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# From Black Wednesday to Brexit: Macroeconomic shocks and correlations of equity returns in France, Germany, Italy, Spain, and the United Kingdom

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**Abstract**

This paper investigates whether macroeconomic shocks, such as the UK's referendum decision to leave the European Union ("Brexit"), the 2008 Financial Crisis, the 1992 ERM Crisis ("Black Wednesday"), and the 1987 stock market crash ("Black Monday"), had a positive impact on portfolio risk diversification. We estimate weekly dynamic conditional correlations and then optimal sectoral portfolio allocations between 1973 and 2019. Our results show that correlations of equity returns increased as a consequence of economic integration among European countries from the mid-1980s until the late 2000s, and decreased in the United Kingdom after Black Wednesday and the Brexit referendum. We tested the existence of a correlation change-point on June 27, 2016 by applying Wied et al. (2012)'s [*Econometric Theory*, *28*(3), 570–589] correlation structural break test, which we modified to account for dynamic conditional correlations. Application of this test confirms that the referendum date was a break-point in nearly all UK manufacturing industries. The failure of Lehman Brothers and the 1987 stock market crash were also identified as structural breaks in equity correlations. Moreover, our findings suggest that the Brexit vote may constitute a long-term trend reversal of the convergence of equity return correlations in European markets, akin to Black Wednesday, rather than a shock like the 1987 and 2008 financial crises, which merely intensified a historical upward trend in correlations of European equity returns.

KEYWORDS

Brexit, dynamic conditional correlation (DCC) of equity returns, European financial integration, portfolio diversification, structural break in dynamic correlations

## 1 | INTRODUCTION

Since the 2016 UK referendum on membership of the European Union, there has been a flurry of research on the implications of the British decision to leave the European Union ("Brexit") on the United Kingdom and European economies. Most of this research consists of stock market event-studies centred on short-term impacts (Oehler, Horn, & Wendt, 2017; Ramiah, Pham, & Moosa, 2017; Schiereck, Kiesel, & Kolaric, 2016; Tielmann & Schiereck, 2017). Howarth and Quaglia (2017) adopt a distinct approach and infer the potential ramifications of

Brexit by extensively documenting the influence of the United Kingdom on the regulatory and structural integration of European financial markets in the past two decades. All these papers found that Brexit had a negative impact on the stock returns of British and European firms in most industries, whilst Howarth and Quaglia (2017) argue convincingly that Brexit may considerably alter the nature of European financial integration. These findings are not entirely unexpected. The Brexit referendum result is one of a long series of macroeconomic shocks that have affected European markets, viz., the 2011–2014 Eurozone Debt Crisis, the 2008 Financial Crisis, the ERM crisis in 1992, and the stock market crash of 1987. Each of these events resulted in a drop in stock market shares, as evidenced by, inter alia, Adams, Füss, and Glück (2017); Cappiello, Engle, and Sheppard (2006); Cappiello, Kadareja, and Manganelli (2010); Bekaert, Campbell, Harvey, Lundblad, and Siegel (2013); Longin and Solnik (2001); Bera and Kim (2002). However, this recent literature overlooks the fact that Brexit may increase the divergence of stock returns, which is a positive outcome from a portfolio risk diversification perspective.

This paper adopts this perspective and investigates the evolution of correlations of equity returns and of optimal portfolio allocation of listed companies in the five largest European economies from the date the United Kingdom joined the European Union on January 1, 1973 until November 25, 2019. We analyse sectoral correlations by estimating dynamic conditional correlations (DCC-GARCH), which we then use to estimate time-varying portfolio weights. We then test whether the date of the Brexit vote, the 2008 Financial Crisis, the 1992 Exchange Rate Mechanism (ERM) crisis, and the 1987 stock market crash constitute break-points in pairwise equity correlations between UK firms and French, German, Italian, and Spanish companies.

Our results show that the correlations between equity returns in all industrial sectors bar Oil and Gas have declined since the referendum vote. They increased in more than a third of UK industries between 1986 and 1992, that is, between the Single Market Act and Black Wednesday, and in all industries during the housing boom of 1998–2008. In addition, we found that the impacts of macroeconomic shocks are asymmetric. Global shocks such as the 2008 Financial Crisis and the 1987 stock market crash increase pairwise correlations, whereas European shocks such as Brexit and the 1992 ERM crisis, actually decrease correlations between UK and EU equity returns. The Eurozone Debt Crisis of 2011–2014 affected the eurozone correlations, but not those with UK equities. The date of the Brexit referendum result is shown to be a correlation structural break by a test statistic proposed by Wied, Krämer, and Dehling (2012b); Wied, Ziggel, and Berens (2013); Wied, Arnold, Bissantz, and Ziggel (2012a); Galeano and Wied (2014), which we modify to account for dynamic conditional correlations (DCCs). We found significant results in all industries covered in our sample. In addition, we found that the date Britain withdrew from the ERM, that of the failure of Lehman Brothers, and that of the 1987 stock market crash were equally change-points in correlations.

The movement in equity returns correlations between UK firms and those of France, Germany, Italy, and Spain is mirrored in the time-varying portfolio allocations. Lower equity correlations potentially increase the opportunities for cross-border risk diversification, particularly after 1992 ERM crisis and the Brexit vote.

Several papers use DCCs to estimate the extent of financial integration in the European Union, (among others, Büttner & Hayo, 2011; Degiannakis, Duffy & Filis, 2014; Kim, Moshirian, & Wu, 2005). Degiannakis, Duffy, and Filis (2014), for instance, find strong evidence of time-varying economic integration in the EU-12 by estimating the correlation of the business cycle of European Union member states between 1980:Q1 and 2012:Q4. The time period covered by Degiannakis et al. (2014) is almost as extensive as ours and documents the impact of major events such as the completion of the single market and the ERM on business cycle correlations. Kim et al. (2005) suggest from a bivariate EGARCH framework with time-varying conditional correlations that the European Monetary Union (EMU) has contributed to stock market integration. The findings of those authors are corroborated by Büttner and Hayo (2011), who compared the role of monetary union on eurozone and non-eurozone countries.

The relative importance of industry factors in equity returns has been established in Cappiello et al. (2010), Bekaert, Hodrick, and Zhang (2009), and Carrieri, Errunza, and Sarkissian (2004, 2012), for instance, although with mixed evidence, (e.g., Eiling, Gerard, & de Roon, 2006; Eiling, Gerard, Hillion, & de Roon, 2012; Hou, Karolyi, & Kho, 2011). Ferreira and Gama (2005) and Ferreira and Ferreira (2006) show an increase in the impact of industry-specific factors on equity markets in the European Union from the 1990s onwards. Carrieri et al. (2004) show that economic and financial integration may not be homogeneous across industries within a country, particularly within the United States. Griffin and Karolyi (1998) found higher industry effects in traded – rather than in non-traded – goods industries, although their main results indicate that industry effects have a low impact on the returns of country-wide indices. More recently, Ferreira and Gama (2010) investigated whether industry correlations remain constant over time, and what factors affect their variability. The analysis focuses on global industrial portfolios, and on the impacts of US recessions on industry correlations. Strong evidence is found that between 1979 and 2008 industrial correlations were asymmetrically time-varying, that is, correlations tended to increase (decrease) during recessions (economic booms). In addition, market volatility led to an increase in industrial correlations. Interestingly, average correlations in some industries (e.g., Oil and Gas) were consistently lower than in Industrials over the sample period considered.

Our approach differs from that adopted in these papers and the existing literature on the consequences of macroeconomic shocks and of Brexit by focusing on risk diversification. However, our results are consistent with, and extend, the current literature. Firstly, we found evidence of a decade-long strong upward trend in correlations between equity returns in the United Kingdom and European Union, confirming previous findings that monetary union had less impact on equity market integration than the European Union (Bekaert et al., 2013; Cappiello et al., 2010; Ferreira & Ferreira, 2006). Secondly, the Brexit vote generated a sudden trend reversal in correlations, upholding the findings of event studies such as Schiereck et al. (2016) and Tielmann and Schiereck (2017). Moreover, by focusing on correlations across countries within industries, we were able to show that the Brexit vote created cross-country portfolio diversification opportunities, even in the context of deep economic integration. As Ferreira and Gama (2005), Ferreira and Ferreira (2006), and Ferreira and Gama (2010) have shown, increasing economic and financial integration leads to industry-based portfolio diversification strategies becoming as effective as cross-countries strategies. Our result is in accordance with Eiling et al. (2006, 2012); Hou et al. (2011), but particularly with Carrieri et al. (2004) who show that economic integration is not homogeneous across industries. We found indications that some British industries, such as Oil and Gas and Mining, are less integrated with the rest of the European Union than others.

The paper proceeds as follows: Section 2 reviews the recent literature on diversification gains and European financial integration. Section 3 describes the sample and method to implement the research, and presents the statistic used to test for structural breaks in correlations. Section 4.1 shows the results of the DCC estimation and Section 4.2 shows those of the break tests. Section 5 concludes and precedes the Data S1.

## 2 | DIVERSIFICATION GAINS AND INTEGRATION OF EUROPEAN FINANCIAL MARKETS

There is a vast literature on the main drivers of diversification gains in international equity returns. The discussion since Lessard (1974)'s seminal paper has centred on whether country or industry factors account for the diversification gains of international portfolios. Most empirical work found evidence that country effects tend to dominate industry effects, for example, Roll (1992); Heston and Rouwenhorst (1994); Griffin and Karolyi (1998); Arshanapalli, Doukas, and Lang (1997); Eiling et al. (2012), among others. However, there is equally strong evidence in those same works and in others that the impact of industry factors on asset allocation became more significant in the late 1990s, particularly in Carrieri et al. (2004, 2012); Eiling et al. (2012). The crucial factor explaining the rising impact of industry-based portfolio diversification is the deepening of global economic and financial integration, and in particular, market deregulation and harmonization of economic policies in the European Union post-Maastricht (Carrieri et al., 2004; Ferreira & Gama, 2010).

The degree of economic and financial integration among the member states of the European Union is generally measured in the literature by business cycle synchronization, which is seen as the main indicator of economic convergence (see, inter alia, Borsi & Metiu, 2015; Crespo-Cuaresma & Fernández-Amador, 2013a, 2013b; De Haan, Inklaar, & Jong-A-Pin, 2008; Degiannakis et al., 2014; Gayer, 2007; Papageorgiou, Michaelides, & Milios, 2010; Weyerstrass, van Aarle, Kappler, & Seymen, 2011). The overwhelming evidence points towards business cycle convergence since at least the 1990s. Crespo-Cuaresma and Fernández-Amador (2013a, 2013b) and Papageorgiou et al. (2010) analyse European economic integration from its onset with a very long sample, 1960–2009, and find that business cycle synchronization was more pronounced during certain periods of time (e.g., 1990s) and less in others (1980s, 2000–2009). Emerging evidence indicates that the 2008 Financial Crisis induced a divergence of business cycles, for example, in Grigoraş and Stanciu (2016).

There is much less consensus on the impact of monetary union on business cycle convergence and, more specifically, on equity markets integration (De Haan et al., 2008; Papageorgiou et al., 2010). Crespo-Cuaresma and Fernández-Amador (2013a, 2013b) find overwhelming evidence that the business cycles of eurozone countries have converged almost monotonically from the creation of the ERM in 1979, passing through the Maastricht Treaty, to culminate with the monetary union in 1999. These papers corroborate the seminal research of Artis and Zhang (1997, 1999) on the role of EMU on business cycles convergence. Inklaar and de Haan (2001), however, find no evidence of a systematic relationship between business cycle homogeneity and monetary integration. Using a longer sample than Artis and

Zhang (1999), they show that most cycles were better correlated during the period 1971–1979 than in the period 1979–1987.

Regarding the issue of monetary union and financial integration, Fratzscher (2002) demonstrates that between 1980 and 2002 the integration of European equity markets could be explained by the drive towards monetary union. His results are particularly relevant for assessing the implications of Brexit for financial markets, since the United Kingdom is not a member of the monetary union. Kim et al. (2005) also found evidence of a marked increase in regional and aggregate financial integration within the eurozone between January 2, 1989 and May 23, 2003. Baele, Ferrando, Hördahl, Krylova, and Monnet (2004) obtain similar results from the estimation of the law of one price in several markets of the eurozone. Their findings are corroborated by Hardouvelis et al. (2006), and by Hardouvelis et al. (2007) at the sectoral level. From a sample of weekly data between February 7, 1992 and June 26, 1998, the authors found clear evidence of deeper equity markets integration among EMU members than between EMU countries and the United Kingdom.

Cappiello et al. (2010) and Bekaert et al. (2013) also compare the financial integration of eurozone versus non-euro members, but their results strongly differ from those of Fratzscher (2002) and Kim et al. (2005). Their empirical analysis is more extensive and covers a longer period of time, in addition to explicitly studying the impact of both the European Union and the Monetary Union on stock markets at the sectoral level in the EU27 countries. The authors show that membership of the European Union did reduce discount rates and expected growth differentials within industries across countries between 1990 and 2007. However, a regression analysis supports their conclusion that joining the eurozone did not have a significant impact on these variables.

The lack of definite evidence pointing at the importance of monetary union in the integration of financial markets is an important dimension in the debate on the financial consequences of Brexit. The Brexit referendum occurred nearly a quarter of a century after the 1992 Maastricht Treaty, at a time characterized by reduced divergence of financial regulatory frameworks, fiscal, and monetary policies, accounting rules and by high correlations of equity returns across countries. If European financial integration has deepened on account of monetary union, then Brexit should not have any major implications. If, on the other hand, membership of the single market is a major determinant of financial integration, then Brexit may lead to a segmentation of the European equity market and possibly to the return of the dominance of country factors over industry factors in European equity portfolios.

Most of post-Brexit research focuses on the direct impact of the Brexit vote on stock returns in various industries. Tielmann & Schiereck, 2017, Schiereck et al. (2016) and Ramiah et al. (2017), conduct an event study on the impact of the referendum outcome on the stock returns of European Union, United Kingdom, and non-EU banks, of companies in the logistics industry and on all UK industries, respectively. Tielmann and Schiereck (2017)'s study of cumulative abnormal return (CAR) is centred on the day after the referendum, Friday, June 24, 2016, with an event window of 4 days before the 24 June and 10 days after the 24 June. Schiereck et al. (2016) find large, negative average cumulative average returns during the [0; + 1] event window, where the event date is June 24, 2016. Ramiah et al. (2017) analyse the impact of the Brexit vote on abnormal returns (ARs) between June 2010 and July 2016, and on cumulative abnormal returns (CARs) up to 10 days after the Brexit vote. All three papers conclude that there were strong negative impacts on stock returns on the day the result of the Brexit Referendum was published and on the following day. Ramiah et al. (2017) found negative ARs and CARs in banking, equity investment instruments, financial services, food producers, life and non-life insurance, oil and gas producers, software and computer services, and travel and leisure. Unexpectedly, Ramiah et al. (2017) also found that the ARs and CARs of sectors such as aerospace and defence and beverages also reacted negatively. These sectors tend to be less affected by external factors due to national security issues and national consumer preferences, and they were not expected to react as much to the Brexit vote (Tielmann and Schiereck (2017)). British logistics firms were more affected than their European counterparts, which the authors attribute to the fact that British logistics companies are much more restricted geographically than Continental European companies. Schiereck et al. (2016) compare the aftermath of the Brexit vote with that of the Lehman Brothers' bankruptcy on equity markets. Even though the collapse of Lehman Brothers resulted in market-wide share price losses, banks' share prices did not perform much worse than the general market. The Brexit announcement, in contrast, resulted in a sharp drop in share prices that was largely concentrated on EU financial institutions.

None of the findings above are unexpected. The Brexit referendum result is one of a long series of macroeconomic shocks that have affected European markets, viz., the 2011–2014 Eurozone Debt Crisis, the 2008 Financial Crisis, the ERM crisis in 1992, and the stock market crash of 1987. Each of these events resulted in a drop in stock market shares. The analysis of the impact of these shocks on equity volatility and correlation is more interesting. Raddant (2016) analyses the correlation of market indices, and stock volatility by estimating a univariate GARCH model for the stock market indices of France, Germany, Spain and Italy. The main impact of the vote was an increase in stock market volatility in all countries. A network representation of the correlation matrix of de-garched returns of all stocks in these countries up to 4 weeks after the Brexit vote shows that British companies form a cluster separate from that of French, German, and most Italian and Spanish stocks. The nodes of smaller Spanish companies scatter randomly around the main cluster, and some – but not all – Italian stock also form a separate group.

The link between equity correlations and financial integration was first proposed by Forbes and Rigobon (2002) who argued that the correlations of European equity returns would be equal to one if the integration of European stock markets were complete. Their estimations of the equity correlations of monthly individual stocks in France, Germany, Italy, Spain, Sweden, and the United Kingdom between 1975 and 1996 showed that correlations rose from an annual average of 20% in the 1970s to about 60% in the 1980s. In addition, the Netherlands have the most integrated market, and Italy, Spain, and Sweden the least integrated. Interestingly, Forbes and Rigobon (2002) found that the peaks in correlations occur in periods of large negative returns, namely, the crash of 1987 and the Kuwait crisis of 1991.

The finding that equity correlations increase during economic crises has been replicated in Longin and Solnik (2001); Bera and Kim (2002); Cappiello et al. (2006); Adams et al. (2017), although the direct link between correlation and equity market integration is generally rejected. Longin and Solnik (2001) argue that in an asset pricing sense, it is possible for markets to be fully integrated without high correlations between assets markets. Most authors resort to estimating co-movements between asset returns. Cappiello et al. (2010) estimate the probability of co-movements between equity markets before and after the introduction of the euro, and found that the degree of co-movement among euro area economies increased after 1999. Their analysis equally investigates whether co-movements were driven by specific industry dynamics, which may be diluted at the aggregate level. They found that co-movements were stronger in consumer goods and financial industries.

## 3 | EMPIRICAL ANALYSIS

Our data consist of weekly equity returns of all manufacturing companies listed and incorporated in

**TABLE 1** DCC-GARCH estimation of equity returns of individual firms grouped by industry-1973–2019

| Industry | $a_1$ | *SE* | t | *Pr*(>\| *t*\| ) | $b_1$ | *SE* | t | *Pr*(>\| *t*\| ) |
|---|---|---|---|---|---|---|---|---|
| Aerospace and Defense | 0.0080 | 0.0013 | 6.0542 | 0.000 | 0.989 | 0.002 | 436.534 | 0.000 |
| Automobile | 0.0102 | 0.0014 | 7.3905 | 0.000 | 0.985 | 0.003 | 353.161 | 0.000 |
| Beverages | 0.0061 | 0.0009 | 7.0098 | 0.000 | 0.994 | 0.001 | 996.602 | 0.000 |
| Chemicals | 0.0071 | 0.0012 | 5.7253 | 0.000 | 0.989 | 0.003 | 352.209 | 0.000 |
| Construction | 0.0028 | 0.0117 | 0.2402 | 0.810 | 0.989 | 0.116 | 8.519 | 0.000 |
| Food | 0.0106 | 0.0029 | 3.5955 | 0.000 | 0.983 | 0.007 | 149.324 | 0.000 |
| Food Producers | 0.0028 | 0.0006 | 4.7337 | 0.000 | 0.993 | 0.001 | 737.554 | 0.000 |
| General Industrial | 0.0067 | 0.0010 | 6.5475 | 0.000 | 0.988 | 0.003 | 382.862 | 0.000 |
| General Retail | 0.0041 | 0.0007 | 5.4941 | 0.000 | 0.991 | 0.002 | 460.971 | 0.000 |
| Industrial Engineering | 0.0027 | 0.0010 | 2.6207 | 0.009 | 0.988 | 0.008 | 124.307 | 0.000 |
| Industrial Transport | 0.0053 | 0.0014 | 3.6876 | 0.000 | 0.991 | 0.003 | 319.96 | 0.000 |
| Media | 0.0052 | 0.0011 | 4.8352 | 0.000 | 0.991 | 0.003 | 305.716 | 0.000 |
| Mining | 0.0102 | 0.0293 | 0.3490 | 0.727 | 0.983 | 0.042 | 23.360 | 0.000 |
| Oil and Gas | 0.0147 | 0.0035 | 4.2431 | 0.000 | 0.983 | 0.005 | 212.134 | 0.000 |
| Personal Goods | 0.0070 | 0.0009 | 7.5492 | 0.000 | 0.989 | 0.002 | 594.487 | 0.000 |
| Support Services | 0.0026 | 0.0005 | 4.7376 | 0.000 | 0.984 | 0.006 | 161.167 | 0.000 |
| Travel | 0.0073 | 0.0006 | 11.6299 | 0.000 | 0.989 | 0.001 | 887.409 | 0.000 |

*Note:* Estimation of DCC parameters in $\vec{Q}_t = (1-a_1-b_1)\bar{\vec{Q}} + a_1 z_{t-1} z_{t-1}^{\top} + b_1 \vec{Q}_{t-1}$ for weekly stock returns in France, Germany, Italy, Spain, and the United Kingdom between June 1, 1975 and November 25, 2019. The estimation for the industry Industrial Metals did not converge.

France, Germany, Italy, Spain, and the United Kingdom. All data series were provided by Thomson Reuters Datastream Eikon from January 1, 1973 to November 25, 2019. The raw data are share prices in local currencies, subsequently converted into US dollars at the weekly rate, in accordance with Cappiello et al. (2006, 2010); Eiling et al. (2012), among others. Exchange rates were also provided by Thomson Reuters Datastream Eikon, with the exception of the euro to US dollar exchange, which was downloaded from Eurostat. All exchange rate series were only available from January 6, 1975 onwards. Since we are interested in the change in sectoral correlations of equity returns from the entry of the United Kingdom into the European Union onwards, only companies that are active during this whole period are used in the DCC-GARCH estimation. Furthermore, in order to estimate the DCC-GARCH parameters, data series with missing observations and constant variance were eliminated from the sample. Industries where listed companies are exclusively British, viz., Tobacco and Electronics, or exclusively non-British, such as Utilities, were also excluded from the sample. We estimate DCC for Level 3 industry portfolios, where the industry level is defined by Datastream. Its classification system is analogous to the FTSE's Industry Classification Benchmark (ICB) whereby each company is allocated to the industrial sector that most closely represents its primary source of revenue and other publicly available information. Datastream's Level 3 corresponds to ICB's supersector level.

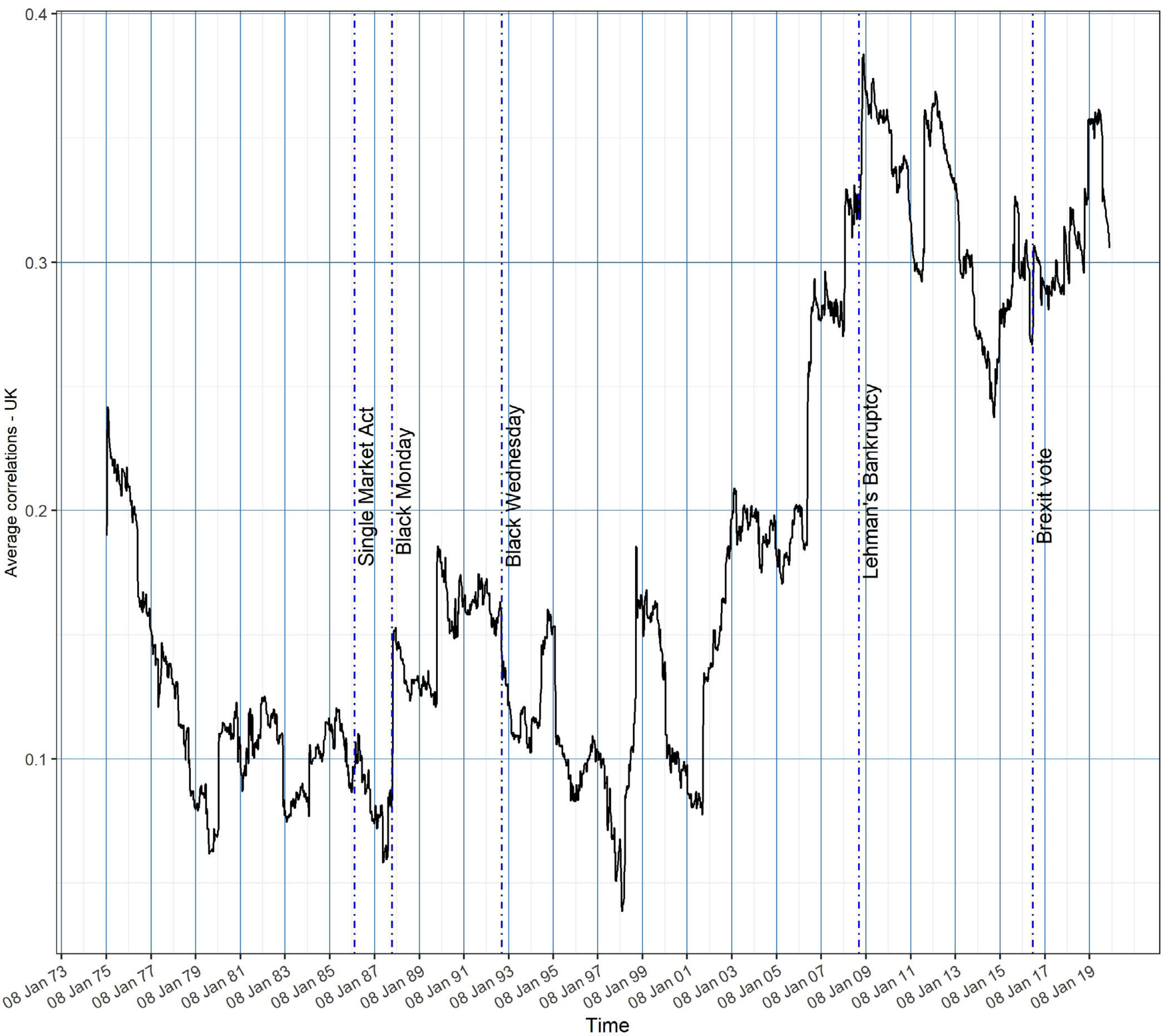


**FIGURE 1** Correlation in Aerospace and Defence 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

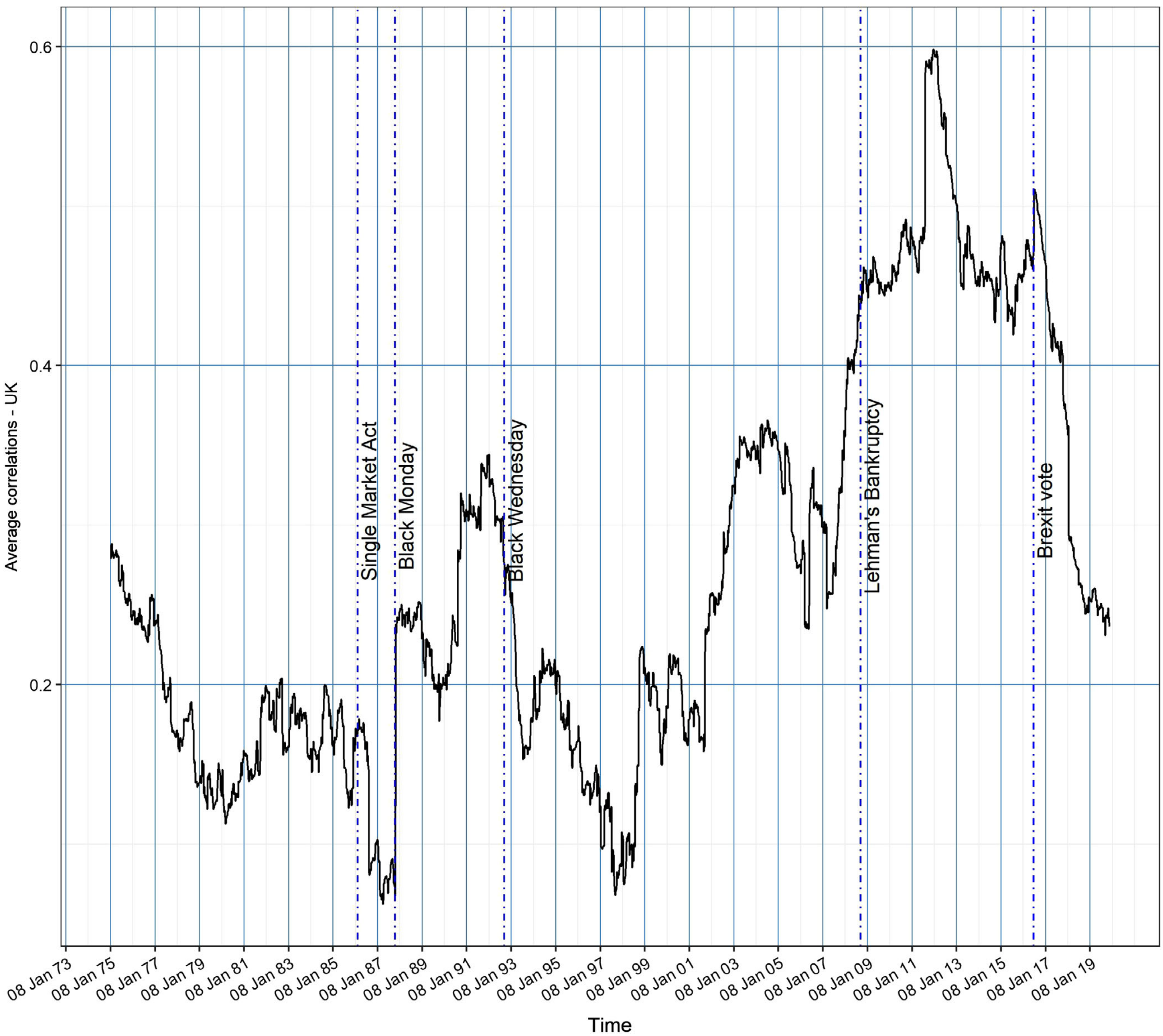


**FIGURE 2** Correlation in Automobile and Parts 1973–2018 [Colour figure can be viewed at wileyonlinelibrary.com]

## 3.1 | Correlation dynamics and portfolio weights

This section presents the model that we will use to estimate the time-varying correlations of equity returns, and the time-varying optimal portfolio weights. The model is a dynamic conditional correlation GARCH model (DCC-GARCH) developed by Engle (2002), and incorporates the corrections made by Aielli (2013). Furthermore, owing to the large number of companies under consideration in some industries, the model was estimated using the three-step procedure to estimate large dynamical conditional matrices as in Aielli (2013), Ledoit and Wolf (2004, 2012), and particularly, Engle, Ledoit, and Wolf (2017). The three-step procedure implies the following:

1. Fit a univariate GARCH to each asset and divide asset return by the resulting conditional volatility.
2. Estimate an unconditional correlation matrix and use it for correlation targeting by non-linear shrinkage.
3. Maximize the composite likelihood to obtain the DCC.

Step 1 is common to all DCC frameworks, and step 3 is analogous to the usual DCC estimation, except that $\bar{\mathbf{Q}}$ in Equation (5) below is now replaced by the correlation matrix estimated in step 2.

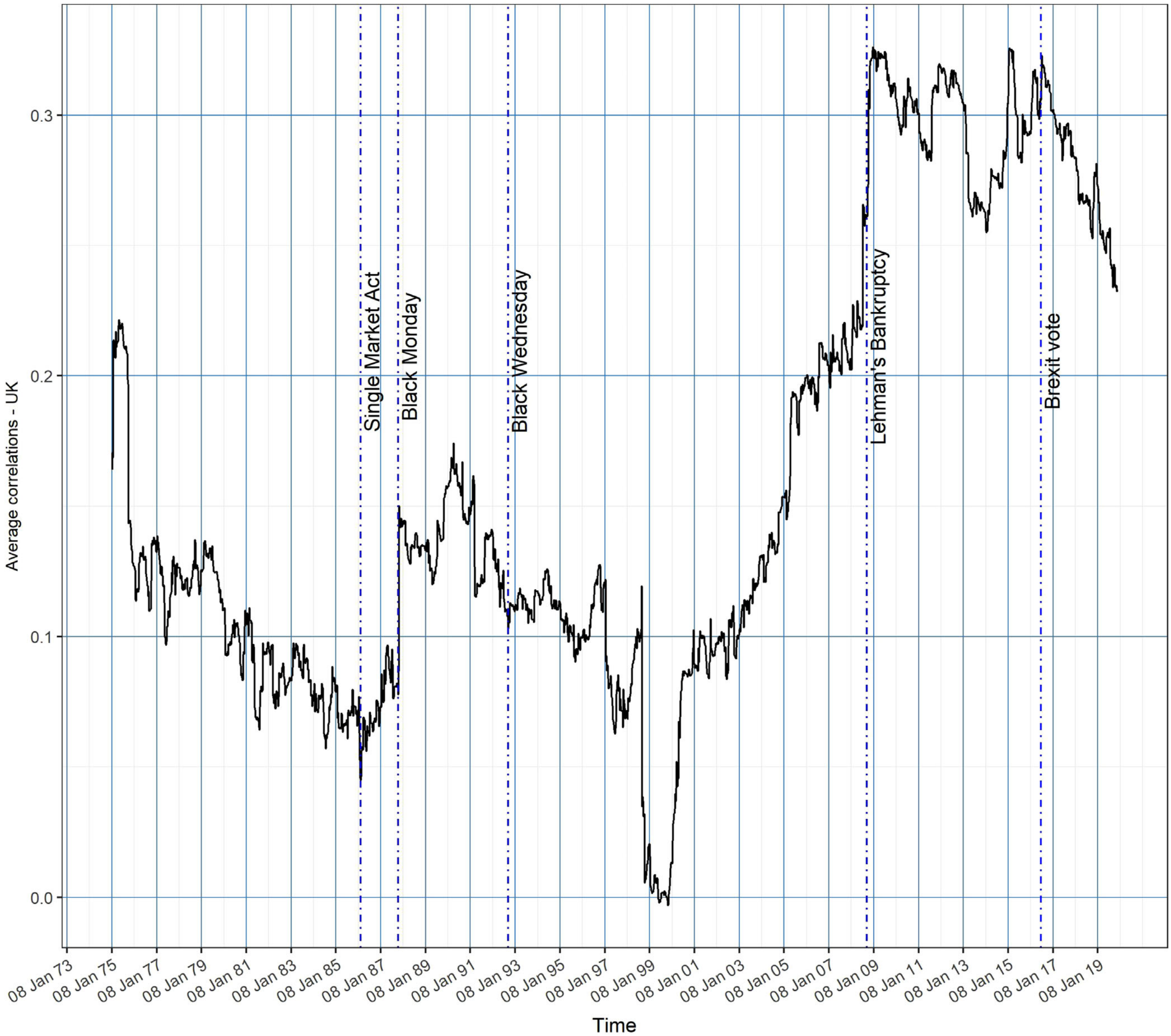


**FIGURE 3** Correlation in Beverages 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

The DCC-GARCH is represented here by the following system of equations:

$$\mathbf{r}_t = \mu_t \boldsymbol{\varepsilon}_t \tag{1}$$

$$\boldsymbol{\varepsilon}_t = \mathbf{H}_t^{1/2} \mathbf{z}_t \tag{2}$$

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t \tag{3}$$

$$\mathbf{R}_t = diag(\mathbf{Q}_t)^{-1/2} \mathbf{Q}_t diag(\mathbf{Q}_t)^{-1/2} \tag{4}$$

$$\mathbf{Q}_t = (1 - a_1 - b_1)\bar{\mathbf{Q}} + a_1 \boldsymbol{\eta}_{t-1} \boldsymbol{\eta}_{t-1}^{\top} + b_1 \mathbf{Q}_{t-1} \tag{5}$$

for $t = 1, \ldots, T$, where:

| | |
|---|---|
| $\mathbf{r}_t$ | $n \times 1$ vector of log returns of $n$ assets at time $t$. $r_{i,t} = ln(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ is the stock price of company $i$ at time $t$ |
| $\boldsymbol{\mu}_t$ | $n \times 1$ vector of expected values of $\boldsymbol{r}_t$ |
| $\boldsymbol{\varepsilon}_t$ | $n \times 1$ vector of errors such that $E[\boldsymbol{\varepsilon}_t] = 0$ and $E[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t^{\top}] = \mathbf{H}_t$ |
| $\mathbf{H}_t^{1/2}$ | $n \times n$ matrix such that $\mathbf{H}_t$ is the conditional variances of $\boldsymbol{\varepsilon}_t$. |
| $\mathbf{D}_t$ | $n \times n$ diagonal matrix of conditional standard deviations of $\boldsymbol{\varepsilon}_t$ at time $t$ |
| $\mathbf{R}_t$ | $n \times n$ conditional correlation matrix of $\boldsymbol{\varepsilon}_t$ at time $t$ |
| $\boldsymbol{\eta}_t$ | $n \times 1$ vector of de-garched errors, $\mathbf{D}_t^{-1/2} \mathbf{z}_t$, s.t. $E[\boldsymbol{\eta}_t] = 0$ and $E[\boldsymbol{\eta}_t \boldsymbol{\eta}_t^{\top}] = \mathbf{I}$ |

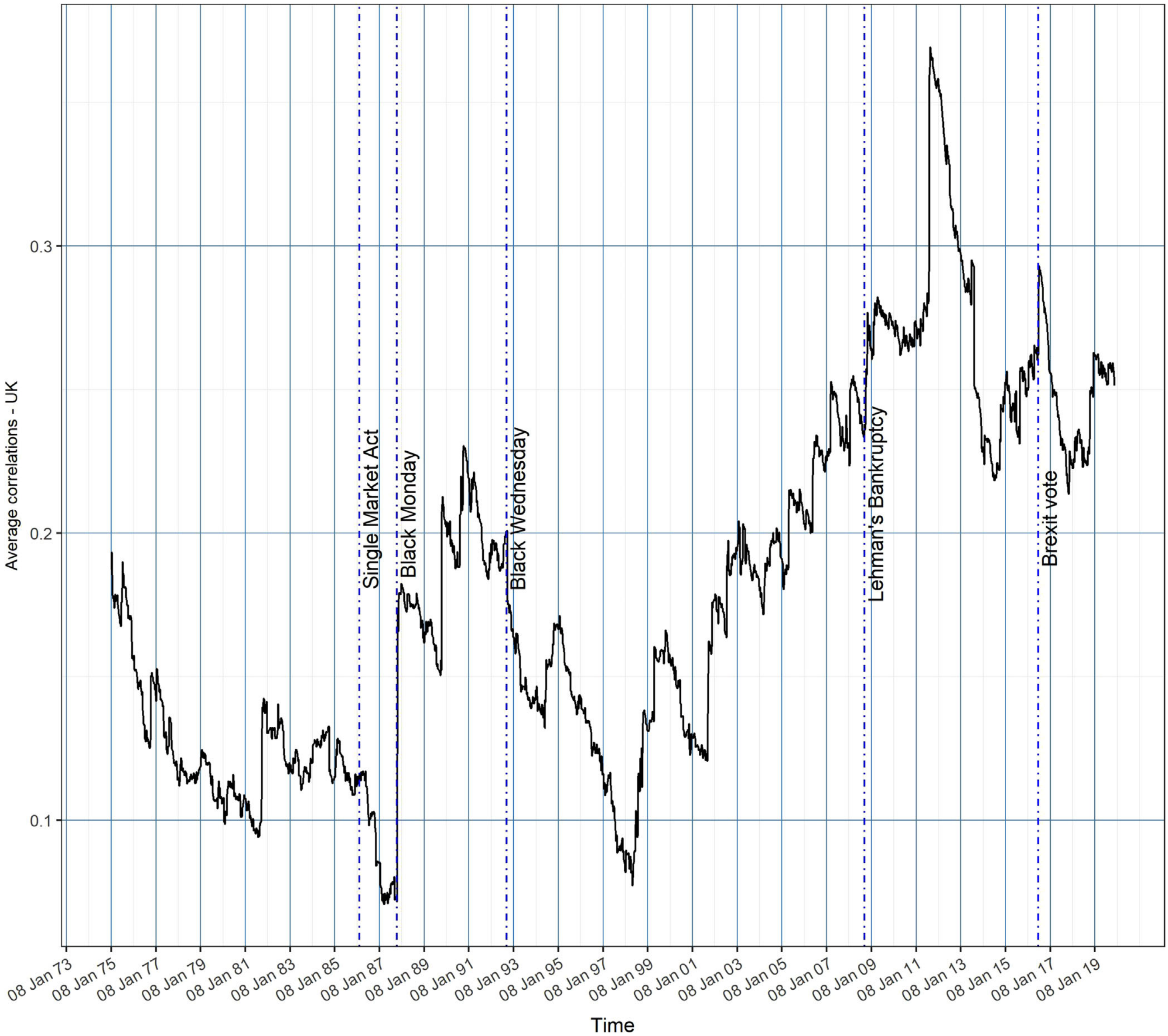


**FIGURE 4** Correlation in Chemicals 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

The elements of the diagonal matrix $\mathbf{D}_t$ are the standard deviations obtained from univariate GARCH (p,q) models, $\sqrt{h_{i,t}}$, where $h_{i,t} = \alpha_{i0} + \sum_{q=1}^{Q_i} \alpha_{i,q} a_{i,t-q}^2 + \sum_{p=1}^{P_i} \beta_{i,p} h_{i,t-q}$. $\widehat{\mathbf{Q}}$ is the unconditional matrix of the standardized residuals $z_t$. The parameter $a_i$ shows the sensitivity of $\mathbf{Q}_t$ to previous shock, and $b_j$ represents the persistence of correlations in previous periods. The estimations of the parameters $a_1$ and $b_1$ are presented in Subsection 3.3. The time-varying correlation matrices defined in Equation (4) allow us to build a time-varying optimal Markowitz portfolio by choosing the weights of each company in the portfolio that minimize its variance, subject to a desired level of return, $\mu_p$, for each time $t = 1, ..., T$.

Let $\mathbf{w_t} \in \mathbb{R}^n$, $t = 1, ..., T$, be an $n \times 1$ vector of weights, $\mathbf{r_t} \in \mathbb{R}^n$, $t = 1, ..., T$, be the $n \times 1$ vector of equity returns defined in Equation (1) above, and $\mathbf{1} \in \mathbb{R}^n$ an $n \times 1$ vector of ones. In the absence of short-sales constraints, the optimal portfolio weights satisfy the constrained optimization problem

$$\text{minimise} f(\mathbf{w}_t) = \frac{1}{2}\mathbf{w}_t^\top \boldsymbol{H}_t \mathbf{w}_t \tag{6}$$

$$\text{subject to}\, g_1(\mathbf{w}_t) = \mathbf{w_t}^\top \mathbf{r_t} - \mu_p = 0 \tag{7}$$

$$g_2(\mathbf{w}_t) = \mathbf{w_t}^\top \mathbf{1} - 1 = 0 \tag{8}$$

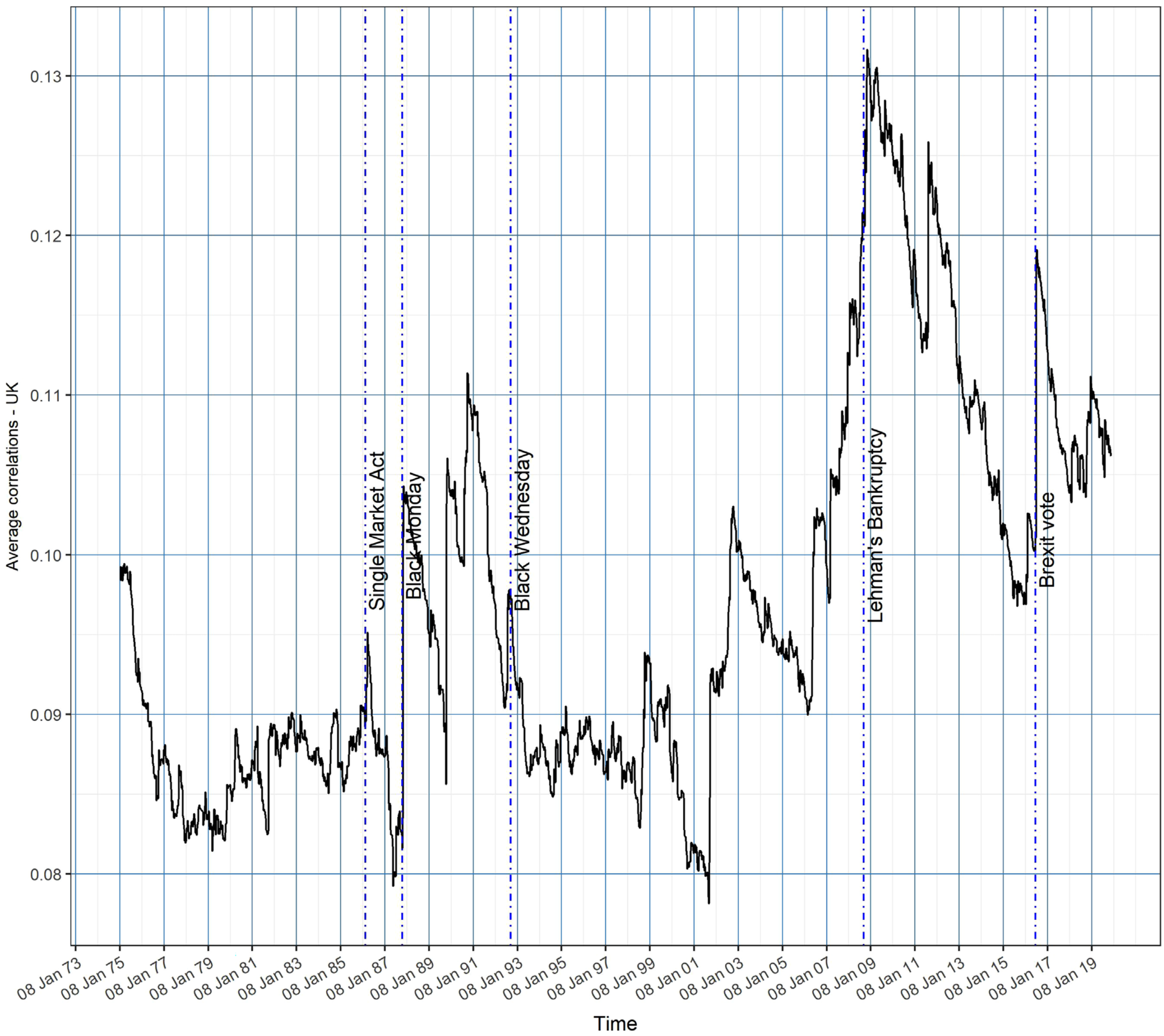


**FIGURE 5** Correlation in Construction 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

$\mu_p$ is calculated as the equity return average of each company over the whole sample period, viz., between January 1, 1973 and November 25, 2019. The constraint $g_1(\mathbf{w}_t)$ ensures the desired level of return is obtained and the constraint $g_2(\mathbf{w}_t)$ ensures that the sum of weights is equal to 1. This optimization has analytical solution

$$\bar{w} = c_1\widehat{\mathbf{H}_\mathbf{t}^{-1}}\mathbf{1} + c_2\widehat{\mathbf{H}_\mathbf{t}^{-1}}\mathbf{r_t} \tag{9}$$

where $\widehat{\mathbf{H}_\mathbf{t}^{-1}}$ is the DCC estimator of Equation (3) and

$$c_1 \equiv \frac{C-\mu B}{Ac-B^2} \quad \text{and} \quad c_2 \equiv \frac{\mu A - B}{AC-B^2} \tag{10}$$

with

$$A \equiv \mathbf{1}^\top \widehat{\mathbf{H}_\mathbf{t}^{-1}}\mathbf{1} \quad B \equiv \mathbf{1}^\top \widehat{\mathbf{H}_\mathbf{t}^{-1}}\mu \quad \text{and} \quad C \equiv \mu^\top \widehat{\mathbf{H}_\mathbf{t}^{-1}}\mu \tag{11}$$

## 3.2 | Structural break test

The structural break test was implemented using a modification of an algorithm proposed by Wied, Krämer, et al. (2012b). In their paper, a sample of $T$ observations of the return vector $(r_{1,t} \quad r_{2,t})^T$ is considered, and an algorithm tests the null hypothesis of constant correlations $\rho_t$, $t = 0, \ldots, T$, against the alternative hypothesis of a change-point at $t = t_c$, $0 \leq \ldots \leq t_c \leq \ldots \leq T$. $\rho_t$ denotes the true but unknown unconditional correlation between $r_{1,t}$ and $r_{2,t}$ at time $t$.

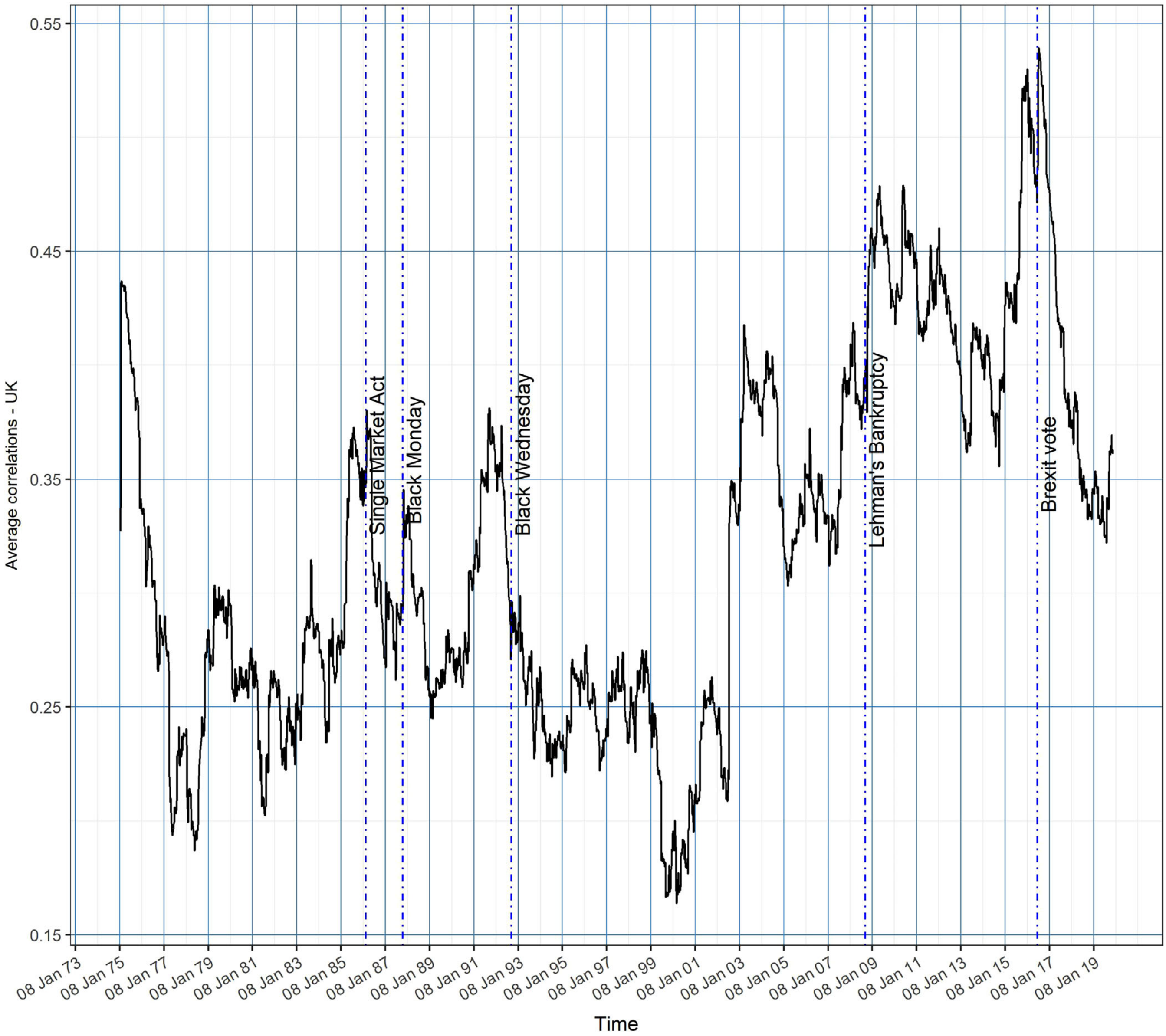


**FIGURE 6** Correlation in Food 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

Wied, Krämer, et al. (2012b)'s test is based on the model-free statistic

$$Q_T = \widehat{D} \max_{2 \le t \le T} \frac{t}{\sqrt{T}} |\widehat{\rho}_t - \widehat{\rho}_T| \tag{12}$$

where $\widehat{\rho}_t$ is the sample correlation over the period 1, ..., $t \le T$. It should be clear from Equation (12) that the correlation coefficient is calculated over a moving subsample of [2,..,T]. The purpose of $\frac{t}{\sqrt{T}}$ is to rescale the volatility of $\widehat{\rho}_t$, which tends to be higher at the beginning of the sample when only a few observations are available, whereas $\widehat{D}$ is required for the asymptotic distribution of $Q_T$ (Section 2 Wied, Krämer, et al., 2012b). Wied, Krämer, et al. (2012b) prove that under the null hypothesis and several moment and dependency restrictions, the test statistic $Q_T$ is asymptotically Kolmogorov distributed. The date of the single change-point is defined as follows:

$$t_c = argmax \widehat{D} \max_{2 \le t \le T} \frac{t}{\sqrt{T}} |\widehat{\rho}_t - \widehat{\rho}_T| \tag{13}$$

This test for structural change in correlations has been successfully applied to the analysis of constant correlations of stock index returns in the U.S. Adams et al. (2017), and to portfolio management (Galeano & Wied, 2014; Wied et al., 2013; Wied, Arnold, et al., 2012a). In all these applications, the correlation coefficients are always static, even though Adams et al. (2017) estimate DCCs that are not used in the


**FIGURE 7** Correlation in Food Producers 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

structural break test. Berens, Weiss, and Wied (2015) extend the algorithm developed in Wied, Krämer, et al. (2012b) to constant and dynamic conditional correlations (CCC and DCC), by calculating Equation (12) in combination with the CCC/DCC estimations. In their paper, Berens et al. (2015)) acknowledge that at a daily frequency the algorithm that produces (12) is not feasible and the authors restrict their structural breakpoint test to the constant conditional correlations (Berens et al., 2015, p. 141). However, a simple modification of Wied, Krämer, et al. (2012b)'s statistic allows the direct application of the DCC estimators found in Section 3.1 above.

The estimated DCC correlation coefficients form a sample $\rho_{i,j,1}, \ldots, \rho_{i,j,T}$, $i \neq j, = 1, \ldots, N$, where $T$ is the total number of weeks in the sample, and $N$ is the number of firms in the industry. We test the hypothesis that

$$\rho_{i,j,t} = \theta \begin{cases} \rho_{i,j,t}^{(1)} & \text{if} \quad 1 \leq k \leq k^* \\ \rho_{i,j,t}^{(2)} & \text{if} \quad k^* < k \leq T \end{cases} \tag{14}$$

where $k^*$ is an unknown change-point. Let $k^* = \tau^* T$ with fixed $0 < \tau^* < 1$. Since by definition $\rho_{ij,t} = E\left[\left(r_{i,t}/h_{i,t}^{1/2}\right)\left(r_{j,t}/h_{j,t}^{1/2}\right)\right]$ Engle (2002), an estimator $\widehat{t}_c$ of $k^*$ can be defined as follows:

$$\widehat{t}_c = \min\left\{k : \left|U_k\right| = \max_{1 \leq t \leq T} \left|U_j\right| \right\} \tag{15}$$

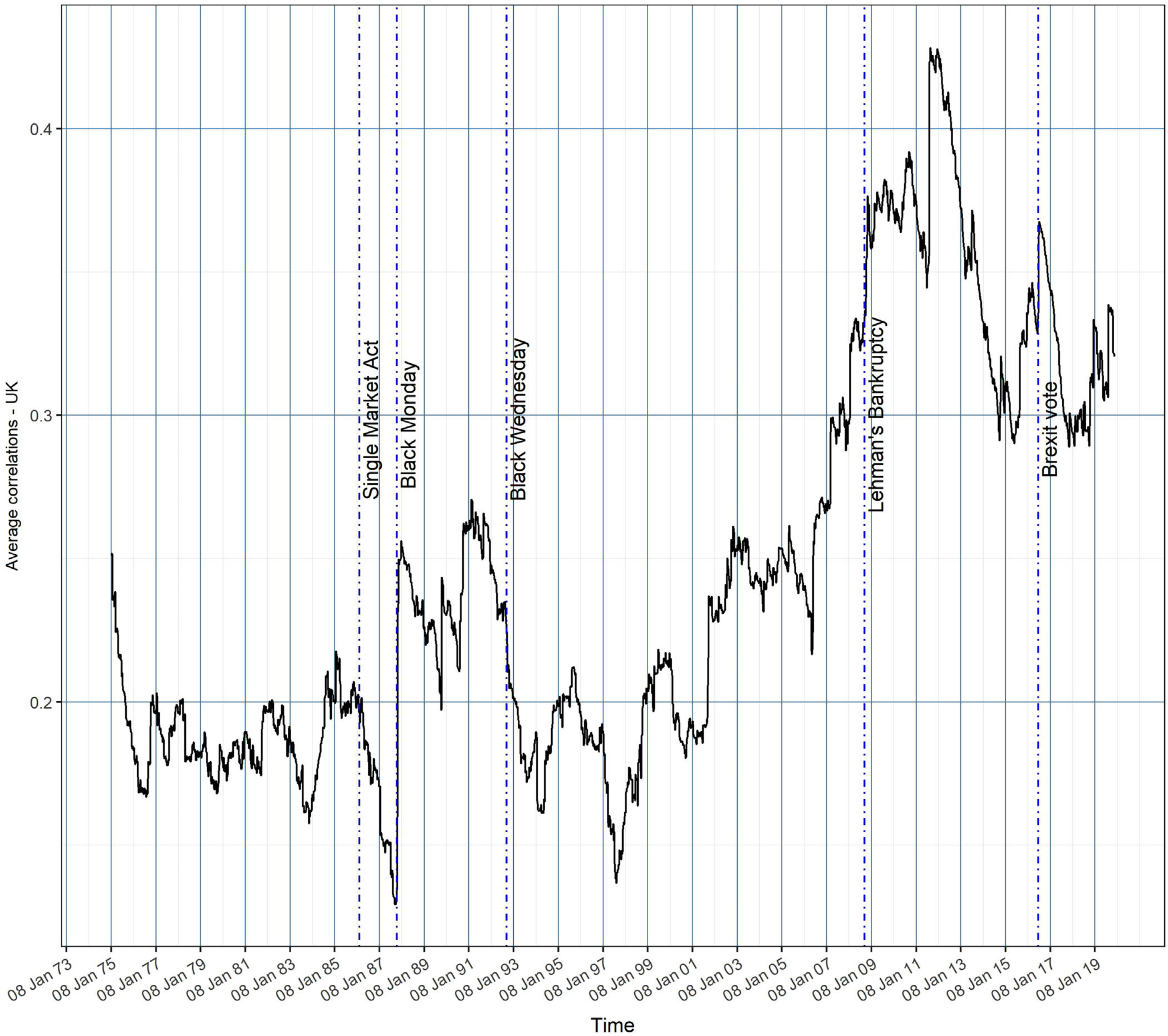


**FIGURE 8** Correlation in General Industrials 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

where

$$U_T(t) = T^{1/2}\frac{k(T-k)}{T^2}\left(\frac{1}{k}\sum_{t=1}^{k}X_{i,j,t} - \frac{1}{T-k}\sum_{t=k+1}^{T}X_{i,j,t}\right) \tag{16}$$

and $X_{i,j,t} \equiv \rho_{i,j,t}$, $i \neq j, = 1, ..., N$ and $t = 1, ..., T$.

It should be clear from Equation (16) that the first sum is the average DCC correlation over the first $k$ weeks of the sample, while the second sum is the average DCC correlations calculated over the remaining $T - k$ weeks.[1] $U_T(t)$ is a CUSUM test that was first developed for independent processes to detect breaks in their mean by Page (1955) and in their variance by Inclan and Tiao (1994). Kokoszka and Leipus (1998, 2000) extended the theory to dependent processes, viz., ARCH(∞), while Andreou and Ghysels (2002); Rapach and Strauss (2008), among others, applied CUSUM tests to GARCH (1,1) processes. Andreou and Ghysels (2003) investigated the existence of structural breaks in the co-movements of MGARCH models, and assumed that $\rho_{ij,t} = E\left[\left(r_{i,t}/\sigma_{i,t}^{1/2}\right)\left(r_{j,t}/\sigma_{j,t}^{1/2}\right)\right]$, for $i = 1, 2$. If $\sigma_{i,t}^{1/2}$ is estimated by a GARCH(1,1), then this specification corresponds to the de-garched model assumed in the previous section. Recent theoretical results support this approach.

In a ground breaking article, Fermanian and Malongo (2017) prove that a DCC(p,q) is a stationary and invertible data generating process (DGP) with finite $2p$

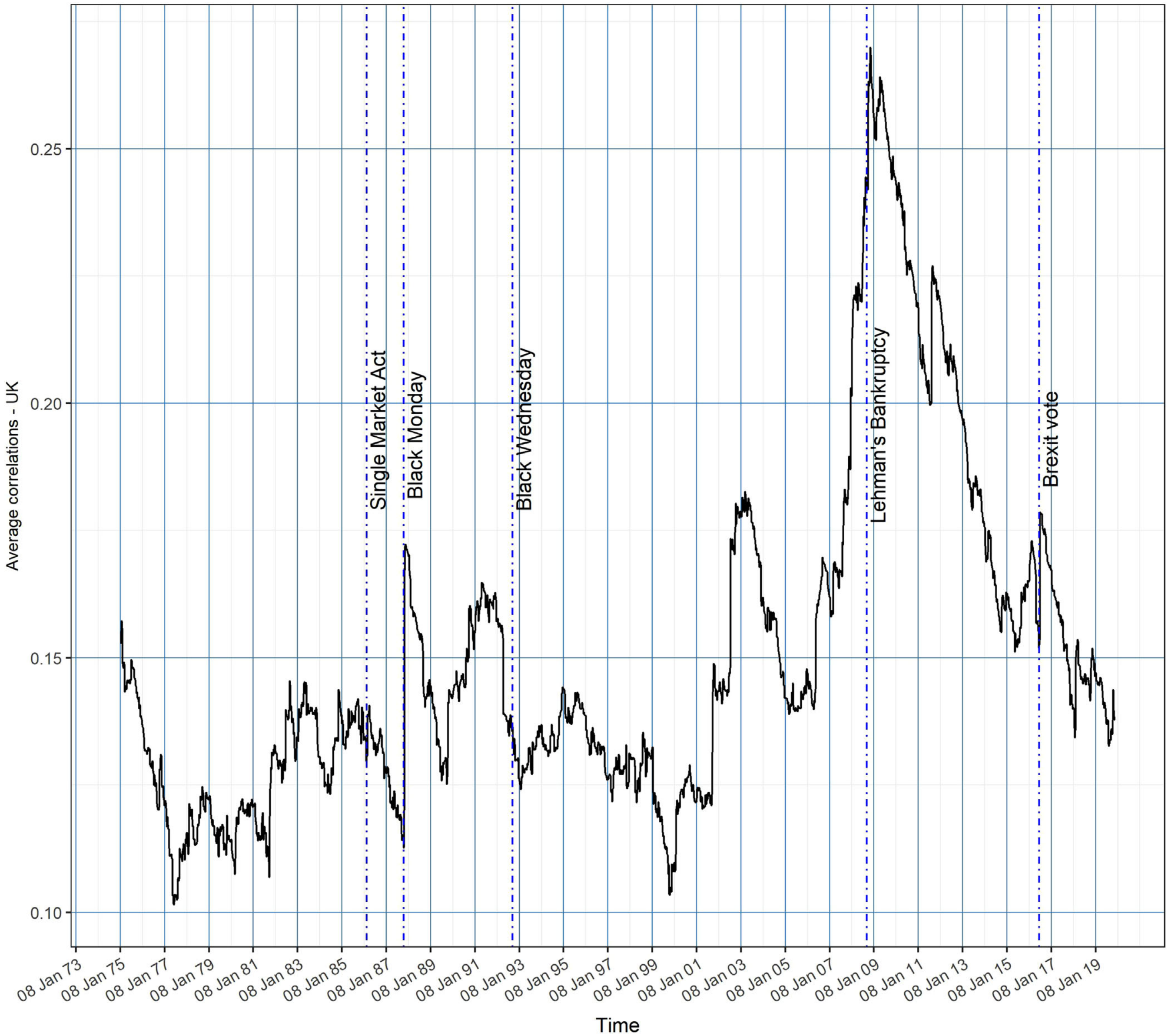


**FIGURE 9** Correlation in General Retail 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

$-th$ moments. In particular, a DCC(p,q) can be rewritten as a random coefficient AR(1) process that is a Markov chain. Some of these results had been partially proven in the literature. Aielli (2013) for instance shows that $E[(\rho_{ij,t})^2]$ is finite. McAleer (2017) presents the DCC model as a stationary and invertible random coefficient autoregressive process, and McAleer, Chan, Hoti, and Lieberman (2008) develop an econometric theory of such a model. This literature ensures that a DCC(1,1) satisfies the assumptions of Wied, Krämer, et al. (2012b)'s test statistic, and we can determine the asymptotic distribution of $U_T(t)$

$$\max_{1 \le t \le T} \widehat{D} \,|\, U_T \,| \overset{D[0,1]}{\longrightarrow} \max_{1 \le t \le T} |\, B^0(t) \,| \tag{17}$$

where $B^0(t)$ is a Brownian Bridge, and $\overset{D[0,1]}{\longrightarrow}$ means weak convergence in the space $D[0, 1]$. The results of the application of Equation 17 to test the existence of a breakpoint at the date of the Brexit referendum are shown in Section 4.2.

### 3.3 | Estimation results of DCC parameters

Table 1 shows the estimators of the DCC(1,1) parameters by industry.[2] The estimation results of the univariate GARCH for each company's returns can be found in the supplement. The parameter $a_1$ is significant at 1% for all


**FIGURE 10** Correlation in Industrial Engineering 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

industries. The persistence parameter $b_1$ is significant at 1% for all industries without exception.

It should be noted that $a_1$ has a small value for all industries, showing that past shocks have a small impact on the correlations $\vec{Q}_t$. The persistence parameter $b_1$ is close to 1 for all industries, which suggests that past correlations have a large effect on current correlations.

## 4 | EMPIRICAL RESULTS

This section shows the time-varying pairwise correlations by industry between 1973 and 2019 and the results of the structural break tests. Correlations between a UK company and a French, German, Italian or Spanish company are considered, while equity return correlations of UK companies with each other, and between non-UK companies are relegated to a supplement available on request. For ease of presentation, all the correlations involving a UK and a non-UK firm are averaged by industrial sector and plotted in Figures 1–17.

### 4.1 | DCC correlations between 1973 and 2019

We identify five sub-periods in our sample covering the UK membership of the EU. The first spans the period


**FIGURE 11** Correlation in Industrial Transportation 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

between the entry of the United Kingdom into the European Union and the Single Market Act, January 1, 1973 to February 17, 1986. The second phase takes place between the Single Market Act and Black Wednesday, September 16, 1992, when the United Kingdom was forced to withdraw from the ERM. The third ends with the collapse of Lehman Brothers, which we use to approximate the date of the 2008 Financial Crisis. The fourth culminates with the Brexit referendum vote in June 2016, and precedes the post-Brexit period. The date of the signature of the Single Market Act is a significant milestone since it kick-started the completion of the single market achieved on December 31, 1992. Black Wednesday is still viewed as a traumatic economic event in the United Kingdom, and is considered by analysts as the beginning of the political process that led to Brexit (Keegan, Marsh, & Roberts, 2017). The Maastricht Treaty was signed by the United Kingdom in February 1992, but its actual ratification by the British Parliament in 1993 was much more controversial than that of the Single Market Act.

Overall, we found that average pairwise correlations between British and French, German, and Italian companies increased sharply from 1998 to 2008 in all industries. In the Food, Food Producers, Travel and Leisure, and Personal Goods, the increase in correlations started in the early 2000s. This increase in correlations coincides with the housing boom that lasted a decade from 1998 until 2008. In fact, in most industries, there is an almost uninterrupted upward trend in correlations

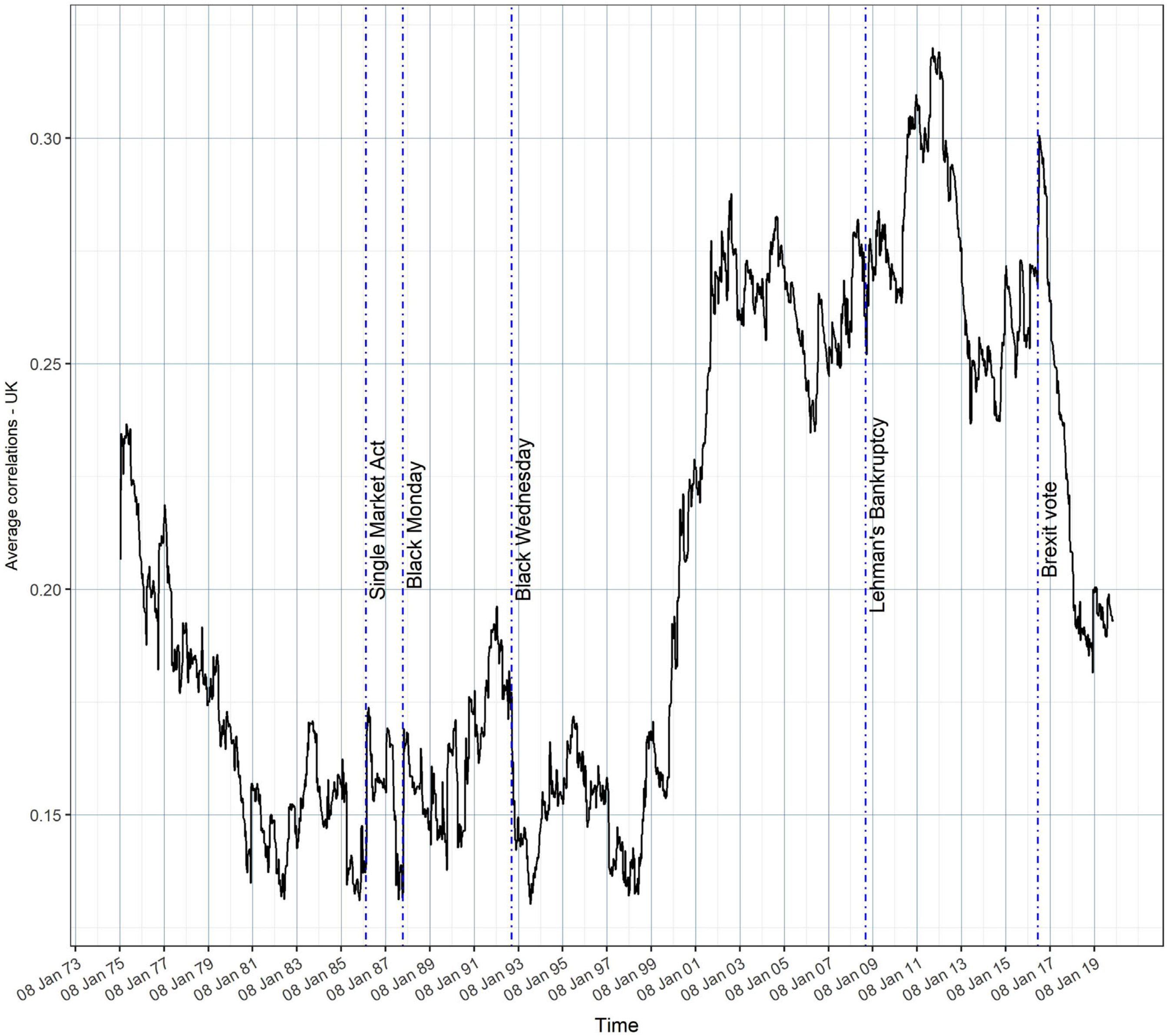


**FIGURE 12** Correlation in Media 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

starting in 1998 and culminating in 2008. The 2008 Financial crisis led to a sharp rise in pairwise correlations in most sectors, with the exception of Aerospace and Defence, Chemicals (peak in 2012), Construction, General Industrials (peak in 2012), General Retail, Industrial Engineering, Media (peak in 2012) Oil and Gas (decrease in 2011). The last three sectors are clearly more related to national preferences (Media), and global factors (Mining and Oil and Gas). All the companies in Mining and Oil and Gas operate outside the European Union. Regarding Industrial Transportation, we note that the terrorist attacks of 11 September 2001 and July 2007 had a more significant impact than the 2008 Financial Crisis. Most of these findings are not unexpected and are consistent with most of the literature on financial market integration.

There is equally strong evidence that correlations rose after the adoption of the Single Market Act in 1986 up until 1992. A major upward break occurred after the 1987 crisis ("Black Monday") in all industries bar Oil and Gas, where correlations fluctuated around the crisis date. The preceding period, 1973–1978, was unusually characterized by a decline in pairwise correlations in most industries. In Construction, Food, General Industrials, General Retail, Industrial Engineering, correlations appeared not to follow any specific trend. This result is not unexpected considering that many trade and financial restrictions still existed in the European Economic Community

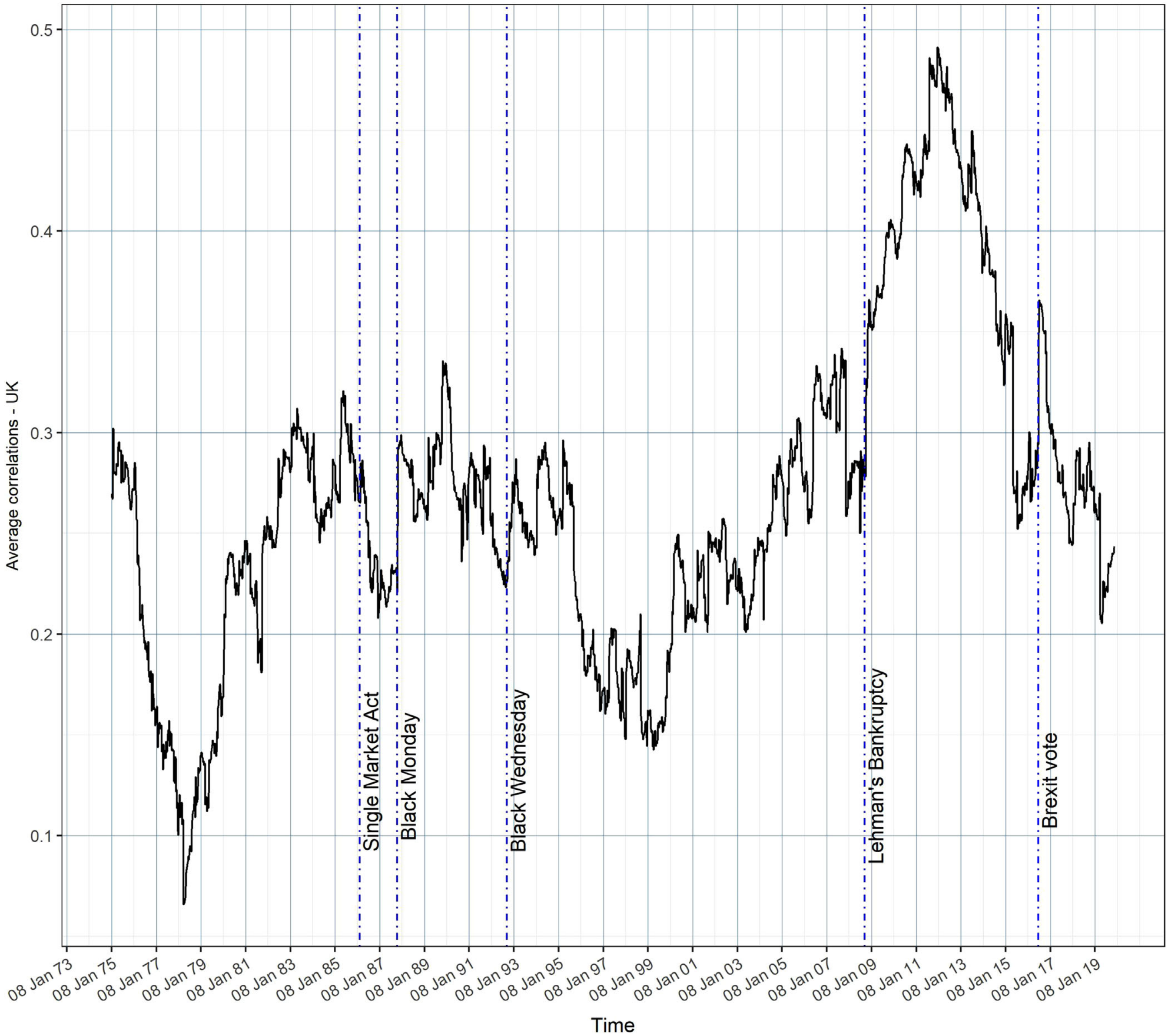


**FIGURE 13** Correlation in Mining 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

before the 1986 Single Market Act and the creation of the European Union by the Maastricht Treaty in February 1992.

1992 is also the year the United Kingdom was forced to withdraw from the ERM. The immediate impact of Black Wednesday was a sharp decline in correlations until 1998. There were a couple of exceptions, viz., Beverages (drop in 1999) and Mining (drop in 1996). For Food Producers, there was a distinct reversal of trend in 1992. During the period coinciding with the adoption of the euro, there was no overwhelming evidence that equity correlations decreased. It appears clearly that monetary union had no major impact on the return correlations of British and eurozone industries. Black Wednesday appears to be a much more relevant landmark for the United Kingdom than monetary union, of which the United Kingdom is not a member. Our results differ from those of Hardouvelis, Malliaropulos, and Priestley (2006, 2007), and are more aligned with those of Cappiello et al. (2010) and Bekaert et al. (2013), who show that membership of the European Union has a greater impact on convergence of yields and companies' growth rates. This discrepancy can be accounted for by the fact that Hardouvelis et al. (2006, 2007)'s sample does not actually cover the monetary union period, but rather the 5 years running up to the adoption of the euro, namely February 7, 1992 to June 26, 1998. During this time frame, we found a decrease in sectoral pairwise correlations of equity returns, which these authors interpret as a decoupling between the United Kingdom and the euro

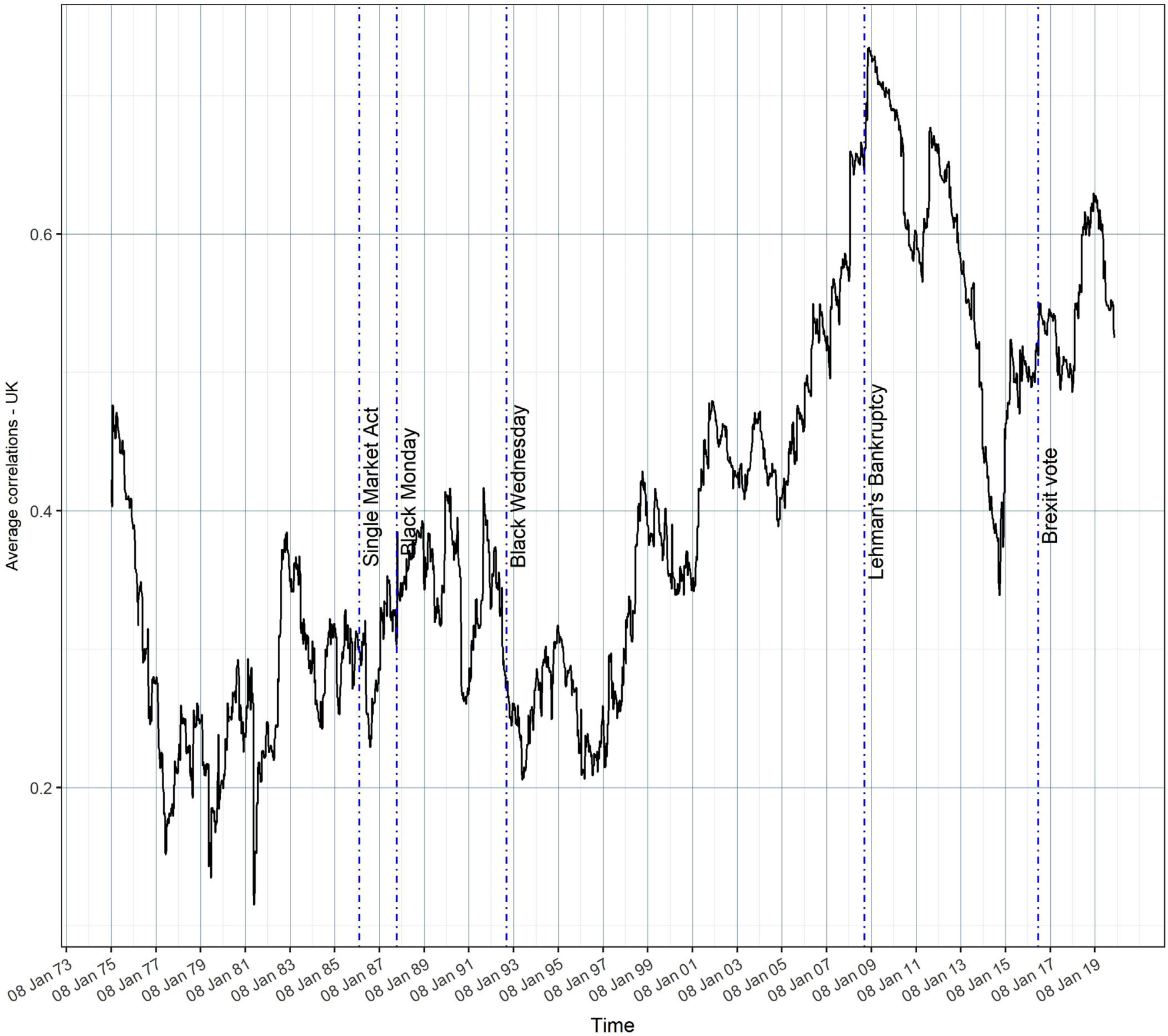


**FIGURE 14** Correlation in Oil and Gas 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

area. Although we found that monetary union may have intensified financial convergence between its members, it did not prevent further convergence of equity returns between United Kingdom and eurozone companies.

The period between September 15, 2008 and June 27, 2016 (Brexit vote) is characterized by a general declining trend in correlations of equity returns accompanied by high volatility and peaks in 2012 in all industries. A very marked increase in correlation occurred in all industries in the run-up of the referendum vote, and was immediately followed by an equally marked trend reversal. Since June 27, 2016 pairwise correlations have decreased in all industries, except Chemicals, Mining, Oil and Gas, and Personal Goods, where correlations actually went up.

These findings suggest that industries that are more integrated with the world market, such as Mining and Oil and Gas, are less likely to be affected by Brexit than industries where equity correlations with EU companies are higher owing to decades of economic and financial integration. Clearly, although the United Kingdom is fully economically integrated with EU countries, it still has industries that show some degree of segmentation from the single market. Greater diversification benefits can potentially be achieved with industry-specific diversification, rather than across countries. Our results are consistent with


**FIGURE 15** Correlation in Personal Goods 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

those of Carrieri et al. (2004), who found similar diversification benefits in US industries.

## 4.2 | Structural break tests

Table 2 shows the results of the structural break tests applied to the average DCCs between UK and EU firms plotted in Figures 1–17, within each sub-period defined in section 4.1. The table shows the date where the statistic reaches its highest value, the value of the test statistic, and its corresponding *p* value. The algorithm evaluates (16) for each conditional correlation within the subsample against the unconditional correlation of the previous sub-period. Industry-specific breakpoints were also identified by the test statistic[3] and are available on request. We only report the output of the structural break tests of the macroeconomic events discussed in Section 4.1. The test results suggest that the referendum date was a correlation change-point in all industries, except Mining, where the break-point was statistically identified the week after the referendum.

We first note that all tests are significant at 1 and 5%, in all industries. Variations may occur in the date of the break, which in some cases is the week after a major macroeconomic shock. As expected, the week following the failure of Lehman Brothers constitutes a break-point in all industries except Food Producers,


**FIGURE 16** Correlation in Support Services 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

Mining, and Personal Goods. However, in these industries, the break-point occurs between August 2007 and December 2008. Although we have chosen the date of the Lehman Brothers bankruptcy as a potential break-point of correlations, it is clear that this is only one of the major events of the 2007–2008 Financial crisis. It is now accepted that it started in April 2007, with the failure of a U.S. real estate investment trust, New Century, which specialized in sub-prime mortgages. In this context, we may conjecture that any change-point identified between April 2007 and December 2008 is related to the 2007–2008 financial crisis.[4]

A break-point was detected 2 weeks after Black Wednesday in all industries, except General Industrial where there is a break-point on October 16, 1989. We found a point-change on Black Monday (October 19, 1987) in all industries, except Personal Goods (May 18, 1987). In the previous sub-period, 1973–1986, all the breakpoints were in the 1970s, and all were significant, bar in Beverages and in Industrial Engineering.[5]

The results of the structural break tests corroborate those of the DCC estimation, and also suggest that the 1987 stock market crash led to an increase in equity returns correlations between UK and EU companies. It is worth noting that the main structural shocks we identified in Section 4.1 impacted correlations with a lag of 1 to 2 weeks, whereas the Brexit vote had an immediate impact. Although a time lag in the propagation of a financial shock

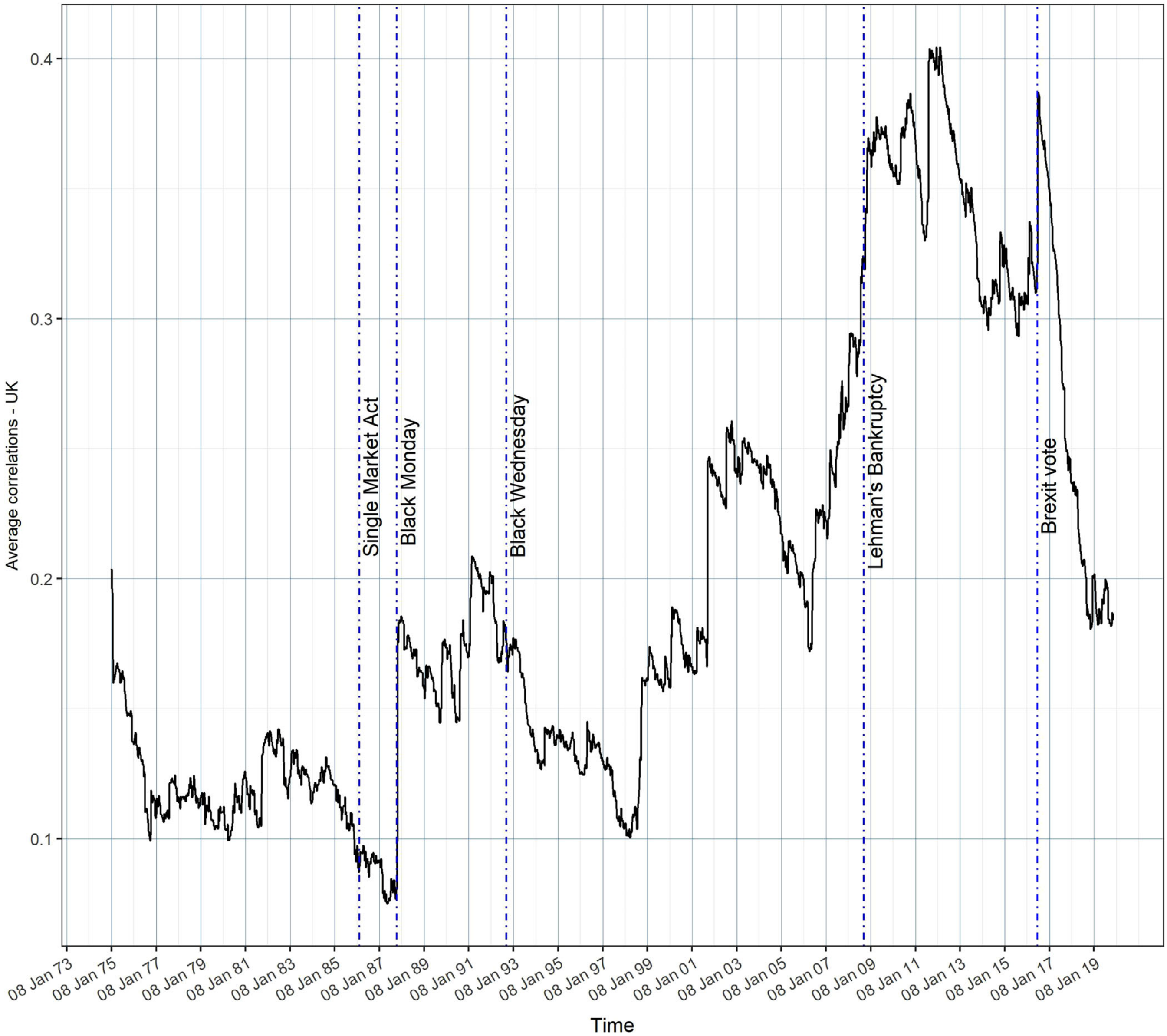


**FIGURE 17** Correlation in Travel and Leisure 1973–2019 [Colour figure can be viewed at wileyonlinelibrary.com]

is more likely than an immediate impact, the effects of the Brexit vote might have been felt immediately, since Brexit implies a permanent break in economic, financial, and regulatory integration with the European Union.

More importantly, our results are consistent with, and extend, the current literature. Firstly, we found evidence of a decade-long strong upward trend in correlations between equity returns in the United Kingdom and European Union, confirming previous findings that monetary union had less impact on equity market integration than the European Union (Bekaert et al., 2013; Cappiello et al., 2010; Ferreira & Ferreira, 2006). Secondly, the Brexit vote generated a sudden trend reversal in correlations, upholding the findings of event studies such as Schiereck et al. (2016) and Tielmann and Schiereck (2017). Moreover, by focusing on correlations across countries within industries, we were able to show that the Brexit vote created cross-country portfolio diversification opportunities, even in the context of deep economic integration. As Ferreira and Gama (2005), Ferreira and Ferreira (2006), and Ferreira and Gama (2010) have shown, increasing economic and financial integration leads to industry-based portfolio diversification strategies becoming as effective as cross-countries strategies. Our result is in accordance with Eiling et al. (2006, 2012); Hou et al. (2011), but particularly with Carrieri et al. (2004) who show that economic integration is not homogeneous across industries. Finally, our findings

**TABLE 2** Structural break tests by industry

| Industry | Date | $U_T$ | *p* value | Date | $U_T$ | *p* value |
|---|---|---|---|---|---|---|
| Aerospace and Defense | October 19, 1987 | 0.324 | .00 | September 28, 1992 | 0.047 | .00 |
| Automobile | October 19, 1987 | 0.494 | .03 | September 28, 1992 | 0.385 | .00 |
| Beverages | October 19, 1987 | 0.314 | .00 | September 28, 1992 | 0.130 | .00 |
| Chemicals | October 19, 1987 | 0.253 | .00 | September 28, 1992 | 0.067 | .00 |
| Construction | October 19, 1987 | 0.040 | .00 | September 28, 1992 | 0.274 | .00 |
| Food | October 19, 1987 | 0.072 | .00 | September 28, 1992 | 0.685 | .26 |
| Food Producers | October 19, 1987 | 0.049 | .00 | September 28, 1992 | 0.225 | .00 |
| General industrials | October 19, 1987 | 0.244 | .00 | October 16, 1989 | 0.320 | .00 |
| General Retail | October 19, 1987 | 0.082 | .00 | September 28, 1992 | 0.026 | .00 |
| Industrial Engineering | October 19, 1987 | 0.061 | .00 | October 16, 1989 | 0.183 | .00 |
| Industrial Transport | October 19, 1987 | 0.103 | .00 | September 28, 1992 | 0.026 | .00 |
| Media | October 19, 1987 | 0.194 | .00 | September 28, 1992 | 0.256 | .00 |
| Mining | October 19, 1987 | 0.069 | .00 | September 28, 1992 | 0.368 | .00 |
| Oil and Gas | October 19, 1987 | 0.467 | .02 | September 21, 1992 | 1.190 | .88 |
| Personal Goods | May 18, 1987 | 0.060 | .00 | September 28, 1992 | 0.081 | .00 |
| Support Services | October 19, 1987 | 0.034 | .00 | September 28, 1992 | 0.270 | .00 |
| Travel | October 19, 1987 | 0.357 | .00 | September 28, 1992 | 0.160 | .00 |
| **Industry** | **Date** | $U_T$ | ***p* value** | **Date** | $U_T$ | ***p* value** |
| Aerospace and Defense | September 22, 2008 | 0.152 | .00 | June 27, 2016 | 0.089 | .00 |
| Automobile | September 22, 2008 | 0.044 | .00 | June 27, 2016 | 0.033 | .00 |
| Beverages | September 22, 2008 | 0.077 | .00 | June 27, 2016 | 0.136 | .00 |
| Chemicals | September 22, 2008 | 0.062 | .00 | June 27, 2016 | 0.099 | .00 |
| Construction | September 22, 2008 | 0.010 | .00 | June 27, 2016 | 0.272 | .00 |
| Food | September 22, 2008 | 0.070 | .00 | June 27, 2016 | 0.072 | .00 |
| Food Producers | 09/06/2008 | 0.019 | .00 | June 27, 2016 | 0.239 | .00 |
| General Industrials | September 22, 2008 | 0.042 | .00 | June 27, 2016 | 0.028 | .00 |
| General Retail | September 22, 2008 | 0.047 | .00 | 02/05/2016 | 0.175 | .00 |
| Industrial Engineering | September 22, 2008 | 0.017 | .00 | June 27, 2016 | 0.239 | .00 |
| Industrial Transport | September 22, 2008 | 0.049 | .00 | June 27, 2016 | 0.131 | .00 |
| Media | September 22, 2008 | 0.105 | .00 | June 27, 2016 | 0.084 | .00 |
| Mining | 12/11/2007 | 0.042 | .00 | 02/05/2016 | 0.010 | .00 |
| Oil and Gas | September 22, 2008 | 0.342 | .00 | June 27, 2016 | 0.249 | .00 |
| Personal Goods | September 22, 2008 | 0.038 | .00 | June 27, 2016 | 0.198 | .00 |
| Support Services | September 22, 2008 | 0.028 | .00 | June 27, 2016 | 0.264 | .00 |
| Travel | September 22, 2008 | 0.054 | .00 | June 27, 2016 | 0.065 | .00 |

*Note:* Estimation of Equation (16) for weekly pairwise correlations between the returns of a UK company and those of a company in France, Germany, Italy, or Spain over January 1, 1973 and September 30, 2018. “Date” is the day $U_T$ reaches a maximum.

suggest that the Brexit vote may constitute a long-term trend reversal of the convergence of equity return correlations in European markets, akin to Black Wednesday, rather than a shock like the 1987 and 2008 financial crises, which merely intensified the historical upward trend in correlations of European equity returns.

### 4.3 | Markowitz portfolio weights and portfolio performance

The evaluation of portfolio performance is carried out by estimating the information ratio (IR), where the benchmark portfolio is the 1/*N* portfolio, which is viewed in

**TABLE 3** Annualized information ratio in percent – by industry

| | **Aerospace and Defense** | | | | |
|---|---|---|---|---|---|
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −161.49 | −65.25 | −91.07 | −75.50 | −35.46 |
| 1st Qu. | −9.44 | −7.51 | −7.52 | −10.35 | −5.90 |
| Median | −0.38 | 0.45 | 0.46 | −1.16 | 1.42 |
| Mean | −1.23 | −0.38 | 0.41 | −0.90 | 1.40 |
| 3rd Qu. | 8.17 | 7.89 | 8.10 | 9.29 | 7.36 |
| Max. | 109.10 | 49.41 | 72.04 | 62.50 | 77.23 |
| | **Beverages** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −71.68 | −32.80 | −47.78 | −108.58 | −20.17 |
| 1st Qu. | −5.77 | −4.37 | −4.25 | −3.85 | −2.26 |
| Median | −0.47 | 0.28 | −0.05 | 0.10 | −0.07 |
| Mean | −0.29 | 0.50 | 0.05 | 0.44 | 0.07 |
| 3rd Qu. | 4.67 | 4.33 | 4.70 | 3.76 | 2.42 |
| Max. | 83.01 | 51.38 | 47.96 | 70.28 | 26.52 |
| | **Construction** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −75.82 | −86.60 | −115.97 | −215.14 | −90.89 |
| 1st Qu. | −12.18 | −11.81 | −12.29 | −17.26 | −11.44 |
| Median | −0.60 | −1.77 | −0.29 | −0.71 | −1.76 |
| Mean | 0.14 | 0.42 | 0.91 | −0.60 | −1.17 |
| 3rd Qu. | 10.06 | 12.90 | 13.41 | 17.23 | 9.63 |
| Max. | 334.93 | 109.05 | 88.12 | 142.01 | 142.01 |
| | **Food Producers** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −96.67 | −40.84 | −35.27 | −44.40 | −31.50 |
| 1st Qu. | −8.87 | −5.40 | −5.37 | −5.53 | −5.92 |
| Median | −0.85 | −0.12 | −0.19 | −0.68 | 0.28 |
| Mean | −1.00 | −0.14 | −0.24 | −0.12 | 0.28 |
| 3rd Qu. | 6.90 | 4.80 | 4.50 | 6.13 | 5.93 |
| Max. | 53.01 | 73.39 | 51.10 | 40.76 | 40.76 |
| | **General Retail** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −78.86 | −70.79 | −63.00 | −109.95 | −98.09 |
| 1st Qu. | −9.28 | −10.22 | −7.58 | −9.43 | −9.32 |
| Median | −0.74 | −1.82 | 0.11 | 2.69 | 1.00 |
| Mean | −1.37 | −1.357 | 0.54 | 1.50 | 1.09 |

**TABLE 3** (Continued)

| | **General Retail** | | | | |
|---|---|---|---|---|---|
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| 3rd Qu. | 7.97 | 7.76 | 8.12 | 11.69 | 11.03 |
| Max. | 67.39 | 57.76 | 54.27 | 127.91 | 123.88 |
| | **Industrial Transportation** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −54.78 | −35.52 | −76.63 | −120.61 | −32.43 |
| 1st Qu. | −7.55 | −5.28 | −4.87 | −6.46 | −4.76 |
| Median | 0.22 | −0.39 | −0.25 | 0.00 | −0.79 |
| Mean | −0.57 | −0.30 | −0.32 | −0.62 | −0.81 |
| 3rd Qu. | 6.05 | 4.35 | 5.02 | 5.86 | 3.62 |
| Max. | 71.28 | 58.38 | 53.86 | 37.94 | 36.01 |

the literature as the "naive" diversification portfolio (DeMiguel, Garlappi, & Uppal, 2007).

$$\text{Information ratio}_t = \frac{E[R_{A,t}] - E[R_{DS,t}]}{\sqrt{h_t}} \tag{18}$$

for $t = 1, \ldots, T$ weeks. $E[R_{A,t}]$ is the expected return of the active portfolio in week $t$, constructed by multiplying the time-varying optimal weights resulting from Equations (6)–(8) by the equity returns in US\$; $E[R_{DS,t}]$ is the expected return of the benchmark portfolio in week $t$ and in US\$, and $h_t$ is the GARCH variance of $D_t = E[R_{A,t}] - E[R_{DS,t}]$.

The annualized IRs are summarized in Tables 3–5. Measures of central tendency and dispersion are shown for each industry, and each sub-period identified in Section 4.1. A negative IR indicates that the Markowitz portfolio underperforms the naive alternative where each firm has equal weight. Post-Brexit mean IRs increase relative to the previous period, September 2008–June 2016, in half of all industries. The IR falls in Construction, General Retail, Industrial Transportation, Oil and Gas, Personal Goods, Support Services, and Travel and Leisure. This shows that the estimated optimal portfolio performs better than the benchmark in most cases after the Brexit vote. The weight of UK assets in the active portfolio increases by an average of 4 % after the date of the Brexit vote, while the weight of the EU assets decreases by less than 1 % over the same period. Finally, it should be noted that despite the rise in the IR the benchmark portfolio still outperforms the Markowitz portfolio in some industries.

In the period following the Lehman Brothers failure, the most extreme minima were found in industries particularly affected by the 2008 financial crisis, for example, Construction (minimum IR of −215%) and Automobile and Parts (minimum of −122%). Mining was the industry posting the second lowest minimum IR over this period, −183%. The negative sign suggests that the naive diversification outperformed the Markowitz portfolio, while the extreme values evidence the impact of the crisis on these industries. The distribution of the IR in these industries is also skewed to the left, with extreme negative values higher in absolute terms than the extreme positive values.

The distribution of the information ratio in the period following Black Wednesday leading to the 2008 Financial Crisis mirrors that of the IR in the post-Brexit period. More precisely, we note an increase in the mean information ratio (Aerospace and Defence, Construction, General Retail, Automobile and Parts, Chemicals, Food, General industrials, Industrial Engineering, Oil and Gas, Travel and Leisure). The extrema are also more pronounced in this period relative to the preceding 5 years (1987–1992). These findings reinforce the proposition that regional shocks, such as the 1992 ERM Crisis and Brexit, had analogous implication on British industries, and in particular, on those that have more economic and financial links with the European Union. On the contrary, industries such as Oil and Gas and Mining tend to be more exposed to global shocks, for example, the 1987 and 2008 Crises.

TABLE 4 Annualized information ratio in percent – by industry

| | January 1, 1973–October 19, 1987 | October 19, 1987–September 21, 1992 | September 21, 1992–September, 15, 2008 | September 15, 2008–June 27, 2016 | Post-Brexit |
|---|---|---|---|---|---|
| | **Automobile and Parts** | | | | |
| Min. | −63.32 | −46.40 | −76.90 | −122.05 | −63.32 |
| 1st Qu. | −8.82 | −9.16 | −10.32 | −16.29 | −12.27 |
| Median | −0.76 | −1.34 | 0.34 | −0.36 | −2.17 |
| Mean | −0.87 | −2.38 | 0.44 | −0.55 | −0.38 |
| 3rd Qu. | 7.45 | 6.68 | 10.44 | 14.81 | 8.90 |
| Max. | 43.07 | 59.02 | 105.50 | 124.14 | 75.92 |
| | **Chemicals** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −86.63 | −76.52 | −58.94 | −66.48 | −44.65 |
| 1st Qu. | −9.27 | −8.46 | −7.73 | −9.37 | −7.26 |
| Median | −0.45 | 0.82 | −0.03 | 0.36 | 1.54 |
| Mean | −0.85 | −0.97 | 0.00 | 0.23 | 2.84 |
| 3rd Qu. | 7.49 | 8.94 | 7.67 | 9.03 | 10.68 |
| Max. | 109.36 | 37.20 | 59.91 | 61.36 | 108.03 |
| | **Food** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −77.09 | −48.99 | −33.10 | −51.89 | −71.03 |
| 1st Qu. | −5.83 | −6.77 | −3.84 | −6.50 | −4.57 |
| Median | −0.44 | 0.17 | 0.38 | 0.45 | −0.19 |
| Mean | −0.46 | −0.15 | 0.32 | −0.08 | 0.19 |
| 3rd Qu. | 5.88 | 7.02 | 4.19 | 6.02 | 5.65 |
| Max. | 66.67 | 46.26 | 40.74 | 62.12 | 58.72 |
| | **General Industrials** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −66.13 | −61.53 | −55.96 | −66.86 | −89.47 |
| 1st Qu. | −9.10 | −8.21 | −8.55 | −10.50 | −6.70 |
| Median | −0.36 | 0.20 | 0.17 | −0.72 | 1.25 |
| Mean | −0.90 | 0.75 | 0.54 | −0.75 | 0.06 |
| 3rd Qu. | 7.76 | 10.27 | 9.17 | 10.05 | 9.01 |
| Max. | 100.06 | 87.10 | 106.81 | 68.33 | 74.03 |
| | **Industrial Engineering** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −97.57 | −61.60 | −92.95 | −92.27 | −49.24 |
| 1st Qu. | −8.65 | −9.29 | −9.24 | −14.41 | −11.39 |
| Median | −0.75 | 0.17 | −0.52 | −2.05 | −1.48 |
| Mean | −0.12 | 0.65 | 0.80 | −0.69 | 0.42 |
| 3rd Qu. | 8.41 | 7.76 | 9.96 | 10.43 | 9.94 |
| Max. | 75.30 | 63.56 | 294.29 | 131.21 | 75.08 |

**TABLE 5** Annualized information ratio in percent – by industry

| | **Mining** | | | | |
|---|---|---|---|---|---|
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −103.347 | −76.36 | −142.24 | −183.3 | −94.60 |
| 1st Qu. | −8.66 | −6.32 | −8.79 | −11.04 | −11.74 |
| Median | −0.23 | 1.60 | −0.93 | 1.39 | 2.64 |
| Mean | −0.46 | 0.65 | −0.17 | 2.019 | 2.93 |
| 3rd Qu. | 8.68 | 7.80 | 7.77 | 14.42 | 17.58 |
| Max. | 97.28 | 100.07 | 553.18 | 166.19 | 113.80 |
| | **Media** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −72.50 | −88.54 | −100.43 | −85.84 | −43.77 |
| 1st Qu. | −10.83 | −8.11 | −8.71 | −9.15 | −9.98 |
| Median | −0.49 | 1.90 | −0.14 | −0.60 | 0.27 |
| Mean | −1.74 | 1.96 | −0.32 | −1.218 | 1.80 |
| 3rd Qu. | 7.54 | 10.49 | 7.71 | 8.32 | 8.78 |
| Max. | 75.64 | 75.05 | 91.85 | 45.12 | 170.66 |
| | **Oil and Gas** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −105.31 | −85.07 | −74.49 | −54.20 | −45.18 |
| 1st Qu. | −8.09 | −8.93 | −4.60 | −5.17 | −3.59 |
| Median | −0.28 | −0.11 | −0.08 | 0.33 | 0.26 |
| Mean | −1.32 | −1.08 | −0.03 | 0.31 | 0.04 |
| 3rd Qu. | 6.55 | 4.84 | 4.72 | 5.37 | 4.28 |
| Max. | 109.56 | 49.39 | 74.17 | 58.93 | 27.80 |
| | **Personal Goods** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −59.53 | −91.81 | −84.47 | −169.19 | −24.22 |
| 1st Qu. | −7.81 | −5.51 | −7.32 | −7.15 | −6.14 |
| Median | −0.47 | 0.33 | 0.36 | −0.01 | −1.43 |
| Mean | −0.65 | −0.40 | 0.75 | 1.34 | −0.72 |
| 3rd Qu. | 7.23 | 6.42 | 7.90 | 7.48 | 3.83 |
| Max. | 51.32 | 49.18 | 83.38 | 743.21 | 27.47 |
| | **Support Services** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −60.53 | −46.15 | −88.52 | −89.86 | −30.18 |
| 1st Qu. | −9.16 | −7.26 | −7.33 | −6.20 | −7.07 |
| Median | −0.48 | 0.95 | 0.98 | 1.59 | 0.81 |
| Mean | −0.76 | 1.78 | 0.76 | 1.06 | 1.02 |

(Continues)

TABLE 5 (Continued)

| | Support Services | | | | |
|---|---|---|---|---|---|
| | January 1, 1973–October 19, 1987 | October 19, 1987–September 21, 1992 | September 21, 1992–September, 15, 2008 | September 15, 2008–June 27, 2016 | Post-Brexit |
| 3rd Qu. | 6.33 | 9.01 | 9.27 | 9.09 | 6.91 |
| Max. | 82.03 | 97.83 | 57.98 | 56.74 | 54.13 |
| | **Travel and Leisure** | | | | |
| | **January 1, 1973–October 19, 1987** | **October 19, 1987–September 21, 1992** | **September 21, 1992–September, 15, 2008** | **September 15, 2008–June 27, 2016** | **Post-Brexit** |
| Min. | −78.54 | −46.81 | −98.80 | −86.20 | −60.64 |
| 1st Qu. | −11.47 | −10.39 | −11.48 | −12.42 | −16.02 |
| Median | 1.71 | −0.29 | 0.87 | 1.22 | −2.42 |
| Mean | 0.64 | −0.28 | −0.04 | 1.74 | −0.70 |
| 3rd Qu. | 12.54 | 10.08 | 9.89 | 15.83 | 14.13 |
| Max. | 79.51 | 50.86 | 136.13 | 83.05 | 103.82 |

## 5 | CONCLUSION

We analyse the correlations of equity returns of listed companies in the five largest European economies from the date the United Kingdom joined the European Union on January 1, 1973 until November 25, 2019. We estimate time-varying dynamic conditional correlations (DCC-GARCH), and then estimate optimal sectoral portfolio weights over the same period. Our results show that pairwise correlations increased as a consequence of economic integration among European countries, as a result of global macroeconomic shocks (2008 crisis and Black Monday), but decreased after European macroeconomic shocks (Brexit referendum and Black Wednesday). Sectoral differences exist as to the extent of the Brexit impact. In some industries, correlations fall markedly after the Brexit referendum vote without the date of the vote being a structural break-point. This finding is supported by the results of a test for correlation change-point proposed by Wied, Krämer, et al. (2012b). We also found evidence that Black Wednesday, that is, the day the United Kingdom was forced out of the ERM in 1992 had a strong negative impact on pairwise correlations of equity returns in nearly all industries. The failure of Lehman Brothers and the October 19, 1987 stock market crash were equally found to be significant structural breakpoints in correlations. However, their impacts differed from those of Black Wednesday and Brexit. The first two shocks were followed by a marked increase in equity return co-movements, while the last two initiated a divergence of equity returns. This decrease in correlations between UK firms and those of France, Germany, Italy, and Spain improved opportunities for risk diversification. Consequently, optimal portfolio weights of most UK companies have increased since the Brexit vote, suggesting that greater sectoral diversification benefits within industries across countries can be obtained by investing in UK companies.

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## DATA AVAILABILITY STATEMENT
Data subject to third party restrictions.

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## ENDNOTES

[1] Equation (16) can be further simplified to $U_T(t) = T^{-1/2}\left(\sum_{t=1}^{k} X_{i,j,t} - \frac{k}{T}\sum_{t=1}^{T} X_{i,j,t}\right)$.

[2] All estimations were carried out using R and the rmgarch package (Ghalanos, 2015).

[3] There is a break-point in 2012 in many industries, as was seen in Section 4.1.

[4] Among the factors that contributed to the depth of the 2008 Financial crisis was the sudden and complete evaporation of liquidity, which Gorton (2008, p. 63) dates as early as August 10, 2007.

[5] These results are not shown in Table 2, but are available from the author on request.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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