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Industry Risk and Market Integration

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Traditionally, integration has been studied at the country level. With increasing economic integration, industrial reorganization, and blurring of national boundaries (e.g., European Union (EU)), it is important to investigate global integration at the industry level. We argue that country-level integration (segmentation) does not preclude industry-level segmentation (integration). Indeed, our results suggest that a country is integrated with (segmented from) the world capital markets only if most of her industries are integrated (segmented). We also show that although global industry risk is small, it can be priced for certain industries. Industries that are priced differently from either the world or domestic markets represent incremental opportunities for international diversification.

Key words: imperfect industry integration; global industry risk; conditional asset pricing; industry information variables; portfolio diversification
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1. Introduction

There is a large body of research on capital market integration and international diversification. Based on international asset-pricing models of Solnik (1974), Stulz (1981), Adler and Dumas (1983), and Errunza and Losq (1985), many empirical papers provide economic and statistical evidence of integration or segmentation at the country level.[1] While integration at the country level has been extensively examined, the analysis of global integration processes at the industry level has not received much attention. Hence, this paper focuses on the differences between country-level and industry-level integration, investigates whether global and local industries risk are priced, and studies the attendant implications for portfolio diversification strategies.

We follow Chan et al. (1992), Bekaert and Harvey (1995), and De Santis and Gerard (1997) to estimate national equity returns from G-7 countries under the assumption of a mildly segmented world market. We employ a conditional asset-pricing framework with the world and country risks. We perform the estimation of 18 local industries in these countries using the same econometric model but allowing for differences in the country risks across industries. Next, we extend our model to account for global industry risk and estimate the exposure of local industry returns to the world, country and global industry risks simultaneously. Finally, we use Sharpe ratios to demonstrate the economic benefits of industry-specific diversification.

Our results can be summarized as follows. First, we find that the world price of risk is positive and statistically significant. The prices of country-specific risks excepting the United States are not significantly different from zero. Although these results are similar to those reported in previous studies, they are important since we do not impose any restrictions on the signs of the prices of risks. Second, we also find that in the 1990s, the United States, unlike other developed markets in the G-7 group, became "partially integrated" with the world market, i.e., its equity returns are priced based on both the world market risk and its own country (variance) risk. Given the remarkable outperformance of the U.S. market during our sample period as well as its large weight in the world market portfolio, such a result is not unexpected. Third, our tests illustrate that the estimated price of the U.S. market risk is statistically highly significant for many U.S. industries. This finding is consistent with our intuition that if a country is partially integrated with the world market, a substantial proportion of her industries will (not) be integrated with the world market. Thus, in general, a country-level integration (segmentation) does not preclude an industry-level segmentation (integration). Fourth, we show that these findings are not driven by the compounding effect of country and global industry risks. We observe a large variation in global industry exposure and show that global industry risk

[1] See for example, Jorion and Schwartz (1986), Errunza et al. (1992), Bekaert and Harvey (1995), De Santis and Gerard (1997), Domowitz et al. (1997), and Hardouvelis et al. (1999).

is important in the pricing of certain industries. Our findings imply that investors should use *both* cross-country and cross-industry diversification as a way to improve portfolio performance.

The investigation of global integration at the industry level is important because of increasing economic integration, industrial reorganization, and blurring of national boundaries (e.g., the European Union (EU)). Indeed, it is possible that even if a country is integrated with the world capital market, some of her industries may not be integrated owing to, for example, industry-specific foreign ownership restrictions, absence of or low-volume exports, or limited presence of firms from those industries on foreign exchanges. On the other hand, a country that is segmented from the world market may have industries that are not segmented to the same degree.[2] Hence, identifying whether there is a sizable industry-specific risk exposure is central for a comprehensive analysis of world market integration.

The question of industry integration is also related to the importance of industrial structure for international diversification strategies. Although there are a number of studies that suggest the dominance of the country factor, there is evidence of the importance of industry factors.[3] More recently, Griffin and Karolyi (1998) and Griffin and Stulz (2001) conclude that industries that produce internationally traded goods may have a sizable exposure to industry-specific shocks. Indeed, if industry risk is priced, an investor can construct a portfolio with better risk-return characteristics by diversifying it across industries in addition to geographic diversification. If not, geographic diversification is sufficient for portfolio risk reduction.

The importance of industry factors in equity returns has also emerged in the recent literature on the momentum in stock returns. Moskowitz and Grinblatt (1999) find that industry momentum strategies in the United States are profitable after controlling for size, book-to-market equity ratio, and individual securities momentum effects. They attribute this result to the existence of time-varying industry risk premiums. Rouwenhorst (1998) shows that momentum strategies are also profitable in Europe, which suggests that time-varying risk premiums on global industries can give rise to this phenomenon. Finally, Griffin et al. (2003) find that momentum profits are not consistent with standard macroeconomic risk-based explanations.

Thus, while all the previous studies have examined the importance of industry effects versus country effects in securities pricing, these questions remain open: Can local industries be priced differently from a country as a whole, or do they have any exposure to the respective global industries? Our paper sheds light on these important issues.[4] In addition, as portfolio managers are paying increasing attention to global industry rotation strategies, the identification of priced industries is relevant also from a practical point of view.[5]

The rest of the paper is organized as follows. In §2, we introduce the intuition and formal layout of our asset-pricing specification of industry-level integration and outline the econometric methodology. Section 3 describes the data and rationale for the selected instrumental variables. Our test results along with some robustness issues are presented in §4. In this section we also illustrate the benefits of industry diversification across specific local and global industries. Section 5 concludes.

2. The Model and Estimation Methodology

2.1. The Model of Partial Industry Integration

Denote r_j the excess returns in country j. If we assume that country j is integrated with the world then its expected return at time t given the information at time $t-1$ is determined based on its conditional covariance with the world market return, namely:

$$\mathrm{E}_{t-1}(r_{j,t}) = \lambda_{w,t-1}\,\mathrm{Cov}_{t-1}(r_{j,t}, r_{w,t}), \tag{1}$$

where $r_{w,t}$ is the excess return on the world market portfolio and $\lambda_{w,t-1}$ is the conditional price of the world market risk. If country j is segmented, its

[2] As an example of countries that are integrated at the market level consider the G-7 countries, given the results of De Santis and Gerard (1997). Using data from Sarkissian and Schill (2003), we find that across many industry groups, electricity firms among firms from other industries have the most limited presence on foreign exchanges in terms of both number of firms and their respective market caps (except for the U.K. firms). Therefore, it is likely that the degree of integration of electricity-generating firms is lower than that of an average G-7 country. As an example of an industry that may be more integrated than a country as a whole, consider the aviation industry. While the usual econometric tests are likely to classify many developing countries as segmented rather than integrated (e.g., Mexico, based on Carrieri et al. 2002 and Karolyi 2004), the demand for air travel on airlines of practically all countries is directly affected by global shocks to that industry.

[3] For example, Lessard (1976), Errunza and Padmanabhan (1988), Grinold et al. (1989), Drummen and Zimmermann (1992), and Heston and Rouwenhorst (1994) report that country risks are much more important than industry risks. Roll (1992) and Archanapalli et al. (1997), however, find that industry factors can explain substantial variation in national stock returns.

[4] Fedorov and Sarkissian (2000) analyze differences in the degree of integration among several industries from an emerging market, however, they do not account for the possibility of global industry exposure.

[5] See Weiss (1998) or Cavaglia et al. (2000).

expected return at time t given the information at time $t-1$ is determined only through its conditional variance with its market return:

$$\mathrm{E}_{t-1}(r_{j,t}) = \lambda_{j,t-1}\,\mathrm{Var}_{t-1}(r_{j,t}), \tag{2}$$

where $r_{j,t}$ is the excess return on the country j index and $\lambda_{j,t-1}$ is the conditional price of country j risk. Models (1) and (2) are the conditional versions of the CAPM of Sharpe (1964) under the assumption of integration or segmentation respectively.

Following Chan et al. (1992), Bekaert and Harvey (1995), and De Santis and Gerard (1997), we combine Models (1) and (2) to obtain a conditional asset-pricing model of imperfect integration where the expected return on country j is determined based on its conditional covariances with the world risk and respective country risk. Thus,

$$\mathrm{E}_{t-1}(r_{j,t}) = \lambda_{w,t-1}\,\mathrm{Cov}_{t-1}(r_{j,t}, r_{w,t}) + \lambda_{j,t-1}\,\mathrm{Var}_{t-1}(r_{j,t}, r_{j,t}). \tag{3}$$

At the industry level, the asset-pricing relation (3) is transformed to:

$$\mathrm{E}_{t-1}(r_{ij,t}) = \lambda_{w,t-1}\,\mathrm{Cov}_{t-1}(r_{ij,t}, r_{w,t}) + \lambda_{j,t-1}\,\mathrm{Cov}_{t-1}(r_{ij,t}, r_{j,t}),$$

where r_{ij} is the excess return on industry i in country j. This relation is valid only if there are no differences in integration among industries, so that all of them are priced similar to the country as a whole. However, while a country may be integrated, some of its constituent industries may not be. For instance, a country with a diversified economy, mature financial market, no general restrictions on foreign ownership of domestic assets, and extensive trade with other countries is likely to be integrated with the world capital market. Nevertheless, a particular industry within that country may not be well connected to the world due to industry-specific foreign ownership restrictions, absence of or low-volume exports from that industry, etc. Alternatively, a country might be segmented from the world, but some of her industries may not be. For instance, a country with a rudimentary financial market and restrictions on foreign ownership of domestic assets is likely to be segmented from the world capital market. Yet, some industries in that country may have substantial overseas sales and thus may be less segmented from the world than the country as a whole. Therefore, for industry returns, we can rewrite Equation (3) as follows:

$$\mathrm{E}_{t-1}(r_{ij,t}) = \lambda_{w,t-1}\,\mathrm{Cov}_{t-1}(r_{ij,t}, r_{w,t}) + \lambda_{j(i),t-1}\,\mathrm{Cov}_{t-1}(r_{ij,t}, r_{j,t}), \tag{4}$$

where $\lambda_{j(i),t-1}$ is the "industry-specific" price of country risk.

While Model (4) allows for partial integration of industries, it may not be fully sufficient to capture the dynamics of all industry returns because it does not account for the possible existence of global industry risk. There is some evidence of the importance of industry shocks in the pricing of assets (e.g., see Griffin and Karolyi 1998, Griffin and Stulz 2001). Indeed, a relatively integrated industry from a generally segmented country might have the largest exposure neither to the world nor the domestic market risk but to its global industry risk. In addition, country indexes are composed of local industries, and each global industry index is a composite of local industry indices in different countries. As Roll (1992), Heston and Rouwenhorst (1994) and others point out, if industrial composition differs across countries, country risks are driven in part by industry effects while industry risks are driven in part by country effects. Therefore, Relation (4) may be misspecified due to the omission of local industry's exposure to its corresponding global industry risk.

To address this issue, we adapt the econometric model of asset returns of Moskowitz and Grinblatt (1999). In that model, each security return can have an exposure to portfolios that mimic economy-wide factors as well as to less pervasive risk factors, which are orthogonal to the main ones and have zero unconditional mean. The main risk factors therefore are the only source of unconditional mean returns for security returns. Using this setup, we specify a conditional asset-pricing relation where the expected return on industry i in country j is determined by its conditional covariances with the world risk, country risk, and "pure" industry risk.

$$\mathrm{E}_{t-1}(r_{ij,t}) = \lambda_{w,t-1}\,\mathrm{Cov}_{t-1}(r_{ij,t}, r_{w,t}) + \lambda_{j(i),t-1}\,\mathrm{Cov}_{t-1}(r_{ij,t}, r_{j,t}) + \lambda_{i,t-1}\,\mathrm{Cov}_{t-1}(r_{ij,t}, u_{i,t}), \tag{5}$$

where $u_{i,t}$ denotes a pure global industry i shock, which is orthogonal to both worldwide and country-specific shocks and has zero unconditional mean, while the time-varying coefficient $\lambda_{i,t-1}$ is the price of the pure global industry i risk; that is, $\lambda_{i,t-1} = \mathrm{E}_{t-1}(u_{i,t})/\mathrm{Var}_{t-1}(u_{i,t})$. We call this asset-pricing relation a model of imperfect industry integration.[6]

Note that Model (5), similar to Moskowitz and Grinblatt (1999), is defined only in conditional framework with the time-varying price of global industry

[6] Global multifactor models that accommodate global industry risk have already been used in practice. For example, BARRA's global equity model includes country risk along side style risk, industry risk, and currency risk. In BARRA's view, industry risk is much more important than currency risk for active portfolio management.

risk. Unconditionally, the expected value of $\lambda_{i,t-1}$ is zero since $E(u_{i,t}) = 0$ by construction. The intuition for the time-varying price of global industry risk is as follows. On average, investors' residual expected compensation for taking a long position in an industry is zero. However, during certain time periods, this compensation becomes nontrivial. Investors might accept a negative compensation if a particular industry is expected to provide some hedging advantage; otherwise, they would require a positive reward. In effect, Equation (5) is in the spirit of asset-pricing models of Merton (1973) and Ross (1976). In this specification, the return on any industry i in country j is determined by its covariance with three state variables: the world and country portfolios as well as the residual portfolio on global industry i. Finally, note that postulating the existence of the time-varying industry risk premium is an empirical question because there is no formal model that suggests what other additional factors might be significant in a conditional framework.

2.2. Methodology

Estimating Models (4) and especially (5) in a fully conditional framework with time-varying prices of risks jointly across industries and countries is practically impossible. Therefore, we present our main results in the paper when the prices of world and country risks are time invariant. In the robustness section (§4.4) we model the time variation in the world price of risk.

First, similar to Chan et al. (1992), Bekaert and Harvey (1995), and De Santis and Gerard (1997), we estimate Model (3) with the world and country risk premiums, namely:

$$\begin{aligned} r_{j,t} &= \lambda_w \operatorname{Cov}_{t-1}(r_{j,t}, r_{w,t}) + \lambda_j \operatorname{Var}_{t-1}(r_{j,t}) + \varepsilon_{j,t} \\ r_{w,t} &= \lambda_w \operatorname{Var}_{t-1}(r_{w,t}) + \varepsilon_{w,t} \\ h_{j,t} &= c_j + a_j^2 \varepsilon_{j,t-1}^2 + b_j^2 h_{j,t-1} \\ h_{w,t} &= c_w + a_w^2 \varepsilon_{w,t-1}^2 + b_w^2 h_{w,t-1} \\ h_{j,w,t} &= c_{jw} + a_j a_w \varepsilon_{w,t-1} \varepsilon_{j,t-1} + b_j b_w h_{j,w,t-1}, \end{aligned} \tag{6}$$

where $h_{j,t}$ is the conditional variance of excess returns in country j, $h_{w,t}$ is the conditional variance of the world excess returns, $h_{j,w,t}$ is the conditional covariance between the world and country j returns, $\varepsilon_t = [\varepsilon_{w,t}, \varepsilon_{j,t}] \sim N(0, H_t)$, and H_t is the conditional variance-covariance matrix.

The estimation methodology that we implement is similar to that of De Santis and Gerard (1997, 1998). Specifically, we jointly estimate the conditional asset-pricing model across several security returns (local industry returns across countries) using a multivariate GARCH (1, 1) parameterization for the error terms in which H_t is modeled as:

$$H_t = H_0 * (\iota\iota' - aa' - bb') + aa' * \varepsilon_{t-1}\varepsilon_{t-1}' + bb' * H_{t-1},$$

where ι is the $(N \times 1)$ unit vector, a and b are the $(N \times 1)$ vectors (N is the number of asset returns to be estimated). The matrix H_0 is initially set to the variance-covariance matrix of excess returns and shocks and then updated at each iteration with the values of the covariance matrix of estimated residuals. In other words, we assume that the current variance depends only on the lagged conditional variance and lagged squared errors, while the current covariance depends only on the lagged covariance and lagged cross-product of errors. The parameterization of H is certainly restrictive since there is some evidence of volatility spillovers across international equity markets (e.g., see Karolyi and Stulz 1996 or Bekaert and Harvey 1997). However, econometrically, the estimation of a multivariate GARCH system with a general matrix H is extremely difficult.[7]

Because of numerous deviations from normality in excess equity returns (see Table 1) we estimate the parameters of the model using the quasi-maximum likelihood estimation (QML) of Bollerslev and Wooldridge (1992). The QML estimator is consistent and distributed normally asymptotically allowing us to conduct regular statistical inference. As with the standard maximum likelihood estimation, QML estimates are obtained by maximizing the log likelihood function over the parameter space Θ. To obtain the parameter vector Θ, we employ the Berndt et al. (Berndt et al. 1974) optimization algorithm.

The price of the world market risk must in theory be the same in Models (3), (4), and (5). Therefore, we obtain the estimate of λ_w from the country-level integration test (6) and subsequently use it in the estimation of models of industry-level integration. There are two primary reasons, economic and econometric, to keep the price of the world risk constant across all estimations.

First consider the economic point of view. A joint estimation of λ_w and λ_j using country returns in Model (6) can produce an economically more plausible value of λ_w. Notice further that while the estimates of $\lambda_{j(i)}$ allow us to make inference about the risk exposure of *local* industries (our left-hand-side variable in industry-level tests) across countries, the inference based on λ_w can be related only to the corresponding *global* industry in its exposure to the world risk. Given that global asset-allocation strategies are aimed at selecting particular industries within countries, it is interesting to examine which industries are priced differently across countries in terms of their local market exposure.

[7] There is also evidence of asymmetric volatility in financial markets (e.g., see Bekaert and Wu 2000). Incorporating asymmetry would further complicate our estimation and we leave this extension for future work.

Table 1 Summary Statistics of Excess Returns

	Mean	S.D.	Min	Max	ρ	B-J	$Q_4(R^2)$
Panel A: National and the world excess equity returns							
Canada	0.1106	2.2194	−12.2875	7.5753	−0.059	464.1[a]	41.27[a]
France	0.1685	2.5230	−9.3609	12.4056	−0.129	85.44[a]	18.58[a]
Germany	0.1251	2.4613	−11.8183	13.4058	−0.147	181.2[a]	48.91[a]
Italy	0.1427	3.3394	−12.9256	10.4532	−0.101	18.88[a]	44.8[a]
Japan	0.0208	3.4825	−12.5196	16.8277	−0.075	143.3[a]	6.91
U.K.	0.1395	2.1172	−9.0481	8.5224	−0.149	31.78[a]	21.2[a]
U.S.	0.2555	2.0234	−12.3082	7.5726	−0.168	345.2[a]	10.23[a]
World	0.1367	1.8655	−8.5393	6.1432	−0.127	78.44[a]	24.27[a]
Panel B: Global industry excess equity returns							
Banks	0.1548	2.8062	−10.3114	11.3833	−0.112	65.03[a]	21.81[a]
Building materials	0.0303	2.3261	−7.8812	9.1282	−0.055	73.06[a]	48.66[a]
Chemicals	0.1316	2.1452	−7.2159	9.7829	−0.066	74.62[a]	19.23[a]
Diversified industrials	0.1643	2.0153	−8.0116	8.3946	−0.126	67.31[a]	61.31[a]
Electricity	0.0218	1.6484	−6.1546	8.4187	−0.106	114.1[a]	5.88
Electronic equipment	0.2379	2.2978	−9.7858	7.9497	−0.073	44.26[a]	19.41[a]
Engineering	0.0898	2.5268	−9.2782	9.0135	−0.022	52.60[a]	21.76[a]
Food	0.0805	1.5449	−4.8738	5.5050	−0.061	11.46[a]	13.77[a]
Gas distribution	0.1048	1.9707	−7.4138	9.2801	−0.054	76.46[a]	12.35[a]
Household goods	0.1044	2.3201	−9.1480	7.8004	−0.041	53.89[a]	35.14[a]
Insurance	0.1893	2.1173	−10.4478	10.0849	−0.069	152.1[a]	48.85[a]
Media	0.2269	1.8503	−9.1539	7.8173	−0.104	159.0[a]	13.00[a]
Oil expl. and production	0.0000	2.6081	−10.6711	9.8202	0.029	49.63[a]	47.28[a]
Paper and packaging	0.0522	2.5297	−8.7079	14.1384	−0.051	169.0[a]	22.40[a]
Pharmaceuticals	0.2911	2.3598	−11.7275	7.3556	−0.140	67.35[a]	8.15
Retailers, general	0.2681	2.3240	−10.5129	9.0735	−0.145	107.1[a]	36.56[a]
Telecommunications	0.2789	2.1973	−6.1741	8.3180	−0.140	12.35[a]	5.73
Transport	0.0427	2.2504	−7.7310	7.9003	−0.070	26.91[a]	39.01[a]

[a]Denotes statistical significance at the 5% level.

Second, consider the econometric point of view. Imposing the restriction that λ_w is the same for all industries in a given country allows us to have a more powerful test of our parameters of interest. In addition, an inclusion of even one extra coefficient to estimate in our multivariate GARCH system makes the computation of the Hessian matrix substantially more complicated. Thus, our industry-level integration tests based on (4) can be written as:

$$\begin{aligned} r_{ij,t} &= \hat{\lambda}_w \operatorname{Cov}_{t-1}(r_{ij,t}, r_{w,t}) \\ &\quad + \lambda_{j(i)} \operatorname{Cov}_{t-1}(r_{ij,t} r_{j,t}) + \varepsilon_{ij,t} \\ h_{ij,t} &= c_{ij} + a_{ij}^2 \varepsilon_{ij,t-1}^2 + b_{ij}^2 h_{ij,t-1} \\ h_{ij,w,t} &= c_{ijw} + a_{ij}\hat{a}_w \hat{\varepsilon}_{w,t-1}\varepsilon_{ij,t-1} + b_{ij}\hat{b}_w h_{ij,w,t-1} \\ h_{ij,j,t} &= c_{ijj} + a_{ij}\hat{a}_j \hat{\varepsilon}_{j,t-1}\varepsilon_{ij,t-1} + b_{ij}\hat{b}_j h_{ij,j,t-1}, \end{aligned} \tag{7}$$

where $h_{ij,t}$ is the conditional variance of excess returns on industry i in country j, $h_{ij,w,t}$ and $h_{ij,j,t}$ are the conditional covariances between local industry i returns in country j and the world and country j excess returns, respectively, and $\varepsilon_{ij,t}$ is the error term.

Finally, to estimate (5) we must define the functional form of the price of global industry risk, $\lambda_{i,t}$. We mentioned above that $\lambda_{i,t}$ cannot be estimated in an unconditional setting since its unconditional expected value is zero. This feature of the model leads to a possibility of representing its time variation as a simple linear function of information variables, that is, $\lambda_{i,t-1} = \eta' \mathbf{Z}_{t-1}$, where η is the vector of coefficients and $\mathrm{E}[\mathbf{Z}] = 0$. In other words, unlike the prices of the world and country risks, the price of global industry risk can have positive and negative values. Now, under the same conditions as in (7), Model (5) can be written as:

$$\begin{aligned} r_{ij,t} &= \hat{\lambda}_w \operatorname{Cov}_{t-1}(r_{ij,t}, r_{w,t}) + \lambda_{j(i)} \operatorname{Cov}_{t-1}(r_{ij,t}, r_{j,t}) \\ &\quad + \lambda_{i,t-1} \operatorname{Cov}_{t-1}(r_{ij,t}, \hat{u}_{i,t}) + \varepsilon_{ij,t}, \\ \hat{u}_{i,t} &= \lambda_{i,t-1} \operatorname{Var}_{t-1}(\hat{u}_{i,t}) + \varepsilon_{i,t} \\ \lambda_{i,t-1} &= \eta' \mathbf{Z}_{t-1} \\ h_{i,t} &= c_i + a_i^2 \varepsilon_{i,t-1}^2 + b_i^2 h_{i,t-1} \\ h_{ij,t} &= c_{ij} + a_{ij}^2 \varepsilon_{ij,t-1}^2 + b_{ij}^2 h_{ij,t-1} \\ h_{ij,w,t} &= c_{ijw} + a_{ij}\hat{a}_w \varepsilon_{ij,t-1}\hat{\varepsilon}_{w,t-1} + b_{ij}\hat{b}_w h_{ij,w,t-1} \\ h_{ij,i,t} &= c_{iji} + a_{ij} a_i \varepsilon_{ij,t-1}\varepsilon_{i,t-1} + b_{ij} b_i h_{ij,i,t-1} \\ h_{ij,j,t} &= c_{ijj} + a_{ij}\hat{a}_j \varepsilon_{ij,t-1}\hat{\varepsilon}_{j,t-1} + b_{ij}\hat{b}_j h_{ij,j,t-1}, \end{aligned} \tag{8}$$

where $h_{i,t}$ is the conditional variance of global industry i shock and $h_{ij,i,t}$ is the conditional covariance between local industry i returns in country j and the global industry shocks.

The pure industry i shock, $u_{i,t}$, is defined only through its conditional variance since it must be orthogonal to the world and country-specific risk factors. We use the estimated residuals from the regression of excess returns of global industry i on the world and country excess equity returns as our proxy for $u_{i,t}$. That is,

$$r_{i,t} = \alpha + \beta_{iw} r_{w,t} + \sum_{j=1}^{J} \beta_{ij} r_{j,t} + u_{i,t}, \qquad (9)$$

where J is the number of countries. Thus, the estimated residuals $\hat{u}_{i,t}$ are uncorrelated with the world market and country returns by construction.[8]

3. Data

3.1. Returns Data

We use weekly returns from January 7, 1991, to October 11, 1999, or 458 observations from the G-7 countries—Canada, France, Germany, Italy, Japan, United Kingdom, and the United States. The set of industries consists of 18 categories. All country and local industry returns are converted into U.S. dollars using the corresponding exchange rates. We also form global industry returns for the consequent construction of global industry shocks. Global industry returns are formed by the market capitalization weighted average of U.S.-dollar-denominated local industry returns. To obtain excess returns, we subtract the seven-day Euro-dollar rate from all gross equity returns. The data we use are from *Datastream*.[9]

The size of our sample across time and assets is motivated from the following considerations. Across time, our sample is limited to the 1990s because: (i) this time period does not include several world business cycles, and so the modeling of the time variation in the world and countrywide risks becomes relatively less important than for a longer time series, and (ii) many local industry indices are unavailable for the 1970s or 1980s. Across assets, our sample is limited to the G-7 countries and 18 industries because: (i) it is important for the purpose of our paper to deal with markets that are generally similar at the country level to be able to detect any dissimilarities among them at a more disaggregated industry level, and (ii) some local industries at the classification level we consider are not represented even in the majority of G-7 countries.[10]

Table 1 shows the mean, standard deviation, minimum and maximum values, and first-order autocorrelation of all global excess returns. It also shows the Bera-Jarque (B-J) test for normality, B-J of returns, and the fourth-order Ljung-Box statistic for the squared excess returns, $Q_4(R^2)$. Panel A reports these statistics for the returns on local country indexes as well as the world portfolio. The United States has the highest mean weekly excess return of 0.26% and the lowest volatility, while Japan has experienced the lowest average return over the same period (0.02%) and the volatility second only to that for Italy. The B-J test is significant for all returns highlighting the importance of accounting for the deviations from normality in estimating our models. The serial autocorrelation is negative for all returns ranging from −0.06 for Canada to −0.17 for the United States. The rejection of the hypothesis of zero autocorrelation of squared returns suggests the use of GARCH parameterization for the second moments of returns.

Panel B shows the summary statistics data for global industry returns. The industries with the highest mean excess returns are pharmaceuticals and telecommunications having values of 0.29% and 0.28% respectively, while the lowest average excess return is registered for the oil exploration and production sector—almost zero. Other industries related to energy and commodities such as electricity, paper, and transport also have low mean excess returns. The electricity sector also has the second-lowest standard deviation in the sample. Similar to countries' excess returns, all of industry returns are nonnormal and, for almost all of them, the fourth-order Ljung-Box statistic is significant.

[8] Our pure industry shock is not exactly equivalent to that in Roll (1992), Heston and Rouwenhorst (1994), and Griffin and Karolyi (1998). By making each $u_{i,t}$ orthogonal to the world market and country factors, we do not eliminate the potential impact of one global industry on another. However, our primary goal is to achieve the orthogonality of the industry-specific risk factor with respect to the two base factors proxying the risks in the cases of full integration or complete segmentation. In fact, any of the risk factors can represent some mixture of influences. For example, a given country-specific risk factor may be confounded by other countries' risk dynamics. Moreover, if our "pure" global industry shock encompasses certain effects from some other global industries, it is likely that returns on the corresponding local industry also absorb some variation from other respective local industries.

[9] We use *Datastream* Global Equity indices. They represent approximately 75%–80% of the total market capitalization in the respective countries and local industries. While *Datastream* backfilled both country and industry indices until 1999, due to the short calendar sample, the survivorship bias in our data is much less severe than in many other studies on market integration. Note that although the global MSCI Industry indices go back to the 1970s, the corresponding information at the local (country) industry level is not always available.

[10] In choosing the industry disaggregation level on *Datastream* our choice was among Levels 3, 4, and 5. In our view, Level-4 classification is the most appealing one due to the following tradeoff. On one hand, we would like to retain potential cross-sectional variability in the point estimates of industry risk in our tests. On the other hand, due to data limitations we are unable to work with the same large group of industries for all our countries.

3.2. Global Industry Instruments

As in any conditional asset-pricing model, a careful selection of instruments is important. There are two considerations here. First, the instruments must be observable at the same frequency as the other data and they must show some sizable correlation with the variables that they are supposed to predict. The previous empirical work on international asset pricing provides useful information on important world and country-specific instruments.[11] Since this paper, to the best of our knowledge, is the first that deals with the time-varying price of industry risk, we select a set of meaningful information variables that can potentially have some explanatory power for global industry shocks. Notice that since "pure" industry shocks have zero unconditional means, all instruments we select are demeaned.

Our first instrument is the lagged global industry return (IR). In a way, this choice is motivated by the recent literature on momentum strategies in stock returns (e.g, see Moskowitz and Grinblatt 1999 or Rouwenhorst 1998). If there is a momentum in global industry returns, higher current returns in a given industry may lead to a positive industry shock next period. One of the important differences among global industries is the change in their market capitalization relative to the market capitalization of the entire world. Negative changes can be associated with a declining market share of a particular industry while positive changes are associated with an expanding industry.[12] Thus, our second instrument is the change in the proportion of a given global industry capitalization with respect to the world market capitalization (MC). Both these instruments are nonpersistent time series.

In many papers on conditional asset pricing, the dividend yield is often cited as one of the most useful information variables. We construct the dividend yield (DY) for each global industry using the market capitalization weighed average of dividend yields on the corresponding local industries in the G-7 countries. The last information variable we use is the global industry price-to-earnings (P/E) ratio, which is again formed as the market capitalization weighed average of P/E ratios for the corresponding local industries in the G-7 countries.[13] Our use of the P/E ratio is motivated by the well-known differences in the P/E ratios across industry sectors. For example, consumer products companies have very different P/E ratios than banks or computer companies; growth companies have usually higher P/E ratios than value firms (e.g., see Fama and French 1992).

Table 2 **Summary Statistics of Global Industry Instruments**

		First-order autocorrelations			Average cross-correlations			
	Mean SD	Mean	Min	Max	IR	MC	DY	PE
IR	0.0229	−0.09	−0.21	0.03	1.00	0.48	−0.08	0.06
MC	0.0166	−0.11	−0.25	0.00		1.00	−0.04	0.04
DY	0.0037	0.99	0.98	1.00			1.00	−0.46
PE	0.0713	0.98	0.93	0.99				1.00

Since each of our four global industry information variables is formed for each of the 18 industry groups, Table 2 gives only the average statistics for our instrument set. For each instrument, it shows the average standard deviation, minimum, maximum, and the mean values of the first-order serial correlations as well as average cross-correlations. As expected, the first two instruments, the global industry returns and relative changes in the industry market capitalization are nonpersistent series but the global industry dividend yields and P/E ratios are persistent with the average autocorrelation in excess of 0.975. The average cross-correlation data reveal that pairwise correlations among our instruments are similar or lower than those in other studies.[14]

There is some controversy about the forecasting potential of dividend yields and other variables that show close-to-unity serial correlation. Ferson et al. (2003), Goyal and Welch (2003), Valkanov (2003), and others argue that the predictive power of dividend yield and other highly persistent time-series is spurious or inflated at best. However, our estimation results below show that while the level of persistence for dividend yields is almost the same for all 18 industries, its predictive power is limited only to certain industries that have several common characteristics. For example, large companies, which often can be found in the utilities sector, usually pay more dividends than companies in other industries. Therefore, changes in the dividend yield for those larger companies may provide more information about their future earnings than for smaller dividend-paying firms.[15]

Table 3 provides the OLS regression results of the pure industry shocks on the set of demeaned global industry information variables. The table reports the estimates of the regression coefficients on each of the

[11] See, for example, Harvey (1991), Ferson and Harvey (1993), and Bekaert and Harvey (1995).

[12] One should not, however, interpret our rationale as an assumption that the relative importance of a given industry changes on a weekly basis.

[13] When P/E or dividend yields on local industries were not available, the averages were conducted based on the remaining countries' data.

[14] See, for example, Harvey (1991), Dumas and Solnik (1995), and De Santis and Gerard (1997).

[15] Campbell and Yogo (2002) find that dividend yield and especially the P/E ratio show some predictive power for stock returns even after accounting for possible statistical biases.

Table 3 Predictability of Global Industry Instruments

	IR_{t-1}	MC_{t-1}	DY_{t-1}	PE_{t-1}	R^2 (%)	F
Banks	0.0061	−0.0327	0.4994[b]	−0.0402[b]	1.22	1.39
Building materials	0.0686[a]	−0.0954[a]	0.1157	−0.0033	2.03	2.34[a]
Chemicals	0.0473	−0.0612	0.2778[a]	0.0034	1.65	1.90
Diversified industrials	−0.0001	−0.0595[b]	−0.0317	−0.0171	1.54	1.77
Electricity	−0.0295	−0.0092	0.6006[a]	−0.0542[a]	3.57	4.19[a]
Electronic equipment	0.0296	−0.0779	−0.1601	0.0015	0.95	1.08
Engineering	0.0765[a]	−0.0760[b]	−0.0660	0.0004	2.44	2.83[a]
Food	0.0292	0.0250	0.9403[a]	0.0088	2.48	2.87[a]
Gas distribution	0.0189	−0.0144	0.4223[a]	0.0421[a]	1.02	1.16
Household goods	0.0774[a]	−0.1282[a]	0.1843	0.0009	2.97	3.46[a]
Insurance	0.0371	−0.0531	0.4877[a]	−0.0233[a]	2.74	3.19[a]
Media	0.0138	0.0023	−0.1169	0.0046	1.03	1.18
Oil expl. and production	0.0990[b]	−0.0740	0.5013[b]	0.0005	1.82	2.09[b]
Paper and packaging	0.1378[a]	−0.2124[a]	0.4244	0.0043	4.65	5.52[a]
Pharmaceuticals	−0.0423	−0.0443	−0.5440	−0.0463	1.40	1.60
Retailers, general	−0.0216	−0.0082	−0.7266	−0.0474	0.88	1.00
Telecommunications	−0.0275	−0.0230	−0.2412[a]	−0.0101[a]	1.73	1.99[b]
Transport	0.0441[b]	−0.0494	0.3922	0.0033	1.25	1.43

[a, b]Denote statistical significance at the 5% and 10% levels, respectively.

four information variables, the R-squared adjusted for the degrees of freedom, and the F-statistics of the joint significance of regressors. The intercepts are not shown because they are indistinguishable from zero in all regressions. We can observe that taken jointly, instruments are able to predict industry shocks of some industries such as electricity, insurance, oil, and paper. Significant F-statistics are primarily attributed to significant slopes on lagged DY or P/E ratios in some cases while in other cases, lagged industry returns and changes in the industry market capitalization relative to the world emerge as more important contributors. The R-squared statistics range from as low as 0.9% for the general retailers sector to more than 4.6% for paper and packaging and they are greater than 2% for all industries with significant F-statistic. This range of R-squared is comparable to those found in other papers. For example, the test results reported by Ferson and Harvey (1993) on country-level returns show the range of R-squared between 1.1% and 10.5%. Thus, it is important to note that in spite of fact that global industry shocks have neither the world nor any country-specific variation components, their remaining variation still appears to be substantial enough to exhibit a reasonable relation to the respective industry-specific instruments.

4. Empirical Evidence

4.1. Tests of the Country-Level Integration

Table 4 presents the results of estimation of Model (6) jointly for all seven countries with the time-invariant prices of the world and country risks. We impose no restriction on the signs of the prices of risks. For each country and the world, the table reports the estimates of the prices of risks with their p-values as well as the average and root mean square pricing errors for all excess returns, AE and RMSE respectively. All the estimated GARCH coefficients, which we do not show in this and subsequent tables for the sake of brevity, are highly significant, thus supporting the parameterization of the variance-covariance matrix of our models. These estimates as well as the results of residual diagnostic tests are available from the authors on request.

The estimate of the world price of risk, $\lambda_w = 6.71$, is positive and statistically different from zero showing that expected equity returns in all countries are sensitive to the world market risk. Thus, unlike other

Table 4 Country-Level Integration

	λ_W	λ_{CN}	λ_{FR}	λ_{GM}	λ_{IT}	λ_{JP}	λ_{UK}	λ_{US}
Price of risk	0.0671[a]	−0.0122	0.0055	−0.0059	−0.0058	−0.0041	−0.0027	0.0290[a]
AE	−0.016	−0.070	−0.030	0.007	−0.233	−0.022	−0.033	−0.085
RMSE	2.21	2.51	2.45	3.34	3.47	2.11	2.00	1.85
B-J	36.70[a]	129.0[a]	42.53[a]	47.76[a]	13.64[a]	82.23[a]	13.81[a]	184.1[a]
$Q_4(\varepsilon^2)$	2.97	1.11	9.97[a]	21.74[a]	9.46	2.38	3.76	0.36

[a]Denotes statistical significance at the 5% level.

authors (e.g., De Santis and Gerard 1997, Hardouvelis et al. 1999), we are able to obtain an economically plausible and statistically significant price of the world market risk without imposing any constraints or modeling it as a time-varying parameter. The prices of country-specific risks are not distinguishable statistically from zero for all countries except the United States, which has $\lambda_{US} = 2.90$. At first, this estimation outcome looks surprising since the United States is supposed to be the most integrated country; it is also in direct contradiction with the results of De Santis and Gerard (1997) who show that all G-7 countries are fully integrated. However, our observation interval covers the 1990s, a period of remarkable outperformance of the U.S. market. Also, the U.S. market has a large weight in the world market portfolio. Hence, our finding that the expected U.S. equity market return is a positive function of its own conditional variance is very intuitive and interesting by itself.[16] The table also reports the average and mean square pricing errors for each of the estimated prices of risks. The lowest average pricing error of 0.007 is found for Germany, while the highest one, −0.233, for Italy. More importantly, the RMSE is again the largest for Italy, while it is the lowest for the United States. These test statistics indicate that the model is capturing the dynamics of equity returns in the United States better than in any other country. Our results imply that if an industry risk is priced for any industry, it will constitute a deviation from a full integration model for all G-7 countries except the United States. However, this does not exclude U.S. industries from being exposed to global industry shocks, in addition to their sensitivity to the countrywide risk.

Table 4 also shows that the residuals of all excess returns fail the Bera-Jarque normality test. This suggests that our model parameterization cannot fully account for nonnormality of returns.[17] Nevertheless, the values of this test statistic for residuals are markedly lower than that for excess returns. Finally, the test for the fourth-order autocorrelation in residuals fails to reject the null for all countries but France and Germany. These results show that our GARCH (1, 1) specification is able to capture some nonnormality and a significant amount of autocorrelation in national market excess returns for the majority of countries.

4.2. Tests of the Industry-Level Integration

The test results in the preceding subsection imply that there should be no industry-specific price of country risk for all countries except the United States, and so one could use Model (8) only for the pricing of U.S. industries. However, to ensure the overall consistency, we conduct the estimation of Model (8) jointly for all the countries in our sample using the estimated values of the prices of world risk and corresponding returns' residuals. We should expect that all or almost all $\lambda_{j(i)}$s, when j is not the United States, are insignificantly different from zero. However, since the U.S. variance risk is priced, we should expect that the U.S. market price of risk is statistically significant for a sizable proportion of U.S. industries.

Tables 5 and 6 report the estimation results of the econometric model (8). Table 5 shows the point estimates of $\lambda_{j(i)}$ for each industry i based country j price of risk.[18] The pattern of test results is quite interesting. As expected, the vast majority of the industry-specific prices of country risks in all countries except the United States are statistically zero. The industries with the largest number of significant at the 5% level exposure to country risk across all countries excluding the United States are food and oil exploration and production, both of which are priced locally in Japan and the United Kingdom. Engineering and household goods exhibit marginal significance with respect to three and two local market risks, respectively. The overall picture proves that all G-7 countries but the United States are well integrated with the world market, thus substantiating the test results of Model (3).

More importantly, we observe that the point estimates of local market price of risk in the United States are significant for eight industries, thus again confirming the test results of Model (3). These industries are electricity, electronics, insurance, media, oil exploration, retailers, telecommunications, and pharmaceuticals. The price of the U.S. market risk based on six out of eight industries is positive in line with the theory, however, the negative sign on the risk premium on electricity and oil exploration and production should not be overemphasized: It suggests that the average excess returns on those industries are too low to be explained by the positive world market risk premium of 6.71. Note that the excess returns on these two industries have the lowest means (see Table 1).

Among the eight locally priced (at the 5% level) U.S. industries, six of them—namely, telecommunications, pharmaceuticals, retailers, electronics, electricity, and insurance—rank in the top half of our sample based on

[16] The behavior of the United States is reminiscent of the Japanese market performance in the 1980s—see Harvey (1991). Interestingly, using a different framework, Dumas et al. (2003) find that the level of U.S. stock market correlation with other markets is consistent with correlation levels obtained under both integration and segmentation hypotheses.

[17] Similar results are reported, for instance, in De Santis and Gerard (1997).

[18] Note that the industries that are not available on *Datastream* are shown with "N/A," while industries for which the estimation of Model (8) did not converge are denoted as "—."

Table 5 Industry-Level Integration: Estimates of Industry-Specific Country Risks

	λ_{CN}	λ_{FR}	λ_{GM}	λ_{IT}	λ_{JP}	λ_{UK}	λ_{US}	ΔRMSE
Banks	−0.0032	0.0040	−0.0088	−0.0104	−0.0023	0.0199	0.0155	−0.003
Building materials	−0.0156	−0.0091	−0.0313	−0.0174	−0.0087	−0.0458[a]	0.0057	0.002
Chemicals	0.0076	0.0021	−0.0036	−0.0104	−0.0034	−0.0252	0.0072	−0.002
Diversified industrials	—	−0.0015	−0.0034	−0.0290[a, c]	0.0051	0.0492	0.0280	0.001
Electricity	—	N/A	0.0332	0.0266[b, c]	−0.0021	0.0325	−0.0741[a]	−0.010
Electronic equipment	0.0403	0.0149	−0.0075	0.0487	—	0.0202	0.0409[a, c]	0.004
Engineering	0.0392[b]	−0.0029	−0.0207[b]	−0.0129	−0.0053[b]	0.0035	0.0070	0.001
Food	0.0179	−0.0096	−0.0368	−0.0002	−0.0094[a]	−0.0316[a]	0.0142[b]	−0.004
Gas distribution	—	0.0499	−0.0568	0.0060	−0.0058	0.0013	0.0067	0.001
Household goods	0.140[b, c]	0.0116	−0.0460[b, c]	0.0059	—	−0.0412	0.0311	0.004
Insurance	0.0241	0.0064	−0.0019	−0.0021	−0.0033	−0.0270	0.0222[a]	−0.003
Media	0.0251	0.0258	0.0302	0.0023	0.0023	0.0263	0.0230[a]	−0.001
Oil expl. and production	−0.0168	−0.0797	N/A	N/A	−0.0150[a]	−0.1179[a, c]	−0.0379[a]	0.002
Paper	—	−0.0348	−0.0273	−0.0149	−0.0129[b]	−0.0098	−0.0208	−0.004
Pharmaceuticals	0.0728	0.0317	−0.0116	−0.0175	0.0080	0.0481[b]	0.0370[a, c]	−0.005
Retailers	−0.0213	0.0485[a, c]	−0.0171	−0.0069	0.0052	−0.0088	0.0363[a, c]	−0.001
Telecommunications	0.0011	N/A	0.0273[b]	0.0049	—	0.0269	0.0394[a]	−0.003
Transport	−0.0381	−0.0284	0.0131	0.0088	—	−0.0052	0.0087	0.002

[a, b]Denote statistical significance at the 5% and 10% levels, respectively.
[c]Denotes statistical significance at the 5% or 10% levels based on Equation (4).

average market capitalization. Since the U.S. market is partially integrated, we would expect these industries to show significant local pricing given their large share in the U.S. equity market index. On the other hand, it maybe that the oil exploration and production industry with its relatively low market capitalization is priced in the United States because of its strong links to the U.S. business cycle. The same reasoning might be applied to media, since as a nontradable industry it is likely to have exposure to local risk. Yet, the U.S. banking industry, which is the third in terms of its market capitalization, has no evidence of local pricing. With a major trend towards globalization of the banking industry, this result is not surprising.

The last column of Table 5 shows the change in the root mean squared errors (ΔRMSE) across industries from the estimation of Model (7). (For brevity, we do not report the estimation results of Model (7) in a separate table.) The RMSE decreases for 10 out of 18 industries, thus, providing certain support for three-factor relation (5). In other words, the industries for which the ΔRMSE is negative (e.g., banking, pharmaceuticals, telecom, etc.) are those whose return variation cannot be explained only based on the domestic or world market risks. Investing in these industries can potentially represent an additional source of diversification beyond the geographic diversification. As for the industries with positive ΔRMSE,

Table 6 Industry-Level Integration: Estimates of Global Industry Parameters

	Const.	IR	MC	DY	PE	χ^2	Ps-R^2
Banks	−0.0330	−0.0163	1.7234	0.0736	−0.0032	1.42	0.49
Building materials	0.0090	0.0293[a]	−4.0515	0.0350	−0.0035	4.54	2.60
Chemicals	−0.0315	0.0102	−0.8235	0.1835[a]	0.0048	5.50	1.79
Diversified industrials	−0.0240	0.0147	−8.1657[a]	−0.0153	−0.0218	8.42[b]	1.12
Electricity	−0.0104	−0.0421[a]	1.9447	0.3197[a]	−0.0171	27.75[a]	3.11
Electronic equipment	0.0147	0.0447	−11.97[a]	−0.0715	0.0066	5.85	0.70
Engineering	−0.0179	0.0041	2.2938	−0.1787	−0.0028	6.98	−0.77
Food	−0.1072	0.0095	0.6468	0.7534[a]	0.0061	26.23[a]	2.83
Gas distribution	−0.0221	0.0039	−0.9479	0.1207	0.0081	1.77	0.78
Household goods	0.0381	0.0778[a]	−8.3079[b]	−0.2118	−0.0047	7.61	2.91
Insurance	−0.0655[a]	0.0377[a]	−7.1840[a]	0.2646[b]	−0.0165	8.88[b]	3.33
Media	−0.0880[a]	0.0014	−0.3724	−0.1416	−0.0058	2.10	0.57
Oil expl. and production	−0.0293	0.0029	−0.2370	0.0332	−0.0002	3.60	0.68
Paper and packaging	−0.0121	−0.0273[b]	−3.7973[a]	0.1331	0.0023	7.25	5.54
Pharmaceuticals	−0.0480	−0.0026	−0.7532	−0.0738	−0.0075	1.24	0.98
Retailers, general	−0.0616[a]	0.0057	−0.4126	−0.0931	−0.0148	5.17	−0.47
Telecommunications	−0.0271	−0.0129	−0.5967	−0.1065	−0.0044	3.33	1.58
Transport	−0.0221	0.0302	−0.8637	−0.4009	0.0043	3.78	0.92

[a, b]Denote statistical significance at the 5% and 10% levels, respectively.

their pricing is based solely on their exposure to the domestic or world market risks and they cannot constitute a substantial diversification source.

Table 6 reports for each global industry the point estimates of the coefficients of vector η, the robust chi-square test results of the null hypothesis of no time variation in the price of the industry risk, and the pseudo R-squared. The chi-squared test shows that out of 18 global industries, we reject the null of no time variation in $\lambda_{i,t}$ for four industries: electricity and food at the 5% significance level, and diversified industrials and insurance at the 10% significance level. Among these industries, the electricity sector shocks appear to be priced the most. Interestingly, Griffin and Karolyi (1998), using a different framework, report that the ratio of the variance of a pure electricity shock to the variance of its global industry index return in excess of the world market return is the largest among 66 aggregate industries that they examine. Almost all statistically priced industries such as electricity, food, and insurance also exhibit large pseudo R-squared.[19]

Note that our results suggest that the pricing of industry portfolios does not depend on the classification of respective industries as traded or non-traded. Rather, the global industry risk component arises when over some time periods neither the world nor the country-specific risk is sufficient to capture the time variation in local industry returns (see Equation (5)). In other words, industry shocks can be significant for both non-traded-goods and traded-goods industries. For example, in the case of electricity, which is a nontraded good, the overall demand may be independent to a certain degree from the world business cycle and driven, say by weather patterns.[20] Similarly, food, which can be classified as a traded good, also shows global industry risk because its demand is largely independent from world economic conditions.

Across the four priced industries, the coefficient on the dividend yield is positive for three industries, corroborating with an economic intuition that the current increase in an industry's dividend yield is likely to be followed by an increase in that industry's returns. The estimated coefficient on the lagged industry returns is generally positive (for 13 out of 18 sectors). This implies the existence of some momentum between industry returns and shocks even though the first-order autocorrelation for the vast majority of global industry returns is negative (see Table 1). The relation between industry returns and P/E is opposite. The current increase in the global industry P/E ratio seems to suggest that industry returns will be lower next period. Only four intercepts are significant at the 5% or 10% significance levels.

We perform two diagnostic tests for the residuals of local industry excess returns. The first one, the fourth-order Ljung-Box statistic, shows that, similar to the country-level test, the squared error terms show significant autocorrelation only for some industries from France, Germany, and Italy. This means that our model captures a significant amount of autocorrelation in local industry excess returns in most of the countries. The second test is the Engle and Ng (1993) joint test for asymmetry in the residuals from the estimation of Model (8). While there are some local industries that exhibit asymmetry in the residuals, we do not find overwhelming evidence on the misspecification of our model. These results are available on request.

4.3. Industry Diversification Gains

Our results imply that there must be benefits for two types of industry-specific diversification: first, across specific local industries and, second, across specific global industries. We illustrate the benefits of these types of diversification using the rolling-window Sharpe ratios assuming no restriction on short selling. We compute the optimal portfolios over five-year periods rebalancing them every week. Furthermore, from the time series of realized returns, we then test the ex-post performance of our diversification strategies using the Jobson-Korkie (1981) test for the equality of Sharpe ratios.

Figure 1 highlights the benefits of *local industry diversification* for a hypothetical investor who resides outside the United States in one of the other six industrialized countries. This setting is chosen because our results show that all G-7 countries except the United States are fully integrated with the world capital market. The figure shows the Sharpe ratios for optimally diversified portfolios of assets from all industrialized countries excluding the United States (we call it the G-6 portfolio). As expected, the optimal portfolio of the G-6 countries' assets and those U.S. industries that are nonpriced in the United States based on Model (8) estimation results (see Table 5), have a larger Sharpe ratio than the G-6 portfolio. More importantly, the optimal portfolio of the G-6 countries' assets and those U.S. industries that are priced in the United States command sizably larger Sharpe ratio than the G-6 portfolio with nonpriced U.S. industries. The Jobson-Korkie (1981) test of the equality in the Sharpe ratios gives a difference of 0.03 in favor of the portfolio of G-6 countries and priced U.S. industries relative

[19] For each asset in estimation we compute a pseudo R-squared as the ratio between the explained sum of squares and the total sum of squares for Model (8). There is no guarantee that the pseudo R-squared are positive for all assets.

[20] Among the G-7 group of countries, only Canada and France export electricity, which represents a very small proportion of total exports by those countries (see, for example, the 1996 International Trade Statistics Yearbook).

Figure 1 **Five-Year Rolling Sharpe Ratios: Benefits of Local Industry Diversification**

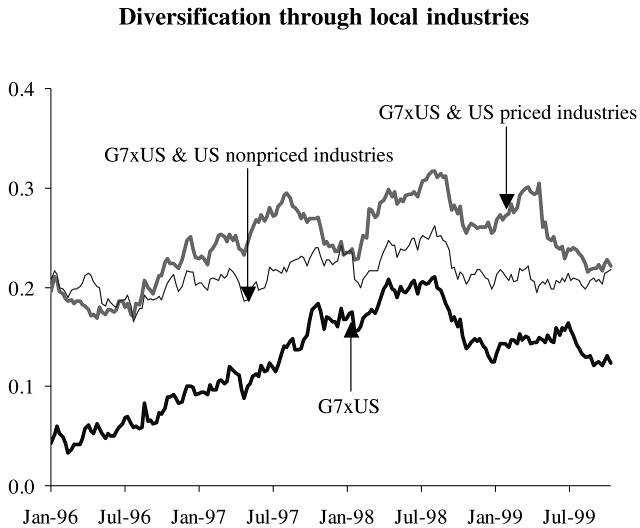
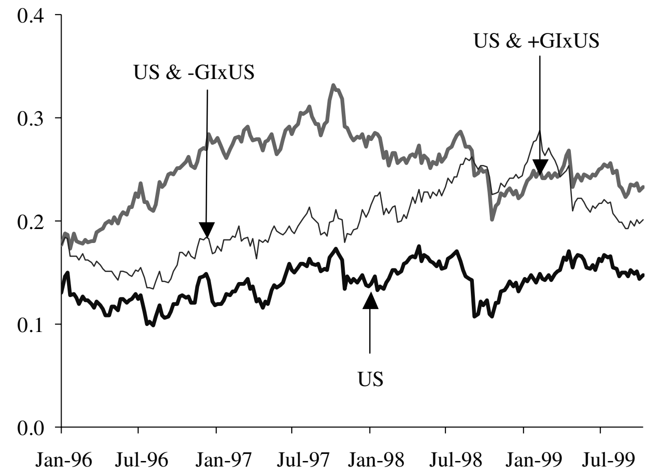


Figure 2 **Five-Year Rolling Sharpe Ratios: Benefits of Global Industry Diversification**



to that composed of the G-6 countries and nonpriced U.S. industries. While this difference is economically sizable, it is statistically insignificant (its p-value is 0.79). However, as noted by Jobson and Korkie (1981), their test on the equality of the Sharpe ratios has very low power.[21]

Figure 2 shows the benefits of *global industry diversification* for a hypothetical investor who resides in the United States. This setting is motivated by two considerations. First, the United States is different from other countries in terms if its integration with the world capital market. Second, and more importantly, we would like to show that the global industry diversification gains come from global industries irrespective of the performance of local U.S. industries. There is no concern about the possible overlap of these new results with those in the previous figure. This concern can potentially arise since most of the global industries that reduce the estimation RMSE simultaneously induce a significant pricing of many corresponding local industries, including those in the United States (see Table 5). Since there are only four global industries that are priced, we choose our two groups of global industries as follows. The first group of global industries includes those industries that lead to larger RMSEs (positive ΔRMSEs), while the second group includes those that lead to smaller RMSEs (negative ΔRMSEs). For both groups, we consider global industry portfolios that exclude the respective U.S. industries. The figure therefore depicts the Sharpe ratios for the U.S. market index, for the portfolio of the U.S. market index plus the first group of global industries, and for the portfolio of the U.S. market index plus the second group of global industries. Interestingly, the last portfolio has the highest Sharpe ratio almost during the entire sample. The Jobson-Korkie (1981) test of the equality in the Sharpe ratios gives a difference of 0.10 in favor of the portfolio composed of the U.S. equities and the second group of global industries relative to that composed of the U.S. equities and the first group of global industries. This difference is also marginally significant (its p-value is 0.08). Note that finding statistical significance even at the 10% level is quite surprising using the Jobson-Korkie (1981) test.

In sum, we demonstrate that if a country is partially integrated with the world market, it has a substantial proportion of both integrated and segmented industries. Fully integrated countries can still have industries that show some degree of segmentation from the world market. As a result, greater diversification benefits can potentially be achieved with industry-specific rather than countrywide diversification. We also find statistically significant pricing of global industry risk for some industries implying that portfolio managers should account for not only the world and country risks but also relevant industry exposure. The number of significantly priced global industries is small in our data. However, we are still able to show that investing in certain global industries can have additional diversification benefits for portfolio managers as well.

4.4. Robustness Issues

We now subject our results to several robustness checks. First, it might be the case that we detect

[21] The average difference in returns between the portfolio of G-7 countries excluding the United States plus U.S. priced industries and the portfolio of G-7 countries excluding the United States plus U.S. nonpriced industries is 0.554% on a weekly basis (28.8% annually). This difference is statistically different from zero even at the 1% level.

time variation for certain global industries simply because we do not explicitly account for the time variation in the currency risk. This problem might appear particularly significant in light of the work of Dumas and Solnik (1995) and De Santis and Gerard (1998) who argue that the exchange-rate risk is priced conditionally. More recently however, Griffin and Stulz (2001) show that exchange-rate shocks have almost no explanatory power for industry returns in different countries and common industry shocks are much more important. They find this result to be particularly strong for weekly returns—the same frequency we use in our paper. Griffin and Stulz observe their findings in an unconditional setting, but we believe that in a conditional setting, the relative importance of industry and currency shocks should not change.[22] While we are unable to estimate our model with the time-varying industry and currency risk, we can test it using different base currencies.

To understand the impact of exchange rates on our results, we have estimated Models (6) and (8) using data denominated in German marks, Japanese yen, and British pounds.[23] These results qualitatively are very similar to those based on U.S. dollars. For example, the range of the estimates of the world price of risk is from 3.60 in Japanese yen to 5.40 in German marks, while the range of the corresponding *p*-values is from 0.10 to 0.035. Again, the United States appears to be the least-integrated country in the G-7 group and a large proportion of her industries are significant priced relative to the market. Further details on these tests are available on request.

The next important issue is the constancy of the world market and country risk premiums in our estimations. First, at the country level, Equation (6), the time variation in these risk premiums has already been examined in Bekaert and Harvey (1995) and De Santis and Gerard (1997). Second, as we mentioned earlier in the paper, the joint estimation of (5) across countries and industries is practically impossible due to the multidimensionality of these data. Note however that similar to De Santis and Gerard, in our country-level integration tests we find that most of the G-7 countries are well integrated with the world. This implies that the econometric model (3) is fully sufficient for the estimation of industry returns for all G-7 countries except the United States. This estimation would completely avoid the need for modeling the country-specific risk. Therefore, only the constant price of the world market risk can potentially have an important impact on our results across all countries.

[22] Note that Chan et al. (1992), Bekaert and Harvey (1995), and De Santis and Gerard (1997) also do not explicitly account for the currency risk.

[23] We used a synthetic German mark rate after January 1999.

The information variables we use in the estimation of the time-varying world market risk are the lagged world market return as well as the lagged world dividend yield and the lagged three-month U.S. Treasury bill yield obtained from *Datastream*. Hence, we estimate the equivalent of Model (8) with the time-varying world market risk in two ways. In the first case, we again apply a two-stage procedure: We estimate $\lambda_{w,t}$ from system (6) with the time-varying world market risk and then use its values in the estimation of industry returns. However, this method leads to biased results because the resulting $\lambda_{w,t}$ overfits the data in the first-stage estimation and therefore performs badly in the second stage, which can be viewed as an out-of-sample estimation. This outcome is very similar to many recent studies on the predictive power of standard information variables that perform well in sample but very poorly out-of-sample (e.g., Bossaerts and Hillion 1999). In the second case, we estimate the time-varying $\lambda_{w,t}$ directly within Model (8). This method often precludes our algorithm from convergence for certain industries, although the outcomes of those estimations that converge are qualitatively similar to the earlier results. The details on these tests are also available on request.

Thus, not accounting for the foreign exchange risk or the time variation in the world price of risk in our model does not have a significant influence on the main results in our paper. First, a country is fully integrated with (segmented from) the world capital markets only if most of her industries are integrated (segmented). Second, some local industries appear to have an exposure to their respective global industry risk, which is unrelated to risks of the broad home or the world markets.

5. Conclusion

We use conditional asset-pricing framework and study global integration processes at the industry level. In our model, the return on a local industry is related to its sensitivity to the world risk, country-specific risk, and global industry risk. We show that country-level integration (segmentation) does not preclude industry-level segmentation (integration). We also find that there are cross-sectional differences in the impact of global industry risk on the pricing of local industries. Our results imply that greater diversification gains can potentially be achieved if local industry investment is country specific. Thus, investors should use *both* cross-country and cross-industry diversification as a way to improve portfolio performance. This implication is very intuitive and seems similar to the one proposed by Archanapalli et al. (1997) who argue that investors should diversify across regions and industries rather than only across regions. However, the main contribution of our results is that we explicitly identify the industries that are better suited for diversification purposes and quantify their relative risk exposure to global industry risk.

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