International portfolio diversification: do industry factors dominate country factors?*

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Comments welcome

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Abstract.

Despite recent reports to the contrary, we find that even recently—the 1991-2000 period—the country factor still dominates industry influences. This conclusion is robust to different test formats although the relative magnitude of the two sources of variation changes widely. One factor affecting the degree of country-factor dominance is the presence or absence of small-cap stocks in the sample: small-caps have an above average variability (after controlling for industry and country effects) and are also less sensitive to their global industry index than large-caps. Another factor that matters is the country coverage (especially the presence of emerging markets) and the level of industry aggregation (NACE 3 versus 4, for example). Methodology matters too. Heston and Rouwenhorst (1994) rank the world, country, and industry 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 into the assessment of the relative importance of country *v* industry factors, taking care to purge out the variability due to estimation error. By this metric, the dominance of the country factor becomes unassailable.

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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 industry 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 industry 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 industry 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 industry 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 industry 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 (1994) likewise concludes that within the EMU country specific factors still dominate industry 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 sectorial allocations.[1] In recent years industry 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 issue worth raising, however, is the link between data coverage and external validity. Gerard *et al.* study the G7 countries and ten level-three FTSE industries, 1973-1998. Carrieri *et al.* add 10 more OECD countries but stick to the 10 level-three industries, 1990-2001. Campa and Fernandes add 22 emerging countries to the 17 OECD ones, and work with 36 level-four industries. Brooks and Del Negro, finally, choose 44 countries and 39 sectors, 1985-2001. These choices matter. The importance of industry factors increases the lower the level of aggregation; four-level sector indices or factors, for instance, explain more than three-level ones. Likewise, the chance that 44 industry 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. Also the 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. We find that the country-*v*-industry variance ratio can be steered anywhere in the range 2.5 to 10, but not below unity.

The second issue we'd like to raise is the role assigned to exposures in the empirical work. Most of this literature relies on factor models[2] and bases the conclusion on the relative variability of country versus industry 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 industry into portfolios, which can be equally or value weighted depending on the design; from these portfolios, world, country and industry factors are then constructed after taking into account the overlaps between the country and sec-

[1] 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 sectorial 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 sectorial and country allocation.

[2] Gerard, Hillion and De Roon (2003) rely much more on portfolio theory. They study Sharpe ratio's obtained from stocks pre-grouped into either country portfolios or industry portfolios, In addition, they test whether industry 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).

tor membership lists. Strictly speaking, the assumptions underlying this variance-analysis model are that a stock has a unit exposure to its own country and industry factor, and a zero exposure to all other country or industry factors. Also the choice of the test metric, viz. the relative variance of the country and industry 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 industry factors are unconstrained rather than set equal to unity. The zero restrictions on the exposures to other country or industry factors are maintained: a model without any prior restrictions at all would have led to the identification problem familiar from standard (exploratory) factor analysis.[3] The approach of Marsch and Pfleiderer (1997), lastly, allows unrestricted coefficients, but at the cost of abandoning the one-step approach. They 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—and we purge this of for estimation variance in the exposures. Our conclusion is that the ratio of factor-generated variance is even more tilted towards countries than the ratio of factor variances themselves.

1. Test Design Issues

1.1 What does variance analysis buy us?

In the Heston-Rouwenhorst tradition, every firm j is associated with one country $k = K(j)$ and one industrial 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 of mean zero across countries, and likewise for the industry factors. (We return to the issue of weighting schemes later.) In practice, this analysis-of-variance type model is estimated by cross-sectional regressions with two sets of dummies indicating j's country or industry affiliation, and with the constraint that the weighted average country or industry effect be zero each period:[4]

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

[4] 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 industry factors as differential effects vis-a-vis the world market.

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

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

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

Heston and Rouwenhorst 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 industry 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 industry factor has an impact on the world market factor proportional to the number of shares in that country or industry; 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∗industry portfolio; the matching WLS weighting scheme 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 industry 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 industry-based classifications to correct the simple country-by-country and industry-by-industry equally weighted mean returns. Let N_k denote the number of stocks in country k, and $n_{i,k}$, $i = 1,...I(N)$ the number of stocks within country k that belong to each industry 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:[5]

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

Lastly, we work out the sum across the indicator and, to facilitate the interpretation, bring in the zero-average constraint (3):[6]

$$\begin{aligned} CR_k &= \omega + \kappa_k + \sum_{i=1}^{I(N)} \frac{n_{i,k}}{N_k} \iota_i \\ &= \omega + \kappa_k + \sum_{i=1}^{I(N)} \left[\frac{n_{i,k}}{N_k} - w_i \right] \iota_i \\ \kappa_k &= CR_k - \omega - \sum_{i=1}^{I(N)} \left[\frac{n_{i,k}}{N_k} - w_i \right] \iota_i \end{aligned} \tag{4}$$

Thus, the country factor starts from the standard country-k index return in excess of the world return ω and corrects this for industry factors if and to the extent that the country's industry 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 industry factors:

$$\begin{aligned} IR_k &\equiv \frac{1}{M_i} \sum_{j:I(j)=i} R_j \\ \iota_i &= IR_k - \omega - \sum_{k=1}^{K(N)} \left[\frac{m_{k,i}}{M_i} - v_k \right] \kappa_k \end{aligned} \tag{5}$$

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[5] 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.

[6] If we consider the value-weighted country index (4) 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 industry i; and for the equally weighted-across domestic sector indices-country index N_k becomes the number of sector indices in country k, and $n_{i,k} = 1$, $i = 1,...I(N)$.

where M_i denotes the number of stocks that constitute industry i and $m_{k,i}$ the number of these stocks that are from country k.[7] (5) states that the return of industry i may differ from the return on the world market if (*i*) there is a pure industry effect *i.e.* due to industry economic shocks, the performance of industry i in each country may differ from the average firm in that country; or if (*ii*) the geographical composition of industry 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 industry indices. While one strength of this approach is simplicity and transparency, there is a potential drawback that echoes the concern voiced by Brooks & Del Negro about the exposures. If one's purpose is to check the relative importance of country v industry factors behind stock returns, it should not be taken for granted that country factors *generate* more variance than industry 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 (see Appendix). 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.

1.2 Constrained or Confirmatory Factor Analysis

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 industry $I(j)$:

$$\begin{aligned} R_{j,t} &= \omega_t \beta_j + \sum_{k=1}^{K(N)} \kappa_{k,t} \gamma_{j,k} + \sum_{i=1}^{I(N)} \iota_{i,t} \delta_{j,i} + \varepsilon_{j,t} \\ \text{subject to } \gamma_{j,k} &= 0 \text{ if } k \neq K(j), \text{ and unconstrained otherwise,} \\ \delta_{j,i} &= 0 \text{ if } i \neq I(j), \text{ and unconstrained otherwise.} \end{aligned} \tag{6}$$

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, Cai and Warnock (2003) show that some firms do exhibit foreign exposure (besides home-market sensitivity), and that this foreign exposure is related to the firm's for-

[7] For value-weighted sector index M_i equals market capitalization in sector i, and $m_{k,i}$, $k = 1,...K(N)$ equals market capitalization within sector i that belong to each country k; and for equally weighted-across domestic sector indices-sector index M_i equals the number of country indices in sector i, and $m_{k,i} = 1$, $k = 1,...K(N)$.

eign/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, 10 times the number of variables.

A two-step approach that avoids the zero constraints is the Fama and Macbeth (1973) procedure adopted by Marsh and Pfleiderer (1997). One first uses provisionally estimated factor returns to compute sensitivities via time-series OLS,

$$R_{j,t} = \hat{\omega}_t \beta_j + \hat{\kappa}_{K(j),t}\gamma_{j,K(j)} + \hat{\iota}_{I(j),t}\delta_{j,I(j)} + \varepsilon_{j,t} \tag{7}$$

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):

$$\begin{aligned} R_{j,t} &= \omega_t \hat{\beta}_j + \sum_{k=1}^{K(N)} \kappa_{k,t}\hat{\gamma}_{j,k} + \sum_{i=1}^{I(N)} \iota_{i,t}\hat{\delta}_{j,i} + \varepsilon_{j,t} \\ \text{subject to } \gamma_{j,k} &= 0 \text{ if } k \neq K(j), \text{ and unconstrained otherwise,} \\ \delta_{j,i} &= 0 \text{ if } i \neq I(j), \text{ and unconstrained otherwise.} \end{aligned} \tag{8}$$

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, the present paper relies on country*sector portfolio returns—equally or value-weighted—as left-side variables in (8), 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).

1.3 Research Questions

1.3.1 The effects of sample selection

The first question that motivated this paper was whether there is any unconditional answer, irrespective of the country and size coverage, of the level of industry classification, and of the time period and weighting scheme. We document that, within a country, small stocks are characterized by larger variances—after controlling for country and industry affects, that is—and exhibit lower exposures to world industry factors. Thus, when expanding the size coverage, the world industry factors become better diversified (as unrelated firms are brought in) and exhibit lower variance. Also, the average firm's exposure to world industry factors drop. Something similar happens when emerging markets are brought into the picture: these are weakly related to the world market and to industry factors, and have larger variances, all of which strengthens the country factor. Lastly, the weighting scheme matters, for the same reasons. When emerging countries are added and receive as much weight as big countries that are well integrated, or when emerging-countries' smaller stocks get as much weight as the larger firms typical for OECD countries, the world industry factors explain less and the importance of country effects grows. We illustrate how country and size coverage affect the relative importance of country and industry factors.

1.3.2 The role of exposures

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,

$$\mathrm{var}(\gamma\kappa) = \frac{\sum_{k=1}^{K(N)} \sum_{j:K(j)=k} \sum_{t=1}^{T} \left[\gamma_{j,K(j)}\kappa_{k,t} - \overline{\gamma\kappa}\right]^2}{NT-1} \tag{9}$$

We relate this variance to $\mathrm{var}(\kappa)$. In computing $\mathrm{var}(\gamma\kappa)$ we purge from the cross-sectional variability the part created by estimation errors, as described in the appendix. The appendix also identifies 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.

2. Empirical Results

1.4 Data

Monthly dollar stock returns were obtained from an international database for the period 1980-1999, *i.e.* 240 months, described in De Moor and Sercu (2004). This database has been constructed from DataStream's "research" and "dead" lists for 39 countries, with the explicit purpose to avoid the survival bias and size bias that plague Datastream's standard "market" lists. The files were purged of multiple listings, derivatives quotes and other contaminations. In addition, this database has been fine-combed for errors in dollar returns, market values and book-to-market data (if available). The coverage is unusually complete, especially at the low end of the size spectrum. From the monthly dollar returns of individual assets we calculated equally and value weighted level-3 and level-4 industry portfolios for every country. Obviously not each country is present in all level-3 and level-4 industries and *vice versa*.

Our first issue is the robustness with respect to coverage and sample selection (small-firm and EM coverage, time period, level of industry classification, and weighting). Most of these effects have been documented in this literature except for the small-firm effect. Section 2.1 shows how the inclusion of small firms is likely to strengthen the country factor. We then study, in Section 2.2, to what extent the results of the standard variance-analysis approach are effectively affected by sample-selection decisions. We find that country factors dominate in each and every design. Lastly we investigate to what extent the conclusions of the variance-analysis approach are altered if exposures are brought into the picture. We find Fama-Macbeth factors to be indistinguishable from Heston-Rouwenhorst ones; but the variance ratio tilts even more in favor of the country factor when the variable studied becomes the product of factor times estimated exposure.

1.5 The behavior of small firms

We document that small firms have more variance and less affinity to world industry factors.

1.5.1 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 market cap for 1980-1999. For each of the 20 percent 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 percent largest firms. We lastly compute for every country the difference between the average small-cap and the average large-cap standard deviation. Appendix Table 8 shows the results. 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 industry 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: 2 size indicators, 39 country dummies and 34 level 4 industry 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 industry code associated with $j : S = 1 \text{ or } 2$; $K = 1 \text{ to } 39$; $L = 1 \text{ to } 34$. The coefficients a and $b_1 = -b_2$, along with their White-corrected t-statistics are shown in Table 1, while the country and industry coefficients are summarized in Appendix Table 10. The difference between small-caps and large-caps within a given country *re* stock variability are statistically very significant ($t = 11.89$) and large ($2 \times 0.57 = 1.14$ percent per month).

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.

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

1.5.2 Fact 2: Small stocks have weak world-industry affinities

To see whether small-caps are less sensitive to their world industry 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 industry (34) and size category (2). This generates potentially $2 \times 34 \times 39 = 2652$ 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-industry 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 industry exposure estimates β_p, their t-statistics and the industry model's R^2 s.

In an exploratory simple test we again compute the average t-statistic for the big-stock versus small-stock industry indices within each country. The 2 times 39 average t-statistics are shown columns 5 and 6 in Appendix Table 9. In the table we count only 7 (for small stocks) and 32 (for big-stocks) out of 39 countries where the average industry exposure t-statistic is above the 95% significance level.

Although this tentatively indicates that small-caps are less exposed to their industry index, we still need to control for country and industry effects, which may have induced dependencies that invalidate the hypergeometric test. Thus, in the second step, we regress the measure of industry affinity on three sets of dummies (2 size, 34 country and 39 industry 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, the coefficients for the other indicators are shown in Appendix Table 10. Note that, in Table 2, for each measure of world-industry affinity there is a significant difference between small-caps and large-caps. If we control for country and industry effects, small-caps are significantly less exposed to their industry index ($\Delta\beta = -0.28$) than are large-caps relative to the grand mean (0.48). Their typical t-statistics for the industry 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).

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

	$X_p = \widehat{\beta_p}$		$X_p = t\left(\widehat{\beta_p}\right)$		$X_p = R_p^2$	
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-industry affinity of a country/size class/industry 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-stat, or R_p^2 of the industry exposure regression (11).

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

1.6 Robustness of the dominance of the country effect w.r.t. coverage

1.6.1 Base Case

As our base-case sample we select one that would please a traditional mainstream mutual fund: we consider 21 OECD countries[8] 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).

Table 3 summarizes the results. The key figures are the variances in the bold-faced lines at the bottom of the first numerical columns of panels A and B. At 28 (ppm[2]—percent per month squared), the typical country-factor variance is more than three times larger than the average industry-factor variance. This suggests that the allocation across countries is more important than the weights assigned to the industries.

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

Table 3: Base Case: OECD, 80%, level 3, 1990-1999, WLS:#shares, restrictions weights: #shares; equally weighted index returns

Panel A: country factors

'	$\mathrm{var}(\kappa)$	$\frac{\mathrm{var}(\kappa)}{\mathrm{var}(CR_k-\omega)}$	$\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)$	$\frac{\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)}{\mathrm{var}(CR_k-\omega)}$
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: industry factors

'	$\mathrm{var}(\iota)$	$\frac{\mathrm{var}(\iota)}{\mathrm{var}(IR_k-\omega)}$	$\mathrm{var}\left(\sum_{k=1}^{K(N)}\frac{m_{k,i}}{M_i}\kappa_k\right)$	$\frac{\mathrm{var}\left(\sum_{k=1}^{K(N)}\frac{m_{k,i}}{M_i}\kappa_k\right)}{\mathrm{var}(IR_k-\omega)}$
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%

Before moving on to the robustness issue of this finding, we briefly discuss the importance of the industry corrections which were made to the raw country return (in excess of the world factor) to obtain the final country factor and *vv*. Panel A shows that only a small portion of the variance of excess country returns can be traced to industry-specific effects: the average variance of the correction for differential industry effects is ,on average, only 1.98% of the variance of the raw country factor. The reason is twofold: first, given that we consider OECD countries and use broad industry definitions, industry weights within each country are never very far from world weights; second, the industry factors themselves have a smaller variance, as we just found out.

Panel B shows that, although most of the variance of excess industry returns can likewise be attributed to industry-specific effects (88.64%), the importance of corrections for differential[9] country weights, at 16,06%, is much larger than the variability of industry corrections in country returns (1.98%). An obvious reason is that the average variability of excess index returns is much larger for countries than for industries (28.70 against 9.22)[10]. But also the average country imbalance effect in industry returns is larger than the average industry imbalance effect in countries (1.05 against 0.41). Note that the imbalance effects need differential weights and factor variability. We can write the raw country return as follows:

$$CR = \omega + \kappa + w_I \iota \tag{13}$$

Taking variances and ignoring covariances we get:

$$\operatorname{var}(CR - \omega) = \operatorname{var}(\kappa) + w_I^2 \operatorname{var}(\iota) \tag{14}$$

where ω, κ and ι are the world-, country and industry factors and---by averaging (14)--- $w_I^2 \operatorname{var}(\iota)$ the average industry imbalance effect in country returns that can be decomposed in the average variability of industry factors ($\operatorname{var}(\iota)$) and the average differential industry weights (w_I). In the same way we can decompose the average country imbalance effect in industry returns:

$$\operatorname{var}(IR - \omega) = \operatorname{var}(\iota) + w_C^2 \operatorname{var}(\kappa) \tag{15}$$

Evaluating (14) and (15) we notice that the average differential weights are not very different ($w_I = 0.19$ and $w_C = 0.16$). We therefore show that the difference between the average country imbalance effect in industry returns and the average industry imbalance effect in countries (1.05 against 0.41) is, to a large extent, attributed to the higher average variability of country factors (28.40 against 8.48)

[9] i.e. weights different from the world portfolio weights

[10] Not in Table 3, it is the cross-country and cross-industry average of the quotient between column 1 and 2 (or column 3 and 4)

1.6.2 Robustness of the dominance of the country effect w.r.t. sample coverage

Table 4: Summary of robustness checks: $\mathrm{var}(\kappa)/\mathrm{var}(\iota)$

Base case:	3.35
Robustness to coverage and weighting	
• time period: 1980-89 instead of 1990-1999	4.50
• country coverage:	
o add emerging markets	7.58
o lose non-G7 markets	2.62
• industry classification: level-4 instead of level 3	2.84
• size coverage: all stocks instead of top 80% (in value)	3.53
• value-weighted	3.29
• equally weighted across sector indices	5.72
Robustness to dissimilarities of exposures	
• two-stage Fama-MacBeth: 2nd-stage $\mathrm{var}(\kappa)/\mathrm{var}(\iota)$	3.67
• two-stage Fama-MacBeth: 2nd-stage $\mathrm{var}(\gamma\,\kappa)/\mathrm{var}(\delta\,\iota)$	8.63
• *idem*, corrected for estimation error	10.92

In this section we check whether the country effect in international portfolio diversification is robust to variations in the test design. We explore variations to the base case in time period, country coverage, industry classification, size coverage, weighting schemes, exposure handling and correction for estimation error. We will show that the country-effect domination is robust. Table 4 summarizes the results, more detailed figures are provided in Appendix Tables 1 to 8.

Time period. The base case considers the nineties (1990-1999) whereas the time-period variant studies the eighties (1980-1989). We note that the variance ratio $\mathrm{var}(\kappa)/\mathrm{var}(\iota)$ is larger in the eighties (4.50 against 3.35) which means that industry effects have become relatively less unimportant in the nineties. Country effects remain massively dominant.

Country coverage. In the first country coverage variant we add 15 non-OECD countries to the data base. The variance ratio rises from 3.35 tot 7.58, that is, adding emerging markets makes country effects even more dominant. This confirms that emerging countries are less integrated into the world market and therefore a source of largely diversifiable risks. In practical terms it means that when emerging countries are added to one's portfolio, the country weights become even more crucial. In the second country coverage variant we only retain the G7 countries. The variance ratio drops from 3.35 to 2.62, that is, in the G7 region specific country effects become relatively less important compared to the OECD region but still dominate specific industry effects in the nineties

Industry classification. As expected, one can weaken the relative importance of sector effects to country effects by adopting more aggregated industry classification. When we go from a level-3, 10-class industry classification to a level-4, 34-classes one, the country-industry variance ratio drops from 3.35 to just 2.84, meaning that narrowly-defined industries are less diversified and therefore more volatile. The 10-level industry classification is the only design choice, in the base case, discernibly disfavors sectors, and even this effect is not really overwhelming.

Size coverage. In the base case, the sample contains only the biggest stocks per country based on the average dollar marketcaps of 1980-1999. If, instead, we include all stocks. The impact is unexpectedly puny: there is only a small rise in the variance ratio for the all-stock sample (3.53) relative to the 80%-sample (3.35).

Value-weighting. In this variant, by value weighting we lower the impact of small stocks both in the data sample as in the estimation procedure. We start from value-weighted instead of equally weighted sector indices at the left-side of (2); in the cross-sectional regressions we weight each portfolio's return by its dollar marketcap instead of the number of companies in the portfolio; and in the constraints (3) the country and sector factors are weighted by the country's or industry's dollar market cap instead of its number of companies. Table 4 shows that value-weighting hardly affects the variance ratio: it drops from 3.35 to 3.29. Given the small-firm effect documented in the preceding variant a drop in the ratio was to be expected also here, but the effect turns out to be quite marginal.

Equally weighted across sector indices. In light of our finding that value weighting makes no appreciable difference, we wonder whether equal weighting of indices (instead of equal weighting of individual companies) is unimportant too. So in this variant we equally weight across indices by running (2) with OLS and using the number of indices as weights in (3). Even though EMs are not included, there still is a rather strong negative link between the number of traded companies and the variance of the country factor. As a result, the country weights become even more crucial relative to sector weights (with a variance ratio of 5.72 against 3.35.)

1.7 Robustness of the dominance of the country effect w.r.t. different exposures

The base case 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 $\text{var}(\gamma\kappa)/\text{var}(\delta\iota)$ may be much larger than the ratio $\text{var}(\kappa)/\text{var}(\iota)$. 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 (8) 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 U.S. 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 ($\chi^2 = 3353.08$; $p\text{-value} = 0.00$) 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 $\text{var}(\gamma\kappa)/\text{var}(\delta\iota)$ may differ from the ratio $\text{var}(\kappa)/\text{var}(\iota)$.

Step 2 is similar to the Heston-Rouwenhorst regression except that estimated gammas and deltas are used instead of industry 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, as can be seen from Appendix Figure 1 and Appendix Table 11; the average pairwise correlation between the two estimates of the factors is 0.994. Not surprisingly, then, the ratio of the average country variance over average sector variance is hardly affected, becoming 3.67 instead of 3.35.

In that set of computations, the factors are estimated on the basis of the exposures, but the fundamental test metric is still the ratio of the average factor variances. In the third step we study the variances of the products of factor return and exposure. The last line but one in Table 4 shows that if one takes into account also the exposures, country factors dominate sector risks even more than in the Heston and Rouwenhorst procedure, and the effect is huge (8.63 to one against 3.67). Thus, country exposures seem to exhibit more variability across stocks than sector sensitivities, which boosts the average amount of stock-return variance generated by the country factor.

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. Our correction for this estimation error, along the lines set out in the Appendix, boosts the domination of country factors even further, to 10.92. Thus, correcting for errors makes var($\delta\iota$) fall more than var($\gamma\kappa$), meaning that estimated industry exposures are more imprecise than estimated country exposures. This should not have been a huge surprise in light of the lower variability of industry returns.

The general conclusion of this subsection is that, although the standard procedure of ignoring exposures does produce the correct relative ranking of country and sector factors as generators of stock returns, it does underestimate the magnitude by which the country factor dominates the sector factor.

3. Conclusion

An investor seeking international portfolio diversification would like to know what type of deviations from the world-portfolio weights add most risk: country misbalancing, or sector misbalancing. Heston and Rouwenhorst (1994) adopt a procedure to estimate world-, country- and industry factors. In the case of a country factor, for instance, one starts from the raw country-index return in excess of the world return, from which one then subtracts sector-factor returns weighted by the country's differential sector weights, that is, the sector's weight in the country versus in the world.

In this paper we verify the robustness of the relative dominance of country- versus industry factors in international portfolio diversification. We consider many variations on a base-case format and show that the dominance of the country factor is robust, although the magnitude of its dominance varies widely depending on the design. Especially the introduction of emerging countries into the data sample boosts the country dominance. We also explain the rise in the country dominance if one introduces small-caps into the data sample: these stocks have significantly more variability than large-caps when controlling for country and industry effects, and they are significantly less sensitive to their global industry index.

If one is concerned with the data generating process of stock returns or if the portfolio holds a rather small number of assets, one would like to know what factor has the largest impact on the return of a randomly chose stock. This calls for a study of $\mathrm{var}(\gamma\kappa)$ instead of $\mathrm{var}(\kappa)$. This would not make a difference if all non-zero factor exposures are equal across all stocks, but we show that this is not statistically acceptable. Hence we extend the Heston-Rouwenhorst procedure to estimate the factor exposures. One has to realize however, that comparing the factor-generated variance like $\mathrm{var}(\gamma\kappa)$—instead of the pure factor variance $\mathrm{var}(\kappa)$— could still give the wrong ranking as exposures are just estimates; part of the estimated factor-generated variance $\mathrm{var}(\gamma\kappa)$ is due to estimation error and needs to be corrected. Correcting for error variance in the exposures, we are even more inclined to accept the dominance of the country factor. The ultimate degree of dominance is quite different from the one suggested by the variance-analysis model.

This work covers the eighties and nineties, not the post-millennium period. The impact of the late-nineties bubble industries (ICT, Bio-pharma) is spread out over the entire ten-year sample period. Shifting the sample period from the eighties and nineties to the end-nineties and post-millennium period could perhaps breakdown the country effect dominance.[11] However, this does not invalidate the robustness tests of this work

[11] The dominance reversion toward industry effects is suggested in Rouwenhorst's website (http://mayet.som.yale.edu/~geert/) and Morgan Stanley (2003, 2004)

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Appendix: decomposing var($\gamma\kappa$)

Suppose the true generating process is the linear model with unrestricted exposures as given in (8). In computing $\mathrm{var}(\gamma\kappa)$ 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 (9); and $\mathrm{E}(.)^2$ denotes the square of the expectation, not the expectation of the square. In the last line of the equation array below, we have used $\mathrm{cov}(\gamma,\kappa) = \mathrm{E}[\mathrm{cov}(\gamma,\kappa|k)] + \mathrm{E}\{[\mathrm{E}(\gamma|k) - \mathrm{E}(\gamma)][\mathrm{E}(\kappa|k) - \mathrm{E}(\kappa)]\}$, 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

$$
\begin{aligned}
\mathrm{var}(\gamma\kappa) &= \mathrm{E}\left(\gamma^2\kappa^2\right) - \mathrm{E}(\gamma\kappa)^2 \\
&= \left[\mathrm{E}\left(\gamma^2\right)\mathrm{E}\left(\kappa^2\right) + \mathrm{cov}\left(\gamma^2,\kappa^2\right)\right] - [\mathrm{E}(\gamma)\mathrm{E}(\kappa) + \mathrm{cov}(\gamma,\kappa)]^2 \\
&= \left[\mathrm{var}(\gamma) + \mathrm{E}(\gamma)^2\right][\mathrm{var}(\kappa) + \mathrm{E}(\kappa)^2] + \mathrm{cov}\left(\gamma^2,\kappa^2\right) \\
&\quad -[\mathrm{E}(\gamma)\mathrm{E}(\kappa) + \mathrm{cov}(\gamma,\kappa)]^2 \\
&= \left[\mathrm{var}(\gamma) + \mathrm{E}(\gamma)^2\right][\mathrm{var}(\kappa) + \mathrm{E}(\kappa)^2] + \mathrm{cov}\left(\gamma^2,\kappa^2\right) \\
&\quad -[\mathrm{E}(\gamma)\mathrm{E}(\kappa) + \mathrm{cov}(\mathrm{E}(\gamma|k),\mathrm{E}(\kappa|k))]^2
\end{aligned} \tag{16}
$$

This shows us why, in a general model the ranking on the basis of factor-generated variance, like $\mathrm{var}(\gamma\kappa)$, may differ from a ranking on the basis of factor variance, like $\mathrm{var}(\kappa)$.[12] The equation (16) also provides clues on how to adjust the empirical counterpart of (16) 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:

$$
\begin{aligned}
\mathrm{var}(\hat{\gamma}) &= \mathrm{var}(\gamma) + \mathrm{E}\left(\mathrm{SE}(\hat{\gamma})^2\right) \\
\Rightarrow \mathrm{var}(\gamma) &= \mathrm{var}(\hat{\gamma}) - \mathrm{E}\left(\mathrm{SE}(\hat{\gamma})^2\right)
\end{aligned} \tag{17}
$$

$$
\begin{aligned}
\mathrm{cov}\left(\hat{\gamma}^2,\kappa^2\right) &= \mathrm{cov}\left(\gamma^2,\kappa^2\right) + \mathrm{cov}\left(\mathrm{SE}(\hat{\gamma})^2,\kappa\right) \\
\Rightarrow \mathrm{cov}\left(\gamma^2,\kappa^2\right) &= \mathrm{cov}\left(\hat{\gamma}^2,\kappa^2\right) - \mathrm{cov}\left(\mathrm{SE}(\hat{\gamma})^2,\kappa^2\right).
\end{aligned} \tag{18}
$$

[12] 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 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

Appendix Table 1: Time Period: OECD, 80%, level 3, 1980-1989, WLS:#shares, restrictions weights: #shares; equally weighted index returns

Panel A: country factors*

‘	$\mathrm{var}(\kappa)$	$\frac{\mathrm{var}(\kappa)}{\mathrm{var}(CR_k-\omega)}$	$\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)$	$\frac{\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)}{\mathrm{var}(CR_k-\omega)}$
Australia	43.05	96.84%	1.86	4.19%
Germany	23.50	95.20%	0.29	1.19%
Belgium	31.19	100.20%	0.07	0.22%
Canada	18.24	95.21%	2.49	12.98%
Denmark	37.16	99.34%	0.35	0.93%
France	35.49	102.28%	0.04	0.12%
Ireland	26.98	99.20%	0.47	1.73%
Italy	50.71	100.69%	0.50	1.00%
Japan	24.16	106.15%	0.16	0.70%
Netherlands	22.27	98.52%	0.08	0.35%
Norway	41.06	95.67%	0.62	1.43%
Austria	49.82	101.44%	0.27	0.56%
Sweden	45.50	99.93%	0.62	1.36%
Switzerland	16.44	94.68%	0.51	2.93%
U.K.	18.54	101.63%	0.05	0.27%
U.S.	6.70	101.85%	0.01	0.20%
Cross-country average	**30.68**	**99.30%**	**0.52**	**1.88%**

* Spain, Finland, Greece, New-Zealand and Portugal suffered from data gaps during the eighties

Panel B: industry factors ‘

	$\mathrm{var}(\iota)$	$\frac{\mathrm{var}(\iota)}{\mathrm{var}(IR_k-\omega)}$	$\mathrm{var}\left(\sum_{k=1}^{K(N)}\frac{m_{k,i}}{M_i}\kappa_k\right)$	$\frac{\mathrm{var}\left(\sum_{k=1}^{K(N)}\frac{m_{k,i}}{M_i}\kappa_k\right)}{\mathrm{var}(IR_k-\omega)}$
Basic Industries	1.40	54.37%	1.23	47.99%
Cyclical Consumer Good	1.52	95.41%	0.46	28.64%
Cyclical Services	1.04	74.09%	0.25	18.05%
General Industries	1.91	113.53%	0.09	5.28%
Information Technology	10.56	75.77%	1.16	8.32%
Non-cyclical Consumer	1.50	94.54%	0.06	3.65%
Non-cyclical Services	4.43	106.66%	0.66	15.90%
Resources	25.07	98.56%	1.88	7.40%
Financials	4.25	108.81%	0.26	6.54%
Utilities	16.53	131.34%	1.82	14.43%
Cross-sector average	**6.82**	**95.31%**	**0.79**	**15.62%**

Appendix Table 2: Country Coverage: G7, 80%, level 3, 1990-1999, WLS:#shares, restrictions weights: #shares; equally weighted index returns

Panel A: country factors

‘	$\mathrm{var}(\kappa)$	$\dfrac{\mathrm{var}(\kappa)}{\mathrm{var}(CR_k-\omega)}$	$\mathrm{var}\left(\sum_{i=1}^{I(N)}\dfrac{n_{i,k}}{N_k}\iota_i\right)$	$\dfrac{\mathrm{var}\left(\sum_{i=1}^{I(N)}\dfrac{n_{i,k}}{N_k}\iota_i\right)}{\mathrm{var}(CR_k-\omega)}$
Germany	18.09	93.90%	0.18	0.94%
Canada	14.96	92.91%	1.72	10.67%
France	16.75	97.95%	0.04	0.22%
Italy	39.29	104.35%	1.12	2.96%
Japan	46.54	99.45%	0.16	0.34%
U.K.	13.44	102.22%	0.05	0.40%
U.S.	8.78	98.16%	0.04	0.42%
Cross-country average	22.55	98.42%	0.47	2.28%

Panel B: industry factors ‘

	$\mathrm{var}(\iota)$	$\dfrac{\mathrm{var}(\iota)}{\mathrm{var}(IR_k-\omega)}$	$\mathrm{var}\left(\sum_{k=1}^{K(N)}\dfrac{m_{k,i}}{M_i}\kappa_k\right)$	$\dfrac{\mathrm{var}\left(\sum_{k=1}^{K(N)}\dfrac{m_{k,i}}{M_i}\kappa_k\right)}{\mathrm{var}(IR_k-\omega)}$
Basic Industries	2.19	33.02%	3.26	49.14%
Cyclical Consumer Good	2.18	79.55%	0.83	30.12%
Cyclical Services	1.10	98.71%	0.22	19.67%
General Industries	1.33	82.46%	0.57	35.12%
Information Technology	17.69	82.19%	1.20	5.57%
Non-cyclical Consumer	3.95	90.91%	0.24	5.44%
Non-cyclical Services	4.75	90.69%	0.70	13.29%
Resources	26.64	100.19%	4.10	15.40%
Financials	7.37	95.89%	0.38	4.89%
Utilities	18.83	105.63%	1.62	9.09%
Cross-sector average	8.60	85.92%	1.31	18.77%

Appendix Table 3: Country Coverage: ALL, 80%, level 3, 1992-1999, WLS:#shares, restrictions weights: #shares; equally weighted index returns

Panel A: country factors

‘	$\mathrm{var}(\kappa)$	$\dfrac{\mathrm{var}(\kappa)}{\mathrm{var}(CR_k-\omega)}$	$\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)$	$\dfrac{\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)}{\mathrm{var}(CR_k-\omega)}$
Argentina	116.21	101.46%	1.10	0.96%
Australia	16.21	100.20%	0.58	3.56%
Germany	13.66	92.83%	0.18	1.24%
Belgium	11.52	91.24%	0.12	0.97%
Brazil	201.72	100.94%	0.94	0.47%
Colombia	85.39	98.16%	1.22	1.40%
China	299.30	99.24%	0.18	0.06%
Chili	53.00	102.80%	1.02	1.98%
Canada	12.33	86.71%	1.53	10.77%
Denmark	12.45	92.17%	0.27	1.98%
Spain	22.88	94.68%	1.08	4.48%
Finland	41.26	98.30%	0.13	0.30%
France	14.82	98.28%	0.04	0.24%
Greece	125.54	100.60%	0.28	0.23%
Hong Kong	75.34	102.60%	1.01	1.38%
Indonesia	127.51	98.64%	0.61	0.47%
India	133.43	99.63%	0.14	0.11%
Ireland	16.13	96.22%	0.48	2.84%
Italy	43.75	104.44%	1.18	2.82%
Japan	45.18	99.48%	0.12	0.26%
Korea	137.11	100.52%	0.10	0.07%
Luxemburg	13.96	99.80%	2.24	16.02%
Mexico	78.83	100.94%	0.17	0.22%
Malaysia	151.44	100.69%	0.33	0.22%
Netherlands	14.08	107.69%	0.17	1.33%
Norway	30.50	96.64%	0.25	0.79%
New Zealand	29.75	97.69%	0.55	1.82%
Austria	16.31	90.62%	0.28	1.57%
Peru	155.73	104.81%	4.79	3.23%
Philippines	107.26	110.88%	3.38	3.49%
Portugal	25.79	97.21%	0.54	2.05%
South Africa	36.46	102.15%	1.06	2.97%
Sweden	32.24	97.91%	0.17	0.53%
Singapore	47.66	102.98%	0.10	0.23%
Switzerland	12.50	90.38%	0.31	2.26%
Taiwan	71.60	108.40%	2.11	3.20%
Thailand	72.79	100.71%	0.26	0.35%
U.K.	13.52	103.20%	0.05	0.41%
U.S.	6.94	94.45%	0.07	1.02%
Cross-country average	**64.67**	**99.14%**	**0.75**	**2.01%**

*Because Brazil, Colombia, China, India and Peru (and Luxemburg) have data gaps in the period 1990-03/1992, we shift the time period from 1990-1999 to 03/1992-1999. Korea and Mexico are considered non-OECD as they entered the OECD union after 1990 (Korea: 12 Dec 1996, Mexico: 18 May 1994).

Panel B: cross-sector

‘	$\mathrm{var}(\iota)$	$\frac{\mathrm{var}(\iota)}{\mathrm{var}(IR_k-\omega)}$	$\mathrm{var}\left(\sum_{k=1}^{K(N)}\frac{m_{k,i}}{M_i}\kappa_k\right)$	$\frac{\mathrm{var}\left(\sum_{k=1}^{K(N)}\frac{m_{k,i}}{M_i}\kappa_k\right)}{\mathrm{var}(IR_k-\omega)}$
Basic Industries	1.84	49.02%	1.44	0.38%
Cyclical Consumer Good	2.16	67.57%	0.78	0.24%
Cyclical Services	1.25	101.54%	0.36	0.29%
General Industries	1.35	88.60%	0.40	0.26%
Information Technology	21.14	90.01%	1.04	0.04%
Non-cyclical Consumer	3.46	88.64%	0.17	0.04%
Non-cyclical Services	4.80	82.39%	0.64	0.11%
Resources	25.06	98.00%	2.40	0.09%
Financials	7.91	104.31%	0.24	0.03%
Utilities	16.38	100.98%	0.69	0.04%
Cross-sector average	8.53	87.10%	0.82	0.15%

Appendix Table 4: Industry Classification: OECD, 80%, level 4, 1990-1999, WLS:#shares, restrictions weights: #shares; equally weighted index returns

Panel A: country factors

‘	$\mathrm{var}(\kappa)$	$\frac{\mathrm{var}(\kappa)}{\mathrm{var}(CR_k-\omega)}$	$\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)$	$\frac{\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)}{\mathrm{var}(CR_k-\omega)}$
Australia	19.31	102.29%	1.32	7.00%
Germany	17.56	94.45%	0.29	1.55%
Belgium	12.86	92.02%	0.27	1.93%
Canada	12.76	84.78%	2.13	14.14%
Denmark	13.13	92.62%	0.51	3.58%
Spain	19.33	96.44%	1.69	8.44%
Finland	42.20	99.65%	0.16	0.39%
France	15.50	97.08%	0.06	0.37%
Greece	174.66	102.09%	0.71	0.42%
Ireland	17.81	102.14%	0.53	3.03%
Italy	37.02	105.87%	1.16	3.33%
Japan	48.41	99.30%	0.24	0.49%
Netherlands	15.53	101.28%	0.15	0.99%
Norway	31.36	92.56%	0.73	2.15%
New Zealand	28.32	96.24%	0.80	2.73%
Austria	28.07	90.22%	0.74	2.37%
Portugal	24.59	96.55%	1.07	4.21%
Sweden	31.65	96.95%	0.20	0.60%
Switzerland	11.92	93.99%	0.44	3.43%
U.K.	12.73	104.29%	0.09	0.70%
U.S.	9.02	96.16%	0.08	0.89%
Cross-country average	29.70	97.00%	0.64	2.99%

Appendix Table 4: continued

Panel B: industry factors

‘	$\text{var}(\iota)$	$\frac{\text{var}(\iota)}{\text{var}(IR_k - \omega)}$	$\text{var}\left(\sum_{k=1}^{K(N)} \frac{m_{k,i}}{M_i}\kappa_k\right)$	$\frac{\text{var}\left(\sum_{k=1}^{K(N)} \frac{m_{k,i}}{M_i}\kappa_k\right)}{\text{var}(IR_k - \omega)}$
aerospace & defense	5.96	72.70%	1.89	23.00%
automobile & parts	3.24	68.41%	2.32	49.11%
banks	11.08	104.86%	0.57	5.39%
beverages	4.06	62.252%	1.92	29.45%
chemicals	2.47	35.00%	2.97	42.11%
construction & materials	4.75	57.77%	2.86	34.74%
diversified industry	4.00	74.08%	1.22	22.59%
electricity	20.67	103.56%	1.05	5.27%
electronics & electrics	5.05	96.75%	1.15	22.11%
engineering & machinery	1.82	61.09%	0.94	31.60%
food & drug retailers	4.59	84.10%	0.55	10.06%
food producers	3.47	77.51%	0.89	19.97%
forestry & paper	4.93	96.37%	0.45	8.72%
household good & textile	2.35	96.98%	0.27	11.22%
healthcare	8.06	58.75%	4.19	30.53%
i/t hardware	20.18	85.40%	0.88	3.73%
insurance	8.02	88.00%	1.16	12.73%
leisure & hotels	3.59	98.42%	0.35	9.49%
life assurance	10.28	78.45%	2.99	22.81%
media & entertainment	4.03	86.56%	0.85	18.26%
mining	45.25	89.00%	5.11	10.05%
oil and gas	33.41	105.65%	2.78	8.80%
personal care and house	6.48	97.38%	0.39	5.83%
pharma & biotech	20.32	92.82%	0.55	2.52%
real estate	4.32	73.39%	0.90	15.32%
general retailers	7.59	98.09%	0.16	2.01%
software & services	20.48	81.52%	1.93	7.70%
specialty & other finance	6.48	97.95%	0.30	4.49%
steel & other metals	4.32	54.98%	2.58	32.80%
support services	2.24	65.85%	1.49	43.82%
telecom services	13.30	79.42%	3.40	20.28%
tobacco	39.70	99.32%	3.58	8.96%
transport	2.78	77.62%	0.73	20.40%
other utilities	16.44	110.47%	1.65	11.07%
Cross-sector average	10.46	82.66%	1.62	17.85%

Appendix Table 5: Size Coverage: OECD, 100%, level 3, 1990-1999, WLS: #shares, restrictions weights: #shares; equally weighted index returns

Panel A: country factors

‘	$\mathrm{var}(\kappa)$	$\frac{\mathrm{var}(\kappa)}{\mathrm{var}(CR_k - \omega)}$	$\mathrm{var}\left(\sum_{i=1}^{I(N)} \frac{n_{i,k}}{N_k} \iota_i\right)$	$\frac{\mathrm{var}\left(\sum_{i=1}^{I(N)} \frac{n_{i,k}}{N_k} \iota_i\right)}{\mathrm{var}(CR_k - \omega)}$
Australia	18.68	100.40%	0.77	4.12%
Germany	15.82	95.40%	0.12	0.74%
Belgium	11.66	91.95%	0.15	1.20%
Canada	15.20	93.32%	1.62	9.98%
Denmark	13.55	95.56%	0.34	2.37%
Spain	21.47	96.97%	0.86	3.88%
Finland	40.38	99.38%	0.14	0.35%
France	14.76	97.99%	0.04	0.26%
Greece	157.86	101.30%	0.31	0.20%
Ireland	14.45	99.39%	0.39	2.69%
Italy	36.03	104.26%	0.91	2.64%
Japan	48.64	99.31%	0.14	0.28%
Netherlands	14.36	104.97%	0.12	0.90%
Norway	32.17	95.70%	0.25	0.75%
New Zealand	29.54	99.19%	0.48	1.60%
Austria	24.52	93.68%	0.32	1.20%
Portugal	23.38	98.25%	0.45	1.90%
Sweden	28.76	96.99%	0.18	0.60%
Switzerland	12.14	92.60%	0.26	1.98%
U.K.	11.89	102.69%	0.04	0.38%
U.S.	9.82	98.04%	0.05	0.46%
Cross-country average	**28.34**	**97.97%**	**0.38**	**1.83%**

Panel B: industry factors

‘	$\mathrm{var}(\iota)$	$\frac{\mathrm{var}(\iota)}{\mathrm{var}(IR_k - \omega)}$	$\mathrm{var}\left(\sum_{k=1}^{K(N)} \frac{m_{k,i}}{M_i} \kappa_k\right)$	$\frac{\mathrm{var}\left(\sum_{k=1}^{K(N)} \frac{m_{k,i}}{M_i} \kappa_k\right)}{\mathrm{var}(IR_k - \omega)}$
Basic Industries	2.00	37.66%	2.52	47.64%
Cyclical Consumer Good	1.86	79.71%	0.78	33.79%
Cyclical Services	1.01	98.85%	0.18	17.79%
General Industries	1.24	81.29%	0.53	35.35%
Information Technology	17.16	80.46%	1.33	6.25%
Non-cyclical Consumer	3.62	90.00%	0.21	5.29%
Non-cyclical Services	4.28	91.32%	0.36	7.76%
Resources	24.28	99.76%	3.79	15.61%
Financials	7.19	92.73%	0.50	6.57%
Utilities	17.60	107.29%	1.42	8.66%
Cross-sector average	**8.02**	**85.91%**	**1.17**	**18.48%**

Appendix Table 6: Value-Weighting: OECD, 80%, level 3, 1990-1999, WLS: marketcaps, restrictions weights: marketcaps; value weighted index returns

Panel A: country factors

‘	$\mathrm{var}(\kappa)$	$\dfrac{\mathrm{var}(\kappa)}{\mathrm{var}(CR_k-\omega)}$	$\mathrm{var}\left(\sum_{i=1}^{I(N)}\dfrac{n_{i,k}}{N_k}\iota_i\right)$	$\dfrac{\mathrm{var}\left(\sum_{i=1}^{I(N)}\dfrac{n_{i,k}}{N_k}\iota_i\right)}{\mathrm{var}(CR_k-\omega)}$
Australia	24.93	102.62%	1.66	6.83%
Germany	17.82	102.18%	0.56	3.22%
Belgium	15.03	95.52%	0.99	6.30%
Canada	16.83	100.77%	0.72	4.29%
Denmark	21.19	111.48%	0.94	4.96%
Spain	26.76	111.20%	1.78	7.42%
Finland	56.53	87.76%	3.98	6.17%
France	14.64	97.98%	0.28	1.86%
Greece	149.58	103.60%	1.58	1.09%
Ireland	21.30	107.30%	1.63	8.22%
Italy	47.81	111.39%	1.62	3.77%
Japan	29.67	103.90%	0.22	0.76%
Netherlands	11.98	106.98%	1.84	16.40%
Norway	38.97	99.32%	2.32	5.92%
New Zealand	30.94	111.66%	1.80	6.51%
Austria	28.08	97.51%	1.57	5.46%
Portugal	34.51	115.22%	1.88	6.26%
Sweden	21.08	93.58%	0.62	2.75%
Switzerland	16.95	92.96%	1.78	9.74%
U.K.	8.89	93.38%	0.58	6.13%
U.S.	8.97	105.00%	0.24	2.86%
Cross-country average	30.59	102.44%	1.36	5.57%

Panel B: industry factors

‘	$\mathrm{var}(\iota)$	$\dfrac{\mathrm{var}(\iota)}{\mathrm{var}(IR_k-\omega)}$	$\mathrm{var}\left(\sum_{k=1}^{K(N)}\dfrac{m_{k,i}}{M_i}\kappa_k\right)$	$\dfrac{\mathrm{var}\left(\sum_{k=1}^{K(N)}\dfrac{m_{k,i}}{M_i}\kappa_k\right)}{\mathrm{var}(IR_k-\omega)}$
Basic Industries	6.56	78.14%	1.33	15.82%
Cyclical Consumer Good	6.41	110.45%	2.32	40.05%
Cyclical Services	2.66	96.99%	0.23	8.44%
General Industries	2.86	74.00%	0.77	19.87%
Information Technology	22.24	101.04%	0.77	3.52%
Non-cyclical Consumer	6.04	79.00%	1.64	21.49%
Non-cyclical Services	7.79	92.35%	1.11	13.12%
Resources	17.99	102.50%	3.66	20.87%
Financials	7.59	103.76%	1.19	16.34%
Utilities	12.91	106.99%	0.33	2.74%
Cross-sector average	9.31	94.52%	1.34	16.23%

Appendix Table 7: OLS: OECD, 80%, level 3, 1990-1999, OLS, restrictions weights: #indices; equally weighted index returns

Panel A: country factors

‘	$\mathrm{var}(\kappa)$	$\dfrac{\mathrm{var}(\kappa)}{\mathrm{var}(CR_k-\omega)}$	$\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)$	$\dfrac{\mathrm{var}\left(\sum_{i=1}^{I(N)}\frac{n_{i,k}}{N_k}\iota_i\right)}{\mathrm{var}(CR_k-\omega)}$
Australia	17.94	98.73%	0.04	0.20%
Germany	8.31	99.91%	0.01	0.08%
Belgium	8.77	100.54%	0.01	0.08%
Canada	13.79	99.71%	0.01	0.05%
Denmark	10.60	101.51%	0.07	0.67%
Spain	21.76	100.94%	0.01	0.03%
Finland	28.11	100.14%	0.01	0.04%
France	7.79	100.54%	0.01	0.09%
Greece	102.83	99.62%	0.06	0.06%
Ireland	16.67	99.75%	0.11	0.64%
Italy	31.26	100.40%	0.01	0.02%
Japan	54.31	99.86%	0.01	0.01%
Netherlands	6.09	99.52%	0.01	0.13%
Norway	24.83	99.65%	0.01	0.03%
New Zealand	26.66	97.74%	0.31	1.13%
Austria	19.67	99.98%	0.01	0.05%
Portugal	19.72	98.35%	0.08	0.41%
Sweden	19.96	99.87%	0.01	0.05%
Switzerland	6.91	100.28%	0.05	0.79%
U.K.	7.77	99.28%	0.01	0.09%
U.S.	14.99	99.97%	0.01	0.04%
Cross-country average	22.32	99.82%	0.04	0.22%

Panel B: industry factors

‘	$\mathrm{var}(\iota)$	$\dfrac{\mathrm{var}(\iota)}{\mathrm{var}(IR_k-\omega)}$	$\mathrm{var}\left(\sum_{k=1}^{K(N)}\frac{m_{k,i}}{M_i}\kappa_k\right)$	$\dfrac{\mathrm{var}\left(\sum_{k=1}^{K(N)}\frac{m_{k,i}}{M_i}\kappa_k\right)}{\mathrm{var}(IR_k-\omega)}$
Basic Industries	1.81	90.02%	0.04	2.44%
Cyclical Consumer Good	1.62	98.07%	0.03	1.90%
Cyclical Services	0.71	97.25%	0.02	4.04%
General Industries	1.03	91.15%	0.02	2.61%
Information Technology	14.95	98.91%	0.12	0.85%
Non-cyclical Consumer	1.52	106.46%	0.02	1.99%
Non-cyclical Services	3.42	102.55%	0.05	1.54%
Resources	6.67	96.57%	0.18	2.74%
Financials	1.78	98.59%	0.02	1.61%
Utilities	5.54	91.39%	0.33	5.54%
Cross-sector average	3.90	97.10%	0.09	2.53%

Appendix Table 8: Re-estimated factors, exposures*** and estimation corrected for error

$\mathrm{var}(\hat{\omega})$	$\mathrm{var}(\hat{\kappa})$	$\mathrm{var}(\hat{\iota})$	$\mathrm{var}(\hat{\kappa})/\mathrm{var}(\hat{\iota})$
16.50	**30.54**	**8.32**	**3.67***
$\mathrm{var}\left(\widehat{\omega\beta}\right)$	$\mathrm{var}(\widehat{\kappa\gamma})$	$\mathrm{var}\left(\widehat{\iota\delta}\right)$	$\mathrm{var}(\widehat{\kappa\gamma})/\mathrm{var}\left(\widehat{\iota\delta}\right)$
16.18	**25.48**	**2.95**	**8.63***
$\mathrm{E}\left(SE\left(\hat{\beta}\right)^2\right)$	$\mathrm{E}\left(SE(\hat{\gamma})^2\right)$	$\mathrm{E}\left(SE\left(\hat{\delta}\right)^2\right)$	
0.07	0.06	0.11	
$\mathrm{cov}\left(SE\left(\hat{\beta}\right)^2, \omega^2\right)$	$\mathrm{cov}\left(SE(\hat{\gamma})^2, \kappa^2\right)$	$\mathrm{cov}\left(SE\left(\hat{\delta}\right)^2, \iota^2\right)$	
0.00	-0.76	-0.19	
$\mathrm{E}(\omega)^2$	$\mathrm{E}(\kappa)^2$	$\mathrm{E}(\iota)^2$	
1.27	0.004	0.003	
$\mathrm{var}(\omega\beta)$	$\mathrm{var}(\kappa\gamma)$	$\mathrm{var}(\iota\delta)$	$\mathrm{var}(\kappa\gamma)/\mathrm{var}(\iota\delta)$
14.85**	**24.36****	**2.23****	**10.92**

*column 2 / column 3

**row 2 – (row 3 * row 1) – (row 3 * row 5) – row 4

*** H_0: $\gamma_j = \iota_j$ for $j = 1,...N$ has $\chi^2 = 3353.08$ and p-value $= 0.00$

Appendix Table 9: Variability and industry exposure: small- and large-caps compared.

	average standard deviation			avg industry sensitivity t-statistics	
	small-caps	large-caps		small-caps	large-caps
Argentina	**15,18**	14,98		0,88	**2,43**
Australia	**11,86**	9,39		1,18	**5,62**
Germany	**12,26**	11,80		1,63	**5,29**
Belgium	8,30	**9,78**		1,76	**4,45**
Brazil	18,51	**24,58**		0,37	**2,24**
Colombia	10,93	**11,75**		-0,87	1,00
China	**14,32**	14,13		-0,22	-0,08
Chili	9,97	**10,58**		0,72	1,70
Canada	**15,64**	12,54		1,50	**8,07**
Denmark	7,20	**10,15**		0,12	**3,68**
Spain	12,15	**12,24**		**2,64**	**4,80**
Finland	**14,25**	14,14		1,26	**4,10**
France	**12,78**	10,70		1,45	**6,74**
Greece	**24,90**	23,52		0,15	-0,56
Hong Kong	12,54	**18,90**		1,31	**4,74**
Indonesia	**14,12**	13,04		0,26	1,50
India	**19,63**	16,38		-0,09	-0,11
Ireland	9,81	**10,52**		0,77	**4,92**
Italy	**12,08**	10,66		**2,70**	**4,42**
Japan	**14,62**	11,61		**4,83**	**13,47**
Korea	19,39	**21,19**		1,40	**3,57**
Luxemburg	8,05	**8,30**		0,58	**2,64**
Mexico	10,22	**12,66**		0,47	**3,97**
Malaysia	**18,79**	13,54		**2,04**	**2,78**
Netherlands	**10,74**	10,50		1,94	**7,51**
Norway	**14,06**	13,64		0,95	**4,18**
New Zealand	8,36	**10,91**		0,92	**2,91**
Austria	9,97	**10,37**		1,49	**3,33**
Peru	13,53	**23,01**		0,88	0,85
Philippines	**13,43**	12,66		1,30	**3,60**
Portugal	**14,23**	10,47		0,33	**3,46**
South Africa	12,35	**12,65**		1,35	**4,93**
Sweden	**12,73**	10,68		1,54	**4,80**
Singapore	10,14	**11,80**		1,67	**4,63**
Switzerland	**9,56**	8,64		**2,21**	**6,36**
Taiwan	12,69	**15,57**		0,78	**2,83**
Thailand	13,40	**14,69**		1,23	**2,25**
U.K.	**11,89**	11,03		**3,48**	**10,00**
U.S.	**15,74**	14,30		**4,85**	**15,89**
# high stdev	21	18	#significant	7	32

Columns 2 and 3 show the average standard deviation for small- and large-caps, respectively; column 5 and 6 show the average t-statistics for industry exposure, again for small- and large-caps respectively.

Appendix Table 10: The strength of the industry affiliation, small v large caps.

Coefficients and t-statistics of four analysis-of-variance regressions with right-side variables: 2 size, 39 country and 34 industry dummies; and left-side variables: (1) stock standard deviations, (2a) industry exposure estimates, (2b) industry exposure t-statistics, and (2c) industry model R-squares

	(1)		(2a)		(2b)		(2c)	
	coef	t–stat	coef	t–stat	coef	t–stat	coef	t–stat
Average	13.30	130.35	0.48	33.06	2.71	51.09	0.12	50.21
Small–cap	0.57	11.89	-0.14	-11.40	-1.88	-42.31	-0.05	-23.15
Large–cap	-0.57	-11.89	0.14	11.40	1.88	42.31	0.05	23.15
Argentina	3.02	3.85	0.38	3.83	-1.22	-3.37	-0.02	-1.17
Australia	-2.95	-7.47	0.09	1.68	0.60	2.93	0.05	5.18
Germany	-1.27	-5.33	-0.14	-2.61	0.77	4.01	-0.01	-1.69
Belgium	-4.02	-8.55	-0.07	-1.15	0.06	0.25	-0.03	-2.86
Brazil	8.67	17.98	0.25	3.58	-1.59	-6.12	0.01	0.46
Colombia	-0.04	-0.03	-1.29	-9.33	-2.33	-4.59	-0.01	-0.55
China	0.87	3.49	-0.60	-9.99	-2.98	-13.61	-0.11	-10.84
Chili	-1.95	-2.57	-0.13	-1.41	-1.22	-3.68	0.00	0.22
Canada	-0.49	-2.39	0.00	0.00	2.07	11.22	0.05	6.13
Denmark	-3.74	-8.34	-0.19	-2.70	-0.88	-3.50	-0.03	-2.35
Spain	0.32	0.64	0.30	4.10	1.02	3.83	0.04	3.57
Finland	0.24	0.44	0.30	4.35	-0.27	-1.09	0.03	2.76
France	-2.09	-9.37	-0.02	-0.48	1.34	7.26	0.00	-0.09
Greece	10.82	25.32	-1.11	-15.41	-3.52	-13.33	-0.03	-2.70
Hong Kong	2.81	4.65	0.03	0.29	0.46	1.44	0.02	1.45
Indonesia	0.75	1.61	-0.34	-5.08	-1.90	-7.75	-0.02	-1.38
India	4.47	15.15	-0.49	-8.33	-3.00	-13.81	-0.10	-10.05
Ireland	-3.65	-4.66	0.03	0.39	-0.02	-0.05	0.00	0.33
Italy	-1.16	-3.02	0.09	1.43	0.85	3.57	-0.03	-2.45
Japan	-0.21	-1.23	0.43	8.36	6.49	34.33	0.15	17.87
Korea	7.04	30.45	0.38	6.72	-0.43	-2.08	-0.06	-6.64
Luxemburg	-4.24	-3.25	-0.06	-0.35	-1.65	-2.83	-0.01	-0.54
Mexico	-1.81	-2.72	0.13	1.52	-0.73	-2.38	0.01	0.59
Malaysia	3.47	11.17	0.43	7.22	-0.61	-2.80	-0.03	-3.18
Netherlands	-3.16	-7.50	-0.01	-0.13	1.82	7.82	0.01	1.04
Norway	0.32	0.79	0.08	1.31	-0.40	-1.66	0.01	1.21
New Zealand	-3.16	-4.44	0.32	3.75	-0.73	-2.33	0.00	0.07
Austria	-1.99	-3.41	-0.08	-0.91	-1.03	-3.36	-0.06	-4.25
Peru	4.41	4.64	0.09	0.90	-1.99	-5.16	-0.07	-4.00
Philippines	-0.20	-0.19	0.70	6.20	-0.15	-0.37	0.04	2.16
Portugal	-0.45	-0.73	-0.10	-1.29	-0.72	-2.45	0.04	3.00
South Africa	-1.39	-3.55	0.10	1.59	0.28	1.18	-0.01	-1.07

Sweden	-2.66	-7.91	0.09	1.60	0.38	1.75	-0.02	-1.81
Singapore	-2.23	-4.21	0.09	1.30	0.28	1.05	0.02	1.39
Switzerland	-3.43	-8.71	-0.05	-0.81	1.58	7.03	0.06	5.74
Taiwan	-0.02	-0.06	-0.01	-0.08	-1.11	-4.46	-0.06	-5.71
Thailand	0.73	2.03	-0.01	-0.08	-1.28	-5.35	-0.08	-7.18
U.K.	-2.31	-14.11	0.17	3.45	4.08	22.26	0.07	8.96
U.S.	0.68	5.83	0.18	3.63	7.66	42.92	0.17	20.76
aerospace & defense	-1.00	-1.87	-0.27	-2.63	0.03	0.07	-0.01	-0.42
automobile & parts	-0.43	-1.67	-0.06	-0.90	0.38	1.66	0.00	0.22
banks	-3.85	-23.93	-0.05	-0.95	0.16	0.87	-0.03	-3.86
beverages	-2.89	-7.41	-0.06	-0.87	0.15	0.63	-0.03	-2.63
chemicals	-0.88	-4.20	0.23	4.04	1.13	5.49	0.02	1.73
construction & materials	-0.46	-2.46	0.02	0.44	0.93	5.06	0.00	-0.44
diversified industry	-1.18	-4.08	0.15	2.70	0.57	2.83	0.02	2.38
electricity	-3.78	-11.39	-0.28	-3.97	-1.37	-5.36	-0.05	-4.56
electronics & electrics	1.49	8.16	0.18	3.14	0.91	4.41	0.02	1.69
engineering & machinery	-0.12	-0.67	0.02	0.31	1.17	5.72	0.02	2.37
food & drug retailers	-0.82	-2.21	-0.03	-0.43	-1.01	-3.84	-0.04	-3.35
food producers	-1.82	-8.64	0.05	0.90	0.53	2.80	-0.02	-2.45
forestry & paper	-1.64	-4.42	-0.01	-0.21	0.77	3.44	0.02	1.54
household good, textiles	-0.22	-1.25	-0.15	-2.86	0.17	0.91	0.00	-0.23
healthcare	1.58	5.97	-0.09	-1.26	-1.48	-5.82	-0.03	-2.81
i/t hardware	5.65	23.19	0.05	0.72	-0.05	-0.19	0.01	0.54
insurance	-1.73	-5.74	0.21	3.42	0.17	0.72	0.03	2.71
leisure & hotels	0.39	1.73	-0.14	-2.43	-0.95	-4.44	0.00	0.15
life assurance	-3.30	-6.58	0.06	0.55	-0.66	-1.73	-0.02	-1.30
media & entertainment	1.37	6.12	0.21	3.52	0.22	0.99	0.02	2.27
mining	3.49	13.29	-0.09	-1.35	1.43	5.83	0.05	4.16
oil and gas	0.16	0.72	0.15	2.19	1.99	8.06	0.04	3.57
personal care and house	-0.64	-1.39	0.00	-0.04	-0.15	-0.51	0.02	1.24
pharma & biotech	1.42	5.39	0.03	0.44	-0.43	-1.90	-0.02	-1.62
real estate	-1.05	-4.38	0.01	0.24	0.00	0.00	-0.02	-1.86
general retailers	1.55	7.42	-0.10	-1.77	-0.60	-2.76	-0.04	-4.38
software & services	10.34	57.22	0.04	0.62	-0.40	-1.83	0.05	5.46
specialty & other finance	0.75	2.59	-0.26	-3.71	-1.08	-4.23	-0.02	-2.00
steel & other metals	-0.82	-2.92	0.07	1.31	0.39	1.86	0.03	3.67
support services	1.48	7.03	0.13	2.00	0.27	1.11	0.02	2.24
telecom services	4.49	16.32	0.23	4.07	-0.87	-4.18	0.03	3.40
tobacco	-2.70	-3.48	-0.17	-1.81	-1.05	-3.01	-0.02	-1.02
transport	-1.12	-4.75	-0.01	-0.26	-0.19	-0.99	-0.03	-3.05
other utilities	-3.72	-10.30	-0.05	-0.70	-1.07	-3.85	-0.01	-1.03

Appendix Table 11: Correlation between Heston-Rouwenhorst and Fama-McBeth factors

Factors	Corre-	Factors	Correla-
Country factors		**World factor**	
Australia	0.986	World	1.000
Germany	0.997	**Industry factors**	
Belgium	0.991	Basic Industries	0.984
Canada	0.991	Cyclical Consumer	0.985
Denmark	0.992	Cyclical Services	0.994
Spain	0.988	General Industries	0.991
Finland	0.997	Information Technology	0.999
France	0.996	Non-cyclical Consumer	0.995
Greece	0.997	Non-cyclical Services	0.994
Ireland	0.988	Resources	0.994
Italy	0.998	Financials	0.996
Japan	1.000	Utilities	0.999
Netherlands	0.992		
Norway	0.997	Average	0.994
New Zealand	0.982		
Austria	0.994		
Portugal	0.991		
Sweden	0.996		
Switzerland	0.995		
U.K.	0.999		
U.S.	0.999		

Appendix Figure 1: Heston-Rouwenhorst vs. Fama-McBeth factor variances