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Correlation dynamics of global industry portfolios☆

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ABSTRACT

This paper investigates the time series of realized correlations between global industries and the world market over the 1979–2008 period. The behavior of industry correlations is characterized by long-term swings, with a period of historically low correlations in the late 1990s. The Telecommunications and the Financials industries show a positive secular trend. Global industry correlations move countercyclically. Furthermore, there is evidence that industry correlations are higher for market downside moves than for upside moves.

1. Introduction

Do global industry correlations change over time? Do industry correlations behave differently depending on downside or upside movements? These questions are important for several applications such as portfolio selection and risk management. In portfolio selection, if correlations change over time, the number of industries needed to achieve a given level of diversification also changes over time. And if all stocks tend to fall together when the market falls, portfolios become less diversified just when that benefit is most needed. In risk management, correlation is a crucial input in estimation of measures of portfolio Value-at-Risk.

Heston and Rouwenhorst (1994) have shown that pure country factors dominate pure global industry factors. Since then, several authors find evidence supporting the growing importance of global

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industry factors over country-specific factors in determining equity returns; see L'Her et al. (2002) and Cavaglia et al. (2004).

Bekaert et al. (2009) dispute the conclusion that industry factors have gained in importance, contending that any decline in industry portfolios correlation during the 1990s has been reversed. Lower country-return correlations relative to industry-return correlations would support the Heston–Rouwenhorst conclusions that country factors dominate industry factors.

We know a considerable amount about cross-country correlation (see, for example, Longin and Solnik, 1995, 2001). So far, however, there is little to no empirical analysis of the correlation of global industries. Our goal is thus to contribute to the literature on international investment by characterizing global industry portfolio correlation dynamics in terms of long-term trends and asymmetries. Moreover, global industries presumably diversify away country-specific sources of return variation, and thus allow for a new perspective on the global stock correlations minimizing the dynamics of country factors in explaining the variation of returns.

Our methodology is characterized by several distinct features. First, we use a simple and time-varying measure of correlation—realized correlation (see, for example, Andersen et al., 2001). We use daily index return data (in each month) to construct a time series of correlation at the monthly frequency, which we treat as "observable" and consequently suitable for posterior analysis using standard econometric models.[1]

Second, we study the time series behavior and asymmetries in global industry correlations with the world market portfolio. We use the FTSE/Dow Jones Industry Classification with 42 sectors grouped into ten industries. The industry grouping allows for insights on easily identified individual industry groups, based on a correlation measure that by the averaging process minimizes noise.

Finally, we use time-varying estimates of correlation to investigate asymmetries relative to the aggregate market movement (up and down), for the global industry groups.

The literature offers some key results that are related to our work. In the case of cross-country correlations, Longin and Solnik (1995) and Solnik and Roulet (2000) show that correlation is time unstable, with tendency to increase over time; Solnik et al. (1996) show that correlation is positively related to the level of country volatility; Longin and Solnik (2001) that correlation is higher in bear markets; and Erb et al. (1994) that correlation is related to the coherence between a country's business cycles and its market phase.

In the case of global industry portfolios, Ferreira and Gama (2005) find between 1974 and 2001 no noticeable long-term trend in industry-specific or world portfolio risk (in developed markets). Yet the late 1990s are characterized by an increase in the ratio between global industry-specific risk and world risk; this implies a reduced global industry portfolio correlation during the late 1990s. Moreover, we know that for local US industry portfolios, correlation with the US market tends to increase for down market periods. However, different testing procedures yield different conclusions on the statistical significance of that increase (Ang and Chen, 2002; Hong et al., 2007).

We establish several empirical findings about global industry correlations. First, historically Oil and Gas has the lowest correlations (50.4%), while Industrials have the highest (75.4%).

Second, global industry correlations change over time, with a noticeable decrease in correlations for the late 1990s period, except for the Technology industry. Furthermore, there is evidence of a statistically significant positive secular trend for both the Telecommunications industry and the Financial industry.

Third, industry correlations move countercyclically. Global industry correlation increases during US NBER-dated recessions relative to expansions. This effect is most notable for the Basic Materials industry (an increase of about 9.2 percentage points).

Finally, global industry correlations are higher for downside moves than for upside moves. These effects persist across portfolios of sectors sorted by industry.

[1] Relative to multivariate GARCH alternatives we do not impose a parametric model to describe the time evolution of covariances or volatilities, but we still allow correlations to change over time. Relative to rolling window estimates (e.g. Solnik et al., 1996) realized correlation minimizes autocorrelation and ghost effects.

Our results are robust to definition of correlation coefficient, number of observations used to estimate realized correlation, and potential influence of outliers.

2. Research design

The starting point for estimating correlations is to obtain estimates of variances and covariances. French et al. (1987) use daily data within each month to obtain non-overlapping monthly estimates of market variance. Andersen et al. (2001) extends 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 world market portfolio. We calculate the estimates as follows:

$$\mathrm{COR}_{i,t} = \frac{\mathrm{COV}_{i,t}}{\sqrt{\mathrm{VAR}_{i,t} \times \mathrm{VAR}_{m,t}}} = \frac{\sum_{d \in t}(r_{i,d} - \mu_{i,t}) \times (r_{m,d} - \mu_{m,t})}{\sqrt{\sum_{d \in t}(r_{i,d} - \mu_{i,t})^2 \times \sum_{d \in t}(r_{m,d} - \mu_{m,t})^2}} \quad (1)$$

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 in month t. Variance and covariance estimates are obtained at the monthly horizon.[2]

To study the behavior of market correlation for individual global industries, we use the FTSE/Dow Jones Industry Classification Benchmark (Level 2 Industrial Classification in Datastream) to aggregate 42 individual global sectors (Level 4 Industrial Classification in Datastream) correlation estimates into ten groups representing the industries Oil and Gas, Basic Materials, Industrials, Consumer Goods, Healthcare, Consumer Services, Telecommunications, Utilities, Financials, and Technology.[3]

We can interpret the average correlation as an estimate of the correlation of a "typical" (randomly selected) sector within the given industry group for a given month. Thus, it differs from the correlation computed using the returns of previously sorted portfolios of industries because we do not eliminate by aggregation the idiosyncratic factors within each industry group. Nevertheless, we have a measure of correlation for individual global industries that by the averaging process minimizes noise.

The sample consists of daily US dollar-denominated global sectors total return indexes (including dividends), calculated by Datastream, from January 1979 through December 2008. At one particular time, each global sector index can include stocks from all countries or from just a subset of countries, and the particular stocks may also vary as Datastream revises its indices quarterly. Datastream data is preferred because of long time series of daily returns is available and the coverage of the industry structure in each national market is comprehensive. Datastream covers 53 countries in 2008, and the coverage within each country is approximately 80% of total market capitalization. The individual stocks are value-weighted aggregated within each market to form the national sector indices and across countries to form the global sector indices. We also use the value-weighted world portfolio return from Datastream to proxy for the world portfolio return.

3. Time series of industry correlations

Do global industry correlations change over time? We provide a graphical analysis of the time evolution of global industry correlations, and discuss relevant statistics concerning the time series properties of the series.

[2] 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. Thus, the correlation with the market is a positive function of the average pairwise correlations. Ang and Chen (2002) and Hong et al. (2007) also rely on the correlation with the market to study correlation asymmetries in US markets.

[3] The FTSE/Dow Jones Industry Classification Benchmark (ICB) is available online at http://www.icbenchmark.com. Of the 42 sectors (Level 4 in Datastream) we have not considered Nonequity Investment Instruments (no data available in Datastream) and Alternative Energy (not available since 1979 in Datastream).

3.1. Graphical analysis

Fig. 1 shows the behavior of each industry correlation. In all industries except for Technology, there is a clear downward move in the late 1990s. For the Technology industry, the plot suggests that the market correlation increased from the mid-1990s onwards, until stabilizing in 2004.

The downward move in the late 1990s is in line with the findings in Ferreira and Gama (2005). In fact, the higher increase in global industry-specific risk relative to that of world portfolio volatility implies a reduction in global industry correlation.

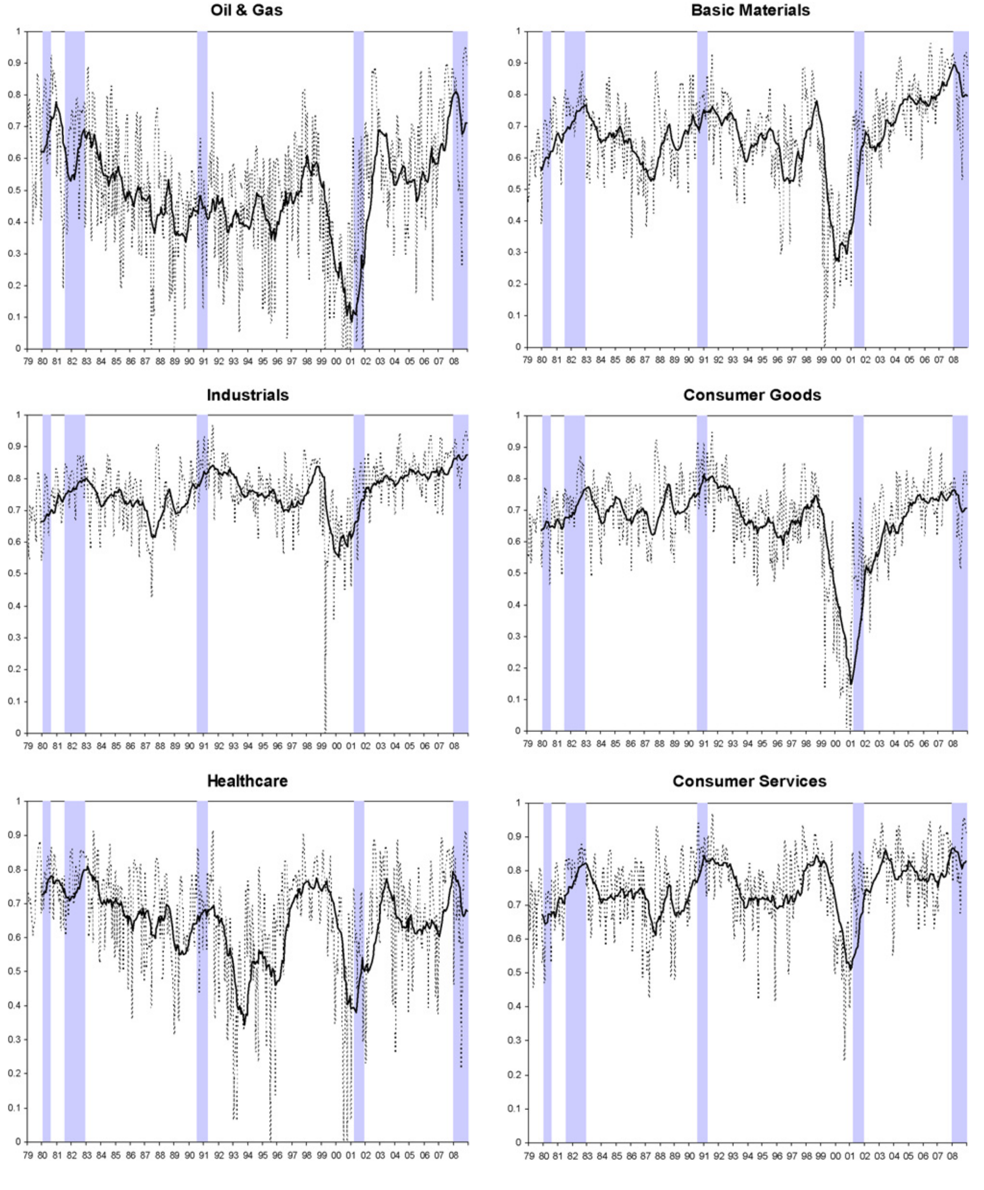
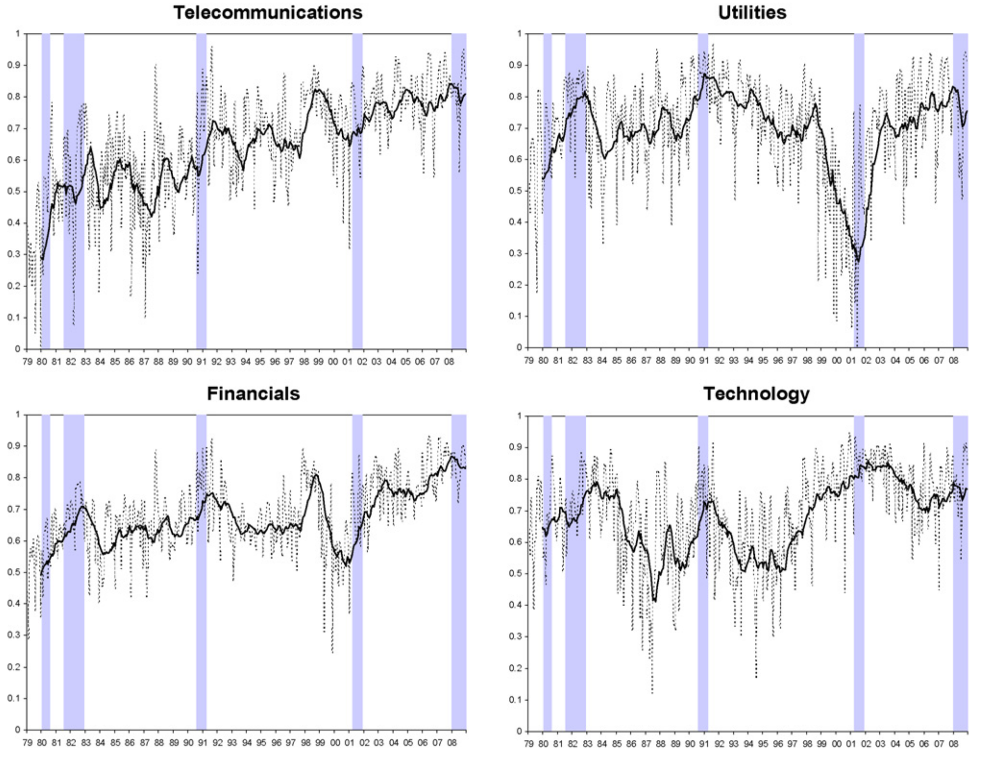


Fig. 1. Global industry correlation.



These plots show the equal-weighted average correlation of the global Datastream Level 4 (ICB Sector) portfolios in each Datastream Level 2 (ICB Industry) group. The backward 12-month moving averages are also shown (solid line). NBER-dated US recessions are shaded in gray. Relevant Peak (Trough) reference dates are: January 1980 (July 1980); July 1981 (November 1982); July 1990 (March 1991); March 2001 (November 2001); and December 2007. All data are US dollar-denominated.

Fig. 1. (*Continued*)

Also, Fig. 1 shows a tendency for an increase in correlation during economic recessions (the grey vertical bars represent the periods between consecutive peaks and troughs in the US economy official NBER dates). During recessions, we see both a cluster of correlation peaks and an increase in the slow moving component. Particularly clear is the increase in correlation series during the 2001 US recession.[4]

3.2. *Trends*

Table 1 investigates the stochastic behavior of correlation for the whole sample period.

On average, global industry correlation is lower for Oil and Gas and higher for Industrials. The correlation series do not present unit roots. Thus, average correlation series seem to be stationary, which means that fluctuations around the long-run mean do not have permanent effects on its behavior. This is consistent with the long-term temporary swings already uncovered in the graphic analysis.

One important issue for international investors is to evaluate whether correlation is constant over time. We can diagnose time instability in the correlation series by testing for long-term trends. Follow-

[4] We use the US business cycle as a proxy for what might be called a world business cycle. This choice is determined for operational reasons (to our knowledge, there is no “officially” dated world business cycle), and recognizes the importance of the US economy in the world (about 25% of the World GDP in 2007, according to the World Bank).

Table 1
Global industries correlation trends.

	Mean	Std Dev	ρ_1	ADF	Trend	t-PS$_T$
Oil and Gas	0.504	0.227	0.387	−3.399	−0.485	−0.78
Basic Materials	0.663	0.162	0.596	−3.139	2.273	−0.19
Industrials	0.754	0.107	0.459	−4.596	2.462	0.60
Consumer Goods	0.663	0.153	0.667	−3.140	−2.193	−0.84
Healthcare	0.646	0.175	0.358	−6.056	−2.076	−1.13
Consumer Services	0.747	0.114	0.479	−5.598	2.131	0.83
Telecommunications	0.643	0.176	0.570	−6.599	11.200	9.72
Utilities	0.692	0.177	0.490	−3.279	−0.328	−0.36
Financials	0.674	0.121	0.550	−4.339	5.705	2.33
Technology	0.681	0.154	0.495	−3.725	4.412	0.57

The table reports linear trend tests for the global industry correlation with the world market portfolio. All data are US dollar-denominated. We use the Datastream Level 2 (ICB industry) classification to group (within-group monthly cross-sectional average) the individual global Datastream Level 4 (ICB sector) portfolios correlation in the ten groups listed. Mean is the time series average of the monthly estimates. Std Dev 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 10,000. 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.

ing Longin and Solnik (1995), we specify a simple linear trend model for the sole purpose of testing for a trend. To test for the significance 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 have unit roots.

Trends tests reveal industry diversity. Trend coefficients are negative for 4 industries (Oil and Gas, Consumer Goods, Healthcare, and Utilities) and positive for the other 6 (Basic Materials, Industrials, Consumer Services, Telecommunications, Financials, and Technology). The overall evidence shows generally insignificant trends. The exceptions are a statistical significant upward trend for Telecommunications (representing an increase of 40.3% in 1979–2008) and for Financials (an increase of 20.5% in 1979–2008).

Table 2
Time and cross-sectional effects of global industry correlations.

	Mean correlation						Time
	1979–1983	1984–1988	1989–1993	1994–1998	1999–2003	2004–2008	Effects (p-value)
Oil and Gas	0.642	0.468	0.414	0.488	0.380	0.634	0.000
Basic Materials	0.669	0.627	0.695	0.648	0.532	0.810	0.000
Industrials	0.732	0.714	0.785	0.755	0.704	0.834	0.000
Consumer Goods	0.684	0.696	0.742	0.668	0.462	0.726	0.000
Healthcare	0.744	0.658	0.566	0.643	0.596	0.668	0.000
Consumer Services	0.728	0.709	0.774	0.753	0.711	0.809	0.000
Telecommunications	0.466	0.533	0.626	0.704	0.724	0.803	0.000
Utilities	0.680	0.684	0.800	0.707	0.517	0.764	0.000
Financials	0.600	0.623	0.683	0.678	0.657	0.802	0.000
Technology	0.697	0.596	0.617	0.613	0.811	0.751	0.000
Cross-effects (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	

The table reports under mean correlation the time series mean industry correlation with the VW world portfolio for 6 non-overlapping 60-month periods. All data are US dollar-denominated. We use the Datastream Level 2 (ICB industry) classification to group (within-group monthly cross-sectional average) the individual global Datastream Level 4 (ICB sector) portfolios correlation in the ten groups listed. Time effects is the p-value of a Wald test for the restriction that mean estimates are equal across time periods, for a given industry group. Cross-effects is the p-value of a Wald test for the restriction that mean estimates are equal across industry groups, for a given time period. The statistics are based on a joint estimation of the ten industry group equations using SUR. Standard errors are heteroskedasticity and autocorrelation robust using Newey–West correction with 5 lags.

3.3. Time and cross-sectional effects

Our evidence suggests that long-term swings, rather than a secular trend, characterize the behavior of global industry correlations. To further document these patterns, we calculate the average correlation for five equally spaced subperiods of 60 months. The statistical significance of the time variation in average correlation in each subperiod is based on the regression (defined for a given industry group p correlation series):

$$\mathrm{COR}_{p,t} = \sum_{s} \theta_{p,s} I_s + \gamma \mathrm{COR}_{p,t-1} + \varepsilon_{p,t} \tag{2}$$

where $\mathrm{COR}_{p,t}$ is the average correlation with the world market portfolio in month t for industry group p; and I_s is equal to one if the month t observation occurs during the subperiod s, and zero otherwise. We estimate jointly the ten equations each relating to each industry group using the seemingly unrelated regression (SUR) technique to increase the efficiency of estimators, and because it allows for a direct test of differences across groups.

We use a joint Wald χ^2 test on the industry effects for the null hypothesis $\theta_{1,s} = \ldots = \theta_{10,s}$ for each period s. We test for time effects using a joint test for the null hypothesis $\theta_{p,1} = \ldots = \theta_{p,5}$ for each industry group p.

Table 2 presents the results. The up and down moves in correlation (time effects) are statistically significant for all industries. Also, the 1999–2003 period cannot be considered a period of low correlations (in historical terms) for the Telecommunications and Technology industries.

As the last row of Table 2 shows, our industry classification yields an effective differentiation scheme across industry groups, as all subperiod mean estimates are statistically different.

3.4. Cyclical behavior

Erb et al. (1994) find higher cross-country correlations in the G-7 countries 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 countercyclically (e.g., DeStefano, 2004), and so do market and industry-specific volatility (Campbell et al., 2001).

The behavior of the 12-month moving averages plotted in Fig. 1 during periods of US economic contraction suggests that months characterized by a US contraction are also characterized by higher correlations. Most obvious is an upward move in correlation at the beginning of 2001.

Table 3
Correlation between global industry correlations and NBER expansions.

	Correlation lead (months)								
	−12	−6	−3	−1	0	+1	+3	+6	+12
Oil and Gas	−0.08	−0.09	−0.06	−0.16	−0.13	−0.13	−0.17	−0.20	−0.11
Basic Materials	−0.02	−0.11	−0.13	−0.20	−0.20	−0.20	−0.15	−0.09	−0.02
Industrials	0.02	−0.08	−0.10	−0.19	−0.19	−0.19	−0.17	−0.13	−0.02
Consumer Goods	0.11	0.06	−0.01	−0.10	−0.09	−0.09	−0.08	−0.06	−0.04
Healthcare	−0.03	−0.10	−0.08	−0.13	−0.10	−0.12	−0.12	−0.11	−0.13
Consumer Services	0.07	−0.07	−0.07	−0.16	−0.15	−0.17	−0.13	−0.11	−0.04
Telecommunications	0.06	0.12	0.09	0.01	−0.01	−0.02	−0.04	−0.01	0.06
Utilities	0.04	0.02	0.02	−0.06	−0.05	−0.05	−0.06	−0.05	−0.03
Financials	0.02	−0.04	−0.08	−0.17	−0.16	−0.16	−0.10	−0.05	0.03
Technology	−0.05	−0.14	−0.11	−0.16	−0.17	−0.19	−0.21	−0.17	−0.12

The table reports the correlations of the global industry correlation with the value-weighted world portfolio 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 global industry correlations series lead (lag) the business cycle. We use the Datastream Level 2 (ICB industry) classification to group (within-group monthly cross-sectional average) the individual global Datastream Level 4 (ICB sector) portfolios correlation in the ten groups listed. Relevant Peak (Trough) reference dates are: January 1980 (July 1980); July 1981 (November 1982); July 1990 (March 1991); March 2001 (November 2001); and December 2007. All data are US dollar-denominated.

Table 4
Global industry correlations for down and up markets.

	Mean correlation		Down = Up
	Down	Up	
Oil and Gas	0.526	0.492	0.090
Basic Materials	0.688	0.650	0.003
Industrials	0.779	0.740	0.000
Consumer Goods	0.677	0.655	0.005
Healthcare	0.667	0.634	0.027
Consumer Services	0.770	0.735	0.001
Telecommunications	0.671	0.627	0.007
Utilities	0.719	0.677	0.016
Financials	0.692	0.664	0.021
Technology	0.704	0.668	0.072
Cross-effects	0.000	0.000	

The table analyses under mean correlation the average industry correlation for the months the market return is negative (Down) and the months the market return is positive (Up). All data are US dollar-denominated. The table uses the VW world portfolio returns. We use the Datastream Level 2 (ICB Industry) classification to group (within-group monthly cross-sectional average) the individual global Datastream Level 4 (ICB sector) portfolios correlation in the ten groups listed. Down = Up is the *p*-value of a Wald test for the restriction that mean estimates are equal during Down and Up market months, for a given industry group. Cross-effects is the *p*-value of a Wald test for the restriction that mean estimates are equal across industry groups, for a given market move. The statistics are based on a joint estimation of the ten industry group equations using SUR. Standard errors are heteroskedasticity and autocorrelation robust using Newey–West correction with 5 lags.

To explore the relation between the US business cycle and the global industry correlation with the world portfolio, Table 3 presents at different lags (and leads) the cross-correlation between each industry group correlation series and a dummy variable that equals one during NBER-dated US expansions, and zero otherwise. Thus, a negative correlation indicates a higher correlation between global industries and the aggregate world market during US economic recessions.

The contemporaneous (lag 0) cross-correlation is negative for all industries. Clearly, global industry correlations increase during US recessions.[5]

Also, the negative estimates of cross correlations in the short-term lag (and remain negative up to the long-term lead), suggest that global industry correlation starts to increase prior to the end of an NBER-dated US expansionary period. Moreover, the cross-correlation tends to be higher (in absolute value) when the correlation is leading (positive lead). This suggests that the increase in correlation becomes more significant after the onset of recessions.

These results are consistent with the Campbell et al. (2001) findings that industry and especially market volatility are countercyclical in the US. 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 declines during economic recessions.

4. Asymmetries in industry correlations

Do industry correlations behave differently depending on downside or upside movements? We first test whether global industry correlation, on average, is higher for down market moves than for up market moves. We then test for asymmetries in industry correlation relative to the sign and size of market moves for the different industry groups.

Is global industry correlation on average higher for down market moves than for up market moves? To address this question, we calculate the average correlation conditional on the sign of monthly market returns (up and down). Following the analysis of time effects, the statistical significance of the variation in average correlation, conditional on the sign of market moves is based on the regression

[5] The increase in correlation, that is, the (positive) difference between average correlations during recessions and average correlations during expansions (the magnitude of the move), ranges between 9.2% for Basic Materials and 2.8% for Utilities.

(defined for a given industry group p correlation series):

$$\mathrm{COR}_{p,t} = \alpha_p^- I^- + \alpha_p^+ I^+ + \gamma \mathrm{COR}_{p,t-1} + \varepsilon_{p,t} \tag{3}$$

where $\mathrm{COR}_{p,t}$ is the average correlation with the world market portfolio in month t for industry group p; and I^- (I^+) is an indicator variable for the months the return is on average negative (positive). We estimate jointly the ten equations each relating to each industry group using the seemingly unrelated regression (SUR). We use a joint Wald χ^2 test on the industry effects for the null hypothesis $\alpha^-{}_1 = \ldots = \alpha^-{}_{10}$ and $\alpha^+{}_1 = \ldots = \alpha^+{}_{10}$. We test for differences in the average correlation in up and down markets using a joint test for the null hypothesis $\alpha^-{}_p = \alpha^+{}_p$ for each industry group p.

Table 4 presents the results. For all industry group series, market correlation is on average higher during markets down months relative to market up months. The increase in correlation ranges between 4.4 percentage points for the Telecommunications and 2.1 percentage points for the Consumer Goods industries, both statistically significant.

Longin and Solnik (2001) find an asymmetric relation between country portfolio correlations with the US stock market and the (signed) threshold used to define the (signed) return exceedances. We investigate the contemporaneous relation between monthly realized industry correlation and the sign and size of market returns over the entire distribution of returns. Specifically, we estimate the following equation defined for a given industry group p correlation series:

$$\mathrm{COR}_{p,t} = \alpha_p + \delta_p^- I^- \left| r_{m,t} \right| + \delta_p^+ I^+ \left| r_{m,t} \right| + \gamma_p \mathrm{COR}_{p,t-1} + \eta_p r_{m,t-1} + \varepsilon_{p,t} \tag{4}$$

where $\mathrm{COR}_{p,t}$ is the portfolio p industry correlation with the world market portfolio during month t, I^- (I^+) is an indicator variable for the months the market return is on average negative (positive), and $r_{m,t}$ is the market return in month t. The parameters δ_p^- and δ_p^+ measure the contemporaneous relation between industry correlation and world portfolio returns during falling and rising months, for each industry group. The lagged variables are included to pick up any serial correlation in the correlation and the absolute returns series.

An asymmetric relation between correlation and returns implies a different link between correlation and the size of market returns in rising and falling markets. This difference could arise from the sign of the link (e.g., for down months the correlation increases with market returns, while in up months it declines), 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).

Table 5
Asymmetries in global industry correlations.

	Down	*t*-Stat	Up	*t*-Stat	Down = Up (*p*-value)
Oil and Gas	0.839	2.17	−0.555	−1.31	0.002
Basic Materials	0.533	2.22	−0.547	−1.83	0.001
Industrials	0.548	4.12	−0.376	−1.83	0.000
Consumer Goods	0.685	3.70	−0.089	−0.41	0.002
Healthcare	0.747	2.93	−0.045	−0.13	0.017
Consumer Services	0.785	5.77	−0.137	−0.63	0.000
Telecommunications	0.922	2.77	−0.109	−0.30	0.004
Utilities	0.324	0.92	−0.584	−1.83	0.013
Financials	0.609	3.19	−0.100	−0.44	0.001
Technology	0.797	3.56	0.268	0.94	0.072
Cross-effects (*p*-value)	0.219		0.303		

The table analyses the relationship between monthly world portfolio returns and the industry correlation series. All data are US dollar-denominated. The table uses the VW world portfolio returns. We use the Datastream Level 2 (ICB Industry) classification to group (within-group monthly cross-sectional average) the individual global Datastream Level 4 (ICB sector) portfolios correlation in the ten groups listed. 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 industry group. Cross-effects is the *p*-value of a Wald test for the restriction that slope estimates are equal across industry groups. The coefficient estimates and test statistics are based on a joint estimation of the ten industry group equations using SUR. Standard errors are heteroskedasticity and autocorrelation robust using Newey–West correction with 5 lags.

Table 6
Robustness checks: trends and time effects.

	(1)	(2)	(3)	(4)	(5)
Panel A: trend t-PST (5%)					
Oil and Gas	−0.69	−0.56	−0.72	−0.85	−0.64
Basic Materials	−0.15	−0.10	−0.11	0.24	0.07
Industrials	0.82	0.63	0.87	1.02	0.79
Consumer Goods	−0.98	−0.73	−0.83	−0.85	−0.80
Healthcare	−1.43	−1.11	−1.07	−2.40	−1.03
Consumer Services	0.61	0.89	1.02	−0.16	1.19
Telecommunications	9.67	7.56	10.60	6.90	12.82
Utilities	−0.50	−0.32	−0.33	−0.14	−0.25
Financials	2.80	2.24	2.51	2.58	2.26
Technology	0.57	0.55	0.56	0.10	0.67
Panel B: time effects					
Oil and Gas	0.000	0.000	0.000	0.003	0.000
Basic Materials	0.000	0.000	0.000	0.000	0.000
Industrials	0.000	0.000	0.000	0.000	0.000
Consumer Goods	0.000	0.000	0.000	0.000	0.000
Healthcare	0.000	0.007	0.000	0.000	0.000
Consumer Services	0.015	0.001	0.000	0.003	0.000
Telecommunications	0.000	0.000	0.000	0.000	0.000
Utilities	0.000	0.000	0.000	0.000	0.000
Financials	0.000	0.000	0.000	0.000	0.000
Technology	0.000	0.000	0.000	0.002	0.000

The table analyses five modified datasets: (1) rolling-average of two days returns; (2) correlation series constructed from daily data within a two-month estimation window; (3) replaces the observations below (above) the 2.5% (97.5%) percentile by the respective percentiles; (4) the equal weighted average return of the Datastream Level 4 ICB sectors returns proxy for world portfolio return; (5) Fisher Z correlation coefficients as dependent variable. All data are US dollar-denominated. Panel A presents the Vogelsang (1998) t-PS_T test statistic (at the 5% level) for the significance of deterministic linear trends. The 5% critical values for the t-PS_T test is 1.72. Panel B presents the p-value of a Wald test for the restriction that mean estimates are equal across time periods, for a given industry group. The statistics are based on a joint estimation of the ten industry group equations using SUR. Standard errors are heteroskedasticity and autocorrelation robust using Newey–West correction with 5 lags.

The sign effect resembles the asymmetric effect documented by Longin and Solnik (2001). The size effect is related to the volume-absolute returns contemporaneous asymmetric relation (e.g. Jain and Joh, 1988).

Table 5 presents the results. First, we show that a strong asymmetric sign effect characterizes the overall contemporaneous link between correlation and market returns. Overall, global industry correlation is positively related to absolute returns in down markets. In up markets, the relation is either negative or positive but statistically insignificant. Second, the evidence suggests that an asymmetric size effect also characterizes correlation. Except for Basic Materials and Utilities, the strength of the link (measured by the coefficients δ_p^- and δ_p^+) is higher in down months than in up months. Moreover, we reject that $\delta_p^- = \delta_p^+$ for the ten industry groups. This result suggests that an increase in volatility (as measured by the absolute return) as a stronger impact on correlation for down months than for up months.

Finally, the asymmetric effect persists across economic sectors. As the cross-effects line of Table 5 shows, the negative and positive links are not statistically different across groups.

What might explain the asymmetric effect? We argue that an information diffusion asymmetry is a reasonable candidate to explain the industry correlation asymmetric behavior. If it is more likely that negative news has marketwide implications and positive news reflects industry-specific events, it is possible that falling market returns occur because of 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 correlations in down months than in up months.[6]

[6] We do not dismiss the possibility of a market volatility effect (Chakrabarti and Roll, 2002) rather than a market volatility bias (Forbes and Rigobon, 2002) for three reasons. First, the effects of market volatility are (implicitly) taken into account by

Table 7
Robustness checks: cross-correlations and asymmetries.

	(1)	(2)	(3)	(4)	(5)
Panel A: contemporaneous cross-correlation					
Oil and Gas	−0.13	−0.20	−0.13	−0.07	−0.17
Basic Materials	−0.22	−0.22	−0.21	−0.18	−0.19
Industrials	−0.20	−0.23	−0.20	−0.20	−0.21
Consumer Goods	−0.11	−0.10	−0.09	−0.08	−0.11
Healthcare	−0.10	−0.14	−0.10	−0.10	−0.11
Consumer Services	−0.15	−0.19	−0.15	−0.16	−0.15
Telecommunications	−0.01	−0.09	−0.01	−0.02	−0.03
Utilities	−0.04	−0.10	−0.07	−0.05	−0.11
Financials	−0.16	−0.20	−0.16	−0.19	−0.15
Technology	−0.17	−0.23	−0.17	−0.21	−0.17
Panel B: asymmetries					
Oil and Gas	0.001	0.009	0.006	0.002	0.001
Basic Materials	0.000	0.000	0.001	0.000	0.000
Industrials	0.000	0.000	0.000	0.000	0.000
Consumer Goods	0.002	0.000	0.003	0.006	0.000
Healthcare	0.046	0.003	0.017	0.027	0.007
Consumer Services	0.000	0.000	0.000	0.000	0.000
Telecommunications	0.003	0.001	0.003	0.002	0.000
Utilities	0.011	0.000	0.010	0.000	0.000
Financials	0.003	0.000	0.001	0.000	0.000
Technology	0.050	0.049	0.065	0.067	0.099

The table analyses five modified datasets: (1) rolling-average of two days returns; (2) correlation series constructed from daily data within a two-month estimation window; (3) replaces the observations below (above) the 2.5% (97.5%) percentile by the respective percentiles; (4) the equal weighted average return of the Datastream Level 4 ICB sectors returns proxy for world portfolio return; (5) Fisher *Z* correlation coefficients as dependent variable. All data are US dollar-denominated. Panel A reports the correlations of the global industry correlation with the VW world portfolio with a dummy variable that is one during a NBER-dated US expansion and zero during a NBER-dated US recession. Panel B presents the *p*-value of a Wald test for the restriction that slope estimates are equal in falling and rising markets, for a given industry group. The coefficient estimates and test statistics are based on a joint estimation of the ten industry group equations using SUR. Standard errors are heteroskedasticity and autocorrelation robust using Newey–West correction with 5 lags.

5. Robustness

We address five issues in this section. First, 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. Second, the sensitivity of our results to the noise reduction associated with a wider window to estimate the realized correlation. Third, the effect of extreme observations. Fourth, the extent to which the cross-sectional characteristics of industry correlation are a simple manifestation of the unavoidable fact that larger size industries are weighted more heavily in the world portfolio and thus are expected to be more correlated with the market. Finally, the impact of using a bounded variable as dependent variable.

We thus redefine the sample in five different ways. In specification 1, we use a simple rolling-average of two-day 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. In specification 2, we extend the estimation window to two months, thus doubling approximately the number of daily observations used to estimate each observation of the realized correlation series.[7] In specification 3, we perform a 5% winsorization of the correlation series (we replace the observations of each quartile correlation series in the upper

including of the lagged absolute return variable (a proxy for volatility) as an explanatory variable. Second, we condition on the sign of monthly market returns, not on their size. Third, as Chakrabarti and Roll (2002) argue, if the true volatility of the driving factor is expected to be higher for the conditional set, one would correctly expect an increase in the conditional correlation.

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

(lower) 2.5% percentiles by the 97.5% (2.5%) percentile). This procedure decreases the influence of the (extreme) observations, but leaves them as important upward or downward moves in correlation. Specification 4 uses the equal weighted average return of the Datastream Level 4 sectors returns to proxy for world portfolio return. Finally, specification 5 uses Fisher *Z* correlation coefficients as dependent variable.[8]

Results are presented in Tables 6 and 7. Panel A (Panel B) of Table 6 replicates the trends tests (time-effects tests) in Table 1 (Table 2). Panel A (Panel B) of Table 7 replicates the contemporaneous cross correlations (asymmetric tests) of Table 3 (Table 5).

A strong message emerges. The key findings remain unaffected. In whole specifications, the industry groups with significant trend coefficients remain the same (Telecommunications and Financials). Also, long-term (60-month) time effects characterize the behavior of industry correlation. Contemporaneous (lag) negative cross correlations with dummy for NBER-dated expansions documents the increase in correlation during the downturns of US Business cycles. Finally, the nature of the link between correlation and returns is different for down and up months, an evidence of correlation asymmetry relative to sign and size of market returns.

6. Conclusion

Our investigation of the time series of realized correlations between global industries and the world market reveals that global industry correlations fluctuate over time, but there is no significant long-term trend for most industries (the exceptions are Telecommunications and Financials). Global industry correlations are countercyclical. They are, moreover, higher for downside moves than for upside moves. Correlation asymmetry is pervasive across industries.

The characterization of global industry correlation structure yields both reassuring and disturbing information for global equity investors. On the one hand, our results confirm, for industry portfolios, two features that characterize cross-country correlations. Industries are more correlated in falling markets than in rising markets, and industry correlation is positively related to market volatility. During market turmoil, global industry diversification is less able to reduce portfolio risk. Also unfavorable is the evidence that the link between correlation and volatility is stronger in rising markets than in falling markets. Thus, the negative effects for portfolio diversification of the increase in volatility are most pervasive during up rather than down markets.

Yet industry correlations do not show a systematic increase over time, and the late 1990s were characterized by low correlations. Thus, industry portfolios constitute an interesting dimension for international diversification, as opposed to the increasingly correlated country portfolios.

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[8] To conserve space only a subsample of the robustness results are presented in this section (Tables 5–8). The remaining results are available upon request.

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