EUROPEAN CENTRAL BANK

WORKING PAPER SERIES

NO. 425 / JANUARY 2005

ECB-CFS RESEARCH NETWORK ON CAPITAL MARKETS AND FINANCIAL INTEGRATION IN EUROPE

GEOGRAPHIC VERSUS INDUSTRY DIVERSIFICATION

CONSTRAINTS MATTER

by Paul Ehling and Sofia Brito Ramos

EUROPEAN CENTRAL BANK

WORKING PAPER SERIES

NO. 425 / JANUARY 2005

ECB-CFS RESEARCH NETWORK ON CAPITAL MARKETS AND FINANCIAL INTEGRATION IN EUROPE

GEOGRAPHIC VERSUS INDUSTRY DIVERSIFICATION

CONSTRAINTS MATTER [1]

by Paul Ehling [2]

and Sofia Brito Ramos [3]

In 2005 all ECB publications will feature a motif taken from the €50 banknote.

1 This paper supersedes "Geographical versus Industrial Diversification: A Mean Variance Spanning Approach". Financial support from the National Center of Competence in Research, "Financial Valuation and Risk Management" (Ehling) and the Fundacao para a Ciencia e Tecnologia (Ramos), is gratefully acknowledged. The National Center of Competence in Research is managed by the Swiss National Science Foundation on behalf of the Swiss federal authorities. We would like to thank Gopal Basak, Jean-Pierre Danthine, Vihang Errunza, Christian Gourieroux, Albert Holly, Raymond Kan, Michael Rockinger, Olivier Scaillet, René Stulz, Ernst-Ludwig von Thadden, seminar participants at the FAME Workshops, the 5th Conference of the Swiss Society for Financial Market Research (2002), the Euro Conference at NYU (2002), the University of Geneva seminar, the ECB workshop on Capital Markets and Financial Integration in Europe (2002), the European Investment Review Conference (2002), the NFA Annual Meeting (2002), the Macro Brown Bag Lunch at the Wharton School (2003), MFA Annual Meeting (2003), CEMAF/ISCTE Lisbon (2003), and EFMA Annual Meeting (2003) for helpful discussions and comments.

2 Corresponding author. Finance Department, Smeal College of Business, 609P Business Administration Building, Pennsylvania State University, University Park, PA 16802-3008, United States; tel.: +1 814 865 5191; fax +1 814 865 3362; e-mail: pxe11@psu.edu

3 CEMAF/ISCTE, ISCTE-School of Business, Av. Forcas Armadas, edificio ISCTE, 1649-026 Lisboa, Portugal; e-mail: sofia.ramos@iscte.pt

ECB-CFS Research Network on
"Capital Markets and Financial Integration in Europe"

This paper is part of the research conducted under the ECB-CFS Research Network on "Capital Markets and Financial Integration in Europe". The Network aims at stimulating top-level and policy-relevant research, significantly contributing to the understanding of the current and future structure and integration of the financial system in Europe and its international linkages with the United States and Japan. After two years of work, the ECB Working Paper Series is issuing a selection of papers from the Network. This selection is covering the priority areas "European bond markets", "European securities settlement systems", "Bank competition and the geographical scope of banking activities", "international portfolio choices and asset market linkages" and "start-up financing markets". It also covers papers addressing the impact of the euro on financing structures and the cost of capital.

The Network brings together researchers from academia and from policy institutions. It has been guided by a Steering Committee composed of Franklin Allen (University of Pennsylvania), Giancarlo Corsetti (European University Institute), Jean-Pierre Danthine (University of Lausanne), Vítor Gaspar (ECB), Philipp Hartmann (ECB), Jan Pieter Krahnen (Center for Financial Studies), Marco Pagano (University of Napoli "Federico II") and Axel Weber (CFS). Mario Roberto Billi, Bernd Kaltenhäuser (both CFS), Simone Manganelli and Cyril Monnet (both ECB) supported the Steering Committee in its work. Jutta Heeg (CFS) and Sabine Wiedemann (ECB) provided administrative assistance in collaboration with staff of National Central Banks acting as hosts of Network events. Further information about the Network can be found at http://www.eu-financial-system.org.

The joint ECB-CFS Research Network on "Capital Markets and Financial Integration in Europe" aims at promoting high quality research. The Network as such does not express any views, nor takes any positions. Therefore any opinions expressed in documents made available through the Network (including its web site) or during its workshops and conferences are the respective authors' own and do not necessarily reflect views of the ECB, the Eurosystem or CFS.

Address
Kaiserstrasse 29
60311 Frankfurt am Main, Germany

Postal address
Postfach 16 03 19
60066 Frankfurt am Main, Germany

Telephone
+49 69 1344 0

Internet
http://www.ecb.int

Fax
+49 69 1344 6000

Telex
411 144 ecb d

ISSN 1561-0810 (print)
ISSN 1725-2806 (online)

CONTENTS

Abstract

This research addresses whether geographic diversification provides benefits over industry diversification. In the absence of constraints, no empirical evidence is found to support the argument that country diversification is superior. With short-selling constraints, however, the geographic tangency portfolio is not attainable by industry portfolios. Results with upper and lower constraints on portfolio weights as well as an out-of-sample analysis show that geographic diversification almost consistently outperforms industry portfolios, although we cannot establish statistical significance.

JEL *classification*: G11, G15.

Keywords: Diversification gains, EMU, geographic diversification, industry diversification, block-bootstrap tests.

Non-technical summary

Stock returns are driven largely by country factors. This fact appears to hold even until recently, although industry effects in stock returns are on the rise. A related stylized piece of evidence is the much lower correlation of country indexes compared to industry indexes. Not surprisingly, the portfolio management industry adopted the country allocation model as means of a simplified diversification strategy.

Interestingly, however, there is little empirical evidence that country diversification has a significantly better performance than industry diversification. Further, restricting international portfolio diversification strategies to country (industry) dimension may well be costly. On top of that, even if factor dominance or correlation structures directly translate into superior performance, constraints on portfolio strategies can counteract these forces.

This paper deals with the question whether geographic portfolio allocation really offers benefits over industry motivated diversification strategies. Since neither the traditional approach of analyzing the influence of country factors in stock returns nor the naive comparison of average correlations allows to directly test for diversification gains we adopt a different strategy. Namely, we use a mean-variance efficiency test to address the performance of both diversification strategies.

Our approach allows us direct comparison of the two diversification strategies from a pure performance perspective without relying on unobservable country or industry factors. It is also possible to compare either strategy with any other benchmark of interest. Finally, and most important, the test is flexible enough to incorporate short sales constraints and even upper and lower bounds on portfolio positions, which is not analyzed in the previous literature. These appear to be meaningful issues as portfolio managers are generally under strict constraints that force them to follow a certain benchmark quite closely.

Overall we find unconstrained country and industry diversification to be statistically equivalent. This result is puzzling for three reasons. First, it implies that banks may have consistently been following the wrong approach. Second, it is contrary to the implications stemming from the country and industry factor methodology. Third, country indexes are on average much less correlated than industry indexes. Thus, conventional wisdom suggests that countries outperform industries.

Introducing short-selling constraints shrinks the efficient frontier of industry diversification dramatically. In particular, industry portfolios cannot attain the country tangency portfolio return. That is, the tests imply that the industry efficient frontier lies well inside the country frontier. Notice that the findings with short-selling constraints are exactly the opposite of our unconstrained results.

While it represents a more realistic approach, imposing short-selling constraints also leads to improbable portfolio weights, such as zero weights in representative countries of the EMU portfolio. To circumvent this issue, we introduce upper and lower constraints on the portfolio weights in order to capture constraints on portfolio strategies that might resemble common restrictions in the portfolio management industry due to indexing. Geographic diversification again dominates industry portfolios. However, the statistical evidence for a difference is weak.

In conclusion, we use a flexible methodology to measure the performance of geographic and industry diversification. Our results justify the focus on country diversification, however, only if portfolio constraints are introduced. Overall, the difference between the two analyzed strategies is small.

I. Introduction

Common practice in portfolio management is a top-down approach to asset allocation. A first step is to decide on country allocation weights, for instance. The second step involves the choice of representative stocks and their weights in the countries under consideration. Most banks in Europe have followed a geographical diversification strategy for international portfolios over the last decade.

Another approach is to determine the factors driving covariation in stock returns. Heston and Rouwenhorst (1994), for example[1], find that the country factor dominates the industry factor, and country diversification is typically a superior strategy.

The traditional choice of country diversification has come into question from two directions. First, events such as the deregulation of markets or the elimination of international barriers to capital movements are considered catalysts of market integration that may, therefore, affect the typical dominance of country factors[2]. The prime example is the European Monetary Union or EMU. It is often said that country-specific policy shocks will be dampened down as a result of a single monetary policy and coordinated fiscal policies constrained by the Stability and Growth Pact. Therefore, the top-down approach should now start at the industry or sector level. This seems to be accepted by large investment banks, and some have reorganized their research departments according to industry[3].

[1] See also Errunza and Padmanablan (1988), Grinold, Rudd and Stefek. (1989), Becker et al. (1992), Drummen and Zimmermann (1992), Roll (1992), Arshanapalli, Doukas and Lang (1997), Griffin and Karolyi (1998), Rouwenhorst (1999) and Heckman, Narayanan and Patel. (1998).

[2] "While country influences will continue to be important, the intra EMU-Europe activity will likely over time shift away from country level decisions, and more toward active stock and sector strategies". Global Equity and Derivative Markets, Special Edition: Europe. Morgan Stanley Dean Witter Quantitative Strategies, June 1998, 54-55.

[3] A survey by Goldman Sachs reports that 70% of portfolio managers interviewed had reconsidered their method of asset allocation, and 64% were willing to change to a sector basis allocation (Brookes (1999)).

Second, a number of empirical studies have found mixed results as to country and industry effects. Some of these studies provide evidence that industry factors are already more important than country factors (Cavaglia, Brightman and Aked (2000) and Galati and Tsatsaronis (2001)). The results of others suggest only that industry effects are becoming increasingly important while countries are losing explanatory power (Baca, Garbe and Weiss (2000); Brooks and Del Negro (2002a) and Isakov and Sonney (2003)). These findings do not support the view that industry factors are the most important. Most of the literature relies on the Heston and Rouwenhorst (1994) methodology, which itself has come under criticism because of the severe restrictions of the underlying factor model (see Brooks and Del Negro (2002b)).

The goal of this paper is to re-examine the performance of geographic and industry allocation. We use a mean-variance efficiency test proposed by Basak, Jagannathan, and Sun (2002) (hereafter BJS (2002)) to address the performance of both diversification strategies. The test measures the difference between the variance of a benchmark and a mimicking portfolio with identical returns. We also introduce a block-bootstrap version of the BJS (2002) test to assess its small-sample properties.

Our approach allows us direct comparison of the two diversification strategies from a pure performance perspective without relying on unobservable country or industry factors. It is also possible to compare either strategy with any other benchmark of interest. Furthermore, the test is flexible enough to incorporate short sale constraints and upper and lower bounds on portfolio positions, which are not analyzed in the previous literature. These appear to be meaningful issues as portfolio managers are generally under strict constraints that force them to follow a certain benchmark quite closely.

We focus on weekly country and sector index data of the EMU entrants during January 1991-September 2003. The sample is also divided into different subperiods, *pre-convergence*, *convergence* and *euro*, not only to capture time patterns but also to identify effects that may stem from actions undertaken by the new monetary authority.

Over the full sample period, 1991-2003, we find unconstrained geographic and industry diversification to be statistically equivalent. Our results also suggest no major differences across the subperiods. The signs of the BJS test, 11 out of 12 signs, indicate that the industry efficient frontier lies outside the country frontier, although the tests show no statistical significance. Thus, in the case of unconstrained diversification, we find no empirical evidence to support the argument that geographic diversification is a superior approach.

This result is puzzling for three reasons. First, it implies that banks may have consistently been following the wrong approach. Second, it is contrary to the implications of the Heston and Rouwenhorst (1994) methodology. Third, country indexes are on average much less correlated than industry indexes. Thus, conventional wisdom suggests that country diversification should outperform industry diversification.

Introducing short-selling constraints shrinks the efficient frontier of industry diversification dramatically. In particular, industry diversification cannot attain, over the entire sample and in two of three subperiods, the country tangency portfolio return. That is, the tests suggest that the industry efficient frontier lies well inside the country frontier. Notice that the findings with short-selling constraints are exactly the opposite of our unconstrained results. It is intriguing that the importance of low correlation between the ingredients of a portfolio emerges only in the constrained optimization.

A possible explanation for the poor performance of country allocation in the absence of constraints is that industry indexes are more exposed to the dominant single factor in equity returns. Green and Hollifield (1992) argue that if stocks or, even worse indexes, are highly correlated and exhibit a high diversity of betas, then we can form portfolios with essentially zero factor risk. Such a portfolio, however, will take a large negative position in one stock or an index to finance an even larger positive position in another stock, or index.

Industry indexes are not only more highly correlated than countries, but also show a much greater diversity of betas with respect to the EMU index. This suggests that industry portfolios are better suited to eliminate the factor risk stemming from the single dominant factor in stock returns, e.g., the EMU index. It also implies that industry diversification must be affected to a much greater extent than geographic diversification when short-selling constraints are imposed.

As for comparison with other benchmarks, the efficiency of a passive benchmark like the EMU index is always rejected whether short-selling constraints are imposed or not. In other words, both geographic and industry diversification have a significantly lower standard deviation than the EMU index[4]. A structure with a lower level of aggregation, such as industry-country pairs, clearly outperforms both industry and geographic diversification in an unconstrained or constrained optimization.

While it represents a more realistic approach, imposing short-selling constraints also leads to improbable portfolio weights, such as zero weights in some representative countries of the EMU portfolio (corner solutions). To circumvent this issue, we introduce upper and lower constraints on the portfolio weights in order to capture constraints on portfolio strategies that might resemble common restrictions in the portfolio management industry due to indexing. Geographic diversification again dominates industry, although the tests do not always show statistical significance.

Our block-bootstrap analysis provides a rich set of information: First, it establishes that the p-values of the BJS (2002) test are robust in small samples.

Second, it shows that unconstrained portfolio weights have large estimation errors, which are subsequently reduced when constraints are introduced. In particular, we find that bootstrap confidence intervals for unconstrained minimum variance portfolio weights are so wide that they always include the origin. Of course, the confidence in-

[4] This is, of course, not surprising since both diversification strategies essentially eliminate the EMU factor risk.

tervals for unconstrained tangency portfolios are much wider. Because portfolio weights are important ingredients for the BJS (2002) test it is not surprising that the test lacks the power to reject the null hypothesis. This result supports what has been a frequent conjecture in previous analyses of mean-variance efficiency tests, and adds to our understanding why power is lacking.

Third, out-of-sample results, based on the portfolio weights from the block-bootstrap analysis, provide supportive evidence for the argument that controlling estimation error through the use of constraints is overall beneficial for portfolio performance. Our results also indicate that geographic diversification performs better independently of whether portfolio constraints are introduced or not, but we cannot distinguish the strategies statistically.

Recent research also addresses country and industry diversification strategies but use a different methodology. Hillion and de Roon (2002), for example, use mean-variance spanning tests (See also Eiling, Gerard and de Roon.). Their analysis incorporates the risk-free rate, so they test performance of country strategies versus industry diversification only at the corresponding tangency portfolio. We apply the BJS (2002) test to the minimum-variance portfolio also, with a methodology flexible enough to incorporate important restrictions such as short-selling and upper and lower bounds on portfolio weights, which are evidently of practical importance.

The Gerard, Hillion and de Roon (2002) results are consistent with our conclusions. They argue that without short sales restrictions, country and industry diversification are a redundant strategy relative to one another. Additionally, their industry portfolios are also more affected by short sales constraints than country portfolios, but the authors do not provide tests to support the argument.

This paper proceeds as follows: In Section I, we present the BJS (2002) test. Section II describes the data and reports the empirical results. Section III shows the distribution of the portfolio weights with and without constraints and section IV is devoted to an out-of-sample comparison of geographic and industry diversification. Concluding remarks follow in Section V. Finally, we describe our block-bootstrap simulations in the Appendix.

II. Test Methodology

This section presents the efficiency measure applied in the empirical analysis to investigate whether country diversification or industry diversification is the superior approach for an internationally diversified investor.

We measure the mean-variance efficiency of a diversification strategy using the Basak, Jagannathan, and Sun (2002) test. Let r be the return on any benchmark asset with well-defined first two moments, $E(r_t) = \beta$ and $Var(r_t) = \nu$, for $t \in [0, T]$. The matrix R includes the returns on p primitive assets with $E(R_t) = \mu$, $Cov(R_t) = \sum$, and $Cov(R_t, r_t) = \gamma$. We assume there is a mean-variance efficient combination of the primitive assets with a return r_t^{β} that equals the return on the benchmark asset, $E\left(r_t^{\beta}\right) = \beta$. The measure of efficiency of the primitive assets with respect to the benchmark is defined as $\lambda = Var\left(r_t^{\beta}\right) - \nu$.

The optimization problem seeks to replicate the return on the benchmark asset and is given by

$$\min_{w} w' \sum w - \nu \qquad (\mathcal{P}1)$$

$$\begin{aligned} \text{s.t.} \quad w'\overline{1} &= 1 \\ w'\mu &= \beta \end{aligned}$$

where w is the vector of portfolio weights in the primitive assets, and $\overline{1}$ is a vector of ones.

A major strength of this approach is that one can incorporate short-selling constraints into the problem, which typically reduces the expected return along with increasing risk of efficient portfolios. The short-selling constraints that most investors face represent important obstacles in the overall decision on allocation. We will refer to ($\mathcal{P}2$) as the original problem ($\mathcal{P}1$), but with short-selling constraints, $w_i \geq 0$.

The measure of efficiency for both problems is the value of the Lagrangian:

$$\lambda = L = w'\Sigma w - \nu + \delta_1 \left(w'\bar{1} - 1\right) + \delta_2 \left(w'\mu - \beta\right) - \delta_3' w \tag{1}$$

where δ_1, δ_2, and δ_3 are the Lagrange multipliers of the restrictions. The multiplier δ_3 is active only for the problem ($\mathcal{P}2$). Whenever λ is positive, the mimicking portfolio of the p primitive assets has a higher variance than the benchmark, and therefore it is mean-variance inefficient. Conversely, a negative value implies that the the mimicking portfolio is efficient.

BJS (2002) show that test statistic under the null hypothesis: $\lambda = 0$ takes the form

$$\xi = \frac{T^{\frac{1}{2}} \left(\lambda - \lambda_0\right)}{\lambda_\sigma} = \frac{T^{\frac{1}{2}} \lambda}{\lambda_\sigma} \tag{2}$$

where λ_σ denotes the standard deviation of the measure of efficiency. The test statistic is standard normally distributed for large T.

Our mimicking portfolios always optimize either country or industry indexes. In the first step, we optimize one of the two diversification strategies in order to construct a benchmark. In a second step, we solve the problems ($\mathcal{P}1$) or ($\mathcal{P}2$). Finally, we perform the BJS (2002) test.

We also introduce an estimation-based block-bootstrap version of the BJS (2002) test to asses its small-sample properties. Because we cannot detect a small-sample bias, the significant test statistics in the tables to follow are based on the standard BJS (2002) test.

One of the merits of this approach is that we can directly compare geographic versus industry diversification both with and without short-selling. Performance comparisons are based on the distance between one point on the country allocation frontier and another point on the industry allocation frontier with the same return. The minimum-variance portfolio (MVP) and the tangency portfolio (TP) are the referred benchmarks points.

The BJS (2002) test is related to work on portfolio efficiency in Kandel, McCulloch and Stambaugh (1995), Wang (1998), and Li, Sarkar, and Wang (2003). As for spanning tests (Huberman and Kandel (1987)) our approach focuses on mean-variance efficiency, but the BJS (2002) test provides a major advantage over a spanning test. To test whether country diversification outperforms industry diversification using a spanning test, the test sets, by construction, the benchmark as a combination of geographic and industry diversification[5]. In response Gerard, Hillion and de Roon (2002) derive a version of the standard mean-variance spanning test to circumvent this problem.

III. Main results

We describe the data and present our main results, both with and without short sales constraints. Finally, we incorporate upper and lower bounds on the portfolio weights to analyze a more realistic diversification approach.

[5] This is, however, an implausible diversification strategy since each single stock shows, then, up once in a country portfolio and a second time in an industry portfolio.

A. Data

We use Datastream country and sector indexes for the 11 EMU constituents: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. The data provided by Datastream include weekly US dollar-denominated returns from 12 January 1991 through 5 September 2003 (representing 731 observations)[6].

The sample is divided into different subperiods not only to capture time patterns but also to incorporate effects attributable to actions of the new monetary authority. The subperiods are labelled *pre-convergence*, *convergence*, and *euro*. Table 1 shows the dates of the periods.

The starting date of the *convergence* subperiod is associated with the signing of the Maastricht treaty, and the end of the subperiod (31 December 1998) is associated with the fixing of the conversion rates.

We focus the analysis on level three of the Datastream sector classification, which represents ten sectors: Basic Industries (BI), Cyclical Goods (CG), Cyclical Services (CS), Financials (FI), General Industries (GI), Information Technology (IT), Noncyclical Consumer Goods (NCG), Noncyclical Consumer Services (NCS), Resources (RE), and Utilities (UT). Using this industry classification, we compute industry indexes by building market value-weighted indexes.

[6]The starting date of our sample is associated with the introduction of a Datastream index for Portugal. The movement toward full liberalization of capital movements in Europe starts only in the late 1970s and early 1980s. Complete freedom of capital movements was attained in the late 1980s (Bakker, 1996).

B. Descriptive statistics

Table 2, Panel A reports the descriptive statistics for the country indexes for the whole period and the three subperiods. As the entire sample represents a rather long period when many important structural changes occurred in Europe, we concentrate on the subperiods.

The descriptive statistics indicate country returns apparently experienced different cycles over the time period of interest. During the *convergence*, for instance, almost all European stock markets experienced a dramatic increase in value, yielding rather high double-digit returns. In contrast, in *pre-convergence*, only Greece experienced a return higher than 16%, and in the *euro* subperiod, there are only two countries with positive index returns. The average mean in the *pre-convergence* subperiod is 1.68%, and in the *euro* subperiod, the average mean return is -5.23%. Compare the two figures to a mean of 20.45% in the *convergence* subperiod.

Correlations also show variation over time. In the *convergence* subperiod, there is a uniform increase of correlation between countries while the correlation between countries and industries stays stable. A less pronounced and uniform drop in correlations for both countries and between countries and industries follows in the *euro* subperiod. The surges and drops in correlations, however, occur at different levels. Correlations within countries tend to be lower than correlations between countries and industries, but these relationships also become less pronounced over time.

Panel B of Table 2 reports correlations for industries. We see that correlations for industries are higher than the correlation of an industry with countries. In the *euro* subperiod, the level of correlation drops but unlike the findings for countries, industry correlations seem on average to be more stable and higher.

C. Geographic versus industry diversification under unconstrained maximization

We apply the BJS (2002) test to solve problem ($\mathcal{P}1$). Geographic and industry diversification are used in turn as benchmarks and tested against the opposite strategy. The annualized means and standard deviations of the TPs and MVPs for each diversification strategy are shown in Panel A of Table 3. Table 4 presents the test statistics. Because the sign of the test statistic is identical to the sign of the measure of efficiency, λ, we do not report λ. A positive sign implies that the benchmark strategy is mean-variance efficient, and, a negative sign implies that it is inefficient.

In Table 4 Panel A, the benchmark strategy is geographic diversification, while industry indexes are the primitive assets. The test statistic for the TP is negative suggesting that the benchmark is not optimal. The sign for the MVP is positive. For both of the tests, however, we cannot reject the null hypothesis. In Panel B, industry diversification represents the benchmark, and countries play the role of the primitives. Both test statistics for the TP and the MVP on the industry frontier are positive, although not statistically significant[7]. Therefore, we cannot reject the null that diversification strategies, country and industry, exhibit identical variance for a given return. In the G-7 countries, Gerard, Hillion and de Roon (2002) also find that geographic diversification and industry diversification are always redundant strategies relative to each other using a spanning methodology.

The result is puzzling because country indexes show on average much lower correlations than industry indexes. Thus, conventional wisdom in a portfolio optimization context would suggest that country diversification should outperform industry diver-

[7]Note that a negative sign in Panel A does not necessarily imply a positive sign in Panel B, and vice-versa. This is because the TPs or the MVPs show different mean returns, so the frontiers can, in principle, cross.

sification. Moreover, the Heston and Rouwenhorst (1994) methodology implies that diversification along the dimension of the dominant factor - the country factor - produces a lower portfolio variance for a given number of stocks. Yet, the signs of three of four test statistics (one significant) imply that the industry frontier lies outside the country frontier.

The results for the subperiods reinforce our overall findings. All test statistics in Table 4 Panel A are negative, indicating that the benchmark geographic diversification strategy is inefficient compared to industry diversification. In the *pre-convergence* subperiod we see that at the TP on the country diversification frontier the test is significant at a 5% confidence level while for Panel B tests are not significant. We do not report results for the *euro* subperiod because mean returns are negative.

Again, the test statistics with industry diversification as the benchmark, both in the *pre-convergence* and the *convergence* subperiod, are evidence that the industry frontier lies outside the country frontier in the mean-variance space (results not significant). Thus, we conclude that geographic and industry strategies cannot be distinguished statistically.

Investors, of course, are not just limited to geographic or industry diversification. We would like to examine the efficiency of geographic and industry diversification against other benchmarks.

First, we can apply the top-down approach to portfolio diversification at a lower level of index aggregation; that is, we look at the performance of our diversification strategies compared to a diversification based on country-industry index combinations. The French Information Technology industry is an example of one of these combinations.

We solve problem ($\mathcal{P}$*1*) with roughly 110 country-industry index pairs[8] and find that for both country and industry diversification as mimicking strategy, the test statistics are always positive and statistically significant at the 5% confidence level (Panels C and D in Table 4)[9]. In other words, a diversification strategy based on country-industry pairs clearly outperforms geographic as well as industry diversification.

The same result, obtained by comparing Sharpe ratios, leads Adjouté and Danthine (2002) to speculate on whether cost structure or a behavioral explanation is more appropriate to explain the fact that portfolio managers have favored the geographic diversification model.

Second, we address the efficiency of a passive strategy such as the market portfolio relative to country and industry diversification. Our EMU market index is a value-weighted index constructed from the Datastream country or industry indexes. The mean and standard deviation of the EMU index are reported in Table 3. The results in Table 4, Panels E and F, suggest that either strategy outperforms the EMU index. That is, all test statistics are both negative and significant at the 1% confidence level.

D. Country versus industry diversification with short-selling constraints

Most portfolio managers face short-selling constraints, but standard mean-variance analysis does not take into account these constraints on the performance of strategies. To ascertain the impact of short-selling constraints, we test constrained country and industry diversification against the opposite strategy and against benchmarks (annualized

[8] The sample size varies across samples and subsamples as some of the indexes were introduced after the starting date of our time series while other indexes have disappeared.

[9] In the *convergence* subperiod the test at the TP is weakly insignificant, with a p-value of 11%.

means and standard deviations of the TPs and MVPs for each diversification strategy are shown in Panel B of Table 3)[10].

The test results for problem ($\mathcal{P}2$) are shown in Table 5. Strikingly, over the full sample the return of the country TP is not attainable by industry allocation (Panel A). This is a remarkable result. The test statistic for the MVP is positive, reflecting the efficiency of the benchmark, although we cannot reject the null hypothesis. Further, note that the portfolio of the primitive assets is not an efficient portfolio, suggesting that the mean-variance frontier of countries lies above the industry frontier. Panel B reports the results where industry diversification serves as the benchmark. Test statistics for both the TP and the MVP are positive. This is not a contradictory result for two reasons. First, the rejection of the hypothesis is weakly significant. Second, the country indexes span a significantly broader frontier than the industry indexes. That is, the industry TP and MVP have similar mean returns, 6.20% and 5.74%, while the country mean return for the TP is more than 300% higher than the return of the country MVP, that is, 9.45% versus 2.76%. Introducing short-selling constraints shrinks the efficient locus of industry diversification, while country diversification is affected to a much lesser extent. Further, industry portfolios cannot attain the country returns around the country TP.

Our first result is consistent with Gerard, Hillion and de Roon (2002), who find that under short sales restrictions geographic diversification dominates industry diversification, but we obtain evidence that country diversification is statistically significant from industry diversification at the country TP.

The results for the subperiods confirm these findings. When country diversification is the benchmark, in two of three cases the country TP is not attainable by industry

[10] As there are no analytical formulas for the TP and the MVP with short sales constraints, we compute first the efficient frontier with short sales constraints. Then, the global minimum-variance portfolio is the portfolio with the minimum variance and the tangency portfolio is the portfolio that maximizes the Sharpe ratio with a risk-free rate of zero, in the positive part of the frontier.

diversification (Panel A). Panel B shows that geographic diversification mimics industry diversification quite well. Test statistics are negative in four of six tests and statistically significant for both tests in the *euro* subperiod. This clearly suggests that country allocation outperforms industry allocation in the presence of short-selling constraints.

A striking aspect is that the *convergence* subperiod represents the only time the efficient frontiers of country and industry diversification are very similar; e.g., whether optimization is unconstrained or constrained, the null hypothesis is never rejected. This empirical feature of the data may be a factor in the current disagreement on this topic, since many investors take past performance as indicative for the future.

Our results in the *euro* subperiod do not confirm that this is an ongoing trend, however. That is, the country frontier dominates the industry frontier under short-selling constraints in the *euro* subperiod as in the *pre-convergence* subperiod and, more important, over the complete sample. Thus, our results are contrary to recommendations in the portfolio management industry that industry diversification is the most suitable strategy since industry correlations are much lower than in previous periods and because of the growing importance of industry factors.

Panels C and D of Table 5 report test results when country-industry pairs represent the benchmark. Neither country nor industry portfolios can ever attain the TP of the country-industry pairs, confirming the potential advantages of the country-industry structure. For the MVP, the test statistics are always positive over the entire sample period as well as statistically significant in five of six subperiods. The passive EMU benchmark is inefficient relative to country and industry diversification (Panels E and F). That is, the test statistics are negative and highly significant.

E. An explanation

Over the 1991-2003 period and also in several subperiods, industry diversification proves to be statistically equivalent to geographic diversification. However, when short-selling constraints are introduced, geographic diversification clearly dominates industry diversification. Both these findings are surprising. The first result is puzzling because of the low correlation structure of countries relative to industries. The second puzzle builds on the first. If these two approaches to international diversification are so similar, then, it is not clear why one diversification strategy should suffer so much more from short-selling constraints than the other. That is, there seems to be great difference between the two approaches in short positions under the unconstrained optimization. Therefore, what is the intuition behind these results?

It is well-known that the Markowitz algorithm (1991) leads to extreme portfolio positions (Green and Hollifield, 1992) and that the outcome is almost never balanced. That is, optimal portfolio allocation does not imply that the resulting portfolio will be well diversified.

A typical reaction is to enforce a balanced portfolio strategy; see, for instance, Black and Litterman (1992). Essentially, this approach assumes that the extreme portfolio weights are due to estimation errors in the inputs. Thus, constraining portfolio weights is intended to reduce estimation risk (Jagannathan and Ma, 2003). To be more concrete, the optimization algorithm tends to overweight securities that have large estimated returns, negative correlations, and small variances (and the converse), and these securities are the most likely to have large estimation errors (Michaud, 2001).

Given the extreme positions of industry indexes, one might ask whether such indexes are more prone to measurement errors. But both kinds of indexes are composed of the same assets. A priori there is no reason industry indexes would be more subject to measurement error than country indexes.

Green and Hollifield (1992) argue that estimation risk is not the source of the unbalanced portfolio weights in optimal portfolios. They shed light on this important issue by showing the importance of factor risk for optimal portfolios. If stock or index returns are driven by one dominant factor, and there is evidence that this is the case, we can form portfolios with zero factor risk. Such a portfolio will take a large negative position in one stock, or an index, to finance an even larger positive position in other stocks, or indexes. Green and Hollifield (1992) also provide empirical evidence that if factor risk stemming from the single dominant factor in stock returns is the reason for unbalanced portfolios, then stock returns must be highly correlated and show a great diversity of betas.

Therefore, if industry portfolios with a higher correlation structure than country portfolios also exhibit higher diversity of betas than country portfolios, then, industry portfolios are better suited to eliminate factor risk. Thus industry portfolios must perform better than country portfolios. To ascertain the validity of this hypothesis, we use the simplest one-factor model possible, the capital asset pricing model, with the value-weighted EMU index as a proxy for the market portfolio. In untabulated results we find that industry portfolios have a much greater diversity of betas than country portfolios. According to these arguments, one should consequently expect the industry frontier to lie outside the country frontier (Figure 1).

However, if short positions are not permitted factor risk cannot be eliminated. It is only in these circumstances, that the lower correlation structure of countries plays a role. This implies that factor risk stemming from the single dominant factor in stock returns has a much stronger influence on portfolio formation than correlations among particular stocks or indexes. It is worth noting, that even when short positions are not permitted, a very thin part of the industry frontier may lie outside the country frontier as in Figure 1.

F. Geographic and industry allocation with bounds on the weights

Portfolio managers are generally restricted from avoiding investments in a large fraction of available assets as suggested by portfolio weights obtained with short-selling constraints. We thus examine the performance of geographic and industry diversification under portfolio constraints that are linked to the market capitalization of the particular indexes.

The BJS (2002) test can deal with lower (l) and upper bounds (u) on portfolio weights, i.e., $l \leq w \leq u$, so we recompute the optimization problem ($\mathcal{P}1$) adding lower and upper bounds on the portfolio weights. In practice such lower and upper bounds will vary from bank to bank, thus, we define both a loose and a tight margin. The margins of the tight strategy are $(u, l) = W \times (1 \pm 0.05)$, and the margins of the loose strategy are $(u, l) = W \pm 0.02$, where W denotes the weights of the countries and industry indexes on the EMU index.

The results for the tight strategy are easy to summarize. Under tight restrictions, the TP and MVP have very similar return and risk (Table 6, Panel A). Geographic diversification is an efficient benchmark strategy, although, the results are not statistically significant (Table 7, Panel A). When industry diversification is the benchmark (Table 7, Panel B), only the MVP is attainable (and inefficient, although results are not statistically significant). Hence, we cannot reject the equivalence of strategies.

In the subperiods, the mean-variance frontiers do not produce common returns which prevent us from computing the test. In the *pre-convergence* subperiod, the industry frontier lies above the country frontier, while in the *convergence* and *euro* periods, the country efficient frontier lies above the industry efficient frontier.

With looser constraints, the efficient frontiers rise, and TP and MVP portfolios diverge more (Table 6, Panel B). The country diversification efficient frontier lies above the industry frontier, except in the *pre-convergence* subperiod, which means that the

TP of country portfolios is almost never attainable (Table 7, Panel C). The MVP is attainable and efficient, although statistically insignificant. When industry diversification is the benchmark (Table 7, Panel D) the TP is inefficient while the MVP is efficient. Again none of the test statistics are statistically significant. In the subperiods, country diversification dominates industry diversification at a statistically significant level in the *pre-convergence* subperiod (Table 7, Panel C).

IV. Bootstrapping portfolio weights

The extreme sensitivity of portfolio weights to changes in the means (see Best and Grauer (1991)) is a major obstacle in mean-variance analysis. The true parameters of return time series are not only unknown variables but also unknowable variables. Consequently, the estimation of parameters from historic data introduces severe estimation error in the optimization procedure. To evaluate the importance of estimation error, we conduct a sequence of bootstrap experiments. The analysis aims to give an idea about the distribution of the portfolio weights with and without constraints. The distribution of portfolio weights is important from a pure practical point of view; in addition, it is of interest for our purpose to ascertain whether the diversification strategies present similar or different statistical properties for the weights.

Britten-Jones (1999) examines the distribution of unconstrained portfolio weights under independently multivariate Normal distribution. We extend the analysis to portfolio weights with constraints, using a numerical study, without relying on the multivariate Normal distribution. Our block-bootstrap analysis[11] is based on a rolling sampling window method which is helpful in accounting for patterns of long-term dependence in the data.

[11] For details see the Appendix.

Table 8 reports the sample mean, the bootstrap mean, the bootstrap standard deviation, and the first quartile of the bootstrap efficient portfolio weights for minimum variance portfolios. Panel A contains the unconstrained, the short-selling constrained, and the tight and loose constrained country portfolio weights. First, we observe that most of the country portfolio weights from the data sample are similar to the mean of the bootstrap data. As in Britten-Jones (1999) we find that efficient portfolio weights have large sampling error. In our case, however, bootstrapping leads to such high standard deviations that only the portfolio weights for Italy and Spain can be regarded as statistically different from zero if one relies on standard confidence bounds. In essence, the two standard deviation intervals for the eight other countries cannot be interpreted as informative at all, since they always include the origin.

On the other hand, because some of the bootstrap portfolio weight distributions are clearly non-normal, standard confidence bounds can be misleading. This fact is evidenced by the relatively large values for the first quartile of the bootstrap distributions. Nevertheless, even after constructing confidence intervals without relying on the two standard error rule, some of the confidence bounds still contain the origin.

Panel A of Table 8 also reports results for our various constrained strategies. Short-selling restricted portfolio weights from the block-bootstrap shows mean values very similar to the data. Notice that only three first quartiles, for Austria, Italy and Spain, present values different from zero. This again suggests that confidence bounds for the remaining countries cannot be used to establish portfolio weights to be significantly different from zero.

Under the tight and loose constrained strategies bootstrap means and sample means almost coincide. This is, of course, not a surprising result since index weights are relatively stable. It is only for these strategies that we find portfolio weights to have small standard deviations. That is, even portfolio weights as small as one percent exhibit two standard deviation confidence intervals bounded away from zero. This holds even for the strategy with loose constraints, where, in principle, negative weights are feasible for indexes with market capitalization smaller than two percent of total capitalization.

Panel B of Table 8 provides our results for industry portfolios. In short, the patterns described above for country index portfolios also apply for industry portfolio weights. Therefore, we find it difficult to discriminate among the distributions of country and industry portfolio weights.

It is important to point out that while results in Britten-Jones (1999) and Li, Sharkar, and Wang (2003) find huge variances in unconstrained tangency portfolios, to our understanding, none of these papers goes so far to conclude that confidence bounds are so huge that no useful information can be deduced from them.

On the other hand, standard deviations of tangency portfolio weights in Eun and Resnick (1988) are, at least, as large as the mean of the corresponding portfolio weight and in some cases an order of magnitude larger[12]. Furthermore, Best and Grauer (1991) show that small changes in one of the expected returns of a portfolio lead to extreme changes in many portfolio weights. They report that several portfolio weights change by several hundred multiples of the change in the expected return.

In earlier versions of the paper we implemented a simpler bootstrap procedure that preserved the covariance structure of index returns but failed to account for long-term dependence in the data. Unlike the results above, we found confidence bounds for minimum variance portfolios to be smaller while tangency portfolios showed even larger variations. These earlier results are available upon request.

[12] We choose to omit our results for tangency portfolio weights simply because confidence bounds are even larger than for the MVP. Austria for example shows a mean portfolio weight in our bootstrap experiments for unconstrained strategies of -0.70 and a standard deviation of 11.00.

V. Out-of-sample analysis

Until now we essentially assume that the average returns and the estimated covariance structure are good proxies for the true underlying data generating process. Even if this assumption is indeed satisfied, the out-of-sample performance of mean-variance portfolios may be very different. Of course, since we cannot know the true underlying data generating process the task of constructing efficient portfolios is even harder. Therefore, estimation is key to successful investments and, thus, investors should be interested in the out-of-sample properties of geographic and industry diversification.

Studies find that mean-variance efficient portfolios have usually a poor out-of-sample performance (see Jobson and Korkie (1980, 1981) and Best and Grauer (1991)). In particular, the sample means of returns represents an extremely inaccurate ingredient to the optimization problem. We are, of course, more interested in out-of-sample differences between geographic diversification and industry diversification than in their absolute performance.

It is important to remark that we do not examine the out-of-sample performance of geographic diversification and industry diversification based on the predictive power of the usual suspects like the T-bill rate (Breen, Glosten, and Jagannathan (1989)) or past index returns (Ferson and Harvey (1993)). This is because we do not want to contaminate the results with eventually disparate abilities of the chosen predictors for the two diversification strategies. However, the reader should keep in mind, that when the mean returns are estimated with rolling windows, predictability may affect the results indirectly if one of the investment approaches exhibits stronger persistence.

We continue to focus on the MVP and analyze the performance of geographic and industry diversification with and without constraints. The out-of-sample experiments take the following form: At the end of each week, we estimate the covariance structure of the country and industry indexes, respectively. We are interested in the performance of these portfolios under four scenarios: unconstrained portfolio weights, nonnegativity constraints, and two scenarios with portfolio weights linked to the market capitalization of the indexes. As above the scenarios with constraints associated with the market capitalization of the indexes consider a tight and a loose constraint, respectively.

We examine here the out-of-sample performance of the MVP based on estimates of the covariance structure from the block-bootstrap experiments only. In earlier versions of the paper we implemented an exhaustive analysis of out-of-sample portfolios. These results as well our new results for the TP are available from the authors. Overall, we find that the example presented below is representative.

For our purpose, the resulting country and industry out-of-sample time series are tested for differences in their means. We assume equal variances for the t-tests unless the null hypothesis of equal variance (F-test) is rejected at a ten percent significance level. Table 9 reports summary statistics (mean, variance, and the p-value for the t-test) for the out-of-sample experiments. The mean and variance of the time series are annualized.

Three major lessons can be drawn from Table 9. First, it does not appear to be the case that nonnegativity constraints or upper and lower bounds on portfolio weights affect the return and risk profile of the analyzed portfolio strategies in a dramatic way. For instance, both the means of returns as well as their standard deviations remain approximately at the same level independently of whether the portfolio strategies involve constraints or not.

Second, untabulated results suggest that the estimation method used for the covariance structure of the country and industry indexes may have a substantial influence on the outcomes. In particular, for unconstrained strategies, rolling windows and increasing estimation windows outperform the portfolio strategy with fixed weights, e.g. known covariance structure. Apparently, an investor could attain about a hundred percent higher return with unconstrained country diversification if he consistently updates his estimate instead of focusing on a constant covariance structure.

Third, country diversification almost always outperforms industry diversification in absolute return terms. However, we can never reject the null hypothesis that the means of the two experimental out-of-sample time series are identical. Notice that the smallest p-value in Table 9 is as high as thirty-three percent.

Overall, our results match well with conclusions in Eun and Resnick (1988). Controlling estimation risk is almost always beneficial. The MVP performs nearly as well as the TP if estimation risk is taken into account. But, in general, statistical discrimination among strategies is difficult.

Finally, notice that while we find evidence for the existence of factor risk driving extreme weights in unconstrained optimization (see Green and Hollifield (1992)) we also find evidence of estimation risk. Our results are supportive for the view that constraints are helpful because estimation risk has a much larger impact on the performance of portfolio strategies than factor risk.

VI. Conclusions

We have compared country and industry diversification based on standard mean-variance theory using the Basak, Jagannathan, and Sun (2002) test. This test allows comparison with several benchmarks in the presence of short-selling constraints, and with lower and upper bounds on portfolio weights.

According to the mean-variance tests, geographic diversification and industry diversification are statistically equivalent strategies. Geographic and industry portfolios outperform the EMU index but underperform a diversification strategy based on country-industry pairs. All these results prevail in the subperiods analyzed. When restricting short sales positions, geographic diversification outperforms industry diversification. The mean-variance frontier of country indexes is wider than the industry frontier.

The difference in performance with and without short-selling is intriguing. We investigate the plausibility of an explanation provided by Green and Hollifield (1992): If stocks, or indexes, are highly correlated and exhibit a wide diversity of betas, one can form portfolios with essentially zero factor risk. Such a portfolio, however, will take a large negative position in one index to finance an even larger positive position in another index. As we compare the features of both country and industry data, we find that industry index data follow that pattern perfectly. They exhibit not only higher correlations than countries, but also large negative positions in optimal portfolios and a much greater diversity of betas with respect to the EMU market index. Thus, there are reasons to believe that the results in industry diversification might be driven by exposure to a dominant factor.

A striking aspect in the subperiods is that geographic diversification and industry diversification at the respective tangency portfolios are equivalent in the *convergence* subperiod. Yet in the *euro* subperiod country diversification clearly outperforms industry diversification. Our evidence seems to be at odds with recent research that advocates industry. However, one should approach this evidence with utmost caution, since the *euro* subperiod is marked by a strong bear market that might have influenced the results.

Overall, country diversification performs better when we impose realistic constraints, which supports the traditional wisdom on geographic allocation. However, the statistical evidence for a difference between the strategies is weak. We argued in this paper that the lack of power stems most likely from the noisy estimation of portfolio weights.

References

[1] Adjaouté, K., and J.P. Danthine, 2002, European financial integration and equity returns: A theory-based assessment, Second European Central Banking Conference Paper.

[2] Arshanapalli, B., J. Doukas and L. Lang, 1997, Common volatility in the industrial structure of global capital markets, Journal of International Money and Finance 2, 189-209.

[3] Baca, S. P., B. L. Garbe, and R. L. Weiss, 2000, The rise of sector effects in major equity markets, Financial Analysts Journal 56, 34-40.

[4] Bakker, A. F. P., 1996, The Liberalization of Capital Movements in Europe, Kluwer Academic Publishers.

[5] Basak, G., R. Jagannathan, and G. Sun, 2002, A direct test for the mean-variance efficiency of a portfolio, Journal of Economic Dynamics and Control 26, 1195-1215.

[6] Beckers, S., R. Grinold, A. Rudd, and D. Stefek, 1992, The relative importance of common factors across the European equity markets, Journal of Banking and Finance 16, 75-99.

[7] Best, M. J. and R. R. Grauer, 1991, On the sensitivity of mean-variance-efficient portfolios to changes in assets means: some analytical and computational results, Review of Financial Studies 4, 315-342.

[8] Black, F., and R. Litterman, 1992, Global portfolio optimization, Financial Analysts Journal, 28-43.

[9] Breen, L., and L.R. Glosten and R. Jagannathan, 1989, Economic significance of predictable variations in stock index returns, Journal of Finance 44, 1177-1189.

[10] Britten-Jones, M., 1999, The sampling error in estimates of mean-variance efficient portfolio weights, Journal of Finance 54, 655-671.

[11] Brookes, M., 1999, The impact of the EMU on portfolio management: European banking after the EMU, EIB Papers 4 (1).

[12] Brooks, R., and M. Del Negro, 2002a, The rise in comovement across national stock markets: market integration or global bubble?, IMF Working Paper.

[13] Brooks, R. and M. Del Negro, 2002b, International divesification strategies, Federal Reserve Bank of Atlanta Working Paper 2002-23.

[14] Cavaglia, S., C. Brightman, and M. Aked, 2000, The increasing importance of industry factors, Financial Analysts Journal 56, 41-56.

[15] Drummen, M., and H. Zimmermann, 1992, The structure of European stock returns, Financial Analyst Journal 48, 15-26.

[16] Eiling, E., B. Gerard, and F. de Roon, 2004, Asset allocation in the Euro-zone: Industry or Country Based?, Working Paper.

[17] Errunza, V., and P. Padmanablan, 1988, Further evidence on the benefits of portfolio investments in emerging markets, Financial Analyst Journal 44, 76-78.

[18] Eun, C. S. and B. G. Resnick, 1988, Exchange rate uncertainty, forward contracts, and international portfolio selection, Journal of Finance 43, 197-215.

[19] Ferson, W. and C. Harvey, 1993, The risk and predictability of international equity returns, Review of Financial Studies 6, 527-566.

[20] Galati, G., and K. Tsatsaronis, 2001, The impact of the Euro on Europe's financial markets, BIS Working Paper 100.

[21] Gerard, B., P. Hillion, and F. de Roon, 2002, International portfolio diversification: industrial structure, country and currency effects revisited, Working Paper.

[22] Green, R. C., and B. Hollifield, 1992, When will mean-variance efficient portfolios be well diversified?, The Journal of Finance 47, 1785-1809.

[23] Griffin, J. M., and G.A. Karolyi, 1998, Another look at the role of the industrial structure of markets for international diversification strategies, Journal of Financial Economics 50, 351-373.

[24] Grinold, R., A. Rudd, and D. Stefek, 1989, Global factors: fact or fiction?, The Journal of Portfolio Management, Fall, 79-88.

[25] Hall, P. and B. Y. Jing, 1996, On sample reuse methods for dependent data, Journal of Royal Statistical Society Series B 58, 727-737.

[26] Hall, P., B. Y. Jing and S. N. Lahiri, 1998, On the sampling window method for long-range dependent data, Statistica Sinica 8, 1189-1204.

[27] Heckman, L., S. Narayanan and S. Patel, 1998, Country and industry importance in European returns, Salomon Smith Barney Working Paper.

[28] Heston, S. L., and K.G. Rouwenhorst, 1994, Does industrial structure explain the benefits of international diversification?, Journal of Financial Economics 36, 3-27

[29] Huberman, G., and S. Kandel 1987, Mean-variance spanning, The Journal of Finance 42, 873-888.

[30] Isakov, D., and F. Sonney, 2003, Are practitioners right? On the relative importance of international portfolios in international stock returns, FAME Research Paper No. 72.

[31] Jagannathan, R. , and T. Ma, 2003, Risk reduction in large portfolios: Why imposing the wrong constraints helps, The Journal of Finance 57, 1651-1683.

[32] Jobson, J. D. and B. Korkie, 1980, Estimation for Markowitz efficient portfolios, Journal of the American Statistical Association 75, 544-554.

[33] Jobson, J. D. and B. Korkie, 1981, Putting Markowitz Theory to Work, The Journal of Portfolio Management 7, 70-74.

[34] Kandel, S., R. McCulloch, and R.F. Stambaugh, 1995, Bayesian inference and portfolio efficiency, Review of Financial Studies 8, 1-53.

[35] Li, K., A. Sarkar, and Z. Wang, 2003, Diversification benefits of emerging markets subject to portfolio constraints, Journal of Empirical Finance 10, 57-80.

[36] Markowitz, H., 1991, Portfolio Selection: Efficient Diversification of Investments, Blackwell.

[37] Michaud, Richard O., 2001, Efficient asset management: a practical guide to stock porfolio optimization and asset allocation, Oxford University Press.

[38] Roll, R., 1992, Industrial structure and the comparative behaviour of international stock market indexes, The Journal of Finance 47, 3-42.

[39] Rouwenhorst, K. G., 1999, European equity markets and the EMU. Financial Analysts Journal 55, 57-64.

[40] Wang, Z., 1998, Efficiency loss and constraints on portfolio holdings. Journal of Financial Economics 48, 395-375.

A. Appendix: Bootstrapping portfolio weights

We implement a block-bootstrapping procedure in which blocks of country and industry data are used to compute the BJS test statistics. The block-bootstrap data is constructed by the sampling window method of Hall and Jing (1996). For convergence of this method to the asymptotic distribution of the (normalized) sample mean see Hall, Jing and Lahiri (1998). We use this method because the sampling window method is, in particular, helpful in accounting for patters of autocorrelation or other long-term dependence. In contrast, a simple replication of data with replacement (across the time series) may preserve the covariance structure, the skewness as well as the fat tails of the return distributions but disregards long-term dependence.

The bootstrap experiments are carried out as follows: First recall that the data are indexed by $t \in [0, T]$. The sampling window method uses the first $\widehat{T}$ observations in T to compute the first bootstrap BJS test statistics, ξ_1. The size of the sampling window, $\widehat{T}$, is assumed to be strictly smaller than T, that is, $t = 1, \ldots \widehat{T}$ and $\widehat{T} < T$. The subscript denotes that the BJS test statistics is from the first data window of size $\widehat{T}$. Next we use the second window ranging from $t = 2$ until the $\left(\widehat{T} + 1\right)$th observation. The last window is $t = T - \widehat{T} + 1, \ldots T$.

Hall, Jing and Lahiri (1998) argue that the procedure should be implemented with $\widehat{T} = c \times T^{1/2}$ where $c = 1, \ldots, 9$. We chose $c = 9$ to maximize the likelihood that mean returns are positive. We also conducted block-bootstrap experiments with $c = 1, 3, 4, 5, 6$ and do not find that our results depend on the choice of c.

BJS also conduct a sampling window simulation to show that the normality assumption is reasonable. Based on the squared correlation between the quantiles of their data and the quantiles of the Standard Normal distribution they conclude that the normality assumption is imperfect but sufficiently realistic. We confirm their results by showing that the bootstrap p-values are sufficiently close to the p-values from the Standard Normal distribution and, further, never affect our conclusions.

Figures and Tables

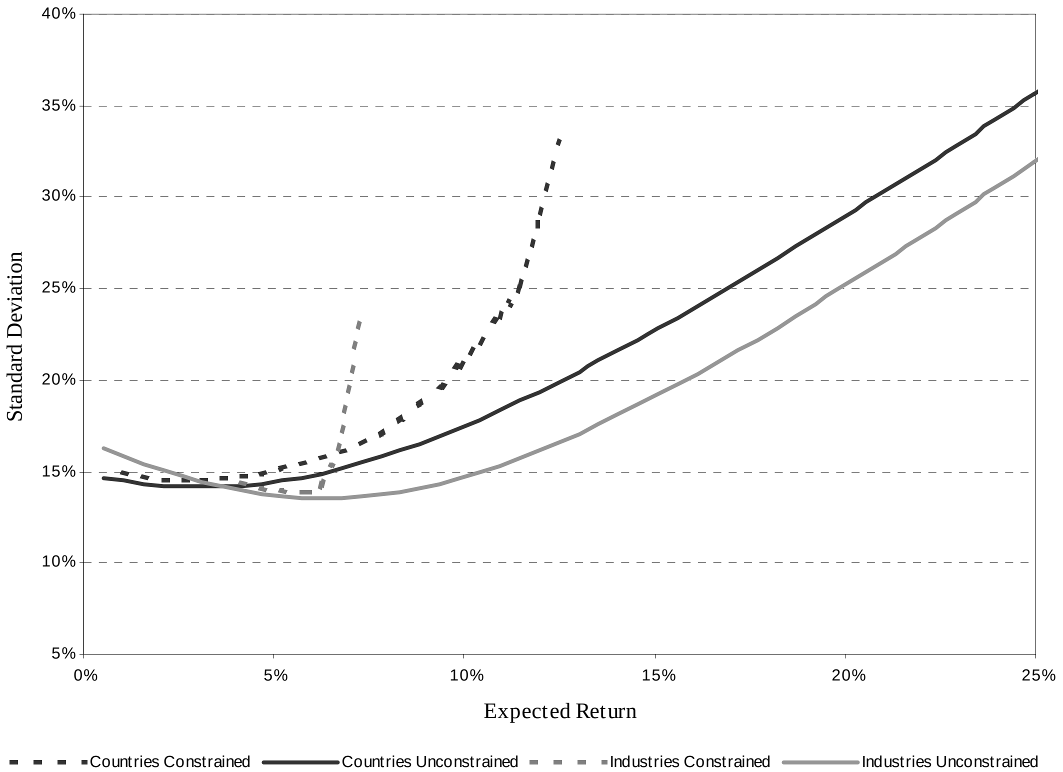

Figure 1: Mean variance frontiers of country and industry diversification without and with short selling constraints.

TABLE 1: Description of subperiods

The table shows the data range and observations for the whole sample as well as the sub-periods. The data provided by DataStream is ranging from January 12, 1990 till the beginning of September of 2003 (713 return observations). The Convergence subperiod goes from January 1995 to January 1999. The starting date of the Convergence subperiod is associated with the signature of the Maastricht treaty and the end (December 31, 1998) with the fixing of the conversion rates. The starting date of the time series is associated with the introduction of a DataStream index for Portugal on January 5, 1990.

Sample	Data Range	Observations
Whole	12/01/1990-05/09/2003	713 observations
Pre-Convergence	12/01/1990-30/12/1994	260 observations
Convergence	06/01/1995-25/12/1998	208 observations
Euro	01/01/1999-05/09/2003	245 observations

TABLE 2: Descriptive statistics

By columns: Annualized mean (Mean), standard deviation (Stdv.), and average correlations, (Corr(C)) and (Corr(I)). The weekly returns are calculated in US dollar for the period January 12, 1990 until September 05, 2003, with a sample size of 713. Mean and standard deviation are in percentages. Notice that the correlation of each index with itself is excluded from Corr(C) and Corr(I). Pre-Convergence subperiod goes from January 1990 until December 1994 (260 observations). Convergence subperiod ranges from January 1995 until December 1998 (208 observations). Euro subperiod ranges from January 1999 until September 2003 (245 observations). Countries are Austria (AU), Belgium (BG), Finland (FI), France (FR), Germany (GE), Greece (GR), Ireland (IR), Italy (IT), Netherlands (NL), Portugal (PT) and Spain (SP). Industries are Basic Industries (BI), Cyclical Consumer Goods (CCG), Cyclical Services (CS), Financials (FI), General Industrials (GI), Information Technology (IT), Non-cyclical Consumer Goods (NCG), Non-cyclical Services (NCS), Resources (RE), and Utilities (UT). Industry indexes are computed by building market value-weighted indexes based on DataStream level three sector classification. Source: DataStream and own calculations.

Sample	1991-2003				Pre-Convergence				Convergence				Euro			
	Panel A: Countries															
	Mean	Stdv.	Corr(C)	Corr(I)	Mean	Stdv.	Corr(C)	Corr(I)	Mean	Stdv.	Corr(C)	Corr(I)	Mean	Stdv.	Corr(C)	Corr(I)
AU	-0.20%	19.02%	0.45	0.49	-3.61%	23.87%	0.53	0.65	0.59%	15.10%	0.53	0.57	2.73%	16.05%	0.36	0.35
BG	2.18%	17.30%	0.57	0.64	-2.00%	15.33%	0.59	0.74	22.37%	14.86%	0.58	0.66	-10.52%	20.65%	0.55	0.59
FI	10.72%	31.49%	0.41	0.47	6.42%	24.55%	0.36	0.43	28.12%	25.82%	0.51	0.58	0.52%	40.99%	0.39	0.44
FR	4.31%	18.51%	0.62	0.75	-0.14%	16.88%	0.57	0.81	16.98%	16.42%	0.60	0.77	-1.72%	21.55%	0.66	0.72
GE	2.22%	19.80%	0.64	0.76	0.39%	18.31%	0.61	0.82	15.88%	16.37%	0.64	0.77	-7.43%	23.57%	0.67	0.72
GR	12.16%	32.02%	0.37	0.37	16.02%	34.64%	0.32	0.36	31.45%	29.27%	0.43	0.42	-8.31%	31.26%	0.37	0.36
IR	6.40%	19.09%	0.50	0.54	1.86%	19.13%	0.51	0.60	23.88%	16.54%	0.52	0.54	-3.62%	20.87%	0.48	0.51
IT	2.24%	22.21%	0.52	0.63	-2.77%	23.03%	0.44	0.61	17.88%	21.08%	0.49	0.58	-5.72%	22.23%	0.63	0.69
NL	5.53%	17.49%	0.62	0.73	5.33%	12.77%	0.58	0.76	21.73%	16.61%	0.64	0.77	-8.01%	21.84%	0.64	0.72
PT	1.03%	18.74%	0.51	0.53	-3.14%	18.10%	0.48	0.57	19.81%	19.24%	0.55	0.59	-10.48%	18.83%	0.51	0.47
SP	6.01%	19.59%	0.60	0.68	0.18%	19.18%	0.53	0.69	26.30%	19.30%	0.63	0.74	-5.02%	20.08%	0.63	0.65
Average	4.78%	21.39%	0.53	0.60	1.68%	20.53%	0.50	0.64	20.45%	19.15%	0.56	0.63	-5.23%	23.45%	0.54	0.57

Sample	1991-2003				Pre-Convergence				Convergence				Euro			
	Panel B: Industries															
	Mean	Stdv.	Corr(I)	Corr(C)	Mean	Stdv.	Corr(I)	Corr(C)	Mean	Stdv.	Corr(I)	Corr(C)	Mean	Stdv.	Corr(I)	Corr(C)
BI	1.30%	17.89%	0.71	0.65	-1.89%	17.17%	0.84	0.69	8.08%	14.53%	0.74	0.67	-1.07%	20.98%	0.63	0.63
CG	2.50%	18.03%	0.71	0.67	0.01%	15.21%	0.84	0.69	18.16%	13.18%	0.75	0.68	-8.16%	23.44%	0.64	0.67
CS	1.70%	19.55%	0.73	0.66	-2.69%	17.54%	0.83	0.66	11.84%	15.80%	0.78	0.69	-2.26%	23.98%	0.65	0.66
FI	2.30%	19.14%	0.72	0.69	-2.12%	15.83%	0.83	0.69	19.83%	17.64%	0.72	0.71	-7.88%	23.07%	0.68	0.68
GI	7.79%	32.72%	0.55	0.53	4.68%	20.40%	0.75	0.59	30.82%	28.52%	0.61	0.57	-8.45%	44.48%	0.46	0.50
IT	6.33%	15.59%	0.63	0.57	4.31%	14.19%	0.82	0.66	20.34%	14.26%	0.77	0.67	-3.40%	17.82%	0.46	0.46
NCG	6.36%	22.47%	0.60	0.58	6.71%	16.75%	0.79	0.63	27.54%	17.42%	0.73	0.65	-12.00%	30.08%	0.47	0.54
NCS	5.69%	15.16%	0.59	0.56	6.26%	14.56%	0.76	0.64	21.54%	13.83%	0.60	0.55	-8.77%	16.94%	0.49	0.53
RE	6.32%	19.72%	0.48	0.43	4.41%	15.03%	0.59	0.48	13.50%	18.43%	0.58	0.48	2.24%	24.62%	0.41	0.40
UT	0.07%	21.10%	0.68	0.62	-2.92%	18.26%	0.78	0.63	10.09%	19.55%	0.74	0.67	-5.27%	24.87%	0.61	0.59
Average	4.04%	20.14%	0.64	0.60	1.68%	16.49%	0.78	0.64	18.17%	17.31%	0.70	0.63	-5.50%	25.03%	0.55	0.57

TABLE 3: Annualized mean and standard deviation of TP and MVP

By columns: Annualized mean (Mean), standard deviation (Stdv.). The weekly returns are calculated in US dollar for the period January 12, 1990 until September 05, 2003. Pre-Convergence subperiod goes from January 1990 until December 1994 (260 observations). The Convergence subperiod ranges from January 1995 until December 1998 (208 observations). Euro subperiod ranges from January 1999 until September 2003 (245 observations). The overall sample size is 713 observations. MVP stands for minimum variance portfolio and TP for the tangency portfolio. The EMU index is computed by building a market value-weighted index based on DataStream country indexes.

	Sample	1991-2003		Pre-Convergence		Convergence		Euro	
		Panel A: Mean Variance frontier without constraints							
		Mean	Stdv.	Mean	Stdv.	Mean	Stdv.	Mean	Stdv.
TP	Countries	31.77%	45.13%	44.53%	41.42%	74.17%	31.36%	-	-
	Industries	18.43%	23.16%	64.14%	39.43%	59.89%	22.81%	-	-
	C-I Pairs	137.31%	48.89%	117.36%	24.66%	85.10%	11.87%	714.24%	133.05%
MVP	Countries	3.12%	14.14%	3.89%	12.24%	10.91%	12.03%	-	-
	Industries	6.30%	13.54%	5.96%	12.02%	14.86%	11.36%	-	-
	C-I Pairs	3.09%	7.34%	7.20%	6.11%	20.78%	5.87%	2.45%	7.80%
		Panel B: Mean Variance frontier with short selling constraints							
		Mean	Stdv.	Mean	Stdv.	Mean	Stdv.	Mean	Stdv.
TP	Countries	9.45%	19.85%	8.67%	15.99%	23.77%	13.71%	2.70%	15.90%
	Industries	6.20%	14.09%	6.10%	13.81%	24.47%	14.02%	2.29%	24.71%
	C-I Pairs	15.08%	13.96%	22.88%	14.38%	35.88%	11.21%	18.20%	16.12%
MVP	Countries	2.76%	14.47%	3.65%	12.52%	15.05%	12.65%	0.00%	14.17%
	Industries	5.74%	13.87%	5.05%	12.81%	17.68%	12.22%	0.00%	18.69%
	C-I Pairs	2.08%	8.49%	4.68%	7.82%	15.08%	7.74%	0.52%	10.70%
		Panel C: Mean and Standard Deviation of the EMU index							
		Mean	Stdv.	Mean	Stdv.	Mean	Stdv.	Mean	Stdv.
	EMU index	3.79%	16.85%	0.14%	14.94%	18.58%	14.85%	-4.91%	19.97%

TABLE 4: Efficiency test for country and industry diversification

This table presents the test statistics of the BJS (2002) efficiency test. The Pre-Convergence period goes from January 1990 until December 1994 (260 observations). The convergence period ranges from January 1995 until December 1998 (208 observations). The euro period ranges from January 1999 until September 2003 (245 observations). The overall sample size is 713 observations. TP stands for the tangency portfolio and MVP denotes the minimum variance portfolio. The mimicking portfolio is the country or industry based portfolio on the mean-variance frontier with the same expected return as the benchmark. Country-Industry pairs (C-I pairs) are the industry indexes within the ten EMU countries, e.g. level three sector classification of DataStream. Countries are Austria (AU), Belgium (BG), Finland (FI), France (FR), Germany (GE), Greece (GR), Ireland (IR), Italy (IT), Netherlands (NL), Portugal (PT) and Spain (SP). Industries are Basic Industries (BI), Cyclical Consumer Goods (CCG), Cyclical Services (CS), Financials (FI), General Industrials (GI), Information Technology (IT), Non-cyclical Consumer Goods (NCG), Non-cyclical Services (NCS), Resources (RE), and Utilities (UT). Industry indexes are computed by building market value-weighted indexes based on DataStream level three sector classification. Source: DataStream and own calculations.

Sample	1991-2003	Pre-Convergence	Convergence	Euro
	Panel A: benchmark: countries, mimicking portfolio: industries			
TP	-0.33	-2.21**	-0.87	-
MVP	0.35(b)	-0.11(b)	-0.69(b)	-
	Panel B: benchmark: industries, mimicking portfolio: countries			
TP	0.68	1.09	0.87	-
MVP	1.76*	0.46	0.97	-
	Panel C: benchmark: C-I pairs, mimicking portfolio: countries			
TP	2.40**	2.15**	3.82***	2.48***
MVP	9.14(b)***	4.70***	4.26***	4.76***
	Panel D: benchmark: C-I pairs, mimicking portfolio: industries			
TP	2.35**	3.13***	1.59***	1.94**
MVP	5.57(b)***	7.54***	6.03***	3.04***
	Panel E: benchmark: EMU index, mimicking portfolio: countries			
EMU Index	-5.89***	-2.95***	-3.29***	-4.65 ***
	Panel F: benchmark: EMU index, mimicking portfolio: industries			
EMU Index	-3.88***	-3.43***	-2.78***	-4.72***

* Statistically significant at 10%, ** statistically significant at 5%, *** statistically significant at 1%. (a) The test is not feasible because the return of the benchmark is not attainable by the primitive assets. (b) Indicates that the portfolio of the primitive assets is not an efficient portfolio. (c) The test is not feasible because the mean-variance frontier of the mimicking portfolio lies above the benchmark one

TABLE 5: Efficiency tests for country and industry diversification with short-selling constraints

This table presents the test statistics of the BJS (2002) efficiency test with no short selling. The Pre-Convergence period goes from January 1990 until December 1994 (260 observations). The convergence period ranges from January 1995 until December 1998 (208 observations). The euro period ranges from January 1999 until September 2003 (245 observations). The overall sample size is 713 observations. TP stands for the tangency portfolio and MVP denotes the minimum variance portfolio. The mimicking portfolio is the country or industry based portfolio on the mean-variance frontier with the same expected return as the benchmark. Country-Industry pairs (C-I pairs) are the industry indexes within the ten EMU countries, e.g. level three sector classification of DataStream. Countries are Austria (AU), Belgium (BG), Finland (FI), France (FR), Germany (GE), Greece (GR), Ireland (IR), Italy (IT), Netherlands (NL), Portugal (PT) and Spain (SP). Industries are Basic Industries (BI), Cyclical Consumer Goods (CCG), Cyclical Services (CS), Financials (FI), General Industrials (GI), Information Technology (IT), Non-cyclical Consumer Goods (NCG), Non-cyclical Services (NCS), Resources (RE), and Utilities (UT). Industry indexes are computed by building market value-weighted indexes based on DataStream level three sector classification. Source: DataStream and own calculations.

Sample	1991-2003	Pre-Convergence	Convergence	Euro
	Panel A: benchmark: countries, mimicking portfolio: industries			
TP	(a)	(a)	-0.04	(a)
MVP	1.03(b)	1.35(b)	-0.37(b)	0.63(b)
	Panel B: benchmark: industries, mimicking portfolio: countries			
TP	1.73*	-0.96	0.08	-2.18**
MVP	1.88*	-0.50	0.78	-3.04***
	Panel C: benchmark: C-I pairs, mimicking portfolio: countries			
TP	(a)	(a)	(a)	(a)
MVP	7.32(b)***	4.96***	3.93***	4.00***
	Panel D: benchmark: C-I pairs, mimicking portfolio: industries			
TP	(a)	(a)	(a)	(a)
MVP	2.71(b)***	5.66***	5.17***	0.90
	Panel E: benchmark: EMU index, mimicking portfolio: countries			
EMU Index	-5.48***	-2.74***	-3.60***	-4.54***
	Panel F: benchmark: EMU index, mimicking portfolio: industries			
EMU Index	-3.16***	-2.25**	-2.86***	-4.47***

* Statistically significant at 10%, ** statistically significant at 5%, *** statistically significant at 1%. (a) The test is not feasible because the return of the benchmark is not attainable by the primitive assets. (b) Indicates that the portfolio of the primitive assets is not an efficient portfolio. (c) The test is not feasible because the mean-variance frontier of the mimicking portfolio lies above the benchmark one

TABLE 6: Annualized mean and standard deviation of the TP and MVP with upper and lower bounds

By columns: Annualized mean (Mean), standard deviation (Stdv.). The margins of the tight strategy are W×(1±0.05), while the margins of the loose strategy are characterized as follows W±(2 percentage points), with W denoting the mean of the percentage weight of the (country or indsutry) index in the EMU index. The Pre-Convergence period goes from January 1990 until December 1994 (260 observations). The convergence period ranges from January 1995 until December 1998 (208 observations). The euro period ranges from January 1999 until September 2003 (245 observations). The overall sample size is 713 observations.

	Sample	1991-2003		Pre-Convergence		Convergence		Euro	
		Panel A: Upper and lower bonds defined as *W×(1±0.05)*							
		Mean	Stdv.	Mean	Stdv.	Mean	Stdv.	Mean	Stdv.
TP	Countries	4.01%	16.86%	0.73%	14.84%	19.12%	14.79%	-	-
	Industries	4.03%	16.96%	1.13%	15.27%	17.99%	14.71%	-	-
MVP	Countries	3.98%	16.83%	0.71%	14.77%	18.89%	14.75%	-5.26%	20.21%
	Industries	3.96%	16.86%	1.03%	15.23%	17.61%	14.62%	-6.18%	19.6%
		Panel B: Upper and lower bonds defined as *W±0.02%*							
		Mean	Stdv.	Mean	Stdv.	Mean	Stdv.	Mean	Stdv.
TP	Countries	4.60%	17.02%	1.48%	14.71%	20.16%	14.85%	-	-
	Industries	4.42%	16.86%	1.68%	15.1%	18.87%	14.66%	-	-
MVP	Countries	3.84%	16.43%	0.94%	14.46%	18.4%	14.43%	-5.36%	19.37%
	Industries	4.01%	16.43%	1.46%	14.97%	17.4%	14.23%	-5.84%	18.93%

TABLE 7: Efficiency test for country and industry diversification with upper and lower bonds

This table presents the test statistics of the BJS (2002) efficiency test with upper and lower bounds. The margins of the tight strategy are W×(1±0.05), while the margins of the loose strategy are characterized as follows W±(2 percentage points), with W denoting the mean of the percentage weight of the (country or indsutry) index in the EMU index. The Pre-Convergence period goes from January 1990 until December 1994 (260 observations). The convergence period ranges from January 1995 until December 1998 (208 observations). The euro period ranges from January 1999 until September 2003 (245 observations). The overall sample size is 713 observations. TP stands for the tangency portfolio and MVP denotes the minimum variance portfolio. The mimicking portfolio is the country or industry based portfolio on the mean-variance frontier with the same expected return as the benchmark Industry indexes are computed by building market value-weighted indexes based on DataStream level three sector classification. Source: DataStream and own calculations.

Sample	1991-2003	Pre-Convergence	Convergence	Euro
	Upper and lower bonds defined as *W×(1±0.05)*			
	Panel A: benchmark: countries, mimicking portfolio: industries			
TP	0.15	(c)	(a)	-
MVP	0.12	(c)	(a)	(a)
	Panel B: benchmark industries, mimicking portfolio: countries			
TP	(a)	(a)	(c)	-
MVP	-0.25	(a)	(c)	(c)
	Upper and lower bonds defined as *W±0.02%*			
	Panel C: benchmark: countries, mimicking portfolio: industries			
TP	(a)	2.15 (b)	(a)	-
MVP	0.48 (b)	2.6(b)	-0.03	(a)
	Panel D: benchmark industries, mimicking portfolio: countries			
TP	-0.13	(a)	-1.89	-
MVP	0.33	-0.57	-	0.58(b)

* Statistically significant at 10%, ** statistically significant at 5%, *** statistically significant at 1%. (a) The test is not feasible because the return of the benchmark is not attainable by the primitive assets. (b) Indicates that the portfolio of the primitive assets is not an efficient portfolio. (c) The test is not feasible because the mean-variance frontier of the mimicking portfolio lies above the benchmark.

TABLE 8: Bootstrap distribution of minimum variance portfolio (MVP) weights

By columns: Sample mean, bootstrap mean, bootstrap standard deviation (Stdv.), and bootstrap 1st quartile. Panel A contains country portfolio weights and Panel B contains industry portfolio weights. The margins of the tight strategy are W×(1±0.05), while the margins of the loose strategy are characterized as follows W±(2 percentage points), with W denoting the percentage weight of the (country or industry) index in the EMU index from the last observation in each bootstrap data set. Bootstrap replications involve a block wise sampling across the country or industry return time series. Sample windows are constructed as follows: The size of the sampling window is 240 observations. The first data window ranges from the first observation to the 240th data point. The second window ranges from the second observation to the 241st data point. We proceed until the last window with 240 observations is reached. The bootstrap distribution contains 473 observations. The original weekly returns are calculated in US dollar for the period January 12, 1990 until September 05, 2003, with a sample size of 713. Countries are Austria (AU), Belgium (BG), Finland (FI), France (FR), Germany (GE), Greece (GR), Ireland (IR), Italy (IT), Netherlands (NL), Portugal (PT) and Spain (SP). Industries are Basic Industries (BI), Cyclical Consumer Goods (CCG), Cyclical Services (CS), Financials (FI), General Industrials (GI), Information Technology (IT), Non-cyclical Consumer Goods (NCG), Non-cyclical Services (NCS), Resources (RE), and Utilities (UT). Industry indexes are computed by building market value-weighted indexes based on DataStream level three sector classification. Source: DataStream and own calculations.

Panel A: Countries																
	Unconstrained				No short sales				Tight constrained				Loose constrained			
	Sample Mean	Bootstrap Mean	Bootstrap Stdv.	Bootstrap 1st Quartile	Sample Mean	Bootstrap Mean	Bootstrap Stdv.	Bootstrap 1st Quartile	Sample Mean	Bootstrap Mean	Bootstrap Stdv.	Bootstrap 1st Quartile	Sample Mean	Bootstrap Mean	Bootstrap Stdv.	Bootstrap 1st Quartile
AU	0.2863	0.3306	0.1842	0.1966	0.2321	0.1950	0.1237	0.1209	0.0126	0.0101	0.0033	0.0067	0.0320	0.0399	0.0202	0.0149
BG	0.1901	0.1688	0.0923	0.1068	0.1761	0.1170	0.1287	0.0000	0.0452	0.0419	0.0051	0.0388	0.0630	0.0379	0.0046	0.0351
FI	0.0148	-0.0265	0.0532	-0.0646	0.0000	0.0166	0.0280	0.0000	0.0267	0.0350	0.0125	0.0246	0.0081	0.0343	0.0131	0.0232
FR	0.1454	0.1932	0.1359	0.0602	0.0377	0.0558	0.0807	0.0000	0.2531	0.2526	0.0275	0.2337	0.2286	0.2377	0.0219	0.2188
GE	-0.3139	-0.1759	0.1369	-0.2743	0.0000	0.0167	0.0494	0.0000	0.2598	0.2419	0.0294	0.2139	0.2535	0.2389	0.0269	0.2139
GR	-0.0126	-0.0001	0.0435	-0.0384	0.0000	0.0315	0.0391	0.0000	0.0113	0.0137	0.0053	0.0092	0.0291	0.0233	0.0165	0.0142
IR	0.1843	0.1420	0.1229	0.0231	0.1689	0.1068	0.1229	0.0000	0.0150	0.0163	0.0017	0.0150	0.0342	0.0152	0.0035	0.0136
IT	0.0418	0.0852	0.0327	0.0592	0.0116	0.0438	0.0362	0.0073	0.1137	0.1235	0.0161	0.1079	0.0997	0.1215	0.0151	0.1069
NL	0.2758	0.2511	0.2828	0.0513	0.1735	0.3022	0.2823	0.0000	0.1644	0.1664	0.0214	0.1473	0.1582	0.1563	0.0271	0.1333
PT	0.2209	0.1025	0.0381	0.0772	0.2001	0.0865	0.0844	0.0013	0.0125	0.0150	0.0032	0.0131	0.0319	0.0160	0.0073	0.0126
SP	-0.0330	-0.0709	0.1194	-0.1934	0.0000	0.0281	0.0535	0.0000	0.0858	0.0837	0.0115	0.0785	0.0617	0.0790	0.0088	0.0747

Panel B: Industries																
	Unconstrained				No short sales				Tight constrained				Loose constrained			
	Sample Mean	Bootstrap Mean	Bootstrap Stdv.	Bootstrap 1st Quartile	Sample Mean	Bootstrap Mean	Bootstrap Stdv.	Bootstrap 1st Quartile	Sample Mean	Bootstrap Mean	Bootstrap Stdv.	Bootstrap 1st Quartile	Sample Mean	Bootstrap Mean	Bootstrap Stdv.	Bootstrap 1st Quartile
BI	0.1192	0.1262	0.2024	-0.0672	0.0000	0.0726	0.1008	0.0000	0.1032	0.0854	0.0195	0.0723	0.1183	0.0814	0.0222	0.0654
CG	-0.0958	-0.0763	0.1198	-0.1940	0.0000	0.0008	0.0081	0.0000	0.0464	0.0436	0.0075	0.0391	0.0261	0.0434	0.0074	0.0389
CS	0.2319	0.3294	0.1730	0.1613	0.0818	0.2070	0.1922	0.0156	0.0616	0.0610	0.0067	0.0567	0.0787	0.0587	0.0105	0.0535
FI	-0.2309	0.0391	0.2780	-0.1576	0.0000	0.0873	0.0900	0.0000	0.2759	0.2775	0.0193	0.2657	0.2704	0.2670	0.0154	0.2569
GI	-0.0525	-0.0788	0.1243	-0.1913	0.0000	0.0046	0.0190	0.0000	0.0689	0.0756	0.0110	0.0651	0.0525	0.0724	0.0085	0.0651
IT	-0.0361	-0.0748	0.0710	-0.0944	0.0000	0.0011	0.0064	0.0000	0.1110	0.0979	0.0213	0.0825	0.0969	0.0979	0.0213	0.0825
NCG	0.3873	0.3315	0.1441	0.2199	0.3030	0.1646	0.1271	0.0000	0.0448	0.0544	0.0194	0.0419	0.0626	0.0494	0.0175	0.0379
NCS	0.0860	-0.1070	0.1225	-0.1988	0.0302	0.0001	0.0013	0.0000	0.0915	0.0822	0.0111	0.0740	0.0671	0.0807	0.0108	0.0738
RE	0.1776	0.1746	0.1064	0.0919	0.1513	0.1824	0.1398	0.0647	0.1012	0.1265	0.0384	0.0870	0.1164	0.1303	0.0223	0.1135
UT	0.4132	0.3361	0.0756	0.2875	0.4338	0.2795	0.0996	0.2092	0.0955	0.0961	0.0129	0.0901	0.1110	0.1188	0.0237	0.0947

TABLE 9: Out-of-sample performance of minimum variance portfolios (MVP)

By columns: annualized country mean and standard deviation (Stdv.), annualized industry mean and standard deviation (Stdev.), and the p-value of a t-test for difference in means for unconstrained minimum variance portfolios, minimum variance portfolios with short-selling constraints, and minimum variance portfolios with tight and loose constraints around the market capitalization of country and industry indexes, respectively. The t-tests assume equal variances unless the null hypothesis of equal variance (F-test) is rejected at a ten percent significance level. The reported p-values assume one-tail distributions. The p-values for two-tail distributions are twice as large as the p-values of a one-tail distribution. The margins of the tight strategy are W×(1±0.05), while the margins of the loose strategy are characterized as follows W±(2 percentage points), with W denoting the percentage weight of the country (or industry) index in the EMU index for the last observation in the bootstrap data. Each set of portfolio weights is based on the sample windows from a block-bootstrap return time series. Sample windows are constructed as follows: The size of the sampling window is 240 observations. The first data window ranges from the first observation to the 240th data point. The second window ranges from the second observation to the 241st data point. We proceed until the last window with 240 observations is reached. The bootstrap distribution contains 473 portfolio weight observations. Weekly out-of-sample returns are constructed by multiplying index returns with the optimal bootstrap portfolio weights from the previous week. The original weekly returns are calculated in US dollar for the period January 12, 1990 until September 05, 2003, with a sample size of 713. Countries are Austria (AU), Belgium (BG), Finland (FI), France (FR), Germany (GE), Greece (GR), Ireland (IR), Italy (IT), Netherlands (NL), Portugal (PT) and Spain (SP). Industries are Basic Industries (BI), Cyclical Consumer Goods (CCG), Cyclical Services (CS), Financials (FI), General Industrials (GI), Information Technology (IT), Non-cyclical Consumer Goods (NCG), Non-cyclical Services (NCS), Resources (RE), and Utilities (UT). Industry indexes are computed by building market value-weighted indexes based on DataStream level three sector classification. Source: DataStream and own calculations.

	Unconstrained			No short sales			Tight constrained			Loose constrained		
	Country	Industry	p-value	Country	Industry	p-value	Country	Industry	p-value	Country	Industry	p-value
Mean	6.99%	4.76%	37.81%	7.93%	4.49%	32.86%	5.19%	5.74%	47.52%	5.40%	5.63%	48.93%
Stdv.	0.29%	0.29%		0.33%	0.34%		0.46%	0.43%		0.44%	0.42%	

European Central Bank working paper series

For a complete list of Working Papers published by the ECB, please visit the ECB's website (http://www.ecb.int)

395 "Fiscal sustainability and public debt in an endogenous growth model" by J. Fernández-Huertas Moraga and J.-P. Vidal, October 2004.

396 "The short-term impact of government budgets on prices: evidence from macroeconomic models" by J. Henry, P. Hernández de Cos and S. Momigliano, October 2004.

397 "Determinants of euro term structure of credit spreads" by A. Van Landschoot, October 2004.

398 "Mergers and acquisitions and bank performance in Europe: the role of strategic similarities" by Y. Altunbas and D. Marqués Ibáñez, October 2004.

399 "Sporadic manipulation in money markets with central bank standing facilities" by C. Ewerhart, N. Cassola, S. Ejerskov and N. Valla, October 2004.

400 "Cross-country differences in monetary policy transmission" by R.-P. Berben, A. Locarno, J. Morgan and J. Valles, October 2004.

401 "Foreign direct investment and international business cycle comovement" by W. J. Jansen and A. C. J. Stokman, October 2004.

402 "Forecasting euro area inflation using dynamic factor measures of underlying inflation" by G. Camba-Méndez and G. Kapetanios, November 2004.

403 "Financial market integration and loan competition: when is entry deregulation socially beneficial?" by L. Kaas, November 2004.

404 "An analysis of systemic risk in alternative securities settlement architectures" by G. Iori, November 2004.

405 "A joint econometric model of macroeconomic and term structure dynamics" by P. Hördahl, O. Tristani and D. Vestin, November 2004.

406 "Labour market reform and the sustainability of exchange rate pegs" by O. Castrén, T. Takalo and G. Wood, November 2004.

407 "Banking consolidation and small business lending" by E. Takáts, November 2004.

408 "The great inflation, limited asset markets participation and aggregate demand: FED policy was better than you think" by F. O. Bilbiie, November 2004.

409 "Currency mismatch, uncertainty and debt maturity structure" by M. Bussière, M. Fratzscher and W. Koeniger, November 2004.

410 "Do options-implied RND functions on G3 currencies move around the times of interventions on the JPY/USD exchange rate? by O. Castrén, November 2004.

411 "Fiscal discipline and the cost of public debt service: some estimates for OECD countries" by S. Ardagna, F. Caselli and T. Lane, November 2004.

412 "The real effects of money growth in dynamic general equilibrium" by L. Graham and D. J. Snower, November 2004.

413 "An empirical analysis of price setting behaviour in the Netherlands in the period 1998-2003 using micro data" by N. Jonker, C. Folkertsma and H. Blijenberg, November 2004.

414 "Inflation persistence in the European Union, the euro area, and the United States" by G. Gadzinski and F. Orlandi, November 2004.

415 "How persistent is disaggregate inflation? An analysis across EU15 countries and HICP sub-indices" by P. Lünnemann and T. Y. Mathä, November 2004.

416 "Price setting behaviour in Spain: stylised facts using consumer price micro data" by L. J. Álvarez and I. Hernando, November 2004.

417 "Staggered price contracts and inflation persistence: some general results" by K. Whelan, November 2004.

418 "Identifying the influences of nominal and real rigidities in aggregate price-setting behavior" by G. Coenen and A. T. Levin, November 2004.

419 "The design of fiscal rules and forms of governance in European Union countries" by M. Hallerberg, R. Strauch and J. von Hagen, December 2004.

420 "On prosperity and posterity: the need for fiscal discipline in a monetary union" by C. Detken, V. Gaspar and B. Winkler, December 2004.

421 "EU fiscal rules: issues and lessons from political economy" by L. Schuknecht, December 2004.

422 "What determines fiscal balances? An empirical investigation in determinants of changes in OECD budget balances" by M. Tujula and G. Wolswijk, December 2004.

423 "Price setting in France: new evidence from survey data" by C. Loupias and R. Ricart, December 2004.

424 "An empirical study of liquidity and information effects of order flow on exchange rates" by F. Breedon and P. Vitale, December 2004.

425 "Geographic versus industry diversification: constraints matter" by P. Ehling and S. B. Ramos, January 2005.