Country and Sector Effects in International Stock Returns Revisited*

Lieven De Moor†
European University College Brussels
Katholieke Universiteit Leuven

Piet Sercu‡
Katholieke Universiteit Leuven

First version: 14/02/2004
Current version: 17/08/2006

Abstract The starting point of this paper is the Heston and Rouwenhorst (1994) methodology, that decomposes stock returns into four factors: market factor, country factor, sector factor and idiosyncratic factor; all with unit exposures. First, we explain why discarding small firms may overstate the relative importance of sector effects in international stock returns. We show that small caps have an above average variability (after controlling for sector and country effects) and are less exposed to their global sector index than large caps. Secondly, we show that the unit exposure assumption in Heston and Rouwenhorst (1994) is empirically not valid. We subsequently generalize the HR-methodology by taking into account the unequal distribution of exposures along countries and sectors. Thirdly, we decompose the stacked

---

[*] This paper is an updated version of the earlier title: "Portfolio Diversification: Do Industry Factors Dominate Country Factors?"

[†] Corresponding author: Lieven De Moor, Stormstraat 2, B-1000 Brussels, Belgium. Tel.: +32 498 61 64 63. Fax.: +32 2 210 12 22. E-mail: lieven.demoor@ehsal.be

[‡] Piet Sercu, Naamsestraat 69, B-3000 Leuven, Belgium. Tel.: +32 16 32 67 56. Fax.: +32 16 32 67 32. E-mail: piet.sercu@econ.kuleuven.be

The authors thank Marno Verbeek, Geert Dhaene, Constant Beckers, Stefan Duchateau, Bruno Solnik, Koen Inghelbrecht and seminar participants at the Katholieke Universiteit Leuven, the European University College Brussels, the French Finance Association (Paris, 2005) and the Financial Management Association (Stockholm, 2006) for helpful discussions and valuable comments on earlier drafts of this paper. Lieven De Moor gratefully acknowledges financial support from the Fund for Scientific Research - Flanders (Belgium).

variance of exposures and factors into his moments and correct it for estimation error in the exposures. We show that ignoring exposures and estimation error in the exposures may also overstate the impact of sector effects on international stock returns. Lastly, we show that there is no necessary link between the outcome of the HR-methodology and benefits of international risk diversification.

JEL-Classification: G12

Keywords: Sector Effects, Country Effects, Risk Diversification, Small Firms

1. Introduction

Due to technological progress, trading agreements and weakening economic and political frontiers, international financial markets seem more integrated than, say, ten years ago. EMU, for example, is widely viewed as having weakened the importance of countries relative to EMU-wide risk factors such as regional market risk and EMU sector risks. In effect, Hardouvelis *et al.* (2002) find that national markets have become more exposed to pan-European market risk as the realization of the EMU became more certain; and Emiris (2002) likewise shows that a common factor has become increasingly important in explaining total variation in the European security markets.

In a seminal study, Heston and Rouwenhorst (1994) find that country risks used to dominate sector risks, and an unresolved issue is whether recent integration has been sufficiently important to reverse that conclusion. Some recent work does conclude that the contribution of country risks has actually fallen below that of sector factors. Campa and Fernandes (2003) and Carrieri, Errunza and Sarkissian (2003) provide evidence that, although country risks have dominated indeed over a longer period, in the 1990s sector risks have overtaken country risks, at least within the OECD. Also Isakov and Sonney (2002), Baca *et al.* (2000) and Cavaglia *et al.* (2000) find that sector factors have become dominant. Even more pronounced results are obtained by Galati and Tsatsronis (2003), who conclude that the contribution of country factors has become insignificant since the mid-nineties and that sector factors are the most prominent factors since the launch of the euro. But other studies disagree. For example, Sentana (2002) finds that European country-specific risks are not yet completely eliminated and concludes that European markets have not completely integrated. Rouwenhorst (1999b) likewise concludes that within the EMU country specific factors still dominate sector risks. Also Brooks and Del Negro (2003), employing a different methodology, maintain that the country factor remains dominant. Gerard, Hillion and De Roon (2003), lastly, conclude that, while the country dimension is probably more important over the entire sample period, both end up being about equally strong.

The issue is of more than academic interest. In top-down portfolio management one traditionally starts from geographical allocations: the manager decides first on the country allocation grid (revealing a conviction that the country profile is the prime determinant of overall performance) and next selects the best securities within each national market. But around the time of the introduction of EMU, a debate on the benefits of geographical versus industrial diversification erupted, and many held that the first step should now be to set the sectoral allocations.[4] In recent years sector investment funds emerged and research departments of investment firms are often reorganized by sectors (see, for example, Bolliger, 2001). All this suggests that diversification across sectors is now often viewed as more effective than across countries within the EMU, or at least as complementary to geographical diversification (see Ehling and Ramos, 2002; Ramos, 2003; Gerard, Hillion and De Roon, 2003).

One popular issue worth raising, however, is the link between data coverage and external validity. Gerard *et al.* study the G7 countries and ten Level-3 FTSE sectors, 1973-1998. Carrieri *et al.* add 10 more OECD countries but stick to the 10 Level-3 sectors, 1990-2001. Campa and Fernandes add 22 emerging countries to the 17 OECD ones, and work with 36 Level-4 sectors. Brooks and Del Negro, finally, choose 44 countries and 39 sectors, 1985-2001. These choices matter. The importance of sector factors increases the lower the level of aggregation; Level-4 sector indices or factors, for instance, explain more than Level-3 ones. Likewise, the chances that 34 sector portfolios span many portfolios are better than the odds when one has just 10 sector indices. The importance of country factors, on the other hand, strongly depends on the degree of international coverage and size bias in the stock sample. Emerging countries have a stronger idiosyncratic component than developed ones, so the country coverage is one more aspect that affects the answer.

Issue 1: Size coverage matters. While large-cap portfolios by country are well spanned by a world factor and foreign large-cap factors or exchange rates, the small-cap sections of the national markets seem to behave rather idiosyncratically, see Eun, Huang, and Lai (2003). We show that these small-cap stocks also have an above-average variance. It follows that one can increase the importance the country factor relative to the sector effect by widening the size coverage, and this is especially true if stocks are weighted equally. More generally, in light of the above one can’t help wondering whether, by suitably selecting a sample, it might not be possible to get any answer one wants.

---

[4] A survey by Goldman Sachs and Watson Wyatt, reported by Brookes (1999) in effect revealed a strong preference among fund managers to reconsider their allocation strategies towards diversification along the sectoral line. A full 65% of the fund managers reported that the EMU would lead them to organize their European equity portfolio on a sector basis, with the remainder often adopting a mixture of both sectoral and country allocation.

Issue 2: The role assigned to exposures in the empirical work. Most of this literature relies on factor models[5] and bases the conclusion on the relative variability of country versus sector factors. Campa and Fernandes (2003) and Carrieri, Errunza and Sarkissian (2003) follow Heston and Rouwenhorst (1994) and work with variance analysis. Stocks are implicitly grouped by country or by sector into portfolios, which can be equally or value weighted depending on the design; from these portfolios, world, country and sector factors are then constructed after taking into account the overlaps between the country and sector membership lists. Strictly speaking, the assumptions underlying this variance-analysis model are that a stock has a unit exposure to its own country and sector factor, and a zero exposure to all other country or sector factors. Also the choice of the test metric, *viz.* the relative variance of the country and sector factors, reflects an assumption that stocks' exposures to these factors are identical, or at least sufficiently similar.

Brooks and Del Negro (2003) generalize the standard variance-analysis model to essentially a confirmatory factor analysis, where stocks' exposures to their own country and sector factors are unconstrained rather than set equal to unity. The zero restrictions on the exposures to other country or sector factors are maintained: a model without any prior restrictions at all would have led to the identification problem familiar from standard (exploratory) factor analysis.[6] Our approach allows unrestricted coefficients, but at the cost of abandoning the one-step approach. We adopt Fama and MacBeth (1973)'s two-stage approach: start from provisionally estimated factor returns to compute sensitivities via time-series OLS, and in a second step extract, via cross-section regressions on these estimated sensitivities, the revised factors. We verify whether this makes much of a difference. Under this approach, we select as the fundamental metric the relative variance of the product of exposure and factor return—a measure of stock-return variability *generated by* the factor. Our conclusion is that the ratio of factor-generated variance is tilted towards countries than the ratio of factor variances themselves, or stated differently, ignoring exposures may overestimate the impact of sector effects on international stock returns.

---

[5] Gerard, Hillion and De Roon (2003) rely much more on portfolio theory. They study Sharpe ratios obtained from stocks pre-grouped into either country portfolios or sector portfolios. In addition, they test whether sector portfolios are spanned by country funds or *vice versa*, and whether either are spanned by the InCapm factors (the world market and the exchange rates).

[6] If both the factors and the exposures have to be estimated at the same time from the same dataset and with no constraints, there is an infinite possible number of solutions.

Issue 3: We point out that the variance of an estimated variable is partly due to the variance of its estimation error. This is, for example, the case with the variance of the estimated exposure. The variance of the estimated exposure equals the variance of the true exposure plus the variance of its estrimation error. We derive an expression of the stacked variance of exposures and factors which enables correction for estimation error. We show that this econometric issue has a significant impact on the relative ranking of country versus sector effects. More precisely, we show that ignoring estimation error may overestimate the relative impact of sector effects on international stock returns.

Issue 4: We show that there is no necessary link between the outcome of the Heston and Rouwenhorst (1994) procedure and benefits of risk diversification. We show an example where, although, country effects have relatively more impact than sector effects on the variance of individual stock returns, diversification across sector indices can be a more effective tool for risk reduction than diversifying across country indices. We argue that the Heston and Rouwenhorst (1994) methodology does not tell us anything about the correlations among sectors or countries and no conclusion can be made to international risk diversification. Worldwide risk diversification is about covariances, not about variances and variance components only.

Robustness checks with respect to emerging markets coverage, time period, level of sector classification, and weighting schemes have already been thoroughly documented in the existing literature and text books. It suffices to note that we found similar results.

The paper is organized as follows. Section 2 describes our data. Section 3 explains the Heston and Rouwenhorst (1994) methodology. Section 4 shows how the inclusion of small firms tones down the sector-specific effects. In Section 5, we investigate to what extent the conclusions of the variance-analysis approach are altered if exposures are brought into the picture. We find Fama and MacBeth (1973)-like factors to be indistinguishable from Heston and Rouwenhorst (1994) ones; but the variance ratio tilts even more in favor of the country-specific effects when the variable studied becomes the product of factor times estimated exposure. In Section 6, we derive the components of the stacked variance of exposures and factors. We then propose a procedure to purge estimation error out of the calculated stacked variance, and conclude that ignoring this estimation error overestimates the importance of the sector effects. Lastly, in Section 7, we compute the mean-variance frontiers for equally-weighted country and sector indices, and compare the benefits of international risk diversification with the outcome of the Heston and Rouwenhorst (1994) methodology. We conclude that the Heston and Rouwenhorst (1994) methodology is not necessarily linked to international risk diversification. Section 8 concludes.

2. The Dataset

Our aim was to create an international complete and clean equity list, offering maximal coverage within and across countries, minimal data errors and minimal duplications. The Datastream Research lists are quite international and claim to contain all quotes on (all) the exchange(s) of the specified country. This means that a large number of small firms are included. Unfortunately these lists also contain small, illiquid and penny stocks, as well as secondary or tertiary listings; in addition, it suffers from survivorship bias. The Datastream Dead lists are the "dead-version" of the Datastream Research lists, containing all delisted stocks on (all) the exchange(s) of the specified country. We merged both lists, cleaned the merged list for unwanted assets and cleaned the time series for bad data (see Section 2.1). As our aim is to compose an international database, we chose countries on the basis of data-availability taking into account coverage within and across regions: North America (Canada, United States), Latin America (Argentina, Brazil, Chile, Colombia, Mexico, Peru), Japan, Asia-ex-Japan (China, Hong Kong, India, Indonesia, Malaysia, Philippines, Singapore, South Korea, Taiwan, Thailand), Euro-in countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxemburg, Netherlands, Portugal, Spain), Euro-out countries (Denmark, Greece, Norway, Sweden, UK), Switzerland, Australasia (Australia, New Zealand), South-Africa.

2.1 Cleaning the Data List:

- Dual listings within and across Exchanges (e.g. ADR's, GDR's, preferred shares, warrants, certificates, shares from the same company but with different voting rights, identical shares)
- Error shares (e.g. shares with no name, one-day shares)
- Special sectors (e.g. funds, trusts, investment companies, financial holding companies) i.e. shares that include dual information on individual companies.

2.2 Cleaning the Time Series:

The resulting equity list contains 44318 listed and delisted time series of dollar returns, not prices or local-currency returns. We applied a filter that eliminates small, illiquid and penny stocks. Penny stocks have a large probability to contain errors. They are often fallen stocks which are highly speculative and illiquid. Small companies are also sensitive to errors, they have limited liquidity and can be subject to high price pressure or price manipulation. Also, they often represent too little value to warrant attention. In practice this means that an end-of-month price formation of a stock with a market capitalization smaller than $10,000,000 or a monthly trading volume smaller than $100,000 or a price smaller than $1, are eliminated. If trading volume information is not available, we considered an unchanged monthly price (in local currency) as a sign of low trading volume for that month and unreliable price formation and hence both returns based on this price are eliminated. Lastly, we eliminated all stock quotes corresponding to a negative book-to-market value.

After applying this filter we still encountered a few high-return errors. Apparently Datastream contains some returns that are simply too good to be true and can be very influencial for regression results. The few high-return errors we encountered were: (1) decimal-sign shifting; (2) anomalously low first price of a series (probably theoretical or illiquid); (3) high reported return not corresponding to a similar change in the market capitalization, price or to a huge dividend payout; (4) data reported before actual introduction date or after the actual delisting date; (5) obvious typos; (6) wrongly handled equity offerings. All these were treated as missing observations.

2.3 Descriptive Statistics

Monthly dollar stock returns were obtained from this international database for the period 1980-1999, *i.e.* 240 months. From these monthly dollar returns of individual assets we calculated equally and value weighted Level-3 and Level-4 sector portfolios for every country. Obviously not each country is present in all Level-3 and Level-4 sectors and *vice versa*. The stock list contains 44318 unbalanced time series with the geographical and sectoral distribution shown in Figures 1 to 5.

3. Heston and Rouwenhorst (1994) Explained

3.1 Theoretically

In the Heston and Rouwenhorst (1994) tradition, every firm j is associated with one country $k=K(j)$ and one sector $i=I(j)$. The return of the stock is generated by four factors: the world factor; the factor of the stock's country, $\kappa_{K(j),t}$; the factor of the stock's industrial sector, $\iota_{I(j),t}$; and a purely idiosyncratic risk, $\varepsilon_{j,t}$:

$$R_{j,t} = \omega_t + \kappa_{K(j),t} + \iota_{I(j),t} + \varepsilon_{j,t} \tag{1}$$

The country factors have a weighted mean of zero across countries, and likewise for the sector factors. In practice, this analysis-of-variance type model is estimated by cross-sectional regressions with two sets of dummies indicating j's country or sector affiliation, and with the constraint that the weighted average country or sector effect be zero each period:[7]

$$R_{j,t} = \omega_t + \sum_{k=1}^{K(N)} \kappa_{k,t} 1_{\{k=K(j)\}} + \sum_{i=1}^{I(N)} \iota_{i,t} 1_{\{i=I(j)\}} + \varepsilon_{j,t}\ , \tag{2}$$

$$\text{s.t. } \sum_{k=1}^{K(N)} v_{k,t}\kappa_{k,t} = 0 \text{ and } \sum_{i=1}^{I(N)} w_{i,t}\iota_{s,t} = 0\ . \tag{3}$$

These cross-sectional regressions are run every period, thus generating a time series of world, country and sector factors needed for the analysis.

Heston and Rouwenhorst (1994) use individual-stock returns as left-hand-side variables. For reasons explained below we work, instead, with country*sector portfolios as regressands. The construction of the portfolios matches the weighting scheme v and w in the constraints and the weights in the cross-sectional WLS regressions. One approach is to weight each stock equally in the left-hand-side portfolios; if v and w are then set equal to the number of shares in the country or sector and the regressions use Weighted Least Squares (WLS) with weights equal to the number of shares in the regressand portfolio, then the factors ω, κ and ι are equally weighted across all shares. That is, each country or sector factor has an impact on the world market factor proportional to the number of shares in that country or sector; and each country*sector portfolio has an impact on the corresponding country or sector factor proportional to the number of shares in that country*sector portfolio. Alternatively, one can adopt value weights in the country*sector portfolio; the matching WLS weighting scheme

[7] The zero-sum constraint is a standard way of avoiding perfect collinearity among the regressors without having to drop one dummy per set of indicators. This way, the intercept can be interpreted as a world market factor; and the country and sector factors as differential effects vis-à-vis the world market.

then is to use the market capitalizations of the left-hand-side portfolios, and the matching scheme in the constraints is to set v and w equal to the market capitalization in the country and sector. Then ω, κ and ι are value-weighted across all shares. For completeness, one could also apply Ordinary Least Squares (OLS) and use equal weights v or w; then ω, κ and ι are equally weighted across all domestic sector portfolios.

Brooks and Del Negro (2003) object that, in (1), all stocks from a given country are assumed to have equal exposures to the country factor, and likewise in the sector dimension. In defense of the variance-analysis model it could be argued that (1) is not really meant to capture the true return-generating process; rather, it is intended as a device that allows one to compute and combine equally or value weighted indices into factors in a simple, transparent way. To see this, start from a model simplified to $R_{j,t}=\omega_t+\varepsilon_{j,t}$. Clearly, the OLS ω estimate that results from a cross-sectional regression on a constant would be the equally weighted world market return; and while one could question whether one should weight equally when constructing a market return, the computation of such a market return in itself does not assume that all stocks have equal market sensitivities. Likewise, if one adds one set of dummies, say the nationality indicators, *s.t.* a zero-sum constraint, then each OLS-estimated $\kappa_{k,t}$ becomes the country's equally weighted mean return in excess of the grand mean, which in turn is measured by ω_t. Again, the mere computation of the equally weighted country returns does not assume that all stocks are equally exposed to that market factor.

Obviously, if there is just a world factor and a set of country factors, we do not really need regression in the first place. Regression becomes useful only as of two or more sets of dummies because regression then allows one to sort out the overlaps between the country-based and sector-based classifications to correct the simple country-by-country and sector-by-sector equally weighted mean returns. Let N_k denote the number of stocks in country k, and $n_{i,k}$ with $i=1,\ldots I(N)$ the number of stocks within country k that belong to each sector i. (We temporarily omit time subscripts, for notational simplicity.) Consider, for example, the country index equally weighted across shares and its relation to the country and sector factors. Below, we start from the definition of the equally weighted country return, and then substitute the factor model (1), taking into account that all stocks are from the same country k. We next take the constants out of the averaging operation and also use the feature that in each cell the residuals sum to zero:[8]

$$
\begin{aligned}
CR_k &\equiv \frac{1}{N_k} \sum_{j:K(j)=k} R_j \\
&= \frac{1}{N_k} \sum_{j:K(j)=k} \left(\omega + \kappa_k + \sum_{i=1}^{I(N)} \iota_i 1_{\{i=I(j)\}} + \varepsilon_j \right) \\
&= \omega + \kappa_k + \frac{1}{N_k} \sum_{j:K(j)=k} \sum_{i=1}^{I(N)} \iota_i 1_{\{i=I(j)\}}. \qquad (4)
\end{aligned}
$$

Lastly, we work out the sum across the indicator and, to facilitate the interpretation, bring in the zero-average constraint (3):[9]

$$
\begin{aligned}
CR_k &= \omega + \kappa_k + \sum_{i=1}^{I(N)} \frac{n_{i,k}}{N_k} \iota_i \\
&= \omega + \kappa_k + \sum_{i=1}^{I(N)} \left[\frac{n_{i,k}}{N_k} - w_i \right] \iota_i \\
\kappa_k &= CR_k - \omega - \sum_{i=1}^{I(N)} \left[\frac{n_{i,k}}{N_k} - w_i \right] \iota_i. \qquad (5)
\end{aligned}
$$

Thus, the country factor starts from the standard country-k index return in excess of the world return ω and corrects this for sector factors if and to the extent that the country's sector weights, $n_{i,k}/N_k$ in the case of equal weighting, differ from the weights w_i used in the world-market factor ω. This corrected country k return then estimates the effect of local monetary and fiscal policies, differences in institutional and legal regimes and regional economic shocks which all affect the performance of the average stock of the country. A similar result holds for the sector factors:

$$
\begin{aligned}
IR_k &\equiv \frac{1}{M_i} \sum_{j:I(j)=i} R_j \\
\iota_i &= IR_k - \omega - \sum_{k=1}^{K(N)} \left[\frac{m_{k,i}}{M_i} - v_k \right] \kappa_k, \qquad (6)
\end{aligned}
$$

where M_i denotes the number of stocks that constitute sector i and $m_{k,i}$ the number of these stocks that are from country k.[10] (6) states that the return of sector i may differ from the return

---

[8] This follows from the orthogonality between the residuals and the regressors, $e_j' 1_{\{k=K(j)\}} = 0$, which boils down to the mean residual for all stocks from the country.

[9] If we consider the value-weighted country index, (5) holds with N_k the market capitalization in country k, and $n_{i,k}$, i=1…$I(N)$ the market capitalization within country k that belong to each sector i; and for the equally-weighted (across domestic sector indices) country index N_k becomes the number of sector indices in country k, and $n_{i,k}$=1, i=1…$I(N)$.

on the world market if (*i*) there is a pure sector effect *i.e.* due to sector economic shocks, the performance of sector *i* in each country may differ from the average firm in that country; or if (*ii*) the geographical composition of sector *i* is different from the geographical composition of the world market. Similar results also hold for value weights.

In short, one difference between Brooks and Del Negro on the one hand, and Eun *et al.* or Carrieri *et al.* on the other, is that the former are after a data generating process for stock returns, exposures and all, while the latter are content with computing factors from equally- or value-weighted country and sector indices. While one strength of this approach is simplicity and transparency, there is a potential drawback that echoes the concern voiced by Brooks and Del Negro about the exposures. If one's purpose is to check the relative importance of country *v* sector factors behind stock returns, it should not be taken for granted that country factors *generate* more variance than sector factors if and only if the former *have* more variance. A sufficient condition for this to be true would be that all stocks have equal exposures, but this is by no means necessary. At this stage, the message is that after estimating the factors via variance analysis, a second step is needed: verify whether the distribution of the sensitivities is similar across factors.

3.2 Empirically

As our base-case sample we select one that would please a traditional mainstream mutual fund: we consider 21 OECD countries[11] only, and within each country we discard the smallest stocks. Specifically, went down the list of average-cap ranked stocks until we had picked up 80% of the country's total average market capitalization. Equally weighted Level-3 country*sector portfolio returns are calculated for every country for the period 1990-1999. For every month, the cross-sectional regression equation (2) is run using WLS with weights equal to the number of stocks generating the sector index at that month. The weighted sum for the country and sector factors is set equal to zero with weights equal to the number of shares in portfolio (*k,i*).

---

[10] If we consider the value-weighted sector index, (6) holds with M_i the market capitalization in sector *i*, and $m_{k,i}$, k=1…$K(N)$ the market capitalization within sector *i* that belong to each country *k*; and for the equally-weighted (across domestic sector indices) sector index M_i becomes the number of country indices in sector *i*, and $m_{k,i}$=1, k=1…$K(N)$.

[11] Korea and Mexico were considered non-OECD as they entered the OECD union after 1990 (Korea: 12 Dec 1996, Mexico: 18 May 1994).

Table 3 summarizes the results. Panel A shows that only a small portion of the variance of excess country returns can be traced to sector-specific effects: the variance of the sector imbalance effect[12] in country returns is, on average, only 1.98% of the variance of the excess country returns. The reason is twofold: first, given that we consider OECD countries and use broad sector definitions, sector weights within each country are never very far from world weights; second, the sector factors themselves have a smaller variance, as we just found out.

Panel B shows that, although most of the variance of excess sector returns can likewise be attributed to sector-specific effects (88.64%), the importance of country imbalance effects[13] in excess sector returns, on average at 16.06%, is much larger than the sector imbalance effects in excess country returns (1.98%). This means that, on average, the volatility of sector indices is more influenced by specific country effects (at 16.06%), than the volatility of country indices depends on specific sector effects (at 1.98%). An obvious reason is that the average variability of excess index returns is much larger for countries than for sectors (28.70 against 9.22)[14]. But also the country imbalance effect in sector returns is larger than the sector imbalance effect in country returns (on average 1.05 against 0.41). We can write the country return as follows:

$$CR = \omega + \kappa + w_I \iota . \tag{7}$$

Taking variances and ignoring covariances we get:

$$\operatorname{var}\left(CR - \omega\right) = \operatorname{var}\left(\kappa\right) + w_I{}^2 \operatorname{var}\left(\iota\right), \tag{8}$$

---

[12] The part of a country's return variance that is due to its sector weights being different from the world portfolio sector weights is called the sector imbalance effect of that country. The sector imbalance effect is $\operatorname{var}\left(\sum_{i=1}^{I(N)} \frac{n_{i,k}}{N_k} \iota_i\right)$ or $\operatorname{var}\left(\sum_{i=1}^{I(N)} \left[\frac{n_{i,k}}{N_k} - w_i\right] \iota_i\right)$. Note that the sector imbalance effect is generated by the combination of differential sector weights—i.e. weights different from the world portfolio sector weights $\frac{n_{i,k}}{N_k} - w_i$ —and pure sector factors ι_i.

[13] The part of an sector's return variance that is due to its country weights being different from the world portfolio country weights is called the country imbalance effect of that sector. The country imbalance effect is $\operatorname{var}\left(\sum_{k=1}^{K(N)} \frac{m_{k,i}}{M_i} \kappa_k\right)$ or $\operatorname{var}\left(\sum_{k=1}^{K(N)} \left[\frac{m_{k,i}}{M_i} - v_k\right] \kappa_k\right)$. Note that the country imbalance effect is generated by the combination of differential country weights—i.e. weights different from the world portfolio sector weights $\frac{m_{k,i}}{M_i} - v_k$ —and pure country factors κ_k.

[14] These figures can be obtained by dividing the numbers in column 1 (or 3) by the numbers in column 2 (or 4) in Table 3, and then taking the cross-country and cross-sector average.

where ω, κ and ι are the world-, country and sector factors and $w_I^2 var(\iota)$ the sector imbalance effect in country returns. The sector imbalance effect consists of differential sector weights w_I^2—i.e. weights different from the world portfolio sector weights—and pure sector factors $var(\iota)$. Equivalently, we can decompose the country imbalance effect in sector returns:

$$\operatorname{var}(IR-\omega)=\operatorname{var}(\iota)+w_C^{\,2}\operatorname{var}(\kappa). \quad (9)$$

Evaluating (8) and (9) we notice that the differential weights are not very different (w_I=0.19 and w_C=0.16). The implication is that the difference between the country imbalance effect in sector returns and the sector imbalance effect in countries (on average 1.05 against 0.41) is, to a large extent, attributed to the higher variability of the pure country factor compared to the pure sector factor (on average 28.40 against 8.48).

The pure country-factor variance is the country-index volatility if it has the same sectoral composition as the market portfolio, after taking out a common world volatility. The pure sector-factor variance is the sector-index volatility if it has the same geographical composition as the market portfolio, after taking out a common world volatility. At 28.40 (ppm^2—percent per month squared), the typical country-factor variance is more than three times larger than the average sector-factor variance (8.48). This means that, on average, country-specific effects are more volatile than sector-specific effects. Or, stated differently, country effects dominate sector effects. The pure world-factor variance (16.52) lies between the pure country variance (28.40) and the pure sector variance (8.48). This underlines the importance of specific country and sector effects in international stock returns.

From all countries, the country-specific effects of Greece (e.g. local political, economical and financial regimes and decisions) generate the highest variance at 154.08, taking out the world effects and any sectoral effect. In Canada, 10.44% of the country's excess volatility is explained by its specific sector-mix. Compared to other countries, Canada seem to be relatively specialized in a few sectors compared to the world portfolio. From all sectors, the specific effects of the IT, Resources and Utilities sectors (e.g. sector specific shocks) generate the highest variances, taking out the world effects and any country-specific effect. In the Basic Industries sector, 43.73% of the sector's excess volatility is explained by its specific geographical distribution. Compared to other sectors, Basic Industries seems to be relatively geographically concentrated.

We found that, at least in the nineties, country-specific effects explain more sector-index volatility than sector-specific effects explain country-index volatility, and that country effects are more volatile than sector effects. Nevertheless, this does not necessarily mean that international sector diversification would be less effective than international country diversification. The Heston-Rouwenhorst methodology is all about variances. Risk diversification is also about covariances. We discuss this issue later on in Section 7.

4. The Role of Small Stocks

4.1 Fact 1: Small-cap stocks are more volatile than large-cap stocks

To see whether small-cap stocks have more variability than large-caps we rank all individual stocks of a given country—both OECD and emerging—on the basis of average marketcap for 1980-1999. For each of the 20% smallest stocks we compute the standard deviation of the monthly dollar return of all individual stocks for the period 1980-1999, and likewise for the 20% largest firms. We lastly compute for every country the difference between the average small-cap and the average large-cap standard deviation. Out of 39 countries, in only 21 the average standard deviation for small-cap stock returns is larger then the average standard deviation of its large-cap section. Thus, the *prima facie* support for the notion that, within a country, small are more volatile than large-caps is surprisingly weak.

But the size factor may be obscured by country and sector factors. To get a clearer view on these effects we cross-sectionally regress the estimated standard deviations of all individual stocks in the top or bottom quintile on three sets of dummies: two size indicators, 39 country dummies and 34 Level-4 sector ones:

$$\begin{aligned} &\sigma_j = a + \sum_{s=1}^{2} b_s 1_{\{S(j)=s\}} + \sum_{k=1}^{39} c_k 1_{\{K(j)=k\}} + \sum_{i=1}^{34} c_i 1_{\{I(j)=i\}} + \varepsilon_i, \\ &\text{s.t. } \sum_{s=1}^{2} b_s = \sum_{k=1}^{39} c_k = \sum_{i=1}^{34} c_i = 0, \end{aligned} \tag{10}$$

where σ_j is the standard deviation of stock *j* and where *S(j), K(j)* and *I(j)* indicate the size class, country, and sector code associated with *j*: S=1 *or* 2; K=1 to 39; L=1 to 34. The coefficients *a* and b_1=-b_2, along with their White-corrected *t*-statistics are shown in Table 1. The difference between small-caps and large-caps within a given country *re* stock variability are statistically very significant (t=11.89) and large (2*0.57=1.14 percent per month).

The next step in the argument is that these small stocks also have weaker world-sector exposure, that is, that the extra volatility has local or idiosyncratic roots.

4.2 Fact 2: Small stocks have weak world-sector affinities

To see whether small-caps are less sensitive to their world sector index than are large-caps, we adopt a two-step procedure. First, all individual stocks are grouped into portfolios based on the intersection of their country (39 of them), Level-4 sector (34) and size category (2). This generates potentially 2*34*39=2652 portfolios, of which 1400 are effectively available. We compute, for each of these intersection portfolios *p*, the equally weighted monthly dollar return R_p for the period 1980-1999, and regress it on the appropriate world-sector index return *IR*:

$$R_{p,t} = \alpha_p + \beta_p IR_{I(p),t} + \eta_{p,t} \tag{11}$$

The result is a cross-section of sector exposure estimates β_p, their *t*-statistics and the sector model's R^2's.

In an exploratory simple test we again compute the average *t*-statistic for the big-stock versus small-stock sector indices within each country. We counted only 7 (for small stocks) and 32 (for big-stocks) out of 39 countries where the average sector exposure t-statistic is above the 95% significance level.

Although this tentatively indicates that small-caps are less exposed to their sector index, we still need to control for country and sector effects, which may have induced dependencies that invalidate the hyper-geometric test. Thus, in the second step, we regress the measure of sector affinity on three sets of dummies (two size, 34 country and 39 sector ones):

$$\begin{aligned} X_p &= a + \sum_{s=1}^{2} b_s 1_{\{S(p)=s\}} + \sum_{k=1}^{39} c_k 1_{\{K(p)=k\}} + \sum_{i=1}^{34} c_i 1_{\{I(p)=i\}} + \varepsilon_p, \\ \text{s.t. } &\sum_{s=1}^{2} b_s = \sum_{k=1}^{39} c_k = \sum_{i=1}^{34} c_i = 0, \end{aligned} \tag{12}$$

where the measure X_p is either the exposure itself (β_p), or its *t*-statistic, or the regression's R^2. The coefficients for the constant and the size effect are provided in Table 2. Note that, in Table 2, for each measure of world-sector affinity there is a significant difference between small-caps and large-caps. If we control for country and sector effects, small-caps are significantly less exposed to their sector index ($\Delta\beta$=-0.28) than are large-caps relative to the grand mean (0.48). Their typical *t*-statistics for the sector exposure are 3.76 apart, with the small-cap *t* around 0.83 versus around 4.59 for large-caps. R^2, lastly, on average drops from 0.17 (large-cap) to essentially zero (small-cap).

In light of the above, the expected effect of adding small firms into the database on sector-generated variability in stock returns is double. First, the average exposure to the sector drops, which lowers the variance explained by the factor. Second, since more firms are added into the world sector index that have essentially no correlation with what goes on at the world level, the sector index benefits from a diversification effect: its variance drops.

Table 4 confirms our intuition. The base-case sample contains only the 80% biggest stocks per country based on the average dollar marketcaps of 1980-1999. The role-of-small-stocks sample contains all stocks. As expected, the average variance of the sector factor goes down (8.48 against 8.02) when the smallest stocks come into the picture, whereas the country factor remains more or less status quo (28.40 against 28.34). Stated differently, ignoring small stocks in the dataset overestimates the impact of sector effects on international stock returns.

5. The Role of Exposures

The most general linear factor model would be one with unconstrained factors and exposures, with the familiar drawback that the model is not identified, that is, an infinite number of rotations is possible. Brooks and Del Negro solve this by postulating that stock *j* is exposed only to its own country *K(j)* and its own sector *I(j)*:

$$R_{j,t} = \omega_t \beta_j + \sum_{k=1}^{K(N)} \kappa_{k,t} \gamma_{j,k} + \sum_{i=1}^{I(N)} \iota_{i,t} \delta_{j,i} + \varepsilon_{j,t},$$

$$\text{subject to } \gamma_{j,k} = 0 \text{ if } k \neq K(j) \text{, and unconstrained otherwise,} \qquad (13)$$

$$\delta_{j,i} = 0 \text{ if } i \neq I(j) \text{, and unconstrained otherwise.}$$

Brooks and Del Negro also provide an EM estimation procedure, and asymptotic properties. The approach is quite similar to Confirmatory Factor Analysis, where one imposes a sufficient number of constraints to pin down the correct rotation and where hypotheses testing becomes possible.

Like many pure factor models this procedure is somewhat of a black box. This becomes more of a problem since the zero restrictions imposed on the coefficients are inevitably not fully valid, and the impact of this simplifying assumption on the estimates is hard to trace. *A priori*, one would expect firms that are active abroad through trade or investments to be exposed to foreign factors too. In fact, Warnock and Cai (2004) show that some firms do exhibit foreign exposure (besides home-market sensitivity), and that this foreign exposure is related to the firm's foreign/total sales ratio. Another problem is that, in our case, the number of left-hand-side variables is very large relative to the length of the time series. The rule of thumb in the street is rather the inverse: in confirmatory factor analysis the number of observations is, ideally, ten times the number of variables.

We propose a Fama and MacBeth (1973)-like procedure. We first use provisionally estimated factor returns (from the Heston and Rouwenhorst (1994) procedure) to compute sensitivities via time-series OLS,

$$R_{j,t} = \hat{\omega}_t \beta_j + \hat{\kappa}_{K(j),t} \gamma_{j,K(j)} + \hat{\iota}_{I(j),t} \delta_{j,I(j)} + \varepsilon_{j,t}, \tag{14}$$

and then uses these estimated sensitivities to re-estimate the factors themselves via cross-sectional regression. In a way, the first-pass estimated betas, gammas and deltas—the world, country and sector sensitivities—replace the dummies in (2):

$$\begin{aligned} R_{j,t} &= \omega_t \hat{\beta}_j + \sum_{k=1}^{K(N)} \kappa_{k,t} \hat{\gamma}_{j,k} + \sum_{i=1}^{I(N)} \iota_{i,t} \hat{\delta}_{j,i} + \varepsilon_{j,t}, \\ &\text{subject to } \gamma_{j,k} = 0 \text{ if } k \neq K(j), \text{ and unconstrained otherwise,} \\ &\delta_{j,i} = 0 \text{ if } i \neq I(j), \text{ and unconstrained otherwise.} \end{aligned} \tag{15}$$

The two-step procedure does provide a way out of the identification problem of standard ("exploratory") factor analysis, but the obvious drawbacks are the inconsistency between the first- and second-pass factors, and the fact that the second-stage regression in no way takes into account the estimation errors that are brought in in step 1. To partially remediate this problem, we rely on country*sector portfolio returns—equally or value-weighted—as left-side variables in (15), rather than the standard individual-stock returns. As already pointed out by Fama and MacBeth (1973), exposure estimates for portfolios suffer less from errors-in-variables than do estimates for individual stocks. As a convenient by-product, portfolios also allow us to work with balanced panels without inducing survival bias (although the number of shares in a portfolio does vary over time).

If there are systematic differences in exposures across factors, a comparison of equally or value-weighted factor portfolios might not tell us what factors have the biggest impact on stocks. We ask the question whether the ranking on the basis of factor variance is the same as the ranking on the basis of factor-generated variance. In the case of country risk, for instance, factor-generated variance is defined as the variance across the stacked vectors, country by country, with elements $\gamma_{j,K(j)}\kappa_k$. Recall that γ is a country exposure and κ the corresponding country factor return. Thus,

$$\operatorname{var}(\gamma\kappa)=\frac{\sum_{k=1}^{K(N)}\sum_{j:K(j)=k}\sum_{t=1}^{T}\left[\gamma_{j,K(j)}\kappa_{k,t}-\overline{\gamma\kappa}\right]^2}{NT-1}. \tag{16}$$

The Heston and Rouwenhorst (1994) procedure ignores the possibility that, for instance, the variance of country sensitivities γ across stocks may be larger than the variance of the sector sensitivities δ, so that the ratio var(γκ)/var(δι) may be much larger than the ratio var(κ)/var(ι). The first ratio is arguably the more important one, as it looks at the stock-return variance generated by the factor rather than the variance of the factor itself.

We accordingly add two steps to the base case. First, we estimate world, country and sector exposures by running OLS time-series regressions (15) using the estimated factors from the base case as regressors. These exposures are still constrained in the sense that, say, a German steel company cannot be exposed to, for instance, the US factor and or the Construction factor; but the non-zero coefficients are no longer set equal to unity *a priori*, as is done in the variance-analysis model. We calculate the Wald statistic for the null hypothesis that for each portfolio its country exposure equals its sector exposure. This null is rejected by a very wide margin (χ^2=3353.08; p-value=0.00) even without testing whether that supposedly common value might be unity. This means that exposures are not of the [1,0] type, creating room for the possibility that the ratio var(γκ)/var(δι) may differ from the ratio var(κ)/var(ι). Step 2 is similar to the Heston and Rouwenhorst (1994) regression except that estimated gammas and deltas are used instead of sector and country dummies. This produces a revised set of factor returns. In terms of variances, the second-pass factor returns turn out to be almost indistinguishable from the original ones. (The average pairwise correlation between the two estimates of the factors is 0.994.)

In Table 4, the base-case procedure applies Hesten and Rouwenhorst (1994) i.e. it ignores exposures and computes the variance of the factors. The role-of-exposures procedure, in Table 4, studies the variances of the products of factor-specific return and exposure. This table shows that if one takes into account the exposures, the average sector variance drops (8.02 against 2.95) fare more than the average country variance (28.40 against 25.48). Thus, country exposures seem to exhibit more variability across stocks than sector sensitivities. Stated differently, ignoring exposures may overestimate the impact of sector effects relative to country effects.

The remaining problem with this result is that the exposures are estimated with error, which inflates the variance of the product of exposure and factor; that is, part of the observed cross-sectional variance must be due to estimation error. This is the subject of the next section.

6. The Role of Estimation Error

We relate (16) to *var(κ)*. In computing *var(γκ)* we purge from the cross-sectional variability the part created by estimation errors,

Suppose the true generating process is the linear model with unrestricted exposures as given in (15). In computing *var(γκ)* we want to take into account the information on variability created by estimation errors. This requires a decomposition of the variance of the product into factor- and exposure-related moments. Below, the operators E() and cov() refer to similar operations across the stacked vector of products $\gamma\kappa$ as in (16); and $E(.)^2$ denotes the square of the expectation, not the expectation of the square. In the last line of the equation array below, we have used $\text{cov}(\gamma,\kappa)=E[\text{cov}(\gamma,\kappa|k)]+E\{[E(\gamma|k)-E(\gamma)][E(\kappa|k)-E(\kappa)]\}$, in which expression the conditional covariances are all zero because, conditional on the country k, the factor is common across all stocks and therefore is not a source of covariance with the loadings. The result is

$$\begin{aligned}
\text{var}(\gamma\kappa) &= \text{E}(\gamma^2\kappa^2)-\text{E}(\gamma\kappa)^2 \\
&= \left[\text{E}(\gamma^2)\text{E}(\kappa^2)+\text{cov}(\gamma^2,\kappa^2)\right]-\left[\text{E}(\gamma)\text{E}(\kappa)+\text{cov}(\gamma,\kappa)\right]^2 \\
&= \left[\text{var}(\gamma)+\text{E}(\gamma)^2\right]\left[\text{var}(\kappa)+\text{E}(\kappa)^2\right]+\text{cov}(\gamma^2,\kappa^2) \\
&\quad -\left[\text{E}(\gamma)\text{E}(\kappa)+\text{cov}(\gamma,\kappa)\right]^2 \\
&= \left[\text{var}(\gamma)+\text{E}(\gamma)^2\right]\left[\text{var}(\kappa)+\text{E}(\kappa)^2\right]+\text{cov}(\gamma^2,\kappa^2) \\
&\quad -\left[\text{E}(\gamma)\text{E}(\kappa)+\text{cov}\left(\text{E}(\gamma|k),\text{E}(\kappa|k)\right)\right]^2. \qquad (17)
\end{aligned}$$

This shows us why, in a general model the ranking on the basis of factor-generated variance, like var($\gamma\kappa$), may differ from a ranking on the basis of factor variance, like var(κ).[15] The

[15] For instance, the factor-generated country variance can be higher than the factor-generated sector variance although the variance of the country factor is smaller than the sector variance if (i) the mean square exposure to country risk is larger than the mean square exposure to sector risk i.e. if on average the dispersion of the exposure to country risk is higher than the dispersion of the exposure to sector risk or higher absolute exposures to country risk enhance the impact of country risk on stock returns, or (ii) if the covariance between square exposures and square factor returns is higher for countries than

equation (17) also provides clues on how to adjust the empirical counterpart of (17) for the available information on estimation error. Indeed, in reality we observe only estimated exposures, $\hat{\gamma}$, whose cross-sectional variance is inflated by estimation error. The estimated standard error for each company's exposure, $\mathrm{SE}(\hat{\gamma})$ can be used to correct the observed cross-sectional variance as follows:

$$\operatorname{var}(\hat{\gamma}) = \operatorname{var}(\gamma) + \mathrm{E}\left(\mathrm{SE}(\hat{\gamma})^2\right),$$
$$\Rightarrow \operatorname{var}(\gamma) = \operatorname{var}(\hat{\gamma}) - \mathrm{E}\left(\mathrm{SE}(\hat{\gamma})^2\right). \tag{18}$$

$$\operatorname{cov}\left(\hat{\gamma}^2, \kappa^2\right) = \operatorname{cov}\left(\gamma^2, \kappa^2\right) + \operatorname{cov}\left(\mathrm{SE}(\hat{\gamma})^2, \kappa\right),$$
$$\Rightarrow \operatorname{cov}\left(\gamma^2, \kappa^2\right) = \operatorname{cov}\left(\hat{\gamma}^2, \kappa^2\right) - \operatorname{cov}\left(\mathrm{SE}(\hat{\gamma})^2, \kappa^2\right). \tag{19}$$

We also identify the second and fourth moments that drive the difference between the two variances. Notably, the factor-generated variance is higher, holding constant the variance of the country factor itself, (*i*) if the mean square exposure to country risk is bigger, or (*ii*) if high-variance countries tend to have highly dispersed exposures, or (*iii*) if across countries the mean country returns are correlated with the mean exposures.

In Table 4, the base-case procedure applies Hesten and Rouwenhorst (1994) i.e. it ignores exposures and computes the variance of the factors. The role-of-exposures procedure, in Table 4, studies the variances of the products of factor-specific return and exposure. This table shows that if one takes into account the exposures, the average sector variance drops (8.02 against 2.95) fare more than the average country variance (28.40 against 25.48). Thus, country exposures seem to exhibit more variability across stocks than sector sensitivities. Stated differently, ignoring exposures may overestimate the impact of sector effects relative to country effects.

In Table 4, the role-of-estimation-error procedure corrects for estimation error in the estimated exposures, which boosts the var(γκ)/var(δι) ratio even further, to 10.92. Thus, correcting for estimation error in the exposures makes the average sector variance fall relatively more (2.95 against 2.23) than the average country factor (25.48 against 24.36), meaning that sector exposures are estimated less accurately than country exposures. This should not have been a huge surprise in light of the lower variability of sector returns. Stated

for sectors i.e. if high dispersed country exposures tend to go together with high dispersed country factor returns; that is, the timing of the exposures is different between countries and sectors.

differently, ignoring estimation error in the exposures may overestimates the impact of sector effects in international stock returns.

7. Heston and Rouwenhorst (1994) and Risk Diversification

The research issue in Heston and Rouwenhorst (1994) is to what extent the difference in country-index volatility is due to genuine country-specific factors as opposed to differences in the sectoral mix across countries. To this end the method tries to compute pure country and pure sector variances i.e. the volatility of countries and sectors as if they have the same sectoral or geographical composition as the global market index, and after taking out a common world factor. More specifically, the Heston and Rouwenhorst (1994) methodology decomposes each raw country return into three components: a world factor, a country-specific weighted-average sector effect, and a pure country factor. In the same vein the raw sector return is decomposed into a world component, a sector-specific weighted-average country effect, and a pure sector factor.

The Heston and Rouwenhorst (1994) issue soon becomes linked to the slightly different question whether country factors are more important than sector factors, on average. A third possible question can be raised: if, say, the average pure country volatility is larger than the average pure sector variance, does this mean that diversification across countries reduces more risk than diversification across sectors, in an international portfolio? (The question was first asked by Solnik, 1977). The answer is: Not necessarily. The Heston and Rouwenhorst (1994) methodology does not tell us anything about the correlations among sectors or countries. If the average pure country variance is larger than the average pure sector variance, it is probably more effective to reduce risk by diversification across countries within a sector than sector diversification within a country. However no conclusion can be made to risk diversification within an international or intersectoral portfolio. Worldwide risk diversification is about covariances, not about variances and variance components only. So the Heston and Rouwenhorst (1994) methodology cannot generally be compared to portfolio approaches like Gerard, Hillion and De Roon (2003).

In this section we show for the base-case sample that although the average country-specific volatility is larger than the average sector-specific variance, diversification across sectors reduces more risk than diversification across countries, in an international portfolio. To do so, we calculate the mean-variance portfolio frontier according the mathematics of the portfolio frontier in Merton (1972),

$$\begin{aligned}
&\sigma^2\left(\tilde{r}_p\right)=\frac{1}{D}\left(C\left(\mathrm{E}\left[\tilde{r}_p\right]\right)^2\right)-2A\mathrm{E}\left[\tilde{r}_p\right]+B,\\
&A=1^T V^{-1}e,\\
&B=e^T V^{-1}e,\\
&C=1^T V^{-1}1,\\
&D=BC-A^2,
\end{aligned} \tag{20}$$

where e denotes the N-vector of expected rates of returns on the N risky assets, $\mathrm{E}[r_p]$ denotes the expected rate of return on portfolio p, and **1** is an N-vector of ones. In our sample, the rate of return on any asset cannot be expressed as a linear combination of the rates of return on other assets—assets are said to be linearly independent and their covariance matrix $\boldsymbol{V}$ is nonsingular. The covariance matrix is also symmetric because $\mathrm{cov}(r_j,r_i)=\mathrm{cov}(r_i,r_j)$ for all i, j. Such a symmetric matrix is said to be positive definite if for arbitrary N-vector of constants w, with $w\neq 0$, $w^T V w>0$, where ^{T} denotes "transpose" and where $w\neq 0$ means there is at least one element of w that is not zero. For unbalanced samples, the covariance matrix may be non-positive definite and (20) may generate negative variances in the portfolio frontier.

We calculate the mean-variance frontiers for a balanced sample 10 equally-weighted Level-3 and 34 Level-4 sector indices and 39 country indices from March 1992 to December 1999. Appropriate spanning tests will, then, prove the significance of these graphical conjectures. A spanning test proves whether two opportunity sets are significantly different by testing whether one sample of indices spans the other.

$$\mathrm{R}^{\mathrm{x}}=\mathrm{A}+\mathrm{B}'\mathrm{R}^{\mathrm{y}}+\mathrm{E}, \tag{21}$$

with $\mathbf{R^x}$ and $\mathbf{R^y}$ the matrices of two samples of indices, **A** the matrix of intercepts, **B** the matrix of sensitivities and **E** the matrix of error terms. Testing for **A** significance is testing whether the opportunity set generated by $\mathbf{R^y}$ is significantly different from the opportunity set generated by $\mathbf{R^x}$ —or testing whether the **x** indices can be spanned by the **y** indices. This spanning test is equivalent to testing whether the ratio of the maximum Sharpe ratio of $\mathbf{R^x}$ relative to the maximum Sharpe ratio of $\mathbf{R^y}$ is significantly different from one. If **A** is significant, diversification across the sample of indices generating the *left* mean-variance frontier is a more effective tool to reduce risk than diversification across the sample of indices generating the *right* mean-variance frontier.

From Figure 6 and the appropriate spanning tests we conclude that—both graphically and statistically—the 34 Level-4 sector indices cannot be spanned by the 39 country indices, that subsequently cannot be spanned by 10 Level-3 sector indices. The spanning test of Level-

4 indices on country indices and country indices on Level-3 sector indices generate significant **A** matrices (Wald statistics = 293.67 and 70.45, p-values = 0.00 and 0.00).[16] First, this means that the number of indices plays an important role in the ability to reduce international risk. (From 39 country indices one can compose a lower variance portfolio than from 10 sector indices.). Second, and far more important, Figure 3 shows that diversification across 34 Level-4 sector indices is a potentially more effective method to reduce risk than diversifying across 39 country indices. In contrast, we found from the Heston and Rouwenhorst (1994) methodology that the average country-specific volatility was substantially larger than the average sector-specific variance. These apparently contradictory result, illustrates that the Heston and Rouwenhorst (1994) methodology does not tell us anything about the correlations among sectors or countries and that no conclusion can be made to international risk diversification. Stated differently, there seems to be no necessary link between the Heston and Rouwenhorst (1994) methodology and international risk diversification opportunities.

8. Conclusion

The starting point of this paper is the Heston and Rouwenhorst (1994) methodology. The Heston and Rouwenhorst (1994) methodology is basically a genius cooking recipe to calculate pure country and pure sector factors out of international stock returns. A pure country (sector) factor can be interpreted as a portfolio containing only stocks of a specific country (sector) but with the same sectorial (geographical) composition as the market portfolio. The basic assumption in Heston and Rouwenhorst (1994) is the decomposition of stock returns into four factors: market factor, country factor, sector factor and idiosyncratic factor; all with unit exposures. This procedure produces a time series of returns for each sector and each country, from which variances are computed. Comparing the average country factor variance with the average sector factor variance, tells what effects, pure country or pure sector effects, has the largest impact on stock returns. We address four important issues with respect to the Heston and Rouwenhorst (1994) methodology.

[16] Inspection of the individual intercepts does not reveal any extraordinary significant Level-4 or country indices that alone could account for the overall matrix A significance or mean-variance opportunities. Especially the IT sectors seemed to be only insignificantly positive. Campbell (2001) uses a disaggregated approach to study the volatility of common stocks at the market, sector, and firm levels. Over the period from 1962 to 1997 there has been a noticeable increase in firm-level volatility relative to market volatility. Especially the ICT sector generated high volatility such that this sector alone could actually shift the sector frontier to the left. However we find that this is not the case.

First we investigate the role of small firms in the outcome of the Heston and Rouwenhorst (1994) procedure. We show that small caps have an above average variability (after controlling for sector and country effects) and are less exposed to their global sector index than large caps. Stated differently, small firms are more volatile than large firms even after controlling for country and sector effects; and this extra volatility does not come from extra exposure to their sector benchmark. Therefore, by adding small stocks to the pure sector factors, we actually add a diversification effect to the sector factors, which reduces the average sector factor variances. Thus, small firms reduce the relative importance of sector effects.

Secondly, Heston and Rouwenhorst (1994) rank the world, country, and sector factors on the basis of their own variance, but this ranking may miss the ranking on the basis of stock-return variance explained if exposures are dissimilarly distributed across factors. Finding that the assumption of similar exposures is, in general, not realistic, we incorporate the distributions of the exposures. We explicitly show that the unit exposure assumption in Heston and Rouwenhorst (1994) is empirically not valid. We therefore generalize the Heston and Rouwenhorst (1994) methodology by taking into account the unequal distribution of exposures along countries and sectors. This is important because with unequal sector and country exposures, the country and sector variances are unequally transferred to stock returns. The relative country versus sector variance ranking may be different from the relative country versus sector *generated* variance ranking. We show that taking into account exposures enlarges the relative impact of country effects. Stated differently, ignoring the inequality of country and sector exposures underestimates the relative importance of country effects.

Thirdly, we point out that the variance of an estimated variable is partly due to the variance of its estimation error. This is, for example, the case with the variance of the estimated exposure. The variance of the estimated exposure equals the variance of the true exposure plus the variance of its estimation error. We derive an expression of the stacked variance of exposures and factors which enables correction for estimation error. We show that this econometric issue has a significant impact on the relative ranking of country versus sector effects. More precisely, we show that correcting for estimation error significantly enlarges the relative importance of country effects or, stated differently, ignoring estimation error underestimates the relative impact of country effects.

Lastly, we show that there is no necessary link between the outcome of the Heston and Rouwenhorst (1994) procedure and benefits of risk diversification. We show an example where, although, country effects have relatively more impact than sector effects on the variance of individual stock returns, diversification across sector indices can be a more effective tool for risk reduction than diversifying across country indices. This example shows that the Heston and Rouwenhorst (1994) procedure is a story of variances, whereas, risk diversification is a story of covariances, and therefore no obvious conclusions can be made from one to the other.

References

Baca, S.P., B.L. Garbe and R.A. Weiss, 2000. The Rise of Sector Effects in Major Equity Markets. Financial Analysts Journal 56, 34-40.

Bolliger, G., 2001. Characteristics of Individual Analysts' Forecasts in Europe. Working Paper, FAME, No. 33.

Brookes, M., 1999. European Banking After EMU: The Impact of EMU on Portfolio Management. Working Paper, EIB, Vol. 4, No. 1.

Brooks R. and M. Del Negro, 2003. Risk Factors in International Stock Returns. Working paper.

Campa J. M. and N. Fernandes, 2003. Sources of Gains from International Portfolio Diversification. Working paper.

Carrieri F., Errunza V. and S. Sarkissian, 2003. The Dynamics of Geographic versus Sectoral Diversification: A Causal Explanation. Working paper.

Cavaglia, S., C. Brightman and M. Aked, 2000. The Increasing Importance of Industry Effects. Financial Analysts Journal 56, 41-54

Ehling, P. and S. B. Ramos, 2002. Geographical versus Industrial Diversification: A Mean-Variance Spanning Approach. Working Paper, FAME, No. 80.

Emeris, M., 2002. Measuring Capital Market Integration. Working Paper, BIS, No. 12.

Eun C., Huang W. and S. Lai, 2003. International Diversification with Large- and Small-Cap Stocks. Working paper.

Fama, E.F. and J. Macbeth, 1973. Risk, return and equilibrium: empirical tests, Journal of Political Economy 81(3), 607-636

Galati, G. and K. Tsatsaronis, 2003. The Impact of the Euro on Europe's Financial Markets. Financial Markets, Institutions and Instruments 12, 165-222

Gerard B., Hillion P. and F de Roon, 2003. International Portfolio Diversification: Industry, Country and Currency Effects Revisited. Working paper.

Hardouvelis, G., D. Malliaropulos, D. and R. Priestley, 2002. EMU and Stock Market Integration. Unpublished Manuscript.

Heston, S. and G. Rouwenhorst, 1994. Does Industrial Structure Explain the Benefits of International Diversification? Journal of Financial Economics 36, 3-27.

Isakov D. and F. Sonney, 2003. Are Practitioners Right? On the Relative Importance of Industrial Factors in International Stock Returns. Working paper.

March, T. and P. Pfleiderer, 1997. The Role of Country and Industry Effects in Explaining Global Stock Returns. Mimeo. U.C. Berkeley and Stanford University.

Ramos, S.B., 2003. A Model of Geographical and Industrial Diversification. Unpublished Manuscript.

Sentana, E., 2002. Did EMS Reduce the Cost of Capital? Economic Journal 112, 786-809

Sharaiha, Y., E. Ametistova and S. Emrich, 2003. Global Investing (Revisited) - Country versus Sector Effects. Morgan Stanley Quantitative Strategies, August

Sharaiha, Y., E. Lufkin and S. Emrich, 2004. Global Equity and Derivatives Markets. Morgan Stanley Quantitative and Derivatives Strategies, March

Warnock, F. E. and F. Cai, 2004, International Diversification at Home and Abroad. FRB International Finance Discussion Paper No. 793

Tables

Table 1: Size effect, within countries, in volatility: top *v* bottom quintile

coefficient	estimate	t-statistic
a	13.30	130.35
$b_1(=-b_2)$	0.57	11.89

Key to Table: Standard deviations of monthly returns are regressed on a constant, a size indicator ($1_1(j)$=1 iff j is in the lower size quintile, $1_2(j)$=1 iff j is in the top size quintile), as well as country and sector dummies whose coefficients are not shown in the table.

Table 2: Size effect, within countries, in world sector affinity: top-bottom quintile

	$X_p=\beta_p$		$X_p=t(\beta_p)$		$X_p=R_p^2$	
coefficient	estim	t-stat	estim	t-stat	estim	t-stat
a	0.48	33.06	2.71	51.09	0.12	50.21
$b_1(=-b_2)$	-0.14	11.40	-1.88	-42.31	-0.05	-23.15

Key to Table: A proxy for world-sector affinity of a country/size class/sector portfolio p is regressed on a constant, a size indicator ($1_1(j)$=1 iff j is in the lower size quintile, $1_2(j)$=1 iff j is in the top size quintile), as well as country and sector dummies (whose estimated coefficients are shown in the appendix. The proxy X_p is either β_p, its t-statistic, or R_p^2 of the sector exposure regression (12).

Table 3: Country and sector factors from the base-case sample

Panel A: country factors

$\text{var}(\omega) = 16.52$	$\text{var}(\kappa)$	$\frac{\text{var}(\kappa)}{\text{var}(CR_k - \omega)}$	$\text{var}\left(\sum_{i=1}^{I(N)} \frac{n_{i,k}}{N_k} \iota_i\right)$	$\frac{\text{var}\left(\sum_{i=1}^{I(N)} \frac{n_{i,k}}{N_k} \iota_i\right)}{\text{var}(CR_k - \omega)}$
Australia	18.47	100.03%	0.84	4.52%
Germany	15.97	94.24%	0.16	0.96%
Belgium	12.26	93.04%	0.13	0.96%
Canada	14.87	92.60%	1.68	10.44%
Denmark	13.95	95.63%	0.27	1.87%
Spain	20.29	96.78%	1.04	4.96%
Finland	40.74	99.55%	0.14	0.35%
France	14.56	98.36%	0.03	0.22%
Greece	154.08	101.26%	0.33	0.21%
Ireland	15.01	98.63%	0.56	3.68%
Italy	37.98	104.90%	1.03	2.84%
Japan	48.38	99.48%	0.15	0.30%
Netherlands	14.57	105.62%	0.13	0.95%
Norway	32.34	95.56%	0.29	0.84%
New Zealand	31.00	98.82%	0.53	1.70%
Austria	26.72	94.48%	0.28	0.97%
Portugal	23.70	98.48%	0.49	2.05%
Sweden	28.17	97.01%	0.15	0.53%
Switzerland	12.09	93.00%	0.29	2.22%
U.K.	12.10	102.95%	0.05	0.41%
U.S.	9.16	97.56%	0.05	0.52%
Cross-country average	**28.40**	**98.00%**	**0.41**	**1.98%**

Panel B: sector factors

	$\text{var}(\iota)$	$\frac{\text{var}(\iota)}{\text{var}(IR_k - \omega)}$	$\text{var}\left(\sum_{k=1}^{K(N)} \frac{m_{k,i}}{M_i} \kappa_k\right)$	$\frac{\text{var}\left(\sum_{k=1}^{K(N)} \frac{m_{k,i}}{M_i} \kappa_k\right)}{\text{var}(IR_k - \omega)}$
Basic Industries	2.09	40.33%	2.27	43.73%
Cyclical Consumer Good	2.10	83.02%	0.68	26.90%
Cyclical Services	1.10	103.73%	0.17	16.28%
General Industries	1.35	90.51%	0.43	28.76%
Information Technology	17.97	82.10%	1.19	5.43%
Non-cyclical Consumer	3.94	92.00%	0.18	4.14%
Non-cyclical Services	4.75	92.20%	0.54	10.39%
Resources	26.15	99.77%	3.54	13.50%
Financials	7.10	94.96%	0.32	4.34%
Utilities	18.24	107.78%	1.22	7.18%
Cross-sector average	**8.48**	**88.64%**	**1.05**	**16.06%**

Key to table: As our base-case sample we select one that would please a traditional mainstream mutual fund: we consider 21 OECD countries[17] only, and within each country we discard the smallest stocks. Specifically, went down the list of average-cap ranked stocks until we had picked up 80% of

[17] Korea and Mexico were considered non-OECD as they entered the OECD union after 1990 (Korea: 12 Dec 1996, Mexico: 18 May 1994).

the country's total average market capitalization. Equally weighted Level-3 country*sector portfolio returns are calculated for every country for the period 1990-1999. For every month, the cross-sectional regression equation (2) is run using WLS with weights equal to the number of stocks generating the sector index at that month. The weighted sum for the country and sector factors is set equal to zero with weights equal to the number of shares in portfolio (k,i).

Table 4: Summary of robustness checks

	Average country variance	Average sector variance	Ratio
Base case	28.40	8.48	3.35
Role of small stocks	28.34	8.02	3.53
Role of exposures	25.48	2.95	8.63
Role of estimation error	24.36	2.23	10.92

Key to table: As our *base-case* sample we select one that would please a traditional mainstream mutual fund: we consider 21 OECD countries[18] only, and within each country we discard the smallest stocks. Specifically, went down the list of average-cap ranked stocks until we had picked up 80% of the country's total average market capitalization. Equally weighted Level-3 country*sector portfolio returns are calculated for every country for the period 1990-1999. For every month, the cross-sectional regression equation (2) is run using WLS with weights equal to the number of stocks generating the sector index at that month. The weighted sum for the country and sector factors is set equal to zero with weights equal to the number of shares in portfolio (k,i). The *role-of-small-stocks* sample contains all stocks. The *role-of-exposures* procedure studies the variances of the products of factor-specific return and exposure. The *role-of-estimation-error* procedure corrects for estimation error in the estimated exposures.

[18] Korea and Mexico were considered non-OECD as they entered the OECD union after 1990 (Korea: 12 Dec 1996, Mexico: 18 May 1994).

Figures

Figure 1: Geographical distribution of the stock list (in %)

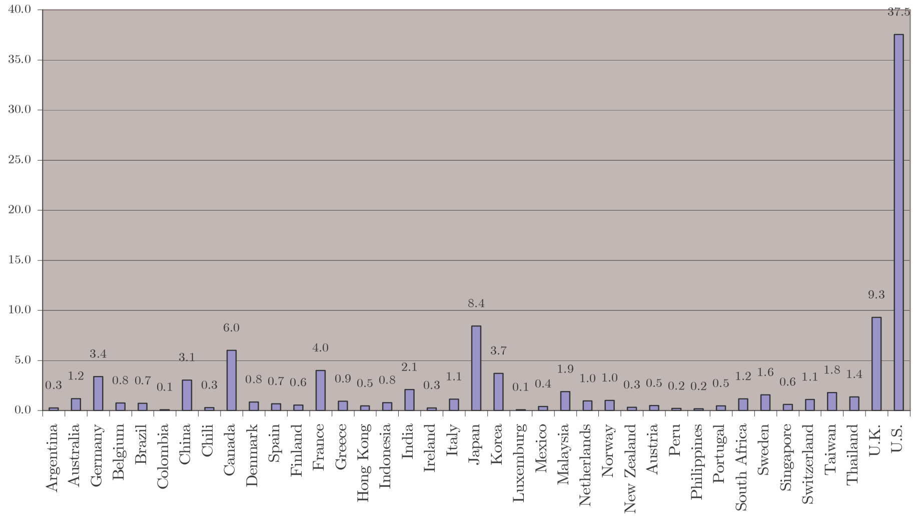


Figure 2: Equally weighted country indices: mean monthly return

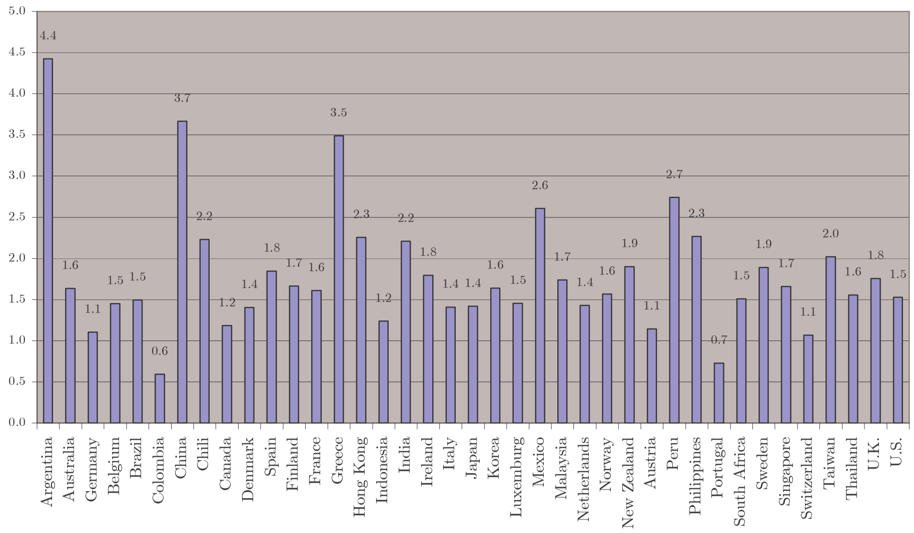


Figure 3: Equally weighted country indices: standard deviation of monthly return

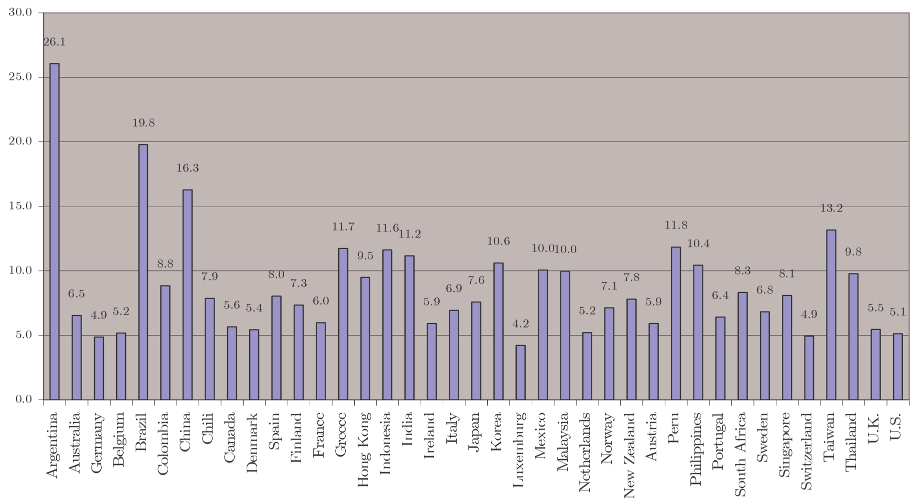


Figure 4: Equally weighted country indices: skewness of monthly return

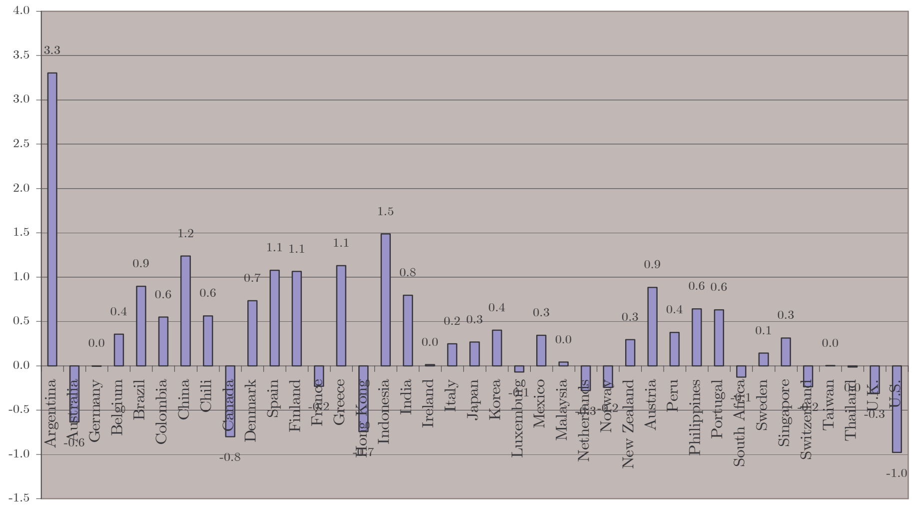


Figure 5: Equally weighted country indices: excess kurtosis of monthly return

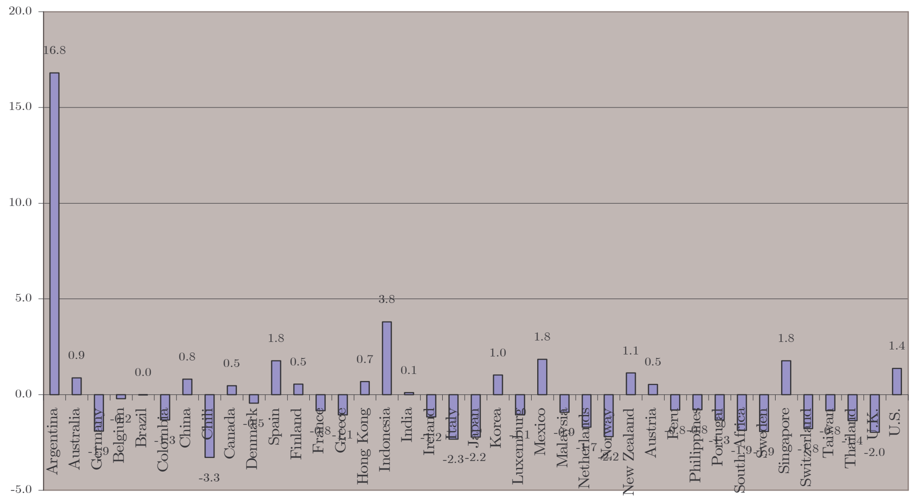
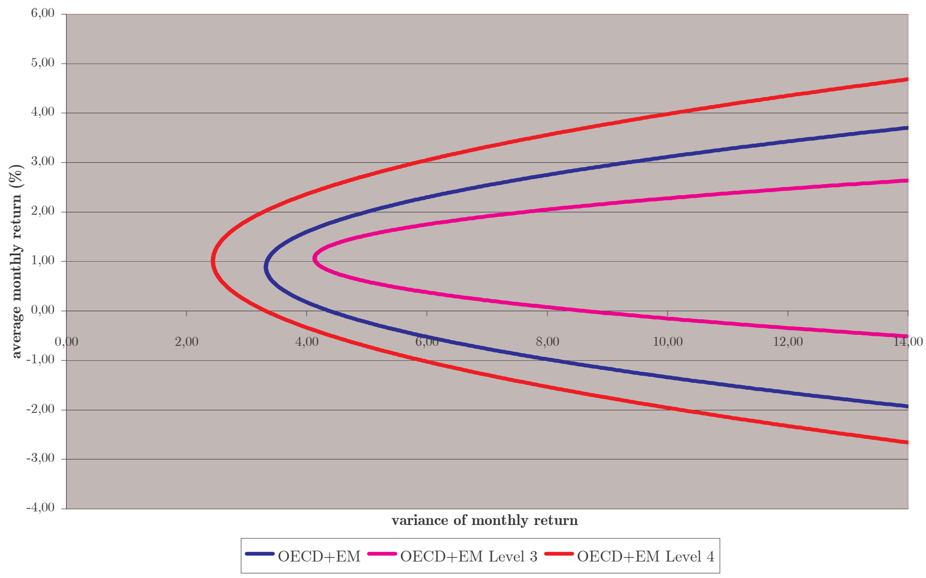


Figure 6: Mean-variance frontiers



Key to Figure: the mean-variance frontiers are calculated for a balanced sample 10 equally-weighted Level-3 and 34 Level-4 sector indices and 39 country indices from March 1992 to December 1999.