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Return and Risk-Return Ratio Based Momentum Strategies: A Fresh Perspective

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Abstract

In this study, we contribute to existing literature on momentum strategies by assessing a modified version of risk-return ratio based security selection criterion in an untested market – the KOSPI 200 over June 2006 to June 2012. Besides conventional risk-return ratios such as the Sharpe ratio, we also employ the use of risk-return ratio based ranking criterion first introduced in Biglova et al. (2004) when ranking securities to form portfolios for these strategies. These ratios take into account the non-normality and kurtosis that are ubiquitous in equity time series returns. In contrast to their approach however, we invert the ordinal ranking of negative risk-return ratios to be consistent with the interpretation of negative ratios presented in Sharpe (1994). Applying these methods, this study quantifies and compares the performance of returns based and risk-return ratio based momentum strategies while estimating the transaction costs involved in implementing such strategies. For return based momentum strategies, we show that most strategies involving a 3 or 6 month formation period exhibit statistically significant positive returns, while those with a 9 or 12 month formation period do not. In addition, all risk-return ratio based strategies failed to generate returns that are significantly greater than zero.

JEL classification numbers: G11, G14
Keywords: momentum strategies, risk-return ratio based selection criteria, portfolio turnover

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1 Introduction

Momentum refers to the short-term continuation of return performance based on prior short term returns or risk-adjusted returns. Implicit in the examination of momentum strategies is the selection of outperforming and underperforming securities based on past returns and an investigation into the dynamics of their future returns. Having garnered much attention for its simplicity in execution and apparent profitability, the performance of momentum strategies is now well documented in academic literature.

Present academic literature is largely in support of the presence of momentum returns. Early studies on momentum find their roots in Levy (1967), which showed that the relative-strength trading rule of purchasing stocks with higher than average prices over a prior 27 week period led to significant abnormal returns. In support of such a concept was the relative success of the mutual funds studied by Grinblatt and Titman (1989, 1991), who showed that the majority of mutual funds in their sample displayed a tendency to purchase stocks that returned positively over a previous quarter. Also congruent with such findings was evidence from Copeland and Mayers (1982) and Stickel (1985) on the predictive power of Value Line rankings, of which was primarily driven by a relative-strength methodology. Later on, Rouwenhorst (1998) proceeded to show that an internationally diversified portfolio of top performing securities outperformed the bottom performing portfolio by 1 per cent per month over 1980 to 1995. The author also proceeded to dissect the source of returns with the use of factor models, showing that momentum returns weigh traditional return drivers of firm size and market return negatively. Modern literature have then continued to consistently support the presence of significant momentum-strategy returns, in particular Jegadeesh and Titman (2001), Hu and Chen (2011) and Elsayeda (2012), while Biglova et al. (2004) and Bornholt and Malin (2011) have shown that augmenting stock selection criteria in momentum strategies with volatility and risk metrics have further improved momentum returns.

Still, while the wealth of evidence in support of momentum strategies remains convincing, employing a momentum strategy brings with it several forewarnings. First and foremost, seasonality in returns could serve to skew results if momentum strategies were initiated in certain months. For instance, tax-loss harvesting has shown to manifest itself in the January Effect and November effect, both of which significantly alters the performance of momentum strategies initiated in those months. Debondt and Thaler (1985) first showed in their study of contrarian trading strategies – through a largely similar methodology as present momentum strategies, save for its long term time horizons – that bottom performing loser portfolios experience abnormally large January returns as far as five years after portfolio formation. Jegadeesh and Titman (1993) then showed in their relative strength momentum strategy how January returns differed significantly from those during the other months, and that January returns were inversely related to firm size. To add on to the conundrum, the author further showed that consistently large returns in April were evident and was possibly explained by corporations having to transfer money to their pension funds by 15 April in order for the latter to qualify for a tax deduction in the prior year. Support for the presence of the January effect then continues to show in modern literature, most notably in Chu, Liu and Rathinasamy (2004), Anderson, Gerlach and DiTraglia (2007) and Moller and Zilca (2008). Johnston and Paul (2005) then showed how similar tax loss selling manifests itself in the November effect, and Das and Rao (2011) display international empirical evidence with Loughran (1997), showing that the value premium in January is three to nine times that of other months, with results being robust to sample period and value-growth indicators used. From the perspective of momentum strategies, Grinblatt and Moskowitz (2004) then showed that a significant fraction of momentum profits arrive from short positions initiated in November. Such is evidence to show that seasonality plays a large part in the success of momentum strategies.

Next, research on exploiting the performance persistence of securities that perform well on a risk-adjusted basis through momentum strategies is virtually non-existent. Long standing research and the present body of literature have largely been focused on central tendency measure of returns, oblivious to second and higher order moments despite there being widespread evidence of how security returns follow non-normal and leptokurtic distributions. In that respect, alternative measures of ranking securities that consider higher order moments have still hardly been studied. Only recently did Biglova et al. (2004) introduce the concept of incorporating the Sharpe Ratio from Sharpe (1994) and newly conceived quantile-based coherent risk measures, known as the STARR Ratio and Rachev Ratio and detailed in Martin, Rachev, and Siboulet (2003) and Biglova et al. (2004b), in the security ranking and selection process. The authors successfully showed that the application of the STARR Ratio and Rachev Ratio to daily data led to the best performing momentum strategies based on cumulative returns and independent performance measures that employ coherent risk measures. These measures outperformed the Sharpe Ratio and traditional return-based ranking methodologies. Later on, the authors expanded their study to the 517 stocks in the S&P 500 index over the period of 1996 to 2003 in Rachev et al. (2007), finding that although the traditional return-based ranking methodology returned an annualised 15.35% while the alternative Rachev Ratio gave an annualised 10.32% return, the latter measure provided considerably better risk-adjusted performance. Further, they concluded that the stable Paretian distribution hypothesis provides a better fit to momentum returns, and further conclude that implicit in momentum investing is the exposure to heavy tail distributions, making the application of coherent risk measures all the more important in momentum strategies.

Lastly, transaction costs serve to significantly erode returns. This is especially so given the frequent rebalancing required and the significant weighting of momentum portfolios to small and illiquid securities. Lesmond et al. (2004) found that momentum strategies involved the trading of stocks with relatively high costs, while Grinblatt and Moskowitz (2004) found that the majority of momentum returns were derived from trading small and illiquid stocks, though after trading costs momentum strategies remained profitable. Li, Brooks and Miffre (2009) quantified such costs in their study covering the UK equity market by integrating bid-offer spread and broker commission costs into their momentum model. The authors found that based on effective spread estimates computed from the Lee and Ready (1991) model, a 6 month holding cum investment period momentum strategy returned 5.79% after fees, a full 19.95 percentage points less than the annual momentum profit gross of fees.

Alas, we aim to quantify in this paper returns based momentum strategy cumulative returns in a previously untested market over a recent long-term horizon encompassing the global financial crisis. On top of that, we investigate how the use of risk-return ratio based ('risk based') selection criterion affect the results, while estimating the turnover required to execute such strategies. The rest of this paper is structured as follows: Section 2 touches upon the background of our study, Section 3 our data and methodology, while Section 4 presents the results of our study and an evaluation of the results. We then conclude in section 5 and provide references in section 6.

2 Background

This study aims to contribute to existing literature by examining the returns of a range of momentum strategies in a presently untested market over a recent span of time. We investigate how momentum strategies performed amongst the KOSPI 200 index securities in the period of June 2006 to June 2012 which aptly comprises both a low volatility and a high volatility regime that is the Global Financial Crisis, with the aim of showing how a range of momentum strategies perform throughout a period of contrasting economic and trading regimes. While doing so, this study is the first to combine the classical momentum study employed in early literature, a seasonality study, the novel risk based security selection methodology pioneered by Biglova et al. (2004), and finally, a presentation of portfolio turnover figures as well.

The range of strategies considered first spans different combinations of portfolio formation and holding periods. We perform the classical momentum study applied since early literature to determine how a permutation of portfolio formation period *J* months (the length of time which each security is observed and their respective cumulative returns are ranked) and holding period *K* months (the length of time that each chosen portfolio is held for and contributes to the returns of the strategy) fares in terms of returns when the strongest past performing securities are bought and an equal dollar amount of the weakest past performing securities are sold short. Previous studies have shown that each combination had significantly varying profitability, and it is such profitability which we will compare and examine the statistical significance of.

Then, we incorporate risk based security ranking methodologies to surmount the limitations past studies faced with regards to non-normal return distributions. These risk based methodologies are in the form of the Sharpe Ratio and the recently developed STARR Ratio and Rachev Ratio, of which were employed to significant success in ground-breaking research by Biglova et al. (2004) and Rachev et al. (2007), and of which have not been adopted by studies performed since then. Unlike these two studies, however, we offer a significantly different interpretation and treatment of negative Sharpe Ratios and STARR ratios as per stated in Sharpe (1994) and discussed further in Sharpe (1998) with regards to the Sharpe Ratio. That is, with a long/short strategy akin to momentum strategies, the risk adjusted performance of an investment correlates positively with the magnitude of any negative Sharpe Ratio. Put in other words, a highly negative Sharpe Ratio should be viewed favourably vis-à-vis a less negative Sharpe Ratio. This interpretation is converse to that when assuming the borrowing-lending scenario in CAPM and is supported by Sharpe (1994) and Sharpe (1998) when used in the context of going long and short positive and negative Sharpe Ratio securities respectively. It is of note, however, that by design the Rachev Ratio is almost immune to such ambiguity of interpretation – by design, both the numerator and denominator of the Rachev Ratio are positive in virtually all circumstances.

Finally, we display turnover figures for the range of strategies considered and allow the reader to evaluate based on the reader's own transaction cost function how attractive each strategy remains when transaction costs are taken into account.

It is hence through an especially holistic examination of the performance of the classical and the most recent in momentum strategies to the KOPSI 200 in the economic regime-varying 2006 to 2012 period that this study aims to contribute to existing literature.

3 Methodology

3.1 Data

Daily closing price and market capitalisation data for the period June 2005 to June 2012 were extracted from the Bloomberg Professional service for each of the KOSPI 200 index constituents. In order to best reflect the investable opportunity set throughout the entire period, index constituents were refreshed every 12 months. Also, congruent with performing the momentum simulations from an ex-ante investment perspective, we included in the data extraction process the price data of firms which have been removed from the KOSPI 200 index but have not been entirely delisted from the stock exchange. Such is necessary as a momentum investor, post having a stock he has invested in removed from the index, would still hold a stock as long as it was deemed a buy or sell during the formation period.

The price data was adjusted for normal cash dividends (regular cash, interim, income, estimated, partnership distribution, final, interest on capital, distributed and prorated), abnormal cash dividends (special cash, liquidation, capital gains, memorial, return of capital, rights redemptions, return premium, preferred rights redemption, proceeds/rights, proceeds/shares, proceeds/warrants) and capital changes (spin-offs, stocks splits/consolidations, stock dividend/bonus, rights offerings/entitlement). Such would ensure maximum return representativeness, given that momentum strategies involving long and short positions in securities will be exposed to the relevant long or short holding yields and costs.

Finally, the price data was checked for missing data points – apart from those prior to stock listing and after delisting – of which were highly uncommon but which would serve to bias volatility statistics in the later part of our study. While such a situation was highly uncommon, we performed such a check to ensure that stocks were not ranked and considered if there was one or more months' worth of data missing from the formation period.

Apart from price data, the study also involved the use of the daily closing yield to maturity of the generic Korean 3 month government bill, which similarly was extracted from the Bloomberg Professional service.

3.2 Classical Momentum Study

The aim of this study is to investigate the empirical returns of the return based momentum strategy over the period of June 2006 to June 2012 in the KOSPI 200, given 16 distinct permutations of J and K, where J = 3, 6, 9 or 12 and K = 3, 6, 9 or 12, and a 1 month time lag between the end of the J-month portfolio formation period and the K-month portfolio holding period.

The first step involves identifying the bottom decile performers and top decile performers in an ordinal ranking of cumulative returns over the J-month formation period for each month between June 2005 and June 2012. Only securities with a full set of data in the formation period are considered for ranking. These two distinct groups, which are updated each month, are referred to as the recommended Winner and Loser securities respectively. It is of note that in order to apply the 1 month lag between the formation period and holding period, the J-month formation period for any month comprises the J-month period starting $(J + 1)$ months prior to the start of the holding period. For instance, the 3-

month formation period for June 2007 comprises of February, March and April 2007. Such a lag, of which has become standard practice since Jegadeesh and Titman (1993), is applied in order to circumvent the bid-ask spread, price pressure and lagged reaction effects that were detailed in Jegadeesh (1990) and Lehmann (1990).

Next, recommended Winner and Loser portfolios are formed on each holding month by having them hold the recommended Winner or Loser securities from the relevant *J*-month holding period. Due to the need for time-overlapping of portfolios, however, these recommended portfolios are not exactly the ones the strategy will hold (only the first portfolio held consists entirely of recommended securities, i.e. the June 2006 held portfolio). Instead, the held portfolios are formed according to the rule that in any given month, each portfolio held consists of an equally weighted basket of the current month's and previous (K – 1) months' held portfolios. These time-varying portfolios are rebalanced every month to reflect the held portfolios of the most recent *K*-months in equal weight. It is of note that time-overlapping periods have become the standard since Jegadeesh and Titman (1993), and is necessary in order to negate the bias created due to cyclicality or seasonality in monthly return patterns.

Finally, the monthly returns of these portfolios over the June 2006 to June 2012 period under study are calculated. The monthly Winner portfolio returns are then subtracted by the monthly Loser portfolio returns to derive the Winner Minus Loser portfolio returns, which represents the strategy of going long past winners and shorting past losers, essentially forming a zero cost portfolio. The above process is then repeated for all 16 permutations of *J* and *K*. These are, in the form *J/K*, 3/3, 3/6, 3/9, 3/12, 6/3, 6/6, 6/9, 6/12, 9/3, 9/6, 9/9, 9/12, 12/3, 12/6, 12/9, 12/12. One-tailed t-tests are then performed to investigate if each strategy's Winner Minus Loser cumulative return, i.e. the momentum return, is statistically greater than zero.

3.3 Risk-Return Based Security Selection

In this section, we apply the risk based security ranking methodology introduced with much success in Biglova et al. (2004), as explained in Section 1, to the 6/6 portfolio. The portfolio selection process, the nature of overlapping time periods and the one month lag between formation and holding periods are similar to that described in Section 3.2, except for the ranking methodology. In Section 3.2 for the 6/6 case in particular, we ranked securities based on cumulative return performance during the 6-month formation period and derived the Winner and Loser's portfolio performance over the 6-month holding period. Now, instead of cumulative returns, we will instead rank securities based on the following three risk based ratios:

1. *Sharpe Ratio*. Adopted from Sharpe (1994), a security's Sharpe Ratio is the ratio of its mean excess return over the risk free rate to the standard deviation of the excess return:

$$S_i = \frac{E[R_i - R_f]}{\sqrt{Var[R_i - R_f]}} \tag{1}$$

where, in our study,

R_i: Daily return on a security i

R_f: Daily risk free rate calculated from the yield to maturity of the 3 month South Korean government bill

What makes this study unique, however, is its significantly different interpretation and treatment of negative Sharpe Ratios as previously explained in Section 2 above. In line with that, we sort securities from high positive Sharpe Ratios to low positive Sharpe Ratios, followed by highly negative Sharpe Ratios to less negative Sharpe Ratios. The same is performed for the STARR Ratio.

2. *STARR Ratio.* Adopted from Martin, Rachev, and Siboulet (2003), a security's STARR ratio is the ratio between the security's mean excess return to its Conditional Value at Risk (CVaR) at the (1-α) confidence level.

$$STARR_i(\alpha) = \frac{E[R_i - R_f]}{CVaR_{(1-\alpha)}[R_i - R_f]} \tag{2}$$

The CVaR is also commonly known as the Expected Tail Loss (ETL) and in this study, the CVaR is calculated on a non-parametric basis and is equal to the mean of the lowest (100α)% of daily returns for each security. We calculate the STARR Ratio for α = 0.01, 0.05, 0.1, 0.25 and 0.5, similar to those used in Biglova et al. (2004) and Rachev et al. (2007).

As mentioned in the description of the Sharpe Ratio above, the STARR ratio faces the same treatment of negative values when sorting as when Sharpe Ratios are used.

3. *Rachev Ratio (R-Ratio).* Adopted from Martin, Rachev, and Siboulet (2003), a security's R-Ratio is the ratio between the ETL of the negative of the excess return at the (1-γ_1) confidence level to the ETL of the excess return at the (1-γ_2) confidence level.

$$RRatio_i(\gamma_1, \gamma_2) = \frac{ETL_{\gamma_1}[R_f - R_i]}{ETL_{\gamma_2}[R_i - R_f]} \tag{3}$$

In the non-parametric case, as with this study, the R-Ratio is calculated as the ratio of the mean of the highest (100γ_1)% of returns to the mean of the lowest (100γ_2)% of daily returns for each security. We calculate the R-Ratio for (γ_1, γ_2) = (0.01, 0.01), (0.05, 0.05), (0.09, 0.09), (0.5, 0.01) and (0.5, 0.05), similar to those used in Biglova et al. (2004) and Rachev et al. (2007).

The Rachev Ratio is sorted in increasing order, unlike the Sharpe and STARR Ratios. It is both by the design of the ratio and the near impossibility of the Rachev Ratio being negative given the number of sample points in the 6-month formation period that such a sorting methodology is utilised. As a side note, it could be said that the circumvention for the non-monotonic sorting methodologies required with the Sharpe and STARR Ratios makes the Rachev Ratio more intuitive and eases communication when in use among practitioners.

Once the securities under study have been ranked each month according to the above three ratios, we continue to apply the formation and holding methodologies as set out in section 3.2 to derive momentum return statistics for each of the three ratios above with each of the abovementioned parameters.

3.4 Portfolio Turnover

Finally, we calculate turnover figures for the momentum strategies under examination in order to allow readers to evaluate the cost of implementing the said momentum strategies based on their own transaction cost function. Each month's turnover is calculated as the percentage of stocks that are dissimilar between two portfolios – the equally weighted Winner Minus Loser portfolio of a particular month and the Winner Minus Loser portfolio of the subsequent month. The turnover for a particular strategy is then calculated as the average monthly turnover over the entire period under study, and is presented as a monthly figure, just like return figures are in this study.

4 Results and Discussion

The results from adopting the range of momentum strategies under study over the period June 2006 to June 2012 are displayed on the following page. Specifically, the returns of the returns based momentum strategy and risk based momentum strategy are displayed in tables 1 and 2, with highlighted cells corresponding to those of the Winner Minus Loser portfolio. The range and central tendency of portfolio turnover over all strategies are then stated in the subsequent discussion.

It is clear from the results that some of the classical returns based strategies achieved statistically significant positive returns in the Winner Minus Loser portfolio over the study period at the 95% confidence level of a one-tailed T-test. Namely, these are the 3/6, 3/9, 3/12, 6/6, 6/9, 6/12 portfolios. Such figures contribute to the well-established body of research in support of returns based momentum strategies. Further supporting the often discovered result of mean reversion, i.e. the 'reversal' of momentum in the longer term, the 9 and 12 month formation period portfolios show returns that are statistically insignificant from zero across the board.

Surprisingly, however, and in contradiction with the Biglova et al. (2004) study – the first and only paper applying the Sharpe ratio and newly developed Rachev and STARR ratios to momentum strategies – the 6/6 portfolios failed to display any statistically significant positive returns, even though the 6/6 return-based strategy did. Such a result holds for all ratios tested – the Sharpe Ratio and STARR ratio, of which negative values were treated differently from Biglova et al. (2004) but in a manner in which Sharpe (1994) and Sharpe (1998) espoused, and the Rachev ratio, of which values were sorted in increasing order, similar to the methodology in Biglova et al. (2004).

Table 1: Momentum Strategy Returns – Returns Based Security Selection

J, Formation Period (Months)	K, Holding Period (Months)	Portfolio	Mean Monthly Return	Standard Deviation of Return	T-Statistic
3	3	Winner (W)	0.98%	8.64%	
		Loser (L)	0.14%	8.95%	
		W - L	0.84%	6.30%	1.14
	6	W	0.95%	8.45%	
		L	-0.40%	9.09%	
		W - L	1.34%	6.62%	1.73
	9	W	0.91%	8.52%	
		L	-0.80%	9.08%	
		W - L	1.71%	6.13%	2.38
	12	W	0.69%	8.41%	
		L	-1.05%	8.88%	
		W - L	1.73%	5.23%	2.83
6	3	W	1.35%	9.34%	
		L	-0.26%	10.26%	
		W - L	1.61%	9.53%	1.44
	6	W	1.36%	9.07%	
		L	-0.67%	9.86%	
		W - L	2.03%	9.06%	1.91
	9	W	1.33%	8.96%	
		L	-1.09%	9.68%	
		W - L	2.42%	8.03%	2.57
	12	W	1.08%	8.87%	
		L	-1.24%	9.48%	
		W - L	2.31%	7.21%	2.74
9	3	W	-11.19%	11.43%	
		L	-9.48%	9.83%	
		W - L	-1.71%	10.21%	-1.43
	6	W	-11.19%	11.42%	
		L	-9.68%	8.92%	
		W - L	-1.51%	9.63%	-1.34
	9	W	-11.13%	11.52%	
		L	-9.89%	8.44%	
		W - L	-1.24%	8.86%	-1.20
	12	W	-10.90%	11.39%	
		L	-10.08%	8.12%	
		W - L	-0.82%	7.72%	-0.91
12	3	W	-11.02%	11.92%	
		L	-9.81%	10.13%	
		W - L	-1.21%	11.57%	-0.89
	6	W	-10.77%	12.01%	
		L	-10.00%	9.05%	
		W - L	-0.77%	10.33%	-0.63
	9	W	-10.38%	12.07%	
		L	-10.32%	8.56%	
		W - L	-0.07%	9.25%	-0.06
	12	W	-10.05%	11.82%	
		L	-10.72%	8.26%	
		W - L	0.67%	8.17%	0.70

Table 2: Momentum Strategy Returns - Risk Based Security Selection, 6/6 portfolios

Ratio	Portfolio	Mean Monthly Return	Standard Deviation of Return	T-Statistic
Sharpe Ratio	Winner (W)	0.78%	8.89%	
	Loser (L)	0.07%	7.10%	
	W - L	0.71%	5.85%	1.04
Rachev(0.09,0.09)	W	0.35%	8.10%	
	L	0.82%	8.26%	
	W - L	-0.46%	4.69%	-0.85
Rachev(0.5,0.5)	W	0.82%	8.85%	
	L	-0.59%	8.11%	
	W - L	1.41%	7.19%	1.68
Rachev(0.5,0.01)	W	0.70%	8.88%	
	L	-0.35%	7.66%	
	W - L	1.05%	6.26%	1.43
Rachev(0.05,0.05)	W	0.65%	7.90%	
	L	0.60%	8.15%	
	W - L	0.06%	4.10%	0.12
Rachev(0.01,0.01)	W	0.60%	7.50%	
	L	0.51%	7.55%	
	W - L	0.09%	3.30%	0.23
STARR(0.25)	W	0.74%	8.77%	
	L	0.19%	7.15%	
	W - L	0.54%	5.61%	0.83
STARR(0.5)	W	0.73%	8.70%	
	L	0.20%	7.11%	
	W - L	0.53%	5.53%	0.82
STARR(0.05)	W	0.76%	8.81%	
	L	0.08%	7.19%	
	W - L	0.68%	5.81%	1.00
STARR(0.1)	W	0.76%	8.85%	
	L	0.11%	7.15%	
	W - L	0.65%	5.76%	0.97
STARR(0.01)	W	0.71%	8.71%	
	L	-0.01%	7.05%	
	W - L	0.72%	5.68%	1.08

5 Conclusion

In this study, we contributed to the present momentum strategy literature by testing newly introduced risk based security selection criterion in an untested market. While second and higher order moments of return distributions were not taken into account previously, the use of novel risk based ranking criterion used in this study takes into account the non-normality and kurtosis in equity time series returns. Further to that, we modified the model by utilising an approach to treating negative Sharpe and STARR ratios that is novel to the risk based momentum model employed in this study. Applying these methods, this study quantified and juxtaposed momentum strategy cumulative returns with returns based and risk based ranking measures.

In support of the long standing and well documented momentum returns, we demonstrated the profitability of the returns based momentum strategy with the 3/6, 3/9, 3/12, 6/6, 6/9, 6/12 period strategies, with momentum returns being eroded by the phenomena of mean reversion in the longer term, as evident from insignificant returns when the 9 and 12 month formation period is employed. Further to that, we discovered a contradiction to the results of Biglova et al. (2004) – the first and only study on momentum returns using the novel risk ratios adopted in this study – by demonstrating how risk based ranking criterion failed to generate statistically significant returns in the specific equity market and time period under study. Such lacklustre profitability is then further worsened by transaction costs that are congruent with an approximate 174% annual portfolio turnover necessary to maintain such a strategy, while the lack of momentum returns to be had is further supported by the 87% monthly turnover of the sixth of the 6/6 portfolio which is reconstituted each month.

Alas, while we have demonstrated the lack of profitability of risk based-momentum strategies in a specific market and time period, we refrain from making general conclusions with respect to their profitability. Such is simply because the body of literature that examines the effectiveness of such risk based measures is small – this makes only the second paper applying risk based criterion to momentum strategies, and is the only paper to have modified the model to be congruent with the treatment of negative Sharpe and STARR ratios espoused by Sharpe (1994) and Sharpe (1998). In that vein, further research should be made into risk based momentum strategies, so that this novel strategy may be tested in a wider range of markets, time periods and trading regimes.

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