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Muga, Luis; Santamaría, Rafael

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ABSTRACT

In this paper we use generally applicable non-parametric methods in an attempt to sort out the possible sources of momentum in stock markets (behavioural theories or omitted risk factors). Specifically, we present the results of bootstrap analysis and stochastic dominance tests for the Spanish stock market. Our results from the bootstrap analysis are found to depend on the resampling method used (with or without replacement). Nevertheless, the various stochastic dominance techniques applied have led us to the same conclusion, namely, that the winner portfolio stochastically dominates the loser portfolio, which is not consistent with the general asset-pricing models developed for risk-averse investors. This suggests the interest of analysing theories that relax the unbounded rationality assumptions that support many of the classical asset pricing models.

KEYWORDS:

Momentum, stocks, behavioural finance, bootstrap, stochastic dominance

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1.- Introduction.

More than ten years since Jegadeesh and Titman (1993) first drew attention to the presence of a momentum effect in the US market, the abnormal returns to this type of strategy have still not been explained to the unanimous satisfaction of researchers. Thus it is one of the main anomalies that continue to challenge the market efficiency hypothesis.

The vast body of evidence that testifies to the presence of the momentum effect, both inside and outside the US market, enables us to rule out data mining as the cause, while also revealing that the phenomenon is not exclusive to any one market. Thus, Jegadeesh and Titman (2001) found that momentum persisted in the US market, beyond the time horizon of their original study, right through the 1990s. Rouwenhorst (1998) also found evidence for twelve European countries; Chui, Titman and Wei (2000) for Asian basin; Hon and Tonks (2003) for the UK, Glaser and Weber (2001) for Germany and Forner and Marhuenda [2003] and Muga and Santamaría [2006a] for Spain. Hameed and Kusnadi (2002) found evidence in six Asian countries, though only at the country level. Going further, Fong, Wong and Lean [2005], using international indices, find evidence to support the presence of the momentum effect in both developed and emerging markets. Several authors, among them Rouwenhorst [1999], Van der Hart et al [2003] and Griffin et al [2003] and Muga and Santamaría [2006 b], have analysed momentum in emerging markets. The overriding conclusion from all this literature is that, while momentum exists in emerging markets, it is less intense than in the more developed ones.

The market efficiency hypothesis predicts that any pattern, once discovered by investors, will gradually fade, unless exploitation proves impossible or the gains do not compensate the risk and/or costs involved. Since the empirical evidence has shown that this pattern did not fade over time, the literature has tried to find a reasonable explanation for the fact. Research has evolved along two very different paths. On the one hand, there are authors who claim that the abnormal profits gained from investing in momentum strategies are compensation for some risk factor. On the other hand, there are those who claim that they are the result of the behaviour of investors, who do not always base their decisions on the risk/return trade-off. There is also another view, though with fewer and fewer subscribers, that reckons such returns to be due to methodological error. It is also important to note that transaction costs [see Lesmond, Schill and Zhou (2004) and Korajczyk and Sadka (2004)] may be a major disincentive to arbitrageurs tempted to take positions that might eventually dilute momentum returns.

In this intense debate, it is worth mentioning the work of Conrad and Kaul (1998), who, using methodology based on bootstrapping techniques, conclude that the momentum effect is due to cross sectional variations in stock returns, and is therefore more likely to be due risk factors.

The available empirical evidence, however, suggests that traditional risk assessment models are unable to explain the abnormal returns generated by the momentum effect. Indeed, Fama and French (1996) admit that their three-factor model fails to capture this anomaly. On the strength of this evidence, explanations have been sought in the literature based on risk factors that were omitted in the traditional models. Thus, Chordia and Shivakumar (2002) and Avramov and Chordia (2006) suggest that stock returns continuation in the medium term is due to a range of macroeconomic risk factors. Another outstanding contribution in this vein is that of Wu (2002), who, using conditional risk assessment models, obtains some promising, though not entirely conclusive, results. Some authors have also suggested different levels of liquidity risk (Pastor and Stambaugh, 2003, Sadka, 2006), asymmetric risk (Ang, Chen and Xing, 2002) or conditional coskewness (Harvey and Siddique, 2000) as possible causes of the anomaly. However they find only a partial explanation for the phenomenon.

Alternatively, *behavioural finance* has produced several explanations to momentum effect, such as Barberis, Sheleifer and Vishny (1998), who propose that the momentum effect appears as a result of conservatism and representativeness heuristic biases in the decisions of some investors. Daniel, Hirshleifer and Subrahmanyam (1998) also suggest the presence of overconfidence or self-attribution bias among agents as a possible source of abnormal returns to momentum strategies. Hong and Stein (1999), meanwhile, develop a model in which momentum is due to the slow diffusion of information and the presence of momentum traders in the market who trade under the assumption of continuation in stock returns. The common theory in all this research is that various types of behavioural bias lead to an overreaction in stock prices that should revert in the long term. Thus, in addition to predicting a medium term momentum effect, these behavioural models predict long-term stock price reversal. In response to this, Jegadeesh and Titman (2001) are more inclined towards one of these behavioural theories as the most likely cause of the momentum effect, since they obtain long-term reversal of momentum strategy returns in the US market. This reversal is more consistent with the behavioural theories described earlier than with risk-based explanations, which would predict a returns continuation beyond the holding period in these strategies.

This paper probably marked a turning point in the debate over behavioural causes and risk factors as possible sources of momentum. Their conclusions, together with those reported in Jegadeesh and Titman (2002), seriously challenge those obtained by Conrad and Kaul (1998) who claim the momentum effect to be due to cross sectional dispersion in stock returns. The main objection to the approach of Conrad and Kaul is their use of the bootstrap with replacement method. According to Jegadeesh and Titman (2001, 2002), this procedure could be generating an artificial momentum effect, since, when bootstrapping with replacement, the same observation may appear both in the formation period and in the holding period. These authors therefore propose the use of bootstrapping without replacement which, in their case, leads to the conclusion that the momentum effect is not due to cross sectional variations in stocks, thus contradicting the evidence presented by Conrad and Kaul (1998).

In a later paper, Karolyi and Kho (2004) compare the two bootstrap procedures, with and without replacement, finding the results to differ, as predicted by the above evidence. They argue that both procedures are biased, however, thus making it difficult to discern which of the results is more accurate.

An alternative means of discerning between behavioural theories and risk-based models is the stochastic dominance method. Fong, Wong and Lean (2005), in particular, using international indices, show that those with a better past performance stochastically dominate those with a poor past performance, which allows us to assert that preference for the winner portfolio over the loser portfolio is not consistent with general asset-pricing models. These findings are robust to various stochastic dominance tests recently performed using different assumptions about the time-series returns. Due to their generality and potential for comparing two alternatives, these tests are proving very promising for the analysis of momentum strategies.

This is the interesting frame of reference to which this study belongs. Its aim is to provide evidence that may help to discriminate between the possible causes (behavioural theories or omitted risk factors) of the momentum effect, by means of generally applicable non-parametric methods. Specifically, we present the results of bootstrap analysis and stochastic dominance tests for the Spanish stock market[1].

The paper aims to contribute to the literature from several different angles. Firstly, following the paper of Karolyi and Kho (2004), this study undertakes a bootstrap analysis with and without replacement, assuming different return generating models. Unlike these authors, however, we resample blocks of returns in the same period to avoid destroying any cross sectional patterns in the stock returns. We have also shown that bootstrapping with replacement may not be an useful tool for our purpose because, for the problem that concerns us, given the number of available observations, small sample bias is clearly less important than the obvious reiteration bias caused by the replacement procedure. Finally, various different stochastic dominance techniques are also applied, specifically those proposed in Barret and Donald (2003) Davidson and Duclois (2000) and Chow (2001), who make different assumptions about return time series. The last one, as far as we know, is the first time that it is applied for this purpose. Moreover, rather than international market indices as in Fong, Wong and Lean (2005), in our paper we use individual stocks because of their greater practical implications.

The rest of the paper is structured as follows. The second section describes the database used for the various analyses, the third presents the methodology employed and estimates of momentum in the Spanish stock market. The bootstrap technique is described in section four together with the main results obtained thereby. The fifth section describes the procedure and results of the various stochastic dominance tests. Finally, the sixth section contains a summary of the results obtained throughout the paper, followed by the conclusions and possible paths for future research.

[1]Most of the past evidence regarding the existence of the momentum effect in the Spanish stock market is to be found in the research by Forner and Marhuenda (2003) (2006) and Muga and Santamaría (2006a and 2006c). There is also evidence, consistent with that obtained for other markets, to suggest that abnormal returns to momentum strategies cannot be explained by the traditional risk assessment models, [Forner and Marhuenda (2006) or Muga and Santamaría (2006a)]. The explanation is still not entirely convincing, even when asymmetric risk factors are added, Muga and Santamaría (2006c). Clear findings also fail to emerge from tests of the implications drawn from the different behavioural models, [Forner and Marhuenda (2004) or Muga and Santamaría (2006a)]. This is due both to the type of portfolio analysis that is required and to the relatively small number of stock listed in the Spanish stock market.

2.- The database.

This study uses daily adjusted returns to stocks listed in the Spanish stock market from January 1971 to May 2004, and the General Index of the Madrid Stock Exchange. Virtually all of the post 1981 data are drawn from the Intertell database, although some gaps in these had to be filled with the closing prices of the Stock Exchange Association, all returns being adjusted for dividends, rights offerings and splits, based on information drawn from the Madrid stock Exchange. Returns prior to that data were obtained from information supplied in the weekly bulletins of the Spanish Savings Banks Federation (Confederación Española de Cajas de Ahorros, C.E.C.A.). This left us with a total sample of 194 firms listed in the Spanish stock market at some time during the sample period, with a minimum of 40 at the start of the sample period and a maximum of 145 in November 1998.

To adjust the momentum strategies for the risk factors of the Fama French three-factor model used in the bootstrap analysis, market profitability is approximated by the monthly return of the Madrid Stock Exchange Index and the monthly interest rate on one-year bills of exchange in the secondary market was taken as the risk-free return. The SMB and HML factors were constructed following Fama and French (1993), which required capitalisation and book value data for the stocks listed in the continuous market in Spain from the late nineties onwards.[2] Finally, the conditional models were estimated using dividend yield (DY) and the term structure (TERM), which is given by the difference between long and short term bond yields[3], as instrumental variables.

3.- The momentum effect in the Spanish stock market.

3.1.- Methodology

In line with the existing literature, the methodology used in this paper is similar to that described by Jegadeesh and Titman (1993) in their seminal article on the momentum effect. The cited authors base their approach on the analysis of a set of momentum strategies being held at a given moment of time, all of which together form the momentum portfolio at that point of time. Portfolios are formed with 3, 6, 9 and 12 month formation (J) and holding (K) periods, giving a total of 16 momentum portfolios formed in calendar time.

[2] Because of the peculiarities of the bootstrap analysis selected for this study, it was performed only for the time period January 1991 to December 2000 and not for the entire sample, as will be explained later.

Jegadeesh and Titman (1993) skip a period between the formation and the holding period, in order to avoid potential microstructure bias, or contamination of the results by very short-run return reversals (the opposite of the momentum effect) documented in studies such as Jegadeesh (1990) and Lehmann (1990).

Momentum portfolios can also be constructed in event time, for which momentum returns are measured over a given period of time, independently of any strategies that may be formed in subsequent periods. The drawback of this approach for the present purpose is that returns to the different strategies may be highly correlated, thus making it necessary to adjust the statistic used to test the significance of the various strategies.

Although the definition of winners and losers, as proposed by Jegadeesh and Titman (1993) is based on deciles, such a procedure is immensely challenging in small markets such the Spanish stock market, given the need for a certain degree of portfolio diversification. For the purposes of this study, therefore, the winner portfolios will be formed from the top-performing quintile during the formation period and the loser portfolios on the bottom-performing quintile during that period[4].

Finally, note that, to avoid overestimating the potential momentum effect and possibly falling prey to the effects of survivorship bias, non-survivors are replaced by an equal-weighted index of the entire stock sample during that period.

3.2.- Empirical evidence.

The results for the January 1973 to May 2004 estimation period are consistent with the previous evidence with respect to the presence of the momentum effect in the Spanish stock market[5].

The calendar time returns for the different momentum strategies in the winner and loser portfolio are presented in Panel A of Table 1. The momentum returns range between 0.95% per month for J=3 and K=3 and 1.72% per month for J = 12 and K = 3. The adjusted returns using the Fama-French model are shown in Panel B of Table 1[6]. In this case, the momentum returns range between 1.02% per month for J=3 and K=12 and

[3]Data for the instrumental variables, DY and TERM, were supplied by Belén Nieto at the University of Alicante

[4] This is in line with the procedure used by Forner and Marhuenda (2006).

[5] Forner and Marhuenda (2006) find monthly returns ranging between 0.5% and 1.3% for January 1965 to December 2000.

[6] HML and SMB factors are only available from 1982. For this reason the adjusted returns using Fama-French model have been computed for the 1982-2004 period. The momentum raw returns for this period are very similar to those obtained for the whole period (1973-2004). These results are available from authors upon request.

1.68% per month for J = 12 and K = 3. In both cases the all sixteen strategies are statistically significant as shown by the t statistic.

The results in Panel A permit us to assert that the profitability is not equally divided between the two momentum portfolios. It is seemingly due to the behaviour of winner stocks. Nevertheless, the results using adjusted returns (Panel B) show that both the winner and loser portfolios contribute to the momentum. Moreover, the results in section 5.2 permit us to assert that the loser portfolios contribute more than winner portfolio to the momentum effect.

The returns to the momentum strategies measured in event time are shown in Table 2, where they can be seen to be consistent with those estimated in calendar time. The momentum returns range between 0.92 % per month for J = 3, K = 3, and 1.78% per month for J = 12, K = 3. All 16 strategies were again shown to be statistically significant using the Newey and West (1987) t statistic, and a bootstrapped and skew adjusted t statistic as proposed by Lyon, Barber and Tsai (1999). Our results for Spanish stock market show that returns to the momentum strategies (1.33% per month for J=6 K=6) are very close to those obtained in more developed markets[7] (Jegadeesh and Titman 2001 or Rouwenhorst 1998).

Summing up, we can assert that there is significant positive momentum in the Spanish stock market during the January 1973 to December 2004 estimation period. The possible causes of this phenomenon, however, are quite another issue, which will be addressed by means of two different procedures, the first one based on the bootstrap technique, the other on stochastic dominance.

4.- Results of the bootstrap analysis.

The debate that pervades the literature as to the true nature of the momentum effect has given rise to a variety of techniques aimed at settling the dispute between the so-called rational explanations and those that rely on aspects of investor behaviour.

One of the econometric techniques most frequently used in the attempt to provide a global explanation for this phenomenon are the bootstrap methods, though they have also received some criticism. As indicated earlier, the first study in which a technique of this type was used to determine whether abnormal returns to momentum strategies are more likely to be due to risk factors or to behavioural issues was that of Conrad and

[7] Jegadeesh and Titman (2001) obtain a momentum return of 1.39% per month for the US in the 1990s and Rouwenhorst (1998) 1.16% per month for a sample of developed markets.

Kaul (1998). Bootstrap analysis with replacement led these authors to conclude that returns to momentum strategies are due to cross-sectional dispersion in stock returns, the most likely cause of which is the presence of some omitted risk factor in the traditional models, which are apparently unable to explain this anomaly.

According to Jegadeesh and Titman (2001, 2002), however, because of the way the momentum portfolios are constructed, the bootstrap procedure used by Conrad and Kaul (1998) may bias the results. To be more specific, when resampling with replacement, the same observation may be found in the formation period and the holding period, thereby artificially producing the anomaly, and the longer the formation and the holding periods the larger the bias. They therefore recommend that the appropriate bootstrap technique to analyse this phenomenon is resampling without replacement. Using this alternative bootstrap method, they obtain results that are the opposite to those found by Conrad and Kaul (1998). That is, the momentum returns do not appear to be generated by cross-sectional variation in the stocks. Karolyi and Kho (2004), however, point out that this second procedure may also be sensitive to small-sample bias, since it allows a fairly significant role to outliers.

4.1.- Methodology.

Given that both bootstrap procedures may potentially bias the results, this paper adopts the solution used in Karolyi and Kho (2004), which is to use both procedures, with and without replacement, and compare their results for the Spanish stock market case.

Following the same work, we also test several alternative return generation models to determine which is the best adapted to the generation of returns to momentum strategies. We begin with a random walk with drift model that was used by Conrad and Kaul (1998) to determine whether cross-sectional dispersion in returns is on its own sufficient to explain the momentum effect. We also consider the Fama French three-factor model, which includes the market factor and a further two factors designed to capture risks related to size (SMB) and book-to-market ratio (HML).

These models were then extended to include a return lag and a market return lag in order to capture potential auto-correlation and cross correlation in the stock returns (Conrad and Kaul 1989 and Lo and Mackinlay 1990).

Finally, conditional information was incorporated into the Fama French models, due to the fact that researchers such as Chordia and Shivakumar (2002) and Wu (2002) propose momentum returns may vary over time depending on the state of the economy. The variables used to incorporate the conditional information were lagged dividend yield (DY) and the term structure (TERM), the long-term and short-term bond yield differential, both these variables were mean-subtracted for use as instruments in the conditional models[8].

Each of the described models was estimated individually for all the return series of the stocks considered, in order to obtain the corresponding parameters and errors. The errors thus obtained were then standardised by dividing them by the standard deviation of the error series. Having standardised the error series, random sampling (once with replacement and again without replacement) is used to obtain a new series equal in length to the original. Finally, after estimating the model parameters, and random sampling the error, new series were formed for the original model and the momentum strategies were constructed using the methodology described in the preceding section. Each of the procedures was repeated 500 times.

The bootstrap procedures used in this paper differ substantially from those used in Karolyi and Kho (2004), however. In the latter, errors generated by the different models for each of the stocks are independently sampled. This yields time series of the same length as the original ones, enabling each simulation to replicate a momentum effect similar to the real one in terms of the number of stocks involved. Nevertheless, as noted by the authors themselves, this way of sampling the errors in the stocks may lead to the loss of possible cross-sectional correlation between the different return series. The recommended sampling procedure to overcome this problem is to extract the blocks of errors, for a given time period, from the set as whole, thus leaving any possible cross-sectional correlation intact.

The problem that arises with this sampling method is that returns must be available for all the stocks used in the bootstrap procedure in every month of the estimation period. Any missing data in the return series would prevent the comparison needed to construct the momentum portfolios, which, as explained earlier, are based on past stock returns.

The simplest way of surmounting this problem is to take a large enough sample of stocks with data available for the whole period. Thus, when it comes to sampling the

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[8] In Karolyi and Kho (2004), moreover the above models are extended with a GARCH-type structure. This was not done in our case, however, because the parameters for most of the selected assets were non-significant using monthly data.

errors of the various bootstrap analyses, there are no instances of missing data that would prevent us from constructing the various momentum strategies.

Taking into account the described constraints that prevent us from performing the bootstrap analysis with all the stocks in the original sample in order to obtain the blocks of monthly returns, we selected from the sample the 72 assets that are continuously listed on the Spanish stock market during the period January 1991 to December 2000[9].

4.2.- Results

Prior to the bootstrap procedures, a test is required to determine whether in fact the chosen sample continues to present the momentum effect, since previous evidence relating to the presence of this anomaly in the Spanish stock market during the 1990s tends to suggest the contrary. Thus, while the results of Forner and Marhuenda (2006) show momentum to have faded during that period, Muga and Santamaría (2006a) found that although the pattern weakened it cannot be said to have faded completely.

The returns to the different momentum strategies for the sample considered during the 1990s are shown in Panels A and B of the Table 3. Of the sixteen strategies constructed from the different combinations of formation and holding periods, eleven are found to be significant using raw returns and twelve using adjusted returns.

Having confirmed the presence of momentum, albeit weak, in the study sample, we present the results of the various bootstrap analyses in Table 4[10].

The results for the first of the models, random walk with drift (see panel A of Table 4), are consistent with the existing international evidence. That is, bootstrap with replacement, as proposed by Conrad and Kaul (1998), shows simulated momentum returns close to those of the original sample, with a maximum monthly return of 0.85% and a minimum monthly return of 0.47%. Furthermore, the p-values(1) (those that indicate the percentage of simulations that have yielded a negative return) show that eleven of the sixteen strategies are significant. However, when bootstrap without replacement is used, as proposed by Jegadeesh and Titman (2002), none of the bootstrap strategies turns out to be significant according to the p-value(1). The simulated returns,

[9] The reason for this choice of time period was that data are required for a minimum number of stocks, for portfolio diversification reasons, and a long enough time horizon, to avoid as far as the possible the small sample bias to which bootstrap analysis is susceptible.

[10] This table presents the returns obtained through the various bootstrap simulations for each of the momentum strategies, a first p value, p-value (1), showing the percentage of simulations that have yielded

meanwhile, range between 0.09% per month for the J9/K6 strategy and 0.15 % per month for the J6/K3 strategy[11].

These results confirm the evidence presented both by Conrad and Kaul (1998) for bootstrap with replacement and Jegadeesh and Titman (2002) for bootstrap without replacement. Thus, bearing in mind the bias in both procedures, as noted above, it is not possible to draw any clear conclusion with respect to issue under investigation. Furthermore, as noted by Karolyi and Kho (2004), the statistics literature offers no suitable guidance as to the appropriate choice of method.

By extending this model or the Fama French model to include auto-correlation and cross-sectional correlation terms, (see panels B, C, and D in Table 4), we obtain results similar to those described for the random walk with drift. Thus, it can be seen that several of the momentum strategies prove significant according to p-value(1) simulated for the bootstrap procedures with replacement, but none of them is significant according to the p-value(1) in the procedure without replacement. Furthermore, the mean returns obtained in the simulations are noticeably higher in the bootstrap procedures with replacement. These results provide sufficient support to confirm the overall conclusions drawn from the first model, based on random walk with drift.

There is a change in the results, however, when conditional information is incorporated into the Fama-French three-factor model and the extension with auto-correlation and cross-sectional correlation (see panels 5 and 6 in Table 4). The bootstrap procedure with replacement continues to give simulated returns close to the original ones and p-values(1) indicating the significance of most of the simulated strategies. The results obtained without replacement present a substantial change, however, since, when conditional information is incorporated into the model, it is possible to observe an overall increase in the simulated returns to the various strategies, versus the models that did not contain conditional information. This change is of little practical importance, however, since none of the simulated returns comes close to the real returns to the momentum strategies, although some emerge as being significantly different from 0 according to the p-value(1).

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a negative return and a second p value, p-value(2), showing the percentage that have outperformed the original sample.

[11] These results are consistent with those reported in Forner and Marhuenda (2004) using a similar procedure.

This phenomenon can also be observed in the results reported by Karolyi and Kho (2004), since, in the simulations without replacement, the simulated returns increase almost to the level of the original momentum returns.

The results also include p-value(2), which shows what the percentage of simulations that outperform the original sample, enabling comparison with the results of Karolyi and Kho (2004). These authors find that, generally speaking, in bootstrap analyses only a small percentage of simulations exceed the real returns, either with or without replacement. Our percentages were higher, however, and the simulated returns were also closer to the real ones. This discrepancy is probably due to differences in the bootstrapping procedures used, since, in their case, independent stock sampling may lead to a partial loss of cross-sectional correlation, which may be causing the momentum, a possibility that is avoided by using the bootstrap procedure employed in this study.

In summary, the results of the various bootstrap analyses performed in this study are consistent with prior evidence. The results obtained using bootstrapping with replacement suggest that returns to momentum strategies are due to cross-sectional dispersion in the stocks. This result weakens, however, when bootstrap procedures without replacement are used, unless conditional information is introduced into the return generating models, in which case it appears that cross-sectional dispersion might partially, but not entirely, explain returns to momentum strategies.

Taking into account the size of the available sample, it appears more reasonable to assume the bias is due to the possible repetition of values across the formation and holding periods when bootstrapping with replacement. It is worth mentioning, in this respect, that the results are consistent with this reasoning. Suffice it to say that potential bias when bootstrapping with replacement will be greater for longer formation and holding periods, where there will be a higher probability of artificial repetitions across periods. In line with this argument, the results with replacement are generally more significant for longer J and K, suggesting the possible presence of such bias. The fact that this behaviour pattern does not appear in bootstrapping without replacement (where there should be a similar degree of small sample bias across the different strategies, since we have the same number of observations) suggests that the results of the bootstrap with replacement might be due to this bias. All this leads us to give more credit to the results obtained via the bootstrap without replacement procedure, which suggest the time series performance as the main cause of the momentum effect.

Nevertheless, the discrepancy in the results of the various bootstrap methods raises the issue of whether it would be worth employing an alternative type of technique, namely stochastic dominance, with a view to obtaining more robust findings with respect to the source of momentum returns.

5.-Results of the stochastic dominance method.

Another way of analysing the possible causes of positive returns to momentum strategies is via stochastic dominance techniques. This type of techniques probably offer the broadest potential for the analysis of the issue that concerns us, since they provide a general framework for the study of economic behaviour under uncertainty and impose few constraints with respect to the investor's utility function, thus facilitating comparisons (see Levy 1998). With respect to our present purpose, stochastic dominance techniques can be used to ascertain whether the winner portfolio dominates the loser portfolio in a given market over a set time period, that is, whether the difference between loser and winner portfolios[12] can be explained using a general asset-pricing model with risk-averse investors.

5.1.- Methodology.

The literature has presented several stochastic dominance testing methods. The robustness of our results was tested by means of three different methods, namely, the KS test (Barret and Donald, 2003), the DD test (Davison and Duclous, 2000), and the MCSD test (Chow, 2001). The first of these is based on a Kolmogorov-Smirnov type test that compares the objects at all points and is defined for different orders of stochastic dominance, especially the first, second and third orders. The DD test is a simplification of the KS test that compares the cumulative distribution functions over an arbitrary set of points. Finally, *marginal conditional stochastic dominance,* (MCSD) is quite different and restricted exclusively to second order stochastic dominance (see Shalit and Yitzhaki, 1994).

The KS test is applied to our particular problem as follows. There are two separate return series, k (returns to the winner portfolio), and l (returns to the losers), of the same size for both samples, in which the cumulative distribution functions (CDFs) are given

[12] Fong, Wong and Lean (2005) were the first to apply stochastic dominance techniques to analyse the momentum effect and to test whether the loser portfolio was stochastically dominated by the winner portfolio.

by W and L, respectively. The KS test, therefore, tests the following null and alternative hypotheses:

$$H_o^s : f_s(z,W) \le f_s(z,L) \quad \forall z \in [0,\bar{z}]$$

$$H_1^s : f_s(z,W) > f_s(z,L) \quad \text{for some } z \in [0,\bar{z}]$$

$f_s(z,F)$ is the function that integrates function F to the order s-1. That is,

$$f_1(z,W) = W(z)$$

$$f_2(z,W) = \int_0^z W(t)dt = \int_0^z f_2(t,W)dt$$

$$f_3(z,W) = \int_0^z \int_0^s W(s)dsdt = \int_0^z f_2(t,W)dt$$

The null hypothesis that the winners dominate the losers can be tested using the following statistic proposed by Barret and Donald (2003):

$$\hat{K}_s = \left(\frac{N}{2}\right)^{1/2} \sup_z \left[f_s(z,\hat{W}) - f_s(z,\hat{L})\right]; \text{ where } N \text{ is the sample size.}$$

It should be noted that, for s≥2, the Barret-Donald KS test is analytically intractable because the limiting distribution of K_s depends on the underlying CDFs. Thus, all the p-values are calculated using simulations based on the Barret and Donald (2003) procedure.

DD, meanwhile, is designed to test:

$$H_o^s : f_s(z_j,W) \le f_s(z_j,L) \quad \text{for any } j \in \{1,...,m\}$$

$$H_1^s : f_s(z_j,W) > f_s(z_j,L) \quad \text{for some } j \in \{1,...,m\}$$

Unlike in the KS test, the hypothesis to be tested here refers to dominance for a fixed number of points only. It could therefore be less powerful than the previous test in certain situations, since it may fail to take into account all the implications of stochastic dominance (see Barret and Donald 2003). However, this type of test can be used on both dependent and independent series drawn from a joint distribution, unlike the first, which requires independence. It might therefore provide a useful complement to increase the robustness of our conclusions.

A simple way to test the hypothesis is to calculate S_s. The null hypothesis should be rejected if S_s is large enough. $\hat{S}_s = \max\{\hat{t}_s(z_j)\}$ where $\hat{t}_s(z_j) = \hat{\Delta}_s(z_j)/\sqrt{\hat{\Omega}_{s,jj}}$;

$\hat{\Delta}_s(z_j) = f_s(z_j, W) - f_s(z_j, L)$; and $\hat{\Delta}_s$ is the k vector of estimates of $\Delta_s(z_j)$, $\hat{\Omega}_s$ is the estimate of the variance and covariance matrix $\hat{\Delta}_s$. Note, furthermore, that this statistic does not have a standard distribution, and that the p values will be calculated according to the procedure used in Barrett and Donald (2003).

Unlike the above two tests, MCSD is meant to provide the conditions under which, beginning with a given portfolio, all risk-averse investors should prefer to marginally substitute one asset from one portfolio with one from the other. Thus, the test is based on the assumption that investors make only marginal adjustments to their portfolios under certain conditions, without altering the "core". In this context, Chow (2001) creates a statistic for the critical values of the studentised maximum modulus (SMM), with which it is possible to determine the complete confidence interval for a set of MCSD estimators.

The calculation of this statistic is based on the assumption that investors are utility-maximising and risk-averse. According to Chow (2001):

A distribution, *k*, dominates the market if:

$Z^k(\tau_i) \geq$SMM(α;m;∞) for all *i*, and some with strict inequality.

A distribution, *k*, dominates another distribution, *l*, if:

$Z^{k-l}(\tau_i) \geq$SMM(α;m;∞) for all *i*, and some with strict inequality.

Where, $Z^k(\tau_i) = \dfrac{\bar{\phi}^k(\tau_i)}{S^k(\tau_i)}$ for i=1,…, m and

$$Z^{k-l}(\tau_i) = \frac{\bar{\phi}^k(\tau_i) - \bar{\phi}^l(\tau_i)}{S^{k-l}(\tau_i)} \quad \text{for } i=1,\ldots,m.$$

The estimator in the numerator $\bar{\phi}^k(\tau_i)$ measures the mean conditional excess return of asset *k* relative to the market portfolio, under the predetermined target return, τ_i .

$$\bar{\phi}^k(\tau_i) = N^{-1}\left[\sum_{t=1}^{N} r_t^{p,k} I(\tau_i) - \sum_{t=1}^{N} r_t^M I(\tau_i)\right]$$

N is the number of returns in the series under scrutiny, $r_t^{p,k}$ is the return to asset k in portfolio p at t, r_t^M is the market return at t. $I(\tau_i)$ is a dummy variable. More specifically, $I(\tau_i) = 0$ if $r_t^M > \tau_i$ for t=1,…N; otherwise $I(\tau_i)$=1; i=1,…,m is the set of predetermined target returns.

Under certain conditions, the vector of estimates ($\overline{\phi}^k(\tau_1)$, …, $\overline{\phi}^k(\tau_m)$) for a vector of target returns {τ | i=1,2,…m} is asymptotically normal and $\sqrt{N}\left(\overline{\phi}-\phi\right)$ has a normal zero mean limit distribution with mK- varied and covariance matrix $\pi = J\varphi J'$, where φ and J are defined as follows:

$$\varphi = \begin{bmatrix} \left[\alpha_{ij}^{11}\right] & \cdots & \left[\alpha_{ij}^{1k}\right] & \left[\gamma_{ij}^{1}\right] \\ & \cdots & & \\ \left[\alpha_{ij}^{k1}\right] & \cdots & \left[\alpha_{ij}^{kk}\right] & \left[\gamma_{ij}^{k}\right] \\ \left[\gamma_{ij}^{1}\right] & \cdots & \left[\gamma_{ij}^{k}\right] & \left[\beta_{ij}\right] \end{bmatrix} \text{ where } \left\{ \begin{aligned} \alpha_{ij}^{kl} &= Cov(r_k^p I(\tau_i), r_l^p I(\tau_j)) \\ \gamma_{ij}^{k} &= Cov(r_k^p I(\tau_i), r^M I(\tau_j)) \\ \beta_{ij} &= Cov(r^M I(\tau_i), r^M I(\tau_j)) \end{aligned} \right\}$$

$$J = \begin{bmatrix} \mu & & \mu^T \\ & . & . \\ & . & . \\ & \mu & \mu^T \end{bmatrix}, \text{ where } \mu = \begin{bmatrix} 1 & & \\ & . & \\ & & . \\ & & 1 \end{bmatrix} \text{ and } \mu^T = \begin{bmatrix} -1 & & \\ & . & \\ & & . \\ & & -1 \end{bmatrix}$$

Hence, the asymptotic standard errors for the sample estimations are[13]:

$$S^k(\tau_i) = \left(\frac{\pi_{tt}}{N}\right)^{1/2} \qquad \text{where} \quad t=(k-1)m+i \text{ ; } i=1,\ldots m \text{ and } k=1,\ldots K$$

$$S^{k-l}(\tau_i) = \left(\frac{\pi_{tt} + \pi_{vv} - 2\pi_{tv}}{N}\right)^{1/2} \qquad \text{where} \quad t=(k-1)m+i \text{ ; and } v=(l-1)m+i.$$

The first stochastic dominance criterion assumes that investors have an insatiable appetite for wealth, the second, that they are also risk-averse, and the third, that they have a preference for positively skewed return distributions. Since the conditions for the first criterion are too strict for it to be fulfilled, this study focuses on second and third order stochastic dominance. The results of these three tests of the Spanish stock market are reported in the following section.

[13] The test is robust to the presence of heteroskedasticity in the data series (See Chow, 2001).

5.2.- Results.

Table 5 presents the results of the KS test for second and third order stochastic dominance for the Spanish stock market during the period January 1973 to December 2004.

The results of the KS test for second order stochastic dominance, (see columns 2 and 3 of Table 5) show that the null hypothesis that the winner portfolio dominates the loser portfolio cannot be rejected at the standard levels of significance for any of the strategies analysed. (The p-values for the sixteen strategies are all higher than 0.5). However, the alternative hypothesis that the loser portfolio dominates the winners has p-values very close to 0, and can therefore be rejected at the standard levels of significance for second order stochastic dominance.

Interpretation of these results is straightforward. At least all risk-averse investors show a preference for the winner portfolio over the loser portfolio involved in the momentum strategy. This assertion is possible because the hypothesis that the loser portfolio dominates the winners can be rejected at the 1% level, whereas in no case could the opposite hypothesis be rejected at the standard levels of significance.

The results of the KS third order stochastic dominance test are largely consistent with those presented for second order (see columns 4 and 5 of Table 5). Thus, they reject the hypothesis that the loser portfolio dominates the winners while being unable to reject the opposite hypothesis for any of the sixteen momentum strategies considered. These results also raise doubts as to possibility of any general asset-pricing model with risk-averse investors being capable of explaining the momentum effect in the Spanish stock market.

The results of the DD test (see Table 6) are found to be consistent with those of the KS test. In other words, for second order stochastic dominance, in no case is it possible to reject the hypothesis that the winner portfolio dominates the losers (all p-values higher than 0.6), while the hypothesis that the loser portfolio dominates the winner portfolio is rejected in all strategies. The results for the third order stochastic dominance DD test also reject that the winner portfolio dominates the losers (all p-values higher than 0.6) for all strategies and dominance of winners by losers is also rejected for all strategies[14].

[14] Although in this case, the significance level for the J = 3 K = 3 strategy is 10%

Summing up, the results of these two differentiated tests lead to the same conclusions. The winner portfolio stochastically dominates the losers for second and third order stochastic dominance. It is important to stress that the KS and DD tests lead to the same outcome, despite being based on different assumptions, since this of course increases their robustness.

Finally, the MCSD test proposed by Chow (2001) was also used. Following the recommendations of the said author, this test was performed on ten target returns, using the Madrid Stock Exchange General Index as the reference.

Table 7 presents the values of the $Z^{k-l}(\tau_i)$ statistic for the sixteen strategies considered. In this test, the null hypothesis is that the winner portfolio does not stochastically dominate the losers. Following the approach described in the methodology section, the results of this test are restricted to second order stochastic dominance. As shown, the statistic values are positive for all the strategies analysed. Furthermore, the maximum value of the statistic in all cases exceeds the critical value for a 5% level of significance.[15] Therefore, this test can also be said to confirm that winners stochastically dominate losers in the second order sense.

Overall, the results obtained through the various stochastic dominance tests enable us to confirm that the winner portfolio stochastically dominates losers for any risk-averse investor (second order stochastic dominance). Hence, momentum strategy returns in the Spanish stock market do not appear to be consistent with asset-pricing models devised for risk-averse investors. This tips the balance towards explanations based on investor behaviour, in line with the conclusions reported by Fong, Wong and Lean (2005) in an international market index setting.

To conclude our investigation of stochastic dominance tests, since Chow's (2001) MCSD can be used to analyse whether momentum returns are due to winners or losers, we tested to see whether winners dominate the market and whether losers are dominated by the market.

Panel A of Table 8 gives the values of the $Z^{k}(\tau_i)$ statistic for the winners' dominance of the market. For all but three of the strategies (J=9 K=3; J=9 K=6; J=12 K=3) this statistic is negative; therefore the winner portfolio cannot be said to dominate the market. Likewise, panel B of Table 8 gives the values of the $Z^{l}(\tau_i)$ statistic for the

[15] The critical value for the case in hand are 2.81 for the 5% level of significance.

losers' dominance of the market. This time all the values are negative, which enables us to assert that the market stochastically dominates the loser portfolio. In addition, for all strategies, the statistic has some absolute value that exceeds the critical value for a 1% level of significance. Thus we are able to conclude that the loser portfolio is stochastically dominated by the market in the second order sense.

The results displayed in Table 8 extend the conclusions of the stochastic dominance analysis. Firstly, all three tests show that winners dominate losers for any risk-averse investor. Secondly, we also find reason to believe that the momentum effect has more to do with behaviour patterns than with risk factors, since the tests reveal the loser portfolio to be the main driver of momentum returns in the Spanish stock market during the estimation period. This is because the market portfolio dominates the loser portfolio for all strategies while, generally speaking, the winner portfolio cannot be said to dominate the market portfolio. These findings provide the rationale for potential future research into issues such as the characteristics of the securities that form the loser portfolio or investor behaviour with respect to loser portfolios (see Grimblat and Titman, 2004).

6.- Conclusions.

This paper has used general non-parametric methods in an attempt to sort out the possible sources of momentum in stock markets. For this purpose, we present the results for the Spanish stock market during the January 1973 to May 2004 estimation period.

The first of the techniques to be applied was bootstrap analysis, which is used in the literature to ascertain whether returns to momentum strategies are due to cross-sectional dispersion in the stocks return or to the time series behavior. In our bootstrap analysis we resample blocks of returns in the same period to avoid destroying any cross sectional patterns in the stock returns

In line with the literature, the results from the bootstrap analysis are found to depend on the resampling method used (with or without replacement) thus the conclusions are inevitably questionable, given the bias present in both procedures and the lack of any specific guidelines for choosing between the two. In our opinion, however, for the problem that concerns us, given the number of available observations, small sample bias is clearly less important than the obvious reiteration bias caused by the replacement procedure, as this analysis has shown. This leads us to the conclusion that momentum returns are partially or totally incompatible with explanations based on omitted risk factors.

Furthermore, the various stochastic dominance techniques, applied as described above (the KS test, the DD test and the MCSD test) have led us to the same conclusion, namely, that the winner portfolio stochastically dominates the loser portfolio, which is not consistent with the general asset-pricing models developed for risk-averse investors.

The results suggest that theories that relax the unbounded rationality assumptions in classical asset pricing models and allow for more flexible environments (see Lo, 2004) may provide further insights into the causes of momentum profits. However, there may be other potential causes including high transaction costs, which may make momentum strategies practicably impossible to implement (Lesmond, Schill and Zhou 2004) or returns due to liquidity differentials between winners and losers.

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TABLE 1: Calendar time momentum 1973 – 2004
*PANEL A in this table reports the monthly returns to the 16 Winner, Loser, and momentum portfolios, measured in calendar time, for the period January 1973 to May 2004 in the Spanish stock market. J, is the formation period and K is the holding period. PANEL B shows the adjusted returns using the Fama-French model for the period January 1982 – May 2004. * denotes 5% significance according to the t test*
.

PANEL A

	K	3	6	9	12
J	Winners	0.898 *	0.990 *	0.986 *	0.998 *
3	Losers	-0.052	-0.080	-0.057	-0.047
	Momentum	0.950 *	1.070 *	1.043 *	1.045 *
	Winners	1.191 *	1.146 *	1.126 *	1.059 *
6	Losers	-0.191	-0.182	-0.184	-0.103
	Momentum	1.383 *	1.329 *	1.310 *	1.162 *
	Winners	1.389 *	1.360 *	1.234 *	1.118 *
9	Losers	-0.213	-0.328	-0.240	-0.142
	Momentum	1.603 *	1.689 *	1.474 *	1.261 *
	Winners	1.330 *	1.244 *	1.110 *	0.975 *
12	Losers	-0.396	-0.341	-0.206	-0.116
	Momentum	1.726 *	1.586 *	1.317 *	1.091 *

PANEL B

	K	3	6	9	12
J	Winners	0,296	0,320	0,336	0,324
3	Losers	-0,802 *	-0,787 *	-0,751 *	-0,699 *
	Momentum	1,099 *	1,107 *	1,087 *	1,023 *
	Winners	0,560 *	0,533 *	0,523 *	0,432 *
6	Losers	-0,942 *	-0,888 *	-0,821 *	-0,733 *
	Momentum	1,502 *	1,421 *	1,345 *	1,165 *
	Winners	0,715 *	0,691 *	0,581 *	0,478 *
9	Losers	-0,934 *	-0,952 *	-0,854 *	-0,770 *
	Momentum	1,649 *	1,643 *	1,434 *	1,248 *
	Winners	0,681 *	0,602 *	0,474 *	0,363
12	Losers	-1,002 *	-0,941 *	-0,812 *	-0,746 *
	Momentum	1,682 *	1,543 *	1,286 *	1,109 *

TABLE 2: Event time momentum effect 1973 - 2004

*This table reports the monthly returns to the 16 momentum portfolios, measured in event time, for the period January 1973 to May 2004 in the Spanish stock market. J is the formation period and K is the holding period. * denotes 5% significance according to the t statistic adjusted by the Newey West(NW) procedure or the bootstrap method proposed by Lyon, Barber and Tsai (1999) (B).*

	K=3	NW	B	K=6	NW	B	K=9	NW	B	K=12	NW	B
J=3	0.986	*	*	1.080	*	*	1.059	*	*	1.074	*	*
J=6	1.393	*	*	1.329	*	*	1.335	*	*	1.188	*	*
J=9	1.614	*	*	1.703	*	*	1.492	*	*	1.266	*	*
J=12	1.786	*	*	1.605	*	*	1.337	*	*	1.106	*	*

TABLE 3: Calendar time momentum effect 1992 - 2000

*PANEL A in this table the monthly returns to the 16 momentum strategies, measured in calendar time, for the period January 1992 to December 2000 in the Spanish stock market for the 72 stocks selected in the bootstrap analysis. J is the formation period and K is the holding period. PANEL B shows the adjusted returns using the Fama-French model for the period January 1982 – May 2004. ** and * denote 5% and 10 % significance according to the t test*

PANEL A

	K=3	**K=6**	**K=9**	**K=12**
J=3	0.443	0.588	0.743 *	0.763 **
J=6	0.776	1.114 **	1.077 **	0.912 **
J=9	1.240 *	1.301 **	1.193 **	0.964 *
J=12	1.184 *	1.231 *	0.927	0.694

PANEL B

	K=3	**K=6**	**K=9**	**K=12**
J=3	0,503	0,584	0,773 **	0,802 **
J=6	0,757	1,109 **	1,099 **	0,906 **
J=9	1,270 **	1,331 **	1,217 **	1,002 **
J=12	1,257 **	1,256 **	0,967 *	0,755

TABLE 4: Bootstrap analysis

This table reports the mean simulated returns in monthly % for the 16 momentum strategies using bootstrap procedures with and without replacement for the different return generating models used in the study. It also gives p values(1), which indicate the proportion of simulations in which there is a below zero return to a particular strategy and p values(2), which indicate the proportion of simulations in which there is a higher than real return.

PANEL A: Random walk with drift:

$$R_{i,t} = \alpha_i + \varepsilon_{i,t}$$

		Bootstrap with replacement				**Bootstrap without Replacement**			
		K=3	**K=6**	**K=9**	**K=12**	**K=3**	**K=6**	**K=9**	**K=12**
J=3	**Mean**	0.477	0.481	0.512	0.502	0.126	0.127	0.138	0.138
	p-value(1)	(0.154)	(0.100)	(0.042)	(0.064)	(0.378)	(0.332)	(0.302)	(0.256)
	p-value(2)	(0.520)	(0.372)	(0.226)	(0.220)	(0.190)	(0.048)	(0.016)	(0.002)
J=6	**Mean**	0.605	0.634	0.589	0.651	0.152	0.134	0.104	0.118
	p-value(1)	(0.156)	(0.112)	(0.098)	(0.052)	(0.360)	(0.378)	(0.370)	(0.348)
	p-value(2)	(0.378)	(0.148)	(0.136)	(0.268)	(0.076)	(0.006)	(0.002)	(0.006)
J=9	**Mean**	0.743	0.768	0.768	0.775	0.106	0.099	0.119	0.144
	p-value(1)	(0.100)	(0.064)	(0.062)	(0.040)	(0.402)	(0.406)	(0.370)	(0.336)
	p-value(2)	(0.202)	(0.168)	(0.200)	(0.336)	(0.000)	(0.002)	(0.002)	(0.010)
J=12	**Mean**	0.823	0.845	0.844	0.817	0.128	0.129	0.143	0.133
	p-value(1)	(0.078)	(0.076)	(0.062)	(0.044)	(0.354)	(0.382)	(0.348)	(0.362)
	p-value(2)	(0.248)	(0.230)	(0.406)	(0.578)	(0.008)	(0.006)	(0.012)	(0.048)

PANEL B: Random walk with drift, auto-correlation and cross-correlation.

$$R_{i,t} = \alpha_i + \beta_{1,i} R_{i,t-1} + \beta_{2,i}.R_{m,t-1} + \varepsilon_{i,t}$$

		Bootstrap with replacement				**Bootstrap without Replacement**			
		K=3	**K=6**	**K=9**	**K=12**	**K=3**	**K=6**	**K=9**	**K=12**
J=3	**Mean**	0.572	0.539	0.505	0.500	0.196	0.158	0.145	0.133
	p-value(1)	(0.118)	(0.076)	(0.060)	(0.052)	(0.328)	(0.296)	(0.298)	(0.274)
	p-value(2)	(0.588)	(0.358)	(0.250)	(0.272)	(0.266)	(0.078)	(0.012)	(0.006)
J=6	**Mean**	0.708	0.655	0.655	0.648	0.193	0.143	0.109	0.119
	p-value(1)	(0.116)	(0.112)	(0.056)	(0.068)	(0.328)	(0.348)	(0.374)	(0.362)
	p-value(2)	(0.438)	(0.190)	(0.180)	(0.276)	(0.074)	(0.006)	(0.002)	(0.006)
J=9	**Mean**	0.764	0.722	0.736	0.751	0.124	0.148	0.132	0.082
	p-value(1)	(0.086)	(0.094)	(0.070)	(0.090)	(0.390)	(0.338)	(0.362)	(0.424)
	p-value(2)	(0.190)	(0.168)	(0.180)	(0.320)	(0.010)	(0.006)	(0.004)	(0.008)
J=12	**Mean**	0.845	0.856	0.837	0.835	0.125	0.138	0.104	0.087
	p-value(1)	(0.080)	(0.066)	(0.066)	(0.042)	(0.418)	(0.352)	(0.390)	(0.420)
	p-value(2)	(0.276)	(0.276)	(0.412)	(0.580)	(0.016)	(0.004)	(0.020)	(0.044)

TABLE 4 (Cont): Bootstrap analysis

This table reports the mean simulated returns in monthly % for the 16 momentum strategies using bootstrap procedures with and without replacement for the different return generating models used in the study. It also gives p values (1), which indicate the proportion of simulations in which there is a below zero return to a particular strategy and p values (2), which indicate the proportion of simulations in which there is a higher than real return.

PANEL C: Fama French Model.

$$R_{i,t} = \alpha_i + \beta_{1,i} R_{m,t} + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \varepsilon_{i,t}$$

		Bootstrap with replacement				Bootstrap without Replacement			
		K=3	**K=6**	**K=9**	**K=12**	**K=3**	**K=6**	**K=9**	**K=12**
J=3	**Mean**	0.390	0.391	0.458	0.497	0.071	0.071	0.160	0.189
	p-value(1)	(0.182)	(0.134)	(0.058)	(0.034)	(0.416)	(0.424)	(0.226)	(0.146)
	p-value(2)	(0.442)	(0.284)	(0.174)	(0.180)	(0.152)	(0.028)	(0.008)	(0.006)
J=6	**Mean**	0.504	0.559	0.702	0.655	0.043	0.144	0.245	0.209
	p-value(1)	(0.174)	(0.080)	(0.032)	(0.030)	(0.420)	(0.364)	(0.198)	(0.212)
	p-value(2)	(0.328)	(0.090)	(0.176)	(0.242)	(0.024)	(0.004)	(0.000)	(0.004)
J=9	**Mean**	0.816	0.831	0.837	0.764	0.233	0.304	0.283	0.203
	p-value(1)	(0.038)	(0.026)	(0.026)	(0.030)	(0.256)	(0.172)	(0.164)	(0.204)
	p-value(2)	(0.188)	(0.152)	(0.194)	(0.320)	(0.006)	(0.004)	(0.002)	(0.006)
J=12	**Mean**	0.994	0.973	0.882	0.780	0.364	0.324	0.222	0.119
	p-value(1)	(0.028)	(0.026)	(0.024)	(0.036)	(0.170)	(0.142)	(0.226)	(0.346)
	p-value(2)	(0.338)	(0.294)	(0.452)	(0.570)	(0.022)	(0.002)	(0.012)	(0.022)

PANEL D: Fama French Model with auto- correlation and cross -correlation.

$$R_{i,t} = \alpha_i + \beta_{1,i} R_{m,t} + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} R_{i,t-1} + \beta_{5,i} R_{m,t-1} + \varepsilon_{i,t}$$

		Bootstrap with replacement				Bootstrap without Replacement			
		K=3	**K=6**	**K=9**	**K=12**	**K=3**	**K=6**	**K=9**	**K=12**
J=3	**Mean**	0.256	0.316	0.450	0.491	-0.043	0.039	0.146	0.164
	p-value(1)	(0.246)	(0.164)	(0.072)	(0.024)	(0.578)	(0.436)	(0.276)	(0.194)
	p-value(2)	(0.294)	(0.214)	(0.168)	(0.154)	(0.090)	(0.018)	(0.006)	(0.000)
J=6	**Mean**	0.441	0.595	0.696	0.666	-0.034	0.170	0.222	0.220
	p-value(1)	(0.196)	(0.100)	(0.030)	(0.030)	(0.554)	(0.326)	(0.222)	(0.174)
	p-value(2)	(0.256)	(0.106)	(0.160)	(0.236)	(0.012)	(0.002)	(0.004)	(0.004)
J=9	**Mean**	0.789	0.795	0.873	0.776	0.179	0.282	0.300	0.222
	p-value(1)	(0.068)	(0.030)	(0.008)	(0.018)	(0.314)	(0.198)	(0.156)	(0.186)
	p-value(2)	(0.206)	(0.142)	(0.196)	(0.310)	(0.006)	(0.004)	(0.004)	(0.008)
J=12	**Mean**	0.964	0.975	0.864	0.779	0.338	0.309	0.253	0.158
	p-value(1)	(0.024)	(0.018)	(0.024)	(0.032)	(0.176)	(0.176)	(0.206)	(0.292)
	p-value(2)	(0.320)	(0.278)	(0.428)	(0.556)	(0.018)	(0.004)	(0.018)	(0.038)

TABLE 4 (Cont): Bootstrap analysis

This table reports the mean simulated returns in monthly % for the 16 momentum strategies using bootstrap procedures with and without replacement for the different return generating models used in the study. It also gives p values (1), which indicate the proportion of simulations in which there is a below zero return to a particular strategy and p values (2), which indicate the proportion of simulations in which there is a higher than real return.

PANEL E: Conditional Fama French Model.

$$R_{i,t} = \alpha_{1,i} + \alpha_{2,i}.Z(t) + \beta_{1,i}R_{m,t} + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}R_{m,t}Z(t) + \beta_{5,i}SMB_tZ(t) + \beta_{6,i}HML_tZ(t) + \varepsilon_{i,t}$$

		Bootstrap with replacement				Bootstrap without Replacement			
		K=3	K=6	K=9	K=12	K=3	K=6	K=9	K=12
J=3	Mean	0.621	0.418	0.535	0.639	0.292	0.095	0.239	0.328
	p-value(1)	(0.076)	(0.114)	(0.030)	(0.014)	(0.204)	(0.352)	(0.130)	(0.028)
	p-value(2)	(0.654)	(0.314)	(0.212)	(0.322)	(0.318)	(0.040)	(0.012)	(0.004)
J=6	Mean	0.528	0.583	0.772	0.828	0.128	0.149	0.353	0.391
	p-value(1)	(0.124)	(0.072)	(0.012)	(0.002)	(0.374)	(0.342)	(0.104)	(0.042)
	p-value(2)	(0.278)	(0.290)	(0.204)	(0.372)	(0.052)	(0.004)	(0.006)	(0.016)
J=9	Mean	0.849	0.909	0.892	0.877	0.305	0.411	0.402	0.402
	p-value(1)	(0.034)	(0.018)	(0.022)	(0.012)	(0.246)	(0.108)	(0.108)	(0.058)
	p-value(2)	(0.204)	(0.176)	(0.222)	(0.408)	(0.010)	(0.002)	(0.016)	(0.034)
J=12	Mean	1.175	1.101	0.912	1.093	0.564	0.472	0.496	0.321
	p-value(1)	(0.002)	(0.006)	(0.010)	(0.004)	(0.056)	(0.090)	(0.054)	(0.138)
	p-value(2)	(0.464)	(0.392)	(0.634)	(0.710)	(0.048)	(0.012)	(0.082)	(0.110)

PANEL F: Conditional Fama French Model with auto-correlation and cross-correlation.

$$R_{i,t} = \alpha_{1,i} + \alpha_{2,i}.Z(t) + \beta_{1,i}R_{m,t} + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}R_{m,t}Z(t) + \beta_{5,i}SMB_tZ(t) + \beta_{6,i}HML_tZ(t) +$$
$$= \beta_{7,i}R_{i,t-1} + \beta_{8,i}R_{m,t-1} + \varepsilon_{i,t-1}$$

		Bootstrap with replacement				Bootstrap without Replacement			
		K=3	K=6	K=9	K=12	K=3	K=6	K=9	K=12
J=3	Mean	0.499	0.356	0.538	0.619	0.261	0.065	0.247	0.332
	p-value(1)	(0.120)	(0.126)	(0.026)	(0.006)	(0.254)	(0.390)	(0.130)	(0.040)
	p-value(2)	(0.556)	(0.221)	(0.232)	(0.284)	(0.326)	(0.034)	(0.016)	(0.012)
J=6	Mean	0.438	0.591	0.778	0.787	0.048	0.169	0.358	0.417
	p-value(1)	(0.186)	(0.070)	(0.014)	(0.002)	(0.476)	(0.326)	(0.116)	(0.044)
	p-value(2)	(0.231)	(0.134)	(0.214)	(0.314)	(0.034)	(0.006)	(0.008)	(0.014)
J=9	Mean	0.840	0.933	1.007	0.927	0.320	0.447	0.540	0.449
	p-value(1)	(0.040)	(0.008)	(0.002)	(0.004)	(0.214)	(0.106)	(0.038)	(0.058)
	p-value(2)	(0.214)	(0.194)	(0.294)	(0.471)	(0.008)	(0.006)	(0.008)	(0.042)
J=12	Mean	1.153	1.075	1.007	0.965	0.557	0.502	0.469	0.360
	p-value(1)	(0.002)	(0.004)	(0.004)	(0.010)	(0.068)	(0.074)	(0.072)	(0.112)
	p-value(2)	(0.452)	(0.372)	(0.564)	(0.752)	(0.064)	(0.022)	(0.091)	(0.126)

TABLE 5: KS stochastic dominance test

The second column of this table reports the p values for the null hypothesis that the winner portfolio stochastically dominates the loser portfolio (W>L) in the second order sense for all the momentum strategies considered for the period January 1973 to May 2004, while the third column reports the p values for the opposite hypothesis, that the loser portfolio stochastically dominates the winner portfolio(L>W) in the second order sense. Columns four and five give the same results as columns two and three for third order stochastic dominance.

	s=2		s=3	
JxK	**W>L**	**L>W**	**W>L**	**L>W**
3x3	0.556	0.001	0.480	0.004
3x6	0.556	0.000	0.542	0.002
3x9	0.569	0.000	0.538	0.002
3x12	0.581	0.000	0.557	0.001
6x3	0.569	0.000	0.484	0.000
6x6	0.559	0.000	0.487	0.000
6x9	0.557	0.000	0.497	0.000
6x12	0.588	0.000	0.567	0.000
9x3	0.550	0.000	0.474	0.000
9x6	0.568	0.000	0.493	0.000
9x9	0.585	0.000	0.510	0.000
9x12	0.597	0.000	0.514	0.000
12x3	0.550	0.000	0.484	0.000
12x6	0.557	0.000	0.560	0.000
12x9	0.572	0.000	0.556	0.000
12x12	0.589	0.000	0.562	0.000

TABLE 6: DD stochastic dominance test

The second column of this table reports the p values for the null hypothesis that the winner portfolio stochastically dominates the loser portfolio(W>L) in the second order sense for all the momentum strategies considered for the period January 1973 to May 2004, while the third column reports p values for the opposite hypothesis, that the losers stochastically dominate the winners(L>W) in the second order sense. Columns four and five give the same results as columns two and three for third order stochastic dominance.

	s=2		s=3	
JxK	**W>L**	**L>W**	**W>L**	**L>W**
3x3	0.683	0.007	0.678	0.061
3x6	0.680	0.004	0.373	0.039
3x9	0.679	0.006	0.672	0.041
3x12	0.680	0.005	0.674	0.033
6x3	0.676	0.000	0.669	0.009
6x6	0.679	0.000	0.675	0.012
6x9	0.677	0.000	0.674	0.011
6x12	0.678	0.001	0.673	0.015
9x3	0.670	0.000	0.672	0.003
9x6	0.674	0.000	0.671	0.001
9x9	0.677	0.000	0.668	0.004
9x12	0.677	0.000	0.668	0.007
12x3	0.672	0.000	0.662	0.001
12x6	0.671	0.000	0.660	0.003
12x9	0.670	0.000	0.660	0.008
12x12	0.669	0.001	0.662	0.014

TABLE 7: Chow's Test

This table reports the values of the $Z^{k-l}(\tau_i)$ statistic, where k denotes the winner portfolio, l the losers and i the decile of the distribution of the market portfolio used as the reference. High enough values of this statistic lead to the rejection of the null hypothesis that the winners do not dominate the losers, where the critical value is 2.81 for a 5% level.

	$Z^{k-l}(\tau_i)$									
JxK	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
3x3	1.01	2.39	3.09	3.58	3.83	4.36	4.34	3.39	3.49	3.40
3x6	1.45	2.25	3.10	3.82	4.20	4.84	5.31	4.67	4.66	4.69
3x9	1.59	2.60	3.17	3.93	4.10	4.80	5.62	5.20	5.09	5.15
3x12	2.06	3.10	3.58	4.27	4.83	5.53	6.37	5.97	5.95	5.80
6x3	1.91	2.46	3.20	3.76	4.03	4.67	5.28	4.69	4.47	4.49
6x6	1.62	2.10	2.64	3.39	3.53	4.19	5.05	4.75	4.66	4.75
6x9	1.74	2.56	2.97	3.68	4.02	4.70	5.64	5.35	5.30	5.22
6x12	1.64	2.53	2.87	3.58	4.09	4.80	5.78	5.46	5.50	5.09
9x3	1.66	2.60	3.35	4.18	4.39	4.95	5.64	5.19	4.96	5.03
9x6	1.94	2.93	3.52	4.36	4.82	5.45	6.27	5.96	5.88	5.82
9x9	1.70	2.77	3.20	3.97	4.47	5.13	5.99	5.69	5.72	5.47
9x12	1.65	2.54	2.90	3.60	4.15	4.79	5.73	5.42	5.45	4.93
12x3	2.04	3.28	3.62	4.34	4.70	5.29	5.97	5.49	5.38	5.28
12x6	1.74	2.87	3.18	3.88	4.26	4.86	5.57	5.31	5.43	5.19
12x9	1.45	2.41	2.64	3.32	3.62	4.20	5.03	4.77	4.90	4.51
12x12	1.35	2.14	2.23	2.81	3.21	3.79	4.62	4.41	4.41	3.87

TABLE 8: Chow's test. Winners and Losers

Panel A of this table reports the values of the $Z^k(\tau_i)$ statistic, where k denotes the winner portfolio and i the decile of the distribution of the market portfolio used as the reference. High enough values of this statistic lead to the rejection of the null hypothesis that the winners do not dominate the market, where the critical value is 2.81 for a 5% level. Panel B of this table presents the results for the $Z^l(\tau_i)$ statistic in an analogous fashion.

Panel A: Dominance of Winners over the market

	$Z^k(\tau_i)$									
JxK	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
3x3	-0.63	-0.33	0.65	0.76	1.06	0.95	0.98	0.42	1.11	1.15
3x6	-0.83	-0.94	0.27	0.55	0.88	0.88	1.25	0.96	1.75	1.79
3x9	-0.75	-0.68	0.31	0.60	0.76	0.75	1.29	1.09	1.90	1.92
3x12	-0.54	-0.46	0.39	0.63	1.03	0.98	1.53	1.35	2.27	2.12
6x3	-0.09	-0.10	1.01	1.39	1.90	1.88	2.21	1.88	2.63	2.57
6x6	-0.26	-0.41	0.59	1.10	1.37	1.47	2.12	1.85	2.62	2.53
6x9	-0.20	-0.13	0.59	1.06	1.37	1.47	2.20	1.91	2.78	2.58
6x12	-0.52	-0.27	0.35	0.82	1.25	1.34	2.07	1.79	2.71	2.32
9x3	0.19	0.80	1.87	2.37	2.79	2.91	3.36	3.01	3.72	3.60
9x6	0.27	0.70	1.49	2.14	2.67	2.86	3.46	3.19	3.99	3.68
9x9	-0.16	0.41	1.00	1.61	2.17	2.34	2.98	2.71	3.54	3.16
9x12	-0.38	0.09	0.62	1.20	1.76	1.90	2.55	2.32	3.11	2.61
12x3	0.34	1.03	1.55	2.06	2.46	2.62	3.10	2.71	3.48	3.15
12x6	-0.16	0.37	0.86	1.44	1.98	2.13	2.66	2.52	3.37	2.91
12x9	-0.49	-0.12	0.34	0.95	1.40	1.52	2.14	1.98	2.78	2.35
12x12	-0.69	-0.41	-0.06	0.42	0.85	0.98	1.59	1.49	2.16	1.65

Panel B: Dominance of Losers over the market

	$Z^l(\tau_i)$									
JxK	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
3x3	-1.76	-3.01	-2.90	-3.42	-3.41	-3.95	-3.93	-3.37	-2.91	-2.85
3x6	-2.19	-3.03	-2.96	-3.45	-3.46	-3.98	-4.15	-3.77	-3.11	-3.12
3x9	-2.32	-3.24	-3.00	-3.45	-3.38	-3.94	-4.21	-3.90	-3.15	-3.13
3x12	-2.48	-3.40	-3.21	-3.58	-3.64	-4.12	-4.36	-4.09	-3.34	-3.18
6x3	-2.31	-2.88	-2.94	-3.28	-3.09	-3.74	-4.17	-3.76	-2.99	-3.02
6x6	-2.17	-2.77	-2.70	-3.13	-2.96	-3.56	-4.00	-3.81	-3.12	-3.22
6x9	-2.26	-3.08	-3.00	-3.35	-3.36	-3.88	-4.30	-4.13	-3.40	-3.38
6x12	-2.13	-2.97	-2.91	-3.25	-3.32	-3.82	-4.19	-4.03	-3.35	-3.13
9x3	-2.21	-2.85	-2.85	-3.45	-3.21	-3.73	-4.16	-3.83	-3.03	-3.06
9x6	-2.46	-3.31	-3.31	-3.78	-3.77	-4.21	-4.64	-4.43	-3.71	-3.73
9x9	-2.29	-3.20	-3.20	-3.61	-3.62	-4.09	-4.45	-4.24	-3.62	-3.48
9x12	-2.21	-3.02	-2.98	-3.31	-3.36	-3.80	-4.19	-3.98	-3.41	-3.11
12x3	-2.58	-3.55	-3.50	-3.97	-3.97	-4.41	-4.82	-4.49	-3.74	-3.76
12x6	-2.39	-3.38	-3.40	-3.78	-3.70	-4.16	-4.52	-4.25	-3.71	-3.64
12x9	-2.13	-3.07	-3.01	-3.35	-3.25	-3.71	-4.09	-3.85	-3.39	-3.17
12x12	-2.00	-2.85	-2.73	-3.04	-3.07	-3.49	-3.87	-3.65	-3.17	-2.86