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Rare disaster and renewable energy in the USA: new insights from wavelet coherence and rolling-window analysis

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Abstract

The increasing trend of economic and political crises in different parts of the world has made global economies highly vulnerable because of having globally as well as regionally integrated economic systems. In such an environment, switching to alternative energy products, such as renewable energy production, may be devastating. Therefore, the aim of this paper is to provide novel insights for the relationship between rare disaster risks and renewable energy production (REN) of the USA by utilizing the time series monthly data from 1973 to 2016. Using time-varying continuous wavelet power spectrum, the wavelet coherence, and the modified bootstrap rolling-window analysis, the results reveal significant linkages between all the categories of rare disaster risks and renewable energy production. Rare disaster risks and REN are linked with each other, and both the variables have time-varying cyclic and anti-cyclic effects on each other with robust and significant predictability from rare disasters to REN. These findings have novel implications for many stakeholders. For instance, producers of energy may safely switch to renewable energy production since disasters are found to have potential to leave cyclic effect on renewable energy at most.

Keywords Rare disaster · Renewable energy production · Wavelet transformation · Rolling-window analysis

1 Introduction

The global economy is continuously facing challenges associated with energy security, particularly in electricity supply, transportation fuel and operating industries (Bhattacharya and Kojima 2012). This is due to the fact that fossil fuels being the major source of global energy supply comes from are nonrenewable and may potentially be depleted in the near future (Alper and Oguz 2016; Lin and Moubarak 2014; Wüstenhagen and Menichetti 2012). The world's rising population and its growing demand for energy underscore the risks of energy depletion and environmental degradation (Balat 2005; Suman 2018).

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Hence, the transition toward renewable energy sources is crucial to ensure the sustainability of future energy (Belloumi 2009; Ikram et al. 2020). Additionally, global warming associated with CO2 emissions from most conventional energy products has convinced the world that alternate energy sources like renewable energy may help in saving ecosystems.

As a result, many countries opted for renewable energy in order to reduce carbon emissions, especially after the establishment of the Kyoto Protocol (Farinelli 2004; Holburn 2012; Menegaki 2011; Menyah and Wolde-Rufael 2010; Shahbaz et al. 2012). Moreover, in the aftermath of the Fukushima Daiichi nuclear disaster in Japan and increasing public concern about risks related to nuclear technology power generation, have paved a path for the growth of renewable energy industry (Bird et al. 2014; Chang et al. 2015; Chen et al. 2014; Esteban and Portugal-Pereira 2014; Alvarez-Herranz et al. 2017; Suman 2018; Farhani and Balsalobre-Lorente 2020).

Considering the importance of renewable energy, understanding its resilience toward any potential risks and threats would ensure its long-run sustainability. In this regard, the potential studying risks like the political and economic disasters in different parts of the world become more relevant (Berkman et al. 2017; Etkin et al. 2018). This is due to the renewable energy industry which is a high capital and technology-intensive industry which requires a large amount of investment, thus exposing a higher uncertainty level to the investors. Among all, the political, economic and resource risk has been found to play an essential role in the renewable energy investment risk identification (Wu et al. 2020).

Nowadays, as economies become integrated regionally as well as globally, any significant disaster in one part of the world significantly affects the economy elsewhere in the world. It seems to be particularly true for many developed countries like the USA, as she shares strong trade relations with rest of the world. Thus, the main objective of this study is to investigate the linkages between the rare disaster risks and renewable energy production in the USA. Moreover, the different disasters take place at different times; therefore, it is important to see their time-varying effects. In doing so, we have employed time-varying analyses based on wavelet coherence transformation and bootstrap rolling-window techniques to achieve the objective of the study.

We choose to investigate the effect of disasters on renewable energy because of two main reasons. Firstly, the use of renewable energy has risen significantly in the USA following various incentives by the government to promote the industry (Bowden and Payne 2010; US Energy Information Administration 2019a). As in the year 2018, about 20 percent of the world electricity has been produced by renewable energy, and it is forecasted that almost two-thirds of the global energy supply will be based on renewable energy in year 2050 (US Energy Information Administration 2019b). Moreover, the renewable energy is also making it possible to provide access to electricity to more people, even if they live in isolated areas (REN21 2019).

Secondly, the scarce literature available on the effects of disaster risks mostly focuses on the stock market return and volatility (Barro 2006a, 2009; Demirer et al. 2018), bond returns and volatility (Gupta et al. 2018), and exchange rate return and volatility (Gupta et al. 2019a). Unfortunately, the literature is comparatively limited regarding the relationship between energy production against disaster risks; particularly, it is silent on renewable energy production. The study of renewable energy is important since such projects include particular risk dynamics, such as huge capital investment, subject to the change in government energy policy, fluctuating energy prices and technological advancements among others.

Theoretically, a growing literature has considered time-varying disaster risks as a potential predictor for asset pricing. Based on the work of Rietz (1988), numerous studies have concluded rare disaster risk as a significant determinant of financial market returns (Barro 2009; Gourio 2008a, b; Barro and Ursúa 2008, 2012; Barro and Jin 2011; Berkman et al. 2017; Nakamura et al. 2013; Wachter 2013; Farhi and Gabaix 2016; Manela and Moreira 2017). More specifically, the study of Gourio (2012) finds that disasters and investment rates are directly related, and there exists a significant chance of collapse of investment with an increase in the probability of a rare disaster, thereby leading to the risk of a recession. In this vein, since renewable energy projects are heavily dependent on huge investments, the risk of rare disasters may have significant relationship with renewable energy production. Similarly, the study of Wachter (2013) links rare disasters with consumption shocks in order to drive the stock returns. On this basis, the relationship between rare disasters and consumption becomes directly related to production activities, since it is the outcome of production. If consumption disturbs because of the probability of occurrence of a specific disaster, it would inversely affect the production.

Referring to the prevailing literature provides overwhelming evidence on the relationship between the stock market and energy products, with significant influence of rare disasters on stock market returns, one could naturally ask that whether such an influence exists from time-varying rare disasters to energy products like the renewable energy production. Theoretically, if the rate of investment and consumption are greatly influenced by the size and probability of a disaster (Barro 2006b, 2009; Gourio 2012; Wachter 2013), then following the argument of Bernanke (2016) that there exists a co-movement between stocks and oil as they both are reactive to a common factor reflecting global aggregate demand, one obvious channel that links disaster risks to energy production is the possible influence of disasters on expectations for growth of both output and consumption.

However, the empirical investigation of the dynamic relationship between rare disaster risks and renewable energy production is far from being exhaustive. Therefore, the contributions of this paper are manifold: First, to the best of our knowledge, this is the first study that investigates the links between rare disaster risks and renewable energy production. Second, this study achieves its objective by employing dynamic nonlinear methodology of wavelet transformation in order to achieve the findings of the relationship based on time and frequency domain, since the occurrence of disasters takes place at varying time periods. Moreover, besides the advantages of the method to work with a nonstationary data, the wavelet analysis is superior compared to other traditional time series approaches due to its ability to examine the link between the two variables across time and frequency domain simultaneously, whereas the traditional time series analysis could only conduct it separately (Aguiar-Conraria et al. 2008; Batool et al. 2019; Grinsted et al. 2004). Hence, wavelet will provide an in-depth understanding of the dynamic link between rare disaster risk and renewable energy production in the case of USA, so that an effective policy suggestion can be provided to safeguard the renewable energy supply. Third, the study also employs an additional methodology of rolling-window bootstrap Wald test in order to achieve the robustness of our main time-varying findings based on wavelet transformation. This will contribute by robust empirical findings in the literature for the theoretical relationship between rare disaster risks and renewable energy production not tested before.

The results of the study conclude significant linkages between all the categories of rare disaster risks and renewable energy production. Moreover, this linkage shows that a feedback relationship exists, suggesting that both rare disasters and renewable energy have time-varying cyclic and anti-cyclic effect on each other. However, the results conclude dominant cyclic effect from rare disaster to renewable energy but not the other way round. Further, these results are found robust with rolling-window Granger causality, suggesting unanimously that rare disaster risks have significant predictability power on renewable energy production.

The rest of the paper is organized as follows. Section 2 reviews the literature on the link between risk and renewable energy. Section 3 discusses the data and methodology used in this study, followed by the discussion on the empirical findings in Sect. 4. Finally, the conclusion and policy are presented in Sect. 5.

2 Literature review

Following the rising concerns toward the environment and energy security, renewable energy has emerged as an alternative source of energy across countries (Alagappan et al. 2011). The shift toward the renewable energy usage has improved the environmental quality through the reduction in carbon emissions and helps in realizing several goals under the Sustainable Development Goals (SDGs) including SDG7 on affordable and clean energy, SDG9 on industry innovation and infrastructure, SDG11 on sustainable cities and communities, SDG12 on responsible consumption and production as well as SDG13 on climate action (Alvarez-Herranz et al. 2017; Nuriyev et al. 2019; Gatto and Drago 2020; Ikram et al. 2020; Wu et al. 2020; Zafar et al. 2020).

In addition, the technological advancement in renewable energy production has substantially reduced the production cost, which results in higher interest in renewable energy sources (Wu and Huang 2014). The rising demand for renewable energy has attracted many investors, which makes the renewable energy industry become more competitive (Bhattacharya et al. 2016; Nuriyev et al. 2019; Reboredo et al. 2017). As a result, more renewable sources have been installed especially in the area with cheap land (Fraser 2020).

In spite of several benefits of renewable energy sources, however, renewable energy production faces considerable challenges due to the risk associated with the industry (Kim et al. 2017; Liu and Zeng 2017; Wüstenhagen and Menichetti 2012). As argued by Sadorsky (2012), the renewable energy industry is among the riskier industries and thereby exposes the investors toward greater risk. Hence, understanding the effects of risks on renewable energy production is crucial to ensure its resilience toward any shock (Liu and Zeng 2017; Nuriyev et al. 2019; Reboredo et al. 2017). As a result, the energy resilience has become an important development agenda addressed by the United Nations under the Agenda 2030 (Gatto and Drago 2020).

In view of this, lack of information about the potential risks may bring huge damage to the renewable energy industry if the issue is not tackled appropriately. As supported by Lin and Bie (2016), due to the rising concerns over the risk of the disastrous incident, including natural catastrophe and manmade assault, the importance of the energy resilience becomes more apparent. Although the risk could not be completely solved, however, the negatives consequences of extreme events can be reduced through proper planning. Hence, understanding the effects of potential risk is important, so that a wise energy policy intervention can be established to minimized any potential risk or conflicts (Månsson 2014).

Although the literature on renewable energy has been discussed greatly in past studies, less attention has been given on the potential risks associated with the industry. As argued by Francés et al. (2013), although the shift toward the usage of renewable energy aimed at reducing the environmental problem, its effects on energy security remain uncertain. According to this study, the main difference between the risk in renewable energy sources and traditional energy sources is related to the secondary energy risks, such as the price volatility, supply disruptions and environmental destruction, rather than the primary risk which involved the geopolitical and technical risk.

Besides that, a study carried out by Sadorsky (2012) using a variable beta model to explore the systematic risk in the renewable energy industry found that sales growth has a negative effect on firm's risk, while oil prices exhibit a positive relationship. In contrast, Gatzert and Kosub (2016) investigation in the European country reveals that the policy and regulatory risk is the primary challenge to the renewable energy industry, thereby ensuring the stability of the policy and regulatory framework is necessary to ensure the stability of the renewable energy. This result is consistent with the study done by Holburn (2012), which suggests that the renewable energy industry is prone to regulatory risk.

On the other hand, Liu and Zeng (2017) has developed a causal loop diagram using the dynamics method to evaluate the investment risk in renewable energy. By considering three main types of risks in renewable energy industry which are the technical risk, policy risk and market risk, findings of the study reveal that the policy risk was the primary driver of investment in the initial development stage, while the market risk has been found to be the main drivers of investment during the maturity stage when both policy and technical risk decline. However, this study suggests the inclusion of other types of risk in order to have a better understanding of the resilience of the renewable energy industry.

In a more recent study carried out by Wu et al. (2020) among 54 countries have considered 32 risk factors which is classified under the technical, political, economic, resources, social and environmental as well as the Chinese factors. Interestingly, among all the risks included, the risk associated with the political, economic and resources has been found to be the most crucial in the renewable energy investment. In contrast, a study done by Nuriyev et al. (2019) in Azerbaijan based on the analysis on expert's opinions argued that the energy policy, grid access and financial risks are the most important factors.

Some studies on risk and renewable energy have also discussed the impact of climate change threats toward energy security. For example, the study conducted by Shadman et al. (2016) has examined the impacts of drought on electricity production in the ASEAN-6 countries. This study argued that, despite the benefits of renewable energy in reducing the environmental problems, however, this industry is greatly at risk with the change in the climate. Besides that, since the disaster risks continuously change over-time, this study highlighted the importance of addressing the changing disaster risks on the energy policy to ensure the resilience of the energy supply.

Consequently, with the global economy continues to become challenging, it is important to ensure the sustainability of the renewal energy industry. In light of the above discussion, to ensure the future sustainability of renewable energy, it is important to understand the potential risk involved in such industry. The study on the role of rare disaster risk on renewable energy has not been given its due attention in the literature. In particular, rare disaster risk refers to an economic phenomenon that rarely occurs, but the impact is devastating. Following the seminal work of Rietz (1988), many studies have considered the roles of rare disasters, such as wars and economic crises, to unfold the equity premium puzzle. Consistently, Barro (2006a) and Gabaix (2012) have also supported the rare importance disaster, which can help to explain not only the equity premium puzzle but also to solve other macroeconomic puzzles.

An influential work by Berkman et al. (2011) has used the international political crises, obtained from the International Crisis Behavior (ICS) database, as a measure of rare disaster risk to investigate the link between the changes in disaster risk and stock market prices. In particular, this study includes six dummy variables to account for the crisis severity which are the violence break, violence, full-scale war, grave threat, protracted conflict, and great power involvement. In addition, all the crises are aggregated into a single measurement to represent the crisis severity index. Findings of this study support that the change in disaster risk has a significant influence on the stock market returns and its volatility, which is consistent with the disaster risk model. Similarly, by using the same measure, Berkman et al. (2017) also found a positive relationship between the probability of disaster and market risk premium.

Following Berkman et al. (2011, 2017), a study carried out by Gupta et al. (2019a, b) supports that the rare disaster risk affects both returns and volatility in exchange rate, while only volatility is affected in the bond market. Similarly, Demirer et al. (2018) extended their investigation in the commodity market and found that the rare disaster risk has a significant effect on the oil market returns and volatility. Since the majority of the literature on rare disaster risk has focused on the equity market, further investigation on the impact of rare disaster risk on the renewable energy industry could help to untangle any issue related to the sustainability of the renewable energy supply. The failure to consider the rare events in the disaster risk analysis will severely underestimate the risk associated (Etkin et al. 2018). Considering the rare events in the risk analysis will not only help to identify the flaws in the system but also result in better policy intervention.

In light of the above literature review discussions, the main objective of this study is to examine the causality between the rare disaster risk categories and renewable energy production in the USA. The contribution of this study is twofold. First, to the best of our knowledge, this is the first study that explores the link between rare disaster risk and renewable energy supply. So far, the study on rare disaster risk has mainly been a focus in the equity market, while no studies have been done to discover this potential threat in the renewable energy sector. Secondly, this study utilized the advanced methodology which is based on wavelet coherence and rolling-window analysis to determine the direction of the causality. This method is more flexible since it can be applied for both stationary and nonstationary data and allow the analysis to distinguish between time horizons and thereby help to identify causality at various time frequency.

3 Data and methodology

This section provides a detail discussion on the data and methodology used to examine the relationship between rare disaster risks and renewable energy production (REN) of the USA.

3.1 Data

In our study's empirical analysis, we have used monthly data of renewable energy production and dummy variables which represents several types of rare disaster risks variables, covering the time period from 1973-01 to 2016:12 for the USA. The renewable energy data are extracted from EIA Web site, and total number of observations are 573. The data of rare disaster risks are obtained from the comprehensive ICB[1] database. The database covers exhaustive information related to 464 global political crisis occurred from 1918 to 2013 on monthly basis including 1036 crisis actors. The detailed discussion about the ICB database

[1] https:// sites.duke.edu/icbdata.

Table 1 Results of descriptive statistics. *Source*: Authors estimation

Variables	Mean	Min	Max	SD	Skew	Kurtosis	JB	*P* value
Renewable energy production	6.264	5.718	6.848	0.225	0.475	3.964	19.922	0.000
All disasters	0.386	0.000	3.000	0.624	1.421	4.059	202.290	0.000
Violent	0.155	0.000	2.000	0.373	2.121	6.210	622.562	0.000
War	0.097	0.000	1.000	0.296	2.731	8.460	1312.289	0.000
Violent break	0.059	0.000	2.000	0.251	4.454	23.792	1125.330	0.000
Protracted	0.265	0.000	2.000	0.487	1.594	4.605	280.365	0.000
Major power	0.379	0.000	2.000	0.607	1.363	3.759	176.144	0.000
Grave	0.081	0.000	2.000	0.281	3.316	13.110	3216.225	0.000
Crisis severity	1.422	0.000	12.000	2.273	1.317	3.712	163.876	0.000

and variables construction is provided by Brecher and Wilkenfeld (1997). The ICB database identifies the crisis breakpoint as an event, act or changes illustrated by these three conditions: (1) danger to basic value, (2) extreme chances of involvement in military hostilities, and (3) time pressure for response. We have followed Berkman et al. (2011, 2017) for creating the most influential disaster risks dimensions for our study using the ICB data. There are seven crisis variables—(1) violent, (2) war, (3) violent break, (4) protracted, (5) major power, (6) grave, and (7) crisis severity index (detail definition of each dimension is available in "Appendix"). These risk variables are constructed as monthly counts for the respective rare disaster risk category. Moreover, for these crisis factors, dummy variables are created, which equates to zero if a certain crisis does not occur in a specific month, and 1 otherwise. In order to understand which risk factor holds comparatively more information in predicting renewable energy production, all dummy variables are normalized with zero mean and variance of 1. The descriptive statistics in Table 1 show that all the studied variables are skewed with excess kurtosis. Moreover, the null hypothesis of normality is rejected, with JB test statistic being significant at 1% level of significance for all the variables. This, in turn, provides preliminary support for relying on the wavelet approach for our analysis (Raza et al. 2017; Sharif et al. 2017a, b; Mishra et al. 2019; Batool et al. 2019).

3.2 Methodology

3.2.1 Wavelet transform method

The wavelet transform method provides a more reliable outcome as compared to the Fourier transform particularly when the objective is to detect the transitory effects across time and frequencies (Tiwari et al. 2015). Moreover, Fourier transform assumes our current study's events are not cyclic and are spread evenly across different time intervals (Kim and In 2003). Interestingly, wavelet transform method performs analysis of original time series with varying length of wavelets endogenously: it measures low-frequency movements by extending into long wavelets function; and to measure high-frequency movements it compresses into short wavelet function (Aguiar-Conraria and Soares 2011). The cross-wavelet techniques are useful for analyzing the interactions between time series at numerous frequencies and the over-time evolution. The cross-wavelet power of two time series demonstrates the situation of confining covariance between time series. In time–frequency space, the wavelet coherency represents the correlation coefficient. Moreover, the term "phase" is a frequency function, and it denotes the series position in the pseudo-cycle (Aguiar-Conraria et al. 2008).

3.2.2 The continuous wavelet transform (CWT)

This type of wavelet transform represented by $W_x(m,n)$ is developed by investigating a specific wavelet $\psi(.)$ against the time sequence $x(t)$ such that it belongs to space $L^2(\mathbb{R})$, such that,

$$W_x(m,n) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{n}}\psi\left(\frac{t-m}{N}\right)\mathrm{d}t. \tag{3.1}$$

An important facet of CWT is its competency to decay and afterward flawless reconstruction of a time series $x(t)$ such that it belongs to space $L^2(\mathbb{R})$:

$$x(t) = \frac{1}{C_\psi}\int_{0}^{\infty}\left[\int_{-\infty}^{\infty} W_x(m,n)\psi_{m,n}(t)\mathrm{d}u\right]\frac{dn}{N^2}, N > 0. \tag{3.2}$$

In addition, the CWT preserves the power of the studied time sequence; the equation is written as follows:

$$\parallel x \parallel^2 = \frac{1}{C_\psi}\int_{0}^{\infty}\left[\int_{-\infty}^{\infty}\left|W_x(m,n)\right|^2\mathrm{d}m\right]\frac{dn}{N^2}. \tag{3.3}$$

We use these features in our research to explain the wavelet coherence (WC), which measures the correlation between two time series (Tiwari et al. 2015).

3.2.3 The wavelet coherence (WC)

Following Torrence and Webster (1999), the modified model of the wavelet coherence coefficient is written as below:

$$R^2(m,n) = \frac{\left|N\left(N^{-1}W_{xy}(m,n)\right)\right|^2}{N\left(N^{-1}\left|W_x(m,n)\right|^2\right)\cdot N\left(N^{-1}\left|W_y(m,n)\right|^2\right)} \tag{3.4}$$

where R represents the smoothing operator, with $0 \le R^2(m,n) \le 1$. A value of zero for R^2 (WC correlation coefficient) depicts the absence of association, and a value close to one shows that the two time series are highly connected. Therefore, R^2 depicts the interaction through the local linear association between two variables' stationary series at each scale and is similar to the squared correlation coefficient in linear regression.

Table 2 Results of the Narayan and Popp (2010) unit root test with two structural breaks

	Level				First difference			
	t statistic	TB1	TB2	*k*	*t* statistic	TB1	TB2	*k*
Model M1: two structural breaks at unknown dates in the level								
Renewable production	−1.712	5/10/2009	1/8/2009	1	−26.320***	5/10/2009	1/8/2009	1
All	−2.111	12/4/2008	7/22/2008	2	−25.682***	12/4/2008	7/22/2008	2
Violent	−2.517	12/28/2010	4/21/2011	1	−36.338***	12/28/2010	4/21/2011	1
War	−2.786	12/4/2008	11/15/2010	3	−35.438***	12/4/2008	11/15/2010	2
Violent break	−2.369	11/13/2008	12/12/2008	2	−25.870***	11/13/2008	8/25/2010	4
Protracted	−2.647	11/27/2008	11/25/2009	4	−16.573***	11/27/2008	11/25/2009	5
Major power	−2.785	5/17/2009	5/5/2011	1	−43.823***	5/17/2009	5/5/2011	1
Grave threat	−2.486	5/17/2009	8/18/2010	0	−22.137***	5/17/2009	8/18/2010	0
Crisis severity	−3.235	6/29/2012	1/26/2012	3	−18.499***	6/29/2012	1/26/2012	2
Model M2: two structural breaks at unknown dates in the level as well as in the slope								
Renewable Production	−1.552	5/10/2009	1/8/2009	1	−21.649***	5/10/2009	1/8/2009	0
All	−2.026	12/4/2008	7/22/2008	3	−25.495***	12/4/2008	7/22/2008	2
Violent	−3.681	12/28/2010	4/21/2011	0	−36.282***	12/28/2010	4/21/2011	0
War	−3.197	12/4/2008	11/15/2010	4	−35.738***	12/4/2008	11/15/2010	3
Violent break	−2.617	11/13/2008	12/12/2008	3	−26.583***	11/13/2008	8/25/2010	2
Protracted	−2.328	11/27/2008	11/25/2009	2	−16.893***	11/27/2008	11/25/2009	1
Major power	−3.186	5/17/2009	5/5/2011	5	−44.142***	5/17/2009	5/5/2011	4
Grave threat	−3.060	5/17/2009	8/18/2010	4	−22.193***	5/17/2009	8/18/2010	2
Crisis severity	−3.219	6/29/2012	1/26/2012	2	−18.389***	6/29/2012	1/26/2012	2

4 Empirical analysis and discussion

4.1 Unit root testing

The traditional tests of unit root do not have the power to predict structural breaks in the time series. Our variables, rare disaster risks, and renewable energy production, classically have structural breaks due to the nature of the disaster data, and the dynamics of geopolitical risks and the business cycle for renewable production. Therefore, having those breaks should be accounted for the accuracy of unit root tests. To undertake the structural breaks and to achieve the robustness of our results, this study employs the ADF-type unit root test by following Narayan and Popp (2010). This beauty of this test is that it incorporates two structural breaks at levels as well as slopes of the time series. Moreover, the timing of the potential breaks is not required in this test, as it endogenously determines the dates within the model. Further, this test allows breaks under both kinds of hypotheses, null as well as alternative. We do not need to explain the technicalities of unit root test of Narayan and Popp (2010) since the test has been in the wide use of existing financial and economic studies already. Table 2 presents the summarized results of unit root test of Narayan and Popp (2010) for our study variables.

It is clear from the unit root results that in the level, our renewable production and disaster variables are nonstationary; however, in the first difference, they all are stationary regardless that breaks are present in the level only or in both the level and slope. In addition, the presence of breaks in the variables' series indicates that the association between renewable production and disasters may vary over the time period. Therefore, the presence of structural breaks signifies the use of an analysis based on wavelet transformation and rolling-window causality as compared to the linear modeling.

This table displays the results of the Narayan-Popp unit root test for models M1 and M2 as explained in Narayan and Popp (2010). Models M1 (M2) assume two structural breaks at unknown dates in the level (level and slope) of each series. The critical values for model M1 are −4.731, −4.136, and −3.825 at the 1%, 5%, and 10% significance levels, respectively.

4.2 Interpretation of structural shocks

As mentioned in Table 2, most of the structural shocks in renewable productions and disasters are found during the period 2008–2010. This was the period of the world economic crisis, which led to a variety of crises and reduced gross domestic production and capital formation rates of USA. As a result, the investments in renewable projects declined which disturbed renewable production badly during the period. Further, a few breaks are coming during the period 2011–2012, which is the period of European debt crisis that caused a significant increase in interest rates. Consequently, policymakers and investors showed serious concerns about the spillover effects of this crisis on other counties outside Europe. Since global financial markets are integrated with each other, a default in one region may cause successive defaults in other parts. These structural breaks create volatility and uncertainty in the economy, thereby leading to the state of crisis in the country.

4.3 BDS test for nonlinearity

Next, before we start the discussion on our main findings, we check the robustness of the nonlinear relationship between renewable production and rare disaster variables in order to motivate the use of wavelet transformation and rolling-window analysis. For that, we statistically employ the test of Brock et al. (1996, BDS) on the residuals of renewable production and disaster variables' equations used in the linear causality model. Therefore, Table 3 reports the results of BDS test of nonlinearity. In this table, enough evidence is available for the rejection of the null of i.i.d. residuals at various considered dimensions (m). Therefore, the results reconfirm the presence of nonlinear relationship between renewable production and disasters. Hence, the application of wavelet transformation and rolling-window analysis considered robust and reliable.

4.4 Discussion of results

As mentioned earlier, the objective of this study is to examine the time-varying causality between different rare disaster risks and renewable energy production in the USA. Therefore, the results of a well-calibrated time-varying analysis of wavelet transformation are presented as follows.

Table 3 Results of BDS test for nonlinearity. *Source*: Authors estimation

Country	$m=2$	$m=3$	$m=4$	$m=5$	$m=6$
Renewable energy production equation residual					
Renewable production	11.859***	31.121***	33.921***	37.507***	41.680***
Rare disaster risk equation residual					
All	27.978***	31.121***	33.921***	37.507***	41.680***
Violent	34.648***	37.185***	39.919***	43.344***	48.151***
War	27.136***	31.334***	34.403***	38.892***	43.581***
Violent break	42.643***	46.645***	50.765***	55.818***	62.354***
Protracted	59.698***	64.205***	69.575***	77.206***	87.592***
Major power	11.820***	14.656***	15.531***	16.887***	18.622***
Grave	44.088***	47.856***	51.466***	56.478***	63.717***
Crisis severity	33.254***	36.615***	39.370***	42.723***	46.599***

***, **, *represent level of significance at 1%, 5, and 10%, respectively

4.4.1 Results of continuous wavelet transform

First, we present the results of continuous wavelet transform (CWT) for REN, all disaster risk, violent risk, war risk, violent break risk, protected risk, major power risk, grave threat risk, and crisis severity index risk for the USA in Fig. 1. In the case of REN, the robust variation outlines are found in lower and upper–lower level periods only under 4–8 and 8–16 scales, respectively. However, these variations outlines are largely found throughout the time period 1973–2016. Conversely, the significant variation in all disaster risk is observed in medium and high levels under 16–32 and 32–64 scales, respectively, and these variations are visible only in later years from 1995 onward. As far as variation in individual risks is concerned, the significant variation pattern in the cases of violent risk and war risk is quite similar; that is, upper–lower and medium scales of these risks show a significant variation, largely throughout the time period. Additionally, the high level of violent risk, 32–64 scale, also shows a significant variation in early years from 1973 until 1981. Interestingly, the robust variation in violent break risk is found across all the scales, lower, upper–lower, medium, high, and upper high scales, but in varying time periods. Moreover, the significantly strong variation is visible only in medium and high levels under 16–32 and 32–64 scales, respectively, during the period 1992–2006 for protected risk and 1995–2010 for major power risk. Next, the lower, upper–lower, and medium levels of grave threat risk show significant variations at varying times throughout the period of 1973–2016. Lastly, the period of 1995–2013 of crisis severity index risk shows a significant variation in upper–lower, medium, and high levels at 8–64 scales.

Overall, the outcomes of CWT suggest that all the variables performed well during the period 1973–2016 (Tiwari et al. 2015). Particularly, this is evident from the outcomes of CWT that REN and all disaster risks share the significant island during 1995–2016, REN and violent, REN and war, REN and violent break, and REN and grave threat largely share throughout the time period, REN and protected share during 1992–2006, REN and major power share during 1995–2010, and REN and crisis severity index share the island during 1995–2013. However, the relationship of these different risk variables with renewable energy production (REN) is not completely coherent from the outcomes of CWT, and the connection is also low in some instances; therefore, we move to the wavelet coherence

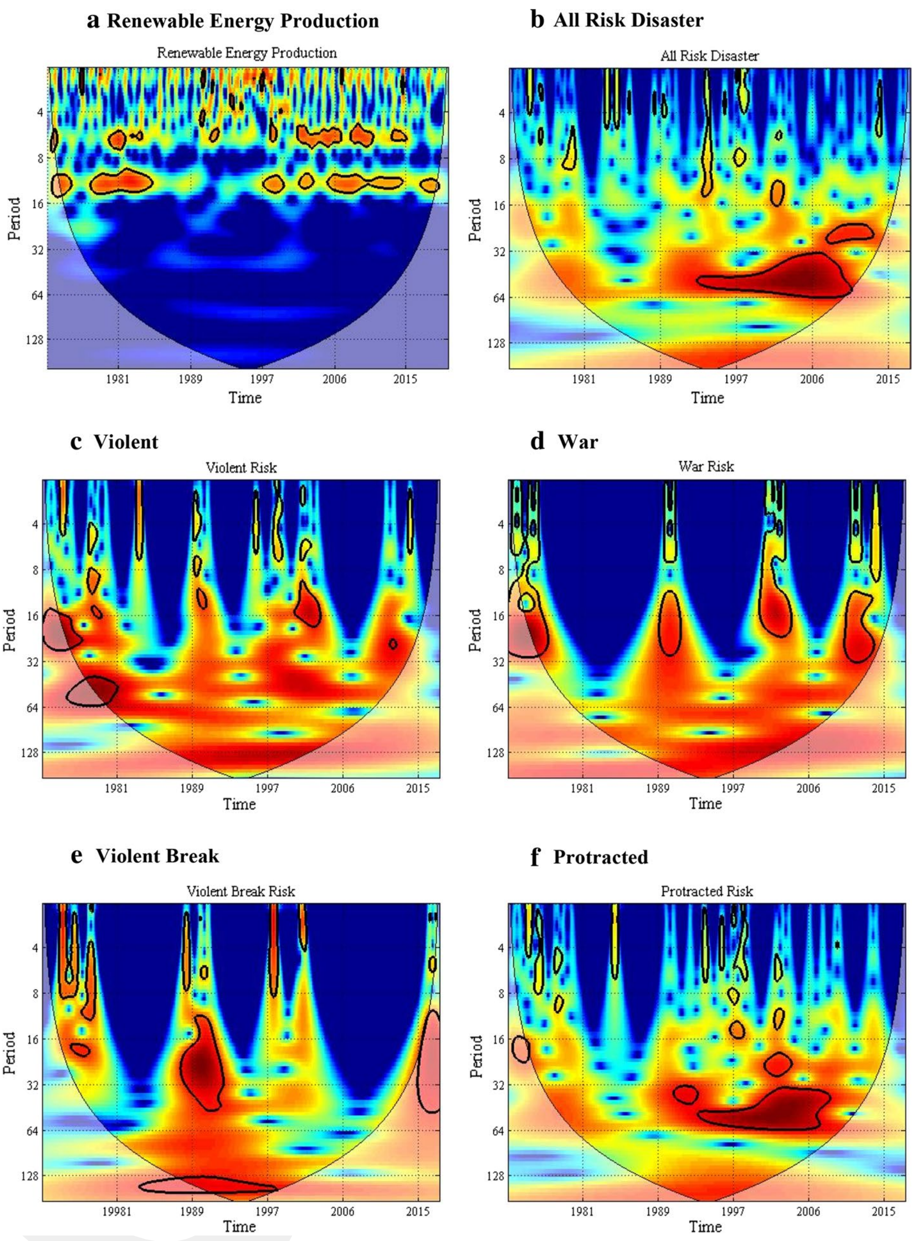


Fig. 1 Results of continuous wavelet transform between renewable production and rare disaster risk in the USA

transformation to achieve independent bivariate coherent relationships. The findings are confined with the theoretical postulations of endogenous environmental growth model (Elbasha and Roe 1995), that is environmental externalities can be mitigated with the help of renewable energy production if the risk of disasters is minimized.

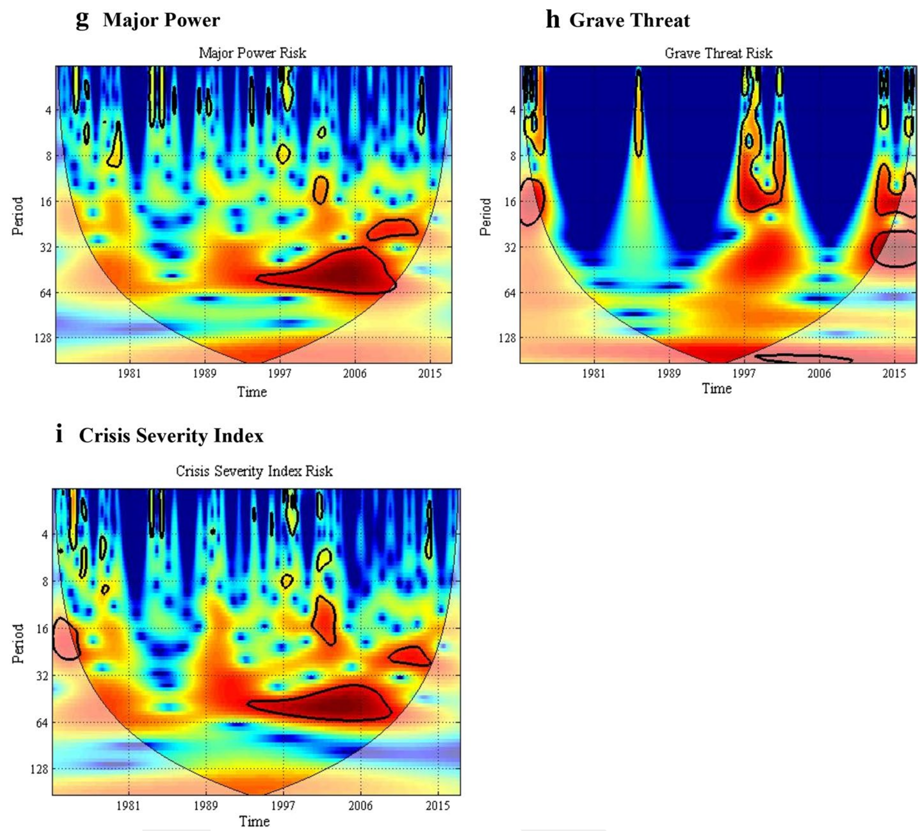


Fig. 1 (continued)

4.4.2 Results of wavelet coherence transform

The results of the wavelet coherence transform (WCT) are visible in Fig. 2. The WCT performs the detection of co-movement between the two series over the domain of time and frequency (Batool et al. 2019). As shown in Fig. 2, the outcomes of REN-ALL Risk Disaster show that in the periods of 8–16 and 32–64-year cycle during 2006–2015 and 1975–1985, respectively, the direction of arrows is left-side down meaning that REN-ALL are out-phase and maintaining anti-cyclic effect with leading effect by ALL Risk Disaster. On the contrary, however, there is a cyclic effect between REN-ALL, again leading by ALL Risk Disaster, in the cycle periods of 4–8 (2000–2004) and 128 onward (1989–2000). This shows that the disasters have leading effect on renewable production, provided that this effect is cyclic during short run and very long run and anti-cyclic during medium run. This is in accordance with the theoretical rationale that the state of disaster causes uncertainty in business cycle, thereby negatively affects investments required for renewable energy production. However, the counter possibility is that risk of disasters may influence the substitution of conventional energy products with renewable production.

As far as the WCT for REN and independent disaster risk category is concerned, the outcomes of REN-VIOLENT Risk depict that the direction of arrows is left side

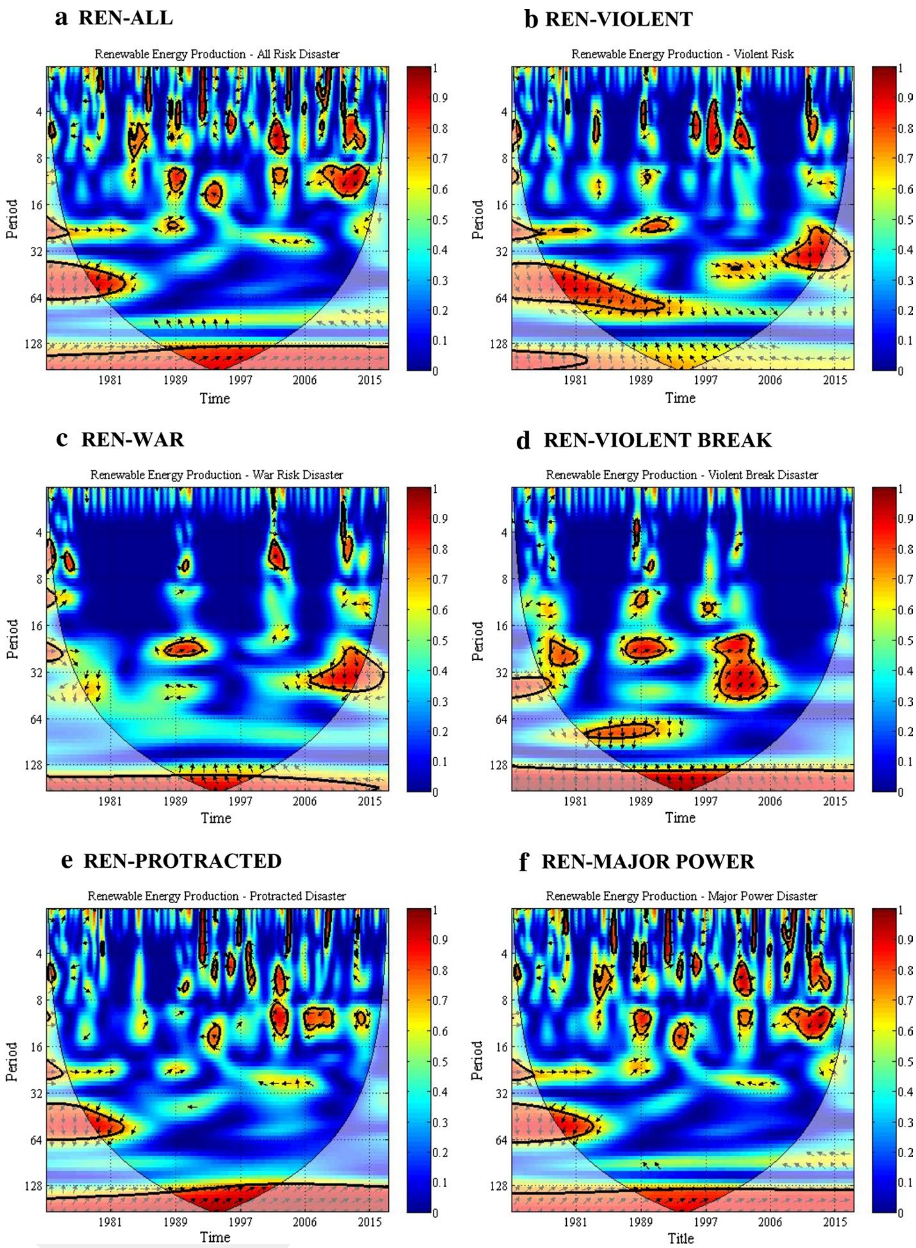


Fig. 2 Wavelet coherence transform between renewable production and rare disaster risk in the USA

down in the 32–64-cycle period during the time of 1980–1995. This shows the anti-cyclic effect, while VIOLENT risk is taking as a leading effect. However, some in-phase cyclic effect is also visible in the relationship of REN-VIOLENT during 1998–2004 in short run, 4–8-cyclic period. In this shared island, the leading effect is again assumed by VIOLENT risk. Overall, it is clearly understood that violent disaster risk has leading

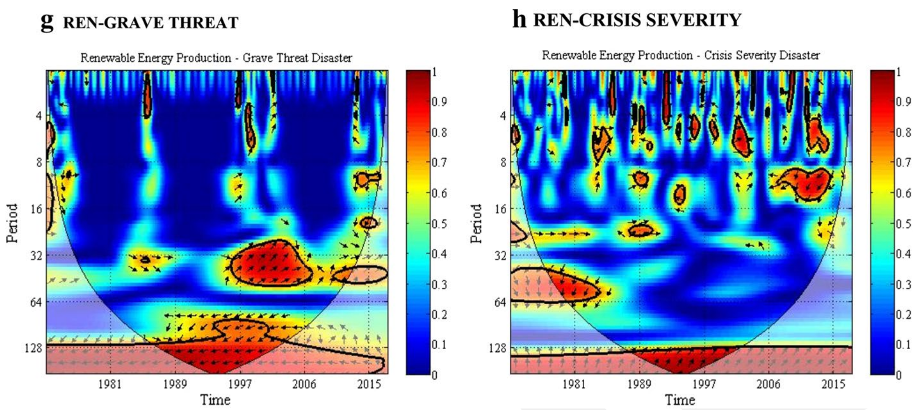


Fig. 2 (continued)

effect on renewable production in short and medium run. In the case of WCT for REN-WAR, the direction of arrows is right side upward in 4–8 and 16–32-cycle periods during 1999–2003 and 1988–1993, respectively, and right side downward partially in 16–32 as well as 32–64-cycle periods during the time of 2006–2010. This confirms in-phase cyclic effect, provided that the effect is from WAR to REN before economic crisis of 2008 and REN to WAR during the 2008 crisis period. Conversely, the out-phase anti-cyclic effect is also visible during 1989–1997 in a very high run, 128–onward-cycle period, explaining the lead role from REN to WAR.

Moreover, the WCT for REN-VIOLENT BREAK presents the arrows as right side up in the 16–64-cycle period, largely during the time of 1987–2006. This shows in-phase cyclic effect led by VIOLENT BREAK. However, the anti-cyclic effect with arrows left side down in early years in medium run, 16–32-cycle period is also found concluding similar leading role from VIOLENT BREAK to REN. In the very high run, there is also anti-cyclic effect but leading from REN during 1989–2000. The WCT for REN with risk categories of PROTECTED and MAJOR POWER is quite similar. Their outcomes show anti-cyclic effect with left-side down arrows in 8–16 and 32–64-cycle periods with leading effect by PROTECTED and MAJOR POWER risks. Conversely, during the time period of 1989–2004, the very long run, 128-onward-cycle period, and short run, 4–8-cycle period, of both these risks find right-side up arrows, representing cyclic effect with similar direction of leading effect. Overall, there appear to be both cyclic and anti-cyclic effects of VIOLENT BREAK, PROTECTED, and MAJOR POWER risks on REN in short run, medium run, and long run at different time periods.

Further, the robust outcomes of WCT between REN-GRAVE THREAT conclude right side upward arrows in the 16–64-cycle period and left side downward arrows in 64-onward-cycle period during the period 1996–2006 and 1988–2004, respectively. This shows GRAVE THREAT leads REN in medium run and high run but with cyclic effect in medium and anti-cyclic effect in long run. Lastly, the WCT for REN-CRISIS SEVERITY shows cyclic effect from CRISIS SEVERITY in the short run, 4–8-cycle period, and very long run, 128-onward-cycle period, from 1989 to 2004. On the contrary, the direction of arrows with left-side down is visible in 8–16 and 32–64-cycle periods. These anti-cyclic effects are found during 1978–1985 and 2006–2015, respectively, with leading role by CRISIS SEVERITY. The lead role is found robust in the relationship between REN-CRISIS SEVERITY.

To sum up, this study finds that all rare disaster risks have enough predictive power to lead renewable energy production, although this lead assumes both cyclic and anti-cyclic effects with respect to different scale and time periods. These findings are largely consistent with the existing literature on the effect of rare disaster risks on business cycle (Gourio 2012), stock market return and volatility (Barro 2006a, 2009; Demirer et al. 2018), bond returns and volatility (Gupta et al. 2018), and exchange rate return and volatility (Gupta et al. 2019a), suggesting that disaster probabilities affect asset prices, consumption, investment rate, and exchange rate, thereby affecting energy price processes. Further, the severe nonlinearity between rare disaster risks and renewable energy production based on time domain is in accordance with an endowment economy model (Weitzman 2007), which postulates nonnormal consumption growth rate. The model assumes that when a disaster risk is relatively likely, it makes conditional distribution of consumption growth strongly nonlinear.

4.5 Robustness analysis

In this section, we present the robust results of our main analysis by using the rolling-window causality approach.

4.5.1 Rolling-window causality

This sub-section briefly discusses the methodology of the rolling-window technique. The rolling-window causality (RW) provides better directional predictability among the studied variables (Shahzad et al. 2017). Following Hurn et al. (2015) and Shi et al. (2016), we use the rolling-window approach as robust check to our main analysis. Zapata and Rambaldi (1997) view bootstrapped RW results to be more efficient and appropriate for both large and small samples as it consists of superior size and explanatory power characteristics. Likewise, irrespective of the cointegration properties, bootstrap displays maximum accuracy in all estimations (Mantalos 2000). In light of the above-mentioned findings the bootstrap Granger causality test in our analysis depends on bivariate VAR(p) specification as follows:

$$y_t = \Theta_0 + \Theta_1 y_{t-1} + \cdots + \Theta_p y_{t-p} + \in_t \quad t = 1, 2, 3, \ldots, T \tag{4.5.1}$$

where $\in_t = \left(\in_{1t}, \in_{2t}\right)'$ is an independent white noise process with 0 mean and $\sum$—the nonsingular covariance matrix. To further simplify representation, y_t is separated into two sub-vectors. The first y_{t1} is related to the rare disaster risks[2] and second y_{t2} is regarding the renewable energy production. Equation 1 can be rewritten as follows:

$$\begin{bmatrix} y_{t1} \\ y_{t2} \end{bmatrix} = \begin{bmatrix} \theta_{10} \\ \theta_{20} \end{bmatrix} + \begin{bmatrix} \theta_{11}(L) & \theta_{12}(L) \\ \theta_{21}(L) & \theta_{22}(L) \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} + \begin{bmatrix} \in_{1t} \\ \in_{2t} \end{bmatrix} \tag{4.5.2}$$

[2] This consists of 8 categories that we have created for rare disaster risks namely, all disasters, violent, war, violent break, protracted, major power, grave, and crisis severity.

where $\theta_{ij}(L) = \sum_{k=1}^{p} \theta_{ij,k} L^k, \quad i,j = 1,2$ and lag operator, L is $L^k x_t = x_{t-k}^2$. Here, we test our null hypothesis that renewable energy production does not Granger cause the rare disaster risks with the imposition of restrictions $\theta_{12,i} = 0$ for $i = 1,2,\ldots,p$.

We utilize the rolling and recursive RW Granger causality techniques to address the challenge of structural instability associated with structural breaks. These structural changes can change the dependence direction between factors. In the rolling-window approach, the rolling-window size is fixed, and each subsample determines directional dependence. The recursive RW calculate test statistics for backward extending sample series. The Wald test is computed for the backward extending sample series for every observation of interest $\left(n \in \left[n_0, 1\right]\right)$. Thus, the sample series endpoint is fixed at n and the beginning point expend backward from $\left(n - n_0\right)$, it also serves as the minimum sample size accommodating regression, to 0. For every subsample regression, Wald statistic obtained is represented by $W_{n2}(n)$, with the sup-Wald stated as:

$$supW_n\left(n_0\right) = \sup\left\{W_{n_2}\left(n_1\right) : n_1 \in \left[0, n_2 - n_0\right], n_2 = n\right\} \tag{4.5.3}$$

In the directional relationship, let n_e and n_f denote the originating and terminating points, respectively. These points are calculated as the first chronological observation that correspondingly surpasses or drops below the critical value. In a specific switch case, below mentioned crossing times are used as dating rules:

$$\begin{aligned} \text{Rolling} : \hat{n}_e &= \inf_{n \in \left[n_0, 1\right]} \left\{n : W_n\left(n - n_0\right) > cv\right\} \quad \text{and} \quad \hat{n}_n \\ &= \inf_{n \in \left[\hat{n}_e, 1\right]} \left\{n : W_n\left(n - n_0\right) > cv\right\} \quad \text{and} \quad \hat{n}_n, \end{aligned} \tag{4.5.4}$$

$$\begin{aligned} \text{Recursive Rolling} : \hat{n}_e &= \inf_{n \in \left[n_0, 1\right]} \left\{n : SW_n\left(n_0\right) > scv\right\} \quad \text{and} \quad \hat{n}_n \\ &= \inf_{n \in \left[\hat{n}_e, 1\right]} \left\{n : SW_n\left(n_0\right) > scv\right\} \quad \text{and} \quad \hat{n}_n, \end{aligned} \tag{4.5.5}$$

where cv and scv denote the critical values of the W_n and SW_n statistics, respectively. Now, we turn our attention to multiple switches case in the sample period. The ith directional dependence's origination and termination points are denoted by n_{ie} and n_{if} for consecutive episodes $i = 1,2,\ldots,I$. The calculation of the dates related to the multiple switches' first episode and specific switch case is the same. For $i \geq 2$, n_{ie} and n_{if} are:

$$\text{Rolling} : \hat{n}_{ie} = \inf_{n \in \left[\hat{n}_{i-1t}, 1\right]} \left\{n : W_n\left(n - n_0\right) > cv\right\} \tag{4.5.6}$$

$$\begin{aligned} \text{Recursive Rolling} : \hat{n}_{ie} &= \inf_{n \in \left[\hat{n}_{i-1t}, 1\right]} \left\{n : SW_n\left(n_0\right) > scv\right\} \quad \text{and} \quad \hat{n}_{if} \\ &= \inf_{n \in \left[\hat{n}_{ie}, 1\right]} \left\{n : SW_n\left(n_0\right) > scv\right\}, \end{aligned} \tag{4.5.7}$$

Fig. 3 The rolling-window Granger causality from Rare Risk Disaster to Renewable Energy Production in the USA. *Note*: These figures represent the test statistic sequence (on the *y*-axis) of the rolling-window-based bootstrapped Wald tests and the corresponding 5% critical values. The time period is on the *x*-axis. Panel A shows the homoscedastic version of Granger causality from Rare Risk Disaster to Renewable Production, whereas Panel B carries the heteroscedasticity-consistent version of the tests

Moreover, we follow Shi et al. (2016) and take into account both the standard and the heteroscedastic-consistent versions of the test statistics. Therefore, the sub-sample Wald statistic for the heteroscedastic-consistent version (i.e., $\tilde{W}_{n_1 n_2}$) is defined as:

$$\tilde{W}_{n_1,n_2} = \mathrm{T}_w\left(R_{\hat{\theta}n_1,n_2}\right)'\left[R\left(\hat{O}^{-1}_{n_1,n_2}\tilde{W}_{n_1,n_2}\hat{O}^{-1}_{n_1,n_2}\right)R'\right]^{-1}\left(R_{\hat{\theta}n_1,n_2}\right), \tag{4.5.8}$$

where $\hat{O}_{n_1,n_2} \equiv K_m \oplus \hat{Q}_{n_1,n_2}$ with $\hat{Q}_{n_1,n_2} \equiv \left[\sum_{t=[Tn_1]}^{[Tn_2]}\left(\sum_{i=[Tn_1]}^{[Tn_2]} x_i q_{ii}\right)x_t'\right]$ with q_{ii} is the ith row and ith column of Q, and $\tilde{W}_{n_1,n_2} \equiv \frac{1}{T_w}\sum_{t=[Tn_1]}^{[Tn_2]} \hat{\mathrm{E}}_t\hat{\mathrm{E}}_t'$ with $\hat{\mathrm{E}}_t \equiv \hat{\epsilon}_t \oplus x_t$. Thus, the Wald statistic that is heteroscedastic consistent is:

$$S\tilde{W}_n\left(n_0\right) = \sup\left\{\tilde{W}_{n_1,n_2} : n_1 \in \left[0, n_2 - n_0\right], n_2 = n\right\} \tag{4.5.9}$$

The simulation outcome by Hurn et al. (2015) underscores that the RW suffers from extreme size distortion, yet it has maximum accuracy when it comes to detection rate. The performance of recursive RW is fairly balanced in unidirectional case. However, in bidirectional case RW outperforms recursive RW. We follow Hurn et al. (2015) approach by using AIC in estimating each window's optimal lag length. Moreover, we prefer using bootstrap Wald test approach over LA-VAR-based Wald statistic to better estimate finite sample distribution (see Shahzad et al. 2017).

4.5.2 Results of rolling-window methodology

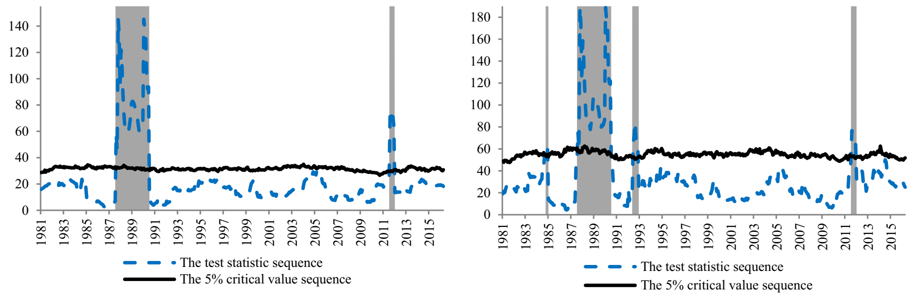
Next, we briefly discuss the RW bootstrap Wald statistics results for testing the directional predictability from rare disaster risks to the renewable energy production of the USA. This technique gives the best results as compared to the forward and recursive rolling methodologies for stationary and potentially integrated systems, respectively (Hurn et al. 2015; Shi et al. 2016). Therefore, the outcomes of rolling-window provide reasonable confirmation to our main results. Figure 3 displays the outcomes of rolling-window Granger causality from rare risk disaster to renewable energy production in the USA. The outcomes correspond to 5% critical values, considering both "homoscedasticity in Panels A," and "heteroscedasticity in Panels B."[3]

The robust outcomes reveal significant events of directional predictability from rare disaster risks to renewable energy production in all the categories of risks. Notably, both the assumptions of homoscedasticity and heteroscedasticity show similar outcomes for all the risks. However, the heteroscedasticity assumption shows significant outcomes of directional predictability in different time periods, particularly when the risk of disaster is

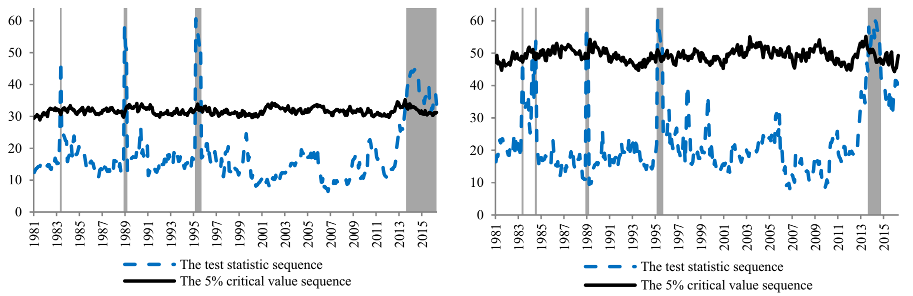
[3] Homoscedasticity is a state where the variance of error term remains the same across all the values. Heteroscedasticity is a state of violation of homoscedasticity when the variance of error term does not remain the same. This study follows the tests of Hurn et al. (2015) and Shi et al. (2016) for heteroscedastic-consistent versions. Their studies find that heteroscedastic-consistent tests should be given more emphasis; therefore, this study mainly focuses on the heteroscedastic-consistent estimates.


Panel A: Homoscedasticity
Panel B: Heteroscedasticity
a ALL Risk Disaster
The test statistic sequence
The 5% critical value sequence
b Violent
The test statistic sequence
The 5% critical value sequence
c War
The test statistic sequence
The 5% critical value sequence
d Violent Break
The test statistic sequence
The 5% critical value sequence

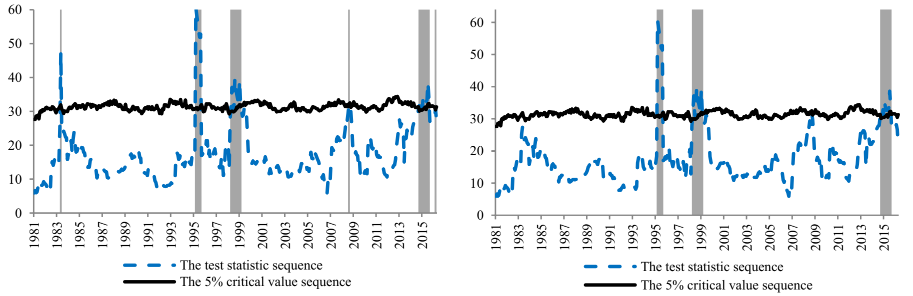
e Protracted



f Major Power



g Grave Threat



h Crisis Severity Index

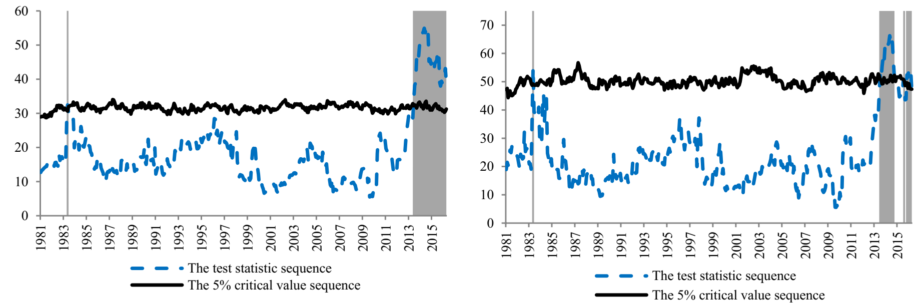


Fig. 3 (continued)

high. For instance, in the risk categories of ALL, VIOLENT, VIOLENT BREAK, MAJOR POWER, and CRISIS SEVERITY INDEX, the heteroscedasticity-consistent assumption shows a significant prediction at various time periods even when the risk is high. Overall, it is visible that most significant effects of rare disaster risks on renewable energy production are found in the time periods of 1983, 1986, 1989, 1990, 1994, 2001, 2002–2006, 2007–2008, 2009, 2011, 2013, 2014, and 2015. The major crises events which took place during those years and influenced US economy were invasion of Grenada, US involvement militarily in the Gulf of Syrte I and II crisis, invasion of Panama, Gulf war, Iraq-Kuwait conflict, Afghanistan war, Iraq regime change, North Korea and Iran nuclear crisis, world economic crisis, North Korea nuclear satellite launch, Libyan civil war, Syria chemical weapon crisis, and Turkey-Russia jet incident, respectively.[4]

The outcomes of the rolling-window bootstrap Wald test in Fig. 3 confirm the main results of wavelet coherence transform presented in Fig. 2, representing a significant predictability from rare disaster risks to renewable energy production in different time periods. Also, the time periods for this predictability in both the methodologies are largely same. Therefore, it is safely concluded that surge in disaster risks significantly affects renewable energy production through the channels of changes in business cycle and investment uncertainty.

5 Conclusion and policy

The increasing trend of economic and political crises in different parts of the world has made global economies highly vulnerable due to regional integrated economic systems. In such an environment, switching to alternative energy products, such as renewable energy production, may be devastating. Therefore, it is imperative to understand the dynamic relationship between such crises and renewable energy production in order to make sustainable decisions and produce efficiently. In this paper, we investigate the novel idea of a time-varying causal relationship between rare disaster risks and renewable energy production of the USA. Moreover, unlike most of the existing literature, we employ nonlinear methodologies to investigate this relationship using wavelet transformations and rolling-window analysis, since our diagnostic analysis signifies the nonlinear properties in the variables. Besides the advantages of the method to work with a nonstationary data, the wavelet analysis is superior compared to other traditional time series approaches due to its ability to examine the link between the two variables across time and frequency domain simultaneously unlike the traditional time series analysis.

We find robust findings that all the categories of rare disaster risks used in our investigation and renewable energy production have significant linkages with each other. Although both the variables have time-varying cyclic and anti-cyclic effects on each other, rare disaster risk leads renewable energy at most, and this lead is mostly a cyclic effect from disaster to renewable energy. Additionally, the robustness check using the rolling-window analysis also confirms unanimously that rare disaster risks have a significant predictability power on renewable energy production.

Following the US effort to reduce its carbon emission and meets the goals of the Kyoto Protocol, the share of the renewable energy in the US energy mix has continued to grow

[4] The ICB (https://sites.duke.edu/icbdata/) provides an overview of these crises events.

over-time. Since the renewable energy plays a crucial role in the future energy production, ensuring its resilience toward any potential risks is crucial to increase the investors' confidence toward the renewable energy industry. Findings of this study support that the producers of energy may safely switch to renewable energy production since disasters are found to have potential to leave cyclic effect on renewable energy at most. However, they should also consider the economic and political environment while making decision to produce renewable energy in order to avoid any minimal potential of anti-cyclic effect. Accordingly, investors may safely direct their investments to renewable projects to achieve the benefits of diversity and brighter future prospects. To meet the increasing needs of green energy with increasing rate of population, governments may incentivize renewable energy products and devise policies favorable to such projects. Hence, with a prudent policy framework and supports, this will help in achieving a sustainable growth in this sector and assist the country in moving toward becoming the world renewable energy leaders.

Future research in this field can consider other leading renewable energy countries as well as countries that are more exposed to the rare disaster risk. In addition, further investigation according to the types of the renewable energy can also be considered so as the analysis can be done at a much deeper level. Moreover, the future research can be done using multivariate variable techniques like partial and multiple wavelet coherence, nonlinear ARDL, etc.

Appendix

Variable definitions

We have followed Berkman et al. (2011, 2017) for creating the rare disaster risks variables. For these variables, we use the monthly count for the risk factors falls under various mentioned groups.

(1) a violent break (Violent Break) includes all the crises that starts with a violent act, (2) a violent (Violent) crisis includes all the crises that comprises either serious clashes or full-scale war, (3) a war (War) includes all the crises that involves full-scale wars, (4) all crises that involve grave value threats (Grave Threat), (5) protracted conflicts (Protracted) include all crises with protracted conflict, protracted crisis outside this conflict, and (6) major power (Major Power) includes the crises only if at least one superpower or great power is there in both side of conflict. Finally, we also construct a crisis severity index (Crisis Severity Index) that summarizes different aspects of crisis severity into one measure by aggregating the six variables above.

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