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ESSAYS ON INTERNATIONAL EQUITY MARKETS

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Abstract

This dissertation consists of three papers on international equity markets. The first paper uses a volatility decomposition method to study the time series of equity volatility at the world, country and local industry levels. Between 1974 and 2001 there is no noticeable long-term trend in any of the volatility measures. Then in the 1990s, there is a sharp increase in local industry volatility compared to market and country volatility. Thus, correlations among local industries have declined and more assets are needed to achieve a given level of diversification.

The second paper studies the impact of sovereign debt rating news of one country on the stock market returns of other countries between 1989 and 2003. The information spillover effect is asymmetric and large. A one-notch credit ratings downgrade is associated with a statistically significant negative two-day return spread of other countries relative to the US stock market of 28 basis points, on average. Upgrades have no significant impact on return spreads of countries abroad. Moreover, there is evidence of downgrades spillover effects at the industry level.

The third paper investigates the time series of correlations between global industries and aggregate world market over the 1979-2003 period. The behavior of industry correlations is characterized by long-term swings, in particular with a period of low correlations in the late 1990s. Small and value (low price-earnings ratio) industries have lower correlations. Moreover, global industry correlations are counter-cyclical. Global industry correlations are greater for downside moves than for upside moves. Correlation asymmetry is the largest among small industries.

JEL classification: F30, G15

Keywords: Volatility, Correlation, Spillover effects, Asymmetries

Resumo

Esta dissertação engloba três artigos sobre os mercados internacionais de acções. O primeiro artigo utiliza um método de decomposição de variância para estudar a evolução temporal da volatilidade ao nível do mundo, do país e da indústria local. Entre 1974 e 2001, não há evidência de tendências de longo prazo em qualquer nível de volatilidade. No final da década de 90, observa-se um forte aumento do risco da indústria local relativamente ao risco do país e do mercado mundial. Em conformidade, a correlação entre indústrias locais decresce e mais activos são necessários para obter um dado nível de diversificação.

O segundo artigo estuda o impacto de alterações de *ratings* da dívida pública de um país nos mercados accionistas de outros países entre 1989 e 2003. O efeito de *spillover* é assimétrico e significativo. Em média, um ponto de *downgrade* do rating da dívida pública de um país está associado a um diferencial de retorno face ao mercado dos EUA de 28 pontos base (em dois dias) nos mercados accionistas dos restantes países. Os *upgrades* não têm um impacto significativo nos restantes países. Adicionalmente, o efeito de *spillover* dos *downgrades* manifesta-se ao nível das indústrias.

O terceiro artigo analisa as sucessões cronológicas da correlação entre indústrias globais e o mercado mundial entre 1979 e 2003. O comportamento das correlações é caracterizado por flutuações longas, sendo o final da década de 90 caracterizado por baixas correlações. A correlação é inferior nas indústrias de menor dimensão e *value* (rácio *price-earnings* baixo). Os períodos de recessão caracterizam-se por um aumento das correlações industriais. As correlações das indústrias são maiores para performances negativas do mercado do que para performances positivas. Esta assimetria é maior nas indústrias de menor dimensão.

Classificação JEL: F30, G15

Palavras-chave: Volatilidade, Correlação, Efeitos *spillover*, Assimetrias

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Overview

This dissertation analyzes three empirical issues in international equity markets: volatility (Chapter 1), information spillover effects (Chapter 2), and correlation (Chapter 3). Each chapter is written as an independent and self-contained paper. This brief overview provides the motivation, methodology, and main findings of each paper.

The first paper primary goal is to describe the historical behavior of international equity markets total volatility components and to study the implications for international diversification. We address three main research questions. First, have world, country, and local industry risks changed over time? Second, has the power of international diversification to reduce risk decreased? Finally, given the recent evidence in the literature, we take another look at the question of the relative efficiency of country versus industry diversification for global equity investors. These are important questions for global portfolio managers. If the risk that must be diversified away has increased, there are more opportunities for international diversification, but more assets are needed to achieve a given level of diversification.

We extend the Campbell, Lettau Malkiel and Xu (2001) total risk decomposition method to an international setting. This allows us to measure and study the time series behavior of risk components without the need to keep track of covariances or estimate risk exposure parameters for countries and industry portfolios. Moreover, the methodology measures industry risk on a country basis, which is an alternative to the Heston and Rouwenhorst (1994) fixed-effects model assumption that asset exposures to global industry shocks are equal across countries. We use local industry daily index return data, which include 21 developed markets over the 1974-2001 period.

The paper major findings are the following. First, there is no evidence of a statistically significant long-term trend in any of the volatility components, although local and global industry volatility shows a sharp increase after 1995 (reaching an all-time peak in April 2000). Accordingly, the ratio of local industry to world risk experienced a considerable increase during the late 1990s. The average ratio is 3.23 for the 1996-2001 period compared to 2.50 in the 1974-1995 period. This increase cannot be attributed solely to the new economy bubble. Second, local industry risk dominates world and country risk, except during the 1990-1995 period, when country risk is on average the most important component. Third, the October 1987 crash was felt at both world and country levels, but had less of an effect on local industry risk. Fourth, lagged local industry risk is helpful in forecasting world and country level volatility, while the converse is not true. Finally, the ratio of global industry risks to country risk increased during the late 1990s. This ratio becomes greater than one in the late 1990s.

Overall, the paper results show that risk components importance have changed over time, and that global diversification opportunities using local industry portfolios have increased after 1995. Moreover, the results support that global industry diversification has become relatively more efficient than geographic diversification only in the late 1990s, although this could be a temporary result. This is consistent with the early evidence in Heston and Rouwenhorst (1994) and the recent evidence in Cavaglia, Brightman, and Aked (2000).

The second paper addresses the question: does sovereign debt ratings news in one country impact other countries stock markets? Brooks, Faff, Hillier, and Hillier (2004) find that sovereign ratings downgrades have a negative impact on the re-rated country stock market returns. Kaminsky and Schmukler (2002) show that emerging market sovereign ratings news is contagious to bond and stock markets of other emerging markets. Gande and Parsley (2003) find that the international spillover effect on the sovereign debt market is asymmetric. In fact, only downgrades abroad are associated with a significant increase in sovereign bond spreads. Furthermore, there is a need for a through empirical investigation of the cross-country stock market impact of ratings news with: 1) a sample that includes both emerging and developed countries; and 2) a methodology that specifically addresses the (potential) asymmetry of market reactions and the tendency for ratings changes to cluster in time.

The paper basic methodology is an extension to the across-market case of the Gande and Parsley (2003) research design to study across-countries debt market spillover effect. Specifically, we consider a large set of countries that includes not only emerging but also developed markets; we explicitly control for recent rating activity worldwide; we characterize the spillover effects economically (e.g., by including controls for capital flows and level of economic and financial development); we study the role of exchange rates in spillover effects; and we present several new results of cross-country and cross-market news spillover at the industry level. The impact of sovereign rating news on industry portfolios is of particular relevance given the increased perception by investors and empirical evidence that industry factors are becoming more important than country factors in explaining stock returns.

The paper major findings can be summarized as follows. Ratings changes in one country contain valuable information for the aggregate stock market returns of other countries, but only downgrades On average, a one-notch ratings downgrade abroad is associated with a statistical significant negative two-day stock return spreads vis-à-vis the US stock market of 28 basis points across non-event countries, whereas no significant pattern is found for ratings upgrades. This pattern is not affected by taking into account time invariant characteristic that proxy for underlying similarities between countries (cultural, regional and institutional environment as well as level of economic and financial development). Also, ratings downgrades are associated with a depreciation of the US dollar exchange rate against the non-event country currencies. Thus, the appreciation of non-event country currencies relative to the US dollar (partially) hedges the negative wealth effect of ratings downgrades abroad. Finally, the paper evidence shows that ratings downgrades announcements are also noticed at the local industry level. Sovereign ratings downgrades abroad are associated with a highly statistical significant negative two-day return spread (25 basis points) of industry portfolios vis-à-vis their counterpart industry in the US.

Overall, our findings are robust across different empirical specifications, namely explicitly accounting for recent rating activity, alternative ways to measure the impact in the stock market (dependent variable), and sub-samples of countries and industries.

The third paper studies international equity markets correlation at the global industry level. While much is known about cross-country correlation, on the other hand the global industries correlations have not been studied in the literature. The goal is to contribute to the literature on international investments with the characterization of global industry portfolios correlation in terms of time series behavior and asymmetries.

Two features characterize the methodology. First, realized correlation is estimated using within month daily index return data, which allows the construction of a time series of correlations between global industries and aggregate world market over the 1979-2003 period. Second, we study the correlations for different groups of industries, specifically size and price-earnings ratio.

The paper findings can be summarized as follows. Global industry correlations fluctuate over time and the 1999-2003 period is characterized by low correlations. However, there is not a significant long-term trend. Also, correlation is lower for small and value (low price-earning ratio) industries. Moreover, global industry correlations are counter-cyclical. With respect to asymmetries, global industry correlations are greater for downside moves than for upside moves. Correlation asymmetry is insignificant only for the resources and utilities industries. Correlation asymmetry is the largest among small industries. These findings are robust to the use of value or equal weighted aggregate market index, two-days returns, two-month estimation window, outliers correction, and the returns currency denomination.

We further investigate correlation behavior by decomposing it in realized betas and volatility ratios (market to industry). There is a similarity between correlation and betas behavior over the long-run. Industry betas and, especially, volatility ratios increase for downside market moves.

The characterization of global industries correlations yields both reassuring and disturbing news for global equity investors. On the bad side, our results confirm for global industry portfolios, two features that characterizes cross-country correlations. Industry correlations increase for downside market moves (Longin and Solnik (2001)) and increase during recessions (Erb, Harvey, and Viskanta (1994)). Thus, the power of global industry diversification to reduce portfolio risk decreases during bad times. On the positive side, we find that industry correlation does not show a systematic increase over time, which is in contrast with the findings of a positive trend in cross-country correlation (Solnik and Roulet (2000)).

Contents

List of Tables

List of Figures

CHAPTER 1

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

(with Miguel Ferreira)

1.1. Introduction

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

The historical evolution of total risk is particularly important for global portfolio managers of undiversified international portfolios. If the risk that must be diversified away has increased, there are both more opportunities for international diversification and more assets needed to achieve a given level of diversification. The benefits of investing abroad may become harder to achieve, but the compensation for pursuing such an investment strategy is also greater. If investors face wealth constraints or transaction costs, increased diversifiable risk implies less diversification of their investment portfolios, unless they have superior stock selection capabilities. Total volatility is also an issue for taking advantage of mispriced individual assets, for pricing equity derivatives, and for measuring the market risk of equity portfolios (e.g., Value-at-Risk).

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

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

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

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

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

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

Our primary goal is to describe the historical behavior of total volatility components and to study the implications for international diversification. We address three main questions. First, has the relative importance of world, country, and local industry risk changed over time? Second, has the power of international diversification to reduce risk been weakening? Finally, given the conflicting evidence in the literature, we take another look at the question of the relative efficiency of country versus industry diversification for global equity investors.

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

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

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

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

Second, the October 1987 crash was felt at both world and country levels, but had less of an effect on local industry risk. A period of increased local industry volatility may be seen since the beginning of 1987. The early 1990s may be considered an atypical period in historical terms; during the 1990-1995 period, the share of country risk in total risk is unusually high, and total risk is on average lower than in the surrounding years.

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

Fourth, the ratio of local industry to world risk experienced a considerable increase during the final years of our sample. The average ratio is 3.23 for the 1996-2001 period compared to 2.50 in the 1974-1995 period. Accordingly, the average contemporaneous pairwise correlation

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

between local industry portfolios declines considerably from 0.287 (1974-1995) to 0.203 (1996-2001). Thus, the benefits of international portfolio diversification have become greater and the diversification of global portfolios using local industry portfolios has become harder to achieve as more assets are needed.

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

The paper is organized as follows. Section 1.2 presents 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 1.3 gives details on the data set. Section 1.4 presents the empirical findings concerning the historical evolution of the disaggregated volatility measures. Section 1.5 discusses the implications for global portfolio management. Section 1.6 offers concluding comments.

1.2. Methodology

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

1.2.1. Total Volatility Decomposition

The volatility of a typical (or average) local industry is described by three components: world market volatility, average country volatility, and average local industry volatility.[4] We

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

provide a decomposition of volatility that does not require the estimation of covariances or betas for local industries or countries, which is the most appealing feature of the Campbell et al. (2001) methodology applied to international stock markets. In fact, beta time-dependence and error estimation are well documented in the literature and there is some controversy on which factors should be used in multifactor international asset pricing models to describe the cross-section of expected returns.

The excess return of industry i portfolio in country c for period t is denoted R_{ict}.[5] 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. According to a weighting scheme based on market capitalization, $x_{ict} = MV_{ict} / \sum_{i \in c} MV_{ict}$, where MV_{ict} denotes the market value of the local industry portfolio ic (assumed known at time t). Let x_{ct} denote the weight of country c in the world market portfolio (if market values are used as weights, then $x_{ct} = \sum_{i \in c} MV_{ict} / \sum_c \sum_i MV_{ict}$). 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:

$$R_{ct} = R_{wt} + e_{ct}, \tag{1.1}$$

and similarly for local industry portfolio returns:

$$R_{ict} = R_{ct} + u_{ict} = R_{wt} + e_{ct} + u_{ict}. \tag{1.2}$$

Equation (1.2) 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:

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

$$
\begin{aligned}
\mathrm{Var}(R_{ict}) &= \mathrm{Var}(R_{wt}) + \mathrm{Var}(e_{ct}) + \mathrm{Var}(u_{ict}) \\
&\quad +2\ \mathrm{Cov}(R_{wt}, e_{ct}) + 2\ \mathrm{Cov}(R_{wt}, u_{ict}) + 2\ \mathrm{Cov}(e_{ct}, u_{ict}).
\end{aligned} \tag{1.3}
$$

While the local industry return variance in equation (1.3) includes covariance terms, the cross-sectional weighted average sum of all the basic asset total variance across all local industry portfolios is free of individual covariance terms, provided that we use the same non-stochastic weighting scheme to compute the averages that we use to compute country and world portfolios returns.[6] Thus, the volatility of a typical local industry portfolio is given by:

$$
\begin{aligned}
\sum\nolimits_{c\in w} x_{ct} \sum\nolimits_{i\in c} x_{ict} \mathrm{Var}(R_{ict}) &= \mathrm{Var}(R_{wt}) + \sum\nolimits_{c\in w} x_{ct} \mathrm{Var}(e_{ct}) \\
&\quad + \sum\nolimits_{c\in w} x_{ct} \sum\nolimits_{i\in c} x_{ict} \mathrm{Var}(u_{ict}) \\
&= \sigma^2_{wt} + \sigma^2_{et} + \sigma^2_{ut},
\end{aligned} \tag{1.4}
$$

where σ^2_{wt} represents the variance of the world market portfolio; σ^2_{et} is the weighted average of country-level variance across all countries; and σ^2_{ut} is the weighted average of within-country industry-level variance across all local industries and countries. The RHS of equation (1.4) can be interpreted as the expected variance of a typical local industry portfolio.

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

In the framework of the single factor international capital asset pricing model (ICAPM) of Grauer, Litzenberger, and Stehle (1976), where the factor is the excess return on the world

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

portfolio, which allows for country and local industry betas to be different from unity, the excess return on an individual local industry portfolio is written as:[7]

$$R_{ict} = \beta_{ic} R_{ct} + \tilde{u}_{ict} = \beta_{ic} \left(\beta_c R_{wt} + \tilde{e}_{ct} \right) + \tilde{u}_{ict} = \beta_{ic} \beta_c R_{wt} + \beta_{ic} \tilde{e}_{ct} + \tilde{u}_{ict}, \tag{1.5}$$

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

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

$$\sigma^2_{et} = \sigma^2_{\tilde{e}t} + CSV_t(\beta_c)\sigma^2_{wt}, \tag{1.6}$$

$$\sigma^2_{ut} = \sigma^2_{\tilde{u}t} + CSV_t(\beta_{ic})\sigma^2_{\tilde{e}t} + \left[CSV_t(\beta_{iw}) - CSV_t(\beta_c) \right] \sigma^2_{wt}, \tag{1.7}$$

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 (1.6) 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-sectional variance of β_c, times σ^2_{wt}. By the same reasoning, equation (1.7) shows that the biases in the proposed estimate of local industry risk depend on the variation of world returns, country residuals, and betas. Cross-sectional variation in country and local industry betas can produce common variation in our variance components - market, country and local industry. However, we will show in Section 1.4.2 that cross-sectional variation in betas has only a small effect on the historical behavior of our volatility measures.

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

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

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

1.2.2. Estimation

We use daily data within a month to construct sample variance estimates for that month. The volatility components of equation (1.4) are estimated as follows. Let d refer to days in month t. For the world portfolio variance $W_t \equiv \hat{\sigma}^2_{wt}$ in month t:

$$W_t = \sum\nolimits_{d \in t} (R_{wd} - \mu_{wt})^2, \tag{1.8}$$

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

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

$$C_t = \sum\nolimits_c x_{ct} \sum\nolimits_{d \in t} e^2_{cd}, \tag{1.9}$$

where x_{ct} stands for the weight of country c in the world portfolio in month t, which we measure by using the end-of-month $t-1$ market capitalization, and e^2_{cd} is the square of the market-adjusted country-specific residual from equation (1.1).

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

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

$$I_t = \sum\nolimits_c x_{ct} \sum\nolimits_{i \in c} x_{ict} \sum\nolimits_{d \in t} u_{icd}^2, \tag{1.10}$$

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 (1.2), for each local industry portfolio in the sample.

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

1.3. 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 January 1974 to December 2001. DS indices are preferred over other domestic industry indices because: (1) they are constructed on a uniform basis across countries; (2) they are not backfilled when new constituents are added or deleted; (3) a long time series of daily data is available; and (4) a comprehensive coverage of the industry structure of each domestic stock market is assured. These aspects are important because they eliminate anomalous behavior of the indices attributable to differences in technical aspects of index construction, and, as Griffin and Karolyi (1998) point out, broad industrial classifications may not provide enough cross-sectional variation in returns to distinguish between country- and industry-specific sources of variation.[10]

The 21 developed markets analyzed are selected according to criteria as follows: (1) coverage by the MSCI developed markets database; (2) no classification ever as an emerging market by the S&P/IFC EMDB ; and (3) data availability. Thus, both the number of local

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

industry portfolios and the number of countries represented in the world portfolio are allowed to change over the sample period.[11]

To compute daily excess returns, we subtract the 30-day Treasury bill continuously compounded return divided by the number of trading days in a month from the daily logarithmic stock index rate of return.

Tables 1.1 and 1.2 provide descriptive statistics of the country portfolios and the global industry portfolios. Daily country and global industry portfolio excess returns are computed using a value-weighted average of the available local industry portfolio aggregate either by countries or global industries.

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

Table 1.2 shows that the number of countries that include a particular global industry has changed dramatically over the last three decades. The average maximum number of countries that contribute to a given global industry portfolio is almost three times the average minimum number of countries. Also, the representation of global industry portfolios in the world portfolio is less concentrated than the representation of country portfolios. No single global industry portfolio accounts on average for more than 9% in the world portfolio (banks). Interestingly, the most volatile global industry portfolios are software and computer services (24.6% annualized standard deviation) and information technology (21.9%).

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

Tables 1.1 and 1.2 together show that, in our sample, the opportunities for global investment increased substantially during the last three decades, largely because of an increased number of industries available in each country.

1.4. Historical Evolution of Total Volatility Components

Have the risks of world, country, and local industry return components been changing over time? We provide a graphical analysis of the time evolution of the W, C, and I risk measures, estimated using equations (1.8) through (1.10), and discuss relevant descriptive and test statistics concerning the major features of the estimated volatility series.

1.4.1. Graphical Analysis and Descriptive Statistics

Figures 1.1, 1.2, and 1.3 plot our estimates of the world, country, and local industry volatility. To facilitate interpretation, we report annualized standard deviation, and backward 12-month moving average.

Stulz (1999) finds that world portfolio volatility presents considerable time variation, but has not shown a tendency to increase over time, and that the 1970s and the 1990s were periods of relatively low volatility. The time pattern revealed by the plots in Figure 1.1 is consistent with his results.

The all-time high for the W series corresponds to the October 1987 crash (58.6% annualized standard deviation). The second-highest value occurs in August 1990 (28.2% annualized standard deviation), and clusters of volatility spikes are visible in 1974, 1982, and 1990-1992. There is also evidence of an increase in world volatility for the 1997-2001 period. In fact, the smoothed 12-moving average plot suggests that W has a slow-moving component, reinforcing the idea of persistent behavior.

Figure 1.2 shows that the country risk measure (C) behaves much the same as the world volatility (W). The 1987 crash had a slightly less pronounced effect on C (53.8% annualized standard deviation in October 1987) but with similar timing. Similar to world risk, the country volatility shows no upward trend.

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

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

The local industry risk plot presented in Figure 1.3 shows a different pattern from the patterns of W or C. The 1987 crash impact is not concentrated around that single month (October), and its extent is much less pronounced.[12] In October 1987, the average industry risk reached 29% (annualized standard deviation), but the period of higher volatility at the local industry level started earlier (the average annualized standard deviation for the first semester of 1987 is 21%, well above its 12-month moving average).[13]

The most striking feature of Figure 1.3 is the significant rise toward the end of the sample period when the maximum for industry volatility was reached in April 2000 (37.7% annualized standard deviation). This evidence is consistent with the growing importance of global industry effects in explaining international return variation, which may be a temporary phenomenon associated with the information technology bubble; see Brooks and Catão (2000).

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

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

The time evolution of the volatility components over time indicates that monthly volatility estimates are time-varying; that periods of high volatility are concentrated around specific times and are followed by periods of relative stability; and, that there is some evidence the series may be diverging upward from some lower bound, which leaves open the possibility there may be an upward trend. Especially clear is a rise in local industry risk toward the end of our sample.

Table 1.3 reports summary statistics for the monthly variance measures for the G21 developed world. Panel A presents results for the whole sample period from 1974 through 2001 and Panels B-F for four non-overlapping subperiods of 72 months each and a middle subperiod of 48 months. Panels B (1974-1979) and C (1980-1985) capture the dynamics of the earlier years. Panel D (1986-1989) covers the high-volatility period, especially at world and country levels, surrounding the 1987 crash. Panel E (1990-1995) represents a period of relatively low level and stability in all series. Finally, Panel F (1996-2001) covers the high industry-level volatility period that we have remarked on.

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

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

The numbers in Panel A of Table 1.3 also imply that the degree of unconditional variance of a typical investment in a local industry portfolio that is due to the world portfolio volatility,

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

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

or the R^2 of a world market model, is about 22.8% for the whole sample period (downweighted crash). The shares of C and I are 31.7% and 45.6%, respectively.

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

1.4.2. Volatility Trends

The short-lived effect of the 1987 crash on volatility at world and country levels becomes clear when we compare the autocorrelations for the raw data and the downweighted crash data. Autocorrelation structure in Table 1.3 indicates that all series show a high degree of positive serial correlation, especially I. When we downweight the impact of the crash, W and C are considerably more autocorrelated. This high persistence, together with the evidence on an upward trend in the volatility series, raises a question about the nature of possible trends.

Table 1.3 also reports the results of parametric augmented Dickey-Fuller (ADF) t tests and semi-parametric Phillips-Perron (PP) Z_t tests with an intercept for a unit root in the individual volatility series. The hypothesis of a unit root is rejected at the 5% level, whether or not the 1987 crash is downweighted and whether or not a deterministic time trend is included in the regression, with the exception of the ADF t test for the industry series. Thus, the volatility series seem to be stationary, so deviations from the long-run mean do not produce permanent effects on the behavior of the risk measures. This conclusion is consistent with the temporary swings we have already noted in Figures 1.1-1.3.

To test for the significance of a possible deterministic linear time trend in the volatility series, we employ the Vogelsang (1998) $t - PS_T$ trend test, which performs well in finite samples with serial correlation. The results reported in the last two columns of Table 1.3 reveal that the highest slope is for industry risk (0.0716×10^{-4}), which is three times higher than for the world risk measure and about 2.8 times higher than the linear trend coefficient for the country risk measure in the raw data set. The $t-PS_T$ show that the trend coefficients are not statistically positive at the 5% level even for I, and so we are unable to reject the null hypothesis of no deterministic time increase for all volatility series. In fact, volatility measures are higher by the end of our sample, but this does not seem to be the consequence of a long-term upward trend.

Table 1.4 shows that time patterns are fairly robust to the regional coverage of the sample and data frequency.[16] The level of disaggregated volatility estimates naturally changes, but that does not imply different patterns for the historical behavior of the volatility series estimated from daily data for the G21 world portfolio. For instance, when only the G7 countries and Switzerland are analyzed, the average sample estimates from daily data are 0.1181×10^{-2} for W, 0.1353×10^{-2} for C, and 0.2043×10^{-2} for I, almost identical to the estimates constructed for the G21 world portfolio. When we exclude the US market from the world portfolio, we obtain similar results. The maximum for the W and C series is still recorded in October 1987, and the final years of our sample are still characterized by huge increase in local industry risk.

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

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

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

weights) of the cross-sectional variance of country betas is only 0.016. Hence, the cross-sectional variation in betas explains only a small proportion of the covariation between W and C.

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

1.4.3. Individual Countries Risk Measures

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

If one is interested only in the behavior of local industry volatility in each country, we can easily develop a measure of industry-specific volatility per country. We simply do not take an average across countries of the industry-specific volatility for each country. That is, from equation (1.2) and before taking the average across countries in equation (1.4), it can be shown that:

$$\sum_i x_{ict} Var(R_{ict}) = Var(R_{ct}) + \sum_i x_{ict} Var(u_{ict}). \tag{1.11}$$

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

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

$$R_{ct} = \beta_c R_{wt} + \varepsilon_{ct}. \tag{1.12}$$

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

$$Var(R_{ct}) = \beta_c^2 Var(R_{wt}) + Var(\varepsilon_{ct}). \tag{1.13}$$

Table 1.5 reports the individual country results, which give a strong message. The increased industry volatility documented for the late 1990s at the world level, is also seen in most individual countries. Linear trend coefficients are positive for 17 countries, although not statistically significant. The results for the subperiods show that industry volatility is on average higher for 1996-2001 than for previous years, for all countries with the exception of New Zealand.[17]

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

Two features strike us the most with regard to country risk. First, for three countries (France, Norway, and the 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 varies more across countries than industry risk. These findings strengthen the intuition that the characteristics of variance measures may vary considerably across countries, particularly notable at the country risk level. Countries with higher industry risk also tend to be riskier at the country level (the correlation between average industry variance and average country variance across countries is 0.53).

Thus, we are not surprised to see that smaller countries, countries with more weight given to a single industry, and countries with greater variation in the number of industry portfolios also tend to have more country risk. The correlation across countries between

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

average country variance and country market capitalization is -0.375. The correlation of the average country variance with the average weight of the largest local industry portfolio is 0.502, and the correlation with the difference between maximum and minimum number of industries for a given country is 0.571.

1.4.4. Individual Global Industry Risk Measures

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

$$R_{it} = R_{wt} + u^*_{it}. \tag{1.14}$$

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

$$\sum_i x_{it} Var(R_{it}) = Var(R_{wt}) + \sum_i x_{it} Var(u^*_{it}). \tag{1.15}$$

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

$$R_{it} = \beta_i R_{wt} + v^*_{it}. \tag{1.16}$$

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

$$Var(R_{it}) = \beta^2_{iw} Var(R_{wt}) + Var(v^*_{it}). \tag{1.17}$$

Aggregate global industry variance, $\sum_i x_{it} Var(u^*_{it})$, is estimated using daily returns within each month. Individual global industry variances, $Var(v^*_{it})$, are estimated using a two step procedure. The first step consists of estimating betas by an ordinary least squares regression of global industry monthly excess returns on world monthly excess returns. In the second step, daily squared residuals from equation (1.16) are summed within a month to obtain a monthly estimate for the variance of each global industry portfolio.

Panel A of Table 1.6 presents descriptive statistics and linear trend coefficient for the global industry risk measure and Panel A of Figure 1.4 plots the series. Comparing industry risk measured locally and globally, both series present positive linear trend coefficients, although values are not statistically significant. In addition, both series show a significant increase in the late 1990s; global industry risk reaches a historical maximum of 29.6% in April 2000. The average global industry risk for the 1996 to 2001 period is about 1.7 times higher than its unconditional mean and 2.5 times higher than in the early period between 1974 and 1979.

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

To further investigate this hypothesis and obtain insights into the impact of the new economy stocks on the behavior of the aggregate risk measures, we reestimate global industry risk excluding the TMT industries.[18] Descriptive statistics on global industry risk excluding the TMT industries are also shown in Panel A of Table 1.6, and Panel B of Figure 1.4 plots the series.

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

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

These results show that, at a global level, the TMT industries represented an important component of the increase in industry risk toward the late 1990s, but the increase in risk is not driven solely by these industries. The old economy also presented an important increase in industry risk.

Panel B of Table 1.6 presents results for the 10 individual global industries with the largest average market capitalization.[19] There is no statistically significant time trend, although the coefficients are positive for most global industries. The results suggest that smaller global industries, with less variation in the number of countries where they operate, or that are more concentrated in a single country, tend to be riskier. The correlation across global industries of the average industry specific risk with the global industry market capitalization is -0.234. The correlation of the average industry specific risk with the difference between the maximum and minimum number of countries represented is -0.129, and the correlation with the average weight of the most important country in each global industry is 0.583. Interestingly, the global industry with highest 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 1996-2001 period, the point estimate of average industry-specific risk is higher than its unconditional mean for 35 of 38 industries.

Heston and Rouwenhorst (1994) conclude that country diversification is more efficient than industry diversification. More recent evidence, e.g., Cavaglia et al. (2000), shows that

[19]Results for other industries are not shown here, but are available upon request.

industry diversification became as important as country diversification in the late 1990s. The results in Table 1.6 suggest that the ratio of global industry risk to country risk has been fairly stable over the years, with the exception of the notable increase from 1995 onward. This ratio fluctuated around an average of 0.7 until 1989, followed by a period it was visibly lower (on average 0.5 between 1990 and 1995), and finally a period of sustained increase in the late 1990s (on average greater than 1.0 after 1998). The ratio of local industry risk to country risk (see Table 1.3) also shows a clear increase in the late 1990s. Thus, the results suggest that towards the end of our sample period, international diversification power increases if an industry dimension is privileged over a geographic dimension. These results are consistent with the fixed-effects model evidence in Heston and Rouwenhorst (1994) and Cavaglia et al. (2000).

1.4.5. 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 mean and variance decompositions. By definition: $\sigma_{it}^2 = \sigma_{ut}^2 + \sigma_{et}^2 + \sigma_{wt}^2$ is the total volatility of a "typical" investment in a local industry portfolio [see equation (1.4)] for period t. Then, taking expected values and dividing the RHS elements by the LHS, we obtain a decomposition for the mean total volatility:

$$1 = E(\sigma_{ut}^2)/E(\sigma_{it}^2) + E(\sigma_{et}^2)/E(\sigma_{it}^2) + E(\sigma_{wt}^2)/E(\sigma_{it}^2). \tag{1.18}$$

Specifying a sample period, we can estimate the expected values by their sample means, using the volatility estimators defined in equations (1.8)-(1.10). Similarly, for the variance of total volatility:

$$\begin{aligned} 1 \quad = \quad & Var(\sigma_{ut}^2)/Var(\sigma_{it}^2) + Var(\sigma_{et}^2)/Var(\sigma_{it}^2) + Var(\sigma_{wt}^2)/Var(\sigma_{it}^2) \qquad (1.19) \\ & +2Cov(\sigma_{ut}^2, \sigma_{et}^2)/Var(\sigma_{it}^2) + 2Cov(\sigma_{ut}^2, \sigma_{wt}^2)/Var(\sigma_{it}^2) \\ & +2Cov(\sigma_{et}^2, \sigma_{wt}^2)/Var(\sigma_{it}^2). \end{aligned}$$

From the results in Table 1.3, we know that the variance of a randomly selected local industry portfolio increases about 125% over the whole sample period (from 0.3224×10^{-2} in the 1970's to 0.007245 in the late 1990s, compared to a long-run unconditional mean of 0.4620×10^{-2}), and that the most significant increase occurred in the late 1990s. The means in the first column of Table 1.7 confirm that local industry risk has gained increased importance.

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

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

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

The high-frequency movements of the three volatility measures already noted in Figures 1.1-1.3 appear to be correlated, and the contemporaneous correlation estimates reported in

Panel A of Table 1.8 confirms this. To investigate the causality issue, we estimate bivariate and multivariate vector autoregression (VAR). We use crash downweighted variance series, and the multivariate version of the Akaike information criterion is used to select the VAR lag length (10 lags for the pair W and C and 6 lags for the remaining pairs and the trivariate system).

Panels B and C of Table 1.8 report the p-values of a standard F-test on each equation for the null hypothesis that the lags 1 to k of each variable do not help to forecast the dependent variable for the VAR systems.

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

1.5. Global Portfolio Management Implications

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

Declining correlations among individual assets returns would let the volatility of the market portfolio remain stable even if individual volatilities rise. Thus, the growing increase in the importance of local industry risk relative to the common factor (world risk) noticed toward the end of our sample (and plotted in Panel A of Figure 1.5) is consistent with reduced correlations among local industry portfolios.

Panel B of Figure 1.5 plots the equal-weighted average pairwise correlation among local industry portfolios available in our sample. We use both monthly and daily returns.[20]

[20] In international stock market studies, one cannot ignore the effects of non-overlapping trading hours on the correlation between assets traded in non-contemporaneous markets, which are more significant with the use

Correlations are calculated each month, between all pairs of industry portfolios for which 60 months (260 days) of data are available for that month. The number of estimated monthly (daily) pairwise correlations ranges from about 36,000 to over 153,000 (184,000) as the number of basic assets changes over time. Monthly correlations are systematically higher for the whole sample (0.265 average) than daily estimates (0.146), which is consistent with the daily downward biases for positively related markets.

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

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

To illustrate this point, we construct portfolios containing different numbers of randomly selected assets, and compute the simple average of the difference between each portfolio standard deviation and the standard deviation of an equally weighted portfolio of all assets used in the calculations. For each year-end, we randomly group (without replacement) local

of daily data. Kahya (1997) shows that the estimated correlations of daily returns for positively (negatively) related markets are biased downward (upward). There is no significant bias associated with the use of monthly data.

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

industry portfolios with at least 60 consecutive monthly return observations available up to that date. Panel A of Figure 1.6 plots annualized excess standard deviations over time for portfolios of 2, 5, 20, and 40 assets calculated from monthly returns.[22]

The peak in excess standard deviation is reached in 2000 for all portfolios (10.7%), and all exhibit a modest increase up through 1995. For the 2-randomly selected local industry portfolio, the excess standard deviation is 8.0% in 1995 compared with 7.7% in 1978. For the larger portfolios, the pattern is the same, although at much lower values.

Panel B of Figure 1.6 plots annualized excess standard deviation against number of assets in the portfolio calculated from monthly returns. Data for these plots are obtained by averaging the yearly estimates of excess standard deviations over the sample periods. As is shown, the increase in local industry risk for the 1996-2001 period implies that more basic assets are needed to reduce excess standard deviation. For instance, estimates show that to reduce excess volatility to about 2%, 12 industry portfolios are needed in the 1996-2001 period. In earlier sample periods, the same level of diversification could be reached with approximately 9 industries.

1.6. Conclusion

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

We find that between 1974 and 2001, world and country risk remained fairly stable. Industry risk, both at the local and the global level, however, displayed a huge increase during the late 1990s, after a long period of relative stability. This increase is not attributable solely to the new economy bubble. Local industry risk dominates world and country risk,

[22]Similar results using daily returns are not shown here, but are available upon request.

except during the 1990-1995 period, when country risk is on average the most important component. World risk is systematically the least important component of total risk.

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

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

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Table 1.1: Descriptive Statistics for Country Portfolios

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

		Returns			Size	Industries		Max
Countries	Mnemonic	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 1.2: Descriptive Statistics for Global Industry Portfolios

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

		Returns			Size	Countries		Max
Industries	Mnemonic	Obs.	Mean	Stdev	(US $ M.)	Max	Min	weight
Aerospace & Defense	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 & Build. Mat.	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 & Electrical Eq.	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 Prod. & 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	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, Entert. & 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 & 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. Prod.	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 & Comp. Services	SFTCS	7305	4.5%	24.6%	236,811	20	2	86.8%
Specialty & Other Finance	SPFIN	7305	4.7%	19.5%	284,771	17	7	62.1%
Steel & 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 1.3: Descriptive Statistics for World, Country, and Industry Risks

Descriptive statistics for monthly variance measures constructed from daily data, W, C, and I as described in equations (1.8) to (1.10), respectively. Mean, standard deviation (Stdev), minimum (Min), maximum (Max), and median (Med) estimates of monthly variances are multiplied by 100. ρ_k is the autocorrelation of order k, Skew is the skewness, Kurt is the excess kurtosis, ADF is the augmented Dickey-Fuller test for unit root with an intercept, and PP is the Phillips-Perron test for unit root with an intercept. The 5% critical value for the unit root ADF and PP tests with intercept is –2.87. Trend is the linear trend coefficient multiplied by 10^4, and $t - PS_T$ is the Vogelsang test for deterministic linear trends whose 5% critical value is 1.72. The lines W^{dc} and C^{dc} are for a modified dataset where the October 1987 observation is replaced by the second-highest observation in the respective series.

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

Table 1.4: 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 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 1.5: Volatility Measures by Countries

Descriptive statistics for industry and country level variance for individual countries. Industry volatility is constructed using equation (1.11) and country volatility using the residuals from a world market model according to equation (1.13). 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 test statistic for deterministic linear trends whose critical value is 1.72.

Country	β	$se(\beta)$	Industry Variance				Country Variance			
			Mean	Stdev	Trend	$t\text{-}PS_T$	Mean	Stdev	Trend	$t\text{-}PS_T$
Australia	1.02	0.08	0.2580	0.1864	-0.0264	-1.39	0.3626	0.5292	-0.0446	-0.63
Austria	0.54	0.09	0.2497	0.1894	0.0823	0.56	0.2319	0.2649	-0.0248	-0.21
Belgium	0.76	0.06	0.2579	0.2453	-0.0193	-0.74	0.1880	0.1689	-0.0191	-1.01
Canada	0.89	0.05	0.3684	0.9885	0.0515	-0.48	0.1207	0.1356	0.0098	-0.03
Denmark	0.65	0.07	0.3136	0.2228	0.0263	-0.39	0.2221	0.1508	-0.0192	-1.12
Finland	1.15	0.13	0.7085	0.9375	0.0917	-0.36	0.6181	0.7135	0.7356	0.68
France	1.02	0.06	0.3213	0.2661	0.0532	-0.13	0.2534	0.2378	-0.0685	-4.07
Germany	0.80	0.06	0.1922	0.2168	0.1067	0.30	0.1935	0.1597	0.0106	0.34
H. Kong	1.21	0.11	0.2530	0.2240	0.0323	-0.22	0.7001	1.1762	-0.0671	-0.80
Ireland	0.84	0.08	0.4769	0.3551	0.4268	0.79	0.2435	0.1932	0.0371	-0.05
Italy	0.84	0.08	0.2715	0.3087	-0.0228	-1.25	0.4121	0.4429	-0.0677	-1.19
Japan	1.10	0.06	0.2169	0.1914	0.0472	0.30	0.2082	0.2396	0.0890	0.59
Netherlands	0.85	0.04	0.2253	0.2408	0.1115	0.31	0.1603	0.1435	-0.0137	-1.29
N. Zealand	0.84	0.10	0.3969	0.2897	-0.0491	-0.69	0.3826	0.3857	-0.1194	-0.95
Norway	1.03	0.09	0.4717	0.3440	0.0806	-0.06	0.4097	0.3903	-0.1286	-2.65
Singapore	1.18	0.09	0.3587	0.5980	0.0925	0.12	0.4356	0.6057	-0.0569	-1.01
Spain	1.02	0.08	0.3128	0.3491	0.0225	-0.24	0.2593	0.3636	-0.0479	-0.67
Sweden	1.12	0.08	0.4742	0.3573	0.2359	0.98	0.3680	0.3929	0.0323	-0.39
SW	0.82	0.05	0.1479	0.1455	0.0318	0.52	0.1713	0.1492	-0.0151	-0.80
UK	1.06	0.06	0.2241	0.1726	0.0434	-0.07	0.2290	0.2722	-0.1109	-1.96
US	0.87	0.03	0.1688	0.1795	0.0793	0.23	0.0940	0.2088	0.0192	0.91

Table 1.6: Global Industry Volatility

Panel A shows descriptive statistics for global industry variance. Industry volatility is constructed monthly using equation (1.15). $t - PS_T$ is the Vogelsang 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 in the 10 industries with largest average market capitalization for the whole sample period according to equation (1.17). 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
Panel A.1: 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					
Panel A.2: 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 Industry Variance						
	β	$se(\beta)$	Mean	Stdev	Trend	t-PS_T
Banks	1.02	0.04	0.0768	0.0986	0.0006	-0.04
Electricity	0.57	0.04	0.0651	0.0841	0.0176	0.51
Electronic & Electrical Equipment	1.13	0.03	0.0569	0.0595	0.0122	-0.05
Information Technology Hardware	1.24	0.06	0.1790	0.2473	0.1058	0.43
Insurance	0.90	0.04	0.0553	0.0624	0.0186	0.15
Oil & Gas	0.80	0.05	0.1328	0.1527	0.0498	0.36
Pharmaceuticals	0.81	0.04	0.0822	0.0878	0.0277	0.34
Retailers General	0.99	0.04	0.0926	0.1177	0.0341	0.05
Specialty & Other Finance	1.33	0.05	0.1218	0.1329	0.0186	0.48
Telecom Services	0.78	0.05	0.1240	0.2248	0.0071	0.06

Table 1.7: 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 (1.18) and (1.19). W and C refer to a modified dataset where the October 1987 observation is replaced by the second-highest observation in the respective series.

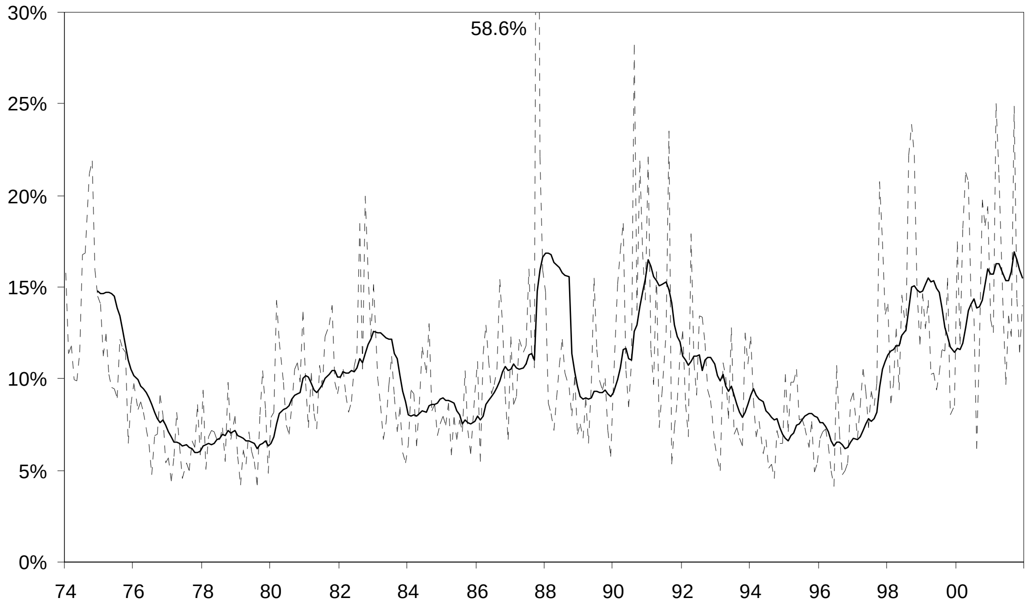
	Mean	Variance-Covariance		
		W	C	I
Panel A: 1974-2001 (N = 336)				
W	22.8%	9.6%		
C	31.7%	14.4%	8.3%	
I	45.6%	19.5%	19.7%	28.2%
Panel B: 1974-1979 (N = 72)				
W	23.3%	12.5%		
C	34.6%	20.0%	13.7%	
I	42.1%	20.5%	21.3%	11.1%
Panel C: 1980-1985 (N = 72)				
W	21.8%	11.4%		
C	31.9%	15.6%	11.9%	
I	46.3%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

Table 1.8: Correlation Structure and Granger-causality Tests

This table shows the correlation structure (Panel A) and the p-values of Granger-causality bivariate VAR tests (Panel B), and trivariate VAR tests (Panel C) for the monthly variance measures constructed from daily data, W, C, and I as described in equations (1.8)-(1.10). W and C refer to a modified dataset where the October 1987 observation is replaced by the second-highest observation in the respective series. The VAR lag-length (10 lags for the pair W and C and 6 lags for the remaining pairs and the trivariate system) was determined by the multivariate version of the AIC criterion. The p-values refer to the F-test of the null hypothesis that the lags 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.

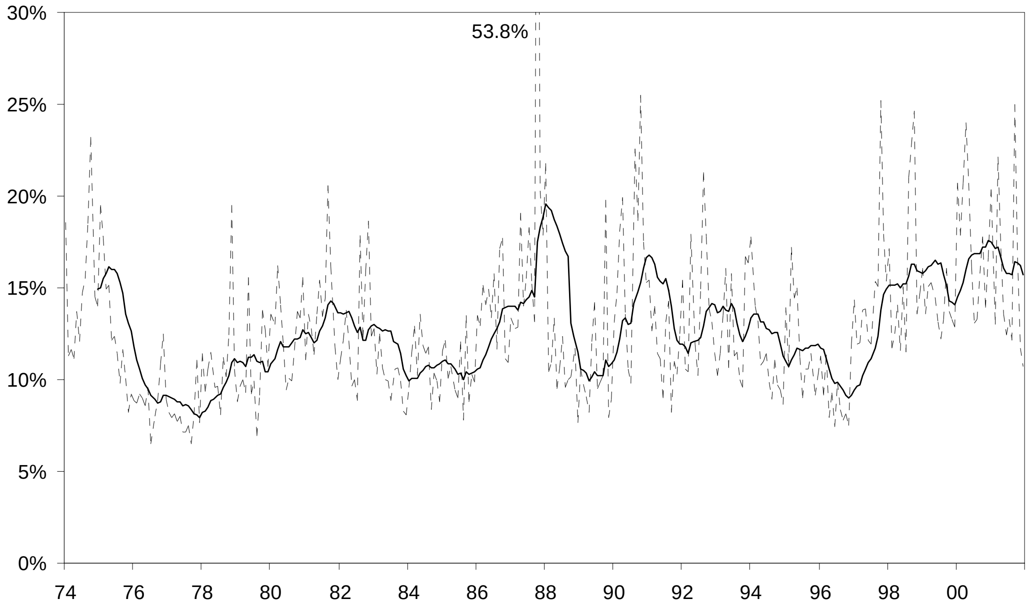
Panel A: Correlations			
	W	C	I
W	1	0.808	0.593
C		1	0.647
I			1
Panel B: Bivariate VAR			
	W_t	C_t	I_t
W_{t-k}		0.5595	0.2617
C_{t-k}	0.0113		0.2290
I_{t-k}	0.0020	0.0084	
Panel C: Trivariate VAR			
	W_t	C_t	I_t
W_{t-k}		0.5845	0.6405
C_{t-k}	0.5493		0.5832
I_{t-k}	0.0057	0.0158	

Figure 1.1: World Volatility



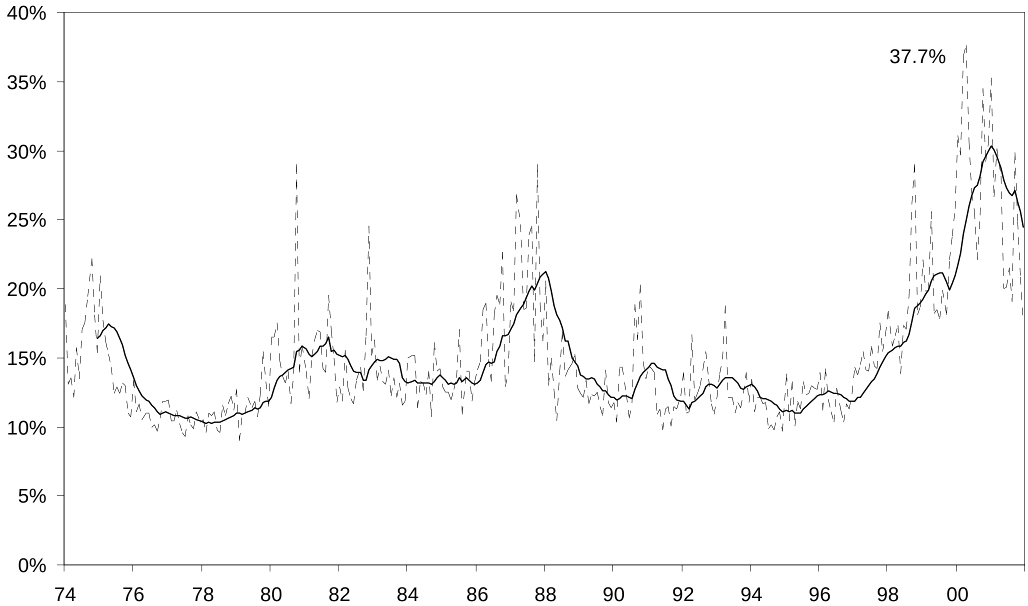
This figure shows annualized standard deviation within each month of daily world market returns (dashed line), calculated using equation (1.8), for the period from 1974 to 2001. Backwards 12-month moving average of W is also shown (solid line).

Figure 1.2: Country Volatility



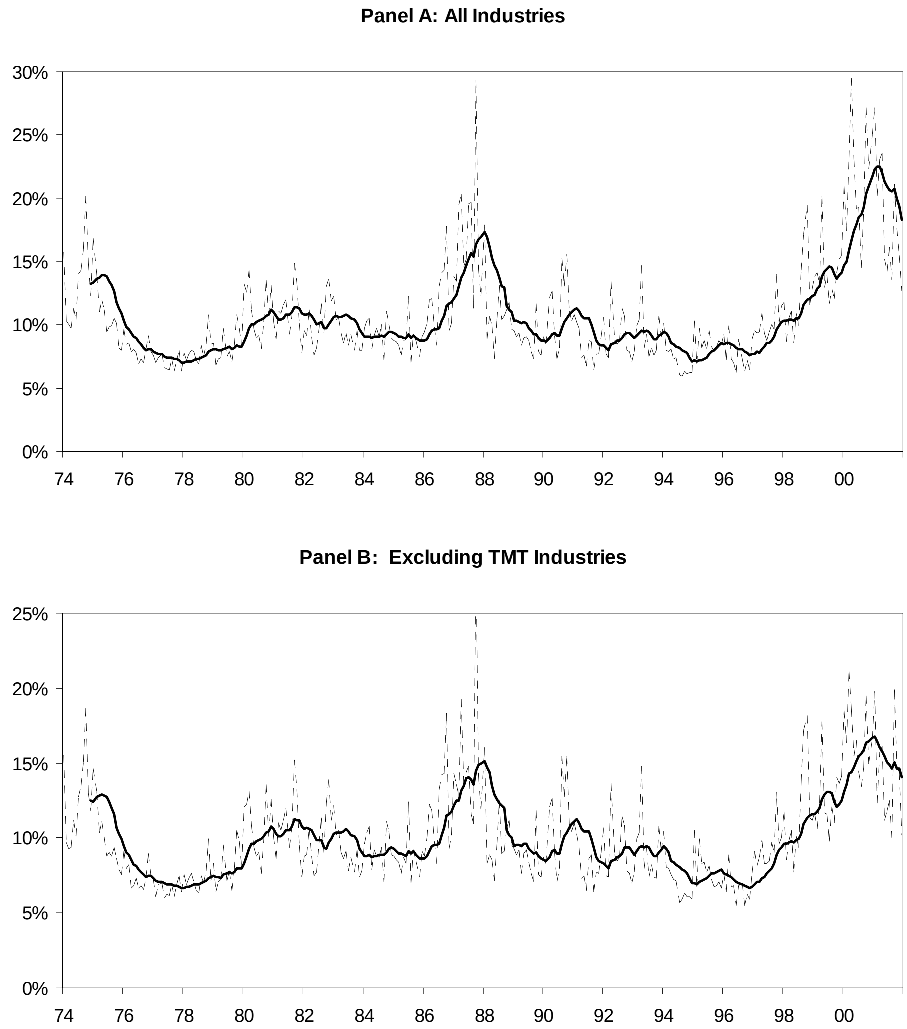
This figure shows annualized standard deviation within each month of daily country returns relative to the world market (dashed line), calculated using equation (1.9), for the period from 1974 to 2001. Backwards 12-month moving average of C is also shown (solid line).

Figure 1.3: Local Industry Volatility



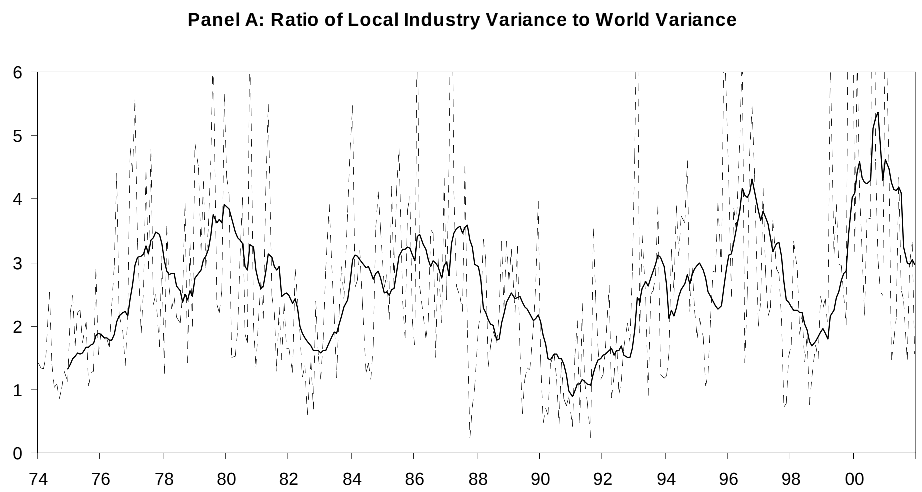
This figure shows annualized standard deviation within each month of daily local industry returns relative to the the local industry country (dashed line), calculated using equation (1.10), for the period from 1974 to 2001. Backwards 12-month moving average of I is also shown (solid line).

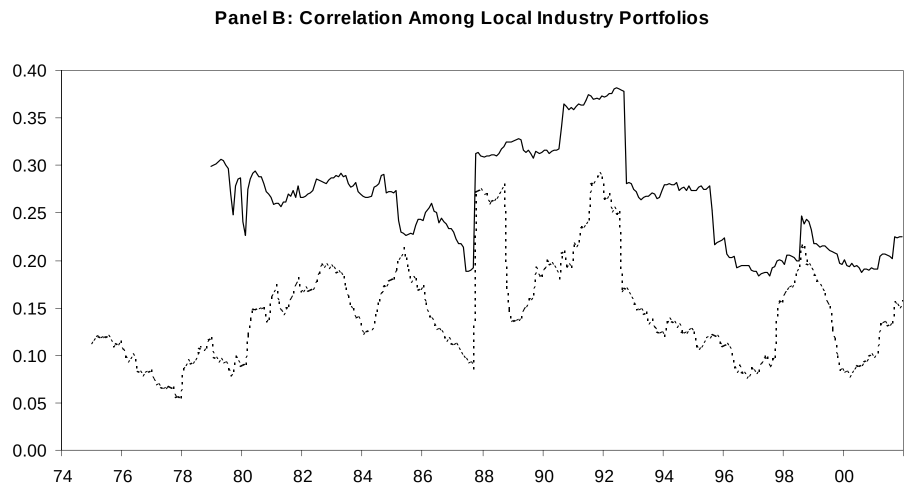
Figure 1.4: Global Industry Volatility



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

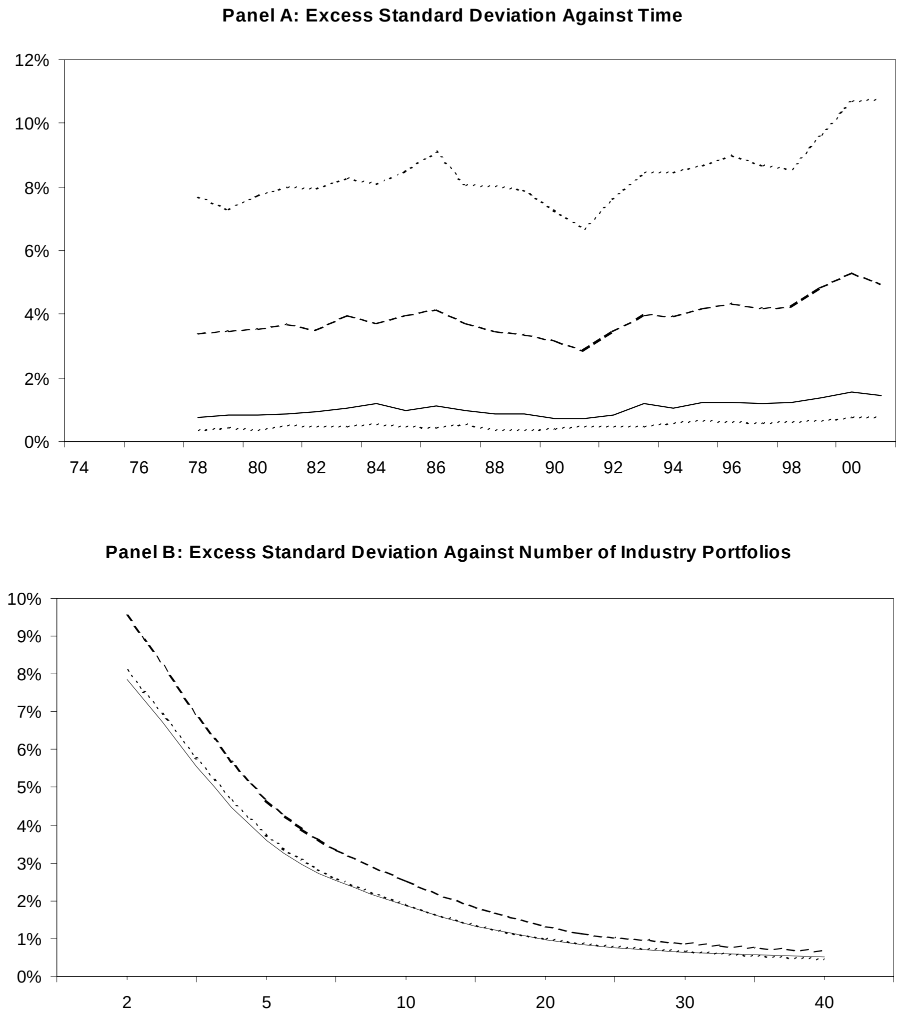
Figure 1.5: Ratio of Local Industry to World Variance and Average Correlation for Local Industry Portfolios





Panel A shows ratio of local industry variance to world variance (dashed line). Monthly variance measures are constructed from daily data as described in equations (1.8) and (1.10). Backwards 12-month moving average is also shown (solid line). Panel B shows equally weighted average pairwise correlation across local industry portfolios. The solid (dashed) line is a plot of the monthly estimates of average monthly (daily) correlation coefficients computed using a rolling window of 60 (260) monthly (daily) observations.

Figure 1.6: International Diversification Benefits Against Time and Number of Local Industry Portfolios



Panel A shows annualized standard deviation of equally weighted portfolios containing 2, 5, 20, and 40 randomly selected basic assets, in excess of the standard deviation of the equal weighted portfolio containing all assets used in the calculations. Panel B shows 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).

CHAPTER 2

Does Sovereign Debt Ratings News Spillover to International Stock Markets?

(with Miguel Ferreira)

2.1. Introduction

Does sovereign debt ratings news in one country impact other countries stock markets? In this paper, we find evidence that yes, indeed sovereign ratings unfavorable news spillover to other countries stock markets. We focus on the cross-country stock market reaction to the announcements by Standard & Poor's (S&P) of a sovereign credit rating or credit outlook change.

Brooks, Faff, Hillier, and Hillier (2004) study *own* country stock market impact of sovereign debt ratings changes. They find that sovereign ratings downgrades have a negative impact on the re-rated country stock market returns. Gande and Parsley (2003) study international spillover effects on the sovereign debt market and find this spillover to be asymmetric. In fact, downgrades abroad are associated with a significant increase in sovereign bond spreads (12 basis points), but upgrades have an insignificant effect. Kaminsky and Schmukler (2002) show that emerging market sovereign ratings news are contagious to bond and stock markets of other emerging markets, particularly during periods of turmoil and among neighbor countries.

We extend the Gande and Parsley (2003) international spillovers pool regression model to investigate the information spillover effect not only *across countries*, but also *across assets*. That is, we focus on spillovers of credit ratings or credit outlooks of one country (the event country) to stock market return spreads (the return differential vis-à-vis the US market) of all other countries (the non-event countries). Relative to Kaminsky and Schmukler (2002) our study contributes in several ways: we consider a much larger set of countries that includes not only emerging but also developed markets; we explicitly control for recent rating activity worldwide; we characterize the spillovers economically, e.g., by including controls for capital flows and level of economic and financial development; we study the role of exchange rates in spillovers; and we present several new results of cross-country and cross-asset news spillover at the industry level. The impact of sovereign rating news on industry portfolios is of particular relevance given the increased perception by investors and evidence that industry factors are becoming more important than country factors in explaining stock returns; see, for example, Brooks and Catão (2000).

A sovereign credit rating represents an assessment by the rating agency on the capacity and willingness of sovereign obligators to ensure timely all sovereign debt service. They are understood by rating agencies as a forward-looking estimate of sovereign governments default probability; see S&P (2004). In most situations, the sovereign ceiling doctrine applies, i.e. the rating assigned to non-sovereign debt issues (or issuers) is the same as or lower than that assigned to the sovereign of the country of domicile. Thus, sovereign ratings revisions also relate to non-sovereign debt instruments; see, for example, Radelet and Sachs (1998) and Bank for International Settlements (2004).[1]

A stock market reaction to sovereign ratings downgrades is expected because a downgrade can affect the country's ability to borrow in international markets, and consequently, contribute to a credit crunch, which negatively impacts the stock market. Other mechanisms provide further support of the link between sovereign ratings and stock markets. For instance, sovereign ratings can provide information on the future economic health of the rated country, which have been overlooked by the stock market participants, and governments' can

[1]The final version of the Basel II provides examples of the sovereign rating ceiling doctrine. Under the standardized approach to calculate minimum capital requirements for bank claims (option 1), all banks incorporated in a given country will be assigned a risk weight one category less favorable than that assigned to claims on the sovereign of that country. For claims on corporates, no claim on an unrated corporate can be given a risk weight more favorable to that assigned to its sovereign of incorporation.

take policy actions that directly affect companies future prospects (e.g., raising corporate taxes to compensate an increase in debt service following a downgrade). Moreover, because many institutional investors can only hold investment grade instruments, rating upgrades (downgrades) may have a positive (negative) impact on securities prices; see Radelet and Sachs (1998) and Kaminsky and Schmukler (2002).

The empirical question we address is whether sovereign rating news of one country is also relevant for other countries. If ratings changes are understood by market players as re-rated country specific issues without further implications, little information impact is expected. However, the behavior (either rational due to liquidity constraints or irrational herding) of investors and the financial-real sector linkages across countries could act, and often do, as transmission vehicles of country shocks; see Dornbusch, Park, and Claessens (2000).

Following Gande and Parsley (2003), we also distinguish between two kinds of reactions: common versus differential information spillovers. The reasoning is straightforward and relates the information content of events to the reaction in non-event countries. For example, if a positive rating event for a given country triggers a reaction of the same sign across all other countries, we refer to this as a common information effect. If a positive rating event entails a widespread undetermined (or negative) reaction, for instance due to global portfolio rebalancing actions, we refer to this as a differential effect.

Our major findings can be summarized as follows. First, we find ratings changes in one country to contain valuable information for the aggregate stock market returns of other countries. This spillover effect is found to be asymmetric, both in the direction of the reaction as well as in terms of economic impact. On average, a one-notch ratings downgrade abroad is associated with a statistical significant negative two-day stock return spreads vis-à-vis the US stock market of 28 basis points across non-event countries, whereas no significant pattern is found for ratings upgrades.

Second, controlling for time invariant characteristic that proxy for underlying similarities between countries, does not affect the asymmetric spillover pattern. Specifically, we control for the cultural, regional and institutional environment as well as level of economic and financial development.

Third, we do not find evidence of differential effects for downgrades. For upgrades, we find evidence of differential spillovers among countries with highly negatively correlated portfolio flows vis-à-vis the US. In fact, there is a negative significant association between return spreads and the indicator variable for highly negatively correlated portfolio flows. This suggests that the typical insignificant positive common spillover effect for upgrades is eroded by these differential effects.

Fourth, we find ratings downgrades to be associated with a depreciation of the US dollar exchange rate against the non-event country currencies. On average across non-event countries, sovereign ratings downgrades abroad are associated with a negative local currency denominated return spread of 42 basis points. Accordingly, we find downgrades to be associated with statistically significant positive exchange rate return of 12.5 basis points. In other words, we find that the appreciation of non-event country currencies relative to the US dollar (partially) hedge the negative wealth effect of ratings downgrades abroad.

Finally, we show that ratings downgrades have a slightly smaller economic effect for local industry portfolios than for country portfolios. Nevertheless, sovereign ratings downgrades abroad are associated with a highly statistical significant negative two-day return spread of industry portfolios vis-à-vis their counterpart industry in the US of 25 basis points.

Overall, the above conclusions are robust across different empirical specifications, namely explicitly accounting for recent rating activity, alternative ways to measure the impact in the stock market (dependent variable), and sub-samples of countries or industries.

The remainder of the paper is organized as follows. Section 2.2 reviews related work on sovereign ratings. Section 2.3 details the empirical strategy and presents the data. Section 2.4 presents and discusses our empirical results on country portfolios. Section 2.5 contains results on industry portfolios. Section 2.6 concludes.

2.2. A Selective Review of the Sovereign Ratings Literature

This section briefly reviews the related work on sovereign ratings. We focus on three issues: the determinants of sovereign ratings, the timing of sovereign ratings revisions, and their impact on capital markets.

Cantor and Packer (1996) debut the empirical research on the determinants and impact of sovereign credit ratings. Their cross-sectional regression results suggest that both agencies (S&P or Moody's) share the same criteria (per capita income, GDP growth, inflation, external debt, economic development, and default history), although weight macroeconomic variables differently. The fiscal and external balances positions are found to be irrelevant for both agencies. Moreover, Cantor and Packer (1996) also show that sovereign ratings appear to contain additional information relevant for pricing sovereign bonds beyond the publicly available macroeconomic indicators.

Juttner and McCarthy (2000) show that the explanatory power of Cantor and Packer (1996) key macroeconomic variables changes considerably through time, namely after the Asian crisis. Also they test for new variables, such as interest rate differentials, indicators of financial sector strength/fragility, and real exchange rates, which could help to restore the explanatory power.

Another strand of research focus on the timing of ratings revisions - are rating agencies proactive or reactive in relation to financial crises? Provided that sovereign ratings disclosures have some market impact, early ratings downgrades during euphoric periods would help dampen expectations and smooth crises. However if ratings lag the market, upgrades (downgrades) during euphoric (turmoil) periods would reinforce expectations (add panic among investors), consequently reinforcing crisis cycles.

The actions of ratings agencies in the periods surrounding the 1994-1995 Mexico crisis and later during the Asian crisis, downgrading ratings after the crisis erupted rather than anticipating them (Reisen and von Maltzan, 1999) suggests that ratings changes do lag the market. Moreover, Reinhart (2001) concludes that sovereign ratings are a poor predictor of crises and that they perform much worse than other indicators of financial distress (e.g. real exchange rates or debt-to-export ratios), although financial crises are hard to predict.

Given the evidence on the relevance of publicly available information for sovereign ratings assessment, which makes it possible for markets to anticipate ratings announcements, it comes at surprise that financial markets react to ratings revisions. Of course, it could be that ratings agencies' superior research or access to privileged information concerning countries' willingness to service sovereign debt, enables them to add value to informative signals overlooked (or not accessible) by market participants, thus rendering ratings revisions important news events.

The literature (to our knowledge, relatively scarce) on the market impact of sovereign ratings revisions finds several interesting results. First, there is some controversy on whether or not sovereign ratings revisions announcements impact the sovereign bonds prices of the re-rated countries. Cantor and Packer (1996) event study shows that even though agency actions could have been preceded by a similar change in market expectations, the immediate effect of announcements over sovereign bond yield spreads relative to US Treasuries is positive (negative) for ratings downgrades (upgrades). While for all events together the announcement effect is statistically significant, disaggregating between upgrades and downgrades shows that only the former effect is statistically significant.

Larraín, Reisen, and von Maltzan (1997) show that the aggregate impact of ratings changes (or imminent revisions) announcements by the two leading agencies on bond yield spreads is of the expected sign, but statistically significant only for the emerging markets subsample. The split of events according to the announcements categories shows that the immediate impact is statistically significant, only when a country is put on watch for a possible downgrade.

Reisen and von Maltzan (1999) findings also question Cantor and Packer (1996) results. A significant market impact (two-day event window) is found only for emerging markets and when all agencies' announcements (Moody's, Standard and Poor's, and Fitch IBCA) are combined. The analysis according to the announcements categories shows that the impact in bond yield spreads in emerging markets comes from imminent upgrades and actual downgrades.

Second, Gande and Parsley (2003) find evidence of a significant asymmetric reaction of sovereign yield spreads (relative to the US bond market) to announcements concerning other sovereigns. Sovereign ratings upgrades have no discernible impact, while a one-notch rating downgrade of a sovereign bond is associated with a 12 basis points (on average) increase in other sovereign bonds yield spread relative to the US, as a percentage of the US yield. Moreover, the authors propose a new research design to ascertain the market impact of news that has several advantages over the traditional event study or time series regression methods. Namely, it avoids the "event window" contamination problem either by measuring spreads over a short window of two days as well as by explicitly controlling for the intensity of past events, but still keeping substantial flexibility to test alternative hypothesis.

Third, the re-rated country stock market returns are positively related to sovereign ratings (or credit outlook) changes; see Kaminsky and Schmukler (2002). This spillover effect across asset market (within a country) is in fact asymmetric, in line with the stylized findings on the firms' stock price reaction to corporate bond ratings revisions. Brooks et al. (2004) using standard event-studies methodology show that the event-day impact of ratings revisions is statistically significant only for downgrades (abnormal one-day stock market returns of -1.97% to S&P announcements). This is a particular characteristic of S&P and Fitch IBCA announcements and of foreign currency ratings.[2]

Finally, there is some evidence of a positive relation between ratings changes and stock market returns in emerging markets. Kaminsky and Schmukler (2002) address this issue in the context of a pool regression and events study methods. They show that ratings and outlooks changes of emerging sovereigns are positively related to the stock market returns of other emerging countries. However, Kaminsky and Schmuckler (2002) do not test for asymmetric effects nor control for time and country-specific effects, and the estimation procedure

[2]Kaminsky and Schmukler (1999) also study the relevance of news relating to sovereign risk reassessments. The authors look at the type of news that moves the markets during the Asian crisis and find a stock market of 10% (on average) downturn in the days credit ratings downgrades are announced.

does not allow the use of low frequency macroeconomic data. The events study confirms previous findings on the procyclical behavior of ratings agencies (upgrades tend to occur during good times and downgrades during bad times) and supports a positive (negative) reaction of emerging stock markets following other sovereign ratings upgrades (downgrades) news.

Overall, there is evidence that country-specific macroeconomic data plays a key role in sovereign debt ratings assessment by the ratings agencies. Sovereign ratings revision activity tends to follow the market trend either because an anticipation effect by market participants or, more likely, because rating agencies behave pro-cyclically.

If there is no doubt on the characteristics of own stock market and cross-country bond market impact of ratings (and/or outlooks) revisions - the same cannot be said about the own bond market reaction. Furthermore, there is a need for a thorough empirical investigation of the cross-country stock market impact of ratings news with a sample that includes both emerging and developed countries, and a methodology that specifically addresses the (potential) asymmetry of market reactions and the tendency for ratings to cluster in time.

2.3. Research Design

2.3.1. Data

We investigate the cross-country spillover effects of sovereign ratings revisions using the S&P history of sovereign ratings for those countries analyzed by Gande and Parsley (2003) and that are covered by the TF Datastream Global Equity Indices database. The data cover the period from July, 3 1989 to December, 31 2003. The starting date corresponds to the first complete month for which S&P credit outlook information is available.

S&P foreign currency long term ratings history is preferred to other agencies' ratings history because of data availability. Moreover, S&P tends to be more active making ratings revisions (Kaminsky and Schmukler (2002)), and tend to lead other agencies re-ratings (Brooks et al. (2004) and Gande and Parsley (2003)). In addition, foreign currency ratings announcements by S&P seem to have a larger own country stock market impact (Brooks et al. (2004)) and seem not to be fully anticipated by the market (Reisen and von Maltzan (1999)).[3]

The countries in our dataset obey two criteria: the existence of publicly traded US dollar denominated sovereign debt, and the availability of country level portfolio total return index data in the TF Datastream database. The 29 countries meeting these criteria are the following: Argentina, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, Finland, Greece, Hungary, Indonesia, Ireland, Israel, Italy, Korea, Malaysia, Mexico, New Zealand, Philippines, Poland, South Africa, Spain, Sweden, Thailand, Turkey, UK, and Venezuela. Thus, we build a geographically balanced sample that includes both emerging and developed countries. Moreover, the stock market indexes considered here represent about 80% of each stock market capitalization and are constructed using similar methods across countries.

We also use data on several country-specific control variables (Table A.1 in the Appendix to this chapter, presents in detail the variables definitions and data sources). Classification of countries into emerging or developed is based on Morgan Stanley Capital International, S&P and ISI Emerging Markets. A country is classified as emerging if it is listed as emerging in at least one of the above sources.[4]

We consider bilateral dummy variables for sharing a common language, adjacency, legal tradition, and membership to a formal trade bloc, either the North American Free Trade Agreement (Nafta), the Mercado Comun del Sur (Mercosur), the European Union (EU), or the Association of South East Asian Nations (Asean). In addition, we explicitly control for the physical distance between countries, computed as the great circular distance between capital cities. These variables aim to control for historical factors that may influence spillover effects because they proxy for similarities between countries that could heighten common spillover effects; see Gande and Parsley (2003). Moreover, "geographical factors" akin to our control variables are standard controls in the literature explaining cross-country economic

[3]Sovereigns ratings history are drawn from the S&P website: http//www.standardandpoors.com

[4]Greece is the only country in our sample that was upgraded from emerging to developed either by S&P or MSCI . In this paper we classify Greece as a emerging market. Countries classified as developed are Austria, Belgium, Canada, Denmark, Finland, Ireland, Italy, New Zealand, Spain, Sweden, and United Kingdom.

flows and also relate to linkages across stock markets (Portes and Rey (1999) and Rose (2000)).

We also consider monthly bilateral capital and trade flows between each country and the US. Specifically, gross flows (sales plus purchases) of foreign stocks are obtained from the US Treasury's website (http://www.treas.gov). Monthly bilateral trade flows are obtained from the US Census Department website (http://www.census.gov).

We explicitly control for crisis periods by including dummy variables for the European Exchange Rate Mechanism crisis of 1992-93, the Tequila crisis of 1994, the Asian Flu of 1997, and the recent Russian, Brazilian, Turkey and Argentina crisis (49 events in total). Finally, we use Bekaert, Harvey, and Lundblad (2003) "official liberalization" dates to control for emerging market segmentation from the world market due to regulatory constraints on international capital flows.

2.3.2. Ratings Events

We define a rating event as a change in either the explicit credit rating or the credit outlook assigned to a specific sovereign foreign currency debt. Thus, we follow the recent work on the spillover effects of sovereign ratings revisions by accounting for effective ratings announcements as well as information on imminent rating actions in a comprehensive credit rating (CCR) measure. The changes to CCR define our ratings events.

Table A.2 in the Appendix to this chapter, presents the details on the numerical coding of the CCR measure. First, we map letter explicit ratings to numerical codes by a linear transformation to a scale from 0 (the lowest rating - SD/D) to 20 (the highest rating – AAA). Next, we add the credit outlook information (on a scale between -1 for a negative credit outlook and +1 for a positive credit outlook) to the rating numerical code. Any nonzero change in the comprehensive credit rating measure defines the events of interest: "upgrades", a positive change resulting from an upward move in the (letter) credit ratings of the sovereign or from a favorable revision in the credit outlook information; and, "downgrades", a negative change resulting from a downward move in the (letter) rating or from an unfavorable revision in the credit outlook.

Table 2.1 describes the sovereigns ratings events sample. There are 106 (109) upgrades (downgrades) between July 1989 and December 2003. The vast majority of events is announced individually (for one country at given day), though multiple event days occurs for 14.2% (3.6%) of the upgrades (downgrades) cases. The time clustering of events can also be evaluated looking at the average time elapsed between events and the time periods in which they occur. Panel B of Table 2.1 show that about 50% of the events (54 upgrades and 50 downgrades) occur within a window of two weeks (ten trading days). Panel C shows that about 50% of the events (54 upgrades and 44 downgrades) corresponds to announcements made after 1998.

The strong temporal association of events suggests the use of a short event-window when evaluating ratings revisions impact and to explicitly control for worldwide recent rating activity. The use of long event widows can bias the results because stock returns in the (longer) event window can already incorporate ratings changes in other countries beyond the one being evaluated. Moreover, if markets see ratings revisions in the context of recent rating activity, today's reaction will be a function of prior ratings revisions. In fact, Kaminsky and Reinhart (2000) show that the domestic market susceptibility to crises elsewhere rises sharply if a core group of countries (not a single country) is already infected. If the same type of behavior characterizes the home reaction to sovereign rating changes abroad, this implies that events in other countries can cumulate.

Also shown in Table 2.1 is the breakdown of events according to the classification of countries into emerging or developed (Panel D). The vast majority of events, about 85%, occurs in emerging markets. This shows the importance of investigating if rating news also affects developed stock markets, an issue that has been overlooked in the literature.

Figure 2.1 plots the number of events on a given year between 1990 and 2003 (no event occurs in the second semester of 1989). There is an increase in rating activity in the years surrounding the 1994 Mexican crisis. Downgrades show a visible increase in 1997 and 1998, probably associated with revisions induced by the Asian crisis and Russian default, with a peak of 17 events in 2001. Interestingly, upgrades are most noticeable in the years of 1999, 2000, and 2003, which is suggestive of a cyclical element in the ratings revision activity.

2.3.3. Testing Procedures

This section details the empirical strategy we use to test for international cross-asset market spillover effects. We extend the methodology used by Gande and Parsley (2003) to study the impact of rating changes in international stock markets. We measure the non-event country $j(\neq i)$ stock market response to a rating event in country $i(\neq j)$ by the daily logarithmic change in country j total return index relative to the equivalent change in the US market total return index (the benchmark). To account for time zone differences between stock markets, we cumulate the "stock market spreads" in a standard two-day window [0,1].[5]

Specifically, we pool the data for all countries (j) excluding the event country (i), at each event time (t), and estimate the following benchmark regression separately for upgrades and downgrades:

$$r_{j,t} = \alpha + \beta_1 Event_{i,t} + \sum_k \beta_k X_k + \epsilon_{ij,t}, \forall j \neq i, \tag{2.1}$$

where $r_{j,t}$ represents the cumulative [0,1] return spread. The indices i and j represent countries and t event time. $Event_{i,t}$ is any non-zero change in the comprehensive credit rating. For easy of interpretation, we use the absolute value of $Event_{i,t}$ in the downgrades regression. Since we analyze separately upgrades and downgrades, this allows for the interpretation of the stock market reaction as "in the expected direction given the announcement". Matrix X contains full sets of year and country dummies (29 event-country and 29 non-event country) and the levels of event and non-event country comprehensive credit ratings. The latter

[5]The use of simple "market-adjusted" abnormal stock returns can be found, for example, in Kaminsky and Schmukler (2002) and Griffin and Stulz (2001). In the literature that focus on the bond market reaction to sovereign ratings revisions the standard approach relies in bond yield spreads relative to comparable maturity US bonds yields, namely due to the difficulties in finding a relevant event-free period (see, for example, Reisen and von Maltzan, 1999). In a later section as robustness check, we also evaluate market model residuals (abnormal returns) and results are similar.

controls for nonlinearities in market reaction relative to the position of each country pair in the ratings scale.

This approach has two major advantages. First, it has a great flexibility for testing alternative hypothesis. For instance, to control for time invariant country-specific characteristics in subsequent regressions, the matrix X is expanded to include additional controls: emerging/developed status, common language, adjacency, physical distance, legal tradition, and membership to a formal trade bloc. Likewise, testing for the impact of crisis periods or stock market liberalizations is done by adding specific variables to the matrix X.

Second, we control for the temporal clustering of events either by measuring the change in stock prices over a short-window of two days, rather than relying on a longer-window (e.g., 30 days) and by explicitly controlling for the intensity of past events with the inclusion of a new variable, *Lag Event*, which measures the net rating change (event-country prior CCR changes excluded) in the preceding two (or three) weeks. Thus, we control for nonlinearities in sense of Kaminsky and Reinhart (2000) relative to the recent worldwide history of rating activity.

2.4. Empirical Results on Country Portfolios

2.4.1. Asymmetric Spillover Effects

Table 2.2 reports estimates of the coefficients in equation (2.1). There is strong evidence of an asymmetric common information spillover effect of stock markets to sovereign debt ratings changes abroad. Sovereign debt credit ratings upgrades are associated with a positive effect on stock market prices relative to the US, while downgrades with a negative return spread. In other words, on the days a sovereign credit rating (either implemented or credit outlook) for a particular country is upgraded, our results suggest that the remaining countries do better than the US market. When a country is downgraded, the results show that the remaining countries do much worse than the US market.

However, only for downgrades the effect is statistically significant at the 5% level. The downgrade effect is also economically larger than the upgrade effect. A one-notch negative event in one country is associated with an average negative two-day stock market return spread abroad of 28 basis points, while positive events are associated with positive return spreads of about a half of that magnitude.

Negative news in the sovereign debt market, but not positive ones, does seem to have impact in the international stock markets. Gande and Parsley (2003) argue that either because of pre-event information disclosure of the imminent positive change by the event country government or a reluctance of ratings agencies to lower ratings due to marketing factors (Larraín, et al. (1997)), downgrades (but not upgrades) can be recognized by the stock market participants as a wake-up call, especially if in the context of bad times.

Interestingly, the level of event country CCR is significant only for upgrades. The higher the event country CCR the lower the non-event country stock market response for ratings upgrades, suggesting that the effect of upgrades is most noticed for low level sovereign ratings. Moreover, when we control for the clustering in time of events in other countries by including in the regression a measure (*Lag Event*) for the rating activity in the prior two weeks, we find that only for upgrades does rating history matter. This reinforces the intuition that downgrades are understood by the stock market as surprises while the same does not happen for upgrades. The insignificance of the lagged event variable coefficient for downgrades, also does not offer support to a delayed stock market reaction to a rating change abroad.

This comes at odd with the typical reaction of sovereign debt markets to other countries sovereign rating revisions. In fact, Gande an Parsley (2003) show that only for downgrades does the level of event country CCR and the recent rating activity have explanatory power. That is, our results suggest that stock markets are more efficient reacting to sovereign debt bad news than to incorporating sovereign debt good news.

Overall, our results support an asymmetric common information effect in international stock markets of a CCR downgrades. Across asset markets and across countries, bad news in one country is interpreted as negative news in other countries. Positive news has no discernible impact.[6]

[6]The probit model estimates and Granger-causality tests in Gande and Parsley (2003), whose sample of countries is similar to ours, allow the rejection of spillover effects on the comprehensive credit ratings themselves.

Table 2.3 expands the matrix X to include controls for emerging/developed country status, adjacency (sharing of land border) and distance between countries, sharing a common official language, membership in a trade bloc, and origin of legal systems.

The results in Table 2.3 offer additional support of the previous findings of a common information spillover effect. Sovereign debt ratings downgrades induce a statistically significant negative response in stock markets abroad, while the positive response to ratings upgrades is statistically insignificant and contaminated by the recent history of rating activity. The magnitude, sign, and statistical significance of the event variable remains virtually unchanged relative to Table 2.2, while the adjusted R^2 of both regressions increases slightly.

Among the economic characterization variables, only the physical distance is statistically significant both in the upgrades and the downgrades regressions. We interpret the opposite sign of the physical distance variable relative to the event variable, as evidence that an increase in distance between the capital cities reduces the average wealth impact of spillovers. Likewise, our results suggest that sharing a common trade bloc increases the negative (positive) international stock market wealth impact of sovereign debt ratings downgrades (upgrades).[7]

The coefficient for the development status (i.e., when the event and non-event country are both developed) is also significant in the downgrades regression. The positive significant coefficient indicates that downgrades in developed countries have a smaller effect in stock markets of other developed countries relative to the average impact (notice this does not mean that overall downgrades have no effect in developed stock markets). Interestingly, the emerging status dummy has a negative coefficient in the downgrades regression, suggesting an increased impact among emerging stocks markets (excluding the event country) of a negative event in an emerging market.

In other words, these results allow us to rule out the possibility that spillover effects are anticipated by rating agencies and that ratings are adjusted simultaneously across countries.

[7]We do run regressions using physical distance measured in logarithms rather than in thousands of kilometers. Results (not tabulated here) confirm that only downgrades have a statistically significant in international stock markets, and the greater distance, the smaller is the impact.

By the same reasoning, in the upgrades regression, the positive coefficient for emerging status, signals that among these countries upward ratings revisions have an increased positive wealth impact, relative to the average.[8]

2.4.2. Differential Spillover Effects

This section looks at differential spillover effects. It could be the case that for some stock markets the response is of different sign of the common information spillover. For instance, global portfolio rebalancing induced by the own market negative response to sovereign downgrades (Brooks et al., 2004) could induce spillover effects abroad of different sign relative to the common negative reaction.

We investigate this issue by explicitly accounting for foreign equity portfolio (and trade) flows linkages. Following the reasoning of Gande and Parsley (2003), we hypothesize that common information spillover effects should dominate for two countries with highly positively correlated portfolio (or trade) flows. Conversely, differential spillover effects should exist between countries with highly negatively correlated portfolio (or trade) flows.

Empirically, this hypothesis is investigated considering the time series correlation of gross portfolio (or trade) flows vis-à-vis the US for each country in our sample. At each event date, we use a moving window of the most recent 6 months of portfolio (and trade) flows to compute the correlation between the event country flows and all the remaining (non-event) countries. Next, we construct a dummy variable that takes the value one to those country pairs with high positive correlation (the top quartile of the cross-sectional distribution), and zero otherwise. Similarly, a dummy variable is also constructed for those country pairs that fall in the bottom quartile (highly negative correlation). Results are reported in Table 2.4.

Two findings stand out. First, controlling for the portfolio (or trade) flows correlation does not change our basic findings that only for downgrades there is a significant common information spillover effect. In fact, the statistically insignificance of the highly positively correlated portfolio (or trade) flows dummy does not allow for conclusions regarding the

[8]Gande and Parsley (2003) show that among developed markets, sovereign ratings downgrades abroad have a smaller effect on sovereign bond markets.

increased impact in the expected direction of ratings news for such country pairs. Nevertheless, for the highly positively correlated portfolio flows dummy, the positive (negative) sign in the upgrades (downgrades) regression suggests that, as hypothesized, for these country pairs' ratings news could have an increased impact of the expected sign.

Second, there is evidence of differential information effects only for upgrades. Relative to the typical reaction to ratings upgrades abroad, we find a decrease of about 33 (26) basis points in stock return spreads for countries with highly negatively correlated portfolio (or trade) flows with the event country. This is surprising given the positive (but statistically insignificant) common reaction to upgrades and suggests a possible explanation for the inexistence of a statistically significant spillover for ratings upgrades.[9]

Overall, the investigation on differential spillover effects suggests a far more homogenous reaction of international stock markets (non-event countries) to ratings downgrades than to ratings upgrades. This yields some support to the hypothesis that global equity portfolio rebalancing actions may induce differential price reactions across non-event stock markets, but only for ratings upgrades. Gande and Parsley (2003) find a statistical significant differential spillover effect in international sovereign debt markets, but only for downgrades. Thus, our results suggest a more homogeneous reaction of stock markets to ratings downgrades than the one observed for debt markets. In contrast, debt markets show a more homogeneous reaction to upgrades than stock markets.

2.4.3. Crisis Periods and Stock Market Liberalizations

In this section, we analyze the sensitivity of our results to the inclusion of controls for crisis periods and liberalization of local equity markets.

First, we evaluate if the events that occur during periods of capital markets turmoil (49 events) could be driving our results. Table 2.5 (first specification) reports regression results

[9] We do run regressions (not tabulated here) using 12-month horizon portfolio and trade flows correlations. For upgrades only the highly negatively correlated portfolio flows dummy (not the trade flows) is statistically significant, suggesting a decrease in stock return spreads of about 30 basis points. This robustness suggests that the transmission channel is stronger for portfolio than for trade linkages, and that only in the short run could trade flows play a role as a transmission mechanism. We also run regressions including the four dummy variables simultaneously, and the conclusions remain virtually unchanged.

including a dummy variable that controls for the European Exchange Rate Mechanism crisis of 1992-93, the Tequila crisis of 1994, the Asian Flu of 1997, and the recent Russian, Brazilian, Turkey and Argentina crises. The basic results remain unchanged. Specifically, only negative ratings news are associated with a significant international stock market reaction. Interestingly, the crisis dummy is only significant for the upgrades regression and presents a negative coefficient. This result suggests that information content of ratings upgrades during periods of turmoil is overcome by the negative expectations stock market players are acting upon.

Second, we evaluate the effect of regulatory constraints on foreign capital inflows on the ability of a country's stock market to react to a rating change abroad. If foreign investors' actions are relevant to transmit information across markets, we expect smaller spillover effects for those countries in which regulation places a barrier to the trade of local equities by foreign investors. In fact, for 13 countries in our sample, the "official liberalization date" proposed by Bekaert and Harvey (2000) occurs after our initial sample period. To account for this effect, we expand the basic specification to include a non-event country dummy variable that equals one if a rating change occurs before the country official liberalization, and zero otherwise.[10] Table 2.5 (second specification) presents the results.

Spillovers continue to exist only for downgrades and the liberalization effect is not statistically significant. The sign of the (no) liberalization dummy variable is negative for upgrades which offers support to the hypothesized effect. Concerning downgrades, the negative sign of the (no) liberalization dummy variable coefficient, comes at odds with the hypothesized effect, because it suggests an even stronger reaction to ratings news abroad when the country is not liberalized. Given the probable greater importance that country specific factors have on equity price behavior for these countries during the periods of no liberalization, these

[10] Countries in question are: Argentina, Brazil, Chile, China, Colombia, Hungary, Indonesia, Israel, Korea, Philippines, Poland, South Africa, and Venezuela. For those few countries not included in Bekaert et al (2003) sample, we use the major regulatory reform concerning foreign investors in Campbell Harvey's Country Risk Analysis website: http://www.duke.edu/~charvey/Countryrisk/couindex.htm.

opens the possibility of irrational herding from domestic investors as a probable cause for this behavior.[11]

2.4.4. Local Currency Returns and Exchange Rates

Next, we look with further detail to the definition of stock market return spreads by explicitly removing currency effects from its calculation. That is, we use local currency denominated returns to compute the differential return vis-à-vis the US market. In addition, we also look at exchange rate returns on event days.[12]

Panel A of Table 2.6 presents the results. The impact of upgrades remains insignificant and similar to the one found using US dollar denominated return spreads. More interesting is the increase both in the economic and statistical significance of the negative impact of downgrades on international stock markets. Using local currency returns, we find downgrades to be associated with a response of the stock markets abroad of 42 basis points (negative two-day stock return spreads), which is 13 basis points higher (in absolute terms) than the equivalent impact measured in US dollars. This suggests that foreign exchange rates are in part hedging the decrease in the market value of the foreign country equity investment.

In fact, Panel B of Table 2.6 shows that ratings downgrades are associated with a statistically significant depreciation of the US dollar exchange rate against non-event country currencies of about 13 basis points (two-day event window). In other words, we find the appreciation of non-event country currencies relative to the US dollar to hedge in part the negative stock market wealth effect of ratings downgrades abroad. Concerning positive rating events, we find exchange rates reaction to be negative (0.5 basis points) and statistically insignificant, mirroring the results obtained for the stock market reaction.

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[11] Additional specifications (not tabulated here) show that results remain virtually the same if portfolio flows correlation dummies are omitted when testing for liberalization effects.

[12] Exchange rates are defined as the number of US dollars per unity of foreign country currency. Daily exchange rate returns are defined as the first difference of consecutive exchange rate observations (in logarithms). Daily returns are cumulated (day 0 plus day +1) on event dates.

2.4.5. Stock Market Correlations

This section tests whether cross-country correlation matrices between event and non-event days are equal. If the finding of an international stock market downgrade spillover effect is more than the manifestation of the existent correlation across countries, the correlation structure itself should change on event days. Moreover, we argue that the insignificance of differential spillover effects (namely for downgrades) is consistent with an increase in correlations.

To investigate these issues, we follow Gande and Parsley (2003) research design and randomly select (with replacement) a matched (across countries) sample of non-event date return spreads for each event, imposing the additional condition that the non-event days are sampled within the window [-60,-21] days relative to the event date. The sampling exercise is performed $10,000$ times, and a cross-country correlation matrix is computed using each randomly selected sample of non-event days return spreads. We focus the subsequent analysis on downgrades - the events for which there is evidence of spillovers.

The first issue of concern is whether correlation matrices differ between event and non-event periods. Following Gande and Parsley (2003), Longin and Solnik (1995) and Kaplanis (1988), we test this hypothesis using the Jennrich (1970) test statistic:

$$\chi^2 = \frac{1}{2}tr(Z^2) - dg'(Z)S^{-1}dg(Z), \tag{2.2}$$

where $tr(.)$ and $dg(.)$ are the trace and diagonal of a matrix; $Z = c^{\frac{1}{2}}R^{-1}(R_1 - R_2)$, in which $R = (n_1R_1 + n_2R_2)/(n_1 + n_2)$ and $c = (n_1n_2)/(n_1 + n_2)$, R_1 and R_2 are the correlations matrices to be compared, and n_1 and n_2 are the number of observations on which they are based; and, $S = (\delta_{ij} + r_{ij}r^{ij})$, in which δ_{ij} is the Kronecker delta and r_{ij} (r^{ij}) denotes the elements of R (R^{-1}). The Jennrich (1970) test statistic has a chi-square distribution with $p(p-1)/2$ degrees of freedom, with p being the dimension of the correlation matrices.[13]

[13]Note that the Jennrich (1970) test is robust to changing volatilities from event to non-event samples (the samples whose correlations are being tested). This is important in our context because as shown by Forbes and Rigobon (2002) among others, conditional correlation estimates are volatility dependent, which may bias conventional pair-wise tests designed to evaluate correlation changes. As shown by Chakrabarti and Roll (2003), these biases should be a concern only when sub-samples correspond to periods of observed abnormally

The results support the conclusion that the downgrades spillover effect is not a simple manifestation of the existent correlation structure, as correlations itself change in event days relative to non-event days. The simulations yield a median test statistic of 577.96, while its 5% critical value is 453.98 (for a chi-square distribution with 406 degrees of freedom). Moreover, we reject, at the 5% level, the null hypothesis of equal correlation matrices across all the $10,000$ simulations. Thus, our results strongly suggest that the correlation structure itself changes on event days.

The second issue of concern is whether correlation increases (or decreases) during the events periods relative to non-events periods preceding the rating change. To evaluate the sign of correlations changes, we perform an element-by-element comparison between the event days' correlation matrix and each of the randomly sampled non-event day correlation matrices. Specifically, we compute the proportion of pairwise correlation coefficients which represent net increases from non-event periods to event periods. As expected, the results suggest that correlations increase in the event days. Across all $10,000$ matrices evaluations, we find the proportions of net increases to be higher than the proportions of net decreases in 70.6% of the time. Moreover, the 55.6% average proportions of net increases is statistically significant at the 5% level.

In summary, the two correlations-based tests show that we can reject the hypothesis of constant correlation structure between event and non-event periods, and that correlations increase during event periods.

2.4.6. Additional Tests

In this section, we address the following issues: window size used to measure the cumulative impact of consecutive ratings changes, the way return spreads are measured, and the estimation procedure. In addition, we look at the impact of ratings events for a sub-sample of the largest economies.

high volatility of the driving factor and it is reasonable to assume that both the driving factor volatility and idiosyncratic volatility should be constant.

Table 2.7 performs two robustness checks. In Panel A, we expand the window to measure the cumulative impact of consecutive ratings changes to a three-week window instead of a two-week window. In Panel B, we use market model adjusted spreads (taking the US stock market as benchmark) instead of simple return spreads. Specifically, we follow Goh and Ederington (1993) and use a rolling window of 36 months (excluding the event months -1, 0, and +1) centered at each event month, to compute the market model parameters using monthly returns. Then we use the estimated parameters to compute daily abnormal returns, which we cumulate during the two-day (0,1) event window.[14]

Our basic findings continue to hold. In particular, statistically significant common information spillovers are only found for ratings downgrades. Only for upgrades does recent rating activity or highly negatively correlated portfolio (or trade) flows have a statistically significant impact. Also, crisis periods seem to be relevant only to upgrades, and distance acts to decrease the economic importance of spillovers both for upgrades and downgrades. The economic impact of upgrades decreases substantially to 5 basis points when recent rating activity is measured using a three-week window (3.5 basis points for abnormal returns). We interpret this findings as evidence that favors the hypothesis of an higher anticipation effect for upgrades than for downgrades. The magnitude of the negative impact of downgrades remains basically unchanged at 28 basis points.

Next, we look at the estimation procedure. Instead of estimating split regressions for upgrades and downgrades, we pool all events and allow the spillover effects to be asymmetric using different slopes for upgrades and downgrades. This procedure forces the influence of the additional variables to be same across events. Specifically, we pool the data for all countries (j) excluding the event country (i), at each event time (t), and estimate the following regression:

[14] Given the evidence that rating revisions, namely downgrades, tend to occur after periods of poor own country performance (e.g. Reisen and von Maltzan, 1999), the use of a simple backward-looking window would generate downward biased beta estimates.

$$r_{j,t} = \alpha + \beta_U I_U Abs(Event_{i,t}) + \beta_D I_D Abs(Event_{i,t}) + \sum_k \beta_k X_k + \epsilon_{ij,t}, \forall j \neq i, \tag{2.3}$$

where $r_{j,t}$ represents the cumulative [0,1] return spread; the indices i and j represent countries and t event time; I_U (I_D) is an indicator variable that equals one if the event is positive (negative), and zero otherwise; and $Event_{i,t}$ is any non-zero change in the comprehensive credit rating. To facilitate interpretation we use of the absolute value of $Event_{i,t}$ which allows allows for the interpretation of the stock market reaction as "in the expected direction given the announcement" since we specify different slopes for upgrades and downgrades.

Table 2.8 presents the results. In the regression in column (1), matrix X contains full sets of year and country dummies (29 event-country and 29 non-event country), levels of event and non-event country comprehensive credit ratings, and control (*Lag Event*) for the clustering in time of events in other countries. Subsequently, we expand matrix X to include portfolio and trade flows correlation dummies (column 2), time invariant controls (column 3), and crisis periods (column 4).

We find spillovers to be statistically significant only for downgrades. A downgrade abroad is associated with a worse performance in non-event countries relative to that of the US market of 39 basis points. Upgrades abroad have a statistically insignificant reaction. The impact of recent rating activity is positive and differential spillover effects are found for country pairs with highly negatively correlated portfolio (or trade) flows. The signs of the coefficients of these variables agree with those found for the statistically significant coefficients in the split regressions model.

The introduction of time invariant controls does not change the basic findings. None of the coefficients is statistically significant, which could be a result of imposing equal coefficients for upgrades and downgrades. For instance, in the split regressions model, we find distance to have a statistically significant negative (positive) coefficient for upgrades (downgrades) suggesting that the decrease in distance between event and non-event countries increases the impact of rating changes abroad. In the single regression model, the distance coefficient is positive, but statistically insignificant. Moreover, the introduction of the crisis control also does not change our basic findings.

Finally, we extend our results by looking at a subsample of countries. We use Gross Domestic Product (GDP) to proxy for country size. The news related with the most important (larger) countries are subject to more attention and scrutiny by global investors (visibility hypothesis). Moreover, larger countries have greater importance in the international debt market. Thus, by focusing on larger countries events, we expect information spillovers to be economically more significant.[15]

We focus on those countries (15) with purchasing power adjusted GDP greater than 300 billions USD in 2002. Table 2.9 presents the results for two different cases: 1) larger event country and impact on *all* countries, and 2) larger event-country and impact *only* on larger non-event country. In both cases average return differentials vis-à-vis the US increase relative to the all countries regression (see Table 2.5), and interestingly the impact is statistically significant both for upgrades and downgrades.[16]

Specifically, when we look at the impact on *all* countries of the larger country events (Panel A), we find ratings upgrades to be associated with a significant positive two days return spread of 33 basis points and downgrades with a significant negative return spread of 43 basis points. When we look at the impact on *only* larger countries of the events on other larger countries (Panel B), we find the stock market impact to be of about 30 basis points for upgrades (significant at the 10% level), and about 55 basis points for downgrades (significant at the 5% level).

Gande and Parsley (2003) also analyze the impact of sovereign rating news on larger countries on the sovereign debt yield spreads of other larger countries. Similar to our all country results for the equity market, only downgrades abroad are associated with a statistically significant common information spillover effects and with a greater impact on non-event

[15]GDP data is drawn from the World Bank website: http://www.worldbank.org.

[16]The number of events reduces to 60 upgrades and 76 downgrades. The countries whose events (if any) are included are: Argentina, Brazil, Canada, China, Indonesia, Italy, Korea (South), Mexico, Philippines, Poland, South Africa, Spain, Thailand, Turkey, and United Kingdom.

country sovereign bond yield spreads (about 17 basis points) for larger countries relative to the all countries sample.

In the sovereign debt market, the differential effects also appear for downgrades but not for upgrades using the sample of larger countries. However, for the stock market our results suggest that stock market differential spillover effects are a characteristic of smaller countries. When larger country events' impact is measured on other larger markets, none of the portfolio (or trade) correlation dummies is statistically significant. However, when their impact is measured on all countries (excluding event country), country pairs with highly negatively correlated portfolio flows present a smaller impact for upgrades.[17]

2.5. Empirical Results on Industry Portfolios

This section investigates the existence of cross-country spillover effects at the industry level. Here our definition of event restricts to a sovereign rating comprehensive credit rating negative change, for which international spillover effects are found in country portfolios.

Akhigbe, Madura, and White (1997) find that individual firm bond ratings downgrades are associated with a statistically significant negative abnormal stock return for the rival firms (in the same industry). There is no evidence of industry spillover effects for bond ratings upgrades. Thus, they conclude that only bond ratings downgrades are informative for the firm's industry.

We look at industry spillover effects from a complementary perspective relative to that of Akhigbe et al. (1997). Since our focus is cross-country sovereign ratings changes spillover effects, we ask whether a country level event contains any information relevant for industries in other countries. In other words, we are looking for cross-market and cross-country spillover effects at the industry level.

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[17] We also run regressions (results not tabulated here) for two alternative sample of countries. We consider a sample of economically developed countries measured by GDP per capital and a sample of financially developed countries measured by marker capitalization/GDP. In both cases, we find that the impact of downgrades in stock return spreads is of greater magnitude.

The study of local industry portfolios adds to the analysis the impact of industry-specific risk, a component of global equity portfolio volatility that experiences significant time variation in the 1990s (Ferreira and Gama (2004)). Moreover, not all industries may react in the same way to international events. Roll (1992) shows that a major source for the low correlation across country portfolio returns are the differences in the industrial structure of each country. Brooks and Catão (2000) show that the technology, media, and telecommunications sector has a crucial role in the increase of importance of industry factors in explaining stock return variation towards the late 1990s. Griffin and Karolyi (1998) show that pure industry effects (rather than country effects) have increased importance in explaining stock return variation for traded-goods industry than for non-traded goods industries. These examples of a growing body of empirical literature that documents the increasing importance the industry dimension gained in recent years, further justifies looking at industries in addition to countries in studies dealing with international stock market linkages.

We proceed as follows. We use the cumulative two-day [0,1] return spread of each local industry portfolio relative to the same industry in the US as dependent variable. TF Datastream Level 3 local industry portfolios are considered, which are based on a value-weighted aggregation of stocks in a maximum of 10 industries per country. We use the same set of countries, with the exception of Venezuela because there is no data on industry portfolios available from TF Datastream. Next, we pool the data for all local industry portfolios excluding the event country, at each event time. Thus, our data set as a panel structure with 109 events, 28 countries, and 10 industries. Since not every industry is available for every country at each event date, the effective number of data point used in the local industry portfolio regressions (24,639) is less than the maximum of 29,430 data points.

Table 2.10 presents the results of estimating regression (2.1) with the industry portfolio return spreads denominated in US dollars. We start with the basic specification (column 1) and then sequentially add controls for non-linearity in the relation arising from the cumulative impact of recent rating activity (column 2), country level time invariant control variables (column 3), crisis periods (column 4), and industry-specific effects (column 5).

Similarly to country portfolios, the common (across all industries) spillover effect of sovereign ratings downgrades is negative (25 basis points) and highly significant. Differences are noticed for the impact of recent rating activity and for the event country comprehensive credit rating level which are both negative and statistically significant. The introduction of country level time invariant controls (and crisis control) does not change the overall results as in country portfolios. Only distance is positive and significant, i.e., for local industries located in countries far apart, the effect of downgrades is reduced.

Moving into the local industry level slightly reduces the economic impact of ratings downgrades (3 basis points) relative to country portfolios. This could be a consequence of adding industry idiosyncratic sources of return variation (which are presumably diversified away in country portfolios), which may mitigate an otherwise more strong negative reaction.

Finally, we introduce a dummy variable to characterize the spillover effects for each industry, with exception of Basic Industries which is the benchmark. Results show some variation across industries in the impact of ratings news abroad. For instance, for the Resources industries the stock market impact of ratings downgrades abroad is smaller in 21 basis points, while for Financials is greater in 19 basis points, relative to the average.[18]

To conclude this section, we characterize the industry dimension of sovereign ratings downgrades using subsamples of industries. First, we take Griffin and Karolyi (1998) classification of industries into traded and non-traded goods, in which the latter are defined as those for which high transportation cost prevent international trade. They argue that for traded-goods stocks the importance of variation in global industry factors is higher because firms' profitability, cash-flows, and asset values may be more sensitive to price fluctuations of internationally traded goods (input or output to the industry) and changes in the terms of competition.

[18]We do run regressions (not tabulated here) to study the role of the Resources, Financials, and Information Technology industries may have on the industry-level international impact of ratings downgrades abroad. The main conclusion is that the behavior of these industries per se does not have a major impact on spillovers. In fact, when the Resources industry is excluded, the economic impact of downgrades spillovers on the remaining industries increases about 2.5 basis points and when the Financials industry is removed it decreases by the same order of magnitude, which is obviously small. When the Information Technology industry is removed from the sample, a reduction of about 4 basis points in the economic impact of downgrades is noticed.

We use a conservative approach to classify our 10 industries. We consider as traded goods industries the Resources, Basic Industries, Cyclical Consumer Goods, and Information Technology industry, and as non-traded goods industries the Cyclical Services, Non-Cyclical Services, Utilities, and Financials industry. Because in Level 3 of TF Datastream classification stocks are classified in a broad grouping scheme of 10 industry groupings, we drop two industries (General Industries and Non-Cyclical Consumer Goods) whose composition is mixed.

Second, we form two groups of five industries each according to their market capitalization in 2002. Specifically, we sum (across all countries) the market capitalization of each industry in each country and study the downgrades impact within the 5 largest or smallest industries, alternatively.[19]

Table 2.11 presents the results. With respect to the traded versus non-traded industries (Panel A), we find spillover effects to be statistically significant in both cases. However, the effect of downgrades is economically more significant for traded goods industries (about 29 basis points, negative) than for non-traded goods (20 basis points, negative). This difference is probably due to non-traded goods industries' firms being less sensitive to international sources of variation, of which a foreign country sovereign rating downgrade is an example.[20]

Concerning the industry size subsamples (Panel B), we see that focusing on smaller industries yields a noticeable increase (in absolute terms) in the economic impact of sovereign ratings abroad (to about 33 basis points, negative), while for larger industries we find a smaller impact (about 18 basis points, negative). Despite the differences across industry groups, the negative impact of downgrades is always statistically significant.[21]

[19]Larger industries are (in decreasing order): Financials, Non-cyclical Services, Resources, Non-cyclical Consumer Goods, and Cyclical Services.

[20]Griffin and Stulz (2001) show that exchange rates shocks are marginally more important for traded goods industries than for non-traded goods. If, as with country portfolios, for industries portfolios exchange rates act to decrease (in absolute terms) the downgrades effect, this specific influence cannot explain our results. In fact, results obtained with local currency denominated local industry portfolio return spreads (not reported here, but available upon request) suggest that the exchange rate hedging effect is somewhat larger for traded goods than for non-traded goods industries.

[21]We also run regressions (results not shown here) industry by industry. The negative effect of rating downgrades is found in nine industries (excepction is the Non-Cyclical Services industry) and statistically significant in four industries.

2.6. Conclusion

This paper studies the cross-asset and cross-country impact of sovereign debt rating news. Specifically, we investigate whether a sovereign rating change (implemented or credit outlook/watch move) for a given country impacts the stock market returns in other countries.

Consistent with the own country stock market reaction to ratings changes, we find evidence of asymmetric spillovers. Ratings upgrades abroad have no discernible impact on stock market return spreads, while ratings downgrades are associated with a economically and statistically significant negative return spread. This suggests that only downgrades abroad convey information to stock markets. These findings are robust to control variables that proxy for latent linkages across markets, crisis periods, the nature of affected markets, the currency in which returns are measured, and to differences in the industrial structure of each country. Moreover, the economic impact of ratings downgrades is greater for larger countries and industries with larger foreign exposure (traded goods industries).

While common information spillover dominate the reaction of markets to a rating downgrade abroad, there is some evidence of differential effects for ratings upgrades. We find that ratings upgrades abroad are associated with differential spillovers among countries with highly negatively correlated portfolio flows (vis-à-vis the US). Also, we show that exchange rates offer a hedging component to foreign investments in relation to the negative effects of ratings downgrades abroad.

This paper shows that ratings revisions abroad have an instantaneous impact on international stock markets. An extension is the investigation whether the adjustment is confined to the event window or the markets show a delayed reaction. For instance an event day noisy overreaction would imply an aftermath pattern of correction that could be detected using a longer observation window. Another extension to this paper is related to the bond and stock market co-movement. Our results are in line with the international bond market negative reaction to ratings changes abroad. Thus, an increase in correlation between bond and stock markets is expected for the days a rating (or credit outlook) downgrade abroad is announced relative to the no news days.

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Table 2.1: Description of Sovereign Ratings Events

This table shows the number of comprehensive credit ratings changes that occur on a single day (Panel A), on a given week window from each other (Panel B), for the periods from 1989 to 1998 and from 1990 to 2003 (Panel C), and in countries in which the stock market is classified as emerging or developed (Panel D).

	Upgrades		Downgrades		All	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Panel A: Number of Events On a Single Day						
1	91	85.8	105	96.3	196	91.2
2	8	7.5	4	3.7	12	5.6
3	3	2.8	0	0.0	3	1.4
4	4	3.8	0	0.0	4	1.9
Panel B: Number of Events Within a Window						
1-week	37	34.9	35	32.1	72	33.5
2-week	54	50.9	59	54.1	113	52.6
3-week	69	65.1	74	67.9	143	66.5
4-week	75	70.8	81	74.3	156	72.6
Panel C: Number of Events by Subperiod						
1989-1998	52	49.1	65	59.6	117	54.4
1999-2003	54	50.9	44	40.4	98	45.6
Panel D: Number of Events by Development Status						
Emerging	88	83.0	95	87.2	183	85.1
Developed	18	17.0	14	12.8	32	14.9
Total	106	100.0	109	100.0	215	100.0

Table 2.2: International Stock Market Impact of Sovereign Rating News

This table presents the coefficient estimates of equation (2.1). In the first specification, we include the Event variable (the change in the comprehensive credit rating). In the second specification, we add the Lag Event variable (the cumulative change in the comprehensive credit ratings of non-event countries during the two weeks preceding the event). In both specifications, matrix X contains the levels of event country and non-event country comprehensive credit ratings, and full sets of year and country (event and non-event) dummies. The dependent variable is the cumulative two-day [0,1] non-event country stock market return spread relative to the US stock market, denominated in US dollars. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	Upgrades				Downgrades			
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	2.4788	4.354	2.4923	4.378	1.3582	1.909	1.3682	1.893
Event	0.1247	1.143	0.1096	1.010	-0.2853	-2.044	-0.2855	-2.041
Lag Event			0.1258	2.605			-0.0081	-0.156
CCR (event country)	-0.3601	-8.526	-0.3834	-8.771	0.0017	0.041	0.0018	0.042
CCR (non-event country)	0.0499	1.292	0.0490	1.273	-0.0650	-1.216	-0.0647	-1.216
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.106		0.107		0.081		0.0803	
Number of observations	2862		2862		2877		2877	

Table 2.3: International Stock Market Impact of Sovereign Rating News - Cultural, Legal and Institutional Controls

This table presents the coefficient estimates of equation (2.1). In the first specification, we include only the Event variable (the change in the comprehensive credit rating). In the second specification, we add the Lag Event variable (the cumulative change in the comprehensive credit ratings of non-event countries during the two weeks preceding the event). In both specifications, matrix X contains the levels of event and non-event country comprehensive credit ratings, country status as emerging/developed, adjacency (sharing of land border), distance between countries, sharing a common official language, membership in a trade bloc, origin of legal systems, and full sets of year and country (event and non-event) dummies. The dependent variable is the cumulative two-day [0,1] non-event country stock market return spread relative to the US stock market, denominated in US dollars. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	Upgrades				Downgrades			
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	1.5589	1.775	1.5820	1.805	2.1894	1.820	2.1962	1.813
Event	0.1270	1.170	0.1117	1.034	-0.2834	-2.030	-0.2837	-2.027
Lag Event			0.1284	2.648			-0.0083	-0.161
CCR (event country)	-0.3569	-8.510	-0.3807	-8.771	0.0026	0.061	0.0026	0.062
CCR (non-event country)	0.0558	1.457	0.0549	1.438	-0.0652	-1.211	-0.0650	-1.210
Emerging	1.4074	1.955	1.3971	1.943	-1.4572	-1.639	-1.4537	-1.638
Developed	-0.7384	-0.996	-0.7224	-0.975	1.9813	2.128	1.9785	2.128
Adjacent	-0.3141	-0.857	-0.3154	-0.864	0.4444	1.030	0.4443	1.030
Distance	-0.0392	-2.516	-0.0391	-2.514	0.0452	2.118	0.0452	2.117
Language	0.0981	0.560	0.1001	0.572	0.2508	1.125	0.2508	1.125
Trade Bloc	0.2585	1.003	0.2632	1.022	-0.1610	-0.386	-0.1606	-0.385
Common Law	-0.2496	-1.137	-0.2517	-1.146	-0.0640	-0.185	-0.0641	-0.185
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.111		0.112		0.082		0.082	
Number of observations	2862		2862		2877		2877	

Table 2.4: Common and Differential Spillover Effects

This table presents the coefficient estimates of equation (2.1). In the first (second) specification, we include controls for countries with highly correlated portfolio (trade) flows vis-à-vis the US. Correlations are computed over a lagged rolling window of 6 months. In both specifications, we consider the Event variable (the change in the comprehensive credit rating) and matrix X contains the Lag Event variable (the cumulative change in the comprehensive credit ratings of non-event countries during the two weeks preceding the event), the levels of event and non-event country comprehensive credit ratings, country status as emerging/developed, adjacency (sharing of land border), distance between countries, sharing a common official language, membership in a trade bloc, origin of legal systems, and full sets of year and country (event and non-event) dummies. The dependent variable is the cumulative two-day [0,1] non-event country stock market return spread relative to the US stock market, denominated in US dollars. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	Upgrades				Downgrades			
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	1.6187	1.846	1.6447	1.853	2.2429	1.852	2.1791	1.802
Event	0.1124	1.037	0.1115	1.033	-0.2838	-2.028	-0.2829	-2.024
Lag Event	0.1288	2.647	0.1286	2.651	-0.0084	-0.163	-0.0084	-0.162
CCR (event country)	-0.3808	-8.798	-0.3805	-8.775	0.0025	0.060	0.0029	0.069
CCR (non-event country)	0.0531	1.391	0.0558	1.457	-0.0658	-1.225	-0.0636	-1.184
Portfolio flows - pos. cor.	0.0498	0.424			-0.0018	-0.012		
Portfolio flows - neg. cor.	-0.3256	-2.601			-0.1456	-1.054		
Trade flows - pos. cor.			-0.1216	-1.013			0.0303	0.211
Trade flows - neg. cor.			-0.2559	-2.150			-0.1239	-0.899
Emerging	1.4406	2.013	1.4254	1.979	-1.4611	-1.647	-1.4348	-1.617
Developed	-0.7699	-1.042	-0.7379	-0.992	1.9742	2.125	1.9561	2.105
Adjacent	-0.3213	-0.882	-0.3104	-0.856	0.4340	1.003	0.4480	1.036
Distance	-0.0370	-2.390	-0.0384	-2.457	0.0456	2.144	0.0460	2.150
Language	0.1146	0.658	0.1090	0.623	0.2573	1.158	0.2534	1.136
Trade Bloc	0.2580	1.004	0.2579	1.007	-0.1684	-0.403	-0.1741	-0.418
Common Law	-0.2835	-1.289	-0.2518	-1.144	-0.0458	-0.133	-0.0603	-0.174
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.115		0.113		0.081		0.081	
Number of observations	2862		2862		2877		2877	

Table 2.5: International Stock Market Impact of Sovereign Rating News - Crisis and Liberalizations Controls

This table presents the coefficient estimates of equation (2.1). In the first (second) specification, we include controls for crisis (no liberalization) periods. In both specifications, we consider the Event variable (the change in the comprehensive credit rating) and matrix X contains the Lag Event variable (the cumulative change in the comprehensive credit ratings of non-event countries during the two weeks preceding the event), the levels of event and non-event country comprehensive credit ratings, controls for countries with highly correlated portfolio (or trade) flows vis-à-vis the US computed over a rolling window of 6 months, country status as emerging/developed, adjacency (sharing of land border), distance between countries, sharing a common official language, membership in a trade bloc, origin of legal systems, and full sets of year and country (event and non-event) dummies. The dependent variable is the cumulative two-day [0,1] non-event country stock market return spread relative to the US stock market, denominated in US dollars. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	Upgrades				Downgrades			
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	1.6490	1.861	1.7976	2.003	2.1581	1.778	2.3095	1.880
Event	0.0918	0.851	0.1124	1.037	-0.2951	-2.102	-0.2835	-2.027
Lag Event	0.1253	2.550	0.1291	2.650	0.0012	0.023	-0.0081	-0.157
CCR (event country)	-0.3751	-8.733	-0.3800	-8.778	0.0012	0.027	0.0026	0.063
CCR (non-event country)	0.0531	1.388	0.0472	1.214	-0.0646	-1.203	-0.0686	-1.249
Portfolio flows - pos. cor.	0.0447	0.380	0.0470	0.401	-0.0046	-0.031	-0.0060	-0.041
Portfolio flows - neg. cor.	-0.3204	-2.558	-0.3246	-2.581	-0.1518	-1.098	-0.1511	-1.092
Trade flows - pos. cor.	-0.1276	-1.062	-0.1229	-1.021	0.0285	0.199	0.0271	0.189
Trade flows - neg. cor.	-0.2422	-2.047	-0.2371	-1.993	-0.1311	-0.949	-0.1270	-0.918
Emerging	1.4554	2.034	1.3727	1.899	-1.4433	-1.627	-1.5029	-1.665
Developed	-0.7741	-1.046	-0.6875	-0.919	1.9571	2.109	1.9814	2.122
Adjacent	-0.3144	-0.869	-0.3145	-0.869	0.4385	1.011	0.4438	1.022
Distance	-0.0364	-2.347	-0.0358	-2.312	0.0464	2.178	0.0461	2.164
Language	0.1214	0.696	0.1233	0.707	0.2606	1.173	0.2567	1.156
Trade Bloc	0.2570	1.007	0.2582	1.011	-0.1825	-0.438	-0.1907	-0.457
Common Law	-0.2806	-1.267	-0.2864	-1.296	-0.0409	-0.119	-0.0414	-0.120
Crisis	-0.4599	-2.077			0.2190	0.998		
Liberalization (no)			-0.5105	-1.113			-0.3628	-0.840
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.116		0.115		0.081		0.081	
Number of observations	2862		2862		2877		2877	

Table 2.6: International Stock Market Impact of Sovereign Rating News - Local Currency and Exchange Rate Effects

This table presents the coefficient estimates of equation (2.1) for two alternative definitions of the dependent variable. In Panel A, we use the cumulative two-day [0,1] non-event country stock market return spread relative to the US stock market, denominated in local currency. In Panel B, we use the cumulative two-day [0,1] logarithmic change in the US dollar price of one unit of non-event country currency. Both panels consider the Event variable (the change in the comprehensive credit rating). Matrix X contains the Lag Event variable (the cumulative change in the comprehensive credit ratings of non-event countries during the two weeks preceding the event), the levels of event and non-event country comprehensive credit ratings, controls for countries with highly correlated portfolio (or trade) flows vis-à-vis the US computed over a rolling window of 6 months, country status as emerging/developed, adjacency (sharing of land border), distance between countries, sharing a common official language, membership in a trade bloc, origin of legal systems, and full sets of year and country (event and non-event) dummies. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	Panel A: Local Currency Spreads				Panel B: Exchange Rate Returns			
	Upgrades		Downgrades		Upgrades		Downgrades	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	1.5728	2.065	2.3079	2.265	0.0843	0.174	-0.1519	-0.276
Event	0.0964	1.034	-0.4212	-3.286	-0.0058	-0.114	0.1252	2.445
Lag Event	0.0701	1.602	-0.0061	-0.135	0.0561	2.527	0.0075	0.343
CCR (event country)	-0.2989	-7.378	-0.0655	-1.708	-0.0770	-3.483	0.0665	3.898
CCR (non-event country)	0.0324	0.986	-0.0408	-0.926	0.0205	0.916	-0.0236	-0.937
Portfolio flows - pos. cor.	0.0263	0.243	-0.0422	-0.322	0.0194	0.372	0.0380	0.659
Portfolio flows - neg. cor.	-0.1866	-1.869	-0.1494	-1.182	-0.1345	-1.792	-0.0020	-0.042
Trade flows - pos. cor.	-0.1430	-1.461	0.0038	0.030	0.0140	0.205	0.0245	0.455
Trade flows - neg. cor.	-0.1425	-1.345	-0.1160	-0.909	-0.0985	-1.729	-0.0149	-0.352
Emerging	0.9966	1.634	-0.9765	-1.343	0.4571	1.136	-0.4660	-1.205
Developed	-0.4533	-0.712	1.0472	1.355	-0.3193	-0.812	0.9080	2.224
Adjacent	-0.3330	-1.207	-0.1065	-0.285	0.0136	0.076	0.5470	2.784
Distance	-0.0199	-1.425	0.0273	1.475	-0.0165	-2.214	0.0192	2.373
Language	0.0982	0.637	0.2361	1.199	0.0218	0.267	0.0248	0.275
Trade Bloc	0.1642	0.751	0.1152	0.336	0.0936	0.718	-0.2979	-1.453
Common Law	-0.2089	-1.081	-0.0023	-0.008	-0.0687	-0.645	-0.0385	-0.313
Crisis	-0.5225	-2.647	0.1647	0.815	0.0698	0.717	0.0552	0.653
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.109		0.106		0.079		0.059	
Number of observations	2862		2877		2862		2877	

Table 2.7: International Stock Market Impact of Sovereign Rating News - Lag Event Window and Returns Definition

This table presents the coefficient estimates of equation (2.1). In Panel A, we measure the recent rating activity (Lag Event) during a window of three weeks preceding the event. In Panel B, we use the market model parameters estimated monthly over a centered window of 36 months (excluding event months -1, 0, +1) to compute abnormal daily returns, which are cumulated in the two-day [0,1] event window. In this specification, we use returns denominated in US dollars, US stock market as the benchmark, and the Lag Event variable is measured during the two-week period preceding the event. In both panels, matrix X contains the levels of event and non-event country comprehensive credit ratings, controls for countries with highly correlated portfolio (or trade) flows vis-à-vis the US computed over a rolling window of 6 months, country status as emerging/developed, adjacency (sharing of land border), distance between countries, sharing a common official language, membership in a trade bloc, origin of legal systems, crisis periods, and full sets of year and country dummies. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	Panel A: Three-week Lag Event				Panel B: Abnormal Returns			
	Upgrades		Downgrades		Upgrades		Downgrades	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	1.6665	1.882	2.1282	1.744	2.0280	1.755	0.8484	0.649
Event	0.0491	0.454	-0.2886	-2.000	0.0355	0.242	-0.2858	-2.060
Lag Event	0.1345	2.947	0.0118	0.287	0.0748	1.363	0.0801	1.526
CCR (event country)	-0.3785	-8.870	0.0044	0.099	-0.3106	-6.951	-0.0012	-0.028
CCR (non-event country)	0.0531	1.389	-0.0650	-1.210	0.0636	1.306	-0.0414	-0.685
Portfolio flows - pos. cor.	0.0454	0.386	-0.0046	-0.031	0.0224	0.168	0.0435	0.277
Portfolio flows - neg. cor.	-0.3202	-2.559	-0.1518	-1.097	-0.3341	-2.388	-0.2399	-1.627
Trade flows - pos. cor.	-0.1275	-1.060	0.0284	0.198	-0.2292	-1.683	0.0757	0.512
Trade flows - neg. cor.	-0.2420	-2.047	-0.1311	-0.949	-0.2248	-1.698	-0.1032	-0.708
Emerging	1.4550	2.034	-1.4493	-1.631	1.7413	2.042	-0.6467	-0.672
Developed	-0.7722	-1.044	1.9625	2.111	-1.3784	-1.567	1.5262	1.516
Adjacent	-0.3138	-0.870	0.4380	1.012	-0.3525	-0.841	0.1872	0.401
Distance	-0.0364	-2.342	0.0464	2.179	-0.0465	-2.604	0.0409	1.757
Language	0.1212	0.694	0.2606	1.173	0.1357	0.728	0.1456	0.619
Trade Bloc	0.2568	1.007	-0.1823	-0.438	0.0484	0.173	0.0831	0.173
Common Law	-0.2811	-1.269	-0.0409	-0.119	-0.3273	-1.356	-0.0483	-0.132
Crisis	-0.4602	-2.094	0.2240	1.034	-0.5172	-2.287	0.2562	1.193
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.117		0.081		0.089		0.072	
Number of observations	2862		2877		2261		2560	

Table 2.8: International Stock Market Impact of Sovereign Rating News - Single Regression Model

This table presents the coefficient estimates of equation (2.3). Column (1) includes Event - Upgrades (Event variable multiplied by an indicator variable for positive events), Event - Downgrades (absolute value of the Event variable multiplied by an indicator variable for negative events), and matrix X contains the Lag Event variable (the cumulative change in the comprehensive credit ratings of non-event country sovereign debt during the two weeks preceding the event), the levels of event and non-event country comprehensive credit ratings, and full sets of year and country (event and non-event) dummies. We sequentially expand matrix X to include controls for countries with highly correlated portfolio and trade flows vis-à-vis the US (column 2), set of time invariant controls (column 3), and crisis periods control (column 4). The dependent variable is the cumulative two-day [0,1] non-event country stock market return spread relative to the US stock market, denominated in US dollars. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	(1)		(2)		(3)		(4)	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	1.7948	4.153	1.9102	4.369	1.8055	2.420	1.7794	2.388
Event - Upgrades	0.0438	0.558	0.0449	0.571	0.0483	0.614	0.0352	0.446
Event - Downgrades	-0.3874	-3.776	-0.3872	-3.779	-0.3858	-3.764	-0.3504	-3.368
Lag Event	0.0698	2.175	0.0697	2.166	0.0702	2.179	0.0565	1.704
CCR (event country)	-0.1388	-4.979	-0.1387	-4.987	-0.1377	-4.951	-0.1292	-4.661
CCR (non-event country)	-0.0065	-0.194	-0.0063	-0.189	-0.0027	-0.080	-0.0030	-0.091
Portfolio flows - pos. cor.			0.0341	0.352	0.0249	0.256	0.0251	0.258
Portfolio flows - neg. cor.			-0.2263	-2.372	-0.2238	-2.354	-0.2229	-2.347
Trade flows - pos. cor.			-0.0345	-0.358	-0.0450	-0.466	-0.0453	-0.469
Trade flows - neg. cor.			-0.1828	-1.934	-0.1847	-1.960	-0.1843	-1.957
Emerging					0.0374	0.064	0.0326	0.056
Developed					0.6236	1.026	0.6266	1.031
Adjacent					0.0175	0.061	0.0152	0.053
Distance					0.0047	0.344	0.0047	0.345
Language					0.1392	0.962	0.1388	0.960
Trade Bloc					0.0443	0.184	0.0465	0.193
Common Law					-0.1746	-0.882	-0.1742	-0.879
Crisis							-0.2834	-2.115
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.055		0.056		0.056		0.057	
Number of observations	5739		5739		5739		5739	

Table 2.9: International Stock Market Impact of Sovereign Rating News - Larger Countries

This table presents the coefficient estimates of equation (2.1) for ratings news in the 15 largest countries (PPP adjusted 2002 GDP greater than 300 billions USD). We consider two cases: larger event country news and impact in all countries (Panel A), and larger event news and impact on larger countries (Panel B). In both panels, we consider the Event variable (the change in the comprehensive credit rating), and matrix X contains the Lag Event variable (the cumulative change in the comprehensive credit ratings of non-event countries during the two weeks preceding the event), the levels of event and non-event country comprehensive credit ratings, controls for countries with highly correlated portfolio (or trade) flows vis-à-vis the US computed over a rolling window of 6 months, country status as emerging/developed, adjacency (sharing of land border), distance between countries, sharing a common official language, membership in a trade bloc, origin of legal systems, crisis periods, and full sets of year and country (event and non-event) dummies. The dependent variable is the cumulative two-day [0,1] non-event country stock market return spread relative to the US stock market, denominated in US dollars. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	Panel A: Large event countries and all non-event countries				Panel B: Large event and non-event countries			
	Upgrades		Downgrades		Upgrades		Downgrades	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	5.1784	4.549	2.7138	2.091	6.8252	4.659	3.2611	1.799
Event	0.3339	2.883	-0.4331	-2.830	0.2982	1.729	-0.5519	-2.489
Lag Event	0.1894	2.718	0.1108	1.906	0.1176	1.090	0.1826	1.883
CCR (event country)	-0.7367	-9.968	0.0398	0.845	-0.8582	-7.933	0.0299	0.423
CCR (non-event country)	0.0103	0.213	-0.1218	-2.052	-0.0243	-0.415	-0.1124	-1.317
Portfolio flows - pos. cor.	-0.1167	-0.781	-0.0420	-0.241	-0.0282	-0.125	-0.2081	-0.770
Portfolio flows - neg. cor.	-0.3065	-1.956	-0.1630	-1.009	-0.2420	-1.037	-0.2348	-0.903
Trade flows - pos. cor.	-0.2205	-1.403	-0.0609	-0.368	-0.2740	-1.225	0.2127	0.823
Trade flows - neg. cor.	-0.1280	-0.833	-0.3734	-2.323	-0.0944	-0.382	-0.3035	-1.162
Emerging	0.7376	0.843	-2.2270	-2.258	-0.0258	-0.026	-1.5478	-1.165
Developed	0.5892	0.619	2.9580	2.901	1.3220	1.166	2.4095	1.696
Adjacent	-0.0029	-0.006	0.6658	1.352	-0.4280	-0.521	1.4427	1.182
Distance	-0.0489	-2.233	0.0279	1.114	-0.0396	-1.222	0.0071	0.180
Language	0.3874	1.561	0.1631	0.589	0.2548	0.715	-0.0362	-0.086
Trade Bloc	0.0522	0.123	-0.0968	-0.173	0.0912	0.152	-0.5383	-0.581
Common Law	-0.5580	-1.574	-0.1362	-0.285	-0.5875	-1.071	0.3142	0.454
Crisis	-0.2470	-1.034	-0.5142	-2.228	-0.2265	-0.622	-0.5999	-1.685
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.169		0.111		0.156		0.084	
Number of observations	1654		2047		816		1000	

Table 2.10: Industry Portfolios Impact of Sovereign Rating News

This table presents the coefficient estimates of equation (2.1) at the industry level (TF Datastream Level 3 local industry portfolios). The dependent variable is the cumulative two-day [0,1] US dollar denominated return spread of each local industry portfolio relative to the same industry in the US. In the first specification (column 1), we include the absolute value of a negative change in the comprehensive credit rating (Event), and matrix X contains the levels of event country and non-event country comprehensive credit ratings, and full sets of year and country (event and non-event) dummies. Sequentially, we add to the regression the Lag Event variable (column 2), country status as emerging/developed, adjacency (sharing of land border), distance between countries, sharing a common official language, membership in a trade bloc, origin of legal systems (column 3), crisis periods (specification 4), and industry-specific dummies (column 5). All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

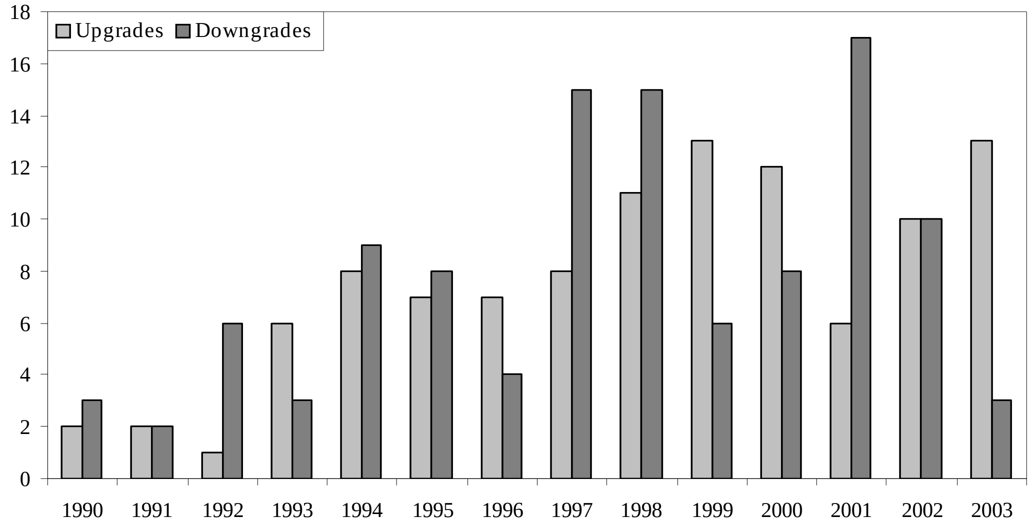
	(1)		(2)		(3)		(4)		(5)	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	1.5287	5.929	1.6041	6.129	1.2375	4.494	1.2465	4.503	1.2967	4.480
Event	-0.2510	-4.053	-0.2523	-4.068	-0.2514	-4.050	-0.2500	-4.015	-0.2502	-4.031
Lag Event			-0.0549	-2.391	-0.0553	-2.414	-0.0564	-2.422	-0.0562	-2.412
CCR (event country)	-0.0464	-2.282	-0.0460	-2.263	-0.0455	-2.238	-0.0453	-2.220	-0.0454	-2.231
CCR (non-event country)	0.0109	1.592	0.0109	1.594	0.0099	1.438	0.0099	1.437	0.0094	1.364
Emerging					0.1356	0.646	0.1355	0.646	0.1358	0.648
Developed					0.3028	1.182	0.3026	1.181	0.2981	1.163
Adjacent					0.1964	1.031	0.1963	1.031	0.1943	1.022
Distance					0.0412	4.494	0.0412	4.494	0.0414	4.507
Language					0.0493	0.505	0.0493	0.504	0.0501	0.512
Trade bloc					-0.1140	-0.653	-0.1140	-0.653	-0.1105	-0.633
Common Law					0.0500	0.324	0.0500	0.324	0.0501	0.324
Crisis							-0.0253	-0.250	-0.0241	-0.238
Cyclical Consumer Goods									-0.0114	-0.107
Cyclical Services									-0.1006	-1.047
Financials									-0.1860	-1.903
General Industries									-0.0402	-0.395
Information Technology									-0.1467	-0.994
Non-cyclical Consumer Goods									0.1308	1.376
Non-cyclical Services									-0.1497	-1.385
Resources									0.2138	1.933
Utilities									-0.0309	-0.295
Year dummies	yes		yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes		yes	
Adjusted R^2	0.046		0.047		0.048		0.048		0.049	
Observations	24639		24639		24639		24639		24639	

Table 2.11: Industry Portfolios Impact of Sovereign Rating News - Industry Groups

This table presents the coefficient estimates of equation (2.1) at the industry level for groups of industries (TF Datastream Level 3 local industry portfolios). Panel A compares downgrades impact in traded versus non-traded goods industries. Panel splits the sample into two groups of 5 industries each (larger versus smaller industries) according to the market capitalization for 2002. The dependent variable is the cumulative two-day [0,1] US dollar denominated return spread of each local industry portfolio relative to the same industry in the US. Both Panels include the absolute value of a negative change in the comprehensive credit rating (Event), and matrix X contains the Lag Event variable (the cumulative change in the comprehensive credit ratings of non-event countries during the two weeks preceding the event), the levels of event and non-event country comprehensive credit ratings, country status as emerging/developed, adjacency (sharing of land border), distance between countries, sharing a common official language, membership in a trade bloc, origin of legal systems, crisis periods, and full sets of year and country (event and non-event) dummies. All t-statistics (t-stat) are heteroscedasticity robust using the White correction.

	Panel A				Panel B			
	Traded		Non-traded		Large		Small	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	0.8415	1.640	1.6352	3.957	1.0897	2.971	1.3789	3.299
Event	-0.2934	-2.565	-0.2000	-2.275	-0.1756	-2.185	-0.3274	-3.436
Lag Event	-0.0995	-2.492	0.0253	0.719	-0.0272	-0.839	-0.0851	-2.550
CCR (event country)	-0.0547	-1.485	-0.0369	-1.279	-0.0605	-2.250	-0.0292	-0.948
CCR (non-event country)	0.0372	2.804	-0.0236	-1.901	-0.0045	-0.483	0.0266	2.588
Emerging	0.3885	1.102	0.1449	0.407	0.1929	0.663	0.1143	0.379
Developed	0.0668	0.154	0.2983	0.731	0.1607	0.461	0.4015	1.075
Adjacent	0.2656	0.810	0.0454	0.158	0.2632	1.038	0.1149	0.403
Distance	0.0288	1.859	0.0411	3.064	0.0377	3.016	0.0455	3.372
Language	-0.1298	-0.759	0.2177	1.519	0.1425	1.096	-0.0589	-0.402
Trade Bloc	-0.1183	-0.400	-0.1947	-0.722	-0.2056	-0.878	0.0016	0.006
Common Law	0.1909	0.705	0.0428	0.193	0.0592	0.288	0.0469	0.202
Crisis	-0.1649	-0.949	0.0390	0.254	0.1014	0.731	-0.1688	-1.145
Year dummies	yes		yes		yes		yes	
Event country dummies	yes		yes		yes		yes	
Non-event country dummies	yes		yes		yes		yes	
Adjusted R^2	0.053		0.048		0.048		0.053	
Number of observations	9349		9964		12865		11774	

Figure 2.1: Comprehensive Credit Rating Changes



This figure plots the number of comprehensive credit ratings upgrades (grey box) and downgrades (black box) by year.

Appendix

Table A.1: Variables Definition and Sources

Variable	Description	Sources
Emerging	Dummy variable that equals one if event and non-event country are classified as emerging, and zero otherwise	Morgan Stanley Capital International (http://www.msci.com) Standard & Poor's (http://www.standardandpoors.com) ISI Emerging Markets (http://www.securities.com)
Developed	Dummy variable that equals one if event and non-event country are not classified as emerging, and zero otherwise	Morgan Stanley Capital International (http://www.msci.com) Standard & Poor's (http://www.standardandpoors.com) ISI Emerging Markets (http://www.securities.com)
Adjacent	Dummy variable that equals one if event and non-event country share a land border, and zero otherwise	CIA (http://www.cia.gov/cia/publications/factbook/fields/2096.html)
Distance	The physical distance between event and non-event country computed as the GCD between countries' capital cities	Kristian S. Gleditsch (http://weber.ucsd.edu/∼kgledits)
Language	Dummy variable that equals one if event and non-event country share a common language (official), and zero otherwise	CIA (http://www.cia.gov/cia/publications/factbook/fields/2098.html).
Trade Bloc	Dummy variable that equals one if event and non-event country share the same trade bloc, Nafta, Mercosur, Asean, or EU, and zero otherwise	Nafta (http://www.nafta-sec-alena.org) Mercosur (http://www.mercosur.org.uy) Asean (http://www.aseansec.org/home.htm) EU (http://www.europa.eu.int)
Common law	Dummy variable that equals one if event and non-event country share the common law legal tradition, and zero otherwise	La Porta et al. (1997).
Crisis	Dummy variable that equals one if event occurs during international financial crisis periods, and zero otherwise	Kaminsky and Schmukler (2002), Karoliy (2003), Kaminsky et al. (2003).
Liberalization	Dummy variable that equals one for periods before the officialliberalization date	Bekaert et al. (2003).
Portfolio flows	Gross (purchases plus sales) transactions in foreigner equities between each country and the US	US Treasury (http://www.treas.gov).
Trade flows	Gross (exports plus imports) trade flows between each country and the US	US Census Department (http://www.census.gov).

Table A.2: Comprehensive Credit Rating Definition

Explicit Credit Rating (ECR)		Credit Outlook	
Rating	Numerical Code	Information	Add to ECR
AAA	20	Positive	1
AA+	19	CW - Pos	0.5
AA	18	Stable/CW - Dev	0
AA-	17	CW - Neg	-0.5
A+	16	Negative	-1
A	15		
A-	14		
BBB+	13		
BBB	12		
BBB-	11		
BB+	10		
BB	9		
BB-	8		
B+	7		
B	6		
B-	5		
CCC+	4		
CCC	3		
CCC-	2		
CC/C	1		
SD/D	0		

CHAPTER 3

Correlations of Global Industry Portfolios: An Empirical Investigation of Trends and Asymmetries

(with Miguel Ferreira)

3.1. Introduction

Have global industries correlations decreased? Is correlation related to industry specific characteristics? In this paper, we find that indeed global industry correlation changes over time. The late 1990s period is characterized by low correlations. Furthermore, industry correlations are counter-cyclically and small and value (low price-earnings ratios) industries have lower correlations. Industry correlations increase for market downturns. Correlation asymmetry is found among all size, price-earnings ratios, and economic sector groups (only exceptions are resources and utilities), but is more pronounced among small industries.

The increasing integration of economies and the globalization of business activities suggest that global factors should play an increasingly important role in the pricing of securities. Recent research supports this implication. Diermeier and Solnik (2001) find strong evidence that firms are priced globally and that it is incorrect to assume that the companies headquarters location (or the market its stock is listed) captures the major source of influence in its stock return behavior.[1]

In addition, several papers find evidence supporting the growing importance of global industry factors relative to that of country specific factors in determining equity returns. For example, Cavaglia, Brightman, and Aked (2000) and Baca, Garbe, and Weiss (2000),

[1]See also, Brooks and del Negro (2003), Cavaglia, Cho, and Singer (2001), and Lombard, Roulet, and Solnik (1999).

show that for developed equity markets, from the mid 1990s onwards, the importance of country-specific factors declines while that of global industry factors increases. In fact, Brooks and Catao (2000) show that the importance of global industry factors increases for both developed and emerging markets, and this is primarily explained by technology stocks. In contrast with developed markets, emerging markets do not present a decrease in country-specific factors (Serra (2000)).

These recent evidence is at odds with previous work by Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998) that shows the dominance of pure country factors relative to pure global industry factors. Accordingly, "slicing" the world by industries rather than only by countries could be a useful tool to increase the benefits of international diversification strategies in terms of risk reduction

While much is known about cross-country correlation (and as we know correlations play a key role in assessing the power of diversification), on the other hand the empirical analysis of the correlation of global industries is an issue that, to our knowledge, has been overlooked in the literature. Thus, our goal is to contribute to the literature on international investments with the characterization of global industry portfolios correlation dynamics, in particular in terms of long-term trends and asymmetries.[2]

Our methodology is characterized by several distinct features. First, we use a simple and time-varying measure of correlation - realized correlation (e.g., Andersen, Bollerslev, Diebold, and Ebens (2001)). Specifically, we use within month daily index return data to construct a time series of correlation at the monthly frequency, which are treated as "observable" and consequently suitable for posterior analysis using standard econometric models. Relative to multivariate GARCH alternatives (e.g., Engle (2002)), we do not need to impose a parametric model to describe the time evolution of covariances or volatilities, but still allowing these variables to change over time. Relative to rolling window estimates (e.g., Solnik, Boucrelle, and Le Fur (1996)), realized correlation minimizes autocorrelation and "ghost effects".

[2]Global industries presumably diversify away country specific sources of return variation, and thus allow for a new look at the global stock correlation minimizing the dynamics of country factors in explaining the variation of returns.

Second, we study the time series behavior and asymmetries of the correlation for alternative groups of industries, based on size, price-earnings ratio, and economic sectors. In fact, we characterize the structure of correlation with the market according to two global industry characteristics: market capitalization (size) and price-earnings ratios (PER). These characteristics are known to have predictive power to explain the cross-section of expected stock returns; see, for example, Banz (1981), Basu (1983), Fama and French (1992,1998), Haugen and Baker (1996). Recently, Lewellen (2004) demonstrates the ability of market-level financial ratios to predict market returns, and Lewellen (1999) examines the relation between US industry portfolios returns and lagged book to market ratios.

Finally, we use time-varying estimates of correlation to investigate asymmetries relative to the market trend (up and down). Relative to the traditional "exceedance correlations" method for testing asymmetries (e.g., Ang and Chen (2002) and Longin and Solnik (2001)), we do not compare time-constant estimates of correlation obtained from pre-sampled returns that are either higher or lower a given threshold.

The literature offers some key results that are related to our work. With respect to cross-country correlations, the literature shows that: (1) correlation is time unstable with tendency to increase over time (e.g. Solnik and Roulet (2000), Longin and Solnik (1995), Tang (1995)); (2) correlation is positively related to the level of country volatility (e.g. Solnik, Boucrelle and Le Fur (1996)); (3) correlation is higher in bear markets (e.g. Longin and Solnik (2001)); and (4) correlation is related to the coherence between countries' business cycles and its market phase (Erb, Harvey, and Viskanta (1994).[3]

With respect to global industry portfolios, Ferreira and Gama (2004) find that between 1974 and 2001 there is no noticeable long-term trend in industry-specific or world portfolio risk (for developed markets). In contrast, the late 1990s are characterized by an increase

[3]Serra (2000) shows that within emerging markets, between 1990 and 1996 aggregate correlation across sector portfolios (0.54) is substantially higher than across country portfolios (0.07). Also, Meric and Meric (1989) show that for a sample of 17 developed markets, between 1973 and 1987 the correlation between global industries (0.619) is higher than between countries (0.398). These results are in line with the earlier results on the dominance of pure country factors in explaining security variation of Heston and Rouwenhorst (1994) and Griffin and Karoliy (1998), but are silent about the cross-section and time-series properties of global industry correlation, the subject of our paper.

in the ratio between global industry specific risk and world risk. This implies a decrease in global industry portfolio correlation during that short period. Moreover, we know that for local US industry portfolios, correlation with the US market tends to increase on the downside. However, different testing procedures yield different conclusions on the statistical significance of that increase; see Ang and Chen (2002) and Hong, Tu, and Zhou (2003).

The remainder of the paper is organized as follows. Section 3.2 describes the variables and sample used in this paper. Section 3.3 investigates the time series properties of global industry correlations. Section 3.4 studies the relationship between correlation and returns. Section 3.5 presents results for global industry market betas and volatility ratios. Section 3.6 concludes.

3.2. Research Design

3.2.1. Estimation

The starting point for estimating correlations is to obtain estimates of variances and covariances. French, Schwert, and Stambaugh (1987) and Schwert (1989) use daily data within the month to obtain non-overlapping monthly estimates of market variance. Andersen, Bollerslev, Diebold, and Ebens (2001) extend this approach to measure daily realized covariance and correlation using intraday data. We follow this approach and measure monthly realized variance (VAR), covariance (COV), and correlation (COR) using daily returns for global industry portfolios and the market (world) portfolio. Specifically, we calculate the following estimates,

$$\mathrm{VAR}_{i,t} = \sum_{d \in t} (r_{i,d} - \mu_{i,t})^2, \tag{3.1}$$

$$\mathrm{COV}_{i,t} = \sum_{d \in t} (r_{i,d} - \mu_{i,t})(r_{m,d} - \mu_{m,t}), \tag{3.2}$$

$$\mathrm{COR}_{i,t} = \frac{\mathrm{COV}_{i,t}}{\sqrt{\mathrm{VAR}_{i,t}\mathrm{VAR}_{m,t}}}, \tag{3.3}$$

where $r_{j,d}$ denotes the world portfolio ($j \equiv m$) or global industry portfolio i ($j \equiv i$) logarithmic returns on day d of month t, and $\mu_{j,t}$ is the average daily return of portfolio j on month t. Variance and covariance estimates are obtained at the monthly horizon. To assure that the variance estimator is not negative, we follow Schwert (1989) and do not include the one lagged cross-product of square returns suggested by French, Schwert, and Stambaugh (1987) aiming at accounting for the return series autocorrelation. The correlation of each industry portfolio with the world portfolio proxies for the average correlation of each industry with the remaining industry portfolios, as the covariance with the market is the average of the pairwise covariances and correlation is a rescaled covariance.[4]

We note that the pervasive effects of non-overlapping trading periods over correlation (namely the downward biases documented, for example, by Kayha (1997)) should be more serious for the estimates comparing different countries than for those comparing different global industries. The global industry indexes are computed as a weighted average of local industry indexes in the same trading day (when available). For instance, information arriving the global market after Japan closes on a given day, would be reflected in the global industries indexes through the close in the US market. Thus, the global level of information relevant for pricing arriving the markets during a given trading day is reflected in the global industry indexes. In contrast, global information available after a market close can only be reflected by the early closing country stock markets indexes in the next trading day.

We study the behavior of correlation for industry groups based on market capitalization (size) and price earnings ratio (PER). These attributes are chosen because they are determinants of the cross-section of expected returns; see, e.g., Banz (1981), Basu (1983), Fama and French (1992, 1998), Haugen and Baker (1996).[5] Specifically, we use for each global industry portfolio (i) in each month (t), the following attributes,

[4]Thus, the correlation with the market is a positive function of the average pairwise correlations. Ang and Chen (2002) and Hong, Tu, and Zhou (2002) also rely on the correlation with the market to study correlation asymmetries in the US market.

[5]Bekaert, Harvey, Lundblad, and Siegel (2004), use local industry price-earnings ratios as a source of information about countries' growth opportunities. The study confirms empirically the intuition that countries with heavy wheightings on high PER industries have high implied growth opportunities.

$$\text{Size}_{i,t} = \sum_{c \in i} P_{c,t} N_{c,t}, \tag{3.4}$$

$$\text{PER}_{i,t} = \frac{\sum_{c \in i} P_{c,t} N_{c,t}}{\sum_{c \in i} E_{c,t} N_{c,t}}, \tag{3.5}$$

where P_c is the price of each stock c included in the global industry i, on month t, $N_{c,t}$ is the number of shares in issue for each stock, and $E_{c,t}$ is the earnings per share on month t for constituent c (negative earnings per share are treated as zero).

We use the cross-industry distribution of size and PER at the beginning of each month to classify each industry into one of four groups for each characteristic: Q1, the industries in the first quartile (lowest), Q2 and Q3, respectively, the industries in the second and third quartiles, and Q4 (highest) the industries in the fourth quartile. The correlation with the world portfolio for a given quartile in a given month is measured by the cross-sectional average of the correlation with the world portfolio of the industries that in that month are classified in that quartile.

We can interpret the quartile average correlation as an estimate of the correlation of a "typical" (randomly selected) industry within the quartile for a given month. Thus, it differs from the correlation computed using the returns of previously sorted portfolios of industries (e.g. Ang and Chen (2002)), because we do not eliminate by aggregation the idiosyncratic factors within each quartile. Nevertheless, we have a measure of correlation for individual global industries, which minimizes noise by the averaging process, and do not impose a monthly rebalancing to look across industry characteristics.

3.2.2. Data Description

We use Datastream Global Equity indexes from January 1979 to December 2003. Daily returns are computed as the first difference of logarithmic daily index levels, expressed in US dollars, with dividends reinvested. In addition, market capitalization, and price earnings ratios for each global industry portfolio are also from Datastream.

While the regional setup varies over time, as new countries begin to be covered by Datastream (the world portfolio covers 45 countries in 2003), the industrial setup remains unchanged over the sample period. We consider both the aggregate world market index, and 35 global industry indexes that group firms according to the Financial Times Actuaries Standards 2003 sectors classification (Level 4 in Datastream). At each point in time, each global industry index can include stocks from all countries or just from a subset of those, and the particular stocks may also vary as Datastream revises its indexes annually.

Table 3.1 presents descriptive statistics of the time series of monthly returns, market capitalization (size, in millions of US dollars), price earnings ratios (PER), and correlation with the market. The highest cross-industry variation is found for average size and the lowest for average correlations. Average size range between a minimum of 68,043 million US dollars for the investment companies industry and a maximum of 1,219,467 million US dollars for the banks industry, with a coefficient of variation of 81.4%. Correlations range between a minimum of 37.5% for the mining industry and a maximum of 82.1% for the chemicals industry, with a coefficient of variation of 14.8%.

Our results suggest that industries with low returns, high size and high PER are more correlated with the market. The cross-sectional correlation of mean realized correlation with mean returns is -39.6% (with a t-statistic of -2.48), with mean size is 35.4% (t-statistic 2.17), and with mean PER is 25.2% (t-statistic 1.49).

Also, the figures in Table 3.1 suggest that in our sample there is no linear association between industry size and industry PER, as the cross industry correlation between the two time series mean estimates is 1.4% (with a t-statistic of 0.081).

3.3. Time Series of Industry Correlations

3.3.1. Graphical Analysis

Figure 3.1 plots the time series of the equal-weighted average (monthly cross-section) of the 35 global industry portfolios' correlation with the world market portfolio. Aggregated global industry correlation have not been increasing over time. We have periods of high correlation, for instance the early 1990s, when the maximum is reached (95.2% in August 1991), but these do not seem to persist. In fact, average global industry correlation shows wide fluctuations at the monthly frequency and a slow moving U-shaped pattern during the 1980s and the 1990s. Most noticed is the sharp downward move after 1997, a period characterized by a cluster of low correlation spikes, namely in April 1999 (22.5%, the minimum) and January 2001 (25.2%, the second lowest). These low levels are followed by a recovery to historical levels by 2003. Overall, the time evolution of aggregated industry correlation, suggests a pattern characterized by temporary long-term swings and the absence of a secular increase in correlation.

The downward move in the late 1990s, is in line with the findings of Ferreira and Gama (2004). The higher increase in global industry specific risk relative to that of world portfolio volatility, implies a decrease in global industry correlation.

Also noticed is the tendency of an increase in correlation during economic recessions. In Figure 3.1, the shaded areas represent the periods of US contraction, as officially dated by NBER. During recessions, both a cluster of correlation peaks as well as an increase in the slow moving component is noticed. Particularly evident is the increase in correlation during the 2001 US recession.

Figures 3.2 and 3.3 show correlation for the lowest (Panel A) and highest (Panel B) quartiles of size and PER, respectively. Both for size and PER groups , the lowest quartile (Q1) show wider movements than the highest (Q4) quartile at the low frequency (12-month moving average). Also, there is no evidence of a secular increase. All the series reach its maximum in August 1991, with monthly estimates above 90% (a feature that also characterize the middle quartiles). April 1999, is a month of unusually low (and negative) realized correlations for the lowest quartiles of size (-10.2%) and PER (-13.1%). For the highest quartile of size, April 1999 also represents the time series minimum, but with a positive value

(42.1%). For the highest quartile of PER, the time series minimum is reached in January 2001 (28.0%) and August 2000 represents the second lowest estimate (31.8%).[6]

3.3.2. Trends

Table 3.2 presents descriptive statistics for the quartile correlation time series and investigates the stochastic behavior of correlation for the whole sample period. Panel A uses the value-weighted world portfolio return from Datastream, and Panel B uses the equal-weighted (EW) average return of the 35 global industry portfolios to proxy for the world portfolio return.[7]

Over the whole sample period, global industry correlation is lower for the lowest size or price earnings ratios quartiles. The fairly high autocorrelation, does not mean that the series are integrated. Given that correlation is bounded, technically it can not have a unit root. Nonetheless, since perfect correlation (either positive or negative) is unnoticed in practice, correlation can still exhibit nonstationary behavior. The null hypothesis of a unit root is rejected by the Augmented Dickey-Fuller (ADF) t test, for all series, at the 5% level (the number of lags is determined by the Akaike Information Criterion) Thus, average correlation series seem to be stationary, which means that fluctuations around the long-run mean do not produce permanent effects on its behavior.[8] This is consistent with the long-term temporary swings already uncovered in the graphical analysis.

One important issue for international investors is to evaluate whether correlation remains constant over time. We can diagnose the time instability in the correlation series by testing for long-term trends. Following Longin and Solnik (1995) a simple linear trend model is specified with the sole purpose of testing the existence of a trend. To test for the significance

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[6]For the other quartiles of size the minimum estimate is reached in January 2001 (10.7% Q2, and 22.2% Q3). For the PER Q2 quartile, April 1999 is the minimum (6.0%), and for the PER Q3 quartile, the time series minimum is reached in December 1999, with 30.2%.

[7]The EW world return is used to ascertain to what extent the cross sectional characteristics of industry correlation, especially for the size quartiles, are a simple manifestation of the, unavoidable, fact that higher size industries weight more on the world portfolio and thus are expected to be more correlated with the market, in a reality characterized by cross industry positive covariances.

[8]Extensive testing shows that rejection of the null with the Phillips-Perron Z_t test is possible for every lag up to 18. As an alternative procedure to handle the bounded variables problem, Cavaliere (2005) uses Monte Carlo simulations to estimate new critical values for the Phillips-Perron Z_t test. Our estimates of the Z_t statistic (not reported, but available upon request) are all below the bounded critical values.

of the trend coefficient we use the $t - PS_T$ test of Vogelsang (1998), which performs well in finite samples for series with serial correlation, and is valid whether or not the errors contain a unit root. Specifically, we estimate the following regression,

$$COR_{Q,t} = \alpha_{0,Q} + \alpha_{1,Q}T + \epsilon_{Q,t}, \tag{3.6}$$

where $COR_{Q,t}$ is the correlation with the market portfolio estimate (alternatively it refers to the correlation with the VW world portfolio returns or the correlation with the EW world portfolio returns) for quartile Q during month t, and T is a time trend. $\alpha_{1,Q}$ measures the expected monthly increase in correlation.[9]

Panel A of Table 3.2 show that the trend coefficients are not statistically significant, although their signs are different. For the all-industry average correlation, the trend coefficient is negative. For the size-based quartiles, the evidence suggests the existence of a long-term "size effect" in the behavior of industry portfolios correlation with the market. In fact, the trend coefficient is negative for Quartiles 1 through 3 and is positive for Quartile 4. For the price earnings based quartiles, the evidence suggests a U-shaped behavior. The correlation in the extreme quartiles tends to increase, while that in the middle quartiles tends to be decreasing in the long run.

As Panel B of Table 3.2 shows, the overall characteristics of these patterns are not affected by the definition of the world portfolio return. The signs of the (insignificant) trend coefficients do suggest the same basic pattern: largest industries and extreme PER industries have higher correlations over the long run. The main change relative to Panel A is that the monotonic increase with size no longer holds, as the fourth quartile estimate is now lower than the one for the third quartile. However, difference is small and the estimated correlation for the fourth quartile is higher than the estimated average correlation for the second and first quartiles.

[9]We do run regressions with Fisher z correlation coefficients as dependent variable to minimize the effects on the residuals' distribution of using a bounded variable as dependent variable. The conclusions are unaffected, so these results are not reported, but are available on request.

Our results point out to a positive relation between industry correlation and size, that is not due simply to a "mechanical" size effect. A possible explanation is a diversification effect. Indeed, if industries with higher market value are also industries characterize by a more diversified portfolio of activities, namely at the international level, than higher correlation would result from the expected lower industry-specific risk.[10]

The absence of an upward trend (or suggestion of downward trend) in industry correlation with the market, is in contrast with Longin and Solnik (1995) finding of a positive (and statistically significant in 4 countries) linear trend in the conditional correlation of the G-7 countries stock market index with the US market, between 1960 and 1990. Also, Solnik and Roulet (2000) show that their estimate of "cross-sectional" correlation of 15 developed stock markets returns with the world portfolio returns has a positive and statistically significant trend slope (between 1971 and 1998).

3.3.3. Time and Quartile Effects

Our evidence suggests that long-term swings rather than a secular trend, characterizes the behavior of global industry correlations. To further document these patterns, we calculate the average correlation for 5 equally-spaced sub-periods of 60 months. The statistical significance of the time variation in average correlation in each sub period, is based on the following regression,

$$COR_{Q,t} = \sum_{P} \theta_{Q,P} I_P + \gamma COR_{Q,t-1} + \epsilon_{Q,t}, \tag{3.7}$$

where $COR_{Q,t}$ is the quartile $Q = 1, 2, 3, 4$ correlation with the world portfolio during month t, and I_P is equal to one if the month t observation occurs during the sub-period $P = 2, ..., 8$, and zero otherwise. Given that it is feasible that the residuals in each quartile regression would be contemporaneously correlated with the residuals in the other quartile regressions, we estimate jointly the four equations relating to each characteristic (size or PER), using the Seemingly Unrelated Regressions(SUR) technique, to increase the efficiency of estimators,

[10] We thank Peter Ritchken for pointing this to us.

and because it allows for a direct test of the differences across quartiles. Lagged correlation is introduced to capture the high persistence exhibit by the correlation series. Standard errors are heteroskedasticity and autocorrelation robust using the Newey-West correction with five lags.

We test for quartile effects (time measured) with a joint Wald χ^2 test for the null hypothesis $\theta_{1,P} = ... = \theta_{4,P}$, for each period P. We test for time effects with a joint test for the null hypothesis $\theta_{Q,1} = ... = \theta_{Q,5}$ for each quartile Q.[11]

Table 3.3 presents the results.[12] Panel A uses value-weighted world portfolio returns. The 1999-2003 period is characterized low realized correlations. In all quartiles of size (with the exception of the highest size quartile Q4) and all quartiles of PER, the mean correlation is lower for the 1999-2003 period, relative to all the other sub-periods. For the largest size quartile, the decrease in correlation following the upward move in the 1989-1993 period, is not strong enough to reach beginning of the sample values. The up and down moves in correlation (time effects) are statistically significant for all quartiles, with the exception of the lowest size (Q1) quartile.

The lower industry correlations for the 1999-2003 period, are in contrast with the cross-country correlation increase in the late 1990. For example, Statman and Scheid (2004) show that correlations between the US stock market and other international stock markets reach a peak of 0.86 in December 2003.

The absence of time effects in the lowest size group is interesting for global investors, as these "small" industry portfolios, are also the ones less correlated with the world portfolio. In fact, in the five sub-periods, for the size characteristic, the least correlated quartile is always the lowest size quartile, and the cross quartile mean differences (quartile effects) are statistically significant. Interestingly, size is more powerful than for PER in explaining

[11]As Judge et al. (1988) mention, testing for time effects based on the individual significance of individual differential coefficients (t test) would not be advisable, because the individual coeficients significance depend on the parameterization adopted.

[12]We do run regressions with Fisher z correlation coefficients as dependent variable to minimize (but not eliminating) the effects on the residuals' distribution of using a bounded variable as dependent variable. The conclusions are unaffected, so these results are not reported, but are available on request.

the cross-section of correlation, as the statistical significance of the restriction that mean correlation is equal across quartiles is much higher for the size quartiles.

Panel B addresses the importance of the expected increase in correlation with the world portfolio for its relative most important components, by using as benchmark the equal-weighted returns of the 35 global industry portfolios. The overall effect in the sub-period means is an increase in the smallest size and lowest PER quartiles correlation, and a decrease in the largest size and highest PER quartile correlation. Surprisingly, the differences are more noticed for the PER quartiles than for the size quartiles. These differences are related to the statistical significance of the time and quartile effects, and not to their overall patterns (lower correlation for the 1999 to 2003 period, and for the Q1 of size or PER).

For the size quartiles, we cannot reject the restriction that mean estimates are different for the 1999-2003 period, and we find statistically significant quartile effects in all other sub-periods, and significant time effects in all but the smallest size quartile.

For the PER quartiles, we find statistical insignificant time effects in the lowest quartile, while for the other quartiles there still is considerable time variation in the level of correlation. Most interesting, with the EW world returns as benchmark, the PER quartile effects lose statistical significance. This suggests that after controlling for the size effects on the correlation estimates (via an equalization of size in the determination of world returns), a statistically significant independent PER effect does not emerge.[13]

To conclude this section, we look at the interaction between size and PER in determining the correlation level. We have already seen that smallest and growth industries have lower correlations. Which of the characteristics dominate (if any)? To illustrate this issue, we perform a double sort of the correlation industry groups' series. First, industries are classified according to the size quartiles. Second, within each size quartile, industries are classified according to the PER quartiles. Thus, the monthly average of industries correlations allows the construction of a time series of industries correlations for the 16 industry groups created

[13]Fama and French (1992) show that the individual explanatory power of E/P is lost in a multivariate regression which also includes Size, when explaning the cross section of expected returns.

(e.g. Q1 PER of the Q1 size).[14] In addition, we also perform the double sorting of the industries correlations, using the reverse procedure. That is first sorting on PER and next on size, within each PER quartile.

Table 3.4 presents the time series mean correlation for each of the 16 groups, together with the difference between the first and fourth quartile (columns differences). First, the PER effects are most noticed for the smallest industries. The PER range for the size Q1 (10.5%) is at least twice the PER range for the other quartiles of size.

Second, the size effects are more pronounced for the low PER industries, and are economically most significant (measured by the range between size quartiles) than PER effects. In other words, size effects dominate PER effects. In fact, when we move from the Q1 to Q4 of size (for a given PER) the increase in correlation is greater than when we move from Q1 to Q4 of PER (for a given size).

Panel B uses equal-weighted world portfolio returns. The removal of industry capitalization effects on the computation of world returns, reinforces the intuition that size effects dominate PER effects. When we first sort on size, the PER effects (except for the Q1 of size) decrease substantially relative to VW world returns. When we first sort on PER, again we observe a decrease in size effects relative to VW returns, but these are always greater than the PER effects. This reinforces the importance of size for the estimated level of realized correlation.

3.3.4. Global Economic Sectors

This section investigates the time series behavior of market correlation behavior for individual global economic sectors. We use FTSE Economic sectors classification to aggregate individual industries correlation into 10 groups representing the economic sectors resources, basic industries, general industries, cyclical consumer goods, non-cyclical consumer goods, cyclical Services, non-cyclical services, utilities, information technology, and financials. For

[14]The procedure assures that at least two global industry portfolios' correlation is averaged monthly to estimate the monthly realized correlation for a given industry group.

example, the correlation for the resources sector is proxied by the average correlation of the mining and oil & gas global industries.

Table 3.5 presents the results. Panel A uses the value-weighted world portfolio returns. The average correlation shows significant variation across sectors. Correlation is the lowest for the resources sector (47.8%) and the highest for the cyclical services sector (75.1%). Overall, the sector correlation series seem to be stationary.[15] Trends tests also support differences in the time series behavior of the sector correlations. Trend coefficients are negative for six sectors and are positive for the remaining four - cyclical services, non-cyclical services, information technology, and financials. Similarly to evidence on size and PER groups, there is no evidence of significant trends for the majority of the sectors correlations time series. Nevertheless, a statistical significant downward trend is found for the resources sector (representing a decrease of 12.7% between 1979 and 2003) and non-cyclical consumer goods sector (a decrease of 26.5%) and a marginally significant positive trend for the non-cyclical services sector (an increase of 16.5%).

Panel B uses the equal-weighted world returns to define market trends and compute industry correlations. There is minor effects on the cross-section of mean correlation (the range is virtually the same, about 27.3%). Also, the signs of the trend coefficients do not change, though in absolute value they become smaller. Indeed, statistical significant trends are found for the non-cyclical consumer goods sector (negative trend, implying a decrease of 26.3%) and, interestingly, a significant positive trend for the financials sector (an increase of 10.8%).[16]

3.3.5. Robustness

This section addresses the influence of the potential downward bias in correlation coefficients estimated from daily data due to the effects of non-overlapping trading hours across national markets, the sensitivity of our results to the noise reduction associated with a wider window

[15] For the basic industries and utilities sector, the null of a unit root is rejected by the ADF $T(\rho-1)$ at the 5% level.

[16] The non-cyclical services sector positive trend coefficient is statistically significant at the 10% level ($t-PS_T(10\%)=1.719$, critical value of the $t-PS_T(10\%)$ is 1.33).

to estimate the realized correlation, the importance of extreme observations, and the currency to express returns.

Table 3.6 redefines the sample in two alternative ways. First, we use a simple rolling-average of two-days returns to minimize the effects of non-overlapping trading hours across national stock markets, as in Forbes and Rigobon (2002). Monthly realized correlation for the individual industry portfolios are then computed from these returns. Second, we extend the estimation window to 2 months, thus doubling (approximately) the number of daily observations used to estimate each observation of the realized correlation series.[17]

As the result show, reducing non-overlapping trading hours effects as the non surprising effect of an increase in mean correlation estimates (about 3%), the signal of the nonsignificant trend coefficient for the Q4 of PER relative to EW world returns, which is now negative, and, an overall decrease in the first order serial correlation. Most relevant, the key findings remain the same. Likewise, enlarging the estimation window to 2-month, does not have significant effects on the time evolution of correlation. For the size and PER quartiles, trend coefficients retain the same signs and statistical insignificance.

In Table 3.7, firstly, we follow the intuition of Campbell et al. (2001) and perform a 5% winsorization of the correlation series (we replace the observations of each quartile correlation series in the upper (lower) 2.5% percentiles by the 97.5% (2.5%) percentile). This procedure decreases the influence of the (extreme) observations being replaced, but leaves them as important upward or downward moves in correlation. Secondly, because correlations are not immune to exchange rate movements (e.g. Odier and Solnik (1993)) we redenominate the daily return series in Deutschemarks (DM) by adding to the US$ denominated logarithmic returns the logarithmic variation of the DM/US$ exchange rate (from January 1999 onwards, we use the fixed DM/EUR= 1.95583 exchange rate to obtain a notional DM/US$ exchange rate), and estimate the correlation coefficients from these returns.[18]

[17] We use a 2-month window and not the more traditional quarterly window, because we define falling and rising markets by the sign of market returns, thus reducing substancially the sample of quarterly down market periods.

[18] Our basic results consider global industry returns denominated is US dollars. As such, we cannot adopt the view of a global investor fully hedged in exchange rate risk by computing global industry returns denominated

Results using the "winsorized" data set remain virtually unaffected. Over the long, the time series mean is identical in all quartiles, and as expected the standard deviation (first order serial correlation) decreases (increases), albeit marginally. Moreover, the statistically insignificant trend coefficients retain the same signs, and present a slight increase.

Results using the German DM denominated do reveal the influence of exchange rate movements. As with the US dollars denominated returns, quartile correlations using the German DM denominated returns are lower for the lowest quartiles of size and PER.

Most differences are notice in the long run behavior of industry quartiles correlation. The correlation trend coefficients for a German-oriented perspective are now all positive, and significant for quartiles Q1 and Q4 of size and PER. This shows that the time series behavior of correlation is strongly affected by the exchange rate moves.

Table 3.8 replicates Table 3.3 using the DM denominated returns quartile correlation series, to further document the temporal behavior of correlation for a different global investors' perspective. Results show that the 1999 to 2003 period was a period of low correlations relative to the two preceding 60 months periods (1989 to 1993 and 1994 to 1998), but not relative to the initial periods (1979-1983 and 1984-1988). As a result of low initial correlation estimates, an upward trend naturally emerges. But a careful look at Table 3.8, also reveals a long-term "inverted-U" shaped pattern characterizing the behavior of correlation (computed from German DM) over the last 25 years. This suggests that the conclusion for a decrease in the benefits of global sector rotation strategies over the long run, for those investors that measure returns using the German DM, as implied by the positive trend coefficients, may be misleading, as the recent tendency is precisely the opposite.

3.3.6. Cyclical Behavior

Erb et al. (1994) find that cross country correlation among the G-7 is higher when two countries are both in recession than when they are in different market phases or are both in expansion. Correlation is linked to the business cycle, because expected returns behave

in local currencies. We adress the issue of exchange rates influences indirectly by adopting the view of a Germany-based investor. Exchange rates are drawn from The Federal Reserve Board.

countercyclically (e.g., DeStefano (2004)), and so does market and industry-specific volatility (Campbell et al. (2001)).

This section explores the relation between the US business cycle and the global industry correlation with the world portfolio.[19] Indeed, the behavior of the 12-moving average plotted on Figures 3.1-3.3 during the periods of US economic contraction (the solid grey columns represent the period between consecutive peaks and troughs, as "officially" dated by NBER for the US economy), suggests that months characterized by a US contraction are also characterized by higher correlations. Most noticed is the upward move in correlation for the beginning of 2001.

Table 3.9 analyzes this issue further. We compute at different lags (and leads) the cross-correlation between each quartile correlation series with the world portfolio and a dummy variable that equals one for NBER dated US expansion periods, and zero otherwise. Thus, a negative sign means that the correlation between global industries and aggregate world market is higher during US economic recessions.[20]

The contemporaneous cross correlations between global industries correlations and the US expansion indicator are negative for all quartiles of size and PER. Clearly, the global industry correlations increase during US recession. Among the size (PER) quartiles, Q1 (Q2) tend to have the most negative contemporaneous correlation. How big is the magnitude of these moves? For the smallest size quartile, the average global industry correlation is about 10.3% higher during recessions than during expansions. For the largest size quartile the effect is smaller, as the correlation increase is only of 3.1%. Movements for the PER quartiles are

[19] We use the US business cycle as a proxy for what might be called a world business cycle. This choice was determined by operational reasons (to our knowledge, there is not an "officially" dated world business cycle), and rest on the importance the US market as on the Datastream world portfolio (about 46% in 2003), and the US economy in the world (about 30% of the World GDP in 2003, according to the World Bank - WDI). Moreover, there is some controversy on whether national business cycles have become more synchronized over time. For example, Bordo and Helbling (2003) find increase synchronization over the last 125 years for 16 developed countries. On the other hand, Doyle and Faust (2004) find no evidence of greater output growth rates correlations between the G-7 countries, since 1971.

[20] Forbes and Rigobon (2002) show that the measured increase in correlation could simply be a volatility effect. Thus, one cannot conclude that the true linkages across markets - measured by the unconditional correlation - indeed increase during periods of turmoil. However, Chakrabarti and Roll (2002) argue that in situations when the true volatility also increases, higher correlation can be correctly associated with higher volatility.

also less pronounced: 8.6% for Q2 (the largest increase) and 4.0% for Q4 (the smallest increase).

The cross-correlations at different leads and lags reveal an interesting pattern. For the short term lag (up to 3 months) cross correlations are negative, while starting from the 6 month lag, cross correlations tend to be positive. Concerning the various leads up to the 12 month lead, cross correlation are always negative. Thus, the results suggest that global industry correlation increases prior to the end of an expansionary period (short term lag effect), and after the start of an economic recessions in the US (lead effect).

These results are in line with Campbell et al. (2001) findings that industry and, especially, market volatility are counter-cyclical in the US. US market volatility is about three times higher in recessions than in expansions, while industry-level volatility roughly double. Thus, even a well diversified portfolio is exposed to more volatility when economy turns down. Global industry correlations with the world market are also higher during economic recessions. The message to global investors is straightforward: the power of global industry diversification decreases during economic recessions.

3.4. Asymmetries in Industry Correlations

Longin and Solnik (2001) find an asymmetric relation between country portfolios correlation with the US stock market and the (signed) threshold used to define the (signed) return exceedances. For negative return exceedances the correlation estimates tend to increase with the absolute level of the threshold, while for positive return exceedances that does not happen.[21]

In this section, we investigate the contemporaneous relation between monthly realized market-industry correlation and the sign and size of market returns. We investigate the time series relationship between realized correlations and returns, over the entire distribution of

[21]Conditional on the absolute level of returns, correlation is expected to increase when we move to the extremes of the return distribution. Thus an asymmetric effect emerges if this behavior is different in rising and falling markets.

returns. Specifically, we estimate jointly for each characteristic (size and PER), the following regression defined for a given quartile Q correlation series:

$$COR_{Q,t} = \alpha_Q + \delta_Q^- I^- |R_{m,t}| + \delta_Q^+ I^+ |R_{m,t}| + \gamma_Q COR_{Q,t-1} + \eta_Q |R_{m,t-1}| + \epsilon_{Q,t}, \qquad (3.8)$$

where $COR_{Q,t}$ is the quartile Q correlation with the world portfolio during month t, I^- (I^+) is an indicator variable for the months the return is on average negative (positive), and $R_{m,t}$ is the market return during month t. The parameters of interest are δ_Q^- and δ_Q^+. They measure the contemporaneous relation between correlation and world portfolio returns during falling and rising months, respectively, for each industry characteristic quartile. The lagged variables are included to pick up the serial correlation in the correlation and the absolute returns series. Standard errors are heteroskedasticity and autocorrelation robust using Newey-West correction with five lags. We estimate simultaneously the four equations relating to each characteristic (size or PER), using the Seemingly Unrelated Regressions (SUR) technique.

An asymmetric relation between correlation and returns implies that the link between correlation and the size of market returns is different in rising and falling markets. This difference could arise from the sign of the link (e.g., for down months the correlation increases with the market returns while in up months it decreases), or from the size of the link (e.g. both for falling and rising markets correlation increases with returns, but the increase is steeper for falling markets than for rising markets). The "sign effect" resembles the asymmetric effect documented by Longin and Solnik (2001). The "size effect" draws its intuition from the volume-absolute returns contemporaneous asymmetric relation (e.g. Karpoff (1987), Jain and Joh (1988)) and the contemporaneous asymmetric relation between stock dispersion and returns (e.g. Duffee (2001).[22]

[22]We do run regressions with Fisher z correlation coefficients as dependent variable. The conclusions are unaffected, so these results are not reported, but are available on request. Critics may reasonably argue that specification (3.8) may easily lead to unfeasible estimates of expected correlation, given the bounds of correlation. In fact, that need not be case for reasonable values of market returns and correlations. For example, assume that $\alpha = 0.4$, $\delta^- = 1.1, \gamma = 0.35$, and $\eta = 0.4$. If lagged correlation is 0.80, it would need

Table 3.10 presents the results. First, we show that a strong asymmetric "sign effect" characterizes the contemporaneous link between correlation and market returns. Global industry correlation is positively related to absolute returns in down markets. In up markets, the relation is never statistically significant.[23]

Second, the evidence suggests that an asymmetric size effect also characterizes correlation. The strength of the link (measured by the coefficients δ_Q^- and δ_Q^+) is higher for down months than in up months. Moreover, we can reject the restriction that $\delta_Q^- = \delta_Q^+$, in all quartiles of size and PER.

Finally, the asymmetric effect is pervasive across industry groups. The link between correlation and falling market returns tends to be more pronounced for the smallest industries relative to the largest industries, although the quartile effects are not statistically significant. This tendency does not result from the fact that higher size industries weight more on the world portfolio, as the results using the equal-weighted returns shows.

For the PER quartiles results are mixed. Based on VW world returns, the strength of the link in down markets tends to be higher for Q4 relative to Q1. However, when market capitalization effects are normalized in the computation of world returns (EW world returns), the strength of the contemporaneous relationship between correlation and market returns tends to be higher for Q1 relative to Q4 (note that the slope coefficients across PER quartiles are not statistically different, as the Wald test for the restriction that $\delta_{Q1}^- = ... = \delta_{Q4}^-$ shows).

We also analyze the link between correlation and returns for the FTSE-classified global economic sectors. Table 3.11 presents the results. Correlation is positive and significantly linked to (absolute) returns in falling markets and statistically insignificant in rising markets. The asymmetry is not found in only two sectors - resources and utilities. For these traditional sectors, we did not find a statistical significant relationship between sector correlation and (absolute) market returns, though the signs of the slope coefficient suggest that it is positive in falling markets and negative in rising markets.

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a negative world return of less than -20% a month in the current and lagged period so that equation (3.8) would imply an expected correlation greater than 1.

[23]Conclusions are unaffected when intercepts are allowed to be different for down and up markets. Since the intercept dummies were found to be statistically insignificant, we do not report the additional results.

What might explain the asymmetric effect? Following Duffee (2001) we argue that an information diffusion asymmetry is a reasonable candidate-explanation for the industry correlation asymmetric behavior. If it is more likely that negative news have market wide implications and positive news reflect industry specific events, it is possible that falling market returns originates from trades made on the basis of more homogeneous (across industries) information than rising market returns. More agreement between investors on the downside is consistent with higher correlation for down months than for up months.[24]

Intuitively, this explanation suggests that if betas tend to exhibit little asymmetry across falling and rising markets (e.g., Brown, Nelson, and Sunier (1995) and Ang, Chen, and Xing (2002)), the ratio of market volatility to total industry volatility would increase during falling markets, as the importance of market-wide factors relative to industry specific-factors would increase on the downside.

3.4.1. Robustness

Here, we look at the contemporaneous relationship between quartile correlation and market returns for alternative estimates of correlation. In Table 3.12 we perform two exercises. First, we use within month two-days rolling average daily returns to estimate monthly correlations. Second, we use daily returns but realized correlation is estimated using a two-month window. Main findings remain unaffected. Correlation increases with returns, but only in down markets and this effect is pervasive across size and PER quartiles.

Table 3.13 reports the results for two additional exercises using within month daily data. First, we perform a 5% winsorization of the correlation series. Second, we express the returns in Deutschemark (DM). The finding that correlations increase with the magnitude of returns,

[24]We do not discard the possibility of a market volatility effect (Chakrabarty and Roll (2002)) as opposed to a market volatility bias (Forbes and Rigobon (2002)) for three reasons. First, the effects of market volatility are (implicitly) taken into account by the inclusion of the lagged absolute return variable (a proxy for volatility) as explanatory variable. Second, we condition on the sign of the monthly market returns, not on their size. Third, as Chakrabarty and Roll (2002) argue, if the true volatility of the driving factor is expected to be higher for the conditional set, then one would correctly expect an increase in conditional correlation. Indeed, at the market level, there is a negative contemporaneous relation between stock returns and volatility (Guo (2002)).

but only in falling markets, remains unaffected. Interestingly, using DM denominated returns, while the strength of the link among size quartiles does not change (economically most relevant for the smallest industries), on the other hand the link for the PER quartiles shows a clear "U-shaped" pattern.

To conclude this section, we address the following question. Is the positive relation between correlation and volatility asymmetric? We have already seen that the level of correlation is positively related to the magnitude of the market returns in falling markets. Now, we test if the contemporaneous relation between correlation and volatility is symmetric relative to the sign of returns and if it is related to the industry characteristics (size and PER). To test these hypotheses, we extend the regression model of Solnik et al. (1996), and estimate using the SUR technique (alternatively considering the join set of equations defined for the quartiles of each industry characteristic), the following regression,

$$\Delta COR_{Q,t} = \alpha_Q + \delta_Q^- I^- \Delta VAR_t + \delta_Q^+ I^+ \Delta VAR_t + \gamma_Q \Delta COR_{Q,t-1} + \eta_Q \Delta VAR_{t-1} + \epsilon_{Q,t}, \quad (3.9)$$

where $\Delta COR_{i,t}$ is the first difference of the quartile Q correlation with the world market during month t, I^- (I^+) is an indicator variable for the months the return is on average negative (positive), and ΔVAR_t is the first difference of the world market variance series. The parameters of interest are δ_Q^- and δ_Q^+. They measure the contemporaneous relation between correlation changes and world variance changes during falling and rising months, respectively, for each industry characteristic quartile. The lagged variables are included to pick up the serial correlation in the correlation and the volatility series. Standard errors are heteroskedasticity and autocorrelation robust using Newey-West correction with five lags.

Table 3.14 presents the results. Panel A uses the value-weighted portfolio returns and Panel B the equal-weighted portfolio returns. A strong message emerges. Changes in correlation are positively related to changes in volatility, and the increase in correlation related to change in volatility is most noticed in rising markets than in falling markets. In other words, when volatility increases so does correlation, as the statistically significant positive sign of either δ_Q^- and δ_Q^+ shows. However, the increase in volatility has a stronger impact on correlation for upside moves than downside moves (the $\chi^2_{(1)}$ test for the restriction $\delta_Q^- = \delta_Q^+$ is significant). Moreover, the ratio of δ_Q^+ of δ_Q^- is always greater than three (the minimum is found for the lowest size quartile), which illustrates the economic significance of this effect. The link between correlation and volatility is asymmetric, being the strongest for upside market moves.

Across the industry quartiles, we see that size (but not PER) helps to differentiate the relationship between changes in correlation and changes in market volatility. While significant quartile effects are found for both down and up slopes among size quartiles, the same does not occurs for the PER quartiles. Also, the findings are not affected by the use of the equal-weighted world portfolio return.[25]

3.5. Betas and Volatility Ratios

In this section we analyze the behavior of betas and volatility ratios. Do betas and volatility ratios display the same pattern of correlations over time? We note that by a simple manipulation of equation (3.3), we can obtain estimates (we use within the month daily data) of realized betas of global industry portfolios relative to the world portfolio ($\beta_{i,t}$) and of the ratio of world volatility to global industry volatility ($\pi_{i,t}$). Specifically,

$$COR_{i,t} = \frac{COV_{i,t}}{VAR_{m,t}} \frac{\sqrt{VAR_{m,t}}}{\sqrt{VAR_{i,t}}} = \beta_{i,t}\pi_{i,t}. \tag{3.10}$$

where $\beta_{i,t} = COV_{i,t}/VAR_{m,t}$ is the realized market beta of industry portfolio i, and $\pi_{i,t} = \sqrt{VAR_{m,t}/VAR_{i,t}}$ is the realized ratio of market volatility to industry total volatility, for month t.

We use the cross-industry distribution of size and PER at the beginning of each month to classify each industry into one of four groups for each characteristic. The betas with the world portfolio (or the volatility ratios) for a given quartile is measured by the cross-sectional

[25]The asymmetric relation between correlation and volatility suggests that the unconditional correlation heteroskedasticity bias correction (Forbes and Rigobon (2002)) in a time series framework can lead to misleading conclusions, as it equally penalizes high volatility states correlation regardless the sign of market returns.

average of the betas (or volatility ratios) with the world portfolio of the industries that in that month are classified in that quartile.[26]

Table 3.15 presents the time series properties of realized betas and volatility ratios. Panel A uses the value-weighted world portfolio returns. The results show that beta is lower for industries with smallest size and lowest PER (Q1) compared to industries with largest size and highest PER (Q4), respectively. Betas series for size and PER quartiles are stationary, while a unit root is not rejected by the ADF t-test (constant model) for all but the smallest quartile of size.[27] Trends tests reveal the existence of significant negative (positive) trends for the smallest (highest) quartile of size. These results are consistent with Daves, Ehrhardt, Kuhlemeyer, and Kunkel (2000) finding of a shift in the systematic risk of small versus large firms. Before 1980, smaller firms tend to have greater risk systematic risk than larger firms. After 1980, the situation is reversed. For the PER quartile beta series, we document two significant downward trends for the Q1 and Q2 quartiles.

With respect to volatility ratios, we find that smallest size and lowest PER quartiles present lower mean volatility ratios. Quartile volatility ratios series are stationary.[28] Smallest size and lowest PER quartiles present the only significant trend coefficients (positive).

Panel B uses the equal-weighted world market portfolio return. For all quartiles of size and PER, there is an increase in mean betas. The trends test for the size quartiles remain unchanged, while for the PER quartiles, three significant trends are found: two are negative (Q2 and Q3), and a positive trend for Q4. The time series behavior of PER quartile betas is more influenced by the effects of market capitalization on the determination of world returns, than the behavior of size quartile betas. With respect to volatility ratios, we note a decrease in the time series mean for all quartiles (the lowest estimates are found for the higher quartiles of size and PER). Volatility ratios have no significant trend.

[26]Note that this procedure does not imply that for a given quartile, the correlation equals the product of betas times volatility ratios, as the average of products is different from the product of averages, for non independent variables.

[27]In fact, rejections with the Phillips-Perron (PP) test ate possible for all lags up to 18, and wether or not a time trend is included in the regression.

[28]For the Q2 size quartile, the null of a unit root is rejected by the ADF $T(\rho - 1)$ at the 10% level.

The long-term behavior of betas and volatility ratios shows interesting similarities to the one of industry correlations. Realized betas (volatility ratios) are lower (higher) for the smallest size and lowest PER industries. The negative (positive) trend in the smallest (largest) industries correlations is associated with a similar trend in betas and a reversed trend in volatility ratios. This suggests that betas, not volatility ratios, are the key determinant of the long run behavior of correlations.

Table 3.16 looks at the contemporaneous relationship between realized betas (and volatility ratios) and market returns.[29] Panel A uses the value-weighted world portfolio returns. We do not find a statistically significant link between betas and market returns in either falling or rising markets. The absence of a statistically significant asymmetric effect is in line with the finding of no leverage effects in conditional betas by Brown, Nelson, and Sunier (1995) for the US market. In contrast, the contemporaneous relation between volatility ratios and returns is asymmetric. Volatility ratios are positively related to the magnitude of returns, but only for down markets. In up markets no discernible pattern is found. The strongest link on the downside is found for the smallest size and lowest PER quartiles. Panel B uses the equal-weighted world returns. The asymmetric patterns of betas and volatility ratios remain unaffected, i.e., there is a strong positive link between volatility rations and returns for down markets.

With respect to the contemporaneous relationship to market returns, the similarities of the results for correlation and for the volatility ratios are evident. This suggests that the role of volatility ratios should not be discarded in explaining correlation asymmetries. But volatility ratios do not seem to explain the entire asymmetric movement of correlation, as realized betas also tend to be positively related to returns in falling markets, except for the higher quartiles of size and PER.

To gain further insight into the importance of betas and volatility ratios to the time series variation of global industries correlations, we perform a volatility decomposition. A simple logarithmic transformation of the absolute value of industry correlation (see definition(3.3))

[29]We use equation (3.8) and the estimation procedure thus described. We replace the realized correlation series by the realized beta series or the realized volatility ratios.

yields $ln(|\mathrm{COR}_{i,t}|) = ln(|\beta_{i,t}|) + ln(\pi_{i,t})$, Then, taking the time series variance of each component and dividing the RHS elements by the LHS, we obtain a decomposition for the time series variance of absolute correlation over a specified sample period,

$$\begin{aligned} 1 &= \mathrm{VAR}[ln(|\beta_{i,t}|)]/\mathrm{VAR}[ln(|\mathrm{COR}_{i,t}|)] \\ &\quad +\mathrm{VAR}[ln(\pi_{i,t})]/\mathrm{VAR}[ln(|\mathrm{COR}_{i,t}|)] \\ &\quad +2\mathrm{COV}[Ln(|\beta_{i,t}|), ln(\pi_{i,t}]/\mathrm{VAR}[ln(|\mathrm{COR}_{i,t}|)]. \end{aligned} \tag{3.11}$$

The absolute value of the covariance (and therefore of correlation and beta) is used because we are interested in the magnitude of the linear association between industries and market return. Also, the logarithmic transformation of the individual industry correlation series renders consistency to the decomposition when applied to the average correlation of industry groups, as $1/q \sum_{i \in Q} ln(|\mathrm{COR}_{i,t}|) = 1/q \sum_{i \in Q} ln(|\beta_{i,t}|) + 1/q \sum_{i \in Q} ln(\pi_{i,t})$, where q is the number on industry portfolios in each industry group Q (e.g., smallest size).

Table 3.17 presents the results of this exercise. Panel A uses value-weighted world returns. For all but the highest quartiles of size and PER, most of the time series variation in absolute correlation is due to the variation in betas. For the highest quartiles, the most important component is the variation in volatility ratios. This result characterizes the quartile correlation series both in up and down markets. Another consistent characteristic is the negative covariance between betas and volatility ratios. These covariance is higher (in absolute terms) in down markets relative to up markets, in all but the highest quartiles of size and PER, for which the situation is reversed.

Panel B uses equal-weighted world returns. The importance of time series variance in volatility ratios increases. Except for the largest size and highest PER quartiles, which show the opposite patterns, the importance of the negative covariance decreases (in absolute terms) as well as that of betas.

3.6. Conclusion

This paper investigates the time series of realized correlations between global industries and aggregate world market over the 1979-2003 period using within-month daily data. We find that global industries correlations fluctuate over time, but there is not a significant long-term trend. We find that small and value (low price-earnings ratio) industries have lower correlations. Moreover, global industry correlations are counter-cyclical. Global industry correlations are greater for downside moves than for upside moves. Correlation asymmetry is the largest among small industries, but it is pervasive across industry groups.

The characterization of global industry correlation structure yields both reassuring and disturbing information for global equity investors. On the bad side, our results confirm for industry portfolios, two features that characterize cross-country correlations. Industry correlation is higher in falling markets than in rising markets and industry correlation is positively related to market volatility. During market turmoil, the power of global industry diversification to reduce portfolio risk decreases.

On the positive side, we find that industry correlation does not show a systematic increase over time, and the late 1990s is indeed a period characterized by low correlations. Also favorable is the evidence that the link between correlation and volatility is stronger in rising markets than in fall markets. Thus, the negative effects for portfolio diversification of the increase in volatility are most noticed during rising markets than during falling markets.

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Table 3.1: Descriptive Statistics of Global Industries

The table shows descriptive statistics for the raw variables used in the paper, at the monthly frequency. Returns is the global industry portfolio returns, expressed in US dollars. Size is the monthly market capitalization expressed in millions of US dollars. PER is the monthly estimate of the price-earnings ratio. Correlation is the monthly estimate of the correlation with the DS value-weighted world portfolio, using equation (3.3). *Mean* is the time series average of the monthly estimates. *Stdev* is the time series standard deviation.

	Returns		Size		PER		Correlation	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Mining	0.0098	0.0769	101103	61409	15.92	5.45	0.3746	0.2491
Oil & Gas	0.0108	0.0515	634703	477644	15.14	7.02	0.5802	0.2401
Chemicals	0.0091	0.0476	301687	172996	17.70	5.15	0.8210	0.1693
Construction & Build. Mat.	0.0080	0.0528	228429	137526	17.43	4.81	0.7343	0.1837
Forestry & Paper	0.0072	0.0575	86557	51275	17.69	6.42	0.6698	0.2037
Steel & Other Metals	0.0067	0.0681	129147	74251	26.54	16.77	0.6711	0.1963
Aerospace & Defence	0.0097	0.0573	100625	83318	14.88	5.06	0.5964	0.2004
Diversified Industrials	0.0086	0.0480	243782	239425	15.25	4.10	0.7075	0.1592
Electronic & Elect. Eq.	0.0103	0.0565	432790	367436	22.10	7.13	0.8116	0.1329
Engineering & Machinery	0.0069	0.0559	218147	137248	22.03	5.60	0.7950	0.1441
Automobiles & Parts	0.0075	0.0509	320625	200965	15.92	6.95	0.7299	0.1693
Household Goods & Textiles	0.0079	0.0560	145800	104982	22.28	5.13	0.7260	0.1769
Beverages	0.0116	0.0434	204623	162587	20.38	6.43	0.6154	0.2460
Food Producers & Processors	0.0108	0.0393	268145	182728	16.63	4.53	0.7359	0.2273
Health	0.0124	0.0490	175160	184579	21.55	7.40	0.5635	0.2096
Personal Care & H. Products	0.0113	0.0431	153900	135420	20.39	7.56	0.5953	0.2127
Pharmaceuticals & Biotech.	0.0126	0.0435	666645	725210	23.77	7.36	0.7196	0.1793
Tobacco	0.0150	0.0604	96619	73166	12.16	3.61	0.4278	0.2445
Retailers, General	0.0108	0.0516	372554	322421	20.66	5.97	0.7552	0.1228
Leisure & Hotels	0.0108	0.0540	169408	181210	24.57	7.70	0.7003	0.1594
Media & Entertainment	0.0099	0.0496	300604	298701	22.43	8.52	0.8078	0.1190
Support Services	0.0105	0.0500	98701	121844	21.24	6.22	0.7202	0.1522
Transport	0.0080	0.0500	250321	156928	24.17	7.98	0.7719	0.1526
Food & Drug Retailers	0.0120	0.0420	146445	129368	19.61	5.47	0.6744	0.2050
Telecom Services	0.0086	0.0549	795100	874625	20.50	9.74	0.6814	0.1942
Electricity	0.0090	0.0407	383679	224993	13.82	4.15	0.6734	0.2086
Utilities, Other	0.0102	0.0460	158778	128968	15.20	4.28	0.6820	0.1815
Information Tech. Hardware	0.0092	0.0742	732260	943797	26.59	13.55	0.7276	0.1519
Software & Comp. Services	0.0118	0.0753	341613	530512	28.54	16.13	0.6063	0.2030
Banks	0.0107	0.0546	1219467	1054172	16.48	5.94	0.7819	0.1684
Insurance	0.0109	0.0494	393343	356715	18.19	5.04	0.7810	0.1392
Life Assurance	0.0120	0.0522	110798	112309	17.85	5.64	0.6050	0.2060
Investment Companies	0.0095	0.0466	68043	58777	27.22	8.37	0.6236	0.1808
Real Estate	0.0092	0.0582	158516	124151	21.06	6.50	0.6172	0.2010
Speciality & Other Finance	0.0107	0.0714	398611	317457	21.29	6.78	0.7904	0.1245

Table 3.2: Descriptive Statistics of Global Industries Correlations by Size and PER

The table shows descriptive statistics, unit root and linear trend tests for the global industry quartile correlation with the world portfolio. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. We use the beginning of month cross-industry distribution of Size or PER to classify each industry into one of the four non-overlapping 25% percentiles. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the VW world portfolio (or the EW world portfolio) of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3). *Mean* is the time series average of the monthly estimates. *Stdev* is the time series standard deviation. ρ_1 is the first order serial correlation coefficient. *ADF* is the Augmented Dickey-Fuller (ADF) t test statistic (the number of lags is determined by the AIC method). *Trend*, is the linear trend coefficient multiplied by 10^4. $t - PS_T$ is the Vogelsang (1998) test statistic (at the 5% level) for the significance of deterministic linear trends. The 5% critical values for the ADF t test is –2.87, and for the $t - PS_T$ test is 1.72.

	Mean	Stdev	ρ_1	ADF	Trend	t-PS_T
Panel A: VW world returns						
Size						
Q1 smallest	0.582	0.131	0.437	-5.109	-1.524	-1.46
Q2	0.665	0.128	0.549	-4.331	-1.657	-0.40
Q3	0.738	0.125	0.639	-3.455	-2.801	-0.12
Q4 largest	0.742	0.090	0.520	-7.199	2.262	1.13
Price-earnings ratio						
Q1 smallest	0.632	0.129	0.493	-6.877	0.122	0.00
Q2	0.685	0.129	0.442	-4.867	-2.339	-0.88
Q3	0.698	0.121	0.597	-4.139	-2.720	-0.65
Q4 highest	0.713	0.094	0.442	-5.120	1.191	0.51
Panel B. EW world returns						
Size						
Q1 smallest	0.630	0.111	0.391	-3.735	-1.373	-1.41
Q2	0.688	0.110	0.461	-4.863	-0.683	-0.32
Q3	0.750	0.107	0.541	-3.434	-2.212	-0.14
Q4 largest	0.724	0.097	0.502	-7.437	1.724	0.80
Price-earnings ratio						
Q1 smallest	0.658	0.110	0.436	-7.512	1.195	0.59
Q2	0.712	0.108	0.362	-5.169	-1.451	-0.70
Q3	0.717	0.104	0.518	-3.328	-2.446	-0.90
Q4 highest	0.707	0.097	0.463	-5.051	0.138	0.09

Table 3.3: Time and Quartile Effects of Global Industries Correlations by Size and PER

The table reports under *Mean Correlation* the time series mean industry quartile correlation estimates for 5 non-overlapping 60 months periods. *Time Effects* is the $p-value$ of a Wald test for the restriction that mean estimates are equal across time periods, for a given quartile. *Quartile Effects* is the $p-value$ of a Wald test for the restriction that mean estimates are equal across quartiles, for a given time period. The statistics are based on a joint estimation of the four equations that characterize a given industry characteristic (equation (3.7)) using the *Seemingly Unrelated Regressions*. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the VW world portfolio (or the EW world portfolio) of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3).

	Mean Correlation					Time Effects
	1979-83	1984-88	1989-93	1994-98	1999-03	(p-value)
Panel A: VW world returns						
Size						
Q1 smallest	0.625	0.575	0.579	0.581	0.551	0.301
Q2	0.675	0.656	0.727	0.676	0.588	0.014
Q3	0.727	0.755	0.824	0.770	0.615	0.000
Q4 largest	0.721	0.699	0.782	0.762	0.746	0.002
Quartile effects (p-value)	0.022	0.000	0.000	0.000	0.000	
Price-earnings ratio						
Q1 smallest	0.636	0.611	0.652	0.685	0.578	0.033
Q2	0.713	0.674	0.742	0.680	0.618	0.022
Q3	0.714	0.706	0.752	0.712	0.604	0.010
Q4 highest	0.687	0.696	0.769	0.712	0.702	0.000
Quartile effects (p-value)	0.059	0.079	0.002	0.399	0.001	
Panel B: EW world returns						
Size						
Q1 smallest	0.657	0.639	0.630	0.614	0.608	0.536
Q2	0.690	0.681	0.741	0.686	0.644	0.031
Q3	0.742	0.764	0.821	0.769	0.657	0.000
Q4 largest	0.711	0.683	0.764	0.747	0.717	0.003
Quartile effects (p-value)	0.004	0.000	0.000	0.000	0.219	
Price-earnings ratio						
Q1 smallest	0.642	0.643	0.678	0.697	0.630	0.145
Q2	0.729	0.707	0.759	0.694	0.674	0.059
Q3	0.733	0.733	0.761	0.714	0.647	0.024
Q4 highest	0.699	0.687	0.761	0.711	0.678	0.001
Quartile effects (p-value)	7.731	6.099	6.810	0.655	5.100	

Table 3.4: Correlations of Global Industries Correlations by Double-sort of Size and PER

The table reports time series mean estimates of correlation for double sorts based on beginning of month Size and PER. All data is US dollar denominated. In each section, the variable in the first column (on the left) is used for the first sort and the variable in the top row is used for the second sort. For instance, the first row of the top section, reports the mean estimates for the quartiles of PER (second sort) within the first quartile of PER (first sort). Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. The correlation for a given cell in a given month is measured by the cross-sectional average of the correlation with the VW world portfolio (or the EW world portfolio) of the industries that in that month are classified in that cell, according to the double sort procedure. The individual global industry correlation is estimated monthly using equation (3.3).

Panel A: VW world portfolio return						
		Price-earnings ratio				
		Q1 lowest	Q2	Q3	Q4 highest	Q4-Q1
Size	Q1 smallest	0.511	0.574	0.610	0.616	0.105
	Q2	0.645	0.662	0.685	0.666	0.021
	Q3	0.719	0.731	0.740	0.754	0.035
	Q4 largest	0.718	0.709	0.759	0.768	0.050
		Size				
		Q1 smallest	Q2	Q3	Q4 largest	Q4-Q1
PER	Q1 lowest	0.519	0.603	0.654	0.717	0.199
	Q2	0.614	0.678	0.725	0.719	0.106
	Q3	0.618	0.668	0.726	0.755	0.137
	Q4 highest	0.617	0.699	0.748	0.766	0.149
Panel B: EW world portfolio return						
		Price-earnings ratio				
		Q1 lowest	Q2	Q3	Q4 highest	Q4-Q1
Size	Q1 smallest	0.565	0.625	0.658	0.657	0.092
	Q2	0.678	0.691	0.708	0.675	-0.003
	Q3	0.745	0.755	0.754	0.749	0.004
	Q4 largest	0.708	0.706	0.743	0.735	0.027
		Size				
		Q1 smallest	Q2	Q3	Q4 largest	Q4-Q1
PER	Q1 lowest	0.575	0.638	0.681	0.714	0.139
	Q2	0.661	0.708	0.753	0.726	0.065
	Q3	0.661	0.695	0.745	0.754	0.093
	Q4 highest	0.646	0.703	0.732	0.736	0.090

Table 3.5: Descriptive Statistics of Global Industries Correlations by Economic Sector

The table analyses correlation for a grouping procedure based on the FTSE Economic sectors classification (listed on the first column). Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. The correlation for a given Economic sector in a given month is measured by the cross-sectional average of the correlation estimates using the VW world portfolio (or the EW world portfolio) of the industries that are classified in that Economic sector. The individual global industry correlation is estimated monthly using daily data (equation (3.3)). $Mean$ is the time series average of the monthly estimates. $Stdev$ is the time series standard deviation. ρ_1 is the first order serial correlation coefficient. ADF is the Augmented Dickey-Fuller (ADF) t test statistic (the number of lags in the ADF regression is determined by the AIC method). $Trend$, is the linear trend coefficient multiplied by 10^4. $t - PS_T$ is the Vogelsang (1998) test statistic (at the 5% level) for the significance of deterministic linear trends. The 5% critical values for the ADF t test is –2.87, and for the $t - PS_T$ test is 1.72. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags.

	Mean	Stdev	ρ_1	ADF	Trend	t-PS_T
Panel A: VW world returns						
Resources	0.477	0.192	0.335	-7.734	-4.229	-1.91
Basic Industries	0.724	0.160	0.549	-2.657	-2.927	-0.31
General Industries	0.728	0.110	0.347	-7.924	-0.221	-0.64
Cyclical C. Goods	0.728	0.158	0.557	-4.057	-0.150	0.17
Non-Cyclical C. Goods	0.610	0.170	0.606	-3.982	-8.838	-2.34
Cyclical Services	0.751	0.099	0.476	-4.786	1.797	0.76
Non-Cyclical Services	0.678	0.151	0.505	-4.534	5.522	1.72
Utilities	0.678	0.180	0.493	-2.840	-4.094	-0.17
Information Technology	0.667	0.158	0.509	-3.456	4.227	0.02
Financials	0.700	0.114	0.459	-4.244	3.709	1.19
Panel B: EW world returns						
Resources	0.497	0.175	0.269	-8.564	-1.697	-1.20
Basic Industries	0.743	0.124	0.464	-3.636	-0.669	-0.22
General Industries	0.747	0.099	0.296	-8.679	-0.053	-0.70
Cyclical C. Goods	0.731	0.140	0.474	-4.518	1.309	0.37
Non-Cyclical C. Goods	0.648	0.151	0.568	-4.309	-8.776	-2.07
Cyclical Services	0.770	0.091	0.437	-4.848	1.105	0.42
Non-Cyclical Services	0.688	0.146	0.477	-4.902	4.969	1.65
Utilities	0.683	0.164	0.359	-3.484	-2.599	-0.11
Information Technology	0.658	0.145	0.406	-5.119	1.108	-0.60
Financials	0.706	0.107	0.431	-4.700	3.602	1.80

Table 3.6: Robustness Check: 2-day Returns and 2-month Estimation Window

The table analyses two modified datasets. First, in the columns under *Two-day returns*, daily returns are replaced by a rolling-average of two days returns. Second, in the columns under *Two-month window*, correlations series are constructed from daily returns within a two month estimation window. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. We use the beginning of estimation period cross-industry distribution of Size or PER to classify each industry into one of the four non-overlapping 25% percentiles. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation of the industries that in that month are classified in that quartile. *Mean* is the time series average of the monthly estimates. *Stdev* is the time series standard deviation. ρ_1 is the first order serial correlation coefficient. *ADF* is the Augmented Dickey-Fuller (ADF) t test statistic (the number of lags is determined by the AIC method). *Trend*, is the linear trend coefficient multiplied by 10^4. $t-PS_T$ is the Vogelsang (1998) test statistic (at the 5% level) for the significance of deterministic linear trends. The 5% critical values for the ADF t test is –2.87, and for the $t-PS_T$ test is 1.72.

	Two-day Returns						Two-month Estimation Window					
	Mean	Stdev	ρ_1	ADF	Trend	t-PS_T	Mean	Stdev	ρ_1	ADF	Trend	t-PS_T
Panel A: VW world returns												
Size												
Q1 smallest	0.618	0.145	0.392	-5.318	-1.482	-1.29	0.590	0.114	0.485	-5.122	-3.050	-1.32
Q2	0.691	0.137	0.478	-4.770	-1.416	-0.52	0.674	0.113	0.609	-4.312	-2.617	-0.29
Q3	0.757	0.129	0.601	-5.306	-3.199	-0.26	0.746	0.113	0.647	-3.832	-5.839	-0.11
Q4 largest	0.749	0.102	0.487	-5.373	2.238	1.16	0.747	0.080	0.528	-4.926	4.623	1.03
Price-earnings ratio												
Q1 smallest	0.650	0.140	0.448	-7.251	0.393	0.08	0.638	0.113	0.528	-6.797	0.776	0.14
Q2	0.710	0.134	0.369	-5.248	-1.897	-1.11	0.695	0.108	0.509	-4.601	-4.514	-0.69
Q3	0.718	0.129	0.556	-4.405	-2.922	-0.91	0.706	0.108	0.670	-3.872	-5.177	-0.50
Q4 highest	0.739	0.106	0.371	-11.926	0.557	0.32	0.719	0.083	0.318	-5.948	1.879	0.38
Panel B. EW world returns												
Size												
Q1 smallest	0.663	0.123	0.345	-8.203	-1.251	-1.39	0.638	0.095	0.403	-5.516	-2.795	-1.26
Q2	0.714	0.118	0.393	-5.386	-0.474	-0.42	0.698	0.094	0.512	-4.860	-0.769	-0.19
Q3	0.769	0.113	0.494	-7.317	-2.565	-0.31	0.759	0.093	0.543	-3.550	-4.638	-0.14
Q4 largest	0.732	0.109	0.455	-5.500	1.674	0.77	0.729	0.085	0.492	-3.798	3.600	0.78
Price-earnings ratio												
Q1 smallest	0.676	0.120	0.378	-8.019	1.500	0.81	0.664	0.094	0.444	-7.637	2.925	0.76
Q2	0.735	0.114	0.292	-5.595	-1.095	-0.89	0.722	0.089	0.412	-3.903	-2.863	-0.50
Q3	0.738	0.112	0.482	-3.568	-2.576	-1.26	0.726	0.090	0.568	-4.356	-4.685	-0.75
Q4 highest	0.732	0.110	0.403	-11.448	-0.448	-0.22	0.714	0.086	0.357	-5.678	-0.173	0.00

Table 3.7: Robustness Checks: Winsorization and DM Returns

The table analyses two modified datasets, both based on daily returns . First, in the columns under *Winsorization (5%)*, we replace the observations below (above) the 2.5% (97.5%) percentile by the respective percentiles. Second, in the columns under *DM returns*, we add to the US$ denominated logarithm returns, the logarithm variation of the $DM/US\$$ exchange rate (from January 1999 onwards, we use the fixed $DM/EUR = 1.95583$ exchange rate to obtain a notional $DM/US\$$ exchange rate). Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. We use the beginning of month cross-industry distribution of Size or PER to classify each industry into one of the four non-overlapping 25% percentiles. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation of the industries that in that month are classified in that quartile. $Mean$ is the time series average of the monthly estimates. $Stdev$ is the time series standard deviation. ρ_1 is the first order serial correlation coefficient. ADF is the Augmented Dickey-Fuller (ADF) t test statistic (the number of lags is determined by the AIC method). $Trend$, is the linear trend coefficient multiplied by 10^4. $t - PS_T$ is the Vogelsang (1998) test statistic (at the 5% level) for the significance of deterministic linear trends. The 5% critical values for the ADF t test is –2.87, and for the $t - PS_T$ test is 1.72.

	Winsorization (5%)						DM Returns					
	Mean	Stdev	ρ_1	ADF	Trend	$t\text{-}PS_T$	Mean	Stdev	ρ_1	ADF	Trend	$t\text{-}PS_T$
Panel A: VW world returns												
Size												
Q1 smallest	0.584	0.120	0.464	-5.733	-1.211	-1.27	0.690	0.112	0.454	-3.671	2.853	1.80
Q2	0.667	0.119	0.563	-3.444	-1.292	-0.37	0.743	0.111	0.579	-3.288	3.185	1.03
Q3	0.740	0.116	0.651	-3.513	-2.484	-0.09	0.795	0.104	0.571	-2.803	1.807	0.62
Q4 largest	0.742	0.087	0.524	-7.153	2.332	1.22	0.799	0.090	0.546	-3.009	3.849	2.12
Price-earnings ratio												
Q1 smallest	0.635	0.115	0.552	-5.670	0.571	0.17	0.725	0.112	0.528	-3.002	3.320	1.38
Q2	0.688	0.116	0.475	-5.497	-1.909	-0.86	0.772	0.104	0.451	-3.573	1.850	0.92
Q3	0.698	0.117	0.591	-4.192	-2.613	-0.67	0.771	0.102	0.623	-3.208	0.992	0.49
Q4 highest	0.714	0.086	0.453	-8.491	1.323	0.60	0.762	0.099	0.521	-3.932	5.391	2.40
Panel B. EW world returns												
Size												
Q1 smallest	0.630	0.105	0.404	-3.727	-1.245	-1.34	0.728	0.093	0.428	-3.916	2.637	1.89
Q2	0.689	0.104	0.481	-3.739	-0.468	-0.28	0.762	0.094	0.525	-2.991	3.795	1.71
Q3	0.752	0.100	0.551	-3.456	-1.948	-0.11	0.805	0.088	0.483	-2.846	2.193	0.93
Q4 largest	0.725	0.091	0.510	-6.117	1.890	0.94	0.785	0.097	0.531	-3.062	3.553	1.71
Price-earnings ratio												
Q1 smallest	0.660	0.100	0.480	-7.366	1.380	0.74	0.746	0.095	0.501	-3.771	4.051	2.29
Q2	0.714	0.101	0.385	-5.098	-1.237	-0.67	0.794	0.086	0.407	-3.514	2.338	1.38
Q3	0.718	0.099	0.505	-3.427	-2.233	-0.92	0.787	0.086	0.551	-3.357	1.077	0.62
Q4 highest	0.709	0.088	0.463	-8.253	0.306	0.15	0.757	0.102	0.528	-3.268	4.572	1.81

Table 3.8: Time and Quartile Effects: DM Returns

The analises time and quartile effects for an alternative dataset denominated in German DM returns. We add to the US dollar denominated logarithm returns, the logarithm variation of the DM/US exchange rate (from January 1999 onwards, we use the fixed $DM/EUR = 1.95583$ exchange rate to obtain a notional DM/USD exchange rate). The table reports under *Mean Correlation* the time series mean industry quartile correlation estimates for 5 non-overlapping 60 months periods. $Time\ effects$ is the $p - value$ of a Wald test for the restriction that mean estimates are equal across time periods, for a given quartile. $Quartile\ effects$ is the $p - value$ of a Wald test for the restriction that mean estimates are equal across quartiles, for a given time period. The statistics are based on a joint estimation of the four equations that characterize a given industry characteristic (equation (3.7)) using the *Seemingly Unrelated Regressions*. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the VW world portfolio (or the EW world portfolio) of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3).

	Mean Correlation					Time Effects
	1979-83	1984-88	1989-93	1994-98	1999-03	(p-value)
Panel A: VW world returns						
Size						
Q1 smallest	0.643	0.683	0.680	0.756	0.687	0.000
Q2	0.694	0.712	0.774	0.804	0.731	0.000
Q3	0.727	0.796	0.853	0.859	0.742	0.000
Q4 largest	0.743	0.761	0.825	0.852	0.812	0.000
Quartile effects (p-value)	0.019	0.001	0.000	0.007	0.015	
Price-earnings ratio						
Q1 smallest	0.669	0.704	0.730	0.807	0.712	0.000
Q2	0.730	0.760	0.801	0.821	0.748	0.000
Q3	0.732	0.777	0.798	0.824	0.727	0.000
Q4 highest	0.680	0.717	0.806	0.821	0.786	0.000
Quartile effects (p-value)	0.094	0.154	0.003	0.002	0.000	
Panel B: EW world returns						
Size						
Q1 smallest	0.675	0.735	0.725	0.776	0.730	0.000
Q2	0.709	0.732	0.786	0.810	0.774	0.000
Q3	0.742	0.801	0.849	0.858	0.774	0.000
Q4 largest	0.734	0.747	0.810	0.843	0.790	0.000
Quartile effects (p-value)	0.030	0.003	0.001	0.013	0.149	
Price-earnings ratio						
Q1 smallest	0.676	0.731	0.753	0.815	0.753	0.000
Q2	0.744	0.787	0.817	0.830	0.790	0.000
Q3	0.750	0.797	0.804	0.825	0.759	0.000
Q4 highest	0.692	0.706	0.799	0.820	0.768	0.000
Quartile effects (p-value)	0.528	0.367	0.083	0.021	0.014	

Table 3.9: Correlation between Global Industries Correlations and NBER Expansions

The table reports the correlations of the global industry quartile correlation with a dummy variable that is one during a NBER-dated US expansion and zero during a NBER-dated US recession. A positive (negative) lead measures the number of months the quartile correlations series lead (lag) the business cycle. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. We use the beginning of month cross-industry distribution of Size or PER to classify each industry into one of the four non-overlapping 25% percentiles. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the VW world portfolio (or the EW world portfolio) of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3).

	Correlation Lead (months)								
	-12	-6	-3	-1	0	+1	+3	+6	+12
				Panel A: VW world portfolio returns					
				Size					
Q1 smallest	0.034	-0.087	-0.153	-0.275	-0.261	-0.259	-0.263	-0.203	-0.156
Q2	0.162	0.077	-0.006	-0.124	-0.111	-0.144	-0.167	-0.134	-0.136
Q3	0.203	0.065	-0.023	-0.118	-0.106	-0.116	-0.087	-0.065	-0.034
Q4 largest	0.145	0.008	-0.023	-0.124	-0.114	-0.140	-0.155	-0.135	-0.116
				Price-earnings ratio					
Q1 smallest	0.173	0.078	-0.006	-0.143	-0.131	-0.154	-0.174	-0.138	-0.115
Q2	0.064	-0.052	-0.108	-0.228	-0.222	-0.231	-0.211	-0.132	-0.148
Q3	0.174	0.003	-0.040	-0.131	-0.122	-0.149	-0.163	-0.179	-0.140
Q4 highest	0.117	0.017	-0.081	-0.164	-0.140	-0.138	-0.130	-0.079	-0.024
				Panel B: EW world portfolio returns					
				Size					
Q1 smallest	-0.011	-0.091	-0.146	-0.262	-0.254	-0.249	-0.246	-0.172	-0.123
Q2	0.126	0.051	-0.028	-0.129	-0.111	-0.146	-0.167	-0.130	-0.122
Q3	0.157	0.042	-0.039	-0.126	-0.111	-0.119	-0.087	-0.061	-0.038
Q4 largest	0.150	-0.006	-0.043	-0.147	-0.136	-0.153	-0.163	-0.149	-0.128
				Price-earnings ratio					
Q1 smallest	0.145	0.096	0.017	-0.117	-0.104	-0.128	-0.142	-0.107	-0.074
Q2	0.016	-0.071	-0.122	-0.230	-0.218	-0.224	-0.195	-0.110	-0.129
Q3	0.136	-0.013	-0.050	-0.136	-0.126	-0.152	-0.168	-0.181	-0.135
Q4 highest	0.113	-0.039	-0.128	-0.205	-0.189	-0.183	-0.175	-0.117	-0.076

Table 3.10: Asymmetries in Global Industries Correlations by Size and PER

The table analyses the relationship (equation (3.8)) between monthly world portfolio returns and the industry quartile correlation series. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. $t-stat$ is the t-statistic for the coefficient on the left. $Down$ (Up) is the slope coefficient for the months the market returns is negative (positive). $Down = Up$ is the $p-value$ of a Wald test for the restriction that slope estimates are equal in falling and rising markets, for a given quartile. $Quartile\ effects$ is the $p-value$ of a Wald test for the restriction that slope estimates are equal across quartiles, for a given industry characteristic. The coefficient estimates and test statistics are based on a joint estimation of the four equations that characterize a given industry characteristic using the *Seemingly Unrelated Regressions*. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the VW world portfolio (or the EW world portfolio) of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3).

	Down	t-stat	Up	t-stat	Down = Up (p-value)
Panel A: VW world returns					
Size					
Q1 smallest	0.966	3.39	-0.007	-0.03	0.002
Q2	0.805	3.77	-0.111	-0.52	0.000
Q3	0.652	3.02	-0.167	-0.80	0.001
Q4 largest	0.703	4.68	-0.102	-0.62	0.000
Quartile effects (p-value)	0.614		0.909		
Price-earnings ratio					
Q1 smallest	0.667	2.55	-0.195	-0.82	0.005
Q2	0.763	3.42	-0.074	-0.31	0.004
Q3	0.703	3.19	-0.063	-0.31	0.003
Q4 highest	0.910	5.53	-0.035	-0.19	0.000
Quartile effects (p-value)	0.747		0.903		
Panel B: EW world returns					
Size					
Q1 smallest	1.098	4.41	0.115	0.41	0.001
Q2	0.958	5.52	0.013	0.06	0.000
Q3	0.773	4.64	-0.069	-0.29	0.000
Q4 largest	0.838	5.42	-0.014	-0.07	0.000
Quartile effects (p-value)	0.445		0.866		
Price-earnings ratio					
Q1 smallest	0.937	4.36	-0.097	-0.36	0.000
Q2	0.934	4.94	0.010	0.04	0.000
Q3	0.969	5.52	0.159	0.76	0.000
Q4 highest	0.859	5.74	0.020	0.10	0.000
Quartile effects (p-value)	0.885		0.654		

Table 3.11: Asymmetries in Global Industries Correlations by Economic Sectors

The table analyses correlation for a grouping procedure based on the FTSE Economic sectors classification (listed on the first column). Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. *Down* (*Up*) is the slope coefficient for the months the market returns is negative (positive). $Down = Up$ is the $p - value$ of a Wald test for the restriction that slope estimates are equal in falling and rising markets, for a given quartile. $Sector\ effects$ is the $p - value$ of a Wald test for the restriction that slope estimates are equal across quartiles, for a given industry characteristic. The coefficient estimates and test statistics are based on a joint estimation of the four equations that characterize a given industry characteristic using the *Seemingly Unrelated Regressions*. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the VW world portfolio (or the EW world portfolio) of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3).

	Down	t-stat	Up	t-stat	Down = Up (p-value)
Panel A: VW world returns					
Resources	0.321	0.74	-0.687	-1.75	0.045
Basic Industries	0.755	2.57	-0.238	-0.85	0.003
General Industries	0.670	3.39	-0.215	-1.01	0.000
Cyclical C. Goods	0.949	3.49	-0.003	-0.01	0.002
Non-Cyclical C. Goods	0.915	3.33	-0.015	-0.05	0.013
Cyclical Services	0.855	5.12	-0.013	-0.06	0.000
Non-Cyclical Services	0.914	3.11	0.018	0.07	0.003
Utilities	0.175	0.38	-0.503	-1.55	0.138
Information Technology	1.004	3.36	0.489	1.65	0.141
Financials	0.843	4.05	0.074	0.33	0.001
Sector effects (p-value)	0.520		0.219		
Panel B: EW world returns					
Resources	0.716	1.56	-0.506	-1.10	0.023
Basic Industries	0.990	5.39	-0.024	-0.08	0.000
General Industries	0.826	4.55	-0.025	-0.11	0.000
Cyclical C. Goods	0.981	4.30	0.254	0.84	0.020
Non-Cyclical C. Goods	1.135	4.91	0.191	0.58	0.006
Cyclical Services	0.940	6.20	0.147	0.71	0.000
Non-Cyclical Services	0.954	3.36	-0.116	-0.42	0.001
Utilities	0.590	1.90	-0.534	-1.51	0.004
Information Technology	1.003	3.58	0.560	1.67	0.185
Financials	0.922	5.06	0.019	0.08	0.000
Sector effects (p-value)	0.683		0.135		

Table 3.12: Robustness Checks for Correlation Asymmetries: 2-day Returns and 2-month Estimation Window

The table analyses two modified datasets. In the columns under *Two-day returns*, daily returns are replaced by a rolling-average of two days returns. In the columns under *Two-month window*, correlations series are constructed from daily returns within a two month estimation window. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. $t-stat$ is the t-statistic for the coefficient on the left. $Down$ (Up) is the slope coefficient for the months the market returns is negative (positive). $Down = Up$ is the $p-value$ a Wald test for the restriction that slope estimates are equal in falling and rising markets, for a given quartile. $Quartile\ effects$ is the $p-value$ of a Wald test for the restriction that slope estimates are equal across quartiles, for a given industry characteristic. The coefficient estimates and test statistics are based on a joint estimation of the four equations that characterize a given industry characteristic using SUR. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the world portfolio of the industries that in that month are classified in that quartile.

	Two-day Returns				Down = Up	Two-month Window				Down = Up
	Down	t-stat	Up	t-stat	(p-value)	Down	t-stat	Up	t-stat	(p-value)
Panel A: VW world portfolio returns										
Size										
Q1 smallest	0.993	3.51	-0.212	-0.63	0.001	1.032	5.95	-0.013	-0.08	0.000
Q2	0.731	3.25	-0.376	-1.48	0.000	0.709	3.76	-0.102	-0.55	0.000
Q3	0.474	2.23	-0.408	-1.72	0.001	0.654	3.71	-0.219	-1.29	0.000
Q4 largest	0.649	3.69	-0.295	-1.41	0.000	0.595	4.53	-0.050	-0.34	0.000
Quartile effects (p-value)	0.253		0.892			0.000		0.444		
Price earnings ratios										
Q1 smallest	0.676	2.33	-0.435	-1.52	0.002	0.718	3.21	0.084	0.46	0.005
Q2	0.685	3.19	-0.428	-1.40	0.000	0.732	4.13	-0.055	-0.26	0.000
Q3	0.628	2.68	-0.178	-0.76	0.005	0.625	4.38	-0.088	-0.63	0.000
Q4 highest	0.733	4.61	-0.258	-1.01	0.000	0.753	6.20	-0.166	-0.98	0.000
Quartile effects (p-value)	0.961		0.643			0.586		0.508		
Panel B: EW world portfolio returns										
Size										
Q1 smallest	1.076	4.60	-0.143	-0.40	0.001	1.015	7.27	-0.071	-0.46	0.000
Q2	0.912	5.27	-0.226	-0.81	0.000	0.790	5.73	-0.083	-0.45	0.000
Q3	0.655	4.26	-0.302	-1.12	0.000	0.615	4.69	-0.271	-1.70	0.000
Q4 largest	0.802	4.75	-0.178	-0.73	0.000	0.734	5.07	0.016	0.09	0.000
Quartile effects (p-value)	0.287		0.935			0.004		0.040		
Price earnings ratios										
Q1 smallest	0.945	4.35	-0.358	-1.16	0.000	0.799	4.45	-0.003	-0.02	0.000
Q2	0.848	4.90	-0.311	-0.91	0.000	0.806	6.20	-0.109	-0.51	0.000
Q3	0.911	5.41	-0.005	-0.02	0.000	0.703	5.93	-0.028	-0.18	0.000
Q4 highest	0.762	4.80	-0.142	-0.54	0.000	0.801	5.87	-0.110	-0.64	0.000
Quartile effects (p-value)	0.746		0.406			0.608		0.889		

Table 3.13: Robustness Checks for Correlation Asymmetries: Winsorization and DM Returns

The table analyses two modified datasets, both based on daily returns . In the columns under *Winsorization (5%)*, we replace the observations below (above) the 2.5% (97.5%) percentile by the respective percentiles. In the columns under *DM returns*, we add to the US$ denominated logarithm returns, the logarithm variation of the $DM/US\$$ exchange rate. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. *Down* (*Up*) is the slope coefficient for the months the market returns is negative (positive). $t-stat$ is the t-statistic for the coefficient on the left. $Down = Up$ is the $p-value$ of a Wald test for the restriction that slope estimates are equal in falling and rising markets, for a given quartile. $Quartile\ effects$ is the $p-value$ of a Wald test for the restriction that slope estimates are equal across quartiles, for a given industry characteristic. The coefficient estimates and test statistics are based on a joint estimation of the four equations that characterize a given industry characteristic using SUR. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation of the industries that in that month are classified in that quartile.

	Winsorization (5%)				Down = Up	DM Returns				Down = Up
	Down	t-stat	Up	t-stat	(p-value)	Down	t-stat	Up	t-stat	(p-value)
Panel A: VW world portfolio returns										
Size										
Q1 smallest	0.882	3.24	0.080	0.35	0.006	0.850	5.16	-0.067	-0.32	0.000
Q2	0.713	3.41	-0.067	-0.33	0.001	0.666	5.25	-0.069	-0.35	0.000
Q3	0.575	2.84	-0.154	-0.78	0.001	0.614	5.30	-0.102	-0.48	0.000
Q4 largest	0.653	4.58	-0.065	-0.41	0.000	0.586	4.54	-0.050	-0.28	0.000
Quartile effects (p-value)	0.685		0.766			0.175		0.982		
Price earnings ratios										
Q1 smallest	0.598	2.64	-0.122	-0.60	0.004	0.738	5.82	-0.094	-0.42	0.000
Q2	0.671	2.89	-0.014	-0.06	0.014	0.700	4.89	-0.023	-0.11	0.000
Q3	0.662	3.11	-0.032	-0.16	0.005	0.542	4.14	-0.150	-0.82	0.000
Q4 highest	0.799	5.51	0.001	0.01	0.000	0.732	4.59	-0.027	-0.14	0.000
Quartile effects (p-value)	0.789		0.928			0.188		0.605		
Panel B: EW world portfolio returns										
Size										
Q1 smallest	1.004	4.31	0.161	0.63	0.002	0.771	5.58	-0.004	-0.02	0.000
Q2	0.915	5.45	0.063	0.30	0.000	0.621	5.30	-0.066	-0.34	0.000
Q3	0.731	4.64	-0.032	-0.15	0.000	0.530	5.07	-0.158	-0.76	0.000
Q4 largest	0.777	5.55	0.009	0.05	0.000	0.591	4.51	-0.111	-0.50	0.000
Quartile effects (p-value)	0.538		0.824			0.153		0.776		
Price earnings ratios										
Q1 smallest	0.811	4.34	-0.053	-0.24	0.000	0.704	5.91	-0.096	-0.50	0.000
Q2	0.905	5.01	0.087	0.36	0.001	0.593	4.50	-0.033	-0.18	0.000
Q3	0.904	5.43	0.193	0.95	0.001	0.554	4.85	-0.110	-0.65	0.000
Q4 highest	0.792	5.74	0.071	0.39	0.000	0.639	4.63	-0.144	-0.59	0.000
Quartile effects (p-value)	0.682		0.643			0.271		0.902		

Table 3.14: Asymmetries in Global Industries Correlations and Volatility

The table analyses the relationship between monthly world portfolio volatility and the industry quartile correlation series (equation (3.9)). Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. *Down* (*Up*) is the slope coefficient for the months the market returns is negative (positive). $t - stat$ is the t-statistic for the coefficient on the left. $Down = Up$ is the $p - value$ of a Wald test for the restriction that slope estimates are equal in falling and rising markets, for a given quartile. $Quartile\ effects$ is the $p - value$ of a Wald test for the restriction that slope estimates are equal across quartiles, for a given industry characteristic. The coefficient estimates and test statistics are based on a joint estimation of the four equations that characterize a given industry characteristic using the *Seemingly Unrelated Regressions*. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the VW world portfolio (or the EW world portfolio) of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3).

	Down	t-stat	Up	t-stat	Down = Up (p-value)
Panel A: VW world returns					
Size					
Q1 smallest	17.768	2.52	56.061	5.78	0.000
Q2	14.561	2.42	59.354	5.10	0.000
Q3	10.296	1.98	50.672	5.04	0.000
Q4 largest	11.324	3.01	45.933	5.21	0.000
Quartile effects (p-value)	0.000		0.060		
Price-earnings ratio					
Q1 smallest	14.503	2.80	54.196	5.43	0.000
Q2	13.317	2.17	63.733	5.33	0.000
Q3	12.593	2.10	54.102	6.13	0.000
Q4 highest	12.069	3.00	47.086	4.29	0.001
Quartile effects (p-value)	0.398		0.123		
Panel B: EW world returns					
Size					
Q1 smallest	13.715	2.15	58.860	7.16	0.000
Q2	12.021	2.22	63.277	5.44	0.000
Q3	8.024	1.74	53.816	5.37	0.000
Q4 largest	10.624	3.00	48.219	5.26	0.000
Quartile effects (p-value)	0.000		0.027		
Price-earnings ratio					
Q1 smallest	12.038	2.49	58.908	6.70	0.000
Q2	10.678	1.97	64.967	5.85	0.000
Q3	9.759	1.80	59.337	6.68	0.000
Q4 highest	11.220	2.98	48.216	4.54	0.000
Quartile effects (p-value)	0.133		0.106		

Table 3.15: Descriptive Statistics of Global Industries Betas and Volatility Ratios by Size and PER

The table analyses realized betas and volatility ratios. We use within month daily data expressed in US dollars. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. We use the beginning of month cross-industry distribution of Size or PER to classify each industry into one of the four non-overlapping 25% percentiles. The realized betas (volatility ratios) for a given quartile in a given month is measured by the cross-sectional average of the betas (volatility ratios) of the industries that in that month are classified in that quartile. The individual global industry betas (volatility ratios) are estimated monthly using equation (3.10). *Mean* is the time series average of the monthly estimates. *Stdev* is the time series standard deviation. ρ_1 is the first order serial correlation coefficient. *ADF* is the Augmented Dickey-Fuller (ADF) t test statistic (the number of lags is determined by the AIC method). *Trend*, is the linear trend coefficient multiplied by 10^4. $t - PS_T$ is the Vogelsang (1998) test statistic (at the 5% level) for the significance of deterministic linear trends. The 5% critical values for the ADF t test is –2.87, and for the $t - PS_T$ test is 1.72.

	Betas						Volatility ratios					
	Mean	Stdev	ρ_1	ADF	Trend	t-PS_T	Mean	Stdev	ρ_1	ADF	trend	t-PS_T
Panel A: VW world returns												
Size												
Q1 smallest	0.783	0.214	0.479	-3.128	-10.500	-3.19	0.809	0.172	0.520	-9.741	7.270	2.10
Q2	0.882	0.193	0.711	-1.806	-13.400	-1.19	0.837	0.188	0.700	-2.409	12.900	1.48
Q3	0.942	0.155	0.676	-2.580	-5.437	-0.21	0.854	0.120	0.397	-11.330	4.997	1.33
Q4 largest	1.045	0.101	0.698	-1.996	7.571	2.12	0.781	0.105	0.530	-9.562	-2.546	-0.77
Price-earnings ratio												
Q1 smallest	0.813	0.190	0.467	-5.331	-7.349	-1.85	0.851	0.158	0.497	-10.043	7.005	2.27
Q2	0.848	0.175	0.531	-6.192	-7.873	-2.21	0.876	0.163	0.537	-9.455	7.653	1.66
Q3	0.919	0.163	0.606	-4.144	-8.974	-1.50	0.822	0.139	0.567	-9.182	6.056	1.62
Q4 highest	1.067	0.129	0.272	-9.043	2.917	0.98	0.736	0.107	0.421	-5.703	1.418	0.78
Panel B. EW world returns												
Size												
Q1 smallest	0.908	0.159	0.399	-7.791	-6.218	-2.64	0.746	0.129	0.474	-10.335	2.475	0.72
Q2	0.970	0.138	0.590	-2.144	-8.880	-1.34	0.771	0.141	0.667	-2.995	7.243	1.11
Q3	1.023	0.114	0.454	-3.311	0.222	0.35	0.790	0.095	0.356	-9.013	0.045	-0.61
Q4 largest	1.097	0.194	0.626	-2.171	13.900	2.12	0.730	0.127	0.646	-4.138	-6.162	-1.49
Price-earnings ratio												
Q1 smallest	0.905	0.141	0.287	-8.970	-1.770	-0.76	0.786	0.124	0.441	-10.755	1.954	0.52
Q2	0.941	0.116	0.314	-8.292	-2.695	-2.13	0.808	0.115	0.438	-7.854	2.154	0.40
Q3	1.010	0.110	0.316	-12.960	-3.878	-2.23	0.761	0.114	0.571	-5.091	1.274	0.05
Q4 highest	1.136	0.185	0.399	-7.791	7.959	2.52	0.685	0.115	0.536	-4.642	-2.267	-1.12

Table 3.16: Asymmetries in Global Industries Betas and Volatility Ratios by Size and PER

The table analyses the contemporaneous link between realized betas (volatility ratios) and market returns. We use regression (3.8) with monthly correlation replaced by monthly betas or volatility ratios. Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is expressed in US dollars. $t-stat$ is the t-statistic for the coefficient on the left. $Down$ (Up) is the slope coefficient for the months the market returns is negative (positive). $Down = Up$ is the $p-value$ of a Wald test for the restriction that slope estimates are equal in falling and rising markets, for a given quartile. $Quartile\ effects$ is the $p-value$ of a Wald test for the restriction that slope estimates are equal across quartiles, for a given industry characteristic. The coefficient estimates and test statistics are based on a joint estimation of the four equations that characterize a given industry characteristic using SUR. Standard errors are heteroscedasticity and autocorrelation robust using Newey-West correction with 5 lags. The betas (volatility ratios) for a given quartile in a given month is measured by the cross-sectional average of the betas (volatility ratios) of the industries that in that month are classified in that quartile. The individual global industry betas (volatility ratios) are estimated monthly using equation (3.10).

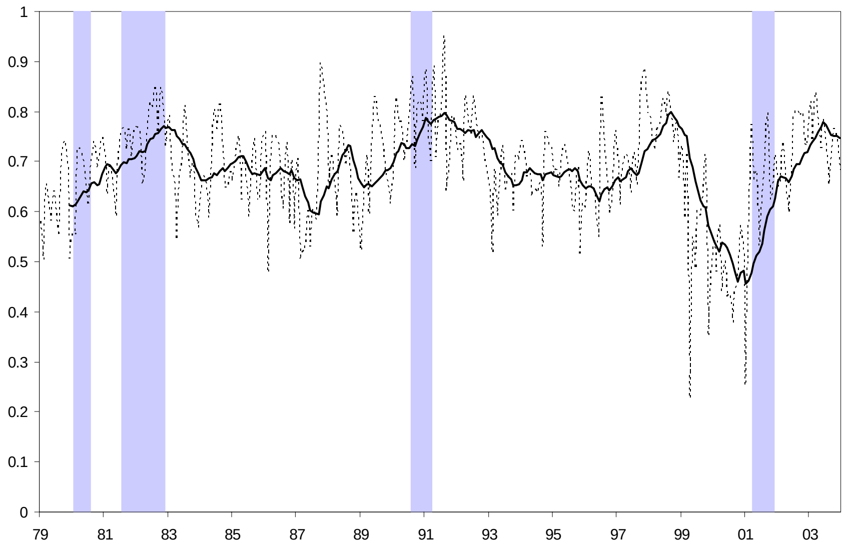
	Betas				Down = Up	Volatility ratios				Down = Up
	Down	t-stat	Up	t-stat	(p-value)	Down	t-stat	Up	t-stat	(p-value)
Panel A: VW world portfolio returns										
Size										
Q1 smallest	-0.017	-0.04	-0.142	-0.34	0.808	1.199	3.28	-0.052	-0.14	0.001
Q2	0.232	0.77	-0.282	-0.87	0.213	0.915	2.24	-0.136	-0.39	0.023
Q3	0.325	0.99	-0.292	-0.99	0.085	0.899	2.81	0.165	0.59	0.033
Q4 largest	-0.132	-0.77	0.124	0.72	0.177	0.653	2.99	-0.097	-0.45	0.003
Quartile effects (p-value)	0.672		0.777			0.416		0.674		
Price earnings ratios										
Q1 smallest	-0.494	-1.23	-0.344	-0.86	0.768	1.194	3.58	-0.159	-0.43	0.001
Q2	0.144	0.39	-0.196	-0.55	0.426	0.969	2.26	-0.007	-0.02	0.029
Q3	0.140	0.44	0.262	1.01	0.743	0.938	3.29	-0.117	-0.47	0.001
Q4 highest	0.312	1.01	-0.244	-0.93	0.076	0.758	3.49	0.280	1.22	0.037
Quartile effects (p-value)	0.194		0.440			0.637		0.166		
Panel B: EW world portfolio returns										
Size										
Q1 smallest	0.147	0.18	0.267	0.32	0.888	1.003	4.50	-0.072	-0.24	0.000
Q2	0.126	0.21	-0.056	-0.07	0.797	0.747	3.19	-0.183	-0.66	0.001
Q3	0.101	0.40	-0.114	-0.30	0.522	0.801	3.85	0.185	0.75	0.009
Q4 largest	-0.361	-0.71	-0.103	-0.18	0.652	0.915	3.36	0.034	0.13	0.005
Quartile effects (p-value)	0.806		0.947			0.567		0.534		
Price earnings ratios										
Q1 smallest	-0.149	-0.46	-0.097	-0.27	0.904	1.024	4.30	-0.100	-0.30	0.000
Q2	0.218	0.96	-0.104	-0.31	0.244	0.787	3.53	0.044	0.19	0.002
Q3	0.128	0.66	0.520	1.95	0.157	0.878	4.20	-0.129	-0.61	0.000
Q4 highest	-0.188	-0.46	-0.330	-0.76	0.769	0.892	3.30	0.292	1.11	0.029
Quartile effects (p-value)	0.613		0.239			0.812		0.126		

Table 3.17: Variance Decomposition of Global Industries Correlations

The table reports a variance decomposition of the quartile absolute correlation series, using equation (3.11). Panel A uses the DS value-weighted world portfolio returns, and Panel B uses the cross industry equal-weighted average returns to proxy for the world portfolio returns. All data is US dollar denominated. We use the beginning of month cross-industry distribution of Size or PER to classify each industry into one of the four non-overlapping 25% percentiles. $V(\beta)$ is the weight of the time series variance of betas on the time series variance of correlation. $V(\pi)$ is the weight of the time series variance of volatility ratios, and $C(\beta, \pi)$ is the weight of the time series covariance between betas and volatility ratios. The columns under *All months* use all observations. The columns under *Down months* (*Up months*) use the observations for the months the world return is negative (positive).

	All Months			Down Months			Up Months		
	V(β)	V(π)	2C(β,π)	V(β)	V(π)	2C(β,π)	V(β)	V(π)	2C(β,π)
Panel A: VW world returns									
Size									
Q1 smallest	1.24	0.47	-0.71	1.44	0.44	-0.88	1.14	0.47	-0.61
Q2	1.32	0.65	-0.97	1.63	0.56	-1.19	1.06	0.68	-0.75
Q3	1.08	0.24	-0.32	1.36	0.20	-0.55	0.93	0.26	-0.18
Q4 largest	0.53	0.72	-0.25	0.58	0.58	-0.16	0.51	0.78	-0.29
Price-earnings ratio									
Q1 smallest	1.15	0.39	-0.54	1.42	0.41	-0.83	1.00	0.34	-0.35
Q2	1.27	0.42	-0.69	1.57	0.42	-0.99	1.12	0.41	-0.53
Q3	1.09	0.37	-0.46	1.24	0.24	-0.47	0.93	0.46	-0.38
Q4 highest	0.67	0.77	-0.44	0.63	0.64	-0.26	0.70	0.87	-0.57
Panel B. EW world returns									
Size									
Q1 smallest	0.79	0.50	-0.29	0.95	0.60	-0.55	0.75	0.46	-0.21
Q2	0.74	0.76	-0.50	0.87	0.73	-0.60	0.68	0.75	-0.43
Q3	0.65	0.44	-0.09	0.66	0.32	0.01	0.65	0.50	-0.15
Q4 largest	0.84	1.08	-0.92	1.08	1.37	-1.45	0.74	0.96	-0.70
Price-earnings ratio									
Q1 smallest	0.73	0.45	-0.18	0.88	0.57	-0.45	0.68	0.39	-0.07
Q2	0.69	0.48	-0.18	0.83	0.47	-0.30	0.65	0.49	-0.13
Q3	0.65	0.54	-0.19	0.60	0.51	-0.11	0.67	0.54	-0.21
Q4 highest	0.71	1.17	-0.88	0.73	1.19	-0.91	0.70	1.20	-0.91

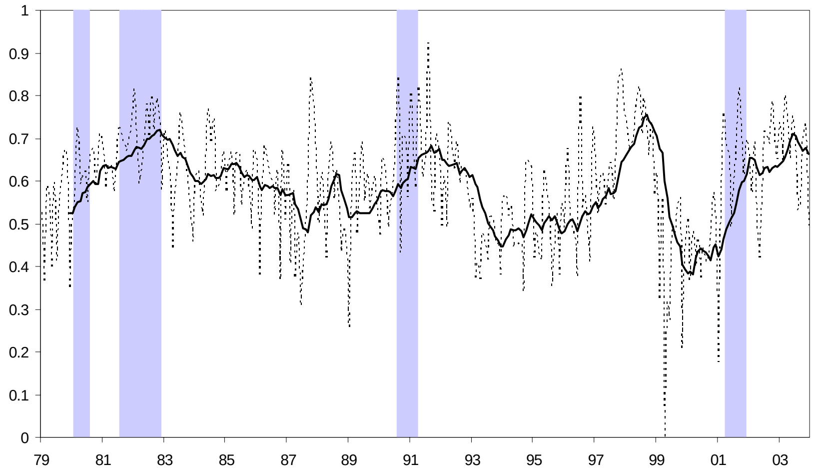
Figure 3.1: Global Industry Correlation



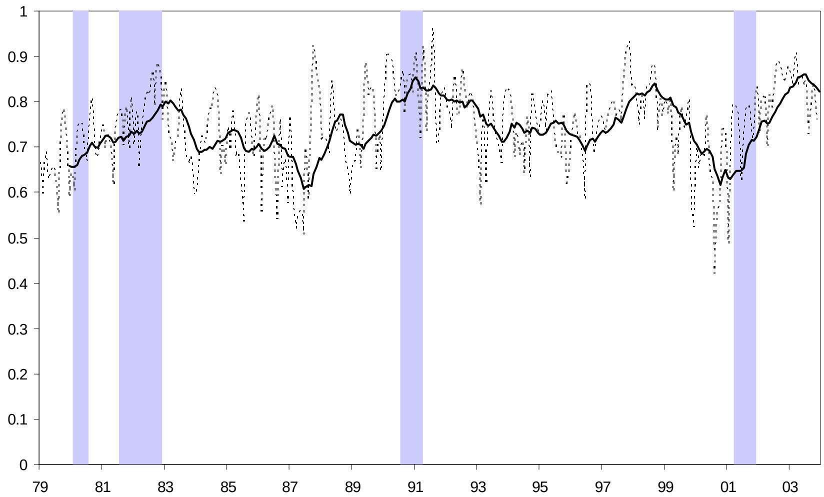
The figure shows the cross-sectional equal-weighted average correlation of the 35 global industry portfolios returns with the DS value-weighted world portfolio returns (dashed line). The backwards 12-moving average is also shown (solid line). NBER-dated US recessions are shaded in gray. The individual global industry correlation is estimated monthly using equation (3.3). Returns are US dollar denominated.

Figure 3.2: Correlation and Size

Panel A: Q1 (smallest)

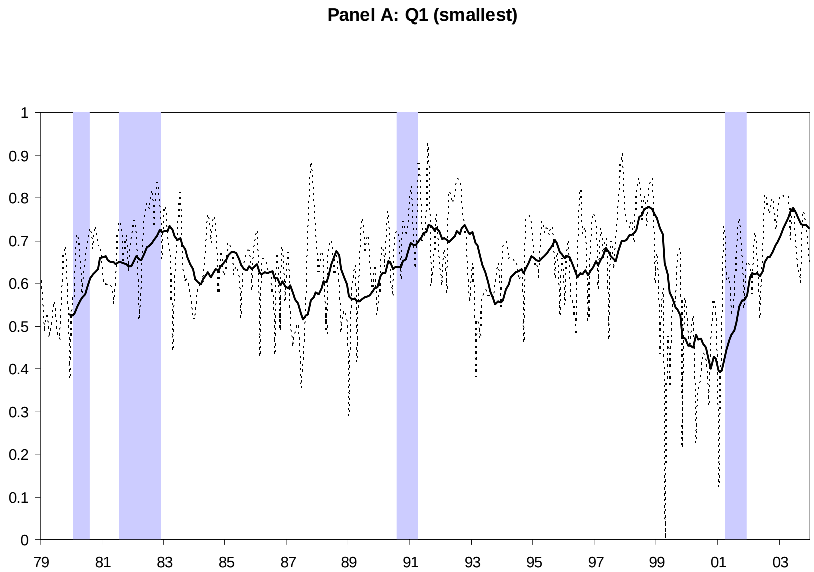


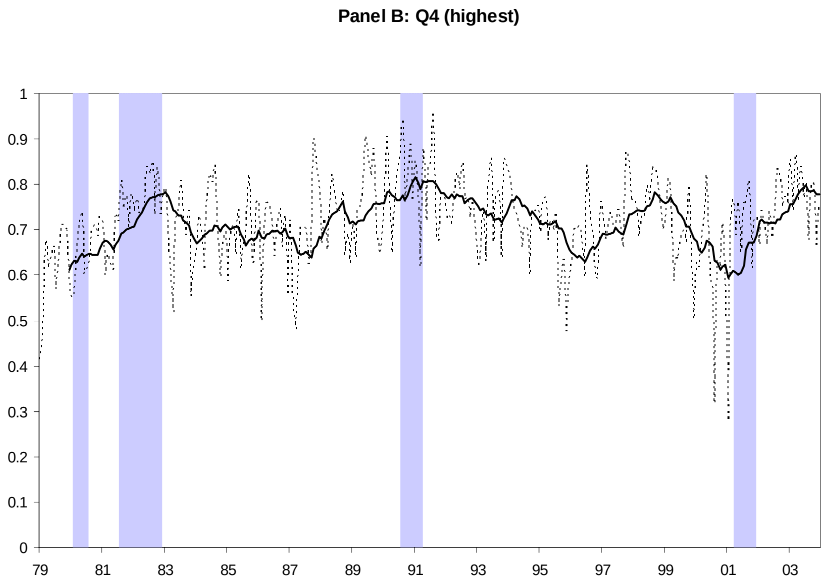
Panel B: Q4 (largest)



Panel A (Panel B) shows the equal-weighted average correlation of the global industry portfolios in the lowest (highest) quartile of Size. The backwards 12-moving averages are also shown (solid line). NBER-dated US recessions are shaded in gray. All data is US dollar denominated. We use the beginning of month cross-industry distribution of market capitalization to classify each industry into one of the four non-overlapping 25% percentiles. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the DS value-weighted world portfolio of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3).

Figure 3.3: Correlation and Price-earnings Ratios





Panel A (Panel B) shows the equal-weighted average correlation of the global industry portfolios in the lowest (highest) quartile of PER. The backwards 12-moving averages are also shown (solid line). NBER-dated US recessions are shaded in gray. All data is US dollar denominated. We use the beginning of month cross-industry distribution of price-earnings ratios to classify each industry into one of the four non-overlapping 25% percentiles. The correlation for a given quartile in a given month is measured by the cross-sectional average of the correlation with the DS value-weighted world portfolio of the industries that in that month are classified in that quartile. The individual global industry correlation is estimated monthly using equation (3.3).