MSc BA Finance Thesis

Momentum Effect in the Dutch and Belgian Stock Market

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Abstract: In this paper, the momentum effect in the Dutch and Belgian stock market is described. Using more recent data (ranging from January 1995 to December 2009) than Rouwenhorst (1998), it is concluded that substantial abnormal returns can be obtained using momentum strategies. Moreover, an alternative methodology is developed for creating momentum strategies and observing momentum returns. In the methodology, the abnormal returns are adjusted for the beta of the stock. Even with this adjustment, significant abnormal returns are found, indicating that risk is not the sole driver behind momentum returns. However, the returns do not appear to be as strongly significant compared to returns without risk adjustment, indicating that beta has at least a minor influence in the momentum returns.

Keywords: Momentum effect • Behavioral Finance

JEL Codes: G12 • G14

I. Introduction

The first persons that researched the market anomaly of the momentum effect were Jegadeesh and Titman (1993). Since then, many others like Rouwenhorst (1998), Hameed and Kusnadi (2002), and Muga and Santamaría (2007) have studied and found significant results in various stock markets around the world. The discovery of the momentum effect has even resulted in a particular type of investing; momentum investing (Nofsinger, 2008). Momentum investors buy stocks or mutual funds that have performed well over the last period (e.g. week, month, quarter or year) and hope

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to realize positive results. It is even possible to extend the strategy, as proposed by Jegadeesh and Titman (1993); buying the winner stocks and shorting the loser stocks results in an even greater abnormal return. They call this momentum strategy.

This paper focuses on the momentum effect in the Belgian and Dutch stock market specifically. Moreover, it uses more recent data on the stock market than e.g. Rouwenhorst (1998) has used while examining the stock markets of Belgium and The Netherlands, who uses data between 1980 and 1995. Because the momentum effect was barely identified in these years, it is interesting to see if investors have learned from the recent research of the momentum effect. The question is if it is still possible to gain significant abnormal returns from momentum strategies. The stock markets of the Netherlands and Belgium are tested because most momentum studies are conducted using American or emerging countries data. The only time that the Dutch and Belgian stock market was examined was by Rouwenhorst (1998), which is twelve years ago. A more recent study gives insight if the momentum effect is still present in the Dutch and Belgian stock market.

The paper uses two methodologies for measuring momentum returns. The first one is the methodology that is usually used for measuring momentum returns, applied by e.g. Jegadeesh and Titman (1993). The second methodology is developed by the author. It is based on the event study methodology described by e.g. Brown and Warner (1980) and MacKinlay (1997). The second methodology uses the beta of the stock to adjust for market risk, which is something Jegadeesh and Titman (1993) do not apply in their methodology. They do not use any form of risk adjustment, while there are authors like Tai (2003) who argue that risk is a driver behind the momentum effect. To implement the beta into the second methodology, the market-adjusted model is used to measure the momentum returns, adjusted with the beta of the stock to account for the sensitivity of the stock. The second methodology is split up in two parts; in the first part returns are adjusted with the beta before the returns are ranked, and in the second methodology the returns are adjusted with the beta after the returns have been ranked.

The structure of the paper is as follows: part II provides a literature review, and also includes the main research question. Next in part III, the data collection is described. In part IV, the methodologies are discussed in more detail. In part V, the results and presented and an interpretation is given. Finally, the paper will be summarized, including a conclusion, discussion and recommendation for further research. This can be found in part VI.

II. Literature Review

Presence of the momentum effect

As described before, the momentum effect was first studied and empirically proven by Jegadeesh and Titman (1993). They used a sample of stocks from the NYSE and AMEX indices in the time period ranging from January 1965 to December 1985. Their momentum strategy consisted of going long in past winner stocks and going short in past loser stocks, resulting in a 12.01% compounded excess return per year on average. This was achieved when the winner and loser stocks are based on their past six month return (formation period *J*) and held for six months in the future (holding period *K*).

After the research of Jegadeesh and Titman (1993), many others have researched the momentum effect in various stock markets around the world. E.g. Rouwenhorst (1998) used a sample of 2,190 firms from twelve European countries[1] in the period 1978 to 1995. He finds that the momentum effect is present in all twelve markets, and is similar to the momentum returns found in the United States by Jegadeesh and Titman (1993); monthly returns ranging from 1.16% in Switzerland to 1.32% in Spain on average.

The momentum effect is not only present in developed markets as the United States and Europe. Muga and Santamaría (2007) provided evidence that momentum strategies generate abnormal returns in four Latin American emerging markets,[2] similar to the abnormal momentum returns from developed markets; an average of 1.17% abnormal monthly returns. However, the authors state that the results may be slightly influenced by the limited time span that is used (January 1994 to January 2005). Others claim that the momentum effect is less present in emerging markets, like Hameed and Kusnadi (2002). They researched the momentum effect in six emerging markets in Asia,[3] using slightly more than 1,000 stocks in the sample period from 1979 to 1994. They found statistically small significant returns when the

[1] Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom.
[2] Argentina, Brazil, Chile, and Mexico.
[3] Hong Kong, Malaysia, Singapore, South Korea, Taiwan, and Thailand.

formation period is three months and the holding period is twelve months. However, since these abnormal returns are much smaller than the abnormal returns in the United States and Europe, the authors suggest that the factors that influence the momentum effect are at least less present in the Asian markets, and are thus country-bound. On the contrary, Chui, Wei and Titman (2000) conclude that momentum strategies in seven Asian markets[4] are highly profitable, with the exception of Japan. These markets include the markets Hameed and Kusnadi (2002) have researched. Univocal evidence of the existence of the momentum effect in emerging markets is therefore absent. One can even argue that the presence of the momentum effect is debatable in developed markets, since Chui, Wei and Titman (2000) conclude that it is not present in Japan. This may indicate that the growth phase of the economy, emerging or developed, is not a determining factor of the presence of the momentum effect.

Origin of the momentum effect

This gives rise to the question of what the driver is behind the momentum effect. Grinblatt and Han (2005) argue that it is caused by the disposition effect, described by Shefrin and Statman (1985). The disposition effect is the tendency of investors to hold on to losing stocks for too long and to sell winning stocks too early. This is caused by the fact that humans naturally try to avoid regret and seek pride; as soon as a stock is making a profit, investors want to sell it (seeking pride), but if a stock has gone down for a long time period, they hold on to it because selling it would mean a realized loss, which results in having regret of buying the stock in the first place. According to Grinblatt and Han (2005), the disposition effect causes winning stocks to stay undervalued because they are sold too soon, and losing stocks to stay overvalued because investors hold on to it for too long. In the long-run, the market value of the stock will move to the intrinsic value of the stock, resulting in higher positive returns for winning stocks and higher negative returns for losing stocks. Grinblatt and Han (2005) give strong empirical evidence that the disposition effect is indeed the driver behind momentum returns.

Another behavioral explanation of the momentum effect is given by Cooper, Gutierrez jr. and Hameed (2004); they empirically test for two possible causes. First,

[4] Hong Kong, Indonesia, Korea, Malaysia, Singapore, Taiwan, and Thailand.

they researched if overreaction is the cause, as proposed by Daniel, Hirschleifer and Subrahmanyam (1998). They assume that that overconfidence, which is defined by Daniel, Hirschleifer and Subrahmanyam (1998) as "… *overestimation of the precision of private information signal, but not of information signals publicly received by all*" and the self-attribution bias, where people attribute successes to their own skills and attribute failures to bad luck, of investors contribute to their overreaction. If investors receive confirming news about their past investment choice, their overconfidence increases. The consequence of increasing overconfidence is overreaction, which in turn creates short-term momentum returns. In the long term, the returns are reverted. The second theory Cooper, Gutierrez jr. and Hameed (2004) test is described by Hong and Stein (1999) and Barberis, Shleifer and Vishny (1998), where Cooper, Gutierrez jr. and Hameed (2004) argue that initial underreaction followed by subsequent overreaction causes momentum returns. They assume that private information is absorbed into the market price gradually, resulting in initial underreaction of investors. The result of this is that by the time the private information becomes public information, traders have responded to this in an overreacted manner, resulting in momentum returns. In this theory, prices are reverting to their intrinsic values in the long-run as well. The results from Cooper, Gutierrez jr. and Hameed (2004) suggest that both overreaction, and underreaction followed by overreaction, are indeed drivers behind momentum returns.

If the behavioral theories underlying the momentum effect are indeed true, this must mean that cultural differences explain the difference of the momentum effect in different countries; as explained earlier, e.g. Japanese markets do not show the momentum effect while the American markets do experience the effect. However, there are researchers who disagree with behavioral explanations related to market anomalies. Especially Fama (1998) criticizes the studies done by Barberis, Shleifer and Vishny (1998) and Daniel, Hirschleifer and Subrahmanyam (1998), who test for underreaction and overreaction results. Fama (1998) argues that indeed these two behavioral models work well when they try to explain the anomalies they have been developed for. But when other anomalies like abnormal returns after IPO's or merger announcements are tested with the same models, they fail to explain the returns. Generalizing this result, Fama (1998) states that market anomalies are a result of using specific methodologies, designed for each anomaly specifically. Therefore, he concludes that every model should be concentrated on how it can explain the bigger picture, instead of focusing on one anomaly. A result of this conclusion is that market efficiency is still a valid theory, and that empirically proven market anomalies are a result of chance.

So, in explaining the origin of the momentum effect, looking at behavioral theories does not suffice. This is a reason for researchers to focus on several market factors. For instance, Conrad and Kaul (1998) claim that momentum returns are caused by the cross-sectional variation in the mean returns, i.e. the change of risk with respect to different stocks. Chordia and Shivakumar (2002) conclude that, besides the behavioral theories mentioned earlier, macroeconomic variables such as dividend yield, default spread, the yield on three-month T-bills, and term spread explain the returns created by momentum strategies.

Other empirical evidence explaining momentum results is presented by Moskowitz and Grinblatt (1999). They conclude that momentum is driven by industry-specific variables, and that industry momentum strategies are even more profitable than single stock momentum strategies. Moreover, they conclude that momentum returns disappear as soon as returns are controlled for industry factors, with an exception to one momentum strategy.[5] So besides behavioral or macroeconomic factors, mesoeconomic factors such as industry categorization may explain the presence of momentum in stock returns.

Besides these factors, firm-specific factors can explain momentum returns as well. E.g. Hong, Lim and Stein (2000) empirically show, using NYSE, AMEX, and Nasdaq stocks, that firm size is a strong determinant in generating momentum returns. More firm-specific factors that create momentum profits are, according to Sagi and Seasholes (2007), high revenue volatility, lows cost, and high market-to-book. They conclude that creating portfolios with these types of companies create higher profits than the strategy proposed by Jegadeesh and Titman (1993).

Another completely different explanation of the momentum effect is given by Tai (2003). He investigates several anomalies and finds evidence that the higher returns from three[6] market anomalies, including momentum, are compensation for bearing greater market risk. He uses a version of the Intertemporal Capital Asset Pricing Model, where he finds results that these anomalies are significantly priced within the market. So according to Tai (2003), in essence, the momentum effect (and the other

[5] Using a formation period of twelve months.
[6] Size, book-to-market, and momentum

anomalies tested) is not really an anomaly; the abnormal returns are just compensated for higher risk that is exposed to the investor.

Trough the years many different explanations have been given in the academic literature. This review has summed up the most important ones. Table 1 gives a summary of the different theories to give a short and complete view of the different explanations. However, I will let the reader of this paper decide for himself which explanation of the momentum effect is the most accurate.

Explanation	Field of research	Author(s)
Disposition effect	Behavioral Finance	Grinblatt and Han (2005)
Overreaction	Behavioral Finance	Daniel, Hirschleifer and Subrahmanyam (1998)
		Hong and Stein (1999)
		Barberis, Shleifer and Vishny (1998)
Result of chance	Efficient markets	Fama (1998)
Cross-sectional variation in mean returns	Fundamental Analysis	Conrad and Kaul (1998)
Several macro-economic variables	Fundamental Analysis	Chordia and Shivakumar (2002)
Industry-related variables	Fundamental Analysis	Moskowitz and Grinblatt (1999)
Firm-specific variables	Fundamental Analysis	Hong, Lim and Stein (2000)
Higher risk-return tradeoff	Efficient markets	Tai (2003)

Table 1: A summary of the possible explanations of the momentum effect in stock returns by different authors and with different views on capital markets. Of course, a combination of these factors (With the exception of the explanation of Fama (1998)) may also be a good explanation.

This paper aims to research the momentum effect in the Dutch and Belgian stock markets. By doing so, conclusions can be made concerning the effect of the research of Rouwenhorst (1998), who also studied the presence of the momentum effect in these countries. Have the Dutch and Belgian stock markets really learned from the anomaly? Have the stock markets become more efficient with respect to the momentum effect? Or, did the research of Rouwenhorst (1998) have an opposite effect, and is momentum still present in these markets? If so, this indicates that investors can make a steady abnormal return if they base their investment beliefs upon momentum strategy.

These questions can be summarized in one single all including research question, which is formulated as follows:

Is the momentum effect still present in the Dutch and Belgian stock market?

This research question has to be tested statistically. This will be done with two different methodologies; the methodology of Jegadeesh and Titman (1993), and an event-based methodology which adapts the returns for risk using the beta of the stock. This methodology will be explained further in section IV. The answer to the research question will be given in the concluding remarks, section VI.

III. Data Collection

The data that is used for this research are time-series monthly returns from January 1995 to December 2009, as well as monthly betas with the same time-series. Monthly returns are commonly used in the literature for measuring momentum effect, and are less sensitive to noise inside the returns. Stocks from the following indices will be used: the Dutch AEX and AMX index, and the Belgian BEL-20 and BEL-MID index. The stock returns and betas are obtained from Datastream, where the returns are calculated using the total return index (RI) to account for dividend payouts and stock splits to calculate the stock returns. The betas are calculated using the methodology as described in Cunningham (1973) using the local market index of the Netherlands and Belgium as the market index. Stocks with a value lower than € 1.00 are excluded from the research, because the possible illiquidity can bias the results. Jegadeesh and Titman (2001) give a second reason to exclude small stocks from the research: to avoid the results from being influenced by the bid-ask bounce effect. This effect can be defined as "*…a result of trades taking place at the specialist's bid or ask quote as opposed to the bid-ask midpoint which would be the case if order flow was balanced.*" (Gosnell, Keown and Pinkerton, 1996)). This effect results into the illusion that the stock price has changed, while it actually has not. Since this effect influences stocks will small prices (e.g. stocks lower than € 1.00) relatively more than stocks with higher prices, these small stocks are excluded from the research.

Summary statistics of the monthly return data can be found in table 2. There are several figures that are worth mentioning in the summary statistics. First of all, the mean return appears to be larger in the large-cap indices than in the mid-cap indices;

the AEX and BEL-20 index show an average return of 0.66% and 0.64% respectively, while the AMX and BEL-MID indices show an average return of 0.58% and 0.45%[7]. Furthermore, the BEL-20 index shows a relatively high skewness and kurtosis figure. The skewness is highly negative, indicating a longer but flatter tail on the left side of the mean, and a higher density and the median to the right side of the mean. This means that there are relatively few exceptionally low returns. But the longer tail indicates that these exceptionally low returns are even lower than ‘normal’ exceptionally low returns.

	AEX	**AMX**	**BEL-20**	**BEL-MID**	**Total sample**
Mean	0.66%	0.58%	0.64%	0.45%	0.58%
Median	1.19%	0.99%	1.08%	0.76%	0.98%
Variance	0.012	0.015	0.009	0.010	0.012
Standard deviation	0.111	0.121	0.093	0.102	0.108
Skewness	-0.92	-0.48	-2.28	-0.64	-0.91
Kurtosis	8.59	5.27	34.38	7.66	10.58
n	25	22	20	34	101
Jarque-Bera	13726	3854	151202	10278	70112
Minimum	-116.05%	-84.04%	-158.72%	-78.25%	-158.72%
Maximum	78.02%	84.10%	58.65%	70.67%	84.10%

Table 2: Summary statistics of the logarithmic monthly returns of single stocks over the period January 1995 to December 2009. The indices used are the AEX, AMX, BEL-20 and BEL-MID Index

The relatively high kurtosis indicates a distribution with a sharp peak, including longer and fatter tails, this is also called leptokurtic. For stock returns, this means that there are relatively many returns that are further away from the median and mean than you would expect. The last figures worth mentioning are the minimum values of the returns. Theoretically, these figures cannot get lower than -100%. However, because of the use of logarithmic returns instead of arithmetic returns, this value can get lower than -100%. This was the case with e.g. the stock Fortis from the BEL-20 index. The relative strength index dropped from 2529.20 in October 2008 to 517.22 in November 2008, resulting in the logarithmic return of -158.72.

[7] These differences in large-cap and mid-cap mean returns are however, not statistically significant. The difference between de AEX and AMX mean results in a *t* statistic of 0.28, and the difference between the BEL-20 and BEL-MID result in a *t statistic of 0.79; both insignificant at an α* of 5 percent.

Summary statistics of the betas of the stocks can be found in table 3. There are some very high figures visible, which is mainly caused by the internet bubble in the beginning of the 21st century. In this period, very high positive and negative returns were experienced in the stock market, resulting in high positive and negative betas. Another rather surprising figure is the relatively high variance in the betas of the AMX index; it is more than 0.1 points higher than variance of the AEX index, and almost twice as high as the variance in the BEL-MID index. This indicates that the Dutch stock market is more volatile than the Belgian stock market, something which supported by the variance of the stock markets presented in table 2.

	AEX	**AMX**	**BEL-20**	**BEL-MID**	**Total Sample**
Mean	0.838	0.804	0.835	0.774	0.812
Median	0.729	0.713	0.850	0.765	0.764
Variance	0.274	0.383	0.252	0.214	0.278
Standard deviation	0.524	0.619	0.502	0.463	0.527
n	25	22	20	34	101
Minimum	-4.317	-6.260	-4.270	-2.787	-6.260
Maximum	4.217	7.417	7.376	4.722	7.417

Table 3: Summary statistics of the betas of the stocks of the AEX, AMX, BEL-20, and BEL-MID Index for the period January 1995 to December 2009.

IV. Methodology

This section will discuss two methodologies; one that is developed by Jegadeesh and Titman (1993), and one new methodology, which is partly based on the event study methodology developed by Brown and Warner (1980). To avoid confusion, the first methodology will be referred to as the JT-methodology, and the second methodology will be referred to as the event-methodology. The JT-methodology will be discussed first. As said before, it is a methodology developed by Jegadeesh and Titman (1993) who use a ranking method; for every month, the stocks are ranked by cumulative returns over different previous J months, which is called the formation period. In this research, J = 3, 6, 9, and 12. These are the conventional formation periods used by most of the momentum-studies. In the next step, the stock returns are classified into deciles. The top performing decile is called the winner portfolio and the bottom performing decile is called the loser portfolio. Then, the momentum strategy is to go long in the winner portfolio and short in the loser portfolio. This portfolio will be held for K months, which is called the holding period. In this research, K = 3, 6, 9, 12, and 15. In most research, K is usually limited to 12 months, but because it is generally assumed (see e.g. Jegadeesh and Titman (2001)) that short-term momentum is continued by long-term reversal, K = 15 is added to the research. According to the theory, the momentum returns should be considerably smaller on K = 15 than on K = 3 through 12. The different formation periods and holding periods result into twenty different portfolio strategies. This strategy is applied every month, resulting into a series of monthly returns based upon the returns of the winner and loser portfolios. The winner, loser, and momentum portfolios will all be tested for significant abnormal returns; the winner and momentum portfolios are expected to have positive significant abnormal returns, and the loser portfolios are expected to show negative returns. It remains to be seen if these returns are significant, since other research (e.g. Muga and Santamaría, 2009) has shown that these loser portfolios are usually not significant. The advantage of this strategy is, according to Muga and Santamaría (2009), that a t statistic is the appropriate way to test for significance, meaning the returns do not need to be adjusted for anything. They argue that this is possible because problems like autocorrelation are avoided, since the profitability of the portfolios is measured.

The formula to obtain the student t test statistic is

$$t = \frac{\overline{CAR}_{J,K}}{s/\sqrt{n}} \tag{1}$$

where $\overline{CAR}_{J,K}$ is the average return of the winner portfolio, loser portfolio, or momentum portfolio with different formation periods J and holding periods K, s is the standard deviation of the abnormal returns, and n is the number of abnormal returns used in the sample. The appropriate degrees of freedom is $n – 1$.

Besides the JT-methodology that has just been discussed, another methodology based on the event study methodology (developed by Brown and Warner (1980)) is developed and used. The methodology of an event study is chosen because it is used many times within the financial literature. Moreover, it is a simple and straightforward methodology to test for abnormal returns; and that is exactly what this study is aiming for. Moreover, the event-study methodology can easily be adapted with the use of the beta to adjust for individual stock risk. Another advantage is that other tests can be conducted to calculate the test statistic: the returns are tested for normality, and if this is not found, the nonparametric rank test developed by Corrado (1989) can be used which does not assume normality. The JT-methodology is used as a comparison for the newly developed event-methodology.

The event-methodology will be applied twice, the first time slightly different than the second one. In the first attempt, the raw returns of the stocks are adjusted with the betas of the stocks before the returns are ranked. This will be referred to as the event-methodology I. In the second attempt the returns are adjusted after the stock returns are ranked. This will referred to as the event-methodology II. The difference between these methodologies is that in event-methodology I the risk adjustment affects the formation period *J*, as where in event-methodology II the risk adjustment affects the holding period *K*. The economic meaning behind this is that in event-methodology I the stocks that are chosen in the portfolio, are not mainly beta driven; the risk in the portfolios is reduced. In event-methodology II, the returns are adjusted for market risk; this way it can be observed if the momentum returns are not primarily driven by beta.

Event-methodology I

The first step in the event-methodology is to define an event. In this research, every month can be seen as an event, because, similar as in the JT-methodology, the objective is to receive a monthly time series of abnormal returns. First, the returns are adjusted with the corresponding beta to adjust for stock risk. This is done with the following equation:

$$R'_{i,t} = R_{i,t} - \left(\beta_{i,t} \times R_{m,t}\right), \tag{2}$$

where $R'_{i,t}$ is the adjusted return of stock *i* on time *t*, $R_{i,t}$ is the return of stock *i* on time *t*, $\beta_{i,t}$ is the beta of stock *i* on time *t*, and $R_{m,t}$ is the return of the market on time *t*, measured as the average return of the AEX, AMX, BEL-20, and BEL-MID indices. After the adjustment, the returns are ranked:

$$L'_{i,t} = rank(R'_{i,t}) \tag{3}$$

The top performing decile is attributed to the winner portfolio and the bottom performing decile is attributed to the loser portfolio, based on the rank attributed on the returns. The portfolios are constructed with different formation periods *J*. Here *J* = 3, 6, 9, and 12 as well. Next, the event window is defined. The event window in the event-methodology I is the same as the holding period *K* in the JT-methodology; *K* = 3, 6, 9, 12, and 15 will therefore be used as well. This again results in twenty strategies (four *J*'s times five *K*'s) which will be tested for significance. The portfolio return of each strategy is the average of the adjusted returns with the corresponding *J* and *K*:

$$\overline{CAR'}_{J,K} = \frac{1}{n} \times \sum_{i=1}^{n} CAR'_{i,t} \,, \tag{4}$$

where $CAR'_{i,t}$ is the cumulative abnormal return based on rank $L'_{i,t}$, and $\overline{CAR'}_{J,K}$ is the average cumulative abnormal return for a strategy with a *J* formation period and a *K* holding period. If the holding period is three months, the $\overline{CAR'}$ consists of the average of three monthly returns. If the holding period is six months, the $\overline{CAR'}$ consists of the average of six monthly returns, and so on.

The test that appropriate for calculating significance depends on the normality of the returns; if they are normally distributed the student *t* test will be used:

$$t = \frac{\overline{CAR'}_{J,K}}{s/\sqrt{n}} \,, \tag{5}$$

and if the returns are nonnormally distributed, the Corrado (1989) test will be used:

$$C = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(m_{i0} - \overline{m}\right)}{St\left(\overline{k}\right)} \,, \tag{6}$$

where *C* is the test statistic, *m* is the rank given to each return, $\overline{m}$ is the average rank, and

$$St(\bar{k}) = \sqrt{\frac{1}{t}\sum_{t=1}^{t}\frac{1}{N^2}\sum_{i=1}^{n}\left(m_{it} - \bar{m}_i\right)^2} \ . \tag{7}$$

The Corrado test statistic can be tested with a student t distribution, with n – 1 degrees of freedom.

To test for normality, the Jarque and Bera (1980) test will be used. This is a goodness-of-fit test that assumes under the null hypothesis that the skewness and excess kurtosis of the tested sample is zero. The test uses a chi-square distribution, with two degrees of freedom; the skewness and kurtosis. The formula of the Jarque-Bera (1980) test is

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right), \tag{8}$$

where JB is the Jarque-Bera variable, S is the skewness of the sample, K is the kurtosis of the sample, and n represents the sample size.

Event-methodology II

The methodology is slightly adapted for event-methodology II. Instead of adjusting for market risk, the raw returns are ranked:

$$L_{i,t} = rank(R_{i,t})\,. \tag{9}$$

Based on this ‘raw’ rank, winner and loser portfolios are decided; the top performing decile is again assigned to the winner portfolio and the bottom performing decile is assigned to the loser portfolio. This is the similar ranking method as in the JT-methodology. The event window (holding period K) is again 3, 6, 9, 12, and 15 months. The holding period returns are however, adjusted for market risk, in the same way as in event-methodology I, see equation (2). Furthermore, the average portfolio returns ($\overline{CAR'}_{J,K}$), normality of the returns, and proper test of significance are calculated in the similar way as in event-methodology I.

V. Results and Interpretation

The results from the JT-methodology are presented in table 4. All winner portfolios generate very strong statistically significant returns. Furthermore, the winner portfolios seem to be stronger significant when the holding period *K* increases, except for *J* = 12; the statistics are weaker starting from *K* = 9 and higher.

		K = 3	*K* = 6	*K* = 9	*K* = 12	*K* = 15
J = 3	Winners (*R*)	4.14% (3.53)	7.12% (3.90)	9.61% (4.30)	11.41% (4.08)	12.43% (3.80)
	Losers (*R*)	0.27% (0.19)	0.89% (0.44)	0.00% (0.00)	-0.34% (-0.13)	2.12% (0.70)
	Momentum (*R*)	3.87% (3.68)	6.23% (4.50)	9.61% (5.35)	11.75% (6.08)	10.30% (4.79)
J = 6	Winners (*R*)	4.56% (3.72)	7.73% (4.00)	11.00% (4.67)	12.16% (4.16)	12.06% (3.41)
	Losers (*R*)	0.56% (0.38)	0.63% (0.29)	-1.12% (-0.44)	-0.39% (-0.14)	3.49% (1.13)
	Momentum (*R*)	4.00% (3.46)	7.10% (4.05)	12.12% (5.94)	12.56% (5.81)	8.58% (3.48)
J = 9	Winners (*R*)	3.92% (3.26)	7.50% (3.79)	7.38% (3.66)	7.46% (3.64)	8.32% (4.15)
	Losers (*R*)	-0.51% (-0.30)	-0.83% (-0.37)	-2.21% (-1.03)	-2.87% (-1.34)	-1.73% (-0.86)
	Momentum (*R*)	4.42% (3.22)	8.33% (4.35)	9.59% (5.39)	10.33% (5.88)	10.05% (5.71)
J = 12	Winners (*R*)	4.47% (3.59)	6.45% (3.22)	7.64% (2.94)	8.11% (2.49)	8.98% (2.34)
	Losers (*R*)	-0.25% (-0.15)	0.26% (0.11)	0.69% (0.27)	1.90% (0.69)	3.77% (1.21)
	Momentum (*R*)	4.72% (3.43)	6.19% (3.32)	6.95% (3.33)	6.21% (2.81)	5.22% (1.99)

Table 4: *t* statistics denoted as Winners (*p*), Losers (*p*), and Momentum (*p*), using the JT-methodology, and the total average return on these denoted as Winners (*R*), Losers (*R*), and Momentum (*R*). A simple *t* test has been performed to calculate the probabilities. The *J* in the most left column stands for the formation period of the portfolios. The *K* in the top row stands for the holding period of the portfolios.

It is hard to pinpoint which single holding period *K* generates the most significant results, since it varies across formation periods *J*, but the highest abnormal returns are definitely present when the formation period J is six; The combinations of $J = 6$ / $K = 9$, $J = 6$ / $K = 12$, and $J = 6$ / $K = 15$ give an average abnormal return of 11.00%, 12.16%, and 12.06% respectively. The combinations with a formation period J of three months also generate high average abnormal returns; for $J = 3$ / $K = 12$ and $J = 3$ / $K = 15$ the average is 11.41% and 12.43% respectively. However, the higher variance in these returns somewhat lowers the test statistics.

The theory of mean reversion after a period of twelve months does not get much support from the winner portfolios; all winner portfolios are still statistically significant with a holding period of fifteen months, and do not seem to be systematically weaker than the portfolios with a holding period of twelve months. So, these figures do not support the theory that momentum returns show a reversion to the market return after a period longer than twelve months.

None of the loser portfolios turn out to be statistically significant. This is in line with research of e.g. Muga and Santamaría (2007), where none of the loser portfolio is statistically significant as well. The loser portfolios seem to perform the worst when the formation period J is nine months; for $J = 9$ / $K = 9$ and $J = 9$ / $K = 12$ the portfolios produce the lowest negative, yet insignificant, results. Furthermore, the theory of mean reversion after a period of twelve months seems to hold in case of the loser portfolios; all portfolios with a holding period K of fifteen months have a higher test statistic in comparison with a holding period K of twelve months. For the formation periods $J = 3$, 6, and 12 the test statistic is even positive. However, all these statistics are not significant.

All momentum portfolios show significant results, mainly due to the strong significant results of the winner portfolios. However, the momentum portfolio of $J = 12$ / $K = 15$ is only just significant with a test statistic of 1.985, implying that momentum is less present with higher formation periods and holding periods. Momentum seems present the strongest in the portfolios with a holding period K of nine and twelve months.

To give a summarized view of the impact of different holding periods, line graphs for every formation period are presented in appendix A, and the line graph for the three month formation period is presented in figure 1. The line graphs of the six month, nine month and twelve month formation periods show roughly the same trend as the three month formation period graph.

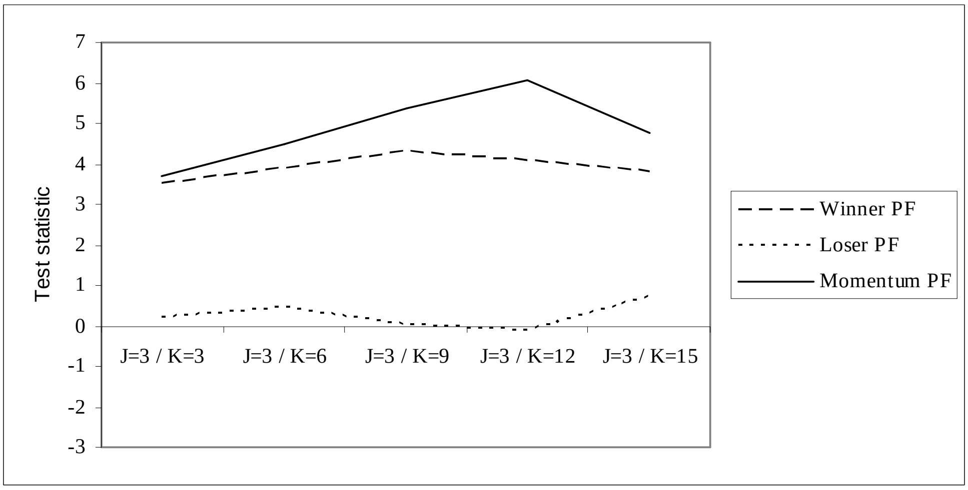

Figure 1: The trend of the use of different holding periods *K* when using a formation period *J* of three months. The different holding periods are placed on the x-axis, while the test statistics are placed on the y-axis.

Looking at the figures in table 4, momentum traders can best use a formation period of six months to create winner and loser portfolios. The highest return is obtained when the portfolios is held for twelve months; the average cumulative abnormal return that is obtained is 12.56%. However, the holding period of nine months gives a return of 12.12%, which implies an added value of 0.44% in three months. Therefore it is interesting for momentum traders to look at the monthly abnormal returns instead of the cumulative abnormal returns with *K* different holding periods.

		K = 3	*K* = 6	*K* = 9	*K* = 12	*K* = 15
J = 3	Winners	1.38%	1.19%	1.07%	0.95%	0.83%
	Losers	0.09%	0.15%	0.00%	-0.03%	0.14%
	Momentum	1.29%	1.04%	1.07%	0.98%	0.69%
J = 6	Winners	1.52%	1.29%	1.22%	1.01%	0.80%
	Losers	0.19%	0.11%	-0.12%	-0.03%	0.23%
	Momentum	1.33%	1.18%	1.35%	1.05%	0.57%
J = 9	Winners	1.31%	1.25%	0.82%	0.62%	0.55%
	Losers	-0.17%	-0.14%	-0.25%	-0.24%	-0.12%
	Momentum	1.47%	1.39%	1.07%	0.86%	0.67%
J = 12	Winners	1.49%	1.08%	0.85%	0.68%	0.60%
	Losers	-0.08%	0.04%	0.08%	0.16%	0.25%
	Momentum	1.57%	1.03%	0.77%	0.52%	0.35%

Table 5: Monthly abnormal returns when using the JT-methodology. The returns are calculated as the returns presented in table 4 divided by the number of months in the respective holding period. *J* stands for formation period, *K* stands for holding period.

These monthly returns are presented in table 5. The results imply other conclusions than the conclusions that were drawn from table 4; if momentum traders want to obtain the highest monthly abnormal return, they should construct their winner and loser portfolios based on the last twelve months, and hold them for three months. This strategy generates a monthly abnormal return of 1.57%. If this is done four times, it would generate an average cumulative abnormal return of 18.84%, which is higher than the 12.56% which is generated when using the strategy with a formation period of six months and a holding period of twelve months.

Event-methodology I results

Before the results from event-methodology I are presented, the returns of this methodology are tested with the Jarque and Bera (1980) test. The results from this test can be found in table 6.

The critical value of a Chi squared test with two degrees of freedom that is appropriate with a 95 percent confidence level is 5.99. So it can be concluded that all portfolios are statistically insignificant; these portfolios are nonnormally distributed that must be tested with the Corrado (1989) test. The conventional *t* test is not needed for event-methodology I.

		$K = 3$	$K = 6$	$K = 9$	$K = 12$	$K = 15$
$J = 3$	Winners	40.82	52.62	36.47	25.35	17.68
	Losers	151.78	105.87	101.93	105.96	72.08
	Momentum	45.27	94.68	98.77	148.29	85.74
$J = 6$	Winners	36.21	43.61	35.20	20.89	11.87
	Losers	124.88	96.58	113.27	95.99	43.42
	Momentum	12.95	32.58	103.70	105.72	39.26
$J = 9$	Winners	33.08	22.79	14.85	11.79	7.05
	Losers	103.61	87.22	85.09	59.70	37.37
	Momentum	8.10	35.88	42.47	35.95	32.85
$J = 12$	Winners	16.46	20.04	13.35	7.07	6.27
	Losers	80.03	51.75	46.35	39.29	33.14
	Momentum	7.55	12.58	16.67	19.30	27.34

Table 6: Jarque Bera test statistics for different *J* and *K* using the event-methodology I.

The results of the Corrado (1989) test which was applied on the event-methodology I returns can be found in table 7, which gives some surprising results. First of all, the winner and loser portfolios are all statistically significant at a five percent confidence level. However, the momentum portfolios show weaker statistics, and some are even statistically insignificant. This is caused by the fact that the average rank of the momentum portfolios is usually closer to zero than the average rank of the winner and loser portfolios. Furthermore, the standard deviation of the momentum portfolios is also higher than the standard deviation of the winner and loser portfolios. The average rank and standard deviation of the portfolios can be found in appendix B.

		K = 3	*K* = 6	*K* = 9	*K* = 12	*K* = 15
J = 3	Winners (*R*)	4.82% (4.58)	8.15% (4.80)	10.59% (4.94)	12.94% (5.18)	14.36% (4.58)
	Losers (*R*)	-0.60% (-3.44)	-1.04% (-4.32)	-1.64% (-5.06)	-2.04% (-5.92)	0.27% (-4.81)
	Momentum (*R*)	5.43% (1.61)*	9.19% (1.21)*	12.23% (1.55)*	14.97% (2.07)	14.10% (1.12)*
J = 6	Winners (*R*)	4.46% (2.74)	7.99% (3.87)	11.54% (4.93)	12.82% (5.51)	13.38% (4.49)
	Losers (*R*)	-0.52% (-4.39)	-0.85% (-4.20)	-2.13% (-6.10)	-1.51% (-6.09)	1.86% (-4.87)
	Momentum (*R*)	4.98% (0.13)*	8.83% (1.10)*	13.67% (2.27)	14.33% (2.05)	11.52% (1.17)*
J = 9	Winners (*R*)	4.41% (2.04)	8.38% (4.05)	10.62% (4.60)	11.91% (4.98)	12.63% (4.38)
	Losers (*R*)	-0.43% (-4.98)	-1.01% (-4.52)	-1.09% (-4.89)	0.38% (-4.41)	2.26% (-4.35)
	Momentum (*R*)	4.84% (0.16)*	9.39% (2.20)	11.72% (2.29)	11.53% (1.75)	10.37% (1.75)
J = 12	Winners (*R*)	5.02% (3.01)	8.10% (4.90)	9.67% (4.84)	10.60% (4.42)	11.86% (4.67)
	Losers (*R*)	-0.01% (-3.93)	0.53% (-2.93)	1.06% (-3.14)	1.90% (-3.27)	3.28% (-3.15)
	Momentum (*R*)	5.04% (0.58)*	7.57% (1.90)	8.61% (1.90)	8.70% (1.77)	8.59% (1.67)

Table 7: Cumulative abnormal returns of the winner, loser and momentum portfolios, using the event-methodology I. Test statistics are given in brackets next to the returns. The *J* in the most left column stands for the formation period of the portfolios. The *K* in the top row stands for the holding period of the portfolios. Insignificant portfolios are marked with a *.

Another surprising result is that the momentum strategies show less significance than the winner portfolios, which is inverse in the case of the JT-methodology. This is caused by the fact that ranks are used instead of raw returns. The high positive returns are compensating for the slightly lower negative returns in the JT-methodology; these are not distributed symmetrically. But when using ranks this compensation drops out; the lowest rank is equally weighted as the highest rank; the effect of the highest and lowest rank are made symmetrical.

The mean-reversal effect after twelve months is slightly visible in these statistics. All fifteen month holding period statistics are weaker than their twelve month holding period equivalents, with the exception of the J = 12 / K = 15 winner portfolio. The fifteen month holding period momentum portfolios of J = 3 / K = 15 and J = 6 / K = 15 even change to insignificant test statistics, compared to their twelve month holding period equivalents. However, the mean reversal in the test statistics is mainly due to higher variance, because the returns are generally higher. For instance, with a formation period of three months, the test statistic and the returns are 5.18 and 12.94% respectively for a holding period of twelve months. If this is compared with the fifteen month holding period equivalent, the test statistic is lower (4.58), but the abnormal return is higher (14.36%). This must mean that the higher variance is lowering the test statistic.

In this strategy, the holding period returns are adjusted with the beta of the stock before the returns are ranked. The advantage of this methodology is that the portfolio is not mainly driven by high beta stocks; high beta stocks have to perform even better and low beta stocks have to perform less better in order to be assigned to the winner portfolio. Momentum traders can use this strategy to create a portfolio with momentum stocks that are less beta driven than the portfolios created with e.g. the JT-methodology.

As a robustness check, the portfolios are also tested with the Student t test. The results from this test can be found in Appendix C. The main difference of the results from the Corrado test and the Student t test is that the loser portfolios and momentum portfolios greatly differ in significance; loser portfolios are significant when using the Corrado test, but insignificant when using the Student t test. Momentum portfolios are significant when using the Student t test, but insignificant when using the Corrado test. Therefore it is very important to use the right test when testing for momentum portfolios, and since the returns are usually nonnormally distributed, the best test to use is the Corrado test.

Event-methodology II results

The event-methodology II uses the same ranks as the JT-methodology; the top decile of the returns is assigned to the winner portfolio and the bottom decile is assigned to the loser portfolio. Then, the returns of the holding period *K* are determined, where the returns are adjusted for beta. First, the returns of the portfolios are tested for normality. These results are presented in table 8.

		K = 3	K = 6	K = 9	K = 12	K = 15
J = 3	Winners	8.20	10.51	7.72	21.12	40.57
	Losers	6708.90	1710.68	687.69	52.66	26.97
	Momentum	687.26	94.50	16.25	37.84	34.02
J = 6	Winners	2.76*	20.21	30.08	59.56	80.30
	Losers	3767.45	906.16	337.38	30.27	4.19*
	Momentum	140.48	23.28	32.86	59.70	66.81
J = 9	Winners	9.18	8.47	28.20	66.55	65.20
	Losers	3684.28	769.92	286.76	12.31	2.96*
	Momentum	121.33	21.26	30.47	66.27	55.75
J = 12	Winners	3.82*	26.99	54.98	69.88	67.49
	Losers	4350.56	923.25	463.00	18.78	13.95
	Momentum	271.81	16.39	0.21*	22.95	22.24

Table 8: Jarque Bera test statistics for different J and K using the event-methodology II. The portfolio returns which are normally distributed are marked with a *.

Again, the critical value of the appropriate Chi-squared test is 5.99. The Jarque-Bera test statistics show more extravagant results than the results from the event-methodology I study; some returns appear to be distributed normally, while there are some heavy outliers within the loser portfolios. These high test statistics is caused by the burst of the internet bubble in March 2000, which give outliers of more than -100%. As mentioned earlier, returns of more than -100% are possible because of the use of continuously compounded returns. Furthermore, the test statistic for winner portfolios appears to increase with an increasing holding period, while the inverse appears for the loser portfolios.

Summarizing, there are five portfolios that are normally distributed. These should be tested with the Student *t* test, but for comparison purposes, all portfolios are first tested with the Corrado (1989) test. The results from this test can be found in table 9. Every portfolio is also tested with the student *t* test, which is presented in Appendix D, table 12. The Corrado test results (presented in table 9) show that most of the portfolios are statistically significant, with exception to one loser portfolio.

		K = 3	*K* = 6	*K* = 9	*K* = 12	*K* = 15
J = 3	Winners (*R*)	2.29% (2.70)	4.04% (3.10)	5.48% (3.15)	5.95% (3.03)	5.97% (3.44)
	Losers (*R*)	-0.98% (-1.80)	-2.30% (-1.83)	-4.04% (-2.06)	-4.94% (-2.04)	-3.72% (-1.68)
	Momentum (*R*)	3.28% (1.89)	6.34% (2.28)	9.52% (2.41)	10.89% (2.40)	9.69% (2.26)
J = 6	Winners (*R*)	2.74% (2.73)	4.55% (3.01)	6.47% (3.26)	6.61% (3.30)	5.13% (3.51)
	Losers (*R*)	-0.80% (-1.72)	-2.42% (-1.97)	-4.81% (-2.05)	-4.35% (-2.00)	-1.74% (-1.59)*
	Momentum (*R*)	3.53% (2.17)	6.97% (2.41)	11.29% (2.79)	10.96% (2.77)	6.86% (2.56)
J = 9	Winners (*R*)	1.88% (1.22)*	4.10% (1.43)*	4.91% (1.62)*	4.61% (1.49)*	3.67% (1.78)
	Losers (*R*)	-2.14% (-3.92)	-3.93% (-3.93)	-4.38% (-4.33)	-3.25% (-3.97)	-1.35% (-3.69)
	Momentum (*R*)	4.02% (2.20)	8.03% (2.41)	9.29% (2.79)	7.86% (2.65)	5.03% (2.46)
J = 12	Winners (*R*)	2.67% (2.83)	3.81% (3.04)	4.13% (3.17)	3.76% (3.15)	3.63% (3.53)
	Losers (*R*)	-1.83% (-3.24)	-2.54% (-3.26)	-2.42% (-3.55)	-1.47% (-3.55)	-0.56% (-3.21)
	Momentum (*R*)	4.49% (3.34)	6.35% (3.50)	6.55% (4.03)	5.23% (4.17)	4.20% (3.96)

Table 9: Cumulative abnormal returns from the event-methodology II test, which adjusts for beta after the stocks have been assigned to winner and loser portfolios. *J* stands for the formation period, and *K* stands for the holding period. The Corrado test has been used to calculate the test statistics, which are presented in brackets behind the returns. The statistics marked with a * are insignificant, other results are significant.

Furthermore, a range of winner portfolios with a formation period of nine months are also statistically insignificant, while their six and twelve month formation period equivalents show highly significant results. This indicates that, regardless of how long the portfolio is held, the usage of a formation period of nine months is less effective than the usage of other holding periods. However, if this is compared with the JT-methodology (table 4) and the event-methodology I (table 7), the usage of different holding periods seems to have no effect on the test statistic. Furthermore, the test statistics of the student *t* test given in Appendix D do not show this insignificance in the holding period of nine months.

Mean reversion after a holding period of more than twelve months does not seem to hold in these results; every fifteen month holding period winner portfolio has a higher test statistic than its twelve month counterpart. However, the fifteen month holding period loser portfolios all have a lower test statistic, yet only two statistics change from significant to insignificant. It can be argued that this is caused by the use of different appropriate tests, but appendix D shows that the Student *t* test gives significant results for almost all other portfolios. Thus, this can be seen as evidence that at least some loser portfolios show a strong mean reversion effect when they are held for a period of more than twelve months.

The adjustment of the returns with the betas after the portfolios have been ranked does not seem to have a significant effect on the test statistics. This indicates that momentum returns are not purely driven by the beta of the stock, i.e. the market risk. However, it should be noted that event-methodology II produces lower cumulative abnormal returns and test statistics than e.g. the JT-methodology, both with the Corrado test (table 9) and the Student *t* test (Appendix D). So, this new methodology suggests that beta has a slight influence, but there are more factors present in explaining the origin of momentum.

VI. Conclusion, Discussion and Further Research

This paper investigated the presence of momentum returns in the Dutch and Belgian stock market during the period 1995-2009. Various methodologies, newly developed and old, have been used to test for the presence. First, the methodology of Jegadeesh and Titman (1993) was used, which gave similar results as earlier research; momentum is still highly present in the Dutch and Belgian stock market. The highest cumulative abnormal return of 12.56% was found when using a formation period of six months and a holding period of twelve months. The highest monthly abnormal return that was found was 1.57%, with a holding period of three months and a formation period of twelve months.

The first new methodology adjusts the returns with the beta of the stock before the stocks are ranked and classified into winner and loser portfolios. The winner and loser portfolios are highly significant with this methodology, but the momentum portfolios show mainly insignificant test statistics because of the extremely high variance which is present within the momentum portfolios. This methodology can be useful for momentum traders because the portfolios are less driven by beta, thus less riskier.

The second new methodology adjusts the returns with the beta of the stock after the stocks are ranked. The main implication of this methodology was to test if momentum strategies are driven by beta. The results of this methodology are still significant, but show less strong abnormal returns and test statistics and some of the portfolios are even insignificant. This gives rise to the idea that momentum portfolios are at least partly driven by beta. However, further research is required before this can be concluded. A test which regresses momentum returns against beta and various other economic and financial factors which could explain the presence of momentum could explain the origin of momentum in even more detail.

The results are mixed concerning the theory of mean reversion after twelve months; several fifteen month holding period statistics are weaker than their twelve month counterparts, and some even change from significant to insignificant. However, other figures show an increase in significance and return. Concluding, it is largely dependent on the formation period that is used and the test that is applied to the results whether momentum returns show a mean reversion effect.

The results from this research give various implications for traders that want to use momentum strategy to generate abnormal returns. First of all, the JT-methodology suggests that momentum effect is still largely present in the Dutch and Belgian stock markets, and that momentum strategies generate significant abnormal returns. However, event methodology II suggests that momentum returns are partly based on the beta of the stock, and that momentum returns are partly a result of a risk-return tradeoff. Momentum traders should thus realize that their strategies are partly based on risk and that momentum trading is not a guarantee for significant abnormal returns. To compensate for this risk, momentum traders can use the event methodology I. This methodology gives a less riskier portfolio, while still significant abnormal returns are generated.

VII. Bibliography

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Brown, Stephen J., and Jerold B. Warner, 1980, Measuring Security Price Performance, *Journal of Financial Economics* 8, 205-258.

Chordia, Tarun, and Lakshmanan Shivakumar, 2002, Momentum, Business Cycle, and Time-varying Expected Returns, *The Journal of Finance* 57, 985-1019.

Chui, Andy Chun Wai, Kuo-Chiang K. Wei, and Sheridan Titman, 2000, Momentum, Legal Systems and Ownership Structure: An Analysis of Asian Stock Markets. Unpublished working paper. University of Texas at Austin.

Conrad, Jennifer, and Gautam Kaul, 1998, An Anatomy of Trading Strategies, *Review of Financial Studies* 11, 489-519.

Cooper, Michael J., Roberto C. Gutierrez jr., and Allaudeen Hameed, 2004, Market States and Momentum, *The Journal of Finance* 59, 1345-1365.

Corrado, Charles J., 1989, A Nonparametric Test for Abnormal Security-Price Performance in Event Studies, *Journal of Financial Economics* 23, 385-395.

Cunningham, S. W., 1973, The Predictability of British Stock Market Prices, *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 22, 315-331.

Daniel, Kent, David Hirschleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *The Journal of Finance* 53, 1839-1885.

Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283-306.

Gosnell, Thomas F., Arthur J. Keown, and John M. Pinkerton, 1996, The Intraday Speed of Stock Price Adjustment to Major Changes: Bid-ask Bounce and Order Flow Imbalances, *Journal of Banking & Finance* 20, 247-266.

Grinblatt, Mark, and Bing Han, 2005, Prospect Theory, Mental Accounting, and Momentum, *Journal of Financial Economics* 78, 311-339.

Hameed, Allaudeen, and Yuanto Kusnadi, 2002, Momentum Strategies: Evidence from Pacific Basin Stock Markets, *Journal of Financial Research* 25, 383-397.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *The Journal of Finance* 55, 265-295.

Hong, Harrison, and Jeremy C. Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, *The Journal of Finance* 54, 2143-2184.

Jarque, Carlos M., and Anil K. Bera, 1980, Efficient Tests for Normality, Homoscedasticity and Serial Independence of Regression Residuals, *Economic Letters* 6, 255-259.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *The Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *The Journal of Finance* 56, 699-720.

MacKinlay, A. Craig, 1997, Event Studies in Economics and Finance, *Journal of Economic Literature* 35, 13-39.

Moskowitz, Tobias, and Mark Grinblatt, 1999, Do Industries Explain Momentum?, *The Journal of Finance* 54, 1249-1290.

Muga, Luis, and Rafael Santamaría, 2007, The Momentum Effect in Latin American Emerging Markets, *Emerging Markets Finance & Trade* 43, 24-45.

Muga, Luis, and Rafael Santamaría, 2009, Momentum, Market States and Investor Behavior, *Empirical Economics* 37, 105-130.

Nofsinger, John R. , 2008. *The Psychology of Investing* (Pearson Education Inc., Upper Saddle River, New Jersey).

Rouwenhorst, Geert K., 1998, International Momentum Strategies, *The Journal of Finance* 53, 267-284.

Sagi, Jacob S., and Mark S. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum, *Journal of Financial Economics* 84, 389-434.

Senna, A. P., 2002, Event Study Tests, a Brief Survey. Unpublished working paper. University of Porto.

Shefrin, Hersch, and Meir Statman, 1985, The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, *The Journal of Finance* 40, 777-790.

Tai, Chu-Sheng, 2003, Are Fama-French and momentum factors really priced?, *Journal of Multinational Financial Management* 13, 359-384.

Appendix A: Graphical overview of the results of the JT-methodology

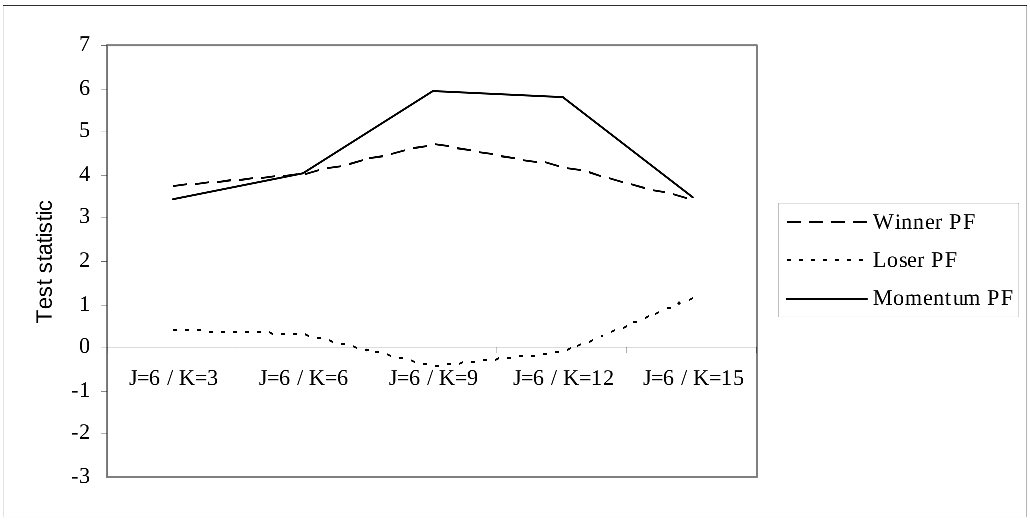

Figure 2: The trend of the use of different holding periods *K* when using a formation period *J* of six months.

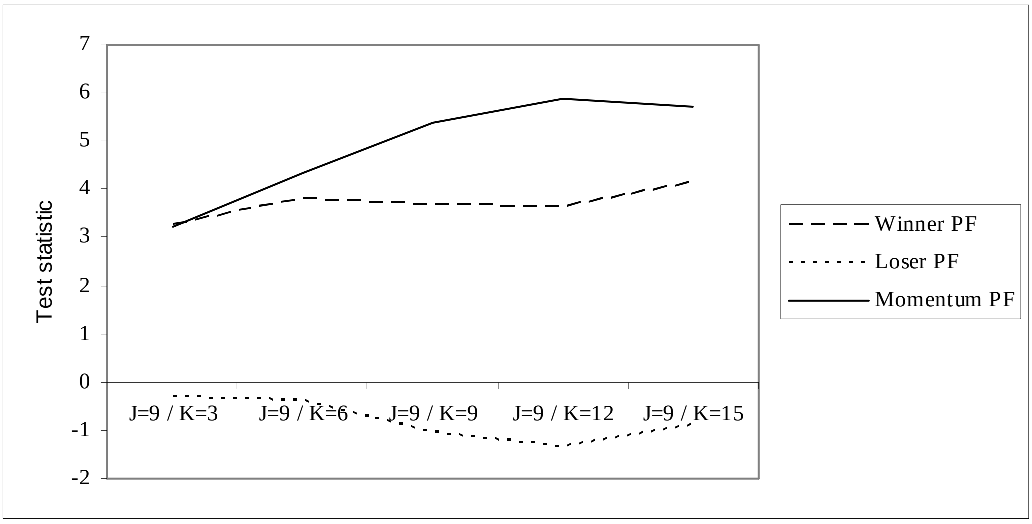

Figure 3: The trend of the use of different holding periods *K* when using a formation period *J* of nine months.

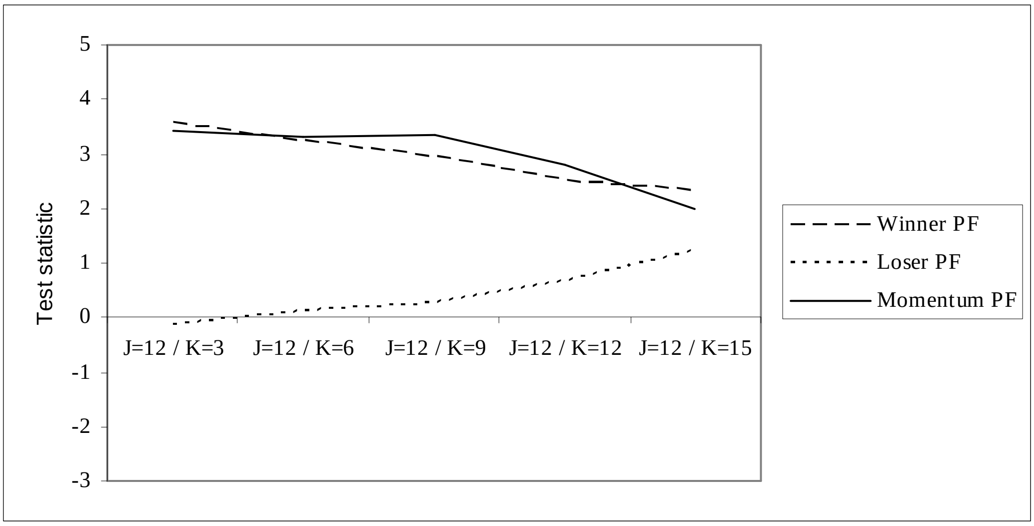

Figure 4: The trend of the use of different holding periods *K* when using a formation period *J* of twelve months.

Appendix B: Average rank and standard deviation of the Corrado test of event-methodology I

			K = 3	K = 6	K = 9	K = 12	K = 15
J = 3		Winner	-6.639	-7.035	-7.422	-7.716	-7.043
	$m_{it} - \overline{m}$	Loser	4.569	5.700	6.919	7.863	6.714
		Momentum	-3.355	-2.729	-3.500	-4.363	-2.342
		Winner	19.07	19.09	19.41	19.09	19.50
	Standard deviation	Loser	17.48	17.20	17.67	17.00	17.72
		Momentum	27.37	29.34	29.23	27.05	26.54
J = 6		Winner	-4.338	-6.153	-7.479	-8.196	-7.130
	$m_{it} - \overline{m}$	Loser	6.715	5.901	8.771	8.848	7.389
		Momentum	-0.309	-2.524	-5.113	-4.332	-2.478
		Winner	20.65	20.52	19.43	18.87	19.98
	Standard deviation	Loser	19.95	18.16	18.40	18.43	19.07
		Momentum	30.14	29.63	28.81	26.79	26.53
J = 9		Winner	-3.476	-6.595	-7.127	-7.794	-7.058
	$m_{it} - \overline{m}$	Loser	8.105	7.216	8.059	7.288	7.232
		Momentum	-0.368	-4.991	-5.171	-3.858	-3.806
		Winner	22.06	20.86	19.66	19.68	20.08
	Standard deviation	Loser	21.03	20.46	20.90	20.79	20.72
		Momentum	29.84	29.03	28.60	27.74	27.10
J = 12		Winner	-4.954	-7.829	-7.649	-7.206	-7.592
	$m_{it} - \overline{m}$	Loser	6.674	4.935	5.142	5.439	5.197
		Momentum	-1.326	-4.463	-4.446	-3.884	-3.500
		Winner	21.09	20.27	19.88	20.30	20.03
	Standard deviation	Loser	21.73	21.40	20.59	20.73	20.37
		Momentum	29.13	29.75	29.44	27.34	25.82

Table 10: Overview of the average rank and the standard deviation of the Corrado test of event-methodology I. *J* is the formation period, *K* is the holding period, $m_{it} - \overline{m}$ is the rank of momentum strategy *i* at time *t* minus the average rank, which can be calculated as 0.5 + (N_i / 2), see Senna (2002).

Appendix C: Student *t* test statistics of event-methodology I.

		K = 3	K = 6	K = 9	K = 12	K = 15
J = 3	Winners	4.171	4.429	4.448	4.432	4.219
	Losers	-0.423	-0.507	-0.690	-0.746	0.088
	Momentum	5.265	6.619	6.764	7.595	6.449
J = 6	Winners	3.614	4.024	4.719	4.427	3.836
	Losers	-0.356	-0.398	-0.856	-0.547	0.612
	Momentum	4.287	5.155	6.905	6.953	4.779
J = 9	Winners	3.502	4.248	4.354	4.052	3.526
	Losers	-0.287	-0.459	-0.416	0.132	0.708
	Momentum	3.915	5.334	5.595	5.022	4.015
J = 12	Winners	4.053	4.155	3.911	3.439	3.166
	Losers	-0.007	0.240	0.425	0.674	1.004
	Momentum	4.096	4.373	4.422	4.023	3.415

Table 11: Student *t* test statistics of event-methodology I. *J* stands for formation period, and *K* stands for holding period.

Appendix D: Student *t* and Corrado test statistics of event-methodology II.

		K = 3	*K* = 6	*K* = 9	*K* = 12	*K* = 15
J = 3	Winners	3.373	4.324	4.592	4.056	3.783
	Losers	-1.442	-2.605	-3.599	-3.578	-2.378
	Momentum	3.537	5.130	5.712	5.664	4.382
J = 6	Winners	3.559	3.960	4.546	4.175	2.825
	Losers	-1.043	-2.465	-3.793	-2.821	-1.028
	Momentum	3.309	4.440	5.733	4.895	2.685
J = 9	Winners	2.340	3.355	3.393	2.828	1.937
	Losers	-2.759	-3.869	-3.320	-2.063	-0.781
	Momentum	3.506	4.833	4.534	3.480	1.902
J = 12	Winners	3.248	3.323	3.052	2.287	1.876
	Losers	-2.408	-2.504	-1.924	-0.983	-0.324
	Momentum	4.049	4.134	3.664	2.462	1.634

Table 12: Results from the event-methodology II test, using the student *t* test. Event methodology II adjusts for beta after the stocks have been assigned to winner and loser portfolios. *J* stands for the formation period, and *K* stands for the holding period.