"Brexit and the dependence structure among the G7 bank equity markets"

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BREXIT AND THE DEPENDENCE STRUCTURE AMONG THE G7 BANK EQUITY MARKETS

Abstract

The UK referendum in June 2016 on leaving the European Union had a negative impact on banking stocks across the major financial markets. This has left with a question dealing with the effect of UK banking institutions on the systemic risk on a global scale. This paper aims at investigating the changes in the dependence structure between the UK bank equity returns and its counterparts in the G7 economies. The methodology used is based on the GJR-GARCH volatility spillover model that accounts for asymmetry and leverage, and copula for the time-varying correlation structure among G7 banks. Taking the data on bank equity return indices for G7 economies, the results indicate the symmetric dependence structure between the UK and Italian banks and the asymmetric dependence between the UK and the rest of G7 banks. This is due to the simultaneous decline in bank shares prices across the Union. Such results are important constituents for cross-country portfolio diversification.

INTRODUCTION

Since becoming a Member of the European Community (now European Union) in 1973, GDP in the UK has grown to an aggregate of 81.4%. In nominal terms, the GDP per capita was $3,426, and by the end of 2018, it has grown to $42,491, reaching a peak of $50,293[1] in 2007. Kierzenkowski, Pain, Rusticelli, and Zwart (2016) argued that the real GDP of the UK since joining the European Community in 1973, and until 2014, has doubled, outpacing other large non-EU economies like the USA, Canada, Australia.

The UK exodus from the European Union is expected to have large negative implications in the economy. After the June 23, 2016 referendum results were obtained immediately, the pound sterling depreciated sharply against the major currencies, 8.4%, 6.3%, and 12% against the US Dollar, Euro, and Yen, respectively. The sterling depreciation continued the days and the weeks after the referendum, reaching a low of 1.22, 1.08, and 127 against the US Dollar, Euro, and Yen. Indeed, the sterling FX rate oscillated between these low and higher rates but far from the ones in the aftermath of the referendum, reflecting the market's assessment of the likelihood of a hard or a soft Brexit.

The Brexit's impact on the real economic activity has started the months after the referendum, but its sizable effects will be known in the long run. However, the increase in uncertainty should have significant short-run impacts on the financial markets. Caporale, Gil-Alana,

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1   Source: World Bank.

and Trani (2018) examined the impact of Brexit on the uncertainty surrounding the European financial markets. They found persistent changes in the FTSE 100 implied volatility and the implied volatility of the sterling vis-a-vis the Euro, US Dollar, and Japanese Yen. Kurecic and Kokotovic (2018) found a negative effect of Brexit on European and US stock indices among other world indices. Around the Brexit event, Burdekin, Hugson, and Gu (2018) found that stocks across the globe witnessed abnormal returns and that countries with high debt to GDP ratio suffered substantial stock market losses. Sultonov and Jehan (2018) evidenced significant changes in the Japanese stock and FX markets.

Little attention has been paid to the contribution of the systemically important financial institutions in the UK to global systemic risk. The paper aims to investigate the underlying changes in the dependence structure of the G7 bank equity returns around Brexit. Time-varying copula models are used to verify the changes in the dependence structure, mainly in tail dependence, as they offer important advantages in the analysis of co-movements of financial time series over other techniques. The paper is structured as follows. Section 1 reviews the relevant literature. Section 2 presents the methodology for the dependence structure. Section 3 describes the data and displays the results. Section 4 discusses the results. The last section concludes.

1. LITERATURE REVIEW

It has been evidenced that the dependence structure in the periods of extreme events or structural change can be captured by tail dependence. In financial asset returns, tail dependence may change over time. As shown by Patton (2006), the tail dependence of DM-USD and Yen-USD potentially changes over time, especially before and after introducing the Euro. The importance of tail dependency during market turmoil is well recognized in market risk modeling. The European Market Infrastructure Regulation (EMIR) is concerned about the speedy increases in co-dependencies between the risk factors and their negative impact on the value of bank portfolios. EMIR mandates the CCPs to test the consistency of correlations over a historical period[2]. However, the covariance, a traditional measure of dependency, is not appropriate because it measures the dependency on the center of the distribution, which is different from the one in the extremes. In the extreme analysis, usual models are the multivariate extreme value theory (EVT) and copulas. McNeil (1999) and Hauksson, Dacorogna, Domenig, Mller, and Samorodnitsky (2001) were the first to investigate the application of multivariate extreme value theory (EVT) in financial risk management. The use of EVT on multivariate extremes of large dimensions is not feasible because of computational constraints. To overcome this, Barone-Adesi Giannopoulos

and Vosper (2018) used the Filtered Historical Simulation (FHS) to get a probabilistic estimation and confidence intervals around the JES of the expected size of losses of investment portfolios, as well the joint expected shortfall (JES). They generated the density of the JES to get standard errors on the tails dependency estimates by repeating 5,000 times a bootstrapping of 5,000,000 simulation trials.

Copulas are an alternative flexible method for modeling the dependence structure of financial time series. They combine the marginal distributions with the copula function to produce a multivariate joint distribution and capture the dependency among the variables. Embrechts, McNeil, and Straumann (2002) and Cherubini et al. (2004) were among those who pioneered multivariate copulas in finance. Palaro and Hotta (2006) implemented multivariate copula in estimating and calculating the VaR of a portfolio.

The modeling of copulas in a multivariate context with the implementation of appropriate tests is examined in Kole, Koedijk, and Verbeek (2007). Nevertheless, the tail dependency assessment with the use of copula requires that the full density of the variables be specified properly. Yet close form solutions for many of the joint densities cannot be derived. Brechmann, Hendrich, and Czado (2013) employed a pair copula structure with D-vine

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2   Shifts in correlations can also be due to "model risk". Kerkhof, Melenberg, and Schumacher (2010) attribute the "model risk" to any of the following components: estimation risk, misspecification risk, and identification risk.

copulas in estimating the market risk of 52-dimensional data set of the Euro Stoxx 50 index. Li (1999) introduced the multivariate copula in the credit risk in assessing the default correlation in the multi-name credit default swaps. Cumming and Noss (2013) were the first to apply copula in risk analysis of the CCPs. They employed multivariate copula in investigating the capital adequacy of CCPs during multiple defaults of the clearing members.

There is now an increasing trend of using dynamic copulas to model dependence between financial assets. Patton (2012) provided a review of the growing literature on time-varying copula models used in financial time series. He discussed various estimation models of the time-varying parameters of dynamic copulas and highlighted an alternation in the copula specification between parametric, semiparametric, and full nonparametric. Manner and Reznikova (2012) tested the performance of various time-varying copulas using simulations. They showed that time-varying copulas, DCC copula, stochastic autoregressive copula, and regime-switching copula perform very well in estimating the Value-at-Risk and the quantile dependence. Their empirical testing on Euro-USD, Yen-USD, and MSCI indexes of Korea and Singapore confirmed their claims. There are now newly emerged dynamic copulas models such as "vines" and "hierarchical Archimedean copulas" that are applied in risk management, contagion, and systemic risk. For example, Krupskii and Joe (2013) measured the tail dependence of various US stock returns and European index returns by fitting several vine copula models. They concluded that these copula models are a good fit to returns data and well-adapted to consider tail risk dependence in portfolio risk management. Fengler and Okhrin (2016) also applied the same copula models to forecast VaR exceedances of portfolios of US stocks. They found that these dynamic copulas have good forecasting ability in portfolio risk management. Finally, Ji, Liu, Cunado, and Gupta (2018) adopted time-varying copula models to investigate the co-movements across markets by analyzing the risk spillover from the US stock market to G7 stock markets. Using a century of stock market data for the G7 countries, they meas-

ured the dependence structure by the conditional VaR (CoVaR) using Markov switching regime dynamic copulas. Their findings highlighted that global systemic risk could be evident from the significant upside and downside risk spillover from the US to other G7 countries.

2. METHODOLOGY

The methodology is based on copulas to allow for heterogeneity in characterizing marginal distributions and to account for specific features of the data such as conditional heteroscedasticity, volatility asymmetries, and leverage effects. For the marginal models, it is considered using an AR model for conditional means, considering any presence of autocorrelation of p order, and GJR-GARCH(p, q) model[3] for conditional volatility, attempting to capture the so-called leverage effect. Let $R_{i,t}$ be the return series, the marginal model is represented as follows:

$$R_{i,t} = \mu_{i,t} + \varepsilon_{i,t} = \alpha_0 + \sum_{j=1}^{p} \alpha_j R_{i,t-1} + z_{i,t}\sigma_{i,t}, \quad (1)$$

$$\sigma_{i,t}^2 = w + \sum_{j=1}^{p}\left(\alpha_j + \gamma_j I_{t-1}\right)\varepsilon_{i,t-j}^2 + \sum_{j=1}^{p}\beta_j \sigma_{i,t-j}^2,$$

with $\varepsilon_{i,t} \sim D\left(0, \sigma_{i,t-j}^2\right)$ representing independent and identically distributed shocks with zero mean and time-varying variance, and $I_{t-1} = 1$ if $\varepsilon_{i,t} < 0$. In this model, the parameters α_j and β_j are the ARCH and GARCH coefficients, respectively, the parameter γ_j captures the leverage effect of the returns. The distribution of shocks follows a skewed Student t distribution to accommodate fat tails and skewness in the returns.

To capture different types of dependence structures, the authors try various copulas from the Elliptical family, such as normal and Student t copulas, and Archimedean family, such as Gumbel copula. These copulas are widely used in the literature because of their appealing properties for modeling dependence between financial asset returns. They allow for tail independence (Gaussian), symmetric tail dependence (Student t), and asymmetric tail dependence (Gumbel). Besides, and as

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3   The orders p and q can be chosen by the Akaike Information Criterion (AIC) or the Schwarz Information Criterion (SIC).

dynamics in mean and volatility in the marginal models are considered, dynamics in the copula dependence parameters (see Patton, 2006) are also considered, and hence the dependence structure evolves in the time-varying path. The functional forms of the time-varying bivariate elliptical and Archimedean copulas used in this paper assume that the dependence parameters follow an ARMA (1,10) process. The time-varying dependence structure for the studied copulas is, respectively, given as follows:

for the time-varying normal copula,

$$C(u,v,\rho) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\rho\sqrt{1-\rho^2}} \times$$
$$\times \exp\left(\frac{-(x^2+y^2+2xy\rho)}{2(1-\rho^2)}\right) dxdy, \quad (2)$$

$$\rho_t = \Lambda_1\left(\Phi_0^N + \Phi_1^N \rho_{t-1} + \right.$$
$$\left. + \Phi_2^N \frac{1}{10}\sum_{j=1}^{10} \Phi^{-1}(u_{t-j}).\Phi^{-1}(v_{t-j})\right),$$

with ρ_t being the related time-varying parameter of the bivariate normal copula, and where Φ^{-1} is the inverse of the standard normal c.d.f and $\Lambda_1(x) = (1-e^{-x})(1+e^{-x})^{-1}$ a logistic transformation to keep the dependence parameter ρ_t within its domain (–1,1);

for the time-varying Student t copula,

$$C(u,v,\rho,\nu) = \int_{-\infty}^{T^{-1}(u)} \int_{-\infty}^{T^{-1}(v)} \frac{1}{2\rho\sqrt{1-\rho^2}} \times$$
$$\times \left(1 + \frac{x^2+y^2+2xy\rho}{\nu(1-\rho^2)}\right)^{-\frac{\nu+2}{2}} dxdy, \quad (3)$$

$$\rho_t = \Lambda_1\left(\Phi_0^T + \Phi_1^T \rho_{t-1} + \right.$$
$$\left. + \Phi_2^T \frac{1}{10}\sum_{j=1}^{10} T^{-1}(u_{t-j}).T^{-1}(v_{t-j})\right)$$

with ρ_t and ν being the related time-varying parameter of the bivariate Student t copula, and where T^{-1} is the inverse of the Student t c.d.f and

$\Lambda_1(x) = (1-e^{-x})(1+e^{-x})^{-1}$ is a logistic transformation to keep the dependence parameter ρ_t within its domain (–1,1);

for the time-varying Gumbel copula,

$$C(u,v,\theta) = \exp\left[-\left((-\log(u))^\theta + (-\log(v))^\theta\right)^{\frac{1}{\theta}}\right], \quad (4)$$

$$\theta_t = \Lambda_2\left(\Phi_0^G + \Phi_1^G \rho_{t-1} + \Phi_2^G \frac{1}{10}\sum_{j=1}^{10}|u_{t-j} - v_{t-j}|\right),$$

with θ_t and ν being the related time-varying parameter of the bivariate Gumbel copula, and $\Lambda_2(x) = (1+e^{-x})^{-1}$ is a logistic transformation to keep the dependence parameter θ_t within its domain.

In all the chosen copulas, the process that governs the time-varying dependence structure is characterized by a persistence effect, represented by the coefficients Φ_0^N, Φ_0^T and Φ_0^G, a variability, represented by the coefficients Φ_1^N, Φ_1^T and Φ_1^G.

3. EMPIRICAL RESULTS

3.1. Data

Daily data on primary bank equity indexes in the G7 countries (US, France, Japan, Italy, Canada, and Germany) from FactSet were collected. These bank equity indexes are market capitalization weighted for the period from January 2, 2013 to May 24, 2019 (U.S. trading days only). The daily returns are defined as $R_{i,t} = \log(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ is the daily closing value of bank index i on day t.

Table 1 reports the summary statistics of daily log-returns of the G7 bank equity indices. Pearson correlation coefficient displays the correlations between each country bank index returns and UK bank index returns. UK bank stocks registered the lowest average returns over the period 2013–2019 among the G7 counterparts. The highest volatility, as indicated by the standard deviation, is seen in Italy and Germany. This is not surprising, especially for the Italian banking sector, as it has suffered from many economic downturns like the debt crisis. The descriptive statistics also show

Table 1. Descriptive statistics for returns on bank equity indices

Country	Mean	Std. dev.	Skewness	Kurtosis	Correlation	
					Pre	Post
UK	−0.032	1.379	−1.201	20.747	1.00	1.00
US	0.037	1.197	−0.291	8.496	0.54	0.43
France	−0.014	1.811	−1.247	21.628	0.77	0.70
Japan	0.004	1.628	0.072	10.363	0.29	0.24
Italy	−0.014	2.228	−0.838	17.530	0.69	0.60
Canada	0.011	0.951	−0.116	8.570	0.54	0.40
Germany	−0.103	2.179	−0.301	10.265	0.74	0.63

that the return distributions are skewed and fat-tailed. Furthermore, the correlations between UK bank index returns and the other G7 returns are highly positive and significant before and after the Brexit referendum. To a lesser extent, Japan's bank returns display a weak correlation with UK bank returns. Nevertheless, a drop in the correlations after the Brexit referendum was noticed, which signals a drop in the dependence structure between the UK banking system and the other G7 banking systems. The effect has plummeted the returns of the European bank returns to a record minimum, during the studied period, much lower than the US, Canada, and Japan.

3.2. Dependence structure

Table 2 summarizes these results by displaying the AR(1)-GJR-GARCH(1,1)-Skewed-t estimated parameters[4]. The latter reflects the short-run dynamics of the volatility, namely α and β, and are all significant for all bank index returns showing that the volatility is intensively reacting to market movements and that shocks to the conditional variance take time to die out. The leverage effect γ is statistically significant for all return series, and there were no remaining autocorrelations in both the standardized residuals and the squared standardized residuals, as indicated by the Ljung-Box and KS statistics.

Table 2. Marginal distribution estimates

Parameter	UK	US	France	Japan	Italy	Canada	Germany
α_0	**−0.037**	**0.021**	**−0.059**	**−0.028**	**−0.026**	**0.012**	−0.108
	(0.029)	(0.027)	(0.042)	(0.029)	(0.045)	(0.022)	(0.051)
α_1	**0.004**	**−0.002**	0.068	0.071	**0.008**	0.079	0.055
	(0.025)	(0.025)	(0.025)	(0.023)	(0.026)	(0.025)	(0.023)
w	0.031	0.103	0.027	0.055	0.064	0.019	0.024
	(0.019)	(0.026)	(0.013)	(0.021)	(0.026)	(0.006)	(0.008)
α_1	0.067	0.097	0.055	0.105	0.072	0.053	0.042
	(0.028)	(0.021)	(0.012)	(0.020)	(0.017)	(0.014)	(0.006)
β_1	0.924	0.840	0.943	0.889	0.915	0.938	0.957
	(0.035)	(0.032)	(0.014)	(0.025)	(0.022)	(0.016)	(0.004)
γ_1	0.609	0.895	0.609	0.499	0.783	0.868	0.439
	(0.212)	(0.174)	(0.166)	(0.111)	(0.170)	(0.236)	(0.172)
Skewness	0.939	0.944	0.927	1.021	0.960	0.915	0.982
	(0.035)	(0.033)	(0.032)	(0.031)	(0.033)	(0.034)	(0.034)
Shape	7.438	6.073	7.539	5.506	7.035	9.916	6.018
	(1.236)	(0.890)	(1.229)	(0.801)	(1.137)	(2.313)	(0.878)
LogLik	−2577.97	−2437.32	−3073.21	−2856.37	−3367.79	−2017.26	−3402.50
Ljung-Box	0.424	0.549	0.786	0.128	0.933	0.927	0.295
KS	0.140	0.363	0.143	0.244	0.375	0.060	0.734

Note: The table reports the estimation results of the marginal distribution using an AR(1)-GJR-GARCH(1,1) Skewed-t model. The standard errors are reported in parentheses. Insignificant values at 5% or less are in bold. Also reported are the *p*-values of the Ljung-Box and Kolmogorov-Smirnov tests for serial correlation in the standardized residuals. Values above 0.05 indicate

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4   Several estimations of an AR(1) return model were also conducted with various volatility specifications, namely asymmetric GARCH, IGARCH, TARCH, and GJR and by alternating between Student – t and Skewed Student – t errors. The estimation results showed that the best goodness-of-fit model for the studied bank returns is with TGARCH-Skewed – t volatility based on the Loglikelihood and AIC criterion.

Table 3 reports the estimation results of the dependence structure for the UK and other G7 bank index return pairs using time-varying copulas. The best copula fits are time-varying Student t copula for the US, France, Canada, Japan, and Germany. This shows a time-varying dependence structure of these countries' banking systems with the UK banking system. The German bank equity market shows to have the greatest dependence with the UK bank equity market, as indicated by Φ_o^T. It is also observed that there is significant dependence persistence, as indicated by the coefficient Φ_1^T, and significant variations between the UK and other G7 bank equity markets, as indicated by the coefficient Φ_2^T, except for the Japanese bank equity market, which displays a lower variation. For the pair of Italy and the UK bank equity returns, the best fit copula is the time-varying normal copula as per the estimated AIC values. This shows that the dependence structure between Italy and the UK bank equity markets is dominantly symmetric, low in level and variation but with high persistence. Such a result could give useful insights for active portfolio risk management.

Figure 1 displays the time-varying dependence structure pair wisely between the UK and the other G7 bank returns. The dependence structure dynamically evolves with an overwhelming increase around the Brexit referendum of mid-June 2016 for the UK and all other G7 countries, except for Japan. This evidence shows that there is a risk spillover transmitted from UK banking system to the US, France, Italy, Canada, and Germany. Japan's banking system remains immune against a Brexit effect, and this is not strange as its banking system differs from European or North American counterparts.

Considering 10 days before and after the Brexit referendum, Table 4 reports the dependences between pairs formed with the UK and each of the

Table 3. Time-varying dependence estimates

Coefficient	US	France	Japan	Italy	Canada	Germany
Normal copula						
Φ_0^N	0.038	0.115*	0.158	0.079	0.711*	0.173*
	(0.135)	(0.048)	(0.197)	(0.051)	(0.173)	(0.107)
Φ_1^N	0.922*	0.853*	0.531	0.874*	−0.518	0.801*
	(0.249)	(0.055)	(0.598)	(0.069)	(0.333)	(0.119)
Φ_2^N	0.024	0.066*	−0.032	0.051*	0.417*	0.039*
	(0.049)	(0.022)	(0.048)	(0.020)	(0.138)	(0.023)
AIC	−390.20	−1120.01	−94.79	−718.39	−335.03	−931.42
Student t copula						
Φ_0^T	0.788*	0.408*	0.402*	0.614*	0.738*	0.796*
	(0.215)	(0.060)	(0.059)	(0.176)	(0.194)	(0.301)
Φ_1^T	−0.410*	0.552*	−0.234	0.203*	−0.520	0.163*
	(0.197)	(0.065)	(0.152)	(0.096)	(0.363)	(0.045)
Φ_2^T	0.160*	0.093*	−0.053*	0.111*	0.306*	0.066*
	(0.046)	(0.016)	(0.031)	(0.019)	(0.106)	(0.025)
v	8.552*	9.801*	18.380*	13.262*	9.845*	9.519*
	(1.354)	(1.607)	(2.351)	(2.965)	(1.725)	(1.407)
AIC	−399.84	−1123.66	−97.86	−715.61	−348.82	−954.83
Gumbel copula						
Φ_0^G	0.031	1.699*	0.266*	0.291*	−1.165*	0.270
	(0.266)	(0.088)	(0.065)	(0.074)	(0.304)	(0.860)
Φ_1^G	0.098	0.915*	0.664*	0.718*	−0.981*	0.612
	(0.664)	(0.051)	(0.045)	(0.069)	(0.015)	(1.315)
Φ_2^G	−2.015	−0.738*	1.689*	−1.443*	−0.313	−0.797
	(1.689)	(0.369)	(0.978)	(0.363)	(1.010)	(2.429)
AIC	−361.02	−1013.98	−79.32	−634.86	−282.94	−849.51

Note: The table reports parameter estimates for different time-varying copula models between G7 and UK bank equity returns. The standard errors are reported in parentheses. An asterisk (*) indicates significance of the parameters at 5%. Akaike Information Criterion (AIC) values (in bold) indicate the best copula fit.
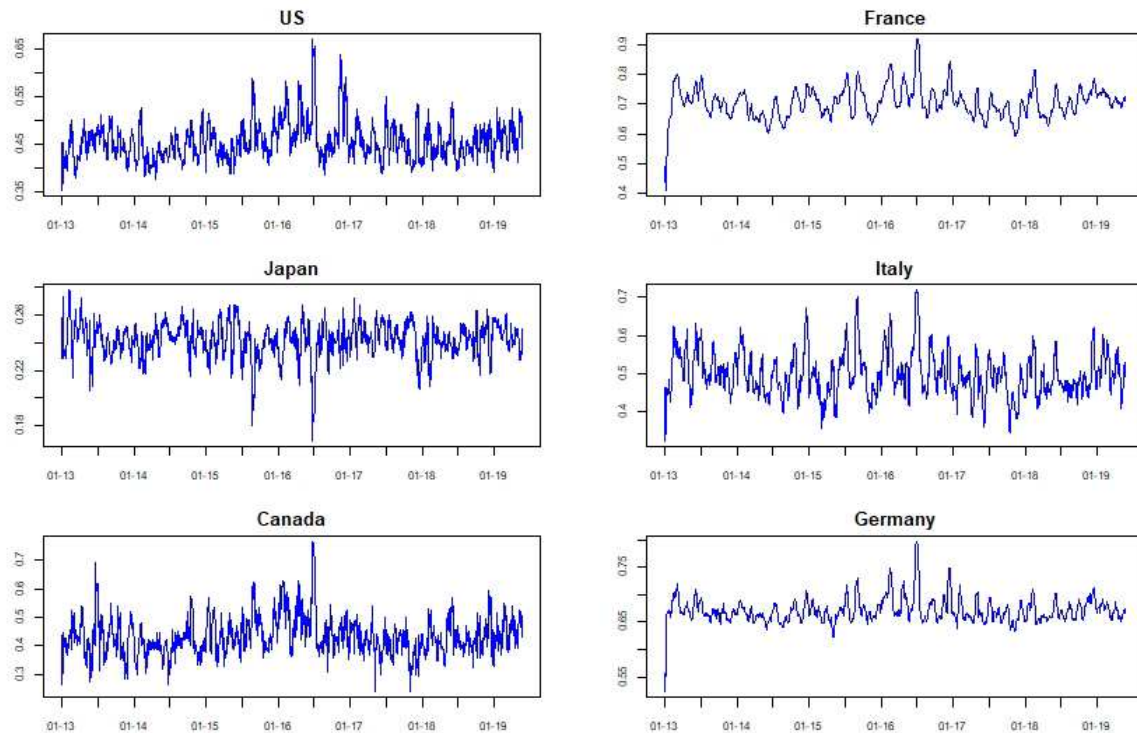
Figure 1. Time-varying dependence of best copula fits between G7 and UK bank equity returns.

G7 bank returns. Obviously, for the European banks, the dependence structure has noticeably jumped after the Brexit referendum more than their North American and Japanese counterparts.

Table 4. Dependence structure before and after the Brexit referendum

Date	US	France	Japan	Italy	Canada	Germany
2016-06-09	0.469	0.725	0.238	0.652	0.432	0.672
2016-06-10	0.461	0.723	0.247	0.650	0.460	0.675
2016-06-13	0.466	0.725	0.239	0.651	0.466	0.679
2016-06-14	0.488	0.731	0.237	0.655	0.524	0.685
2016-06-15	0.473	0.737	0.228	0.657	0.437	0.688
2016-06-16	0.486	0.742	0.232	0.656	0.507	0.689
2016-06-17	0.478	0.756	0.222	0.664	0.524	0.700
2016-06-20	0.497	0.778	0.211	0.676	0.570	0.719
2016-06-21	0.491	0.795	0.213	0.687	0.550	0.730
2016-06-22	0.493	0.810	0.215	0.695	0.551	0.737
Referendum	0.535	0.825	0.205	0.709	0.608	0.745
2016-06-24	0.671	0.855	0.169	0.739	0.765	0.773
2016-06-27	0.636	0.876	0.180	0.762	0.741	0.788
2016-06-28	0.652	0.891	0.185	0.780	0.760	0.795
2016-06-29	0.637	0.902	0.185	0.792	0.723	0.797
2016-06-30	0.644	0.910	0.186	0.801	0.747	0.797
2016-07-01	0.640	0.916	0.189	0.809	0.728	0.796
2016-07-05	0.656	0.918	0.189	0.812	0.700	0.790
2016-07-06	0.634	0.916	0.198	0.812	0.686	0.777
2016-07-07	0.643	0.914	0.196	0.812	0.696	0.769
2016-07-08	0.648	0.913	0.197	0.814	0.690	0.764

4. DISCUSSION

The main results in this paper illustrate evidence of a large co-dependence between the UK banks to other European banks in Germany, Italy, and France. The Brexit announcement has led to an increase in dependence between the UK banks and the European banks, which resulted in a decline in the EU banks' share prices. Major European subsidiaries and branches operating in the UK are Deutsche Bank, BNP Paribas, Societe Generale, ING, and UniCredit. There is an on-going concern on the future of these financial services knowing that the UK is the largest European exporter of financial services.

The results further indicate that the increase in dependency was weaker following the referendum for non-EU G7 countries. Many US investment banks based their EU headquarters in the UK for their operations and used banking and investment services licenses to provide trading and service throughout Europe. However, after the Brexit announcement, there is uncertainty concerning the future operations of banks and the regulatory environment, as it is not clear whether banks located in the UK will still enjoy the same access to EU financial markets as before.

Overall, the dependence structure found between the UK and the other G7 bank equity returns is stronger in a bear market, such as it has happened around Brexit. This is in line with the fact reported on international equity markets (see, for example, Ang & Bekaert, 2002; Das & Uppal, 2004). Besides, such asymmetric behavior is an important ingredient for cross-country portfolio diversification.

CONCLUSION

The underlying changes in the G7 bank equity returns' dependence structure before and after the Brexit referendum were investigated. Time-varying copula models are used to verify the changes in the dependence structure, mainly in tail dependence, as they offer important advantages in the analysis of co-movements of financial time series over other techniques. The results revealed significant persistence and variability in the time-varying dependence structures among G7 bank equity markets. Using the chosen time-varying copulas, it was also found that the UK bank equity market has a high level of dependence with the German bank market and a low level with the Italian bank market. Considering these findings, this suggests an asymmetric risk spillover with a large magnitude from the UK bank returns to its European counterparts and a lower magnitude than the other G7 countries. It is clear that Brexit referendum has injected a great deal of uncertainty to the G7 banking industry, and as it is now evident that the UK is phasing out its EU membership, further research might seek to look at the dependence structure, which would provide additional insights to portfolio managers and market participants.

AUTHOR CONTRIBUTIONS

Conceptualization: Ramzi Nekhili.
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