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Research article

On macroeconomic determinants of co-movements among international stock markets: evidence from DCC-MIDAS approach

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Abstract: This study aims to examine the macro-financial dynamics of the time-varying co-movements between the daily stock market returns of G7 and BRICS-T countries using a two-step procedure. Firstly, we decompose the dynamic conditional correlations between the daily stock market returns into the short-term (daily) and the long-term (quarterly) components using the DCC-MIDAS (Dynamic Conditional Correlation-Mixed Data Sampling) method for the period from 2002 to 2018. Then, we estimate the relationship between the quarterly DCC-MIDAS correlations and quarterly macroeconomic variables that represent the economic-financial proximity between country pairs using the System GMM (Generalized Method of Moments) method. Empirical results suggest that the most important factors which explain the long-term dynamic conditional correlations between the stock market returns of G7 and BRICS-T countries are the differences in GDP growth rates, five-year CDS risk premiums, and EPU (Economy Policy Uncertainty) indices between the country pairs.

Keywords: stock markets; time-varying co-movements; macroeconomics; DCC-MIDAS

JEL Codes: C33, C58, E44, G15

1. Introduction

This paper investigates the macro-financial underlying of the time-varying co-movements among stock market returns in G7 and BRICS-T countries. For this purpose, firstly, we decompose the dynamic conditional correlations among the daily stock market returns of the countries in the sample into the short-term (daily) and the long-term (quarterly) components using the DCC-MIDAS

(Dynamic Conditional Correlation-Mixed Data Sampling) method proposed by Colacito et al. (2011). Then, we estimate the relationship between the long-term dynamic conditional correlations derived from the DCC-MIDAS models and the macroeconomic variables that represent economic-financial proximity between country pairs via the dynamic panel data methodology.

Since the emergence of globalization in the 1980s, the removal of obstacles to international trade and the liberalization of capital movements have gradually led to highly integrated economic and financial systems across the world. News on market conditions spread more quickly and effectively due to significant developments in information and communication technologies, particularly in the last two decades. Thanks to cheaper costs of information market participants can respond to news in the global markets more rapidly, thereby facilitating the acceleration of international capital flows. This process has given rise to the internationalization of stock markets all over the world, and has brought about increased interdependence among stock markets. Particularly, after the adverse effects of the 2008 global financial crisis and the European sovereign debt crisis in global financial markets, the analysis of co-movements among international stock markets have become popular and intriguing issues for researchers, policy makers and investors. In the related literature, the issues on the co-movements among stock markets have been examined by several studies using different methods, country groups, time periods and data frequencies (Hamao et al., 1990; Arouri et al., 2010; Zhou et al., 2012; Dimitriou et al., 2013; Jung and Maderitsch, 2014; Liu et al., 2017 and Das et al., 2018). Although there is a considerable literature on how integration among stock markets occurs, a limited number of studies investigate the macro-financial factors behind integration among stock markets. Furthermore, understanding the major macro-financial dynamics behind the co-movements among stock markets is also crucial as well as knowing whether these relationships exist.

In general, the majority of studies that investigate the reasons of the co-movement among stock markets follow a two-stage procedure. These studies initially examine the interaction among stock markets, and then investigate the causes of this interaction. To explain the interaction among stock markets, these studies use various economic, financial and social variables including bilateral trade, foreign portfolio investments, inflation rate, interest rate, economic growth rate, exchange rate regime-volatility, stock market size, distances between financial centers and cultural effects (Bracker et al., 1999; Pretorius, 2002; Walti, 2005; Tavares, 2009; Asgharian et al., 2013; Mobarek et al., 2016 and Thomas et al., 2019). Stock markets are expected to be highly correlated with each other due to both the strong financial relations between countries and the similarities of economic policies in these countries. The stock market performances of countries that have similar macroeconomic indicators are supposed to converge towards each other, otherwise it is supposed to diverge from each other (Pretorius, 2002). In other words, the low absolute value of the difference between economic indicators from two countries is an indication of having high co-movements between the stock markets of those countries (Luchtenberg and Vu, 2015; Mobarek et al., 2016; Vithessonthi and Kumarasinghe, 2016 and Nitoi and Pochea, 2019). In addition, if there is a strong bilateral trade relationship between two countries, stock markets of those countries are expected to be highly interrelated (Walti, 2011). In the same vein, the empirical results put forward that there is a positive relationship between bilateral trade and stock market co-movements (Pretorius, 2002; Tavares, 2009 and Beine and Candelon, 2011). On the contrary, some studies suggest that there is not a significant relationship between bilateral trade and stock market co-movements (Didier et al., 2012; Vithessonthi and Kumarasinghe, 2016 and Thomas et al., 2019). Besides, it known that the co-movements between stock markets of countries with a similar language and culture in the nearby geography are higher than the co-movements between stock markets of countries with different languages and cultures in the distant geography (Walti, 2005 and Lucey and Zhang, 2010). On this backdrop, an attempt to investigate the macro-financial dynamics of the time-varying co-movements among stock markets is crucial to shed light on financial institutions, financial analysts, portfolio managers and global investors.

The seminal paper of Colacito et al. (2011) puts forward that the fundamental causes of time-varying conditional correlations can be captured by slowly moving processes of dynamic conditional correlations. Thus, economic and financial factors that represent the economic-financial proximity between countries are expected to be connected with slowly moving long-term components rather than rapidly moving short-term components of dynamic conditional correlations between stock market returns. Whereas, in the vast majority of studies in the related literature, dynamic conditional correlations between stock markets have not been decomposed into the short- and long-term components, but instead, the relationships between dynamic conditional correlations and macroeconomic indicators have been directly analyzed without any decomposition (Narayan et al., 2014; Thomas et al., 2019 and Wang and Guo, 2020). However, it is inconvenient to examine the relationships between dynamic conditional correlations and macroeconomic fundamentals without such decomposition. On the contrary to the other econometric time series models, the DCC-MIDAS approach decomposes the short- and long-term components of the dynamic conditional correlations between stock market returns of two countries. By this way, this approach can remove rapidly moving (temporary) effects in the dynamic conditional correlations. It enables us to focus on the relationship between the slowly moving long-term components of dynamic conditional correlations among stock markets and macroeconomic variables.

The central question of this paper is whether the economic-financial proximity between G7 and BRICS-T countries have an impact on the time-varying co-movements between stock markets of those countries. This broad sample enables us to examine the relationships both among advanced economies and among emerging economies as well as the relationships between advanced and emerging economies. By this way, as opposed to the common approach in the literature, this paper considers the relationships among all possible pairs of stock markets instead of keeping just the stock markets of the USA at the center. The empirical analysis of this paper consists of two stages. In the first stage, the DCC-MIDAS method is used to decompose the short (daily) and long-term (quarterly) dynamic conditional correlations among stock market returns. This method enables us to regress the long-term (quarterly) components of dynamic conditional correlations between stock markets of G7 and BRICS-T countries with the quarterly macroeconomic variables that represent the macro-financial proximity between each country pairs. In the second stage of the empirical analysis, the dynamic panel data methodology (the System GMM method) is employed unlike the majority of the literature in order to take the dynamic structure of the dataset into account. From a methodological perspective, one of our contributions is to estimate the DCC-MIDAS models based on the GARCH-MIDAS model with rolling window realized volatility. However, up until now the literature, including Colacito et al. (2011), has estimated the DCC-MIDAS models based on the GARCH-MIDAS model with fixed window realized volatility. To the best our knowledge, this study is the first attempt to investigate the macro-financial dynamics of the time-varying co-movements between the daily stock market returns of G7 and BRICS-T countries.

The remainder of this study structured as follows: Section 2 presents the DCC-MIDAS model; Section 3 reports the data and variables; Section 4 discusses the empirical results; and Section 5 concludes the study.

2. The DCC-MIDAS model

We use the DCC (Dynamic Conditional Correlation)-MIDAS (Mixed Data Sampling) model proposed by Colacito et al. (2011) to decompose the short- and the long-term components of the dynamic conditional correlations between stock market returns of two countries. This model is a multivariate extension of the GARCH-MIDAS model (Engle et al., 2006) which is based on dynamic conditional correlations. In the GARCH-MIDAS model, two components of volatility are distilled, one relating to short-term fluctuations, and the other relating to a secular component. The univariate GARCH-MIDAS process can be written as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t \times g_{i,t}}\xi_{i,t}, \qquad \forall i = 1, \dots, N_t \tag{1}$$

where $\xi_{i,t} | \Omega_{i-1,t} \sim N(0,1)$, and $\Omega_{i-1,t}$ is the information set up to day $(i-1)$ of period t. $r_{i,t}$ is the return of an asset on day i in period t (month, quarter, biannual etc.), $g_{i,t}$ is the short-term variance component which explains daily fluctuations, and τ_t is the slowly moving long-term component. The short-term component $g_{i,t}$ is presumed to follow a GARCH (1,1) model:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{2}$$

with restrictions $\alpha > 0, \beta \geq 0,$ and $\alpha + \beta < 1$. The long-term component τ_t is modeled using the MIDAS regression:

$$\tau_t = m + \theta \sum_{k=1}^{K} \vartheta_k(\omega_1, \omega_2) RV_{t-k} \tag{3}$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{4}$$

where RV_t is the realized volatility, and $\vartheta_k(\omega_1, \omega_2)$ indicates the MIDAS weighting scheme. There are two specifications for the long-term component τ_t. The first one is the component τ which is fixed on days i in a period t and the second one is the component τ which is varied on days i in a period t. Equation (3) represents the GARCH-MIDAS model with fixed time span RV (realized volatility) and Equation (5) indicates the GARCH-MIDAS model with rolling window RV (realized volatility).

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \vartheta_k(\omega_1, \omega_2) RV_{i-k}^{(rw)} \tag{5}$$

$$RV_i^{(rw)} = \sum_{j=1}^{N'} r_{i-j}^2 \tag{6}$$

The MIDAS weighting scheme $\vartheta_k(\omega_1, \omega_2)$ used in Equation (3) and Equation (5) defined by a beta lag polynomial in Equation (7) and an exponentially weighted in Equation (8).

$$\vartheta_k(\omega) = \frac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K} (j/K)^{\omega_1 - 1}(1 - j/K)^{\omega_2 - 1}} \tag{7}$$

$$\vartheta_k(\omega) = \omega^k / (\sum_{j=1}^{K} \omega^j) \tag{8}$$

In the DCC-MIDAS model, the dynamic conditional correlations are decomposed into short-term and slowly moving secular component with the same logic to the GARCH-MIDAS model. We follow a two-stage procedure to estimate the parameters of the DCC-MIDAS model. In the first stage, the parameters of the univariate GARCH-MIDAS model are estimated, and then the DCC-MIDAS model is estimated by using the Quasi-Maximum Likelihood method. The multivariate DCC-MIDAS process can be written as follows:

$$q_{xy,t} = \bar{\rho}_{xy,t}\,(1-a-b) + a\xi_{x,t-1}\xi_{y,t-1} + bq_{xy,t-1} \tag{9}$$

where $\xi_{x,t-1}$ and $\xi_{y,t-1}$ are the standardized residuals from the univariate GARCH-MIDAS model. The $q_{xy,t}$ term is the short-term correlation component, while $\bar{\rho}_{xy,t}$ is the slowly moving long-term component of the dynamic conditional correlations between assets x and y. The parameters a and b must satisfy the stability conditions which are $a, b > 0$ and $a + b < 1$. The long-term correlation component is defined as:

$$\bar{\rho}_{xy,t} = \sum_{k=1}^{K} \vartheta_k(\omega_1, \omega_2) c_{xy,t-1} \tag{10}$$

$$c_{xy,t} = \frac{\sum_t^{k=t-N} \xi_{x,k}\xi_{y,k}}{\sqrt{\sum_t^{k=t-N} \xi_{x,k}^2}\sqrt{\sum_t^{k=t-N} \xi_{y,k}^2}} \tag{11}$$

where $c_{xy,t}$ is the realized correlation, and $\vartheta_k(\omega_1, \omega_2)$ denotes the MIDAS weighting scheme. The correlations can be calculated as:

$$\rho_{xy,t} = \frac{q_{xy,t}}{\sqrt{q_{xx,t}}\sqrt{q_{yy,t}}} \tag{12}$$

where $\rho_{xy,t}$ indicates the dynamic conditional correlations between assets x and y.

3. Data

The data set consists of two parts. In the first part, we make use of daily stock market indices of G7 (USA, Germany, United Kingdom, France, Italia, Japan, Canada) and BRICS-T countries (Brazil, Russia, India, China, South Africa, Turkey) for the period from January 2nd, 2002 to September 19th, 2018[1.] The return series are calculated using:

$$r_{i,t} = 100 \times [ln(P_{i,t}) - ln(P_{i,t-1})] \tag{13}$$

Table 1 shows the descriptive statistics of logarithmic returns of daily stock market indices. All of the log-returns have negative skewness. Besides, all of them have leptokurtic distribution as regards to their kurtosis.

[1]The sample period starts from January 2nd, 2002 in order to keep away from the unstable periods of emerging economies during the 1990s and early 2000s.

Table 1. Descriptive statistics of the daily stock returns.

	Mean	Min	Max	Std. Dev.	Skewness	Kurtosis	Observations
S&P 500	0.0213	−9.4695	10.957	1.1602	−0.2611	13.617	4361
DAX 30	0.0197	−7.4335	10.797	1.4389	−0.0058	8.2199	4361
FTSE	0.0059	−11.750	12.198	1.3560	−0.2598	13.341	4361
CAC 40	0.0035	−9.4715	10.594	1.4085	−0.0048	8.9249	4361
FTSE MIB	−0.0095	−13.331	10.876	1.5021	−0.2054	8.5680	4361
NIKKEI 225	0.0185	−12.111	13.234	1.4430	−0.4737	10.822	4361
S&P/TSE	0.0170	−9.7880	9.3703	1.0185	−0.6833	15.260	4361
BOVESPA	0.0401	−12.096	13.679	1.6898	−0.0996	7.8687	4361
RTS	0.0337	−21.199	20.203	2.0383	−0.4528	14.298	4361
NIFTY 500	0.0599	−12.884	15.034	1.3436	−0.5355	14.207	4361
SHANGHAI	0.0116	−9.2561	9.0345	1.5451	−0.4318	8.1483	4361
FTSE/JSE	0.0386	−7.5807	6.8340	1.1519	−0.1492	6.7317	4361
BIST 100	0.0446	−13.340	12.127	1.7729	−0.1495	7.8664	4361

In the second part, we employ quarterly macroeconomic and financial variables to represent the economic-financial proximity between each country pair, for the period of January, 2006 to August, 2018. The reason why the data set starts with the year of 2006 rather than the year of 2002 in the second stage is the initial observations used for the prediction of the MIDAS weighting scheme in the DCC-MIDAS analysis. To be more precise, we use up to forty-five MIDAS lags for the DCC process for each model. Besides, the country-specific dataset has twenty-two daily observations ($N = 22$) for each month. Thus, the DCC MIDAS method makes use of up to 990 initial observations ($22 \times 45 = 990$), which corresponds to the first four years of daily stock returns, for prediction of the MIDAS weighting scheme. All the data are compiled from the Thomson Reuters Datastream database. Table 2 provides the definitions of the variables used in the empirical analysis.

Broadly, there are three main explanations on why time-varying co-movements among stock markets exist. The first one is the contagion effect that cannot be explained by economic fundamentals, the second one is economic integration which means that if two economies are more integrated then their stock markets will be more interdependent. Finally, the third one is stock market characteristics that affect the extent of interdependence among stock markets. Economic integration contains not only the co-movement in economic factors that affect stock market returns, such as inflation rate, economic growth rate, and interest rate, but also bilateral trade relations. The stronger bilateral trade links between two countries, the higher co-movements between their stock markets. Moreover, according to the cash flow model, various macroeconomic factors, namely inflation rate, economic growth rate, and interest rate, affect the stock market performance (Pretorius, 2002). Since these macroeconomic variables affect stock market returns, the proximity between macroeconomic variables of different countries will impact the co-movement between their stock markets. In other words, as the macroeconomic indicators of two countries approach each other, the co-movement between the stock markets of these countries is expected to increase. In this regard, it is plausible to expect that there is a negative relationship between the time-varying co-movements among stock market returns and the differences in GDP growth rate, inflation rate, term spread, and economic policy uncertainty index. So far, the differences in the economic policy uncertainty indices between country pairs have not been used as regressors in the related literature. The inclusion of those absolute differences is also one of our contributions into the related literature. Besides, as a global factor, the S&P 500 volatility is used in order to take into account possible effects of the US stock market.

In addition, Naifar (2012) puts forward that there is a positive relationship between the stock market volatility and the CDS risk premium. This empirical result implies that an increase in CDS risk premium leads to a rise in stock market volatility. In this regard, the rise in stock market volatility of two countries is expected to increase the co-movement among those stock markets (Min and Hwang, 2012). On this backdrop, we benefit from the differences in five-year CDS risk premium between country pairs in order to apprehend the time-varying co-movements among stock markets. Based on the related literature, our expectation is to have a positive relationship between the five-year risk premium and the stock market co-movements.

Table 3 presents the descriptive statistics of dependent and explanatory variables for the different country pairs. The sample contains 78 country pairs in which 21 of them are the G7 country pairs, 15 of them are the BRICS-T country pairs, and 42 of them are the G7 and BRICS-T country pairs. The long-term dynamic conditional correlations (mean) and the bilateral trade (mean) are higher in the G7 country pairs than in the G7&BRICS-T and the BRICS-T country pairs. Besides, the highest GDP growth rate and the term spread differences (mean) belong to the BRICS-T country pairs and the highest CDS risk premium difference (mean) pertains to the G7&BRICS-T country pairs. On the other hand, the lowest inflation rate and the EPU (Economic Policy Uncertainty) index differences belong to the G7 country pairs.

Table 2. Definitions of the variables.

Variable names	Definition
Panel A: Dependent variable	
Dccmidascorr	*Dccmidascorr* shows the long-term (quarterly) dynamic conditional correlations between stock markets of countries x and y. These correlations are calculated using the DCC-MIDAS model. We then employ the Fisher-Z transformation to adjust the potential problem of non-normality in the dynamic conditional correlation. $\grave{\rho}_{xy,t} = (1/2)\text{In}[(1+\rho_{xy,t})/(1-\rho_{xy,t})]$ For similar analysis, see (Beine and Candelon, 2011; Colacito et al., 2011)
Panel B: Explanatory variables (economic)	
Bilateral trade	*Bilateral trade* indicates the quarterly average bilateral trade between countries x and y. Calculated as: $[(X_{xy,t}/X_{x,t}) + (M_{xy,t}/M_{x,t}) + (X_{yx,t}/X_{y,t}) + (M_{yx,t}/M_{y,t})]/4$ where $X_{xy,t}$ and $M_{xy,t}$ are exports and imports from country x to country y during quarter t. $X_{yx,t}$ and $M_{yx,t}$ are exports and imports from country y to country x during quarter t. $X_{x,t}$, $M_{x,t}$ and $X_{y,t}$, $M_{y,t}$ indicate the total exports and total imports of country x and country y during quarter t, respectively. For similar analysis, see (Bracker et al., 1999; Mobarek et al., 2016)
GDP growth rate	*GDP growth rate* indicates the logarithmic transformation of the absolute differences between the GDP growth rate of country x and country y, during quarter t. $ln\lvert\Delta GDP_{x,t} - \Delta GDP_{y,t}\rvert$. For similar analysis, see (Johnson and Soenen, 2002; Beine and Candelon, 2011)
Inflation rate	*Inflation rate* shows the logarithmic transformation of the absolute differences between the inflation rate of country x and country y, during quarter t. $ln\lvert\pi_{x,t} - \pi_{y,t}\rvert$ For similar analysis, see (Bracker et al., 1999; Pretorius, 2002)
EPU	*EPU*[2] shows the logarithmic transformation of the absolute differences between the economic policy uncertainty index of country x and country y, during quarter t. $ln\lvert EPU_{x,t} - EPU_{y,t}\rvert$ For similar analysis, see (Peng et al., 2018)
Panel C: Explanatory variables (financial)	
Term spread	*Term spread* represents the logarithmic transformation of the absolute differences between term spread rate of country x and country y, during quarter t. Term spread rate is defined by the differences between the long-term 10-year government bond yield and the 3-month interbank rate. $ln\lvert ts_{x,t} - ts_{y,t}\rvert$. For similar analysis, see (Mobarek et al., 2016)
CDS risk premium	*CDS risk premium* represents the logarithmic transformation of the absolute differences between the five-year CDS risk premium of country x and country y, during quarter t. $ln\lvert CDS_{x,t} - CDS_{y,t}\rvert$ For similar analysis, see (Min and Hwang, 2012)
Volatility ratio	*Volatility ratio* shows the ratio of the stock market volatilities of country x and country y, during quarter t. $[\,(Vol_{x,t})/\,(Vol_{y,t})]$ For similar analysis, see (Pretorius, 2002)
Panel D: Control variables (USA factors)	
S&P 500 volatility	*S&P 500 volatility* indicates the volatility of the S&P 500 index during quarter t. $(Vol_{S\&P\ 500,t})$ Related references: (Kim et al., 2015)
Global financial crisis	This is the dummy variable which takes value 1 for the period from 2007 q3 to 2009 q3, else the value is 0. Related references: (Romer, 2012)

[2]The EPU variables are not calculated for the country pairs that includes either Turkey or South Africa due to the lack of data.

Table 3. Descriptive statistics of the dependent and explanatory variables.

	Mean	Min	Max	Std. Dev.	Skewness	Kurtosis	Observations	Country Pairs
All country pairs								
Dccmidascorr	0.402	−0.017	0.968	0.201	0.500	2.752	3978	78
Bilateral trade	0.040	0.0009	0.450	0.052	4.631	31.36	3978	78
GDP growth rate	4.452	0.010	32.37	5.473	2.137	7.895	3978	78
Inflation rate	3.737	0.010	16.47	3.208	1.085	3.851	3978	78
Term spread	1.565	0.013	12.61	1.428	2.359	12.15	3978	78
CDS risk premium	97.41	0.354	663.13	91.12	1.804	8.425	2769	78
EPU	79.79	1.020	609.16	77.47	2.404	10.34	2805	55
Volatility ratio	1.002	0.145	5.144	0.604	1.541	5.982	3978	78
S&P 500 volatility	0.040	0.010	0.191	0.040	2.646	9.659	3978	78
G7 country pairs								
Dccmidascorr	0.553	0.163	0.968	0.210	0.133	1.990	1071	21
Bilateral trade	0.063	0.006	0.450	0.084	3.128	13.05	1071	21
GDP growth	0.753	0.010	4.220	0.627	1.529	6.217	1071	21
Inflation rate	1.094	0.010	5.064	0.852	1.208	4.561	1071	21
Term spread	0.936	0.013	4.719	0.807	1.821	7.173	1071	21
CDS risk premium	42.03	0.715	366.31	61.84	2.815	11.88	783	21
EPU	76.77	1.020	561.95	80.99	2.503	10.64	1071	21
Volatility ratio	1.166	0.271	5.144	0.617	1.464	5.436	1071	21
S&P 500 volatility	0.040	0.010	0.191	0.040	2.646	9.659	1071	21
G7&BRICS-T country pairs								
Dccmidascorr	0.363	−0.017	0.770	0.171	0.194	2.292	2142	42
Bilateral trade	0.032	0.001	0.159	0.029	2.257	8.665	2142	42
GDP growth	5.529	0.010	30.32	5.744	1.943	6.830	2142	42
Inflation rate	5.054	0.051	16.47	3.261	0.688	3.329	2142	42
Term spread	1.635	0.048	11.33	1.397	2.392	12.85	2142	42
CDS risk premium	130.03	0.354	663.13	94.09	1.767	8.647	1493	42
EPU	80.49	2.930	609.16	74.38	2.394	10.60	1428	28
Volatility ratio	0.788	0.145	3.374	0.416	1.228	4.844	2142	42
S&P 500 volatility	0.040	0.010	0.191	0.040	2.646	9.659	2142	42

Notes: *Dccmidascorr* is the dependent variable. *Bilateral trade* shows the ratio of total mutual trade between countries to their total foreign trade volume. *GDP growth rate* indicates the absolute difference between the GDP growth rates, *inflation rate* indicates the absolute difference between the inflation rates, *term spread* indicates the absolute difference between the term spreads, *CDS risk premium* indicates the absolute difference between the five-year CDS risk premiums, and finally, *EPU* shows the absolute difference between economy policy uncertainty indices of country x and country y. For detailed definitions, see Table 2.

4. Empirical results

The central question of this study is whether the economic-financial proximity between G7 and BRICS-T countries have an impact on the time-varying co-movements between stock markets of those countries. The empirical analysis of this study is composed of two stages. In the first stage, we estimate the DCC-MIDAS model based on the GARCH-MIDAS model with rolling window realized volatility to investigate the time-varying co-movements between the stock markets of G7 and BRICS-T countries. To check the robustness of these results, we re-estimate the DCC-MIDAS model based on the GARCH-MIDAS model with fixed window realized volatility. In the second stage, we estimate both the POLS (Pooled Ordinary Least Squares) models and the System GMM (Generalized Method of Moments) models for all country pairs (full sample) including the G7 country pairs, the BRICS-T country pairs, and the G7&BRICS-T country pairs to quantify the macro-financial underlying of the time-varying co-movements among stock markets of those countries. To check the robustness of these results, we re-estimate both the POLS models and the System GMM models for two distinct subsample country pairs which are the G7 country pairs and the G7&BRICS-T country pairs.

4.1. The time-varying co-movements between G7&BRICS-T stock markets

First of all, we decompose the dynamic conditional correlations between log-returns of daily stock market indices of G7 and BRICS-T countries into the short-term (daily) and the long-term (quarterly) components with the help of the DCC-MIDAS model for the period January 2nd, 2002 to September 19th, 2018. The DCC-MIDAS models are separately estimated for 78 country pairs in which 21 of them are country pairs between G7 countries, 15 of them are country pairs between BRICS-T countries and 42 of them are country pairs between G7 and BRICS-T countries. Furthermore, to check the robustness of results, we estimate the DCC-MIDAS model based on both the GARCH-MIDAS model with rolling window realized volatility and the GARCH-MIDAS model with fixed window realized volatility. The estimation results of those models are almost identical. Thus, we only present the estimation results of the DCC-MIDAS models based on the GARCH-MIDAS model with rolling window realized volatility[3].

Table 4 shows the descriptive statistics of the DCC-MIDAS correlations for the G7, European, G7&BRICS-T and BRICS-T country pairs. The DCC-MIDAS correlations (mean) between the stock markets of G7 countries are higher than the DCC-MIDAS correlations (mean) between the stock markets of G7&BRICS-T countries and between the stock markets of BRICS-T countries. Furthermore, the highest DCC-MIDAS correlations (mean) among the G7 country pairs belong to the European country pairs.

[3]All estimation results related to the DCC-MIDAS models are included in the Appendix B.

Table 4. Descriptive statistics of the DCC-MIDAS correlations.

	G7 pairs	European pairs	G7&BRICS-T pairs	BRICS-T pairs
Mean	0.5535	0.7967	0.3630	0.3021
Min	0.1633	0.4102	−0.0179	−0.0058
Max	0.9682	0.9682	0.7702	0.7454
Std. dev.	0.2105	0.1202	0.1716	0.1442
Skewness	0.1339	−1.0128	0.1946	0.4075
Kurtosis	1.9905	3.4721	2.2926	2.7751
Country pairs	21	7	42	15
Observations	1071	306	2142	765

As an illustration, we select three country pairs from the G7 sample. Figure 1 presents the fluctuations of the short- and long-term components of the dynamic conditional correlations over the time for each country pair; USA-Germany, Italia-Canada and UK-France. In Figure 1, the red lines show rapidly moving short-term components of the DCCs between stock markets returns, and the black lines indicate slowly moving long-term components of the DCCs between stock markets returns. As shown in Figure 1, we find that the evolution of the short- and long-term components of the DCCs between stock markets returns are similar, while the long-term DCCs are flatter than the short-term DCCs. Figure 1 also shows that the average long-term DCCs between the log-returns of S&P 500 and DAX 30 are 0.58 for the USA-Germany country pair and the average long-term DCCs between the log-returns of FTSE MIB and S&P/TSE are 0.47 for the Italia-Canada county pair. Lastly, Figure 1 exhibits that the average long-term DCCs between the log-returns of FTSE and CAC 40 are 0.72 for the UK-France country pair.

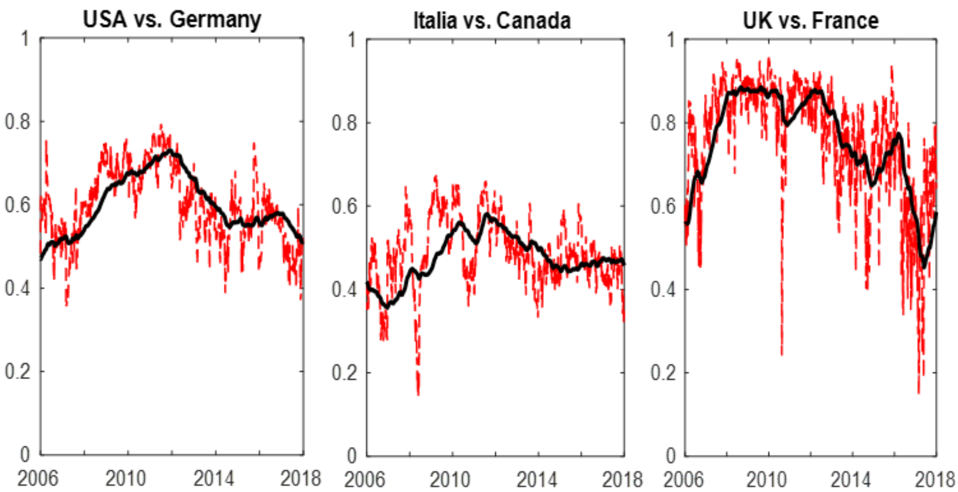

Figure 1. The short- and long-term DCC-MIDAS correlations for selected G7 country pairs. The red lines indicate the short-term correlations and the black lines indicate the long-term correlations.

Table 5 provides the estimation results of the DCC-MIDAS model for the selected G7 country pairs. The results of the S&P 500-DAX 30 pair, the FTSE MIB-S&P/TSE pair, and the FTSE-CAC 40 are given in the first, the second, and the third column, respectively. As shown in Table 5, all parameters are statistically significant at 1% level, except for the weighting parameter. In addition, the stationarity conditions, $a > 0$, $b > 0$, and $a + b < 1$, are satisfied, and the weighting parameter ω is larger than one. This means that the weighting function is rapidly decreasing. The lag numbers of the MIDAS weights in the models are determined according to the values that minimize AIC and BIC.

Table 5. Parameter estimates of the DCC-MIDAS models for selected G7 country pairs.

Dcc-Midas parameters	*S&P 500 vs. DAX 30*	*FTSE MIB vs. S&P/TSE*	*FTSE vs. CAC 40*
a	0.019***(0.002)	0.016***(0.005)	0.066***(0.005)
b	0.963***(0.006)	0.972***(0.007)	0.901***(0.011)
ω	2.163***(0.825)	1.035**(0.510)	1.428***(0.432)
LL	−8476.01	−8815.05	−8990.73
AIC	16958.1	17626.1	17987.5
BIC	16977.1	17635.1	18006.5

Notes: The numbers in the parentheses are standard errors. ***, ** indicate statistical significance at the 1%, 5% level, respectively. LL is the logarithmic likelihood, AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

To illustrate, we also select three country pairs from the G7&BRICS-T sample. Figure 2 presents the fluctuations of the short- and long-term components of the dynamic conditional correlations over the time for each country pair; Germany-South Africa, Japan-Russia and Canada-Brazil. Figure 2 indicates that the short- and long-term components of the DCCs between stock markets returns follow a similar trend while the long-term DCCs are smoother. Moreover, the average long-term DCCs between the log-returns of DAX 30 and FTSE/JSE, between log-returns of the NIKKEI 225 and RTS, and between the log-returns of the S&P/TSE and BOVESPA are 0.56, 0.22, and 0.54 for the country pairs of Germany-South Africa, Japan-Russia, and Canada-Brazil, respectively.

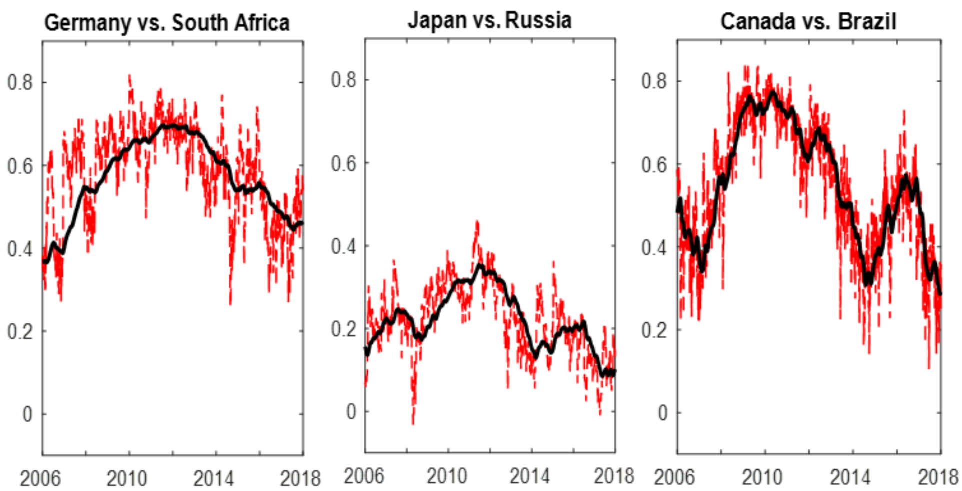

Figure 2. The short- and long-term DCC-MIDAS correlations for selected G7&BRICS-T country pairs. The red lines indicate the short-term correlations and the black lines indicate the long-term correlations.

Table 6 presents the estimation results of the DCC-MIDAS models for selected G7&BRICS-T country pairs. The results of the DAX 30-FTSE/JSE pair, the NIKKEI 225-RTS pair, and the S&P/TSE-BOVESPA pair are provided in the first, the second, and the third column, respectively. In Table 6, all parameters are statistically significant at 1% level, except for the weighting parameter. Besides, the stationarity conditions are satisfied and the weighting parameter ω is larger than one.

Table 6. Parameter estimates of the DCC-MIDAS models for selected G7&BRICS-T country pairs.

Dcc-Midas parameters	*DAX 30 vs. FTSE/JSE*	*NIKKEI 225 vs. RTS*	*S&P/TSE vs. BOVESPA*
a	0.030***(0.005)	0.013***(0.004)	0.037***(0.007)
b	0.951***(0.011)	0.969***(0.014)	0.910***(0.021)
ω	1.497*(0.875)	1.051***(0.095)	1.042***(0.039)
LL	−8813.93	−9495.93	−9503.77
AIC	17633.9	18997.9	19013.5
BIC	17652.9	19016.7	19032.4

Notes: The numbers in the parentheses are standard errors. ***, * indicate statistical significance at the 1%, 10% level, respectively. LL is the logarithmic likelihood, AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

To illustrate, we also choose three country pairs from the BRICS-T sample. Figure 3 shows the fluctuations of the short- and long-term components of the dynamic conditional correlations over the time for each country pair; Russia-China, South Africa-Turkey and India-China. Figure 3 shows that the short- and long-term components of the DCCs between stock markets returns follow a similar pattern while the long-term DCCs are flatter than the short-term DCCs.

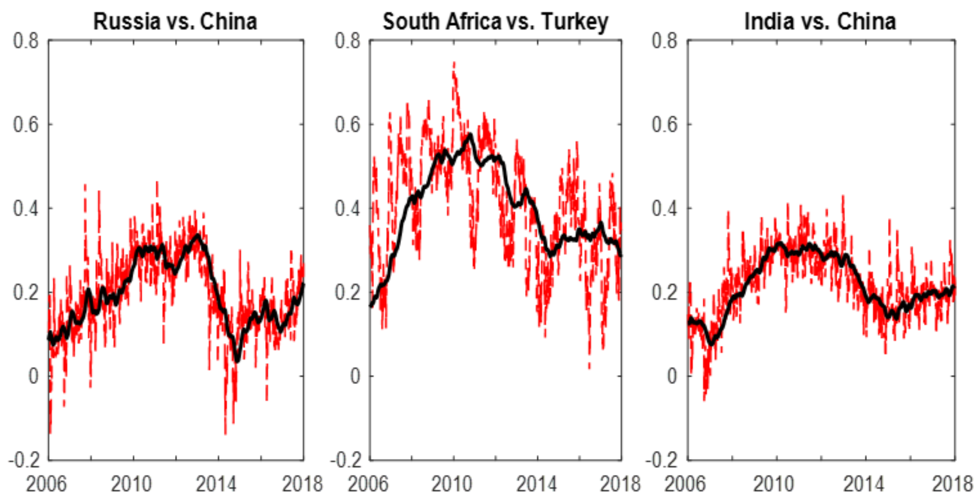

Figure 3. The short- and long-term DCC-MIDAS correlations for selected BRICS-T country pairs. The red lines indicate the short-term correlations and the black lines indicate the long-term correlations.

Furthermore, Figure 3 shows that the average long-term DCCs between the log-returns of RTS and SHANGHAI, and between FTSE/JSE and BIST 100, and between NIFTY 500 and SHANGHAI are 0.19, 0.39, and 0.21 for the country pairs of Russia-China, South Africa-Turkey, and India-China, respectively.

Table 7. Parameter estimates of the DCC-MIDAS models for selected BRICS-T country pairs.

Dcc-Midas parameters	*RTS vs. SHANGHAI*	*FTSE/JSE vs. BIST 100*	*NIFTY 500 vs. SHANGHAI*
a	0.024***(0.007)	0.026***(0.005)	0.020**(0.008)
b	0.894***(0.047)	0.958***(0.011)	0.900***(0.062)
ω	1.969***(0.838)	1.062* (0.606)	1.292** (0.551)
LL	−9398.61	−9380.68	−8993.86
AIC	18803.2	18767.4	17993.7
BIC	18822.1	18786.3	18012.5

Notes: The numbers in the parentheses are standard errors. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. LL is the logarithmic likelihood, AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

Table 7 presents the estimation results of the DCC-MIDAS model for selected BRICS-T country pairs. The results of the RTS-SHANGHAI pair, the FTSE/JSE-BIST 100 pair, and the NIFTY 500-SHANGHAI pair are given the first, the second, and the third column, respectively. As shown in Table 7, all parameters are statistically significant. Besides, the stationarity conditions are satisfied, and the weighting parameter ω is larger than one.

4.2. Determinants of the time-varying co-movements between G7and BRICS-T stock markets

To investigate macroeconomic determinants of the time-varying co-movements between the stock markets of G7 and BRICS-T countries, we make use of both the POLS (Pooled Ordinary Least Squares) method and the System GMM (Generalized Method of Moments) method for the period of January, 2006 to August, 2018. Equation (14) shows the benchmark model. Equations (14–16) are estimated by the pooled OLS method. The dependent variables of these models are quarterly long-term dynamic conditional correlations obtained from the DCC-MIDAS models in previous part. Additionally, we benefit from various quarterly economic and financial variables that represent the economic-financial proximity between countries as explanatory variables explained in Table 2.

$$\rho_{xy,t} = a + \beta_1 Bilateral\ trade_{xy,t} + \beta_2 GDP\ growth\ rate_{xy,t} + \beta_3 Inflation\ rate_{xy,t} + \beta_4 Term\ spread_{xy,t} + \varphi S\&P\ 500\ volatility_t + \lambda GFC_t + \varepsilon_{xy,t} \quad (14)$$

$$\rho_{xy,t} = a + \beta_1 Bilateral\ trade_{xy,t} + \beta_2 GDP\ growth\ rate_{xy,t} + \beta_3 Inflation\ rate_{xy,t} + \beta_4 Term\ spread_{xy,t} + \delta CDS\ risk\ premium_{xy,t} + \gamma EPU_{xy,t} + \varphi S\&P\ 500\ volatility_t + \lambda GFC_t + \varepsilon_{xy,t} \quad (15)$$

$$\rho_{xy,t} = a + \beta_1 Bilateral\ trade_{xy,t} + \beta_2 GDP\ growth\ rate_{xy,t} + \beta_3 Inflation\ rate_{xy,t} + \beta_4 Term\ spread_{xy,t} + \delta CDS\ risk\ premium_{xy,t} + \gamma EPU_{xy,t} + \theta Volatility\ ratio_{xy,t} + \varphi S\&P\ 500\ volatility_t + \lambda GFC_t + \varepsilon_{xy,t} \quad (16)$$

In all equations, $Bilateral\ trade_{xy,t}$ represents the ratio of total mutual trade between countries x and y, at time t to their total foreign trade volume, $GDP\ growth\ rate_{xy,t}$ shows the absolute values of the quarterly GDP growth rate differences between countries x and y, at time t, $Inflation\ rate_{xy,t}$ indicates the absolute values of the quarterly inflation rates differences between countries x and y, at time t, $Term\ spread_{xy,t}$ indicates the absolute values of the quarterly term spread rate differences between countries x and y, at time t, $CDS\ risk\ premium_{xy,t}$ shows the absolute values of the quarterly five-years CDS risk premium differences between countries x and y, at time t, $EPU_{xy,t}$ represents the absolute values of the quarterly Economic Policy Uncertainty Index differences between countries x and y, at time t, $Volatility\ ratio_{xy,t}$ represents the ratio of the stock market volatilities of countries x and y, at time t, $S\&P\ 500\ volatility_t$ indicates the volatility of the S&P 500 index at time t, GFC_t displays Global Financial Crisis dummy variable for the period from 2007 q3 to 2009 q3, and $\varepsilon_{xy,t}$ shows the error term.

Table 8. Estimation results of the POLS models for all country pairs.

Dccmidascorr	*Model 1*	*Model 2*	*Model 3*
Bilateral trade	0.4150***(0.046)	0.5624***(0.064)	0.5509*** (0.064)
GDP growth rate	−0.0360***(0.001)	−0.0458***(0.002)	−0.0468***(0.002)
Inflation rate	−0.0095***(0.002)	−0.0174***(0.003)	−0.0174***(0.003)
Term spread	−0.0138***(0.002)	−0.0365***(0.003)	−0.0373***(0.003)
CDS risk premium		0.0253***(0.003)	0.0233***(0.003)
Economic policy uncertainty		0.0035(0.004)	0.0035(0.004)
S&P 500 volatility	0.8657***(0.070)		0.1735(0.128)
Volatility ratio			−0.0249***(0.006)
Global financial crisis dummy	−0.0262***(0.008)	−0.0853***(0.013)	−0.0941*** (0.015)
Trend	−0.0010***(0.0001)	−0.0068***(0.0003)	−0.0065***(0.0004)
Constant	0.3845***(0.006)	0.4998***(0.022)	0.5159***(0.023)
Number of country pairs	78	55	55
Number of observations	3978	1905	1905
Adjusted R^2	0.209	0.336	0.340
F statistics	151.33***	121.42***	99.29***

Notes: *Dccmidascorr* is the dependent variable. *Bilateral trade* shows the ratio of total mutual trade between countries to their total foreign trade volume. *GDP growth rate* indicates the log transformation of the GDP growth rate differences, *inflation rate* indicates the log transformation of the inflation rate differences, *term spread* indicates the log transformation of the term spread differences, *CDS risk premium* indicates the log transformation of the five-year CDS risk premium differences, and finally, *EPU* shows the log transformation of the economy policy uncertainty index differences between country x and country y. The numbers in the parentheses are standard errors. *** indicates statistical significance at the 1% level. For detailed definitions, see Table 2.

The estimation results of the POLS models are summarized in Table 8, where Model 1, Model 2, and Model 3 correspond to Equations (14), (15), and (16), respectively. As shown in Table 8, the coefficient estimates for bilateral trade are positive and statistically significant in all models. These results are consistent with the studies by Pretorius (2002), Tavares (2009) and Beine and Candelon (2011) which document a positive relationship between bilateral trade and stock market co-movements. These findings indicate that the stronger the bilateral trade links between two countries, the higher the dynamic conditional correlations among their stock markets. Furthermore, we find that the estimated coefficients of GDP growth rate, inflation rate, and term spread' differences are negative and statistically significant in all models. These results are consistent with the findings of Mobarek et al. (2016), Vithessonthi and Kumarasinghe (2016), and Nitoi and Pochea (2019). These results show that the lower the differences in GDP growth rates, inflation rates and term spreads between two countries, the higher the time-varying co-movements between their stock market. We also use the differences in five-year CDS risk premium between country pairs for the determinants of time-varying co-movements between stock market returns. Compatible with expectations, the coefficient estimates for five-year CDS risk premium differences are positive and statistically significant for the Model 2 and the Model 3. Moreover, we investigate the influence of the S&P 500 volatility on the long-term DCCs between G7 and BRICS-T countries' stock markets. The coefficient estimate for the volatility of the S&P 500 is positive and statistically significant for the Model 1. This finding shows that an increase in the volatility of the S&P 500 leads to an increase the long-term DCCs between stock market returns. However, the estimated coefficient for the volatility of the S&P 500 is statistically insignificant in the Model 3 which includes the five-year CDS risk premium. Besides, the volatility ratio is negative and statistically significant which is in line with findings of Thomas et al. (2019). Lastly, we find that the EPU (Economic Policy Uncertainty) index differences between country pairs do not have a statistically significant impact on the time-varying co-movements between stock market returns. For the robustness controls, we also estimate the POLS models for the G7 country pairs and the G7&BRICS-T country pairs. The estimation results of the POLS models for the G7 country pairs and the G7&BRICS-T country pairs are given in the Table A1 and the Table A2 in the Appendix A, respectively. The estimation results of those models have resemblance to each other qualitatively, however those models differ numerically.

In the POLS (Pooled Ordinary Least Squares) method, all observations are collected in a pool and use the OLS method to estimate an equation without considering a cross section and time dimension of a dataset. The properties of the time series should be taken into consideration in the case of having a panel data set in which dynamic structure is dominant. Since the co-movement among stock markets is a dynamic process, the model specifications should contain lagged values of the dynamic conditional correlations Thomas et al. (2019). Therefore, we make use of the System GMM (Generalized Method of Moments) method developed by Arellano and Bover (1995) and Blundell and Bond (1998) to investigate the determinants of the long-term DCCs among stock markets. This methodology is appropriate to handle the dynamic structure of the co-movements among stock markets. Additionally, this methodology also deals with the problem of endogeneity between the explanatory variables. We estimate the following model specifications:

$$\rho_{xy,t} = a + \sum_{k=1}^{3} \delta_k \rho_{xy,t-k} + \beta_1 Bilateral\ trade_{xy,t} + \beta_2 GDP\ growth\ rate_{xy,t} + \beta_3 Inflation\ rate_{xy,t} + \beta_4 Term\ spread_{xy,t} + \varphi S\&P\ 500\ volatility_t + \lambda GFC_t + \varepsilon_{xy,t} \quad (17)$$

$$\rho_{xy,t} = a + \sum_{k=1}^{3} \delta_k \rho_{xy,t-k} + \beta_1 Bilateral\ trade_{xy,t} + \beta_2 GDP\ growth\ rate_{xy,t} + \beta_3 Inflation\ rate_{xy,t} + \beta_4 Term\ spread_{xy,t} + \psi CDS\ risk\ premium_{xy,t} + \gamma EPU_{xy,t} + \varphi S\&P\ 500\ volatility_t + \lambda GFC_t + \varepsilon_{xy,t} \quad (18)$$

$$\rho_{xy,t} = a + \sum_{k=1}^{3} \delta_k \rho_{xy,t-k} + \beta_1 Bilateral\ trade_{xy,t} + \beta_2 GDP\ growth\ rate_{xy,t} + \beta_3 Inflation\ rate_{xy,t} + \beta_4 Term\ spread_{xy,t} + \psi CDS\ risk\ premium_{xy,t} + \gamma EPU_{xy,t} + \theta Volatility\ ratio_{xy,t} + \varphi S\&P\ 500\ volatility_t + \lambda GFC_t + \varepsilon_{xy,t} \quad (19)$$

where $\rho_{xy,t}$ represents long-term (quarterly) dynamic conditional correlations between stock markets of countries x and y, at time t and $\sum_{k=1}^{3} \delta_k \rho_{xy,t-k}$ indicates the lagged values of the dependent variable $\rho_{xy,t}$.

Table 9. Estimation results of the system GMM models for all country pairs.

$(\text{Dccmidascorr})_t$	Model 1	Model 2	Model 3
$(\text{Dccmidascorr})_{t-1}$	1.2794***(0.008)	1.3618***(0.008)	1.3456***(0.010)
$(\text{Dccmidascorr})_{t-2}$	−0.4515***(0.014)	−0.4873***(0.015)	−0.4704***(0.019)
$(\text{Dccmidascorr})_{t-3}$	0.0871***(0.011)	0.0914***(0.008)	0.0799***(0.013)
Bilateral trade	−0.0666(0.065)	−0.0191(0.092)	0.0183(0.084)
GDP growth rate	−0.0011***(0.0001)	−0.0024***(0.0001)	−0.0025***(0.0001)
Inflation rate	−0.0009***(0.0002)	−0.0008***(0.0002)	0.00008(0.0002)
Term spread	−0.0009***(0.0002)	−0.0005(0.0003)	−0.0010***(0.0004)
CDS risk premium		0.0093***(0.0004)	0.0067***(0.0004)
Economic policy uncertainty		−0.0013***(0.0003)	−0.0016***(0.0004)
S&P 500 volatility	0.0904***(0.003)		0.1421***(0.012)
Volatility ratio			−0.0057***(0.001)
Global financial crisis dummy	−0.0021***(0.0004)	0.0012***(0.0004)	−0.0098***(0.0009)
Trend	−0.0002***(0.0001)	−0.0002***(0.00003)	−0.0001***(0.00004)
Constant	0.0869***(0.010)	−0.0076(0.006)	0.0032(0.004)
Number of country pairs	78	55	55
Number of observations	3978	1905	1905
Number of instruments	150	96	98
Wald statistics	1.80e + 06***	336501.38***	2.28e + 06***
AR(1) Arellano-Bond prob	0.000	0.000	0.000
AR(2) Arellano-Bond prob	0.121	0.173	0.134
AR(3) Arellano-Bond prob	0.123	0.118	0.123
Sargan test prob	0.999	0.999	0.998

Notes: *Dccmidascorr* is the dependent variable. *Bilateral trade* shows the ratio of total mutual trade between countries to their total foreign trade volume. *GDP growth rate* indicates the log transformation of the GDP growth rate differences, *inflation rate* indicates the log transformation of the inflation rate differences, *term spread* indicates the log transformation of the term spread differences, *CDS risk premium* indicates the log transformation of the five-year CDS risk premium differences, and finally, *EPU* shows the log transformation of the economy policy uncertainty index differences between country x and country y. The numbers in the parentheses are standard errors. *** indicates statistical significance at the 1% level. For detailed definitions, see Table 2.

The estimation results of the System GMM models are shown in Table 9, where Model 1, Model 2, and Model 3 correspond to Equations (17), (18), and (19), respectively. According to the estimation results in Table 9, the most important factors explaining the long-term DCCs between stock market returns of G7 and BRICS-T countries are the differences in GDP growth rates, five-year CDS risk premiums, and EPU (Economy Policy Uncertainty) indices between country pairs. Overall, the coefficient estimates for GDP growth rate differences are negative and statistically significant for all models. These results are consistent with the findings of Mobarek et al. (2016) and Nitoi and Pochea (2019). This result indicates that as the differences in GDP growth rates between country pairs decrease, the long-term DCCs between stock market returns rise. Moreover, we find that the coefficient estimates for inflation rate difference are negative and statistically significant for the Model 1 and the Model 2. These findings are compatible with the results of Alotaibi and Mishra (2015) and Nitoi and Pochea (2019). Furthermore, according to the estimation results of the Model 1 and Model 3, the estimated coefficients for term spread difference are negative and statistically significant in accordance with the findings of Mobarek et al. (2016) and Vithessonthi and Kumarasinghe (2016). Taken together, these results show that the time-varying co-movements between stock markets of countries with similar inflation rate and term spread are high. Besides, we find that the differences in five-year CDS risk premium between country pairs are positively related to the long-term DCCs among stock market returns in consistent with the results of Min and Hwang (2012) and Güngör and Güngör (2020). We also utilize the differences in EPU (Economic Policy Uncertainty) indices between country pairs as determinants of the time-varying co-movements among stock markets. In line with expectations, the differences in economic policy indices are negative and statistically significant for the Model 2 and the Model 3. These findings show that as the economic policy uncertainty index differences between two counties increase, the long-term DCCs among the stock markets of those countries decline.

Furthermore, we examine impact of the S&P 500 volatility on long-term DCCs between the stock markets of G7 and BRICS-T countries. As expected, the coefficient estimates of the S&P 500 volatility are positive and statistically significant for the Model 1 and the Model 3. These results indicate that a rise in the volatility of the S&P 500 leads to an increase in the long-term DCCs among stock markets. In addition, we find that the volatility ratio is negatively related to the time-varying co-movements among stock market returns in accordance with the findings of Thomas et al. (2019). Empirical findings suggest that as volatility of stock markets gets closer to each other, the time-varying co-movements between those markets increase. In line with the findings of (Didier et al., 2012; Vithessonthi and Kumarasinghe, 2016 and Thomas et al., 2019), we also find that there is a statistically insignificant relationship between the bilateral trade and the long-term DCCs among stock markets. For the robustness controls, we also estimate the System GMM models for the G7 country pairs and the G7&BRICS-T country pairs. The estimation results of the System GMM models for the G7 country pairs and the G7&BRICS-T country pairs are given in the Table A3 and the Table A4 in the Appendix A, respectively. The estimation results of those models have resemblance to each other qualitatively, however those models differ numerically.

5. Conclusions

This paper analyzes the macroeconomic factors expounding the time-varying co-movements between stock market returns of G7 and BRICS-T countries. For this purpose, first DCC-MIDAS models are estimated for 78 country pairs, and then, the dynamic conditional correlations among the daily stock market returns of the countries in the sample are decomposed into the short-term (daily) component and the long-term (quarterly) components. According to the estimation results of the DCC-MIDAS models, it is found that the highest DCC-MIDAS correlations among 78 country pairs belong to the stock markets of G7 country pairs. In addition, the stock market pairs of European countries have the highest DCC-MIDAS correlations among the stock market pairs of G7 countries. Colacito et al. (2011) put forward that fundamental causes of time-varying conditional correlations are captured by slowly moving processes of DCCs. In this respect, economic and financial factors that represent economic-financial proximity between countries are expected to be connected with slowly moving long-term components rather than rapidly moving short-term components of DCCs among stock market returns. Thus, this study examines the relationship between the long-term component of DCCs between G7 and BRICS-T countries' stock markets and macroeconomic variables that represent economic-financial proximity between those countries using the System GMM method for the period from January, 2006 to August, 2018. For this purpose, we use bilateral trade, GDP growth rate, inflation rate, term spread, five-year CDS risk premium and economy policy uncertainty index, volatility of the S&P 500 and volatility rates of stock markets as regressors to analyze the DCC-MIDAS correlations between stock market returns of countries. Furthermore, we also estimate the System GMM models for the G7 country pairs and the G7&BRICS-T country pairs in addition to all country pairs for the robustness controls. These robustness checks enable us to separately examine the relationships both between advanced countries and between advanced and emerging countries.

Empirical results suggest that the most important factors that explain long-term DCCs between stock market returns of G7 and BRICS-T countries are the differences in GDP growth rates, five-year CDS risk premiums, and EPU (Economy Policy Uncertainty) indices between country pairs. The estimated coefficients of the differences in GDP growth rates and economic policy uncertainty indices between country pairs are negative while the differences in five-year CDS risk premiums between country pairs are positive. These findings imply that as the differences in GDP growth rates and EPU indices between country pairs decrease, the long-term DCCs between stock market returns increase. According to the empirical results from the G7 country pairs, the most important variables expounding the DCC-MIDAS correlations among stock market returns of those countries are the differences in term spreads, inflation rates, and five-year CDS risk premiums between G7 country pairs. These results indicate that as the differences in term spreads and inflation rates between G7 country pairs get closer to each other, the time-varying co-movements among those stock markets tend to rise. In addition, the estimation results for the G7&BRICS-T country pairs show that the most significant variables expressing the long-term DCCs between stock market returns of those countries are the differences in GDP growth rates, term spreads, and five-year CDS risk premiums between G7&BRICS-T country pairs. These results indicate that as the differences in GDP growth rates and term spreads between G7&BRICS-T country pairs increase, the DCC-MIDAS correlations between stock markets of those countries decline.

The results of this paper offer important implications for policy makers, financial institutions, financial analysts, portfolio managers and global investors. The higher co-movement between stock markets of two countries will potentially reduce the benefits from portfolio diversification. Thus, global investors and portfolio managers should comprehend the macro-financial dynamics of the time-varying co-movements among stock markets to take efficient investment decisions. Besides, the higher co-movement between stock market of two countries might make these stock markets vulnerable to the same kind of economic and financial shocks. Therefore, the knowledge of policy makers on the determinant factors of co-movement among stock markets will definitely ease to construct a suitable policy to sustain their financial stabilization.

Conflict of interest

The authors declare no conflict of interest.

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