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Have World, Country, and Industry Risks Changed over Time? An Investigation of the Volatility of Developed Stock Markets

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Abstract

This paper uses a volatility decomposition method to study the time-series behavior of equity volatility at the world, country, and local industry levels. Between 1974 and 2001, there is no noticeable long-term trend in any of the volatility measures. Then in the 1990s there is a sharp increase in local industry volatility compared to market and country volatility. Thus, correlations among local industries have declined. More assets are needed to achieve a given level of diversification, and there is more of a penalty for not being well diversified by industry. Local industry volatility leads the other volatility measures.

I. Introduction

The risk reduction benefits of the international diversification of equity portfolios have been accepted for a long time among academicians (e.g., Solnik (1974)). Neither individual nor institutional investors, however, seem to take advantage of the benefits one would expect in a frictionless, fully integrated world: global portfolio composition is biased toward domestic shares (see Lewis (1999)). Kang and Stulz (1997) moreover find that, when investors decide to invest internationally, they do not hold the market portfolio of the countries they choose to invest in. What is the total risk exposure faced by investors with undiversified global stock portfolios? This question is the major motivation of our study.

The historical evolution of total risk is particularly important for global portfolio managers of undiversified international portfolios. If the risk that must be diversified away has increased, there are both more opportunities for international diversification and more assets needed to achieve a given level of diversification.

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The benefits of investing abroad may become harder to achieve, but the compensation for pursuing such an investment strategy is also greater. If investors face wealth constraints or transaction costs, increased diversifiable risk implies less diversification of their investment portfolios, unless they have superior stock selection capabilities. Total volatility is also an issue for taking advantage of mispriced individual assets, for pricing equity derivatives, and for measuring the market risk of equity portfolios (e.g., value-at-risk).

The relevance of exposure to world portfolio risk in explaining the cross section of expected returns has been established in countless empirical tests of international asset pricing models.[1] The empirical evidence in Cavaglia, Hodrick, Vadim, and Zhang (2002) and in Dahlquist and Sällström (2002), for example, shows that exposure to the world return factor is priced both in the cross section of country and global industry portfolio returns, according to various international asset pricing models. Empirical evidence on the importance of country and industry dimensions is less clear.

While Roll (1992) attributes the low correlation among country indices to diverse local industry structures, Heston and Rouwenhorst (1994) decompose stock return volatility into pure country and industry sources of variation and clearly document the dominance of country-specific effects (the average ratio of country to industry variances is 4.5). Griffin and Karolyi (1998) find that when emerging markets are included in the sample the proportion of portfolio variance explained by the time-series variation in pure country effects is higher than previously documented, which again indicates investors would be better off—in terms of risk reduction—if they pursued a geographic diversification strategy rather than an industry one.

Conversely, Cavaglia, Brightman, and Aked (2000), among others, find evidence that industry factors have grown in importance in recent years. Brooks and Catão (2000) also show that industry sectors are becoming more important in explaining portfolio risk and that the global industry factor, primarily associated with the information technology sector, has grown in importance since 1995. More recently, Brooks and Del Negro (2002b) assert that the rise in industry effects is simply a temporary phenomenon associated with the information technology bubble rather than a reflection of greater economic integration across countries.[2]

We take the perspective of a global investor and use local industry portfolios (within country) as our individual assets, to study three sources of risk for internationally tradable equities. Two of the risk sources are diversifiable in a global portfolio: geographic location and industry affiliation. The remaining source represents the systematic component: world portfolio volatility.

Our primary goal is to describe the historical behavior of total volatility components and to study the implications for international diversification. We address three main questions. First, has the relative importance of world, country, and local industry risk changed over time? Second, has the power of international diver-

[1]Karolyi and Stulz (2001) provide an extensive survey of these studies.

[2]This finding is contrary to the increased consensus among the investment community and in the financial press that the industry dimension of diversification is today more important than the geographic dimension.

sification to reduce risk been weakening? Finally, given the conflicting evidence in the literature, we take another look at the question of the relative efficiency of country vs. industry diversification for global equity investors.

We decompose the total volatility of individual assets into specific sources of risk by extending the Campbell, Lettau, Malkiel, and Xu (2001) volatility decomposition method to an international setting. We propose a parsimonious total risk decomposition that allows us, at an appropriate aggregation level, to measure and study the time-series behavior of risk components without the need to keep track of covariances or estimate risk exposure parameters for countries or local industry portfolios, which is an appealing feature of the approach.

The major simplification of this methodology is reliance on the use of market-adjusted residuals of country returns relative to world returns, and of local industry returns relative to country returns, to estimate country and local industry risk measures, respectively. This hierarchical decomposition is consistent with the traditional top-down approach to global asset management of first selecting countries and then industries and stocks. In addition, a simple change of the methodology is consistent with the view of the world for those investors who organize the world portfolio by industries rather than countries.

Our methodology measures industry risk on a country basis, which is an alternative to the Heston and Rouwenhorst (1994) fixed-effects model assumption that asset exposures to global industry shocks are equal across countries whenever they are non-zero. We take the variance of the local industry return in excess of its country of origin return as a measure of local industry risk. Thus, we allow for interactions among countries and industries; i.e., industry-specific shocks may have different impacts across countries. Moreover, our methodology provides a direct estimate of the volatility measures.[3] We use daily data within a month to estimate monthly time series of risk measures, without imposing a parametric multivariate volatility specification.

Our results indicate, first, that international diversification benefits have been substantial over the 1974–2001 period. World risk has always been the least important component of total risk. There is no evidence of a statistically significant long-term trend in any of the volatility series, although local and global industry volatility show a sharp increase after 1995, reaching an all-time peak in April 2000. An increase in local industry volatility is also notable in individual countries. The new economy bubble does not by itself explain the increase in industry risk, although the technology, media, and telecommunications industries play an important role in this phenomenon. World and country risk show a much more modest increase in the 1990s.

Second, the October 1987 crash was felt at both world and country levels, but had less of an effect on local industry risk. A period of increased local industry volatility may be seen since the beginning of 1987. The early 1990s may be considered an atypical period in historical terms; during the 1990–1995 period,

[3]Brooks and Del Negro (2002a) have recently proposed an alternative relaxing the restrictive assumptions of the fixed-effects model. They estimate stocks' exposure to global, country, and industry-specific shocks in a arbitrage pricing theory framework. Their approach, however, does not preserve the simplicity of the fixed-effects model. It imposes strong distributional assumptions and requires a balanced panel.

the share of country risk in total risk is unusually high, and total risk is on average lower than in the surrounding years.

Third, using Granger causality tests, we provide evidence that lagged local industry risk is helpful in forecasting world- and country-level volatility, while the converse is not true.

Fourth, the ratio of local industry to world risk experienced a considerable increase during the final years of our sample. The average ratio is 3.23 for the 1996–2001 period compared to 2.50 in the 1974–1995 period. Accordingly, the average contemporaneous pairwise correlation between local industry portfolios declines considerably from 0.287 (1974–1995) to 0.203 (1996–2001). Thus, the benefits of international portfolio diversification have become greater and the diversification of global portfolios using local industry portfolios has become harder to achieve as more assets are needed.

Finally, the notable increase in the ratio of industry to country risk, at both local and global levels, suggests that industry diversification became a more effective tool for risk reduction in the late 1990s. The share of local industry risk in total risk also increases considerably toward the end of the sample period to more than 50% in 1996–2001 while the share of country risk decreases.

The paper is organized as follows. Section II presents the model used to decompose total volatility, discusses some simplifying econometric solutions to the estimation of the volatility components, and briefly evaluates the exactness of the return structure employed. Section III gives details on the data set. Section IV presents the empirical findings concerning the historical evolution of the disaggregated volatility measures. Section V discusses the implications for global portfolio management. Section VI offers concluding comments.

II. Methodology

We extend the methodology proposed by Campbell et al. (2001) to decompose stock returns volatility into market, industry, and idiosyncratic components to an international setting. We take the perspective of a global investor whose returns are calculated in U.S. dollars. The global investor does not hedge foreign exchange rate risk, and we do not explicitly address currency risk factors. Moreover, we use local industry portfolios within countries as basic assets, and specify the same industry grouping variables across countries.

A. Total Volatility Decomposition

The volatility of a typical (or average) local industry is described by three components: world market volatility, average country volatility, and average local industry volatility.[4] We provide a decomposition of volatility that does not require the estimation of covariances or betas for local industries or countries, which is the most appealing feature of the Campbell et al. (2001) methodology applied to international stock markets. In fact, beta time dependence and error estimation are well documented in the literature and there is some controversy on which factors

[4]By typical we mean a randomly selected local industry portfolio with drawing probability equal to its weight in the world market portfolio.

should be used in multifactor international asset pricing models to describe the cross section of expected returns.

The excess return of the industry i portfolio in country c for period t is denoted R_{ict}.[5] Raw returns are U.S. dollar denominated and the excess return is measured over the U.S. dollar risk-free rate. Let x_{ict} be the weight of industry i in country c. According to a weighting scheme based on market capitalization, $x_{ict} = \mathrm{MV}_{ict} / \sum_{i \in c} \mathrm{MV}_{ict}$, where MV_{ict} denotes the market value of the local industry portfolio ic (assumed known at time t). Let x_{ct} denote the weight of country c in the world market portfolio (if market values are used as weights, then $x_{ct} = \sum_{i \in c} \mathrm{MV}_{ict} / \sum_c \sum_i \mathrm{MV}_{ict}$). The excess return of the country c portfolio for period t is given by $R_{ct} = \sum_{i \in c} x_{ict} R_{ict}$. The excess return of the world (w) portfolio for period t is given by $R_{wt} = \sum_c x_{ct} R_{ct}$.

We assume a simplified country return decomposition,

$$R_{ct} = R_{wt} + e_{ct}, \tag{1}$$

and similarly for local industry portfolio returns,

$$R_{ict} = R_{ct} + u_{ict} = R_{wt} + e_{ct} + u_{ict}. \tag{2}$$

Equation (2) specifies that the return on a local industry portfolio (R_{ict}) equals the sum of the world portfolio return (R_{wt}), its country portfolio-specific residual (e_{ct}), and its local industry-specific residual (u_{ict}).

Thus, the variance of a local industry portfolio return is given by

$$\begin{aligned} \mathrm{Var}(R_{ict}) &= \mathrm{Var}(R_{wt}) + \mathrm{Var}(e_{ct}) + \mathrm{Var}(u_{ict}) \\ &\quad + 2\mathrm{Cov}(R_{wt}, e_{ct}) + 2\mathrm{Cov}(R_{wt}, u_{ict}) + 2\mathrm{Cov}(e_{ct}, u_{ict}). \end{aligned} \tag{3}$$

While the local industry return variance in equation (3) includes covariance terms, the cross-sectional weighted average sum of all the basic asset total variance across all local industry portfolios is free of individual covariance terms, provided that we use the same non-stochastic weighting scheme to compute the averages that we use to compute country and world portfolio returns.[6] Thus, the volatility of a typical local industry portfolio is given by

$$\begin{aligned} \sum_{c \in w} x_{ct} \sum_{i \in c} x_{ict} \mathrm{Var}(R_{ict}) &= \mathrm{Var}(R_{wt}) + \sum_{c \in w} x_{ct} \mathrm{Var}(e_{ct}) \\ &\quad + \sum_{c \in w} x_{ct} \sum_{i \in c} x_{ict} \mathrm{Var}(u_{ict}) \\ &= \sigma_{wt}^2 + \sigma_{et}^2 + \sigma_{ut}^2, \end{aligned} \tag{4}$$

[5] In what follows, the term return is used to express excess return, unless stated otherwise. Following Harvey (1991) we note that these returns may be considered real relative to U.S. inflation because the U.S. inflation components in stock raw returns and in the U.S. dollar nominal riskless interest rate cancel out.

[6] We note that it is not required to assume weights based on market capitalization to assure the model consistency provided that national and world market returns are computed using the same weighting scheme.

where σ_{wt}^2 represents the variance of the world market portfolio, σ_{et}^2 is the weighted average of country-level variance across all countries, and σ_{ut}^2 is the weighted average of within-country industry-level variance across all local industries and countries. The RHS of equation (4) can be interpreted as the expected variance of a typical local industry portfolio.

We can gain further intuition on our methodology by comparing it with alternative models of returns. Our simplified market-adjusted return assumes that all countries have the same exposure to the world market and that all within-country industry portfolios have the same exposure to the country of domicile market portfolio.

In the framework of the single factor international capital asset pricing model (ICAPM) of Grauer, Litzenberger, and Stehle (1976), where the factor is the excess return on the world portfolio, which allows for country and local industry betas to be different from unity, the excess return on an individual local industry portfolio is written as[7]

$$(5) \quad R_{ict} \;=\; \beta_{ic} R_{ct} + \tilde{u}_{ict} = \beta_{ic}\left(\beta_c R_{wt} + \tilde{e}_{ct}\right) + \tilde{u}_{ict} \;=\; \beta_{ic}\beta_c R_{wt} + \beta_{ic}\tilde{e}_{ct} + \tilde{u}_{ict},$$

where β_{ic} denotes the beta of industry portfolio i in country c with respect to the corresponding local market excess return; β_c denotes country c beta with respect to the world market portfolio; $\tilde{e}_{ct}$ is the zero mean country-specific residual; and $\tilde{u}_{ict}$ is the local industry-specific residual.[8]

In this setting, if we take the average of the variance of country returns and the variance of the local industry returns, and compare them with the simplified decomposition equivalent measures, we will find that

$$(6) \qquad \sigma_{et}^2 \;=\; \sigma_{\tilde{e}t}^2 + CSV_t(\beta_c)\sigma_{wt}^2,$$

$$(7) \qquad \sigma_{ut}^2 \;=\; \sigma_{\tilde{u}t}^2 + CSV_t(\beta_{ic})\sigma_{\tilde{e}t}^2 + \left[CSV_t(\beta_{iw}) - CSV_t(\beta_c)\right]\sigma_{wt}^2,$$

where $CSV_t(\beta_c) \equiv \sum_{c\in W} x_{ct}(\beta_c - 1)^2$; $CSV_t(\beta_{ic}) \equiv \sum_{c\in W} x_{ct} \sum_{i\in C} x_{ict}(\beta_{ic} - 1)^2$; and $CSV_t(\beta_{iw}) \equiv \sum_{c\in W} x_{ct} \sum_{i\in C} x_{ict}(\beta_{iw} - 1)^2$.

Equation (6) shows that our estimate of country-level volatility is positively biased in relation to that of the ICAPM by $CSV_t(\beta_c)$, which can be seen as the cross-sectional variance of β_c, times σ_{wt}^2. By the same reasoning, equation (7) shows that the biases in the proposed estimate of local industry risk depend on the variation of world returns, country residuals, and betas. Cross-sectional variation in country and local industry betas can produce common variation in our variance components—market, country, and local industry. However, we will show in Section IV.B that cross-sectional variation in betas has only a small effect on the historical behavior of our volatility measures.

A final note about two features of the proposed volatility decomposition. Local industry risk is less affected by currency fluctuations than world and country-level measures of volatility. Also, the short-term interest rate risk implied by the excess returns specification affects only the world volatility measure, because the same interest rate is subtracted from the local industry portfolio returns.

[7]That is, assuming a perfectly integrated frictionless global stock market, where purchasing power parity holds (see Karolyi and Stulz (2001)).

[8]We assume that the beta of the local industry i with respect to the world market return satisfies $\beta_{iw} = \beta_{ic}\beta_c$.

B. Estimation

We use daily data within a month to construct sample variance estimates for that month. The volatility components of equation (4) are estimated as follows. Let d refer to days in month t. For the world portfolio variance $W_t \equiv \hat{\sigma}^2_{wt}$ in month t,

$$W_t = \sum_{d \in t} (R_{wd} - \mu_{wt})^2, \tag{8}$$

where R_{wd} is the world market portfolio excess return, constructed as the weighted average of the local industry index returns, using all available local industries in a given month, and μ_{wt} is the world portfolio mean return in month t.[9] Weights for month t are based on the U.S. dollar-denominated market value of the local industry portfolios on the last day of month $t-1$, so weights are taken as constant within month t.

For the country-level risk $C_t \equiv \hat{\sigma}^2_{et}$ in month t,

$$C_t = \sum_{c} x_{ct} \sum_{d \in t} e^2_{cd}, \tag{9}$$

where x_{ct} stands for the weight of country c in the world portfolio in month t, which we measure by using the end-of-month $t-1$ market capitalization, and e^2_{cd} is the square of the market-adjusted country-specific residual from equation (1).

For the weighted average of within-country industry-level risk $I_t \equiv \hat{\sigma}^2_{ut}$,

$$I_t = \sum_{c} x_{ct} \sum_{i \in c} x_{ict} \sum_{d \in t} u^2_{icd}, \tag{10}$$

where x_{ict} denotes the weight of industry i in country c in month t, and $\sum_{d \in t} u^2_{icd}$ is the summation over all days of month t of the square of the local industry-specific residual from equation (2) for each local industry portfolio in the sample.

Campbell et al. (2001) justify this simplified approach to estimate volatility components by the fact that all models for volatility estimation based on historical values tend to produce fitted volatility estimates that move close together. Thus, the simple use of daily data to produce monthly sample variance estimates is enough for historical description purposes.

III. Data Description

Our sample consists of daily U.S. dollar-denominated total return indices (including dividends) and market capitalizations for up to 38 industries, calculated by Datastream International (DS), for the period January 1974 to December 2001. DS indices are preferred over other domestic industry indices because: i) they are constructed on a uniform basis across countries; ii) they are not backfilled when

[9] As in Schwert (1989), we allow the mean world portfolio return to fluctuate month to month. Campbell et al. (2001) take the mean return over the entire sample, and report that mean-varying means yield almost identical results.

new constituents are added or deleted; iii) a long time series of daily data is available; and iv) a comprehensive coverage of the industry structure of each domestic stock market is assured. These aspects are important because they eliminate anomalous behavior of the indices attributable to differences in technical aspects of index construction, and, as Griffin and Karolyi (1998) point out, broad industrial classifications may not provide enough cross-sectional variation in returns to distinguish between country- and industry-specific sources of variation.[10]

The 21 developed markets analyzed are selected according to criteria as follows: i) coverage by the MSCI developed markets database; ii) no classification ever as an emerging market by the S&P/IFC EMDB; and iii) data availability. Thus, both the number of local industry portfolios and the number of countries represented in the world portfolio are allowed to change over the sample period.[11] To compute daily excess returns, we subtract the 30-day Treasury bill continuously compounded return divided by the number of trading days in a month from the daily logarithmic stock index rate of return.

Tables 1 and 2 provide descriptive statistics of the country portfolios and the global industry portfolios. Daily country and global industry portfolio excess returns are computed using a value-weighted average of the available local industry portfolio aggregate either by countries or global industries.

TABLE 1

Descriptive Statistics for Country Portfolios

Countries	Mnemonic	Returns Obs.	Returns Mean	Returns Std. Dev.	Size ($U.S. M)	Industries Max.	Industries Min.	Max. Weight
Australia	AU	7,305	2.2%	20.9%	106,330	35	21	35.6%
Austria	OE	5,196	3.6%	17.7%	15,146	24	6	31.0%
Belgium	BG	7,305	2.5%	16.2%	45,379	32	16	27.6%
Canada	CN	7,305	0.6%	14.9%	177,454	37	17	18.4%
Denmark	DK	5,196	4.9%	17.5%	34,823	22	13	27.0%
Finland	FN	3,587	3.0%	30.1%	72,346	28	12	36.1%
France	FR	7,305	4.2%	19.6%	260,418	35	21	16.1%
Germany	BD	7,305	2.6%	17.8%	303,228	36	24	16.7%
Hong Kong	HK	7,305	6.2%	29.8%	128,791	33	9	31.1%
Ireland	IR	3,131	2.0%	18.4%	36,557	27	21	28.5%
Italy	IT	7,305	0.6%	23.5%	142,645	33	17	27.8%
Japan	JP	7,305	0.7%	19.9%	1,747,509	36	30	13.8%
Netherlands	NL	7,305	6.4%	16.6%	173,993	30	21	35.4%
New Zealand	NZ	3,631	−1.7%	21.3%	16,843	26	11	31.7%
Norway	NW	5,717	−0.7%	24.1%	20,456	25	7	46.6%
Singapore	SG	7,305	1.1%	23.2%	45,609	30	9	34.0%
Spain	ES	3,849	2.6%	20.2%	162,518	32	18	32.3%
Sweden	SD	5,196	5.6%	23.7%	85,567	30	8	22.9%
Switzerland	SW	7,305	5.3%	16.5%	163,721	31	14	32.4%
U.K.	UK	7,305	5.6%	19.1%	688,146	38	31	15.0%
U.S.	US	7,305	4.7%	15.8%	3,306,448	38	38	12.3%
G21 World	W	7,305	2.4%	12.0%	7,547,509	646	270	—

Local industry portfolios are aggregated by countries to build the country portfolios. Portfolio returns are value-weighted averages of the relevant local industry portfolio excess returns. Returns and standard deviation values are annualized assuming a 260-day year. Size is average available monthly market values (in $U.S. millions). Maximum and minimum indicate number of local industry portfolios available for a given country portfolio. Max. weight is average weight in each country of the industry portfolio with the highest market value in each month.

[10]Cavaglia et al. (2002), Brooks and Del Negro (2002b), Dahlquist and Sällström (2002), and Brooks and Catão (2000) also rely on DS Global Equity Indices.

[11]The sample starts with 13 countries and 270 local industry portfolios in 1974 and ends with 21 countries and 640 local industry portfolios in 2000. After its inclusion in the database, no country is eliminated. The regional components remain the same from 1990 onward with the addition of Ireland.

TABLE 2

Descriptive Statistics for Global Industry Portfolios

Industries	Mnemonic	Returns Obs.	Returns Mean	Returns Std. Dev.	Size ($U.S. M)	Industries Max.	Industries Min.	Max. Weight
Aerospace & defense	AERSP	7,305	6.5%	16.8%	72,562	12	5	81.4%
Automobiles & parts	AUTMB	7,305	1.8%	15.5%	246,507	15	8	50.9%
Banks	BANKS	7,305	3.5%	14.7%	805,118	21	12	44.5%
Beverages	BEVES	7,305	4.1%	14.8%	143,975	18	9	57.3%
Chemicals	CHMCL	7,305	1.9%	13.5%	228,779	19	10	44.4%
Construction & bldg. materials	CNSBM	7,305	1.5%	14.5%	158,439	21	10	48.2%
Distributors	DISTR	7,305	−1.2%	19.6%	64,195	18	9	74.5%
Diversified industrials	DIVIN	7,305	2.2%	15.1%	153,249	21	12	39.0%
Electricity	ELECT	7,305	3.6%	11.6%	278,227	17	7	57.3%
Electronic & electric equipment	ELTNC	7,305	4.0%	15.7%	322,339	20	7	46.9%
Engineering & machinery	ENGEN	7,305	0.4%	14.4%	171,004	20	10	48.0%
Food & drug retailers	FDRET	7,305	6.5%	12.9%	106,639	17	6	46.4%
Food producers & processors	FOODS	7,305	5.5%	11.3%	191,100	20	10	41.2%
Forestry & paper	FSTPA	7,305	−0.6%	16.8%	64,008	19	6	63.3%
Gas distribution	GASDS	7,305	3.8%	15.4%	66,862	12	7	53.5%
Household goods & textiles	HHOLD	7,305	1.0%	16.2%	105,159	21	6	56.1%
Health	HLTHC	7,305	5.4%	17.6%	117,558	16	4	90.2%
Information tech. hardware	INFOH	7,305	3.0%	21.9%	554,989	17	4	65.5%
Insurance	INSUR	7,305	4.6%	13.2%	283,584	20	8	40.3%
Investment companies	INVSC	7,305	3.4%	12.5%	48,553	17	7	43.3%
Leisure, entertainment, & hotels	LESUR	7,305	4.4%	17.1%	113,521	18	6	54.7%
Life insurance	LIFEA	7,305	6.2%	14.8%	72,392	14	5	42.7%
Media & photography	MEDIA	7,305	2.6%	15.3%	212,302	20	7	56.1%
Mining	MNING	7,305	0.3%	19.5%	50,339	10	5	50.8%
Oil & gas	OILGS	7,305	4.5%	15.6%	449,280	19	8	57.3%
Packaging	PCKGN	7,305	1.9%	13.9%	16,743	16	6	47.9%
Personal care & house. products	PERSH	7,305	4.4%	15.5%	111,676	11	5	74.1%
Pharmaceuticals	PHARM	7,305	6.5%	14.9%	471,423	17	6	56.6%
Real estate	RLEST	7,305	0.6%	16.6%	111,942	21	10	36.6%
Retailers general	RTAIL	7,305	3.5%	16.5%	262,459	19	11	57.9%
Software & computer services	SFTCS	7,305	4.5%	24.6%	236,811	20	2	86.8%
Specialty & other finance	SPFIN	7,305	4.7%	19.5%	284,771	17	7	62.1%
Steel & other metals	STLOM	7,305	−2.0%	18.9%	89,853	18	10	58.0%
Support services	SUPSV	7,305	3.7%	14.1%	59,079	18	4	44.8%
Telecom services	TELCM	7,305	2.2%	16.1%	556,621	21	4	66.0%
Tobacco	TOBAC	7,305	8.3%	19.9%	68,134	12	4	63.0%
Transport	TRNSP	7,305	1.1%	14.0%	186,884	21	10	50.2%
Water	WATER	7,305	6.8%	18.2%	10,432	7	2	70.9%

Local industry portfolios are aggregated by industries to build the global industry portfolios. Portfolio returns are value-weighted averages of the relevant local industry portfolios excess returns. Returns and standard deviation values are annualized assuming a 260-day year. Size is average available monthly market values (in $U.S. millions). Maximum and minimum indicate number of countries available for a given global industry portfolio. Max. weight is average weight in each global industry of the country with the highest market value for that industry in each month.

The U.S. is by far the largest single market in the sample (representing an average weight of 45.8% in our G21 developed world), and it is the only country with data on all industries available since 1974. Because the U.S. returns are not affected by exchange rate risk, it is no surprise to see that they have the second-lowest standard deviation (15.8% annualized). The less representative countries both in terms of market value and number of local industry portfolios are Austria (0.1% average weight, maximum 24 industry portfolios), New Zealand (0.1%, 26), Ireland (0.2%, 27), Norway (0.2%, 25), and Denmark (0.3%, 22).

Table 2 shows that the number of countries that include a particular global industry has changed dramatically over the last three decades. The average maximum number of countries that contribute to a given global industry portfolio is almost three times the average minimum number of countries. Also, the representation of global industry portfolios in the world portfolio is less concentrated than the representation of country portfolios. No single global industry portfolio accounts on average for more than 9% in the world portfolio (banks). Interestingly, the most volatile global industry portfolios are software and computer services (24.6% annualized standard deviation) and information technology (21.9%). Tables 1 and 2 together show that, in our sample, the opportunities for global investment increased substantially during the last three decades, largely because of an increased number of industries available in each country.

IV. Historical Evolution of Total Volatility Components

Have the risks of world, country, and local industry return components been changing over time? We provide a graphical analysis of the time evolution of the W, C, and I risk measures, estimated using equations (8) through (10), and discuss relevant descriptive and test statistics concerning the major features of the estimated volatility series.

A. Graphical Analysis and Descriptive Statistics

Figures 1, 2, and 3 plot our estimates of the world, country, and local industry volatility. To facilitate interpretation, we report annualized standard deviation and the backward 12-month moving average.

FIGURE 1

World Volatility

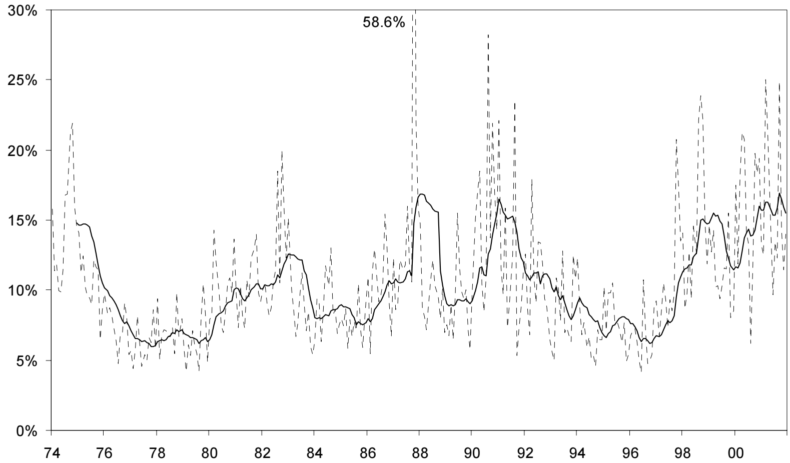


Figure 1 shows annualized standard deviation within each month of daily world market returns (dashed line), calculated using equation (8), for the period 1974 to 2001. The backward 12-month moving average of W is also shown (solid line).

Stulz (1999) finds that world portfolio volatility presents considerable time variation, but has not shown a tendency to increase over time, and that the 1970s and the 1990s were periods of relatively low volatility. The time pattern revealed by the plots in Figure 1 is consistent with his results.

FIGURE 2

Country Volatility

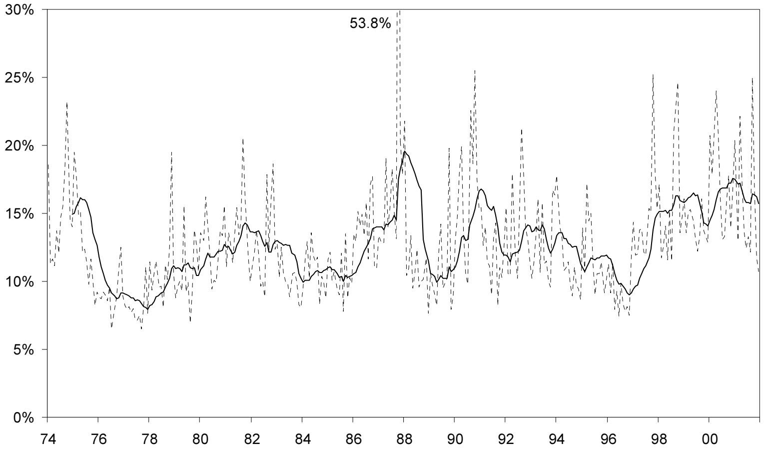


Figure 2 shows annualized standard deviation within each month of daily country returns relative to the world market (dashed line), calculated using equation (9), for the period 1974 to 2001. The backward 12-month moving average of *C* is also shown (solid line).

FIGURE 3

Local Industry Volatility

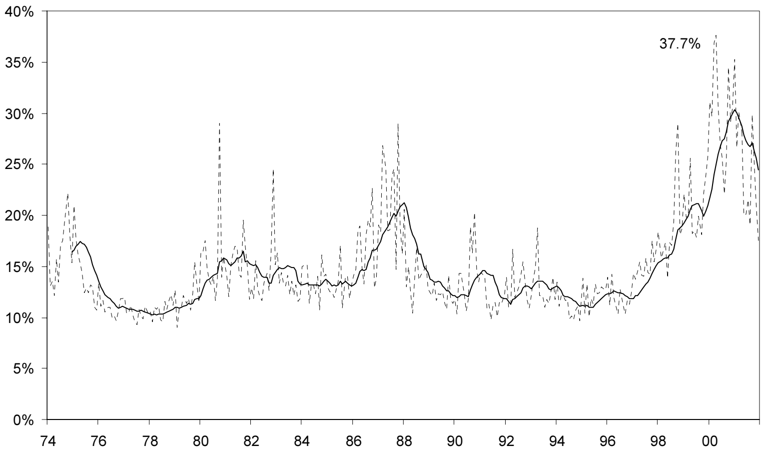


Figure 3 shows annualized standard deviation within each month of daily local industry returns relative to the local industry country (dashed line), calculated using equation (10), for the period 1974 to 2001. The backward 12-month moving average of *I* is also shown (solid line).

The all-time high for the W series corresponds to the October 1987 crash (58.6% annualized standard deviation). The second-highest value occurs in August 1990 (28.2% annualized standard deviation), and clusters of volatility spikes are visible in 1974, 1982, and 1990–1992. There is also evidence of an increase in world volatility for the 1997–2001 period. In fact, the smoothed 12-month moving average plot suggests that W has a slow-moving component, reinforcing the idea of persistent behavior. Figure 2 shows that the country risk measure (C) behaves much the same as the world volatility (W). The 1987 crash had a slightly less pronounced effect on C (53.8% annualized standard deviation in October 1987) but with similar timing. Similar to world risk, the country volatility shows no upward trend.

Volatility spikes in C and W tend to be associated, but are not perfectly synchronized. The same clusters of volatility spikes found in W are also found in C, but additional volatility spikes are also found in the C series in different periods. This imperfect synchronization suggests that country shocks may occur without causing instantaneous spillovers. The slow-moving components of W and C seem to be highly synchronized, however, meaning there may be lead-lag relationships between the two series.

Our estimate of country risk is also consistent with the results in Campbell et al. (2001) for the U.S. market volatility measure and with the Schwert (1998) results for the U.S. and other international major stock markets. Schwert (1998) predicted, however, that after the 1997 mini-crash, market volatility would return to the historical lower levels and that prediction has not yet been confirmed at an international level. Country risk declined since 1997, as a cluster of volatility spikes characterize the final years of the sample. Of course, this raises the possibility that international diversification benefits have not lessened, as the globalization of national economies would suggest.

The local industry risk plot presented in Figure 3 shows a pattern different from the patterns of W or C. The 1987 crash impact is not concentrated around that single month (October), and its extent is much less pronounced.[12] In October 1987, the average industry risk reached 29% (annualized standard deviation), but the period of higher volatility at the local industry level started earlier (the average annualized standard deviation for the first semester of 1987 is 21%, well above its 12-month moving average).[13] The most striking feature of Figure 3 is the significant rise toward the end of the sample period when the maximum for industry volatility was reached in April 2000 (37.7% annualized standard deviation). This evidence is consistent with the growing importance of global industry effects in explaining international return variation, which may be a temporary phenomenon associated with the information technology bubble (see Brooks and Catão (2000)).

The time evolution of the volatility components over time indicates that monthly volatility estimates are time varying; that periods of high volatility are concentrated around specific times and are followed by periods of relative stabil-

[12]This lends some support to the thesis put forward by Roll (1988) relating the 1987 crash to a combination of global and country-specific shocks.

[13]Ex post, we do not eliminate the hypothesis that local industry risk behavior during this period was anticipating the crash event.

ity; and that there is some evidence the series may be diverging upward from some lower bound, which leaves open the possibility there may be an upward trend. Especially clear is a rise in local industry risk toward the end of our sample.

Table 3 reports summary statistics for the monthly variance measures for the G21 developed world. Panel A presents results for the whole sample period 1974–2001 and Panels B–F for four non-overlapping subperiods of 72 months each and a middle subperiod of 48 months. Panels B (1974–1979) and C (1980–1985) capture the dynamics of the earlier years. Panel D (1986–1989) covers the high volatility period, especially at world and country levels, surrounding the 1987 crash. Panel E (1990–1995) represents a period of relatively low level stability in all series. Finally, Panel F (1996–2001) covers the high industry-level volatility period that we have remarked on.

TABLE 3

Descriptive Statistics for World, Country, and Industry Risks

	Mean	Std. Dev.	Min.	Max.	Med.	Skew.	Kurt.	ρ_1	ρ_2	ρ_6	ADF	PP	Trend	$t-PS_T$
Panel A. 1974–2001 ($N = 336$)														
W	0.1118	0.1786	0.0140	2.8629	0.0738	11.311	168.739	0.219	0.135	0.071	−14.61	−15.56	0.0233	0.83
C	0.1519	0.1537	0.0351	2.4129	0.1184	9.900	140.202	0.230	0.173	0.133	−14.45	−15.63	0.0256	1.39
I	0.2104	0.1724	0.0669	1.1813	0.1515	2.790	9.066	0.784	0.714	0.621	−2.64	−6.94	0.0716	0.31
W^{dc}	0.1052	0.1009	0.0140	0.6625	0.0738	2.576	8.040	0.505	0.356	0.258	−3.37	−12.01	0.0235	0.79
C^{dc}	0.1463	0.0937	0.0351	0.5411	0.1184	1.873	4.082	0.501	0.362	0.260	−4.40	−11.93	0.0257	1.56
Panel B. 1974–1979 ($N = 72$)														
W	0.0751	0.0742	0.0148	0.4003	0.0533	2.582	7.724							
C	0.1115	0.0776	0.0351	0.4489	0.0836	2.100	5.118							
I	0.1359	0.0699	0.0669	0.4092	0.1108	2.030	4.121							
Panel C. 1980–1985 ($N = 72$)														
W	0.0830	0.0549	0.0246	0.3328	0.0695	2.389	7.349							
C	0.1212	0.0559	0.0504	0.3516	0.1113	1.734	4.060							
I	0.1762	0.0860	0.0953	0.7018	0.1607	4.092	21.549							
Panel D. 1986–1989 ($N = 48$)														
W	0.1565	0.4043	0.0248	2.8629	0.0843	6.656	45.351							
C	0.1969	0.3368	0.0490	2.4129	0.1374	6.310	42.101							
I	0.2317	0.1381	0.0911	0.6997	0.1781	1.626	2.445							
W^{dc}	0.1107	0.1044	0.0248	0.6625	0.0843	3.758	17.326							
C^{dc}	0.1579	0.0997	0.0490	0.5411	0.1374	1.754	3.787							
Panel E. 1990–1995 ($N = 72$)														
W	0.1064	0.1129	0.0172	0.6625	0.0698	2.764	9.185							
C	0.1535	0.0904	0.0560	0.5411	0.1141	1.885	4.597							
I	0.1349	0.0497	0.0783	0.3423	0.1226	2.062	5.417							
Panel F. 1996–2001 ($N = 72$)														
W	0.1527	0.1258	0.0140	0.5215	0.1164	1.358	1.144							
C	0.1911	0.1160	0.0461	0.5309	0.1551	1.402	1.553							
I	0.3806	0.2657	0.0885	1.1813	0.2834	1.227	0.918							

Descriptive statistics for monthly variance measures constructed from daily data, W, C, and I as described in equations (8)–(10), respectively. Mean, standard deviation, minimum, maximum, and median estimates of monthly variances are multiplied by 100. ρ_k is the autocorrelation of order k, Skew is the skewness, Kurt is the excess kurtosis, ADF is the augmented Dickey-Fuller test for unit root with an intercept, and PP is the Phillips-Perron test for unit root with an intercept. The 5% critical value for the unit root ADF and PP tests with intercept is -2.87. Trend is the linear trend coefficient multiplied by 10^4, and $t-PS_T$ is the Vogelsang test for deterministic linear trends whose 5% critical value is 1.72. The lines W^{dc} and C^{dc} are for a modified dataset where the October 1987 observation is replaced by the second-highest observation in the respective series.

Results are also shown for a modified data set. In this case, the observations of W and C for October 1987 are replaced by the second-highest observation in each series, thus preserving the effect of the event but reducing its influence in the sample.[14]

For the whole sample, the mean of W is about 0.1118×10^{-2}, which implies an annualized standard deviation of 11.6%. This is slightly lower than the average country-specific risk C (average annualized standard deviation of 13.5%). Industry risk I is on average higher than W or C with a mean of 0.2104×10^{-2}, implying an annual standard deviation of 15.9%.[15] Across the five subsample periods, with the exception of the early 1990s, industry risk is always the most important component of total risk, although it has become the most volatile only in the most recent period.

The numbers in Panel A of Table 3 also imply that the degree of unconditional variance of a typical investment in a local industry portfolio that is due to the world portfolio volatility, or the R^2 of a world market model, is about 22.8% for the whole sample period (downweighted crash). The shares of C and I are 31.7% and 45.6%, respectively.

Comparing the values for the subperiods, we again see an increase in average local industry volatility during the last years of our sample. The mean of I for the 1996–2001 period (0.3806×10^{-2}) is about 2.8 times higher than the estimate for the 1974–1979 period (0.1359×10^{-2}) and about 1.8 times higher than its overall sample mean. W and C also rise toward the final years, but not as much as I.

B. Volatility Trends

The short-lived effect of the 1987 crash on volatility at world and country levels becomes clear when we compare the autocorrelations for the raw data and the downweighted crash data. Autocorrelation structure in Table 3 indicates that all series show a high degree of positive serial correlation, especially I. When we downweight the impact of the crash, W and C are considerably more autocorrelated. This high persistence, together with the evidence on an upward trend in the volatility series, raises a question about the nature of possible trends.

Table 3 also reports the results of parametric augmented Dickey-Fuller (ADF) t-tests and semi-parametric Phillips-Perron (PP) Z_t tests with an intercept for a unit root in the individual volatility series. The hypothesis of a unit root is rejected at the 5% level, whether or not the 1987 crash is downweighted and whether or not a deterministic time trend is included in the regression, with the exception of the ADF t test for the industry series. Thus, the volatility series seem to be stationary, so deviations from the long-run mean do not produce permanent effects on the behavior of the risk measures. This conclusion is consistent with the temporary swings we have already noted in Figures 1–3.

To test for the significance of a possible deterministic linear time trend in the volatility series, we employ the Vogelsang (1998) $t - PS_T$ trend test, which performs well in finite samples with serial correlation. The results reported in the last two columns of Table 3 reveal that the highest slope is for industry risk

[14]The local industry volatility measure is not crash downweighted because the October 1987 observation does not correspond to the maximum of the series.

[15]Downweighting the importance of the 1987 crash, the whole sample means for W and C decline to 11.2% and 13.2% (annualized standard deviation), respectively.

(0.0716×10^{-4}), which is three times higher than for the world risk measure and about 2.8 times higher than the linear trend coefficient for the country risk measure in the raw data set. The $t - PS_T$ show that the trend coefficients are not statistically positive at the 5% level even for I, and so we are unable to reject the null hypothesis of no deterministic time increase for all volatility series. In fact, volatility measures are higher by the end of our sample, but this does not seem to be the consequence of a long-term upward trend.

Table 4 shows that time patterns are fairly robust to the regional coverage of the sample and data frequency.[16] The level of disaggregated volatility estimates naturally changes, but that does not imply different patterns for the historical behavior of the volatility series estimated from daily data for the G21 world portfolio. For instance, when only the G7 countries and Switzerland are analyzed, the average sample estimates from daily data are 0.1181×10^{-2} for W, 0.1353×10^{-2} for C, and 0.2043×10^{-2} for I, almost identical to the estimates constructed for the G21 world portfolio. When we exclude the U.S. market from the world portfolio, we obtain similar results. The maximum for the W and C series is still recorded in October 1987, and the final years of our sample are still characterized by a huge increase in local industry risk.

TABLE 4

World, Country, and Industry Risk for Alternative Samples

	Whole Sample				Subperiod Means				
	Mean	Std. Dev.	Trend	$t - PS_T$	1974–1979	1980–1985	1986–1989	1990–1995	1996–2001
Panel A. G7 (incl. Switzerland)									
W	0.1181	0.1821	0.0254	0.86	0.0799	0.0861	0.1623	0.1139	0.1630
C	0.1353	0.1387	0.0207	1.30	0.1013	0.1039	0.1816	0.1431	0.1620
I	0.2043	0.1720	0.0691	0.29	0.1323	0.0861	0.2286	0.1287	0.3690
W^{dc}	0.1116	0.1057	0.0256	0.80	0.0799	0.0861	0.1167	0.1139	0.1630
C^{dc}	0.1305	0.0860	0.0208	1.54	0.1013	0.1039	0.1478	0.1431	0.1620
Panel B. World (excl. U.S.)									
W	0.1489	0.2209	0.0346	1.27	0.0666	0.1234	0.2284	0.1886	0.1640
C	0.1595	0.1135	0.0184	0.16	0.1499	0.1342	0.1414	0.1519	0.2140
I	0.2439	0.1902	0.0599	0.22	0.1690	0.2300	0.2973	0.1425	0.3985
W^{dc}	0.1411	0.1307	0.0348	1.48	0.0666	0.1234	0.1737	0.1886	0.1640
C^{dc}	0.1586	0.1078	0.0184	0.13	0.1499	0.1342	0.1355	0.1519	0.2140
Panel C. World (excl. Japan)									
W	0.1208	0.2342	0.0168	0.02	0.1001	0.0994	0.1761	0.0681	0.1787
C	0.1177	0.1210	0.0112	0.45	0.0956	0.1058	0.1648	0.0948	0.1432
I	0.1995	0.1786	0.0771	0.24	0.1337	0.1672	0.1518	0.1381	0.3910
W^{dc}	0.1109	0.1107	0.0171	−0.14	0.1001	0.0994	0.1070	0.0681	0.1787
C^{dc}	0.1135	0.0732	0.0113	0.38	0.0956	0.1058	0.1357	0.0948	0.1432
Panel D. Monthly Data									
C	0.1446	0.1652	−0.0076	0.25	0.1347	0.1274	0.1886	0.1764	0.1108
I	0.2261	0.1936	0.0620	0.35	0.0015	0.1963	0.2804	0.1414	0.3772

Panels A, B, and C show descriptive statistics for the monthly variance measures constructed from daily data for the G7 including Switzerland (Panel A), and for the world excluding the U.S. market (Panel B) or the Japanese market (Panel C). For Panel D, the variance estimates are constructed using monthly returns. The values under mean, standard deviation, and subperiod means are monthly estimates multiplied by 100. Trend refers to the slope of a linear trend regression for monthly variance measures (multiplied by 10^4). $t - PS_T$ denotes the Vogelsang test statistic for deterministic linear trends whose 5% critical value is 1.72. The lines W^{dc} and C^{dc} refer to a modified dataset where the October 1987 observation is replaced by the second-highest observation in the respective series.

[16]The time patterns global picture is also valid when we aggregate industry classifications from 38 industries to 10 economic sectors, although the estimates for I are strongly downward biased due to the reduced within-country industry dispersion.

With monthly data for the G21 world portfolio, the unconditional annualized average of C is 0.1446×10^{-2}, and the average of I is 0.2261×10^{-2}. The major differences from the daily frequency results are that the spike corresponding to the October 1987 observation for C becomes less important (implied annual standard deviation of 33.1%) and the growing volatility toward the final years is not as clear for C.

Finally, we ask whether the cross-sectional variation in betas may explain the covariation of W, C, and I. As Campbell et al. (2001) note, under the hypothesis that movements in W might produce variation in C if betas differ across countries, the slope coefficient of a regression of C on W would equal the cross-sectional variance of betas across countries. This regression coefficient is 0.751 for the whole sample, while a direct estimate (using average weights) of the cross-sectional variance of country betas is only 0.016. Hence, the cross-sectional variation in betas explains only a small proportion of the covariation between W and C.

The importance of the cross-sectional variation in betas in explaining the covariation between I and the other two volatility measures may be ascertained by a similar calculation. The slope coefficients of regression of I on C and W are 0.887 and 0.348, respectively, which seem too high to be explained by plausible cross-sectional variation in local industry beta coefficients.

C. Individual Countries Risk Measures

Another interesting question is the behavior of the volatility components for individual countries. Volatility measures averaged across countries are informative about an "average" country, but there can be great deal of variation in the industry composition across countries. Country exposure to world shocks may also be different across countries.

If one is interested only in the behavior of local industry volatility in each country, we can easily develop a measure of industry-specific volatility per country. We simply do not take an average across countries of the industry-specific volatility for each country. That is, from equation (2) and before taking the average across countries in equation (4), it can be shown that

$$\sum_i x_{ict} \mathrm{Var}(R_{ict}) = \mathrm{Var}(R_{ct}) + \sum_i x_{ict} \mathrm{Var}(u_{ict}). \tag{11}$$

To avoid an incomplete variance decomposition, we assume a simple world market model, and use the estimated country residuals variance to estimate country-specific volatility. The only new parameters that need to be estimated are country betas, which we take as constant for the whole sample period.

Consider the country decomposition with country betas relative to the world,

$$R_{ct} = \beta_c R_{wt} + \varepsilon_{ct}. \tag{12}$$

In this framework, the variance of country c return is given by

$$\mathrm{Var}(R_{ct}) = \beta_c^2 \mathrm{Var}(R_{wt}) + \mathrm{Var}(\varepsilon_{ct}). \tag{13}$$

Table 5 reports the individual country results, which give a strong message. The increased industry volatility documented for the late 1990s at the world level, is also seen in most individual countries. Linear trend coefficients are positive for 17 countries, although not statistically significant. The results for the subperiods show that industry volatility is on average higher for 1996–2001 than for previous years, for all countries with the exception of New Zealand.[17]

TABLE 5

Volatility Measures by Countries

			Industry Variance				Country Variance			
Country	β	SE(β)	Mean	Std. Dev.	Trend	$t - PS_T$	Mean	Std. Dev.	Trend	$t - PS_T$
Australia	1.02	0.0808	0.2580	0.1864	−0.0264	−1.39	0.3626	0.5292	−0.0446	−0.63
Austria	0.54	0.0927	0.2497	0.1894	0.0823	0.56	0.2319	0.2649	−0.0248	−0.21
Belgium	0.76	0.0553	0.2579	0.2453	−0.0193	−0.74	0.1880	0.1689	−0.0191	−1.01
Canada	0.89	0.0486	0.3684	0.9885	0.0515	−0.48	0.1207	0.1356	0.0098	−0.03
Denmark	0.65	0.0670	0.3136	0.2228	0.0263	−0.39	0.2221	0.1508	−0.0192	−1.12
Finland	1.15	0.1337	0.7085	0.9375	0.0917	−0.36	0.6181	0.7135	0.7356	0.68
France	1.02	0.0648	0.3213	0.2661	0.0532	−0.13	0.2534	0.2378	−0.0685	−4.07
Germany	0.80	0.0565	0.1922	0.2168	0.1067	0.30	0.1935	0.1597	0.0106	0.34
Hong Kong	1.21	0.1081	0.2530	0.2240	0.0323	−0.22	0.7001	1.1762	−0.0671	−0.80
Ireland	0.84	0.0754	0.4769	0.3551	0.4268	0.79	0.2435	0.1932	0.0371	−0.05
Italy	0.84	0.0841	0.2715	0.3087	−0.0228	−1.25	0.4121	0.4429	−0.0677	−1.19
Japan	1.10	0.0560	0.2169	0.1914	0.0472	0.30	0.2082	0.2396	0.0890	0.59
Netherlands	0.85	0.0400	0.2253	0.2408	0.1115	0.31	0.1603	0.1435	−0.0137	−1.29
New Zealand	0.84	0.1018	0.3969	0.2897	−0.0491	−0.69	0.3826	0.3857	−0.1194	−0.95
Norway	1.03	0.0927	0.4717	0.3440	0.0806	−0.06	0.4097	0.3903	−0.1286	−2.65
Singapore	1.18	0.0874	0.3587	0.5980	0.0925	0.12	0.4356	0.6057	−0.0569	−1.01
Spain	1.02	0.0754	0.3128	0.3491	0.0225	−0.24	0.2593	0.3636	−0.0479	−0.67
Sweden	1.12	0.0801	0.4742	0.3573	0.2359	0.98	0.3680	0.3929	0.0323	−0.39
Switzerland	0.82	0.0483	0.1479	0.1455	0.0318	0.52	0.1713	0.1492	−0.0151	−0.80
U.K.	1.06	0.0603	0.2241	0.1726	0.0434	−0.07	0.2290	0.2722	−0.1109	−1.96
U.S.	0.87	0.0335	0.1688	0.1795	0.0793	0.23	0.0940	0.2088	0.0192	0.91

Descriptive statistics for industry and country level variance for individual countries. Industry volatility is constructed using equation (11) and country volatility using the residuals from a world market model according to equation (13). All variances are computed monthly using within-month daily data. Country portfolio betas in relation to world and their standard errors are shown under the β and SE(β) columns, respectively. A linear regression of monthly country excess returns on the monthly world G21 excess return is estimated by OLS to obtain betas. The values under mean and standard deviation refer to monthly estimates multiplied by 100. Trend refers to the slope (multiplied by 10^4) of a linear trend regression for monthly variance measures. $t - PS_T$ denotes the Vogelsang test statistic for deterministic linear trends whose critical value is 1.72.

Overall, smaller countries, or those most concentrated around a single industry portfolio, or those that have more variation in the number of industry portfolios also tend to have higher industry risk. The correlation across countries between average industry variance and country market capitalization is negative (−0.380). Conversely, the correlation of the average industry variance with the average weight of the largest local industry portfolio is 0.396, and the correlation with the difference between the maximum and minimum number of industries for a given country is 0.296.

Two features strike us the most with regard to country risk. First, for three countries (France, Norway, and the U.K.), a statistically significant negative slope is found. Second, average country risk is much closer to industry risk than the equivalent aggregate measures, and it varies more across countries than industry risk. These findings strengthen the intuition that the characteristics of variance measures may vary considerably across countries, particularly notable at the country risk level. Countries with higher industry risk also tend to be riskier at the country level (the correlation between average industry variance and average country variance across countries is 0.53).

[17] Results are available upon request.

Thus, we are not surprised to see that smaller countries, countries with more weight given to a single industry, and countries with greater variation in the number of industry portfolios also tend to have more country risk. The correlation across countries between average country variance and country market capitalization is −0.375. The correlation of the average country variance with the average weight of the largest local industry portfolio is 0.502, and the correlation with the difference between maximum and minimum number of industries for a given country is 0.571.

D. Individual Global Industry Risk Measures

To explore the behavior of global industry portfolio risk, we analyze two measures of risk. The first is based on a version of the variance decomposition method of Campbell et al. (2001) that decomposes the world portfolio into global industries and uses the world market-adjusted return model residuals to estimate global industry-specific variance,

$$R_{it} = R_{wt} + u^*_{it}. \tag{14}$$

As before, when the variances of global industry returns are aggregated using the same weighting scheme used to compute world returns, a measure of the global level of industry risk is obtained without having to estimate covariances or betas for global industries,

$$\sum_i x_{it}\mathrm{Var}(R_{it}) = \mathrm{Var}(R_{wt}) + \sum_i x_{it}\mathrm{Var}(u^*_{it}). \tag{15}$$

The second measure is used to analyze individual industry risk. It is based on the residuals from a simple world market model for global industries, assuming constant betas relative to the world returns for the whole sample period. Consider the global industry return decomposition with global industry betas relative to the world,

$$R_{it} = \beta_i R_{wt} + v^*_{it}. \tag{16}$$

In this framework, the variance of global industry *i* return is given by

$$\mathrm{Var}(R_{it}) = \beta^2_{iw}\mathrm{Var}(R_{wt}) + \mathrm{Var}(v^*_{it}). \tag{17}$$

Aggregate global industry variance, $\sum_i x_{it}\mathrm{Var}(u^*_{it})$, is estimated using daily returns within each month. Individual global industry variances, $\mathrm{Var}(v^*_{it})$, are estimated using a two-step procedure. The first step consists of estimating betas by an ordinary least-squares regression of global industry monthly excess returns on world monthly excess returns. In the second step, daily squared residuals from equation (16) are summed within a month to obtain a monthly estimate for the variance of each global industry portfolio.

Panel A of Table 6 presents descriptive statistics and the linear trend coefficients for the global industry risk measure, and Graph A of Figure 4 plots the series. Comparing industry risk measured locally and globally, both series present positive linear trend coefficients, although values are not statistically significant. In addition, both series show a significant increase in the late 1990s; global industry risk reaches a historical maximum of 29.6% in April 2000. The average global industry risk for the 1996 to 2001 period is about 1.7 times higher than its unconditional mean and 2.5 times higher than in the early period between 1974 and 1979.

TABLE 6

Global Industry Volatility

Panel A. Global Industry Variance

	1974–2001	1974–1979	1980–1985	1986–1989	1990–1995	1996–2001
All Industries						
Mean	0.1108	0.0779	0.0861	0.1379	0.0702	0.1910
Std. dev.	0.1023	0.0547	0.0326	0.1168	0.0363	0.1568
Linear trend $\times 10^4$	0.0333					
$t - PS_T$	0.2647					
Excluding TMT Industries						
Mean	0.0916	0.0680	0.0821	0.1193	0.0680	0.1297
Std. dev.	0.0684	0.0469	0.0317	0.1027	0.0379	0.0849
Linear trend $\times 10^4$	0.0161					
$t - PS_T$	0.2939					

Panel B. Individual Industry Variance

	β	SE(β)	Mean	Std. Dev.	Trend	$t - PS_T$
Banks	1.02	0.0393	0.0768	0.0986	0.0006	−0.04
Electricity	0.57	0.0427	0.0651	0.0841	0.0176	0.51
Electronic & elec. equipment	1.13	0.0326	0.0569	0.0595	0.0122	−0.05
Information tech. hardware	1.24	0.0552	0.1790	0.2473	0.1058	0.43
Insurance	0.90	0.0360	0.0553	0.0624	0.0186	0.15
Oil & gas	0.80	0.0488	0.1328	0.1527	0.0498	0.36
Pharmaceuticals	0.81	0.0420	0.0822	0.0878	0.0277	0.34
Retailers general	0.99	0.0416	0.0926	0.1177	0.0341	0.05
Specialty & other finance	1.33	0.0500	0.1218	0.1329	0.0186	0.48
Telecom services	0.78	0.0460	0.1240	0.2248	0.0071	0.06

Panel A shows descriptive statistics for global industry variance. Industry volatility is constructed monthly using equation (15). $t - PS_T$ is the Vogelsang test statistic for deterministic linear trends whose critical value is 1.72. Mean and standard deviation refer to monthly estimates multiplied by 100. Panel B presents the individual global industry portfolio variance estimates in the 10 industries with largest average market capitalization for the whole sample period according to equation (17). Global industry portfolio betas in relation to world and their standard errors are shown under the β and SE(β) columns, respectively. A linear regression of monthly global industry excess returns on the monthly world G21 excess return is estimated by OLS to obtain betas. Trend refers to the slope (multiplied by 10^4) of a linear trend regression for the monthly variance measures.

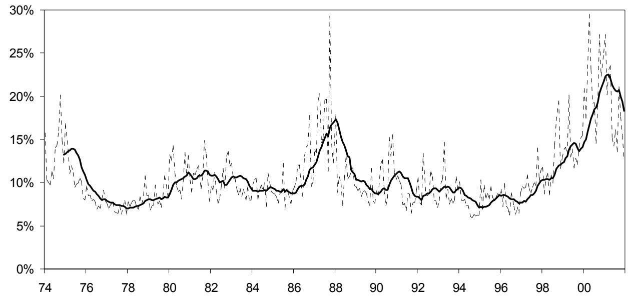
What might explain the increase in local and global industry risk that we document in the last years of the sample? One possibility is that the anomalous behavior of one group of industries, technology, media, and telecommunications companies (TMT), may have caused sufficient cross-sectional dispersion to justify the huge spike in the industry risk series. In fact, Brooks and Catão (2000) show that a global industry factor associated with the new economy stocks emerged in the mid-1990s to become the key determinant of stock return variability, and Brooks and Del Negro (2002b) find that, excluding the TMT stock group, there is a much less pronounced increase in the importance of industry effects in recent years.

To further investigate this hypothesis and obtain insights into the impact of the new economy stocks on the behavior of the aggregate risk measures, we rees-

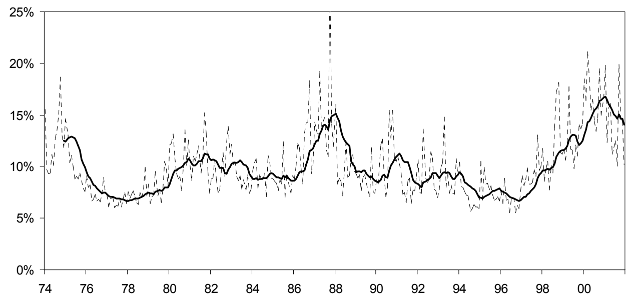
FIGURE 4

Global Industry Volatility

Graph A. All Industries



Graph B. Excluding TMT Industries



Graph A shows annualized global industry standard deviation within each month of daily global industry returns relative to the world market (dashed line) for the period 1974 to 2001. Graph B shows similar estimates excluding technology, media, and telecommunications industries (dashed line). The backward 12-month moving averages are also shown (solid line).

timate global industry risk excluding the TMT industries.[18] Descriptive statistics on global industry risk excluding the TMT industries are also shown in Panel A of Table 6, and Graph B of Figure 4 plots the series.

With the TMT industries excluded, we still see a sharp increase in global industry risk in the late 1990s, although less of an increase than when considering all industries. The historical maximum is reached in October 1987 (28.7% annualized standard deviation), and the second-highest value occurs in March 2000 (21%). The average point estimate for the 1996–2001 period is about 1.4 times higher than its unconditional mean and 1.9 times higher than in the early period between 1974 and 1979. The full sample average global industry volatility for the 1996 to 2001 period is now almost 1.5 times higher than the ex-TMT industry results, a pattern echoed by the standard deviation point estimates.

These results show that, at a global level, the TMT industries represented an important component of the increase in industry risk toward the late 1990s, but

[18]That is, we exclude the information technology hardware, media and photography, software and computer services, and telecom services industries.

the increase in risk is not driven solely by these industries. The old economy also presented an important increase in industry risk.

Panel B of Table 6 presents results for the 10 individual global industries with the largest average market capitalization.[19] There is no statistically significant time trend, although the coefficients are positive for most global industries. The results suggest that smaller global industries, with less variation in the number of countries where they operate, or that are more concentrated in a single country, tend to be riskier. The correlation across global industries of the average industry-specific risk with the global industry market capitalization is -0.234. The correlation of the average industry-specific risk with the difference between the maximum and minimum number of countries represented is -0.129, and the correlation with the average weight of the most important country in each global industry is 0.583. Interestingly, the global industry with the highest average industry-specific variance is mining (18.7%, whole sample annualized standard deviation), followed by information technology (18.6%), tobacco (17.7%), and water (17.5%). For the 1996–2001 period, the point estimate of average industry-specific risk is higher than its unconditional mean for 35 of 38 industries.

Heston and Rouwenhorst (1994) conclude that country diversification is more efficient than industry diversification. More recent evidence, e.g., Cavaglia et al. (2000), shows that industry diversification became as important as country diversification in the late 1990s. The results in Table 6 suggest that the ratio of global industry risk to country risk has been fairly stable over the years, with the exception of the notable increase from 1995 onward. This ratio fluctuated around an average of 0.7 until 1989, followed by a period when it was visibly lower (on average 0.5 between 1990 and 1995), and finally a period of sustained increase in the late 1990s (on average greater than 1.0 after 1998). The ratio of local industry risk to country risk (see Table 3) also shows a clear increase in the late 1990s. Thus, the results suggest that toward the end of our sample period, international diversification power increases if an industry dimension is privileged over a geographic dimension. These results are consistent with the fixed-effects model evidence in Heston and Rouwenhorst (1994) and Cavaglia et al. (2000).

E. Covariation and Causality

To assess the relative importance of each risk factor to the total volatility of a typical within-country industry portfolio holding, we perform mean and variance decompositions. By definition, $\sigma_{it}^2 = \sigma_{ut}^2 + \sigma_{et}^2 + \sigma_{wt}^2$ is the total volatility of a typical investment in a local industry portfolio (see equation (4)) for period t. Then, taking expected values and dividing the RHS elements by the LHS, we obtain a decomposition for the mean total volatility,

$$1 = E(\sigma_{ut}^2)/E(\sigma_{it}^2) + E(\sigma_{et}^2)/E(\sigma_{it}^2) + E(\sigma_{wt}^2)/E(\sigma_{it}^2). \tag{18}$$

[19]Results for other industries are available upon request.

Specifying a sample period, we can estimate the expected values by their sample means using the volatility estimators defined in equations (8)–(10). Similarly, for the variance of total volatility,

$$
\begin{aligned}
(19) \qquad 1 \quad = \quad & \mathrm{Var}(\sigma^2_{ut})/\mathrm{Var}(\sigma^2_{it}) + \mathrm{Var}(\sigma^2_{et})/\mathrm{Var}(\sigma^2_{it}) + \mathrm{Var}(\sigma^2_{wt})/\mathrm{Var}(\sigma^2_{it}) \\
& + 2\mathrm{Cov}(\sigma^2_{ut}, \sigma^2_{et})/\mathrm{Var}(\sigma^2_{it}) + 2\mathrm{Cov}(\sigma^2_{ut}, \sigma^2_{wt})/\mathrm{Var}(\sigma^2_{it}) \\
& + 2\mathrm{Cov}(\sigma^2_{et}, \sigma^2_{wt})/\mathrm{Var}(\sigma^2_{it}).
\end{aligned}
$$

From the results in Table 3, we know that the variance of a randomly selected local industry portfolio increases about 125% over the whole sample period (from 0.3224×10^{-2} in the 1970s to 0.007245 in the late 1990s compared to a long-run unconditional mean of 0.4620×10^{-2}), and that the most significant increase occurred in the late 1990s. The means in the first column of Table 7 confirm that local industry risk has gained increased importance.

TABLE 7

Total Volatility Mean and Variance Decomposition

	Mean	Variance-Covariance		
		W	*C*	*I*
Panel A. 1974–2001 (N = 336)				
W	22.8%	9.6%		
C	31.7%	14.4%	8.3%	
I	45.6%	19.5%	19.7%	28.2%
Panel B. 1974–1979 (N = 72)				
W	23.3%	12.5%		
C	34.6%	20.0%	13.7%	
I	42.1%	20.5%	21.3%	11.1%
Panel C. 1980–1985 (N = 72)				
W	21.8%	11.4%		
C	31.9%	15.6%	11.9%	
I	46.3%	12.4%	19.8%	28.1%
Panel D. 1986–1989 (N = 48)				
W	22.1%	11.6%		
C	31.6%	17.6%	10.6%	
I	46.3%	18.3%	20.4%	20.4%
Panel E. 1990–1995 (N = 72)				
W	27.0%	24.4%		
C	38.9%	28.2%	15.6%	
I	34.2%	12.9%	13.3%	4.7%
Panel F. 1996–2001 (N = 72)				
W	21.1%	7.5%		
C	26.4%	11.8%	6.4%	
I	52.5%	20.6%	19.7%	33.4%

Table 7 shows the results in percentage of the mean and variance decomposition of total volatility, as described in equations (18) and (19) for the monthly variance measures constructed from daily data, *W*, *C*, and *I* as described in equations (8)–(10). *W* and *C* refer to a modified dataset where the October 1987 observation is replaced by the second-highest observation in the respective series.

The share of *I* increased from 42.1% to 52.5% while the share of the other two risk measures declined (*W* dropped by 2.2 and *C* by 8.2 percentage points) from 1974–1979 and 1996–2001, despite the fact that all risk measures rose on average. In the aftermath of the highly turbulent period of the late 1980s, the early 1990s are an important exception with regard to the importance of local industry risk across all subperiods (downweighted dataset). From 1990 through 1995, the average point estimate of the country risk share of total risk is 38.9%, while the share of *I* is slightly lower (34.2%).

Analysis of the variance of total volatility provides further insight into the importance of local industry risk. The variance of *I* represents not only the highest share of total volatility for the whole sample period (downweighted dataset), but the relationship is also systematic across subperiods, again with exception of the early 1990s and the 1970s. In fact, for the 1990–1995 period, the highest contribution to the variance of total volatility is given by the covariance between *W* and *C*, while during the 1970s it is given by the covariance between *C* and *I*. Interestingly, the shares of the covariances between *I* and *C* or *I* and *W* (downweighted data set) in total volatility variance are fairly stable across all subperiods (about 20%), with the exception of the early 1990s (about 13%).

The results for both the mean and volatility decomposition of total volatility strengthen the hypothesis that the total risk components demonstrate atypical behavior during the early 1990s, and that local industry-specific sources of risk become noticeably more important in the late 1990s.

The high frequency movements of the three volatility measures already noted in Figures 1–3 appear to be correlated, and the contemporaneous correlation estimates reported in Panel A of Table 8 confirm this. To investigate the causality issue, we estimate bivariate and multivariate vector autoregression (VAR). We use crash downweighted variance series, and the multivariate version of the Akaike information criterion is used to select the VAR lag length (10 lags for the pair *W* and *C* and six lags for the remaining pairs and the trivariate system). Panels B and C of Table 8 report the *p*-values of a standard *F*-test on each equation for the null hypothesis that the lags 1 to *k* of each variable do not help to forecast the dependent variable for the VAR systems.

TABLE 8

Correlation Structure and Granger Causality Tests

	W	C	I
Panel A. Correlations			
W	1	0.8084	0.5934
C		1	0.64769
I			1
	W_t	C_t	I_t
Panel B. Bivariate VAR			
W_{t-k}		0.5595	0.2617
C_{t-k}	0.0113		0.2290
I_{t-k}	0.0020	0.0084	
Panel C. Trivariate VAR			
W_{t-k}		0.5845	0.6405
C_{t-k}	0.5493		0.5832
I_{t-k}	0.0057	0.0158	

Table 8 shows the correlation structure (Panel A) and the *p*-values of Granger causality bivariate VAR tests (Panel B), and trivariate VAR tests (Panel C) for the monthly variance measures constructed from daily data, *W*, *C*, and *I* as described in equations (8)–(10). *W* and *C* refer to a modified dataset where the October 1987 observation is replaced by the second-highest observation in the respective series. The VAR lag-length (10 lags for the pair *W* and *C* and 6 lags for the remaining pairs and the trivariate system) was determined by the multivariate version of the AIC criterion. The *p*-values refer to the *F*-test of the null hypothesis that the lags one to *k* of the variable indicated in the row are jointly equal to zero in the equation for the variable indicated in the column.

In the bivariate VARs, I appears to Granger cause both W and C. The world risk does not help to forecast any of the other series, while C helps to predict W at the 5% significance level. In the trivariate system, neither W nor C helps to predict any of the other series, while I helps to predict W and also Granger causes C at the 5% significance level. Thus, our evidence supports the hypothesis that local industry risk leads the other volatility series.

V. Global Portfolio Management Implications

Has the power of international diversification to reduce risk been lessened? Is country diversification still the most effective diversification strategy for the global equity investor? In an attempt to corroborate the intuition based on our volatility results, we present results of traditional correlation and portfolio diversification analyses.

Declining correlations among individual assets returns would let the volatility of the market portfolio remain stable even if individual volatilities rise. Thus, the growing increase in the importance of local industry risk relative to the common factor (world risk) noticed toward the end of our sample (and plotted in Graph A of Figure 5) is consistent with reduced correlations among local industry portfolios.

Graph B of Figure 5 plots the equally weighted average pairwise correlation among local industry portfolios available in our sample. We use both monthly and daily returns.[20] Correlations are calculated each month between all pairs of industry portfolios for which 60 months (260 days) of data are available for that month. The number of estimated monthly (daily) pairwise correlations ranges from about 36,000 to over 153,000 (184,000) as the number of basic assets changes over time. Monthly correlations are systematically higher for the whole sample (0.265 average) than daily estimates (0.146), which is consistent with the daily downward biases for positively related markets.

Overall, the average correlation plot confirms our conclusion of reduced correlations. From 1996 through 2001, monthly (daily) pairwise correlations fluctuate around an average of 0.203 (0.125), which is lower than the average for the 1990–1995 period, 0.309 (0.175). The ratio of local industry risk to world risk (I/W) shows the opposite pattern: 3.23 for the 1996–2001 period and 1.0 for the early 1990s. This contrasting behavior between average correlation and the I/W ratio is also clear when we compare the 1996–2001 period with 1974–1995, when the long-term mean of average monthly (daily) pairwise correlation is 0.287 (0.153) and the I/W ratio is on average 2.5.[21]

As lower correlations imply greater diversification opportunities, we conclude that, for global investors who invest in local industry portfolios, the risk

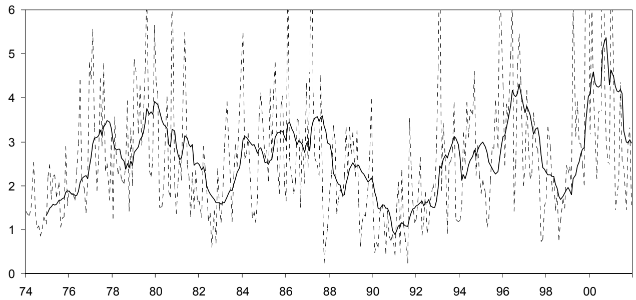
[20]In international stock market studies, one cannot ignore the effects of non-overlapping trading hours on the correlation between assets traded in non-contemporaneous markets, which are more significant with the use of daily data. Kahya (1997) shows that the estimated correlations of daily returns for positively (negatively) related markets are biased downward (upward). There is no significant bias associated with the use of monthly data.

[21]Comparison of the daily correlation plot with a 12-month moving average of the I/W ratio plot also reveals an inverse relation between the two measures (correlation of -0.587 for the whole sample).

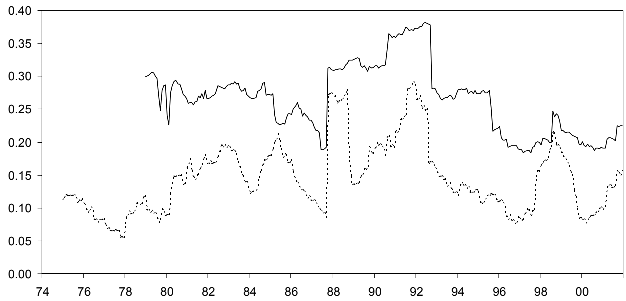
FIGURE 5

Ratio of Local Industry to World Variance and Average Correlation for Local Industry Portfolios

Graph A. Ratio of Local Industry Variance to World Variance



Graph B. Correlation among Local Industry Portfolios



Graph A shows the ratio of local industry variance to world variance (dashed line). Monthly variance measures are constructed from daily data as described in equations (8) and (10). The backward 12-month moving average is also shown (solid line). Graph B shows the equally weighted average pairwise correlation across local industry portfolios. The solid (dashed) line is a plot of the monthly estimates of average monthly (daily) correlation coefficients computed using a rolling window of 60 (260) monthly (daily) observations.

reduction benefits of international diversification rose in the late 1990s over previous years. Another implication of the observed rise in local industry-level volatility relative to world market risk is that more randomly selected assets are needed to achieve a given level of diversification. Similarly, the average volatility of portfolios made of the same number of randomly selected assets will be higher, with an increased amount of idiosyncratic volatility that has to be diversified away.

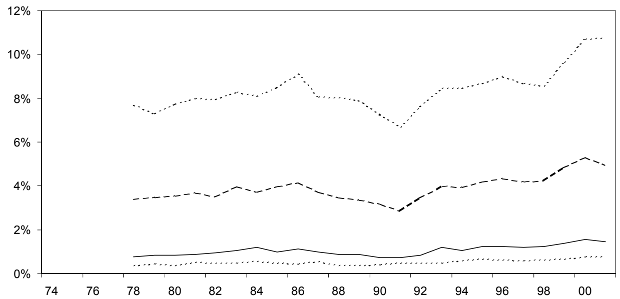
To illustrate this point, we construct portfolios containing different numbers of randomly selected assets, and compute the simple average of the difference between each portfolio standard deviation and the standard deviation of an equally weighted portfolio of all assets used in the calculations. For each year-end, we randomly group (without replacement) local industry portfolios with at least 60 consecutive monthly return observations available up to that date. Graph A of

Figure 6 plots annualized excess standard deviations over time for portfolios of two, five, 20, and 40 assets calculated from monthly returns.[22]

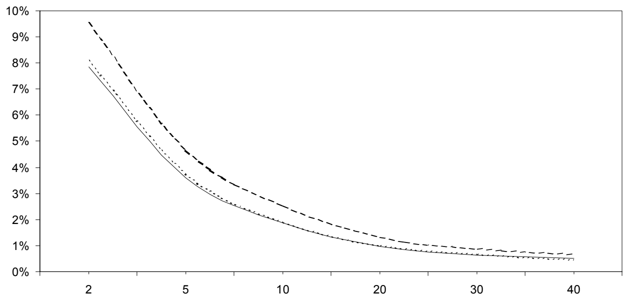
FIGURE 6

International Diversification Benefits against Time and Number of Local Industry Portfolios

Graph A. Excess Standard Deviation against Time



Graph B. Excess Standard Deviation against Number of Industry Portfolios



Graph A shows annualized standard deviation of equally weighted portfolios containing 2, 5, 20, and 40 randomly selected basic assets, in excess of the standard deviation of the equally weighted portfolio containing all assets used in the calculations. Graph B shows excess standard deviation against the number of assets for the six-year subsample periods, 1996–2001 (top dashed line), 1990–1995 (dashed line), and 1980–1985 (solid line).

The peak in excess standard deviation is reached in 2000 for all portfolios (10.7%), and all exhibit a modest increase up through 1995. For the two-asset randomly selected local industry portfolio, the excess standard deviation is 8.0% in 1995 compared with 7.7% in 1978. For the larger portfolios, the pattern is the same, although at much lower values.

Graph B of Figure 6 plots annualized excess standard deviation against the number of assets in the portfolio calculated from monthly returns. Data for these plots are obtained by averaging the yearly estimates of excess standard deviations over the sample periods. As is shown, the increase in local industry risk for the 1996–2001 period implies that more basic assets are needed to reduce excess standard deviation. For instance, estimates show that to reduce excess volatility to about 2%, 12 industry portfolios are needed in the 1996–2001 period. In earlier

[22]Similar results using daily returns are available upon request.

sample periods, the same level of diversification could be reached with approximately nine industries.

VI. Conclusion

We have extended the volatility decomposition method of Campbell et al. (2001) to an international setting in order to take a new look at the historical behavior of volatility in developed stock markets. We study the time-series behavior and international diversification implications of three non-overlapping monthly measures of stock volatility: variance of world portfolio returns, average variance of country returns relative to world returns, and average variance of local industry portfolio returns relative to their countries.

We find that between 1974 and 2001, world and country risk remained fairly stable. Industry risk, both at the local and the global level, however, displayed a huge increase during the late 1990s, after a long period of relative stability. This increase is not attributable solely to the new economy bubble. Local industry risk dominates world and country risk, except during the 1990–1995 period, when country risk is on average the most important component. World risk is systematically the least important component of total risk.

We show that the October 1987 crash had a short-lived but abnormally high impact on both world and country risk, but a much less pronounced impact at the local industry level. Granger causality tests suggest that lagged local industry volatility has explanatory power in forecasting world and country volatility series, but the converse is not true.

Consistent with the behavior of industry risk, toward the end of our sample, pairwise correlations among local industry portfolios drop and, not surprisingly, higher numbers of randomly selected assets are needed to achieve any given level of diversification after 1995. These results suggest that the power of international diversification to reduce risk has not been eroded as the process of globalization might imply. Our results also support a conclusion that industry diversification has become relatively more efficient than geographic diversification in the latter years of our sample only, although this may be a temporary result.

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