Original Article

Time-varying correlations and interrelations: Firm-level-based sector evidence

Received (in revised form): 13th October 2016

P. Evans
is a Senior Lecturer at Swansea University. Her main interests are in the behaviour of financial markets. She has also worked into examining the factors that affect inward investment.

David G. McMillan
is a Professor of Finance at the University of Stirling. He has held a similar position at the University of St Andrews and previous positions at the Universities of Aberdeen and Durham. His research interests include forecasting asset returns and volatility, modelling the linkages between asset prices and macroeconomic variables and examining the behaviour of financial and investor ratios. He has published widely on these topics in internationally respected peer-reviewed journals such as the Journal of Banking and Finance, Journal of International Money and Finance, the Journal of Forecasting, International Journal of Forecasting and the Oxford Bulletin of Economics and Statistics. He is a Co-editor for the Economics and Finance Research Journal and sits of the Editorial Board of numerous internationally respected journals, including the European Journal of Finance.

Fiona J. McMillan
is a Lecturer in Banking and Finance at the University of Dundee. Her research interests primarily lie in the areas of modelling bank performance and risk, the links between the accounting and stock market performance of banks and the behaviour of asset returns. She has published several papers in internationally respected peer-reviewed journals.

Correspondence: David G. McMillan, Division of Accounting and Finance, University of Stirling, Stirling, UK
E-mail: david.mcmillan@stir.ac.uk

ABSTRACT Using firm-level data, we examine stock market correlations and interrelations for the G7 over the period 2000–2013. An examination using aggregate market data supports the view that correlations have risen and particularly so during crisis periods. Using firm-level data, which is tradeable, we establish sector portfolios. We consider three regression approaches. The results support, first, that correlations using firm data are lower than those observed using aggregate market index data. Second, the most important driver for home sector returns is the home market followed by the corresponding US sector. Third, correlations rose during the crisis but have stabilised and even fallen since. This supports the view that markets fall together but rise apart. Fourth, there is evidence that most sector correlations follow a market-wide component, but some sector correlations follow their own component. Subsequently, we examine the key drivers of time-varying correlations. We find that the market-wide component of correlations increases in a US bear market as well as with higher US market volatility and lower US interest rates. However, on a sector basis, there are notable exceptions with some correlations falling in a bear market. Together, these results support the view that diversification benefits remain across market sectors.
Journal of Asset Management (2017) **18,** 209–221. doi:10.1057/s41260-016-0034-3; published online 19 December 2016

Keywords: stock markets; correlations; firm-level; sectors; time-varying
JEL Classification: C22; G12

INTRODUCTION

This paper examines the nature and determinants of time-varying correlations between the G7 markets over the period beginning from 2000, which captures the large market downturns following the dotcom crash and the financial crisis. In doing so, we pay attention primarily to sector-level correlations, which, in turn, are based on individual firm stock price data, as opposed to aggregate market-level behaviour. We view it important to analyse data based on stocks that can be traded as opposed to index data that cannot. The results presented will, therefore, carry greater information and be of increased relevance not only to academics but also market practitioners. Of note, this paper will show that while correlations have typically increased over the sample period and that movements in correlations are linked to the behaviour of the US market, there remains notable exceptions to this that would allow for diversification opportunities.

The common consensus is that over time correlations between markets have increased. This is largely due to deregulation within financial markets as well as the removal of trade barriers (see, for example, Roll, 1989; King *et al*, 1994; Longin and Solnik, 1995; Rangvid, 2001; Goetzmann *et al*, 2001). Further, the literature typically supports the view that correlations rise in periods of market stress (see, for example, King and Wadhwani, 1990; Erb *et al*, 1994; Longin and Solnik, 1995; Karolyi and Stulz, 1996; Forbes and Rigobon 2002; Opschoor *et al*, 2014; Karanassos *et al*, 2016). Given this, an examination of how correlations have varied over the recent past, which includes two notable periods of market stress, is warranted.[1] To date, the majority of the literature uses aggregate market-level index data. While this provides an overview of market behaviour, such index data are not traded and thus may mis-represent the actual strength of correlations. As an exception, Berben and Jansen (2005) and Fasnacht and Loubergé (2007) examine sector-level data, although again using index-based data.

In this paper, we construct sector portfolios using firm-level data for the G7 markets. We then examine the relation between these sector returns with the corresponding US-based series. In addition to sample correlations of the data, we examine regression-based analysis using a CAPM approach, a bi-variate GARCH model and a principal components analysis. Once we establish the nature of the time-varying correlations, we then consider a set of regressions designed to explain such time-variation. In particular, we are interested in considering both the general movement in correlations as captured by the principal components as well as the behaviour of the individual sectors. Notably, we wish to examine whether correlations change with conditions in the US stock market. The paper contributes to the existing literature in three ways. First, as commented, our analysis is based on firm-level data as opposed to index data that are commonly used in the literature. Second, our analysis includes the twin market downturns experienced during the 2000 s as well as the subsequent market recoveries. This offers us a unique opportunity to examine how correlations vary between bull and bear markets. Third, we seek to examine the drivers of time-varying correlations and, in particular, test the view that movements in the US economy and stock market dominate in determining correlations.

The results generally suggest that diversification opportunities remain. Firm-level-based correlations are lower than those reported for the aggregate market. Moreover, correlations appear to fall during bull markets, but do rise in bear markets. Nonetheless, there is evidence that while most sector correlations appear to follow a market-wide component, some sector correlations follow different components. Furthermore, there is evidence that while the financial crisis has raised correlations across all sectors, some sectors respond differently to movements in the US economy as well as movements in market returns and volatility. Again, such differences will provide diversification opportunities. It is hoped the results here are helpful to both portfolio managers in attempting to obtain diversified portfolios and academics interested in modelling market behaviour.

DATA AND DESCRIPTIVE EVIDENCE

We collect individual stock price data for the G7 markets over the time period 3rd January 2000 to 31st December 2013. The data are obtained from Datastream and in addition to the price data, we obtain information on the market sector. The individual stocks are then sorted into sector portfolios, which are used in the analysis below. The individual stocks are obtained from the main indices in each market, and thus, it allows comparison with previously reported aggregate market index correlations. The aim in the data collection exercise is to obtain a number of firms that is broadly equivalent across the markets but without potentially including very small firms. We take firm data for all available firms in the S&P500 for the US, the FTSE350 for the UK, the DAX, MDAX and SDAX for Germany, the SBF120 for France, the MIBTEL for Italy, the TTOCOMP for Canada and the Nikkei225 for Japan.

To provide a benchmark level of correlation between the G7 markets and an initial view as to how correlations have changed over the recent past, we examine sample correlation coefficients. As such, Table 1 presents the correlations between the returns of national markets (index level data) of the G7 countries over the sample period 1973–2012 on a monthly basis.[2] As can be seen from this table, correlations are high or reasonably high. Notably, the correlation between the two North American markets is high, as it is between the European markets themselves as well as between the European markets (especially the UK) and the US. Relatively lower correlations are found for Japan and, to a lesser extent, Italy.

Analysis of these correlations is further enhanced by considering two sub-samples of the data. First, by examining the correlations over the period 1990–2012 and then 2006–2012, reported in Tables 2 and 3, respectively. The use of samples with later starting dates will allow examination of whether correlations have risen over the more recent period compared to one that captures a longer history. The results in Tables 2 and 3 document the previously noted phenomena of rising correlations between these advanced markets. This is particularly true for the grouping of markets noted above, i.e., between the two North American markets and the European markets both within themselves and with the North American markets (again, most notably with the UK). Furthermore, the correlations are noticeably higher in the latter 2006–2012 period compared to the other sample periods. The 2006–2012 sample covers the financial crisis period, and hence provides a result

Table 1: Sample correlations: market index data 1973–2012

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*US*
Canada	1	0.592	0.545	0.461	0.397	0.627	0.773
France		1	0.683	0.610	0.417	0.626	0.626
Germany			1	0.560	0.417	0.577	0.628
Italy				1	0.366	0.503	0.458
Japan					1	0.405	0.430
UK						1	0.704
US							1

Notes: Entries are sample correlation coefficients for monthly stock index returns data over the stated sample period.

Table 2: Sample correlations: market index data 1990–2012

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*US*
Canada	1	0.684	0.695	0.604	0.481	0.728	0.805
France		1	0.875	0.787	0.487	0.829	0.751
Germany			1	0.746	0.456	0.788	0.764
Italy				1	0.416	0.687	0.615
Japan					1	0.478	0.482
UK						1	0.808
US							1

Notes: Entries are sample correlation coefficients for monthly stock index returns data over the stated sample period.

Table 3: Sample correlations: market index data 2006–2012

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*US*
Canada	1	0.763	0.795	0.754	0.673	0.831	0.873
France		1	0.915	0.955	0.702	0.939	0.872
Germany			1	0.876	0.693	0.900	0.897
Italy				1	0.663	0.904	0.846
Japan					1	0.703	0.676
UK						1	0.913
US							1

Notes: Entries are sample correlation coefficients for monthly stock index returns data over the stated sample period.

consistent with the established view that correlations increase at times of market stress. These results thus suggest that gains from diversification have diminished over time and more so during a bear market.

Set against this prevailing view, we examine the stock return correlations between the firm-level-based market sectors in order to examine whether the correlations at this more disaggregated level follow the same pattern of behaviour. As noted above, these data are not obtained by taking sector-level index data but by obtaining individual firm-level data, with the sector portfolio then constructed. Thus, the correlations here can be obtained by investors. Table 4 presents the correlations for each sector against the corresponding US sector. The correlations are obtained over four different sub-samples in order to examine the effect on correlations across different phases of market behaviour. Period 1 covers the years 2000–2003, which is characterised by the dotcom crash. Period 2 covers the years 2004–2006 and is marked by the market recovery from the dotcom crash and is a period when markets performed well. Period 3 covers the years 2007–2009 and Period 4 covers the years 2010–2013; thus, Period 3 covers the financial crisis and Period 4 is the post-crisis recovery.

The results in Table 4 show the average correlations across the six markets of Canada, France, Germany, Italy, Japan, and the UK compared with the US. Immediately apparent is that the correlations at the sector level are lower than at the market level. This suggests that diversification benefits remain. However, it is equally noticeable that correlations have increased from the first half to the second half of the sample (i.e., from Periods 1 and 2 to Periods 3 and 4). Although it is also noticeable that the rate of increase has declined from Periods 3 to 4 and in five cases the correlation itself has declined. Nonetheless, this result supports the view that correlations rise in crisis periods. It is also noticeable that the majority of correlations decreased (albeit some marginally) from Period 1 to Period 2. The period 2004–2006 is marked by the recovery from the dotcom crash and equally supports the view that bull markets are more likely to be associated with

Table 4: Average sample correlation between non-US G7 and G7 market sectors

Sectors	*Period 1*	*Period 2*	*Period 3*	*Period 4*
Automobiles	0.3063	0.2629	0.4466	0.5244
Banks	0.3347	0.2408	0.4158	0.4611
Beverages	0.0838	0.1202	0.2750	0.2984
Chemicals	0.2547	0.2844	0.4568	0.3499
Construction	0.1474	0.2278	0.4362	0.4562
Electricity	0.2338	0.1059	0.3001	0.2635
Electronics	0.2888	0.2414	0.4377	0.4737
Finance	0.2807	0.2716	0.4091	0.4791
Food and drugs	0.2028	0.1635	0.3073	0.3944
Gen. ind.	0.2255	0.2146	0.3679	0.3132
Healthcare	0.0749	0.1107	0.2982	0.3339
Ind. eng.	0.2183	0.2015	0.4597	0.5924
Industrial metals	0.1205	0.2904	0.5137	0.5085
Ind. transport	0.1852	0.1779	0.3688	0.4306
Mining	0.0771	0.2704	0.3581	0.4074
Oil and gas	0.2436	0.3341	0.4894	0.5119
Pharma and bio	0.2094	0.1458	0.2805	0.3129
Real estate	0.0462	0.1420	0.2757	0.3594
Software	0.2894	0.2494	0.3503	0.4268
Technology hardware	0.3659	0.2824	0.3670	0.3942
Telecoms	0.1998	0.1774	0.3036	0.2341

Notes: Entries are average sample correlation coefficients for the stated sectors between the US and the non-US G7 markets. Sample periods are: Period 1, 2000–2003; Period 2, 2004–2006; Period 3, 2007–2009; Period 4, 2010–2013.

falling correlations and a bear market with rising correlations. In terms of the more specific results, we can see that 17 of the 21 sectors have a correlation below 0.5 by the end of the sample. Furthermore, while the correlation of some sectors has increased markedly (e.g., beverages, healthcare and mining) for other sectors, the increase in correlation has been muted (e.g., electricity, technology hardware and telecoms).

REGRESSION-BASED EVIDENCE

To examine the nature of interrelations and correlations in greater detail, we consider three regression-based approaches. First, we consider a market model-type approach and estimate the following equation for each sector and non-US country:

$$r_{s,i,t} = \alpha + \beta r_{\mathrm{s,USA,t}} + \gamma r_{i,t} + \delta r_{\mathrm{USA,t}} + \varepsilon_{s,i,t}, \tag{1}$$

where $r_{s,i,t}$ is the return for sector s on market i at time t, $r_{i,t}$ is the return on market i, with the equivalent values for the US denoted USA. Here we are interested in whether the US variables, both sector and market, dominate the home country market in determining the home country sector returns. The results are presented in Table 5.

These results suggest an interesting pattern that occurs across all sectors. First, the largest coefficient is attached to the home market. This suggests that the key risk factor for sector stock returns remains the home market return and thus the domestic economy. The corresponding US sector is then more important than movement in the US market as a whole. In considering the individual sectors, we can see that the coefficient magnitude arising from the corresponding US sector is low for many of the sectors (e.g., healthcare, real estate, telecoms), while it is larger for several (e.g., chemicals, industrial metals, technology hardware). Notably, those sectors with a higher degree of conditioning from the corresponding US sector are more open to trade (e.g., automobiles). It is also of interest to note that there is a positive correlation of approximately 0.5 between the home

Table 5: Average market model estimates

Home sectors	*US sector*	*Home market*	*US market*
Automobiles	0.199	0.975	−0.153
Banks	0.138	1.183	−0.124
Beverages	0.155	0.580	−0.083
Chemicals	0.214	0.745	−0.149
Construction	0.093	0.787	−0.061
Electricity	0.063	0.487	−0.064
Electronics	0.136	0.809	−0.015
Finance	0.097	0.927	−0.105
Food and drugs	0.062	0.507	−0.041
Gen. ind.	0.095	0.819	−0.055
Healthcare	0.060	0.575	−0.044
Ind. eng.	0.168	0.771	−0.127
Industrial metals	0.233	0.885	−0.198
Ind. transport	0.084	0.611	−0.024
Mining	0.144	0.839	−0.140
Oil and gas	0.216	0.776	−0.196
Pharma and bio	0.177	0.612	−0.099
Real estate	0.033	0.736	−0.005
Software	0.213	0.943	−0.247
Technology hardware	0.277	1.103	−0.224
Telecoms	0.051	0.828	−0.054

Notes: Entries are the average coefficient values across each sector for the non-US G7 markets. The market model is given by Eq. (1).

market β and the coefficient on the US sector. This suggests that the riskier sectors are more affected by international markets.

Subsequently, we estimate a bi-variate DCC-GARCH model (Engle, 2002) for each market sector with the corresponding US sector. This allows us to obtain the time-varying correlation for each market with the US. The DCC-GARCH model builds upon the constant conditional correlation model of Bollerslev (1990), where the conditional covariance matrix is expressed in terms of the following decomposition:

$$\Omega_t = D_t \Gamma_t D_t, \tag{2}$$

where D_t refer to the diagonal matrix of the conditional standard deviations, and Γ_t is the matrix of conditional correlations. Bollerslev (1990) assumes that the correlations were constant, i.e., $\Gamma_t = \Gamma$. To estimate this model, individual GARCH(1, 1) processes are estimated for each series with the standardised residuals (ξ_t) computed in the usual way:

$$\xi_t = D_t^{-1} \varepsilon_t. \tag{3}$$

With the correlations given by,

$$\Gamma = \frac{1}{T} \sum_{t=1}^{T} \xi_t \xi_t'. \tag{4}$$

While the assumption of a constant correlation may be useful in certain circumstances, in the analysis here it is not of practical relevance. Hence, we implement Engle's extension whereby the conditional correlation is allowed to exhibit time-variation in a manner similar to the GARCH(1, 1) model. Specifically, conditional correlations are allowed to fluctuate around their constant (unconditional) values as such:

$$Q_t = (1 - \alpha - \beta)\Gamma + \alpha \xi_{t-1} \xi_{t-1}' + \beta Q_{t-1}, \tag{5}$$

where Q is the time-varying correlation matrix. The estimated correlations are standardised, $\rho_{ij,t} = \Gamma_{t,ij} = Q_{t,ij} / \sqrt{Q_{ii}} \sqrt{Q_{jj}}$, to ensure they lie between −1 and 1. This also ensures both a positive definite matrix as well as readily interpretable correlations.[3]

Our interest here lies is whether the estimated correlations have trended upwards over time. To examine this, Tables 6 and 7

Table 6: Panel unit root tests and trend estimate for DCC correlation

Sectors	*Constants*				*Constants and trends*				*Trends*
	LLU	*IPS*	*F-AFD*	*F-PP*	*LLU*	*IPS*	*F-AFD*	*F-PP*	
Automobiles	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.58e−5
Banks	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.04e−5
Beverages	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.03e−5
Chemicals	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.15e−5
Construction	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.22e−5
Electricity	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.94e−5
Electronics	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.40e−5
Finance	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.93e−5
Food and drugs	0.76	0.13	0.09	0.08	0.13	0.00	0.00	0.00	5.03e−5
Gen. ind.	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.46e−5
Healthcare	0.21	0.00	0.00	0.00	0.01	0.00	0.00	0.00	6.21e−5
Ind. eng.	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.18e−5
Industrial metals	0.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0001
Ind. transport	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.67e−5
Mining	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.90e−5
Oil and gas	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.45e−5
Pharma and bio	0.26	0.00	0.00	0.00	0.07	0.00	0.00	0.00	1.49e−5
Real estate	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.88e−5
Software	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.89e−5
Technology hardware	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−4.7e−6
Telecoms	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.24e−5

Notes: Entries are the *p*-values for the corresponding panel unit root test, except the last column, which is the estimated trend coefficient.

Table 7: Panel unit root tests and trend estimates for DCC correlation: excluding Japan

Sectors	*Constants*				*Constants and trends*				*Trends*
	LLU	*IPS*	*F-AFD*	*F-PP*	*LLU*	*IPS*	*F-AFD*	*F-PP*	
Automobiles	0.63	0.28	0.30	0.33	0.03	0.02	0.00	0.00	7.91e−5
Banks	0.36	0.00	0.00	0.00	0.15	0.00	0.00	0.00	3.66e−5
Beverages	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.49e−5
Chemicals	0.48	0.00	0.00	0.00	0.25	0.0	0.00	0.00	7.39e−5
Construction	0.61	0.39	0.55	0.52	0.10	0.05	0.02	0.01	9.88e−5
Electricity	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.73e−5
Electronics	0.55	0.01	0.00	0.00	0.25	0.00	0.00	0.00	6.45e−5
Finance	0.58	0.00	0.00	0.00	0.17	0.00	0.00	0.00	7.12e−5
Food and drugs	0.76	0.13	0.09	0.08	0.13	0.00	0.00	0.00	5.03e−5
Gen. ind.	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.01e−5
Healthcare	0.54	0.16	0.17	0.13	0.41	0.03	0.04	0.02	7.77e−5
Ind. eng.	0.69	0.44	0.42	0.36	0.01	0.00	0.00	0.00	0.0001
Industrial metals	0.69	0.12	0.03	0.03	0.00	0.00	0.00	0.00	0.0001
Ind. transport	0.62	0.00	0.00	0.00	0.08	0.00	0.00	0.00	8.03e−5
Mining	0.51	0.01	0.00	0.00	0.17	0.00	0.00	0.00	8.62e−5
Oil and gas	0.49	0.02	0.00	0.00	0.27	0.00	0.00	0.00	9.33e−5
Pharma and bio	0.33	0.00	0.00	0.00	0.13	0.00	0.00	0.00	1.73e−5
Real estate	0.73	0.00	0.00	0.00	0.79	0.00	0.00	0.00	7.36e−5
Software	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.48e−5
Technology hardware	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−5.6e−6
Telecoms	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.56e−5

Notes: Entries are the *p*-values for the corresponding panel unit root test, except the last column, which is the estimated trend coefficient.

then report panel unit root tests under different constant and trend assumptions together with the trend term coefficient for these correlation series. Although correlations are globally stationary, evidence within any sample period may indicate a different type of behaviour. We consider the results both including and excluding Japan given its generally lower correlations as noted in Table 1.

We consider two types of panel unit root test. Both tests are based on the same principle as the Dickey–Fuller unit root test, with a null hypothesis of non-stationarity (random walk with drift). First, we consider the test of Levin, Lin and Chu (LLU, 2002) that assumes a common unit root process across the different markets, while second, we consider the tests of Im, Pesaran and Shin (IPS, 2003) and Fisher (1932) that allow for individual unit root processes. The results in both tables support the view that correlations are stationary and thus mean reverting. This implies that they are not drifting consistently towards the value of one. A closer examination of the results shows that if we consider the LLU test only, then evidence of non-stationary behaviour does exist. Looking across all sectors and markets, for 11 sectors the null hypothesis is not rejected, while for the tests that exclude Japan, 17 of the sectors exhibit non-stationary behaviour. However, as noted above, this test is more restrictive in assuming a common autoregressive parameter across all markets. The tests that allow the autoregressive parameter to differ across markets all reject non-stationarity. A panel estimate of the trend component in the correlations is positive (and significant) throughout but very small in magnitude.

The above results all examine the relation between the same sector across different markets with respect to the US market. To consider a different approach, we examine whether there is similarity in these sector correlations across all sectors. Hence, we are interested in whether there exits common movement across all sectors that could be more ascribed to a general market movement. To do this, we consider a principal components analysis of the above time-varying correlations between the non-US G7 markets with the US. Principal component analysis allows us to extract common factors (components) from a group of data series. The components are ordered according to how much of the variation across the series they can account for and are orthogonal to each other, thus representing independent information.

The results of the principal components analysis are reported in Table 8. The evidence reported here demonstrates that the first three principal components account for 80 per cent of the variation in correlations across the 21 sectors. Indeed, the first principal component accounts for just over two-thirds of the movement in correlations across all sectors. Furthermore, we can examine the factor loadings to determine how each sector is related to the main principal components. Examining the factor loadings, we can see that for the first, most important, principal component all sectors have an equivalent loading with the exception of technology and telecoms. Instead, these two sectors dominate the third principle component. This supports the view that movements in correlations are typically driven by market-wide events; however, these events do not affect all sectors and thus there remains the potential for portfolio diversification.

EXPLAINING MOVEMENTS IN CORRELATIONS

This section seeks to examine the causes of movements in the firm-based sector-level correlations between the US and the remaining G7 markets. In order to do this we will use the information based on the time-varying correlations obtained from the DCC-GARCH model. In addition, we can also use the results from the principal components exercise to help in understanding why correlations vary over time.

Therefore, we consider two regression approaches to explain the nature of time-variation within the correlations. In the first set of regressions we use the obtained principal components as the dependent

Table 8: Principal components analysis

Principal components	*Eigenvalues*	*Cumulative values*	*Cumulative proportion*
1	14.1734	14.1734	0.6749
2	1.3343	15.5076	0.7385
3	1.1868	16.6945	0.7950
Factor loadings			
Automobiles	0.2401	0.1753	−0.0184
Banks	0.2246	0.1636	−0.0404
Beverages	0.2132	−0.0383	0.0031
Chemicals	0.2372	−0.0823	0.0257
Construction	0.2525	−0.0321	0.0207
Electricity	0.1695	−0.4837	0.0914
Electronics	0.2549	0.0979	−0.0132
Finance	0.2446	0.0840	−0.0153
Food and drugs	0.2323	0.2107	−0.0331
Gen. ind.	0.2498	0.1808	−0.0241
Healthcare	0.2291	−0.1812	0.0528
Ind. eng.	0.2536	−0.0452	0.0149
Industrial metals	0.2473	0.1565	−0.0263
Ind. transport	0.2426	0.0845	−0.0073
Mining	0.2148	−0.3757	0.1003
Oil and gas	0.1972	−0.2720	0.0259
Pharma and bio	0.2226	0.0841	−0.0172
Real estate	0.1876	−0.3742	0.0754
Software	0.2226	0.3710	−0.0836
Technology hardware	−0.0159	0.1169	0.6964
Telecoms	−0.1118	0.1595	0.6885

Notes: Entries show the first three principal components and the proportion of the variation across all sector correlations that they account for. Entries also report the factor loadings for each sector on the first three components.

variable, while in the second approach we use the correlations obtained from the DCC-GARCH model. In order to explain the movement in correlations, we consider two sets of explanatory variables. First, for the regressions using the obtained principal component variables, we consider the following. A dummy variable designed to highlight the crisis period and thus takes the value of one in the years 2006–2009 inclusive and zero elsewhere. A second dummy variable that represents whether the US market is in a bull or bear state. To obtain this, we take a three-year moving average of the market index and assign a value of one if this is increasing and zero if this is decreasing. We also use a 10-year Treasury bond rate and the standard deviation of the US stock market index, both of these variables enter with a one period lag and will provide a proxy for the state of the US economy and the riskiness of the US market, respectively. Second, for the regressions based on the individual sector correlations, we use the same explanatory variables but expand it to additionally include each individual market's return and standard deviation as well as the specific sectors return and standard deviation.

Examining the results of the first set of regressions, using the principal components as the dependent variable, we can make the following conclusions based on Table 9. For the first principal component, which captures the largest variability across the data, we can see that correlations increase during the financial crisis, when the US market is in a bear state, when US long-term interest rates are failing and when the variability of the US market increases. These results thus accord with the general view from the literature that correlations rise during periods of market stress. Hence, correlations rise during the financial crisis, when the US market is falling and becomes more volatility and when interest rates are lower (low interest rates may signal recessionary conditions, resulting in a capital outflow from the US).

Table 9: Explaining time-varying correlations: principal components

Variables	*PC1*	*PC2*	*PC3*
Dum-FC	1.6581 (20.97)	−0.6232 (−16.86)	0.0597 (1.38)
Dum-Mkt	−2.2515 (−22.13)	−0.7738 (−16.27)	0.1253 (2.26)
US IR	−2.9243 (−78.38)	−0.5291 (−30.33)	0.1080 (5.32)
US SD	0.4958 (19.33)	0.1163 (9.69)	−0.0063 (−0.45)

Notes: Entries are the regression coefficients (and *t*-tests) where regressions use the first three principal components obtained from Table 8 as the dependent variables. These are regressed on a dummy variable covering the financial crisis, a dummy variable representing a US bull market, the US 10-year Treasury bond yield and the standard deviation of the US market.

The results from the second principal component are largely similar with correlations higher with a declining and more volatile US market and lower US interest rates. The only difference concerns the financial crisis dummy, which is now negative. While the first principal component has a positive factor loading across all sectors (except technology hardware and telecoms), the second principal component has a reasonably sized positive factor loading across only several. One explanation for the negative coefficient on the financial crisis dummy may be that these sectors were either less affected by the crisis (e.g., food and software) or received special government help (e.g., automobiles and banks). For the third principal component, for which only technology hardware and telecoms have a positive factor loading, we see the correlation increase with an increasing US market as well as higher interest rates, in contrast to the previous results. Moreover, US market volatility and the financial crisis are not significant. Thus, for these two sectors, the converse result to that established in the literature is found. Here correlations rise with an expanding economy and a bull market. This supports the earlier view that not all sectors respond in the same direction.

Table 10 reports the results for the determinants of time-varying correlations for the individual sectors using a fixed effects panel regression approach.[4] We can see that the dummy variable that relates to the financial crisis is positive and statistically significant for all sectors. Again, this supports the view that correlations rose in the crisis period. For the dummy relating to the US bull/bear market, again we can see some difference across sectors. While this dummy is negative and significant for the majority of the market, indicating that correlations rise during a US bear market. For three sectors, a positive and significant relation is found, such that correlations rise during a bull run and fall in a bear market. For US interest rates, a negative relation is reported for all markets, supporting the view that a weaker US economy is consistent with higher market correlations. For the coefficients relating to market and specific sector returns and standard deviations, the results reveal that no consistent pattern exists, again suggest the potential for markets to move in different directions. In particular, with reference to international market returns, the correlation of only five sectors is significantly affected at the 5 per cent level (with a further four at the 10 per cent level). However, all sectors are affected by the volatility of international market returns. For own sector returns, only three correlations are affected and negatively so, while the own standard deviation significantly affects eight market correlations positively and seven market correlations negatively.

SUMMARY AND CONCLUSIONS

This paper has examined the correlation and interrelations between the G7 markets over the recent past. In particular, the existing

Table 10: Explaining time-varying correlations: sector regressions

	Dum-FC	*Dum-Mkt*	*US IR*	*Σ index return*	*Σ index SD*	*Return sector*	*SD sector*
Automobiles	0.0203 (17.97)	−0.0319 (−32.45)	−0.0685 (−13.77)	6.71 (0.46)	54.57 (0.00)	0.0003 (0.08)	0.0009 (1.68)
Banks	0.0575 (43.97)	−0.0303 (−26.59)	−0.0367 (−63.73)	23.63 (0.00)	109.63 (0.00)	0.0005 (1.38)	−0.0001 (−4.02)
Beverages	0.0272 (21.61)	−0.0209 (−19.10)	−0.0277 (−50.02)	3.17 (0.87)	65.59 (0.00)	−0.0003 (−1.15)	−0.0095 (−6.95)
Chemicals	0.0448 (34.85)	−0.0211 (−18.89)	−0.0509 (−89.96)	7.40 (0.39)	69.53 (0.00)	0.0007 (1.63)	0.0044 (4.95)
Construction	0.0983 (64.59)	−0.0298 (−22.56)	−0.0700 (−104.76)	17.01 (0.02)	95.01 (0.00)	−0.0012 (−2.31)	0.0005 (5.17)
Electricity	0.0316 (21.98)	−0.0290 (−23.13)	−0.0296 (−46.81)	13.04 (0.07)	395.41 (0.00)	−0.0005 (−1.09)	0.0004 (0.52)
Electronics	0.434 (26.36)	−0.0624 (−43.46)	−0.0664 (−91.66)	14.24 (0.05)	56.46 (0.00)	−0.0001 (−1.08)	0.0005 (7.59)
Finance	0.0473 (29.35)	−0.0322 (−22.94)	−0.0652 (−92.08)	12.12 (0.10)	61.36 (0.00)	−0.0002 (−0.36)	0.0001 (0.80)
Food and drugs	0.0172 (17.31)	−0.0137 (−15.84)	−0.0545 (−124.82)	11.71 (0.11)	58.16 (0.00)	−0.0001 (−0.40)	0.0003 (2.84)
Gen. ind.	0.0298 (17.19)	−0.0283 (−18.77)	−0.0670 (−87.93)	5.35 (0.62)	59.63 (0.00)	0.0003 (0.55)	0.0004 (5.21)
Healthcare	0.0712 (43.53)	0.0058 (4.10)	−0.0638 (−88.59)	7.30 (0.40)	181.99 (0.00)	−0.0005 (−0.99)	−0.0008 (−8.63)
Ind. eng.	0.0722 (43.57)	−0.0370 (−25.62)	−0.0866 (−118.66)	15.15 (0.03)	97.45 (0.00)	−0.0005 (−0.97)	0.0001 (−0.52)
Industrial metals	0.0992 (41.84)	0.0073 (3.55)	−0.0944 (−90.69)	11.07 (0.14)	85.16 (0.00)	−0.0012 (−2.35)	0.0004 (7.73)
Ind. transport	0.0454 (26.15)	−0.0352 (−23.35)	−0.0631 (−82.57)	12.35 (0.09)	105.19 (0.00)	0.0001 (0.04)	−0.0002 (−2.85)
Mining	0.0328 (17.33)	0.0071 (4.30)	−0.0233 (−27.99)	9.26 (0.23)	73.66 (0.00)	−0.0002 (−0.51)	0.0004 (7.28)
Oil and gas	0.0521 (26.95)	−0.0094 (−5.54)	−0.0508 (59.68)	14.82 (0.04)	94.58 (0.00)	−0.0019 (−3.10)	0.0036 (2.71)
Pharma and bio	0.0186 (15.96)	0.0028 (2.72)	−0.0277 (−44.30)	4.89 (0.67)	185.50 (0.00)	−0.0002 (−0.68)	−0.0001 (−0.48)
Real estate	0.0662 (39.22)	−0.0188 (−12.85)	−0.0485 (−65.53)	9.15 (0.24)	66.34 (0.00)	0.0008 (1.63)	−0.0005 (−6.71)
Software	0.0070 (5.77)	−0.0320 (−30.01)	−0.0412 (−76.61)	4.83 (0.68)	44.51 (0.00)	0.0007 (1.74)	−0.0001 (−0.77)
Technology hardware	0.0113 (12.93)	−0.0251 (−32.93)	−0.0067 (−17.39)	3.93 (0.79)	54.66 (0.00)	0.0001 (0.63)	−0.0003 (−3.94)
Telecoms	0.0288 (31.25)	−0.0220 (−27.36)	−0.0097 (−23.93)	13.43 (0.06)	179.98 (0.00)	−0.0001 (−0.04)	−0.0002 (−2.85)

Notes: Entries are the regression coefficients (and *t*-tests) from a panel regression where the obtained DCC-GARCH time-varying correlations are the dependent variables. These are regressed on a dummy variable covering the financial crisis, a dummy variable representing a US bull market, the US 10-year Treasury bond yield, the return and standard deviation of each market and the return and standard deviation of the particular sector. The entries under the columns 'Σ Index Return' and 'Σ Index SD' are joint test χ^2 and *p*-values that all index values are zero.

literature identifies the view that stock market correlations have risen over time and are also likely to rise during periods of market stress. The key aim of this paper is to reconsider these conclusions and seek to explain movements in time-varying correlations. However, in contrast to the existing literature which typically uses market index data, the results presented here are based on firm-level data. The advantage of using firm-level data is that the correlations obtained are based on data that is tradeable as opposed to non-tradeable index data.

Unconditional correlations for both market index data (to provide comparability with the preceding literature) and the firm-level data appear to show that correlations have increased. Of note, correlations have increased from the pre-crisis period to the crisis and post-crisis period. However, there is some subtly within these results. Notably, there is evidence that correlations have plateaued and even fallen as we move into the post-crisis period. Additionally, correlations fell just prior to the crisis and during a period of economic growth. This supports the view that while markets fall together they rise separately. Also of interest, we note that the correlations based on firm-level data are lower than those observed at the aggregate market level.

Using three regression-based approaches, we examine both the nature of the interrelations and time-varying correlations between the series. A CAPM style approach suggests that for each market sector the equivalent US sector is more important than the overall movement of the US market in conditioning returns. Although the home market return remains the most important variable. A time-varying correlation model supports the view that correlations exhibit a positive trend over the sample period; however, the slope of the trend is very shallow. Panel unit root tests reject the null of non-stationarity within the sample correlations. A principal components analysis identifies a common component that affects the correlations of all market sectors in the same direction, except two (technology and telecoms), which exhibit their own separate component. Moreover, this principal component accounts for two-thirds of the movement in correlations, while the first three components account for 80 per cent.

Having established the nature of correlations, which indicate the potential for diversification, we seek to explain the nature of the time-variation. Established results argue that correlations rise in times of market stress, which appears to be borne out by those reported here. Notably, correlations across both the market trend identified by the principal components and individual sectors rise during the financial crisis and when the US economy is weak. However, while correlations also generally rise during US bear market periods, this result is not ubiquitous, with some sectors indicting the reverse. Furthermore, the effect of market and sector returns and sector volatility differs across sector correlations.

The analysis of market correlations remains important in the development and understanding of portfolio and risk management. This paper, using firm-level data, examines correlations across market sectors. Notably, we wish to examine the dynamics and determinants of time-varying correlations. Several broad conclusions are reached that suggest diversification benefits may remain. First, firm-level-based correlations are lower than aggregate market index correlations. Second, although time-varying correlations have increased during the crisis period, there is evidence that they may now be falling. Additionally, there is no evidence of a stochastic trend while any deterministic trend is very small. Third, while sector correlations typically move together and follow a general market component, some sectors exhibit a negative relation with that market component with movement governed by a different component. Fourth, evidence exists that while correlations across all sectors rise during periods of weakness in the US economy and when the volatility of the US market rises. The same is not true when the US market experiences a bear period. For most sectors, the correlation does rise as the US market declines; however, for some the converse is true. This all suggests the potential for portfolio diversification.

NOTES

1. Examples of recent work looking at correlations during the financial crisis include Kotkatvuori-Örnberg *et al* (2013) and Hwang *et al* (2013).
2. Returns are calculated as the first-difference of the log price or index.
3. Following Engle (2002) the correlation estimator will be positive definite as the covariance matrix, Q_t, is a weighted average of a positive definite and a positive semi-definite matrix.
4. A potential issue with this regression approach is that the fitted correlation series (ρ) is bounded between -1 and $+1$, whereas OLS regression assumes the dependent variable is unbounded. In order to control for this issue, we also consider the logistic transformation given as: $\log((1 + \rho)/(1 - \rho))$. Estimation results from this approach produce slightly higher coefficient values but the statistical inference (i.e., the significance of the coefficients) remains unchanged. The full results are available upon request.

REFERENCES

Berben, R.P. and Jansen, W.J. (2005) Comovement in international equity markets: A sectoral view. *Journal of International Money and Finance* 24: 832–857.

Bollerslev, T. (1990) Modeling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *Review of Economics and Statistics* 72: 498–505.

Engle, R.F. (2002) Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity model. *Journal of Business and Economic Statistics* 20: 339–350.

Erb, C., Harvey, C. and Viskanta, T. (1994) Forecasting international equity correlations. *Financial Analysts Journal* 50: 32–45.

Fasnacht, P. and Loubergé, H. (2007) International stock market correlations: A sectoral approach. doi:10.2139/ssrn.1071608

Fisher, R.A. (1932) *Statistical Methods for Research Workers*. 4th edn. Edinburgh: Oliver and Boyd.

Forbes, K. and Rigobon, R. (2002) No contagion, only interdependence: Measuring stock market co-movements. *Journal of Finance* 57: 2223–2261.

Goetzmann, W.N., Li, L. and Rouwenhorst, K.G. (2001) *Long-Term Global Market Correlations*. NBER working paper no. 8612.

Hwang, E., Min, H.-G., Kim, B.-H. and Kim, H. (2013) Determinants of stock market comovements among US and emerging economies during the US financial crisis. *Economic Modelling* 35: 338–348.

Im, K.S., Pesaran, M.H. and Shin, Y. (2003) Testing for unit roots in heterogeneous panels. *Journal of Econometrics* 115: 53–74.

Karanassos, M., Yfanti, S. and Karoglou, M. (2016) Multivariate FIAPARCH modelling of financial markets with dynamic correlations in times of crisis. *International Review of Financial Analysis* 45: 332–349.

Karolyi, G.A. and Stulz, R.M. (1996) Why do markets move together? An investigation of US–Japan stock return co-movements. *Journal of Finance* 51: 951–986.

King, M. and Wadhwani, S. (1990) Transmission of volatility between stock markets. *Review of Financial Studies* 3: 5–33.

King, M., Sentana, E. and Wadhwani, S. (1994) Volatility and links between national stock markets. *Econometrica* 62: 901–933.

Kotkatvuori-Örnberg, J., Nikkinen, J. and Äijö, J. (2013) Stock market correlations during the financial crisis of 2008–2009: Evidence from 50 equity markets. *International Review of Financial Analysis* 28: 70–78.

Levin, A., Lin, C.F. and Chu, C. (2002) Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics* 108: 1–24.

Longin, F. and Solnik, B. (1995) Is the correlation in international equity returns constant: 1960–1990? *Journal of International Money and Finance* 14: 3–26.

Opschoor, A., van Dijk, D. and van der Wel, M. (2014) Predicting volatility and correlations with financial conditions indexes. *Journal of Empirical Finance* 29: 435–447.

Rangvid, J. (2001) Increasing convergence among European stock markets? A recursive common stochastic trends analysis. *Economic Letters* 71: 383–389.

Roll, R. (1989) Price volatility, international market links, and their implications for regulatory policies. *Journal of Financial Services Research* 3: 211–246.