of Financial Studies*, Vol. 8 No. 4, pp. 973-993.

[34] Jegadeesh, N. and Titman, S. (2001), "Profitability of momentum strategies: An evaluation of alternative explanations", *Journal of Finance*, Vol. 56 No. 2, pp. 699-720.

[35] Jones, S. L. (1993), "Another look at time-varying risk and return in a long-horizon contrarian strategy", *Journal of Financial Economics*, Vol. 33 No. 1, pp. 119-144.

[36] Kang, J., Liu, M. and Ni, S. X. (2002), "Contrarian and momentum strategies in the China stock market: 1993-2000", *Pacific-Basin Finance Journal*, Vol. 10 No. 3, pp. 243-265.

[37] Keim, D. (1983), "Size-related anomalies and stock return seasonality: Further empirical evidence", *Journal of Financial Economics*, Vol. 12 No. 1, pp. 13-32.

[38] Lee, C. M. C. and Swaminathan, B. (2000), "Price momentum and trading volume", *Journal of Finance*, Vol. 55 No. 5, pp. 2017-2069.

[39] Lehmann, B. (1990), "Fads, martingales, and market efficiency", *Quarterly Journal of Economics*, Vol. 105 No. 1, pp. 1-28.

[40] Li, B., Qiu, J. and Wu, Y. (2010), "Momentum and seasonality in Chinese stock markets", *Journal of Money*, *Investment and Banking*, Vol. 17 No. 5, pp. 24-36.

[41] Liu, L. X. and Zhang, L. (2008). "Momentum profits, factor pricing, and macroeconomic risk", *Review of Financial Studies*, Vo. 21 No. 6, pp. 2417-2448.

[42] Lo, A. and MacKinlay, C. (1988), "Stock market prices do not follow random walks: Evidence from a simple specification test", *Review of Financial Studies*, Vol. 1 No. 1, pp. 41-66.

[43] Lo, A. and MacKinlay, C. (1990), "When are contrarian profits due to stock market overreaction?" *Review of Financial Studies*, Vol. 3 No. 2, pp. 175-205.

[44] Locke, S. and Gupta, K. (2009), "Applicability of contrarian strategy in the Bombay Stock Exchange", *Journal of Emerging Market Finance*, Vol. 8 No. 2, pp. 165-189.

[45] McInish, T. H., Ding, D. K., Pyun, C. S. and Wongchoti, U. (2008), "Short-horizon contrarian and momentum strategies in Asian markets: An integrated analysis", *International Review of Financial Analysis*, Vol. 17 No. 2, pp. 312-329.

[46] Morck, R, Yeung, B. and Yu, W. (2000), "The information content of stock markets: Why do emerging markets have synchronous price movements?" *Journal of Financial Economics*, Vol. 58 No. 1, pp. 215-260.

[47] Moskowitz, T. J. and Grinblatt, M. (1999), "Do industries explain momentum?" *Journal of Finance*, Vol. 54 No. 4, pp. 1249-1290.

[48] Moskowitz, T. J., Ooi, Y. H. and Pedersen, L. H. (2012). "Time series momentum", *Journal of Financial Economics*, Vol. 104 No. 2, pp. 228-250.

[49] Naranjo, A. and Porter, B. (2007), "Including emerging markets in international momentum investment strategies", *Emerging Markets Review*, Vol. 8 No. 2, pp. 147-166.

[50] Novy-Marx, R. (2012), "Is momentum really momentum?" *Journal of Financial Economics*, Vol. 103 No. 3, pp. 429-453.

[51] Rahman, M. A., Chowdhury, S. S. H. and Sadique, M. S. (2015), "Herding where retail investors dominate trading", *Quarterly Review of Economics and Finance*, Vol. 57 No. 3, pp. 46-60.

[52] Rouwenhorst, K. G. (1999), “Local return factors and turnover in emerging stock markets”, *Journal of Finance*, Vol. 54 No. 4, pp. 1439-1464.
[53] Sagi, J. S. and Seasholes, M. S. (2007), “Firm-specific attributes and the cross-section of momentum”, *Journal of Financial Economics*, Vol. 84 No. 2, pp. 389-434.
[54] Shegal, S. and Balakrishnan, I. (2002), “Contrarian and momentum strategies in the Indian capital market”, *Vikalpa*, Vol. 27 No. 27, pp. 13-15.
[55] Shegal, S. and Jain, S. (2011), “Short-term momentum patterns in stock and sectoral returns: Evidence from India”, *Journal of Advances in Management research*, Vol. 8 No. 1, pp. 99-122.
[56] Wongchoti, U. and Pyun, C. S. (2005), “Risk-adjusted long-term contrarian profits: Evidence from non S&P500 high volume stocks”, *Financial Review*, Vol. 40 No. 3, pp. 335-359.
[57] Xu, R. and Qiu, K. (2012), “Contrarian investment strategies – evidence in China stock market 2002-11”, Master’s Thesis, BI Norwegian Business School.