Bachelor Thesis Finance (300TFI)

Investing in Relative Strength: Momentum Strategies Applied to Euronext Stocks

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ABSTRACT

This paper documents that investment strategies that buy stocks that have performed well in the past 3 to 12 months and short sell stocks that have performed poorly during that period, no longer generate significant positive returns in the European securities market, if the positions are held for one year or less. Such zero-cost momentum strategies were capable of yielding excess returns that averaged up to 11.20% annually during the recent decade, when applied to a selection of stocks that were listed on the Euronext-100 and Next-150 indices during that period. However, because of high volatility, these excess returns could not be found statistically significant. The statistical insignificance of these zero-cost returns is contrary to earlier academic work. Long-only momentum strategies that buy past winners yielded significant excess returns of up to 20.72% when applied to the sample, but these returns are likely the result of selection bias. Further analyses show that the zero-cost momentum strategies have not significantly outperformed the European market, nor the indices their stocks were sourced from, although the results do not warrant the claim they have underperformed relative to these benchmarks either. Jensen's alpha is also determined for the zero-cost strategies and is found to be insignificant, even though it is positive for all analyzed strategies. Finally, the persistence of excess returns generated by the zero-cost portfolios is analyzed. The results begin to show negative excess returns if portfolio formation is delayed by 11 months after stock selection. The pattern that emerges from the lagged returns is however much less clear than previous research has postulated, as the excess returns do not remain negative if portfolio formation is delayed much further.

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I. Introduction

A) Conceptualization

As long as financial markets have existed, investors have been interested in predicting stock market price movements. Prior to a 1967 study done by Robert Levy, scholarly sources strongly believed that technical analysis of stock prices was "no more useful in predicting future price movements than throwing a dart at the list of stocks in a daily newspaper". Contemporary statistical analyses showed, time and time again, that successive changes in a stock's price were statistically independent. As a result, stock price movements had always been viewed as mere 'random walks'.[1] After examining 68 different trading rules in his dissertation, Levy came to the conclusion that "a trading rule that buys stocks with current prices that are substantially higher than their average prices over the past 27 weeks realizes significant abnormal returns".[2] This strategy got to be known as Levy's trading rule. Initially, this trading rule elicited much skepticism among other scholars. One famous criticism was made by Jensen and Bennington (1970), who analyzed Levy's trading rule over a longer time period and found that the trading rule does not outperform a buy and hold strategy. They attributed Levy's results to a selection bias.[3] Nevertheless, for the time periods analyzed by Levy, this trading rule was in fact one of the first examples, if not the first example of successful relative strength strategies. Because these relative strength strategies aim to produce significant returns by reaping the benefits of stock price momentum exhibited by past winners, they also became known as momentum strategies.

Studies in the past showed that momentum strategies could yield raw returns of more than 25% annually for long-only portfolios and returns of up to 17% for zero-cost portfolios which buy pas winners and short past losers.[4] This renders stock price momentum a very interesting topic for investors and academics alike. Since Levy (1967), a number of other academics have researched the topic, yielding amongst other things several distinct methods for selecting 'winner stocks' as well as some suggested causes of stock price momentum. Most causes suggested are behavioral in nature, and usually also provide some legitimacy for strategies opposite of relative strength, i.e. relative weakness: the so-called contrarian strategies, where past losers are supposedly undervalued and have a potential for large abnormal returns as a result. An influential paper in that field is De Bondt and Thaler (1985), which showed that past loser actually earned about 25% more than past winners over the period of 36 months after portfolio formation. Despite the supposed causal similarities between contrarian and momentum strategies, this thesis will focus solely on momentum strategies. These momentum strategies usually exhibit return reversals for selected stocks sometime after portfolio formation (arguably when stock prices finally converge to their fundamental values), which is in accordance with criticisms made by Jensen and Bennington (1970). The next page describes the goals of this paper by introducing a proper problem formulation, as well as a description of content.

[1] Levy (1967), p.595
[2] Jegadeesh and Titman (1993), p.66
[3] Idem, p.66
[4] Idem, p.70

B) Problem Formulation

Momentum strategies can differ from one another in several notable dimensions. The main characteristic on which to differentiate these strategies, is the quantitative variable used to separate 'winner' stocks from 'loser' stocks. To this end, Levy's trading rule incorporates some variable which describes how much a stock's quote is above its past average (preferably a relative measure that also incorporates statistical significance). As will be shown in section II, a variety of other variables are available for stock selection today. Other dimensions on which momentum strategies differ, include length of the 'look-back period' (J), length of holding period (K), as well as whether 'lag' (L) is included in the stock selection model, in order to correct for some of the randomness caused by bid-ask spreads and other short-term phenomena relating to stock prices. In short, a variety of momentum strategies exist. I will often denote strategies as either (J,K) or J/L/K. In this paper I will analyze some of the most noteworthy momentum strategies that have been introduced by academic literature, ranging from a simple one-portfolio 11/1/1 strategy to more elaborate multi-portfolio Jegadeesh & Titman strategies. These momentum strategies will be analyzed to see whether they continue to be viable investment strategies in recent times.

The rest of this paper is organized as follows: Section II entails a review of some relevant academic literature, covering a multitude of momentum strategies, models that explain the occurrence of momentum and some evidence of momentum in the European securities market; Section III describes the sample (subsection A), sets forth the momentum returns (subsection B), elaborates on their performance relative to measures of the European market return (subsection C), documents their risk compensation (subsection D) and provides an analysis of their return reversals (subsection E); Section IV provides final thoughts and concludes the paper. Sections V and VI cover the academic references and appendices.

II. Literature Survey

A) Drivers of Stock Price Momentum

Since Levy (1967), substantial evidence has been found in support of his contention of the non-randomness of stock price movements. Nowadays, there is not much controversy about the existence of momentum in stock returns; however, it is much less clear what causes the phenomenon (Hong and Stein, 2000). Traditional asset-pricing models – such as the CAPM, APT or ICAPM – have a hard time explaining observed stock price momentum. All predictable asset returns in these models are ultimately attributed to economic principles, e.g. risk. However, Hong and Stein (1991) argue that there is currently not much evidence to suggest that momentum returns can in fact be attributed to such economic factors. Therefore, many scholars have turned to 'behavioral' models in order to explain the existence of stock price momentum. These behavioral models depart from classical assumptions, e.g. full rationality, and introduce psychological and behavioral concepts to model and explain some irrational behavior on the part of investors, which is then assumed to be the cause of persisting momentum in stock prices. Hong and Stein (1991) aptly comment about a clear disadvantage of such non-classical models: when departing from a set theoretical framework, such as that of classical economics, a virtually unlimited amount of deviations from that framework are possible. Any selection of non-classical assumptions that together form a model, might then inevitably be perceived as arbitrary. Despite such criticisms, some behavioral models that have been constructed in an attempt to explain asset return patterns have been highly influential. The main academic contributions were made by the models of Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1999), DeLong, Shleifer, Summers, and Waldmann (1990), and Hong and Stein (1999).

The first model to be discussed is Barberis, Shleifer, and Vishny (1998), which is a model in which the earnings of an asset follow a random walk, but an investor does not know this. The investor's behavior is governed by two psychological phenomena: conservatism and the representativeness heuristic, given the conviction that the asset price is either trending (i.e. likely to rise further after an increase) or mean-reverting. Conservatism means that individuals change their beliefs only slowly in the face of new evidence, which is consistent with observed market underreactions. The representativeness heuristic can be explained as "the tendency of experimental subjects to view events as typical or representative of some specific class and to ignore the laws of probability in the process" (Barberis, Shleifer and Vishny, 1998). A good example in the stock market are so-called growth stocks, which are viewed as such based on consistent earnings growth in the past. However, investors tend to ignore the fact that there are very few companies that just keep growing and hence ignore the probability that the returns on a growth stock will stagnate. In other words, the representativeness heuristic can lead people to believe they see patterns where none truly exist. Having incorporated conservatism and the representativeness heuristic in their model, Barberis, Shleifer and Vishny show that for plausible parameters values, their model is able to predict stock price momentum as it is observed in their data. Based on their research, the authors state that over horizons of one to twelve months, security prices are often positively autocorrelated and that over longer horizons of perhaps 3 to 5 years they, on average, return to the mean.

This short-term positive autocorrelation and long-term negative autocorrelation was also found by Daniel, Hirshleifer, and Subrahmanyam (1999), who developed their own theoretical model of stock price momentum, based on two other well-known psychological biases: investor overconfidence about the precision of private information and biased self-attribution. The first bias is self-explanatory and the latter simply means that positive investment returns to an individual often lead to an inappropriately large increase of that person's confidence in their own capabilities. Conversely, negative returns decrease confidence, but to a much lesser extent. In fact, investors often blame their portfolio's underperformance solely on externalities. Similar to the previously discussed model, the agents' psychology leads to under- and overreactions in the securities market, which manifest in the occurrence of such phenomena like stock price momentum. According to the authors, investor overconfidence results in negative long-term return autocorrelations (i.e. return reversals), whereas biased self-attribution results in positive short-term return autocorrelations (i.e. securities' price momentum), but also enlarges the return reversal effect. Furthermore, given the biases, public signals on average strengthen investors' beliefs based on private information, which means that public information can further increase overreaction in the securities market. The model shows how continuing overreaction could lead to stock price momentum, as well as how this momentum is reversed in the long run due to further public information that draws prices back to fundamental values. Thus, according to this model, overconfidence and biased self-attribution could explain short-run momentum and long-term return reversals, because these biases are perfectly able to cause the observed market over- and underreactions.

In contrast with the previous model, as well as with the model that was discussed first, DeLong, Shleifer, Summers, and Waldmann (1990) proposed a model that was not based on the assumption that all investors act irrationally. Instead, their model is based on the presence of so-called 'positive feedback investors' in the financial markets. Simply put, positive feedback investors buy securities when their prices rise and sell when these prices fall. Positive feedback trading can result from trend chasing, but also from a stop-loss order, which is common instrument that enables investors to automatically sell an equity position when its price drops below a certain level. Based on the model they propose, the authors claim that a market in which positive feedback traders are active, speculation can destabilize the market, even if the speculation is rational. The destabilization occurs when rational speculators recognize that an initial price increase, justified by available information, will stimulate buying by positive feedback traders in the near future. In anticipation of these purchases, rational speculators at large buy more of the trending stock early in time, which quickly drives its price up beyond fundamental value. When positive feedback traders start buying the stock, they keep prices above fundamental value. Rational speculators in turn start selling the stock, the combined effect of which is stabilizing prices; above fundamental value. Although the price rise is partly rational, it is also partly based on speculation and positive feedback trading. In this model, trading by rational speculators has a destabilizing effect on prices because it triggers positive feedback trading, the effects of which are similar to market overreaction in other models. Furthermore, the authors claim their model is consistent with empirical observations of the overreaction of prices to news and price bubbles. Price bubbles, or in this model: positive-feedback bubbles, essentially manifest themselves as upward asset price momentum, which, combined with the return reversals associated with the burst of a bubble, makes the above model particularly useful in our discussion of momentum investing.

Another model that is based on the interaction between two distinct groups of investors, is the one proposed by Hong and Stein (1999). The authors termed these investor groups: 'momentum traders' and 'newswatchers'. Both types are not fully rational, but boundedly rational instead: agents are not able to process all available public information, rather the two types of agents are able to process a specific subset of public information each. The newswatchers forecast using signals about future fundamentals they privately observe, however, they do not incorporate current or past prices in their forecasts. Momentum traders in contrast, do incorporate past prices in their forecasts, but are limited to simpler functions of these prices while doing so. An important underlying assumption of the model is that "private information diffuses gradually across the news-watcher population". The model then attempts to unify underreaction and overreaction, by incorporating a tendency for the newswatchers to underreact to private information (underreaction follows naturally from combining gradual information diffusion with the assumption that newswatchers do not extract information from prices) and introducing momentum traders that try to exploit the underreaction using simple arbitrage strategies. The 'early' momentum traders only partially eliminate the market underreaction (say, at time t) and in doing so, create an opportunity for 'later' momentum traders (at time t+1) to engage in further arbitrage. The model shows that when momentum traders are limited to simple strategies, prices do not stabilize at fundamental value, instead, the attempts of momentum traders to profit from the underreaction creates an eventual overreaction. This overreaction is consistent with the return reversals that momentum strategies typically exhibit. Having discussed the models that attempt to explain and model the specifics of momentum, several actual momentum strategies and their returns are discussed in the next subsection.

B) Momentum Strategies: Stock Selection and Returns

Besides literature that aims to fundamentally explain the phenomena associated with stock price momentum, other works set out to research actual momentum investment strategies. In that regard, one of the most influential articles since Levy (1967) is Jegadeesh and Titman (1993), in which the authors rank stocks each month based on their individual returns in the last J months and construct equally weighed portfolios based on the top and bottom deciles of the ranking, the winner and loser or buy and sell portfolios respectively, which are then held for K months. For their data, all 16 analyzed zero-cost strategies yielded positive returns that are significant with the exception of only one. Their most successful zero-cost strategy has a formation period of 12 months (over which stock returns are analyzed and winners picked) and a holding period of 3 months. Such strategies can be denoted as (J, K) strategies. The previously mentioned (12, 3) strategy yielded a monthly zero-cost return of 1.31% or 16.9% annually. Possibly a legacy of Levy's trading rule, the focus of most authors is usually on (6, 6) strategies, however. Jegadeesh and Titman (1993) claim the returns of their (6,6) momentum strategy are representative of the returns to the other (J,K) momentum strategies and perform many of their additional analyses solely on this (6,6) strategy.

Besides stock selection based on past returns, other criteria for stock selection have been postulated as well. Moskowitz and Grinblatt (1999) argue for example, that stock price momentum is driven by momentum in the industries to which these stocks' firms belong. Their stock selection model is thus based on industry momentum: past performance is measured as the value-weighted industry return over the past 6 months, of the industry to which each stock belongs. Then, stocks are ranked monthly, in ascending order according to their industries' past performance. Based on these rankings, three portfolios are formed: stocks ranked in the top 30% of industries constitute the winner portfolio, stocks in bottom 30% constitute the loser portfolio, and the remaining stocks constitute the middle portfolio. All of these portfolios are equally weighted. The strategy is to hold a zero-cost portfolio that is long the winner and short the loser portfolios, for 6 months. In contrast to individual stock momentum, industry momentum appears to be most profitable in the very short term (one month). For their data, top strategies were (1, 1) and (12, 1), where the (12 ,1) strategy yielded a raw return of 27.1% annually and 10.7% of zero-cost return, whereas the (1, 1) strategy yielded 25.8% raw returns annually and zero-cost returns of 13.4%.

The stock selection of both Moskowith and Grinblatt (1999) and Jegadeesh and Titman (1993) use a measure of past performance that is seems to be relevant to the continuance of stock returns. George and Hwang (2004) on the other hand, propose a measure which is based on how near a stock's current price is to its highest price in the preceding 52 weeks. Although this does measure past performance relative to the 52-week high, it is not strictly a measure of overall past performance. Rather, this measure was chosen, because the authors believe that momentum returns can be explained by a behavioral model which incorporates an anchor-and-adjust bias, where the 52-week high is the anchor. The exact measure used by George and Hwang (2004) is the ratio of a stock's current price to its 52-week high. Their winner portfolio is an equally weighted portfolio which consists of the 30% of stocks with the highest ratio, whereas their loser portfolio is a similar portfolio with stocks that have the lowest ratio. Applying this stock selection model to their sample, George and Hwang (2004) showed raw returns of 19.7% and zero-cost returns of 5.5% annually were achievable. Despite seemingly inferior returns, pairwise comparison and regression analysis in their article showed the 52-week high strategy is in fact superior to both the strategy of Jegadeesh and Titman (1993) and the industry momentum strategy of Moskowitz and Grinblatt (1999). They also concluded that combining their method with the method proposed by Moskowitz and Grinblatt results in a statistically significant increase in profit from momentum investing.

Besides their stock selection method, George and Hwang (2004) also provide some criticism on existing theories based on over- and/or underreaction by the securities market. They state that their pairwise comparisons and regressions suggest that some price level relative to an anchor could better explain observed momentum than previous work. Furthermore, the results of their model suggest that after an initial price deviation, traders ultimately correct their bias and no longer over- or undercorrect. Grinblatt and Han (2004) however, suggest the acquisition price of a stock is an investor's anchor. George and Hwang (2004) argue in turn, that if acquisition price is indeed a significant anchor for investors, a 52-week low strategy should be profitable. Research shows however, that despite significant regression coefficients for the 52-week low variable, achieved returns for this strategy are not significant and are dwarfed by the returns to Jegadeesh & Titman strategies. All momentum strategies that were discussed in this subsection are based on U.S. stocks though, leaving the question whether stock price momentum as a phenomenon is only present in the American securities market, or whether it occurs outside the U.S. as well. The next subsection attempts to answer this question, by discussing some research that was based on European data.

C) European evidence

Most research on stock price momentum and related investment strategies have been conducted either in the U.S. or with U.S. data. Leaving the question whether stock price momentum is only present in the American securities market. A commonly cited reference for European evidence for stock price momentum is Rouwenhorst (1998). This paper describes stock return momentum for a sample that covers 12 European countries during a sample period that runs from 1980 to 1995. A portfolio of past winners that is internationally diversified was shown to outperform a similarly diversified portfolio of past loser by about 1% per month. The most successful zero-cost portfolio in the paper by Rouwenhorst is the 9/1/3 portfolio, which yielded an average raw return of 18.86% annually. The momentum was found not to be limited to particular countries, as it was present in all sampled markets. Subsamples based on market capitalization all exhibited momentum, although the effect was found to be stronger for small firms than for large firms. The winner stocks outperformed loser stock for a duration of about one year and the momentum returns were not attributable to conventional risk measures. The author states that his European evidence is very similar to findings by Jegadeesh and Titman (1993) for the United States, which makes it unlikely that the findings related to momentum in the U.S. are caused simply by chance. The returns of European momentum portfolios are significantly correlated with the returns of such portfolios in the United States. Furthermore, the paper presents some evidence that European and U.S. momentum strategies have a common component. This suggests there may be a common factor the momentum strategies are exposed to, which causes the profitability of the such strategies.

Van Dijk and Huibers (2002) claim to have confirmed the findings of Rouwenhorst (1998): European momentum strategies were found to be profitable in the medium term and the results were similar for analyzed sub-periods. Excess returns from momentum strategies were found to be positive, even when they were corrected for financial risk. The authors state their evidence shows that past returns over periods shorter than one year can be used in forecasting future returns and that related momentum strategies were profitable for holding periods of 1 to 12 months, when applied to their sample. Van Dijk and Huibers also provide evidence that underreaction of analysts causes the momentum in European stocks. Apparently, analysts of European stocks behave similarly to analysts of U.S. stocks. Analysts of both European and U.S. stocks appear to be biased, as their earnings forecasts do not properly reflect future earnings growth — both before and after companies publish their latest earnings reports. Analysts seem to adjust their earnings forecasts too gradually. The reasons that past price momentum predicts the trend and magnitude of stock returns, are not clear for the authors however. Nevertheless, the European evidence suggests that, at least until recently, momentum strategies have been viable investment strategies in the European securities market. The next section will apply several momentum strategies on a sample of European stocks and check whether the strategies continue to perform as described in previous academic literature.

III. Empirical Findings

A) Sample: selection and statistics

Stocks from the Euronext-100 and Next-150 indices were chosen for the analyses in this paper. This initial sample is composed of the 250 Euronext stocks with the highest market capitalization in early 2012. In order to properly analyze returns on stock, total return indices were used since these include dividends. The sample period runs from January 2002 until December 2011 and the observations are made at the end of each month.[5] Since not all 250 stocks were listed during this entire period, the analyses and results are based solely on those stocks that were. This resulted in a sample of 198 stocks with 120 observations each. Please note that this method does introduce a selection bias into the analyses of this paper, because the sample only includes stocks that have been listed for at least a decade. Furthermore, because the sample was drawn only from the most recent

[5] Data was drawn from the years following 2002, in order to prevent coding problems in the data related to the currency transition of Europe, which was finalized on January 1st 2002.

composition of the two Euronext indices, some level of survivorship bias is also introduced into this paper. Stocks that are included in the Euronext indices are most likely past winners, because their inclusion in the index is determined by market capitalization. This might cause some results in this paper to seem overly optimistic. Since the zero-cost strategies short stocks that were selected subject to the same biases, the effects of the biases are somewhat mitigated for those results. Since the zero-cost strategies mitigate some idiosyncratic risk due to their shorts as well, focus should lie on these portfolios.

With the monthly observations of the stocks' total return indices, monthly returns were calculated by a simple formula: $R_t = (P_t - P_{t-1}) / P_{t-1}$ Where R_t is the (total) return of the stock (a value of 1 equals a return of 100%) in month t and P_t represents the stock's total return index. Due to the nature of this formula, no return can be calculated for the first observation of each variable, i.e. the first date in the time series of each stock's total return index. As a result, we have 119 cases of the total return for each stock. Multiplied with the number of variables (number of stocks), i.e. 198, a total of 23,562 total return observations are used in the following analyses. Descriptive statistics for the aggregate sample of total return observations is presented at the bottom of this page. There, it can be seen that the average total monthly return of all observations in the sample is 0.83%, which is about 10.43% annually, while the volatility of returns was on average about 11.35%. Excess returns are used in most of the following analyses, in order to ascertain whether momentum strategies have offered positive risk premia during the recent decade. The mean monthly excess return was 0.62%, or 7.70% annually, and its standard deviation was 11.37%. Descriptive statistics for the risk-free rate and various returns related to the sample are tabulated next.

The 3-month European interbank rate was chosen as a measure of the risk-free rate in the European securities market.[6] Descriptive statistics for the annual and monthly risk-free rate are tabulated below.

Table 1: Descriptive statistics for the risk-free rate variables. Annual risk-free rate is denoted RFY. The monthly risk-free rate is simply $\sqrt[12]{1+RFY}$ -1 and is denoted RFM below.

	N	Range	Minimum	Maximum	Mean	Std. Deviation
RFY	120	4.64%	0.63%	5.28%	2.53%	1.26%
RFM	120	0.38%	0.05%	0.43%	0.21%	0.10%

By using the monthly risk-free rates, excess stock returns were calculated for the sample by subtracting the monthly risk-free rate from each monthly stock return. Descriptive statistics for both monthly (raw) returns and monthly excess returns of the sample can be found below.

Table 2: Descriptive statistics of the total sample of monthly stock returns. Both raw and excess returns are listed.

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Raw returns	23562	585.17%	-79.30%	505.87%	0.83%	11.35%
Excess returns	23562	585.42%	-79.73%	505.69%	0.62%	11.37%

[6] The 3-month European interbank rate is suggested by Thomson Reuters as the appropriate risk-free rate for all Eurozone members. Source: http://extranet.datastream.com/data/Exchange%20&%20Interest%20Rates/RiskFreeInterestRates.htm

The excess returns to the various momentum strategies that are analyzed in this paper are of such magnitude that one might begin to question the validity of the performed analyses. However, it should be noted that the stock selection model (Appendix A) excludes some months in the beginning of the time series in its calculation of returns. The excluded period is used for analysis of return momentum and no stocks are actually held during this period. Therefore, the frame of reference for the momentum returns should be the means of time series that exclude these periods. Since the length of the excluded period depends on the strategy, more specifically its 'look-back period' (J) and lag (L), descriptive statistics are presented for all relevant subsamples belonging to the J/L/K strategies:

Table 3: Descriptive statistics of the monthly excess stock returns for the time series without the excluded period. The excluded period depends on the J and L parameters of the momentum strategies. The results below are tabulated accordingly.

J/L/K	N	Range	Minimum	Maximum	Mean	Std. Deviation
3/0/K	116	585.42%	-79.73%	505.69%	0.59%	11.40%
6/0/K	113				0.62%	11.41%
9/0/K	110				0.79%	11.34%
12/0/K	107				0.81%	11.35%
3/1/K	115				0.88%	10.99%
6/1/K	112				0.81%	10.93%
9/1/K	109				0.93%	10.90%
12/1/K	106				1.01%	10.86%

Note that the average excess stock return increases as the excluded period (used for analysis and lag) is increased. This is most likely a result of the exclusion of returns during the stock market downturn of 2002, which was arguably an effect of the market uncertainty that resulted from the bursting of the dot-com bubble in 2000 as well as from the terrorist attacks on the New York World Trade Center in 2001. This is an important remark, because most portfolios in subsection B yield excess returns that are larger than the average excess return of the market of 7.7% (i.e. 0.62% annualized). Even the 'loser' portfolios seem to have outperformed the market on average, which would of course raise suspicion about the validity of the performed analyses. When the above means are used for comparison, the validity of the results in this paper seem significantly less questionable. The next section presents the above-mentioned results.

B) Returns

In this section, the excess returns of varying J/L/K momentum strategies are presented. The first strategy that will be discussed, is the simple 11/1/1 strategy, which constructs and holds only one portfolio each month.

11/1/1 strategy

The stock selection model under 'Type A' of Appendix A was used to determine the excess returns of an 11/1/1 strategy. The 11/1/1 notation (J/L/K) of this strategy means stock selection is based on excess returns in the preceding 11 months (J=11), then formation takes place after 1 month of lag (L=1) and portfolios are held for 1 month (K=1). Because the 'winner' and 'loser' portfolio in this strategy are the top and bottom quintiles of the sorted returns, the model differentiates between the top 40 and bottom 40 performers, considering the sample contains nearly 200 stocks. The same analysis was done for the three middle portfolios, which are provided here for completeness. Finally, mean monthly excess returns of the portfolios were calculated, as well as the valuation of the T-statistic for each mean, similarly as in the selection model under 'Type B' of Appendix A. The T-statistic is defined as follows: **T=** $\frac{X - \mu 0}{S / \sqrt{n}}$ where X is the sample mean (i.e. the portfolio's mean excess return); $\mu_0 = 0$ in order to test whether the returns are significantly different from zero; S is the sample standard deviation (standard deviation of portfolio excess returns) and n is the number of observations, i.e. 119 – J – L = 107 for this strategy.[7] The results of this analysis are tabulated below.

Table 4: Annualized excess returns of the 11/1/1 strategy. The annual risk-free rate is observed each month, converted into a monthly rate and subtracted from each monthly stock return. These excess stock returns are then processed by the model. Outcomes were annualized using monthly compounding. T-statistics are in parentheses. Statistically insignificant returns are greyed.

Quintile: Portfolio	Return	(T-value)
1: Sell	9.56%	(0.9838)
2: Middle	10.38%	(1.3967)
3: Middle	9.46%	(1.4019)
4: Middle	12.72%	(2.0465)
5: Buy	16.70%	(2.1620)
5-1: Buy-Sell	6.57%	(1.0545)

As shown in the previous table, only the top two quintile portfolios, both of which are long-only, have yielded statistically significant excess returns. The winner portfolio has yielded an annualized excess return of 16.70%, whereas the runner-up yielded 12.72% annually. The zero-cost excess return of 6.57% that was obtained with the Buy-Sell portfolio seems interestingly high, however, this zero-cost excess return cannot be deemed unequal to zero with statistical significance. Based on these results, it can be concluded that a zero-cost 11/1/1 momentum strategy, when applied to Euronext stocks, would not have yielded significant zero-cost excess returns during the recent decade. Long-only investment strategies that select stocks based on relative strength do seem to have been capable of offering excess returns in the recent decade and might still prove useful to investors, although much of these long-only excess returns could have resulted from the biases in the sample. Next, more advanced multi-portfolio strategies, i.e. Jegadeesh & Titman strategies are discussed.

Jegadeesh & Titman (J,K) strategies

Since the Jegadeesh & Titman (JT) strategies hold the constructed portfolios for more than one month (K>1), at any time t>1 multiple portfolios are held in parallel, hence the term multi-portfolio strategy. The stock selection model under 'Type B' of Appendix A was used to determine returns of the JT strategies. Several variations of this model were used, in order to accommodate K≠3 and L≠1. Because Jegadeesh and Titman (1993) stratify their sample in performance deciles, the 'winner' and 'loser' portfolio in this strategy are the top and bottom deciles of the sorted returns. The model

[7] In order to reject the null hypothesis that the return is equal to 0, a two-tailed T-test with a significance level of 5% was used. Therefore, the T-valuation had to be equal or higher than $| t_{\alpha/2;n-1} | = | t_{0.025;106} | = 1,9826$.

therefore differentiates between the top 20 and bottom 20 performers, considering the sample contains about 200 stocks. Finally, the model lists the mean monthly excess return of the ‘winner’, ‘loser’ and zero-cost portfolios as well as the valuation of the T-statistic for each mean. This T-statistic is defined like before, only with varying n, since J determines the amount of portfolios that can be formed with these time series. The results are presented in two tables: one with lag (Table 5) and the other without lag (Table 6). Note that a lag of one month is used, similar to papers of other authors (e.g. Chen and Zhang, 2007), whereas Jegadeesh and Titman (1993) used a lag of only one week. Lag is used to control for bid-ask spread in testing the strategies. The results of the analyses of these J/L/K strategies are tabulated on the next page. Statistically insignificant cells are greyed according to the critical values in Appendix B.[8]

According to these results, only ‘winner’ portfolios have yielded positive excess returns that are statistically significant. Similar to the results of the 11/1/1 strategy, the zero-cost excess returns of the JT strategies are not significant. Again, long-only strategies that invest in relative strength might be the only viable alternative. Furthermore, the results show that the lag period did not consistently decrease returns for the portfolios, which leads to believe that bid-ask spread and related short-term phenomena do not contribute highly to the momentum returns. In fact, using one month of lag seems to increase momentum returns on average, which is consistent with findings by Jegadeesh and Titman (1993). This implies a negative influence of such short-term phenomena on momentum returns.

The most successful zero-cost JT strategy in this paper is the 9/1/3 strategy with an average excess return of 11.20% annually, although this result is not statistically significant. Contrary to the findings by Jegadeesh and Titman (1993), none of the zero-cost returns in this paper are statistically significant. Note that the most successful European zero-cost strategy found by Rouwenhorst (1998) was also the 9/1/3 stategy, which yielded an average raw return of 18.86% annually for his sample.

The most successful of the long-only strategies that are listed in this paper, is the 12/1/3 strategy that buys past winners. This strategy would have yielded an average excess return of 19.47% annually, if any biases in the sample are disregarded. In the original paper by Jegadeesh and Titman (1993), the most successful zero-cost strategy was a (12,3) strategy, yielding an annualized raw return of 19,42% when one week of lag was used. Their alternative was the (6,6) zero-cost strategy, which had returns that were claimed to be representative of the results for other strategies and yielded an annualized raw return of 14,03% when one week of lag was used. Considering the annual risk-free rate, which averaged about 2.53% for the sample used in this paper, the zero-cost returns found by Jegadeesh and Titman are arguably quite similar in magnitude to the returns found in this paper, albeit not comparable in level of statistical significance.[9] The returns of Jegadeesh and Titman (1993) were found to be slightly higher when using a lag period of 1 week. The results in this paper show a similar effect when using a lag period of 1 month.

[8] The T-statistic is defined with varying n, since J determines the amount of portfolios that can be formed with these time series. All critical values in Appendix C are above 1.98, facilitating interpretation of the results.
[9] The sample period of Jegadeesh and Titman (1993) is January 1965 to December 1989.

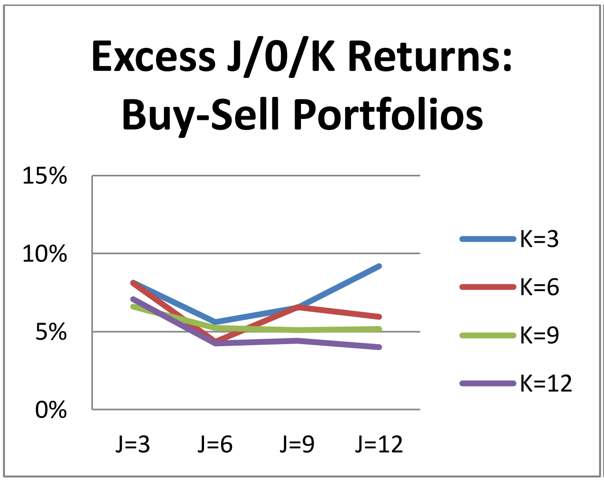
Table 5: Annualized excess returns of J/L/K Jegadeesh & Ttitman (JT) strategies with no lag period. The observed risk-free rates are converted into monthly rates and subtracted from each monthly stock return. The excess stock returns were then processed by the model. Outcomes were annualized using monthly compounding. T-statistics are in parentheses. Statistically insignificant returns are greyed.

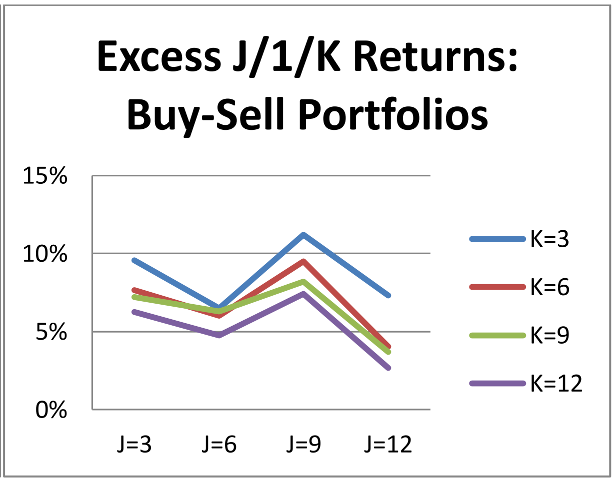
J/0/K	Portfolio	K=3	K=6	K=9	K=12
3	Sell	7.04% (0.5942)	6.57% (0.5892)	6.99% (0.6356)	6.68% (0.6136)
	Buy	15.68% (2.1583)	15.17% (1.9888)	13.99% (1.8741)	14.18% (1.8920)
	Buy-Sell	8.12% (1.0127)	8.11% (1.1622)	6.58% (1.0275)	7.06% (1.1359)
6	Sell	12.75% (1.0146)	12.25% (1.0074)	11.43% (0.9558)	11.97% (1.0022)
	Buy	18.99% (2.3865)	17.08% (2.1311)	17.21% (2.1994)	16.67% (2.1617)
	Buy-Sell	5.59% (0.6322)	4.35% (0.5225)	5.23% (0.6593)	4.23% (0.5545)
9	Sell	11.16% (0.9623)	11.09% (0.9783)	11.71% (1.0468)	12.13% (1.0892)
	Buy	18.35% (2.3004)	18.32% (2.2307)	17.35% (2.1741)	17.02% (2.1760)
	Buy-Sell	6.52% (0.7942)	6.56% (0.8154)	5.09% (0.6771)	4.40% (0.6139)
12	Sell	10.63% (0.9026)	11.23% (0.9689)	11.19% (0.9827)	11.67% (1.0331)
	Buy	20.72% (2.4457)	17.79% (2.1061)	16.88% (2.0635)	16.10% (2.0124)
	Buy-Sell	9.20% (1.0589)	5.96% (0.7168)	5.16% (0.6706)	4.01% (0.5532)

Table 6: Annualized excess returns of J/L/K Jegadeesh & Ttitman (JT) strategies with one month of lag. The observed risk-free rates are converted into monthly rates and subtracted from each monthly stock return. The excess stock returns were then processed by the model. Outcomes were annualized using monthly compounding. T-statistics are in parentheses. Statistically insignificant returns are greyed.

J/1/K	Portfolio	K=3	K=6	K=9	K=12
3	Sell	5.82% (0.5056)	6.99% (0.6348)	7.11% (0.6508)	7.60% (0.6952)
	Buy	15.91% (2.0937)	15.14% (1.9409)	14.78% (1.9395)	14.30% (1.8866)
	Buy-Sell	9.58% (1.2047)	7.66% (1.1269)	7.20% (1.1231)	6.26% (1.0042)
6	Sell	10.25% (0.8359)	10.11% (0.8454)	10.29% (0.8672)	10.83% (0.9139)
	Buy	17.34% (2.0768)	16.65% (2.0339)	17.18% (2.1566)	16.05% (2.0534)
	Buy-Sell	6.48% (0.7418)	6.00% (0.7294)	6.30% (0.8112)	4.75% (0.6351)
9	Sell	6.02% (0.5425)	7.56% (0.6951)	8.30% (0.7671)	8.36% (0.7798)
	Buy	17.83% (2.1373)	17.69% (2.1251)	17.12% (2.1138)	16.33% (2.0746)
	Buy-Sell	11.20% (1.3821)	9.48% (1.2397)	8.19% (1.1555)	7.41% (1.1059)
12	Sell	11.42% (0.9737)	12.85% (1.1228)	12.69% (1.1202)	13.33% (1.1897)
	Buy	19.47% (2.2354)	17.35% (2.0349)	16.81% (2.0404)	16.32% (2.0116)
	Buy-Sell	7.30% (0.8564)	4.03% (0.5093)	3.69% (0.5019)	2.66% (0.3847)

Next, an attempt is made to find patterns in the variations of the model's parameters. In order to discern any patterns in the different strategies, i.e. variations of the parameters J and K, the excess returns of strategies with varying K were plotted on J. The following graphs show the results for L=0 and L=1, i.e. strategies with no lag as well as strategies with a lag of one month:

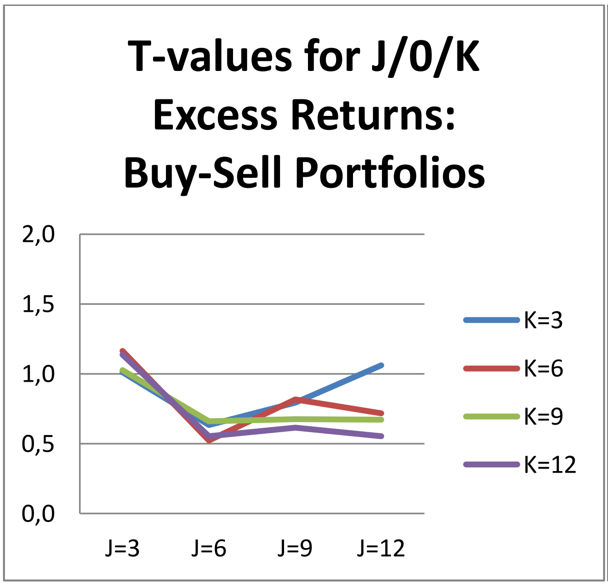


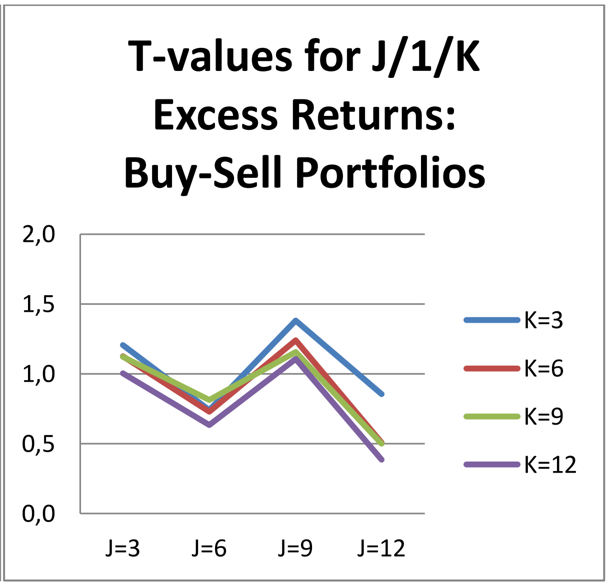


The previous graphs show a pattern in which an increasing value of the K parameter results in a decrease of the excess return of the strategy, generally over all values of J. Similar graphs for the buy and sell portfolios are consistent with this pattern: buy portfolios perform better for smaller K while sell portfolios perform worse, in general. This implies that out of the tested strategies, the optimum momentum strategy for the recent decade would incorporate a short holding period of 3 months.

The pattern that emerges from varying J is much less clear, however. It seems a (6,K) strategy is suboptimal for both J/0/K and J/1/K variations, whereas a (12,K) strategy generally performs worse than other (J,K) variations except the 12/0/3 strategy. This leaves (3,K) and (9,K) as optimal variations of J. Considering the fact that buy portfolios for larger K only yield significant results for J>3, an optimum for all K-variations seems to be a (9,K) strategy. Combined with the supposed optimum holding period of 3 months, the (9,3) strategy seems to be optimal overall. However, when looking solely at the excess returns of (J,K) variations, the (3,3) strategy presents itself as a viable alternative. As determined before, the (9,3) zero-cost strategy is indeed the most profitable, with average excess returns of 11.20% annually when one month of lag is used. The (3,3) zero-cost strategy yielded an average excess return of 9.58% annually. However, none of the zero-cost excess returns are significant in this paper.

In order to support the above inferences, the statistical significance of the zero-cost returns is also graphed for variations of J and K. The resulting graphs, which can be found on the next page, show a pattern that is very similar to the one that is discernible from the graphed excess returns. This supports the claims made about optimal strategies. Furthermore, it implies that the statistical significance of the excess returns of zero-cost strategies are largely determined by their means and less by their standard deviations. This in turn, provides some evidence that the higher returns of the more profitable zero-cost momentum strategies are not due to some selection bias that favors more volatile stock, although this might have been expected since all portfolios are constructed from a sample of stocks with relatively large market capitalizations that are all listed on the same stock exchange.





In conclusion of this subsection, the claim can be made that none of the zero-cost momentum strategies would have yielded statistically significant excess returns during the recent decade. However, the long-only buy portfolios of various momentum strategies seem to have been able to yield significant excess returns during that period, although much of their returns might be due to biases in the sample used for this paper. The next subsection discusses the performance of the long-only and zero-cost momentum strategies, relative to proxies of the European market performance.

C) Benchmarking

In order to analyze the performance of the momentum strategies relative to the European market, the momentum returns have to be compared to some measure of the European market return. The FTSE World Europe Euro Mid Cap index (also denoted as FTSE W EUROPE E :M) was chosen to be this measure, more specifically its total return index. This index was chosen, based on model-building and simple linear regressions of a multitude (>300) of European total return indices on the returns to a newly constructed Euronext index that includes the Euronext-100 and Next-150 total return indices. A value-weighted average of the two indices was chosen, since the individual indices are also value-weighted. This weighted average of the two Euronext indices was calculated for each data point in the time series, according to the formula below, where the Euronext-100 and Next-150 total return indices are denoted EUNX100 and EUNX150 respectively:

$$\text{EUNX250} = \frac{EUNX100}{EUNX100+EUNX150} \cdot \text{EUNX100} + \frac{EUNX150}{EUNX100+EUNX150} \cdot \text{EUNX150}$$

Descriptives of the (total) returns to this EUNX250 index are displayed below:

Table 7: Descriptives of the monthly returns to the constructed value-weighted EUNX250 index.

	N	Range	Minimum	Maximum	Mean	Std. Deviation
EUNX250 raw returns	119	38.74%	-20.43%	18.30%	0.61%	5.90%
EUNX250 excess returns	119	39.01%	-20.82%	18.19%	0.40%	5.93%

The mean monthly return of this total return index is 0.61%, which constitutes an annualized 7.6%. Excess returns of this index averaged 0.40% monthly, or 4.91% annually. Model-building and regressions performed by a statistical package suggested the following indices, which constitute the optimal benchmark indices for the EUNX250 index, and hence for such stocks as in this paper's sample, as tabulated below:

Table 8: Top benchmarking indices according to model-building and regression of various total return indices on the returns of the constructed EUNX250 index. The unstandardized regression coefficients and unadjusted R squares that resulted from regression are also listed.

INDEX	Alpha (p-value)	Beta (p-value)	R^2
FTSE EUROMID FINANCIALS E	0.005 (.036)	0.800 (.000)	.837
FTSE EUROMID GENERAL INDS E	0.003 (.324)	0.629 (.000)	.607
FTSEUR1ST 300 INDS TRANSPT E	0.003 (.318)	0.862 (.000)	.674
FTSE W EUROPE E :M	**0.002 (.153)**	**1.037 (.000)**	**.929**
FTSEUR1ST 300 MINING E	0.001 (.862)	0.432 (.000)	.421
FTSEUR1ST 300 BASIC MATS E	0.001 (.817)	0.688 (.000)	.663
FTSEUR1ST 300 GEN RETAILERS E	0.002 (.547)	0.774 (.000)	.544
FTSEUR1ST 300 PORTUGAL E	0.005 (.182)	0.748 (.000)	.574
FTSEUR1ST 300 EZ OIL & GAS PROD E	0.003 (.516)	0.754 (.000)	.427
FTSEUR1ST 300 EZ INDS ENG E	0.001 (.689)	0.539 (.000)	.656
MSCI EUROPE E	0.004 (.071)	1.131 (.000)	.867
FTSE W EUROPE E :L	0.004 (.072)	1.119 (.000)	.844

Note that the financials index in the previous table yielded a significantly positive alpha in the regression of its returns on those of the value weighted Euronext index, which means that the 250 Euronext stocks with the highest market capitalization on average outperformed the financials index during the recent decade. This could have resulted from the 2002 stock market downturn and the financial crisis following late 2007, both of which are present in the time series and affected the financial sector in particular. Based on the alphas, the Euronext stocks did not significantly outperform any of the other indices, however.

From the results of the performed regressions, the FTSE World Europe Euro Mid Cap index had the highest R^2 of all indices, i.e. 0.929, meaning that of the tested indices, it is the best predictor of the returns to the constructed EUNX250 index. Because the EUNX250 index is used as a proxy for the performance of the stock in the sample used for this paper, the FTSE World Europe Euro Mid Cap index should also be the best benchmark for the momentum strategies that are analyzed in this paper. Before any comparative analyses are performed, the descriptive statistics of the FTSE World Europe Euro Mid Cap index are presented.

Table 9: Descriptives of the monthly returns to the FTSE World Europe Euro Mid Cap index.

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Raw returns	119	36.53%	-17.91%	18.62%	0.39%	5.48%
Excess returns	119	36.80%	-18.30%	18.51%	0.18%	5.51%

As stated before, focus should lie on the zero-cost portfolios, because they mitigate some of the effects of the sampling biases. Therefore, only the zero-cost JT strategies are benchmarked. A statistical package was used to construct mean comparison tables, based on paired comparison. Paired comparison was used, because the (excess) returns are paired by the dates of observation. The first paired mean comparison that was performed, benchmarks the JT zero-cost strategies with the FTSE World Europe Euro Mid Cap index. The second paired mean comparison benchmarks with the EUNX250 total return index, because this value-weighted index should be a good proxy for the returns of a value-weighted long position in the stocks of the Euronext-100 and Next-150 indices. The paired mean comparison tables can be found on this page and the next.

The benchmark with the FTSE World Europe Euro Mid Cap index shows that the market index outperformed almost half the JT zero-cost strategies, although none of the outcomes are significant. Based on these results, it cannot be concluded that zero-cost momentum strategies were capable of significantly outperforming the market during the recent decade. Since the significance is determined by a two-tailed test, none of the zero-cost strategies applied to the sample have significantly underperformed either, based on the paired mean comparison. The benchmark with the EUNX250 index shows that in fact, almost all JT zero-cost strategies were outperformed by this proxy of a value-weighted long position in the sampled stocks, although these results are also not significant. Again, based on the paired mean comparison it can neither be concluded that zero-cost momentum strategies were capable of significantly outperforming the benchmark, nor can it be concluded that the zero-cost strategies significantly underperformed relative to the benchmark, during the recent decade.

Table 10: Paired mean comparison of monthly excess zero-cost returns of various JT momentum strategies and the monthly excess returns of the FTSE World Europe Euro Mid Cap index. Listed statistics are for each variable that resulted from subtracting the excess returns of the benchmark index from the excess returns of the JT momentum strategy. The excluded period of the JT strategies was excluded from the excess index returns as well.

	Mean	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
3/1/3-FTSE	0.34%	10.54%	0.99%	0.342	113	.733
6/1/3-FTSE	0.01%	10.80%	1.03%	0.009	110	.993
9/1/3-FTSE	0.30%	9.84%	0.94%	0.316	108	.753
12/1/3-FTSE	-0.23%	9.97%	0.97%	-0.237	105	.813
3/1/6-FTSE	0.23%	9.58%	0.89%	0.256	114	.798
6/1/6-FTSE	-0.09%	10.40%	0.98%	-0.088	111	.930
9/1/6-FTSE	0.17%	9.50%	0.91%	0.184	108	.855
12/1/6-FTSE	-0.49%	9.60%	0.93%	-0.523	105	.602
3/1/9-FTSE	0.19%	9.36%	0.87%	0.222	114	.825
6/1/9-FTSE	-0.06%	10.16%	0.98%	-0.065	111	.948
9/1/9-FTSE	0.09%	9.30%	0.90%	0.103	107	.918
12/1/9-FTSE	-0.52%	9.35%	0.91%	-0.568	105	.572
3/1/12-FTSE	0.12%	9.26%	0.86%	0.139	114	.890
6/1/12-FTSE	-0.19%	10.07%	0.95%	-0.195	111	.846
9/1/12-FTSE	0.01%	9.12%	0.87%	0.008	108	.994
12/1/12-FTSE	-0.60%	9.10%	0.88%	-0.677	105	.500

Table 11: Paired mean comparison of monthly excess zero-cost returns of various JT momentum strategies and the monthly excess returns of the EUNX250 total return index. Listed statistics are for each variable that resulted from subtracting the excess returns of the benchmark index from the excess returns of the JT momentum strategy. The excluded period of the JT strategies was excluded from the excess index returns as well.						
	Mean	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
3/1/3-EUNX250	0.11%	10.91%	1.02%	0.111	113	.912
6/1/3-EUNX250	-0.22%	11.12%	1.06%	-0.204	110	.839
9/1/3-EUNX250	0.03%	10.19%	0.98%	0.034	108	.973
12/1/3-EUNX250	-0.47%	10.35%	1.01%	-0.469	105	.640
3/1/6-EUNX250	-0.02%	9.90%	0.92%	-0.019	114	.985
6/1/6-EUNX250	-0.34%	10.76%	1.02%	-0.330	111	.742
9/1/6-EUNX250	-0.10%	9.83%	0.94%	-0.104	108	.918
12/1/6-EUNX250	-0.73%	9.97%	0.97%	-0.754	105	.453
3/1/9-EUNX250	-0.05%	9.73%	0.91%	-0.058	114	.954
6/1/9-EUNX250	-0.31%	10.56%	1.00%	-0.312	111	.756
9/1/9-EUNX250	-0.17%	9.64%	0.93%	-0.183	107	.855
12/1/9-EUNX250	-0.76%	9.75%	0.95%	-0.800	105	.425
3/1/12-EUNX250	-0.13%	9.65%	0.90%	-0.141	114	.888
6/1/12-EUNX250	-0.43%	10.47%	0.99%	-0.439	111	.662
9/1/12-EUNX250	-0.26%	9.47%	0.91%	-0.284	108	.777
12/1/12-EUNX250	-0.84%	9.52%	0.93%	-0.910	105	.365

Both paired mean comparisons were also performed for the long-only JT buy strategies, which did show significant outperformance of both benchmarks by the long-only portfolios. However, it is likely these results are mainly caused by the sampling biases and are therefore excluded from this paper. Besides through benchmarking, the relative merit of an investment strategy can also be determined by the level of risk compensation, as measured by alpha. This is the topic of the subsection that follows.

D) Compensation for Risk

In the previous subsections it was proven that none of the zero-cost JT momentum strategies yielded significant positive excess returns and that these strategies neither outperformed the chosen European market index, nor the proxy of a simple value-weighted long position in the sampled stocks. Despite these results, none of the performed analyses have rendered the zero-cost momentum strategies strictly inferior either, because none of the relevant results have been statistically significant. The topic of this subsection is risk compensation, which is one dimension of the momentum strategies´ performance that has not been properly analyzed. The common measure for this risk compensation is the financial notion of alpha[10]. It measures whether investors are appropriately compensated for the risk they bear by holding the security for which the alpha is determined. Measuring alpha can be done by means of linear regression, where the excess return of a security is written as the sum of three components: $(R_i – r_f) = \alpha_i + \beta_i(R_{Mkt} – r_f) + \varepsilon i$ where α_i is the intercept term of the regression, β_i is the regression coefficient of the market risk premium or excess return ($R_{Mkt} – r_f$ where R_{Mkt} is the market return and r_f is the risk-free interest rate) and also the security's ex-post beta for the sample period. The final term εi is the error term of the regression equation, and has an expectancy of zero. The

[10] Alpha plays a major role in technical analysis of securities and has its foundation in the famous CAPM model.

regression can be done for any kind of security, including zero-cost portfolios formed by momentum strategies. The intercept of the regression, α_i is the security's (Jensen's) alpha[11], which is exactly what needs to be determined in order to conclude anything about the risk compensation of zero-cost momentum strategies. In order to run the required regression of (R_i – r_f) on (R_{Mkt} – r_f), the previously determined excess returns to the momentum portfolios and to the FTSE World Europe Euro Mid Cap index are used. Results from the regressions are tabulated below.

Table 12: **Alphas for J/1/K zero-cost JT momentum strategies. The market return is the return to the FTSE World Europe Euro Mid Cap index. The risk-free rate is the 3 month interbank rate for all Eurozone members, converted to monthly yields. P-values are in parentheses. Coefficients are unstandardized and the R square is unadjusted.**

Strategy	Alpha (p-value)	Beta (p-value)	R^2
3/1/3	0.007 (.233)	-0.540 (.000)	.193
6/1/3	0.005 (.467)	-0.510 (.000)	.137
9/1/3	0.008 (.167)	-0.415 (.000)	.109
12/1/3	0.006 (.335)	-0.409 (.002)	.091
3/1/6	0.005 (.331)	-0.428 (.000)	.165
6/1/6	0.005 (.462)	-0.477 (.000)	.136
9/1/6	0.007 (.231)	-0.376 (.001)	.099
12/1/6	0.004 (.564)	-0.376 (.002)	.087
3/1/9	0.005 (.339)	-0.418 (.000)	.176
6/1/9	0.005 (.401)	-0.489 (.000)	.161
9/1/9	0.006 (.263)	-0.390 (.000)	.123
12/1/9	0.003 (.544)	-0.399 (.000)	.113
3/1/12	0.004 (.411)	-0.414 (.000)	.181
6/1/12	0.004 (.506)	-0.502 (.000)	.181
9/1/12	0.006 (.270)	-0.407 (.000)	.149
12/1/12	0.003 (.635)	-0.387 (.000)	.119

The previous results show alphas that are positive but insignificant and betas that are negative with statistical significance. Since the positive alphas are insignificant, it cannot be concluded that the zero-cost JT momentum strategies were capable of compensating investors over and above the level of risk borne by holding the long and short positions these strategies entail. Since the alphas are also not negative with statistical significance, it can neither be concluded that the zero-cost strategies would have insufficiently compensated investors for financial risks, based on the used sample. The significant negative betas that were found, imply that the excess returns of the zero-cost momentum strategies would decrease if the excess returns of the market index increase, and vice versa. This is probably caused by the short positions of the zero-cost portfolios, although the value of the betas, -0.434 on average, is somewhat peculiar. Since the strategy has equal amounts long and short positions, the beta should be around 0 under the assumption that the shorted loser portfolio and winner portfolio have similar returns during an upward overall market trend. The negative betas for the zero-cost portfolios imply that loser portfolios perform better relative to the winner portfolios in an upward market trend. This suggests contrarian strategies might have performed well during the sample period. However, the zero-cost momentum strategies that are analyzed in this paper have not

[11] Berk, Jonathan and DeMarzo, Peter, 2007. Corporate Finance. Boston: Pearson Education, Inc. pp.382-383

shown any significant performance in their capability to properly compensate financial risk. Based on the insignificant alphas, their risk compensation cannot be determined as strictly insufficient either. This subsection concludes the analysis of the zero-cost momentum strategies´ relative performance. The next subsection concludes the empirical research in this paper, by discussing how the excess returns of JT momentum portfolios develop over longer periods of time by increasing the lag period.

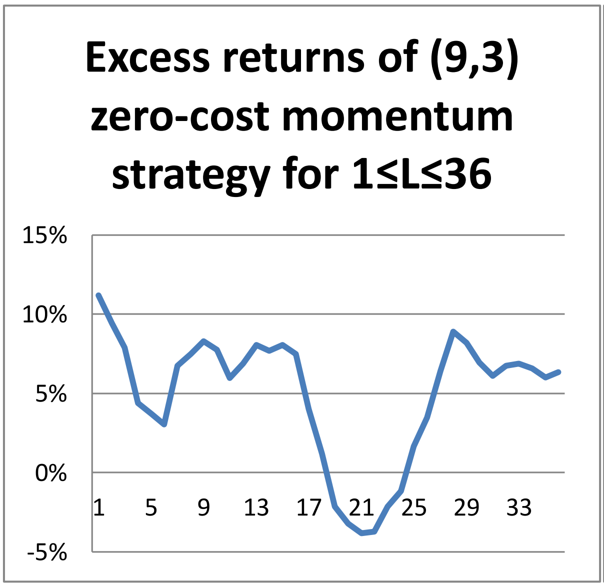
E) Return Reversals

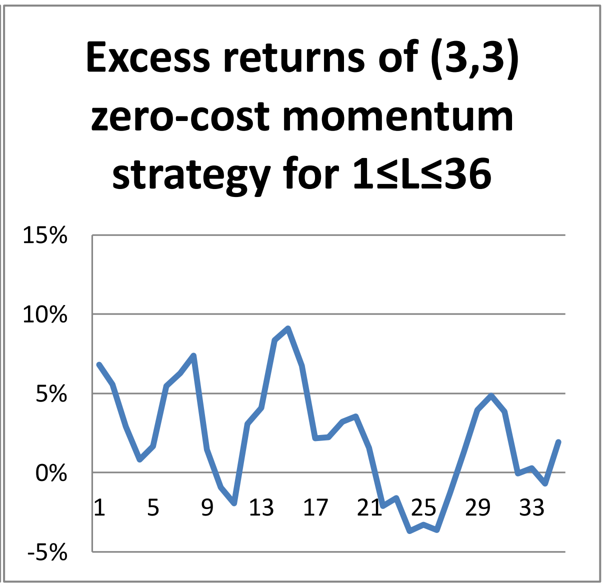
Return reversals of momentum portfolios can be measured using methods described by Jegadeesh and Titman (1993) as well as by George and Hwang (2004). This entails delaying portfolio formation by a variable amount of months after stock selection has taken place and measuring the performance of these lagging portfolios. Delayed portfolios can be constructed by specifying large lag periods (L≥1) in the model. The lagged returns will be checked for lag periods of up to 36 months. These returns will again be checked for significance by applying T-tests. Since the focus of this paper should be on the zero-cost portfolios in order to mitigate some of the effects of the sampling biases, the tables on this page and the next contain the lagged excess returns for the optimal zero-cost portfolios suggested in subsection B, i.e. the (9,3) and (3,3) strategies. The tabulated excess returns are also graphed at the bottom of the page, in order to facilitate analysis. Unlike the results of Jegadeesh and Titman (1993), the results tabulated here show no clear pattern of zero-cost returns permanently dissipating. The (3,3) zero-cost excess returns became negative after lag of about 11 months, whereas the (9,3) zero-cost excess returns did not become negative until after about 19 months of lag, although both return reversals occurred only briefly. After its return reversal, the (9,3) zero-cost excess returns were positive for lag periods of 25 months or more. The pattern of the (3,3) zero-cost lagged excess returns is much more erratic, but does seem to show a trend towards 0 as the lag period increases. Jegadeesh and Titman (1993) found significant positive zero-cost returns for lag periods up to about 12 months, after which the zero-cost returns become insignificant and remain negative for a lengthy period thereafter. This characteristic of momentum returns does not seem to hold for the recent data.

Table 13: Annualized lagged excess returns of the zero-cost (9,3) momentum strategy

L	Mean	T-value	L	Mean	T-value	L	Mean	T-value
1	11,20%	1,3821	13	8,04%	1,5744	25	1,66%	0,3296
2	9,42%	1,1802	14	7,70%	1,5102	26	3,48%	0,6809
3	7,90%	0,9950	15	8,06%	1,6359	27	6,41%	1,1998
4	4,39%	0,5958	16	7,48%	1,4376	28	8,91%	1,5524
5	3,70%	0,5366	17	4,01%	0,8125	29	8,19%	1,3642
6	3,03%	0,4451	18	1,20%	0,2357	30	6,94%	1,1078
7	6,76%	1,1806	19	-2,14%	-0,4176	31	6,11%	0,9899
8	7,49%	1,2903	20	-3,21%	-0,6150	32	6,74%	1,1033
9	8,30%	1,4278	21	-3,82%	-0,7287	33	6,88%	1,1612
10	7,76%	1,3719	22	-3,73%	-0,7387	34	6,57%	1,1781
11	5,98%	1,0866	23	-2,13%	-0,4195	35	6,01%	1,1096
12	6,87%	1,3124	24	-1,18%	-0,2326	36	6,35%	1,2310

Table 14: Annualized lagged excess returns of the zero-cost (3,3) momentum strategy								
L	Mean	T-value	L	Mean	T-value	L	Mean	T-value
1	9,58%	1,2047	13	3,08%	0,6178	25	-3,69%	-0,9469
2	6,81%	0,9093	14	4,07%	0,9070	26	-3,29%	-0,9123
3	5,56%	0,7617	15	8,35%	1,9308	27	-3,61%	-0,9733
4	2,92%	0,4379	**16**	**9,10%**	**2,1562**	28	-1,25%	-0,3222
5	0,84%	0,1441	17	6,75%	1,5851	29	1,34%	0,3095
6	1,67%	0,3031	18	2,16%	0,5244	30	3,96%	0,8769
7	5,46%	0,9466	19	2,24%	0,5734	31	4,87%	1,1174
8	6,26%	1,1415	20	3,20%	0,8384	32	3,87%	0,9343
9	7,37%	1,4084	21	3,55%	0,8466	33	-0,06%	-0,0138
10	1,46%	0,2978	22	1,56%	0,3740	34	0,28%	0,0575
11	-0,94%	-0,1856	23	-2,09%	-0,5062	35	-0,68%	-0,1402
12	-1,93%	-0,3539	24	-1,60%	-0,3781	36	1,94%	0,4033





The results on this page conclude the empirical research; the paper will be concluded in the next section, by presenting a summary and conclusions as well as recommendations for further research.

IV. Final Thoughts

A) Summary and conclusions

The empirical research in this paper has shown that investment strategies that buy stocks that have performed well in the past 3 to 12 months and short sell stocks that have performed poorly during that period, do not generate significant positive returns in the European securities market, for holding periods up to one year. Such zero-cost momentum strategies were capable of yielding excess returns that averaged up to 11.20% annually during the recent decade, when applied to a selection of stocks that were listed on the Euronext-100 and Next-150 indices during that period. However, because of high volatility, none of these excess returns could be found statistically significant. The statistical insignificance of these zero-cost returns is contrary to earlier studies of European stocks, e.g. Rouwenhorst (1998) and Van Dijk and Huibers (2002). Long-only momentum strategies that buy past winners yielded significant excess returns of up to 20.72% when applied to the sample, but these returns were likely the result of selection bias and were not analyzed further. The excess returns were found to be larger on average, if portfolio formation was delayed by one month after stock selection, which is consistent with existing literature. Additional analyses showed that the zero-cost momentum strategies have not significantly outperformed the European market, as measured by the FTSE World Europe Euro Mid Cap index, nor did the zero-cost momentum strategies outperform the indices their stocks were sourced from. However, the results did not warrant the claim they have underperformed relative to these benchmarks either. Moreover, Jensen's alpha was also determined for the zero-cost strategies and was found to be insignificant, even though it was positive for all analyzed strategies. Finally, the persistence of excess returns generated by the zero-cost portfolios was analyzed. The (3,3) strategy began to show negative excess returns if portfolio formation was delayed by 11 months after stock selection, while the (9,3) strategy did not do so until formation was delayed by 19 months. Other studies usually find such return reversals if portfolio formation is delayed by roughly one year, which seems similar to findings in this paper. The pattern that emerged from the lagged returns was however much less clear than previous research has postulated, as the excess returns in this paper did not remain negative if portfolio formation was delayed much further. Based on the results in this paper, investors in European stock may have been better off pursuing investment strategies which are not based on stock price momentum. The insignificant performance of the zero-cost momentum strategies over the course of a year, combined with the erratic pattern of their lagged excess returns thereafter, show that momentum strategies have indeed lost much of their original appeal.

B) Recommendations

Any further research on the application of momentum strategies to Euronext stocks should use an unbiased sample and preferably a longer sample period. The zero-cost momentum returns described in this paper are interestingly high, but could not be found statistically significant. Moreover, future research could control for January effects, e.g. by separately analyzing the returns of each momentum strategy for months excluding January. Additional analyses of value weighted positions in stocks selected by the momentum strategies might also be of interest, in order to to complement the equally weighted positions analyzed in this paper. Finally, constructed portfolios could be analyzed for their average capitalization and risk (beta) to further explore the fundamentals of momentum returns.

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VI. Appendices

A) Stock Selection Model (MATLAB code)

```
% Type A: 11/1/1 Convention as on French's site
clearvars -except Raex
T=size(Raex,1);
Rlow=zeros(T-12,1);
Rhigh=zeros(T-12,1);
for t=1:T-12
    means=mean(Raex(t:t+10,:));
    [sortedreturns,stockindices]=sort(means);
    Rlow(t,1)=mean(Raex(t+12,stockindices(1:40)));
    Rhigh(t,1)=mean(Raex(t+12,stockindices(158:198)));
end

% Type B: 3 month Holding Period, L months lagging; J/L/3
clearvars -except Raex
J=3; % Look-back period in months
L=1; % Lag period in months
T=size(Raex,1);
Rlow3=zeros(T-L-J,3);
Rhigh3=zeros(T-L-J,3);
Rlow3(:,:)=NaN;
Rhigh3(:,:)=NaN;
for t=1:T-L-J-2
    for i=1:3
        means=mean(Raex(t:t+J-1,:));
        [sortedreturns,stockindices]=sort(means);
        Rlow3(t+i-1,i)=mean(Raex(t+J-1+L+i,stockindices(1:20)));
        Rhigh3(t+i-1,i)=mean(Raex(t+J-1+L+i,stockindices(178:198)));
    end
end
for t=T-L-J-1
    for i=1:2
        means=mean(Raex(t:t+J-1,:));
        [sortedreturns,stockindices]=sort(means);
        Rlow3(t+i-1,i)=mean(Raex(t+J-1+L+i,stockindices(1:20)));
        Rhigh3(t+i-1,i)=mean(Raex(t+J-1+L+i,stockindices(178:198)));
    end
end
for t=T-L-J
    for i=1
        means=mean(Raex(t:t+J-1,:));
        [sortedreturns,stockindices]=sort(means);
        Rlow3(t+i-1,i)=mean(Raex(t+J-1+L+i,stockindices(1:20)));
        Rhigh3(t+i-1,i)=mean(Raex(t+J-1+L+i,stockindices(178:198)));
    end
end
Rlow=transpose(nanmean(transpose(Rlow3)));
Rhigh=transpose(nanmean(transpose(Rhigh3)));
MeanRlow=mean(Rlow)
SDRlow=std(Rlow);
TSTATRlow=MeanRlow/(SDRlow/sqrt(size(Rlow,1)))
MeanRhigh=mean(Rhigh)
SDRhigh=std(Rhigh);
TSTATRhigh=MeanRhigh/(SDRhigh/sqrt(size(Rhigh,1)))
Rzero=Rhigh-Rlow;
MeanRzero=mean(Rzero)
SDRzero=std(Rzero);
TSTATRzero=MeanRzero/(SDRzero/sqrt(size(Rzero,1)))
```

B) Critical values

Table 15: Absolute critical values of the 5%-level two-tailed T-statistic for J/L/K strategies. The critical values are not dependent on parameter K and hence will hold for all values of K.									
L	**J=3**	**J=6**	**J=9**	**J=12**	**L**	**J=3**	**J=6**	**J=9**	**J=12**
0	1.9808	1.9814	1.9820	1.9826	**19**	1.9850	1.9858	1.9867	1.9876
1	1.9810	1.9816	1.9822	1.9828	**20**	1.9853	1.9861	1.9870	1.9879
2	1.9812	1.9818	1.9824	1.9830	**21**	1.9855	1.9864	1.9873	1.9883
3	1.9814	1.9820	1.9826	1.9833	**22**	1.9858	1.9867	1.9876	1.9886
4	1.9816	1.9822	1.9828	1.9835	**23**	1.9861	1.9870	1.9879	1.9890
5	1.9818	1.9824	1.9830	1.9837	**24**	1.9864	1.9873	1.9883	1.9893
6	1.9820	1.9826	1.9833	1.9840	**25**	1.9867	1.9876	1.9886	1.9897
7	1.9822	1.9828	1.9835	1.9842	**26**	1.9870	1.9879	1.9890	1.9901
8	1.9824	1.9830	1.9837	1.9845	**27**	1.9873	1.9883	1.9893	1.9905
9	1.9826	1.9833	1.9840	1.9847	**28**	1.9876	1.9886	1.9897	1.9908
10	1.9828	1.9835	1.9842	1.9850	**29**	1.9879	1.9890	1.9901	1.9913
11	1.9830	1.9837	1.9845	1.9853	**30**	1.9883	1.9893	1.9905	1.9917
12	1.9833	1.9840	1.9847	1.9855	**31**	1.9886	1.9897	1.9908	1.9921
13	1.9835	1.9842	1.9850	1.9858	**32**	1.9890	1.9901	1.9913	1.9925
14	1.9837	1.9845	1.9853	1.9861	**33**	1.9893	1.9905	1.9917	1.9930
15	1.9840	1.9847	1.9855	1.9864	**34**	1.9897	1.9908	1.9921	1.9935
16	1.9842	1.9850	1.9858	1.9867	**35**	1.9901	1.9913	1.9925	1.9939
17	1.9845	1.9853	1.9861	1.9870	**36**	1.9905	1.9917	1.9930	1.9944
18	1.9847	1.9855	1.9864	1.9873	**37**	1.9908	1.9921	1.9935	1.9949