Journal of Business Studies Quarterly
2014, Volume 5, Number 3 ISSN 2152-1034

Journal of Business Studies Quarterly jbsq.org

The Momentum Strategies: A New Criterion of Classification

Mohamed Sahbi NAKHLI, LaREMFiQ, University of Kairouan, Tunisia
Lotfi BELKACEM, LaREMFiQ, University of Sousse, Tunisia

Abstract
The objective of this study is to test the performance of the momentum strategies and to develop a new criterion of classification based on the mean-conditional value at risk framework. According to the methodology of Jegadeesh and Titman (1993), we find that the momentum strategies are profitable in the French stock exchange market. By introducing a new criterion of classification which is entitled Bootstrapped mean-CVaR, we show that, on the return-risk framework, this criterion is more advantageous than those of Jegadeesh and Titman and the Sharpe ratio.

Keywords: Momentum strategies, conditional value at risk, bootstrap.

JEL Classification: G12; C15

1. Introduction

Several studies document the existence of a momentum effect in the stock returns. For instance, in the U.S. stock market, Jegadeesh and Titman (1993) show that strategies that buy stocks with high returns and sell stocks with poor returns over a horizon of three to twelve months earn significant abnormal returns over the same horizon. Similar evidence has been detected by Rouwenhorst (1998) who finds that momentum strategies are profitable in 12 European markets.

Consistent with behavioural finance theory, the momentum phenomenon attracts the attention of several authors because it challenges the market efficiency hypothesis. Barberis *et al.* (1998), Daniel *et al.* (1998) and Hong and Stein (1999) develop models to study this effect. They find that behavioural biases lead investors to underreact to new information or to follow positive feedback strategies that lead to a delayed reaction to news. Berk (1997) reports that the stocks which have low-market capitalization may earn high momentum returns. Chan *et al.* (1996) argue that the stock price momentum and the earnings surprise are positively related. Pástor and Stambaugh (2003) and Sadka (2006) show that liquidity risk factors are positively related to momentum in U.S. individual stocks. Avramov *et al.* (2007) find that momentum profits are higher among stocks with low credit ratings. Jiang *et al.* (2005) and Zhang (2006) show that momentum returns are greater for high return volatility stocks. Chordia and Shivakumar (2002) find that momentum profits are related to lagged macroeconomic factors.

In addition, many studies employ bootstrap1 methods for momentum strategies. Using bootstrap method with replacement in order to eliminate the time-series relations that may be present in the real data, Conrad and Kaul (1998) suggest that only the cross-sectional difference in expected returns has the potential to explain the profits of momentum strategies. In a subsequent study, Jegadeesh and Titman (2002) show that the bootstrap method with replacement of stock returns creates a small sample bias. To eliminate the existence of this bias, Jegadeesh and Titman use a bootstrap method without replacement. The application of this method shows that the cross-sectional variation in expected returns contributes very little to momentum profit. To ensure the random effect of the draws, Nakhli and Belkacem (2013) develop a new resampling procedure called the mixed bootstrap method. The empirical results show the existence of a small sample bias in the bootstrap method with replacement, and that the time-series relations of stock returns are the main source of momentum profits. To avoid the problem of data-snooping, Ericsson and González (2003) use the bootstrap method to examine the performance of the momentum strategies. Overall, they find strong evidence of a momentum effect. While splitting the sample in two parts, they show that the market has become more efficient. Using a new estimation-based bootstrap simulation procedure, Karolyi and Kho (2004) examine whether a number returns-generating models that allow for time-varying expected returns can explain the momentum returns.

The classification of stocks plays an important role in the construction of momentum portfolios. Although several studies use past performance of stocks as a selection criteria, Rachev et al. (2007) analyze momentum strategies that are based on reward-risk stock selection criteria. A usual choice of reward-risk criterion is the ordinary Sharpe ratio related to the static mean-variance framework. The mean-variance model is applied if stock returns follow the normal distribution or the utility function is quadratic. However, empirical evidence rejects the assumption that stock returns are normally distributed. This assumption lead Rachev *et al*. (2007) to introduce a classification criterion using the conditional value at risk as a measure of risk.

While the conditional value at risk has the advantage to determine the average loss that occurs when portfolio loss exceeds a given confidence level, the principal limit of this method is that the conditional value at risk is primarily limited by the sample size. During the ranking period of the momentum portfolios, we use monthly data for a period of one year at most. To increase the sample size during this period, we introduce the bootstrap method. Hence, we introduce a new criterion of classification of the individual returns during the ranking period of momentum portfolios. This criterion is a combination between the conditional value at risk and the bootstrap method. For this reason, we call this criterion of classification: ***"bootstrapped Mean-CVaR"***. The application of this criterion of classification allowed us to conclude that, on the mean-risk framework, the momentum strategy which is based on this criterion is more advantageous than those of Jegadeesh and Titman (1993) and the Sharpe ratio.

The rest of this paper is organized as follows: The second section discusses the data and the methodology. In the third section, we examine the performance of the momentum strategies. The fourth section exposes the momentum strategies based on the Sharpe ratio. The fifth section introduces a new criterion of classification which is entitled *Bootstrapped mean-CVaR*. And finally, in the sixth section, we compare the three criteria of classification.

[1] The bootstrap is a resampling procedure introduced by Efron (1979).

2. Data and Methodology

In this study, we consider monthly returns of all stocks listed on the French stock exchange market and available in DATASTREAM international from January 1995 to December 2010. As in Jegadeesh and Titman (2001), we exclude stocks that, at the beginning of the holding period, have market capitalization that would place them in the bottom decile[2]. In addition, the stocks are excluded if they have fewer than 24 monthly returns available[3]. Therefore, our sample includes a total of 305 stocks.

To analyse the profitability of momentum strategies, we refer to the methodology used by Jegadeesh and Titman (1993). At the beginning of each month, all stocks are ranked in ascending order based on their past J months returns (where J = 3, 6, 9 and 12). Based on this ranking, five equal-weighted quintile portfolios are formed: The quintile portfolio with the highest stock returns is the winner portfolio, whereas the quintile portfolio with the lowest returns is the loser portfolio. In each overlapping period, the strategy buys the winner portfolio and sells the loser portfolio. Finally, we hold this position for the next K months (where K = 3, 6, 9 and 12). This gives us 16 combinations of J and K months, therefore, 16 momentum strategies.

3. Performance of the momentum strategies

Table 1 presents the average monthly profits of the 16 momentum investment strategies according to the methodology of Jegadeesh and Titman (1993) and the Student test of these profits. The first observation that can be drawn from this table is that momentum strategies generate significant positive returns except for the 3-month/3-month strategy where the winner-loser portfolio yields a negative but insignificant (t-statistic is -0.86) return of -0.0041. Note also that the momentum profit increases with the length of the holding period. For instance, for a 6-month ranking period, the momentum profit for a 3-month holding period is 0.0098 while it is 0.0847 for a 12-month holding period. Comparing the 16 momentum strategies, we find that the 12-month/12-month strategy is the most profitable (the profit of this strategy is 0.0889). In general, we conclude that, the momentum strategies are profitable in the French stock exchange.

4. Momentum strategies based on the Sharpe ratio

In the preceding paragraph, we use the methodology of Jegadeesh and Titman (1993) which allows to classify the stocks according to their individual performance. Otherwise, this criterion of classification does not take into account the risk of these stocks during the formation period of momentum portfolios. Therefore, we take into account the risk of the stocks by classifying them according to their mean-variance framework by using the Sharpe ratio.

[2] This is to ensure that the results are not driven by microstructure biases associated with extremely small stocks.
[3] We follow Karolyi and Kho (2004).

Table 1: Performance of the strategies momentum

At the beginning of each month, all stocks are ranked in ascending order based on their past J months returns (where J = 3, 6, 9 and 12). Based on this ranking, five equal-weighted quintile portfolios are formed: The quintile portfolio with the highest stock returns is the winner portfolio, whereas the quintile portfolio with the lowest returns is the loser portfolio. In each overlapping period, the strategy buys the winner portfolio and sells the loser portfolio. Finally, we hold this position for the next K months (where K = 3, 6, 9 and 12). We use The T-statistics to test the significance of the average of momentum returns.

	Holding periods											
	3 months			6 months			9 months			12 months		
	Loser	Winner	Momentum	Loser	Winner	Momentum	Loser	Winner	Momentum	Loser	Winner	Momentum
Ranking period of 3 months												
Average	0.0361	0.0320	-0.0041	0.0554	0.0729	0.0175**	0.0828	0.1156	0.0328***	0.1061	0.1677	0.0616***
T-stat			-0.8642			2.5694			4.0220			6.2821
Ranking period of 6 months												
Average	0.0283	0.0381	0.0098*	0.0536	0.0852	0.0317***	0.0739	0.1368	0.0629***	0.0989	0.1837	0.0847***
T-stat			1.8650			4.7337			7.5868			8.0421
Ranking period of 9 months												
Average	0.0298	0.0420	0.0123**	0.0482	0.0962	0.0480***	0.0722	0.1437	0.0714***	0.1009	0.1879	0.0870***
T-stat			2.3155			6.3715			7.4363			7.5805
Ranking period of 12 months												
Average	0.0251	0.0478	0.0227***	0.0438	0.0981	0.0544***	0.0678	0.1430	0.0752***	0.0972	0.1861	0.0889***
T-stat			4.1295			7.0597			7.5810			7.6987

* Significant at the 10 percent significance level.
** Significant at the 5 percent significance level.
*** Significant at the 1 percent significance level.

The Sharpe ratio is an indicator that allows the investors to compare the performance of the stocks; it is a measure of the excess return per unit of risk. The Sharpe ratio is presented by this equation:

$$S_i = \frac{(R_i - Rf)}{\sigma_i} \qquad (1)$$

For this reason, we follow this methodology:

i. At the date t, we calculate, for each stock, the Sharpe ratio based on past J months returns,

ii. The stocks are ranked in ascending order based on the Sharpe ratio,

iii. Using the methodology of Jegadeesh and Titman (1993), we calculate the momentum profits.

Table 2 presents the average monthly returns and the standard deviations of the loser, winner and momentum portfolios, as well as the t-statistics of the 16 momentum strategies' profits.

The first remark that we can draw from this table is that the momentum profit is significantly positive for the majority of the momentum strategies (15 among 16 strategies momentum generate significant positive returns) except for the 3-month/3-month strategy that earns a significant negative return which is about -0.0066.

By comparing the results found in table 1 and those in table 2, we note that for the 16 investment strategies, the momentum profits according to the methodology of Jegadeesh and Titman (1993) are higher than those find according to the methodology based on the Sharpe ratio (For example, for the 6-month/6-month strategy, $\prod_{\text{J\&T}} = 0.0317$ > $\prod_{\text{Sharpe}} = 0.0290$). Consequently, by taking into account return–risk stock selection criteria, the profits of the momentum strategies decrease.

Based on the risk of the momentum portfolios, we notice that the volatility of the momentum returns decrease when we take into account the risk in the classification of the stocks during the formation period. For example, for the 9-month/6-month strategy, we find: $\sigma_{\text{Sharpe}} = 0.0712$ < $\sigma_{\text{J\&T}} = 0.01004$. Therefore, the methodology of Jegadeesh and Titman provides momentum return riskier than the methodology based on the Sharpe ratio.

Although the criterion of classification which is based on the Sharpe ratio generates less low momentum return, it allows decreasing the risk of the momentum portfolio. Consequently, each investor chooses the classification criterion which is adapted with his attitude toward risk.

Table 2: The strategies momentum based on the Sharpe ratio

At the date t, the stocks are ranked in ascending order based on the Sharpe ratio. Then, we use the methodology of Jegadeesh and Titman (1993), to calculate the momentum profits. This table presents the average monthly returns and the standard deviations of the loser, winner and momentum portfolios, as well as the t-statistics of the 16 momentum strategies' profits.

	Holding Periods											
	3 months			6 months			9 months			12 months		
	Loser	Winner	Momentum	Loser	Winner	Momentum	Loser	Winner	Momentum	Loser	Winner	Momentum
Ranking period of 3 months												
Average	0.0379	0.0313	-0.0066**	0.0607	0.0718	0.0111**	0.0906	0.1155	0.0249***	0.1191	0.1643	0.0452***
T-stat			-2.0530			2.4838			4.4488			8.0050
Standard deviation	0.0814	0.0716	0.0440	0.1129	0.1098	0.0606	0.1305	0.1301	0.0753	0.1475	0.1464	0.0872
Ranking period of 6 months												
Average	0.0296	0.0372	0.0076*	0.0542	0.0832	0.0290***	0.0821	0.1361	0.0540***	0.1066	0.1789	0.0723***
T-stat			1.9466			5.6081			8.4314			9.3437
Standard deviation	0.0857	0.0740	0.0530	0.1169	0.1101	0.0696	0.1304	0.1300	0.0854	0.1520	0.1493	0.1024
Ranking period of 9 months												
Average	0.0310	0.0426	0.0116***	0.0530	0.0951	0.0421***	0.0810	0.1404	0.0594***	0.1039	0.1815	0.0776***
T-stat			3.0091			7.8924			8.6237			9.3689
Standard deviation	0.0846	0.0704	0.0532	0.1140	0.1037	0.0712	0.1296	0.1250	0.0911	0.1497	0.1453	0.1086
Ranking period of 12 months												
Average	0.0270	0.0484	0.0214***	0.0498	0.0965	0.0467***	0.0766	0.1418	0.0652***	0.1061	0.1862	0.0801***
T-stat			4.9691			7.8983			8.5441			9.0584
Standard deviation	0.0857	0.0697	0.0588	0.1170	0.1038	0.0786	0.1349	0.1262	0.1001	0.1499	0.1525	0.1150

* Significant at the 10 percent significance level.
** Significant at the 5 percent significance level.
*** Significant at the 1 percent significance level

5. New criterion of classification: *Bootstrapped mean-CVaR*

In the first part of this paper, we use the Sharpe ratio as a classification criterion of the stocks during the ranking period (this ratio takes into account the return-variance framework). The starting point of our analysis is the model of Markowitz (1952). According to this model, any investor pursues two conflict goals: the maximization of the expected return and the minimization of the risk, measured by the variance of the stocks. However, the application of the mean-variance optimization is not always valid. Indeed this optimization is valid only if the returns follow a normal distribution or if investor has a quadratic utility function. Therefore, the variance is not an adequate measure of the risk. Consequently, we introduce a criterion of classification based on the value at risk (VaR) to solve the fundamental problems in the use of mean-variance optimization. The value at risk gives only the worst expected loss at a given confidence level, but it is more interesting, in certain cases, to know the magnitude of losses in the tail region of the loss distribution. The conditional value at risk (CVaR) has the advantage to determine the average loss that occurs when portfolio loss exceeds a given confidence level. For this reason, we introduce a criterion of classification based on the mean-CVaR framework. However, the principal limit of this method is that the CVaR is primarily limited by the sample size; we need a larger sample compared to the VaR for the same degree of precision.

The problem which arises for this level: During the formation period of the momentum portfolios, we use monthly data for a period of one year at most (12 observations for each stock). To solve this problem, we introduce the bootstrap method to increase the sample size and consequently, we will be able to use the CVaR to classify the individual stocks' returns. Therefore, we introduce a new criterion of classification of the individual returns during the formation period of momentum portfolios. This criterion is a combination between CVaR and the bootstrap simulation procedure. For this reason, we call this criterion of classification: ***"bootstrapped Mean-CVaR"***.

5.1 Methodology *(bootstrapped Mean-CVaR)*

The algorithm of the criterion of classification ***"bootstrapped Mean-CVaR"*** for J-month/K-month strategy is as follows:

i. At the date t, and from the time series returns of each stock during the classification period $[t-J+1,t]$ (composed of J returns), we randomly draw with replacement a new sample that have the same size as the original sample (J observations),

ii. We replicate this method 1000 times; for each stock, we obtain 1000 bootstrap samples that have the same size as the original sample,

iii. We calculate for each stock, the average return of each bootstrap sample: 1000 averages,

iv. Based on the sample of the 1000 averages, we determine for each stock, during the classification period $[t-J+1,t]$, the bootstrapped CVaR following this method :

$$CVaRb(\alpha)_{i,[t-J+1,t]} = -E\left(R_{i,[t-J+1,t]} / R_{i,[t-J+1,t]} \leq q^{(\alpha)}_{i,[t-J+1,t]}\right) \qquad (2)$$

With: $R_{i,[t-J+1,t]}$ is the return of the stock i during the classification period $[t-J+1,t]$,

$q_{i,[t-J+1,t]}^{(\alpha)}$ is the quantile of order α of the series of 1000 simulated returns of the stock i during the classification period $[t-J+1,t]$,

v. We calculate, for each stock, the ratio between the mean of the returns and the bootstrapped CVaR as follow :

$$Mean-CVaRb(\alpha)_{i,[t-J+1,t]} = \frac{E\left(R_{i,[t-J+1,t]}\right)}{CVaRb(\alpha)_{i,[t-J+1,t]}} \tag{3}$$

With: $E\left(R_{i,[t-J+1,t]}\right)$ is the average return of the stock i during the classification period $[t-J+1,t]$,

vi. We use this criterion of classification for constructing the momentum portfolios and we calculate the momentum return according to the methodology presented in the second section of the paper.

5.2 Empirical results

Table 3 presents the average monthly returns of the winners, losers, and momentum portfolios based on the criterion of classification bootstrapped Mean-CVaR, as well as the t-statistics of the 16 momentum strategies.

The first remark that we can draw from this table is that the momentum strategies, according to the criterion of classification bootstrapped Mean-CVaR, are significantly profitable (for example, the momentum profit of 6-month/9-month strategy is about 0.0564 which is significant with a probability of error of 1%.) except for 3-month/3-month strategy which generates an insignificant negative return of -0.0056.

By comparing the results in this table and those in table 1, we note that the momentum strategies which are based on the methodology of Jegadeesh and Titman generate a profit higher than those based on the criterion of classification bootstrapped Mean-CVaR. For example, for 9-month/9-month strategy, $\Pi_{\text{J\&T}} = 0.0714 > \Pi_{\text{M-CVaRb}} = 0.0601$. Consequently, the taking into account of risk by using the bootstrapped CVaR as a measure of risk provides a decrease in momentum profit.

By comparing the results in table 2 and those in table 3, we find that the momentum strategies which are based on the criterion of classification bootstrapped Mean-CVaR are more profitable than those based on the Sharpe ratio. For example, for 3-month/9-month strategy, $\Pi_{\text{M-CVaRb}} = 0.0284 > \Pi_{\text{Sharpe}} = 0.0249$. According to our analysis, the difference between these two profits is explained by:

- The variance is not an adequate risk measure, because it supposes that the returns can be approximated by a normal random variable or if the utility function of the investor is quadratic. While, CVaR is a risk measure of stocks that have asymmetric return distributions.
- Using the bootstrap method, we can increase the sample size of the returns during the classification period, which allows to increase the precision level of the CVaR.

Table 3 : The strategies momentum based on the criterion of classification "*Bootstrapped mean-CVaR*"

In this table, we use the criterion of classification *Bootstrapped mean-CVaR* for constructing the momentum portfolios. This table reports the average monthly returns of the winners, losers, and momentum portfolios based on the criterion of classification bootstrapped Mean-CVaR, as well as the t-statistics of the 16 momentum strategies.

	Holding Periods											
	3 months			6 months			9 months			12 months		
	Loser	**Winner**	**Momentum**	**Loser**	**Winner**	**Momentum**	**Loser**	**Winner**	**Momentum**	**Loser**	**Winner**	**Momentum**
Ranking period of 3 months												
Average	0.0376	0.0320	-0.0056	0.0597	0.0729	0.0121*	0.0886	0.1169	0.0284***	0.1171	0.1656	0.0485***
T-stat			-1.2654			1.9062			3.5808			5.0575
Ranking period of 6 months												
Average	0.0293	0.0378	0.0085*	0.0531	0.0833	0.0302***	0.0804	0.1368	0.0564***	0.1052	0.1802	0.0750***
T-stat			1.7944			5.1335			7.4513			8.2207
Ranking period of 9 months												
Average	0.0312	0.0429	0.0117**	0.0531	0.0954	0.0423***	0.0805	0.1406	0.0601***	0.1043	0.1824	0.0781***
T-stat			2.3384			6.3530			6.6932			7.4695
Ranking period of 12 months												
Average	0.0273	0.0485	0.0212***	0.0500	0.0968	0.0468***	0.0762	0.1420	0.0657***	0.1052	0.1864	0.0812***
T-stat			4.1929			6.4720			6.9383			7.9343

* Significant at the 10 percent significance level.

** Significant at the 5 percent significance level.

*** Significant at the 1 percent significance level

6. Comparison of the classification criteria

In this paper, we use the methodologies of Jegadeesh and Titman (1993), the Sharpe ratio and the bootstrapped Mean-CVaR to classify the stocks during the formation period of the momentum portfolios.

In order to compare the effect of these classification criteria on the performance of momentum strategies at the end of the detention period, we use five performance measures which are based on the average return, the risk (standard deviation and Conditional value at risk CVaR), and return-risk framework (the average return/standard deviation ratio and the average return/CVaR ratio). The values of these performance measures for the three classification criteria of the 6-month/6-month strategy are reported in table 4.

Based on the average return, we note that the methodology of Jegadeesh and Titman (1993) is the most advantageous criterion since it enables to generate the highest profit which is about 3.17%.

However, the comparison of the risk of the momentum strategies according to the three classification criteria (by using the standard deviation and CVaR) shows that the risk measures values of the Jegadeesh and Titman methodology are highest. Therefore, this criterion is the riskiest.

While the methodology of Jegadeesh and Titman allows to release the highest return, it is also the riskiest criterion. In order to select the most advantageous criterion, it is more appropriate to use a performance measure which integrates not only the return but also the risk. For this reason, we employ the average return/standard deviation ratio and the average return/CVaR ratio.

Based on these two measures, we find that the values of the two ratios for criterion of classification bootstrapped Mean-CVaR are the highest. Consequently, we admit that the momentum strategy based on the criterion of classification bootstrapped Mean-CVaR is the most advantageous.

Table 4: Performance measures of the classification criteria

This table presents five performance measures which are based on the average return, the risk (standard deviation STDV and Conditional value at risk CVaR), and return-risk framework (the average return/standard deviation ratio and the average return/CVaR ratio).

	Performance measures of the classification criteria				
	Average return	STDV	CVaR	Average return/STDV	Average return/CVaR
J&T (93)	0.0317	0.0900	0.2240	0.3522	0.1415
Sharpe Ratio	0.0290	0.0696	0.2083	0.4167	0.1392
Mean-CVaRb	0.0302	0.0712	0.1981	0.4242	0.1524

7. Conclusion

The objective of this paper is to test the performance of momentum strategies on the French stock exchange market and to introduce a new criterion of classification based on the mean-CVaR framework.

According to the methodology of Jegadeesh and Titman (1993), we find that the momentum strategies are profitable on the French stock exchange market.

The taking into account of the risk through the use of classification criterion based on the Sharpe ratio shows that the momentum strategies are significantly profitable, but they generate a momentum profits lower than those based on the methodology of Jegadeesh and Titman (1993).

The previous studies find several limits of the standard deviation as a risk measure. These findings push us to use Conditional Value at Risk (CVaR) to evaluate the risk of the stocks. The principal limit of this measure is that we need a sufficiently large sample to have a precision of the CVaR calculation. To solve this problem, we introduce the bootstrap method to increase the sample size and consequently, we will be able to use the CVaR to classify the individual stocks' returns. Hence, we introduce a new criterion of classification during the formation period of the momentum portfolios which is entitled ***"bootstrapped Mean-CVaR"***. The application of this criterion of classification allowed us to conclude that, on the mean-risk framework, the momentum strategy which is based on this criterion is more advantageous than those of Jegadeesh and Titman (1993) and the Sharpe ratio.

References

Avramov, D. Chordia, T. Jostova, G. and Philipov, A. (2007) 'Momentum and credit rating', *Journal of Finance*, Vol. 62, pp. 2503-2520.

Barberis, N. Shleifer, A. and Vishny, R. (1998) 'A model of investor sentiment', *Journal of Financial Economics*, Vol. 49, pp. 307-343.

Berk, J. (1997) 'Does Size Really Matter?', *Financial Analysts Journal*, Vol. 53, pp. 12-18.

Chan, K. Jegadeesh, N. and Lakonishok, J. (1996) 'Momentum Strategies', *Journal of Finance*, Vol. 51, pp. 1681-1713.

Chordia, T. and Shivakumar, L. (2002) 'Momentum, business cycle and time-varying expected returns', *Journal of Finance*, Vol. 57, pp. 985-1019.

Conrad, J. and Kaul, G. (1998) 'An Anatomy of Trading Strategies', *Review of Financial Studies*, Vol. 11, pp. 489-519.

Daniel, K. Hirshleifer, D. and Subrahmanyam, A. (1998) 'Investor psychology and security market under- and overreactions', *Journal of Finance*, Vol. 53, pp. 1839-1885.

Efron, B. (1979) 'Bootstrap methods: another look at the jackknife', *Annals of Statistics*, Vol. 7, pp. 1-26.

Ericsson, J. and González, A. (2003) 'Is momentum due to data-snooping?', Working paper. Stockholm School of Economics.

Hong, H. and Stein, J. (1999) 'A unified theory of underreaction, momentum trading, and overreaction in asset markets', *Journal of Finance*, Vol. 54, pp. 2143-2184.

Jegadeesh, N. and Titman, S. (1993) 'Returns to buying winners and selling losers: Implications for stock market efficiency', *Journal of Finance*, Vol. 48, pp. 65-91.

Jegadeesh, N. and Titman, S. (2001) 'Profitability of momentum strategies: An evaluation of alternative explanations', *Journal of Finance*, Vol. 56, pp. 699-720.

Jegadeesh, N. and Titman, S. (2002) ‘Cross-Sectional and Time-Series Determinants of Momentum Returns’, *Review of Financial Studies*, Vol. 15, pp. 143-157.

Jiang, G. Lee, C. M. C. and Zhang, G. Y. (2005) ‘Information Uncertainty and Expected Stock Returns’, *Review of Accounting Studies*, Vol. 10, pp. 185-221.

Karolyi, G. and Kho, B. (2004) ‘Momentum strategies: Some bootstrap tests’, *Journal of Empirical Finance*, Vol. 11, pp. 509-534.

Markowitz, H. (1952) ‘Portfolio Selection’, *Journal of Finance,* Vol. 7, pp. 77-91.

Nakhli, M. S. and Belkacem, L. (2013) ‘Sources of Momentum Profits: Bootstrap Methods’, *Managerial Finance*, Vol. 39, pp. 607-619.

Pástor, L. and Stambaugh, R.F. (2003) ‘Liquidity risk and expected stock returns’, *Journal of Political Economy*, Vol. 111, pp. 642-685.

Rachev, S. Jasik, T. Stoyanov, S and Fabozzi, F. (2007) ‘Momentum Strategies Based on Reward-Risk Stock Selection Criteria’, *Journal of Banking and Finance,* Vol. 31, pp. 2325-2346.

Rouwenhorst, KG. (1998) ‘International Momentum Strategies’, *Journal of Finance*, Vol. 53, pp. 267-284.

Sadka, R. (2006) ‘Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk’, *Journal of Financial Economics,* Vol. 80, pp. 309-349.

Zhang, X. F. (2006) ‘Information Uncertainty and Stock Returns’, *Journal of Finance,* Vol. 61, pp. 105-137.