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

Miguel A. Ferreira†
ISCTE School of Business
CEMAF/ISCTE

Paulo M. Gama‡
ISCTE School of Business
University of Coimbra

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†Address: ISCTE School of Business, Complexo INDEG/ISCTE, Av. Prof. Anibal Bettencourt, 1600-189 Lisboa, Portugal. Phone: 351 21 7958607. Fax: 351 21 7958605. E-mail: miguel.ferreira@iscte.pt.

‡Address: Faculdade de Economia da Universidade de Coimbra, Avenida Dias da Silva, 165, 3004-512 Coimbra, Portugal. Phone: +351 23 9790523. Fax: +351 23 9403511. E-mail: pmgama@sonata.fe.uc.pt.

Abstract

This paper extends the Campbell, Lettau, Malkiel, and Xu (2001) volatility decomposition method to study the time series behavior of equity volatility at the world, country and local industry levels. Over the period from 1974 to 2001 there is no noticeable long-term trend in any of the volatility measures. However, there is a sharp increase in local industry volatility relative to market and country in the late 1990's. Thus, correlations among local industries have declined, more assets are needed to achieve a given level of diversification, and the loss for not being well industrially diversified increases. Local industry volatility leads the other volatility measures.

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1 Introduction

The risk reduction benefits from international diversification of equity portfolios have been for a long time a well established fact among academics (Levy and Sarnat (1970) and Solnik (1974)). However, private and institutional investors do not seem to be able to (or willing to) take the advantages one would theoretically expect in a frictionless fully integrated world: global portfolios composition is biased towards domestic shares (Lewis (1999)). In addition, Kang and Stulz (1997) find that when investors decide to invest internationally, they do so by not holding the market portfolio of the countries they select to invest in. The lack of diversification of global stock portfolios suggests that for many investors the exposure to total risk may be high, and this fact constitutes the major motivation for this study.

Especially for global portfolio managers of undiversified international portfolios, the description and interpretation of the historical evolution of total risk is very important. If the share of risk that has to be diversified away has increased, more opportunities for international diversification are available as well as the number of assets needed to achieve a given level of diversification is greater. The benefits of investing abroad become harder to achieve, but also does the compensation for pursuing such an investment strategy. For those that face a wealth constraint and/or incur in transaction costs, an increase in diversifiable risk implies a decrease in the level of diversification of their investment portfolios, unless investors have superior stock selection capabilities. Total volatility is also relevant for those that try to exploit the mispricing of individual assets, for pricing equity derivatives and measuring the market risk of equity portfolios (e.g. Value-at-Risk).

The relevance of the exposure to the world portfolio risk in explaining the cross-section of expected returns has been established in countless empirical tests of international asset pricing models[1]. For example, the empirical evidence in Dahlquist and Sällström (2002) and in Cavaglia, Hodrick, Vadim and Zhang (2002) show that, though other factors may be also relevant, the exposure to the world return factor is priced both in the cross-section of country and global industry portfolio returns, using alternative international asset pricing models. However, empirical evidence concerning the importance of the country and industry dimensions is less clear.

While Roll (1992) attributes the low correlation among country indices particularly to the

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

diverse local industry structures, on the other hand 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). In a subsequent study, Griffin and Karolyi (1998) find that when emerging markets are included in the sample, the proportion of portfolios variance explained by the time series variation in pure country effects is higher than previously documented, which again reinforces that one would be better off – in terms of risk reduction – by pursuing a geographical diversification strategy rather than an industrial one. Conversely, recent work by Cavaglia, Brightman and Aked (2000) and Baca, Garbe and Weiss (2000), among others, find evidence that industry factors have grown in importance in recent years. Also, Brooks and Catão (2000) 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 been growing in importance since 1995. Recently, Brooks and DelNegro (2002b) claim that the rise in industry effects is simply a temporary phenomenon associated with the information technology bubble and not a reflection of greater economic integration across countries[2].

In this paper, we take the perspective of a global investor. We 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 main goal is to describe the historical behavior of total volatility components and to study the implications for international diversification. Specifically, this paper addresses the following questions. First, has the relative importance of world, country and local industry risk changed over time? Second, has the power of international diversification to reduce risk been decreasing? Finally, motivated by the conflicting evidence available in the literature, we take another look to the unsolved problem of the relative efficiency of country versus industrial dimensions for wealth allocation for global equity investors.

We decompose the total volatility of individual assets into specific sources of risk, using measures

[2] This finding contrasts with the increased consensus among the investment community and in the financial press, that the industrial dimension of diversification is nowadays more important than the geographic dimension.

of cross-sectional dispersion, 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, measuring and studying the time series behavior of risk components without having to keep track of covariances or estimate risk exposure parameters for countries or local industry portfolios, which is the most appealing feature of the approach.

The major simplification of this methodology relies in the use of market-adjusted residuals[3] of country returns relatively to world returns, and of local industries returns relatively 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 that "slice" 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's exposures to the global industry shocks are equal, whenever they are non-zero. We use local industry return in excess of their origin country return to measure local industry risk. Thus, we allow for interactions between countries and industries, i.e. industry specific shocks may have different impact across countries. Moreover, our methodology provides a direct estimate of the volatility measures[4]. We use daily data within a month to estimate monthly time series of risk measures, without imposing a parametric multivariate volatility specification[5].

Our results can be summarized as follows. First, we confirm that international diversification benefits have been substantial over the period from 1974 to 2001. In fact, world risk has always been the least important component of total risk. There is no evidence of a statistically significant

[3] The market-adjusted-return model is a restricted market model with betas equal to one. For more details, see Campbell, Lo and MacKinlay (1997).

[4] Brooks and DelNegro (2002a) have recently proposed an alternative relaxing the restrictive assumptions of the fixed-effects model. They estimate the stocks' exposure to the global, country and industry-specific shocks in a APT framework. However, contrary to our methodology, the Brooks and DelNegro (2002a) approach does not preserve the simplicity of the fixed-effects model, imposes strong distributional assumptions and requires a balanced panel.

[5] A parametric specifiction, e.g. multivariate GARCH model may be important for forecasting, but for historical description purposes the simple use of daily data to produce monthly sample variance estimates should be enough. In fact, Merton (1980) showed that a continuous-time process could be approximated using sufficiently high-frequency data.

long-term trend in any of the volatility series. However, local and global industry volatility present a sharp increase after 1995, reaching the all-time peak in April 2000. The increase in local industry volatility can also be noticed in individual countries. The new economy bubble does not by itself explain the increase in industry risk, though TMT industries play an important role in this phenomenon. World and country risk show a much modest increase in the 1990's.

Second, the October 1987 crash was felt at both world and country levels, but had a reduced effect on local industry risk. In fact, a period of increased local industry volatility can be noticed since the beginning of 1987. Moreover, the early 1990's may be considered an atypical period in historical terms. In fact, during the 1990-1995 period, 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 opposite hypothesis is not true.

Fourth, the ratio of local industry to world risk has experienced a notorious increase during the final years of our sample, the average ratio is 3.23 for the 1996-2001 period compared with 2.5 in the 1974-1995 period. Accordingly, the average contemporaneous pairwise correlation between local industry portfolios decreases considerably from 0.287 (1974-1995) to 0.203 (1996-2001). Thus, the benefits of international portfolio diversification have increased and the diversification of global portfolios using local industry portfolios has become harder to achieve as more assets are needed.

Finally, the notorious increase in the ratio of industry, both at the local and global levels, to country risk suggests that industry diversification has become a more effective tool for risk reduction in the late 1990's. The share of local industry risk in total risk also increases considerably towards the end of the sample period, with a share of more than 50% in the 1996-2001 period. In contrast, the share of country risk decreases. In addition, the average volatility of country diversified portfolios exceeds the average volatility of industry diversified portfolios only in the late 1990's (with exception of the period prior to the October 1987 crash).

The paper is organized as follows. In Section 2 we present the model used to decompose total volatility, discuss some simplifying econometric solutions to the estimation of the volatility components, and briefly evaluate the exactness of the return structure employed. Section 3 gives details on the data set. In Section 4 the empirical findings concerning the historical evolution of the disaggregated volatility measures are presented. Section 5 discusses the implications for global portfolio management. Section 6 offers concluding comments.

2 Methodology

In this section the methodology proposed by Campbell et al. (2001) to decompose stock returns volatility into market, industry and idiosyncratic components in a domestic stock market is extended to an international setting. We take the perspective of a global investor whose returns are calculated in US dollars. Thus, the global investor is unhedged in foreign exchange rate risk and we do not explicitly introduce currency risk factors in our approach. Moreover, we use local industry portfolios within countries as primitive assets, and specify the same industry grouping variables across countries.

2.1 Total Volatility Decomposition

In our methodology the volatility of a typical[6] (or average) local industry is described by three components: world market volatility, average country volatility, and average local industry volatility. 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[7] and there is some controversy on which factors should be used in multi-factor international asset pricing models to describe the cross-section of expected returns.

The excess return[8] of industry i portfolio in country c for period t is denoted R_{ict}. Since a US investor perspective is adopted, raw returns are US dollar denominated and the excess return is measured over the US dollar risk free rate. Let x_{ict} be the weight of industry i in country c. If, as in this paper, a weighting scheme based on market capitalization is used then $x_{ict} = MV_{ict}/\sum_{i\in c} MV_{ict}$,

[6] Typical is a shorthand expression for a randomly selected local industry portfolio, with the probability of drawing a specific portfolio equal to its weight in the world market portfolio.

[7] There is a huge literature on this subject. For instance, the fact that betas are not known and need to be estimated, thus inducing error-in-variables problem is addressed by Fama and MacBeth (1973), who suggest the use of portfolios to increase beta estimates precision. Beta time stability also increases with the number of stocks in the portfolio as shown by Alexander and Chevarny (1980). For an additional references on beta time instability, see Harvey (1991). For a defence of the traditional time constant beta see Ghysels (1998).

[8] 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 relatively to US inflation, because the US inflation components in stock raw returns and in the US-dollar nominal riskless interest rate cancel out.

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 $x_{ct} = \sum_{i \in c} MV_{ict} / \sum_c \sum_i MV_{ict}$). The excess return of country c portfolio for period t is given by $R_{ct} = \sum_{i \in c} x_{ict} R_{ict}$. The excess return of 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,

$$\begin{aligned} R_{ict} &= R_{ct} + u_{ict} \\ &= R_{wt} + e_{ct} + u_{ict}. \end{aligned} \tag{2}$$

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,

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

Though the local industry return variance in equation (3) contains covariance terms, the cross sectional weighted average sum of all the primitive assets total variance across all local industry portfolios is free of individual covariance terms, provided that we use the same non stochastic weighting scheme[9] to compute the averages as the one used to compute country and world portfolios returns. Thus, the volatility of a typical local industry portfolio is given by,

[9] 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.

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

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

The risk components σ^2_{et} and σ^2_{ut} in equation (4) convey information about the correlation among country portfolios and local industry portfolios, respectively. Solnik and Roulet (2000) suggest the use of the cross-sectional dispersion of stock market returns (a concept similar to σ^2_{et}) to measure the changes in the global level of correlation among equity markets. As an alternative to the traditional time-series approach to estimate the correlation level of international stock markets, the proposed cross-sectional (and conditional) dispersion-based approach provides a dynamic method for evaluating the time variation in the world market global correlation[10], without having to estimate a large number of parameters or use a long estimation window. Relevant for our study is the inverse monotonic relation between global correlation and country level dispersion shown in Solnik and Roulet (2000), a result also used by Adjaouté and Danthine (2001). The reasoning is straightforward. For some period t, world portfolio returns are estimated as the average returns for the same period on all markets that made that world. If country returns were highly dispersed around the world return in that period t, markets would move in different directions thus promoting ample opportunities for global risk diversification. If, in contrast, country portfolios tracking errors in relation to the world portfolio were small (low dispersion), markets would move in tandem in that particular period (high correlation).

The previous discussion is also relevant for the interpretation of σ^2_{ut}, which can also be interpreted as a measure of the average idiosyncratic risk born by the global investor that take local

[10] For a 150 years perspective on the correlation structure of the major world stock markets, see Goetzman, Li and Rouwenhorst (2002).

industry portfolios as their primitive assets. As Malkiel and Xu (1999) demonstrate, when the amount of risk to be diversified (idiosyncratic risk) increases, more individual assets are needed to reduce portfolios volatility to a certain level, independently of the behavior of the relevant market risk. Thus, the effective level of diversification of poorly internationally diversified portfolios should decrease when the idiosyncratic risk increases. Given the evidence on the equity home bias of global stock portfolios, global investors face additional diversification costs when σ^2_{ut} rises.

Our results also allow us to address a related question: the relative efficiency of country versus industry decisions for global allocation of wealth. That is, what matters most for risk reduction: geographical location or industry classification? As stated by Solnik and Roulet (2000), global investors should "slice" the world by industries rather than by political boundaries, only if global industry indices dispersion around the world portfolio is larger than that of country indices.

To see how the proposed total volatility decomposition method can be used to find an answer to the previous question, it is important to note the hierarchy implicit in the decomposition of the primitive assets return. The world portfolio is decomposed in countries and then countries in industry portfolios (same industries when available). Thus, we are able to measure country indices dispersion around the world and average industry-level dispersion within countries. To the extent that the estimated average industry-level dispersion within countries is correctly proxying for global industry dispersion, the tendency for an increase in the ratio $\sigma^2_{ut}/\sigma^2_{et}$ suggests that industry allocation would be more effective than country allocation for international risk reduction.

Further intuition on our methodology is given by its comparison 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 its country of domicile market portfolio.

In the framework[11] 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,

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

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

where β_c denotes country c beta with respect to the world market portfolio, $\tilde{e}_{ct}$ is the zero mean country specific residual, β_{ic} denotes the beta of industry portfolio i in country c with respect to the correspondent national market excess return[12], and $\tilde{u}_{ict}$ is the local industry specific residual. In this setting, if we take the average of the variance of countries returns and that of the local industry returns, and compared them with the simplified decomposition equivalent measures, we will find that[13],

$$\sigma^2_{et} = \sigma^2_{\tilde{e}t} + CSV_t(\beta_c)\sigma^2_{wt}, \tag{6}$$

$$\sigma^2_{ut} = \sigma^2_{\tilde{u}t} + CSV_t(\beta_{ic})\sigma^2_{\tilde{e}t} + (CSV_t(\beta_{iw}) - CSV_t(\beta_c))\sigma^2_{wt}, \tag{7}$$

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 average cross-section variance of β_c, times σ^2_{wt}. By the same reasoning, equation (7) shows that the biases in the proposed estimate of local industry risk depends on both the variation of world returns, country residuals and betas. However, if the world volatility (and ICAPM country volatility) remains stable and betas are assumed constant, the biases identified above will have minor effect on the historical time pattern of the simplified volatility measures since all point estimates will suffer the same degree of biases[14].

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[15]. Also,

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

[13] We are indebted to John Campbell for helping us with the result in equation (7).

[14] This same type of reasoning could be applied if other benchmark international asset pricing models were specified. The biases in our simplified volatility measures could then be identified, even though close form solutions such as equations (6) and (7) are not easily obtained. However, to the extent that the major source of variations in betas comes from the world market factor, as it is reasonably to assume given its highest relevance for explaining the cross-section of expected returns, the approximations should not be quantitatively much different from the ones identified with the ICAPM.

[15] This happens because the residuals u_{ict} in (2) are measured within country (the currency adjustment canceled out), while the e_{ct} residuals in (1) are measured in relation to a common portfolio return across countries, thus incorporating different exchange rate returns. Nevertheless, currency effects over country risk are somewhat downweighted because country level volatility is estimated from country return in excess of world returns and not country returns.

the short-term interest rate risk implied by the excess returns specification only affects the world volatility measure, because the same interest rate is subtracted from the local industries portfolios returns[16].

2.2 Estimation

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

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

where μ_{wt} is the world portfolio mean return in month t[17], and 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. Weights for month t are based on the US dollar denominated market value of the local industry portfolios in the last day of month $t-1$, thus weights are taken as constant within month t.

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

$$C_t = \sum\nolimits_c x_{ct} \sum\nolimits_{d\in t} e^2_{cd}, \tag{9}$$

where x_{ct} stands for the weight of country c in the world portfolio in month t, that 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 dispersion $I_t \equiv \hat{\sigma}^2_{ut}$,

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

[16] In fact, the proposed volatility decomposition would still be mathematically consistent under a not excess return specification. However, working with returns and not excess returns would introduce additional biases in relation to a return decomposition based on alternative international asset pricing models, namely because of the covariance between risk factor returns and the riskless interest rate and the variance of the riskless rate, which would be needed to be explicitly modelled in the asset pricing benchmark model.

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

where x_{ict} denotes the weight of industry i in country c in month t and $\sum_{d \in t} u_{icd}^2$ 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.

This simplified approach to estimate volatility components is justified by Campbell et al. (2001) 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 would be enough for historical description purposes. In fact, Merton (1980) shows that a continuous-time process could be approximated using sufficiently high-frequency data. Also Andersen and Bollerslev (1998) find that squared daily changes are a noisy estimate of daily realized volatility and consequently this may affect the inference regarding the forecast accuracy. They suggest using data sampled more frequently to obtain better estimates of the volatility dynamics, in particular using intraday data to estimate daily realized volatility. Recently, Andersen, Bollerslev, Diebold and Ebens (2001) have used a similar approach to generate daily volatilities from intra-daily data on individual stocks and study the volatility distribution. In a subsequent study, Andersen, Bollerslev, Diebold and Labys (2003) have found that squared returns from intra-daily data have higher forecasting power than parametric models fitted to daily volatility. Campbell et al. (2001) apply this idea to monthly data and this is a common procedure to studies of volatility such as Schwert (1989).

3 Data Description

Our sample consists of daily US dollar denominated total return indices (including dividends) and market capitalizations for up to 38 industries, calculated by Datastream International (DS), for the period from December 1973 to December 2001 (7305 daily return observations). DS indices are preferred to other domestic industry indices because they are constructed on a uniform basis across countries, are not backfilled when new constituents are added or deleted, a long time series of daily data is available, and a comprehensive coverage of the industry structure of each domestic stock market is assured[18]. These aspects are important because they eliminate anomalous behavior of the indices due to differences in the technical aspects of index construction and, as Griffin and

[18] DS Global Equity Indices represent approximately 75-80% of the total market capitalization.

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[19].

The 21 developed markets studied in this paper were selected and included in the sample according to the following criteria: (i) coverage by the MSCI developed markets database; (ii) never been classified by the S&P/IFC EMDB as emerging markets; and, (iii) data availability in the DS database[20]. Thus, both the number of local industry portfolios and of countries represented in the world portfolio, are allowed to change over the sample period[21].

To compute daily excess returns, we subtract the 30-day T-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 global industry portfolios, respectively. Daily country and global industry portfolio excess returns are computed using a value weighted average of the available local industry portfolios aggregate either by countries or industries, respectively.

Table 1 describes the regional setup. The US is by far the largest single market in the sample (an average weight of 45.8% in our G21 developed world) and the only country with data on all industries available since 1974. Because the US returns are not affected by the exchange rate risk, we are not surprised 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, 24 maximum number of industry portfolios), New Zealand (0.1%, 26), Ireland (0.2%, 27), Norway (0.2%, 25), and Denmark (0.3%, 22)[22].

As can be seen in Table 2, the number of countries included in a particular global industry shows a dramatic change over the last three decades. The average maximum number of countries that contribute for a given global industry portfolio is almost three times the average minimum

[19] Cavaglia et al. (2002), Brooks and DelNegro (2002b), Dahlquist and Sällström (2002), Adjaouté and Danthine (2001), Brooks and Catão (2000) are examples of recent studies that also rely on DS Global Equity Indices.

[20] The two exceptions to the application of this criteria are Austria and Denmark. These countries were only included after January 1982, even though data was available from December 1973 onwards, because careful screening of the local currency series raised serious doubts on the daily frequency of the data.

[21] 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 excluded. The regional setup remains fixed from 1990 onwards with the addition of Ireland.

[22] Given that we report dollar denominated total returns in excess of the US riskless interest rate we are not surprised to find negative estimates of excess returns for a few countries and industries. Local market declines and currency devaluation against the US dollar contribute to explain the fact.

number of countries. Also, the representation of global industry portfolios in the world portfolio is less concentrated than that of country portfolios. No single global industry portfolio weights, on average, more than 9% in the world portfolio (Banks). Interestingly, the most volatile global industry portfolios are Software & 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, because of the increase in the number of industries available in each country.

4 Historical Evolution of Total Volatility Components

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

4.1 Graphical Analysis and Descriptive Statistics

Figures 1, 2, and 3 plot our estimates of the world, country, and local industry variances, respectively. To facilitate the interpretation of the W, C, and I estimates, we report annualized standard deviations, as well as their backward moving averages of order 12.

Stulz (1999) find that the world portfolio volatility presents considerably time variation, but without showing a tendency to increase over time, and that the 1970's and the 1990's are periods of relatively low volatility. The time pattern revealed by the plots in Figure 1 is consistent with those results. The all-time maximum for the W series corresponds to the October 1987 crash (59% annualized standard deviation)[23]. Also, the second highest value (28.2% annualized standard deviation) occurs in August 1990, and clusters of volatility spikes are visible for the following time periods: 1974, 1982, 1990-1992. There is also evidence of an increase in world volatility for the

[23] Our maximum world risk estimate is higher than Stulz (1999) estimate (less than 55% annualized standard deviation), which is reasonably explained by the higher level of diversification of the DS world portfolio index portfolio relative to ours G21 world developed portfolio. Nevertheless, the unconditional correlation between our G21 world sample and the DS world portfolio indices is 99.8%, for the entire sample period.

1997-2001 period. In fact, the smoothed 12-moving average plot suggests that W has a slow-moving component, reinforcing the idea of persistent behavior.

As can be seen in Figure 2, the country risky measure (C) presents a behavior similar to the world volatility (W). The 1987 crash episode had a slightly less pronounced effect on C (54% annualized standard deviation in October 1987) but with similar timing. The short-lived consequences of the October 1987 crash are also evident in both C and W. Similarly to world risk, the country volatility measure presents the absence of an upward trend. Volatility spikes in C and W tend to be associated, but lack perfect synchronization. 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. However, the slow moving components of W and C seem to be highly synchronized, in which case lead-lag relationships between the two series may exist.

Our estimate of country risk is also consistent with the results in Campbell et al. (2001) for the market volatility measure and with Schwert (1998) results for the US and other international major stock markets. However, Schwert (1998) prediction that after the 1997 mini-crash, market volatility would return to the historical lower levels, has not been confirmed yet at an international level. Not only country risk has not decreased from 1997 onwards, as a cluster of volatility spikes characterizes the final years of our sample. Of course, this raises the possibility that international diversification benefits are not decreasing, as the globalization of national economies would suggest.

The local industry risk (I) plot, presented in Figure 3, shows a different pattern from that of W or C. The 1987 crash impact is not concentrated around a single month (October) and its magnitude is much less pronounced[24]. 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)[25]. However, the most striking feature is the significant rise towards the end of the sample period, especially from 1995 onwards, when the maximum for the industry volatility is reached (37.7% annualized standard deviation in April 2000). This evidence

[24]This gives further support to the thesis put forward by Roll (1988) relating the 1987 crash to a combination of global and country specific shocks.

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

is consistent with the increased importance of global industry effects in explaining international return variation, which may be due to a temporary phenomenon associated with the information technology bubble (Brooks and DelNegro (2002b)).

In summary, the time evolution of the volatility components shows that monthly volatility estimates are time-varying, periods of high volatility are concentrated around specific time periods and are followed by periods of relative stability, and there is some evidence that the series may be diverging upwards with a lower bound, which leaves the possibility of an upward trend. Especially notorious is the rise in the local industry risk towards the end of our sample.

Table 3 reports summary statistics for our monthly variance measures for the G21 developed world. Panel A presents results for the whole sample period from 1974 to 2001. For comparison, the sample is divided into four non-overlapping sub-periods of 72 months each and a middle sub-period of 48 months. Panels B (1974-1979) and C (1980-1985) capture the dynamics of the earlier years of our sample. Panel D (1986-1989) captures the high volatility period, especially at the world and country levels, surrounding the 1987 crash. Panel E (1990-1995) represents a period of relatively low level and stability in all series. Finally, Panel F (1996-2001) captures the high industry level volatility period that we have already noticed. Results are also shown for a modified data set, where the observations of W and C for October 1987 are replaced by the second highest observation in each series, thus leaving the event with a strong but decreased influence in the sample[26].

For the whole sample, the mean of W is about 0.001118, 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, greater than W or C, with a mean of 0.002104 implying an annual standard deviation of 15.9%[27]. In fact, across the 5 sub-sample periods, with the exception of the early 1990's, industry risk (I) has always been the most important component of total risk, though it only has become the most volatile for the most recent period[28]. The numbers in the Panel A of Table 3 also imply that the share 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),

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

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

[28] With the exception of the late 1980's if the 1987' crash influence is downweighted.

whereas that of C and I are 31.7% and 45.6%, respectively.

Comparing the values for the sub-periods again stresses the increase in the average local industry volatility during the last years of our sample. The mean of I for the 1996-2001 period (0.003806) is about 2.8 times higher than the estimate for the 1974-1979 period (0.001359) and about 1.8 times higher than its overall sample mean. Also W and C rise towards the final years, but not with the same order of magnitude as I.

4.2 Volatility Trends

The short-lived effect of the 1987 crash on the volatility at the world and country levels becomes clear when we compare the autocorrelations for the raw data and downweighted crash data. As shown in Panel A of Table 4, all series show a high degree of positive serial correlation, specially I. When we downweight the impact of the crash the autocorrelation in W and C is considerably higher. This high persistence together with the evidence discussed so far concerning the possibility of an upward trend in the volatility series, raises the question of the nature of these possible trends.

Panel B of Table 4 reports the results of the parametric Augmented Dickey-Fuller (ADF) $T(\rho-1)$ and t tests and semi-parametric Phillips-Perron Z_ρ and Z_t tests for a unit root[29] in the individual volatility series. The number of lags used in the ADF regressions is determined by the significance of the Ljung-Box test at 5% level, up to 18 lags. For the Phillips-Perron Z_ρ and Z_t tests only the results using a truncation lag of 12 lags are shown[30]. The hypothesis of a unit root is rejected at the 5% level, whether or not the 87' crash is downweighted and whether or not a deterministic time trend in included in the regression[31]. Thus, the volatility series seem to be stationary and, consequently, deviations from the long-run mean do not produce permanent effects on the risk measures behavior. This conclusion is consistent with the temporary swings we have already uncovered in Figures 1 to 3 and Table 3.

To test for the significance of a possible deterministic linear time trend in the volatility series, we employ the Vogelsang $t - PS_T$ trend test, which is robust to serial correlation, as described in

[29] Phillips-Perron tests allow for weaker assumptions concerning the error process and are especially appropriated for positively autocorrelated processes, given their greater power to reject a false null of unit root, possibly with non-constant variance. For more details, see for example Enders (1995).

[30] For the Phillips-Perron Z_ρ and Z_t tests, the rejection of the null of unit root at the 1% is possible for truncation lags up to 18, for all series and whether a deterministic time trend is included or not.

[31] The only exception being the ADF t test for the I series, whose estimate only allows for a rejection of the null at the 10% level (critical values –2.57 and –3.13, for the intercept model and trend model, respectively).

Vogelsang (1998)[32]. This test has the additional advantage that does not require estimates of the trend function error variance.

The results reported in the first line of Panel C of Table 4 reveal that the highest slope is that of I (0.0716×10^{-4}), which is three times higher than that of W and about 2.8 times higher than the linear trend coefficient for C, for the raw data set[33]. However, the $t - PS_T$ show that the trend coefficients are not statistically positive at the 5% level even for I, and therefore 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 that does not seems to be the consequence of a long-term upward trend.

Table 5 shows that the above time patterns are fairly robust to the regional coverage of the sample[34] and data frequency. 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 for W, C, and I are 0.001181, 0.001353, and 0.002043, which are almost identical to the estimates constructed for the G21 world portfolio. When the US market is excluded from the world portfolio, similar results are also obtained. The maximum for the W and C series is still obtained in October 1987, and the final years of our sample are still characterized by the huge increase in local industry risk. With monthly data for the G21 world portfolio the unconditional annualized average of C is 0.001446 and that of I is 0.002261. The major differences relatively to the daily frequency being that the spike corresponding to the October 1987 observation for C becomes less important (implied annual standard deviation of 33.1%) and the rise towards the final years in the volatility is not as clear for C[35].

To conclude this section we ask whether the variation in betas may explain the covariation of W, C, and I. As Campbell et al. (2001) note, assuming constant betas and independence between

[32] We thank Tim Vogelsang for providing the Gauss code for implementation of this test.

[33] Similar results are obtained for the downweighted crash series.

[34] The time patterns global picture is also valid when we increased the industry classification aggregation level, from 38 industries to 10 economic sectors, though the estimates for I are strongly downwardly biased due to the reduced within country industry dispersion.

[35] Interestingly, the slope of a linear trend regression is negative for C (monthly data), but statistically insignificant. However, it should be noted that these monthly measures are based on a single square residual for each month, thus obviously noisy.

the volatility of ICAPM country residuals and W, the slope coefficient of a regression of C on W would equal the cross-sectional variance of betas across countries. Empirically, the regression slope coefficient is 0.751 for the whole sample, whereas 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 only explains 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 ascertain 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 large to be explained by plausible cross sectional variation in local industry beta coefficients.

4.3 Individual Countries Risk Measures

Another interesting issue is to investigate the behavior of the volatility components for individual countries. Volatility measures averaged across countries are informative about an average country. But a great deal of variation in the nature and industrial composition may exist across countries. In addition, country exposure to world shocks may as well be different across countries.

If one is only interested in the behavior of local industry volatility in each country, we can easily develop a measure of industry specific volatility, per country. Simply, we do not take the average across countries of the previously computed 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,

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

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. Thus, the only new parameters that need to be estimate are country betas, which we take as constant for the whole sample period. Consider the following 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,

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

Table 6 reports the individual country results, which give a strong message. The increase in industry volatility documented for the late 1990's at the world level, is also noticed for most individual countries. Linear trend coefficients are positive for 17 countries, though not statistically significant. The results for the sub-periods[36] show that industry volatility was on average higher for the period from 1996 to 2001 in relation to the previous years, for all countries with the exception of New Zealand.

Overall, smaller countries, most concentrated around a single industry portfolio, or 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 with the difference between the maximum and minimum number of industries for a given country is 0.296.

Concerning country risk, two features strike us the most. First, for three countries (France, Norway, and UK) a statistically significant negative slope is found. Second, average country risk is much closer to industry risk than the equivalent aggregate measures and it presents higher variation across countries than industry risk. These findings strength the intuition that the characteristics of variance measures may vary considerably across countries, which is particularly noticed at the country 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). Thus, we are not surprised to see that smaller countries, with most weight given to a single industry and higher variation in the number of industry portfolios also tend to have more country risk. The correlation across countries of the average country variance with the country market capitalization is -0.375, with the average weight of the largest local industry portfolio is 0.502, and with the difference between the maximum and minimum number of industries for a given country is 0.571.

[36] Results not shown here, but available upon request.

4.4 Individual Global Industry Risk Measures

In this section we explore the behavior of global industries portfolio risk. We analyze two measures of risk. The first is based on a variant 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 variance 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,

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

The second is used to analyze individual industries 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 following 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,

$$Var(R_{it}) = \beta_{iw}^2 Var(R_{wt}) + Var(v_{it}^*). \tag{17}$$

We study the following risk measures. Aggregate global industry variance, $\sum_i x_{it} Var(u_{it}^*)$, estimated using daily returns within each month. Individual global industry variances, $Var(v_{it}^*)$, estimated using a two step procedure. The first step consists in estimating betas by an OLS regression of global industry monthly excess returns on world monthly excess returns. In the second step daily squared residuals from equation (16) are summed up within the month to obtain the monthly estimate for the variance of each global industry portfolio. Panel A of Table 7 presents descriptive statistics and linear trend coefficient for the global industry risk measure and Panel A of Figure 4 plots the series.

With respect to the aggregate global industry risk, we find that similarly to local industry risk, the October 1987 crash estimate (29.3% annualized standard deviation) does not correspond to the maximum of the series. Comparing industry risk measured locally and globally, both series present a positive linear trend coefficient though not statistically significant. In addition, both series show a significant increase in the late 1990's with global industry risk reaching 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 and 2.5 times higher than in the initial period between 1974 and 1979.

What might explain the increase in local and global industry risk, that our results document for the last years of our sample? One possibility is that the anomalous behavior of one group of industries (technology, media, and telecommunications stocks, 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-1990's to become the key determinant of stock return variability, and Brooks and Del-Negro (2002b) find that excluding the TMT stocks 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 importance that the "new economy" stocks may have had on the behavior of the aggregate risk measures, we reestimate global industry risk excluding the TMT industries[37]. Descriptive statistics on global industry risk excluding the TMT industries are presented in Panel A of Table 7 and Panel B of Figure 4 plots the series.

Without considering the TMT industries, there is also a sharp increase in the global industry risk in the late 1990's, though the order of magnitude is smaller 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 to 2001 period is about 1.4 times higher than its unconditional mean and 1.9 times higher than in the initial period between 1974 and 1979. In fact, the full sample average global industry volatility

[37] Specifically, we exclude the following industries: IT Hardware, Media & Photography, Software & Computer Services, and Telecom Services.

for the 1996 to 2001 period is almost 1.5 times higher than its ex-TMT industries counterpart, a pattern also shown by the standard deviation point estimates. These results show that, at a global level, the TMT industries had an important contribution to the increase in industry risk towards the late 1990's, but the increase is not solely driven by those industries. The old economy also present an important increase in industry risk.

Panel B of Table 7 presents results for individual global industries. There is no statistically significant time trend, though the coefficients are positive for 33 global industries out of 38. In addition, the results suggest that smaller global industries, with less variation in the number of countries in which they are present, or 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, with the difference between the maximum and minimum number of countries represented is -0.129, and with the average weight of the most important country in each global industry is 0.583. Interestingly, the global industry with higher average industry specific variance is Mining (18.7%, whole sample annualized standard deviation), followed by the Information Technology (18.6%), Tobacco (17.7%) and Water (17.5%). For the 1996 to 2001 period, the point estimate of average industry specific risk is higher than the unconditional mean for 35 out of 38 industries.

4.5 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 the following mean and variance decompositions. By definition, $\sigma^2_{it} = \sigma^2_{ut} + \sigma^2_{et} + \sigma^2_{wt}$, 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 the following decomposition for the mean total volatility,

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

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

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

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 0.003224 in the 1970's to 0.007245 in the late 1990's, compared to a long run unconditional mean of 0.004620), and that the most significant increase occurred in the late 1990's. The results in the second column of Table 8 show that local industry risk I has gained increased importance. The share of I increased from 42.1% to 52.5% while the share of the other two risk measures decreased (the share W and C decreased by 2.2 and 8.2 percentage points, respectively) from the 1974-1979 period to the 1996-2001 period, despite the fact that all risk measures increase on average.

In the aftermath of the high turbulent period of the late 1980's, the early 1990's are an important exception in relation to the highest importance of the local industry risk across all sub-sample periods (downweighted dataset). For the period from 1990 to 1995, the average point estimate of country risk share in total risk is 38.9%, while the share of I is slightly lower (34.2%).

Looking at the variance of total volatility, we gain further insight into the importance of local industry risk. Not only its variance has the highest share in total volatility for the whole sample period (downweighted dataset), as systematically does so across sub-periods, again with the previously noticed exception of the early 1990's and the 1970's. 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 1970's it is given by the covariance between C and I. Interestingly, the share of the covariances between I and C or W (downweighted data set) in total volatility variance are fairly stable across all sub-periods (about 20%), with the exception of the early 1990's (about 13%).

Both the results obtained for the mean and volatility decomposition of total volatility, strength the hypothesis that the total risk components show an atypical behavior during the early 1990's, and that the importance of local industry specific sources of risk noticeably strengths in the late 1990's.

We conclude this section with an investigation of the lead-lag relationships between the total volatility components. In fact, the high frequency movements already noticed in Figures 1 to 3 appear to be correlated across the three volatility measures, and the contemporaneous correlation estimates reported in Panel A of Table 9 confirms it.

To investigate the causality issue, we estimate bivariate and a multivariate VAR systems. We use variance series crash downweighted 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 6 lags for the remaining pairs and the 3-equation system). Panels B and C of Table 9 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.

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 help 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.

5 Global Portfolio Management Implications

Has the power of international diversification to reduce risk been decreasing? Is country diversification still the most effective diversification strategy for the global equity investor? In an attempt to corroborate the intuition based on the volatility results reported above, in this section we present results from traditional correlation and portfolio diversification analyses and estimates of the portfolio risk that would be incurred through alternative international diversification strategies.

5.1 The Power of International Diversification

Declining correlations among individual assets returns allow the volatility of the market portfolio to remain stable even if the individual volatilities rise. Thus, the sustained increase in the importance of local industry risk relative to the common factor (world risk), noticed towards the end of our sample (see figure 5) is consistent with a decrease in the correlations among local industry portfolios.

Figure 6 plots the equal weighted average pairwise correlation among local industry portfolios available in our sample. We use both monthly and daily returns[38]. Correlations are calculated each month, between all pairs of industry portfolios for which 60 months (260 days) of data are available, on 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 primitive assets changes over time. Monthly correlations are systematically higher (0.265 average for the whole sample) than daily estimates (0.146), which is consistent with the daily downward biases for positively related markets.

Overall, the average correlation plot confirms the above mentioned implication. For the period from 1996 to 2001, monthly (daily) pairwise correlation 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 1990's. This contrasting behavior between average correlation and the I/W ratio is also clear[39] when we compare the 1996-2001 period with the 1974-1995, for which 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.

As lower correlations imply greater diversification opportunities, we conclude that for those global investors that take local industry portfolios as investment objects, the risk reduction benefits from international diversification have increased in the late 1990's, in comparison to the preceding years. Another implication of the observed rise in local industry level volatility relative to world market risk is that the number of randomly selected assets needed to achieve a given level of diversification should be higher. Similarly, the average volatility of portfolios made of the same number of randomly selected assets should be higher as a consequence of the increase 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. Each year end, local industry portfolios with at least 60 (260) consecutive monthly

[38] In international stock markets studies, the effects of non-overlapping trading hours on the correlation between assets traded in non-contemporaneous markets, which arise more significantly with daily data, should not be discarded. As shown by Kahya (1997) the estimated correlations of daily returns for positively (negatively) related markets are biased downwards (upwards). There is no significant bias associated with the use of monthly data.

[39] In addition, comparing the daily correlation plot with the 12 moving average of the I/W ratio plot also reveals the inverse relation between the two measures (correlation of -0.587 for the whole sample).

(daily) return observations available up to that date, are randomly group without replacement into portfolios.

Panel A (Panel B) of Figure 7 plots annualized excess standard deviation across time for portfolios containing 2, 5, 20, and 40 assets for monthly (daily) returns. For monthly data, the peak in excess standard deviation is reached in 2000 for all portfolios (10.7%), and all exhibit a modest increase up to 1995. For the 2-randomly selected local industries portfolio, the excess standard deviation is 8% in 1995 compared with 7.7% in 1978. For the larger portfolios, this pattern is also noticed, though at much lower values. The estimates based on one year of daily data reinforce the previous findings. Again the major increase in excess standard deviation is found for the 2-local industries portfolio, the maximum is reached in 2000 (16.7%), and a period of sustained increase has started in 1995.

Panel A (Panel B) of Figure 8 plots annualized excess standard deviation against the number of assets in the portfolio for monthly (daily) frequency. Data for these plots is obtained by averaging, over the sample periods, the yearly estimates of excess standard deviation previously described. As it is shown, the increase in local industry risk noticed for the 1996-2001 period implies that the number of primitive assets needed to reduce excess standard deviation is greater. For instance, monthly (daily) estimates show that to reduce excess volatility to about 2%, 12 (20) industry portfolios are needed in the 1996-2001 period, while in previous sample periods the same level of diversification could be reached with approximately 9 (16).

5.2 Another Look at the Relative Efficiency of Country versus Industry Diversification

Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998) conclude for the greater efficiency of country diversification over global industry diversification. However, recent evidence by Brooks and Catão (2000), Cavaglia et al. (2000), and Baca et al. (2000) show that industry diversification is as important as country diversification in the late 1990's, with agrees with the perception of the investment community as mentioned by Brooks and Catão (2000).

The results in Table 3 suggest that the ratio of local industry risk to country risk (I/C) presents a fairly stable behavior over the years, with exception of the notorious increase from 1995 onwards. In fact, Panel A of Figure 9 shows that up to 1989, the I/C ratio fluctuates around an average of 1.5, followed by a period when it is visible lower (on average 1.0 between 1990 and 1995), and finally a period of sustained increase in the late 1990's (sample average of 2.1). In addition, the ratio of global industry risk to country risk (see Panel B of Figure 9) also shows a clear increase from 1995 onwards, and only by the end of the sample period the ratio is greater than one (with the exception of the 1987 crash episode). Thus, the results suggest that towards the end of our sample period, international diversification power increases if an industrial dimension is privileged over a geographical dimension.

To gain further insight into this issue, and following the suggestion in Serra (2000), we compare the volatility of different portfolios[40], designed to mimic three extreme approaches to international equity investment. The first one is a portfolio that invests in all available primitive assets (local industry portfolios). The monthly variance of this portfolio (MD_t) gives an estimate of the maximum diversification benefits attainable and corresponds to the world risk estimate W_t in equation (8).

The second portfolio consists in diversifying across industries within a single country (Industry diversification), and the monthly variance of this portfolio (ID_t) is given by the weighted average of the monthly variances constructed from daily data of the 21 country indices,

$$ID_t = \sum\nolimits_{c \in W} x_{ct} \sigma_{ct}^2 \equiv \sum\nolimits_{c \in W} x_{ct} \sum\nolimits_{d \in t} (R_{cd} - \mu_{ct})^2, \tag{20}$$

where R_{cd} denotes daily country returns.

The third portfolio consists in diversifying across countries within a single industry (Country diversification), and the monthly variance of this portfolio (CD_t) is given by the weighted average of the monthly variances constructed from daily data of the 38 global industry indices,

$$CD_t = \sum\nolimits_{i \in W} x_{it} \sigma_{it}^2 \equiv \sum\nolimits_{i \in W} x_{it} \sum\nolimits_{d \in t} (R_{id} - \mu_{it})^2, \tag{21}$$

where R_{id} denotes daily global industry returns.

Given that the same local industry portfolios are aggregated either by countries or by industries to build the country and the global industries portfolios, the weighted average return of the three

[40] We recall the stylized result that as the number of assets in the portfolio grows, covariance terms become the key determinant of portfolio volatility.

strategies is the same. Obviously, this is not the case for the volatilities. As can be seen in the Panel A of Figure 10, where the 12-month moving averages of the annualized standard deviations of the MD, ID, and CD series are plotted, the strategy of diversifying simultaneously across countries and industries yield the minimum variance over the whole sample period. Investing in a single industry across markets (CD) has on average lower variance than that of investing in a single country across industries (ID), except for a few months before the 1987 crash[41] and, more evidently, in the late 1990's.

To make this point more clear we plot in Panel B of Figure 10, the 12-moving average of the difference of ID and CD relative to MD, which gives an estimate of the loss (in annualized standard deviation) incurred by not diversifying completely over the two dimensions. For instance, point estimates show that on average the maximum loss for not being well industrially diversified ($loss\_CD$) occurred in January 2001 (16.5% annualized standard deviation) while the minimum occurred in August 1991 (1.5%). The maximum (minimum) loss for not being well geographically diversified ($loss\_ID$) occurred in October 1987 (September 1977) and it amounts to about 20.6% (2.5%). A closer look at this plot also shows that 12-month moving average of the loss for not being well industrially diversified increases sharply in the late 1990's, reaching a peak in January 2001, while the loss for not being well geographically diversified remained fairly stable during this period.

Overall, the above simulation results corroborate the insights based on the volatility decomposition model that choosing the industrial dimension as primary objective for international asset allocation only seems fruitful – in terms of risk reduction – in the last years of our sample. Whether this is a permanent or a temporary phenomenon is yet to be confirmed. In fact, after the peak in January 2001, both the CD and $loss\_CD$ plots show a sustained decrease that is greater than that of the ID and $loss\_ID$, which may be suggestive of a recovery of the merits of the traditional top-down approach (Solnik (2000)) to international investment.

[41] The period immediately before the crash, as noted before, is characterized by high volatility at the local industry level, but not at the country level.

6 Conclusion

In this paper we extend the volatility decomposition method of Campbell et al. (2001) to an international setting and 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: world portfolio return variance, cross-sectional dispersion of country returns relative to world returns, and cross-sectional dispersion of local industry portfolios returns relative to their countries.

We find that between 1974 and 2001, world and country risk have remained fairly stable. Industry risk, both at local and global level, has experienced a huge increase during the late 1990's, after a long period of relative stability. This increase cannot be only justified by the new economy bubble. Local industry risk dominates world and country risk, except during the 1990 to 1995 period, when country risk is on average the most important component of total risk. World risk is systematically the least important component of total risk. Also, we show that October 1987 crash had a short-lived 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 opposite is not true.

Consistent with the behavior of industry risk, towards the end of our sample, pairwise correlations among local industry portfolios decrease and, not surprisingly, the number of randomly selected assets needed to achieve any given level of diversification increases after 1995. These results suggest that the power of international diversification to reduce risk did not eroded as the process of globalization might have implied. In addition, our results support the conclusion that industrial diversification has become relatively more efficient than geographic diversification, only in the latter years of our sample, though this may be a temporary situation.

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Table 1: **Descriptive Statistics for Country Portfolios**

The available (at a particular day) within country industry portfolios are aggregated by countries to build the country portfolios. These portfolios returns are value-weighted averages of the relevant national industry portfolios excess returns. Returns and standard deviation values are annualized considering a 260-day year. Size refer to the average of the available monthly market values (in millions US dollars). The columns under the Industries label refer to the maximum (Max) and minimum (Min) number of local industry portfolios that are available for a given country portfolio. Max weight is the average weight in each country of the industry portfolio with the highest market value, in each month.

		Returns			Size	Industries		Max
Countries	Menmonic	Obs.	Mean	Stdev	(US$ M)	Max	Min	weight
Australia	AU	7305	2.2%	20.9%	106,330	35	21	35.6%
Austria	OE	5196	3.6%	17.7%	15,146	24	6	31.0%
Belgium	BG	7305	2.5%	16.2%	45,379	32	16	27.6%
Canada	CN	7305	0.6%	14.9%	177,454	37	17	18.4%
Denmark	DK	5196	4.9%	17.5%	34,823	22	13	27.0%
Finland	FN	3587	3.0%	30.1%	72,346	28	12	36.1%
France	FR	7305	4.2%	19.6%	260,418	35	21	16.1%
Germany	BD	7305	2.6%	17.8%	303,228	36	24	16.7%
Hong Kong	HK	7305	6.2%	29.8%	128,791	33	9	31.1%
Ireland	IR	3131	2.0%	18.4%	36,557	27	21	28.5%
Italy	IT	7305	0.6%	23.5%	142,645	33	17	27.8%
Japan	JP	7305	0.7%	19.9%	1,747,509	36	30	13.8%
Netherlands	NL	7305	6.4%	16.6%	173,993	30	21	35.4%
New Zealand	NZ	3631	-1.7%	21.3%	16,843	26	11	31.7%
Norway	NW	5717	-0.7%	24.1%	20,456	25	7	46.6%
Singapore	SG	7305	1.1%	23.2%	45,609	30	9	34.0%
Spain	ES	3849	2.6%	20.2%	162,518	32	18	32.3%
Sweden	SD	5196	5.6%	23.7%	85,567	30	8	22.9%
Switzerland	SW	7305	5.3%	16.5%	163,721	31	14	32.4%
UK	UK	7305	5.6%	19.1%	688,146	38	31	15.0%
US	US	7305	4.7%	15.8%	3,306,448	38	38	12.3%
G21 World	W	7305	2.4%	12.0%	7,547,509	646	270	-

Table 2: **Descriptive Statistics for Global Industry Portfolios**
The available (at a particular day) within country industry portfolios are aggregated by industries to build the global industry portfolios. These portfolios returns are value-weighted averages of the relevant national industry portfolios excess returns. Returns and standard deviation values are annualized considering a 260-day year. Size refer to the average of the available monthly market values (in millions US dollars). The columns under the Countries label refer to the maximum (Max) and minimum (Min) number of countries that are represented in a given global industry portfolio. Max weight is the average weight in each global industry of the country with the highest market value for that industry, in each month.

		Returns			Size	Countries		Max
Industries	Menmonic	Obs.	Mean	Stdev	(US $ M.)	Max	Min	weight
Aerospace & Defence	AERSP	7305	6.5%	16.8%	72,562	12	5	81.4%
Automobiles & Parts	AUTMB	7305	1.8%	15.5%	246,507	15	8	50.9%
Banks	BANKS	7305	3.5%	14.7%	805,118	21	12	44.5%
Beverages	BEVES	7305	4.1%	14.8%	143,975	18	9	57.3%
Chemicals	CHMCL	7305	1.9%	13.5%	228,779	19	10	44.4%
Construction & Building Materials	CNSBM	7305	1.5%	14.5%	158,439	21	10	48.2%
Distributors	DISTR	7305	-1.2%	19.6%	64,195	18	9	74.5%
Diversified Industrials	DIVIN	7305	2.2%	15.1%	153,249	21	12	39.0%
Electricity	ELECT	7305	3.6%	11.6%	278,227	17	7	57.3%
Electronic & Electric Equipment	ELTNC	7305	4.0%	15.7%	322,339	20	7	46.9%
Engineering & Machinery	ENGEN	7305	0.4%	14.4%	171,004	20	10	48.0%
Food & Drug Retailers	FDRET	7305	6.5%	12.9%	106,639	17	6	46.4%
Food Producers & Processors	FOODS	7305	5.5%	11.3%	191,100	20	10	41.2%
Forestry & Paper	FSTPA	7305	-0.6%	16.8%	64,008	19	6	63.3%
Gas Distribution	GASDS	7305	3.8%	15.4%	66,862	12	7	53.5%
Household Goods & Textiles	HHOLD	7305	1.0%	16.2%	105,159	21	6	56.1%
Health	HLTHC	7305	5.4%	17.6%	117,558	16	4	90.2%
Information Tech. Hardware	INFOH	7305	3.0%	21.9%	554,989	17	4	65.5%
Insurance	INSUR	7305	4.6%	13.2%	283,584	20	8	40.3%
Investment Companies	INVSC	7305	3.4%	12.5%	48,553	17	7	43.3%
Leisure. Entertainment & Hotels	LESUR	7305	4.4%	17.1%	113,521	18	6	54.7%
Life Assurance	LIFEA	7305	6.2%	14.8%	72,392	14	5	42.7%
Media & Photography	MEDIA	7305	2.6%	15.3%	212,302	20	7	56.1%
Mining	MNING	7305	0.3%	19.5%	50,339	10	5	50.8%
Oil and Gas	OILGS	7305	4.5%	15.6%	449,280	19	8	57.3%
Packaging	PCKGN	7305	1.9%	13.9%	16,743	16	6	47.9%
Personal Care & House. Products	PERSH	7305	4.4%	15.5%	111,676	11	5	74.1%
Pharmaceuticals	PHARM	7305	6.5%	14.9%	471,423	17	6	56.6%
Real Estate	RLEST	7305	0.6%	16.6%	111,942	21	10	36.6%
Retailers General	RTAIL	7305	3.5%	16.5%	262,459	19	11	57.9%
Software & Computer Services	SFTCS	7305	4.5%	24.6%	236,811	20	2	86.8%
Speciality & Other Finance	SPFIN	7305	4.7%	19.5%	284,771	17	7	62.1%
Steel and Other Metals	STLOM	7305	-2.0%	18.9%	89,853	18	10	58.0%
Support Services	SUPSV	7305	3.7%	14.1%	59,079	18	4	44.8%
Telecom Services	TELCM	7305	2.2%	16.1%	556,621	21	4	66.0%
Tobacco	TOBAC	7305	8.3%	19.9%	68,134	12	4	63.0%
Transport	TRNSP	7305	1.1%	14.0%	186,884	21	10	50.2%
Water	WATER	7305	6.8%	18.2%	10,432	7	2	70.9%

Table 3: **Descriptive Statistics for World, Country, and Industry Risks**

This table shows descriptive statistics for the monthly volatility measures constructed from daily data, W, C, and I as described in equations (8) to (10), respectively. Mean, standard deviation (Stdev), minimum (Min), maximum (Max), and median (Med) estimates of monthly variances are multiplied by 100. 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.

	Mean	Stdev	Min	Max	Med	Skew	Kurt
Panel A: 1974-2001 (N = 336)							
W	0.1118	0.1786	0.0140	2.8629	0.0738	11.3107	168.7390
C	0.1519	0.1537	0.0351	2.4129	0.1184	9.9002	140.2024
I	0.2104	0.1724	0.0669	1.1813	0.1515	2.7897	9.0662
W^{dc}	0.1052	0.1009	0.0140	0.6625	0.0738	2.5758	8.0395
C^{dc}	0.1463	0.0937	0.0351	0.5411	0.1184	1.8729	4.0818
Panel B: 1974-1979 (N = 72)							
W	0.0751	0.0742	0.0148	0.4003	0.0533	2.5815	7.7242
C	0.1115	0.0776	0.0351	0.4489	0.0836	2.1003	5.1176
I	0.1359	0.0699	0.0669	0.4092	0.1108	2.0296	4.1205
Panel C: 1980-1985 (N = 72)							
W	0.0830	0.0549	0.0246	0.3328	0.0695	2.3886	7.3493
C	0.1212	0.0559	0.0504	0.3516	0.1113	1.7340	4.0601
I	0.1762	0.0860	0.0953	0.7018	0.1607	4.0916	21.5493
Panel D: 1986-1989 (N = 48)							
W	0.1565	0.4043	0.0248	2.8629	0.0843	6.6561	45.3513
C	0.1969	0.3368	0.0490	2.4129	0.1374	6.3104	42.1006
I	0.2317	0.1381	0.0911	0.6997	0.1781	1.6227	2.4446
W^{dc}	0.1107	0.1044	0.0248	0.6625	0.0843	3.7576	17.3255
C^{dc}	0.1579	0.0997	0.0490	0.5411	0.1374	1.7543	3.7870
Panel E: 1990-1995 (N = 72)							
W	0.1064	0.1129	0.0172	0.6625	0.0698	2.7637	9.1853
C	0.1535	0.0904	0.0560	0.5411	0.1141	1.8851	4.5974
I	0.1349	0.0497	0.0783	0.3423	0.1226	2.0617	5.4167
Panel F: 1996-2001 (N = 72)							
W	0.1527	0.1258	0.0140	0.5215	0.1164	1.3579	1.1437
C	0.1911	0.1160	0.0461	0.5309	0.1551	1.4015	1.5529
I	0.3806	0.2657	0.0885	1.1813	0.2834	1.2268	0.9177

Table 4: **Autocorrelations, Unit Roots, and Deterministic Linear Time Trend Tests**
This table shows the autocorrelations (Panel A), the results of the Augmented Dickey-Fuller and Philips-Perron tests for unit roots (Panel B), and the Vogelsang $t - PS_T$ test for deterministic linear trends (Panel C), for the monthly volatility measures constructed from daily data, W, C, and I as described in equations (8), (9), and (10), respectively. 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. ρ_i represents the seriel correlation coeficient at lag i. The 5% critical values for the unit root $T(\rho - 1)$ and Z_ρ tests are –14.00 (-21.50) when an intercept (intercept and trend) is included in the regression, and for the t and Z_t tests are –2.87 (-3.42). The number of lags in the ADF regression (shown under the lag column) were determined by the Ljung-Box test for no serial correlation up to 18 lags. For the Phillips-Perron Z_ρ and Z_t tests only the results using a truncation lag of 12 lags are displayed. The 5% critical value for the Vogelsang $t - PS_T$ test is 1.72.

Panel A: Autocorrelations					
	ρ_1	ρ_2	ρ_3	ρ_6	ρ_{12}
W	0.219	0.135	0.130	0.071	0.072
C	0.230	0.173	0.196	0.133	0.082
I	0.784	0.714	0.689	0.621	0.535
W^{dc}	0.505	0.356	0.295	0.258	0.252
C^{dc}	0.501	0.362	0.286	0.260	0.193
Panel B: Unit Root Test					
	$T(\rho - 1)$	t	*lag*	Z_ρ	Z_t
Intercept model					
W	-261.58	-14.61	0	-337.56	-15.56
C	-257.87	-14.45	0	-349.50	-15.63
I	-21.27	-2.64	12	-87.77	-6.94
W^{dc}	-39.66	-3.37	12	-238.15	-12.01
C^{dc}	-64.97	-4.40	5	-232.02	-11.93
Intercept and trend model					
W	-265.98	-14.79	0	-328.98	-15.57
C	-265.18	-14.77	0	-336.91	-15.67
I	-31.44	-3.22	12	-112.48	-7.94
W^{dc}	-60.46	-4.10	12	-240.52	-12.22
C^{dc}	-67.58	-4.84	5	-232.47	-12.19
Panel C: Deterministic Linear Trend Test					
	W	C	I	W^{dc}	C^{dc}
Linear trend $\times 10^4$	0.0233	0.0256	0.0716	0.0235	0.0257
$t - PS_T$ (5%)	0.83	1.39	0.31	0.79	1.56

Table 5: **World, Country, and Industry Risk for Alternative Samples**

Panels A to C show descriptive statistics for the monthly variance measures constructed from daily data for the $G7$ plus Switzerland world (Panel A), and for the world excluding the US market (Panel B) or the Japanese market (Panel C). For Panel D, the variance estimates are constructed using monthly returns. The values under Mean, Stdev (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 (5%) 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.

	Whole sample				Subperiod means				
	Mean	Stdev	Trend	$t - PS_T$	1974-79	1980-85	1986-89	1990-95	1996-01
Panel A: G7 + 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 ex-US									
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 ex-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

Table 6: **Volatility Measures by Countries**

This table shows 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 $se(\beta)$ 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 Stdev (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 (5%) test statistic for deterministic linear trends whose critical value is 1.72.

Country	β	$se(\beta)$	Industry Variance				Country Variance			
			Mean	Stdev	Trend	$t - PS_T$	Mean	Stdev	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
US	1.06	0.0603	0.2241	0.1726	0.0434	-0.07	0.2290	0.2722	-0.1109	-1.96
US	0.87	0.0335	0.1688	0.1795	0.0793	0.23	0.0940	0.2088	0.0192	0.91

Table 7: **Global Industry Volatility**

Panel A shows descriptive statistics for global industry variance. Industry volatility is constructed monthly using equation (15). $t - PS_T$ is the Vogelsang $t - PS_T$ (5%) test statistic for deterministic linear trends whose critical value is 1.72. Mean and Stdev (standard deviation) refer to monthly estimates are multiplied by 100. Panel B presents the individual global industry portfolio variance estimates 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 $se(\beta)$ 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.

Panel A: Global Industry Variance						
	1974-01	1974-79	1980-85	1986-89	1990-95	1996-01
All Industries						
Mean	0.1108	0.0779	0.0861	0.1379	0.0702	0.1910
Stdev	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
Stdev	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 Industries Variance						
	β	$se(\beta)$	Mean	Stdev	Trend	$t-PS_T$
Aerospace & Defence	0.90	0.0549	0.1424	0.1566	0.0166	0.12
Automobiles & Parts	0.97	0.0380	0.0870	0.0896	0.0283	0.25
Banks	1.02	0.0393	0.0768	0.0986	0.0006	-0.04
Beverages	0.84	0.0432	0.1064	0.1350	0.0438	0.21
Chemicals	0.99	0.0308	0.0451	0.0727	0.0286	0.35
Construction & Building Materials	1.04	0.0404	0.0856	0.0851	0.0047	-0.41
Distributors	1.11	0.0573	0.2051	0.2191	-0.0272	-1.52
Diversified Industrials	0.94	0.0354	0.0908	0.1746	0.0149	0.24
Electricity	0.57	0.0427	0.0651	0.0841	0.0176	0.51
Electronic & Electric Equipment	1.13	0.0326	0.0569	0.0595	0.0122	-0.05
Engineering & Machinery	1.09	0.0352	0.0596	0.0527	0.0128	0.43
Food & Drug Retailers	0.78	0.0403	0.0775	0.0954	0.0155	-0.16
Food Producers & Processors	0.74	0.0342	0.0466	0.0732	0.0258	0.23
Forestry & Paper	1.06	0.0508	0.1256	0.1367	0.0267	0.02
Gas Distribution	0.82	0.0505	0.1187	0.1588	0.0312	0.29
Household Goods & Textiles	1.12	0.0403	0.1047	0.1058	0.0076	-0.46
Health	0.79	0.0506	0.1617	0.1787	0.0104	0.28
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
Investment Companies	0.97	0.0316	0.0886	0.0712	-0.0097	-1.35
Leisure. Entertainment & Hotels	1.13	0.0428	0.1183	0.1396	0.0065	-0.56
Life Assurance	0.88	0.0439	0.1028	0.0781	0.0034	-0.55
Media & Photography	1.00	0.0361	0.0727	0.1148	-0.0292	-1.47
Mining	1.09	0.0847	0.2920	0.3305	0.0001	-0.44
Oil and Gas	0.80	0.0488	0.1328	0.1527	0.0498	0.36
Packaging	0.90	0.0458	0.1078	0.0933	0.0044	-0.44
Personal Care & House. Products	0.76	0.0427	0.1198	0.2333	0.0496	0.49
Pharmaceuticals	0.81	0.0420	0.0822	0.0878	0.0277	0.34
Real Estate	1.09	0.0528	0.1458	0.1379	-0.0051	-0.87
Retailers General	0.99	0.0416	0.0926	0.1177	0.0341	0.05
Software & Computer Services	1.23	0.0703	0.2871	0.2836	0.0110	-0.70
Speciality & Other Finance	1.33	0.0500	0.1218	0.1329	0.0186	0.48
Steel and Other Metals	1.14	0.0613	0.1676	0.1488	0.0273	0.33
Support Services	0.97	0.0357	0.0813	0.0850	-0.0248	-0.89
Telecom Services	0.78	0.0460	0.1240	0.2248	0.0071	0.06
Tobacco	0.68	0.0664	0.2604	0.2812	0.0720	0.96
Transport	0.94	0.0368	0.0620	0.0558	0.0136	0.47
Water	0.40	0.0602	0.2557	0.2408	0.0177	0.62

Table 8: **Total Volatility Mean and Variance Decomposition**

This table shows the results, in percentage, of the mean and variance decomposition of total volatility, as described in equations (18) and (19). 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. The line I^{dc*} refers to the results of the I series in relation to the downweighted series.

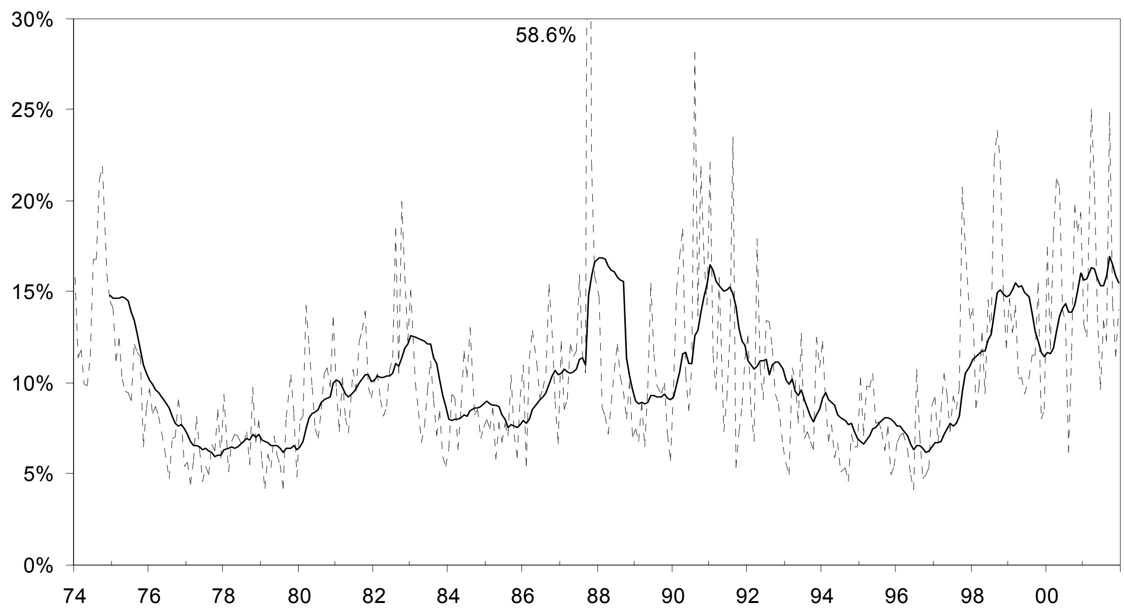
	Mean	Variance	Covariances			
			W	C	W^{dc}	C^{dc}
Panel A: 1974-2001 (N = 336)						
W	23.6%	16.8%				
C	32.0%	12.4%	26.9%			
I	44.4%	15.7%	14.2%	13.8%		
W^{dc}	22.8%	9.6%				
C^{dc}	31.7%	8.3%			14.4%	
I^{dc*}	45.6%	28.2%			19.5%	19.7%
Panel B: 1974-1979 (N = 72)						
W	23.3%	12.5%				
C	34.6%	13.7%	20.0%			
I	42.1%	11.1%	20.5%	21.3%		
Panel C: 1980-1985 (N = 72)						
W	21.8%	11.4%				
C	31.9%	11.9%	15.6%			
I	46.3%	28.1%	12.4%	19.8%		
Panel D: 1986-1989 (N = 48)						
W	26.7%	24.0%				
C	33.7%	16.6%	38.5%			
I	39.6%	2.8%	8.8%	8.1%		
W^{dc}	22.1%	11.6%				
C^{dc}	31.6%	10.6%			17.6%	
I^{dc*}	46.3%	20.4%			18.3%	20.4%
Panel E: 1990-1995 (N = 72)						
W	27.0%	24.4%				
C	38.9%	15.6%	28.2%			
I	34.2%	4.7%	12.9%	13.3%		
Panel F: 1996-2001 (N = 72)						
W	21.1%	7.5%				
C	26.4%	6.4%	11.8%			
I	52.5%	33.4%	20.6%	19.7%		

Table 9: **Correlation Structure and Granger-causality Tests**

This table shows the correlation structure (Panel A) and the p-values of Granger-causality 2-equation VAR tests (Panel B), and 3-equation VAR tests (Panel C) for the monthly volatility measures constructed from daily data, W, C, and I as described in equations 8 to 10, respectively, and by replacing the October 1987 observation of W and C 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 1 to k of the variable indicated in the row are jointly equal to zero in the equation for the variable indicated in the column.

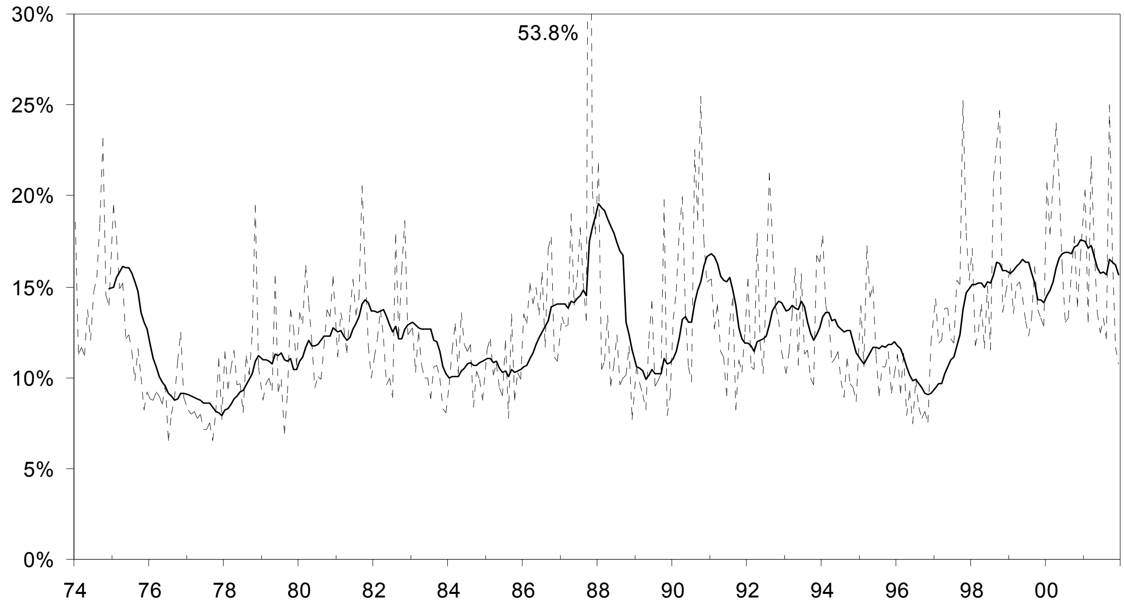
Panel A: Correlations			
	W^{dc}	C^{dc}	I
W^{dc}	1	0.808	0.593
C^{dc}		1	0.647
I			1
Panel B: Bivariate VAR			
	W_t^{dc}	C_t^{dc}	I_t
W_{t-k}^{dc}		0.5595	0.2617
C_{t-k}^{dc}	0.0113		0.2290
I_{t-k}	0.0020	0.0084	
Panel C: Trivariate VAR			
	W_t^{dc}	C_t^{dc}	I_t
W_{t-k}^{dc}		0.5845	0.6405
C_{t-k}^{dc}	0.5493		0.5832
I_{t-k}	0.0057	0.0158	

Figure 1: **World Volatility**



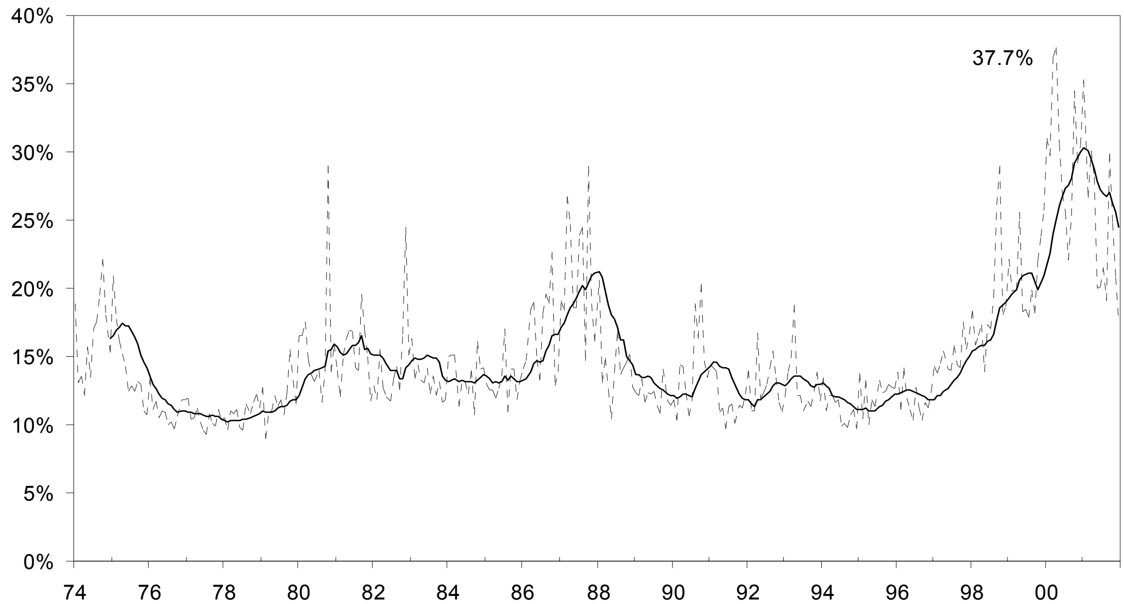
This figure plots the annualized standard deviation within each month of the world portfolio returns (dashed line) and the respective backwards 12-month moving average (solid line), for the period from 1974 to 2001. The risk measure is calculated using daily world market returns and equation (8).

Figure 2: **Country Volatility**



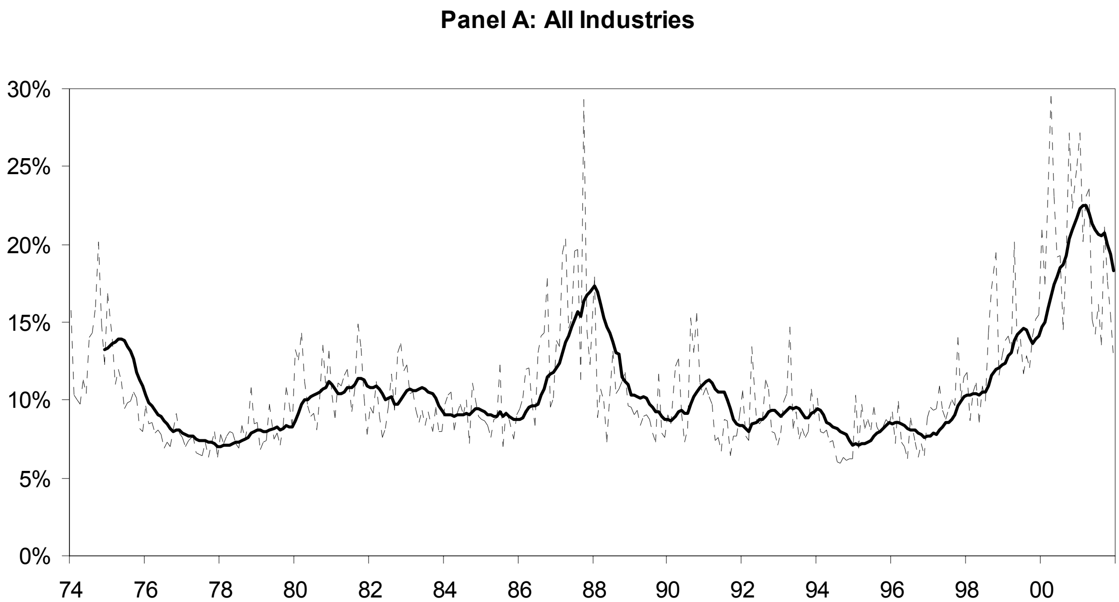
This figure plots the annualized country volatility (dashed line) and the respective backwards 12-month moving average (solid line) for the period from 1974 to 2001. The annualised risk measure is calculated using daily country returns relative to the world returns and equation (9).

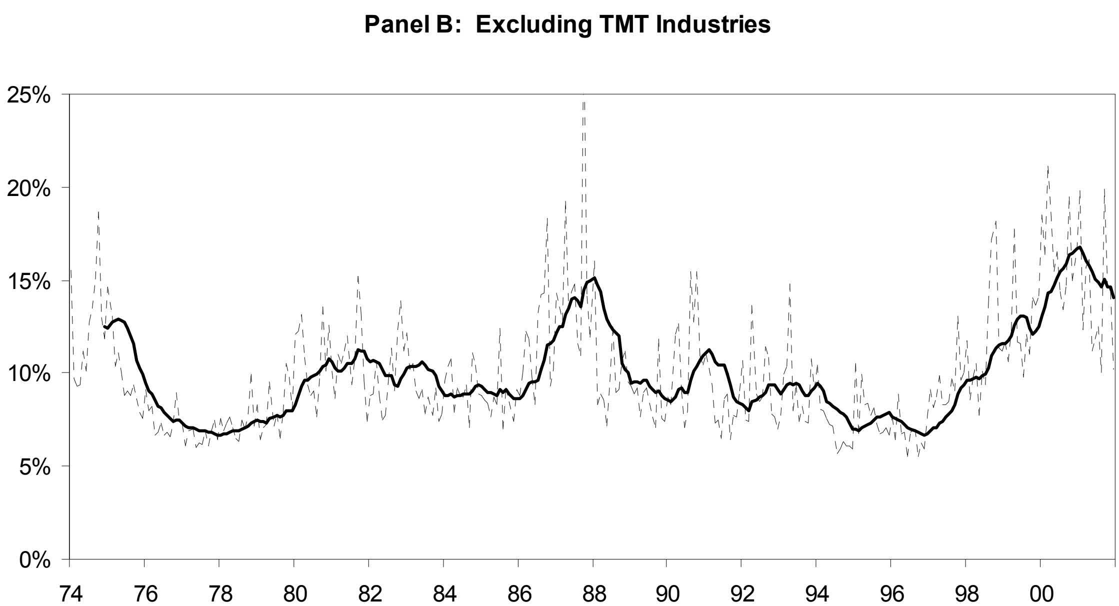
Figure 3: **Local Industry Volatility**



This figure plots the annualized local industry volatility (dashed line) and the respective backwards 12-month moving average (solid line) for the period from 1974 to 2001. The risk measure is calculated using daily local industry returns relative to their country returns and equation (10).

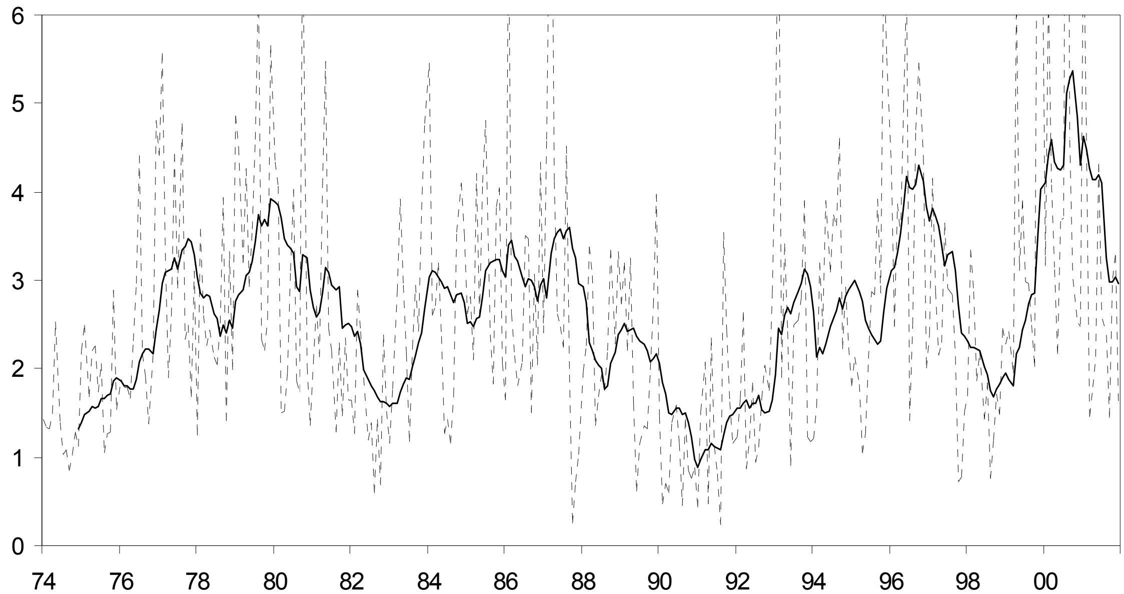
Figure 4: **Global Industry Volatility**





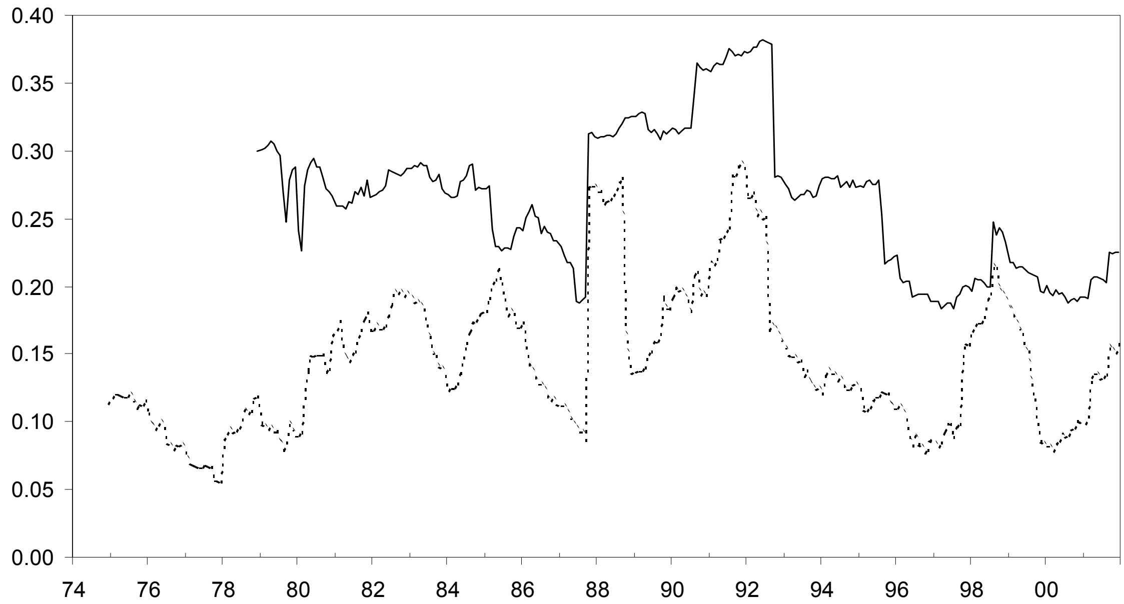
Panel A plots the annualized global industry volatility (dashed line) and the respective backwards 12-month moving average (solid line) for the period from 1974 to 2001, for the sample with all global industries. In Panel B similar plot shows the estimates considering a sample that excludes the TMT industries. The risk measure is calculated using daily global industry returns relative to the world.

Figure 5: **Local Industry Variance vs. World Variance**



This figure plots the ratio of local industry variance to world variance (dashed line) and the respective backwards 12-month moving average (solid line). Monthly variance measures are constructed from daily data as described in equations (8) and (10).

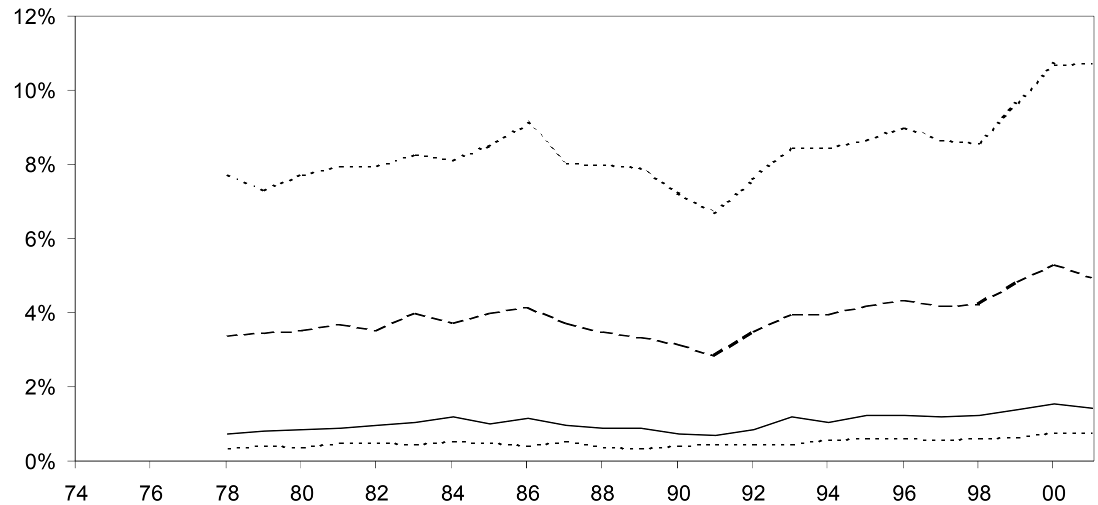
Figure 6: **Correlation Among Local Industry Portfolios**



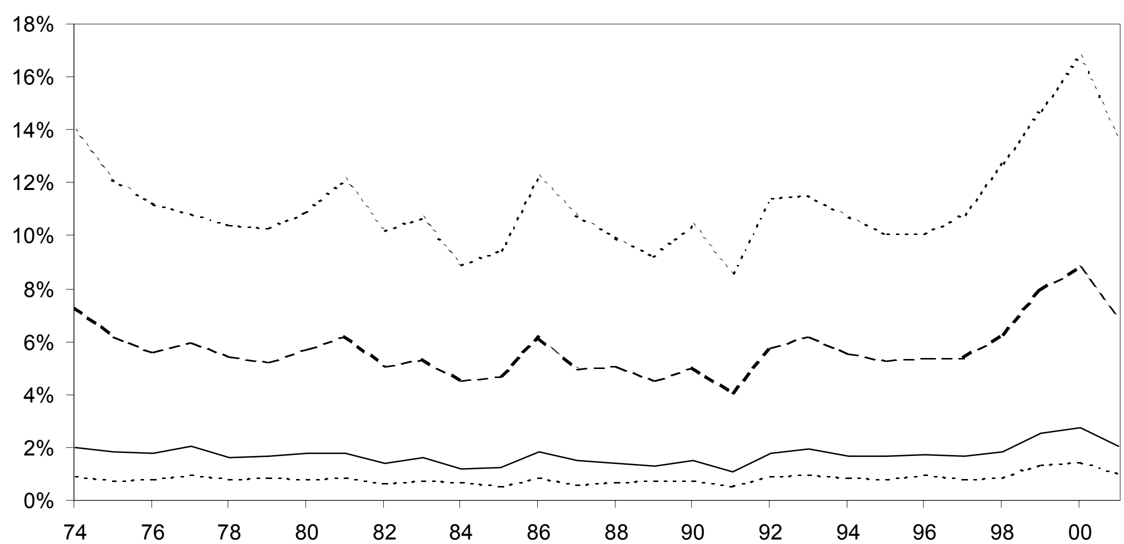
This figure shows the time evolution of the equal weighted average pairwise correlation across local industry portfolios. The solid (dashed) line is a plot of the monthly estimates of average monthly (daily) correlation coefficients computed using a rolling window of 60 (260) monthly (daily) observations.

Figure 7: **International Diversification Benefits vs. Time**

Panel A: Monthly Data



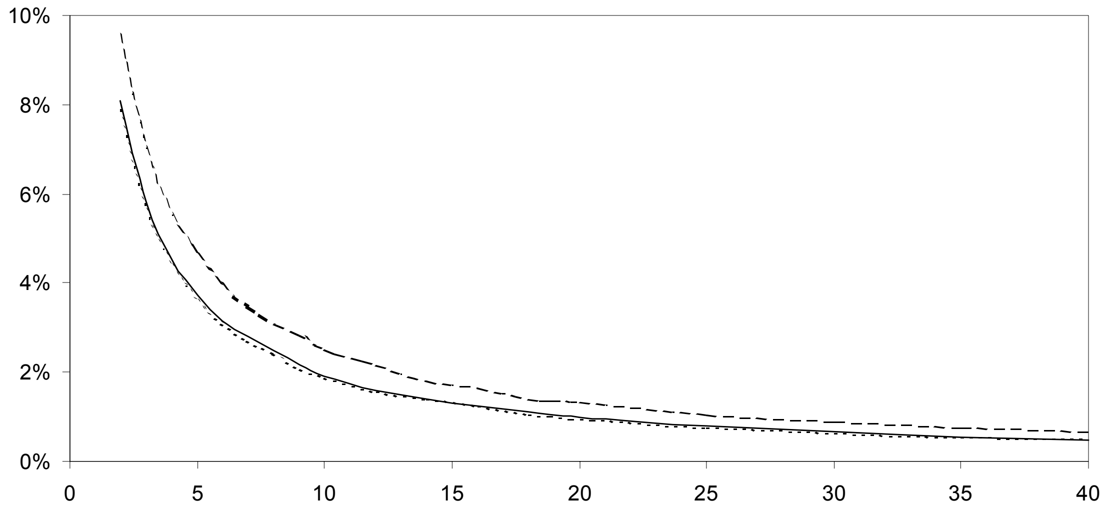
Panel B: Daily Data



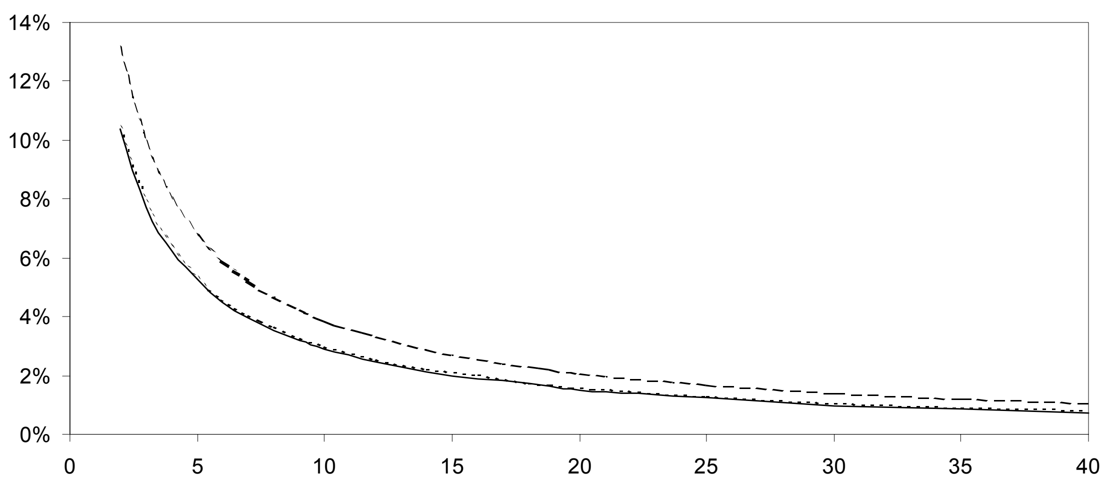
Panel A plots the annualized (multiplied by the square root of 12) standard deviation of equal weighted portfolios containing 2, 5, 20, and 40 randomly selected basic assets, in excess of the standard deviation of the equal weighted portfolio containing all assets used in the calculations. Panel B shows the annualized (multiplied by the square root of 260) standard deviation computed using daily data.

Figure 8: **International Diversification Benefits vs. Number of Local Industry Portfolios**

Panel A: Monthly Data



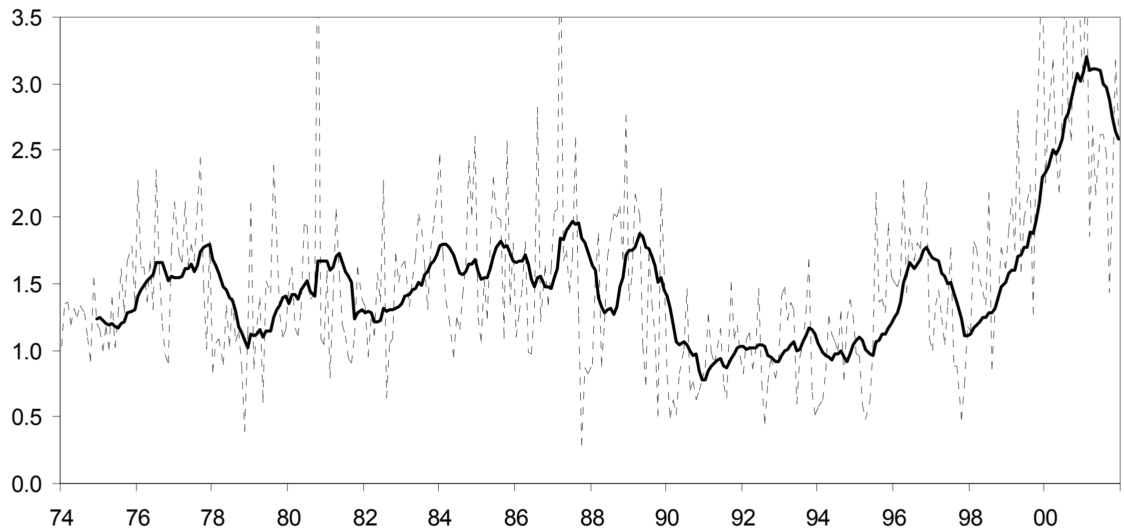
Panel B: Daily Data



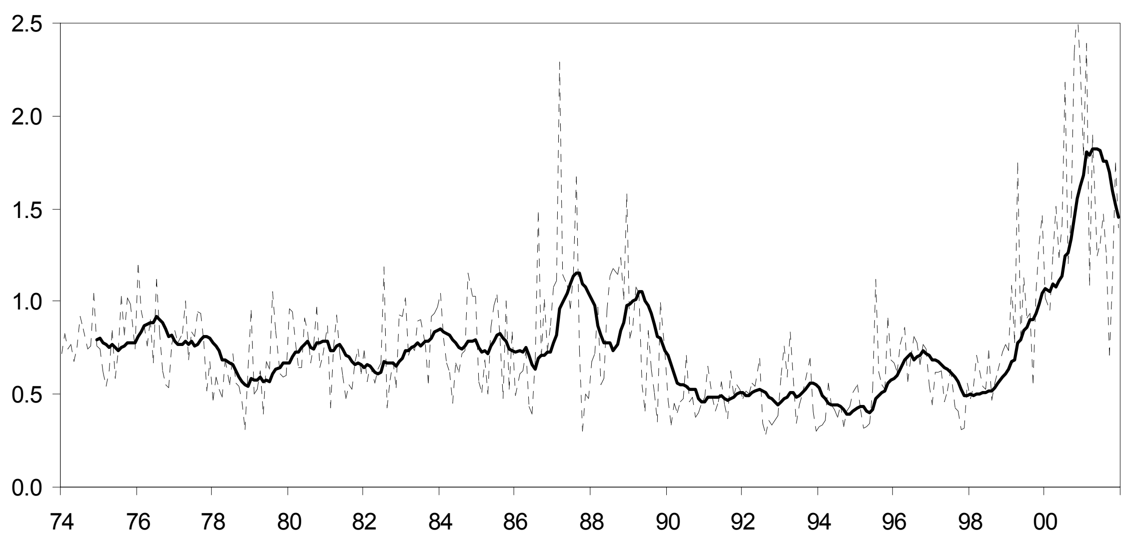
This figure shows the excess standard deviation against the number of assets for the 6-years sub-sample periods, 1996 to 2001 (top dashed line), 1990 to 1995 (dashed line), and 1980 to 1985 (solid line).

Figure 9: **Industry Volatility vs. Country Volatility**

Panel A: Ratio Between Local Industry and Country Volatility

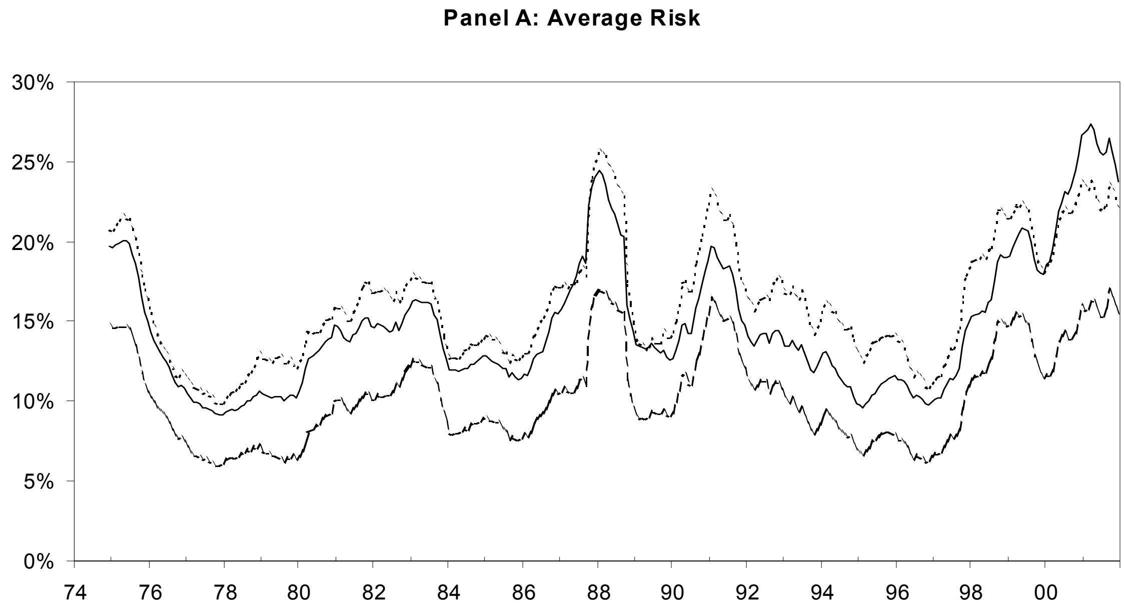


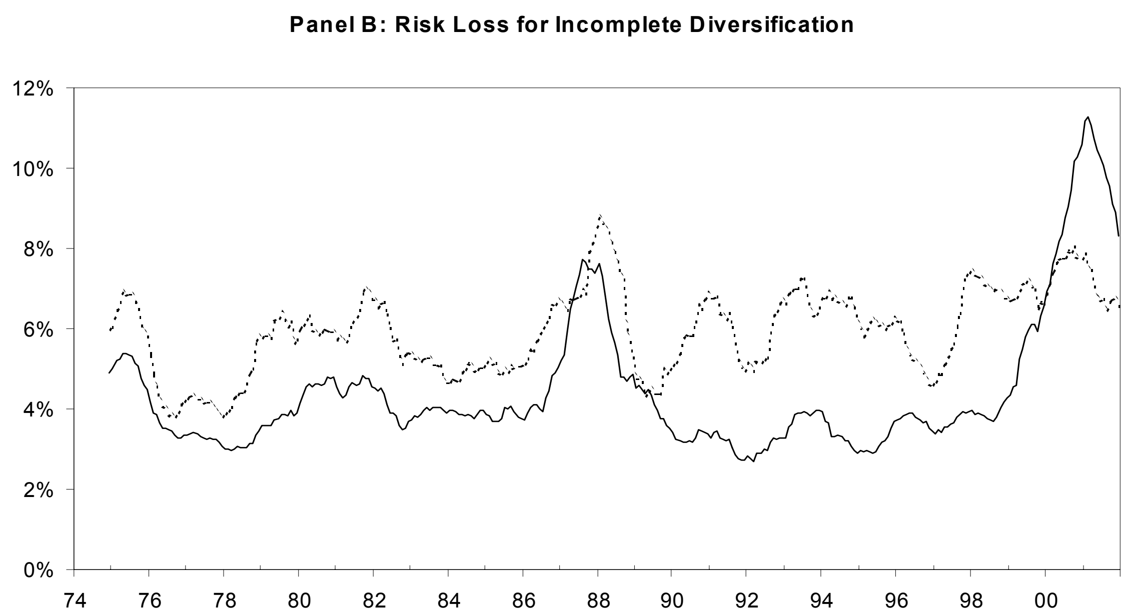
Panel B: Ratio Between Global Industry and Country Volatility



Panel A plots the ratio of local industry variance to country variance (dashed line) and the respective backwards 12-month moving average (solid line). Monthly variance measures are constructed from daily data as described in equations (8) and (9). Panel B plots the ratio o global industry variance to country variance (dashed line) and the respective 12-month moving average (solid line). Global industry variance is calculated using the full sample and equation (15).

Figure 10: **International Diversification Scenarios**





Panel A plots the 12-month moving averages of the annualized standard deviation within each month of the returns to a strategy that diversifies across industries and countries (long dashed line), of the value weighted average of annualised standard deviation of a strategy that diversifies across countries within an industry (solid line) and of a strategy that diversifies across industries within a country (short dashed line). Panel B plots the 12-month moving averages of the difference between the monthly estimate of ID and that of MD (dashed line) and between CD and MD (solid line). MD, ID, and CD estimates are constructed using daily data according to equations (8), (20), and (21), respectively. The annualized standard deviations correspond to the square root multiplied by 100 of the annualized (multiplied by 12) monthly variance estimates.