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Dynamic correlation pattern amongst alternative energy market for diversification opportunities

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Abstract

Last couple of decades witnessed recognition of energy markets as investment commodities which led interest of the international investment community. We investigate the potential of globally diverse alternative energy markets for optimal returns by analysing their correlation pattern. Our study employs daily data spanning from January 2006 to December 2017. To estimate pair-wise return co-movement, we employ rolling window multiple wavelet correlation based on decomposed returns using maximal overlap discrete wavelet transformation to infer implications for both short- and long-run investors. We witness maximum diversification between developed (World, Developed, EU, G7) and emerging (BRIC, Emerging) markets. Most of these combinations exhibit no traces of contagion during the financially and economically turbulent periods. Finally, we use non-linear causality test to highlight increased integration between our sampled alternative energy indices after financial and economic crises periods. Our results carry implications for short- and long-run investors as well as for policy makers.

Keywords: Alternative energy markets, Rolling window wavelets, Wavelets transformation

1 Introduction

Since the last couple of decades, energy has been serving not only as an international commodity but also as an important financial product. Most of the existing literature considers global energy structure as energy commodity whereas only a thin strand of literature also acknowledges its financial attributes. Energy possess features of both commercial as well as financial attributes and because of its increasing demand, it represents itself as a long-run potential and strategic investment for international investors. A careful and well-diversified investment in the energy sector can act as an effective hedging approach to mitigate volatile energy prices and therefore, attracts international investment community. Due to heterogeneous distribution of energy resources, energy companies in different countries seek international cooperation to access more resources. According to Lim and Lam (2014), investments in energy sector in the emerging economies witness increasing importance not only due to escalating commercial value but also for balancing energy structures and ensuring

local energy security. Since the global financial crises of 2008–2009, a significant re-adjustment in the global energy structure is witnessed with more offerings towards the growing trend of diversification. However, attributable to diverse nature of energy policies, resources endowment, investment environment and geopolitics with varying political relationship between countries, cross-border energy investment relationship reflects different characteristics.

Existing literature documents the presence of energy as financial commodities, both in a portfolio (see Ghorbel and Trabelsi 2014; Pan et al. 2016; Rehman et al. 2019) and as a combination of these energy assets with traditional stocks (Chen et al. 2010; Mensi et al. 2013; Balcilar et al. 2015; Shahzad et al. 2019). Besides trading only in cash market, these energy commodities are also traded in the form of energy future contracts using ETC's (Exchange Traded Commodities), with former providing the advantage of leverage (Chng 2009; Lu and Jacobsen 2016). In case of increasing capital market integration, combination of traditional equity with energy-related stocks presents a viable option to hedge energy specific risks (Khalfaoui et al. 2015; Basher and Sadorsky 2016).

The emergence of energy stocks provides an additional avenue of investment and research as a new asset class to investors and scholars, respectively. However, the opportunity of investing in such energy asset class is not risk free and therefore requires suitable hedging or safe haven assets to unwind the associated portfolio risk. Kumar et al. (2012) investigate the relationship between fossil fuel commodities with clean energy investments and report that fuel prices affect returns of clean energy stocks. In another study, Broadstock et al. (2012) use time-varying correlation to capture the sensitivity of Chinese energy stocks to fossil fuel prices and report strong association following the subprime crises of 2007–2008. These results imply that Chinese energy-related stocks amongst the emerging economies exhibit sensitivity to global oil shocks. The discussion on energy investment structures from a global perspective is gaining utmost importance; however, existing literature is rich in terms of studies highlighting the specific disintegrated energy sources focusing on both local and global energy situations, for example, in terms of energy production (Armaroli and Balzani 2007) and supply (Balat and Balat 2009), energy consumption (Guo and Fu 2010) and its use (Neto et al. 2014), energy security (Yergin 2006), energy trade (Wälde and Gunst 2002), energy market (Kleit 2001), etc.

Though existing literature provides rich evidence on the relationship between traditional equity markets, interrelationship amongst alternative energy-related equities highlights future avenue of research mainly attributable to an increasing interest by investors and researchers. There are few studies which highlight the relationship between returns of alternative energy market assets, for example, Miralles-Quirós and Miralles-Quirós (2019) highlight that alternative energy ETF's outperform energy ETF's thereby providing an alternative investment option for investors. Sadorsky (2012) analyses relationship between clean energy and technology companies' stocks and reports that stocks' prices of clean energy equity are more correlated with technology stocks as compared with international oil prices. Similarly, discussion amongst energy equity or between energy and other stocks includes Henriques and Sadorsky (2008), Mollick and Assefa (2013), Efimova and Serletis (2014), Maghyereh et al. (2017) and Kyritsis and Serletis (2018).

More recently, the United Nations climate change conference held in Paris, 2015, emphasised on making investments in clean energy sector for development and meeting ever increasing challenges posed by the climate change. Though private investments in renewable energy sector are gaining importance over time, long-run interest of investors relies on the financial risks and profitability of renewable energy companies. The price fluctuation of energy assets is considered as one of the main energy-related risk factors affecting the financial performance of energy investment projects; however, according to Kumar et al. (2012) and Reboredo (2015), viability of sustainable energy investments also depends on economic grounds. The cheapest and quickest way to reduce energy consumption is through increased energy efficiency, sometimes called an “invisible fuel” with a potential for further improvements in energy efficiency. Investment in energy sector often remains uncertain due to the uncertainty regarding their returns. An existing strand of literature discusses under investment in energy efficiency also known as a “paradox” of “energy efficiency gap” (DeCanio and Watkins 1998; Sola and de Paula Xavier 2007; Schleich 2009; Granade et al. 2009; Thollander and Ottosson 2008; Venmans 2014; Brunke and Blesl 2014). Energy Return On Investment (EROI) is a concept that helps in aligning economic and biophysical perspective by addressing the potential suitability of energy sources to their returns on net available energy to industrial society (see Cleveland et al. 1984; Hall et al. 1986). However, this EORI presents some issues in its definition and measurement, thus requiring separation of the system boundaries. With such process-based analysis, the interlinkages between respective components and the complexity of wider economic system can render problems in definition of the clear internal boundaries.

Existing literature provides rich evidence of cointegration approach in measuring integration amongst different financial assets. Majority of this work includes Johansen (1991) and Escribano and Granger (1998) techniques (see Candelon et al. 2013; Ghosh and Kanjilal 2016; Bondia et al. 2016). Other approaches consider time-varying properties of return to measure stock market integration including dynamic conditional correlation, copulas and wavelets (Christoffersen 2012; Creti et al. 2013; Khalfaoui et al. 2015; Salisu and Oloko 2015).

For returns integration between our sampled alternative energy markets, we apply extension of wavelet approaches. Traditional wavelet approaches are used extensively in existing literature due to their capability to measure correlation in time–frequency space with phase difference providing information about delays and synchronisation between co-movement of given series (Mensi et al. 2018, 2019; Al-Yahyaee et al. 2019). However, standard wavelet correlation estimates and compares large number of wavelet and cross-wavelet correlations. The application of multiple wavelet correlation comprises a single set of multiscale correlation pattern which makes relationship not only easier to analyse and interpret but also provides better insight of an overall statistical relationship about multivariate relationship.

Our contributions in this study are as follows. First, our study is an effort to investigate portfolio diversification opportunities amongst different alternative energy financial markets. The selection of alternative energy market is based on growing investment in this sector and our sample consists of a unique combination of alternative energy assets in the form of different equity indices. Second contribution comes in the form

of methodological aspects where we decompose returns by applying maximal overlap discrete wavelet transformation approach which helps in analysing multiscale features of time series with capability of oversampling the data unlike traditional DWT. This decomposition of returns is helpful in extracting implications for short- and long-run investors which is an important aspect of this study. Third, we use decomposed series for estimating rolling window wavelet correlation followed by analysing bivariate, non-linear causality. Therefore, based on portfolio diversification amongst different global alternative energy assets, our work benefits from novel methodological extensions of wavelet techniques with implications for short- and long-run investors. Finally, our analysis makes use of the pre- and post-crises period that are commonly known to affect most of our sampled markets. Such breaks in our sample period allow to see the presence of contagion in equity markets and its effect on short- and long-run investment horizons.

Our results highlight that alternative energy markets of Emerging and BRIC offer maximum diversification opportunities when combined with the World, Developed, G7 and EU alternative energy equity markets. Such pair-wise combinations highlighted above exhibit low return correlation across entire sample period with little traces of contagion phenomena during a series of crises period. Rest of the paper is structured as follows. Section 2 presents applied methodology. Section 3 explains variables, data sources and preliminary analysis. Section 4 presents analysis and discussion followed by Sect. 5 concluding our study.

2 Methodology

To test the relationship between our sampled global alternative energy indices, we make use of several novel techniques, details of which are as follows.

2.1 Wavelet decomposition

According to Gençay et al. (2002), discrete wavelet transform (DWT) is capable of handling non-stationary time series in a combined time-scale domain. The application of maximal overlap discrete wavelet transform (MODWT) is one of the most commonly used algorithms due to its advantages over traditional DWT (see Percival and Walden 2006). This is because of its ability to handle samples of any size unlike the traditional DWT which restricts sample size up to 2^J , where J represents layers of decompositions. Another feature of MODWT is its invariability to circular shifting of time series which the traditional DWT lacks. Finally, though, both DWT and MODWT are capable of analysing variance based on wavelets and scaling coefficients, the variance estimators of MODWT analysis are comparatively more asymptotically efficient (Percival and Mofjeld 1997; Gençay et al. 2002; Percival and Walden 2006; Polanco-Martínez and Fernandez-Macho 2014; Polanco-Martínez and Abadie 2016).

In this study, we decompose¹ daily log return values by applying MODWT using Daubechies least asymmetric wavelets (LA) with filter of length $L = 8$, i.e., LA(8) (Gençay et al. 2002; Daubechies 1992). Value of maximum decomposition level, i.e. J is derived using $\log_2(N)$ translated into a maximum level of 10 in our case. Since the number of

¹ The MODWT decompositions will be made available to the readers upon request.

feasible wavelet coefficients becomes critically small for high levels, we select wavelet analysis with $J=8$ to avoid boundary coefficients. In this way, the MODWT gives us eight wavelets and one scaling coefficient, i.e. $\tilde{\omega}_{1,t}, \dots, \tilde{\omega}_{8,t}$ and $\tilde{v}_{8,t}$, respectively. For rolling window wavelet correlation (RWWC) explained in later section, we select $J=4$; however, it is technically possible to estimate RWWC up to 5th level but the results in the form of high variability do not provide useful information. The scale of wavelet coefficient, i.e. $\tilde{\omega}_{t,j}$, is defined by the level of transformation. For estimations in our case for all families of Daubechies, the level j coefficients are associated with changes at effective scale $\lambda_j = 2^{j-1}$ days. Furthermore, the MODWT utilises an ideal band-pass filter within the frequency interval of $[1/2^{j+1}, 1/2^j]$ for the scale $1 \leq j \leq J$. By inverting the frequency range and multiplying it by an appropriate time unit Δt , i.e. 1 day in our case, we obtain equivalent periods of $[2^j, 2^{j+1}] \Delta t$ days under the scale level of $1 \leq j \leq J$. In our study under the daily frequency data, the wavelet scale coefficients λ_j ($j=1, \dots, 8$ are linked with time horizon changes of 1, 2, 4, 8, 16, 32, 64 and 128 days, respectively) are associated with 2–4 days' (intra week), 4–8 days' (weekly), 8–16 days' (fortnightly), 16–32 days' (monthly), 32–64 days' (monthly to quarterly), 64–128 days' (quarterly to biannual), 128–256 days' (biannual) scale and 256–512 days' (biannual to annual) scale.

2.2 Rolling window wavelet correlation

To analyse the relationship between our sampled global alternative energy returns at different time periods, we compute MODWT wavelet correlation following the work of Gençay et al. (2002). We present the unbiased wavelet correlation for scale λ_j between two time series X and Y as

$$\tilde{\rho}_{XY} = \frac{\text{cov}(\tilde{W}_{Y,jt}, \tilde{W}_{Y,jt})}{\sqrt{\text{var}\{\tilde{W}_{X,jt}\} \text{var}\{\tilde{W}_{X,jt}\}}} = \frac{\tilde{\gamma}_{XY}(\lambda_j)}{\tilde{\sigma}_X^2(\lambda_j) \tilde{\sigma}_Y^2(\lambda_j)}. \quad (1)$$

In the above expression, $\tilde{\gamma}_{XY}(\lambda_j)$ represents the unbiased estimator of wavelet covariance between market coefficient $\tilde{W}_{Y,jt}$ and $\tilde{W}_{Y,jt}$ whereas $\tilde{\sigma}_X^2(\lambda_j)$ and $\tilde{\sigma}_Y^2(\lambda_j)$ are the unbiased estimators of wavelet variances X and Y , respectively, associated with the scale λ_j . We define the unbiased wavelet variance estimator based on MODWT as

$$\tilde{\sigma}_X^2(\lambda_j) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \tilde{W}_{j,t}^2 \quad (2)$$

where $\tilde{W}_{j,t}^2$ represents j th level of MODWT coefficient for X , $L_j = (2j-1)(L-1)+1$ represents length of scale λ_j (wavelet filter) and $\tilde{N} = N - L_j + 1$ represents number of coefficients not affected by the boundary. We use the work² by Witche and Onwuegbuzie (1999) to construct confidence interval $100(1-2p)\%$ for wavelet coherence. An expression for $100(1-2p)\%$ confidence interval for wavelet coherence is given by $\tanh\{h[\tilde{\rho}_{XY}(\lambda_j)]\} \emptyset^{-1}(i-p)/\sqrt{\tilde{N}_j-3}$, where $\emptyset^{-1}(p)$ represents $100p\%$ points for

² Witche and Onwuegbuzie (1999) present classical results of Fisher Z-transformation of correlation coefficient.

standard normal distribution and $h(\tilde{\rho}_{XY}) = \tanh^{-1}(\tilde{\rho}_{XY})$ denotes the Fisher Z-transformation (Whitcher et al. 2000; Gençay et al. 2002).

To analyse temporal variation of wavelet correlation, we employ a dynamic measure, i.e. rolling window wavelet correlation to measure multi-dimensional correlation in time and frequency space. Since the proposition by Ranta (2010), this measure has been quite useful in several economics studies (Dajcman et al. 2012; Benhmad 2013) due to its advantage in analysing distinct time intervals. We follow the work of Benhmad (2013), Dajcman et al. (2012) and Ranta (2010) by computing pairwise rolling window wavelet correlation (with a window of 250 points per year), by rolling forward one data point and centred around a time. Therefore, we restrict the effective number of wavelets to $J=5$, but analyse the first four scales.³ We also visualise decomposed correlation in a new way following Polanco-Martínez et al. (2018).

2.3 Non-linear causal relationship

The application of linear causality is effective in investigating the presence of causal relationship between different time series; however, it does not capture the presence of non-linearity in the model. Therefore, for non-linear time series like behaviour of different financial and commodities' markets having presence of dynamic structure, i.e. regime shifts, structural breaks, etc., the application of non-linear Granger causality is more appropriate. Baek and Brock (1992) proposed a non-parametric technique to detect the presence of non-linear causal behaviour, an improved version of which was later provided by Hiemstra and Jones (1994). Following the work of Hiemstra and Jones (1994) which tends to over-reject the null hypothesis after being tested, Diks and Panchenko (2006) proposed a non-linear non-parametric Granger causality test to avoid this over rejection issue. We employ the test proposed by Diks and Panchenko (2006) to estimate the non-linear behaviour between global alternative energy indices, explained below.

The null of Granger causality between series X_t and Y_t is based on hypothesis that X_t contains no information about Y_{t+1} (Diks and Panchenko 2006; Bekiros and Diks 2008). We consider $X_t^{lx} = (X_{t-1}, \dots, X_t)$ and $Y_t^{ly} = (Y_{t-1}, \dots, Y_t)$ as delay vectors, where $l_x, l_y \geq 1$ represent delays for X_t and Y_t , respectively. We define null hypothesis as

$$H_0 : Y_{t+1} | (X_t^{lx}, Y_t^{ly}) \sim Y_{t+1} | Y_t^{ly}. \quad (3)$$

Under the null hypothesis, we assume $Z_t = Y_{t+1}$ by dropping time indices in Eq. (3) and that the conditional distribution of Z given $(X, Y) = (x, y)$ is similar to Z given $Y = y$ (Diks and Panchenko 2006; Bekiros and Diks 2008). We express the null hypothesis of Eq. (3) as joint distribution function that the joint probability density function $f_{X,Y,Z}(x, y, z)$ and associated marginals satisfy the following relationship.

³ This is because after the application MODWT to a sub-window containing 250 data points with avoiding the boundary wavelet coefficients, number of data points become much lesser than 250 for the 5th scale. Therefore, we make use of calculations as $N - W$, where $N=1043$ and $w=250$ which makes $N - w=793$ windows, and thus the correlation coefficient.

$$\frac{f_{x,y,z}(x, y, z)}{f_y(y)} = \frac{f_{X,Y}(x, y)}{f_Y(y)} \frac{f_{Y,Z}(y, z)}{f_Y(y)} \quad (4)$$

Therefore, we see clear evidence that X and Y have conditional independence of $Y=y$ for each fixed y (Diks and Panchenko 2006; Bekiros and Diks 2008). According to Diks and Panchenko (2006), the null hypothesis of Eq. (3) can be expressed as

$$q \equiv \mathbb{E}[f_{x,y,z}(X, Y, Z)f_Y(Y) - f_{X,Y}(X, Y)f_{Y,Z}(Y, Z)] = 0. \quad (5)$$

In the above equation, \mathbb{E} represents expectation operator whereas estimator for q according to Diks and Panchenko (2006) is as follows.

$$T_n(\varepsilon_n) = \frac{(2\varepsilon)^{-d_X-2d_Y-d_Z}}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k \neq 1} \sum_{j,j \neq 1} I_{ik}^{XYZ} I_{ij}^Y I_{ik}^{XY} I_{ij}^{YZ} \right] \quad (6)$$

In the above expression, I_{ij}^W represents $I(|W_i W_j| < \varepsilon)$, where I represents characteristics function or indicator. W_i and W_j represent elements of a d_w -variate random vector W . ε is the bandwidth whereas n represents sample size (Diks and Panchenko 2006; Bekiros and Diks 2008). Considering the local density estimator of d_w -variate random vector W can be expressed as $\hat{f}_W W_i = 2 \varepsilon^{-d_W} (n-1)^{-1} \sum_{j,j \neq 1} I_{ij}^W$, we define T statistics according to Diks and Panchenko (2006) as

$$T_n(\varepsilon_n) = \frac{(n-1)}{n(n-2)} \sum_i \left[\hat{f}_{X,Y,Z}(X_i Y_i Z_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{Y,Z}(Y_i, Z_i) \right]. \quad (7)$$

For $\varepsilon_n = C_n^{-\beta}$, with $\beta \in (1/4, 1/3)$ and $C > 0$, and for the lag -1 $l_x = l_y = -1$, the T statistics has asymptotic normal distribution and satisfies the following condition.

$$\sqrt{n} \frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{d} N(0, 1) \quad (8)$$

where \xrightarrow{d} represents convergence in distribution function. S_n denotes asymptotic variance estimator, T_n (Diks and Panchenko 2006; Bekiros and Diks 2008).

3 Data, variables and preliminary analysis

Data for our variables are based on the global alternate energy indices from different developed and emerging equity markets. These alternate energy equity markets are sampled as World, Developed, Emerging, EU, BRIC and G7. The alternative energy indices represent companies deriving most of their revenues from the services and products in alternative energy. We have segregated these alternative energy indices representing different geographic locations, i.e. World, Developed, Emerging, EU, BRIC and G7 region. World alternative energy market index includes broad markets from the developed and emerging countries with large, mid and small cap equities. These free float-adjusted market capitalised weighted indices are composed with respect to the clean technology environmental themes. These equities derive most of their revenues from the services and products of alternative energy, green building, energy efficiency, sustainable water, pollution prevention, etc. Developed alternative energy market index comprises Australia, Austria,

Table 1 Descriptive statistics

Statistic	World	Developed	Emerging	EU	BRIC	G7
Minimum (full sample)	− 0.2232	− 0.2477	− 0.2322	− 0.1810	− 0.5009	− 0.1896
Minimum (pre-GFC)	− 0.1119	− 0.1396	− 0.1034	− 0.1251	− 0.1428	− 0.1509
Minimum (post-GFC)	− 0.2232	− 0.2477	− 0.0901	− 0.1326	− 0.2035	− 0.1106
Maximum (full sample)	0.1644	0.2009	0.1786	0.1728	0.2272	0.2175
Maximum (pre-GFC)	0.0867	0.1128	0.1297	0.1190	0.1738	0.1481
Maximum (post-GFC)	0.0776	0.1134	0.1013	0.1026	0.2272	0.2175
Mean (full sample)	− 0.0003	− 0.0003	− 0.0005	0.0001	− 0.0006	− 0.0003
Mean (pre-GFC)	0.0018	0.0021	0.0007	0.0024	0.0008	0.0019
Mean (post-GFC)	− 0.0004	− 0.0005	− 0.0003	0.0001	− 0.0001	− 0.0005
Std. dev. (full sample)	0.0211	0.0240	0.0242	0.0252	0.0307	0.0268
Std. dev. (pre-GFC)	0.0199	0.0234	0.0274	0.0246	0.0351	0.0303
Std. dev. (post-GFC)	0.0170	0.0199	0.0180	0.0216	0.0228	0.0219
Skewness (full sample)	− 0.7407	− 0.5937	− 0.4573	− 0.3791	− 1.4993	− 0.0688
Skewness (pre-GFC)	− 0.7101	− 0.6543	− 0.0240	− 0.4796	− 0.0036	− 0.3734
Skewness (post-GFC)	− 1.1213	− 0.9650	0.0757	− 0.2805	0.4586	0.3307
Kurtosis (full sample)	12.4934	11.0776	8.3973	6.5982	29.8108	7.6456
Kurtosis (pre-GFC)	4.0811	4.8884	2.1874	4.5754	2.7507	4.3797
Kurtosis (post-GFC)	14.5722	12.6111	2.2453	2.6250	11.9866	6.4478
JB stats (full sample)	20,092*	15,585*	8571.5*	5383.3*	10,755*	7131.1*
JB stats (pre-GFC)	489.37*	671.16*	125.46*	572.78*	517.35*	198.31*
JB stats (post-GFC)	20678*	15483*	481.75*	685.42*	13747*	3996.3*
ADF (full sample)	− 48.614*	− 49.985*	− 51.072*	− 52.135*	− 52.980*	− 51.699*
PP (full sample)	− 48.588*	− 49.854*	− 51.137*	− 52.081*	− 53.100*	− 51.615*
KPSS (full sample)	0.1864	0.2231	0.0500	0.2191	0.0681	0.1829
Q (20) (full sample)	97.433*	77.053*	59.684*	54.933*	68.773*	46.746*
Q ² (20) (full sample)	2937.1*	2055.0*	3822.1*	3310.6*	600.43*	1879.5*
ARCH (20) (full sample)	39.551*	30.257*	58.691*	47.783*	18.313*	32.238*

*Significance level at 5% or better

Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK and the US. Emerging alternative energy market index consists of Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, Qatar, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates. The EU alternative energy index captures mid- and large-cap segments of 15 developed markets in Europe. The BRIC and G7 alternative energy market comprises stocks in BRISC and G7 countries with a focus on products and services deriving revenues from various alternative energy sources.

Timeline for our sampled indices span over 12-year period and ranges from January 2006 to December 2017, based on daily frequency. Data are extracted from Thomson Reuters DataStream. Table 1 presents descriptive statistics for alternate energy returns over three subsample periods, i.e. full sample, pre- and post-crises periods. We see that for all subsamples, alternative energy returns yield negative minimum values; however, BRIC alternative energy market exhibits maximum return values in all sampling periods suggesting more potential in terms of speculative positive returns. However, by looking at the mean values, EU alternative energy market presents itself as the most viable

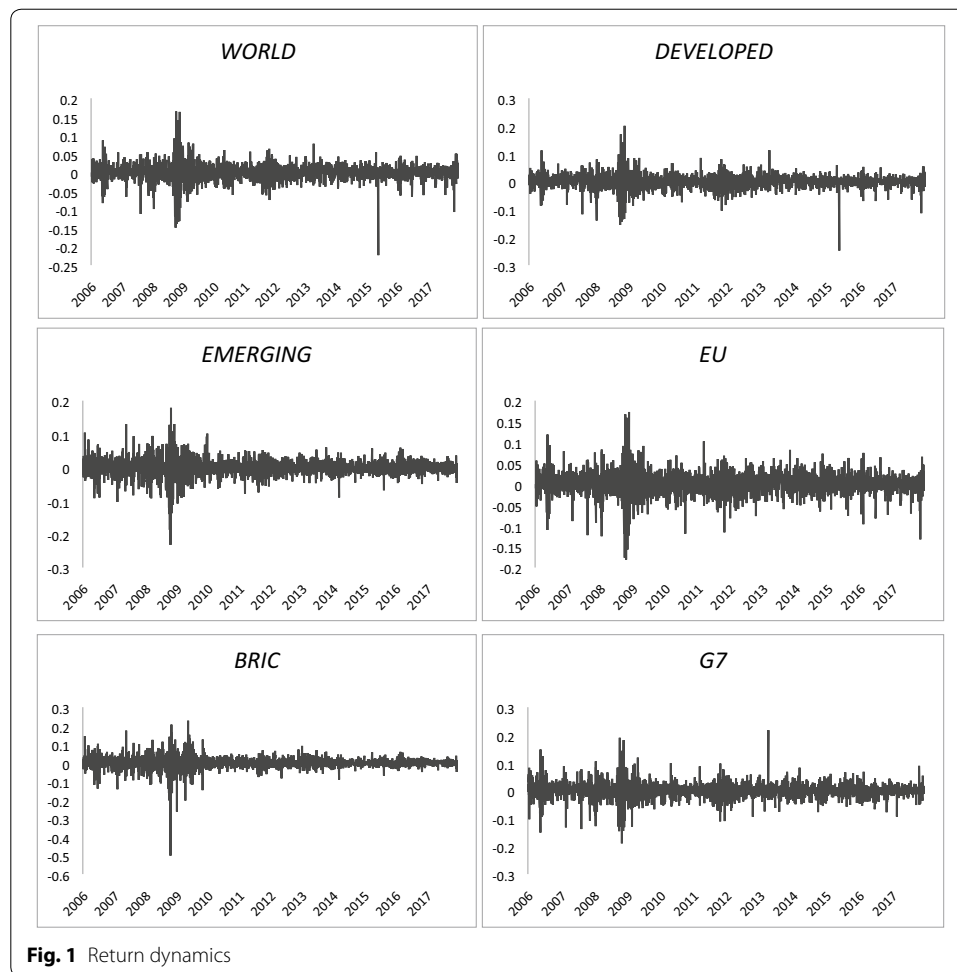


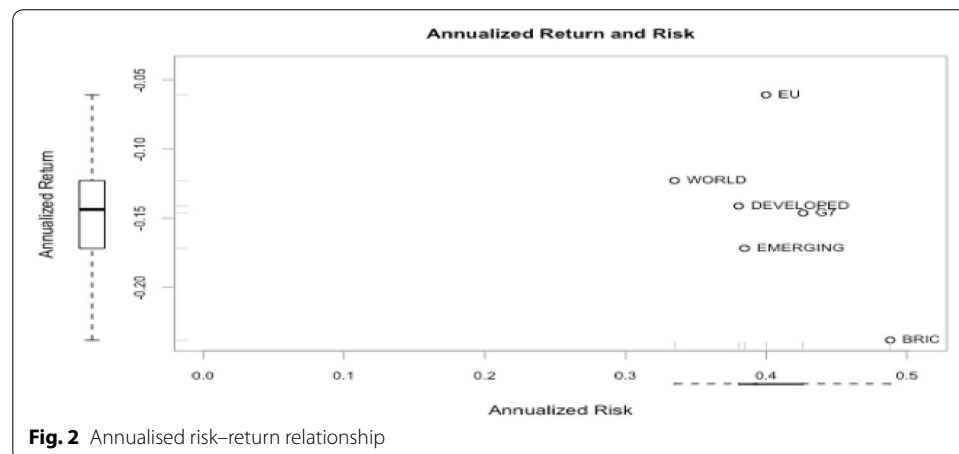
Fig. 1 Return dynamics

option for investment by yielding a daily return of 0.01%, 0.24% and 0.01% in full sample, pre-crises and post-crises periods. It is also interesting to note that all alternative energy markets (except EU) yield positive returns in pre-crises whereas negative returns in post-crises period. Similarly, full sample highlights negative daily return values on average for all alternative energy indices. BRIC alternative energy market exhibits maximum risk in terms of standard deviation of returns across all sampling periods. Jarque–Bera statistic is applied to test the normality of all return series and our results suggest that the data are not normal. Most of the alternative energy markets highlight negatively skewed returns with fat tails and leptokurtic distribution also confirming the results of our normality measures that data are not normally distributed across all subsample periods. We employ ADF and PP tests to check the presence of unit root and KPSS to investigate stationarity properties of returns. Our results do not suggest the presence of unit root (ADF and PP tests) thereby confirming the stationarity of our return series (KPSS test). We apply Ljung box test statistics to investigate the presence of serial correlation in residuals and squared residuals of returns series. Results of $Q(20)$ and $Q^2(20)$ statistics suggest the presence of serial correlation up to 20th lag. Similarly, we apply ARCH LM test to check conditional heteroscedasticity in returns and report its presence in all series.

Table 2 Unconditional correlation

Variables	World	Developed	Emerging	EU	BRIC	G7
Pre-GFC						
World	1*					
Developed	0.9308	1*				
Emerging	0.2553	0.1056	1*			
EU	0.7732	0.8016	0.0931	1*		
BRIC	0.1807	0.0852	0.6013	0.0720	1*	
G7	0.6473	0.6956	0.0600	0.5258	0.0478	1*
Post-GFC						
World	1*	0.9649	0.4558	0.8160	0.3747	0.7185
Developed		1*	0.2704	0.8394	0.2646	0.7540
Emerging			1*	0.2301	0.6846	0.2082
EU				1*	0.2231	0.5850
BRIC					1*	0.1907
G7						1*

*Significance level at 5% or better



Return pattern of all sampled series is plotted in Fig. 1. Though all return series exhibit volatility across the sample period, it seems more evident during the global financial crisis of 2008–2009. These results suggest that the alternative energy assets exhibit sensitive behaviour to global financial turbulences like traditional asset class and are not immune to it. For all series, variation in daily returns remains consistent throughout the sample period; however, it becomes less prominent compared to the global financial crisis of 2008–2009.

Table 2 highlights unconditional correlation statistics between our alternative energy returns across two samples, i.e. pre-crises and post-crises period. We witness that before crises period, developed markets like World, Developed, G7 and EU exhibit high daily return correlation compared to Emerging and BRIC alternative energy market, suggesting more integration and less diversification benefits. Results almost remain similar for post-crises period between most of the markets with an increasing correlation pattern of Emerging and BRIC alternative energy returns with the Developed, G7 and EU markets.

We present annualised risk–return relationship between all the alternative energy indices over the sample period in Fig. 2. All alternative energy markets exhibit high-risk characteristics on the horizontal axis with BRIC market leading the way. These risks are plotted against returns on vertical axis where EU alternative energy market amongst others dominates in terms of annualised return values, thereby presenting itself as a comparatively feasible option for investment.

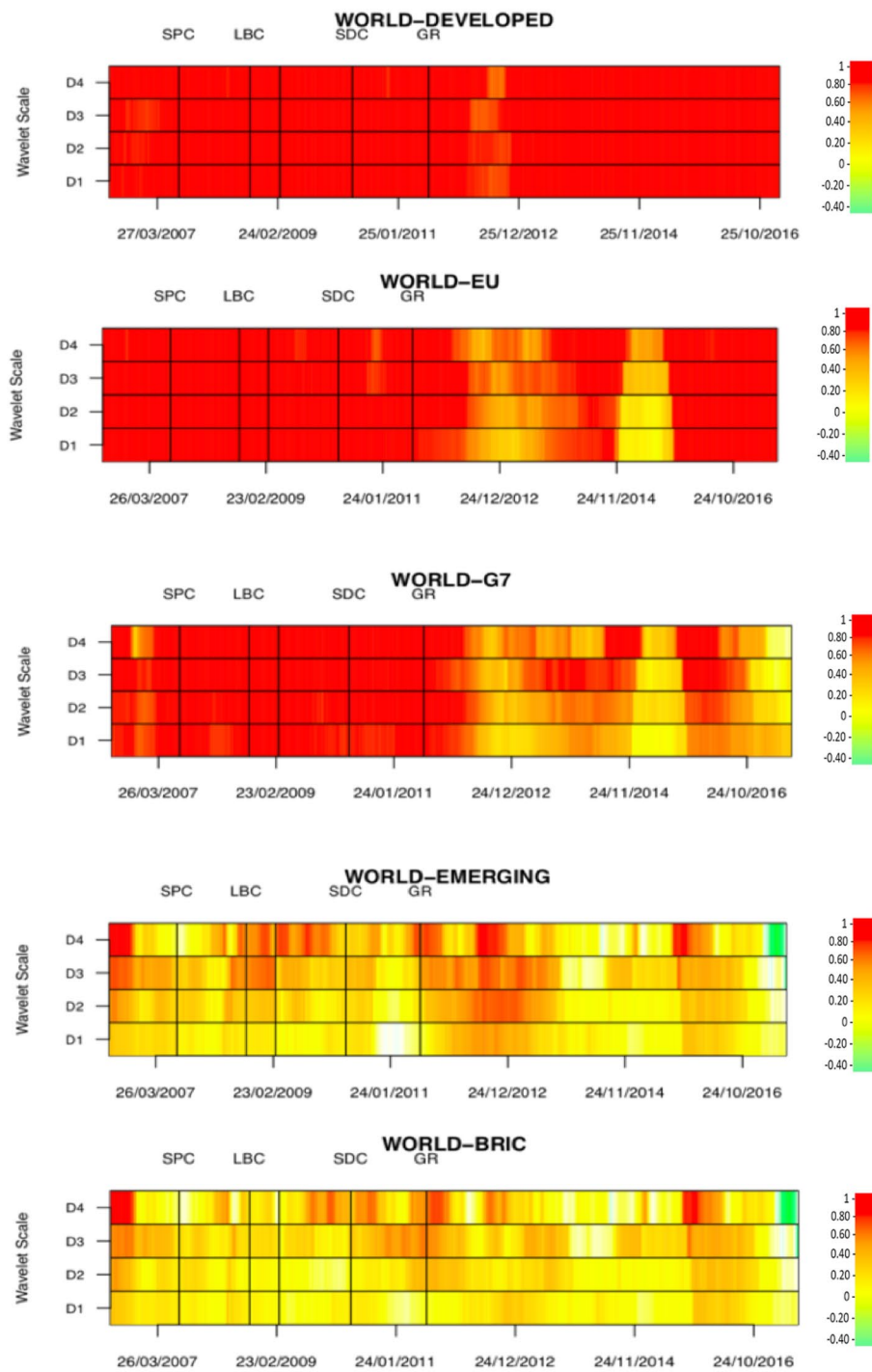
4 Analysis and discussion

4.1 Rolling window wavelet correlation

In this section, we present results of rolling window wavelet correlation (RWWC) for each pair of sampled alternative energy return. We further add to our analysis by adding a break in the timeline representing four major economically and financially turbulent periods. These periods are termed as Subprime Crisis (SPC), Lehman Brother Crisis (LBC), European Sovereign Debt Crisis (SDC) and Greece Sovereign Crisis (GR). Therefore, the three subsample periods, i.e. full sample period, pre-crises period and the post-crises period, are selected due to their relevance to our alternate energy markets sampled from different regions. These crises periods affected all these regions in one way or the other and therefore present important implications. Figure 3a–e presents rolling window wavelet correlation results based on different decomposition levels from D1 to D4, corresponding towards a shift of investment horizon from daily to monthly period. The power of bilateral correlation between each pair of alternative energy market is highlighted in the right corner of each correlation bar as a power spectrum. This power spectrum ranges from a low correlation value (bottom of the scale) to high correlation value (top of the scale) for each correlation bar. The strength of correlation corresponding to respective rolling window is depicted through different colouring schemes, i.e. green, yellow and red being the most prominent highlighting low, medium and high bivariate correlation values, respectively.

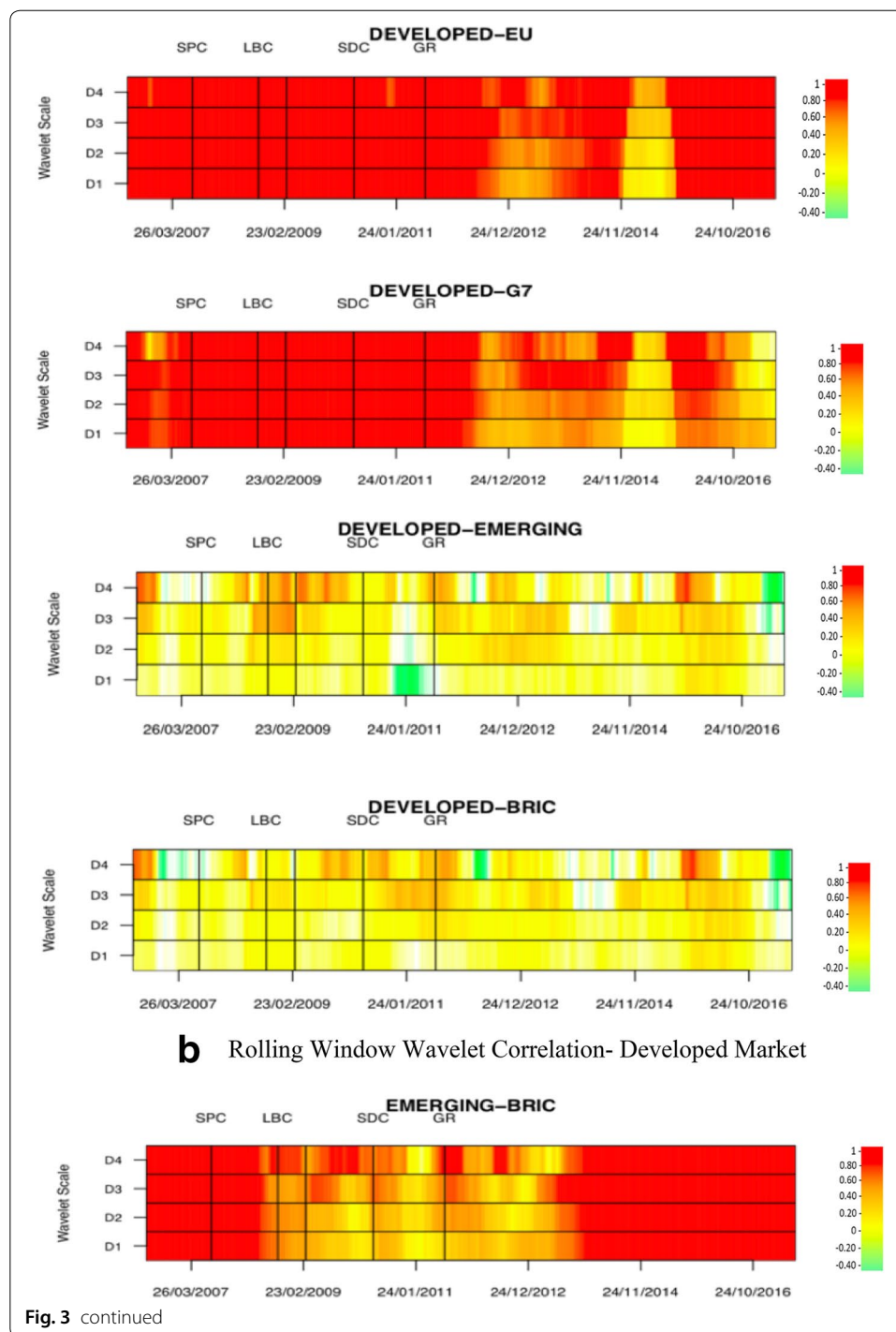
We start our analysis by comparing the World alternative energy index with other alternative energy markets in a pair (Fig. 3a). Result of World–Developed and World–EU pairs suggests high correlation pattern at all decomposed levels across the sample period. However, for World–EU pair, correlation between the two markets falls in the first half of 2014 for short- as well as long-run investment horizons. World–G7 pair presents somewhat different story as we see a substantial shift from high to low correlation pattern across all investment horizons after the crises periods suggesting an opportunity for investment by including these two alternative energy assets in a portfolio. World–Emerging and World–BRIC pairs present a different story altogether. We witness low correlation values across the entire sampling period and at all decomposed levels between these markets. Such low correlation level remains steady even during different financial crises periods suggesting a suitable mix in terms of diversification between these pairs. These alternative energy markets, therefore, highlight opportunities for short- and long-run investors and seem to become immune against the financially and economically turbulent periods.

Results of rolling window multiple wavelets between Developed and rest of the alternative energy markets are depicted in Fig. 3b. Developed alternative energy market behaves similar to the World alternative energy market discussed above as it exhibits



a Rolling Window Wavelet Correlation- World Market

Fig. 3 **a** Rolling window wavelet correlation—world market. **b** Rolling window wavelet correlation—developed Market. **c** Rolling window wavelet correlation—emerging market. **d** Rolling window wavelet correlation—EU market. **e** Rolling window wavelet correlation—BRIC market



high correlation pattern with both its developed alternative energy market counterparts, i.e. G7 and the EU. Developed–EU market pair exhibits high correlation throughout the sample period across all investment horizons except in 2014, where we see moderate correlation at all decomposed levels suggesting potential avenues of diversification for investors. However, return correlation seems to escalate later again until recently.

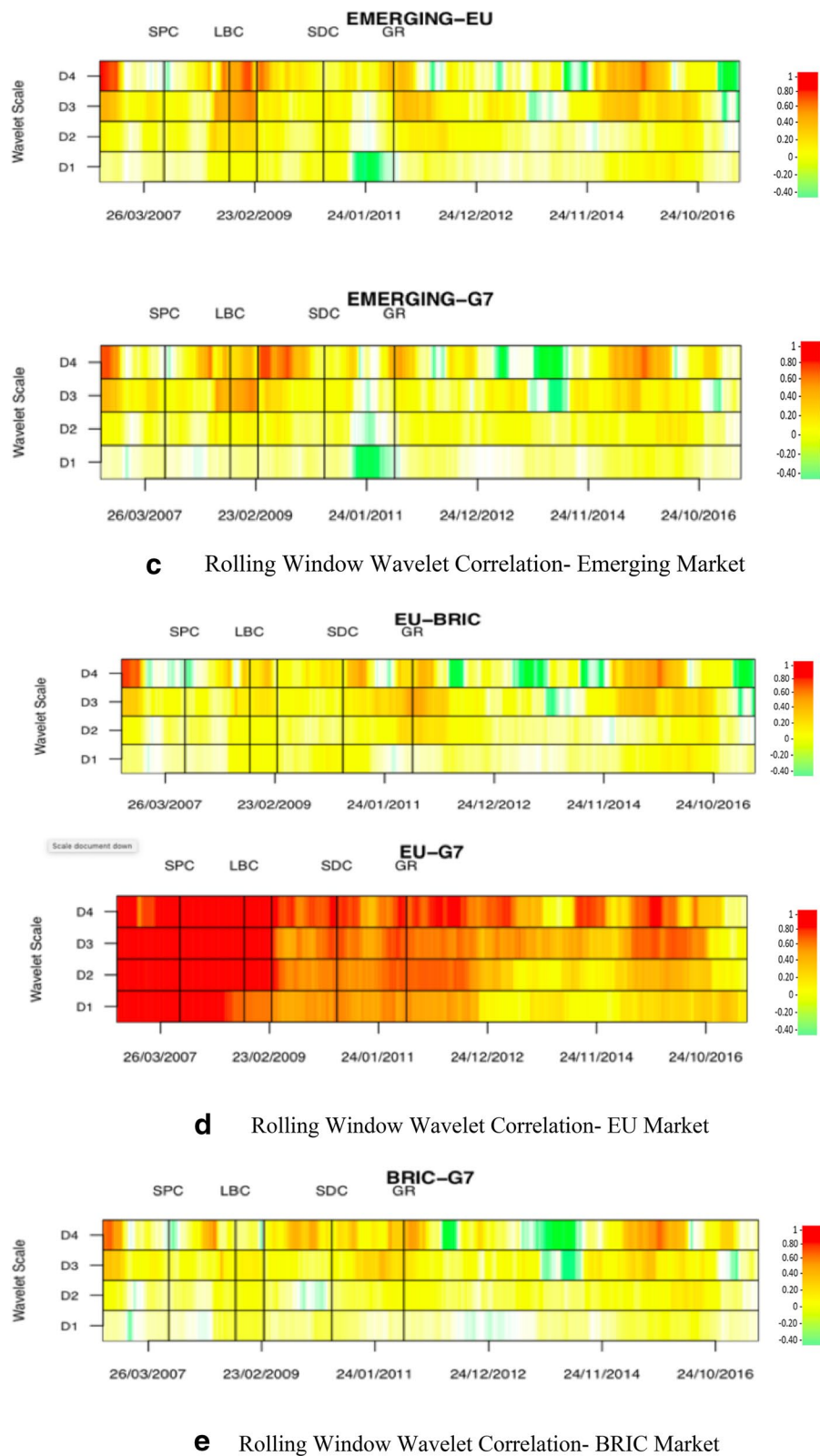


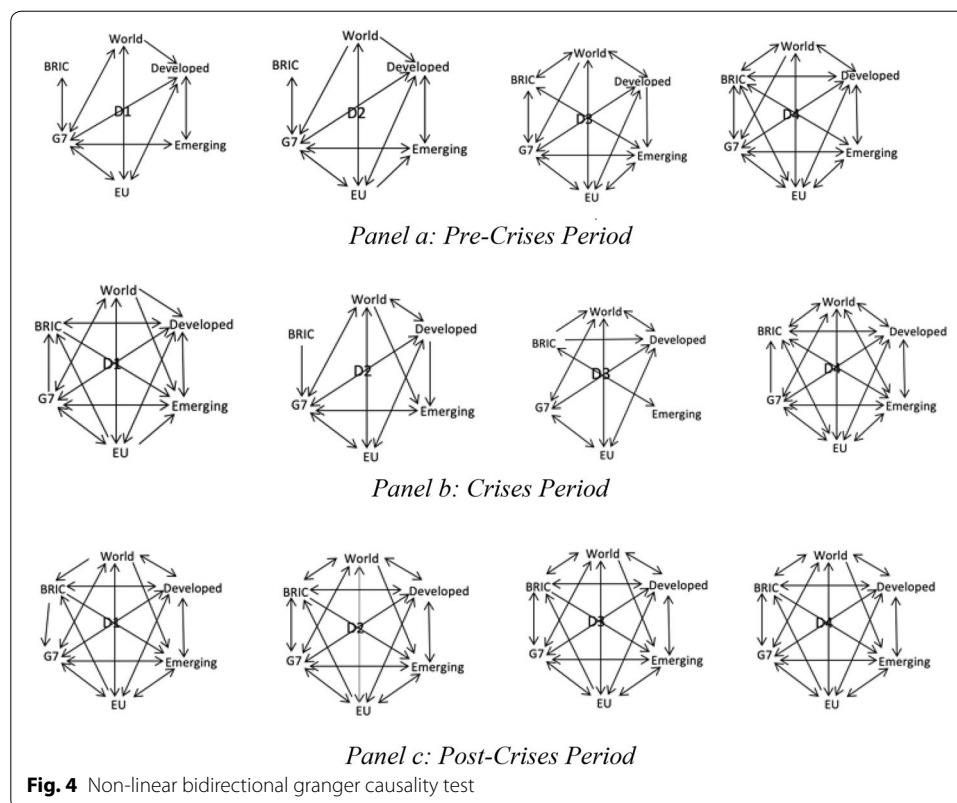
Fig. 3 continued

Developed–G7 alternative energy indices pair experiences high return co-movements until first half of 2011 after which the magnitude of such co-movements declines, implying potential of investment in this market pair. We witness even low correlation pattern at daily to weekly investment horizons from 2015 to 2017 compared to bi-monthly and monthly investment periods, suggesting more potential for short-term investments. We report different findings for Developed–Emerging and Developed–BRIC pair highlighting low daily return correlation. Such low correlation across all decomposed levels entails implications at all investment horizons i.e. from daily to monthly periods. We neither find traces of contagion during the financial crises and economically turbulent period nor report their after effects on return patterns. Therefore, potential diversification benefits can be implied by investing amongst Developed, Emerging and BRIC alternative energy markets.

Figure 3c presents wavelet correlation results of alternative energy Emerging with other markets. For Emerging–BRIC pair, we witness high correlation in pre- and during the Subprime and Lehman brother crises periods. However, after which the correlation reduces to a moderate level of 0.5 till the beginning of 2013. After 2013, however, the correlation again escalates and afterwards maintains a steady high level implying reduced diversification benefits between these two asset classes. Emerging–EU and Emerging–G7 alternative energy market pairs highlight low return correlation throughout the sample period, even during all crises periods with traces of negative correlation as well. These traces of negative correlation are more pronounced in higher investment horizons, i.e. D4 corresponding to monthly investment period. Amongst all other alternative energy market pairs, these two pairs, i.e. Emerging–EU and Emerging–G7, highlight maximum traces of negative correlation and therefore more diversification opportunities.

Figure 3d presents results of wavelet correlation for EU–BRIC and EU–G7 alternative energy market pair. For EU–BRIC combination, we witness low level of correlation pattern across entire period and at all decomposition levels representing short- to long-run investment horizons. Even during all crises periods, return between these markets exhibit least co-movement highlighting immunity to contagion, thereby implying potential for diversification benefits between these assets. Unlike short-run investment horizons, we find traces of negative correlation at monthly level (i.e. D4) suggesting that investments at monthly levels are more feasible than the short-run, i.e. daily or intra-week investments. However, EU–G7 pair exhibits high correlation patterns across entire sample period. This high correlation is more evident during the crises period highlighting its sensitivity to contagion which afterwards reduces to some extent. However, these two assets do not present an optimal investment avenue at any level of investment horizon, i.e. either short- or long-run.

Figure 3e present our last pair-wise combination of alternative energy markets, i.e. BRIC–G7. This market combination presents optimal investment opportunities since the correlation appears at its low level with few traces of negative correlation at monthly investment horizons. These two markets highlight even no sensitivity to the global financial crises and economic turbulent periods, thereby suggesting opportunities for investment between these two markets even during economic and financially uncertain periods.



4.2 Non-linear causality

We present results of non-linear granger causality test between sampled alternative energy markets in Fig. 4. These results are based on bivariate framework between alternative energy markets and are separated for each decomposed level, i.e. from D1 to D4 corresponding to 1, 2, 4 and 8 days, respectively. These decomposed levels are associated with 2–4 days' (intra-week), 4–8 days' (weekly), 8–16 days' (fortnightly) and 16–32 days' (monthly) scale. We further divide our analysis into three subsample divisions for pre-, during and post- crises analysis. This crises timeline contains Subprime Crisis (SPC), Lehman Brother Crisis (LBC), European Sovereign Debt Crisis (SDC) and Greece Sovereign Crisis (GR).

Results of non-linear granger causality test for pre-crisis period are presented in panel *a* of Fig. 4. For intra-week period, Emerging alternative energy markets highlight no causal effect in any direction with the Developed, G7 and EU alternative energy markets. Similarly, BRIC alternative energy returns remain insensitive to World, Developed and the EU alternative energy markets. The results remain similar for weekly investment horizon except few cases where emerging alternative energy market returns become insensitive to World and BRIC whereas become responsive to Developed and EU markets' returns. BRIC alternative energy market highlights no correlation with World, Developed and the EU alternative energy markets across all investment horizons except monthly period where it exhibits sensitivity to both EU and Developed alternative energy market returns. Co-movements between all alternative energy markets remain responsive to each other in fortnightly and monthly investment horizons.

During the crises period, return co-movements of World index with Emerging and BRIC markets and of BRIC market with the Developed markets remain insignificant across intra-week and weekly horizons. For rest of the market pairs, we witness more cases of bidirectional causality on intra-week basis except emerging market which remains recipient of change from other markets, i.e. EU and BRIC in some cases. For returns' decomposition on a weekly basis, results are quite similar except Emerging and BRIC index, role of which changes from bidirectional causality to recipient of change from other markets. In case of fortnightly causality under periods of Subprime Crisis, Lehman Brother Crisis, European Sovereign Debt Crisis and Greece Sovereign Crisis, Emerging markets remain dormant in terms of any causal behaviour with the world, Developed, EU and G7 alternative energy markets. We witness only couple of unidirectional causal relationships running from BRIC towards World and Developed alternative energy markets. All the developed alternative energy markets, i.e. World, EU, Developed and G7, exhibit strong bidirectional causality implying least diversification benefits for investments during the financially distressed periods. However, during such crises period, these developed alternative energy indices remain uncorrelated with Emerging and BRIC markets.

Finally, during post-crises period our estimates highlight unidirectional causality of BRIC with the World and G7 alternative energy returns. Besides these two cases, we witness cases of bidirectional causal behaviour with no evidence of lack of causal relationship between any pair. Results for post-crises period highlight that for all investment periods, i.e. intra-week, daily, fortnightly and monthly, there exists bidirectional causal relationship between each pair. These results suggest that after the crises period, our sampled alternative energy markets exhibit high level of integration, thus reducing any potential diversification benefits.

5 Conclusion

The increasing importance of alternative energy in the recent era has also demonstrated its popularity amongst the investment community. The energy companies and sectors are gaining acceptance in terms of investments along with their role towards socially responsible initiatives. These energy indices not only provide optimal returns on an individual basis but also offer avenues of diversification amongst different securities. Therefore, this study investigates the presence of diversification opportunities between six major alternative energy markets, i.e. World, Developed, Emerging, EU, BRIC and G7. To highlight the presence of integration between these alternative energy markets, we use the extensions in traditional wavelet techniques to measure investment opportunities not only between different investment horizons (i.e. short- and long-run) but pre-, during, and post-crises economic and financial periods. To proceed, we decompose all alternative energy market returns into different decomposed levels using MODWT model. These decomposed series are then used in estimating bivariate rolling window wavelet correlation proposed by Polanco-Martínez et al. (2018). Our estimations are based on subsampling periods comprising Subprime Crisis, Lehman Brother Crisis, European Sovereign Debt Crisis and Greece Sovereign Crisis periods. Our results highlight high level of integration during pre-crises and crises periods between Developed, EU, World and G7 alternative energy markets,

however, with slight variations between different investments horizons. More diversification opportunities exist between the combinations of BRIC and Emerging alternative energy markets with Developed, EU, World and G7, attributable to low evidence of non-linear causality. However, post-crises period exhibits high level of integration amongst all markets due to the presence of bivariate causality between each alternative energy market pair. Our results of rolling window wavelet correlation are supported by the application of non-linear granger causality statistics thus adding robustness to our findings.

Though our study is based on alternative energy markets from different regions, the results are not totally different from the studies employing conventional developed and emerging stock markets. For example, there are many studies that report diversification benefits based on low integration level between emerging and developed markets (see Narayan and Rehman 2017, 2019; Shahzad et al. 2018; Mensi et al. 2017; Gupta and Guidi 2012). Therefore, despite of sampling various alternative energy markets, our study remains silent on the diversification benefits associated with traditional developed and emerging stock markets and hence, presents a future avenue of research.

Our results have implications for investors and policy makers. The increasing role of alternative energy sector has recently attracted the attention of international investment community. However, their role becomes more important when combined in a portfolio with other equity markets. In this way, these assets can act more like a hedger than the speculative assets. Similarly, investment in energy sector has some implications in terms of socially responsible investments. Our study therefore carries implications for investments in alternative energy market. We highlight that BRIC and Emerging alternative energy markets offer maximum diversification opportunities along with Developed, World, G7 and EU markets. Similarly, investing amongst the Emerging and G7 markets can result in optimal returns attributable to low returns' correlation. Such low correlation remains persistent even during different financial and economic crisis periods. Similarly, investors should restrain making investments amongst developed alternative energy markets since these markets are highly integrated with each other. Therefore, in terms of investments, Emerging and BRIC alternative energy markets when combined with World, Developed, EU and G7 yield optimal return opportunities, thus providing hedge against extreme downwards movements in any other market. However, Emerging and BRIC alternative energy markets together in a portfolio yield high correlation values, therefore do not offer optimal returns. Though Emerging and BRIC together are not favourable in terms of investment, they provide good opportunities when mixed with other alternative energy markets like World, Developed, EU and G7. Policy makers can also benefit from the results of our study since high returns from alternative energy sector can result in increased investments. As a result of investor's confidence in this asset class, this sector can increase in its growth by further inducing socially responsible initiatives due to which more investors can be lured for investment purposes. Finally, the inclusion of these alternative energy assets in a portfolio can provide hedge against financial and economic turbulence, thereby having implications for policy makers to increase the role of such alternative energy sources not only for the betterment of energy-related issues but also towards providing cover to the financial community against economic and financial turmoil.

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Appendix

See Tables 3, 4, 5, and 6.

Table 3 Non-linear bidirectional Granger causality test

	Pre-crisis				Crisis				Post-crisis			
	D1	D2	D3	D4	D1	D2	D3	D4	D1	D2	D3	D4
World-developed	→	→	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔
World-emerging	←		↔	↔		→		↔	↔	↔	↔	↔
World-EU	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔
World-BRIC							←	→	↔	↔	↔	↔
World-G7	↔	→	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔
Developed-emerging		↔	→	↔	↔	→		↔	↔	↔	↔	↔
Developed-EU	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔
Developed-BRIC				↔			←	↔	↔	↔	↔	↔
Developed-G7	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔
Emerging-EU		←	↔	↔	←			↔	↔	↔	↔	↔
Emerging-BRIC	↔		↔	↔	←		↔	↔	↔	↔	↔	↔
Emerging-G7		↔	↔	↔	↔	↔		↔	↔	↔	↔	↔
EU-BRIC				↔	→			↔	↔	↔	↔	↔
EU-G7	↔		↔	↔	↔	↔	↔	↔	↔	↔	↔	↔
BRIC-G7	↔	→	←	↔	←	→		→	↔	↔	↔	↔

Table 4 Non-linear Granger causality with decompositions—pre-crisis

Pre-crisis period	Non-linear Granger causality with decomposition				Non-linear Granger causality without decomposition
	D1	D2	D3	D4	
World–developed	1.534 (0.0625)	1.390 (0.0823)	6.465 (0.0000)	6.219 (0.0000)	1.045 (0.1481)
Developed–world	1.133 (0.1286)	1.261 (0.1037)	6.187 (0.0000)	7.166 (0.0000)	−0.188 (0.5746)
World–emerging	1.013 (0.1557)	0.968 (0.1666)	2.389 (0.0084)	5.021 (0.0000)	1.785 (0.0371)
Emerging–world	1.354 (0.0879)	0.531 (0.2978)	1.923 (0.0272)	4.529 (0.0000)	1.545 (0.0615)
World–EU	1.984 (0.0236)	1.568 (0.0584)	5.786 (0.0000)	6.611 (0.0000)	1.378 (0.0841)
EU–world	2.500 (0.0062)	1.949 (0.0256)	5.611 (0.0000)	6.736 (0.0000)	0.863 (0.1941)
World–BRIC	0.140 (0.4445)	0.481 (0.6847)	1.795 (0.0363)	3.997 (0.0000)	1.189 (0.1173)
BRIC–world	1.225 (0.1103)	1.002 (0.1581)	1.509 (0.0657)	4.075 (0.0000)	0.611 (0.2706)
World–G7	2.005 (0.0225)	1.618 (0.0529)	5.558 (0.0000)	6.339 (0.0000)	1.424 (0.0773)
G7–world	2.089 (0.0184)	0.482 (0.3149)	5.005 (0.0000)	6.491 (0.0000)	1.597 (0.0552)
Developed–emerging	0.834 (0.2021)	1.535 (0.0623)	1.690 (0.0455)	3.675 (0.0001)	0.677 (0.2493)
Emerging–developed	0.370 (0.6442)	1.373 (0.0850)	0.433 (0.3324)	3.492 (0.0002)	0.851 (0.1974)
Developed–EU	2.509 (0.0061)	1.371 (0.0852)	6.063 (0.0000)	6.296 (0.0000)	0.747 (0.2276)
EU–developed	3.768 (0.0001)	2.253 (0.0121)	7.326 (0.0000)	6.365 (0.0000)	−0.361 (0.6410)
Developed–BRIC	0.595 (0.2783)	1.001 (0.1584)	0.879 (0.1896)	2.813 (0.0025)	0.329 (0.3711)
BRIC–developed	0.282 (0.3889)	1.190 (0.1170)	0.125 (0.4503)	3.270 (0.0005)	1.589 (0.0560)
Developed–G7	2.658 (0.0093)	1.357 (0.0874)	5.431 (0.0000)	6.099 (0.0000)	1.201 (0.1148)
G7–developed	2.459 (0.0070)	2.085 (0.0186)	5.978 (0.0000)	6.377 (0.0000)	0.624 (0.2661)
Emerging–EU	0.705 (0.2404)	1.155 (0.1240)	1.316 (0.0941)	3.386 (0.0004)	0.457 (0.0324)
EU–emerging	1.029 (0.1516)	1.363 (0.0865)	1.527 (0.0634)	3.945 (0.0004)	1.301 (0.0967)
Emerging–BRIC	2.248 (0.0123)	−0.277 (0.6092)	7.103 (0.0000)	8.172 (0.0000)	0.041 (0.4836)
BRIC–emerging	2.548 (0.0054)	0.629 (0.2648)	6.628 (0.0000)	8.368 (0.0000)	0.216 (0.4146)
Emerging–G7	0.489 (0.3125)	1.317 (0.0940)	1.424 (0.0772)	2.291 (0.0110)	1.616 (0.0530)
G7–emerging	1.170 (0.1211)	1.283 (0.0997)	1.798 (0.0361)	3.825 (0.0001)	1.010 (0.1563)
EU–BRIC	0.783 (0.2168)	−0.263 (0.6037)	0.671 (0.2512)	3.205 (0.0007)	1.077 (0.1408)
BRIC–EU	1.251 (0.1054)	0.996 (0.1595)	1.156 (0.1239)	3.413 (0.0003)	0.906 (0.1826)
EU–G7	2.510 (0.0064)	0.930 (0.1763)	5.964 (0.0000)	6.267 (0.0000)	0.538 (0.2954)
G7–EU	2.674 (0.0038)	0.564 (0.2863)	5.740 (0.0000)	6.340 (0.0000)	0.627 (0.2653)
BRIC–G7	1.298 (0.0971)	1.711 (0.0436)	0.760 (0.2237)	2.503 (0.0062)	1.514 (0.0650)
G7–BRIC	1.428 (0.0766)	1.096 (0.1366)	1.564 (0.0590)	2.805 (0.0025)	1.084 (0.1392)

Table 5 Non-linear Granger causality with decompositions—crisis period

Crisis period	Non-linear Granger causality with decomposition				Non-linear Granger causality without decomposition
	D1	D2	D3	D4	
World–developed	1.896 (0.0290)	2.308 (0.0105)	4.711 (0.0000)	3.928 (0.0004)	0.686 (0.2464)
Developed–world	1.238 (0.1078)	1.719 (0.0428)	3.874 (0.0006)	3.875 (0.0006)	0.838 (0.2011)
World–emerging	1.502 (0.0666)	1.910 (0.0281)	1.083 (0.1395)	2.973 (0.0015)	– 0.856 (0.8039)
Emerging–world	0.541 (0.2942)	– 0.190 (0.5752)	0.997 (0.1595)	2.704 (0.0034)	0.967 (0.1668)
World–EU	2.819 (0.0024)	2.387 (0.0085)	3.984 (0.0000)	3.413 (0.0003)	1.227 (0.1099)
EU–world	2.935 (0.0017)	2.343 (0.0096)	3.858 (0.0001)	3.969 (0.0000)	1.776 (0.0378)
World–BRIC	0.832 (0.2027)	0.045 (0.4819)	1.178 (0.1195)	1.673 (0.0472)	1.110 (0.1336)
BRIC–world	0.687 (0.7539)	0.489 (0.3123)	1.860 (0.0314)	2.304 (0.0106)	0.694 (0.2438)
World–G7	2.593 (0.0048)	2.449 (0.0072)	3.906 (0.0001)	4.277 (0.0000)	1.493 (0.0678)
G7–world	2.619 (0.0044)	2.068 (0.0193)	4.504 (0.0000)	4.003 (0.0000)	1.154 (0.1242)
Developed–emerging	1.954 (0.0254)	1.736 (0.0413)	0.593 (0.2765)	2.877 (0.0020)	– 1.120 (0.8687)
Emerging–developed	1.351 (0.0883)	0.443 (0.3290)	0.375 (0.3537)	2.738 (0.0027)	0.611 (0.2706)
Developed–EU	2.688 (0.0036)	2.413 (0.0079)	4.631 (0.0000)	3.682 (0.0001)	1.306 (0.0957)
EU–developed	3.151 (0.0008)	2.078 (0.0188)	4.326 (0.0000)	4.144 (0.0002)	1.280 (0.1003)
Developed–BRIC	0.755 (0.2253)	0.221 (0.4124)	0.421 (0.3367)	1.618 (0.0528)	1.326 (0.0924)
BRIC–developed	– 0.462 (0.6780)	0.613 (0.2700)	1.302 (0.0964)	2.639 (0.0042)	– 0.512 (0.6957)
Developed–G7	2.239 (0.0126)	1.986 (0.0235)	3.729 (0.0010)	3.940 (0.0000)	1.253 (0.1051)
G7–developed	2.360 (0.0092)	2.181 (0.0146)	4.588 (0.0000)	3.870 (0.0001)	0.819 (0.2064)
Emerging–EU	0.876 (0.1905)	0.127 (0.4493)	0.699 (0.2424)	2.376 (0.0088)	– 0.120 (0.5476)
EU–emerging	2.074 (0.0190)	0.256 (0.3988)	0.143 (0.4433)	2.636 (0.0042)	– 0.097 (0.5386)
Emerging–BRIC	1.081 (0.1398)	0.565 (0.2860)	2.733 (0.0031)	3.297 (0.0005)	0.396 (0.346)
BRIC–emerging	1.519 (0.0644)	0.785 (0.2161)	2.489 (0.0064)	3.186 (0.0007)	– 0.285 (0.6121)
Emerging–G7	1.752 (0.0399)	1.529 (0.0631)	0.729 (0.2330)	2.607 (0.0046)	0.967 (0.1669)
G7–emerging	1.322 (0.0931)	1.878 (0.0302)	0.725 (0.2344)	2.600 (0.0047)	– 0.651 (0.7426)
EU–BRIC	1.777 (0.0378)	– 0.037 (0.5146)	0.255 (0.3992)	1.913 (0.0279)	0.749 (0.2268)
BRIC–EU	0.582 (0.2805)	0.028 (0.4887)	1.246 (0.1064)	2.611 (0.0045)	– 0.726 (0.7661)
EU–G7	2.560 (0.0052)	2.533 (0.0057)	3.133 (0.0009)	4.174 (0.0000)	0.780 (0.2176)
G7–EU	2.122 (0.0169)	2.431 (0.0075)	3.711 (0.0001)	3.632 (0.0001)	1.013 (0.1555)
BRIC–G7	0.945 (0.1724)	1.359 (0.0871)	1.272 (0.1017)	2.668 (0.0038)	0.846 (0.1988)
G7–BRIC	1.868 (0.0309)	1.178 (0.1193)	0.473 (0.3181)	0.991 (0.1607)	0.409 (0.3413)

Table 6 Non-linear Granger causality with decompositions—post-crisis

Post-crisis period	Non-linear Granger causality with decomposition				Non-linear Granger causality without decomposition
	D1	D2	D3	D4	
World–developed	6.631 (0.0000)	7.632 (0.0000)	10.958 (0.0000)	11.830 (0.0000)	3.750 (0.0000)
Developed–emerging	6.625 (0.0000)	6.811 (0.0000)	10.330 (0.0000)	10.769 (0.0000)	4.420 (0.0000)
World–emerging	1.513 (0.0652)	3.350 (0.0004)	3.917 (0.0000)	5.714 (0.0000)	2.583 (0.0049)
Emerging–world	2.770 (0.0028)	4.137 (0.0002)	4.773 (0.0000)	6.072 (0.0000)	1.200 (0.1152)
World–EU	1.513 (0.0652)	3.932 (0.0000)	7.612 (0.0000)	10.317 (0.0000)	2.543 (0.0055)
EU–world	2.770 (0.0028)	3.611 (0.0002)	7.628 (0.0000)	10.643 (0.0000)	3.010 (0.0013)
World–BRIC	1.878 (0.0302)	3.449 (0.0003)	4.024 (0.0000)	6.712 (0.0000)	3.159 (0.0008)
BRIC–world	3.679 (0.0001)	4.514 (0.0000)	4.886 (0.0000)	5.865 (0.0000)	2.126 (0.0168)
World–G7	2.527 (0.0058)	3.404 (0.0003)	6.607 (0.0000)	8.614 (0.0000)	1.316 (0.0940)
G7–world	2.766 (0.0028)	2.031 (0.0211)	6.589 (0.0000)	8.755 (0.0000)	0.852 (0.1972)
Developed–emerging	2.444 (0.0073)	3.581 (0.0002)	3.066 (0.0011)	4.530 (0.0000)	2.078 (0.0189)
Emerging–developed	2.152 (0.0157)	4.046 (0.0003)	3.744 (0.0001)	5.007 (0.0000)	1.537 (0.0622)
Developed–EU	4.644 (0.0000)	4.532 (0.0000)	8.196 (0.0000)	4.530 (0.0000)	2.140 (0.0162)
EU–developed	4.345 (0.0000)	4.166 (0.0000)	8.190 (0.0000)	5.007 (0.0000)	1.851 (0.0321)
Developed–BRIC	2.610 (0.0045)	3.687 (0.0001)	3.451 (0.0003)	6.143 (0.0000)	2.594 (0.0048)
BRIC–developed	3.487 (0.0002)	3.944 (0.0000)	4.095 (0.0002)	5.260 (0.0000)	2.130 (0.0166)
Developed–G7	2.706 (0.0034)	3.529 (0.0002)	7.019 (0.0000)	8.754 (0.0000)	2.366 (0.0090)
G7–developed	1.856 (0.0317)	2.342 (0.0096)	6.965 (0.0000)	9.320 (0.0000)	0.059 (0.4764)
Emerging–EU	3.323 (0.0005)	2.701 (0.0035)	3.340 (0.0004)	4.351 (0.0000)	1.726 (0.0422)
EU–emerging	2.229 (0.0129)	2.578 (0.0050)	2.494 (0.0063)	4.095 (0.0000)	1.433 (0.0759)
Emerging–BRIC	7.079 (0.0000)	6.174 (0.0000)	8.508 (0.0000)	10.167 (0.0000)	4.263 (0.0000)
BRIC–emerging	5.640 (0.0000)	5.769 (0.0000)	5.394 (0.0000)	7.315 (0.0000)	3.536 (0.0002)
Emerging–G7	3.520 (0.0002)	2.395 (0.0083)	8.508 (0.0000)	4.715 (0.0000)	1.422 (0.0775)
G7–emerging	1.678 (0.0467)	2.702 (0.0034)	5.394 (0.0000)	3.840 (0.0000)	2.397 (0.0083)
EU–BRIC	2.518 (0.0059)	2.748 (0.0030)	2.593 (0.0048)	5.455 (0.0000)	2.454 (0.0071)
BRIC–EU	4.217 (0.0000)	3.781 (0.0000)	2.986 (0.0014)	5.252 (0.0000)	1.176 (0.1199)
EU–G7	4.336 (0.0000)	3.434 (0.0003)	5.371 (0.0000)	6.960 (0.0000)	2.403 (0.0081)
G7–EU	4.119 (0.0000)	3.009 (0.0013)	4.956 (0.0000)	7.348 (0.0000)	1.421 (0.0776)
BRIC–G7	3.260 (0.0006)	2.567 (0.0051)	3.828 (0.0001)	4.144 (0.0000)	2.673 (0.0038)
G7–BRIC	2.668 (0.0038)	2.562 (0.0052)	3.419 (0.0003)	4.707 (0.0000)	3.251 (0.0006)

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