Country versus Sector Rotation after the Introduction of the European Monetary Union (EMU)

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Abstract
The introduction of the European monetary union (EMU) led to a convergence of the participating countries in many ways. One particular aspect is the diversification potential among different financial markets. While during the 1990s country effects typically dominated industry effects in magnitude, more recent studies stress the importance of industry diversification when it comes to portfolio construction. We show the increasing correlations among countries' equity market returns and the contemporaneous decrease in sector correlations and confirm the growing importance of industry effects by applying a bootstrapping method. Supported by this finding we implement momentum strategies based on countries and industries, respectively, in order to compare their performance. Due to the better diversification potential, most of the sector models outperform the country frameworks on a risk adjusted basis.

1. Introduction

In the aftermath of the seminal works by Grubel (1968), Levy and Sarnat (1970), and Solnik (1974), researchers widely accepted a large diversification potential between equity markets of different countries. Many empirical studies investigated the question whether benefits of similar magnitude could be obtained by diversification across industries, e.g. Grubel and Fadner (1971), Heston and Rouwenhorst (1994), Heston and Rouwenhorst (1995). An increasing relative importance of sector diversification potential with respect to country effects was already found by Baca, Garbe, and Weiss (2000) before the introduction of the EMU. With a data panel reaching until the end of 1999 they no longer detect a significant difference in the influence of countries with respect to sectors. With a similar data set Cavaglia, Brightman, and Aked (2000) attribute more diversification potential to industries than to countries.

The introduction of the Euro was investigated by Rouwenhorst (1999a). In line with Biais (1999) he predicts a dominating effect of country factors with respect to their industry equivalents after 1999. In contrast, Kraus (2001) finds a dramatic increase in the importance of the industry factors and the unexplained share with the launch of the new currency while the world factor and country factors decrease in importance. He documents a decline in correlations across countries and, even more pronounced, across sectors. This result is attributed to the uneven industry distribution among the ten countries (excluding Luxembourg) participating in the EMU. Therefore, the diversification potential should have improved in line with Adjaouté and Danthine (2004). Similarly, Fratzscher (2002) documents a higher market integration in the EMU lowering the diversification potential across countries. He therefore proposes diversification across industries or regions. In a conditional asset-pricing framework Carrieri, Errunza, and Sarkissian (2004) find country as well as industry risk premia.

Advantages of industry over country diversification are also shown in Flavin (2004). The first part of our paper builds to a large extent on his article. He uses an innovative approach building on Heston and Rouwenhorst (1994) but develops a more efficient estimation method with a panel approach.

Based on the improved sector diversification, Amenc, Malaise, Martellini, and Sfeir (2003) generate portable alpha benefits implementing a sector rotation approach with Dow Jones EURO STOXX Sector Index Futures and Options.

Our contribution is twofold: First, we extend the study by Flavin (2004) to longer time series and apply a more sophisticated bootstrapping method in order to account for asymmetric regressor distributions. It turns out that the industry factors are by far more important than the country factors. Therefore, we investigate secondly whether a dynamic strategy based on industries yields better results than based on countries.

As an example for such a tactical asset allocation we set up momentum strategies that may rely on Dow Jones EURO STOXX Sector Index Futures to show the benefits of industry diversification. Unlike in the article by Amenc, Malaise, Martellini, and Sfeir (2004) we do not only run a simulation but im-plement and test our model with historical data.

The following section describes the data used in the present article. Section 3 describes the model for the investigation of country and industry effects. Its results are given in Section 4. Section 5 describes the momentum strategies and presents the results.

2. Data

For the analysis of sector impacts, we employ weekly total returns and market capitalizations from July 1992 until July 2006 collected from Datastream. The use of weekly data is in line with Kraus (2001) but finer than the monthly dataset of Flavin (2004). The observation period was determined to give a span of comparable length before and after the introduction of the Euro in 1999. Our sample consists of all companies included in Thomson Financial's country indices of the eleven countries that participated in the European monetary union in January 1999, i.e., Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain. Since each company is part of one country and one sector, this yields a consistent sample across the two dimensions.

For the dynamic trading strategy, we use the MSCI country indices and the Dow Jones EURO STOXX sector indices on a monthly basis in order to give a more realistic picture with easily investible indices.

In contrast to Kraus (2001), the analysis is completely carried out in Euro to exclude the effects of exchange rate risk found by Bodart and Reding (1999). Firms with multiple share classes are treated as a single value-weighted portfolio of the respective equity securities. Therefore, our sample contains a total of 1197 equity time series.[1] Each share is assigned according to the Datastream industry classification to one of the following ten sectors: Basic Materials (BMATR), Consumer Goods (CNSMG), Consumer Services (CNSMS), Financial Services (FINAN), Health Care (HLTHC), Industrials (INDUS), Oil and Gas (OILGS), Technologies (TECNO), Telecommunications (TELCM) and Utilities (UTILS). Following Flavin (2004) we apply broad categories for the bootstrap analysis since Griffin and Karolyi (1998) found no superiority of finely grained industry definitions. The number of investigated sample companies broken down by sectors and countries is illustrated in Panel A of Table 1. Their non-uniform distribution is clearly observable, e.g. the concentration of the financial sector in many countries (see Luxembourg with almost half of its sample firms engaged in financial services). Besides, several countries such as Germany, France, Finland and Austria have additional concentrations in the industrial sector. The firms are not equally distributed across countries. While Germany and France together account for more than 40% of the entire sample, Finland and Luxembourg make up only about 3 to 4% each. Panel B of Table 1 illustrates the average market capitalization of the sample firms as well as their respective medians broken down into country and sector affiliations. The average firm size not only varies to a large extent among different countries but also across sectors, e.g. a telecommunication company of average market capitalization might be considered large in the Basic Materials sector. Furthermore, regarding medians, Panel B reveals considerable positive skewness in the distributions of market capitalizations within most single country/sector combinations.

[1] One sample company had to be excluded due to erroneous data.

Table 1: Number and Capitalizations of Sample Companies by Industry and Country

Panel A illustrates the number of sample companies broken down to sector and country affiliations denoted in million Euro. The subsequent Panel B shows the market capitalization of the considered firms, averaged across the respective companies and over time. The number in parentheses denote the corresponding medians.

Panel A	BMATR	CNSMG	CNSMS	FINAN	HLTHC	INDUS	OILGS	TECNO	TELCM	UTILS	TOTAL
Austria	5	3	2	18	1	13	2	0	1	4	49
Belgium	6	12	8	29	7	13	0	8	2	3	88
Finland	7	3	5	4	1	19	1	3	1	1	45
France	8	42	48	43	15	49	7	26	2	8	248
Germany	17	34	22	56	17	63	1	14	2	9	235
Ireland	5	11	6	7	4	11	3	5	1	0	53
Italy	6	23	15	54	3	28	5	4	3	12	153
Luxembourg	1	4	4	14	0	3	0	0	0	3	29
Netherlands	6	16	17	29	3	39	2	15	2	0	129
Portugal	4	4	12	6	1	16	0	3	2	1	49
Spain	9	18	12	31	6	27	2	4	2	8	119

Panel B											
Austria	586.84 (321.27)	249.35 (229.61)	461.29 (461.29)	1,172.38 (408.42)	282.11 (282.11)	563.21 (329.48)	1,844.96 (1,844.96)	– (–)	4,868.42 (4,868.42)	807.04 (791.97)	920.37 (329.48)
Belgium	1,335.24 (656.57)	1,269.85 (138.43)	1,042.77 (597.56)	1,931.04 (216.27)	944.82 (445.78)	657.91 (419.95)	– (–)	206.04 (163.43)	6,447.29 (6,447.29)	616.14 (230.01)	1,353.98 (263.23)
Finland	2,372.24 (1041.30)	458.19 (526.23)	704.11 (756.78)	942.29 (428.77)	1,431.55 (1,431.55)	546.13 (444.68)	6,308.82 (6,308.82)	19,316.53 (1,286.21)	2,041.06 (2,041.06)	7,003.16 (7,003.16)	2,452.90 (640.99)
France	3,056.69 (1,837.21)	2,943.38 (439.99)	2,605.85 (500.70)	3,932.22 (883.64)	2,635.93 (310.52)	2,152.44 (662.08)	9,101.61 (940.29)	2,490.54 (562.64)	32,373.54 (32,373.54)	16,025.64 (6,236.93)	3,647.14 (601.15)
Germany	3,482.23 (854.33)	3,352.12 (358.35)	1,849.58 (932.20)	3,245.57 (941.12)	1,590.02 (626.75)	1,755.24 (402.65)	276.66 (276.66)	3,116.83 (800.62)	40,769.68 (40,769.68)	6,192.41 (1,187.78)	3,027.75 (627.97)
Ireland	26.47 (13.95)	531.94 (467.73)	886.09 (325.43)	2,748.52 (1,700.55)	1,268.02 (215.84)	729.91 (124.69)	88.49 (34.67)	164.85 (99.24)	1,618.94 (1,618.94)	– (–)	874.52 (190.99)
Italy	1,319.05 (245.01)	1,587.34 (570.92)	1,923.15 (1,312.21)	2,905.43 (1,182.18)	622.22 (641.44)	968.52 (440.90)	12,614.08 (2,183.50)	2,460.66 (1,895.64)	5,262.14 (3,143.24)	5,507.87 (1,798.10)	2,705.51 (849.68)
Luxembourg	5.22 (5.22)	178.22 (148.38)	33.68 (37.24)	94.64 (41.08)	– (–)	81.56 (7.36)	– (–)	– (–)	– (–)	88.80 (47.08)	92.72 (47.08)
Netherlands	2,360.29 (1,042.54)	4,612.64 (995.37)	1,824.14 (466.43)	4,452.93 (450.23)	181.22 (135.69)	652.20 (165.68)	844.73 (844.73)	1,005.76 (261.76)	9,171.55 (9,171.55)	– (–)	2,396.96 (363.24)
Portugal	237.04 (73.27)	57.18 (40.69)	667.43 (310.41)	1,503.59 (890.90)	6.25 (6.25)	481.54 (121.13)	– (–)	106.98 (114.52)	4,726.04 (4,726.04)	8,854.34 (8,854.34)	909.10 (129.64)
Spain	340.56 (171.31)	482.81 (174.36)	2,874.12 (2,098.94)	2,874.39 (840.88)	548.69 (362.57)	1,154.00 (481.01)	9,353.60 (9,353.60)	361.57 (210.15)	37,124.80 (37,124.80)	5,349.06 (3,080.59)	2,579.81 (643.93)

Key: BMATR = Basic Materials, CNSMG = Consumer Goods, CNSMS = Consumer Services, FINAN = Financial Services, HLTHC = Health Care, INDUS = Industrials, OILGS = Oil & Gas, TECNO = Technologies, TELCM = Telecommunications, UTILS = Utilities

As our observations are not consisting of a random sample of firms there are potential sources of bias: Thomson Financial does not provide historical constituent lists inducing survivorship bias. However, firm's failure due to default should only be of minor importance as we solely include companies with the highest market capitalizations. Yet, events attributable to mergers and acquisitions are able to generate survivorship bias. This should be of negligible magnitude, however. Furthermore, it influences correlations only to a minor extent.

The correlation structures of weekly returns for the sample countries and industries before and after the introduction of the Euro are illustrated in Tables 2 and 3. Time series were calculated as value-weighted portfolio returns including the sample with the 60% highest market capitalization. This choice seems a bit arbitrary at first sight. However, it seeks to prevent the results from being influenced by small firms with low liquidity. On the other hand, as we include firms revealing the highest capitalization, our sample is likely to be over-populated by companies which outperformed in preceding observation periods inducing bias in case of possibly existing momentum effects.

Focusing on country correlations, the increase of correlation coefficients is mainly due to the increasing dependence between the highly capitalized markets in Germany and France. Its correlation has risen from 0.72 before the EMU to 0.88 afterwards. This finding is also illustrated in Figure 1 which plots pre-Euro country correlations against their respective counterparts after the introduction of the EMU. In connection with Table 2, it can clearly be seen that highly correlated countries (mainly Germany and France) become even more closely connected after 1999. For both countries eight out of ten correlations have risen. The best examples for Euro integration are Italy and Luxembourg where all the correlations with the other EMU countries have increased. The counter-examples are Austria and Ireland where eight out of ten correlations have decreased. For the case of Ireland this might be due to the special economic situation and its long lasting boom in the economy.

Regarding sector correlations in Table 3, a decline of Pearson's coefficient is observable in 35 of 45 cases, which is also illustrated in Figure 1. Especially, the Healthcare, Oil & Gas and the Utilities sector all show only declining correlations. Not surprisingly the lowest value is with 0.11 the correlation between Oil & Gas and Telecommunications. It is striking that the Telecommunications sector is related to five of the remaining ten coefficients that increased. This increase may mainly be attributable to the technology boom after 1999. Another four rising correlations are due to the Financial Services sector.

For the analysis of the momentum strategies we rely on monthly data and use investible sector indices, namely the Dow Jones EURO STOXX Sector indices. These index categories are finer since the following 18 industries are included: Automobiles & Parts, Banks, Basic Resources, Chemicals, Construction Materials, Financial Services, Food & Beverages, Health Care, Industrial Goods & Services, Insurance, Media, Oil & Gas, Personal & Household Goods, Retail, Technology, Telecommunication, Travel & Leisure, and Utilities. On all these sector indices Dow Jones EURO STOXX Sector Index Futures are available which leads to an easy implementation of the strategy. According to Griffin and Karolyi (1998) this finer industry definitions should not change the results.

Table 2: Correlation Matrix for the Euro Zone Countries Before and After the Introduction of the EMU

Correlations are computed using value-weighted portfolios including sample companies displaying the highest 60% of the respective country market capitalization on each observation day. Panel "Pre-Euro" uses data from July 1992 until the introduction of the Euro in January 1999. "Post-Euro" includes observations from January 1999 until July 2006.

Pre-Euro	AT	BG	FN	FR	BD	IR	IT	LX	NL	PT
BG	0.4744									
FN	0.3603	0.4993								
FR	0.4918	0.5623	0.4665							
BD	0.5622	0.6228	0.5510	0.7221						
IR	0.4022	0.4727	0.4692	0.4733	0.5204					
IT	0.3151	0.4309	0.3737	0.4892	0.5061	0.3416				
LX	0.0518	0.0374	0.0420	0.0418	0.0537	0.0343	-0.0461			
NL	0.5093	0.6666	0.5488	0.6643	0.7481	0.5523	0.4737	0.0077		
PT	0.3523	0.4257	0.3188	0.4320	0.4852	0.3314	0.2754	0.0838	0.4496	
ES	0.4979	0.5102	0.4748	0.6012	0.6494	0.4806	0.5149	0.0176	0.6433	0.4502

Post-Euro	AT	BG	FN	FR	BD	IR	IT	LX	NL	PT
BG	0.3877									
FN	0.1151	0.3819								
FR	0.3111	0.7416	0.6492							
BD	0.3226	0.6967	0.6159	0.8817						
IR	0.2678	0.4409	0.2864	0.4709	0.4472					
IT	0.3920	0.7138	0.4338	0.8306	0.7634	0.4804				
LX	0.0718	0.2332	0.0707	0.2137	0.1898	0.0532	0.2498			
NL	0.3535	0.8312	0.5742	0.8798	0.8585	0.4560	0.7961	0.2493		
PT	0.0955	0.3252	0.4304	0.5359	0.5175	0.1952	0.4292	0.1462	0.4724	
ES	0.2747	0.6157	0.5800	0.7919	0.7785	0.4416	0.7151	0.1744	0.7537	0.5392

Key: AT = Austria, BG = Belgium, LX = Luxembourg, FN = Finland, FR = France, BD = Germany, IR = Ireland, IT = Italy, NL = Netherlands, ES = Spain, PT = Portugal

Table 3: Correlation Matrix for Industrial Sectors Before and After the Introduction of the EMU

Correlations are computed using value-weighted portfolios including sample companies displaying the highest 60% of the respective European-wide industry market capitalization on each observation day. Panel “Pre-Euro” uses data from July 1992 until the introduction of the Euro in January 1999. “Post-Euro” includes observations from January 1999 until July 2006.

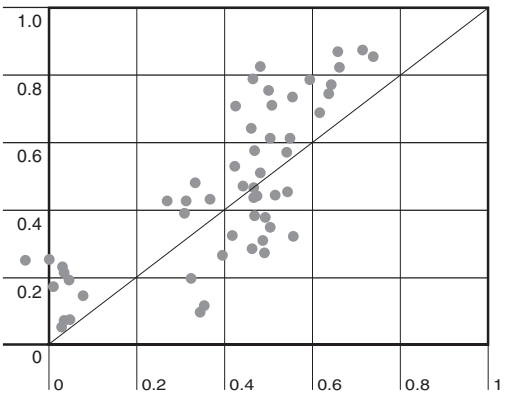
Pre-Euro	BMATR	CNSMG	CNSMS	FINAN	HLTHC	INDUS	OILGS	TECNO	TELCM
CNSMG	0.7838								
CNSMS	0.7606	0.8266							
FINAN	0.7116	0.7912	0.7243						
HLTHC	0.6813	0.6706	0.6941	0.6112					
INDUS	0.7816	0.8213	0.7960	0.7851	0.6783				
OILGS	0.4849	0.6141	0.5622	0.5200	0.5418	0.5847			
TECNO	0.6098	0.7143	0.6351	0.6544	0.5718	0.7222	0.4840		
TELCM	0.4015	0.4832	0.4787	0.4572	0.3741	0.4272	0.3810	0.4092	
UTILS	0.6969	0.6981	0.7156	0.7015	0.6365	0.7112	0.5807	0.5677	0.4910

Post-Euro	BMATR	BMATR	CNSMS	FINAN	HLTHC	INDUS	OILGS	TECNO	TELCM
CNSMG	0.7771								
CNSMS	0.6125	0.7533							
FINAN	0.7462	0.8231	0.7570						
HLTHC	0.4035	0.5386	0.4544	0.5905					
INDUS	0.7342	0.7808	0.8182	0.7608	0.3575				
OILGS	0.4760	0.4767	0.3259	0.5024	0.4524	0.4013			
TECNO	0.4605	0.6303	0.6646	0.5830	0.3361	0.7179	0.2374		
TELCM	0.3432	0.5126	0.6647	0.5382	0.2650	0.6192	0.1093	0.6558	
UTILS	0.5735	0.6382	0.5461	0.6876	0.5367	0.5313	0.4858	0.3630	0.3512

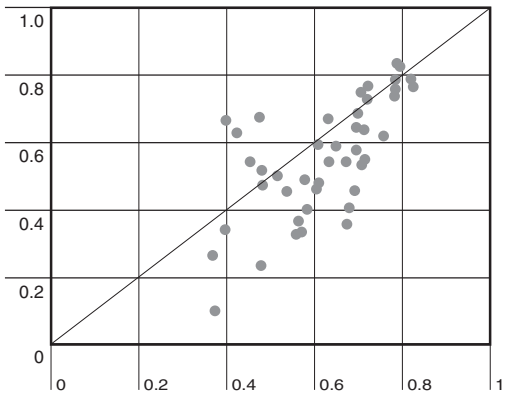
Key: BMATR = Basic Materials, CNSMG = Consumer Goods, CNSMS = Consumer Services, FINAN = Financial Services, HLTHC = Health Care, INDUS = Industrials, OILGS = Oil & Gas, TECNO = Technologies, TELCM = Telecommunications, UTILS = Utilities

Figure 1: Plot of Correlations Pre- and Post-Euro Introduction

Country Correlations



Sector Correlations



3. Country versus Sector Impact

We distinguish between country and industry effects following a similar approach to the setting of Flavin (2004) originally implemented by Heston and Rouwenhorst (1994). The return of a stock *i* at time *t* located in country *k* and taking part of industry *j* is described by:

$$\tilde{R}_{it} = \alpha_t + \beta_{jt} + \gamma_{kt} + \tilde{\epsilon}_{it}, \qquad (3.1)$$

where α influences the returns of all stocks. β_j is the factor loading describing the industry effect and γ_k the respective country effect. This framework neglects any dependencies between return's in°uences due to industry and country. In order to estimate our model we define industry dummies, I_{ij}, that take the value of one if stock *i* belongs to industry *j* and country dummies C_{ik} that take a value of one if stock *i* belongs to country *k* and zero otherwise. Therefore, with $I = 10$ industries and $C = 11$ countries equation 3.1 yields:

$$\tilde{R}_{it} = \alpha + \sum_{j=1}^{I} \beta_j \cdot I_{ij} + \sum_{k=1}^{C} \gamma_k \cdot C_{ik} + \tilde{\epsilon}_{it}, \qquad (3.2)$$

where $\tilde{\epsilon}$ denotes the firm-specific disturbances. They are assumed to have zero mean and finite variance.

Due to the identification problem resulting from the fact that each company belongs to one single country and sector, respectively, a regression estimation would end up in perfect correlation among the regressors – the "dummy variable trap". Flavin (2004), as well as Heston and Rouwenhorst (1994) set further restrictions on the regression equation. However, as Flavin (2004) states, significance tests on the regressors are frequently rejected. He mainly attributes this observation to the fact that the expected abnormal return, driven by sector and country effects reveal to be small. However, we believe that there are several additional aspects to mention. For t-tests to be applicable, the underlying distribution of the test statistic must follow a $t_{(T-(I+C)-1)}$ distribution with the subscript denoting the degrees of freedom. Therefore, $\tilde{\epsilon}_{it}$ has to follow a Gaussian distribution, otherwise rejections of the null hypothesis are not solely attributable to significance. However, this assumption often turns out to be inappropriate. First, the return's expectation values are determined to be $\alpha + \sum_{j=1}^{I} \beta_j \cdot I_{ij} + \sum_{k=1}^{C} \gamma_k \cdot C_{ik}$. This implies the assumption that every return driving factor is included in the framework and ignores any additional systematic influences on $\tilde{R}_i$. Missing return generating factors would inevitably lead to cross sectional correlations among error terms resulting in misspecified test statistics.[2] Furthermore, the proposed setting requires the error terms to be symmetric. This assumption was typically maintained referring to diversification effects occurring in large portfolios. However, this requirement is frequently not met in all country/sector combinations leading

[2] See, for example Lyon, Barber, and Tsai (1999).

to asymmetric error distributions. Furthermore, most settings implicitly require firm-specific disturbances to be homoscedastic over all country/sector combinations. The violation of these assumptions in turn leads to flawed test statistics.

In order to circumvent these problems, we estimate the distribution of the regressors by the application of bootstrap methods.[3] As we only include dummy variables in our framework and need not estimate the regressor's standard errors, we are in the position to avoid regression methods for the estimation and apply a standard ANOVA framework. This solves the problem resulting from the "dummy variable trap". Furthermore, our framework also allows for dynamic changes of regressor values over time. For the formation of the value-weighted sample portfolios, stocks are again chosen according to the rule that 60% of the entire market capitalization on each observation day are included. We form 100 portfolios at every time step. The samples are drawn with replacement. With N_s denoting the number of firms in sample *s*, the estimation of α brakes down to

$$\hat{\alpha} = \frac{1}{N_s} \Sigma_{i=1}^{N_S} R_{is}.$$

Industry and country effects turn out to be

$$\hat{\beta}_j = \frac{1}{N_{js}} \Sigma_{i=1}^{N_S} I_{ij} R_{is} - \hat{\alpha}$$

and

$$\hat{\gamma}_k = \frac{1}{N_{ks}} \Sigma_{i=1}^{N_S} C_{ik} R_{is} - \hat{\alpha}.$$

N_{js} and N_{ks} stand for the number of firms belonging to sector j or country k, respectively.

[3] For a deep and broad survey of the bootstrap, we refer to Shao and Tu (1995).

4. Bootstrap Results

Applying the framework outlined in the previous section, we investigate whether fund managers should concentrate on portfolio construction based on country or industry diversification. We include observations of the entire sample from July 1992 until July 2006. The interpretation of our results resembles those of previous work as Flavin (2004), as well as Heston and Rouwenhorst (1994), who consider the regressors as tracking errors from a benchmark portfolio. In our setting, the intercept term α describes the average return generated by the firms of the entire sample. Deviations from α due to country or industry affiliations are captured by γ and β, respectively. Table 4 illustrates descriptive statistics of the regressor's distributions denoted in per cent per week.

The intercept α in our sample is 34 basis points. As an example, our results reveal that placing 10% more in the Health Care sector – the sector with the highest impact – than in a randomly composed European portfolio would result in an average outperformance of 36 basis points. Similarly, over-weighting Austrian equities by 10% would lead to an average underperformance of about twelve basis points while the impact in Luxembourg with the lowest value is 13 basis points. The overall importance of the sector and country effects can be judged by regarding the average regressor's values. While industry effects account for 0.0821 basis points over the entire sample, country effects, while still positive, only make up 0.0009 basis points on average. Therefore, industry effects are more important according to our framework.

Table 4 also reveals the extreme skewness of regressors' distributions. This seems to be a direct result of sample firms' non-symmetric distributions within sectors and countries, as shown in Panel B of Table 1. Compared to the magnitude of the means, which make up only a few basis points on average, the estimated standard errors of the regressors are extremely high. This phenomenon is in line with the results of previous work, such as Flavin (2004), and Heston and Rouwenhorst (1994). The presence of positive extreme values directly leads to an over-estimation of standard errors as well as the regressor's mean. As numerators and denominators of the t-test statistics are no longer independent of each other, rejection rates are flawed and standard significance tests are no longer applicable. The same argument holds for negative extreme values.

Therefore, we also report sample medians. These reveal the same pattern as averages. While the over-weighting of industry portfolios would result in an outperformance of 0.0258 basis points, a bet on country effects would even lead to an underperformance of 0.0535 basis points a week. Therefore, it seems to be advisable to concentrate on industry diversification when it comes to portfolio formation.

Table 4: Descriptive Statistics of Country and Industry Effects Using Bootstrap Regressions (%)

Descriptive statistics of the bootstrapped regressors. On each step in time 100 sample portfolios are drawn with replacement. They cover 60 % of the entire market capitalization on each observation day.

	Mean	Median	Std.dev.	Skewness
α	0.3412	0.4611	1.7146	21.88
Sector (β)				
BMATR	-0.0358	-0.0947	1.4902	-9.10
CNSMG	-0.0141	-0.0315	1.0040	44.60
CNSMS	-0.0326	-0.0469	1.0079	-286.98
FINAN	-0.0401	-0.0298	0.8162	-622.74
HLTHC	0.3600	0.0083	10.8015	5,203.00
INDUS	-0.0107	-0.0057	0.7293	-555.43
OILGS	0.1311	0.0275	2.7810	209.08
TECNO	0.1948	0.0188	3.1985	242.31
TELCM	0.0214	0.0000	3.9788	120.70
UTILS	-0.0126	-0.0234	1.4909	-36.33
Average	0.0821	0.0258		

	Mean	Median	Std.dev.	Skewness
α				
Country (γ)				
AT	0.1197	-0.1289	1.7383	-78.16
BG	0.0554	-0.0506	1.2547	-176.61
FN	0.1221	0.0837	2.1385	51.34
FR	0.0438	0.0415	1.0117	-296.42
BD	0.0619	-0.0666	0.9882	-463.70
IR	0.1691	0.0045	2.4126	121.90
IT	0.0477	-0.0887	1.8674	29.15
LX	0.1337	-0.2227	2.0917	212.90
NL	0.0404	-0.0197	1.1252	-280.40
PT	0.0129	-0.1376	2.9436	1,323.08
ES	0.1210	-0.0032	3.9468	3,919.74
Average	0.0009	-0.0535		

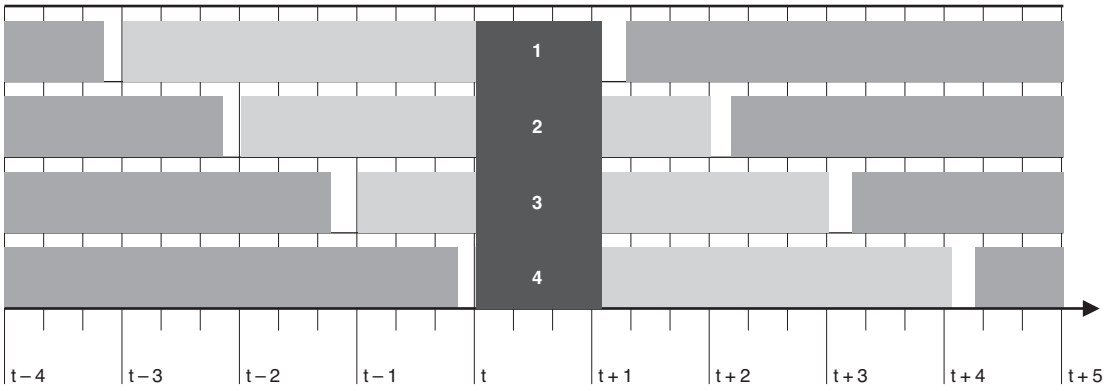
Key: BMATR = Basic Materials, CNSMG = Consumer Goods, CNSMS = Consumer Services, FINAN = Financial Services, HLTHC = Health Care, INDUS = Industrials, OILGS = Oil & Gas, TECNO = Technologies, TELCM = Telecommunications, UTILS = Utilities, AT = Austria, BG = Belgium, LX = Luxembourg, FN = Finland, FR = France, BD = Germany, IR = Ireland, IT = Italy, NL = Netherlands, ES = Spain, PT = Portugal

5. Momentum Strategies for Countries and Sectors

The results in the previous section, especially the importance of industry factors with respect to country factors indicate that an active strategy based on sectors may yield a better performance than a country rotation strategy. Out of the huge number of possible active asset allocation models we choose momentum strategies since they are easy to implement. Furthermore, they do not rely on country or industry specific factors that would make a comparison between country and sector strategies impossible. The momentum strategies are solely based on historic stock performance.

Our momentum models are implemented according to the framework of Jegadeesh and Titman (1993), who find that in the medium term momentum strategies yield significant excess returns. During formation periods we employ a sorting approach to determine the best-performing sectors or countries. Following previous research, we apply zero-investment portfolios in line with Fama and French (1998) and Rouwenhorst (1999b) that can be easily implemented with Dow Jones EURO STOXX Sector Index Futures. During the holding period we take a long position in the best and contemporaneously a short position of equal magnitude in the worst performing country (industry). We further implement the models going long the two best and short the two worst performing countries (industries). Although rebalancing on a daily basis would be possible, this is not realistic for practitioners. In line with previous research of e.g. Fama and French (1992) or Jegadeesh and Titman (1993) our portfolios are rebalanced on a monthly basis.

Figure 2: Portfolio Formation Process for Selection and Holding Periods of Four Months



Following Jegadeesh and Titman (1993), as well as Rouwenhorst (1998), different momentum strategies are tested for holding periods between one and four months. Figure 2 displays the formation and portfolio holdings for the four-month strategy. Based on the returns during the preceding four months, the industry or country portfolios are ranked. According to this ranking, the active portfolio is selected and held for another four months. This procedure is repeated each month based on the rolling four-month

window and, therefore, at each point in time, four different portfolios sum up to the total holding. The advantage of this methodology is that monthly time variations of factor returns are isolated.

We implement the strategies without lag between the formation period and the holding period. In addition, a second framework considers a lag of one month after portfolio formation in order to avoid the short-term return reversal discovered by Jegadeesh (1990) and Lehmann (1990) as in Jegadeesh and Titman (1993) and Rouwenhorst (1998).

In the following, we present results for formation periods for one up to four months. They are based on ten MSCI country indices of the EMU countries excluding Luxembourg and 18 Dow Jones EURO STOXX Sector indices, namely Automobiles & Parts, Banks, Basic Resources, Chemicals, Construction Materials, Financial Services, Food & Beverages, Health Care, Industrial Goods & Services, Insurance, Media, Oil & Gas, Personal & Household Goods, Retail, Technology, Telecommunication, Travel & Leisure, and Utilities.

The Sharpe ratios of the corresponding strategies are tested for difference according to Jobson and Korkie (1981), i.e., we compare a sector strategy directly with its country counterpart. The test statistics are approximately normally distributed and calculated as

$$Z = \frac{\tilde{r}_1 \sigma_2 - \tilde{r}_2 \sigma_1}{\sqrt{\theta}}, \qquad (5.1)$$

where

$$\theta = \frac{1}{T}\left[2\sigma_1^2\sigma_2^2 - 2\sigma_1^2\sigma_2^2\rho + \frac{1}{2}\tilde{r}_1^2\sigma_2^2 + \frac{1}{2}\tilde{r}_2^2\sigma_1^2 - \frac{\tilde{r}_1\,\tilde{r}_2}{2\sigma_1\,\sigma_2}(\rho^2\sigma_1\,\sigma_2 - \sigma_1\,\sigma_2)\right].$$

$\tilde{r}i$ denotes the average excess return of portfolio *i* and σ_i is its standard deviation. ρ stands for the correlation coefficient between the excess returns of the two portfolios and, finally, T represents the number of observations.

Table 5 reports the results for the strategies with one month formation and holding periods. The implementations without lags leads to higher returns of the country strategies while the lag of one month between formation and holding periods yields better returns for portfolio formation based on sectors. All Sharpe ratios of the industry (country) strategies are significantly different on a level of 1% from their respective country (industry) counterparts. Volatilities are higher for the strategies going two sectors (countries) long and short than the strategies that only invest in the best and worst sector (country). But in three out of four cases the performance of these more sophisticated strategies is still better according to the Sharpe ratios.

The higher performance of the country strategies disappears as the results in Table 6 for two months formation and holding periods strategies show. All country strategies yield negative returns leading to negative Sharpe ratios whereas portfolio formations based on industries show positive returns. Three out of four Sharpe ratios are significantly higher. Strategies incorporating a lag of one month end up with Sharpe ratios of 0.33 and 0.27 while those without lag show Sharpe ratios around zero, confirming the short-term contrarian effect. Table 7 displays the results for three months formation and holding period strategies and confirms these findings.

Table 5: Performance of the Momentum Strategies with Formation and Holding Periods of One Month

The upper panel reports the results for taking a long position in the best country (industry) and a short position of equal magnitude in the worst performing country (industry). The lower panel reports the results for going long the two best countries (industries) and simultaneously short in the worst two countries (industries). *** denotes significance on a level of 1% with respect to the corresponding country or industry strategy.

	no lag		**lag**	
	Countries	Industries	Countries	Industries
Return	22.15%	0.90%	-7.65%	4.48%
Volatility	30.71%	29.30%	29.60%	31.16%
Sharpe Ratio	0.62***	-0.07	-0.36	0.05***
Return	28.18%	7.06%	-12.35%	13.15%
Volatility	35.56%	45.44%	40.16%	46.39%
Sharpe Ratio	0.71***	0.09	-0.38	0.22***

Table 6: Performance of the Momentum Strategies with Formation and Holding Periods of Two Months

The upper panel reports the results for taking a long position in the best country (industry) and a short position of equal magnitude in the worst performing country (industry). The lower panel reports the results for going long the two best countries (industries) and simultaneously short in the worst two countries (industries). **/*** denotes significance on a level of 5%/1% with respect to the corresponding country or industry strategy.

	no lag		**lag**	
	Countries	Industries	Countries	Industries
Return	-0.91%	3.09%	-12.02%	11.71%
Volatility	27.54%	26.47%	23.39%	26.20%
Sharpe Ratio	-0.14	0.00	-0.64	0.33***
Return	-4.36%	2.81%	-17.66%	14.50%
Volatility	36.01%	44.59%	33.13%	42.64%
Sharpe Ratio	-0.20	0.00**	-0.62	0.27***

Table 7: Performance of the momentum strategies with formation and holding periods of three months

The upper panel reports the results for taking a long position in the best country (industry) and a short position of equal magnitude in the worst performing country (industry). The lower panel reports the results for going long the two best countries (industries) and simultaneously short in the worst two countries (industries). **/*** denotes significance on a level of 5%/1% with respect to the corresponding country or industry strategy.

	no lag		lag	
	Countries	Industries	Countries	Industries
Return	-7.59%	9.45%	-2.28%	11.05%
Volatility	23.14%	28.43%	22.25%	27.00%
Sharpe Ratio	-0.46	0.23***	-0.24	0.30***
Return	-1.43%	15.64%	4.57%	17.77%
Volatility	31.67%	44.59%	30.14%	43.17%
Sharpe Ratio	-0.14	0.28***	0.05	0.34**

Three out of four country strategies show negative returns while all industry strategies reveal significantly positive Sharpe ratios. The value of 0.34 for the lagged strategy with two industries long and two industries short is well above 0.05 of the respective country strategy. Our results of four months formation and holding period strategies in Table 8 reveal a somewhat mixed picture.

All trading strategies end up with positive returns and Sharpe ratios. The Sharpe ratios for the portfolio formation without lags are smaller for country diversification while the opposite holds for the lagged strategies.

In general, the momentum strategies across industries work better than the respective country frameworks: twelve out of the 16 industry strategies show higher Sharpe ratios than the respective country counterparts – eight of them are significantly higher. On the other hand, only three country strategies show significantly higher Sharpe ratios than their industry equivalents.

6. Summary and Conclusion

In line with most of previous research we have shown the increasing importance of industry diversification with respect to country diversification after the introduction of the EMU. Due to the bootstrap method we avoid the problems encountered by other studies with their relatively small sample sizes. Furthermore, we extend the analysis to weekly data which reduces the correlations but leads to the same general picture: country effects are dominated by industry effects to a large extent.

Table 8: Performance of the Momentum Strategies with Formation and Holding Periods of Four Months
The upper panel reports the results for taking a long position in the best country (industry) and a short position of equal magnitude in the worst performing country (industry). The lower panel reports the results for going long the two best countries (industries) and simultaneously short in the worst two countries (industries). ** denotes significance on a level of 5% with respect to the corresponding country or industry strategy.

	no lag		lag	
	Countries	Industries	Countries	Industries
Return	7.50%	10.65%	10.28%	8.92%
Volatility	24.33%	28.28%	25.48%	27.68%
Sharpe Ratio	0.19	0.27	0.29	0.21
Return	8.56%	14.47%	17.04%	12.30%
Volatility	30.37%	45.63%	31.25%	42.53%
Sharpe Ratio	0.18	0.25	0.45**	0.22

This indicates that active strategies based on industries may lead to better outcomes than strategies based on countries. We test this with momentum strategies built upon countries and Dow Jones EURO STOXX Sector indices which yield an easy practical implementation of such a dynamic strategy since exchange listed derivatives on these underlyings are available. The results are clear: Most of the industry strategies significantly outperform the respective country frameworks on a risk adjusted basis. There is more industry momentum than country momentum in stock prices. Of course, the strategies need further improvement and cannot be applied without refinement but they sustain the general notion that an active strategy involving sector rotation dominates country rotation after the introduction of the Euro.

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