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Abstract

The driving force behind the well-documented medium term momentum effect in stock returns is subject of much debate. Empirical papers that aim to find the determinants of this return continuation, seem to be almost exclusively restricted to US stock markets. Consequently, regional effects have received little attention in these analyses. This paper contributes to the discussion by investigating the presence of country and industry momentum in Europe and addressing the question whether individual stock momentum is subsumed by country or industry momentum. We examine these issues by introducing a portfolio-based regression approach, which allows to test hypotheses about the existence and relative importance of multiple effects using standard statistical techniques. While the traditional sorting techniques are not suited to disentangle a multitude of possibly interrelated effects (e.g. momentum, value, and size), our method can be used even when only a moderate number of stocks are available. Our results suggest that the positive expected excess returns of momentum strategies in European stock markets are primarily driven by individual stocks effects, while industry momentum plays a less important role and country momentum is even weaker. These results are robust to the inclusion of value and size effects.

Keywords: Country risk, Industry risk, Momentum effect, Portfolio selection
JEL classification: G11, G14, G15

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1 Introduction

Stock return continuation on horizons between 6 and 12 months has been documented for the US, Europe, and emerging markets (see e.g. Jegadeesh & Titman (1993), Rouwenhorst (1998), and Rouwenhorst (1999b) respectively). Several authors have recently investigated the sources of this stylized fact, also known as the momentum effect. The ambiguity in the empirical findings has kept the debate about the sources of the momentum effect lively. For example, Moskowitz & Grinblatt (1999) claim that industry effects are almost solely responsible for the momentum effect in the US, while Grundy & Martin (2001) report that industry momentum and individual stock momentum are distinct phenomena. In addition, a six-month momentum effect on a country index level is found by Chan, Hameed & Tong (2000), while Richards (1997) suggests there is no medium term country momentum effect. It is still an open question to what extent these findings on country momentum are related to differences in industry composition of the country indices. These issues are crucial in understanding the factors driving stock momentum and have direct implications for the performance of investment strategies. While the latter two papers focus on the momentum effect in an international context, the emphasis in the literature on the determinants of the momentum effect seems to have been predominantly directed to US stocks.

The aim of this paper is to analyze medium term return continuation in Europe in further detail. In order to determine the source of the momentum effect in Europe, we develop a novel regression method which enables us to distinguish between individual stock, industry, and country effects. Our results provide evidence in the debate whether the individual stock momentum effect is subsumed by industry or country momentum effects. Our analysis of industry effects in Europe can be regarded as an out-of-sample test of hypotheses that have been formulated for US data. The simultaneous inclusion of country and industry effects sheds light on the influence of the industry composition of country indices that seems to have been neglected in the momentum literature so far.

In the analysis of US data, possible regional effects have received little attention. For Europe, regional effects such as country effects are clearly important; see e.g. Rouwenhorst (1999a). Their presence as well as the fact that for some country-industry combinations very few observations are available requires extensions of the existing methodology. Most analyses are based upon average returns within groups of stocks with similar characteristics. This sorting approach assumes that stocks with similar characteristics have identical conditional expected returns, while information regarding stocks with other characteristics is considered irrelevant. In this paper, we present a novel regression approach that uses characteristics of a large variety of portfolios in order to estimate the expected returns on stocks with similar characteristics.

The regression-based approach is more convenient when we want to discriminate between multiple effects that may be operating simultaneously. It is more general than the sorting approaches, since it enables us to incorporate information about the characteristics of other portfolios into the estimation of the expected return of a particular stock. If one decides not to use this additional information, the regression approach reduces to the more familiar sorting methods. A major advantage of our regression approach is the possibility to distinguish between a large variety of effects by imposing a parsimonious structure on the model. The use of sorting methods in this context is limited, since sorting on multiple characteristics may lead to subportfolios with few or even no stocks. Furthermore, the regression approach easily allows for the incorporation of other effects, in addition to the individual, country, and industry effects, which is important, since several papers claim that expected returns on momentum strategies are related to firm size and book-to-market ratios.[1] In addition, the regression framework allows hypotheses about the relative importance of different effects to be formulated and tested in a more natural way than the sorting approach which basically compares average returns of sorted portfolios.

Our empirical results indicate that over the period 1990–2000 the individual component of the momentum effect is stronger than the industry component. In economic terms, individual momentum accounts for almost 60 percent of the total effect, while industries and countries explain about 30 and 10 percent, respectively. Our analysis suggests that a momentum strategy which is diversified with respect to countries and industries yields an expected excess return of about 0.55 percent per month.

The conclusion that individual momentum effects dominate country and industry momentum effects is robust to the inclusion of value and size effects in the model. Country and industry effects are of similar importance, with expected additional returns of about 0.20 percent per month each. The incorporation of these additional effects necessitates the inclusion of interaction effects between momentum, value, and size, as there is clear statistical evidence that momentum effects are not invariant across size and book-to-market categories. In particular, the results indicate that momentum is most pronounced for small growth stocks. This is in accordance with the behavioral theories of Hong & Stein (1999) and Daniel, Hirshleifer & Subrahmanyam (1998), which explain the momentum effect.

This paper is organized as follows. In the next section, the portfolio-based regression approach is explained in detail. We show that by evaluating the composition of a large variety of diversified portfolios, sorted on the basis of relevant characteristics, one can determine which underlying factors are most important in explaining the momentum effect. Section 3 describes the data used throughout this paper and provides some of its stylized facts.

[1] Examples of papers relating momentum to other characteristics are Hong, Lim & Stein (2000), Chen (2000), and Nagel (2001).

In Section 4, we analyze the question whether industry and country momentum exist, and whether they subsume individual momentum. The analysis is expanded by including size and value effects in Section 5. Finally, our conclusions are presented in Section 6.

2 A portfolio-based regression approach

The existing literature on stock selection is usually based on analyzing average returns of portfolios grouped on the basis of one or more characteristics. For example, extensive research has been done on the market capitalization (size), book-to-price ratio (value), and recent past returns (momentum) of firms. These characteristics may be related, and the excess return on portfolios of stocks that are grouped on certain characteristics are potentially subsumed by other characteristics. Thus, for investors it is important to investigate the additional value of sorting on another characteristic. In this paper, we want to distinguish between country, industry, and individual momentum effects. In order to understand their interdependencies, it is important to consider a model that simultaneously allows for these effects. Unfortunately, increasing the number of sorts in a sorting context may dramatically reduce the number of stocks in each portfolio. As a result, idiosyncratic effects may dominate the returns of these portfolios, especially when the initial data set contains only a moderate number of stocks.

In our approach, we explain the returns of well-diversified portfolios using regression analysis. In such analysis, a multitude of effects can be distinguished by using the composition of portfolios, which are sorted on at most two characteristics. Thus, our method does not suffer from idiosyncrasies in returns on three-, four-, or even more-way sorts. For example, the regression approach uses the composition of a size portfolio to estimate the momentum effect. As shown below, this implies that the percentage of stocks in a size portfolio that also belongs to the momentum winner decile is used as a regressor in the analysis.

By using a portfolio-based regression technique it is possible to account for multiple effects and determine which of these effects is most important for the expected positive excess returns. For example, in this paper we investigate the relative importance of country, industry, and individual stock momentum on return continuation. While it is not always immediately clear how to develop meaningful test statistics when relying on sorting methods only, a variety of statistical tools can be used in a regression framework. Test statistics are readily available and well-understood in this context. Moreover, the use of a regression framework allows us to impose a natural (e.g. additive) structure on the model.

The use of portfolio-based regression techniques dates back at least to Roll (1992), who determines industry effects by a regression of country portfolios on the industry composition of these country portfolios. Other papers that use a regression approach are Heston & Rouwenhorst (1994) and Kuo & Satchell (2001). The former paper disentangles country and industry effects, while the latter incorporates value and size effects. These two papers differ fundamentally from Roll (1992) and our paper by the use of individual stock returns instead of well-diversified portfolio returns. Using individual stock returns to minimize a least squares distance could potentially be very sensitive to idiosyncratic behavior of stocks, or, maybe even worse, several data errors.

None of the above papers allows for the presence of interaction effects between the factors. The validity of this implicit restriction is not tested, which might lead to biased estimates and erroneous inferences if the restrictions are inappropriate. Moreover, the precise link with the frequently used sorting procedures is left unspecified in the three papers mentioned above. The methodology presented in this paper fills these gaps.

As mentioned before, most empirical research is based on tests of differences in expected returns of portfolios that are based on sorting stocks on certain characteristics. For example, the seminal paper on the profitability of momentum strategies by Jegadeesh & Titman (1993) first ranks stocks on past six month return and subsequently divides the sample of stocks in ten portfolios with the same number of stocks. The returns of these portfolios are calculated over the subsequent six months. It turns out that the top decile ("winners") performs significantly better than the bottom decile ("losers").

When the influence of two characteristics is investigated, we could use a double sort or a two-way sort. A double sort means that the stocks are first ranked on one characteristic and independently sorted on another. The first portfolio then consists of stocks that are in the bottom in both the first and second sort. This way of sorting is for example used in Lee & Swaminathan (2001), where the characteristics are past returns and volume. Apart from this double sorting method, one can also use a conditional sort. Such a two-way sort means that the stocks are first ranked on a certain characteristic, after which a second sort is performed within the portfolios constructed after the first ranking. For example, Rouwenhorst (1998) first sorts the sample of stocks on size, and within these size deciles he forms momentum deciles. A notable difference between double sorting and two-way sorting is the importance of the order of sorting. For a double sort this is irrelevant, while two-way sorting can be highly sensitive to the order in which the sorts take place, especially when the characteristics are related.[2] We use the double sorting method to create cross-effects later on in the paper, while two-way sorting is used in order to create country-neutral value and size portfolios.

A disadvantage of this sorting approach is the limited applicability when more than two characteristics are subject of investigation, especially when the total number of stocks is moderate. When the number of sorts increases, the number of stocks per portfolio will reduce rapidly. Hence, idiosyncratic firm effects will have much more influence on the average returns

[2]The terminology double sort and two-way sort is used for both unconditional and conditional sorts in different papers. To avoid confusion we reserve double for unconditional and two-way for conditional sorting.

of such portfolios. To alleviate this problem researchers are often forced to work at a higher level of aggregation by using quintiles or tertiles (i.e. divide the sample in five or three parts) rather then deciles. This is illustrated by e.g. Davis, Fama & French (2000), who note that "the advantage of fewer third-pass sorts [...] is that the resulting 27 portfolios always contain some stocks [...] In 1930 and 1931, few portfolios have only one stock." This remark makes clear that to prevent empty subportfolios the number of sorts has to be reduced when only three characteristics are considered. The consequence of this type of solution is that effects which are most pronounced in the extreme deciles are much harder to detect empirically.

The portfolio-based regression technique advocated in this paper is particularly suitable for the simultaneous modeling of a multitude of possibly interrelated effects. While the model can in principle incorporate a large amount of factors, it is presented below with three factors for expositional purposes. The three factors are labeled A, B, and C, and can be thought of as representing country (A), industry (B), and individual (C) momentum effects.

In similar spirit to the characteristics-based asset pricing model by Daniel & Titman (1997), we assume that the conditional expected return on a single stock can be modeled as a function of several effects. That is,

$$\mathrm{E}_t\{R_{i,t+1}\} = \sum_{a=1}^{N_A} \sum_{b=1}^{N_B} \sum_{c=1}^{N_C} \alpha_{a,b,c} X_{i,t}\left(a, b, c\right), \tag{1}$$

where $X_{i,t}\left(a, b, c\right)$ is a dummy variable to indicate whether the stock is in a particular portfolio, and $R_{i,t}$ is the return of stock i in period t. The function $\mathrm{E}_t\{.\}$ denotes the expectation conditional on information up to (and including) period t. This information only consists of the set of dummy variables $X_{i,t}$, or in words, the portfolio a stock belongs to in period t. The parameter $\alpha_{a,b,c}$ is the expected return on a stock with characteristics a, b, and c. For example, if a stock belongs to the worst performing countries, industries, and individual stocks, its expected return would be $\alpha_{1,1,1}$. Basically, the sample of stocks is divided into cells, each of which represents a group of stocks with similar characteristics. The model simply describes the expected return of a stock given that it is known to belong to a particular group.

In our analyses, we prefer modeling the expected return of well-diversified portfolios instead of individual stocks. The advantage of the absence of idiosyncratic effects in well-diversified portfolios compensates for the potential loss of information by modeling at a more aggregated level. Additional arguments to use portfolios instead of individual stock data are the absence of missing observations when portfolios are used, and the reduced influence of poor quality data. Value-weighting the stocks in the portfolios of the regression weakens the impact of these data errors even further, since the reliability of stock data seems to be inversely related to firm size. The expected return on a portfolio p of N stocks with weights

$w_{i,t}^p$, conditional on information up to and including period t, can be written as

$$\begin{aligned} \mathrm{E}_t\left\{R_{t+1}^p\right\} &= \mathrm{E}_t\left\{\sum_{i=1}^{N} w_{i,t}^p R_{i,t}\right\} \qquad (2) \\ &= \sum_{i=1}^{N} w_{i,t}^p \mathrm{E}_t\left\{R_{i,t}\right\} \\ &= \sum_{a=1}^{N_A}\sum_{b=1}^{N_B}\sum_{c=1}^{N_C} \alpha_{a,b,c} X_t^p\left(a,b,c\right), \end{aligned}$$

where $X_t^p(a,b,c) \equiv \sum_{i=1}^{N} w_{i,t}^p X_{i,t}\left(a,b,c\right)$ denotes the holdings of portfolio p in categories (portfolios) a, b, and c. This model expresses the expected return on a portfolio as a weighted average of the expected returns of its stocks.

In order to estimate equation (2), we can formulate it as a regression equation

$$R_{t+1}^p = \sum_{a=1}^{N_A}\sum_{b=1}^{N_B}\sum_{c=1}^{N_C} \alpha_{a,b,c} X_t^p\left(a,b,c\right) + \varepsilon_{t+1}^p, \qquad (3)$$

where $\varepsilon_{t+1}^p \equiv R_{t+1}^p - \mathrm{E}_t\left\{R_{t+1}^p\right\}$, which is uncorrelated with the regressors by construction. It is assumed that the cross-autocorrelation structure is zero, i.e. $\mathrm{E}\left\{\varepsilon_{t+h}^p \varepsilon_t^q\right\} = 0$, for each p, q, t, and $h > 0$. No further assumptions are made on the absence of heteroskedasticity or contemporaneous correlation.

As long as the number of portfolios used as dependent variables P is at least as large as the number of effects $N_A \cdot N_B \cdot N_C$, the unknown parameters can be estimated consistently using the Fama-MacBeth estimator. In other words, consistent estimates can be obtained by first performing cross-sectional regressions using OLS, followed by averaging these cross-sectional estimates over time. The sample covariance matrix of these cross-sectional estimates serves as an estimator for the true covariance matrix of the estimator. Unless stated otherwise, the Fama-MacBeth estimator is used in this paper. Note that this estimator does not require assumptions on heteroskedasticity or contemporaneous correlation, and thus can be used to estimate the model described above. This regression-based approach is numerically equivalent to computing average returns and sample standard deviations of sorted portfolios when these are sorted upon exactly the same characteristics as the regressors X_t^p. Thus, our method reduces to the traditional sorting approach in this special case. In Appendix A it is shown that this still holds when additional portfolios that are non-informative about the effect which is subject of investigation are used for evaluation.

Since the number of parameters in (3) may become large, a more parsimonious way to describe the expected returns on the portfolios is desirable. This is particularly fruitful when the number of sorts or the number of groups within a sort is increased. By imposing structure on the model the number of parameters can be reduced, and hence the efficiency of the estimators can be increased. For example, in line with Roll (1992) and Heston & Rouwenhorst (1994) an additive structure can be imposed. In order to see how the regression equation in (3) is affected by this assumption, rewrite equation (2) as

$$\begin{aligned}\mathrm{E}_t\{R^p_{t+1}\} \;=\;& \alpha_{1,1,1} + \sum_{a=2}^{N_A}\beta^A_a X^p_t(a,\cdot,\cdot) + \sum_{b=2}^{N_B}\beta^B_b X^p_t(\cdot,b,\cdot) + \sum_{c=2}^{N_C}\beta^C_c X^p_t(\cdot,\cdot,c) + \\ &+ \sum_{a=2}^{N_A}\sum_{b=2}^{N_B}\gamma^{AB}_{a,b} X^p_t(a,b,\cdot) + \sum_{a=2}^{N_A}\sum_{c=2}^{N_C}\gamma^{AC}_{a,c} X^p_t(a,\cdot,c) + \sum_{b=2}^{N_B}\sum_{c=2}^{N_C}\gamma^{BC}_{b,c} X^p_t(\cdot,b,c) + \\ &+ \sum_{a=2}^{N_A}\sum_{b=2}^{N_B}\sum_{c=2}^{N_C}\delta_{a,b,c} X^p_t(a,b,c).\end{aligned} \tag{4}$$

The dots in the holding arguments, for example in $X^p_t(a,\cdot,\cdot)$, denote that only the first argument is considered. This means that it refers to the number of stocks that are in group a, irrespective of their position in the other two sorts. The parameter $\alpha_{1,1,1}$ denotes the return on the reference portfolio, which we arbitrarily chose to be the one corresponding to $a = 1$, $b = 1$, and $c = 1$.[3] The other parameters on the first line (denoted β) account for the effects of being in another portfolio than the reference portfolio. The parameters in the second line represent the first-order cross-effects, and those in the third line refer to second-order cross-effects. These first-order cross-effects quantify the additional expected return above the sum of the effects in the first line due to an interaction between two of the effects. For example, a stock in the winner country and in the winner individual portfolio might have a higher expected return than just the winner country momentum effect plus the winner individual effect. A similar reasoning applies for second-order effects which account for interaction between all three effects. Appendix B shows how the parameters of equation (4) can be expressed in terms of those of equation (2).

When we decide to impose an additive structure on the model in equation (4), this implies that all parameters γ and δ are assumed to be zero. Thus, first and higher-order interaction effects are neglected, which implies that the expected returns of cells are related by a simple structure. This way, information from cells that are close to each other may be exploited to obtain more efficient estimates. Imposing the additive structure leads to a substantial reduction of the number of parameters and hence gives more efficient estimates if the restrictions are valid. However, this gain in efficiency may be offset by the introduction of a bias when the imposed restrictions are not in accordance with the data. Therefore, it is relevant to perform a test on the validity of the restrictions. A Wald-test can be conducted

[3] Alternatively, it is possible to replace the reference portfolio by symmetric restrictions to avoid the dummy trap. Doing so changes the interpretation of the coefficients, but it does not change the statistical properties of the model. The advantage of our setup is that one can immediately observe the significance of the difference between the expected returns of winner and loser stocks.

in order to evaluate the hypothesis that all interaction effects, or a subset of them, are jointly zero.

Once the model structure is parsimoniously chosen, the relevant question about the relative importance of the three effects can be investigated. Suppose that the three effects separated are country (A), industry (B), and individual (C) momentum effects. Assuming that the additive structure is appropriate, the reduced form of the expected return of a portfolio can be rewritten as

$$\mathrm{E}_t\{R^p_{t+1}\} = \alpha + \sum_{a=2}^{N_A} \beta^A_a X^p_t(a,\cdot,\cdot) + \sum_{b=2}^{N_B} \beta^B_b X^p_t(\cdot,b,\cdot) + \sum_{c=2}^{N_C} \beta^C_c X^p_t(\cdot,\cdot,c), \tag{5}$$

where α is the expected return on the reference portfolio. The parameters β^A, β^B, and β^C can then be interpreted as the additional expected return for being in another momentum portfolio than the reference portfolio. For analyzing the sources of the momentum effect, we can now formulate and test hypotheses on the values of these parameters. For example, a test on the significance of the parameters $\beta^C_{N_C}$ gives information about the importance of being in the winner individual decile relative to being in the loser decile, conditional on the industry and country momentum portfolios the stock is in.

The momentum effect is typically investigated by looking at the return difference between the extreme deciles, but one would expect a gradual increase in expected returns of deciles closer to the winner. In order to support this idea, a parametric structure on the expected returns of the deciles can be imposed. For example, using a low-order polynomial reduces the number of parameters, and hence further increases the parsimony of the model. Therefore, the restriction that we add to (5) is

$$\beta^C_c = \lambda_0 + \lambda_1 \cdot c + \ldots + \lambda_L \cdot c^L,$$

where L is the order of the polynomial.[4] As a result, equation (5) changes to

$$\mathrm{E}_t\{R^p_{t+1}\} = \alpha + \sum_{a=2}^{N_A} \beta^A_a X^p_t(a,\cdot,\cdot) + \sum_{b=2}^{N_B} \beta^B_b X^p_t(\cdot,b,\cdot) + \sum_{\ell=0}^{L} \lambda_\ell Z^p_t(\ell),$$

where $Z^p_t(\ell) \equiv 1 + \sum_{c=2}^{N_C} \left(c^\ell - 1\right) X^p_t(\cdot,\cdot,c)$. When this additional restriction is imposed, the existence of a momentum effect can be tested by using the return information of all deciles instead of just the winner and loser portfolio. In Section 4, the above models are used in an empirical application to gauge the importance of country, industry, and individual stock momentum on return continuation for European stocks. By disentangling these three effects, we aim to find the driving force(s) behind the momentum effect. In Section 5, we also incorporate value and size effects in our analysis. This way, we allow for the possibility that certain momentum effects are explained by their value or size characteristics.

[4] In this case, it is natural to also impose that $\alpha = \beta^C_1 = \lambda_0 + \ldots + \lambda_L$.

3 Data

Our focus is on large European stocks. The main reason for this choice is that reliable European data for smaller stocks are hardly available. For instance, stock splits are sometimes not accounted for appropriately. In the analysis below, we use data on stocks traded at the developed equity markets that are tracked by Morgan Stanley Capital International (MSCI) from the developed equity markets.[5] Our sample period comprises 131 months, from January 1990 to November 2000. All returns and market values have been converted into Deutschemarks (DEM). We require stocks to have information available on their six month return, market value, and book-to-market ratio to be in our data set.

The underlying sample consists of 1581 stocks in total. These stocks have their major listing on the stock exchange of either Italy, Denmark, Ireland, France, Sweden, Finland, UK, Spain, The Netherlands, Norway, Germany, Portugal, Belgium, and Austria.[6] The number of firms per country varies from 33 for Ireland to 349 for the UK. In total 6 of the 15 countries contain less than 50 stocks, while 4 countries have more than 150. The differences in the number of firms per country has implications for the potential diversification benefits that can be obtained within a country. A list of countries with descriptive statistics can be found in Table 1. Finland is the only country with a value-weighted average monthly return exceeding 2 percent, while Austria and Norway are the only countries with an average below 1 percent (0.23 and 0.80 percent, respectively). Finland is most volatile with a monthly standard deviation of 9.1 percent, and The Netherlands is the least volatile with 4.5 percent. Equally weighting gives similar results.

Classifying firms in industries is less clear cut than the country division. First, it is not clear which and how many industries should be distinguished. Second, many firms are operating in several businesses, which makes it difficult to determine to which industry they primarily belong. For US studies, the SIC is the dominating classification, with appropriate regrouping as proposed in e.g. Moskowitz & Grinblatt (1999). This regrouping does not work well for European stocks, since several industries would contain few or no stocks at all. Therefore, we use the classification in MSCI industries, which aggregates the stocks in 23 industries.[7] The number of firms per industry varies between 9 and 260. In total, 10 out

[5] The returns are obtained from the *Prices* database through Factset. The data on market values and book-to-price ratios are obtained from the *Worldscope* database.

[6] The selection procedure resulted in one stock listed in Luxembourg. This stock has been deleted from the set for convenience.

[7] The MSCI industry classification is new as of 2000, such that several delisted firms had to be manually reclassified from the older classification. This has been done with the help of ABP Investments and MSCI. The actual classification used is available upon request. Firms that switch across industries over time will be classified by their final industry membership, which is the only data available to us. However, we expect this to have only minor influence on the results, as reported for US data by Moskowitz & Grinblatt (1999).

of 23 industries contain less than 50 stocks, while 4 have more than 100. An overview of the industries with descriptive statistics is presented in Table 2. The lowest value-weighted average return is for the industry Automobiles (0.59 percent), while the highest average returns are for Software and Services (2.55 percent). The latter has the highest standard deviation (9.5 percent). The least risky in absolute terms is the industry Utilities with a monthly standard deviation of 4.1 percent. Equally-weighted industry returns are close to their value-weighted counterparts.

We consider the 6-month momentum trading strategy proposed in Jegadeesh & Titman (1993), where a six month evaluation period is used combined with a six month holding period. In each month, the stocks are ranked in descending order on their (total) return over the last six months. In the next step, ten portfolios with the same number of stocks are formed. Ranking takes place each month, independently of the holding period. In each month, the ten decile portfolios consist of a portfolio selected in the current month, as well as the five portfolios formed in the previous five months. The top and bottom deciles are called winner and loser portfolio, respectively. A W–L strategy takes a long position in the winner portfolio and a short position of equal size in the loser portfolio. The excess return on this zero investment strategy is defined as the return on the winner minus the return on the loser portfolio.

The stocks from our database are sorted according to their prior six month return, book-to-price ratio, and market value to obtain the momentum, value, and size portfolios. In addition, we created three country and three industry momentum portfolios. The winner industry portfolio consists of all stocks listed in the top four industries. The loser industry and middle industry portfolio consist of four and fifteen stocks, respectively. We construct the country momentum portfolios similarly. So, the winner and loser country portfolio consist of four countries, while the middle country portfolio contains seven.

Throughout, when a stock is delisted, the residual claim is assumed to be invested in cash with zero return for the remainder of the holding period.[8] No data are available to determine the reason for delisting, so the actual final payment cannot be taken into account when reproducing the strategy's returns. However, we expect that this does not lead to a positive bias in our results. When a firm is delisted because of bankruptcy, this typically results in a large negative final return that is not accounted for in the database. However, these firms tend to be among firms with low past performance, and consequently have higher probability of being among the losers. The omission of the final returns in the database overestimates

[8]This deviates from the methodology in Rouwenhorst (1998). If a firm goes bankrupt the treatment is identical, but not in case of a merger/takeover. Rouwenhorst invest the proceeds in the merged firm or the target. Unfortunately, we do not have data on the reason of delisting, neither on the identity of the merged firm or target.

the actual return on the loser portfolio, hence decreases the return on strategies with short positions in the loser firms. This suggests that our results are conservative. Furthermore, delisting through bankruptcy does not occur frequently for large firms. Takeovers and mergers are usually more important reasons for delisting; see Wang (2000) for a more extensive treatment on the topic of delisting.

In Table 1 and Table 2 we observe no clear value or size effect within individual countries or industries in our sample.[9] For example, during 1990-2000, the UK is the only country with a significant size effect, which has an expected excess return of 1.22 percent per month. In Germany and Belgium, the opposite effect is found, i.e. stocks with a large market capitalization have outperformed small cap stocks. The value effect appears to be present in Spain, Switzerland, and Austria. For the industries Hotels, Restaurants, and Leisure, and Media, we find a significant size effect, while the value effect (1.55 percent) is present in Energy. For most countries and industries the excess return on the momentum portfolio is positive and economically relevant, albeit statistically significant only in a few cases. A country-neutral momentum strategy, which means that the winner and loser portfolios are averaged over each of the countries, yields a significant 0.63 percent (t-value 2.20). In similar fashion we calculate an industry-neutral momentum return, which is even higher with 0.81 percent (t-value 2.66).

4 Do countries or industries explain momentum?

In this section, the portfolio-based regression technique described in Section 2 is used to determine the relative importance of country, industry, and individual momentum effects on the total momentum effect in Europe. Both from a theoretical point of view as well as for the implementation of investment strategies, the question whether the individual momentum effect is subsumed by country or industry momentum is highly relevant.

A wide variety of explanations for the existence of the momentum effect has been documented. For example, Conrad & Kaul (1998) suggest that momentum is mainly due to the cross-sectional dispersion in expected returns. Their results suggest that momentum strategies buy stocks with a high expected return and short stocks with a low expected return and hence yield a positive expected excess return. Several other papers claim that their assumptions are questionable, in particular the constancy of expected returns over time. An attempt to accommodate time-variation in expected returns is presented in Chordia & Shivakumar (2002). Other papers claim that idiosyncratic firm effects (Jegadeesh & Titman (1993)) or industry effects (Moskowitz & Grinblatt (1999)) are responsible for return continuation.

[9] In Heston, Rouwenhorst & Wessels (1999), it is shown that the size effect for European stocks is non-linear in the sense that it is restricted to the smallest three deciles of their sample, which covers many more firms than our sample. The fact that we do not find a size effect is consistent with their results.

On the other hand, several behavioral models have been developed to explain the momentum phenomenon. These models differ in their assumptions about investor behavior, but seem to explain at least part of the stylized facts concerning momentum. For example, Daniel et al. (1998) argue that investors are overconfident and tend to misprice hard-to-value stocks more severely than other stocks. Typically, stocks that are considered most difficult to value are thought to be growth (or glamour) stocks and small illiquid stocks. Barberis, Shleifer & Vishny (1998) argue that investors are conservative when a firm has surprising news. This leads to an initial underreaction of prices to news, which might explain the medium term return continuation. When a sequence of good (bad) news about a firm is released in the market investors falsely extrapolate this sequence into the future, which leads to overvalued (undervalued) firms. In the long-run, when firms fail to meet the high (low) expectations, reversals take place.

Hong & Stein (1999) show that rational behavior by investors with heterogeneous characteristics may lead to medium term momentum and long term mean reversion. The "news watchers" trade on private information, while the "trend chasers" only use past returns to make their investment decisions. Their model predicts that momentum is more pronounced among firms for which new information diffuses only gradually into the market. Typically, these are the smaller firms with only few analysts. These theoretical predictions are empirically confirmed by Hong et al. (2000), who indicate that the momentum effect is more pronounced for firms with low information diffusion.

The model of Barberis & Shleifer (2000) accounts for the presence of style momentum. They argue that investors are herding away from stocks with "old-fashioned" characteristics, and they buy stocks from the "hot" style for a period of time. After a while, the hype is over and a new style gets popular, and the cycle repeats itself. The existence of this style momentum may be the source of the stylized facts about momentum gathered thus far. In Chen (2000) the relation between momentum and style momentum is investigated. He claims that characteristics momentum is distinct from price momentum. Our paper provides new stylized facts for the European stock markets, which may serve as a basis to test or develop new theories.

We use a set of 196 portfolios to disentangle the momentum effect into a country, industry, and an individual stock momentum effect. The portfolios used to evaluate the momentum effect are sorted on these three momentum factors complemented with size and value. The number 196 is obtained as the sum of 22 single-sorted and 174 double-sorted portfolios.[10] To

[10] More precisely, for individual stock momentum deciles are used, while tertiles are used for size, value, country momentum, and industry momentum. This results in $10 + 4 \cdot 3 = 22$ portfolios. Double-sorting on individual momentum and each of the other four factors produces $10 \cdot 12 = 120$ portfolios. Double-sorting on each combination of the other four factors accounts for the remaining $\binom{4}{2} \cdot (3 \cdot 3) = 54$ portfolios in the

reduce the influence of small stocks on the outcome of the analysis all portfolios are value-weighted. The size and value portfolios are country-neutral, which means that the same fraction of the stocks from each country is represented in these portfolios. For example, the "winner" value portfolio consists of the top 33% of value stocks from Austria, the top 33% of value stocks from Belgium, etcetera. The regressors in equation (3) are the holdings of these evaluation portfolios in the effects of interest. These holdings are, like the returns, value-weighted within each portfolio.

In order to determine the momentum effect in our sample, we evaluate the 196 portfolios from our test set. In this case only the holdings of these portfolios in the momentum decile portfolios are used to explain the corresponding portfolio returns. More precisely, we estimate the regression equation

$$R^p_{t+1} = \alpha + \sum_{a=2}^{10} \beta^{MOM}_a X^p_t(a) + \varepsilon^p_{t+1}, \tag{6}$$

where $X^p_t(a)$ denotes the holdings of portfolio p in momentum decile a for period t, by using the Fama-MacBeth estimator. Instead of the usual cross-sectional ordinary least squares (OLS) estimator we use a weighted least squares (WLS) estimator. The weights are the (square root of the) number of stocks in a portfolio. By using this weighting scheme portfolios with a small number of stocks are considered less important than portfolios with a large number of stocks. In this setup, the loser portfolio is chosen to be the reference portfolio.

The estimates for equation (6) using our European sample of stocks from 1990-2000 are reported in Table 3. The existence of a momentum effect in Europe for the last decennium can be investigated by performing a t-test on β^{MOM}_{10}, which denotes the expected return on the winner portfolio relative to the loser portfolio. The use of the portfolio-based regression technique leads to the conclusion that a momentum effect is present in Europe during the last 10 years, albeit statistically insignificant at the 95% level (p-value 0.11).[11] Both the confidence level and the level of the excess return is somewhat below the values reported in Jegadeesh & Titman (1993) and Rouwenhorst (1998). This can be partly explained by the length and coverage of our data set. Since our sample comprises only 10 years, t-values are lower even when means and standard deviations are identical to those for the US.[12] Our data set covers only the larger funds, and there is empirical evidence indicating that momentum profits are weaker for larger stocks; see e.g. Rouwenhorst (1998), and Hong et al. (2000).

analysis. Some intersections contain no stocks and result in missing observations for a small number of of periods.

[11] This result is qualitatively the same as the one obtained from the traditional sorting analysis.

[12] We could also use a measure which is not depending on the length of the sample period, e.g. the information ratio (IR). This measure is defined as the expected return divided by the standard deviation. The IR from our value- weighted momentum strategy equals 0.15. In Rouwenhorst (1998) the IR is 0.15 for the largest equally weighted size decile, in Hong et al. (2000) each of the top three size deciles has an IR below 0.14.

The latter study claims that there is no excess return of winners over losers in the US when the largest market cap quintile is considered.[13] Summarizing, our results on the momentum effect in Europe are in line with the existing literature.

In Section 2, we also described how to impose a polynomial structure on the deciles. If there is a genuine momentum effect, we expect expected returns to vary more or less monotonic over the deciles. One way to incorporate this a priory information is to impose a linear or quadratic structure on the decile coefficients. The regression equation for a polynomial of order L becomes

$$R_{t+1}^{p} = \alpha + \sum_{\ell=0}^{L} \lambda_{\ell} Z_{t}^{p}(\ell) + \varepsilon_{t+1}^{p},$$

where $Z_t^p(\ell) \equiv 1 + \sum_{a=2}^{10} \left(a^{\ell} - 1\right) X_t^p(a)$. The estimation results for this model can be found in Table 4. The statistical tests indicate that imposing a polynomial structure for this problem does not help to make more accurate statements about the presence and magnitude of the momentum effect. The results for polynomials of order three and four are virtually the same as those reported in Table 3.

The main motivation for this paper is to see whether the total momentum effect in Europe is subsumed by momentum effects on a higher level of aggregation, i.e. country and industry momentum. Empirical evidence on this topic can be both valuable for academics and practitioners. The former can use these findings to evaluate theoretical models, while the latter can use it to determine the impact of the investment process on the expected return of momentum strategies.

The number of parameters in equation (3) equals $N = N_A \cdot N_B \cdot N_C$. Our analysis concerning the determinants of the momentum effect consists of three country momentum, three industry momentum, and ten individual momentum effects. Thus, $N_A = N_B = 3$, and $N_C = 10$, which gives 90 parameters in the model. When an additive structure of these effects is imposed, in similar spirit to Roll (1992) and Heston & Rouwenhorst (1994), the parsimony of the model is highly increased, and the number of parameters is reduced to only 14.[14] The intuition behind imposing an additive structure is that the effects are the same for all portfolios (or stocks) conditional upon all other characteristics incorporated into the model. In other words, the individual momentum effect is not different for stocks that are listed in a loser country compared to stocks that are listed in a winner country. This does

[13] The largest quintile is based on NYSE/AMEX breakpoints and consists of about 400 to 500 stocks at each date. The claim of a non-existing momentum effect for these stocks is based on the use of tertile portfolios sorted on past six month returns instead of decile portfolios, which is more common in this line of research.

[14] Due to the additive structure, perfect multicollinearity would result by including $10 + 3 + 3 = 16$ effects. See the first line of equation (4) to obtain the $1 + 2 + 2 + 9 = 14$ free parameters in the model. The first-order interaction effects account for $4 + 18 + 18 = 40$ parameters, and the second-order effects for the remaining 36.

not mean that the country of listing does not influence the expected return of the stocks. In an additive model it just does so independently from the individual and industry effect. Of course, this simplified additive model specification is tested before continuing the analysis. Without proper tests to identify the validity of these restrictions biased parameters estimates might be obtained and hence inferences could be erroneous. Testing the additivity constraints is lacking in most previous papers. The results from the Wald-test indicate that imposing additivity is allowed. The test statistic of 37.3 is well below the 90%-critical value of 47.2.[15]

The regression equation for the additive model we use to distinguish country, industry, and stock momentum is

$$R_{t+1}^{p} = \alpha + \sum_{a=2}^{3} \beta_a^{COU} X_t^p(a,\cdot,\cdot) + \sum_{b=2}^{3} \beta_b^{IND} X_t^p(\cdot,b,\cdot) + \sum_{c=2}^{10} \beta_c^{STOCK} X_t^p(\cdot,\cdot,c) + \varepsilon_{t+1}^p. \quad (7)$$

The estimation results of this model are reported in Table 5. From this table we can see the influences on the expected returns of a stock being in specific momentum portfolios. The expected future return of a stock can be determined given the information about the current groups this stock belongs to. In the case of an additive model, this involves summing the expected returns of each of the components. For example, from Table 5 we infer that the expected return of a stock that is in the group of best four countries, in the middle industries, and in the winning individual decile has an expected return of 1.86 percent per month. This number consists of the return on the reference portfolio (1.13) plus the country winners (0.12) plus the industry middle (0.06) plus the individual winner (0.55). The expected returns for all other combinations can be obtained in similar fashion. See Figure 1 for a graphical representation of these results. There is a clear gradual increase in the expected return by moving from the front to the back of the figure. This suggests that momentum investors who are interested in a high expected return should try to find stocks that are listed in European countries that performed well over the past six months, in industries that performed well over the last six months, and in the top decile that ranks European stocks on the basis of their individual past six month return.

The country momentum effect has contributed least to the momentum effect in Europe over the past decennium, with an additional expected return of 0.12 percent per month.[16] The industry momentum effect is weakly present with an additional expected return of 0.31 percent. The largest effect is the individual momentum effect which contributes roughly 0.55

[15] We test the hypothesis that all cross-terms are jointly zero by performing a Wald-test. The p-value associated with the reported test is 0.407. Calculating the Fama-MacBeth estimator with OLS instead of WLS results in a p-value of 0.135, still not rejecting the null hypothesis of the absence of cross-effects.

[16] Although we consider a different group of countries than Richards (1997) and Chan et al. (2000), our results seem more in line with the former, who indicate there is only weak evidence of medium term return continuation, while the latter report a significant country momentum effect.

percent over the reference portfolio. Our estimation results suggest that the momentum effect based on individual stocks is not subsumed by industry momentum, country momentum, or both. This finding is consistent with Rouwenhorst (1998), who shows that the excess returns of country-neutral momentum strategies in Europe are only slightly lower than those of unrestricted momentum strategies. It is also in accordance with the results for the US stock market reported in e.g. Grundy & Martin (2001), who state that individual momentum and industry momentum are separate phenomena. The conclusion that industry momentum drives the individual momentum effect in the US, which is reported in Moskowitz & Grinblatt (1999), is not supported by our empirical analysis for Europe. Our results indicate that investment professionals who are not allowed to take large country and industry bets might still be able to exploit the momentum effect by stock selection. Our analysis suggests that this reduces the potential expected return by almost a half.

So far, transactions costs have not been incorporated in the analysis. The estimated expected excess return of a momentum strategy for stocks in the winner countries, winner industries, and individual winners is roughly 12 percent per year without transactions costs. Given the fact that we consider a maximum turnover of each stock only twice a year, the break even transactions costs would be about 6 percent for a round-trip. This seems much higher than the upper bound of 2 percent that is used in many empirical studies.[17] Since we are using the larger European stocks for our analyses, we do not expect the influence of transactions costs to exceed the 2 percent level.[18] When trading country or industry portfolios as a whole to capture part of the momentum effect instead of individual stocks we expect transaction costs to decrease rather than increase. It is usually assumed that trading entire country portfolios as a whole is relatively cheap compared to industry portfolios, which are in turn cheaper to trade than individual stocks. If this is the case, the level of expected returns for the three effects documented in this paper could be partially related to the level of transactions costs.

Despite the empirical evidence in Rouwenhorst (1999a) that for a large part of the 90s country effects dominate industry effects to explain expected returns in Europe, it turns out that industry effects are more important to explain medium term return continuation. In order to investigate the possible variation of the influence of these factors over time, the

[17] An exception is Lesmond, Schill & Zhou (2001), who claim that momentum stocks are particularly expensive to trade. They argue that the excess returns on momentum strategies may be fully explained by these trading frictions.

[18] Research of Salomon Smith Barney (December 1999) suggests that when trading the world portfolio of size USD 250 million, round-trip costs would be 96 basis points for extended market indices. This includes a measure for bid-ask costs and volatility costs. Denmark and Ireland are particularly expensive to trade with 190 and 246 basis points for a round-trip, while The Netherlands and Spain are the cheapest with 52 and 50 basis points, respectively.

sample is split in two parts of equal size, 1990–1996 and 1996–2001. The point estimates for the two subperiod are displayed in Table 6. The short sample size does not allow us to make accurate statements. Taking the estimates as they are, we observe that both industry and country effects seem to contribute more in the first half of our sample. Surprisingly, the country momentum effect becomes slightly negative in the post 1996 period, suggesting medium term mean reversion rather than momentum at the country level. The industry momentum effect is still positive in the second part of the sample. The individual momentum effect is positive in both subperiods and somewhat more pronounced in the second half of the 90s. Unfortunately, our sample period is too short for an thorough analysis of the momentum effect at different stages in the macro economy as has been done for the US; see Chordia & Shivakumar (2002) and Cooper, Gutierrez & Hameed (2001) amongst others.

The analyses presented in this section are not only of academic interest. Investment professionals may directly benefit from the decomposition of the momentum effect documented in this paper. For example, consider an investor with a top-down investment process who first determines the industry and country composition of his portfolio, and subsequently selects stocks within these industries and countries. If the individual momentum effect is subsumed by industry or country effects, information about prior six month returns should be evaluated at the country and industry decision level, while at the stock selection stage further use of past six-month returns would not increase expected returns. Our results indicate that while simultaneously taking into account country and industry momentum effects, there are still return continuations at the individual stock level which might be exploited.

5 The impact of value and size effects

In the previous section, the portfolio-based regression technique of Section 2 is used to shed light on the influence of country and industry effects on the expected returns of momentum strategies in Europe during the period 1990-2000. The results indicate that individual stock effects are driving the momentum effect, while industry and country effects are less important. In the analysis of Section 4, we disregard information about other characteristics of stocks. Incorporation of well-known effects such as value and size (see e.g. Fama & French (1992)) could be of interest for investors who already hold portfolios sorted on the basis of those characteristics. In this section, we investigate the impact of inclusion of these characteristics on the analysis presented previously. The key question is still to determine the factors that explain the existence of the momentum effect in Europe.

In order to capture the potential relation between the value and size effect and the momentum effects, the model of equation (7) can be expanded with two additional factors. Whereas a Wald-test previously indicated that the additive model specification is appropriate for (7), this is not the case for this larger model. The p-value corresponding to the hypothesis that cross-effects are jointly zero is less than one percent, which clearly rejects the additive model specification. We decide to add the cross-effects between momentum, size, and value to the model. The regression equation of the resulting model is given by

$$\begin{aligned} R_{t+1}^p \;=\;& \alpha+\sum_{a=2}^{3}\beta_a^{COU}X_t^p(a,\cdot,\cdot,\cdot,\cdot)+\sum_{b=2}^{3}\beta_b^{IND}X_t^p(\cdot,b,\cdot,\cdot,\cdot)+\sum_{c=2}^{10}\beta_c^{STOCK}X_t^p(\cdot,\cdot,c,\cdot,\cdot)+\\ &+\sum_{d=2}^{3}\beta_d^{VAL}X_t^p(\cdot,\cdot,\cdot,d,\cdot)+\sum_{e=2}^{3}\beta_e^{SIZ}X_t^p(\cdot,\cdot,\cdot,\cdot,e)+\\ &+\sum_{c=2}^{10}\sum_{d=2}^{3}\gamma_{c,d}^{MOMVAL}X_t^p(\cdot,\cdot,c,d,\cdot)+\sum_{c=2}^{10}\sum_{e=2}^{3}\gamma_{c,d}^{MOMSIZ}X_t^p(\cdot,\cdot,c,\cdot,e)+\\ &+\sum_{d=2}^{3}\sum_{e=2}^{3}\gamma_{d,e}^{VALSIZ}X_t^p(\cdot,\cdot,\cdot,d,e)+\eta_{t+1}^p. \end{aligned} \tag{8}$$

A Wald-test indicates that cross-effects between country, industry, and individual momentum can be omitted (p-value 0.21), as was the case in the previous section. For expositional purposes, we do not present a table with all estimated coefficients, but we capture our findings in several illustrative figures.

In the upper panel of Figure 2, we observe that the expected return for a stock in the loser country, loser industry, and loser individual momentum portfolio varies depending on its value and size characteristics. For value stocks, the expected return increases with firm size, while for growth stocks the opposite is true. So, a growth stock has higher expected return for small stocks than large stocks. In the lower panel of Figure 2 the estimates for the (inappropriate) additive model are presented. We conclude that the nonlinear interaction effects also seem economically significant, and should therefore be included.

Figure 3 is similar to Figure 2, but now the stock is assumed to be in the winner country, winner industry, and winner individual momentum industry. The value-size combination with a distinct expected return is the small stock and low book-to-market ratio (growth stocks). This particular combination yields a higher expected return than the others. The lower panel of Figure 3 again shows the expected returns when the (inappropriate) additive model is assumed. Evidently, this is the same picture as the one presented in the lower panel of Figure 2, except for a constant term of size 0.92 (= 0.20 + 0.23 + 0.49). The upper and lower panel of Figure 3 again deviate substantially, motivating the use of nonlinear effects relating momentum, value, and size.

In Figure 4, the expected excess return on a zero investment strategy is shown. This strategy consists of a long (short) position in stocks from the winner (loser) country, industry, and individual momentum portfolios. This picture suggests that momentum strategies yield the highest expected excess return for small stocks with growth characteristics. It is worth noting the low expected excess return for value stocks, especially for the stocks with large market capitalization. Apparently, the momentum effect is less pronounced for these combinations. Our results confirm the hypothesis of Hong & Stein (1999), which implies that the momentum effect is stronger for smaller stocks, and the findings of Asness (1997), who concludes that momentum strategies work particularly well for low-value stocks. Empirical evidence supporting these results is presented in Rouwenhorst (1998), and Hong et al. (2000), amongst others. Daniel et al. (1998) argue with their behavioral model that stocks that are harder to value (i.e. growth stocks) by investors generate a higher level of overconfidence and hence are more prone to exhibit momentum. Our findings also support this behavioral theory of investor overconfidence.

In this model with nonlinear effects relating momentum, value, and size the impact from industries and countries is relatively low. This corresponds to the results from our previous analysis without value and size effects. These country and industry effects are equal for each of the value and size combinations, since they are assumed to be additive. The additive expected return from being in the winner industry or country equals 0.22 (t-value 0.72) and 0.24 (t-value 1.17) percent, respectively. The difference between the expected returns on industries and countries has almost disappeared, though a higher t-value for industries remains, indicating less uncertainty about this additional return. The result that value and size effects do not explain medium term return continuation is in accordance with Fama & French (1996) and Jegadeesh & Titman (2001), who claim that the expected return of momentum portfolios cannot be attributed to higher loadings on the value and size factor in the three factor asset pricing model introduced by Fama & French (1993).

In conclusion, the results from this section suggest the importance of incorporating nonlinear effects in the analysis of determining the driving force behind the momentum effect when value and size effects are included. The addition of these latter effects does not alter our conclusion that medium term return continuation is driven by idiosyncratic stock effects. However, concentrating on small and growth stocks seems to further increase the expected return on momentum strategies.

6 Conclusion

While several recent papers have investigated the sources of momentum effects, only few are directed to non-US stock markets. With a few exceptions, regional influences seem to have received little attention when investigating the determinants of the momentum effect. Moreover, regions might have their specific industry compositions, which calls for a simultaneous treatment of both these effects. In this paper, we decompose the expected return on medium term momentum strategies in Europe into country, industry, and individual stock momentum effects.

The analysis is carried out by using a portfolio-based regression technique. This technique explains returns on diversified portfolios by evaluating their composition. This method is introduced for several reasons. First, the return on portfolios formed by the traditional way of sorting stocks on the basis of numerous firm characteristics yields many cells with small numbers of observations when the number of characteristics is large. This implies that the estimates are not very precise because they are influenced by idiosyncratic firm effects. Our method is particularly fruitful when there are only a moderate number of stocks in the data set compared to the number of characteristics we want to investigate, since our method requires sorting in one or two dimensions only. Second, a variety of well-understood statistical techniques is available to test model assumptions and hypotheses concerning the driving force behind momentum strategies. Moreover, an intuitively appealing structure imposed upon the model can be tested quite easily.

Our findings indicate that the momentum effect in Europe over the last decennium is primarily driven by an individual momentum effect. These results suggest that economically important (but statistically insignificant) industry momentum effects explain part of the expected return of the momentum strategies. The evidence of a country momentum effect on top of individual and industry momentum is quite weak. These results do not seem to differ between the first or second half of our sample period. Thus, we conclude that the answer to the title is negative; countries and industries do not seem to explain the momentum effect in Europe during the period 1990–2000.

In order to gauge to what extent these results depend on value and size effects, we also incorporate these in our model to decompose the momentum effect. The additive structure to disentangle the momentum effects is rejected and cross-effects between momentum, value, and size appear to be important. The inclusion of these terms marginally influences the results obtained previously. The impact of country momentum is slightly increased, while industry momentum is slightly decreased, resulting in virtually the same additional expected return for both. Thus, our conclusion that country and industry effects do not explain momentum strategies remains unaltered. The decomposition indicates that a European momentum strategy is most profitable for small growth stocks, while large value stocks exhibit least return continuation. These results confirm behavioral theories of Hong & Stein (1999) and Daniel et al. (1998).

Our findings may also be useful for investment professionals. Since our results suggest that individual stock effects are more important than country or industry momentum effects, an investor who is not allowed to take large bets on countries or industries may still be able to exploit medium term return continuation in Europe. However, these restrictions on countries and industries reduces the estimated expected return on a momentum strategy by roughly

40 percent. Investors restricted to invest in stocks with high market capitalizations only may also benefit from implementing a momentum strategy, since the portfolios we use to evaluate the momentum effect are value-weighted. The reported level of excess returns (about 12 percent per annum) on strategies exploiting medium term return continuation in Europe is at least as high as the levels reported in other studies that focus on large US stocks. The reported expected returns do not take into account transactions costs. Since we are using the larger and most liquid European stocks we do not expect this to have a substantial influence on our results. The exact quantification of transactions costs in this setting is left for future research.

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Table 1: Monthly returns and standard deviations per country in percent per month, January 1990 – November 2000.

The first columns represents value-weighted country portfolios, while the second is equally-weighted. The next column shows the total number of stocks per country portfolio (and a comparison with the number of firms in the sample from Rouwenhorst (1998)). The last three columns contain the average returns on the momentum, size, and value portfolio per country, measured by the excess return on the "winner" minus "loser" deciles/tertiles on these three characteristics. The portfolios are based on the average of the past six months (for all characteristics), and subsequently held over the next six month. In order to reduce market microstructure effect, the first month is skipped between portfolio formation and investment. Significance at the 90% and 95% level is indicated with * and **, respectively.

	value weighted		equally weighted		number			
Country	mean	std dev	mean	std dev	of firms	mom	size	value
Italy	1.13	8.5	1.16	8.7	176	0.30	0.31	-0.30
Denmark	1.14	5.1	1.07	4.8	49	**1.60	0.09	0.24
Ireland	1.11	6.1	0.81	6.0	33	0.98	-0.66	-0.73
France	1.24	5.4	1.26	5.0	165	*0.75	0.36	-0.16
Sweden	1.65	7.1	1.41	6.9	96	-0.59	-0.15	-0.04
Finland	2.02	9.1	1.36	8.0	43	1.21	-0.33	-1.47
UK	1.26	4.9	1.45	5.3	349	*0.87	**1.22	-0.27
Spain	1.14	6.7	0.91	7.1	91	0.20	-0.63	**1.35
Switzerland	1.37	4.8	1.41	4.9	140	0.35	0.42	**1.17
The Netherlands	1.58	4.5	1.43	4.5	67	0.61	-0.30	0.58
Norway	0.80	7.3	1.25	7.8	47	0.29	1.59	0.94
Germany	1.03	5.4	0.71	4.4	171	0.71	**-1.07	-0.72
Portugal	1.00	5.9	0.98	5.8	66	1.03	0.43	-0.72
Belgium	1.26	5.0	1.03	4.8	42	0.61	**-0.94	-0.42
Austria	0.23	6.7	0.34	6.4	46	-0.09	0.89	**1.83

Table 2: Monthly returns and standard deviations per industry in percent per month, January 1990 – November 2000.

The first columns represents value weighted industry portfolios, while the second is equally weighted. The next column shows the total number of stocks per industry portfolio. The last three columns contain the average returns on the momentum, size, and value effect per industry, measured by the excess return on the "winner" minus "loser" deciles/tertiles on these three characteristics. The portfolios are based on the average of the past six months (for all characteristics), and subsequently held over the next six month. In order to reduce market microstructure effect, the first month is skipped between portfolio formation and investment. Significance at the 90% and 95% level is indicated with * and **, respectively.

	value weighted		equally weighted		number			
Industry	mean	std dev	mean	std dev	of firms	mom	size	value
Energy	1.38	5.4	1.27	5.7	34	0.26	0.53	**1.55
Materials	0.86	5.3	0.82	5.4	199	-0.04	-0.43	0.83
Capital Goods	0.71	5.5	0.86	5.4	260	0.07	0.23	0.78
Commercial Services & Supplies	0.74	5.7	1.03	5.2	80	**1.91	0.39	-0.23
Transportation	0.91	5.4	0.95	5.1	59	0.17	0.46	-0.33
Automobiles & Components	0.59	7.1	1.05	6.5	32	-0.51	*1.30	-0.14
Consumer Durables & Apparel	1.45	6.1	1.00	5.3	68	1.27	-0.65	0.08
Hotels, Restaurants, & Leisure	0.69	6.2	1.21	5.8	25	**1.48	**1.58	-0.24
Media	1.55	6.7	1.84	6.7	57	0.89	**1.73	0.59
Retailing	0.97	4.7	1.08	4.5	70	*0.91	0.69	-0.37
Food & Drug Retailing	1.24	4.7	1.23	4.3	27	*0.98	0.84	0.46
Food, Beverages, & Tobacco	1.23	4.4	0.98	4.0	86	0.87	-0.48	0.42
Household & Personal Products	1.83	5.9	1.29	5.4	9	0.51	-1.07	1.38
Health Care Equipment & Services	1.60	6.1	1.53	4.8	35	0.54	0.70	0.23
Pharmaceuticals & Biotechnology	1.69	4.5	2.00	4.1	30	*1.30	1.01	0.33
Banks	1.40	5.7	1.44	5.3	125	0.22	-0.34	*1.23
Diversified Financials	1.29	5.6	1.45	5.2	64	1.01	-0.05	-0.01
Insurance	1.25	5.2	1.20	5.1	123	0.40	-0.23	0.04
Real Estate	0.62	5.1	0.71	4.8	28	0.08	-0.18	0.88
Software & Services	2.55	9.5	3.11	8.9	31	0.44	2.04	0.16
Technology Hardware & Equipment	2.03	8.5	2.49	7.5	24	**2.51	1.33	-1.70
Telecommunication Services	1.82	7.0	2.15	7.8	44	0.80	0.96	0.98
Utilities	1.19	4.1	1.44	4.1	71	-0.40	0.52	0.84

Table 3: Momentum effect in Europe, January 1990 – November 2000.

Results for the portfolio-based regression $R^p_{t+1} = \alpha + \sum_{a=2}^{10} \beta_a^{MOM} X_t^p(a) + \varepsilon^p_{t+1}$, with 196 evaluated portfolios. The portfolios are based on sorts and double-sorts on characteristics country, industry, and individual momentum, value, and size. The first set of results is based on the Fama-MacBeth estimator with cross-sectional WLS, with the square root of the number of stocks per portfolio as weights. The second set of results is calculated with the cross-sectional OLS. The rows indicated with "est" contain the estimates (expected return in percentage per month), and the rows with "t-val" the t-values corresponding to the estimate above it.

		α	β_2^{MOM}	β_3^{MOM}	β_4^{MOM}	β_5^{MOM}	β_6^{MOM}	β_7^{MOM}	β_8^{MOM}	β_9^{MOM}	β_{10}^{MOM}
WLS	est	1.13	0.07	0.19	0.27	0.21	0.34	0.40	0.46	0.54	0.79
	t-val	2.00	0.38	0.82	1.01	0.68	1.00	1.05	1.16	1.20	1.59
OLS	est	1.14	0.09	0.23	0.28	0.23	0.33	0.37	0.47	0.52	0.81
	t-val	2.10	0.55	1.13	1.20	0.84	1.11	1.14	1.35	1.34	1.84

Table 4: The momentum effect in Europe by imposing polynomials on the decile structure, January 1990 – November 2000.

Estimation results for the estimates of the regression equation $R_{t+1}^p = \sum_{l=0}^{L} \lambda_l Z_t^p(l) + \eta_{t+1}^p$, where $Z_t^p(l) \equiv 1 + \sum_{a=2}^{N_A} \left(a^l - 1\right) X_t^p(a)$. The regression equation is evaluated for a third-order polynomial, i.e. $L = 3$. In panel A the results for the hyperparameters are presented, while in panel B these parameters are converted into expected returns for the deciles. For the sake of completeness, the result without fitting the third-order polynomial are also presented in panel B in the row labelled "no".

A	λ_0	λ_1	λ_2	λ_3	λ_4
est	1.037	0.078	0.011	-0.004	0.000
t-val	1.35	0.19	0.09	-0.23	0.37
est	0.942	0.198	-0.033	0.002	–
t-val	1.43	1.03	-0.95	1.04	–
est	1.14	0.026	0.004	–	–
t-val	1.80	0.20	0.39	–	–

B		α	β_2^{MOM}	β_3^{MOM}	β_4^{MOM}	β_5^{MOM}	β_6^{MOM}	β_7^{MOM}	β_8^{MOM}	β_9^{MOM}	β_{10}^{MOM}
No	est	1.13	0.07	0.19	0.27	0.21	0.34	0.40	0.46	0.54	0.79
	t-val		0.38	0.82	1.01	0.68	1.00	1.05	1.16	1.20	1.59
$L = 2$	est	1.17	0.04	0.09	0.14	0.21	0.28	0.36	0.46	0.56	0.66
	t-val		0.39	0.48	0.59	0.72	0.87	1.03	1.21	1.36	1.46
$L = 3$	est	1.11	0.12	0.19	0.24	0.29	0.33	0.39	0.47	0.60	0.79
	t-val		0.99	0.97	0.96	0.96	1.00	1.09	1.24	1.44	1.59
$L = 4$	est	1.12	0.09	0.17	0.23	0.28	0.33	0.37	0.45	0.57	0.78
	t-val		0.58	0.75	0.88	0.96	1.00	1.03	1.12	1.31	1.59

Table 5: The momentum effect in Europe decomposed in a country, industry, and individual stock momentum effect, January 1990 – November 2000.

Estimation results for the portfolio-based regression $R^p_{t+1} = \alpha + \sum_{a=2}^{3} \beta_a^{COU} X_t^p(a,\cdot,\cdot) + \sum_{b=2}^{3} \beta_b^{IND} X_t^p(\cdot,b,\cdot) + \sum_{c=2}^{10} \beta_c^{ST} X_t^p(\cdot,\cdot,c) + \eta^p_{t+1}$, with 196 evaluated portfolios. The portfolios are based on sorts and double-sorts on characteristics country, industry, and individual momentum, value, and size. The results are based on the Fama-MacBeth estimator with cross-sectional WLS. The rows indicated with "est" contain the estimates (expected return in percentage per month), and the rows with "t-val" the t-values corresponding to the estimate above it. The parameter α denotes the reference portfolio, parameter indicated with superscript COU, IND, and ST measure the country, industry, and individual stock momentum effect. The higher the subscript number, the higher the stock scored on that particular characteristic. See also Figure 1 for a graphical representation of these results.

WLS	α	β_2^{COU}	β_3^{COU}	β_2^{IND}	β_3^{IND}
est	1.13	0.00	0.12	0.06	0.31
t-val	1.84	0.01	0.38	0.47	1.31

	β_2^{ST}	β_3^{ST}	β_4^{ST}	β_5^{ST}	β_6^{ST}	β_7^{ST}	β_8^{ST}	β_9^{ST}	β_{10}^{ST}
est	0.04	0.12	0.19	0.14	0.23	0.26	0.27	0.31	0.55
t-val	0.23	0.55	0.80	0.52	0.80	0.81	0.85	0.87	1.44

Table 6: A subperiod analysis of the momentum effect in Europe decomposed in a country, industry, and individual stock momentum effect.

Estimation results for the portfolio-based regression $R^p_{t+1} = \alpha + \sum_{a=2}^{3} \beta_a^{COU} X_t^p(a,\cdot,\cdot) + \sum_{b=2}^{3} \beta_b^{IND} X_t^p(\cdot,b,\cdot) + \sum_{c=2}^{10} \beta_c^{ST} X_t^p(\cdot,\cdot,c) + \eta^p_{t+1}$, with 196 evaluated portfolios. The portfolios are based on sorts and double-sorts on characteristics country, industry, and individual momentum, value, and size. The results are based on the Fama-MacBeth estimator with cross-sectional WLS. The rows indicated with "est" contain the estimates (expected return in percentage per month), and the rows with "t-val" the t-values corresponding to the estimate above it. The parameter α denotes the reference portfolio, parameters with superscript COU, IND, and ST measure the country, industry, and individual stock momentum effect. The higher the subscript number, the higher the stock scored on that particular characteristic. For the sake of completeness, the entire sample period is presented at the first row, while in the second and third row the estimation results for the subperiods are presented.

	α	β_2^{COU}	β_3^{COU}	β_2^{IND}	β_3^{IND}
1990–2001	1.13	0.00	0.12	0.06	0.31
1990–1996	0.46	0.24	0.39	0.09	0.37
1996–2001	1.79	-0.24	-0.16	0.03	0.26

	β_2^{ST}	β_3^{ST}	β_4^{ST}	β_5^{ST}	β_6^{ST}	β_7^{ST}	β_8^{ST}	β_9^{ST}	β_{10}^{ST}
1990–2001	0.04	0.12	0.19	0.14	0.23	0.26	0.27	0.31	0.55
1990–1996	-0.11	-0.09	0.03	0.11	0.15	0.09	0.14	0.30	0.42
1996–2001	0.19	0.32	0.36	0.17	0.32	0.42	0.41	0.33	0.68

Table 7: The momentum effect in Europe decomposed in a country, industry, and individual stock momentum, and value and size effect, January 1990 – November 2000.

Estimation results for the portfolio-based regression $R^p_{t+1} = \alpha + \sum_{a=2}^{3} \beta_a^{COU} X_t^p(a,\cdot,\cdot,\cdot,\cdot) + \sum_{b=2}^{3} \beta_b^{IND} X_t^p(\cdot,b,\cdot,\cdot,\cdot) + \sum_{c=2}^{10} \beta_c^{ST} X_t^p(\cdot,\cdot,c,\cdot,\cdot) + \sum_{d=2}^{3} \beta_d^{VAL} X_t^p(\cdot,\cdot,\cdot,d,\cdot) + \sum_{e=2}^{3} \beta_e^{SIZ} X_t^p(\cdot,\cdot,\cdot,\cdot,e) + \eta^p_{t+1}$, with 196 evaluated portfolios. The portfolios are based on sorts and double-sorts on characteristics country, industry, and individual momentum, value, and size. The results are based on the Fama-MacBeth estimator with cross-sectional WLS. The rows indicated with "est" contain the estimates (expected return in percentage per month), and the rows with "t-val" the t-values corresponding to the estimate above it. The parameter α denotes the reference portfolio, parameter indicated with superscript COU, IND, and ST measure the country, industry, and individual momentum effect. The higher the subscript number, the higher the stock scored on that particular characteristic. The value effect is denoted by VAL, with $d = 3$ the portfolio with the highest book-to-price ratio (value). The size effect is denoted by SIZ, with $e = 3$ the portfolio with the lowest market value (size).

WLS	α	β_2^{COU}	β_3^{COU}	β_2^{IND}	β_3^{IND}	β_2^{VAL}	β_3^{VAL}	β_2^{SIZ}	β_3^{SIZ}
est	1.25	0.04	0.20	0.04	0.23	-0.11	0.06	-0.20	-0.06
t-val	2.16	0.17	0.65	0.37	1.00	-0.82	0.36	-1.44	-0.30

	β_2^{ST}	β_3^{ST}	β_4^{ST}	β_5^{ST}	β_6^{ST}	β_7^{ST}	β_8^{ST}	β_9^{ST}	β_{10}^{ST}
est	0.01	0.10	0.14	0.05	0.14	0.18	0.19	0.25	0.49
t-val	0.09	0.51	0.70	0.24	0.59	0.70	0.72	0.83	1.52

Figure 1: Expected excess returns for stocks in country, industry, and individual stock momentum portfolios in Europe, January 1990 – November 2000.

Excess returns are defined relative to the reference portfolio of stocks in the loser country, loser industry, and loser individual momentum portfolio. The x-axis of this figure contains the individual momentum deciles, the y-axis the country-industry combinations, and the z-axis the monthly expected excess return relative to the reference portfolio (individual loser, country loser, and industry loser). The acronyms used are country (COU), industry (IND), and winner (W), middle (M), and loser (L).

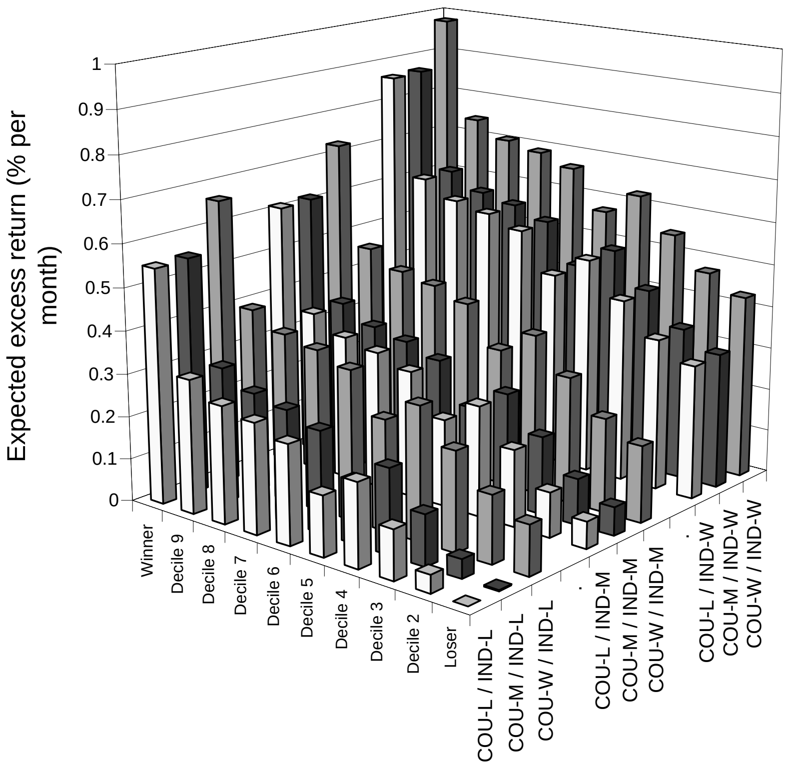
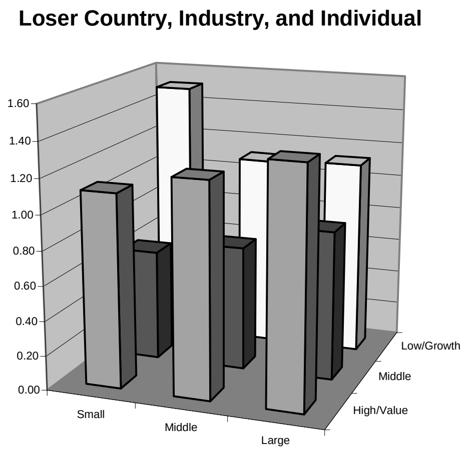


Figure 2: Estimated expected returns for European stocks over 1990–2000 in the loser country, loser industry, and loser individual momentum portfolio with different value and size characteristics. The cross-effects between individual momentum and value, individual momentum and size, and value and size effects have been incorporated in the top panel, while the rejected additive model is assumed on the bottom panel.



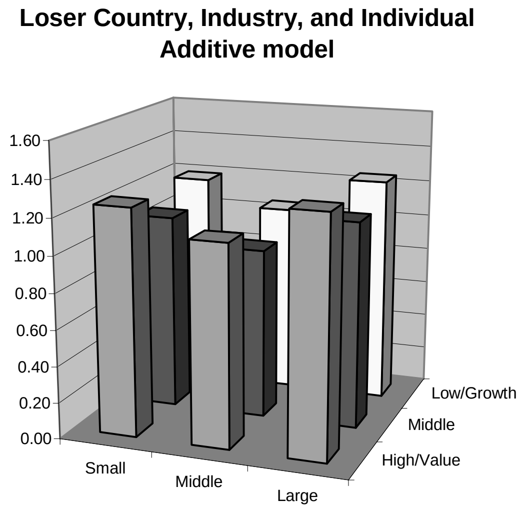
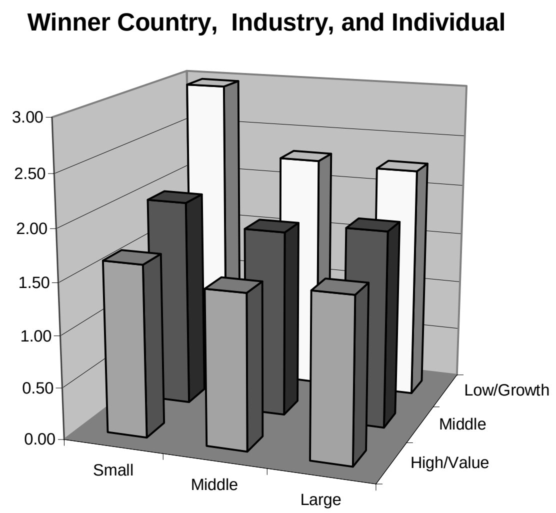


Figure 3: Estimated expected returns for European stocks over 1990–2000 in the winner country, winner industry, and winner individual momentum portfolio with different value and size characteristics. The cross-effects between individual momentum and value, individual momentum and size, and value and size effects have been incorporated in the top panel, while the rejected additive model is assumed on the bottom panel.



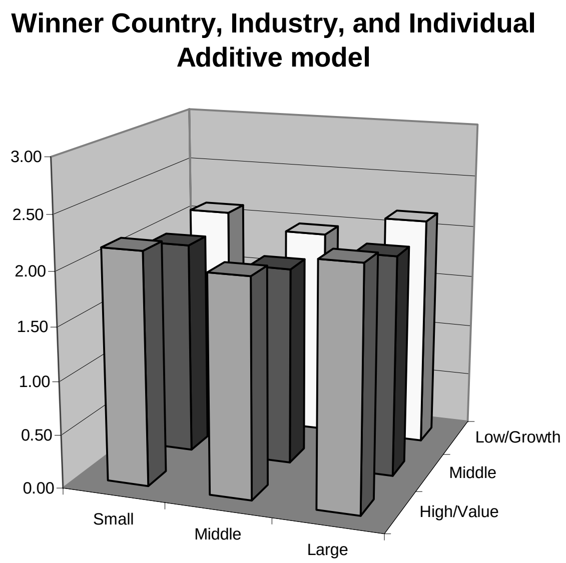
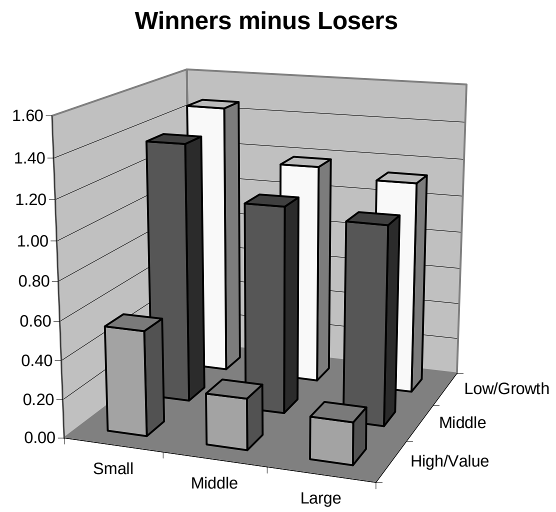
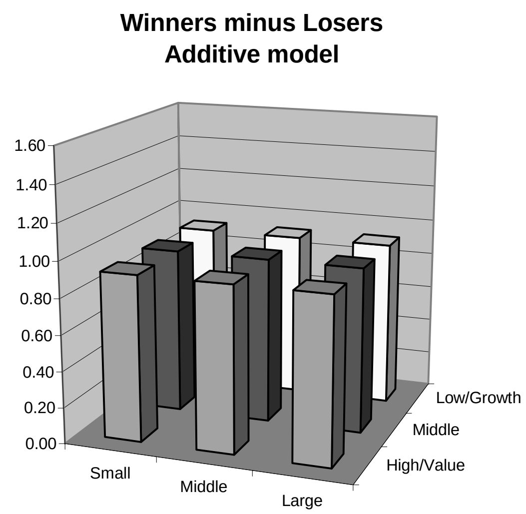


Figure 4: Estimated expected excess returns for European momentum strategy over 1990–2000. The long side of this portfolio consists of stocks in the winner country, winner industry, and winner individual momentum sort, and the short side of this portfolio consists of stocks in the loser country, loser industry, and loser individual momentum sort. The value and size characteristics of these stocks differ and are displayed in the figure below. The cross-effects between individual momentum and value, individual momentum and size, and value and size effects have been incorporated in the model for the expected returns.





A Additional non-informative portfolios

In this section we show that the use of non-informative portfolios as regressands does not influence the estimation and inference about the determinants of the momentum effect. The proof of this assertion is organized as follows. It is shown that the cross-sectional OLS estimator for the coefficients (excluding the constant) remains unaltered when portfolios are added that contain no information about the effect under consideration. The Fama-MacBeth estimator and its variance are the mean and variance from the cross-sectional OLS point estimates. Hence, when it is shown that these cross-sectional parameter estimates are the same with or without including non-informative portfolios, the Fama-MacBeth estimates remain unchanged.

A non-informative portfolio is defined to be a portfolio of stocks with equal holdings in each of the portfolios making up a factor. For example, when three industry momentum portfolios are distinguished to capture the industry momentum effect, a non-informative portfolio would have exactly one-third of its holdings in the winner, middle, and loser portfolio. The return on this portfolio does not yield any information about the return on the industry momentum component, hence the term non-informative portfolio.

Consider the (cross-sectional) linear regression model with $R_{1,i}$ the return on portfolio i and $X_{1,i}$ the holdings of portfolio i in the factor portfolio:

$$R_{1,i} = \beta_0 + \beta_1' F_{1,i} + \varepsilon_{1,i}, \quad i = 1, ..., N_1, \tag{9}$$

under the standard weak assumptions:

$$\mathrm{E}\{\varepsilon_{1,i}|F_{1,i}\} = 0 \quad \forall i,$$
$$\mathrm{E}\{\varepsilon_{1,i}\varepsilon_{1,j}|F_{1,i}, F_{1,j}\} = \sigma_{i,j} < \infty \quad \forall i.$$

The first assumption defines the OLS estimator, and the second assumption requires finite (co)variances for the error terms. Note that a constant term is included in the regression and that the holdings sum to unity. To prevent the dummy variable trap, an arbitrary holding should be left out. In the industry momentum example from above a non-informative portfolio has $F_{1,i} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} \end{bmatrix}$ for each i. In case the portfolios used as regressands are the same as the regressors, the holdings reduce to a set of dummies. The number of portfolios in this case (N_1) equals the number of factor portfolios (K).

The OLS estimator for $\beta = (\beta_0, \beta_1)$ is defined as

$$\begin{bmatrix} \widehat{\beta}_0 \\ \widehat{\beta}_1 \end{bmatrix} = \begin{bmatrix} \iota'\iota & \iota' F_1 \\ F_1'\iota & F_1'F_1 \end{bmatrix}^{-1} \begin{bmatrix} \iota' R_1 \\ F_1' R_1 \end{bmatrix} \tag{10}$$

$$= \begin{bmatrix} \frac{1}{N_1}\left(I + \iota' F_1 \left(F_1'\left(I - \frac{1}{N_1}\iota\iota'\right) F_1\right)^{-1} \frac{1}{N_1} F_1'\iota\right) & -\frac{1}{N_1}\iota' F_1 \left(F_1'\left(I - \frac{1}{N_1}\iota\iota'\right) F_1\right)^{-1} \\ -\left(F_1'\left(I - \frac{1}{N_1}\iota\iota'\right) F_1\right)^{-1} \frac{1}{N_1} F_1'\iota & \left(F_1'\left(I - \frac{1}{N_1}\iota\iota'\right) F_1\right)^{-1} \end{bmatrix} \begin{bmatrix} \iota' R_1 \\ F_1' R_1 \end{bmatrix}.$$

Since our interest lies in the β_1, we do not pay attention to the upper row of the matrix, since this has implications for the intercept β_0 only. We define the product $\widetilde{R}_1 \equiv F_1' R_1$, and this new vector contains the returns of portfolio 2 to N_1. The estimator for β_1 becomes

$$\widehat{\beta}_1 = \left[-\left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota_{K-1}'\right)^{-1} \frac{1}{K}\iota_{K-1}\right]\iota_{N_1}' R_1 + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota_{K-1}'\right)^{-1} \widetilde{R}_1 \tag{11}$$

$$= -\iota_{K-1}\iota_{N_1}' R_1 + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota_{K-1}'\right)^{-1} \widetilde{R}_1, \tag{12}$$

with ι_K a K-dimensional vector with ones, and I_K an identity matrix of dimension $K \times K$. The remainder of this appendix is to show that the expression for $\widehat{\beta}_1$ in (12) is exactly the same if a set of non-informative portfolios is used in addition to the first set of portfolios.

We introduce another set of portfolios (denoted with subindex 2) to estimate the same model

$$\begin{aligned} R_{1,i} &= \beta_0 + \beta_1' F_{1,i} + \varepsilon_{1,i}, \quad i = 1, ..., N_1, \\ R_{2,i} &= \beta_0 + \beta_1' F_{2,i} + \varepsilon_{2,i}, \quad i = N_1 + 1, ..., N_1 + N_2, \end{aligned} \tag{13}$$

for which we want to show that the estimation is not affected if the second set consists of non-informative portfolios only. A non-informative portfolio is defined as one for which the holdings are equal for each factor mimicking portfolio. So, for example, the matrices in the case of $K = 4$ and $N_2 = 2$ are

$$F_1 = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, R_1 = \begin{bmatrix} R_{1,1} \\ R_{1,2} \\ R_{1,3} \\ R_{1,4} \end{bmatrix}, \widetilde{R}_1 = \begin{bmatrix} R_{1,2} \\ R_{1,3} \\ R_{1,4} \end{bmatrix}$$

$$F_2 = \begin{bmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{bmatrix}, R_2 = \begin{bmatrix} R_{2,1} \\ R_{2,2} \end{bmatrix}.$$

The OLS estimator for β is now

$$\begin{bmatrix} \widehat{\beta}_0 \\ \widehat{\beta}_1 \end{bmatrix} = \begin{bmatrix} \iota_{N_1}'\iota_{N_1} + \iota_{N_2}'\iota_{N_2} & \iota_{N_1}' F_1 + \iota_{N_2}' F_2 \\ F_1'\iota_{N_1} + F_2'\iota_{N_2} & F_1'F_1 + F_2'F_2 \end{bmatrix}^{-1} \begin{bmatrix} \iota_{N_1}' R_1 + \iota_{N_2}' R_2 \\ F_1' R_1 + F_2' R_2 \end{bmatrix}.$$

Rewriting this equation for the case in which portfolios are non-informative, i.e. $F_2 = \frac{1}{K}\iota_{N_2}\iota'_{K-1}$,

$$\begin{aligned}
\begin{bmatrix} \widehat{\beta}_0 \\ \widehat{\beta}_1 \end{bmatrix} &= \begin{bmatrix} N_1 + N_2 & \iota'_{N_1}X_1 + \iota'_{N_2}\left(\frac{1}{K}\iota_{N_2}\iota'_{K-1}\right) \\ X'_1\iota_{N_1} + \left(\frac{1}{K}\iota_{N_2}\iota'_{K-1}\right)'\iota_{N_2} & X'_1X_1 + (\frac{1}{K}\iota_{N_2}\iota'_{K-1})'(\frac{1}{K}\iota_{N_2}\iota'_{K-1}) \end{bmatrix}^{-1} \begin{bmatrix} \iota'_{N_1}Y_1 + \iota'_{N_2}Y_2 \\ X'_1Y_1 + (\frac{1}{K}\iota_{N_2}\iota'_{K-1})'Y_2 \end{bmatrix} \\
&= \begin{bmatrix} N_1 + N_2 & \iota'_N X_1 + \frac{N_2}{K}\iota'_{K-1} \\ X'_1\iota_N + \frac{N_2}{K}\iota_K & X'_1X_1 + \frac{N_2}{K^2}\iota_{K-1}\iota'_{K-1} \end{bmatrix}^{-1} \begin{bmatrix} \iota'_N Y_1 + \iota'_N Y_2 \\ X'_1Y_1 + \frac{1}{K}\iota_{K-1}\iota'_N Y_2 \end{bmatrix}. \qquad (1
\end{aligned}$$

Using the partitioned inverse rule on the 2×2 partitioned inverse matrix, we obtain

$$\begin{aligned}
\begin{bmatrix} \widehat{\beta}_0 \\ \widehat{\beta}_1 \end{bmatrix} &= \begin{bmatrix} \cdot & \cdot \\ -\left(F'_1\left(I_{N_1} - \frac{1}{N_1+N_2}\iota_{N_1}\iota'_{N_1}\right)F_1 - A\right)^{-1}B & \left(F'_1\left(I_{N_1} - \frac{1}{N_1+N_2}\iota_{N_1}\iota'_{N_1}\right)F_1 - A\right)^{-1} \end{bmatrix} \\
&\quad \times \begin{bmatrix} \iota'_{N_1}R_1 + \iota'_{N_2}R_2 \\ F'_1R_1 + \frac{1}{K}\iota_{K-1}\iota'_{N_1}R_2 \end{bmatrix}. \qquad (16)
\end{aligned}$$

with

$$\begin{aligned}
A &= \frac{N_1N_2}{K^2}\frac{1}{(N_1+N_2)}\left[\frac{K}{N_1}\left(F'_1\iota_{N_1}\iota'_{K-1} + \iota_{K-1}\iota'_{N_1}F_1\right) - \iota_{K-1}\iota'_{K-1}\right], \\
B &= \frac{1}{N_1+N_2}\left(F'_1\iota_{N_1} + \frac{N_2}{K}\iota_{K-1}\right).
\end{aligned}$$

Now, moving back to the case in which the first group of regressands are the factor mimicking portfolios ($F_1 = I_{K-1}$), the matrix A reduces to $\frac{(2K-N_1)N_2}{K^2(N_1+N_2)}\iota_{K-1}\iota'_{K-1}$. The bottom left part of equation (16) can be rewritten

$$\begin{aligned}
&-\left(F'_1\left(I_{N_1} - \frac{1}{N_1+N_2}\iota_{N_1}\iota'_{N_1}\right)F_1 - A\right)^{-1}B \\
=\ &-\left(I_{K-1} - \frac{1}{N_1+N_2}\iota_{K-1}\iota'_{K-1} - \frac{(2K-N_1)N_2}{K^2(N_1+N_2)}\iota_{K-1}\iota'_{K-1}\right)^{-1}\frac{1}{N_1+N_2}\left(\frac{K+N_2}{K}\iota_{K-1}\right) \\
=\ &-\left(I_{K-1} + \frac{-K^2 - 2KN_2 + N_1N_2}{K^2(N_1+N_2)}\iota_{K-1}\iota'_{K-1}\right)^{-1}\frac{1}{N_1+N_2}\left(\frac{K+N_2}{K}\iota_{K-1}\right).
\end{aligned}$$

Note now that $K = N_1$, the set of factor mimicking portfolios, which implies

$$= -\left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}\frac{1}{K}\iota_{K-1} = -\iota_{K-1}.$$

and the bottom right part of equation (16) reduces to $\left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}$. If we compare this to the formula without the additional non-informative portfolios (only R_1), we see that the estimation results are exactly the same

$$\widetilde{\beta}_1 = -\iota_{K-1}\left(\iota'_{N_1}R_1 + \iota'_{N_2}R_2\right) + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}\left(F'_1R_1 + \frac{1}{K}\iota_{K-1}\iota'_{N_1}R_2\right).$$

Rearranging terms gives

$$\widetilde{\beta}_1 = -\iota_{K-1}\iota'_{N_1}R_1 + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}\widetilde{R}_1 + -\iota_{K-1}\iota'_{N_2}R_2 + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}\frac{1}{K}\iota_{K-1}\iota'_{N_1}R_2.$$

We simplify the most right $\left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}$ to $\left(I_{K-1} + \iota_{K-1}\iota'_{K-1}\right)$ and substitute this in the equation above

$$\begin{aligned}
\widetilde{\beta}_1 &= -\iota_{K-1}\iota'_{N_1}R_1 + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}\widetilde{R}_1 + -\iota_{K-1}\iota'_{N_2}R_2 + \left(I_{K-1} + \iota_{K-1}\iota'_{K-1}\right)\frac{1}{K}\iota_{K-1}\iota'_{N_1}R_2 \\
&= -\iota_{K-1}\iota'_{N_1}R_1 + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}\widetilde{R}_1 + -\iota_{K-1}\iota'_{N_2}R_2 + \frac{1}{K}\left(\iota_{K-1} + (K-1)\,\iota_{K-1}\right)\iota'_{N_1}R_2 \\
&= -\iota_{K-1}\iota'_{N_1}R_1 + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}\widetilde{R}_1 - \iota_{K-1}\iota'_{N_2}R_2 + \iota_{K-1}\iota'_{N_2}R_2 \\
&= -\iota_{K-1}\iota'_{N_1}R_1 + \left(I_{K-1} - \frac{1}{K}\iota_{K-1}\iota'_{K-1}\right)^{-1}\widetilde{R}_1 \\
&= \widehat{\beta}_1
\end{aligned}$$

This is all rearranging terms, where the last line follows from equation (12). This result shows that adding non-informative portfolios does not influence the (cross-sectional) OLS parameter estimates. The Fama-MacBeth approach we employ in this paper uses the average and standard deviation of the cross-sectional parameters as estimates for the true parameters and their uncertainty. Thus, the Fama-MacBeth estimator results in numerically the same answers with or without the inclusion of non-informative portfolios.

B Additive model specification

In Section 2, we started with a regression model, unrestrictedly describing the expected returns on each of the portfolios under consideration. In order to get a more parsimonious model, restrictions that are economically or statistically sensible can be imposed upon the model structure. The regression equation of the complete model is

$$\mathrm{E}_t\{R^p_{t+1}\} = \sum_{a=1}^{N_A}\sum_{b=1}^{N_B}\sum_{c=1}^{N_C} \alpha_{a,b,c} X^p_t\,(a,b,c)\,. \tag{17}$$

In most applications, an additive model for the three factors under consideration is used; see e.g. Roll (1992), Heston & Rouwenhorst (1994), and Kuo & Satchell (2001). In order to be able to test the restrictions that are implied by imposing an additive structure, rewrite equation (17) to

$$\begin{aligned}\mathrm{E}_t\{R^p_{t+1}\} \;=\;& \alpha_{1,1,1} + \sum_{a=2}^{N_A} \beta^A_a X^p_t(a,\cdot,\cdot) + \sum_{b=2}^{N_B} \beta^B_b X^p_t(\cdot,b,\cdot) + \sum_{c=2}^{N_C} \beta^C_c X^p_t(\cdot,\cdot,c) + \\ & + \sum_{a=2}^{N_A}\sum_{b=2}^{N_B} \gamma^{AB}_{a,b} X^p_t(a,b,\cdot) + \sum_{a=2}^{N_A}\sum_{c=2}^{N_C} \gamma^{AC}_{a,c} X^p_t(a,\cdot,c) + \sum_{b=2}^{N_B}\sum_{c=2}^{N_C} \gamma^{BC}_{b,c} X^p_t(\cdot,b,c) + \\ & + \sum_{a=2}^{N_A}\sum_{b=2}^{N_B}\sum_{c=2}^{N_C} \delta_{a,b,c} X^p_t(a,b,c).\end{aligned} \tag{18}$$

Restricting the parameters in the last two lines of (18) to zero results in the additive structure. The parameters of (18) can be expressed in those of (17) in the following way

$$\begin{aligned}&\beta^A_a = (\alpha_{a,1,1} - \alpha_{1,1,1})\,, \quad \beta^B_b = (\alpha_{1,b,1} - \alpha_{1,1,1})\,, \quad \beta^C_c = (\alpha_{1,1,c} - \alpha_{1,1,1})\,, \\ &\gamma^{AB}_{a,b} = (\alpha_{a,b,1} + \alpha_{1,1,1} - \alpha_{a,1,1} - \alpha_{1,b,1})\,, \\ &\gamma^{BC}_{b,c} = (\alpha_{1,b,c} + \alpha_{1,1,1} - \alpha_{1,b,1} - \alpha_{1,1,c})\,, \\ &\gamma^{AC}_{a,c} = (\alpha_{a,1,c} + \alpha_{1,1,1} - \alpha_{a,1,1} - \alpha_{1,1,c})\,, \\ &\delta_{a,b,c} = (\alpha_{a,b,c} - \alpha_{1,1,1} + \alpha_{a,1,1} + \alpha_{1,b,1} + \alpha_{1,1,c} - \alpha_{a,b,1} - \alpha_{1,b,c} - \alpha_{a,1,c})\,.\end{aligned}$$

By substituting these definitions into (18), we obtain the original model of (17).